Movement and outcome variability of the golf swing of amateur golfers with driver and iron clubs

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Declaration

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Abstract

Movement variability may include a functional component but there is a lack of work which examines movement variability in the golf swing and its relationship with shot outcome measures. This research used biomechanical analysis techniques to understand variability in the golf swing. Since human movement variability and measurement error can be a similar magnitude, initial work determined the repeatability of ball launch, clubhead presentation, kinematic and kinetic measurements; using existing literature and three specific investigations. The full body kinematics, ground reaction force kinetics, address position, swing timing, clubhead presentation and ball launch of five, differently skilled male golfers with an iron and a driver club across three testing sessions were examined in a multiple single-subject investigation. These results showed individual specific patterns of variability, and differences between the participants had utility in informing a cohort investigation. Finally, the variability of ground reaction force kinetics, address position, swing timing, clubhead presentation and ball launch variables was examined in one hundred and four amateur golfers, of both genders and a range of abilities, with an iron and a driver club and in a single session. Lower handicap golfers had generally higher task performance and lower variability in outcome measures with both the driver and five-iron club. However, correlations between variability with the driver and the iron were generally low. Lower handicap golfers displayed lower or similar amounts of movement variability, but differences were small and there was significant overlap between the handicap groups. There were no clear differences in the structure of variability between the handicap groups. Movement variability did not appear to be related to outcome variability; rather the data suggest that golfers, irrespective of handicap or gender, use individual-specific movement patterns and a combination of functional movement variability and movement consistency to achieve outcome consistency.

Research communications

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1. Introduction

1.1. Chapter objectives

This chapter provides a short introduction and background to the topic area and introduces the overall aim of the thesis. The specific research questions which have been formulated to address this aim are presented, and a description of the organisation of thesis chapters, which have been constructed to address these research questions and the overall aim of the thesis, provided.

1.2. Context of the thesis

The aim in golf is to use a club to move a ball from the starting point, the teeing area, to the hole in the fewest number of strokes (The R&A and USGA, 2015). Generally played on a large open-air course, the modern game of golf originated in Scotland in the 15th-century (Brasch, 1970), but now has a global reach. Golf is played in 206 countries worldwide (The R&A, 2015), and 2016 saw its reintroduction into the Olympic Games. Sport England (2015) reported that over 1.1 million people in England participate in golf at least once a month; the fifth highest of all sports investigated. Furthermore, the European Tour (2015) reported that 3.5 million people in the UK play a full 18-hole course at least once a year and, when other forms of golf participation were included, just over a fifth of the UK population engage in some form of golf activity each year.

The importance of improved performance is immediately apparent at an elite level, where annual prize money can exceed $10 million for the highest ranked golfers (PGA Tour, 2015), but can positively impact all levels of player. An improved ability to meet the challenges of the game could lead to increased satisfaction and encourage greater engagement. Physical activity through golf participation has been associated with longer life (Farahmand et al., 2009) and improved metabolic (Parkkari et al., 2000) and respiratory health (Weisgerber et al., 2008). Whilst injury and illness risks have been identified, practitioners and policymakers have been encouraged to support participation in golf due to the positive side-effects (Murray et al., 2016).

1.3. Overview of existing research

Biomechanics is the scientific discipline concerned with the application of mechanical principles to understand the movement of biological systems (Bartlett, 1999), and emerged in the 1960's through attempts to apply the laws of physics to sporting movement (Lees, 2002). The British Association of Sport and Exercise Scientists classify biomechanics as one of the fundamental branches of sports science (BASES, 2018). In this regard, it has found application in golf in its ability to facilitate a deeper understanding of the movements which make up the golf swing. It has been applied to the golf swing with the aim of increasing performance (Chu et al., 2010) and decreasing injury (Dale and Brumitt, 2016), and there is a large base of golf biomechanics research which is well accepted in the golfing community (Morrison and Wallace, 2018).

Variability refers to the spread of data; how much a quantity varies. Within investigations into movement, this is made up of inter-individual variability, differences between individuals attempting a movement task, and intra-individual variability, trial to trial differences in movement in an individual's attempts at a repeated task.

Both inter- and intra-individual have been somewhat overlooked in the years that biomechanics has been applied to sporting movements (Bartlett et al., 2007). This is partly due to the assumption of an optimum technique, but there are many different techniques among elite athletes and high performance is not a guarantee of optimal technique. Also, even elite athletes cannot reproduce identical movement patterns, either within or between sessions, despite many years of training (Bauer and Schollhorn, 1997). Over the past decade, examinations of inter- and intra-individual variability have become much more prevalent in the sports biomechanics community and the increased frequency of research has highlighted that variability has the potential to have a positive or functional role in the coordination and control of movement (Bartlett et al., 2007; Preatoni et al., 2013).

Inter- and intra-individual variability has been of interest to motor control theorists for much longer than it has been of interest to biomechanists and there are a number of well-established motor control paradigms which view variability as having a functional role in human movement (Handford et al., 1997). In these paradigms, variability has been postulated to facilitate coordination changes, allow the exploration of alternative movement solutions and afford, or reflect, the ability to flexibly adapt to changes in the environment (Newell and Corcos, 1993). Research in sports and clinical biomechanics also suggests that variability could facilitate reduced injury risk, due to variation in the loading of internal structures (Hamill et al., 1999). However, the movements of interest to sports biomechanists are generally multi-segment movements where inertial coupling and multi-articular structures complicate attempts to understand the impact of variability (Bartlett et al., 2007). Interactions between multiple components of the movement system allow variability in one component to compensate for variability in another, maintaining a consistent outcome which is generally desired in sport (Bootsma and van Wieringen, 1990). The positive role of variability in general movement has been well-documented, but literature regarding variability in the golf swing is limited.

The fundamental areas of golf biomechanics are relatively well researched, but there is little high-quality scientific literature investigating movement variability in the golf swing. Much of the existing information relating to inter- and intra-individual variability in the golf swing has been presented as an aside to more conventional biomechanical investigations (Glazier, 2011) and investigations focusing solely on the variability of the golf swing have tended to focus on the variability of outcome variables (Betzler et al., 2012) or the clubhead during the swing (Tucker et al., 2013). Research into other areas is limited, either in its existence or by fundamental issues in its data collection or analysis (Glazier, 2011). Coaches suggest that golfers should develop a swing which is consistent and repeatable (Smith et al., 2012), ignoring the potential for functional variability. This reflects the commonly held view that variability in the golf swing is undesirable, despite research in other movements which consistently shows this view to be incorrect (Davids et al., 2003). Building an understanding of the variability of the golf swing for differently skilled golfers will allow scientific results, and observations made by coaches and club-fitters, to be interpreted within the proper context of an inherently variable human movement system.

1.4. Purpose of the thesis

The purpose of this thesis is to investigate intra-individual variability in the golf swings of differently skilled golfers. Existing literature in this topic area is limited and, as such, the thesis is primarily concerned with expanding the foundation of research which considers variability in the golf swing. To address this purpose, the following research questions will be considered:

A. *How does the intra-individual variability in the golf swing relate to golfing skill?*

Primarily, this thesis is concerned with investigating differences in variability between differently skilled golfers. Whilst differences in variability between differently skilled participants have been reported in other sports, a general relationship between skill and variability has not been found; rather it has been suggested to be task and variable dependent (Busquets et al., 2016).

B. *Is the relationship between the intra-individual variability of movement and golfing skill different to the relationship between the intra-variability of outcome and golfing skill?*

Existing research has found variability in the outcome of a movement to be different to the variability of the movement itself (Bootsma and van Wieringen, 1990). Research into variability in golf has focused on outcome variables (Betzler et al., 2012) and differences in movement variability between golfers are unclear. Furthermore, research has not jointly considered movement and outcome variability to examine potential relationships.

C. *Is the relationship between the magnitude of intra-individual variability and golfing skill different to the relationship between the structure of intra-individual variability and golfing skill?*

To fully consider the variability of a movement, it is not only necessary to examine how much variability is present, but also how this variability is structured (James, 2004). The structure of variability in the golf swing has not been researched but should be considered to characterise the relationship between golfing skill and variability fully.

D. How does intra-individual variability in the golf swing differ between repeated testing sessions?

Typically, research has considered only the intra-individual variability within a single testing session, but it is also prudent to consider differences in this variability between multiple testing sessions. This is an essential step toward understanding the context within which differences in intra-individual variability are interpreted.

E. How does intra-individual variability in the golf swing differ with different golf clubs?

It is common for golf biomechanics research to consider only one club during an investigation, most often the driver club. However, many clubs are used over a single round of golf and differences in variability, or the relationships between variability and golfing skill, could manifest differently in the golf swing with different clubs.

1.5. Structure of the thesis

To address the overall research aims, this thesis comprises five further chapters which are structured as follows:

Chapter 2 - Literature review

A critical review of the literature pertinent to the research questions, the literature review begins with an examination of the motor control paradigms relevant to understanding movement variability. This provides a basis for the theoretical interpretation and leads into an exploration of functional movement variability. The chapter closes with a thorough evaluation of existing research into variability in the golf swing.

Chapter 3 - Methodology

The theory underpinning the data analysis and experimental methods is examined, and the conceptual frameworks within which the research will reside are explored. The chapter finishes with three methodological investigations, which examine specific aspects of the methodology to quantify the repeatability of measurements across repeated trials. These measures of repeatability provide an assessment of the measurement error in the systems used and help to determine the meaningfulness of differences observed in subsequent studies.

Chapter 4 - Multiple single-subject investigation

This chapter presents a multiple single-subject investigation in which the inter- and intra-session variability of five differently skilled amateur male golfers was thoroughly examined. This investigation provided information about the specific patterns of variability in the golfers studied and, whilst not generalisable to a larger cohort of golfers, provided a valuable basis for further study. Due to the large amount of information gathered during the investigation, the chapter is structured with a general introduction and common methods section, several shorter, specific research investigations and a concluding discussion and summary. The sub-sections consider the variability in shot outcome, ball launch and clubhead presentation, the variability of swing kinematics, the variability of address position and swing timing and the variability of ground reaction force and centre of pressure during the swing.

Chapter 5 - Cross-sectional investigation

This chapter presents a cross-sectional study of the variability of a large group of amateur golfers in a single testing session. The study design and analysis procedures were constructed using the information gathered from the multiple single-subject investigation, and the chapter is structured into similar sections to maximise readability. The sub-sections consider the variability in shot outcome, ball launch and clubhead presentation, the variability of address position and swing timing and the variability of ground reaction force and centre of pressure during the swing.

Chapter 6 - Discussion and summary

This chapter discusses and summarises the results in relation to the specific research questions and examines the implications and limitations of these findings. This discussion allows recommendations for future research to be developed.

2. Literature review

2.1. Chapter objectives

The objective of the literature review is to critically review relevant research on the broader areas of golf biomechanics, motor control and biological movement variability, and the specific topic area of variability in golf. The literature review will outline the theory and rationale for investigations conducted in the main body of the thesis.

2.2. Introduction

Over the course of a round, a golfer must adapt and utilise a range of trajectories to hole the ball using the fewest possible strokes (Hume et al., 2005). Although environmental factors, such as the wind, also influence the final shot outcome, the impact between the club and the ball is the primary determinant of the resultant trajectory of the ball (Betzler et al., 2014). By controlling their movements and through the selection of an appropriate club, the golfer attempts to manipulate this impact to produce a ball flight trajectory which finishes as near to their intended target as possible. The movements utilised by golfers typically sit on a continuum between the full swing and the putt (Hume et al., 2005). The swing with woods and long irons utilises the greatest range of motion and the largest forces, whilst the swing with short irons and wedges utilises a smaller range of motion to manipulate the club dynamics to produce shorter trajectories. The putting movement, generally performed with a putter club, utilises a small range of motion to roll the ball towards the hole in a controlled, accurate manner. The successful golfer must coordinate numerous mechanical degrees of freedom to meet varied demands on both accuracy and velocity, and the study of the golf swing could provide insights into other multi-articular movements.

2.3. Movement variability and human motor control

2.3.1. Introduction

"Variability is inherent within and between all biological systems."

(Newell and Corcos, 1993, p. p1)

Traditionally, inter- and intra-individual variability have been viewed as operational measures; however, sports biomechanists have recognised a need to shift their outlook on variability (Bartlett et al., 2007; Preatoni et al., 2013). The traditional view of variability stems, in part, from the assumptions of a single perfect technique and consistent movement patterns in skilled performers (Bartlett et al., 2007). However, these assumptions have been shown to be incorrect, with large differences in technique observed between elite athletes (Morriss et al., 1997) and a large body of evidence which suggests that athletes, including elite performers, are not able to recreate identical movements within or between sessions (Bartlett et al., 2007). A certain amount of variability is characteristic of all human movement, regardless of task familiarity (Figure 2.1). A shift in outlook can view this variability as more than noise, or error in the system, instead playing a functional role in movement coordination. This potential for functional variability has gained interest within the sports biomechanics community (Bartlett et al., 2007; Langdown et al., 2012; Preatoni et al., 2013) and variability has received more research interest in recent years. However, there is still potential for novel research in many sports, including golf.

Figure 2.1. Inter- and intra-individual variability in a well-learnt motor task; writing (diagram based on Preatoni et al., 2013, p. 70).

It would be wrong to characterise any change in outlook as a modern one, as debate on the nature of movement variability dates back many decades in the field of motor control (for example, Kugler et al., 1980). It would be more apt to say that this debate has taken time to filter into the mainstream sports biomechanics consciousness, possibly due to the need to overcome deep-rooted assumptions of single, ideal movement patterns (Bartlett et al., 2007). Motor control is a sub-discipline of the field of motor behaviour that is primarily concerned with how humans control movement (Fairbrother, 2010) and it provides a theoretical basis for understanding both inter- and intra-individual variability. Motor control studies the interwoven principles of perception, cognition and action (Utley and Astil, 2008) and it is through an understanding of motor control paradigms that the role of human movement variability in sport can be understood.

2.3.2. Bernstein's problem

A fundamental question in motor control theory is how the human, a complex biological system, can coordinate and control a vast number of biomechanical degrees of freedom to produce goal-directed behaviour (Bernstein, 1967). This is often referred to as Bernstein's problem, after influential Russian physiologist Nikolai Bernstein who formulated this problem (Latash, 2000). Bernstein stated that the fundamental problem for the human movement system is how to master redundant degrees of freedom (Bernstein, 1967). Redundancy exists throughout the human body, from a molecular level, where multiple DNA codings specify the same amino acid (Nowak et al., 1997), to the numerous mechanical degrees of freedom at the macro level (Newell and Vaillancourt, 2001). There are seven degrees of freedom in the arm, more than most typical tasks require, and many more combinations of muscle activity which could result in a given movement (Davids et al., 2003). The body must coordinate these degrees of freedom to produce dexterous goal-directed movement and knowledge of the method in which this is achieved would allow considerable insight into the control of human movement.

Different approaches to this redundancy problem are examples of different conceptual frameworks associated with different motor control theories. For example, cost functions have been hypothesised and optimised to infer the methods used to coordinate the human movement system (Prilutsky and Zatsiorsky, 2002). These cost functions include the rate of change of torque, jerk or muscle tension (Wolpert, 1997). An alternative view is that of motor abundance, which hypothesises that, instead of the computationally demanding task of micromanaging every aspect required for motor control, the central nervous system does not differentiate between specific solutions and allows the laws of physics to solve the problem according to the task demand (Latash, 2012).

In motor abundance theory the numerous degrees of freedom which exist in the human motor system are not a problem but a benefit, allowing flexibility through the existence of multiple solutions (Latash, 2012). It has been argued that redundancy has been viewed as a negative feature of a system; implying surplus and a need to overcome inherent complexity to coordinate functional behaviour. This may stem from an imprecise translation of Bernstein's original work with 'redundancy' or 'abundance' both possible translations of the Russian "izbytochnost" (Latash, 2000). A shift of terminology from redundancy to abundance promotes the idea that the complexity of the system is an advantage rather than a challenge to control, and allows a system to be both flexible and stable; effectively dealing with secondary tasks and unexpected perturbations (Latash, 2012).

Whilst many theories exist which attempt to explain the coordination and control of movement in biological systems, this review will focus on two general theoretical perspectives: information processing theory and dynamical systems theory. Information processing theory emerged from the cognitive approach to psychology while dynamical systems theory emerged from the ecological approach. The two theories are often described as incompatible (Anson et al., 2005).

2.3.3. Information processing theory

Sometimes referred to as cognitive motor control, the key principles within information processing theory have a certain commonality with the computer sciences (Handford et al., 1997) and are based on the work of Adams (1971) and Schmidt (1975). In information processing theory, raw sensory information is channelled into the human mind, which is conceptualised as being a limited capacity device, where it must be processed and acted on through the utilisation a stored motor plan (Handford et al., 1997). The theories of indirect perception and motor programming, paralleled with the decoding and processing of information in the computer sciences, posit how this can be achieved (Handford et al., 1997). Indirect perception considers sensory information as in need of interpretation before it can be utilised by the motor system (Handford et al., 1997). This processing is hypothesised as taken place in several computational stages before a suitable motor programme can be given in response. The five-stage information processing model (Schmidt and Wrisberg, 2004) considers the stages as input stimulus, stimulus identification, response selection, response programming and output response; via a suitable motor programme (Adams, 1971).

Rather than a single motor programme for each action, general motor programs with changeable parameters are hypothesised as controlling entire classes of movement, for example throwing or kicking (Schmidt, 2003).

Whilst information processing theory has spent time as the dominant approach in motor control, limitations in are evident in its application to real-world movements involving multiple degrees of freedom. Information processing theory postulates a hierarchical control structure where the human body is 'controlled' by the mind; the perceptual sub-systems provide a stimulus to the higher systems which select movement patterns in a rule-based manner (Handford et al., 1997). Cartesian dualism, where the mind is considered a special organ (Handford et al., 1997), and organismic asymmetry, the preference to search for organism-centred mechanisms (Davids and Araujo, 2010), have been highlighted as limitations in this method. This mechanistic view of motor control is limited by the sheer number of variables which must be specified and the range and depth of sensory information which must be processed by the brain. Well suited to simple movements with few degrees of freedom, information processing theory struggles to explain behaviour in complex multi-articular tasks. For example, Lacquaniti and Maioli (1989) found that participants significantly reorganised muscle responses with no decrease in performance when visual information was removed in a catching task. In mechanical terms, an extremely powerful processor would be required to compute the necessary changes to display such flexibility and adaptation (Handford et al., 1997). One of the most popular alternative approaches is dynamical systems theory, which is popular among proponents of the ecological approach to human movement (Bartlett et al., 2007).

2.3.4. The ecological approach and dynamical systems theory

Ecological science is the multidisciplinary study of living systems, their environments and the interactions between the two (Kugler and Turvey, 1987). The ecological approach to motor control emphasises the system and the organism-environment interactions rather than internal knowledge and control structures (Handford et al., 1997). A systems approach to human movement studies the human system rather than its constituent parts (Williams et al., 1999). It is hypothesised that the integrated sub-systems in the human body must be coordinated and the isolated study of one of these systems, the neural, perceptual or musculoskeletal systems, for example, does not capture its true behaviour (Williams et al., 1999). Another feature hypothesised by an ecological approach is the circular relationship between the perception and movement systems; perception-action coupling (Michaels and Beek, 1995). Perceptual information created by the organism or environment can constrain and coordinate movement; guiding the neuromuscular system to the appropriate pattern of coordination for a task (Michaels and Beek, 1995). This information, including external information such as light, can be directly utilised by the movement system and does not require processing by a higher system (Handford et al., 1997).

Dynamical systems theory, which generally describes the behaviour of complex, dynamical systems, has gained popularity within the ecological approach (Bartlett et al., 2007). It seeks to explain the behaviour of these systems using nonlinear dynamics, which uses mathematical and physical principles to explain the evolution of nonlinear systems over time (Strogatz, 2015; Williams et al., 1999). This is feasible, even in biological systems, due to the ontological reduction of biology to physics at the atomic level. The laws of physics and the underlying mathematics are universal; they do not depend on the detailed composition of the system and apply to all types of system and all time scales (Yates, 1979).

Dynamical systems theory characterises the human movement system as a complex, dynamical system to understand the dynamics of motor coordination. A dynamical system is one where fixed rules describe how quantities evolve over time, either deterministically or stochastically, in response to their own values (Davids et al., 2003). Complex systems are those with many varying components, many levels to the system, nonlinearity of behavioural output, a capacity for patterned relationships to form through self-organisation, and the ability for components to interact to constrain the behaviour of other sub-systems and produce changes in global behaviour (Williams et al., 1999). Examples of complex, dynamical systems include the weather, animal and human colonies, economic markets and the human body (Williams et al., 1999). These systems are best studied at a macroscopic level where patterns can be observed, as microscopic detail might appear chaotic and the system can change between organisational states based on the internal and external pressures (Williams et al., 1999).

Two facets of dynamical systems are that they are open and able to self-organise (Williams et al., 1999). Firstly, complex systems are open; energy is free to enter or leave the system in interactions with the environment. Brief periods of stability are possible, but long-term behaviour is difficult to predict due to the influence of the environment. Secondly, the system uses environmental information to shape pattern formation and sustain functional stability. This self-organisation is spontaneous pattern formation in response to internal and external pressures (Kauffman, 1993). Self-organisation in inanimate and animate systems is similar, but Warren (1990) argues that the openness of biological systems, via sensory systems which are in tune with their environment, allows these systems to be guided by both external and internal changes.

Biological systems are special-purpose; they operate according to relatively few general principles, within restricted energy settings and can achieve states of relative stability as a result (Turvey, 1990). Despite numerous degrees of freedom, most natural systems settle into relatively few stable, preferred states in goal-directed actions. These represent the relatively few functional modes available to the system (Kauffman, 1993) and generally take advantage of coordinative structures to maintain stability (Davids et al., 2003). Coordinative structures act to convert a system with high dimensions and many independent degrees of freedom into a system with low dimensions and relatively few independent degrees of freedom (Kay, 1988). The structures make compensatory adjustments to its components to maintain a stable output with relative autonomy from an external regulator (Latash et al., 2002); in other words, coordinative structures can self-organise (Kelso, 1995). They can appear at different levels including the molecular, cellular and muscular levels and can be assembled instantaneously, temporarily and flexibly (Kay, 1988). The presence of coordinative structures complies with a primary tenet of dynamical systems theory; that deterministic processes can drive fluctuations which seem random (Williams et al., 1999).

A complex, dynamical system has a state space which consists of all hypothetical states of order and settles into areas of dynamic stability, attractors, depending on the internal and external constraints (Kauffman, 1993). In the human movement system, the state space represents all possible states of coordination and the preferred states roughly correspond to states which are functional given the task at hand (Williams et al., 1999). These attractor states are not stored, they are irresistible and evolve as a response to the constraints on the system and the interactions between the system and the wider environment (Handford et al., 1997). In this approach, movement is not prescribed according to a predefined plan; rather coordination arises instantaneously from the constraints acting on the system and variability allows the system to flexibly explore the state space to discover and utilise optimum patterns of coordination (Williams et al., 1999).

Constraints are defined as internal or external limitations which restrict the possible configurations available to the system (Sparrow and Newell, 1998). Rather than constraints causing action; constraints act to exclude actions to guide the dynamics of a movement (Kugler et al., 1980). Newell (1986) argued that the primary constraints on human movement can be divided into organismic, environmental and task constraints and that a combination of these constraints guides the organisation of the neuromuscular system into attractor states (Figure 2.2).

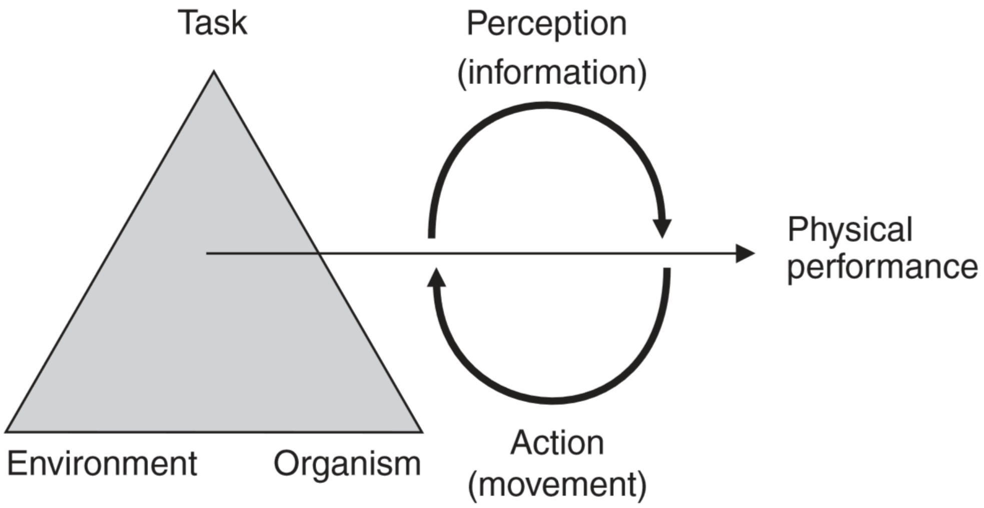


Figure 2.2. Newell's (1986) model of constraints on human motion (adapted by Davids et al., 2003).

Organismic constraints pertain to the individual and can be physical, mental or emotional (Handford et al., 1997). The physical dimensions of an individual are clear organismic constraints, but Kelso (1995) argued that the most influential organismic constraints are cognitive. Organismic constraints have been separated into structural and functional constraints: Structural organismic constraints have the property that they change only very slowly over time, such as height, weight and strength, whilst functional organismic constraints change much more quickly over time, such as anxiety, motivation and physiological fatigue (Newell and Valvano, 1998).

Environmental constraints pertain to the context of the action and the sensory information available to the performer (Handford et al., 1997). Examples of environmental constraints include the lighting, wind, temperature and the location of the performance. Implements, tools and apparatus were initially classified as task constraints but have been revised as environmental constraints (Newell and Jordan, 2007). In general, organismic and environmental constraints are unlikely to fluctuate significantly in the time of a given task, but task constraints can be more obviously influenced by a coach or scientist (Handford et al., 1997).

Task constraints govern the rules, explicit or otherwise, imposed on the movement or the task and are common in sport. For example, rules prohibit the golfer from anchoring the putter against the body when performing their putting stroke (The R&A and USGA, 2015). The goal of the movement is also a key task constraint. The manipulation of task constraints through instruction and goal setting has been shown to influence the interrelation between speed, distance and accuracy (Latash, 1993). Task constraints can be easily manipulated to influence the possible task solutions, and their manipulation by a coach or practitioner has been viewed as an important part of motor skill acquisition (Glazier, 2011).

The organismic, environmental and task constraints act in concert to determine the patterns of coordination and control produced by an individual (Newell et al., 1989). An emerging movement pattern that satisfies the task goal strengthens the attractor states involved, increasing the likelihood that this pattern will be used in the future (Handford et al., 1997). Therefore, the nature of the constraints and their interactions dictate that the state space and its exploration are specific to the individual (Handford et al., 1997). The impact of constraints is dependent on the performer's perception and the state of the system in that specific moment so it is possible for small changes in constraint to have a large impact on the resulting movement and conversely, numerous changes to have little impact (Glazier, 2015; Newell, 1989).

2.3.5. Conclusion

Different motor control paradigms allow different outlooks on the inter- and intra-individual variability seen at all levels of motor performance. Variation does not necessitate error in a movement pattern, rather inter-individual variation is expected due to differing constraints on the performer (Davids et al., 2003). Furthermore, intra-individual variability can indicate an exploration of state space in response to dynamic constraints and could provide adaptability and flexibility or other functional outcomes to the system (Bartlett et al., 2007).

2.4. Functional movement variability

2.4.1. Introduction

In dynamical systems theory, it is theorised that inter- and intra-individual variability in human movement is expected due to the unique, dynamic constraints which act on the human movement system. This allows movement variability to play a positive role in the coordination and control of movement and is often cited as a primary rationale for conducting research on the variability of human movement.

2.4.2. Role, type and source of variability

Dynamical systems theory postulates that variability has four roles in human movement (Kelso and Ding, 1993; Newell and Corcos, 1993): Firstly, variability may represent the stability of a movement pattern around an attractor; large variations suggesting unstable movement patterns and small variations indicating stable patterns. Secondly, variability permits the learning of new motor patterns by allowing flexibility within the system. Thirdly, this flexibility allows parameters to be rescaled to adapt movement to the changing pressures of constraints. Finally, random variation acts as an exploratory behaviour, continuously sampling new movements and allowing the selection of the most appropriate movement for each scenario. It is important to note that the system searches for stability in output, rather than invariance of movement. This stability can be theoretically achieved through both varying or invariant movement patterns but some variability in movement allows the system to be both flexible and adaptable whilst maintaining a stable output (James, 2004). Dynamical systems theory does not postulate all variability as beneficial to the system, rather variability indicates the range of coordination patterns which can be used to complete the task and may be functional, dysfunctional or neutral depending on the context (Bartlett et al., 2007; Preatoni et al., 2013).

Variables associated with human movement can be divided into two types of variables, movement and outcome variables, and interpretations regarding the variability may depend on the variable studied. Outcome variables are related to the pursued objective and it is intuitively expected that expert performers will have lower variability in outcome variables when compared to less skilled performers (Preatoni et al., 2013). Movement variables are those associated with the movement, rather than the outcome of the movement (Lockhart and Stergiou, 2013). Movement variability was described by Bernstein as ‘repetition without repetition’ (Bernstein, 1967); a large amount of movement variability does not necessitate a large amount of outcome variability as the same outcome can be achieved in many ways.

Variability in a nonlinear system is believed to be the outcome of both stochastic fluctuations and deterministically chaotic fluctuations (Kelso and Ding, 1993). The total variability (V_T) in the system consists of noise in the neuromuscular system (V_{eb} - biological error) and functional changes due to the nonlinearity of the system ($\mathrm{V_{nl}}$). Furthermore, in any measurement of the system, there will be a further component, measurement error ($\mathrm{V_{em}}$) which should be minimised through appropriate data collection and processing (Equation 2.1, from James, 2004).

$$\mathrm{V_T = V_{nl} + V_{eb} + V_{em}}$$

Equation 2.1. Total variability in any measurement of a varying biological system (from James, 2004).

Some analyses are assumed to isolate the variability due to the nonlinear dynamics of a system ($\mathrm{V_{nl}}$), whilst others provide an estimation of all sources of variation ($\mathrm{V_T}$). Both approaches have merit, and in some cases, the variability may be best characterised by the total variability (James, 2004). Thought must be given to the composition of variability in the signal throughout the experimental process.

2.4.3. Structure of variability

As noted, variability has been traditionally considered as noise but, more precisely, it has been considered to be random, 'white', noise superimposed on the underlying deterministic signal (James, 2004). This assumption equates variability to randomness, but this is not necessarily the case; highly variable does not mean highly random. As investigations have shown structures of variability other than that of white noise, human movement variability cannot be the result of purely random processes (Newell and Slifkin, 1998). Increased structure of variability can suggest that more deterministic processes are taking place (Riley and Turvey, 2002). The importance of the structure of a signal highlights the limitations of operational measures of variability, such as standard deviation, which focus on the amount of variability only and give no indication of the structure of the variability (Newell and Slifkin, 1998).

The structure of variability has been found to change depending on the task, or other constraints (James, 2004). For example, an inverted U pattern was found in the structure of variability in an isometric force production task, with increased regularity at the extremes of force application (Newell and Slifkin, 1998). Furthermore, the structure of variability associated with pathological gait tends to be either extremely structured (Hamill et al., 1999) or extremely unstructured (Stolze et al., 2002). These results suggest that there is an optimum amount of structure in the variability of gait, like that found in the force production task. There is a suggestion that the ideal structure of variability for many movements lies somewhere between complete randomness and complete regularity (Harbourne and Stergiou, 2009) but there is not a consensus regarding a general structure of variability across all tasks; only general support that it is not a reflection of white Gaussian noise (Newell and Slifkin, 1998).

2.4.4. Functional variability

> *"Humans are designed not only with variability but for variability."*
>
> (Fetters, 2010, p.1)

The potential for functional variability been highlighted throughout the human biological system; variability enables greater success for an organism by allowing choices among options, selection of strategies, flexibility and adaptation (Harbourne and Stergiou, 2009). Principles akin to Darwinism can describe how limited behaviours throughout the different levels of an organism are challenged for survival by more adaptive ones (Adami et al., 2000). According to dynamical systems theory, this should be true for the human movement system in the same way as it is for groups of animals or other levels of the human system. For instance, some variability has been identified as a marker of healthy cardiac function, with lower heart rate variability or increased structure of variability connected to increased mortality rate (Thayer et al., 2009). These results have also been found in patients with hemispheric brain infarction (Korpelainen et al., 1996) and children with central coordination disturbance (Bjelakovic et al., 2010). Transitions to highly structured dynamics have also been observed in other pathologies including Parkinson's tremors, obstructive sleep apnea, sudden cardiac death and epilepsy (Goldberger et al., 2002). Indeed, equilibrium has been equated to death in an organism; a static unchanging state. A healthy organism is indicated by dynamic stability (Harbourne and Stergiou, 2009).

In a sport, variability is postulated to be functional in three ways: Firstly, variability is required to allow coordination changes, for instance from walking to running (Deidrich and Warren, 1995). Secondly, variability may allow for greater distribution of stress, reducing repetitive loading in repeated movements such as running (Hamill et al., 1999). Thirdly, variability allows flexibility and adaptations depending on the context and environment (Scott et al., 1997; Wheat et al., 2005). These three tenets are most easily explored in the context of human locomotion.

Firstly, gait transitions, such as from walking to running, are an unstable state as the system moves to a new area of state space. As step frequency increases, the coordination pattern remains relatively stable. However, at a certain point, a further increase in step frequency will cause an increase in variability as the system shifts to a more stable attractor, the coordination pattern of running (Deidrich and Warren, 1995).

Secondly, variability in movement spreads impact load among different tissues, reducing the potential for tissues to become injured by repetitive loading (Hamill et al., 1999; Heiderscheit et al., 2002). This can be framed, not as a mechanical problem, but as an information problem (Harbourne and Stergiou, 2009). The system is not only taking in information but also generating information through movement, so a reduction in movement variability will result in a lack of information which might usually be used by the system to prevent injury (Harbourne and Stergiou, 2009). Unfortunately, many studies investigating the variability in gait have compared injured and healthy individuals, and it is difficult to know whether the observed reduction in variability in the injured cohorts is a cause or an effect.

Finally, variability can allow flexibility and adaptation. For example, during the long jump approach phase, the variability of toe-board distance decreases as the athlete approaches the board (Scott et al., 1997). Since the jump will be measured from the board and over-stepping the board will result in a foul, controlling the toe-board distance is a task constraint on the athletes’ gait. Small inconsistencies in stride length build up during the run up but in the final steps the stride length can be moderated via visual feedback to ensure low variability in the final foot placement. Thus, there is high variability in the stride length in these last steps as the athlete makes adaptations to account for differences occurring earlier in the run-up (Scott et al., 1997).

2.4.5. Compensatory variability

Compensatory variability refers to the compensation of fluctuations in one variable by fluctuations in another variable. It can partly explain how invariance in outcome is achieved despite variable movements (Bootsma and van Wieringen, 1990) and can be an indication of the reciprocal compensation of a coordinative structure (Latash et al., 2002). Variables may individually display high variability which cancels out when considered together, ensuring stability in the relevant outcome. The seminal example of compensatory variability is that of pistol shooting (Arutyunyan et al., 1969). In this investigation, skilled marksmen could reduce the variability in the spatial orientation of the pistol barrel, not through movement invariance, but compensatory movements at the shoulder and elbow which were associated with increased variability. Novice marksmen did not show these compensatory movements and exhibited greater variability in the spatial orientation of the barrel. Compensatory variability has been observed in table tennis (Bootsma and van Wieringen, 1990), handwriting (Teulings, 1988), juggling (Beek, 1989), postural control (Ko et al., 2003), targeted throwing (Muller and Sternad, 2004) and pistol shooting (Arutyunyan et al., 1969) among others.

A proximal to distal increase in variability along the kinetic chain towards the instant of release has been observed in basketball shooting (Robins et al., 2006), tennis serving (Whiteside et al., 2013) and handball throwing (Wagner et al., 2012). This increase in terminal variability of distal joints is generally considered to be indicative of compensatory variability occurring late in the movement to ensure task success. Skilled performers tend to be more likely to display compensatory variability, exploiting the degrees of freedom in the motor system. Less skilled performers tend to rigidly freeze degrees of freedom, which results in less adaptability to errors and therefore a lower performance. Robins et al. (2008) found that expert performers demonstrated cooperative behaviour between joints of the shooting arm during basketball shooting, offsetting errors in proximal joints with adjustments to the more distal joints. Novice or intermediate performers did not display these compensatory adjustments, and the variability in their movements was construed as less functional. Compensatory variability may be developed alongside task expertise.

2.4.6. The uncontrolled manifold hypothesis and synergy

The uncontrolled manifold hypothesis (Scholz and Schoner, 1999) is a research method and paradigm which investigates the degrees of freedom problem by considering which variables are 'controlled' in a movement. In this case, control refers to stabilisation, the ability of the variable to return to a given state after a perturbation (Scholz and Schoner, 1999) and can be indicated by the variability of a value over time (Scholz and Kelso, 1989), or the reproducibility of variability from trial to trial (Schoner, 1990). The uncontrolled manifold technique attempts to partition variability into that which influences the outcome of a skill and that which does not. This separation is based on a hypothesis which assumes that specific variables are controlled by the system to stabilise output and variables which do not affect the performance are allowed to vary (Latash et al., 2002). The uncontrolled manifold consists of two orthogonal subspaces, with variables which lead to changes in outcome in one subspace and variables which do not affect the outcome in the other. This abstraction of whole system variability into two dimensions is non-trivial in complex movements and tends to give the uncontrolled manifold hypothesis greater utility as a theoretical construct than an experimental method. However, uncontrolled manifold techniques can be used to assess the possible presence of synergies; families of motor patterns which all produce the desired endpoint trajectory (Rosenblatt et al., 2014). Research has found synergies to be present in pistol shooting (Scholz et al., 2000), a sit to stand task (Scholz and Schoner, 1999) and the golf swing (Morrison et al., 2016). Synergies allow flexibility, adaptability and robustness to perturbation whilst minimising endpoint deviation (Scholz and Schoner, 1999).

2.4.7. Variability and motor learning

A view of movement variability as unwanted noise leads to the assumption that the most skilled performer displays little or no variability in their technique (Bartlett et al., 2007), and it could be suggested that the learner with lower variability at the onset of skill development would have greater success, as their variability must decrease less to reach the level of the expert (Harbourne and Stergiou, 2009). However, individuals with greater variability at the onset of skill development generally display greater learning, and eventual success, because the high initial variability allows exploration of different strategies (Harbourne and Stergiou, 2009). The progression of movement variability during learning is typically seen as a U-shaped curve (Wilson et al., 2008). As the learner performs more successfully there is a reduction in variability as successful strategies are strengthened. Then as the learner becomes expert, there is an increase in variability, reflecting the ability of the expert to adapt and adjust their technique. The variability displayed by expert performers is a sign of flexibility and adaptability and may indicate compensatory variability (Robins et al., 2008). However, while this progression is well documented, it may be task or variable dependent (Broderick and Newell, 1999; Button et al., 2003).

Key to understanding the U-shaped theorisation of variability in motor learning are the concepts of 'coordination', 'control' and 'skill' (Chow et al., 2008). Coordination refers to the function which constrains the available degrees of freedom in the movement system into a functional movement pattern. Control refers to the assignment of values to the coordination function, parameterising the relations between the coordination pattern and the components of the movement system. Skill is the optimal assignment of control values to the coordination function (Newell, 1985). Motor learning has been framed as occurring in three corresponding stages (Newell, 1985) but it has also been suggested that these stages of learning can overlap (Chow et al., 2008). The coordination stage represents the learner’s first attempts to establish necessary relationships between the components of the motor system and the movement task. Awkward movements with a high amount of variability are likely to emerge. The functional nature of variability in this stage is in the sampling of many different coordination states, allowing the most effective to be retained. In the control stage of motor learning, the learner becomes more able to manipulate the variables of the movement pattern. The learner gradually becomes attuned to the effect of higher-order derivatives of the movement, allowing greater consistency and less dysfunctional variability. Progressing to the skill stage, the learner can now optimally scale the values to produce adaptive behaviour and can utilise reactive forces to allow for the efficient use of energy (Chow et al., 2008). Variability in movement may have different interpretations depending on the skill of the participant and the stage of motor learning they are currently exhibiting.

2.4.8. Conclusion

It is clear from the literature that there is potential for functional variability in human motor control and learning and that variability should not be overlooked when conducting golf biomechanics research. Functional variability is now a widely used term in the literature, although not all variability is functional; this depends on the context (Preatoni et al., 2013). Bartlett, Wheat and Robins (2007) argued that it is important to frame variability in an appropriate motor control paradigm and encouraged broader, more collaborative research to elucidate the potential of functional variability in sport. In recent years, researchers have acted on this advice, with more innovative and collaborative research taking place (Preatoni et al., 2013).

2.5. Movement variability in golf

2.5.1. Introduction

The ability to consistently repeat itself was proposed by Cochran and Stobbs (1968) as a fundamental foundation of a successful golf swing. Furthermore, it was noted that 'all possible sources of human error, liable to cause variation from swing to swing, must be reduced to a minimum' (Cochran and Stobbs, 1968, p. 8). More recently, a successful swing has been described by golf coaches as ‘repeatable, controlled, simple, accurate, powerful and consistent’ (Smith et al., 2012, p. 228). The concept of a 'perfect swing' remains persistent (for example, Dewhurst, 2015), despite large amounts of evidence suggesting both inter- and intra-individual variability is a persistent feature of human movement (Newell and Corcos, 1993).

2.5.2. Inter-individual variability

Most golfers have an appreciation of the inter-individual differences in movement between golfers attempting the same shot, and a large amount of inter-individual variability was highlighted in early research (Plagenhoef, 1971). Plagenhoef (1971) analysed the swing of over 100 golfers, including 20 touring professionals, and noted that both the swings and resultant ball flight varied considerably between golfers. Indeed, even between two golfers who achieved the same driving distance, 280 yards, there were marked differences in the swing patterns. This is a golf specific example of motor equivalence; the same result achieved using different methods (Davids et al., 2003). Plagenhoef (1971) concluded:

> *“The variations in technique are extreme due to anatomical and ability differences and no personal conclusions should be made on the swing patterns of others. There is no perfect swing for everyone.”*
>
> (Plagenhoef, 1971, p. 189)

More recent research has also found a large amount of inter-individual variability during the golf swing. Zheng et al. (2008a) reported standard deviations in joint angle of 4-9° at address, 4-16° at the top of the backswing and 4-12° at ball contact in a group of 50 male and female professional golfers and Zheng et al. (2008b) reported similar amounts of inter-individual variability across a range of handicaps. Whilst common patterns have been observed (for example, Ball and Best, 2007), there is still much evidence of inter-individual variability in the ground reaction forces of skilled golfers (Wallace et al., 1994). In a small cohort of golfers, Williams and Cavanagh (1983) reported that inter-individual variability in ground reaction force and centre of pressure was as large within handicap groups as it was between handicap groups. Inter-individual variability has also been observed in the hip and torso angles during the swing (Burden et al., 1998), clubhead presentation (Betzler et al., 2014) and temporal characteristics (Burden et al., 1998; 2008b); it is ubiquitous. Many constraints are shared between individuals attempting the same task but individual specific constraints, such as anatomy, muscle strength, intention and prior movement experience, combine to ensure that no single ideal movement solution exists across all individuals (Bartlett et al., 2007).

2.5.3. Intra-individual variability

In a review on the role of movement variability in the golf swing (Langdown et al., 2012), the potential for functional intra-individual variability was discussed, and the lack of research in the topic area was highlighted. However, the study also introduced the concept of strategic shot selection, the choice of shot or club to achieve the required outcome, as another source of variability. Whilst it is true that the same shot outcome can be achieved with a range of clubs and shot types, this would represent a change of task whereas movement variability refers to the differences in repeated attempts at the same task. Strategic shot selection should be considered in the methodology and the task controlled so that it does not become a confounding factor. The main purpose of investigating variability in sports biomechanics is in its hypothesised functional role in repeated attempts at the same task, and this could have been more clearly reflected in the review. The intra-individual variability of repeated golf swings has been the subject of several recent studies, but further research is required. In general, knowledge about intra-individual movement variability within the golf swing is still limited; partly by the number of research papers with variability as their primary subject and partly due to limitations in existing research.

Several studies have found high skilled, low handicapped golfers to have low outcome variability in either clubhead presentation characteristics at impact or shot outcome. Bradshaw et al. (2009) found that a group of ten highly skilled golfers had less variability in clubhead velocity and greater shot success than a group of ten lower skilled golfers. However, these differences are not universal; there are still inter-individual differences in variability between golfers (Kenny et al., 2008). Betzler et al. (2012; 2014) reported the variability of clubhead presentation characteristics and ball impact parameters for a large group of golfers covering a range of handicaps. An on-line three-dimensional motion analysis system was used to track the clubhead at 1000 Hz for 50ms before and after impact; an improvement on the radar gun used by Bradshaw et al. (2009) and the stereoscopic camera system used by Kenny, Wallace and Otto (2008). In general, lower handicap, higher skilled golfers had increased clubhead speed, a squarer clubhead path at contact, increased efficiency and decreased variability of clubhead speed, face angle, club path, attack angle and the location of impact on the club face.

Whilst providing evidence for increased outcome consistency in high skilled golfers, Betzler et al. (2012) did not report any measures of movement variability, limiting their impact on the discussion of movement variability. Conversely, Bradshaw et al. (2009) did provide measures of movement variability; basing the kinematic variables measured on the laws, principles, and preferences of Wiren (1990). In this study, the group of higher skilled golfers were found to be less variable than lower skilled golfers in their stance width and trunk angle at address and lead wrist angle and trail forearm angle at half backswing. There were no differences in variability between the high or low skilled groups at any other point in the golf swing. However, the investigation has several limitations. Firstly, two-dimensional video analysis at a frequency of 50 Hz was used to determine the kinematic variables. This approach is unsuitable for a high-speed, three-dimensional movement such as a golf swing. Secondly, the investigators utilised a flawed approach to separate movement variability and measurement noise which involved subtracting the standard error of the mean from the coefficient of variance. As noted by Glazier (2011), the standard error of the mean should be calculated from repeated measurements of the same trial and not repeated performances. As the percentage of movement variability and measurement error will differ from trial to trial, the standard error of the mean calculated by Bradshaw et al. (2009) contains both movement variability and measurement error and provides no better indication of movement variability than the coefficient of variation. Disregarding this potentially fundamental limitation, the sole use of discrete measures of variability at different points of the swing failed to capture the dynamics of the movement (Bartlett et al., 2007).

Utilising several discrete and continuous measures to provide a more complete investigation of variability in the golf swing, Horan et al. (2011) found that skilled female golfers had higher thorax-pelvis coupling variability than skilled male golfers at the midpoint of the downswing and ball contact. Thorax-pelvis coupling was examined using the average coefficient of correspondence which quantifies the variability of angle–angle data across multiple trials. Regardless of differences between sexes, the variability of hand and clubhead trajectories decreased sequentially from the top of the backswing to ball contact for both males and females. The differences in thorax-pelvis variability combined with the decrease in clubhead variability towards impact suggest that the arms, which were not included in this investigation, may have an important role in the control of the golf swing. The indication that the variability of the clubhead is decreased through the downswing suggests that skilled golfers can minimise outcome variability in agreement with Betzler et al. (2012), but Horan et al. (2011) reported only clubhead speed as an outcome measure. The decrease of clubhead variability through the downswing is an important finding, but the data presented by Horan et al. (2011) does not indicate the method by which this decrease is achieved.

Morrison et al. (2016) investigated outcome variability using an uncontrolled manifold analysis. In this study, the high skilled group had lower variance in both clubhead location and clubhead orientation throughout the swing when compared to the lower skilled group. Both groups showed the same patterns of variance throughout the swing, with variance in clubhead location peaking at the top of the backswing and decreasing through the downswing. In contrast, variance in clubhead orientation was highest in the backswing and after decreasing showed a trend to increase before impact. The uncontrolled manifold analysis suggested that the clubhead variance in the higher skilled golfers had a lower effect on the outcome than in lower skilled golfers but that both skill levels increased their control over the clubhead location leading up to impact, with more control exerted over the clubhead orientation in the early downswing. Interestingly, motor synergies were observed for the control of the orientation of the clubhead but not for the clubhead location. This study is an example of the application of methods from the field of motor control providing insight into the movement variability in the golf swing.

Both Horan et al. (2011) and Morrison et al. (2016) filtered their data using zero-lag fourth-order low-pass Butterworth digital filters with cut-off frequencies of 6-10 Hz and unreported frequencies selected by residual analysis respectively. Filtering data at these frequencies is not uncommon in biomechanics research (Payton and Bartlett, 2018) but the relationships between movement variability and noise are such that it might have been more prudent to filter at a higher frequency or not at all to ensure that elements of the signal were not removed with the noise component (Glazier, 2011). The effect of filtering on the results reported by Horan et al. (2011) and Morrison et al. (2016) is unknown, but maintaining the integrity of the underlying system dynamics is a priority when researching movement variability (van Emmerik et al., 2005).

Langdown et al. (2013a) investigated variability in the address position of two mixed-sex groups of high and low skilled golfers, using an on-line motion analysis system operating at 250 Hz. The address position was chosen as an important determinant of the outcome of the shot, due to the short duration of the movement. The stance width, distance of stance, pelvis and shoulder from the ball, pelvic and shoulder tilt and stance, pelvis and shoulder alignment were chosen as variables defining address position, and the discrete measure variable error was used to assess the variability. The only significant difference in variability found between groups was the high skilled golfers displaying significantly lower shoulder-stance alignment variability. In contrast to Bradshaw et al. (2009), no significant difference was found in stance width variability between groups. Across groups, certain aspects of the address were found to be more variable than others; for example, stance distance to the ball was more variable than the shoulder distance to the ball. In a second study, Langdown (2013b) examined the variability of these same dependent variables at impact. However, no differences in variability were seen across the different skill groups. It is not clear that the dependent variables selected to examine the position at the address are still valid indicators of the movement at contact. The discrete measure of variability is also a limitation as previously discussed, especially at ball contact where the movement is high speed and differences in determining the exact moment of impact could result in large differences. More varied approaches to the analysis of variability are required to discern the relationship between movement variability and outcome variability fully.

Tucker et al. (2013) used a novel scalene ellipsoid volume approach to quantifying variability in marker trajectories to investigate the relationship between outcome variability and movement variability in golf drives. Consistent with the suggestion that movement variability and outcome variability are independent of each other (Preatoni et al., 2013), no correlations were found between the variability of any marker trajectories and initial ball speed. Supporting the findings of Horan et al. (2011), a reduction in wrist variability from top of the backswing to impact was found, however condensing the variability in the backswing and downswing into two discrete variables means the dynamics of the variability are unknown. Utilising the same method, Morrison et al. (2014) found that the variability of clubhead trajectory of skilled golfers increased through the backswing, was most variable at the top of the backswing and decreased through the downswing to contact. This insight was possible as the method was applied to three 20% sections in the backswing and downswing instead of the whole phase. This reduction in variability during the downswing was also found by Morrison et al. (2016) and these findings suggest that there is some 'zeroing in' process during the downswing, where skilled golfers reduce the variability of the clubhead to minimise variability at impact.

Whilst the primary purpose of the investigation was an investigation of swing planes, Kwon et al. (2012) reported values that suggest the intra-golfer variability in swing plane for both clubhead and selected body landmarks is low in highly skilled golfers. Intra-individual variability in swing plane was less than 1° in both direction and inclination throughout the swing with a driver, 5-iron and pitching wedge. Furthermore, variability in swing plane decreased when comparing the phases delimited by the top of the backswing and follow through, early-downswing and follow through and mid-downswing and follow through. This provides further support to the notion that high skilled golfers can control their swing such that the clubhead position is relatively consistent at impact, as found by Morrison et al. (2014) and Tucker et al. (2013).

Other novel investigation methods have increased our understanding of variability in the golf swing. Corke (2015) developed a 'spectral' method of quantifying the variability between groups of signals. After accounting for the median difference between two signals, the method compared the difference in magnitude of the signals for each time step. Completing all pairwise comparisons resulted in a matrix of values which quantified the variability between the group of signals. Perhaps the most important finding from this analysis was that the inter-session variability was significantly higher than intra-session variability for all players. Thus, it may be the case that there is a difference in central tendency between sessions, but no difference in the amount of variability around the mean between sessions, a finding which deserves further investigation. Sweeny et al. (2014) used a theoretical approach to investigate the importance of variability in a golf drive. After collecting kinematic data from ten golfers, a surrogate data set was formed using computer simulation to simulate 1000 swings without the possibility for compensatory coordination. The surrogate data set displayed 28 times more variance in the position of impact and would only have impacted the ball 30% of the time. This suggests that compensatory movements are essential in the golf swing to reduce variability towards impact. The role of compensatory coordination in the golf swing has not been thoroughly investigated to date, with researchers displaying a preference to focus on the variability of discrete measures (for example Bradshaw et al., 2009; or Langdown et al., 2013b), or individual segments (for example Morrison et al., 2014; or Tucker et al., 2013).

A potential limitation of some of the techniques used to assess variability is the requirement of data series of equal length. To achieve this most biomechanical time series must be normalised to a standard length; distorting temporal variability in the data (James, 2004). Corke (2015) presented detailed data about the temporal variability of the golf swing for 13 of high skilled golfers using two different designs of an iron club. In general, temporal variability in the swing was found to be low, and the backswing duration was found to be more variable than downswing duration. This was also found by Zheng et al. (2008b) who also reported that high handicap golfers were more variable in backswing time than low handicap golfers but averaged two swings per golfer which will mask intra-individual variability. Thus, there is some evidence to claim that highly skilled golfers have a low amount of temporal variability in their swing which may provide some justification for techniques which normalise time series to a common length but alternative methods which avoid distorting the original signal should also be investigated.

Kinetic studies investigating variability in the golf swing are limited in comparison to the kinematic studies that have taken place. This is despite the fact that Barrentine et al. (1994) inferred the presence of intra-individual variability in ground reaction force over 20 years ago. It was suggested that highly skilled golfers had more consistent ground reaction force patterns, but no evidence was presented to support this suggestion. Instead, Barrentine et al. (1994) provided a general description of patterns of ground reaction force during the swing. Thus, the variability of ground reaction forces could be an interesting avenue for further research. Langlais and Broker (2014) investigated the intra-individual variability in grip force using a driver and 7-iron. Intra-individual variability in total grip force was found to be around 10% of the mean and much lower than the inter-individual variability. Intra-individual variability in grip force was highest at the takeaway and then uniformly low throughout the swing. With the 7-iron, the variability decreased further at impact. The influence of this study may be limited by the low numbers of shots analysed, eight participants who took four shots with each club each, although it provides interesting detail to the kinetics of the movement.

2.5.4. Conclusion

Existing research on variability in the golf swing paints an incomplete picture. It has been consistently found that highly skilled golfers can successfully limit the variability of the clubhead at impact to obtain consistent launch parameters and shot outcomes (Betzler et al., 2012). There is also growing evidence that the variability of the clubhead decreases during the downswing to ensure this consistency at impact (Horan et al., 2011; Morrison et al., 2014; Tucker et al., 2013). Sweeny et al. (2014) present a persuasive argument for the presence of compensatory coordination within the golf swing, which may be vital in achieving the reduction in variability of the clubhead during the downswing but evidence of this phenomenon is still scarce. The movements of body segments, such as the arms, shoulders and wrists, and their role in achieving outcome consistency has only been explored sporadically (for example, Horan et al., 2011) and so the potential for joint coupling and compensatory variability is unknown. In general, only the magnitude of variability has been considered in existing research, with little acknowledgement of the potential of the structure of variability to contain important information. There is also a dearth of knowledge considering the variability of kinetic measures and the inter-session variability. Recurring limitations in the existing research include the sole use of discrete measures of variability, failure to utilise measures of shot outcome, applying filters at low cut-off frequencies and the use of low-frequency data collection methods (Glazier, 2011). Due to these limitations and the small amount of research, the variability of the golf swing remains a compelling research area.

2.6. Chapter summary

The literature review provided the theoretical background for the thesis through a critical review of existing research and began by exploring the rationale behind a study of movement variability in the context of the relevant theoretical paradigms from the study of motor control. The potentially functional role of movement variability and associated research was then explored to give the research wider context in sport and movement. The literature review finished with research specific to inter- and intra-individual variability in the golf swing. Current literature has provided much evidence pointing to the consistency of highly skilled golfers at impact and their ability to coordinate their movements to reduce the variability of the clubhead during the downswing. However, based on this review there is a lack of research examining both movement and outcome variability and potential differences in this relationship between differently skilled golfers. The next chapter will explore the methodological factors which impact on the ability of the research to address the research questions in a sufficiently rigorous manner.

3. Methodology

3.1. Chapter objectives

The objective of the methodology chapter is to provide a thorough examination of the conceptual framework and methods which will be required to answer the research questions set out in Chapter 1. Alongside theoretical discussion on the methods used, the chapter will include details of investigations which characterised the specific accuracy and repeatability of three methods used in the thesis. It is important to quantify and discuss the impact of the methods, to ensure that robust interpretations can be made from the data gathered in this thesis.

3.2. Introduction

The review of existing literature highlighted the requirement for research which examines the variability of movements and outcomes in the golf swing but several methodological considerations were also raised (Glazier, 2011). This chapter will examine the methodological considerations required for such an analysis to take place. Consideration will be given to the underlying conceptual framework and to the experimental and data analysis methods to be utilised in the research; the choice of methods, their utility in investigations of movement variability and the effect of the methods on our ability to answer the research questions posed in this thesis will all be explored.

The research questions in this thesis are primarily descriptive, as there remains a need for a thorough description of the variability of golfers of different abilities. Some argue that sports science research is overly descriptive (Chalmers, 2006) but describing the size and characteristics of an effect provides a foundation on which to develop innovative hypotheses and interventions with the potential to affect sport performance or injury rate (Bishop, 2008). Movement and outcome variability in golf is still poorly understood and, to progress knowledge in this area, a thorough description which considers all aspects of variability is needed.

3.3. Conceptual framework

Of primary interest in this thesis are differences in variability between multiple sets of data and a clear and consistent definition of variability is paramount to the efficacy of the investigation. The term variability is used in a variety of contexts and domains (Harbourne and Stergiou, 2009), and a comprehensive understanding of its definition and scope within the context of human movement is a key tenet in the conceptual framework of this thesis. This understanding will affect the methods used in the thesis and the interpretation of results, and as such is fundamental. In statistics, variability refers to the spread, or statistical dispersion, of scores (Mullineaux and Wheat, 2018). There are numerous measures of statistical dispersion, including the inter-quartile range, variance and standard deviation (Field, 2013). However, defining variability in terms of the statistical dispersion of the data may not fully encapsulate variability in human movement. The Oxford Dictionaries (2018) provide a more general definition of variability; 'lack of consistency or fixed pattern'. Measures of statistical dispersion do not provide a complete description of variability in these terms, as only one facet of the distribution is described. This research is concerned with the differences between multiple attempts at a movement task, the golf swing, and the definition of variability must be adequate to reflect these variations.

A definition of variability which is only concerned with the statistical dispersion of the data is problematic because two sets of data can share a central tendency and statistical dispersion but differ in the distribution of scores. Consider two sets of data; one with a normal distribution and another with a uniform distribution. The normal distribution has values which are concentrated around an average value with relatively few, but extreme, outlying values whilst the uniform distribution has values which are consistent across the range of values, with no extreme outlying values and less concentration around the average value. The two data sets share a mean and standard deviation but are they equally variable? Either data set may be argued to be more variable according to the non-statistical definition of variability; the normal distribution has more outlying values, but the uniform distribution has fewer values clustered around the mean. However, the difference in the two sets of data can be clearly defined in statistical terms; the two data sets differ in their distribution but not statistical dispersion. Thus, the distribution must be considered alongside the statistical dispersion to describe the variability of the two data sets thoroughly. The convention adopted in this thesis will be to characterise the two datasets as having an equal magnitude of variability, as described by their statistical dispersion, but a differing structure of variability, as described by their distribution.

The issue of description is not limited to discrete data, and a similar issue in the description of variability occurs in continuous data. In this case, consider two time-series: a sine wave and random noise (Figure 3.1). Again, the signals share a mean and a standard deviation, but the random noise shows much less of a fixed pattern; the defining feature of variability according to the non-statistical definition of variability. In this case, the data are ordered and so this is a consideration of the predictability of the signal, not its statistical dispersion. Unlike the random noise, knowledge of the previous states of the sine wave allows prediction of future states with a high degree of accuracy (Harbourne and Stergiou, 2009). The convention adopted in this thesis will be to characterise the signals as having an equal magnitude of variability, as described by their statistical dispersion, but a differing structure of variability, as described by their predictability.

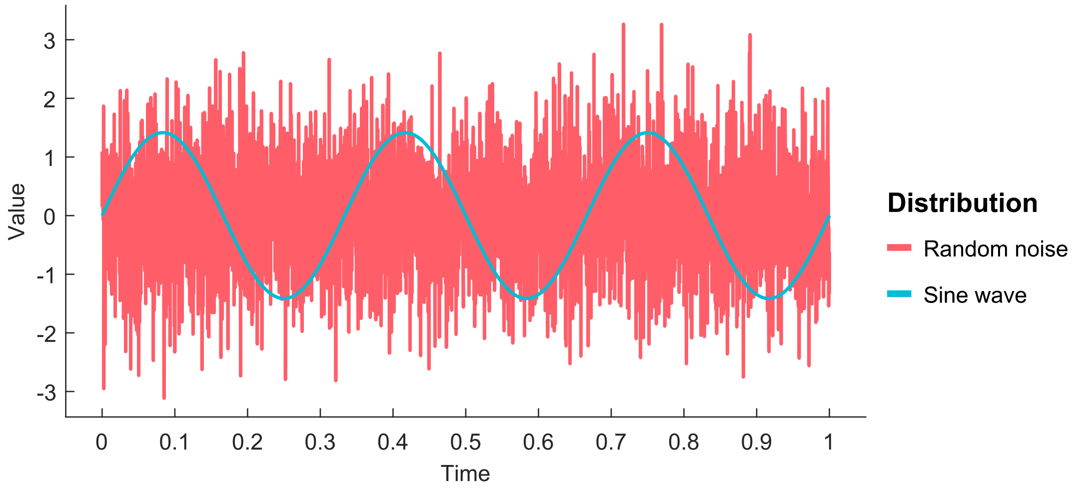


Figure 3.1. Sine wave trajectory and random noise with equal central tendency and dispersion (mean = 0, standard deviation = 1).

These examples show that multiple properties of data must be considered to fully understand the variability, and that the statistical dispersion may be insufficient to detect differences between data sets. The convention adopted in this thesis will be to define variability in terms of the magnitude and structure of variability. The magnitude of variability will be used to refer to *how much variation exists,* which is equivalent to the statistical definition of variability; the spread, or statistical dispersion. The structure of variability will be used to refer to the *composition of the variation*, which covers phenomenon such as the distribution or the predictability of data. This will allow the variability of the golf swing to be accurately characterised and avoid the over-reduction which might occur by only considering the statistical dispersion (Harbourne and Stergiou, 2009).

3.4. Data analysis

Measures of central tendency and statistical dispersion are often used to facilitate comparison between multiple sets of data. These are known as summary statistics and certain measures may be more suitable than others depending on the data. The mean and standard deviation are oft-used summary statistics but are greatly influenced by outliers in the data. Robust statistics, such as the median and median absolute deviation, are less affected by outliers in the data or by skewed distributions (Field, 2013). It is reasonable to expect that outliers and skewed distributions will manifest in golf data, for example: through occasional mis-hit shots which could present as outliers. For certain variables a skewed distribution could be expected regardless of outliers; the average shot distance will likely be closer to the maximum distance for a golfer than to the minimum. Robust statistics are less widely utilised in sports biomechanics research but, for a normal distribution with sufficient sample size, the median is equal to the mean, and the median absolute deviation is related to the standard deviation by a scale factor of ~1.4826 (Rousseeuw and Croux, 1993). These conversion factors allow for comparison to existing research in scenarios where outliers and skewed distributions are not present in the data. For these reasons, robust statistics, specifically the median and median absolute deviation, will be preferred as measures of central tendency and dispersion for golf data reported in this thesis.

Due to the scope of the thesis, outliers are highly likely to be present in the golf data collected. Outlying data are to be expected in large data sets and could indicate error or unique swing biomechanics; a particularly good or bad shot for example. In the case of outlying data indicating measurement error, the data should be removed from the dataset to avoid confounding interpretations but if not indicative of an error, the outliers carry important information regarding the golfer and their swing. Therefore, the identification and management of outliers in the dataset must be carefully considered.

Hawkings (1980), defined an outlier as:

> *"An observation that deviates so much from other observations as to arouse suspicion that it was generated by a different mechanism."*
>
> (Hawkins, 1980, p. 1)

This definition gives insight into the question which must be posed of outlying data; was this data generated by an error or by some other mechanism related to the research? This decision is ultimately subjective, as there is not a rigid mathematical definition of what constitutes an outlier. A multitude of methods have been proposed to identify outliers in different types of data, for example, both univariate and multivariate data (Hodge and Austin, 2004). However, the detection of outliers alone is insufficient; a decision must be made to remove or retain the data. In cases where this decision is unclear, the default position adopted in this thesis will be to retain the data, with robust measures used to reduce their impact on the results.

To aid in the identification of outliers, outlier detection methods will be employed, and the data highlighted by these methods investigated to identify potential measurement error. The outlier detection method utilised in this thesis will be Tukey's fences (1977), as this method is based on robust statistics and therefore compatible with previous considerations. The method uses the interquartile range, the difference between the first and third quartiles of the dataset, to detect outlying values. Specifically, one and a half times the interquartile range is subtracted from the first quartile and added to the third quartile to create limits known as fences. Values more extreme than these fences are considered to be outliers (Laurikkala et al., 2000; Figure 3.2). For discrete variables, the number of outliers will be reported alongside the median and median absolute deviation to provide further information about the data; indicating the presence of extreme values. In cases where the median absolute deviation is similar, the number of outliers would indicate a difference in how a quantity varies, that is, the structure of variability.

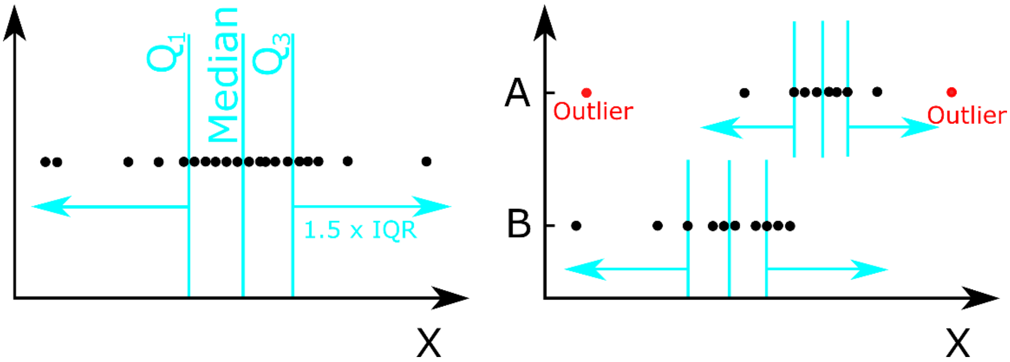


Figure 3.2. Graphical depiction of Tukey's (1977) fences for highlighting outliers in discrete data. Application to entire dataset (left) and individual participants (right). IQR = Interquartile range; Q_1 = First quartile; Q_3 = Third quartile.

Much modern scientific research, including in sports biomechanics, is based on the utilisation of statistical hypothesis testing but the foundation and practical relevance of these methods have been questioned (Nuzzo, 2014), and the misunderstanding and misuse of *p*-values have been raised as issues (Zhu, 2016). This misuse was such that the American Statistical Association released a position statement which sought to clarify the use and purpose of *p*-values and statistical hypothesis testing in science (Wasserstein and Lazar, 2016). Despite the commonly held belief, *p*-values do not measure the probability that the studied hypothesis is true or that the data were produced by random chance. Instead, *p*-values indicate the incompatibility of the data with a null hypothesis or model. On their own, *p*-values provide only weak evidence regarding a hypothesis and no evidence on the size of the effect (Wasserstein and Lazar, 2016). A significant *p*-value provides some evidence about a hypothesis but may have little effect on the probability that the hypothesis is true when the outcome was unlikely to begin. Rather, the entirety of scientific evidence should be weighed when judging a hypothesis (Nuzzo, 2014).

To combat the apparent issues with the misuse of *p*-values several alternative methods have been suggested such as confidence intervals and Bayes factors. However, these approaches are not without their limitations. Rather than reliance on a single index such as a *p*-value, a variety of approaches and summaries should be used, along with sound scientific reasoning (Wasserstein and Lazar, 2016). This avoids an outlook where results are either statistically significant or not, instead of considering statistical hypothesis testing as part of a body of evidence (Bernards et al., 2017). Hypothesis testing will be utilised in this thesis to provide information to the reader, but the interpretation of results will not be purely based on the statistical significance; the size of the difference, existing research and scientific reasoning will also be considered in the discussion.

It has also been suggested that statistical hypothesis testing should be accompanied by measures of effect size to allow the practical significance of a result to be easily determined. *P*-values are dependent on the sample size and measurement precision, and a statistically significant difference can be observed with any size effect (Wasserstein and Lazar, 2016). In sports science, the presence of a difference is not the only point of interest; it is also important to discern the practical significance of the difference as this can be more useful for results-based decision making (Zhu, 2016). A widely used effect size measure is Cohen's *d* statistic; calculated as the difference between the means divided by the pooled standard deviation (Cohen, 1988). This statistic is a standardised effect size but unstandardised measures of effect size, such as the difference between the group means, tend to be simpler to calculate and interpret. This is especially true in cases where the units have intrinsic meaning, such as for physical quantities like speed or distance. Thus, the difference between the mean or median values will be used to describe the practical difference between groups where statistical hypothesis testing is utilised in this thesis.

A specific issue with statistical hypothesis testing is that of data dredging; the testing of large numbers of hypotheses about a particular data set (Wasserstein and Lazar, 2016). Whilst omnibus tests can be used to reduce the number of statistical tests performed, there is always some probability of a false positive in a statistical hypothesis test and running large numbers of tests will increase the likelihood that a false positive is reported as truth (Nuzzo, 2014). The reporting of all hypotheses explored is encouraged to reduce this likelihood, but it remains possible that data dredging may be done somewhat unconsciously. It is also not valid to perform a *post hoc* selection of hypotheses, that is, after observation of the data (Pataky et al., 2013) and performing hypothesis tests on all variables will reduce statistical power (Pataky et al., 2015), inflating the likelihood of a false positive (Nuzzo, 2014). Data reduction techniques have shown utility by allowing meaning to be discerned from a large number of variables while minimising issues such as data dredging (Daffertshofer et al., 2004).

One such data reduction technique, which has found use in sports biomechanics research, is principal components analysis (Daffertshofer et al., 2004). Principal components analysis is a multivariate linear statistical procedure which uses an orthogonal transformation to convert a series of possibly correlated variables into linear uncorrelated variables called principal components. The transformation is defined such that the orientation of the first principal component has the largest possible variance and successive components have the largest variance after the preceding principal component has been removed (Mullineaux and Wheat, 2018). The applications of principal components analysis in sports science have been diverse, and examples of its use include the counter-movement jump (Laffaye et al., 2014), sport climbing (Mermier et al., 2000) and training load (Weaving et al., 2017). Principal components analysis has utility in cases where multiple single variable or pairwise analyses may fail to account for covariance in a data set (Mullineaux and Wheat, 2018) or where patterns are obfuscated by covariance (Shlens, 2014) and is most useful for large multivariate datasets. A principal components analysis yields principal components, principal component scores and eigenvalues as output variables. The principal components define the newly transformed variables, the principal component scores define the coordinates of the original data in the new principal components, and the eigenvalues denote the amount of variance explained in the original data set by each principal component. Examining only the principal components which explain a significant proportion of the variation allows a significant reduction in dimensionality and facilitates the identification of similarities, differences, and patterns in multidimensional data. Principal components analysis is an effective means of describing the inner structure of a data set and will be utilised in this thesis for the analysis of multivariate data.

The research questions in this thesis are concerned with relationships between variables, and this lends itself to the use of regression analysis. Regression analysis includes the use of many techniques which, in general, describe the relationships between dependent variables and predictor variables (Field, 2013). Regression analysis cannot be used to infer causality, but the analyses can be used to model relationships in the data. The efficacy of regression analysis is dependent on the use of an appropriate model and scatter plots, correlation analyses and other checks, such as residual analysis, should be used to check the model fit and the non-violation of assumptions (Field, 2013; Winter et al., 2001). Care should also be taken to ensure that the predictor variables are based on sound rationale and theoretical justification to minimise the finding of chance relationships (Winter et al., 2001).

Time series, ordered sequences of observations of the same variable over time, must be analysed somewhat differently to unordered data. An underlying assumption of time series is of dependence between adjacent observations. The lists of numbers 1,2,3,4,5 and 3,1,4,2,5 are described identically by typical statistical methods but, if the two lists are time series, it should be clear that the dynamics of the systems generating the measurements are different (Myers, 2016). Biomechanical analyses are often concerned with the dynamics of a variable over the time of a movement and these time series are often referred to as biomechanical trajectories.

The extraction of discrete data from continuous time series is not uncommon in biomechanical analyses. Some studies have extracted the value of a signal at a predetermined event, such as impact in the golf swing (Langdown et al., 2013b), or calculated summary metrics, such as the maximum, from a continuous time series (Myers et al., 2008). This approach has been extended to the creation of a new time series via the extraction of values at several different events during a movement (Ball and Best, 2007). It is worth noting that these new series remain time series because uniform gaps between data points are not a requirement, only that measurements are ordered by time (Myers, 2016). Whilst these approaches have significant benefits in terms of data reduction, they appear to be an over-simplification when methods exist which allow the examination of the complete time series. Another common method of working with time series data in biomechanics would be to calculate central tendency and dispersion statistics in a pointwise manner (Milner, 2018). For example, a mean time series could be calculated by taking the mean of each trial at every successive point, creating a new time series which describes the average dynamics over the duration of the original time series. The variability could be described by calculating a standard deviation time series but considerations relating to robustness in the use of summary statistics in discrete data remain. Wherever possible, methods which examine the whole time series will be used in this thesis along with robust measures when calculating summary time series in a pointwise manner.

The measurement of several trials of any movement will likely result in signals of differing lengths due to variability in both amplitude and phase (Chau et al., 2005) but many data analysis procedures require time series of the same length and time-normalisation techniques are common in biomechanics (for example, Smith et al., 2017). One of the most common methods of time-normalisation is to linearly transform the time series to a specified number of points, often 101, between two events which are common to both signals. This method is well utilised in sports biomechanics research (for example Chiu and Chou, 2012; Sanders et al., 2015), but requires the investigator to distort the original signal to achieve time-normalisation which can result in the time series being misaligned in the middle of the time series. Alternative methods such as dynamic time warping (Wang and Gasser, 1997) or curve registration (Chau et al., 2005), which utilise identified landmarks and iteratively estimated means respectively, have been proposed to adjust for this misalignment in phase. However, these techniques also require the distortion of the original time series which results in differentials which are effectively meaningless.

The slope of a curve provides important information about the dynamics of a time series, particularly in sports biomechanics where the slope often indicates the velocity of the movement, and most time-normalising techniques corrupt this source of information. One alternative method is to align the signals on an event of interest, then shorten or extend all signals such that they cover the period of interest for either the longest or shortest signal. Extra data, outside of the period of interest, must be collected to allow signals to be extended in this manner. The signals will only be completely in phase at the event of interest and variability measures will therefore indicate variability in both amplitude and phase. This can make a comparison between signals more difficult but avoiding distortion of the original signals is considered more important to the aims of this thesis and this method is therefore preferred.

Filters, either low-pass filters, splines or other methods are often used to reduce noise in biomechanical signals, but present a conundrum with regard to variability (James, 2004). In theory, filters are used to separate and remove components of the signal indicative of random measurement error (Challis, 2018) but the frequencies associated with the biological signal and random error are likely to overlap. In practice, a filter will either allow some noise to pass through, attenuate some of the biological signal, or do both. Whilst certain methods can estimate the optimum frequency at which to filter the data (for example Challis, 1999), it is likely that different signals will have a different optimum cut-off frequency. Thus, choosing to filter the data presents the option of filtering parts of the data at a non-optimal frequency or filtering at different frequencies, neither of which is ideal (James, 2004). As it is difficult to discern biological variability from noise, the effect of filtering on the biological variability contained in the signal, even at an optimal cut-off frequency, is unknown. It has been suggested that it is more appropriate to avoid filtering when concerned with variability, avoiding any attenuation of the biological signal (Buzzi et al., 2003). The general approach in this thesis will be to prioritise the preservation the original signal, either by not filtering the data or filtering at a higher than usual cut-off frequency. This approach, whilst preserving the maximum amount of information in the signal, is likely to be inappropriate for investigations interested in the derivatives of a signal as any noise in the signal will be amplified in the process of differentiation.

Most statistical hypothesis testing techniques are concerned with the testing of discrete data, but the use of discrete hypothesis testing on values extracted from a continuous time series is not encouraged as a research method. There are multiple values which could be extracted from a signal and the exploration of possibilities prior to testing will lead to misinformed conclusions (Wasserstein and Lazar, 2016). This has been highlighted as a particular issue in biomechanics, where the inspection of trajectories prior to statistical testing is common (Pataky et al., 2015). Methods such as statistical parametric mapping provide a framework for statistical hypothesis testing in continuous data (Pataky, 2012), but tools developed for biomechanics are currently not able to utilise these methods in unbalanced data; where the number of observations differ between groups.

However, the analysis of continuous time series, without *a priori* selection of features, can also be achieved using principal components analysis. Principal components analysis yields principal components of the same dimension as the input data and calculates principal components which describe specific features in the time series. Thus, principal components analysis can be an effective data reduction and feature identification technique for time series data as well as discrete data (Brandon et al., 2013; Daffertshofer et al., 2004). Indeed, the utilisation of principal components analysis on kinematic and kinetic time series data is more prevalent in the biomechanics community that its use on discrete data sets. Examples of activities where principal components analysis has been applied to the analysis of biomechanical time series include gait (Kipp and Palmieri-Smith, 2012), diving (Young and Reinkensmeyer, 2014) and alpine skiing (Federolf et al., 2014). Golf specific examples include analysis of the clubhead delivery plane (Morrison et al., 2018), differences in three-dimensional ground reaction forces in differently skilled golfers (Lynn et al., 2012) and patterns in the centre of pressure and centre of gravity (Smith et al., 2017).

In principal components analysis with time series data, the principal components can be visualised as the difference from the mean trajectory, and the principal component scores as the degree to which each individual trial reflects this feature of the data set. The eigenvalues once again indicate the percentage of the variance in the original data set explained by each principal component. The principal component scores are discrete values which can be used with traditional statistical hypothesis testing methods and their variability can indicate the variability of the trajectory as a whole, a large reduction in data (Foch and Milner, 2014). Principal components analysis can also be used to identify features of the time series, for example, differences in magnitude, shape or phase between time series (Brandon et al., 2013). The meaning of the output of principal components analysis is sometimes considered to be challenging to interpret, but this interpretation can be facilitated by techniques such as single component reconstruction (Brandon et al., 2013), which provides a simplified visualisation of the biomechanical difference captured by each principal component. Principal components analysis allows the identification and description of important characteristics of time series data and provides an effective method of data reduction, both of which will be of significant benefit to the data analysis performed in this thesis.

As with discrete data, outliers can equally present in continuous variables such as time series, although it is also possible for a time series to be an outlier for only part of the total time. Where it is unclear if an outlier is due to measurement error or system dynamics, the default position remains to retain data and utilise robust measures in the analysis. However, unlike with discrete data, the number of outliers does not provide an indication of the distribution the data; other measures are required to elucidate the structure of variability in continuous variables.

The concept of entropy, rooted in classical thermodynamics, has been applied to biological time series to provide an indication of the structure of variability in the signals (Yentes et al., 2013). In thermodynamics, entropy can be conceptualised as the randomness of a system. In information theory meanwhile, it is defined as the loss of information in a signal, that is, how well can you predict future states of the system from current states (Stergiou, 2016). High entropy values indicate low levels of predictability, and lower entropy indicates increased regularity (Yentes et al., 2013). Measures of entropy should not be conflated with measures of complexity, as entropy measures the predictability of a time series over only one scale and a true measure of complexity must examine multiple time scales (Harbourne and Stergiou, 2009). Entropy measures provide a measure of pattern recurrence or regularity and are well suited to biological systems with variability derived from both deterministic and stochastic sources (Stergiou, 2016). However, most measures require long input signals, restricting the use of these tools to movements where these signals are readily available, such as gait (Buzzi and Ulrich, 2004). Nonetheless, entropy measures have found use in the analysis of discrete movements through the use of an alignment process, joining together multiple signals to create a single pseudo-periodic time series with discontinuities at the junctions between signals (Preatoni et al., 2010). It has been suggested that these discontinuities have a negligible effect on the results, as they make up a relatively small proportion of the overall signal.

Two of the most popular algorithms for estimating the entropy of biological signals are approximate entropy and sample entropy. Approximate entropy, developed by Pincus and Singer (1995), was specifically developed for use with experimental time series generated by biological processes and has found much use in the biomechanics literature (Stergiou, 2016). Sample entropy is a modification of approximate entropy, designed to address a bias toward regularity, decrease parameter dependence and improve performance in short time series (Richman and Moorman, 2000). Both algorithms measure the regularity of a signal through by estimating whether two sequences of m points remain similar for incremental sequences of $m+1$ points, with lower values indicating more regular time series. Due to its decreased dependence on parameter lengths, sample entropy will be used as a measure of the predictability of a time series and an indication of the structure of the variability in the time series in this thesis. The algorithm for calculating sample entropy is as follows:

(1) Form a time series, $u = u(1), u(2), \ldots u(N)$, which consists of N evenly spaced measurements

(2) Fix m, the vector length, as an integer value and r, the tolerance, as a positive real number

(3) Form the sequence of vectors $\boldsymbol{x_m} = \boldsymbol{x_m}^{(1)}, \boldsymbol{x_m}^{(2)}, \ldots \boldsymbol{x_m}^{(N-m+1)}$ defined by $\boldsymbol{x}^{(i)} = [u^{(i)}, \ldots u^{(i+m-1)}]$

(4) Define the distance between two vectors as $d[\boldsymbol{x},\boldsymbol{x^*}] = max|u^{(a)} - u^{*(a)}|$ where $u^{(a)}$ are the m scalar components of $\boldsymbol{x}$

(5) For each $1 \leq i \leq N\text{-}m+1$, use the sequence $\boldsymbol{x_m}$ to construct:

$$C_i^m = \frac{(number\ of\ \boldsymbol{x}^{(j)}\ such\ that\ d\left[\boldsymbol{x}^{(i)}, \boldsymbol{x}^{(j)}\right] \leq r)}{(N-m)}$$

where $1 \leq j \leq N\text{-}m+1$ and $i \neq j$

(6) Calculate $B_i = \frac{\sum_i (C_i^m)}{(N-m)}$

(7) Form the sequence of vectors $\boldsymbol{x_{m+1}}$

(8) Calculate $A_i = \frac{\sum_i (C_i^{m+1})}{(N-m)}$

(9) Sample entropy is defined as $\lim_{N\to\infty} \left\{-\ln\left(\frac{A_i}{B_i}\right)\right\}$, however to resolve the limit:

$$Sample\ entropy = -\ln\left(\frac{A}{B}\right)$$

where $A = \frac{(N-m-1)(N-m)}{2} A_i$ and $B = \frac{(N-m-1)(N-m)}{2} B_i$

Equation 3.1. Algorithm for calculating sample entropy of a time series.

As little experimental evidence exists on the effect of discontinuities on the performance of the sample entropy algorithm, this thesis will also use cross-sample entropy; an application of the sample entropy algorithm to two discrete time series. In this method the template vector is taken from one time series and the comparison vectors from the other time series which allows the calculation of entropy between two separate time series without an alignment process. The algorithm for calculating cross-sample entropy is as follows:

(1) Form two time series, $u = u^{(1)}, u^{(2)}, \ldots u^{(N)}$ and $v = v^{(1)}, v^{(2)}, \ldots v^{(N)}$ which consist of N evenly spaced measurements

(2) Fix m, the vector length, as an integer value and r, the tolerance, as a positive real number

(3) Form the sequence of vectors $\boldsymbol{x}_m = \boldsymbol{x}_m^{(1)}, \boldsymbol{x}_m^{(2)}, \ldots \boldsymbol{x}_m^{(N-m+1)}$ and $\mathbf{y}_m = \mathbf{y}_m^{(1)}, \mathbf{y}_m^{(2)}, \ldots \mathbf{y}_m^{(N-m+1)}$ defined by $\boldsymbol{x}^{(i)} = [u^{(i)}, \ldots u^{(i+m-1)}]$ and $\mathbf{y}^{(i)} = [v^{(i)}, \ldots v^{(i+m-1)}]$ likewise

(4) Define the distance between two vectors as $d[\mathbf{x},\mathbf{y}^*] = max|u^{(a)} - v^{*(a)}|$ where $u^{(a)}$ and $v^{(a)}$ are the m scalar components of $\boldsymbol{x}$ and $\mathbf{y}$ respectively

(5) For each $1 \leq i \leq N\text{-}m+1$, use the sequence $\boldsymbol{x}_m$ to construct:

$$C_i^m = \frac{(number\ of\ \boldsymbol{x}^{(j)}\ such\ that\ d\left[\boldsymbol{x}^{(i)}, \boldsymbol{x}^{(j)}\right] \leq r)}{(N-m)}$$

where $1 \leq j \leq N\text{-}m+1$ and $i \neq j$

(6) Calculate $B_i = \frac{\sum_i (C_i^m)}{(N-m)}$

(7) Form the sequence of vectors $\boldsymbol{x}_{m+1}$ and $\mathbf{y}_{m+1}$

(8) Calculate $A_i = \frac{\sum_i (C_i^{m+1})}{(N-m)}$

(9) Cross-sample entropy is defined as $\lim_{N \to \infty} \left\{-\ln\left(\frac{A_i}{B_i}\right)\right\}$, however to resolve the limit:

$$Cross - sample\ entropy = -\ln\left(\frac{A}{B}\right)$$

where $A = \frac{(N-m-1)(N-m)}{2} A_i$ and $B = \frac{(N-m-1)(N-m)}{2} B_i$

Equation 3.2. Algorithm for calculating cross-sample entropy of two time series.

Both measures have no units, are undefined in cases with no similar vectors and are direction independent (Stergiou, 2016).

3.5. Experimental methods

The experimental methods utilised are a key consideration for all scientific inquiry, but this consideration is particularly pertinent when variability is the topic of interest. In any series of measurements, the measured variation is a combination of the intrinsic variability in the system being studied and the measurement error of the system used (Equation 3.3, from James, 2004). This is a simplification of Equation 2.1, formed by combining the variability due to the non-linear dynamics of the system and biological error into a single term; the variability of the system.

$$V_{measured} = V_{system} + V_{measurement\ error}$$

Equation 3.3. Components of total measured variability in a biological system (James, 2004).

All measurement systems are the subject of random error; this is a fundamental limitation to the measurement of any varying system (Bland and Altman, 1996). In the case of movement variability, where differences in movement can be of a similar magnitude to measurement error, measurement error is entwined with the phenomenon being studied, and the careful, rigorous interpretation of measured variability a non-trivial enterprise (James, 2004). Consequently, a consideration of data collection methods has increased importance in investigations of variability, to ensure that the data collected can provide appropriate information regarding the research question. This thesis will characterise the effect of measurement error using existing literature and specific investigations. Whilst it is not feasible, or likely even possible, to fully mitigate the effect of measurement error, effort must be made to understand the components of the measured variability of the golfer and their effect on the interpretation of results.

Another consideration is the number of observations required to gain a true indication of variability. This could be considered analogous to the determination of an appropriate sample size; observations represent a sample from a larger population of possible observations, just as the participants are a subset of a larger population. There is no clear recommendation on the number of trials required, rather, research suggests that this decision is dependent on the research question, task and other constraints on the data collection (James, 2004). Whilst no two trials are identical, Bates (1996) suggested that individuals produce performances randomly, as if they were a random trial generator. This fails to account for a fatigue effect, found in previous work from within the research group, which suggests that this behaviour does not continue indefinitely. Statistically, variability measures tend to stabilise after an undetermined number of trials (Bates et al., 1983) and so the number of trials must balance the stability of measures stabilise against possible fatigue. As such, the optimum number of trials is dependent on the participant as well as the task and the determination of an appropriate number of observations is unavoidably subjective.

Inquiry in the sports sciences is characterised by systematic attempts at analysing the behaviour of sports performers in specific environmental contexts and the setting of the data collection should be considered an important part of the methods. The more the research setting can reflect the performance setting of interest, the more credibly the research has in its application. This is termed the ecological validity of the research (Davids, 1988). Differences in the environment can predispose the performer to different movement strategies, which may also affect the trial-to-trial variability (Newell and Jordan, 2007). To maximise ecological validity, data would be collected in competition, on the golf course, but there are often disadvantages associated with field-based data collection methods. Research conducted in a laboratory setting has reduced ecological validity but can make use of more sophisticated data collection methods, which should help to minimise measurement error (Payton and Bartlett, 2018). For this thesis, field-based methods are not likely to have enough accuracy to allow the variability of the golfer to be determined in any meaningful way, but purpose-built movement laboratories and a careful consideration of task will be used to maximise the ecological validity of the research.

Task constraints affect the coordination of movement and changes in the task have the potential to affect changes in movement (Newell and Jordan, 2007). It is important that differences in movement due to changes in task constraint are not misconstrued for movement variability. Therefore, it is important to ensure task constraints remain constant, both within a session and between sessions. The phenomenon of strategic shot selection proposed by Langdown et al. (2012) provides a useful indicator of how changes in task might manifest in golf as the golfer can achieve the same final location with different shot types and club selections. The task has an important role in ensuring that movement variability reflects movement coordination but is often not considered in golf biomechanics research. An experimental set-up where the golfer strikes shots directly into a net is not uncommon (Dale and Brumitt, 2016; Zheng et al., 2008b), but provides only a broad definition of the task to the golfer; strike the ball into the net. More specific tasks involving striking the golf ball toward a target on a range (Betzler et al., 2014), a simulator (Chu et al., 2010) or a net (Bradshaw et al., 2009), have also been utilised and have the secondary advantage of providing performance feedback to the golfer. As the facilities utilised in this thesis allow the golfer to hit shots onto an outdoor range from an indoor laboratory, a clear definition of task and relevant performance feedback will be possible throughout.

Another benefit of a clearly defined task is that it allows task performance to be used in the classification of skill. Golfing handicap is a widely used measure of skill but is not ideal for biomechanical studies because two individuals can obtain the same handicap with different levels of skill in different areas of the game (Wallace et al., 1994). A golfer might be more proficient at driving the ball but less proficient at putting and short game skills compared to another golfer with the same handicap. Handicap is also slow to react, with an individual having to consistently perform above or below the level of their handicap to affect change; an improving golfer could have a lower than expected handicap based on their immediate skill level. Task performance measures could indicate the skill of the golfer but will be task specific. To provide the reader with the maximum amount of information, and to contribute to the literature in this area, this thesis will present a measure of task performance alongside shot outcome measures and handicap throughout this thesis; this will allow for a rich understanding of the skill of the golfers studied.

Clubhead presentation, ball launch and shot outcome variables are often used as performance measures in biomechanical research (Ball and Best, 2007; Tucker et al., 2013) and there are many commercially available systems which measure, or otherwise calculate these variables. These systems are known as ‘launch monitors’ and they offer valuable information to golfers, coaches, club-fitters, biomechanists and equipment manufacturers but the reliability of this information is rarely independently verified (Leach et al., 2017). Commercially available launch monitors generally make use of one of two measurement technologies, Doppler radar or stereoscopic cameras (Leach et al., 2017), with advantages and disadvantages associated with each technology. A bespoke system for calculating clubhead presentation variables, based on optical motion capture was previously developed in response to the testing needs of the research group (Betzler et al., 2012). This system allows the inspection of raw data and all calculation methods are known, allowing a clearer understanding of the specific error of measurements. In development of the system, testing found the standard deviation of 40 repeated shots hit by a golf robot to be less than 0.15 m·s^{-1}, 0.15°, 0.06°, 0.10° and 1.50 mm for measures of clubhead speed, face angle, club path, attack angle and impact location respectively (Betzler et al., 2012). However, no equivalent system for measuring ball launch or shot outcomes has been developed in the research group. Therefore, commercial methods for the calculation of ball launch and shot outcome variables will be utilised in this thesis.

A specific investigation was performed which investigated the reliability and repeatability of three specific launch monitors and established their base-line repeatability so that future results could be interpreted in context. The aim of this investigation was to describe the repeatability of three commercial launch monitors presented with repeated shots from a golf robot. The three launch monitors concurrently measured a total of 72 shots, with 6 different launch conditions. The repeatability of all launch monitors was comparable, at around 1 m·s^{-1} for measures of ball speed, 1° for measures of launch angle, 1.5° for measures of launch direction, 75 rad·s^{-1} for measures of spin rate and 8° for measures of spin axis. Agreement between launch monitors was generally high, but systematic offsets were present between the units. The information gained allows the variability of measurements taken with the launch monitors to be interpreted with respect to their internal repeatability. The full investigation is presented at the end of the chapter.

The measurement of movement is a keystone of biomechanical research and, as such, measurement techniques are largely well-established and well-documented in the literature. Modern motion capture systems allow the collection of a large amount of kinematic data in a comparatively short amount of time and there are many types of motion capture utilised in modern biomechanics; including inertial, magnetic and optical marker-less and marker-based systems. Optical marker-based motion capture is typically considered to be the gold standard method for measurement of human movement in biomechanical research (Ceseracciu et al., 2014), has been widely utilised in golf (for example Vena et al., 2011; Wheat et al., 2007) and will be utilised as the primary method of motion capture in this thesis.

Optical marker-based motion capture is a mature data collection method and, whilst methods have evolved and improved since its inception, the underpinning theory remains relatively unchanged. In brief, two-dimensional coordinate data from multiple camera views and known parameters of the cameras are used to calculate the three-dimensional coordinates of features interest (Abdel-Aziz and Karara, 1971; Shapiro, 1978). Modern optical motion capture systems automate the identification of features of interest by placing markers at specified locations of interest. The light signatures of these markers are easily detected by software, mostly removing the need for manual identification (Milner, 2018). To calculate three-dimensional coordinates from a series of two-dimensional image coordinates, the internal parameters of the cameras, the focal length and lens distortion for example, and the external parameters, their position and orientation, must be calculated using some form of calibration procedure. For three-dimensional motion capture, this information must be calculated for each camera in the motion capture system and will affect the accuracy and repeatability of measurements made by the system.

As the process of determining camera parameters tends to be manufacturer specific, a specific investigation was performed using the motion capture system and laboratory set up used. This investigation focused on the repeatability of measurements made with the optical motion capture and the effect of changes in calibration on the measurements. This was achieved by applying many calibrations to a series of measurements of objects with known dimensions. The median difference between the reference distance and measured distance during all trials was -0.01 ± 0.28 mm. The average median absolute deviation of this difference was 0.14 ± 0.08 mm. Similarly, the median difference between the reference angle and measured angle during all trials was 0.00 ± 0.04° and the median absolute deviation of this difference during a trial was 0.04 ± 0.02°. In general, small fluctuations of up to 0.5 mm in the distance between markers were observed when objects moved within the measurement volume, the volume covered by the views of two or more cameras. Much larger fluctuations, of up to 5 mm, were observed when the object was moved near the edge of the measurement volume. No meaningful differences were observed between calibrations, including calibrations which were constrained to a very small region of the volume. These results suggest that the accuracy and repeatability of measurements made by the motion capture system are robust to different calibrations. The full investigation is presented at the end of the chapter but, whilst the results provide an indication of the accuracy and repeatability of the motion capture system, the measurement of marker location by the motion capture system is not the only component of error in the measurement of human movement kinematics.

To quantify human movement using optical marker-based motion capture, the body is typically modelled using segments, known as the kinematic model. To measure the movements of these segments, three or more markers, which do not lie along a straight line, are placed on each segment to define and then track the movement of the segment. The coordinate system defined using these markers is known as the technical coordinate systems. However, to give anatomical meaning, this technical coordinate system is transformed to a coordinate system which has relevance to the underlying anatomical structure; the anatomical coordinate system (Besier et al., 2003; Cappozzo et al., 2005). The transformation is typically defined by placing markers on anatomical landmarks to calculate the location of specific anatomical features during a static trial. For instance, one might place markers on bony landmarks on either side of the elbow joint and use measurements of markers to calculate the location of the elbow joint centre. Alternatively, specific movement trials may be recorded which allow the determination of anatomical features; a knee flexion trial used to determine the knee joint axis, for example. Other methods of defining the anatomical coordinate systems include kinematic constraints, optimisation procedures and anthropometric regressions (Davis et al., 1991; Schwartz and Rozumalski, 2005). Once the coordinate systems which make up the kinematic model have been defined, the angles between these coordinate systems are typically calculated using Cardan or Euler angles.

A well-documented source of error in kinematic measurements using optical marker-based motion capture systems is 'skin movement artefact' (Milner, 2018) or 'soft tissue artefact' (Taylor et al., 2010). This is the discrepancy between the movement of markers affixed to the participant's skin and the underlying skeletal movement, caused by movement of soft tissues relative to the skeleton. Studies have used markers affixed using bone pins to investigate this phenomenon. This method is clearly not feasible for sports, but these studies provide a valuable source of information regarding the error which might be attributed to soft tissue artefact. For example, Cappozzo et al. (1996) reported errors of 10% of the flexion-extension range of movement, 50% of the abduction-adduction range of movement and 100% of the internal-external rotation range of movement at the knee during walking. These results show that soft tissue artefact is clearly a major factor in obtaining reliable kinematic data. Whilst it has been suggested that it can be minimised with careful design and application of the marker-set, there is no true consensus on the best method to minimise soft tissue artefact in sport (Milner, 2018) and it remains an obstacle to the measurement of reliable kinematic data in sport (Cereatti et al., 2017).

There is evidence to suggest that errors due to the inconsistent placement of markers can be of greater magnitude than either instrumentation error or soft tissue artefact (Croce et al., 1997). Small differences in the location of markers, either between individuals or in different sessions with the same individual, can lead to differences in anatomical coordinate systems which introduce errors into kinematic measurements. Whilst it has been estimated that the error attributed to the inconsistent location of markers is generally less than 5° (McGinley et al., 2009), errors of greater than 10° have also been reported (Corke, 2015). The characteristic of these errors is an offset in the joint angle between sessions or individuals, rather than a change in the shape of the joint angle trajectory (Croce et al., 1997). However, cross-talk between axes can also occur and will alter the shape of the joint angle trajectories (Croce et al., 2005). Sagittal plane angles have been reported to be more reliable than frontal or transverse angles between sessions (McGinley et al., 2009), which is an indication of this cross-talk effect.

A specific investigation was performed to investigate the inter-session repeatability of joint kinematics in optical motion capture. This investigation sought to investigate errors caused by inconsistent marker placement, specifically errors leading to offsets in the joint angle between sessions. These errors reduce the ability to discern true differences in joint angle between sessions or between individuals. The investigation consisted of multiple applications of a set of markers to the surface of a golf robot and utilised several different conditions to investigate the characteristics of the error. A functional joint centre-based approach was used to determine the kinematic model, as this was hypothesised to be less reliant on marker locations. However, joint angle offsets were still observed with this method, and no alternative solutions were found. The full investigation can be found at the end of the chapter and, although no improvements on current protocol were found, provided valuable experience relating to errors attributable to inconsistent marker application and might be of interest to future investigations into the phenomenon. The investigation highlighted a need to cautiously interpret absolute differences in joint angle when comparing different applications of a marker-set. It may also be appropriate to adopt data analysis procedures which mitigate the impact of this type of error on the interpretation of results, for example, by removing between-session offsets in joint angles before analysis.

Along with measurements of movement, measurements of force, or kinetics, are equally prevalent in biomechanical research. Most often, the forces measured by biomechanists are external forces, those applied by the body on the external environment, however, internal forces have also been measured (for example, Kutzner et al., 2017). External forces include those applied by the athlete on an implement, such as a club or ball, but the most common forces of interest are those between the athlete and the ground. These forces are typically measured using either rigid strain gauge or piezoelectric force platforms (Chockalingam and Healy, 2018), and these types of force platform have been widely utilised in golf biomechanics research (for example Lynn et al., 2012; Smith et al., 2017). Force platforms are typically factory-calibrated and, whilst additional static calibration of the vertical component of the ground reaction force is possible, dynamic calibration of all component forces is difficult to achieve without specialised equipment (Fairburn et al., 2000). Errors in force measurements have been well-documented in the literature and typically the largest errors are typically observed in the centre of pressure, with errors of up to 30mm reported (List et al., 2017). However, the accuracy of centre of pressure measurements is influenced by the vertical load applied to the force platform at the time of measurement, with forces below a given threshold resulting in reduced accuracy (Chockalingam et al., 2002). The accuracy of the ground reaction forces depends mainly on the sensing elements and is less influenced by other factors, such as the mounting or covering, than the centre of pressure. Modern force platforms have a typical accuracy of approximately 0.25% of the applied force for forces between 10 and 5000 N (Chockalingam and Healy, 2018).

3.6. Specific investigations into the accuracy and repeatability of methods.

This section presents a series of investigations which characterised the specific accuracy and repeatability of three methods which were used in the thesis. The investigations provide valuable context about the measurement error associated with these methods which allows rigorous interpretation of measurements of human variability in future chapters. It was not feasible to investigate every aspect of the methods, instead, three main areas of interest were identified using experience within the research group and the extant literature: the repeatability of measurements made with commercial launch monitors, the effect of calibration on measurements made using an optical motion capture system and the repeatability of intersession kinematic measurements using optical motion capture.

3.6.1. A comparative analysis of the repeatability of measurements made with commercial launch monitors.

A. Introduction

The clubhead-ball impact only lasts around 500 µs (Hocknell et al., 1996), but it is the parameters of this impact which primarily influence the outcome of the shot. Measurements of this impact provide useful outcome measures for a biomechanical investigation. Motion capture systems have been successfully used to measure clubhead presentation at impact (Betzler et al., 2014), but limitations mean that bespoke commercial measurement solutions are the preferred method for measuring ball launch. However, the accuracy and repeatability of measurements made by commercial launch monitors are not well established as manufacturer stated accuracy values are generally unclear and not usually independently verified.

At the onset of this investigation, the accuracy and repeatability of commercial launch monitors had not been the subject of independent scientific inquiry, but Leach et al. (2017) have since published a study determining the accuracy of two commercial launch monitors compared to a gold standard reference measure. Leach et al. (2017) investigated a total of 240 shots by eight right-handed male golfers with a driver, 7-iron and utility wedge club. Shots were concurrently measured by two launch monitors, a Doppler radar-based Trackman Pro IIIe and a stereoscopic camera-based Foresight GC2 +HMT. An optical GOM Inspect system, with a manufacturer claimed spatial accuracy of 25 µm, acted as a gold standard reference. Ball launch variables were considered sufficiently accurate and repeatable for research but clubhead variables were found to be more variable and measurements were not considered to be research grade (Leach et al., 2017). This investigation provides valuable information, but as each shot measured was different, the repeatability of measurements made by launch monitors when presented with multiple identical shots is still unclear.

This investigation used concurrent measurements of repeated shots hit by a golf robot to determine and compare the repeatability of three launch monitors. A direct measure of accuracy was not possible, as this would require a gold-standard measurement system to compare against, but the use of three launch monitors enabled the agreement between launch monitors to act as a proxy for accuracy. The main aim of the investigation was to assess the repeatability of initial launch conditions measured by each launch monitor and provide a frame of reference, a lowest detectable variability, within which results from human testing can be interpreted.

B. Methods

Three launch monitors were chosen for this comparison; a Trackman Pro IIIe Doppler radar-based launch monitor (TM; Trackman Golf, Vedbaek, Denmark), a Foresight GC2 stereoscopic camera-based launch monitor (GC2; Foresight Sports, San Diego, CA) and a third stereoscopic camera-based research launch monitor (RLM). Each of the launch monitors selected for use in the investigation was taken from pre-existing research equipment, not specially acquired for this testing, and no special configuration or set up was performed before testing.

The three launch monitors were set up to concurrently monitor shots from a Golf Laboratories Testing Robot (Golf Laboratories, San Diego, CA), which hit shots onto an exterior driving range (Figure 3.3). A flag on the driving range, approximately 200 m downrange, defined the target line for the investigation. The TM and RLM launch monitors each had a calibration procedure, which defined the target line in relation to the orientation of the unit, and this was performed as per manufacturer recommendations before testing. The GC2 launch monitor had no calibration procedure, although it used an accelerometer to adjust for differences in level and was set up such that its front edge was parallel to the target line, as much as this was possible. Otherwise, launch monitors were operated according to manufacturer recommendations and pilot testing confirmed that there was no interference between the launch monitors under these conditions.

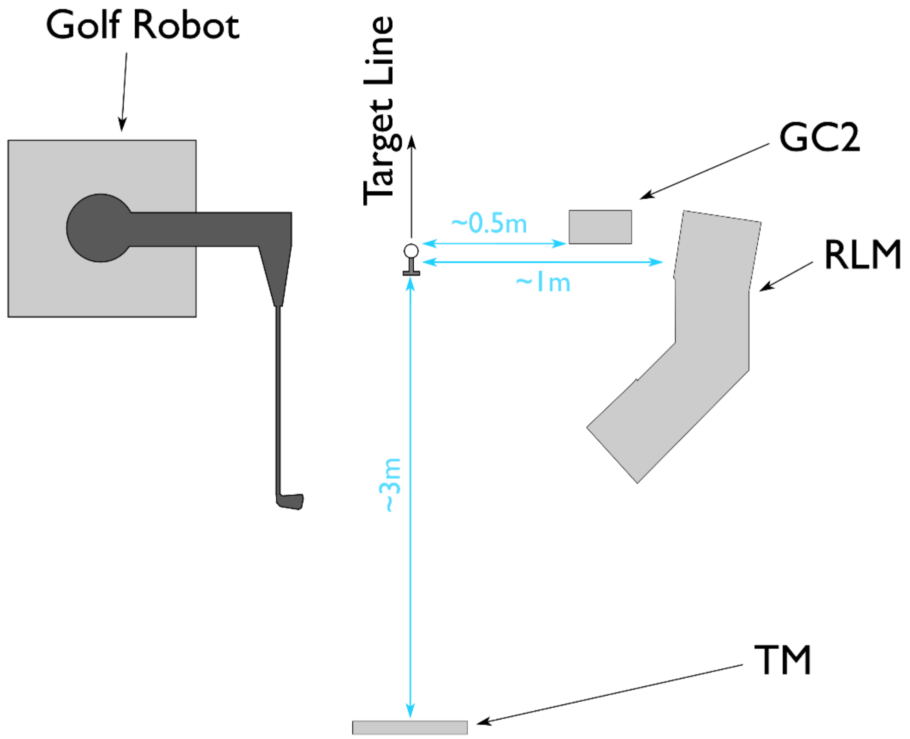


Figure 3.3. Positioning of launch monitors and golf robot in testing.

Two clubs were used in the analysis, a driver and a 5-iron, and tour grade, solid core golf balls were used in the testing. The robot was manipulated to provide launch conditions which were roughly equivalent to that of an average tour player with each club. These launch conditions were obtained with a central strike location and neutral face angle in each case. For each club, two further launch conditions were created by moving the impact location 15 mm up the face and down the face for the iron, and 15 mm toward the heel and toward the toe for the driver. The movement of the strike location altered the launch conditions and resulted in a total of 6 launch conditions studied. 12 shots were hit for each launch condition, giving a total of 72 concurrently measured shots. Between shots, a cloth and a small amount of ethanol were used to clean the face and ensure that debris did not accumulate on the club face during the testing.

The variables calculated by the launch monitors were: ball speed (mph), launch angle (°), launch direction (°), spin rate (rpm) and spin axis angle (°). Definitions of these variables were consistent between launch monitors, except for the RLM launch monitor which reported back-spin and side-spin instead of spin rate and spin axis angle. These values were converted into total spin rate and spin axis to compare to the other two launch monitors. Furthermore, ball speed and spin rate were converted into their SI units, m·s^{-1} and rad·s^{-1} for reporting and analysis. Where a launch monitor failed to measure a variable or variables, but the other launch monitors reported without issue, the shot was not repeated. The number of missing values reported in the results section, as this is an important consideration for biomechanical testing.

Following the testing, launch conditions were exported from the respective software and loaded into MATLAB (R2018a, Mathworks, Natick, MA) where all further analysis was performed. Since one might reasonably assume the error in repeated measurements to be normally distributed (Bland and Altman, 1999), the mean and standard deviation were calculated as descriptive statistics for each launch condition. In a normal distribution, 95% of values sit within two standard deviations of the mean and this range was calculated by multiplying the standard deviation by four to indicate the repeatability of the launch monitors. Agreement between the launch monitors was assessed using Bland and Altman's (1999) limits of agreement, calculated using the entire dataset. Since none of the launch monitors represented a gold standard measure, this analysis was performed in a pairwise manner. For a given pair of launch monitors, the difference in value between the paired measurements were calculated. Missing values were excluded from the calculations. The mean of the paired differences, *m*, indicates the systematic offset between the systems. The 95% limits of agreement, the interval within which 95% of the differences between the two measurements are expected to lie, are then calculated by adding and subtracting 1.96 times the standard deviation of the differences, *s*, from *m* (Bland and Altman, 1999).

C. Results

The data is presented as a scatter plot in Figure 3.4, and the mean and standard deviation of the launch conditions from each of the launch monitors for each of the different shots is shown in Table 3.2. Indicated by the range within which 95% of measurements would be expected for a normal distribution, the repeatability of measurements varied for each of the shot conditions studied and, in general, no launch monitor greatly outperformed the others. On average, the repeatability of ball speed was around 1 m·s^{-1} (~2.2 mph), launch angle around 1°, launch direction around 1.5°, spin rate around 75 rad·s^{-1} (~715 rpm) and spin axis around 8° for all launch monitors. The only exception to this pattern was the RLM launch monitor, which showed much poorer repeatability of spin axis, a 95% range of 23.0° on average. However, one set of spin axis measurements with the RLM launch monitor showed a much higher standard deviation than the other, 20.6° compared to the average of 5.7°. With this set removed, the average 95% range dropped to 11.1° which is closer to the values observed by the other launch monitors.

The limits of agreement analysis (Table 3.1) indicated systematic offsets between the units; however, most of these offsets would be considered practically insignificant. One exception could be the systematic offset in ball speed of approximately 1 $m \cdot s^{-1}$ observed between the GC2 unit and the other two launch monitors. Systematic offsets were also observed between the units in launch angle, launch direction and spin axis, although differences in alignment between the units could easily explain these offsets. There appeared to be no systematic offset between any of the units in spin rate. The agreement between the units is indicated by the range between the upper and lower 95% limits and showed agreement to be generally high and of a similar magnitude for all measurements.

Table 3.1. Pairwise limits of agreement analysis of launch conditions.

		Ball Speed ($m \cdot s^{-1}$)	Launch Angle (°)	Launch Direction (°)	Spin Rate ($rad \cdot s^{-1}$)	Spin Axis (°)
GC2 - RLM	Lower 95% limit	0.2	0.3	-0.8	-45	-24.5
	Mean difference	0.9	0.6	0.6	3	-3.8
	Upper 95% limit	1.5	1.0	2.0	51	16.9
GC2 - TM	Lower 95% limit	0.0	1.0	-3.2	-12	-16.1
	Mean difference	0.8	1.4	-1.6	7	-6.6
	Upper 95% limit	1.5	1.8	-0.1	26	2.9
RLM - TM	Lower 95% limit	-0.6	0.4	-3.7	-40	-23.5
	Mean difference	-0.1	0.8	-2.2	5	-3.0
	Upper 95% limit	0.3	1.3	-0.8	51	17.6

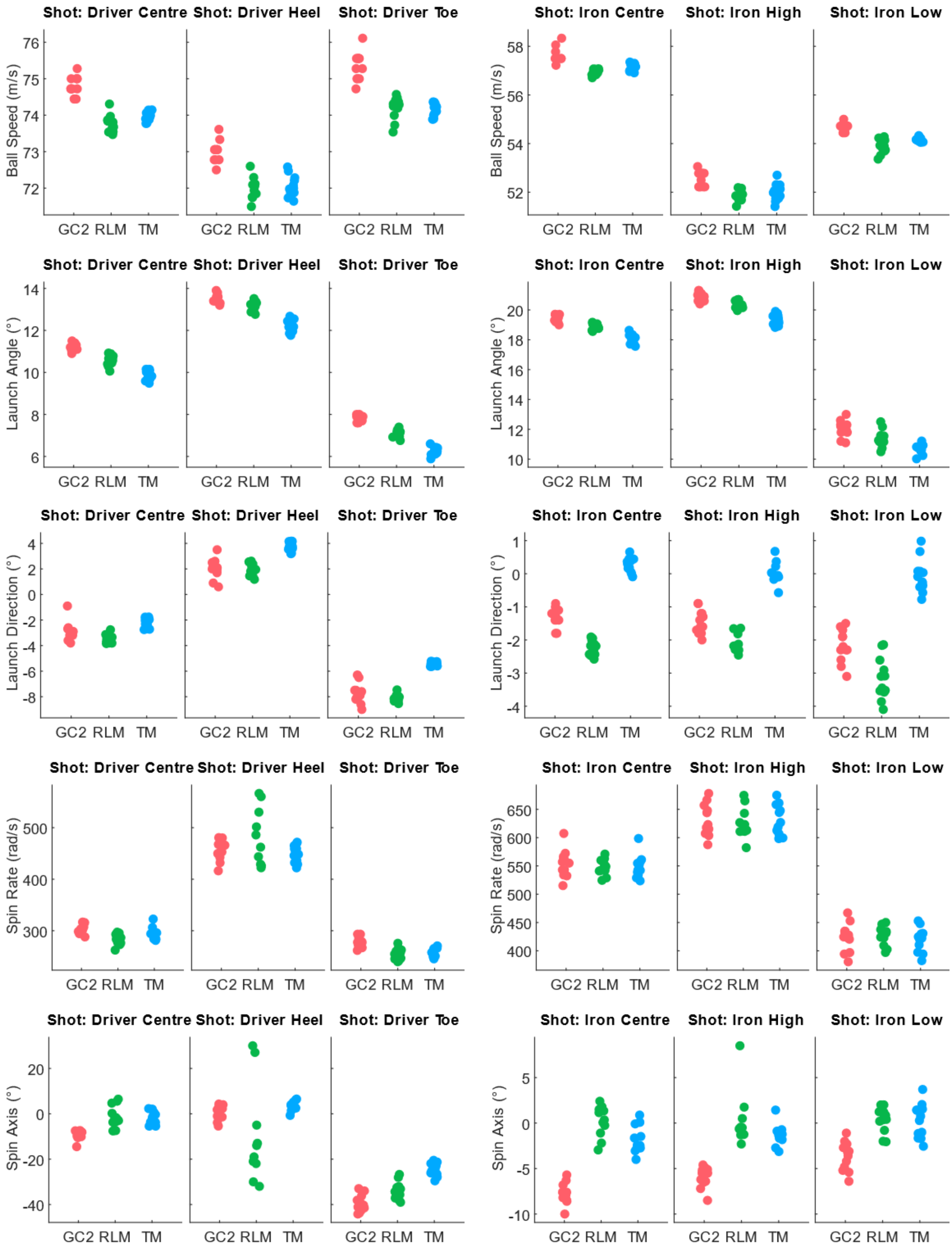


Figure 3.4. Scatter of individual measurements of launch conditions from each launch monitor.

Table 3.2. Mean and standard deviation (Std dev) of initial launch conditions for each of the six shots tested.

		Ball Speed (m·s^{-1})				Launch Angle (°)				Launch Direction (°)				Spin Rate (rad·s^{-1})				Spin Axis (°)			
		Mean	Std dev	95% range	n	Mean	Std dev	95% range	n	Mean	Std dev	95% range	n	Mean	Std dev	95% range	n	Mean	Std dev	95% range	n
Driver Centre	GC2	74.8	0.3	1.0	12	11.2	0.2	0.7	12	-2.9	0.7	2.8	12	304	8	34	12	-9.2	1.9	7.5	12
	RLM	73.8	0.2	0.9	12	10.6	0.2	1.0	12	-3.5	0.3	1.2	12	284	10	39	12	-1.2	4.4	17.8	12
	TM	74.0	0.1	0.5	12	9.9	0.2	0.9	12	-2.3	0.4	1.4	12	295	12	49	9	-2.0	2.6	10.3	12
Driver Toe	GC2	75.3	0.4	1.4	12	7.8	0.1	0.6	12	-7.7	0.7	2.9	12	277	9	38	12	-39.5	3.4	13.8	12
	RLM	74.2	0.3	1.2	12	7.1	0.2	0.6	12	-8.1	0.3	1.1	12	255	10	41	12	-33.7	3.6	14.3	12
	TM	74.2	0.2	0.7	12	6.3	0.2	0.8	12	-5.5	0.1	0.6	12	256	8	33	11	-24.3	2.7	10.7	12
Driver Heel	GC2	73.0	0.3	1.1	12	13.5	0.2	0.8	12	2.0	0.7	2.9	12	456	18	73	12	0.9	3.0	12.1	12
	RLM	72.0	0.3	1.2	10	13.2	0.2	0.9	10	2.0	0.5	1.9	10	483	52	209	10	-9.9	20.6	82.5	10
	TM	72.1	0.3	1.1	12	12.2	0.3	1.1	12	3.8	0.3	1.3	12	450	16	64	12	3.5	1.9	7.6	12
Iron Centre	GC2	57.6	0.3	1.2	12	19.4	0.2	0.9	12	-1.3	0.3	1.1	12	554	23	90	12	-7.7	1.1	4.3	12
	RLM	57.0	0.1	0.5	11	18.9	0.2	0.7	11	-2.2	0.2	0.9	11	549	14	55	11	0.2	1.6	6.5	11
	TM	57.1	0.1	0.6	12	18.1	0.3	1.1	12	0.3	0.2	0.8	12	549	19	75	12	-1.6	1.5	5.9	12
Iron High	GC2	52.5	0.3	1.2	12	20.9	0.3	1.2	12	-1.5	0.3	1.4	12	630	27	108	12	-6.0	1.1	4.2	12
	RLM	51.9	0.2	0.9	10	20.4	0.3	1.0	10	-2.1	0.3	1.1	10	626	26	105	10	0.4	2.9	11.6	10
	TM	52.0	0.3	1.3	12	19.3	0.3	1.4	12	0.0	0.3	1.2	12	630	25	100	12	-1.3	1.1	4.3	12
Iron Low	GC2	54.7	0.1	0.5	12	12.1	0.5	2.0	12	-2.2	0.5	1.9	12	424	23	93	12	-3.7	1.5	6.0	12
	RLM	53.9	0.3	1.1	12	11.4	0.5	2.1	12	-3.2	0.6	2.4	12	426	16	63	12	0.4	1.3	5.2	12
	TM	54.2	0.1	0.3	12	10.7	0.3	1.2	12	-0.1	0.5	1.9	12	420	20	80	12	0.3	1.8	7.2	12
Mean	GC2	64.7	0.3	1.1	12.0	14.2	0.3	1.0	12.0	-2.3	0.5	2.1	12.0	441	18	73	12.0	-10.9	2.0	8.0	12.0
	RLM	63.8	0.2	0.9	11.2	13.6	0.3	1.1	11.2	-2.9	0.4	1.4	11.2	437	21	85	11.2	-7.3	5.7	23.0	11.2
	TM	63.9	0.2	0.7	12.0	12.7	0.3	1.1	12.0	-0.6	0.3	1.2	12.0	433	17	67	11.3	-4.2	1.9	7.7	12.0

D. Discussion

In contrast to investigating jointly measured shots struck by human participants (for example Leach et al., 2017), this investigation considered the repeatability of three commercial launch monitors faced with groups of repeated shots from a golf robot. The investigation examined groups of shots which were as similar as feasibly possible, although an element of variability external to the launch monitors was unavoidable. Whilst it is much more repeatable than a human participant, there is still variability in the swing of the golf robot. Further variability will be present due to manufacturing tolerances in the golf balls used, and the use of the same ball, or set of balls, would not overcome this issue because the striking of a golf ball can alter its characteristics for subsequent shots. These factors will have introduced small differences between the shots in a group but, as the launch monitors measured each shot concurrently, these differences will have been common to each system. As these factors are also present in human testing, the results can indicate the best-case detectable differences in variability during biomechanical testing.

In general, all systems measured a high percentage of shots, with a maximum of 5 shots missed by any launch monitor during the testing. Out of the 72 shots measured, the RLM successfully measured 93% of shots, the GC2 measured 100% of shots, and the TM measured 94% of spin rates and 100% of other variables. Leach et al. (2017) found their TM successfully measured the ball in 98% of trials and their GC2 successfully measured the ball in 90% of trials. Differences in measurement success could be explained by differences in experimental setup, as this necessarily requires some compromise to ensure that all launch monitors can operate successfully.

Systematic offsets in angular data were likely caused by differences in alignment, with consistency between units difficult to achieve due to different calibration and alignment procedures. Care was taken to align the systems relative to each other and the target line, but the small systematic differences observed in the angular data were somewhat inevitable without a more sophisticated method of ensuring alignment. However, Leach et al. (2017) found a systematic bias of 1-2° in launch direction measurements made by their Foresight GC2 launch monitor compared to a gold standard despite the use of an alignment device in their investigation. It is not thought that these small systematic offsets in angle would affect the repeatability of any of the systems studied. The GC2 unit showed a systematic offset where the measured ball speed was approximately 1 $m \cdot s^{-1}$ higher than the other two units. It is not clear if this difference was due to an error in factory calibration or differences in the method used to calculate ball speed. Nonetheless, the inability to inspect the raw data prior to the final output is a disadvantage to scientific researchers, as issues can be difficult to notice; this disadvantage is shared by all the units tested.

Leach et al. (2017) found generally high agreement and concluded that the majority of ball parameters measured by their TM and GC2 units were of sufficient quality to satisfy a research grade of 0.45 $m \cdot s^{-1}$ in ball speed, 1° in launch angle, 1° in launch direction and 5.2 $rad \cdot s^{-1}$ in spin rate. This investigation broadly agreed with the results of the Leach et al. investigation, including finding the launch direction to be more variable that the launch angle, but did not find variability in spin to be lowest in the TM unit, as reported by Leach et al. (2017).

Despite using two distinct methodologies, Doppler radar and stereoscopic imaging, the repeatability of the launch conditions was comparable in the three units. The standard deviation of ball speed, for example, was between 0.1 and 0.4 $m \cdot s^{-1}$ for all conditions and launch monitors. To compare to human golfers, Betzler et al. (2012) reported standard deviations in ball speed of 5.9 $m \cdot s^{-1}$ and 6.8 $m \cdot s^{-1}$ for Category 1 and Category 2 golfers respectively. The variability in launch conditions displayed by human participants is much higher than that seen in the current investigation, which indicates that the launch monitors have enough resolution to identify differences in the variability of launch condition among golfers. This investigation also provides a frame of reference to interpret the variability in launch conditions in human testing; differences in variability lower than the repeatability reported in this investigation are likely indistinguishable from measurement error.

E. Conclusion

This investigation determined the repeatability of measurements of initial launch condition made by three commercial launch monitors and provided an important reference frame within which differences in the variability of human golfers can be interpreted. As measurements from the three units compared favourably with each other, the choice of launch monitor used in future investigations could be based on convenience rather than any other specific advantages in data quality; the TM unit was used in subsequent testing in this thesis. In general, launch monitors can provide valid measurements of initial launch conditions for scientific research.

3.6.2. Repeatability of measurements made with optical motion capture system with attention to the effect of different calibrations

A. Introduction

Marker-based optical motion capture is widely used in the fields of sports and biomechanics, but accuracy and repeatability differs between laboratories (Windolf et al., 2008). There are many factors which can influence the accuracy and repeatability of an optical motion capture system, including camera set up, marker properties and lighting conditions (Maletsky et al., 2007). This investigation will focus on the effect of calibration, for which procedures differ between manufacturers. In the Qualisys system used in this thesis, the camera parameters required for three-dimensional reconstruction are found using a two-part process: linearisation and calibration (Qualisys, 2018). These processes separately calculate the internal and external camera parameters respectively. As the internal camera parameters are assumed to remain constant over a much longer period than the external camera parameters, the linearisation procedure is only required when the camera lens is manually changed, but the calibration procedure must be performed before each data collection session. It is possible for the linearisation to remain unchanged over the course of a biomechanical investigation, but changes of calibration are unavoidable. The effect of differences in calibration on the repeatability of optical motion capture measurements does not appear to have been addressed in the scientific literature and, as such, the aim of this investigation was to quantify the repeatability and accuracy of the motion capture system with specific focus on the effect of different calibrations on these characteristics.

B. Methods

Eight Oqus 3+ cameras (Qualisys, Gothenburg, Sweden) were set up around an indoor golf bay in a configuration previously utilised for the biomechanical testing of golfers (Figure 3.5). Cameras 1 - 4 were attached to aluminium gantry while cameras 5 - 8 were positioned on tripods. Cameras 1, 5, 6, 7, and 8 were fitted with 17mm lenses and cameras 2 - 4 were fitted with 25mm lenses. This configuration achieved an approximate capture volume of 3.0 x 3.0 x 3.0 m^3. The measurement frequency of the motion capture system was 500 Hz and the calibration frequency was 100 Hz; the same as in previous biomechanical testing. Before the testing, all cameras were linearised according to manufacturer's instructions. These settings and the camera set up remained fixed for the duration of the testing. Qualisys Track Manager (QTM) software was used to control the system settings, calibrate the system, record measurements and export data.

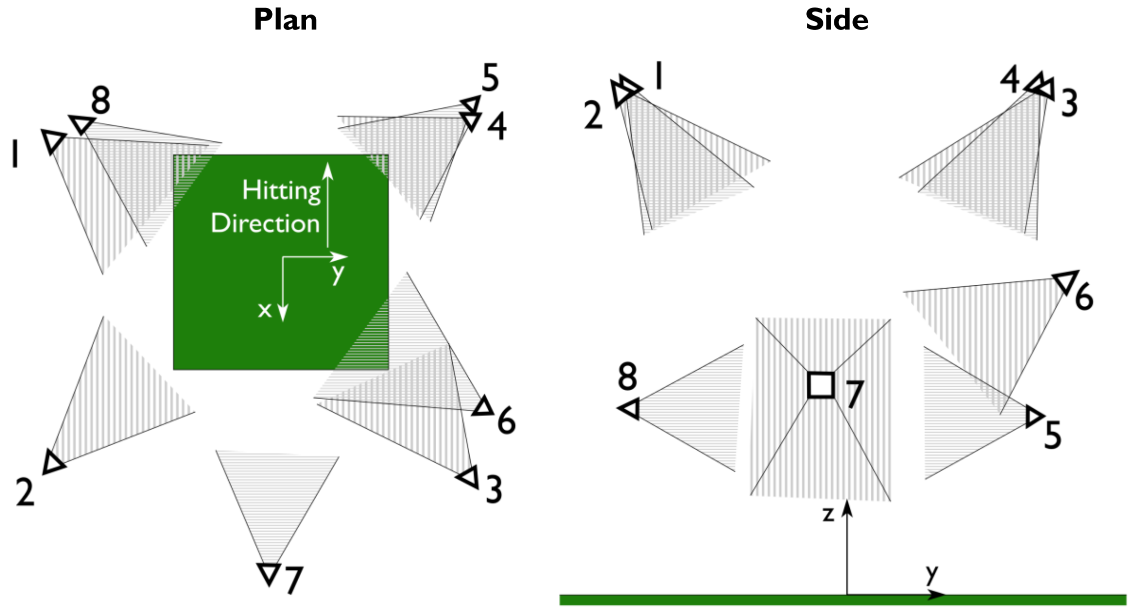


Figure 3.5. Motion capture configuration in indoor golf bay (plan and side view).

To assess accuracy and repeatability, reference objects of known dimension were required to act as a known truth for measurements made by the motion capture system. Manufacturer certified carbon fibre calibration objects, which included two T-shaped calibration wands and a calibration L-frame, were used as reference objects. Furthermore, another reference object was made by affixing markers to an aluminium plate, and measurements of this object validated using Vernier callipers. The precision of the callipers was 0.01 mm, but the accuracy of these measurements was likely worse due to difficulties in measuring the location of the centre of the markers accurately. The angles between markers on the L-frame and plate were calculated using trigonometry and the known distances (Figure 3.6).

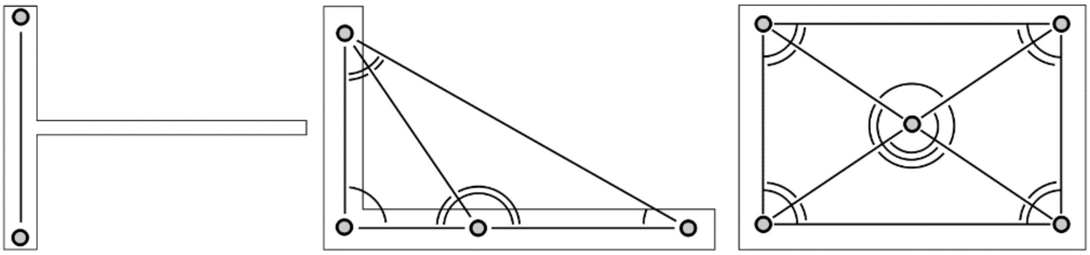


Figure 3.6. Reference objects showing the distances and angles between markers examined during the investigation.

The QTM software allowed the visualisation of two volumes of interest to this investigation; the covered and the calibrated volume (Figure 3.7). The covered volume denotes the approximate volume which is viewed by at least three cameras and is useful in determining the region within which three-dimensional measurements can be made. It is worth noting that it is possible to reconstruct three-dimensional data with two cameras, so the requirement for the region to be viewed by three cameras is a limit set by Qualisys and not a theoretical limit. The calibrated volume shows the volume in which the calibration wand was moved during the calibration and should represent the volume with the most accurate results (Qualisys, 2018).

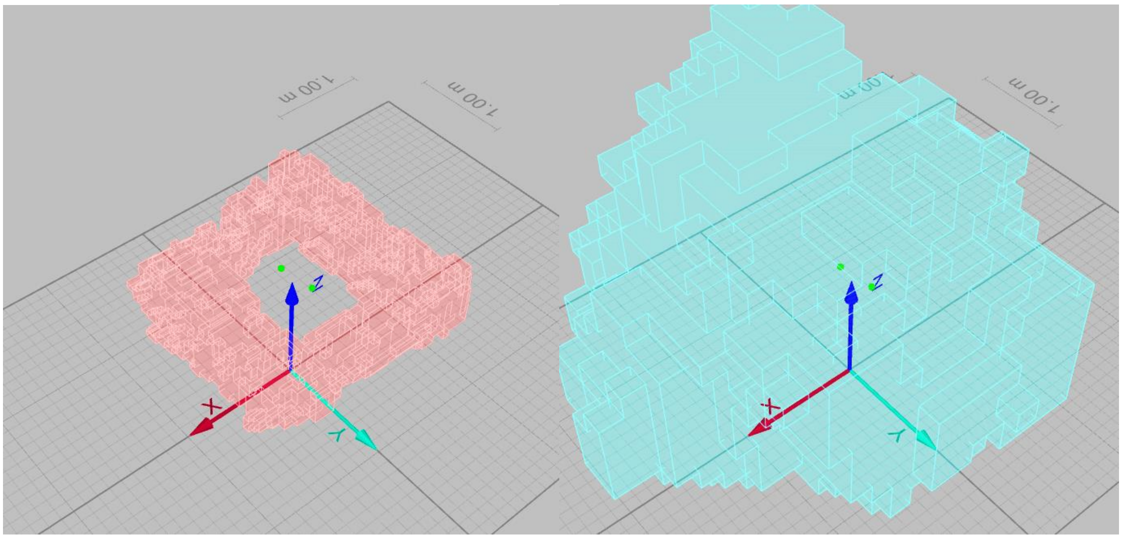


Figure 3.7. Examples of the calibrated (left) and covered (right) volumes as visualised in QTM software.

In the testing procedure, the motion capture system was calibrated multiple times using two manufacturer calibrated T-shaped calibration wands, with inter-marker distances of 302.1 mm and 600.9 mm respectively. A calibration duration of 40 seconds was chosen so that it was possible to move the wand throughout the covered volume during the calibration. However, the movement of the wand during calibration was constrained to manipulate the calibrated volume visualised in QTM. In total, six calibrations, with differently shaped calibrated volumes, were collected with both calibration wands. Three additional calibrations, the 'C', 'tube' and 'tiny flat' calibrations, were performed with only the 602.9 mm wand; for a total of 15 calibrations (Figure 3.8).

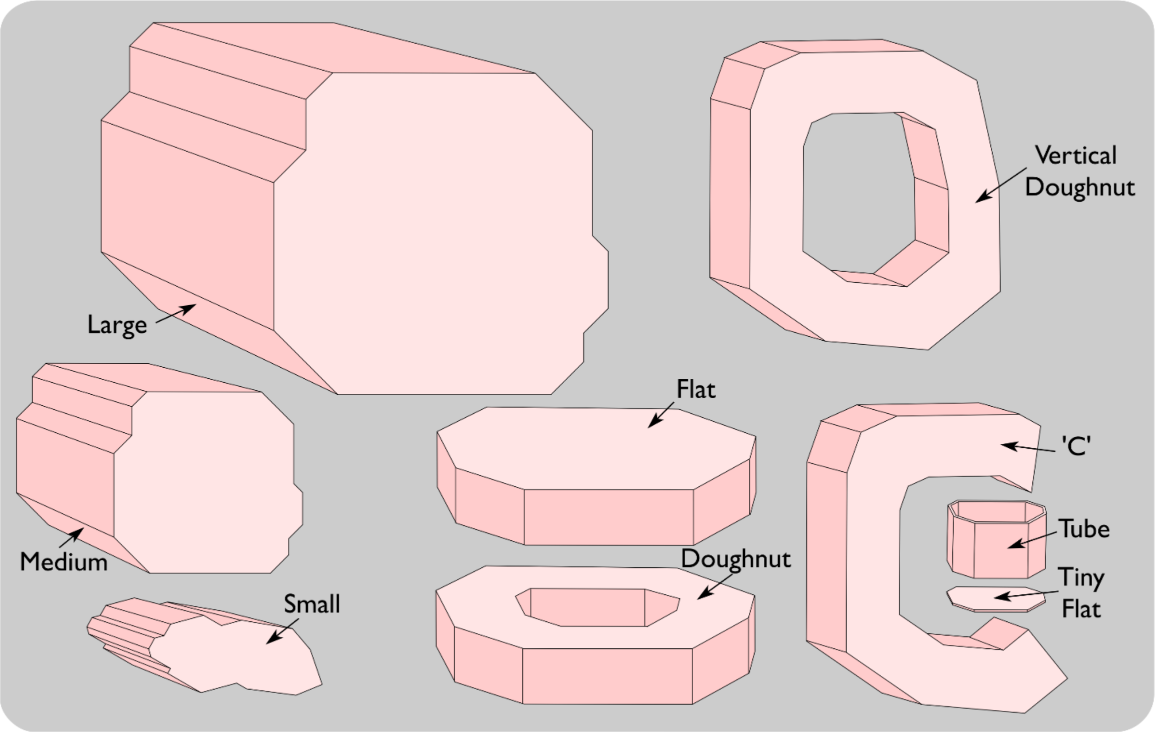


Figure 3.8. Simplified diagrams of calibration volume manipulations performed during the investigation. The 'C', 'tube' and 'tiny flat' calibrations were performed only with the 602.9 mm wand.

Two additional parameters were specified for each calibration; the maximum number of frames and the cameras used in the calibration. Rather than using all the frames in the calibration measurement, frames are evenly sub-sampled from this measurement to calculate the calibration; the 'maximum number of frames' parameter allows the user to control the maximum number of frames sub-sampled from the calibration measurement. The 'cameras used' parameter allows individual cameras to be excluded from the calibration and excludes the specified cameras from subsequent measurements. These parameters were manipulated to investigate their effect on the repeatability of measurements. First, the calibrations were reprocessed with one of four values for the maximum number of calibration frames: 500, 1000, 2500 and 10,000 frames. Second, each of the cameras was sequentially removed from the calibration, with the number of frames fixed at the default of 1000 frames. This resulted in four sets of calibrations with different maximum number of frames and eight sets of calibrations with individual cameras excluded. In total, this reprocessing resulted in 180 unique calibrations; 12 reprocessed sets of 15 original calibrations.

For each calibration, three calibration quality measures were provided by the QTM software: A calibration residual for each camera, the number of points used to calibrate the camera and the standard deviation of the wand length during the measurement. From Qualisys documentation: the camera residual should be as low as possible, ideally under 3mm, and the number of points used in the calibration should be as high as possible, ideally greater than 500 and similar between cameras. The standard deviation of wand length during the calibration is an overall indicator of quality and should be as low as possible (Qualisys, 2018).

Twenty movement trials were performed with each of the four reference objects: the two calibration wands, the calibration L-frame and the plate. During these trials, the reference objects were moved at a range of speeds and orientations, and in different regions of the covered volume. These measurements were automatically processed with each calibration to give a total of 14,400 pseudo-measurements; 80 measurements reprocessed with 180 calibrations. In this batch of measurements, the markers were identified using an automatic identification model and gaps of less than 20 frames were filled using a polynomial fit. A duplicate set of measurements were created using the ‘default’ calibrations; 1000 frames and all cameras included in the calibration. This extra set of trials, 80 measurements processed with 15 calibrations, was processed by an investigator. This processing involved relabelling of wrongly identified markers, and gap filling of longer gaps as would occur in biomechanical analysis. In total, this gave a total of 15,600 pseudo-measurements and the labelled trajectories from these measurements were exported for further data processing in MATLAB (R2018a, Mathworks, Cambridge, UK).

For each measurement trial, the difference between the measured and reference distances and angles was calculated at each time point in the trial (Figure 3.6) and the within-trial median and median absolute deviation of these differences calculated. Robust statistics were used because the within-trial difference trajectories were not inspected for outliers which could bias the results. For the L-frame and plate, which had multiple distances and angles, the median and the median absolute deviation were calculated over all distances and angles. Furthermore, the within-trial median and median absolute deviation of the fitting residuals, often used as indicator of the goodness of fit of the measured coordinates, was calculated for each measurement. Following the main investigation, further measurements were taken which manipulated the calibrated volume and the movement of the reference object to replicate specific facets of the results.

Inspection of the quantile-quantile plots showed the within-trial median and median absolute deviation scores for the difference in distance, the difference in angle and fitting residuals to be non-normally distributed. Therefore, non-parametric statistical hypothesis tests were used in the analysis. The Mann-Whitney U test was used to test the differences between two groups and the Kruskall-Wallis test used to test for differences in more than two groups. *Post hoc* Bonferroni corrected Mann-Whitney U tests were conducted in the case of a significant Kruskall-Wallis test. The median difference between groups was used as an unstandardised effect size measure.

C. Results

Although not precisely correct, for brevity, the median within-trial difference between measured reference distance and the median within-trial median absolute deviation of this difference will be referred to as the distance deviation and the distance variability respectively. Similar abbreviations will be used for the angles and the fitting residuals.

Including all measurements and calibrations, the distance deviation was -0.01 mm, distance variability was 0.14 mm, the angle deviation was 0.00°, and angle variability was 0.04°. The median within-trial fitting residual was 0.79 mm, and the fitting residual variability was 0.08 mm. There was a tendency for the distance and angle deviation to display systematic offsets for the different reference objects, but these tendencies were not consistent; for example, the distance deviation for the 600.1 mm wand and the L-frame were -0.88 mm and 0.19 mm respectively. This is likely to indicate the accuracy of the reference distances as well as the measured distances.

There was no significant difference between the trials processed by the investigator and those processed automatically in either within-trial median (Distance deviation: $U = 7.27x10^{5}$, $p = 0.63$, *median difference = 0.01 mm*; Angle deviation: $U = 1.80x10^{5}$, $p = 0.94$, *median difference = 0.00°*; Fitting residual: $U = 7.28x10^{5}$, $p = 0.58$, *median difference = 0.01 mm*), or within-trial median absolute deviation (Distance variability: $U = 7.02x10^{5}$, $p = 0.32$, *median difference = 0.01 mm*; Angle variability: $U = 1.70x10^{5}$, $p = 0.12$, *median difference = 0.00°*; Fitting residual variability: $U = 7.08x10^{5}$, $p = 0.56$, *median difference = 0.00 mm*). However, the measurements processed by the investigator had fewer frames with markers missing from the measurement. On average,1.8% of frames were missing one or more markers in trials processed by the investigator compared to 6.2% for automatically processed trials.

There was also no difference in distance or angle deviation in the trials processed using calibrations with a different value for the maximum number of included frames; either in the within-trial median (Distance deviation: $H = 1.39$, $p = 0.71$, *maximum median difference = 0.04 mm*; Angle deviation: $H = 0.63$, $p = 0.89$, *maximum median difference = 0.00°*) or the within-trial median absolute deviation (Distance variability: $H = 6.61$, $p = 0.09$, *maximum median difference = 0.01 mm*; Angle variability: $H = 3.24$, $p = 0.36$, *maximum median difference = 0.00°*). However, there was a difference in fitting residual between the calibrations. The Kruskall-Wallis test indicated that there was a statistically significant difference in the median fitting residual ($H = 46.44$, $p < 0.01$, *maximum median difference = 0.18 mm*) and *post hoc* tests indicated that calibrations which included 10,000 frames in the measurement displayed a significantly higher median fitting residual than the other calibrations ($p < 0.01$ in all cases; median difference of 0.13, 0.12 and 0.18 for calibrations including 500, 1000 and 2500 frames respectively). A difference in the within-trial median absolute deviation of fitting residuals was also indicated ($H = 8.10$, $p = 0.04$, *maximum median difference = 0.01 mm*) but no *post hoc* test reached the Bonferroni adjusted significance level, and the median differences between conditions were much smaller. Regarding the calibration quality, there was a statistically significant difference in the number of points used to calibrate each camera ($H = 725.88$, $p < 0.01$, *maximum median difference = 5038 points*), but no statistically significant difference in the standard deviation of wand-length during the calibration ($H = 1.55$, $p = 0.67$, *maximum median difference = 0.05 mm*) or camera residuals ($H = 6.02$, $p = 0.11$, *maximum median difference = 0.03 mm*). As expected, the calibrations with higher values for the maximum number of included frames had a higher number of points used to calibrate the cameras (Median values: 711 (500 frames); 1457 (1000 frames); 3714 (2500 frames); 5748 (10,000 frames)).

Mann-Whitney U tests indicated differences between measurements made in trials with the two different calibration wands. The angle deviation was not significantly different ($U = 0.48x10^{7}$, $p = 0.33$, *median difference = 0.00*°), but the distance deviation ($U = 1.66x10^{7}$, $p < 0.01$, *median difference = 0.07 mm*) and the fitting residual ($U = 2.90x10^{7}$, $p < 0.01$, *median difference = 0.50 mm*) were significantly different between trials calibrated with the two different calibration wands. Trials calibrated with the 302.1 mm wand had a median distance deviation of -0.06 mm and a median fitting residual of 1.09 mm compared to 0.01 mm and 0.59 mm in trials calibrated with the 600.1 mm wand. There was also a difference in the within-trial median absolute deviation between trials calibrated with the two different calibration wands (Distance variability: $U = 2.12x10^{7}$, $p < 0.01$, *median difference = 0.04 mm*; Angle variability: $U = 0.57x10^{7}$, $p < 0.01$, *median difference = 0.01*°; Fitting residual variability: $U = 2.13x10^{7}$, $p < 0.01$, *median difference = 0.01 mm*). Trials calibrated with the 302.1 mm wand had a median distance variability of 0.16 mm, angle variability of 0.05°, and fitting residual variability of 0.08 mm compared to values of 0.12 mm, 0.03° and 0.07 mm for trials calibrated with the 600.1 mm wand. Regarding the calibration quality, there was a statistically significant difference in camera residual ($U = 4589$, $p = 0.04$, *median difference = 0.02 mm*), but no statistically significant difference in the standard deviation of wand-length during the calibration ($U = 3221$, $p = 0.05$, *median difference = 0.15 mm*) or the number of points used to calibrate ($U = 3709$, $p = 0.60$, *median difference = 4 frames*). The calibrations performed with the 302.9 mm wand had higher median camera residuals compared to the 600.1 mm wand (0.53 mm vs 0.51 mm).

There were statistically significant differences in all measures between trials with the differently shaped calibration volumes, except for the angle deviation ($H = 5.19$, $p = 0.74$, *maximum median difference = 0.01*°) but even the maximum observed differences were small real-world effects (Table 3.3). Differences in the distance deviation ($H = 98.81$, $p < 0.01$, *maximum median difference = 0.12 mm*) and the median fitting residual ($H = 314.04$, $p < 0.01$, *maximum median difference = 0.23 mm*) are shown in Figure 3.9. Differences in the distance variability ($H = 58.77$, $p < 0.01$, *maximum median difference = 0.03 mm*), angle variability ($H = 31.16$, $p < 0.01$, *maximum median difference = 0.01*°) and fitting residual variability ($H = 210.40$, $p < 0.01$, *maximum median difference = 0.03* *mm*) are shown in Figure 3.10. Regarding the calibration quality, there was a statistically significant difference in the standard deviation of wand length during the calibration ($H = 108.03$, $p < 0.01$, *maximum median difference = 0.78 mm*), the number of points used to calibrate ($H = 173.19$, $p =< 0.01$, *maximum median difference = 700 frames*) and the camera residual ($U = 318.96$, $p < 0.01$, *maximum median difference = 0.47 mm*). These differences are shown in Figure 3.11.

Table 3.3. Median and median absolute deviation (MAD) of the within-trial differences between measured and reference distance, angle and fitting residual for differently shaped calibration volumes.

Calibration Type	Within-trial median difference between measured and reference distance		Within-trial median absolute deviation in difference between measured and reference distance		Within-trial median difference between measured and reference angle		Within-trial median absolute deviation in difference between measured and reference angle		Within-trial median fitting residual		Within-trial median absolute deviation of fitting residual	
	Median	MAD	Median	MAD	Median	MAD	Median	MAD	Median	MAD	Median	MAD
C	0.05	0.23	0.13	0.07	0.00	0.04	0.03	0.02	0.58	0.17	0.08	0.04
Doughnut	0.01	0.29	0.13	0.07	0.00	0.04	0.03	0.02	0.59	0.17	0.07	0.04
Flat	0.01	0.25	0.13	0.07	0.00	0.03	0.03	0.02	0.68	0.23	0.08	0.04
Large	0.01	0.27	0.12	0.06	0.00	0.04	0.03	0.02	0.63	0.10	0.07	0.03
Medium	-0.02	0.28	0.11	0.05	0.00	0.04	0.03	0.01	0.54	0.08	0.06	0.03
Small	0.01	0.25	0.12	0.07	-0.01	0.04	0.03	0.02	0.54	0.13	0.06	0.04
Tiny flat	-0.03	0.36	0.14	0.10	-0.01	0.04	0.03	0.02	0.77	0.23	0.10	0.06
Tube	-0.01	0.25	0.14	0.09	0.00	0.04	0.04	0.02	0.59	0.20	0.07	0.05
Vertical Doughnut	0.09	0.23	0.12	0.06	0.00	0.03	0.03	0.01	0.61	0.15	0.07	0.03

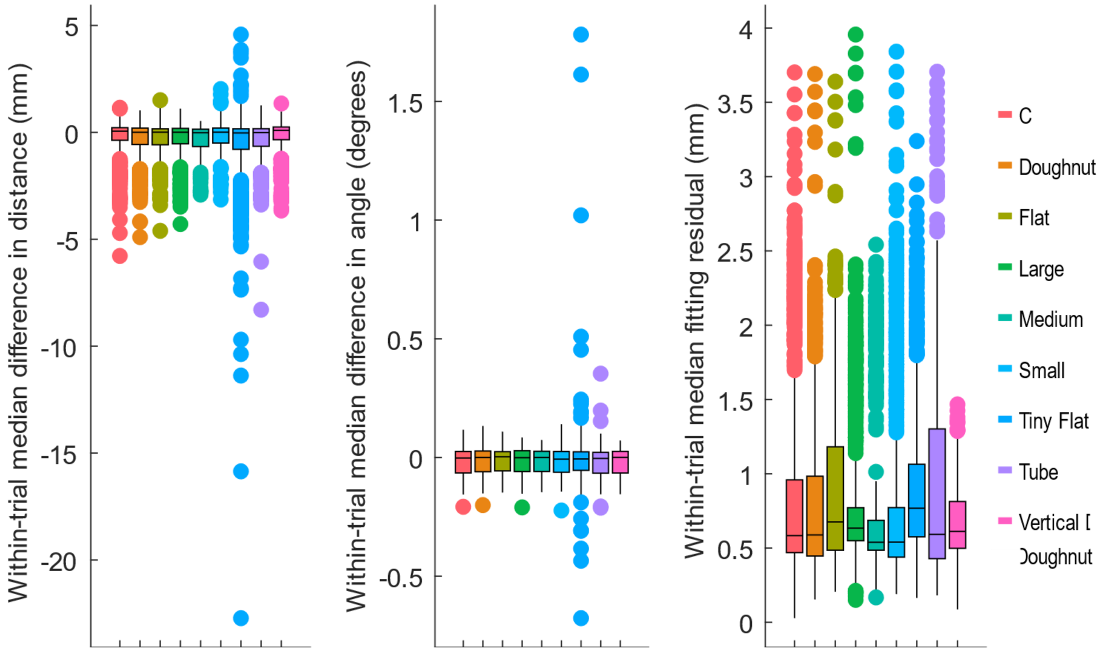


Figure 3.9. Within-trial distance deviation, angle deviation and fitting residual for differently shaped calibration volumes.

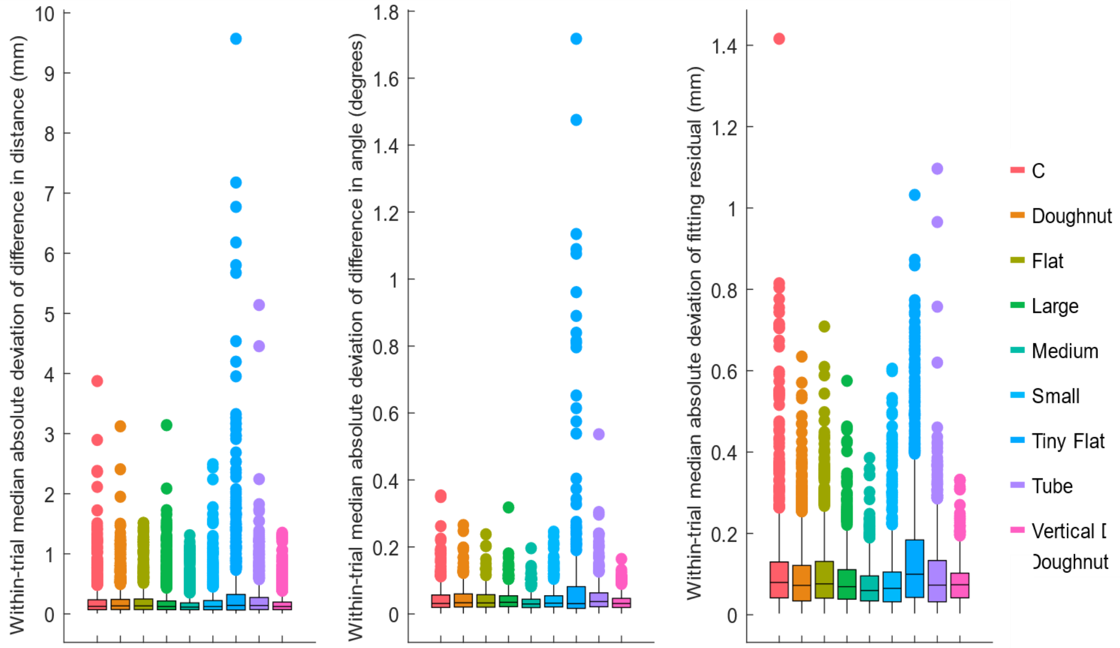


Figure 3.10. Within-trial median absolute deviation of the distance deviation, angle deviation and fitting residual for differently shaped calibration volumes.

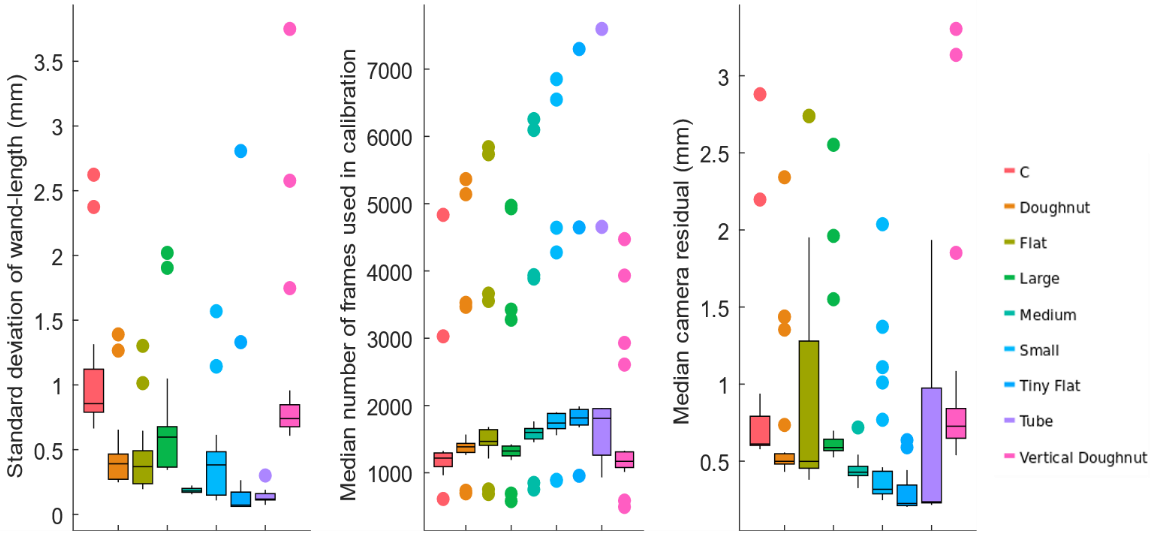


Figure 3.11. Calibration quality of differently shaped calibration volumes.

Trials which included movements which took place at the edge of the covered volume showed lower accuracy and repeatability than trials which took place in the centre of the capture volume. Mann-Whitney U tests found statistically significant differences in all measures, including the within-trial median (Distance deviation: *U = 1.56x10*^{7}*, p < 0.01, median difference = 0.34 mm*; Angle deviation: *U = 0.24x10*^{7}*, p < 0.01, median difference = 0.02°*; Fitting residual: *U = 1.28x10*^{7}*, p < 0.01, median difference = 0.04 mm*) and the within-trial median absolute deviations (Distance variability: *U = 0.40x10*^{7}*, p < 0.01, median difference = 0.17 mm*; Angle variability: *U = 0.09x10*^{7}*, p < 0.01, median difference = 0.03°*; Fitting residual variability: *U = 0.59x10*^{7}*, p < 0.01, median difference = 0.05 mm*). Trials which took place near the edge of the covered volume showed worse accuracy and repeatability compared to trials which took place in the centre of the covered volume. Within-trial fitting residuals were lower, but the within-trial median absolute deviation of fitting residuals was slightly higher in trials which took place at the edge of the covered volume. Closer inspection revealed that differences in the measured distance at the edge of the covered volume were typified by the presence of large outlying values, with errors of up to 5 mm observed in this region.

Reprocessing the data with calibrations which had individual cameras removed gave an indication of the relative importance of each camera to the accuracy and repeatability of the motion capture system. The observed differences were small but, in the layout specified, camera 7 appeared to be the most important. The median within-trial difference between measured and reference distance with this camera removed was -0.07 mm, the biggest difference observed. This finding will be specific to the camera set-up and the regions in which the movements took place. There were no significant differences in the calibration quality values between any of the removed cameras (Standard deviation of wand length: *$H = 1.51$, $p = 0.98$, maximum median difference = 0.18 mm*; Number of frames included: *$H = 3.35$, $p = 0.85$, maximum median difference = 111 frames*; Camera residual: *$H = 12.12$, $p = 0.10$, maximum median difference = 0.16 mm*).

D. Discussion

There are many studies which have examined the accuracy and repeatability of measurements made using motion capture systems. Richards (1999) determined the root mean square error of five optical motion capture systems to be less than 2.0 mm for moving objects and less than 1.0 mm for stationary markers. More recently, Maletsky, Sun and Morton (2007) determined the mean error of one such system to be just 0.03 mm. However, most investigations into the accuracy of optical motion capture have recommended the accuracy and repeatability be determined on a system-by-system basis, as this can be affected by the characteristics and operation of the individual motion capture system (Milner, 2018). The median and median absolute deviation of the difference between the measured and reference distances and angles in this investigation were low compared to existing literature, but this can be explained through using median absolute deviation as measure of statistical dispersion. In normal distributions, the median absolute deviation is related to the standard deviation by a scaling factor of 1.4826. When this scaling factor is applied, the results show comparable accuracy and repeatability to the extant literature.

Numerous statistically significant differences were found between the different calibrations but, as the investigation examined many trials, it is important to consider the real-world implications of these differences. The median differences were generally of an order of magnitude unlikely to significantly impact on the results of biomechanical investigations. However, important differences were observed during the investigation. For example, the within-trial median absolute deviation of the difference between the measured and reference distance between markers was generally less than 0.2 mm within the covered volume, regardless of the calibration used. In trials where the reference object remained within the calibrated volume versus trials where the object moved between calibrated and uncalibrated volume, the differences in the distance between markers were generally less than 0.5 mm. A similar effect was observed for ‘holes’ in the calibrated volume, despite the existence of calibrated volume surrounding these holes. However, much larger fluctuations of up to 5 mm in the distance between markers occurred when objects moved near the edge of the covered volume; this was reflected by an increase in the within-trial median absolute deviation in trials at the edge of the covered volume.

Some limitations of the investigation include the inability to externally verify the dimensions of the reference objects, the automatic processing of data and the use of one of each type of calibration. The manufacturer reference values were not traceable, and no suitable equipment was available to verify the dimensions of the reference objects otherwise, however, multiple reference objects were used in the investigation, and no systematic bias was observed across all measurement objects. The automatic processing of data allowed a vast number of trials to be compared but will have resulted in some marker misidentification. However, these errors should worsen accuracy and repeatability, and thus, the results presented here are more likely to be conservative estimations. The lack of a difference between the automatic and investigator processed trials indicate that this difference might be minor. Previous experience suggested that similar calibration shape resulted in comparable results, so only one calibration of each type was used. Indeed, the robustness of measurements to calibrations with different shapes suggests that this assumption was justified.

E. Conclusion

This investigation presented values for the best-case accuracy and repeatability of an optical motion capture system measuring rigid objects. The measurements were robust to changes in calibration and the movement of the calibration wand during the calibration, but care should be taken to avoid movements which occur near the edge of the covered volume. The variability which can be attributed to the motion capture system is likely to be consistent between sessions and the system should be suitably accurate and repeatable for the biomechanical analysis of movement variability.

3.6.3. Repeatability of intersession kinematic measurements using optical motion capture

A. Introduction

Measurements of marker position by optical motion capture systems have generally been found to be highly accurate and repeatable (Maletsky et al., 2007) but measurements of human kinematics are generally found to be less repeatable than this data would suggest. For example, Wilken et al. (2012) reported that the minimal detectable change for healthy gait kinematics was between 3-5° depending on the joint. For a segment with a length of 300 mm, the forearm for instance, a 1 mm error in marker position would lead to an error in the angle of 0.19°. To consider long-axis rotations, where the effective segment length is much shorter, the same 1 mm error in marker position over a segment length of 50 mm results in an error of 1.15°. Since the repeatability of measurements of marker position by optical motion capture is typically reported to be under 1 mm (Croce et al., 1997; Stagni et al., 2005), other factors must influence the accuracy and repeatability of kinematic measurements in biomechanics. Differences in marker position relative to the underlying anatomy, between individuals or testing sessions, have been suggested as a key source of error in kinematic measurements (Croce et al., 2005). It has been estimated that the error which can be attributed to inconsistent marker placement can be up to 5° (McGinley et al., 2009) and, as such, it presents one of the largest challenges to the collection of reliable kinematic data. This investigation used a mechanical body and different artificial conditions to determine the effect of removing and reapplying motion capture markers on the resultant kinematics in a highly controlled system. It was hypothesised that a functional joint centres approach to building the kinematic model would provide greater repeatability in situations where motion capture markers are removed and replaced, and so this approach was utilised in the testing.

B. Methods

A general method was devised to test the effect of small differences in marker placement on the resultant movement kinematics. Generally, a minimum of two sets of three motion capture markers were applied to a segment, one to be replaced during the investigation and another to remain in place throughout. Using this method allowed the position of replaced markers to be recreated virtually and multiple applications of the marker-set to be compared using a single movement trial. The investigation utilised a Golf Laboratories Testing Robot (Golf Laboratories, San Diego, CA) as a convenient mechanical system. The golf robot consisted of three segments and two joints; one with a single degree of freedom and another with two degrees of freedom (Figure 3.12). This mechanical system was chosen because of its rigid segments and well-defined joints represented a highly controlled testing scenario.

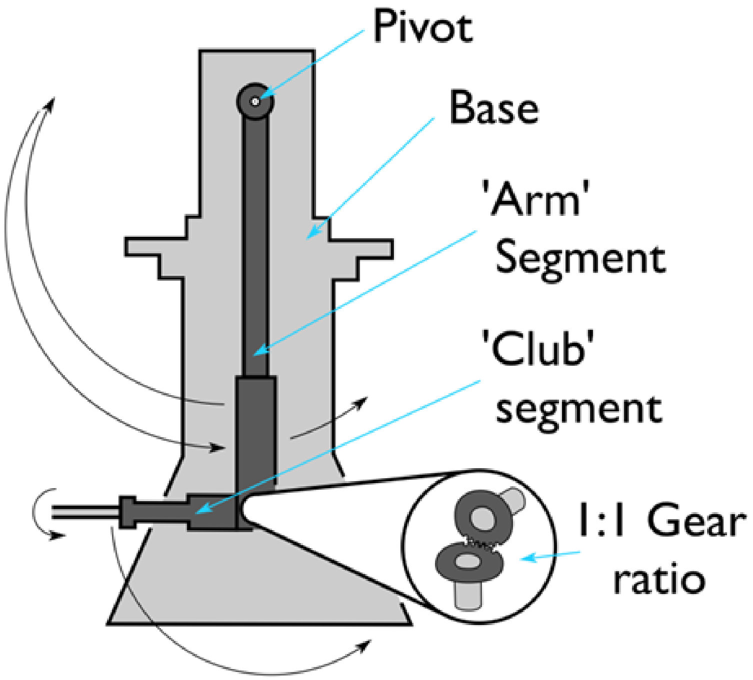


Figure 3.12. Diagram showing the golf robot with base, arm and club segments.

During the investigation, fixtures were created which fitted onto the surface of the golf robot and allowed differences in the surface to be investigated. The surfaces included a flat and raised surface parallel to the plane of movement, a curved surface, and a flat surface slanted at an angle to the plane of movement (Figure 3.13). A further curved surface consisting of moulded gelatine, which would add compliance to the system, was also utilised. Several iterations of the fixtures and fastenings were utilised in the investigation, with the final fixtures made from aluminium and rigidly attached to the robot's surface using a combination of adhesive tape, cable ties and screws. This combination of robot and additional fixtures allowed the effect of different confounding factors to be investigated, within the confines of a highly constrained underlying movement.

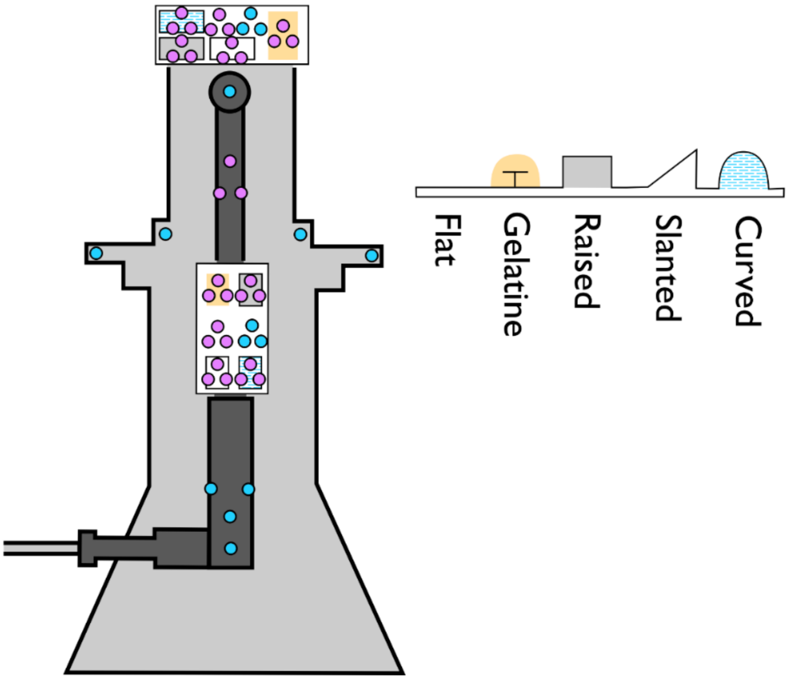


Figure 3.13. Positions of static (blue) and removed (pink) markers on the robot.

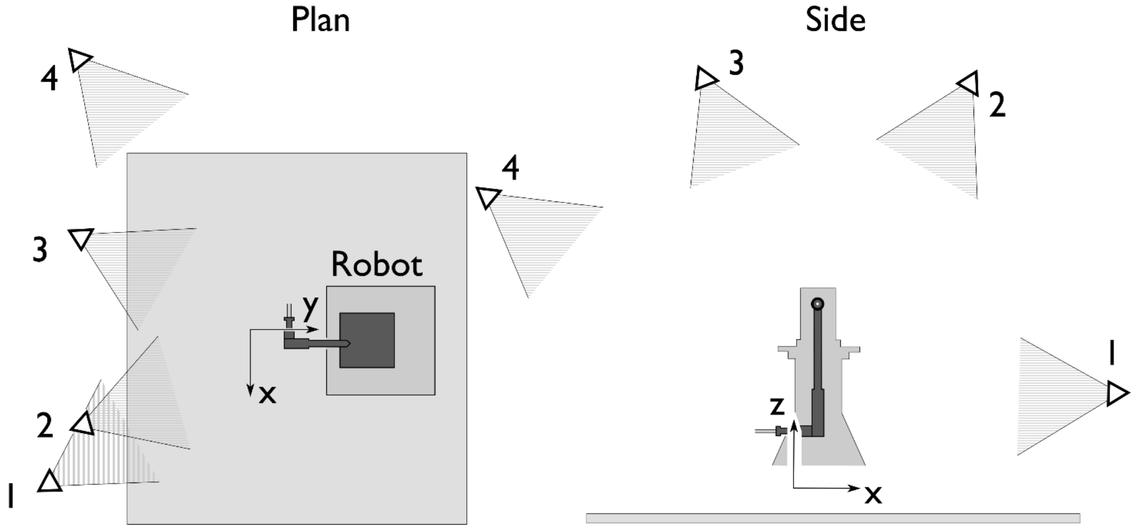


Figure 3.14. Configuration of motion capture cameras in bay for robot testing (plan and side view).

A four-camera optical motion capture system (Figure 3.14, Oqus 3+, Qualisys, Gothenburg, Sweden), operating at 500 Hz, was used to track the movements of spherical, retro-reflective motion capture markers with a diameter of 12 mm. Camera 1 was positioned on a tripod and Cameras 2 - 4 positioned on aluminium gantry. The motion capture system was calibrated immediately before the data collection and operated using Qualisys Track Manager (QTM, Qualisys, Gothenburg, Sweden) software. The marker set, shown in Figure 3.13, was affixed to the surface of the robot and the fixings using double-sided tape designed for human motion capture.

The test procedure was as follows: First, all markers were applied to the system and a static trial of 1 second was collected. Next, a functional joint movement trial, where the arm segment was manually moved through a range of approximately 30° for 10 seconds, was collected to determine the location of functional joint axis for the kinematic model (Schwartz and Rozumalski, 2005). Initial investigations considered the kinematics of both the arm and club segments, but the final testing focused on the movement of the arm segment only. Next, a single reference movement trial with movement like that of the functional joint movement trial was recorded. The process of static trial and functional joint trial was then repeated six times with the markers left in place and six times with a subset of markers removed and replaced in between trials (Figure 3.13). When removing markers, all markers and double-sided tape were removed before reapplying the markers. The subset of markers which remained in place were not used in the joint centre calculations or the kinematic model; rather, they allowed the joint coordinate systems calculated from the removed markers to be tracked during the reference movement, despite markers being replaced between the two trials.

Marker trajectories were labelled in QTM and exported into Visual 3D (C-Motion, Germantown, MD) where kinematic models were constructed for each trial. For each trial, separate kinematic models were defined using the sets of replaced markers (flat, slanted, curved, and so on). Each kinematic model was defined to have a base and an arm segment, with Z denoting the vertical axis, X the medio-lateral axis and Y the anterior-posterior axis. Technical coordinate systems were defined based on the position of the markers in the static trial. Anatomical coordinate systems for the arm were defined, using the respective functional joint movement trial to define a functional joint axis. This rotation axis represented the barrel joint between the base and the arm segments and was used to define the origin and the Y axis of the arm segment. The Z axis was defined using the functional joint trial and the location of a static marker near the wrist of the robot, and the X axis was defined as mutually perpendicular and pointing to the left when facing the robot. No anatomical coordinate systems were defined for the base segment as there was no upstream segment to use as a reference, much the same as the pelvis segment in a human kinematic analysis. The joint coordinate systems defined in these models were tracked with the static markers and applied to the reference movement. This way only the differences in kinematics caused by the removal and re-application of markers were observed.

For each trial and using each kinematic model, the joint angle in the reference movement trial was calculated. For each condition, the joint angle was defined as the angle between the base segment technical coordinate system and the arm segment anatomical coordinate system. This rotation used an XYZ Cardan sequence with the Y component of the joint angle representing movement around the barrel joint between the base and the arm segments. The positions of all markers in the local static coordinate system were calculated in the static trial, and the data from static and reference movement trials were exported to MATLAB (R2015b, Mathworks, Natick, MA) via ASCII file for further analysis.

Joint angle offset trajectories were calculated by subtracting the joint angle from a reference joint angle, calculated from a kinematic model based on the markers which remained in place for all trials and the average joint offset used to characterise any offset observed. Inspection of the quantile-quantile plots showed the joint angle offsets to be non-normally distributed. Therefore, median and median absolute deviation were used as measures of central tendency and dispersion and non-parametric statistical hypothesis tests were used in the analysis. The Mann-Whitney U test was used to test the differences between the joint angle offsets obtained from kinematic models constructed from the static and replaced markers and the median difference used as an unstandardised effect size measure.

C. Results

The median absolute deviation of marker position for all replaced markers was 0.49 mm. In earlier iterations of the investigation, an offset of up to 10°, similar in character to that observed in human motion capture, was observed in the Y component of joint angle (Figure 3.15). However, an investigation revealed compliance between the arm and plastic fixing initially used, despite attempts to ensure that the fixing was rigid. Offsets in the Y component of joint angle were not observed in the final iteration of the investigation, where the offset in joint angle was less than 1° throughout the movement trial, regardless of the location of the markers (Table 3.4). The aluminium plates and non-compliant fixing used in this final iteration resulted in highly consistent joint angles in the X and Y component. However, the joint angle offset in the Z component of joint angle was highly variable with an average offset of -5.2 ± 8.8°when markers were removed and replaced. A Mann-Whitney U test showed this difference to be statistically significant ($U = 1041$, $p < 0.01$, *median difference* = *5.1*°). This component of the joint angle corresponds to rotations along the long axis of the arm segment. The range of this angle during a measurement was small, 3.2 ± 0.3°, and the offset may represent differences in cross-talk during the calculation of joint angle.

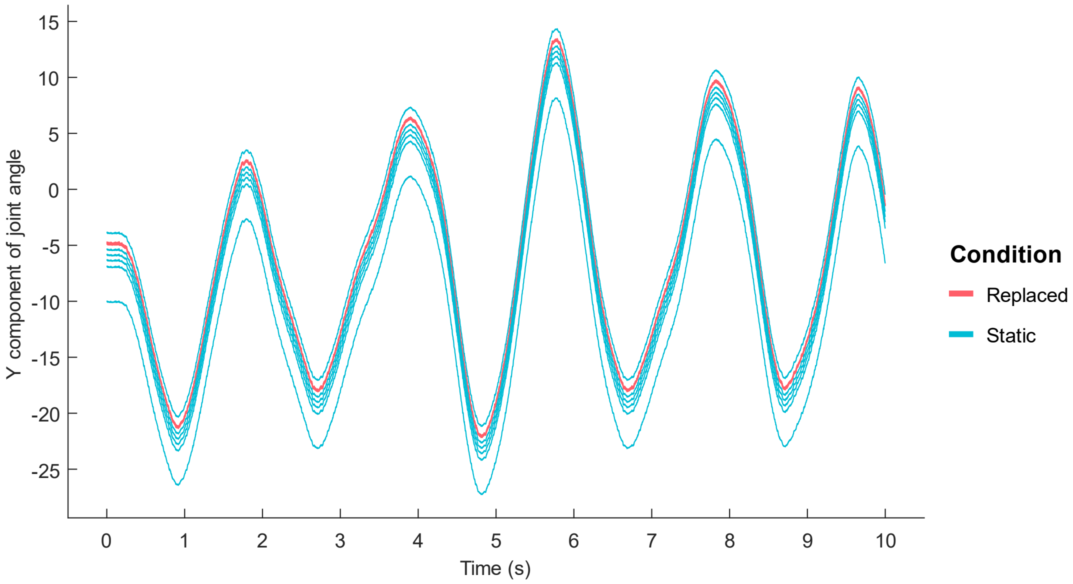


Figure 3.15. Example of joint angle offset observed between different applications of the markers.

Table 3.4. Median and median absolute deviation of joint angle offsets observed for static and replaced markers (measurements from all kinematic models aggregated).

	X component of joint angle (°)		Y component of joint angle (°)		Z component of joint angle (°)	
	Median	± Median absolute deviation	Median	± Median absolute deviation	Median	± Median absolute deviation
Static	0.1	± 0.1	-0.2	± 0.0	-0.1	± 0.1
Removed	-0.5	± 0.2	-0.0	± 0.1	-5.2	± 8.8

D. Discussion

An average deviation in marker position of below 1 mm suggests that the removal and replacement of markers in this investigation was highly consistent, but it is not clear if this level of consistency is achievable with human test subjects. Evidence of previous marker placement was removed before subsequent applications, but both the robot and the fixture provided clear reference landmarks. The identification of landmarks on this system was easier than with a human participant, where landmarks are less defined and differ between individuals, and the results reflect a best-case of marker removal and replacement.

Rather than marker placement, consistency of kinematic analyses is dependent on the consistent definition of anatomical coordinate systems, and a functional joint centres approach was hypothesised to be more robust to differences in marker placement (Besier et al., 2003). In this investigation, the functional joint centre approach was successful in minimising the offset in joint angle about the X and Y axes, the Y axis being the primary movement axis studied, but a large variability in joint angle offset was observed for rotations about the Z axis. When building a kinematic model, functional joint centres are not typically able to define all the axes in the model, some axes must be defined using additional landmarks. Furthermore, the human upper leg segment can be defined based on functional joint centres at the hip and the knee, but the pelvis segment is not typically defined using functional joint centres (Wu et al., 2002). Because of these differences in definition, a functional joint centre's approach can only address part of the error in the hip angle; that related to the upper leg segment. Another issue when utilising Euler or Cardan rotations to calculate the joint angle is for prior rotations to impinge on successive rotations in a phenomenon known as cross-talk (Sinclair et al., 2013) and differences in the anatomical coordinate system could impact on the cross-talk observed in a kinematic measurement. Either or both limitations could explain the offset in joint angle could be minimised in the X and Y axis, but not the Z.

Much research around inter-session repeatability has been conducted in the field of clinical gait analysis, where biomechanical results can have treatment implications, and it has been suggested that an acceptable range of variability can be achieved through experimental rigour (McGinley et al., 2009). However, there is no universally accepted method to assess the repeatability of results within or between laboratories and inter-session repeatability can only be quantified in specific cases. The between-session offset in joint angle is not a recent phenomenon (Croce et al., 1997) and has been highlighted multiple times in the scientific literature (Benedetti et al., 2013; Besier et al., 2003; Gorton et al., 2009; McGinley et al., 2009) but there is no consensus on a solution to this characteristic error. It seems pertinent to acknowledge the specific limitations of the data collection and adopt procedures which limit false interpretations when conducting data analysis; a conclusion also reached by McGinley et al. (2009).

E. Conclusion

Offsets in joint angle can occur due to slight differences in marker location and the subsequent inconsistent definition of the anatomical coordinate system. That functional joint methods do not provide a solution to these errors is likely to be due to a combination of kinematic model, compliance in the human movement system and cross-talk between axes. The data presented in this investigation provides no solution to this issue, but the method and knowledge gained should be of use to those seeking a greater understanding of these errors. Indeed, a solution to these errors is not found within the extant literature, and further investigation is warranted. These errors may be due to fundamental limitations in marker-based optical motion capture and the subsequent calculation of joint angles in three orthogonal components. These limitations could be acknowledged in the data analysis methods chosen; focussing study toward differences in the shape of a joint angle trajectory between sessions, as opposed to the offset between trajectories or the absolute joint angles.

3.6.4. Section summary

To accurately describe the variability of human movement, it is necessary to understand the measurement error associated with measurements of that movement; the specific investigations included in this chapter address some of the issues highlighted in the preceding review of methodological factors.

The investigation into the accuracy and repeatability of launch monitors found the different launch monitors to have different strengths and weaknesses in terms of the repeatability of certain variables, although there were some small differences to existing research in this regard (Leach et al., 2017). The choice of launch monitor, within those investigated, is largely one of convenience with the specific results giving insight into the level of repeatability which could be expected with notionally identical shots. The repeatability of launch monitors was found to be approximately 1 $m \cdot s^{-1}$ for measures of ball speed, 1° for measures of launch angle, 1.5° for measures of launch direction, 75 $rad \cdot s^{-1}$ for measures of spin rate and 8° for measures of spin axis.

The investigation into the accuracy and repeatability of measurements made with an optical motion capture system largely confirmed existing research suggesting a high level of accuracy associated with these measurements (Maletsky et al., 2007; Richards, 1999). However, the finding of robustness to calibration has value in confirming that these errors are unlikely to differ between sessions, where the calibration is necessarily different. Worst accuracy was observed for movements taking place near the edge of the covered volume and care should be taken to avoid movements in these regions. Whilst not specifically investigated here, marker occlusions, soft-tissue artefact and the inconsistent location of anatomical landmarks have been highlighted as greater sources of error in the literature (Besier et al., 2003; Croce et al., 1997).

The investigation into between-session kinematic measurements focused on the characteristic offset in joint angle, caused by the inconsistent location of anatomical landmarks and subsequent differences in marker location. These shifts had been highlighted in the literature (Corke, 2015; Croce et al., 1997). The investigation found that a functional joint centres approach was successful in minimising offsets in joint angle in the X and Y axes. Offsets were still observed in the Z axis, possibly due to a combination of the definition of the kinematic model and cross-talk between axes. Whilst the investigation failed to recommend a solution to the error, the investigation should be of interest to those seeking to research the errors further and highlighted the need to consider these errors in the analysis of kinematic data.

3.7. Chapter summary

This chapter has given a general overview of the theoretical framework adopted by this thesis. A rationale has been presented for the conceptual framework, data collection methods and data analysis procedures utilised in the thesis. The conceptual framework set out a paradigm where both the magnitude and structure of variability should be quantified to thoroughly describe variability and highlighted the requirement to consider the accuracy and repeatability of the specific methods used to minimise the confounding effect of measurement error. The thesis will also utilise a range of novel and traditional data collection and analysis methods, and the specific rationale behind the adoption of these methods was explored.

4. Multiple single-subject investigation into inter- and intra-session variability in the golf swing

4.1. Chapter objectives

This chapter presents a multiple single-subject investigation examining inter- and intra-session variability in the golf swing. Given the lack of existing research which jointly considers movement and outcome variability in the golf swing, this investigation undertook a detailed examination of the variability of five amateur golfers of different skill levels during three separate testing sessions and using two clubs. The aim of this investigation was to examine the individual-specific patterns of movement and outcome variability shown by the golfers.

4.2. Introduction

Achieving outcome consistency in repeated shots is beneficial to a golfer's performance, but it is incorrect to assume that a consistent outcome can only be achieved with consistent movement patterns. Motor equivalence theory indicates that a multitude of different movement patterns can result in the same outcome (Latash, 2016) but research into movement variability in the golf swing has mainly considered outcome measures (Betzler et al., 2012) or measurements of club movement (Morrison et al., 2016). Whilst some research has investigated the variability of body movements, several recurring limitations have been highlighted in the research completed to date (Glazier, 2011). Furthermore, the study of movement and outcome variability in golf has typically considered the two separately, ignoring the potential for compensatory variability and equivalent movement patterns, and the inter-session variability of golfers has rarely been considered.

This investigation utilised a multiple single-subject design to address some of these gaps in the literature. This design has been espoused by Bates et al. (2004) for investigating movement variability due to the unique individual constraints that exist between people. It encourages a greater focus on the intricacies of an individual's coordination, rather than aggregating data in a group to classify the effect on the 'average' person (Bates et al., 2004). Such aggregation can mask individual strategies and result in a loss of information regarding the research question (James and Bates, 1997). The detailed investigation encouraged by these methods allow insights into the variability of individual movement patterns and can inform future group studies through the exploration of the data trends of individuals (James, 2004).

4.3. General methods for a multiple single-subject investigation into inter- and intra-session variability in the golf swing

4.3.1. Section objectives

This section will present an overview of the general data collection methods used in the multiple single-subject investigation; the procedures, definitions and processes which remain constant and relevant for all sub-sections of the investigation. Specific methods, results and discussion will be presented in sub-chapters to maintain readability.

4.3.2. Participants

Five amateur male golfers, from four different CONGU handicap categories (CONGU, 2018), volunteered to participate in the investigation (Table 4.1). Golfers were recruited from staff of The R&A. Participants provided written informed consent and were free from injury at the time of testing. All procedures complied with the ethical approval granted by the University's institutional review board before the commencement of the investigation.

Table 4.1. Participant information.

Participant	Age (Yr)	Height (m)	Mass (kg)	CONGU Handicap	CONGU Handicap Category
1	62	1.82	82.4	13	3
2	25	1.89	84.7	8	2
3	23	1.59	62.7	22	4
4	49	1.68	78.6	18	2
5	53	1.80	89.2	4	1

4.3.3. Procedures

Each of the participants undertook three testing sessions, on separate days over a maximum of four-day period, at The R&A's equipment test centre in St Andrews. Participants utilised their own golf shoes but used standardised iron and driver clubs during the testing (Table 4.2). Retro-reflective markers (added mass < 15 g) were fitted to the clubs before the testing session.

Table 4.2. Characteristic properties of driver and iron clubs used.

	Driver	5-Iron
Club loft (°)	10.5	26.0
Club length (m)	1.14	0.97
Club mass (g)	350.5	438.5
Swingweight (Lorythmic)	D0	D0
Shaft stiffness	Regular	Regular

At each session, participants were given an opportunity to conduct a self-directed warm up before completing ten shots with the driver and ten shots with the 5-iron club. Shots were self-paced and split into two sets of five in the order: driver, 5-iron, driver, 5-iron. Driver and iron shots were hit off a tee placed into artificial turf; tee length was 69.9 mm and 34.9 mm for driver and iron shots respectively. Shots were directed through a 3.0 x 3.0 m doorway toward a target situated approximately 230 m (250 yards) away on a flat driving range. Participants were instructed to hit a straight shot toward the target as if they were playing onto a regular width fairway; no further instruction was given. After each shot, participants were asked to provide a subjective rating of the shot on a scale of zero to five, with five representing a good shot for them as an individual. Shots not captured by the measuring equipment or self-determined as a mis-hit were discarded and repeated and the number of self-determined mis-hits is recorded in the results section.

An eight-camera motion capture system and Qualisys Track Manager (QTM) software (Oqus 300+, Qualisys AB, Gothenburg, Sweden) were used to capture the full body kinematics of the swing. This system had a capture frequency of 500 Hz and a capture volume of approximately 4.0 m x 3.5 m x 2.5 m. This system was linked to two force platforms (OR6-6-2000, AMTI, Watertown, MA), embedded under the artificial hitting surface, which measured ground reaction force and centre of pressure at a frequency of 2000Hz. A separate three-camera motion capture system (Oqus 300+, Qualisys AB, Gothenburg, Sweden), with a capture frequency of 1000Hz and a capture volume of approximately 1.2 m x 0.9 m x 1.0 m, was used along with user-written algorithms to capture clubhead presentation data at impact (Betzler et al., 2012; Corke et al., 2018). All systems were jointly triggered using an acoustic trigger at impact. The eight-camera motion capture system recorded two seconds of data from before and after the trigger. The three-camera motion capture system recorded 0.12 s of data from before and after the trigger. A commercially available Doppler radar-based launch monitor was positioned approximately 2.5 m behind the golfer and measured launch variables and shot outcomes for each shot (Figure 4.1).

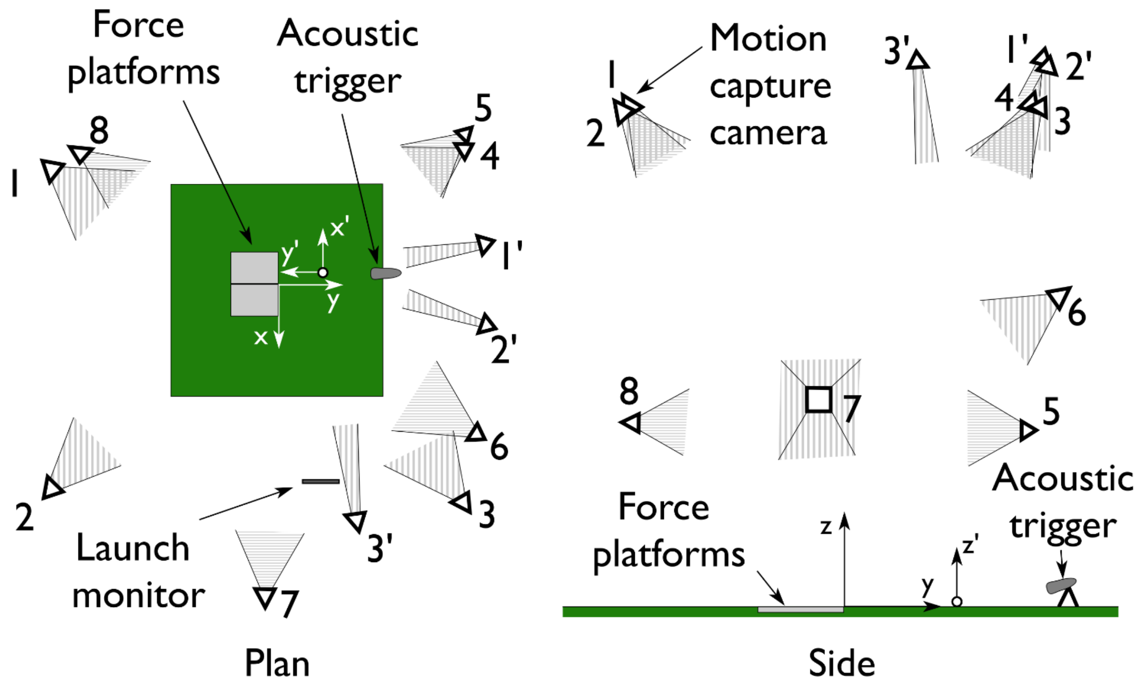


Figure 4.1. Side and plan views showing the positioning of motion capture cameras, force platforms and launch monitor in the golf bay.

The global coordinate system was defined with its origin at the anterior intersection of the force platforms with the X-axis pointing left-right, the Y-axis pointing posterior-anterior and the Z-axis vertical for the golfer at address. Due to the smaller capture volume of the clubhead tracking motion capture system, it was not possible for this system to be calibrated such that its coordinate system matched the global coordinate system. Instead, the clubhead motion capture coordinate system had its origin at an approximate teeing position of the golf ball, with the X-axis pointed towards the target and Y-axis perpendicular and pointing towards the golfer. The Z-axis was in the vertical direction, perpendicular to the plane formed by the X and Y axes (Figure 4.2). A static trial, with six markers jointly measured by both coordinate systems, was collected before the commencement of data collection. The positions of these markers were used to create transformation matrices to convert between coordinate systems.

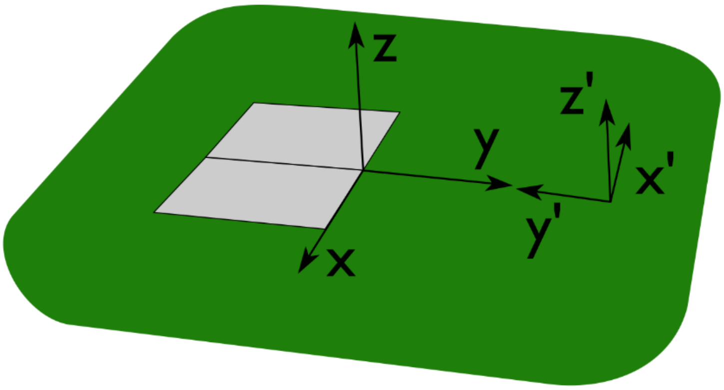


Figure 4.2. The global coordinate system and the clubhead motion capture coordinate system.

4.3.4. Data processing and analysis

After data collection, motion capture data was labelled using Qualisys Track Manager (Qualisys AB, Gothenburg, Sweden). Marker trajectory data were manually inspected and, where the fit was deemed to be appropriate by the researcher, gaps were filled using in-built gap-filling algorithms. A moving average filter with a window length of five frames was used to filter marker coordinate data before exporting to C3D file for processing in Visual 3D (C-Motion Inc., Germantown, MD). Visual 3D was used to calculate biomechanical variables of interest and calculated data was exported from Visual 3D to ASCII file. Clubhead presentation and launch monitor data were exported from their respective software, collated with the participant's subjective scores in Microsoft Excel (Microsoft, Redmond, WA) and exported to CSV file. ASCII and CSV files were loaded into MATLAB (R2018a, Mathworks, Natick, MA) for further analysis.

The purpose of this investigation was to guide future studies through the exploration of individual-specific patterns and the data analysis procedures reflected this purpose. Specifically, the goal was to elucidate potential differences in variability between the golfers, not to generalise these differences to a broader group. Descriptive statistics included multiple measures of both the magnitude and structure of variability. Median-based statistics were generally preferred over mean-based statistics, due to their robustness to outliers in a dataset (Betzler et al., 2012). Where statistical hypothesis testing was utilised, the mean or median difference has been calculated to provide an unstandardised measure of the effect size.

4.4. Constituent investigations of the multiple single-subject investigation into inter- and intra-session variability in the golf swing

4.4.1. Inter- and intra-session variability in shot outcome, ball launch and clubhead presentation of five differently skilled golfers with driver and iron clubs

A. Introduction

The golfer can only influence ball flight by attempting to manipulate the impact between the club and the ball, and the variability in shot outcome, ball launch and clubhead presentation variables are closely related. In this investigation, these variables are jointly considered to indicate of the outcome or endpoint variability of the golfer. Previous research in golf has shown that higher skilled golfers have greater consistency in ball launch and clubhead presentation variables than lower skilled golfers (Betzler et al., 2012) which agrees general findings in wider research (van Emmerik et al., 2016). Outcome variables have been used to indicate skill or task performance, but classification of golfing skill is complicated. Handicap is commonly used to group participants in biomechanical investigations (for example Morrison et al., 2016; or Zheng et al., 2008b) but has significant limitations as a measure of skill. An individual's handicap is calculated over several rounds of golf and two individuals can obtain the same handicap despite having different skill levels in specific areas of the game (Wallace et al., 1990). Handicap adapts slowly to changes in skill and is generally considered to reflect a golfer's potential. As skill classification in biomechanics should be concerned with skill in the specific task at the time of the test, not overall golfing or game management skills, this investigation will present a measure of task performance alongside handicap as indication of a golfing skill. The aim of this section was to describe the outcome variability of the five golfers studied and gain an understanding of the relative skill of the golfers.

B. Methods

The shot outcome variables of interest (Figure 4.3) were measured using the Doppler radar-based launch monitor and defined as follows:

- Carry length – the distance between the first impact of the ball with the ground and the tee (m).
- Carry side – the perpendicular distance between the first impact of the ball with the ground and the target line (m).
- Total length – the distance between the final resting place of the ball and the tee (m).
- Total side – the perpendicular distance between the final resting place of the ball and the target line (m).
- Shot angle - the angle made between the target line and the final shot location, calculated using total distance and total side (°).

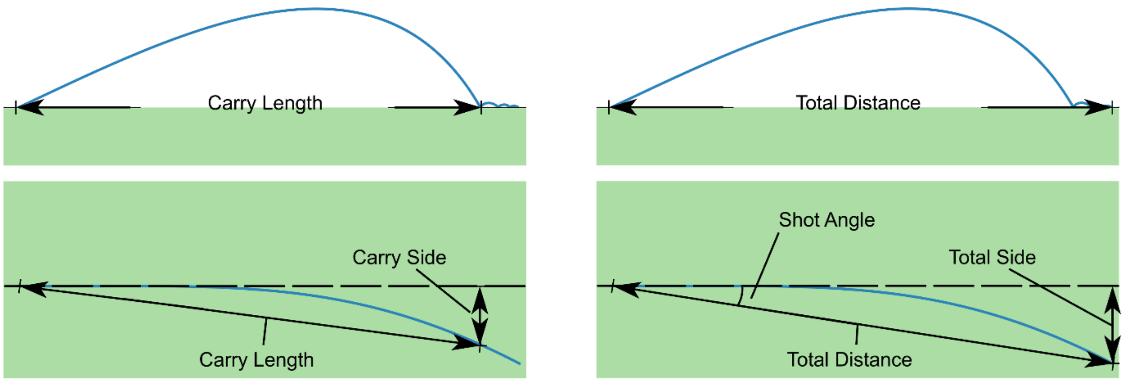


Figure 4.3. Shot outcome variables measured by the Doppler radar-based launch monitor.

The ball launch variables of interest (Figure 4.4) were measured using the Doppler radar-based launch monitor and were defined as follows:

- Ball speed – the initial speed of the ball immediately following impact ($m{\cdot}s^{-1}$).
- Efficiency – the ratio of ball speed measured by the Doppler radar-based launch monitor and clubhead speed measured by the clubhead motion capture (dimensionless).
- Launch angle – the angle of the ball's initial path relative to the horizontal plane (°).
- Launch direction – the angle of the ball's initial path relative to the target line (°).
- Spin rate – the spin rate of the ball measured about its axis of rotation ($rad{\cdot}s^{-1}$).
- Spin axis – the angle the ball's axis of rotation makes with a plane perpendicular to the target line (°).

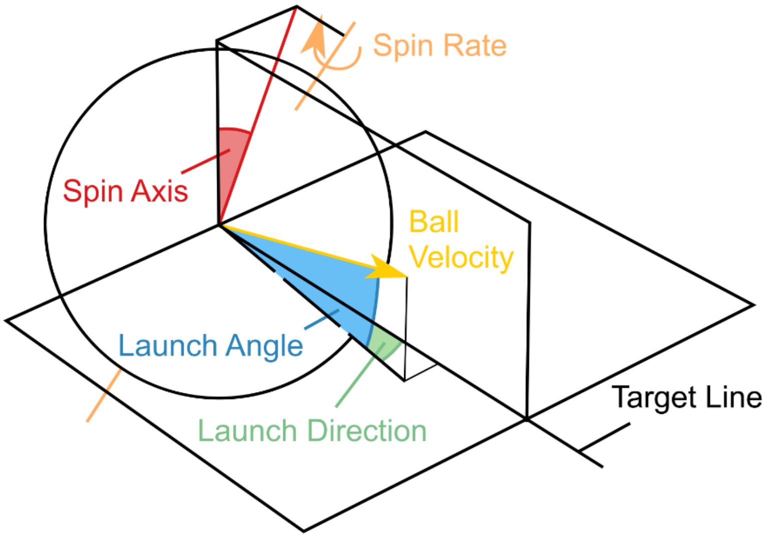


Figure 4.4. Ball launch variables measured by the Doppler radar-based launch monitor.

The clubhead presentation variables (Figure 4.5) were measured using the clubhead motion capture system and previously described custom algorithms (Betzler et al., 2012; Corke et al., 2018) and were defined as follows:

- Clubhead speed – the mean speed of the three (drivers) or two (irons) tracking markers on the clubhead at impact ($m \cdot s^{-1}$).
- Attack angle – the angle of the tracking markers relative to the horizontal plane (°).
- Path angle – the angle of the tracking markers relative to the target line (°).
- Face angle – the angle of the club face relative to the target line, evaluated at the impact location (°).
- Effective loft – the angle of the club face relative to the vertical, evaluated at the impact location (°).
- Effective lie – the angle of the club face relative to the horizontal, evaluated at the impact location (°).
- Impact location – the horizontal (X) and vertical (Y) distances from the impact location to the centre of the club face (mm).

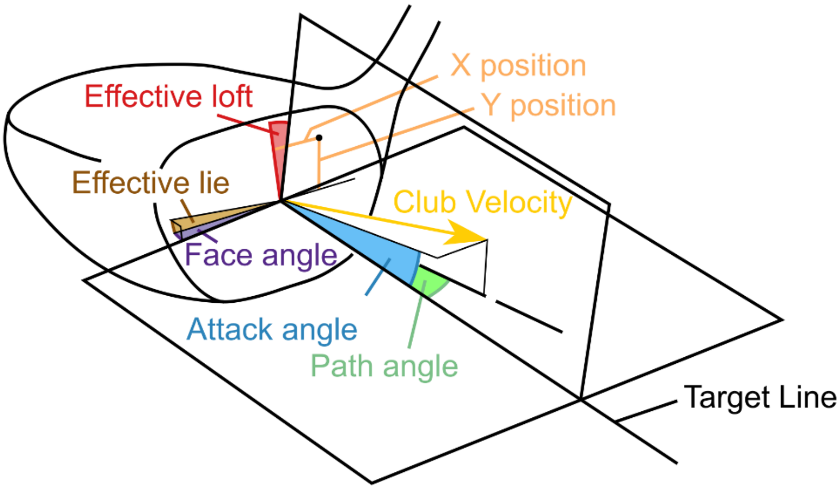


Figure 4.5. Clubhead presentation variables measured by the clubhead motion capture system.

Task performance has been used as a measure of skill in previous research, for example in basketball (Verhoeven and Newell, 2016) but there was no single variable which encapsulated the golfer's performance in the task in this investigation; hit a straight shot for maximum distance. A measure of task performance was formed as a combination of shot distance and deviation from the target line. This 'shot score' variable was calculated as:

$$Shot\ score = \frac{(Reference\ distance - A)}{Reference\ distance}$$

where:

$$A = (Reference\ distance - Total\ length) \times \left(\left(\frac{1}{5000} \times Total\ side^2\right) + 1\right)$$

Equation 4.1. Equation used to calculate shot score variable from shot outcome.

This calculation resulted in a score of less than one for shots shorter than the reference distance, with shots travelling a greater total distance and deviating less distance from the target line earning a greater score. The reference distances for driver and iron shots were 402.3 m and 283.8 m respectively. The driver reference distance was the maximum driving distance of PGA tour players in 2017 (440 yards; PGA Tour, 2017), whilst the iron reference distance was derived as the average carry distance of 5-iron shots by PGA tour players, 194 yards, multiplied by the ratio of the maximum driving distance to average carry distance for PGA tour players (440/275 = 1.6; TrackMan, 2014). The calculation penalised deviation from the target line using a quadratic, so an increase in deviation from the target line resulted in a squared increase in the penalty. The constant, 1/5000, was derived through trial and error to moderate the decrease in shot score caused by an increase in total side (Figure 4.6). The effect of changing this constant can be seen in Appendix B, Figure B.1 and Figure B.2.

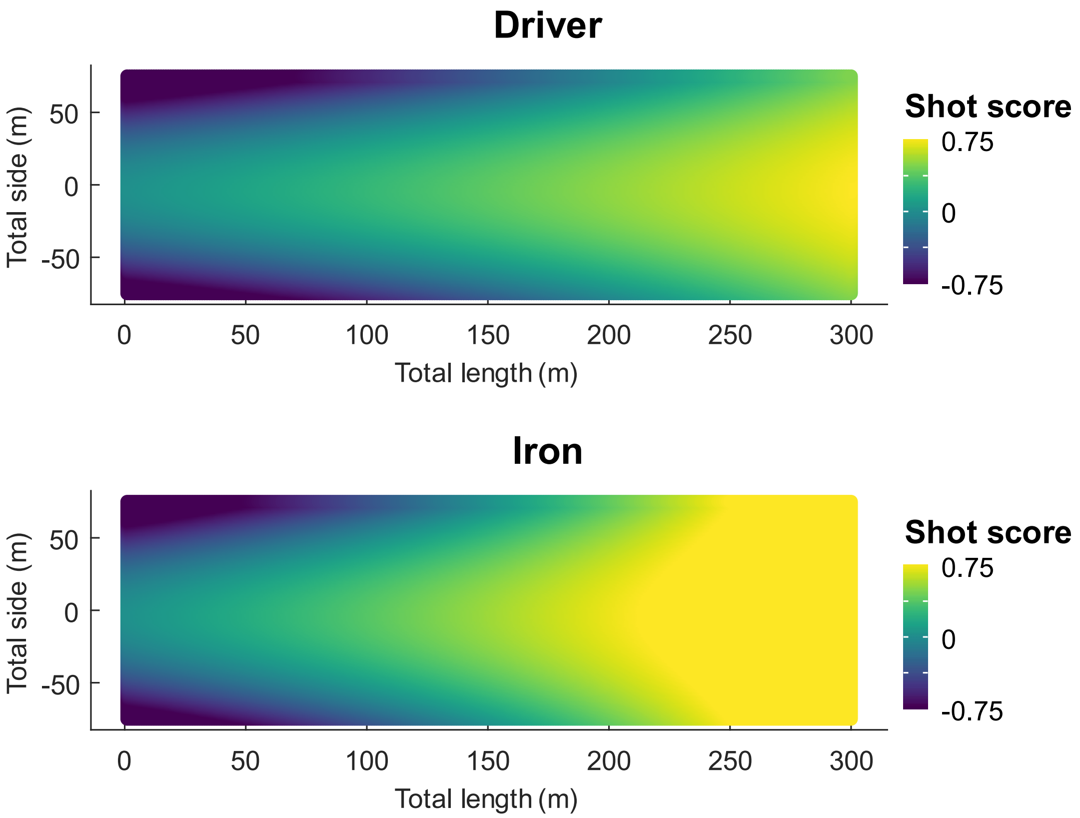


Figure 4.6. Visual representation of shot score for different shot outcomes.

For each variable, the intra-session median was calculated as the median of all shots with each club within the session. Likewise, the intra-session median absolute deviation (*MAD*) was calculated as the median of the absolute deviations from the intra-session median. Tukey's fences (Tukey, 1977) were constructed for the shots within each session, and the number of outliers detected using this method was reported alongside the median and median absolute deviation. ANOVA and MANOVA tests were performed in IBM SPSS Statistics 24 (IBM, Armonk, NY) to assess differences between participants. Significant ANOVA results were followed up with *post hoc* Bonferroni tests. For the MANOVA, Pillai's trace statistic was used, as this measure is robust to violations of test assumptions in cases where the sample sizes are equal, and discriminant analysis was used to follow up statistically significant results (Field, 2013). All statistical tests are accompanied by measures of mean difference as an unstandardised effect size.

C. *Results*

Indicated by the shot outcome and shot score, Participant 2 had the highest task performance with both clubs (Appendix C, Table C.1; Figure 4.7). The median total distance for Participant 2 was 228.0, 254.8 and 243.5 m with the driver club and 187.2, 191.7 and 190.4 m with the iron club for the three sessions respectively. The ordering of participants based on mean shot score was 2, 5, 4, 3, 1 with the driver club and 2, 5, 3, 4, 1 with the iron club. The mean difference between ordered participants was 0.03, 0.09, 0.05 and 0.06 with the driver and 0.05, 0.13, 0.01, 0.03 with the iron. This ordering of performance was not reflected by the participant's handicaps, which suggested the order of skill was 5,2,1,4,3, with Participant 5 being the most skilled golfer. One-way ANOVA indicated that differences in shot score were statistically significant ($F(4,295) = 165.5, p < 0.01$). *Post hoc* Bonferroni adjusted t-tests indicated differences between all participants (*minimum mean difference* $= 0.04, p < 0.01$), except between Participants 3 and 4 (*mean difference* $= 0.02, p = 0.43$).

MANOVA indicated a difference between the participants in the variability of total length and total side for the driver ($V = 1.23, F(8,20) = 4.00, p = 0.01$) but not the iron club ($V = 0.579, F(8,20) = 1.02, p = 0.45$). A follow-up discriminant analysis revealed two discriminant functions which explained 78.9% and 21.1% of the variance (*canonical* $R^2 = 0.77$ and 0.47 respectively). Together, these functions significantly differentiated the participants ($\Lambda = 0.13, \chi^2(8) = 21.8, p = 0.01$), but the second function did not significantly differentiate the participants on removal of the first ($\Lambda = 0.54, \chi^2(3) = 6.6, p = 0.09$). Correlations indicated that total side loaded highly on the first function ($r = 0.99$) and total length loaded highly on the second function ($r = 0.99$). Neither variable loaded highly on the other function ($r = -0.15$ and $r = -0.08$ for total side and total length respectively). The discriminant function plot showed that the first function discriminated Participant 2 from the others and the second function discriminated Participant 3 from the others. Thus, with the driver club, Participant 2 had increased variability of total side (*maximum mean difference* = 9.6 *m*), and Participant 3 had increased variability of total length (*maximum mean difference* = 5.0 *m*).

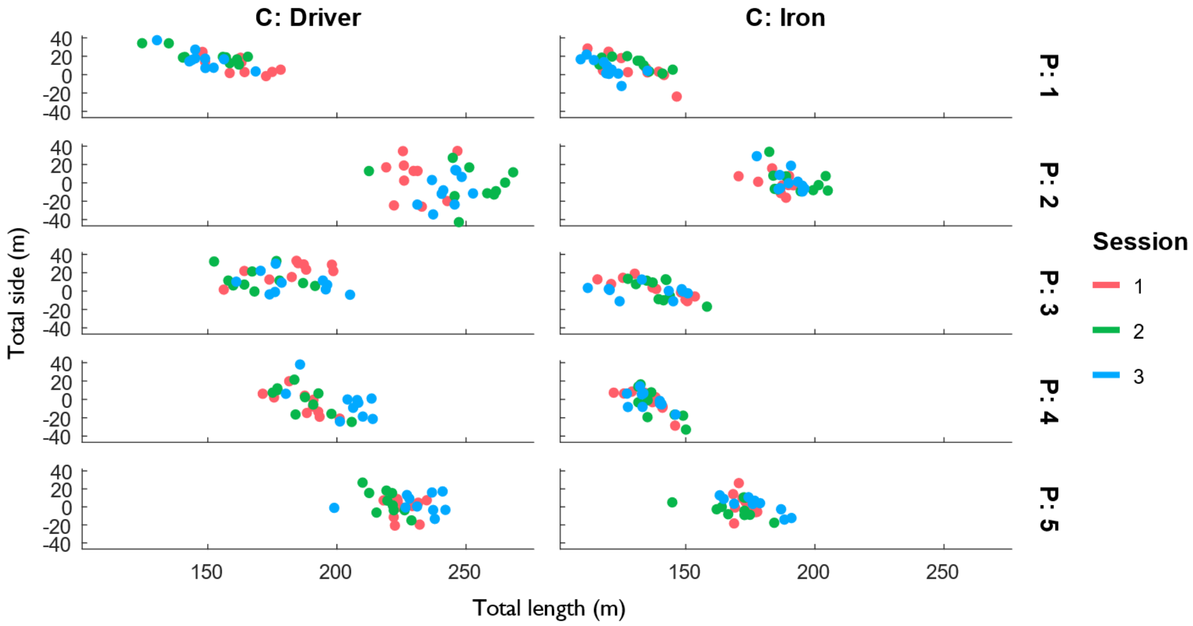


Figure 4.7. Shot outcome, total length and total side, for all participants and sessions.

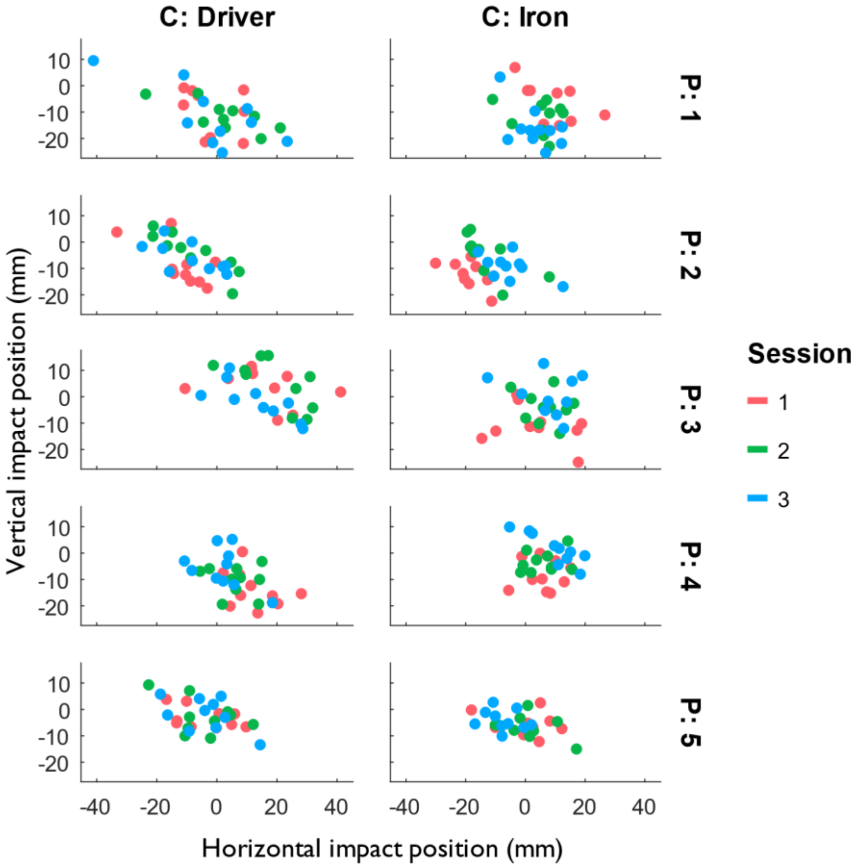


Figure 4.8. Impact location for all participants and sessions with shaded area indicating the approximate grooved area on club face.

Differences in ball speed generally reflected the same patterns as differences in shot outcome (Appendix C, Table C.2). The highest mean efficiency over the three sessions, 1.47 with the driver club and 1.45 with the iron club, was achieved by Participant 5. With both clubs, participants tended to show individual patterns for launch angle, launch direction, spin rate and spin axis which were consistent between sessions. With the driver, for example, Participant 1 had median launch angles of 17.6, 17.6 and 17.3° and spin axis of 1.5, 4.7 and 5.7°, whereas Participant 2 had median launch angles of 9.6, 10.8 and 8.5° and spin axis of -5.7, -9.3 and -10.0°. Similar individual patterns were displayed in the clubhead presentation variables (Appendix C, Table C.3; Figure 4.8) but a larger sample size would be required to comment on whether these patterns were related to skill. MANOVA indicated no clear differences between the participants in the variability of the ball launch or clubhead presentation parameters for the driver (Ball: $V = 2.19, F(24,32) = 1.62, p = 0.10$; Club: $V = 2.77, F(32,24) = 1.68, p = 0.10$) or iron clubs (Ball: $V = 2.08, F(24,32) = 1.45, p = 0.16$; Club: $V = 2.69, F(32,24) = 1.54, p = 0.14$).

Grouping the participants, there was no clear difference in the variability of shot score (Independent t-test: $t(28) = -0.439, p = 0.84$, *maximum mean difference* $= 0.01$), ball launch variables (MANOVA: $V = 0.33, F(5,24) = 2.39, p = 0.07$) or clubhead presentation variables (MANOVA: $V = 0.43, F(8,21) = 1.95, p = 0.11$) between the driver or iron clubs. The maximum mean differences in the variability of ball speed, launch angle, launch direction, spin rate and spin axis were 0.8 $m\cdot s^{-1}$, 0.5°, 1.1°, 25 $rad\cdot s^{-1}$ and 2.3° respectively. For clubhead presentation variables, the maximum mean differences were 0.1 $m\cdot s^{-1}$, 0.3°, 0.3°,0.6°, 0.3°,0.4°, 4.9 mm and 1.4 mm for clubhead speed, attack angle, path angle, face angle, effective loft, effective lie, horizontal impact location and vertical impact location respectively.

D. Discussion

The shot score variable, which rewarded greater total distance and penalised deviation from the target line, ordered participants differently to their handicap and ordered participants differently with the driver and the iron club. Participant 5 had the lowest handicap in the investigation but was outperformed by Participant 2 based on the average shot score. Participant 2 was younger and taller than Participant 5, and their greater task performance could reflect a game based more heavily on increased driving distance. Both handicap and shot score indicate the size of skill differences between the golfers, but differences between the measures highlight the issues with using handicap to classify skill in biomechanical studies. The shot score variable was thought to be more appropriate for this investigation, as it was a direct measure of performance in the task set to the golfers, but it is specific to the task and will not transfer to accuracy-based tasks.

Differences in shot outcome were generally reflected by differences in ball launch and clubhead variables, for example, the golfers with greater total distance also displayed greater ball and clubhead speed. Furthermore, individuals displayed individual specific patterns in ball launch and clubhead presentation variables, for example, favouring an angle of attack.

There were statistically significant differences between the golfers in the variability of the shot outcome, with Participant 2 and 3 showing higher variability in total side and total length respectively, but no differences in ball launch or clubhead presentation variability. There were no clear patterns in the variability of any outcome, launch or clubhead presentation variables. In general, differences in outcome variability between golfers were small, and the variability of the shot outcome, ball launch and clubhead presentation varied between sessions and participants. The research design makes it difficult to elucidate meaningful differences in variability between the participants, particularly because significant evidence already exists which suggests that higher skilled golfers generally display lower variability in clubhead presentation variables (Betzler et al., 2012; Kenny et al., 2008).

4.4.2. Inter- and intra-session variability in body and club kinematics of five differently skilled golfers with driver and iron clubs

A. Introduction

Since initial scientific enquiries, such as those conducted by Cochran and Stobbs (1968), much scientific research has investigated the movements of the golfer, but a comprehensive description of intra-individual variability in the golf swing remains lacking. Except for a growing body of evidence which suggests that the variability of the clubhead decreases through the downswing to impact, particularly in high skilled golfers (Morrison et al., 2016; Tucker et al., 2013), research on kinematic variability during the golf swing is limited. There have been suggestions that high skilled golfers display a low amount of movement variability (Horan et al., 2011) but this has only been reported in a limited number of specific variables and little is known outside of these variables. There is also very little research on the inter-session variability of golfers and no indication as to whether the kinematic variability of golfers is consistent on different days. The aim of this section was to describe the variability of the body and club kinematics for the five golfers studied.

B. Methods

A full body marker set, utilising 67 spherical retroreflective markers with a diameter of 12 mm, was developed based on International Society of Biomechanics recommendations (Wu et al., 2002, 2005) and applied to the participant using hypoallergenic double-sided tape, a cap and a waistband (Appendix A, Table A.1; Figure 4.9). The driver and iron clubs were fitted with eight or nine retroreflective markers respectively, with five of these markers tracked using the body motion capture system (Appendix A, Table A.1), and the other markers tracked using the clubhead tracking system and used to calculate clubhead presentation variables (Betzler et al., 2012; Corke et al., 2018).

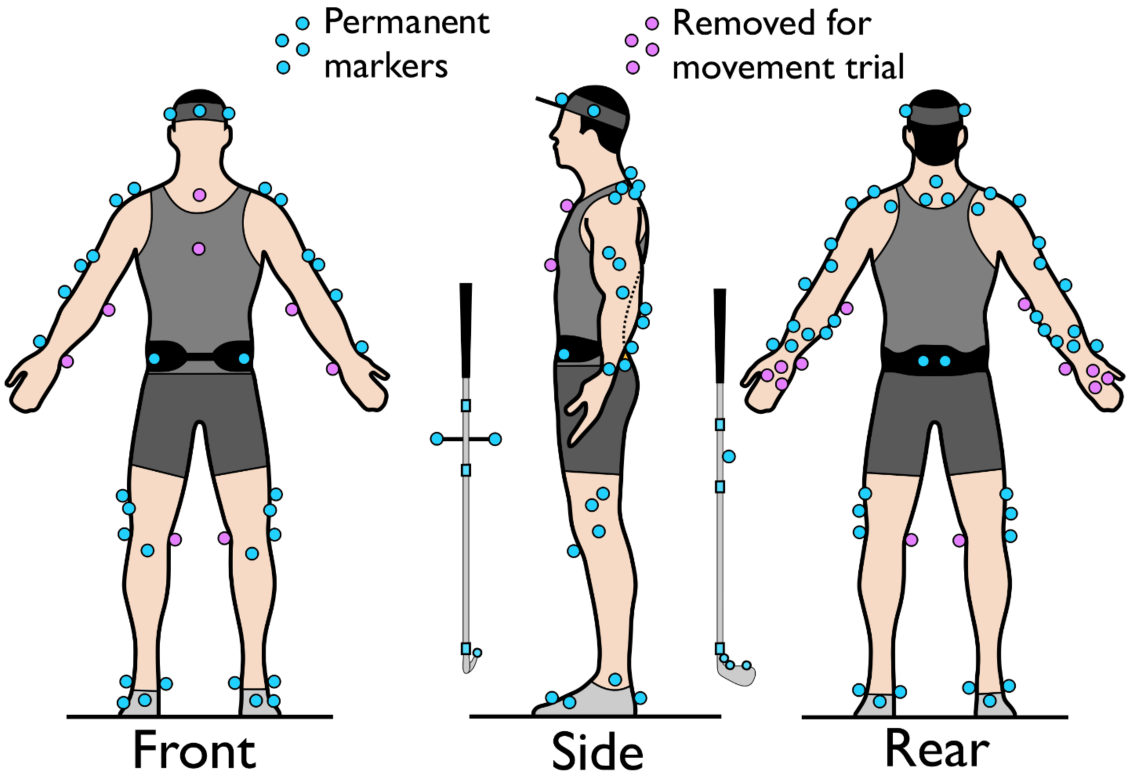


Figure 4.9. Positioning of retroreflective markers on participant.

After the markers were applied, but before the warm-up, a static trial was collected; where the participant stood in a neutral position with arms bent at 90° and the thumbs pointing upwards. The static trial was followed by dynamic trials to calculate functional joint centres/axes at the shoulder, elbow, wrist, hip, knee and ankle joints (Schwartz and Rozumalski, 2005). The dynamic trials for the elbow, knee and ankle consisted of ten seconds of flexion-extension of the joint in question. For the wrist, dynamic trials consisted of five seconds of flexion-extension followed by five seconds of abduction-adduction. For the shoulder and hip, a 14-second trial with the star-arc movement described by Camomilla et al. (2006) was performed. For each trial, the participant mirrored the movements of a researcher to ensure that movements covered a moderate range of motion (30-45°) at a controlled pace to limit the effect of soft tissue artefact (Begon et al., 2007). After the functional joint trials, 14 markers were removed from the participant (Appendix A, Table A.1; Figure 4.9) and a self-directed warm up was completed before the first recorded shot.

A rigid body kinematic model was defined in Visual 3D and applied to the static trial. This rigid body kinematic model uses marker and landmark coordinates to define a series of segments, assumed to be non-linked, ideally rigid, with no inertial properties and arbitrary shape. Landmarks are virtual markers which were defined based on the location of markers, or from the dynamic trials using the Gillette algorithm for calculating functional joint centres (Schwartz and Rozumalski, 2005). Markers and landmarks are assumed to be rigidly attached to each segment and are used to define and track the movement of the local coordinate system of the segment. Landmark and segment definitions are provided in Appendix A, Table A.2 and Table A.3 respectively. After creation, the kinematic model was applied to each swing trial and joint angles calculated using Euler or Cardan rotation sequences defined according to International Society of Biomechanics recommendations (Wu et al., 2002, 2005). The joint angles obtained from the kinematic model were the principal variables of interest in this section of the investigation and definitions are shown in Appendix A, Table A.4. The global club angle, that is the angle between the club segment and the global coordinate system, was used to calculate the eight key events proposed by Ball and Best (2007). Data calculated in Visual 3D was exported to MATLAB for further analysis.

Data analysis was performed separately for each participant, session and club, resulting in six groups of shots for each participant; two clubs for each of the three sessions. For each group of shots, trajectories were aligned at impact and trimmed to the length of the shortest signal starting at takeaway and ending at impact. For each group of shots, a new time series describing the kinematic variability was constructed using point-wise median absolute deviation. Sample entropy and cross-sample entropy were calculated to quantify the structure of variability. In the case of sample entropy, the group of trajectories were joined into one pseudo-periodic time series. Cross-sample entropy was calculated for all paired comparisons for the same club within an individual session. As 10 shots with each club were performed, there were 45 unique pairwise comparisons per group of shots. The entropy measures are generally sensitive to changes in parameters. In this investigation, a vector length, m, of 3 was used, in line with published recommendations (Lake et al., 2002). Sample entropy was calculated for a range of tolerance values, r, and the results inspected to find tolerance values which showed consistent patterns between all groups of shots. The selected tolerance value was 0.9°, although a range of values offered similar results. For each variable, a single principal components analysis was performed on the time series of all groups of shots by all participants with the time series trimmed to the length of the shortest overall signal for this analysis. The principal components analysis was performed using the in-built MATLAB function ‘pca’ and the first n principal components which explained 90% of the variance in the data were retained for analysis. Single component reconstruction

(Brandon et al., 2013) was used to indicate the features described by the principal components.

Some joint angles were determined to be unreliable due to errors primarily caused by marker occlusions during the movement. All data for the participant and the joint angle were removed in these situations. Specifically, Participant 1 displayed errors in the left shoulder angle, the left elbow angle and the left hip angle, Participant 2 displayed errors in the left shoulder angle and the left elbow angle, Participant 3 displayed errors in the right shoulder angle and the right elbow angle and Participant 4 displayed errors in the right elbow angle and the left hip angle.

The median pointwise-median absolute deviation, the cross-sample entropy and principal component scores were analysed as discrete statistics. Tukey's fences (1977) were constructed for each session, and the number of outliers detected using this method used as a descriptive statistic alongside the median and median absolute deviation. MANOVA tests, using Pillai's trace statistic, were performed in IBM SPSS Statistics 24 (IBM, Armonk, NY) to assess differences between participants. Discriminant analysis was used to follow up statistically significant results (Field, 2013). Measures of mean or median difference were calculated as a measure of effect size.

C. Results

Results have been presented for three angles which were selected based on their appearance in the existing literature and their ability to represent the general patterns observed in the investigation. The selected angles are the three components of the global club angle, the pelvis-torso angle and the left wrist angle. Differences between the participants were observed in all the joint angle trajectories, as well as the variability of the trajectories and the structure of this variability; however, consistent patterns across joint angles, such as a participant with consistently more or less variability than the other participants, were not observed.

The global club angle trajectories, pointwise-median absolute deviation trajectories, sample entropy and cross-sample entropy are displayed in Figure 4.10. A MANOVA using Pillai's trace statistic indicated that there were statistically significant differences between the participants in the magnitude of variability, indicated by the median pointwise-median absolute deviation ($V = 1.05$, $F(12,75) = 3.37$, $p < 0.01$, *maximum median difference* = $2.4°$). Follow up discriminant analysis indicated three discriminant functions, explaining 80.5%, 13.4% and 6.1% of the variance (*canonical* $R^2 = 0.82, 0.50$ and 0.36 respectively). In combination, these functions significantly differentiated between the participants ($\Lambda = 0.22, \chi^2(12) = 38.30, p < 0.01$) but the second and third functions did not differentiate on removal of the first ($\Lambda = 0.65, \chi^2(6) = 10.74, p = 0.10$). The correlations between the discriminant functions and the median pointwise-median absolute deviations showed that the variability of the Y and Z components of global club angle loaded highly onto the first discriminant function ($r = 0.42$ and 0.83 respectively). Inspection of the discriminant function plot indicated that Participant 1 and 2 were differentiated from the other participants by this function: Participants 1 and 2 displayed higher average variability in the Y and Z components of global club angle. Grouping the participants, there were no significant differences in average variability in global club angle between the two clubs used ($V = 0.22, F(3,26) = 2.50, p = 0.08$, *maximum median difference* = $0.49°$).

A MANOVA using Pillai's trace statistic also indicated statistically significant differences in the structure of variability in the global club angle, indicated by the cross-sample entropy ($V = 0.83, F(12,4035) = 128.55, p < 0.01$, *maximum median difference* = 0.15). A follow-up discriminant analysis found three discriminant functions which explained 81.5%, 12.6% and 5.9% of the variance in the data (*canonical* $R^2 = 0.76, 0.41$ and 0.30 respectively). The functions significantly differentiated between the participants both in combination ($\Lambda = 0.33, \chi^2(12) = 1513.53, p < 0.01$) and on removal of the first ($\Lambda = 0.76, \chi^2(6) = 375.98, p < 0.01$) and second ($\Lambda = 0.91, \chi^2(2) = 124.08, p < 0.01$) functions. The correlations between discriminant functions indicated that the Z component of global club angle loaded most highly on the first function ($r = 0.85$) and the X component also loaded relatively highly on this function ($r = -0.42$). The Y component of global club angle loaded most highly on the second discriminant function ($r = 0.84$), and all three components loaded highly on the third function ($r = 0.87, 0.54$ and 0.50 for the X, Y and Z components respectively). A more regular structure of variability is associated with a lower value of cross-sample entropy. Inspection of the discriminant function plots and loadings indicated that Participant 3 displayed a less regular structure of variability in the Z component of global club angle than Participants 4 and 5; Participant 5 displayed a less regular structure of variability in the Y component of global club angle than Participant 2; and Participant 1 displayed a more regular structure of variability in the X component of global club angle than Participants 2, 4 and 5.

Grouping the participants, there was a statistically significant difference in the structure of variability of global club angle between the two clubs ($V = 0.08$, $F(3,1346) = 40.76$, $p < 0.01$, *maximum median difference* = 0.02). A follow-up discriminant analysis identified one function which explained 100% of the variance (*canonical* $R^2 = 0.29$) and was associated with increased cross-sample entropy in the X and Z components of global club angle ($r = 0.80$ and *0.37*). The driver club loaded positively onto this function and the iron club loaded negatively. Thus, the driver club was associated with decreased predictability in the X and Z components of global club angle when compared to the iron club.

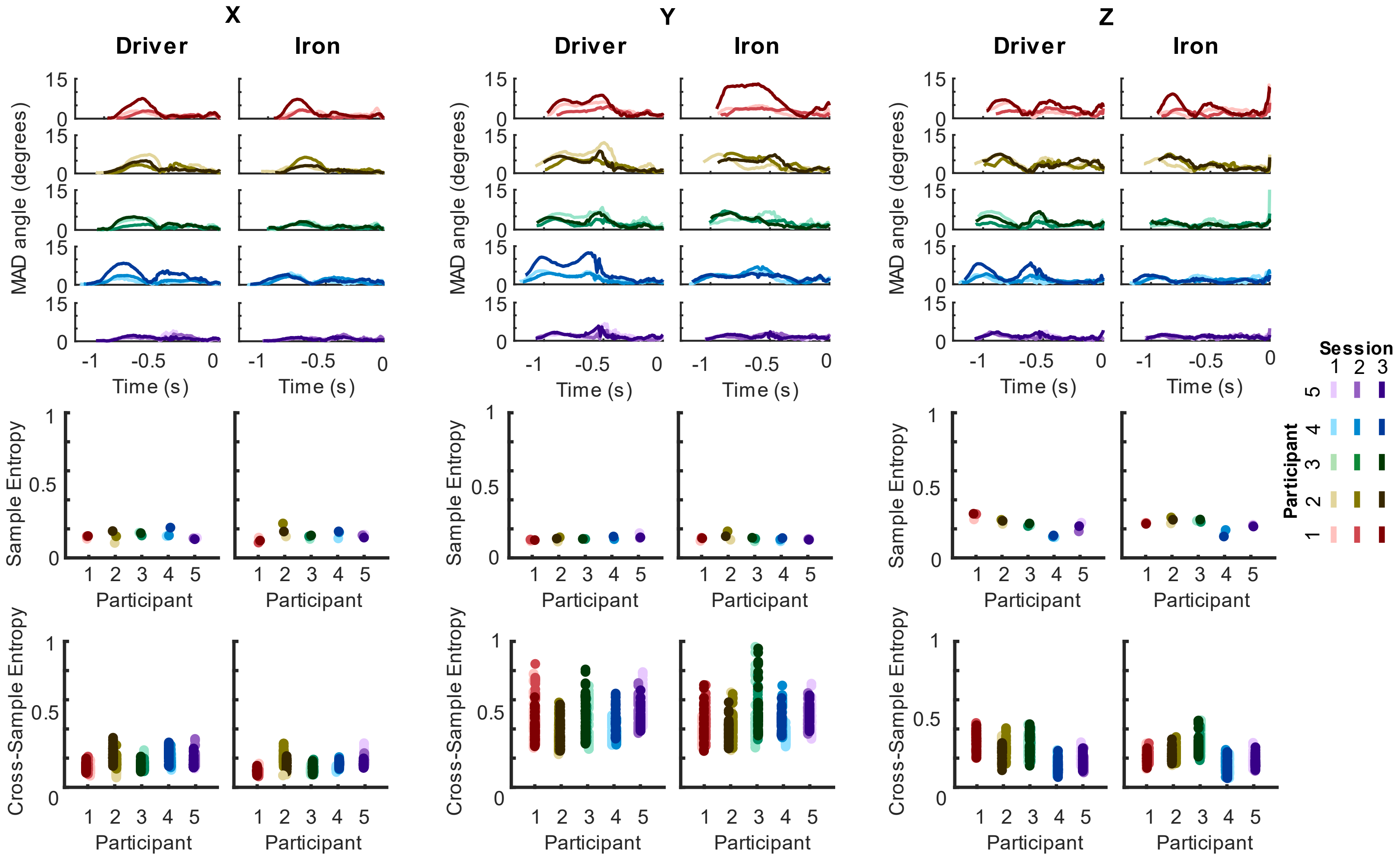


Figure 4.10. Median absolute deviation (MAD) trajectories, sample- and cross-sample entropy scores for the three components of global club angle.

The pelvis-torso angle trajectories, pointwise-median absolute deviation trajectories, sample entropy and cross-sample entropy are displayed in Figure 4.11. A MANOVA using Pillai's trace statistic indicated that there were statistically significant differences in the median pointwise-median absolute deviation between the participants (*$V = 1.08$, $F(12,75) = 3.49$, $p < 0.01$, maximum median difference* = 2.24°). Follow-up discriminant analysis indicated three discriminant functions, explaining 90.0%, 6.4% and 3.6% of the variance (*canonical* $R^2 = 0.88$, *0.44* and *0.34* respectively). These functions significantly differentiated between the participants in combination ($\Lambda = 0.17$, $\chi^2(12) = 44.93$, $p < 0.01$), but the second and third functions did not differentiate on removal of the first ($\Lambda = 0.72$, $\chi^2(6) = 8.39$, $p = 0.21$). The correlations between discriminant functions and the outcome variables showed that the variability of the Z component of pelvis-torso angle, the rotation component, loaded highly onto the first discriminant function ($r = 0.97$). The variability of the Y component of the pelvis-torso angle, forward bend, also loaded highly onto the first discriminant function ($r = 0.36$). The discriminant function plot indicated that Participant 2 was differentiated from the other participants by the first function and, thus, Participant 2 displayed higher average variability in the Y and Z components of pelvis-torso angle. Grouping the participants, there were no significant differences in average variability in global club angle between the two clubs used ($V = 0.01$, $F(3,26) = 0.04$, $p = 0.99$, *maximum median difference* = 0.21°).

Regarding the structure of variability, a MANOVA using Pillai's trace statistic indicated that there were statistically significant differences in the cross-sample entropy of the pelvis-torso angle between the participants ($V = 1.55$, $F(12,4035) = 361.33$, $p < 0.01$, *maximum median difference* = *0.09*). A follow-up discriminant analysis found three discriminant functions which explained 66.4%, 32.0% and 1.6% of the variance (*canonical* $R^2 = 0.90$, *0.81* and *0.31* respectively). The functions differentiated the participants in combination ($\Lambda = 0.06$, $\chi^2(12) = 3752.83$, $p < 0.01$), and on removal of the first ($\Lambda = 0.31$, $\chi^2(6) = 1581.33$, $p < 0.01$) and second functions ($\Lambda = 0.91$, $\chi^2(2) = 131.68$, $p < 0.01$). The correlations between the discriminant functions and the outcome variables showed that the Z component of pelvis-torso angle loaded most highly onto the first function ($r = 0.88$), the Y component loaded most highly onto the second and first functions ($r = 0.83$ and *0.54* respectively), and the X component loaded most highly on the third function ($r = 0.98$). Inspecting the discriminant function plot showed that function 1 differentiated Participant 1 and Participant 3 from each other and the other participants, function 2 differentiated Participant 2 and Participant 5 from each other and the other participants and function 3 differentiated Participant 4 from the other participants. Thus, compared to the other participants, Participant 1 had a lower and Participant 3 had a higher cross-sample entropy in the Z component, Participants 1 and 2 had a lower cross-sample entropy in the Y component and Participant 4 had a higher cross-sample entropy in the X component of pelvis-torso angle.

Grouping the participants, there was a statistically significant difference in the structure of variability of pelvis-torso angle between the clubs ($V = 0.01$, $F(3,1346) = 4.66$, $p < 0.01$, *maximum median difference* < 0.01). A follow up discriminant analysis identified one function which explained 100% of the variance (*canonical* $R^2 = 0.10$) and was associated with increased cross-sample entropy in the Y and Z components of pelvis-torso rotation ($r = 0.45$ and 0.62) and decreased cross sample entropy in the X component ($r = -0.38$). The driver club loaded negatively onto this function and the iron club loaded positively. Thus, the driver club was associated with increased predictability in the Y and Z components and decreased predictability in the X component of pelvis-torso angle when compared to the iron club. However, it should be noted that the effect size of this difference was extremely small.

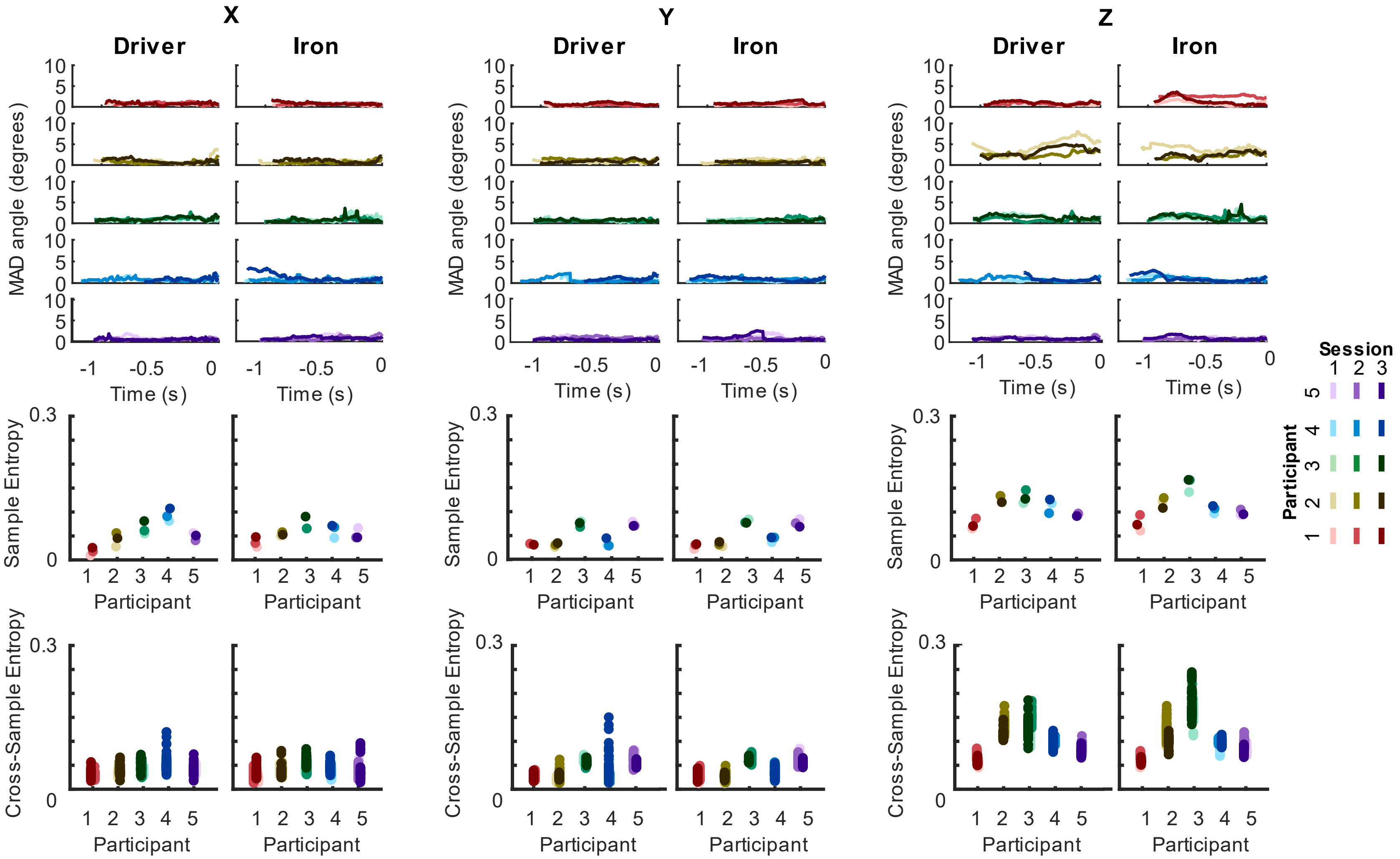


Figure 4.11. Median absolute deviation (MAD) trajectories, sample- and cross-sample entropy scores for each of the three components of the pelvis-torso angle.

The left wrist angle trajectories, pointwise-median absolute deviation trajectories, sample entropy and cross-sample entropy are displayed in Figure 4.12. A MANOVA using Pillai's trace statistic indicated that there were statistically significant differences in the median pointwise-median absolute deviation between the participants ($V = 0.99$, $F(12,75) = 3.09$, $p < 0.01$, *maximum median difference* = $0.93°$). Follow-up discriminant analysis indicated three discriminant functions, explaining 82.8%, 11.4% and 5.8% of the variance (*canonical* $R^2 = 0.81$, 0.46 and 0.35 respectively). These functions significantly differentiated between the participants in combination ($\Lambda = 0.24$, $\chi^2(12) = 36.19$, $p < 0.01$) but the second and third functions did not differentiate on removal of the first ($\Lambda = 0.69$, $\chi^2(6) = 9.15$, $p = 0.17$). The correlations between the discriminant functions and the outcome variables showed that the variability of the X and Y components of left wrist angle, the rotation component, loaded highly onto the first discriminant function ($r = 0.94$ and 0.58). The discriminant function plot indicated that Participants 1 and 2 were differentiated from the other participants by the first function. Thus, Participants 1 and 2 displayed higher average variability in the X and Y components of left wrist angle. Grouping the participants, there were no significant differences in average variability in left wrist angle between the two clubs used ($V = 0.01$, $F(3,26) = 0.11$, $p = 0.96$, *maximum median difference* = $0.17°$).

A MANOVA using Pillai's trace statistic indicated that there were statistically significant differences in the cross-sample entropy of the left wrist angle between the participants ($V = 1.27$, $F(12,4035) = 248.02$, $p < 0.01$, *maximum median difference* = 0.07). A follow-up discriminant analysis found three discriminant functions which explained 54.2%, 38.2% and 7.6% of the variance (*canonical* $R^2 = 0.77$, 0.71 and 0.41 respectively). The functions differentiated the participants in combination ($\Lambda = 0.17$, $\chi^2(12) = 2420.85$, $p < 0.01$), and on removal of the first ($\Lambda = 0.41$, $\chi^2(6) = 1206.20$, $p < 0.01$) and second functions ($\Lambda = 0.83$, $\chi^2(2) = 251.51$, $p < 0.01$). The correlations between the discriminant functions and the outcome variables showed that the X component of left wrist angle loaded most highly onto the first function ($r = 0.91$), the Y component loaded most highly onto the second function ($r = 0.96$), and the X component loaded most highly on the third function ($r = 0.96$). The discriminant function plot showed that function 1 differentiated Participant 5 and the other participants, function 2 differentiated all the participants from each other and function 3 differentiated Participants 1 and 3 from the other participants. Thus, compared to the other participants, Participant 5 had a higher cross-sample entropy in the X component, Participants 1 and 3 had a higher cross-sample entropy in the Z component and the participants were ordered 3, 4, 2, 5, 1 in terms of increasing cross-sample entropy in the Y component of left wrist angle. Grouping the participants, there was no statistically significant difference in the structure of variability between the different clubs ($V = 0.00$, $F(3,1346) = 0.56$, $p = 0.64$, *maximum median difference* < 0.01).

For individual participants, statistically significant differences were observed between sessions in the structure of variability for all participants ($p < 0.01$) but not in the magnitude of variability ($p > 0.22$). For brevity, the full hypothesis test results are not reported, but the maximum median difference in the structure of variability, 0.05, was smaller than the differences observed between participants.

Principal components analysis identified that between 1 and 3 principal components could explain 90% of the variance in the joint angle trajectories. The first principal component was most often associated with a shift in the joint angle trajectory, whilst successive principal components identified differences in the phasing of peak angles or differences in trajectory shape. Inspection of the principal component scores identified that the largest differences in score tended to be between participants, although there were cases where differences between session and club were also observable. The left wrist angle is presented as an example, with the explained variance and principal components shown in Figure 4.13 and principal component scores shown in Figure 4.14.

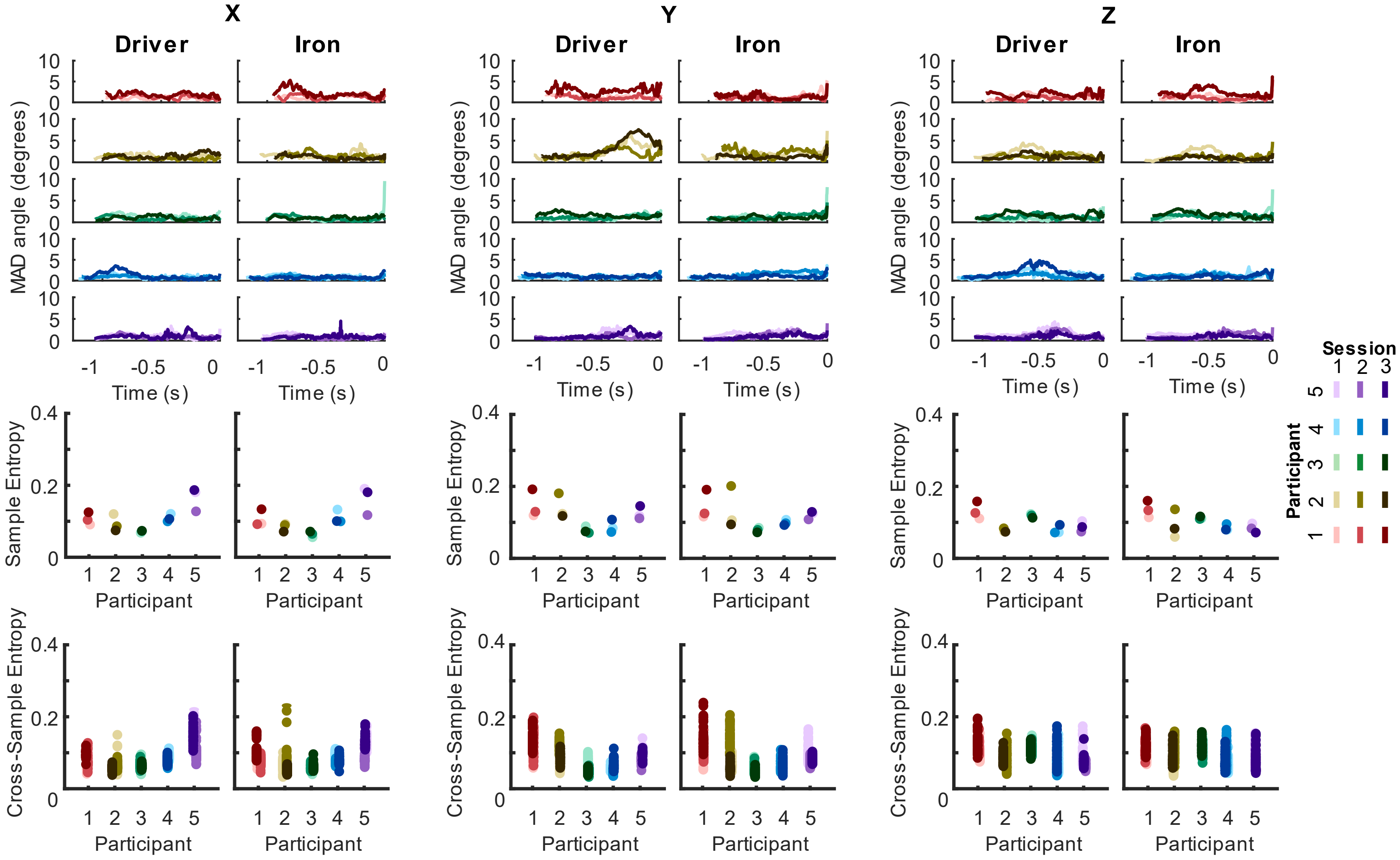


Figure 4.12. Median absolute deviation (MAD) trajectories, sample- and cross-sample entropy scores for each of the three components of the left wrist angle.

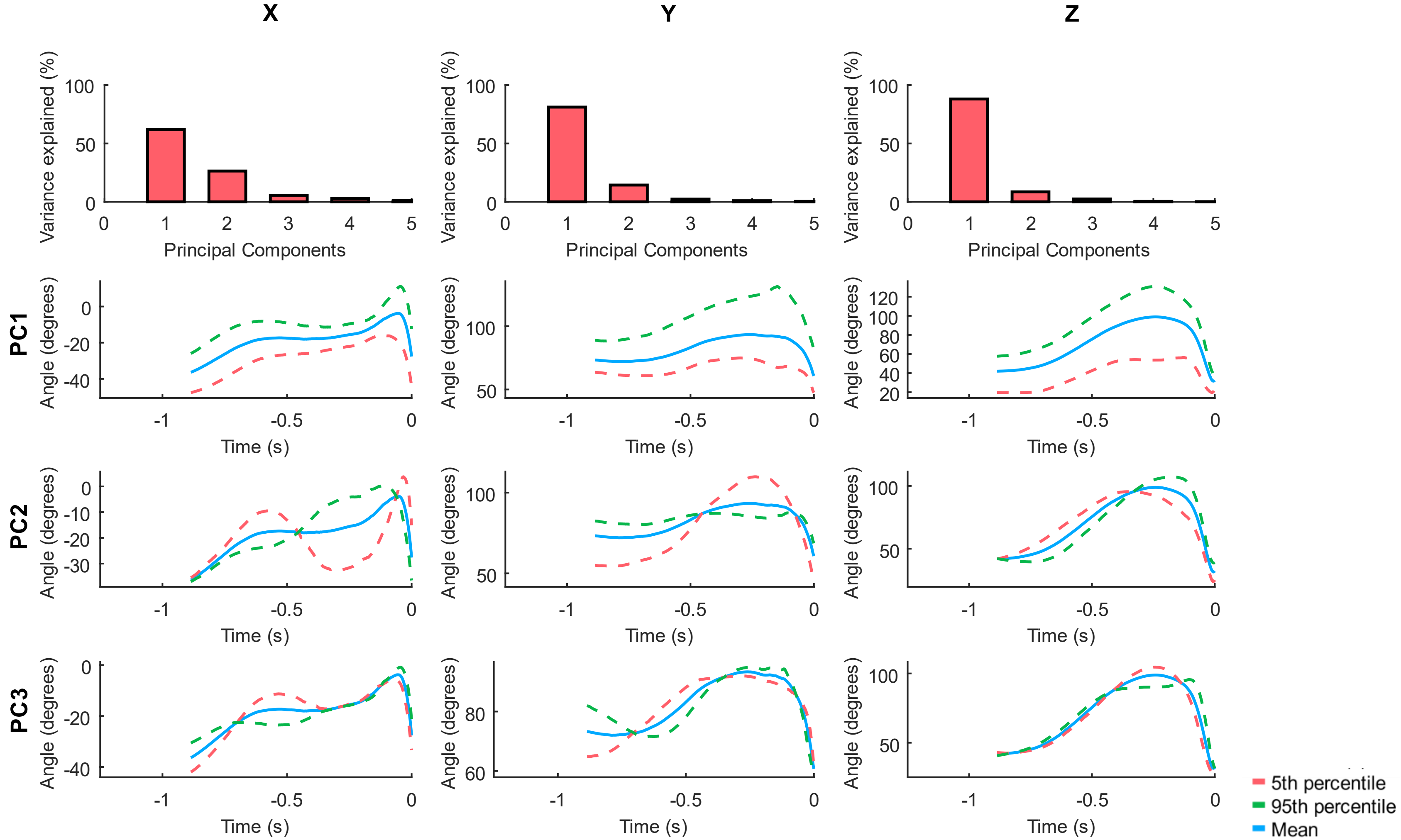


Figure 4.13. Bar of explained variance and a single component reconstruction of the first three principal components of the left wrist angle. Single component reconstruction shows the mean trajectory and the trajectories representing the 5th and 95th percentiles of the principal component scores.

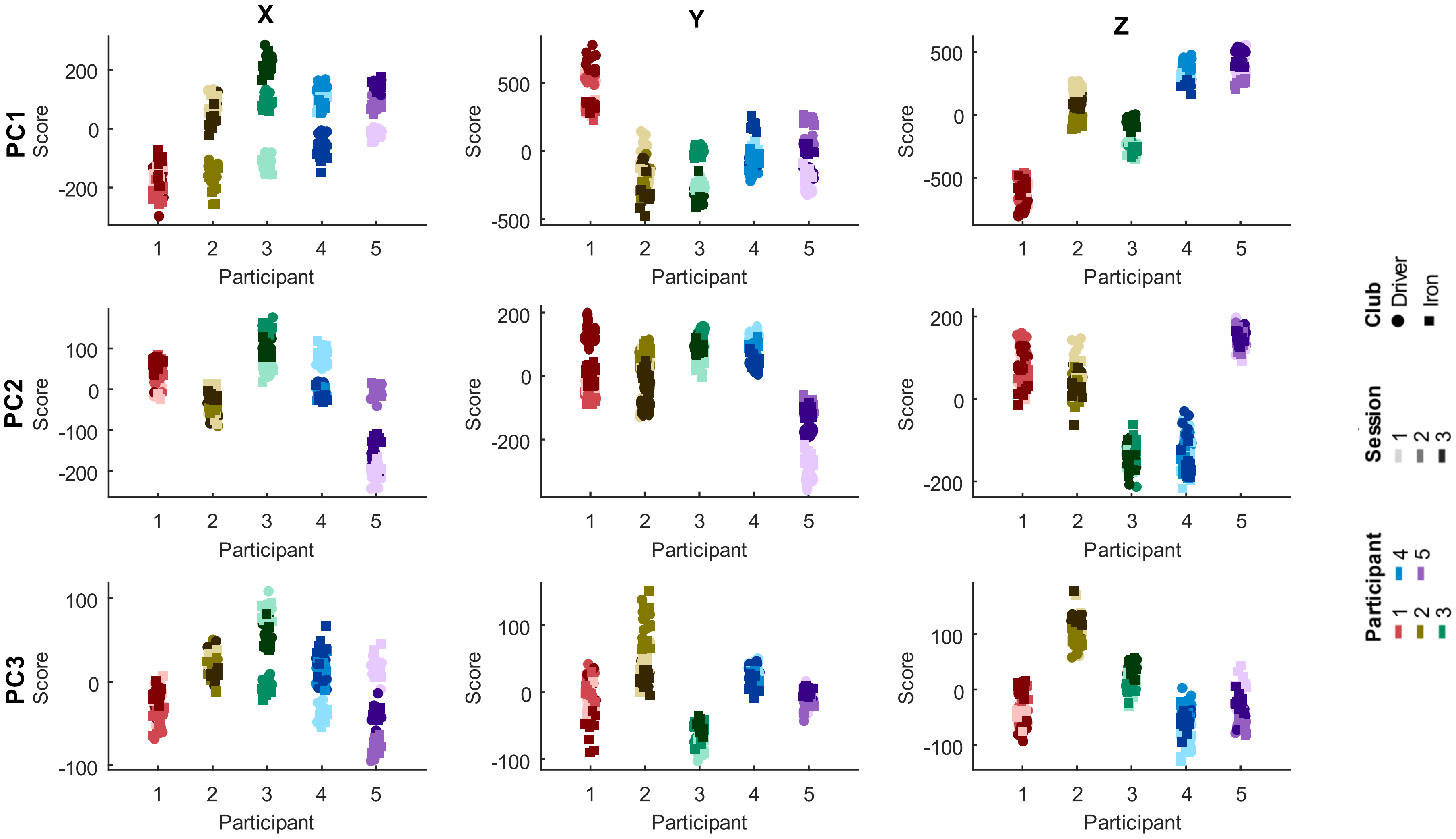


Figure 4.14. Principal component scores for the first three principal components of the left wrist angle. Differences in principal component scores represent differences in the trajectory of the left wrist angle.

D. Discussion

The magnitude and structure of variability in the kinematic variables studied showed differences in variability between the golfers, but no clear pattern in which these differences could be hypothesised to relate to skill level. For example, Participant 5 held the lowest handicap and Participant 2 achieved the best shot outcome during the investigation. However, there were no consistent similarities in the variability displayed by these participants or consistent differences between either of these golfers and the other participants. When compared to the rest of the group, differences in variability were often shared by one of the lower skilled participants. Furthermore, differences between the participants were often not consistent between the components of the joint angles studied. For instance, Participant 3 had a higher cross-sample entropy in the Z component of the left wrist angle, flexion-extension, but a lower cross-sample entropy in the Y component, abduction-adduction. It is possible that different facets of a movement are differently controlled, as hypothesised by the uncontrolled manifold hypothesis (Scholz and Schoner, 1999), but the small differences and the highly individual patterns seen in this investigation makes it difficult to form a strong hypothesis.

Literature suggests that skilled golfers have lower variability in clubhead trajectory and orientation (Morrison et al., 2016) and decreasing clubhead variability through the downswing (Horan et al., 2011). In this investigation, the motion capture volume was not large enough to accurately track the location of clubhead markers throughout the swing and the global club angle was instead measured using markers placed on the shaft. The X component of global club angle displayed a pattern in which the pointwise-median absolute deviation was highest during the first third of the golf swing before decreasing until impact, but the Y and Z components showed less consistent patterns between the individuals.

This investigation quantified the movement of the golfer using joint angles, an approach utilised by Zheng et al. (2008b) but in contrast to the approach based on segment positions utilised by Horan et al. (2011). Horan et al. (2011) found that the variability of the hand trajectory decreased through the downswing in a similar manner to the clubhead, but this pattern did not appear to manifest in the wrist angle. Indeed, no clear patterns were observed in any of the joint angles investigated. There are multiple possible explanations for this lack of pattern in the variability; for example, it could indicate that the position of segments is preferentially controlled rather than their relative orientations or that these patterns are not shared by all golfers. Since there is only a small amount of existing research on the kinematic variability in the golf swing and a small sample size in this investigation, it is not clear whether the observed lack of patterns of kinematic variability is representative of any wider population.

Whilst there were statistically significant differences in the magnitude and structure of variability in global club angle and in joint angles between the participants, sessions and clubs, all differences were relatively small. It is unclear whether these differences would be significant in a larger group of differently skilled golfers. Rather, it was hypothesised that these generally represented individual differences because inter-individual differences in swing pattern were clear throughout the investigation. These inter-individual differences were highlighted in the principal component analysis of joint angle trajectories.

4.4.3. Inter- and intra-session variability in address kinematics and temporal characteristics of five differently skilled golfers with driver and iron clubs

A. Introduction

In some coaching literature, the address position has been suggested as an important determinant of the success of the golf swing (Bradley, 2012; Faldo, 2012). It has been suggested that it is difficult to adjust for variability in address once the swing has begun. Were this the case, the most consistent golfers in shot outcome would also be the most consistent in their address position. Whilst an investigation gave some support to the notion that skilled golfers are more consistent in address position (Bradshaw et al., 2009), following research has not upheld this assertion (Langdown et al., 2013a). Furthermore, in the extant literature, variability in address position has only been investigated in relation to handicap, and the link to shot outcome remains unmade. The timing of the golf swing has also been suggested as a determinant of success in coaching literature (Bradley, 2012; Faldo, 2012) and the timing of movements was identified as an important technical parameter by professional golf coaches (Smith et al., 2012). There is some evidence that the timing of the golf swing is different for differently skilled golfers (Zheng et al., 2008b) but the intra-individual variability of swing timings has not been widely reported in the golfing literature. The aim of this section was to investigate the variability in address position and swing timing of the five golfers studied and will consider whether the golfers who are more consistent in outcome are also more consistent in address position and swing timing.

B. Methods

The takeaway event was defined as the first moment the velocity of the clubhead marker increased over a threshold of 0.3 $m \cdot s^{-1}$ away from the target and the address variables were calculated at the time of this event (Figure 4.15). The address variables of interest were:

- Stance width - the distance between the right and left head of the second metatarsal (2MT) markers (m).
- Stance width as % of shoulder width - Stance width expressed as a percentage of the distance between the right and left shoulder joint centre landmarks (%).
- Stance depth - the perpendicular distance between the ball and a line connecting the right and left 2MT markers (m).

- Ball position - The distance between the L2MT marker and a projection of the ball onto the line connecting right and left 2MT markers (m).
- Torso rotation angle - the rotation angle of the torso segment relative to the target line (°). This is the rotation about the Z axis of the global coordinate system.
- Pelvis rotation angle - the rotation angle of the pelvis segment relative to the target line (°).
- Feet-target line angle - the angle made between the line connecting the right and left 2MT markers and the target line (°).

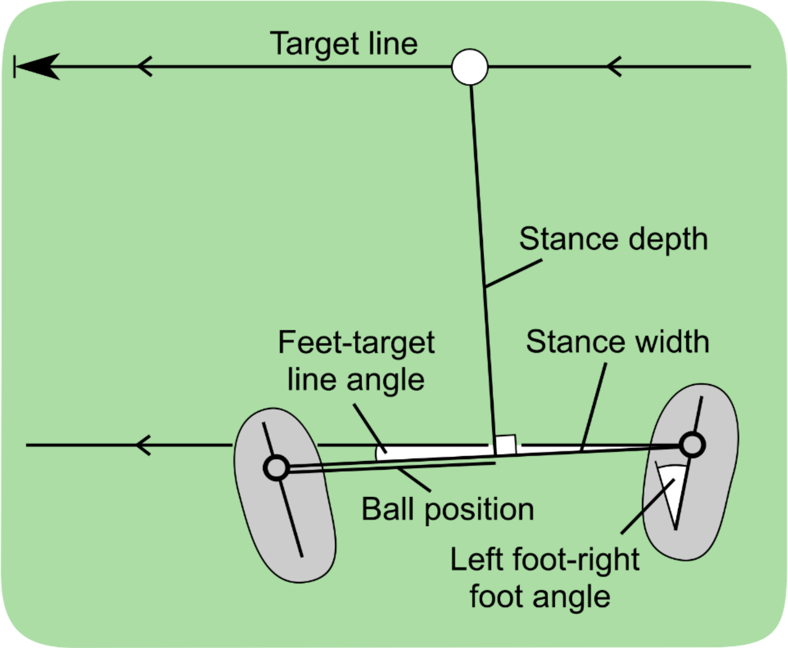


Figure 4.15. Address position variables.

The swing events defined by Ball and Best (2007) were calculated in Visual 3D from the global club kinematics (Figure 4.16). These were:

- Takeaway - the first moment the clubhead marker increases above a threshold velocity of 0.3 m $\cdot$s^{-1} away from the target.
- Mid-backswing - club shaft parallel to the XY plane in the global coordinate system.
- Late-backswing - club shaft parallel to the YZ plane in the global coordinate system.
- Top-backswing - the instant the club reverses direction at the top of the swing.
- Early-downswing - club shaft parallel to the YZ plane in the global coordinate system.

- Mid-downswing - club shaft parallel to the XY plane in the global coordinate system.
- Impact - the instant of club contact with the ball as measured using the audio trigger.

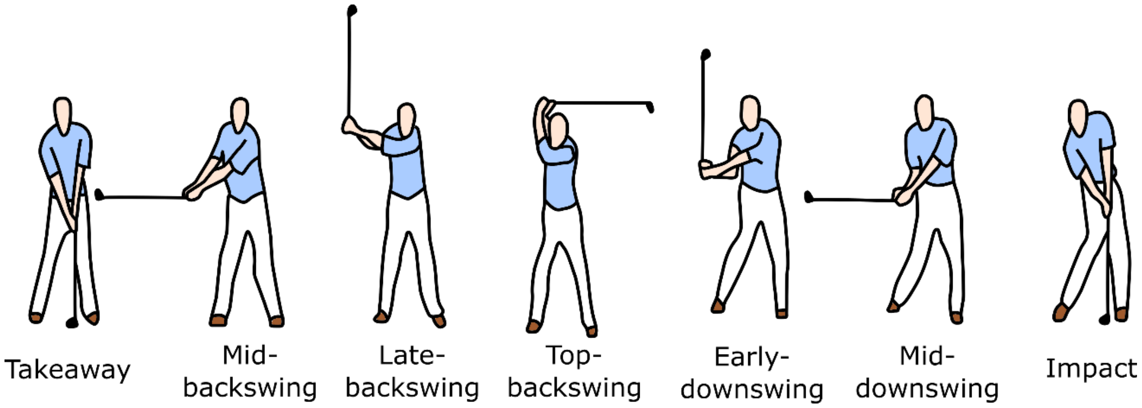


Figure 4.16. **Swing events used to define swing phases (adapted from Ball and Best, 2007a).**

The temporal characteristics of the swing were indicated the definition of swing phases. These swing phases were defined as the time between the following swing events (all measured in s):

- Backswing phase - the time between the takeaway and top-backswing events.
- Downswing phase - the time between the top-backswing and impact events.
- Early-backswing phase - the time between the takeaway and mid-backswing events.
- Mid-backswing phase - the time between the mid-backswing and late-backswing events.
- Late-backswing phase - the time between the late-backswing and top-backswing events.
- Early-downswing phase - the time between the top-backswing and early-downswing events.
- Mid-downswing phase - the time between the early-downswing and mid-downswing events.
- Late-downswing phase - the time between the mid-downswing and impact events.

In cases where the club did not reach the point of being parallel to the YZ plane in the global coordinate system, the late-backswing and early-downswing events and the time taken for the mid-backswing, late-backswing, early-downswing and mid-downswing phases were not calculated.

Data analysis, including descriptive statistics and statistical hypothesis testing, followed the same procedures as those reported in Section 4.4.1: the shot outcome, ball launch and clubhead presentation variables.

C. Results

Participants displayed individual patterns in address variables (Appendix C, Table C.4). For example, with the iron club, Participant 1 displayed a mean stance width of 0.45 m, stance depth of 0.64 m, ball position of 0.17 m and torso, pelvis and feet-target line angles of 3.7°, -5.0° and 2.7°. Conversely, Participant 3 showed a different pattern with an average stance width of 0.33 m, stance depth of 0.70 m, ball position of 0.12 m and torso, pelvis and feet-target line angles of 23.5°, -1.3° and -10.0°. These individual patterns were generally consistent between testing sessions for each participant, with the largest between-session differences being 0.04 m in stance width, 0.12 m in stance depth, 0.13 m in ball position and 12.1°, 6.7° and 6.4° for torso, pelvis and feet-target line angle at address.

A MANOVA test indicated no statistical differences in the variability of stance position for the driver (Stance position: $V = 1.05, F(12,30) = 1.34, p = 0.25$) and stance position or alignment for the iron (Stance position: $V = 1.12, F(12,30) = 1.49, p = 0.18$; Alignment: $V = 1.36, F(12,30) = 2.06, p = 0.053$). For both clubs, the largest mean difference in variability between the participants was 0.01 m, 0.01 m and 0.02 m for stance width, stance depth and ball position and 1.0°, 3.5° and 0.9° for torso, pelvis and feet-target line angle at address. Pillai's trace statistic indicated that the variability of alignment at address was different with the driver club ($V = 1.39, F(12,30) = 2.17, p = 0.046$). A follow up discriminant analysis indicated three discriminant functions which explained 94.8%, 4.0% and 1.2% of the variance (*canonical* $R^2 = 0.92, 0.34$ and 0.13 respectively). In combination, these functions significantly differentiated between the participants ($\Lambda = 0.04, \chi^2(12) = 31.2, p < 0.01$), but the second and third functions did not differentiate on removal of the first ($\Lambda = 0.57, \chi^2(6) = 5.6, p = 0.48$). The correlations indicated that the variability of pelvis angle at address loaded highest on the first function ($r = 0.47$), and neither the torso or feet alignment angle loaded highly on this function ($r = 0.14$ and -0.01 respectively). Function 1 discriminated between

Participant 2 and the other participants and, thus, Participant 2 had higher variability in pelvis rotation angle than the other participants. Participant 2's pelvis rotation angle variability was 3.2° greater than the participant with the next greatest variability with the driver and 1.6° greater than the next greatest with the iron club.

The median time for the backswing was between 0.70 and 0.94 s and between 0.20 and 0.31 s for the downswing for both clubs (Appendix C, Table C.5). MANOVA indicated no differences between backswing or downswing timing between the iron or driver clubs ($V = 0.14$, $F(2,27) = 2.18$, $p = 0.13$). The largest mean difference in timing between the clubs was 0.05 s for the backswing and 0.04 s for the downswing, both for Participant 1. However, there were differences in backswing-downswing timing variability between the golfers, shown by a significant result in MANOVA with the driver ($V = 1.21$, $F(8,20) = 3.80$, $p = 0.01$, *maximum median difference* $= 0.029$), and the iron ($V = 1.04$, $F(8,20) = 2.73$, $p = 0.03$, *maximum median difference* $= 0.024$). Follow-up discriminant analysis indicated two discriminant functions which explained 81.6% and 18.4% of the variance (*canonical* $R^2 = 0.77$ and 0.43 for the driver), and 91.4% and 8.6% of the variance (*canonical* $R^2 = 0.78$ and 0.26 for the iron club). In combination, these functions significantly differentiated between the participants (Driver: $\Lambda = 0.13$, $\chi^2(8) = 21.5$, $p = 0.01$; Iron: $\Lambda = 0.16$, $\chi^2(8) = 19.9$, $p = 0.01$). On removal of the first function, the second function did not significantly differentiate the participants (Driver: $\Lambda = 0.57$, $\chi^2(3) = 6.0$, $p = 0.11$; Iron: $\Lambda = 0.74$, $\chi^2(3) = 3.1$, $p = 0.37$). For both the driver and the iron club, the correlations indicated that the variability of backswing time loaded highly on the first function ($r = 0.91$ and 0.97 respectively), and the variability of downswing time loaded highly on the second function ($r = 0.97$ and 0.99 respectively). Neither backswing nor downswing loaded highly onto the opposite function with either club ($|r| < 0.41$). Inspection of the discriminant function plots showed that the first function differentiated the Participant 2 from the others with both the driver and iron clubs. Participant 3 was also differentiated from the others by the first function with the iron club, but not by as much as Participant 2. The second function differentiated Participant 1 from the others with the driver club. Thus, Participant 2 displayed higher variability in backswing time with both clubs, Participant 1 displayed higher variability in downswing time with the driver and Participant 3 displayed higher variability in backswing time, but not as high as Participant 2, with the iron club.

With the participants grouped, MANOVA indicated that there was no clear difference in the variability of stance position or torso, pelvis and feet-target line angles at address between the two different clubs ($V = 0.23$, $F(6,23) = 1.14$, $p = 0.37$). The maximum mean difference in the variability of stance width, stance depth, ball position, torso angle, pelvis angle and feet-target line angle between the two clubs was 0.00 m, 0.00 m, 0.01 m, 0.2°, 1.2° and 0.2° respectively. MANOVA also indicated no clear difference in the variability of backswing or downswing time between the two different clubs ($V = 0.14$, $F(2,27) = 2.18$, $p = 0.13$). The maximum mean difference in the variability between the two clubs was 0.01 s for both backswing and downswing time.

D. *Discussion*

In general, there was little support for differences in variability between the golfers in any of the address variables, and this agrees with previous literature examining address variability. Bradshaw et al. (2009) observed differences in the variability of stance width and trunk angle between groups of golfers while Langdown, Bridge and Li (2013a) observed differences in the alignment of the shoulders relative to the stance. However, as differences in stance position variability are small, and the total sample size across the studies was only 45, it is possible that differences may be observed in larger groups of golfers. In this study, Participant 2, the golfer with the highest task success according to the shot score variable, displayed greater variability in pelvis rotation at address than the other golfers. These markers were placed on a waistband and shift of the waistband during the session could explain this result, but both previous studies also showed differences in alignment variability at address. It may be that differences in alignment are more easily compensated for during the swing, whereas stance position must remain relatively fixed.

The golfers in this investigation showed individual specific patterns in address variables, like those observed in the clubhead presentation and ball launch variables. With the driver club, Participant 3 generally positioned the ball closer to the rear foot with the driver club compared to Participant 4 (median ball position 0.11 and 0.06 m respectively) and displayed a more positive attack angle (median attack angle 0.4 and 7.5° respectively). This relationship could be expected due to the curvature of the clubhead trajectory, but due to the small sample size the meaningfulness of the relationships between address and ball launch variables are not clear. However, the potential for further relationships between variables would be of interest to golf coaches.

There is little information about the intra-individual variability in swing timing for differently skilled golfers. Corke (2015) reported that swing timing variability was low in a group of highly skilled golfers and that backswing timing variability was higher than downswing timing variability. This investigation broadly agreed with this finding, backswing timing was generally more variable than downswing timing, but there were no clear patterns between the variability of swing timing and the handicap or task performance of the golfers. Inspection of the sub-phases of the swing suggests that the most variable phases are the early-backswing and early-downswing and that the least variable phases are the mid- and late-downswing. Thus, the phases with the most variability in timing tended to be the phases with the slowest club movements. However, the variability of the shortest phases might have been too small to accurately determine because the magnitude of the variability was similar to the time interval between frames.

4.4.4. Inter- and intra-session variability in ground reaction force and centre of pressure of three differently skilled golfers with driver and iron clubs

A. Introduction

Newton's first law states that to change the motion of an object or system, it must be acted on by an unbalanced external force. In golf, the largest external forces are those between the golfer and the ground, the ground reaction forces. Thus, there has been significant interest in the ground reaction forces of differently skilled golfers. No differences in the variability of ground reaction force have been reported in the literature (Barrentine et al., 1994; Koenig et al., 1993), although variability has generally been reported as an aside and not the focus of investigation. As such, there is no clear indication on how intra-individual variability changes through the swing, the structure of variability, or changes between sessions. The aim of this section was to describe the intra- and inter-session variability of ground reaction forces and centre of pressure in the five subjects studied.

B. Methods

Two force platforms were used to capture ground reaction force data, one under the left foot (FP1) and one under the right foot (FP2). The data from these two force platforms were combined using a force structure in Visual 3D to create a virtual single force platform (FS). This allowed the total (FS), left foot (FP1) and right foot (FP2) ground reaction force to be examined for each swing. For FP1, FP2 and FS, the three components of ground reaction force, in the medio-lateral, anterior-posterior and vertical directions (F_x, F_y and F_z), were calculated. Furthermore, the centre of pressure, in the medio-lateral and anterior-posterior directions (COP_x and COP_y) and the free moment around the vertical axis (T_z) were also calculated for the FS. The force platform coordinate system is shown in Figure 4.17. Where required, swing events, calculated from the global club kinematics, were used to define swing phases as described in Section 4.4.3.

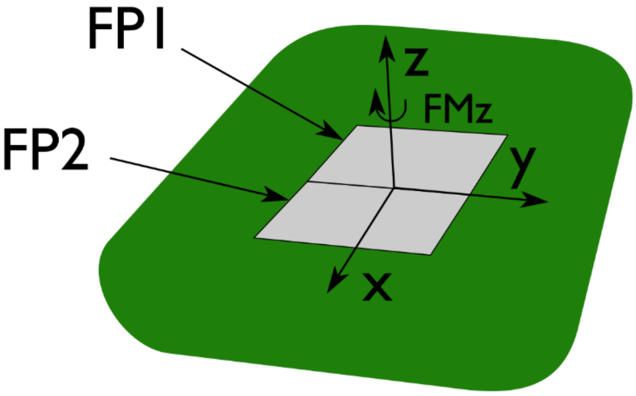


Figure 4.17. The coordinate system for force platform variables.

Due to a data collection error which resulted in unreliable ground reaction forces, ground reaction force data for Participants 1 and 2 was not analysed. Thus, results and data analysis in this section are only applicable to Participants 3, 4 and 5. Ground reaction forces were exported from Visual 3D and all further data processing was performed in MATLAB 2018a (R2018a, Mathworks, Cambridge, UK). Ground reaction force and free moment data were normalised to units of body weight by dividing the ground reaction force by the participant’s body weight in Newtons, obtained from the static trial. Centre of pressure data were normalised to the ball position by subtracting the ball position coordinates in the global coordinate system from the centre of pressure coordinates. All subsequent analysis, including descriptive statistics and statistical hypothesis testing, followed the same procedures as those reported in Section 4.4.2: the body and club kinematics. Sample- and cross-sample entropy parameters were chosen using the methods previously described. These were a vector length, *m*, of 3 and tolerance, *r*, of 0.005 bodyweights for ground reaction forces, 0.003 m for the centre of pressure and 0.0005 bodyweights·m for the free moment.

C. Results

Force pointwise-median absolute deviation trajectories, sample entropy and cross-sample entropy from the three components of GRF measured by the FS are displayed in Figure 4.18. Pointwise-median absolute deviation trajectories, sample entropy and cross-sample entropy of the centre of pressure and free moment, measured by the FS, are displayed in Figure 4.19. A MANOVA using Pillai's Trace statistic indicated no statistically significant differences in the median pointwise-median absolute deviation of the total, left foot or right foot ground reaction force, the centre of pressure or the free moment between the participants (*$V = 1.74$, $F(24,10) = 2.82$, $p = 0.05$, maximum median difference = 0.01 bodyweights, 0.04 m and 0.0006 bodyweights·m*). Grouping the participants, no statistically significant difference was indicated between the clubs used (*$V = 0.80$, $F(12,5) = 1.67$, $p = 0.30$*) and the maximum median differences for an individual across different sessions were of a similar magnitude as the differences between participants (*maximum median difference = 0.01 bodyweights, 0.03 m and 0.0003 bodyweights·m*). However, Pillai's trace indicated statistically significant differences in the cross-sample entropy between the participants (*$V = 1.69$, $F(24,1564) = 354.01$, $p < 0.01$, maximum median difference = 0.10*). The MANOVA was followed up with discriminant analysis which revealed two discriminant functions explaining 72.4% and 27.6% of the variance (*canonical $R^2 = 0.95$* and *0.89* respectively). In combination these functions significantly differentiated the participants (*$\Lambda = 0.02$, $\chi^2(24) = 3057.21$, $p < 0.01$*), and the second function also significantly differentiated the participants on removal of the first function (*$\Lambda = 0.22$, $\chi^2(11) = 1205.69$, $p < 0.01$*). The correlations between outcomes and discriminant functions showed that the cross-sample entropy of all force variables displayed a relatively high positive loading on the first discriminant function (*$0.21 < r < 0.79$*), except for the X and Y components of the centre of pressure (*$r = 0.07$* and *-0.03* respectively) and the Z component of FP1 ground reaction force (*$r = 0.11$*). The largest correlations were the Y component of FP1 ground reaction force (*$r = 0.79$*) and the X component of FS and FP2 ground reaction force (*$r = 0.53$* and *0.53* respectively). The X and Y components of FP1 ground reaction force (*$r = -0.43$* and *0.34* respectively) and the X, Y and Z components of FS ground reaction force (*$r = -0.32$, -0.27* and *0.47*) loaded moderately onto the second discriminant function. The discriminant function plot indicated that the first function differentiated Participant 5 from the other two participants and the second function differentiated all three participants from each other. Inspecting the plot and the correlations indicated that Participant 5 displayed generally higher cross-sample entropy than both other participants in all variables except for the centre of pressure and the Z component of FP1 ground reaction force. Participant 3 displayed higher cross-sample entropy than Participant 4 in the Y component of FP1 ground reaction force and the Z component of FS ground reaction force. Participant 4 displayed higher cross-sample entropy than Participant 3 in the X component of FS ground reaction force and the X component of FP1 ground reaction force. Otherwise, the cross-sample entropy values were similar between these two participants.

Each participant displayed differences in their cross-sample entropy for the different sessions and clubs which were statistically significant (Participant 3, Session: $V = 0.56, F(24,484) = 7.92, p < 0.01$; Participant 4, Session: $V = 0.43, F(24,514) = 5.87, p < 0.01$; Participant 5, Session: $V = 0.46, F(24,514) = 6.34, p < 0.01$; Participant 3, Club: $V = 0.50, F(12,242) = 20.49, p < 0.01$; Participant 4, Club: $V = 0.25, F(12,257) = 7.15, p < 0.01$; Participant 5, Club: $V = 0.68, F(12,257) = 45.82, p < 0.01$), but the maximum median difference between session (0.02) or club (0.02) were relatively small compared to the differences between individuals.

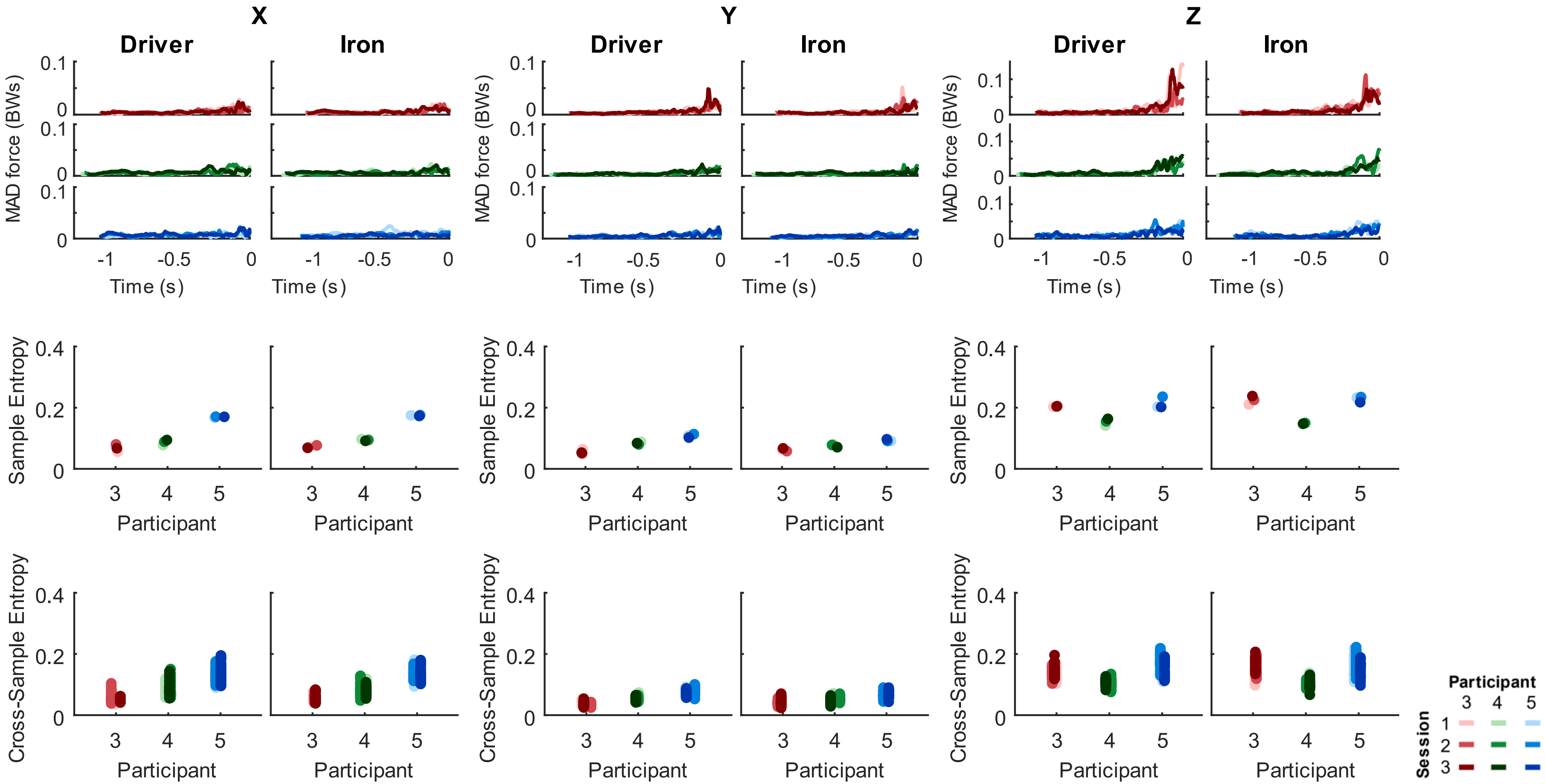


Figure 4.18. Ground reaction force median absolute deviation (MAD) trajectories and sample- and cross-sample entropy scores for each of the three components of ground reaction force measured by the force structure.

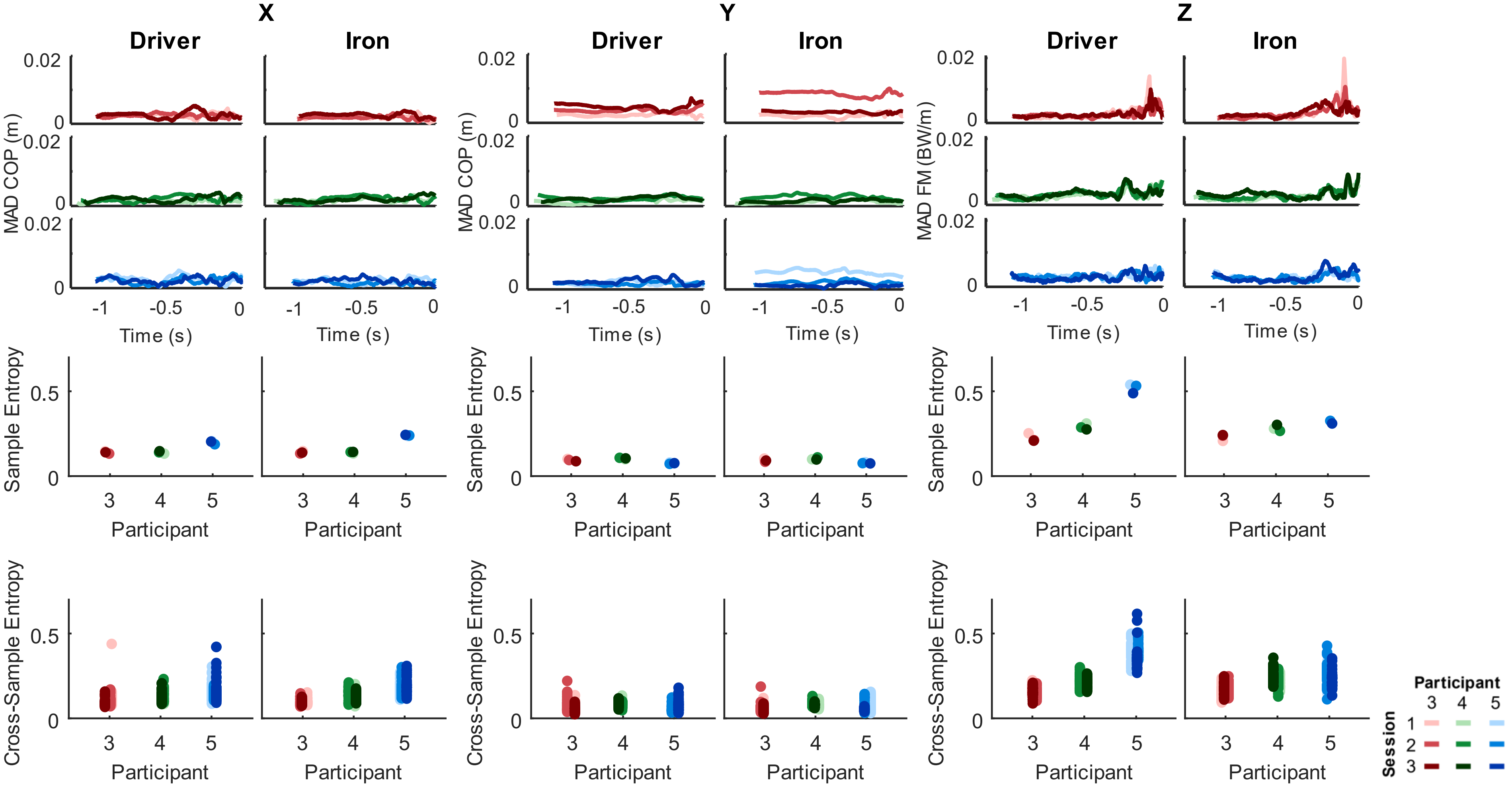


Figure 4.19. Centre of pressure and free moment median absolute deviation (MAD) trajectories and sample- and cross-sample entropy scores.

A maximum of three principal components were required to explain 90% of the variance for all the variables except for the Z component of FP2 ground reaction force, which required four components. A MANOVA test on the principal component scores for the components which explained 90% of the variance found statistically significant differences in the ground reaction force, the centre of pressure and the free moment between the three golfers ($V = 1.99$, $F(64,294) = 888.05$, $p < 0.01$). Follow-up discriminant analysis indicated that there were two discriminant functions which explained 65.4% and 34.6% of the variance in the data (*canonical* $R^2 > 0.99$ and 0.99 respectively). In combination, these functions significantly differentiated the three participants ($\Lambda < 0.01$, $\chi^2(64) = 1717.97$, $p < 0.01$) and the second function also significantly differentiated the three participants on removal of the first function ($\Lambda = 0.01$, $\chi^2(31) = 807.85$, $p < 0.01$). The first principal component of the Y component of FP1 ground reaction force, the X component of FP2 ground reaction force and the Y component of FS ground reaction force loaded moderately onto function 1 ($r = 0.28$, -0.28 and 0.26 respectively). The first principal component of the Z component of FP1 ground reaction force and the Y component of FP2 ground reaction force and the second principal component of the X component of FS ground reaction force and the Y component of FP1 ground reaction force loaded moderately onto function 2 ($r = 0.36$, 0.34, -0.32 and -0.32 respectively). This showed that function 1 differentiated between Participant 3 and the others, and function 2 differentiated between all participants, the functions had values of 23.2, -14.4, -8.8 and 2.4, 13.4, -15.8 for the three participants and the two functions respectively.

Line plots showing the features described by the principal components and the principal component scores highlighted as different between the golfers are shown in Figure 4.20. The features of the ground reaction force which differentiated between the participants were as follows: Participant 3 displayed higher left foot anterior-posterior force which peaked earlier in the swing than the other two participants. Participant 4 displayed higher left foot vertical force which peaked later in the swing than Participants 3 and then 5 respectively. Compared to Participant 3, Participants 4 and 5 displayed greater right foot medio-lateral force toward the target in the first two-thirds of the swing and a greater peak right foot medio-lateral force away from the target immediately prior to impact. Participant 5 displayed lower right foot anterior-posterior force in the second half of the swing and their overall anterior-posterior force remained closest to zero throughout the swing. In the second half of the golf swing, Participant 4's overall anterior posterior force was first directed in anteriorly and then reversed direction before impact whilst Participant 3 displayed the opposite pattern. Compared to the mean, Participant 5 displayed a generally higher left foot anterior-posterior force throughout the swing whilst Participant 4 displayed generally lower force. Finally, Participant 5 displayed an overall medio-lateral force which was closer to zero at around 0.2 s before impact, compared to Participant 3 and Participant 4 who created greater medio-lateral force toward the target around this time.

Similar to the differences in cross-sample entropy, each participant displayed statistically significant differences in principal component scores between sessions and clubs (Participant 3, Session: $V = 1.92, F(64,54) = 19.49, p < 0.01$; Participant 4, Session: $V = 1.86, F(64,54) = 11.35, p < 0.01$; Participant 5, Session: $V = 1.76, F(64,54) = 6.22, p < 0.01$; Participant 3, Club: $V = 0.97, F(32,27) = 23.01, p < 0.01$; Participant 4, Club: $V = 0.99, F(32,27) = 122.00, p < 0.01$; Participant 5, Club: $V = 0.99, F(32,27) = 238.43, p < 0.01$), but the size of the differences between session or club were small compared to the differences between individuals.

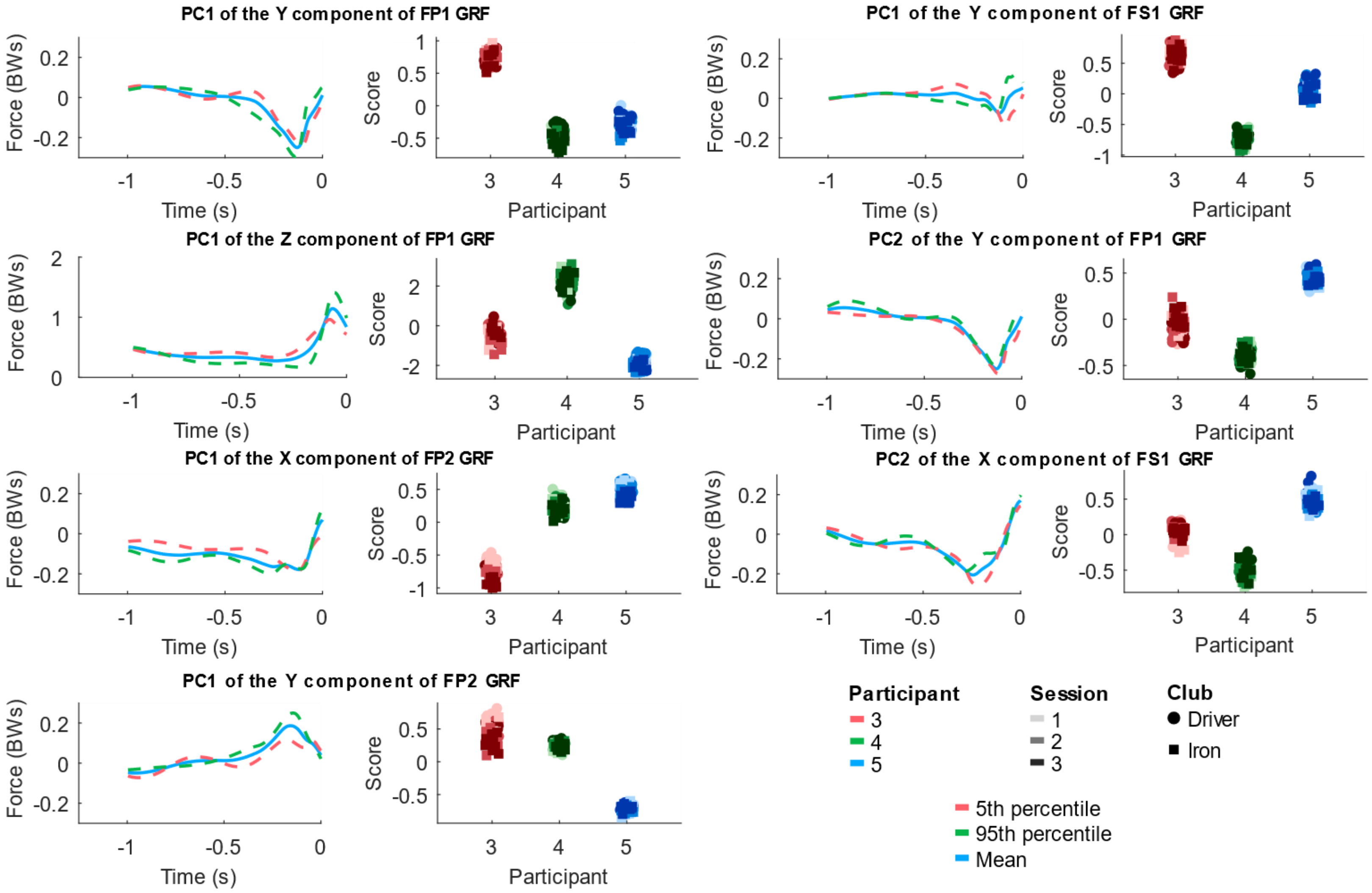


Figure 4.20. Single component reconstruction and principal component scores of principal components highlighted as loading moderately in the discriminant analysis.

D. Discussion

All three golfers displayed similar patterns where the pointwise-median absolute deviation of ground reaction force was uniformly low throughout the backswing before increasing slightly in the downswing. This finding differs from results of previous investigations which have generally shown patterns of decreasing variability, such as in the hand (Horan et al., 2011) or clubhead trajectory (Morrison et al., 2016). Whilst it is not appropriate to speculate on the meaningfulness of this effect in three participants, the increase in ground reaction force variability could be indicative of compensatory variability occurring in other body segments and is worthy of further investigation in a larger group of golfers.

Whilst there was no difference between the three golfers in the magnitude of variability, indicated by the median absolute deviation, there was a difference in the structure of the variability, indicated by the sample and cross-sample entropy. In nine out of the eleven force variables studied, Participant 5 displayed higher cross-sample entropy than the other two participants. That is, the highest skilled golfer was varying their ground reaction force in a less regular manner, which could indicate the participant was utilising more degrees of freedom to enable a greater outcome consistency. That the structure of ground reaction force variability was able to differentiate the highest skilled golfer from the two similarly skilled golfers is worthy of further investigation in a larger group of golfers.

Despite statistical significance, the differences between the golfers in the magnitude and structure of variability between the different sessions and clubs were small, and it is possible that these differences would not present in a larger group of golfers and instead reflect individual coordination patterns. Indeed, the principal components analysis highlights the presence of inter-individual differences in the ground reaction force, the centre of pressure and the free moment between the golfers. It could also be noted that the golfers were relatively consistent in producing their signature ground reaction force; an observation also made by Barrantine et al. (1994).

4.5. Summary and discussion of multiple single-subject investigation into inter- and intra-session movement variability in the golf swing

4.5.1. Section objectives

This section presents a summary and general discussion of the results from the preceding sub-sections of the investigation. Results will be considered jointly with the goal of identifying the future research direction.

4.5.2. Discussion

The primary purpose of this investigation was to characterise the movement and shot outcome variability of a small number of amateur golfers to generate hypotheses for subsequent investigations with a larger cohort of golfers. Thus, the information generated by the investigation should be evaluated based on its ability to meet these aims, rather than its ability to generate generalisable information. The investigation enabled areas for further investigation to be examined in depth and allowed insight into the practicalities surrounding specific areas of the data collection, along with highlighting interesting individual patterns in the golfer's movements. Whilst this investigation presented the results of statistical hypothesis tests, the results of these tests should be interpreted with caution because the false-positive error rate could be influenced by the small sample size and exploratory nature of the investigation. Along with effect sizes, the results of the statistical hypothesis tests have been included for completeness but, instead of focusing on statistically significant results, the entirety of the information gathered in this investigation was used to inform the future research direction.

The variability of clubhead presentation, ball launch and shot outcome measures has been examined in golfers of different ability with both driver (Betzler et al., 2012) and iron clubs (Corke, 2015), but previous research has not examined the variability of both driver and iron clubs in the same cohort. As different club designs are used over a round of golf, performance with multiple club designs is of great interest to sports biomechanics. The differences in clubhead presentation, ball launch and shot outcome variability between the participants in this investigation did not clearly show the decreased variability which has been associated with higher skill in previous investigations. This may reflect inter-individual variability in the overall population, masking overall patterns in a small sample. Inter-individual differences between the golfers and individual specific patterns were clear in many of the variables examined in this investigation. For example, each of the golfers displayed a distinct pattern in the ground reaction force trajectory, with intra-individual variability occurring around this average pattern. These inter-individual differences indicate unique movement solutions were adopted by the golfers and could reflect the unique constraints experienced by the golfers. However, these inter-individual differences could obfuscate differences between the golfers which are associated with the skill of the golfers; a larger sample size is required to elucidate whether differences observed are related to skill.

The results of this investigation give an indication, not only of the areas of research which might be most interesting for future research, but of the practicality of the data collection methods for this research. For example, while differences were observed between the three testing sessions, variability was generally similar from session to session. Inter-session variability is an area which deserves further research, but the addition of extra testing sessions makes participation significantly more onerous on the participant. Likewise, the measurement of full body kinematics increases the time required for a testing session, and these factors will likely reduce the number of participants that can be recruited in a given time. The analysis of kinematic variability did not show clear patterns, but ground reaction force showed interesting differences in the structure of variability and a pattern of increasing variability during the downswing. Ground reaction force could also be thought of as a proxy measure of whole-body kinematics. Therefore, future research will replicate this investigation in a larger cohort but will utilise a single session design and a reduced marker set to maximise the number of participants.

4.5.3. Chapter summary

This chapter presented data from a multiple single-subject investigation of five amateur golfers with a range of skill levels. A comprehensive analysis of shot outcome, full body kinematics and kinetics was presented, and a task-specific measure of skill based on shot outcome developed. This measure of task performance suggested a different skill ordering to the handicap of the golfers, and a different skill ordering with the two clubs used. As it measured task performance, it may be a more appropriate measure of skill than handicap for golfing investigations, but it is specific to the task outlined to the golfers. There were many differences between the golfers studied but, due to the small sample size, it was difficult to discern which of these differences might be related to the skill of the golfer, rather than other non-skill related constraints. The investigation focused on these individual differences, rather than attempting to generalise to a larger cohort, and the information gathered in this investigation informed the cross-sectional investigation examining the variability of amateur golfers which follows in Chapter 5. Table 4.3 shows the variables studied in this chapter and indicates whether they will be the subject of further investigation in Chapter 5.

Table 4.3 Variables studied in multiple single subject and cohort investigations.

Category	Variables	Multiple single subject investigation	Cohort investigation
Shot outcome	Carry length, carry side, total length, total side, shot angle, shot score	✓	✓
Ball launch	Ball speed, efficiency, launch angle, launch direction, spin rate, spin axis	✓	✓
Clubhead presentation	Clubhead speed, attack angle, path angle, face angle, effective loft, effective lie, impact location	✓	✓
Address	Stance width, stance depth, ball position, feet to target line angle	✓	✓
Address	Pelvis and torso rotation angle, stance width as a percentage of shoulder width	✓	✗
Address	Left foot to right foot angle	✗	✓
Swing timing	Backswing and downswing timing	✓	✓
Swing timing	Timing of intermediate swing phases	✓	✗
Kinematics	Full body kinematics	✓	✗
Kinematics	Global club kinematics	✓	✓
Kinetics	Left foot, right foot and total ground reaction force. Centre of pressure and free moment	✓	✓

5. Cross-sectional investigation of the intra-individual variability of a large group of differently skilled golfers

5.1. Chapter objectives

This chapter presents a cross-sectional investigation examining the intra-session variability in a large group of amateur golfers. The investigation was planned based on the results and conclusions of the multiple single subject investigation and the aim of this investigation was to examine generalisable patterns of intra-individual variability in the group of golfers.

5.2. Introduction

The multiple single-subject investigation presented in Chapter 4 provided a detailed examination of the inter- and intra-session variability of a small number of amateur golfers, however, such investigations are not generalisable. Instead, a larger sample size is required to characterise patterns of inter-individual variables which are shared between golfers, and potentially identify relationships to performance or skill. To answer the research questions defined in this thesis, it is necessary to elucidate effects which are generally shared by golfers or that differ between golfers with different characteristics, rather than focus only on individual specific differences. This investigation will use similar experimental procedures to the multiple single-subject investigation but will recruit a much larger group of golfers, use a reduced marker-set and a single testing session. This should enable the investigation to present data which addresses the research question, avoids limitations highlighted in the existing literature and provides high quality evidence as to the presence, or absence, of an effect. The aim of the investigation was to jointly examine the movement and outcome variability of a large, mixed-ability, group of golfers.

5.3. General methods for a cross-sectional investigation of the intra-individual variability in a large group of differently skilled golfers

5.3.1. Section objectives

This section will present an overview of the general data collection methods used in the cross-sectional investigation; the procedures, definitions and processes which remain constant and relevant throughout the investigation. Specific methods, results and discussions for each sub-section of the investigation will be presented in individual sub-chapters to maintain readability.

5.3.2. Participants

One-hundred and four amateur golfers (26 females, 78 males) volunteered to participate in the investigation (Table 5.1, Figure 5.1). To participate in the investigation, participants had to 18 or older, healthy, uninjured, free from musculoskeletal or neurological disorders and participating in regular golfing activity. This was assessed by health history questionnaire and the holding of a current handicap. Participants provided written informed consent and all procedures complied with the ethical approval granted by the University's institutional review board prior to the commencement of the investigation.

Table 5.1. Participant information (mean ± standard deviation).

	Female	Male
Age (Years)	55.2 ± 12.6	50.6 ± 15.0
Height (m)	1.68 ± 0.06	1.81 ± 0.07
Mass (kg)	69.8 ± 10.6	92.2 ± 13.4
Handicap	17.0 ± 7.2	9.5 ± 7.1

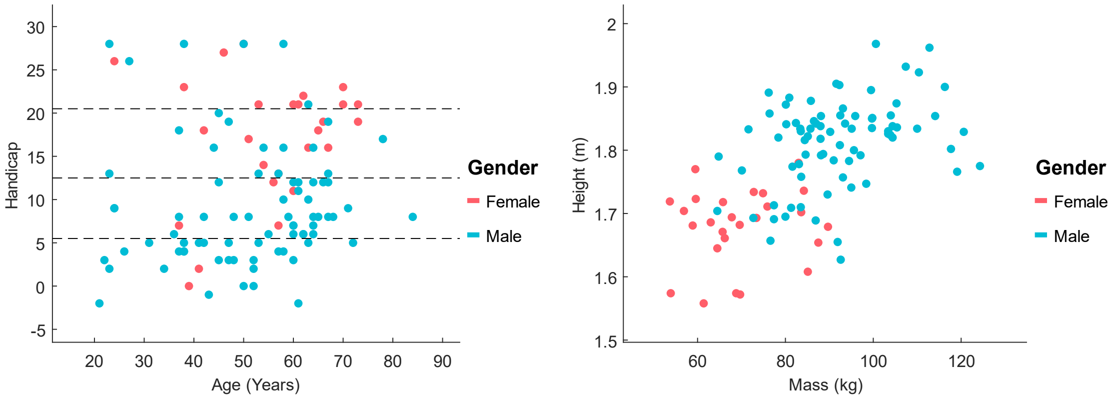


Figure 5.1. Participant information.

The participants covered the range of golfing abilities defined by the CONGU handicapping system (CONGU, 2018). For this investigation, the categories utilised were as follows: Category 1 (handicaps of less than 5.5), Category 2 (handicaps of 5.5-12.4), Category 3 (handicaps of 12.5-20.4) and Category 4 (handicaps of greater than 20.5). Betzler et al. (2012) sampled a large mixed-gender group of amateur golfers and provided a convenient comparison for the characteristics of the population sampled in this investigation (Figure 5.2). Compared with the Scottish Golf data presented by Betzler et al. (2012), this investigation tested proportionally more male Category 1 and

Category 2 golfers and female Category 1 golfers and proportionally fewer male Category 4 golfers and female Category 3 and Category 4 golfers. Compared with the Sport England data presented by Betzler et al. (2012), this investigation tested proportionally more male golfers between the ages of 55-64 and female golfers over the age of 35 and proportionally fewer male golfers between the ages of 25-34. Both biases were generally similar to those reported by Betzler et al. (2012), except for the greater proportion of female golfers sampled in this investigation.

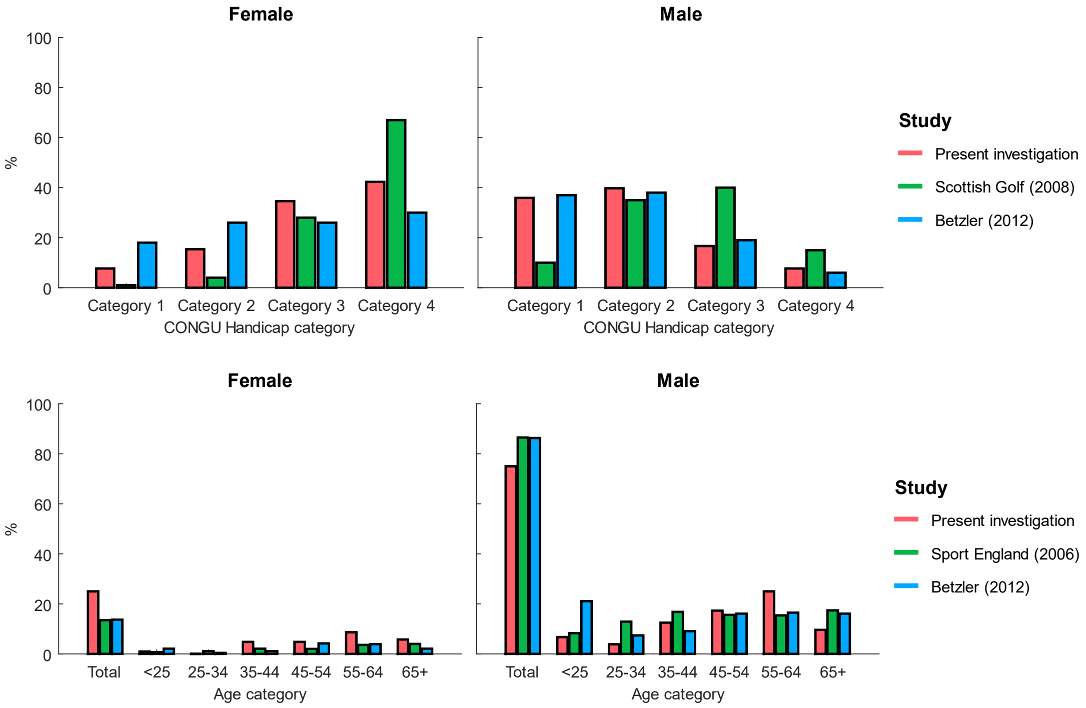


Figure 5.2. Comparison of population data to the overall golfing population and previous comparable research.

5.3.3. Procedures

The participants attended a single testing session at The R&A's equipment test centre in Kingsbarns. Participants utilised their own golf shoes but used standardised iron and driver clubs (Table 5.2). The total mass of markers added to the clubs was ~2 g. Participants were given an opportunity to conduct a self-directed warm up before completing ten shots with the driver and ten shots with the 5-iron club. Shots were self-paced and split into two sets of five in the order: driver, 5-iron, driver, 5-iron. Participants selected a preferred tee length for the testing but, once a tee length had been selected, participants were instructed to use the same tee length for each club throughout the testing. It was permitted to hit the iron shots off the artificial turf. Shots were directed through a 7.0 x 3.0 m doorway toward a target situated approximately 230 m (250 yards) away on a flat driving range. Participants were instructed to hit a straight shot toward the target as if they were playing onto a regular width fairway; no further instruction was given. Participants were asked to provide a subjective rating of each shot on a scale of zero to five, with five representing a good shot for them as an individual. Shots which were not captured by the measuring equipment were discarded and repeated. Due to extra shots being collected and some shots being discarded, the number of valid shots with the driver was between 8 and 14 (mean = 11.5, standard deviation = 0.9) and with the iron was between 6 and 18 (mean = 11.5, standard deviation = 1.4). In total, 1201 driver shots and 1196 iron shots were recorded (Figure 5.3).

Table 5.2. Characteristics of standardised driver and iron clubs used.

	Driver					5-iron			
	A	B	C	D	E	A	B	C	D
Club loft (°)	10.5	10.5	10.5	10.5	10.5	24.5	24.5	24.5	24.5
Club length (m)	1.14	1.14	1.14	1.14	1.10	0.95	0.95	0.95	0.93
Club mass (kg)	323.0	319.8	321.0	327.6	329.0	427.8	430.2	424.0	433.2
Swingweight (Lorythmic)	D1	D1	D1	D1	C9	D1	D1	D1	C9
Shaft stiffness	Extra-stiff	Stiff	Regular	Ladies	Ladies	Extra-stiff	Stiff	Regular	Regular

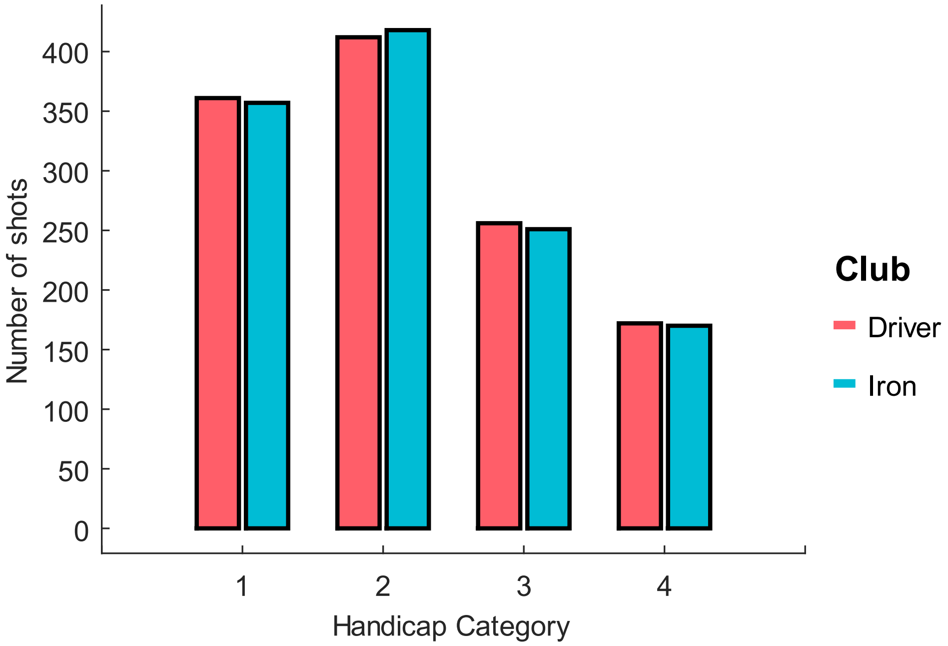


Figure 5.3. Number of shots collected for each CONGU handicap category.

An eleven-camera motion capture system and Qualisys Track Manager (QTM) software (Oqus 300+, Qualisys AB, Gothenburg, Sweden) was used to capture the kinematics of the swing. This system had a capture frequency of 240Hz and a capture volume of approximately 4.0 m x 3.5 m x 2.5 m. The system was linked to two force platforms (OR6-6-2000, AMTI, Watertown, MA) which measured ground reaction force and centre of pressure at a frequency of 1200Hz and were embedded underneath the artificial hitting surface. The motion capture frequency was lower than in multiple single subject investigation to use settings which increased performance in sunny conditions; the force platform capture frequency was then set as a multiple, five, of the motion capture frequency. A separate three camera motion capture system (Oqus 300+, Qualisys AB, Gothenburg, Sweden), with a capture frequency of 1000Hz and a capture volume of approximately 1.2 m x 0.9 m x 1.0 m, was used with user-written algorithms to capture clubhead presentation at impact (Betzler et al., 2012; Corke et al., 2018). All systems were jointly triggered using an acoustic trigger at impact. The eleven-camera motion capture system recorded two seconds of data from before and after the trigger and the three-camera motion capture system recorded 0.12 s of data before and after the trigger. A commercially available Doppler radar-based launch monitor measured launch variables and shot outcomes for each shot. The global coordinate system, used by both motion capture systems, was defined with its origin at the anterior intersection of the force platforms with the X-axis pointing left-right, the Y-axis pointing posterior-anterior and the Z-axis vertical for the golfer at address (Figure 5.4).

A partial marker set, covering the head and the feet, was used for the testing. The marker set used eleven spherical retroreflective markers with a diameter of 12mm (Appendix D, Table D.1), which were applied to the participant using hypoallergenic double-sided tape and a hat (Figure 5.5). The standardised iron and driver clubs were fitted with six or seven retroreflective markers respectively (Figure 5.5). Three of these markers were tracked using the body motion capture system (Appendix D, Table D.1), whilst the other markers were tracked using the clubhead tracking system and used to calculate clubhead presentation variables (Betzler et al., 2012; Corke et al., 2018). Self-directed warm up and familiarisation were conducted after the markers had been applied. Immediately prior to the commencement of the testing a static calibration pose trial was collected. In this trial the participant stood in a neutral position with one foot on each force platform and held the club vertically by the grip.

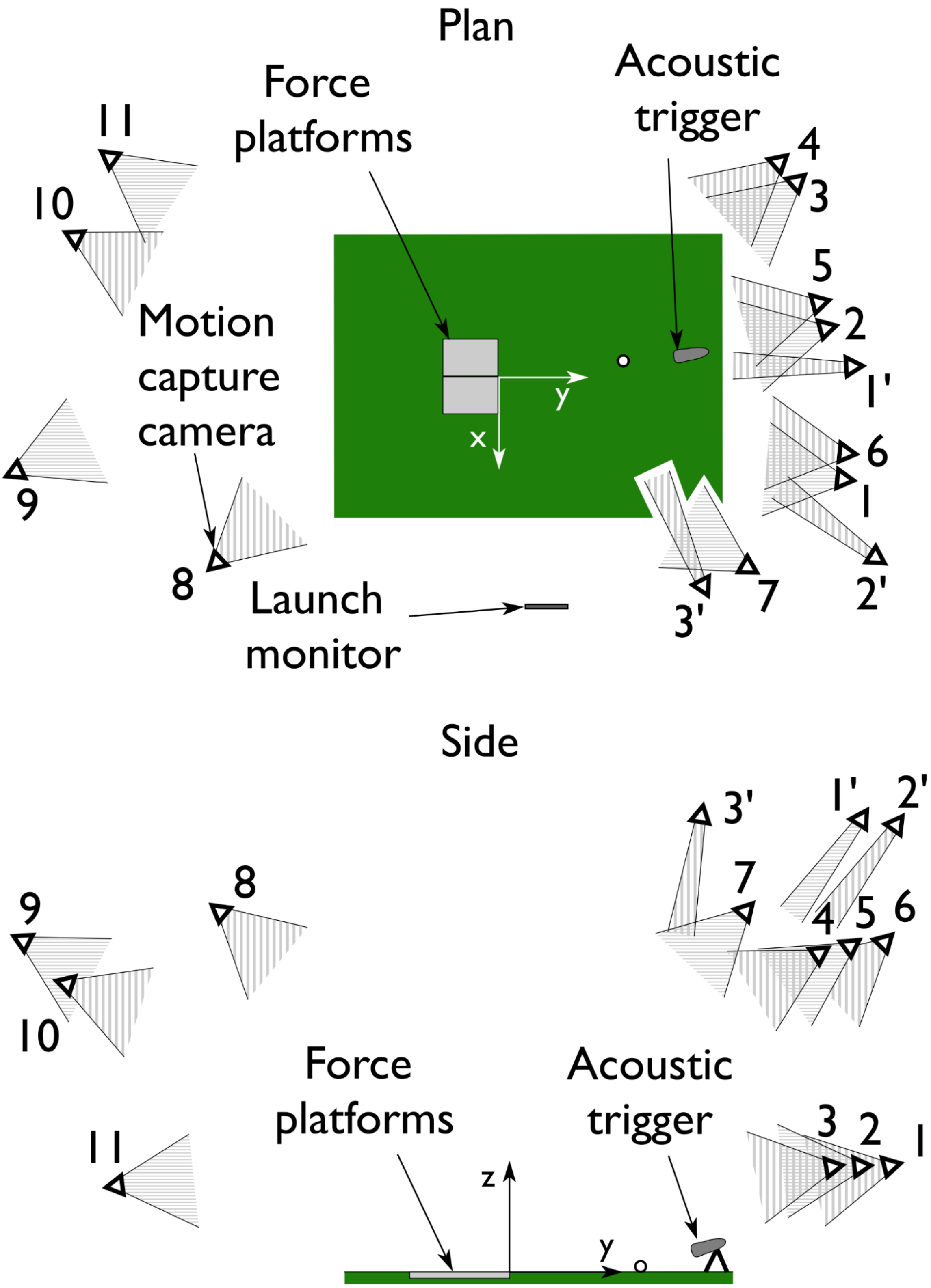


Figure 5.4. The positioning of motion capture cameras, the global coordinate system (XYZ), force platforms and launch monitor in the indoor hitting bay.

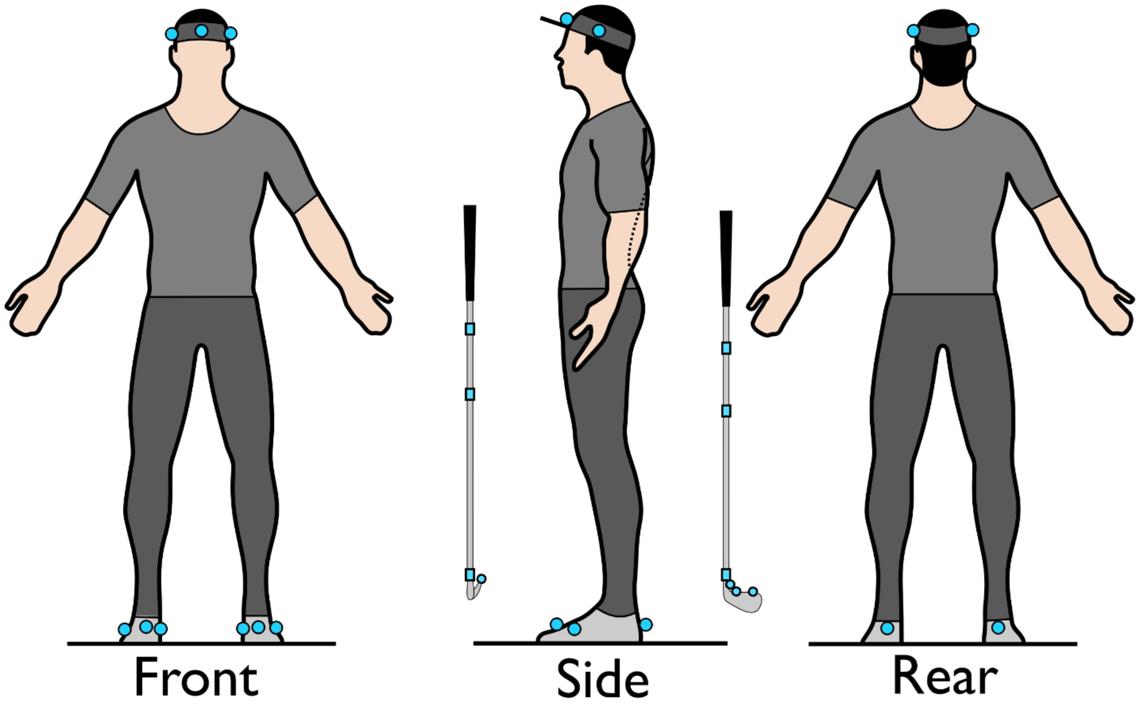


Figure 5.5. Positioning of retroreflective markers on participant.

5.3.4. Data processing and analysis

The marker data from each trial was labelled using Qualisys Track Manager (Qualisys AB, Gothenburg, Sweden). Gaps in marker trajectory were manually inspected and, where the fit was deemed to be an appropriate approximation by the researcher, gaps were filled with inbuilt polynomial, linear or relational filling methods. Marker coordinate data and force platform data was exported to C3D file for processing in Visual 3D (C-Motion Inc., Germantown, MD). For each individual, a rigid body kinematic model was defined and applied to the static trial (Appendix D, Table D.2 and Table D.3). After creation, the kinematic model was applied to each swing trial and joint kinematics were calculated using Cardan rotation sequences according to International Society of Biomechanics recommendations (Wu et al., 2002, 2005). Global club kinematics were calculated using a YXZ Cardan rotation sequence and then used to define eight key events during each swing. These events were defined based on those proposed by Ball and Best (2007). Clubhead presentation and launch monitor data were exported from their respective software and collated with the participant's subjective scores in Microsoft Excel (Microsoft, Redmond, WA). This data was exported to CSV file. ASCII and CSV files were loaded into MATLAB (R2018a, Mathworks, Natick, MA) for further analysis.

Participants were generally grouped by their handicap category for analysis. Descriptive statistics included multiple measures of both the magnitude and structure of variability. Median-based statistics were generally preferred over mean-based statistics, due to their robustness to outliers in a dataset (Betzler et al., 2012). Where statistical hypothesis testing was utilised, the mean or median difference has been calculated to provide an unstandardised measure of the effect size.

5.4. Constituent investigations of the cross-sectional investigation into the intra-individual variability in the golf swing

5.4.1. Intra-individual variability in shot outcome, ball launch and clubhead presentation of a large group of differently skilled golfers with driver and iron clubs

A. Introduction

Previous research has generally found that higher skilled performers have greater endpoint consistency in multiple attempts at a movement task (van Emmerik et al., 2016), and this has also been found to be the case in golf. Betzler et al. (2012) found greater consistency in ball launch and clubhead presentation in higher skilled golfers than lower skilled golfers in golfers performing multiple shots with a driver club. This was not consistently the case in the multiple single-subject investigation, but the strength of the existing research would suggest that this discrepancy is due to individual variation. Whilst the intra-individual variability of shot outcome, ball launch and clubhead presentation variables in driver and iron shots has been investigated separately in the existing literature, no research is evident which considered outcome variability with both driver and iron clubs in the same cohort. The aim of this section of the investigation was to investigate the intra-individual variability in shot outcome, ball launch and clubhead presentation for both iron and driver shots in a large group of golfers. These variables are indicative of endpoint variability, which is important to characterise for the research aims and further sections which will examine movement variability. The section will also use the ‘shot score’ measure, presented in Section 4.4.1, to characterise task performance and indicate the specific skill of the participants.

B. Methods

The shot outcome variables (carry length, carry side, total length, total side and shot angle), ball launch variables (ball speed, efficiency, launch angle, launch direction, spin rate and spin axis) and clubhead presentation variables (clubhead speed, attack angle, path angle, face angle, effective loft, effective lie and impact location) were defined, measured and calculated as described in Section 4.4.1. Additionally, the rate of change of attack angle, path angle and face angle were calculated from the clubhead motion capture system. For the iron shots, the leading edge of the club was measured on the club and the leading edge height relative to the ground used to classify the shots as either 'top', 'thin', 'good' or 'fat' (Corke, 2015; Corke et al., 2018). Additionally, strikes were classified as 'fat' if any of the three virtual markers, defining the bottom edge of the club, were below the level of the ground at impact.

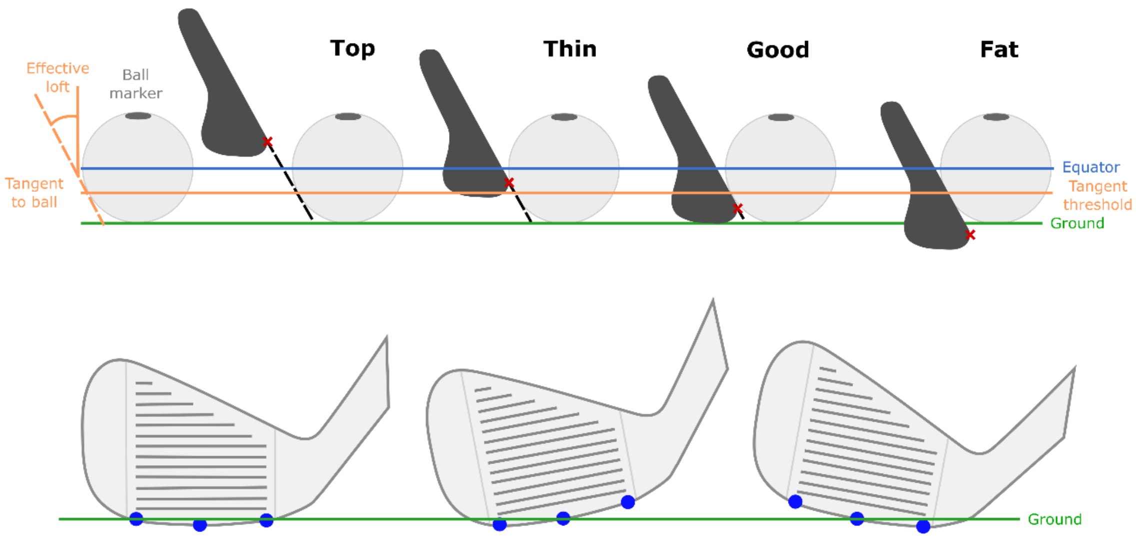


Figure 5.6. Strike classification based on leading edge height at impact and position of virtual marker relative to the ground level (from Corke, 2015).

The shot score variable was calculated using the same method as in Equation 4.1. To account for differences between the genders, different reference distances were used for men and women. The reference distances for men were 402.3 m and 283.8 m for driver and iron shots, the same as in the multiple single subject investigation. For women, reference distances of 352.0 m and 220.0 m were calculated from the maximum driving distance for women in 2017 and the ratio of average driving distance to average 5-iron distance in the manner described in Section 4.4.1 (PGA Tour, 2017; TrackMan, 2014).

Descriptive statistics were calculated on a participant by participant basis for each variable. The median was calculated as the median of all shots with each club within the session. Likewise, the intra-session median absolute deviation was calculated as the median of the absolute deviations from the median. Tukey's fences (1977) were constructed for each participant, and the number of outliers detected using this method was reported alongside the median and median absolute deviation. Participants were assigned to groups based on their CONGU handicap category, and ANOVA and MANOVA tests performed in IBM SPSS Statistics 24 (IBM, Armonk, NY) to assess differences in the variability and the number of outliers between the different groups, genders and clubs. Significant ANOVA results were followed up with *post hoc* Bonferonni adjusted t-tests. Where the ANOVA test assumptions were violated, a Kruskall-Wallis test with *post hoc* Bonferroni adjusted Mann-Whitney tests was used as a non-parametric alternative. For the MANOVA, Pillai's trace statistic was used, as it is generally the most robust of the four possible test statistics (Bray and Maxwell, 1985), and discriminant analysis was used to follow up statistically significant results (Field, 2013). Statistical hypothesis tests are reported with measures of mean or median difference as an effect size.

Pearson's correlation coefficient was calculated to assess the relationship between an individual's variability with the driver club and their variability with the iron club for the shot outcome, ball launch and clubhead variables. Scatter plots were used to visualise this relationship and gauge the presence of extreme outliers which could bias the correlation coefficient. Only one outlier, an extreme ball speed variability with both clubs for a single participant, was removed from the analysis. This did not appear to be an experimental error, as the participant was also highly variable in shot outcome, but the data point was removed to avoid biasing the correlation coefficient. Hinkle, Wiersma and Jurs' (2002) recommendations about interpreting the size of a correlation coefficient were followed; 0.0 - 0.3 = negligible, 0.3 - 0.5 = low, 0.5 - 0.7 = moderate, 0.7 - 0.9 = high, 0.9 - 1.0 = very high. These recommendations are more conservative than the recommendations outlined by Cohen (1988); 0.1 = small, 0.3 = medium and 0.5 = large. However, Cohen (1988) emphasised that it is most important to understand the variance accounted for by one variable by another in the specific context of the research. Given the purpose of the comparison, and the expectation that the variability with the driver and the iron club would be strongly related, the more conservative guidelines were deemed appropriate.

Multiple linear regression was used to analyse the relationships between the median absolute deviation scores, with driver and iron clubs separated in the input. The variability of ball launch variables (ball speed, launch angle, launch direction, spin rate and spin axis) and clubhead presentation variables (clubhead speed, attack angle, path angle, face angle, effective loft, effective lie, and impact location) were used as two sets of input variables, as high correlations exist between the two sets of variables and collinearity within the model variables should be avoided. Two outcome variables were used in the analysis: the variability of total length and shot angle. Whilst a stepwise regression method has been utilised for exploratory model building, it has been argued that these methods are unduly influenced by the specific data, rather than the underlying processes (Field, 2013). Since it was reasonable to hypothesise that an increase in variability of any of the input variables would lead to an increased variability in the output variables, a forced entry method was used. The regression analysis was performed in IBM SPSS Statistics 24 (IBM, Armonk, NY) and included a constant term.

C. Results

The median, mean median absolute deviation and mean number of outliers for the four handicap categories studied are included in Appendix E (Table E.1, Table E.2 and Table E.3 for the shot outcome, ball launch and clubhead presentation variables respectively). Boxplots of the variability in the shot outcome, ball launch and clubhead presentation variables are shown in Figure 5.7, Figure 5.8 and Figure 5.9 respectively.

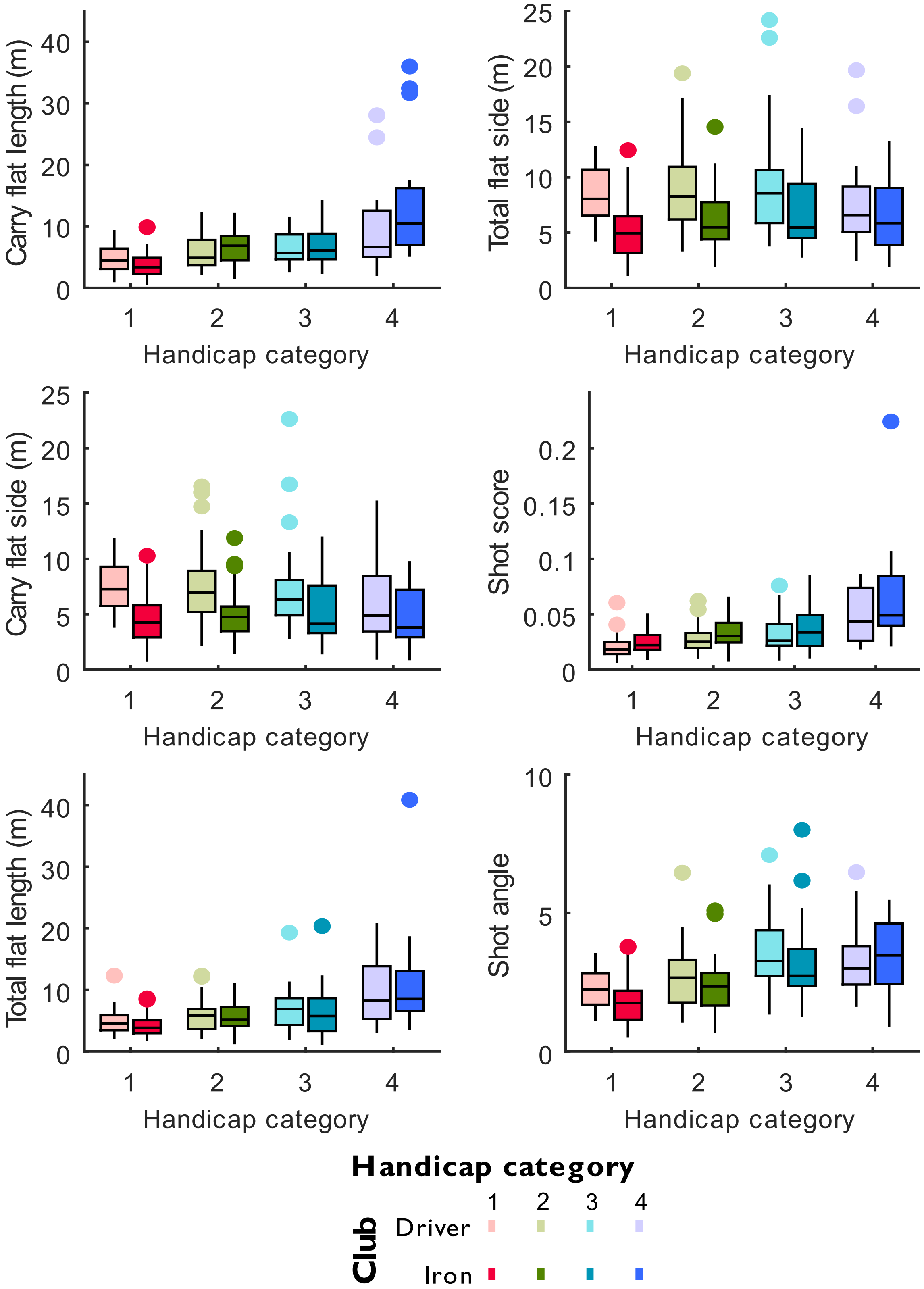


Figure 5.7. Boxplots of the intra-individual shot outcome variability (median absolute deviation) in the four CONGU handicap categories.

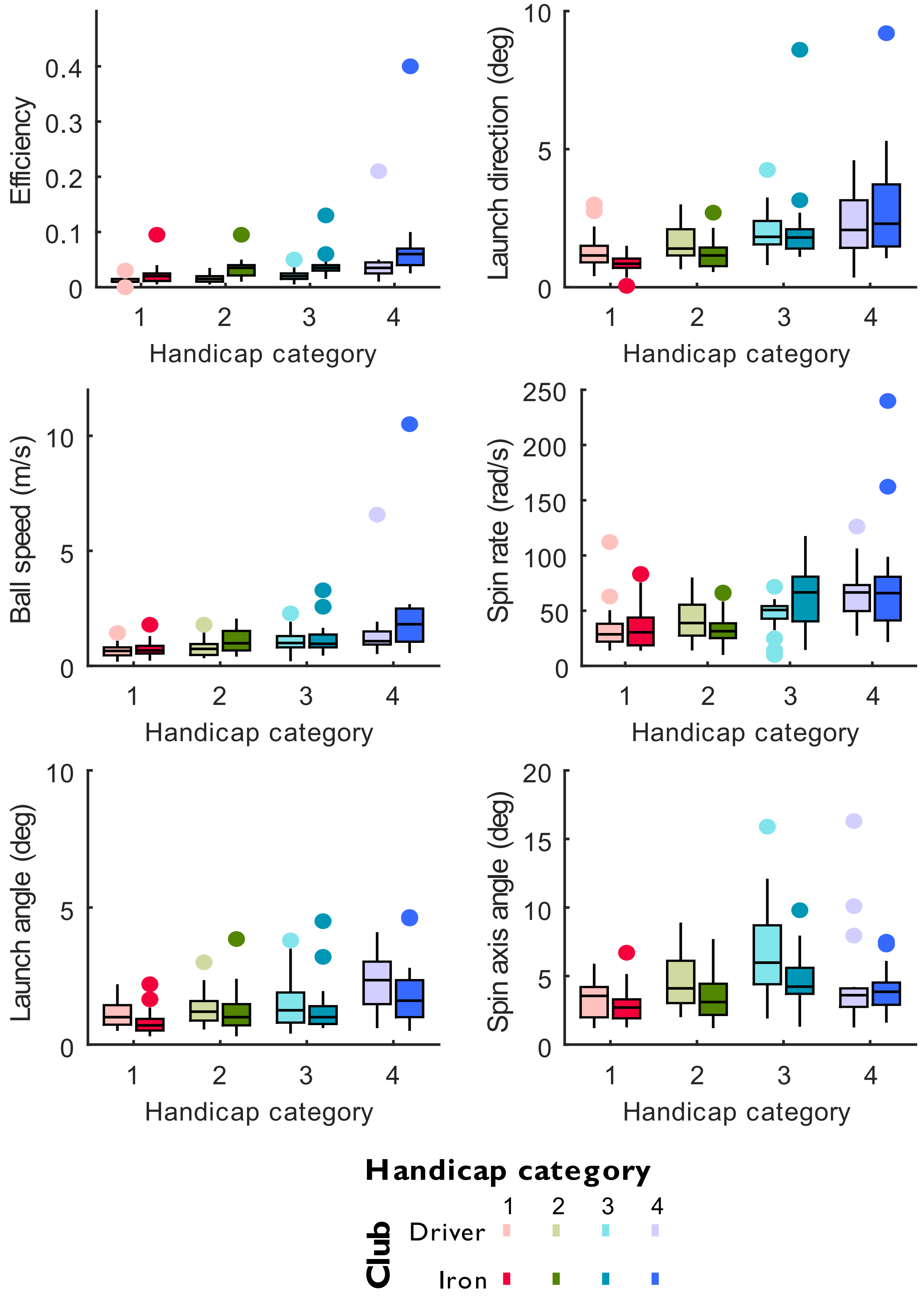


Figure 5.8. Boxplots of the intra-individual ball launch variability (median absolute deviation) in the four CONGU handicap categories.

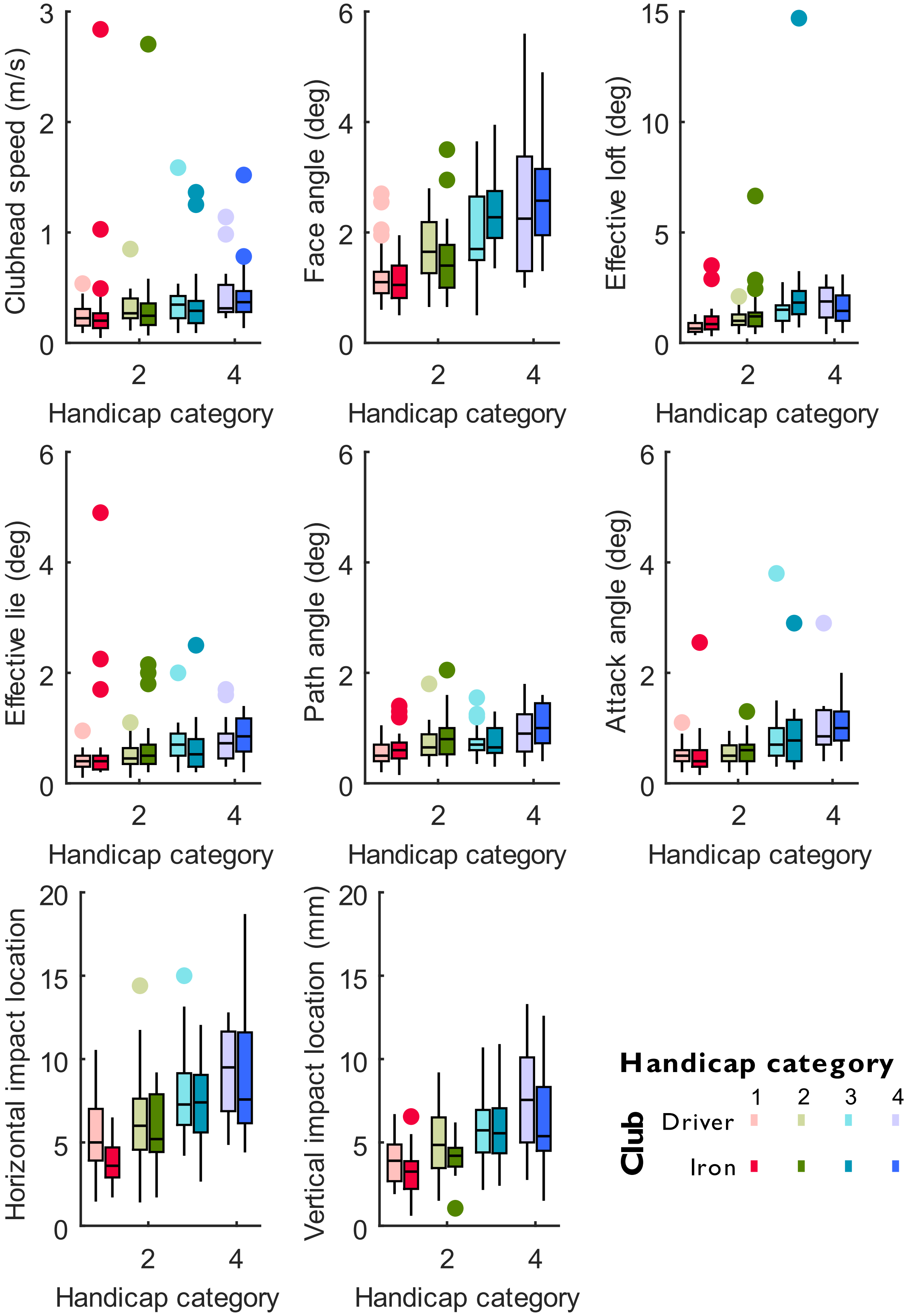


Figure 5.9. Boxplots of intra-individual clubhead presentation variability (median absolute deviation) in the four CONGU handicap categories.

Shot score was highest in Category 1 golfers and decreased successively for the higher handicap categories with both driver (median of 0.89, 0.78, 0.70, 0.64 for Categories 1-4 respectively) and iron clubs (median of 0.96, 0.85, 0.77, 0.70 respectively). This difference was found to be statistically significant ($H(3) = 758.68, p < 0.01$) and *post hoc* tests indicated that the differences between all groups were statistically significant ($p < 0.01$). However, the correlations between handicap and median shot score were low (Driver: $r = -0.24$; Iron: $r = -0.26$) and there was a large overlap between groups. The median absolute deviation of shot score was lowest in Category 1 golfers and increased successively for the higher handicap categories with both driver (median of 0.02, 0.03, 0.03, 0.04 respectively) and iron clubs (median of 0.02, 0.03, 0.03, 0.02 respectively). This difference was also found to be statistically significant ($H(3) = 44.60, p < 0.01$). *Post hoc* tests indicated that the differences between all groups were statistically significant ($p < 0.02$) except for the difference between Category 2 and Category 3 golfers ($U = -9.11, p > 0.99$). The mean number of intra-individual outliers was similar for each category of golfers with both the driver (0.5 outliers per session for all categories) and the iron club (0.4-0.6 outliers per session) and differences were not statistically significant ($F(3) = 0.18, p = 0.95$).

There were statistically significant differences between the handicap categories in the variability of shot outcome, ball launch and clubhead presentation ($V = 0.88, F(66,555) = 3.46, p < 0.01$) and follow-up discriminant analysis indicated three functions which explained 84.5%, 12.5% and 3.1% of the variance (*canonical* $R^2 = 0.79, 0.44$ and 0.24 respectively). These functions significantly differentiated between the participants in combination ($\Lambda = 0.29, \chi^2(66) = 242.49, p < 0.01$), but not when the first function was removed ($\Lambda = 0.76, \chi^2(42) = 53.52, p = 0.11$). The discriminant function plot indicated that function 1 differentiated between all handicap groups. The groups were ordered successively with Category 1 golfers displaying the lowest value in this function. The correlations indicated that the variability of face angle ($r = 0.56$), horizontal impact location ($r = 0.50$), vertical impact position ($r = 0.46$), launch direction ($r = 0.43$), total length ($r = 0.39$), shot angle ($r = 0.37$), launch angle ($r = 0.36$), efficiency ($r = 0.33$) and ball speed ($r = 0.33$) loaded highest on this function. Thus, the four handicap category groups displayed successively lower variability in these variables with Category 1 golfers displaying the lowest variability (Table 5.3).

Table 5.3. Median variability of variables determined to be different between golfers in the four handicap categories.

CONGU Handicap category	Face angle (°)	Horizontal impact location (mm)	Vertical impact location (mm)	Launch direction (°)	Total length (m)	Shot angle (°)	Launch angle (°)	Efficiency ( )	Ball speed ($m \cdot s^{-1}$)
1	1.1	4.5	3.4	1.0	4.1	1.9	0.9	0.02	0.7
2	1.6	5.9	4.3	1.3	5.5	2.4	1.1	0.02	0.8
3	2.1	7.3	5.6	1.8	6.5	3.0	1.1	0.03	1.0
4	2.5	8.8	6.5	2.3	8.5	3.1	1.8	0.05	1.3

Statistically significant differences were also indicated between males and females ($V = 0.47, F(22,185) = 7.37, p < 0.01$). Discriminant analysis indicated a single discriminant function which explained 100% of the variance (*canonical* $R^2 = 0.68$) and significantly differentiated between the groups ($\Lambda = 0.53, \chi^2(22) = 122.75, p < 0.01$). The correlations between the variables and the discriminant functions indicated that the variability of carry side ($r = -0.46$), horizontal impact location ($r = 0.36$), total side ($r = -0.35$), efficiency ($r = 0.35$) and vertical impact position ($r = 0.34$) loaded most highly on the discriminant function. Female golfers loaded more positively onto this function and therefore a positive correlation is associated with a higher value for female golfers. The median values for males and females for these variables are shown in Table 5.4.

Table 5.4. Median variability of variables determined to be different between male and female golfers.

	Carry side (m)	Horizontal impact location (mm)	Total side (m)	Efficiency ( )	Vertical impact location (mm)
Male	6.6	5.8	7.8	0.02	4.3
Female	3.7	7.9	4.7	0.03	5.8

Grouping the participants, there were statistically significant differences between the two clubs used ($V = 0.47, F(22,185) = 7.34, p < 0.01$). The follow-up discriminant analysis indicated a single discriminant function which explained 100% of the variance (*canonical* $R^2 = 0.68$) and significantly differentiated between the groups ($\Lambda = 0.53, \chi^2(22) = 122.35, p < 0.01$). The correlations between the variables and the discriminant functions indicated that the variability of carry side ($r = 0.41$), total side ($r = 0.41$), efficiency ($r = -0.28$) and spin axis ($r = 0.24$) loaded most highly on the discriminant function. The driver club loaded more positively onto this function and therefore the variability of total and carry side and spin axis was higher with the driver club, whilst the variability in efficiency was higher with the iron club (Table 5.5).

Table 5.5. Median variability of variables determined to be different between driver and iron clubs.

	Carry side (m)	Total side (m)	Efficiency ( )	Spin axis (°)
Driver	6.8	8.1	0.02	4.0
Iron	4.3	5.4	0.03	3.3

All correlation coefficients between the variability with the driver club and the iron club were lower than 0.50, indicative of a low correlation in the variability with the two clubs (Hinkle, Wiersma and Jurs, 2002). The highest correlation coefficients were in carry side variability ($r = 0.496$), vertical impact position variability ($r = 0.459$) and face angle variability ($r = 0.457$), and the scatter plot for carry side variability is shown in Figure 5.10.

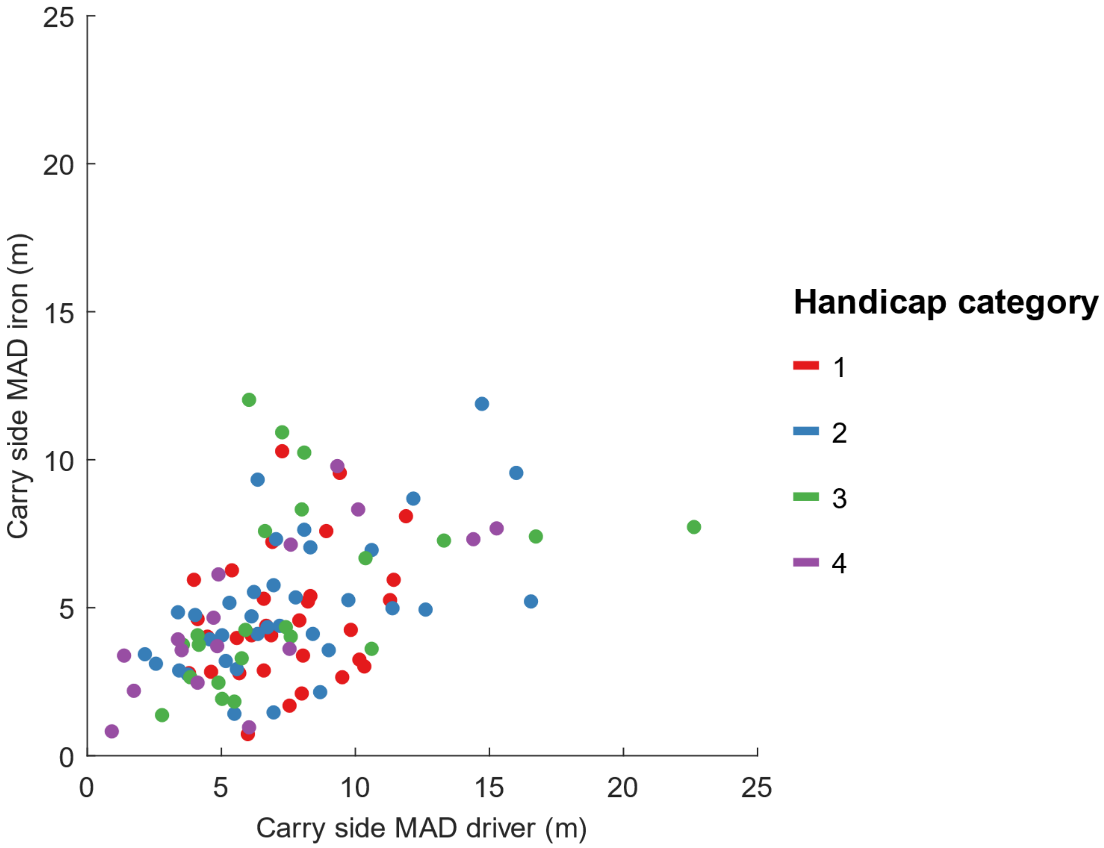


Figure 5.10. The strongest relationship observed in the variability with the driver and iron club: carry side ($r = 0.496$).

Regarding the structure of variability, there were statistically significant differences between the handicap categories in the number of intra-individual outliers in the shot outcome, ball launch and clubhead presentation variables ($V = 0.42$, $F(66,555) = 1.34$, $p = 0.03$). The three functions indicated by follow-up discriminant analysis explained 62.2%, 22.6% and 15.1% of the variance (*canonical* $R^2 = 0.49$, 0.32 and 0.27 respectively), and significantly differentiated between the participants in combination ($\Lambda = 0.63$, $\chi^2(66) = 90.66$, $p = 0.02$) but not when the first function was removed ($\Lambda = 0.83$, $\chi^2(42) = 36.27$, $p = 0.72$). The discriminant function plot indicated that function one differentiated golfers in handicap Categories 1 and 2 from those golfers in Categories 3 and 4. The correlations between the variables and the discriminant functions indicated that the number of intra-individual outliers in horizontal impact position ($r = 0.34$), effective loft ($r = 0.26$), launch direction ($r = 0.24$) and clubhead speed ($r = -0.24$) loaded most highly on this function. Thus, golfers in Categories 1 and 2 displayed more outliers in the horizontal impact position, effective loft and launch direction, but fewer outliers in the clubhead speed. MANOVA indicated no statistically significant differences in the number of individual outliers between the two genders ($V = 0.11, F(22,185) = 1.08, p = 0.37$) or the two clubs used ($V = 0.10, F(22,185) = 0.95, p = 0.53$).

For the iron shots, the differences in leading edge height at impact between the groups (median of 2.3, 3.6, 2.4 and 4.4 mm for Categories 1-4 respectively) were indicated to be statistically significant by a Kruskall-Wallis test ($H(3) = 9.20, p = 0.03$), but *post hoc* Bonferroni adjusted Mann-Whitney U tests were not significant ($p > 0.07$). The median absolute deviation of leading edge height (median of 3.0, 3.8, 4.6, and 5.0 respectively) was significantly different between groups ($H(3) = 29.65, p < 0.01$). *Post hoc* tests indicated that the differences between Category 1 golfers and other categories was statistically significant ($p < 0.02$) but that differences between the other categories were not statistically significant ($p > 0.21$). The mean number of intra-individual outliers for each category of golfers was similar (0.0 - 0.2 outliers per session) and differences between the groups were not statistically significant ($F(3) = 1.61, p = 0.19$).

All regression models were significantly better at predicting variability in outcome than a constant model (Table 5.6) and the parameters of the models are shown in Table 5.7. The model with the highest correlation coefficient ($r^2 = 0.80$) used the variability in iron ball launch variables to predict the variability in the total length of the shot.

Table 5.6. Summaries of linear regression models.

Club	Inputs	Output	r	r^2	Standard error of the estimate	$F(5,98)$	p
Driver	Ball launch	Total length	0.54	0.30	3.20	8.18	< 0.001
Iron			0.89	0.80	2.23	76.94	< 0.001
Driver		Shot angle	0.75	0.56	0.84	24.73	< 0.001
Iron			0.83	0.69	0.75	43.42	< 0.001
Driver	Clubhead presentation	Total length	0.53	0.28	3.28	4.60	< 0.001
Iron			0.63	0.39	3.93	7.65	< 0.001
Driver		Shot angle	0.63	0.40	0.99	8.00	< 0.001
Iron			0.71	0.50	0.96	12.00	< 0.001

Table 5.7. Coefficients of linear regression models, with 95% bias corrected and accelerated confidence intervals calculated from 1000 bootstrap samples.

		Total length						Shot angle					
		Coefficients (*B*)	Confidence intervals		Standard error of *B*	*β*	*p*	Coefficients (*B*)	Confidence intervals		Standard error of *B*	*β*	*p*
			Lower limit	Upper limit					Lower limit	Upper limit			
Driver	Constant	0.68	-1.25	2.61	0.97	-	0.49	0.64	0.13	1.14	0.26	-	0.02
	Ball speed (m·s^{-1})	0.35	-0.79	1.49	0.57	0.07	0.54	0.40	0.10	0.70	0.15	0.23	0.01
	Launch angle (°)	0.81	-0.09	1.71	0.45	0.18	0.08	-0.19	-0.42	0.05	0.12	-0.12	0.12
	Launch direction (°)	0.76	-0.11	1.62	0.44	0.17	0.09	0.46	0.24	0.69	0.11	0.32	0.00
	Spin rate (rad·s^{-1})	0.04	0.01	0.08	0.02	0.24	0.03	0.01	0.00	0.02	0.01	0.12	0.16
	Spin axis (°)	0.25	0.02	0.48	0.12	0.18	0.04	0.22	0.16	0.28	0.03	0.49	0.00
Iron	Constant	0.85	-0.32	2.02	0.59	-	0.15	0.57	0.18	0.96	0.20	-	0.01
	Ball speed (m·s^{-1})	3.61	3.08	4.13	0.26	0.83	0.00	0.16	-0.02	0.34	0.09	0.14	0.07
	Launch angle (°)	1.04	0.40	1.67	0.32	0.19	0.00	-0.20	-0.41	0.02	0.11	-0.13	0.07
	Launch direction (°)	-0.19	-0.68	0.30	0.25	-0.05	0.44	0.61	0.44	0.77	0.08	0.61	0.00
	Spin rate (rad·s^{-1})	0.00	-0.01	0.02	0.01	0.03	0.66	0.00	-0.01	0.01	0.00	-0.04	0.60
	Spin axis (°)	0.03	-0.25	0.31	0.14	0.01	0.83	0.33	0.24	0.43	0.05	0.43	0.00

		Total length						Shot angle					
		Coefficients (*B*)	Confidence intervals		Standard error of *B*	*β*	*p*	Coefficients (*B*)	Confidence intervals		Standard error of *B*	*β*	*p*
			Lower limit	Upper limit					Lower limit	Upper limit			
Driver	Constant	1.76	-0.47	3.98	1.12	-	0.12	0.79	0.12	1.46	0.34	-	0.02
	Clubhead speed (m·s^{-1})	2.15	-2.19	6.49	2.19	0.12	0.33	0.24	-1.08	1.55	0.66	0.04	0.72
	Face angle (°)	0.65	-0.40	1.70	0.53	0.16	0.22	0.46	0.14	0.78	0.16	0.34	0.01
	Effective loft (°)	1.09	-0.50	2.67	0.80	0.18	0.18	0.30	-0.18	0.78	0.24	0.14	0.22
	Effective lie (°)	-0.56	-3.16	2.05	1.31	-0.05	0.67	-0.22	-1.01	0.57	0.40	-0.06	0.58
	Path angle (°)	2.56	0.35	4.78	1.12	0.23	0.02	0.94	0.27	1.61	0.34	0.25	0.01
	Attack angle (°)	0.90	-1.21	3.00	1.06	0.12	0.40	0.33	-0.31	0.97	0.32	0.13	0.31
	Horizontal impact position (mm)	0.04	-0.23	0.31	0.14	0.03	0.76	-0.02	-0.11	0.06	0.04	-0.05	0.58
	Vertical impact position (mm)	-0.16	-0.47	0.15	0.16	-0.10	0.31	0.04	-0.06	0.13	0.05	0.07	0.45
Iron	Constant	-1.20	-3.64	1.24	1.23	-	0.33	0.68	0.09	1.28	0.30	-	0.03
	Clubhead speed (m·s^{-1})	-2.22	-5.17	0.72	1.48	-0.19	0.14	-0.06	-0.78	0.67	0.36	-0.02	0.88
	Face angle (°)	0.39	-0.71	1.50	0.56	0.07	0.48	0.90	0.63	1.17	0.14	0.59	0.00
	Effective loft (°)	-0.02	-0.61	0.58	0.30	-0.01	0.95	-0.07	-0.22	0.07	0.07	-0.09	0.32
	Effective lie (°)	0.08	-1.73	1.89	0.91	0.01	0.93	-0.38	-0.82	0.07	0.22	-0.18	0.10
	Path angle (°)	1.09	-1.30	3.47	1.20	0.08	0.37	-0.21	-0.79	0.37	0.29	-0.06	0.47
	Attack angle (°)	1.06	-1.53	3.66	1.31	0.10	0.42	0.48	-0.16	1.11	0.32	0.17	0.14
	Horizontal impact position (mm)	0.16	-0.15	0.48	0.16	0.10	0.31	-0.01	-0.09	0.07	0.04	-0.02	0.81
	Vertical impact position (mm)	1.08	0.69	1.48	0.20	0.50	0.00	0.13	0.03	0.23	0.05	0.22	0.01

D. Discussion

There was a trend toward decreasing variability for shot outcome measures across the handicap categories, with the lowest handicap category displaying the lowest variability in carry length, total length, shot angle and shot score. This trend did not manifest in the variables of carry or total side, where the variability remained relatively constant across the handicap categories. However, golfers in the lower handicap categories also hit the ball further on average than golfers in the higher handicap categories, and the same variability in carry or total side reflects greater task success for these golfers. The shot angle and shot score variables are calculated from both total length and total side and display the decreased variability which characterised the outcome for golfers in lower handicap categories.

In the clubhead presentation and ball launch variables, the general trends echoed those seen in the shot outcome variables; a decrease in variability across the handicap categories. Not all differences were statistically significant, but the average median absolute deviation was lowest in the Category 1 golfers for every variable. This agrees with previous research by Betzler et al. (2012), who reported generally decreasing variability in ball launch and clubhead presentation variables for a large group of amateur golfers with the driver club. This investigation found similar patterns with both the driver and iron club, but interestingly, the correlations between individual driver variability and iron variability were generally low. That is, an individual's variability with the driver club was not a particularly good predictor of their variability with the iron club, or vice versa. This is surprising as, on average, the higher skilled golfers had a lower variability with both clubs and the task set to the golfers remained the same with both clubs. This could suggest that a change in club influences movement patterns, but also, the use of standardised equipment may have impacted these results. Anecdotally, some participants felt most comfortable with the standard iron club and others with the driver, which may have been reflected in their variability.

There were also differences in the structure of variability, with lower handicap golfers, those in handicap Categories 1 and 2, displaying significantly fewer outlying values in clubhead speed, but significantly more outliers in the horizontal impact position, effective loft and launch direction. In contrast to the multiple single-subject investigation, where participants were able to discard self-reported 'mis-hit' shots, all successfully measured shots were included in the data set in this investigation, but the detection of an outlier does not necessarily mean the shot was mis-hit. It is interesting to note that the lower handicap golfers had a greater number of outliers than the higher handicap golfers in certain variables, as this contrasts with the general finding of greater consistency in the higher skilled golfers. However, since the detection of outliers is based on the individual variability of the data, those participants with a lower intra-individual variability have a smaller range in which a shot would be determined to be an outlier. Differences in the structure of variability could, in part, be due to differences in overall variability but the measure highlights a difference in distribution between the groups of golfers.

Corke (2015) plotted the leading edge height against efficiency for 2249 iron shots hit by 96 amateur and professional golfers from natural turf. It is interesting to compare the figure produced by Corke (2015) to the same figure produced using the data from this investigation, which utilised artificial turf (Figure 5.11). The figures show similar patterns except for those shots where the leading edge of the club is below the bottom of the ball at impact. Specifically, both sets of data contain shots with a leading edge height of between 0 and -15 mm and an efficiency of above 1.2, however, the data from the natural turf also contains many shots with the same leading edge height and an efficiency of between 0.8 and 1.2. These shots with a low leading edge height and a lower efficiency are largely missing from the data gathered in this investigation. This could indicate differences in the club-ground interaction between shots hit from artificial turf and natural turf; where the golfer is able to take a divot from the ground. However, it should be noted that the participants in this investigation could hit their iron shots from a tee if desired, which may have influenced the results by allowing participants to strike the ball with the leading edge below the height of the ball without striking the ground.

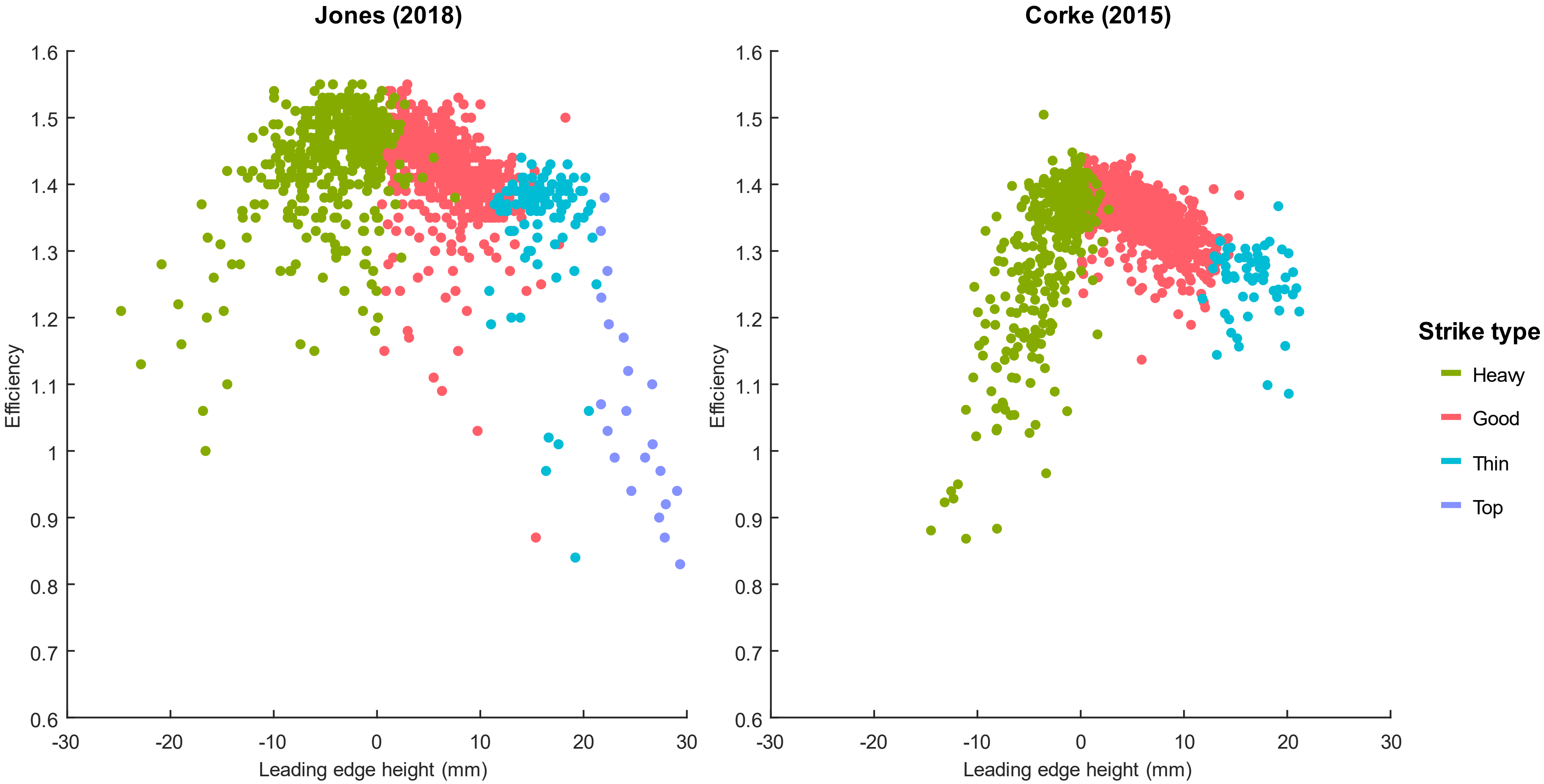


Figure 5.11. Efficiency plotted against leading edge height at impact for strikes classified as 'fat', 'good', 'thin' and 'top' for this investigation (left) and the investigation by Corke (2015)(right).

The regression models displayed a better fit for the iron shots, as indicated by the higher correlation coefficients in these models. Generally, the coefficients in the models were positive, indicating that an increase in variability of the input parameters results in an increased variability of output. There were also negative model coefficients, which appear contrary to expectations, but only positive coefficients had a confidence interval which does not include zero. Considering these coefficients only, with the driver club, variability in total length was associated with variability in spin axis (*B = 0.04*) and spin rate (*B = 0.25*), and the variability in path angle (*B = 2.56*). With the iron club, variability in total length was associated with variability in ball speed (*B = 3.61*) and launch angle (*B = 1.04*), and the variability of vertical impact position (*B = 1.08*). With both clubs, the variability in shot angle was associated with variability in launch direction (Driver: *B = 0.46;* Iron: *B = 0.61*) and spin axis (Driver: *B = 0.22;* Iron: *B = 0.33*), and variability in face angle (Driver: *B = 0.46;* Iron: *B = 0.90*). Furthermore, the variability in shot angle was also associated with the variability in ball speed (*B = 0.40*) and path angle (*B = 0.94*) with the driver club, and the variability of vertical impact position (*B = 0.13*) with the iron club. The differences between the models for the different clubs is striking and suggests that the importance of consistency in the input variables might differ between the two different clubs when outcome consistency is desired. This explanation could also explain the low correlations observed in the variability with each club.

5.4.2. Intra-individual variability in address kinematics and temporal characteristics of a large group of differently skilled golfers with driver and iron clubs.

A. Introduction

It has been suggested that the address position and timing of the golf swing are a determinant of success, but it is unclear whether higher skilled golfers are more consistent in these aspects of the golf swing. Furthermore, it is unknown whether increased variability in the address or swing timing is related to an increased variability in shot outcome. Research into the variability of golfers position at address has shown mixed results, with some investigations finding differences between differently skilled golfers (Bradshaw et al., 2009), and other investigations finding no difference (Langdown et al., 2013a). However, the total sample size across all studies, including the multiple single-subject study included in this thesis, is small, and it would be beneficial to investigate intra-individual variability in address in a larger group of golfers. Variability in swing timing has not been the subject of much research, although there is some suggestion that higher skilled golfers are relatively consistent in their swing timing (Corke, 2015). The aim of this section of the investigation was to investigate the intra-individual variability in address position and alignment, and in swing timing, for both iron and driver shots in a large group of golfers.

B. Methods

The address position variables (stance width, stance depth, ball position, feet-target line angle), and timing variables (backswing time and downswing time) were defined, measured and calculated as described in Chapter 4.4.3. Additionally, the left foot to right foot angle was calculated as the ZXY Cardan angle between the left foot and the right foot coordinate systems. The variability of the sub-phases was not considered in this investigation because the variability of the shortest phases was close to the time between frames in the multiple-single subject investigation and could be unreliable as a result.

Data analysis, including descriptive statistics, statistical hypothesis testing, Pearson's correlation coefficients and multiple linear regression, followed the same procedures as those reported in Section 5.4.1: the shot outcome, ball launch and clubhead presentation variables. No extreme outliers were excluded during the correlation analysis. The variability of address variables and swing timing variables were used as input variables for the multiple linear regression analysis.

C. *Results*

Descriptive statistics for the address variables are included in Appendix E, Table E.4. The intra-individual variability in address variables of the four handicap categories is shown in Figure 5.12.

A MANOVA using Pillai's trace statistic indicated statistically significant differences between the handicap categories in the variability of address ($V = 0.18, F(15,606) = 2.54, p < 0.01$). Follow-up discriminant analysis indicated three functions which explained 92.2%, 6.2% and 1.6% of the variance (*canonical* $R^2 = 0.40, 0.11$ and 0.06 respectively). The functions significantly differentiated between the participants in combination ($\Lambda = 0.83, \chi^2(15) = 38.84, p < 0.01$), but not when the first function was removed ($\Lambda = 0.98, \chi^2(8) = 3.27, p = 0.92$). Inspection of the discriminant function plot indicated that function one differentiated between all handicap category groups. The groups were ordered successively with Category 1 golfers displaying the lowest value and Category 4 golfers the highest value in this function. The correlations between the outcomes and the discriminant functions indicated that all variables loaded positively onto this function; stance width ($r = 0.70$), stance depth ($r = 0.68$), ball position ($r = 0.57$), feet to target line angle ($r = 0.41$) and foot to foot angle ($r = 0.36$). Therefore, golfers in the four handicap category groups displayed successively lower variability in these variables with category one golfers displaying the lowest variability (Table 5.8).

Table 5.8. Median variability determined to be different between the handicap categories.

	Stance width (m)	Stance depth (m)	Ball position (m)	Feet to target line angle (°)	Foot to foot angle (°)
Category 1	0.007	0.006	0.009	0.58	1.06
Category 2	0.007	0.009	0.011	0.64	1.20
Category 3	0.009	0.009	0.011	0.61	1.33
Category 4	0.010	0.009	0.012	0.79	1.51

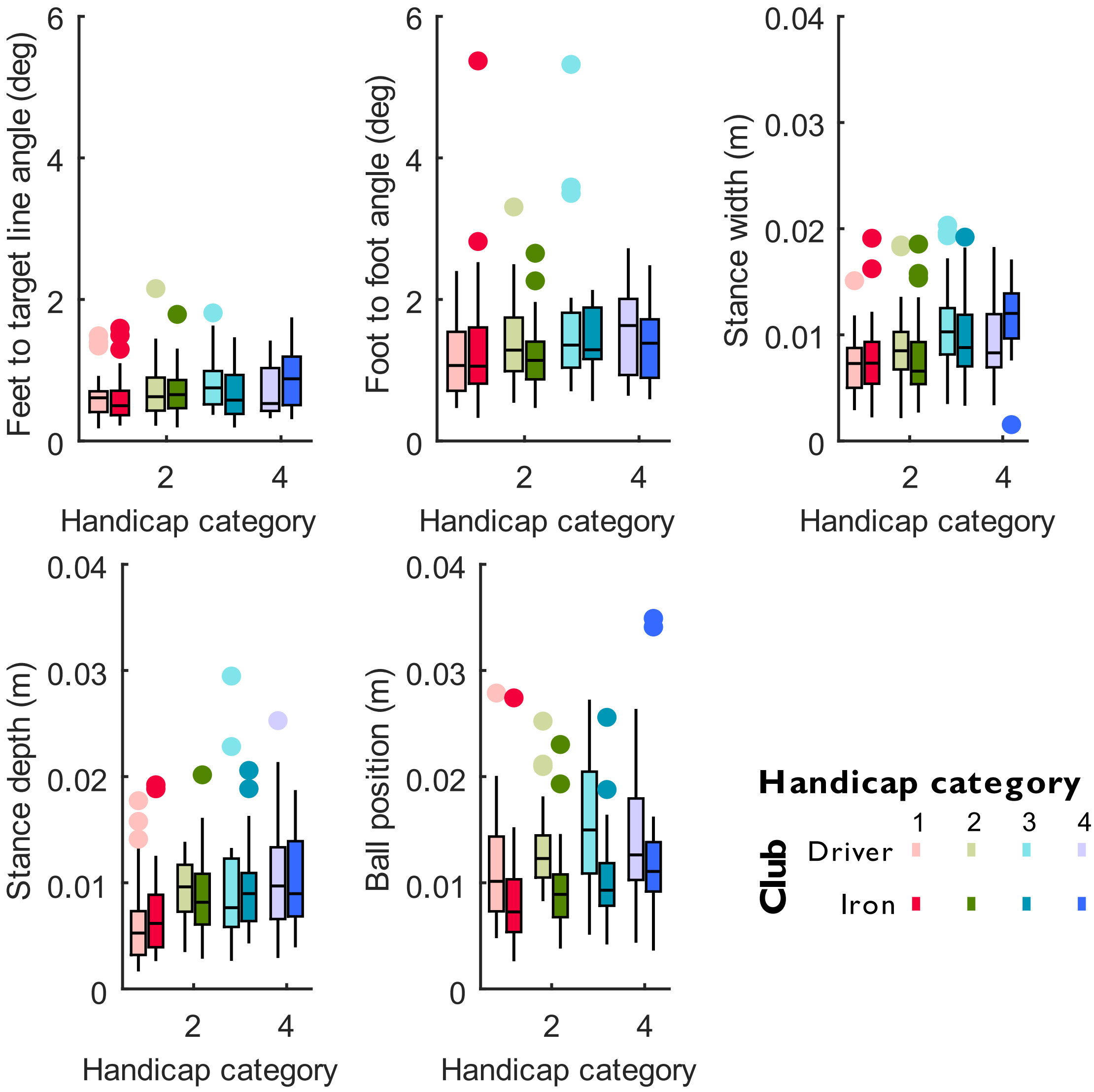


Figure 5.12. Boxplots of the intra-individual address variability (median absolute deviation) in the four CONGU handicap categories.

There were statistically significant differences in the variability of address indicated between males and females (*$V = 0.08$, $F(5,202) = 3.56$, $p < 0.01$*). A follow-up discriminant analysis indicated a single discriminant function which explained 100% of the variance (*canonical* $R^2 = 0.28$) and significantly differentiated between the groups ($\Lambda = 0.92$, $\chi^2(5) = 17.17$, $p < 0.01$). The correlations between the variables and the discriminant functions indicated that all variables loaded positively onto the discriminant function; stance width ($r = 0.83$), foot to foot angle ($r = 0.52$), feet to target line angle ($r = 0.52$), ball position ($r = 0.52$) and stance depth ($r = 0.37$). Female golfers loaded more positively onto this function and therefore the female golfers displayed higher variability in these variables. The median values for males and females are shown in Table 5.9.

Table 5.9. Median variability determined to be different between male and female golfers.

	Stance width (m)	Stance depth (m)	Ball position (m)	Feet to target line angle (°)	Foot to foot angle (°)
Males	0.004	0.008	0.010	0.61	1.20
Females	0.011	0.009	0.012	0.78	1.27

Finally, there were also statistically significant differences in the variability of address between the two clubs used ($V = 0.10, F(5,202) = 4.30, p < 0.01$). A single discriminant function which explained 100% of the variance (*canonical* $R^2 = 0.68$) and significantly differentiated between the groups ($\Lambda = 0.90, \chi^2(5) = 20.58, p < 0.01$) was indicated in the follow-up discriminant analysis. The correlations between the variables and the discriminant functions indicated that the variability of ball position ($r = 0.91$) loaded most highly on the discriminant function. The driver club loaded more positively onto this function and therefore the variability of ball position was higher with the driver club (*median* = *0.012 m*) than the iron club (*median* = *0.009 m*).

No statistically significant differences were indicated in the number of intra individual outliers between the handicap categories ($V = 0.04, F(15,606) = 0.53, p = 0.93$), the genders ($V = 0.02, F(5,202) = 0.82, p = 0.54$), or the two different clubs ($V = 0.04, F(5,202) = 1.71, p = 0.13$).

The correlation coefficients between the median absolute deviation of address variables with the driver club and the iron club were lower than 0.50, indicating a low correlation between the variability with the different clubs. The highest correlation coefficient was in the feet to target line angle variability ($r = 0.327$). Regression models using the address variables as input variability and total length and shot angle as outcome variables were significantly better at predicting variability in outcome than a constant model (Total length: $F = 4.03, p < 0.01$; Shot angle: $F = 4.34, p < 0.01$), but explained only a small percentage of the variance in the data (Total length: $r^2 = 0.09$; Shot angle: $r^2 = 0.10$). For this reason, the model coefficients have been omitted.

Descriptive statistics for the backswing and downswing timing are included in Appendix E, Table E.5. The intra-individual variability in backswing and downswing timing for the four handicap categories is shown in Figure 5.13.

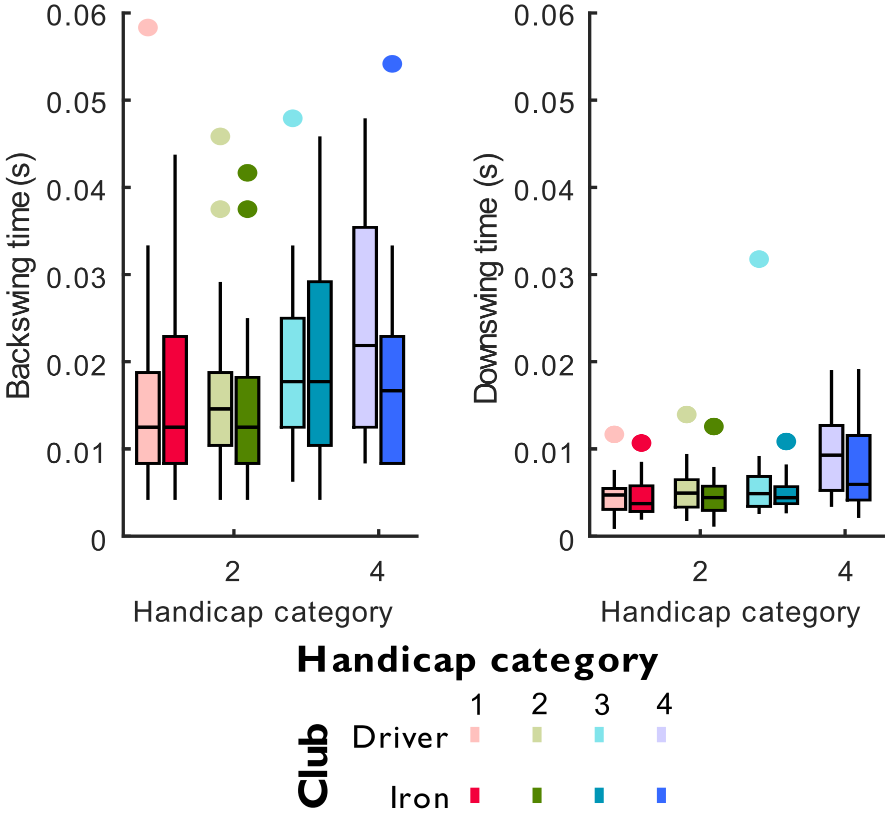


Figure 5.13. Boxplots of the intra-individual backswing and downswing timing variability (median absolute deviation) in the four CONGU handicap categories.

Kruskall-Wallis tests indicated a statistically significant difference between downswing timing variability across the four handicap groups ($H(3) = 20.55$, $p < 0.01$), *post hoc* Bonferroni adjusted Mann Whitney U tests indicated that participants in Category 4 were significantly more variable in downswing time than participants in the three other groups ($p < 0.03$). The median difference in downswing timing variability between participants in Category 4 and the other handicap category groups were 0.002 s. The differences between the handicap category groups in backswing timing variability were also indicated to be statistically significant by a Kruskall-Wallis test ($H(3) = 8.81$, $p = 0.03$) but no differences were indicated by the *post hoc* tests ($p > 0.17$). The maximum median difference in backswing timing variability was 0.004. There was also a statistically significant difference in downswing timing variability between males and females ($U = 5243$, $p < 0.01$). Males had lower downswing timing variability (*median* = *0.004* s) compared to females (*median* = *0.006* s). There were no statistically significant differences in backswing timing variability between the genders ($U = 4673.5$, $p = 0.10$) and no statistically significant differences in either backswing or downswing timing variability between the clubs (Backswing: *U = 4905, p = 0.25*; Downswing: *U = 4679.5, p = 0.09*). There were also no statistically significant differences in the structure of backswing or downswing timing variability between the handicap groups (Backswing: *F = 0.74, p = 0.53*; Downswing: *F = 0.74, p = 0.53*), the genders (Backswing: *F = 1.00, p = 0.32*; Downswing: *F = 0.02, p = 0.90*) or the clubs used (Backswing: *F = 0.65, p = 0.42*; Downswing: *F = 3.28, p = 0.07*).

The correlation between backswing timing variability with the iron and driver club was below 0.50 (*r = 0.344*) which is indicative of a low correlation, however, the correlation between the downswing timing variability indicated a moderate correlation (*r = 0.593*). The scatter plot for downswing variability is shown in Figure 5.14. Further investigation found that median downswing time had a moderate correlation with the median absolute deviation of downswing time with both clubs (*r = 0.577* for both clubs combined). The golfers with a shorter downswing tended to be less variable in downswing time (Figure 5.15).

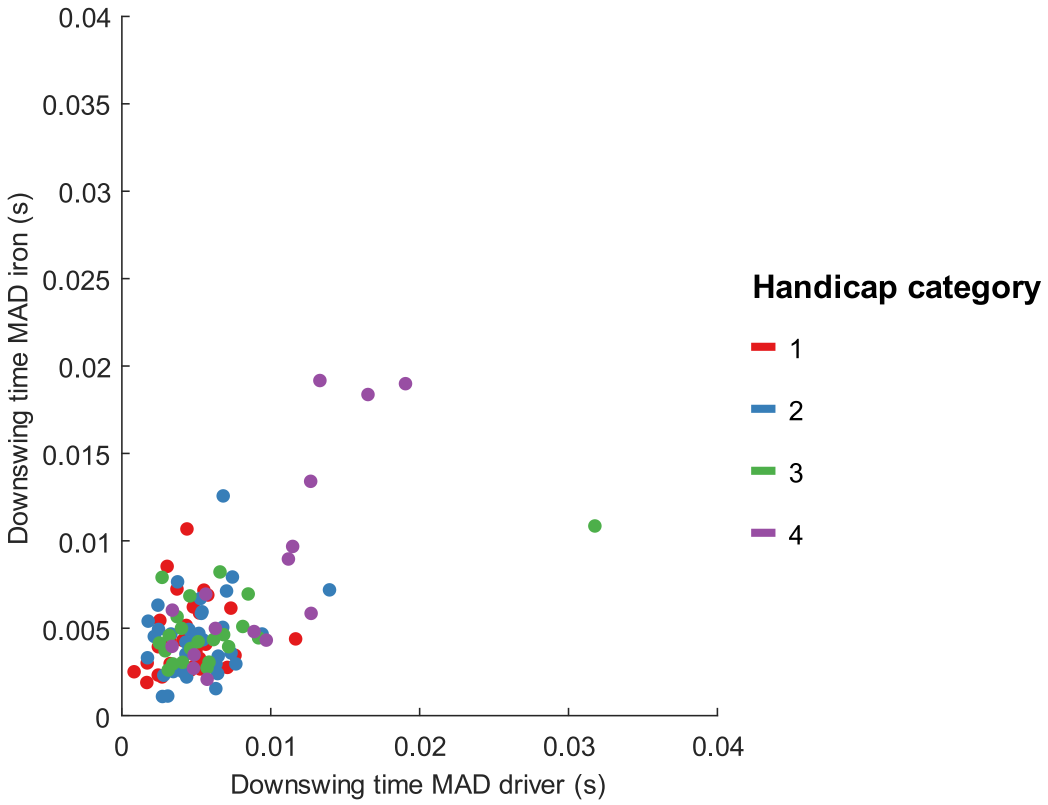


Figure 5.14. The relationship between the downswing timing variability with the driver and iron club (*r = 0.593*).

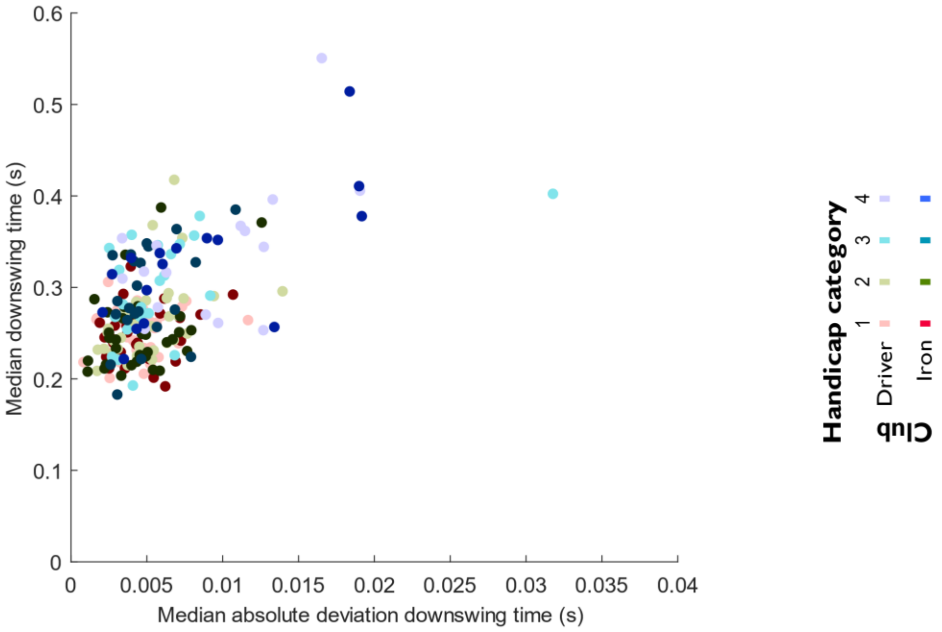


Figure 5.15. The relationship between median downswing time and downswing timing median absolute deviation with the driver and iron club (*r = 0.577*).

The regression models using the backswing and downswing timing variability as input variables and total length and shot angle as outcome variables were significantly better at predicting variability in outcome than a constant model (Total length: *F = 4.42, p = 0.01*; Shot angle: *F = 3.04, p = 0.05*). However, the model coefficients have been omitted as the models explained only a small percentage of the variance in the data (Total length: $r^2 = 0.04$; Shot angle: $r^2 = 0.03$).

D. Discussion

Between differently skilled golfers, differences in variability have been reported in the alignment at address, with differences in variability observed in the pelvis rotation angle (Section 4.4.3), the shoulder to stance alignment angle (Langdown et al., 2013a) and the trunk angle (Bradshaw et al., 2009). However, only Bradshaw (2009) have reported a difference in the variability of the stance position between differently skilled golfers; ten high skilled golfers were reported to have lower variability in stance width than ten lower skilled golfers. This investigation did not examine the alignment of the pelvis or torso segments at address but found statistically significant differences between the four CONGU handicap categories in the magnitude of variability in all the address variables studied. Lower handicap groups of golfers displayed generally lower variability than higher handicap groups.

The differences observed in this investigation were small, with a maximum difference in median absolute deviation of 3 mm in position or 0.45° in foot to foot angle between Category 1 and Category 4 golfers. Furthermore, the correlations between the variability with the driver and the iron club were low and regressions between the variability of address variables and the variability of shot outcome explained only a small amount of the total variance of the data. Thus, lower handicap golfers were generally less variable in address golfers in higher handicap groups but those with the lowest variability with the driver club did not necessarily have the lowest variability with the iron club. Also, as the relationship between variability in address and shot outcome was weak, it is not clear that consistency in address is necessary for obtaining consistency in outcome.

There was also a difference between the two clubs used, with the golfers displaying lower variability in ball position, the relative position of the ball between the feet, with the iron club. The stance position with the driver club is different to that adopted with the iron club; the stance width and stance depth are greater, and the ball is positioned closer to the front foot. The larger distances mean that visual cues are more widely spaced, which might make it more difficult to adopt a consistent address with the driver club. The use of visual cues could also explain why differences in address alignment have been observed in the literature, while differences in address positioning have not been found consistently. Regardless, higher skilled golfers have been found to have lower variability which suggests that the most skilled golfers are able to utilise all available information to adopt a consistent address position, including both visual and proprioceptive information.

Differences were found in the variability of downswing time but not in the variability of backswing time. Category 4 golfers were more variable in the downswing timing that golfers in other handicap category groups. However, downswing time variability and downswing time were moderately correlated, so the golfers with the lowest variability in downswing time tended to also be the golfers with the shortest downswing time. The regression analysis showed that the variability of the timing variables was not highly related to the variability of the shot outcomes. The increased variability in downswing timing for the Category 4 golfers might be related to the lower clubhead speed achieved by the golfers in this category, rather than being related to the differences in skill level.

5.4.3. Intra-individual variability in ground reaction force and centre of pressure of a large group of amateur golfers.

A. Introduction

The ground reaction forces and centre of pressure can provide a useful indication of the movement of the body, and the consistency of the ground reaction force may give an indication of the overall consistency of the movement system. However, the intra-individual variability of the ground reaction force in the golf swing has not been the subject of significant research interest. The multiple single-subject investigation found no differences between golfers in the magnitude of variability of ground reaction force but observed small differences between golfers in the structure of variability. The highest performing golfer displayed the highest sample entropy in ground reaction force variables, indicating decreased regularity in ground reaction force. This could indicate greater complexity in the movement system, but it is not known whether this is an isolated finding or a general pattern for higher skilled golfers. The aim of this section of the investigation was to examine the magnitude and structure of variability in the ground reaction force and centre of pressure in a large group of golfers.

B. Methods

The conventions and measurement of ground reaction force were the same as described in Section 4.4.4. The variables of interest were the force in the medio-lateral, anterior-posterior and vertical directions (F_x, F_y and F_z) for each force platform (FP1 and FP2) and the force structure (FS). Furthermore, the centre of pressure, in the medio-lateral and anterior-posterior directions (COP_x and COP_y) and the free moment around the vertical axis (T_z) were also calculated for the FS.

All data analysis was performed in MATLAB 2018a (R2018a, Mathworks, Cambridge, UK). Ground reaction force and free moment data were normalised to units of body weight by dividing the ground reaction force by the participant's body weight in Newtons, obtained from the static trial. Centre of pressure data were normalised to the ball position by subtracting the ball position coordinates in the global coordinate system from the centre of pressure coordinates. For each group of shots by a single participant with a single club, trajectories were aligned at the impact point and trimmed to the length of the longest signal from takeaway to impact. Median absolute deviation trajectories were constructed for each participant and club by taking the median absolute deviation at each time point for the group of trajectories. As sample- and cross-sample entropy calculations gave similar results in the multiple single-subject investigation, only the sample entropy of the signals were calculated in this investigation. This was facilitated by aligning all signals into a single pseudo-periodic time-series. The sample-entropy parameters remained the same as in the multiple single-subject investigation: a vector length, m, of 3 and tolerance, r, of 0.005 bodyweights for ground reaction forces, 0.003 m for the centre of pressure and 0.0005 bodyweights·m for the free moment. A single principal components analysis, including all participants and both clubs, was calculated for each variable of interest. The principal components which jointly explained 90% of the variance in the data were retained and single component reconstruction used to visualise the meaning of each principal component (Brandon et al., 2013).

The median pointwise-median absolute deviation, sample entropy and principal component scores were analysed as discrete statistics. The number of outliers detected using previously described methods and the median and median absolute deviation were used to describe these measures. MANOVA tests, using Pillai's trace as the test statistic, were performed to assess differences between participants and discriminant analysis was used to follow up statistically significant results (Field, 2013). Measures of mean or median difference are provided as a measure of effect size. Multiple regression analysis, using a forced entry method, was used to examine the relationships between variables and the variability in the outcome variables total length and shot angle, which were selected to indicate variability in outcome. All statistical analysis was performed in in IBM SPSS Statistics 24 (IBM, Armonk, NY).

C. Results

Force pointwise-median absolute deviation trajectories and sample entropy from the three components of ground reaction force measured by the FS are displayed in Figure 5.16 and the centre of pressure and free moment pointwise-median absolute deviation trajectories and sample entropy are displayed in Figure 5.17. Statistically significant differences between the handicap categories were indicated in the median pointwise-median absolute deviation of the ground reaction force from FP1, FP2 and FS, the centre of pressure and the free moment ($V = 0.37, F(36,585) = 2.30, p < 0.01$). The MANOVA was followed up with discriminant analysis which revealed three discriminant functions explaining 72.8%, 19.0% and 8.1% of the variance (*canonical* R^2 =

0.50, 0.29 and *0.19* respectively). In combination these functions significantly differentiated the groups ($\Lambda = 0.66$, $\chi^2(36) = 82.57$, $p < 0.01$) but did not differentiate between the groups on removal of the first function ($\Lambda = 0.89$, $\chi^2(22) = 24.34$, $p = 0.33$). The correlations between the outcome variables and the first discriminant function indicated that most force variables loaded positively onto this function: FP2 force ($r = 0.73$, *0.83* and *0.32* for the X, Y and Z components respectively), FP1 force ($r = 0.65$, *0.77* and *0.31*) and FS force ($r = 0.43$, *0.61* and *0.50*). The centre of pressure ($r = 0.09$ and *0.28* for X and Y components respectively) and the free moment ($r = 0.03$) loaded less on this function. The function differentiated Category 1 golfers from Category 2 golfers and golfers in Categories 3 and 4, with each group displaying progressively larger values in this function. Category 1 golfers displayed lower average variability in ground reaction force compared to golfers in Categories 2, 3 and 4. Category 2 golfers displayed lower average variability than golfers in Categories 3 and 4 but higher average variability than Category 1 golfers. The differences manifested most in the X and Y component of left foot and right foot force, and no differences were indicated in the X component of centre of pressure or the free moment. The maximum median difference in the median variability between the groups was 0.002, 0.002 and 0.004 bodyweights for the X, Y and Z components, 0.002 and 0.007 m for the X and Y components of centre of pressure, and 0.002 bodyweights·m for the free moment.

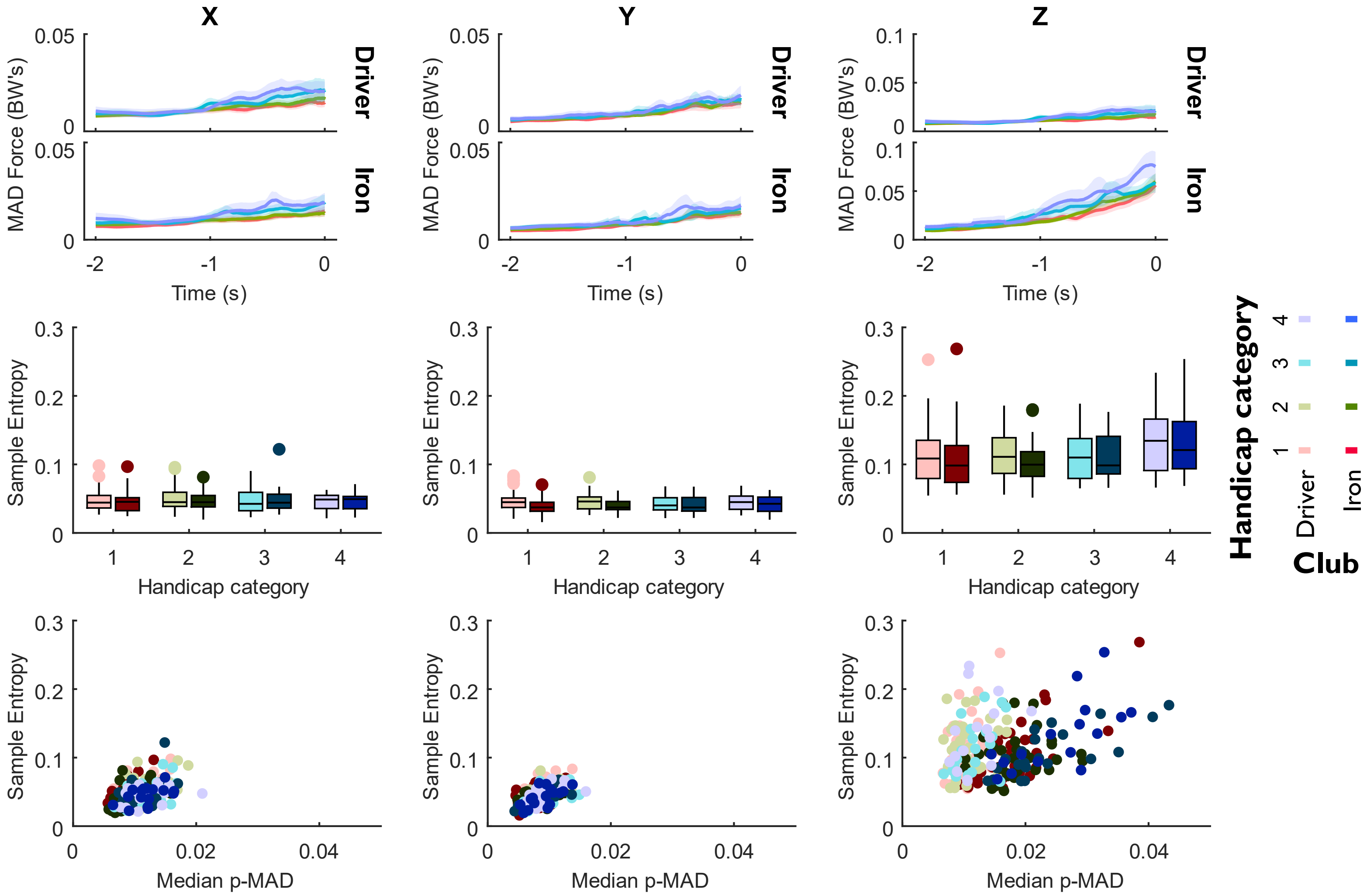


Figure 5.16. Total force median absolute deviation trajectories, sample entropy and sample entropy against average variability for golfers in the four handicap categories.

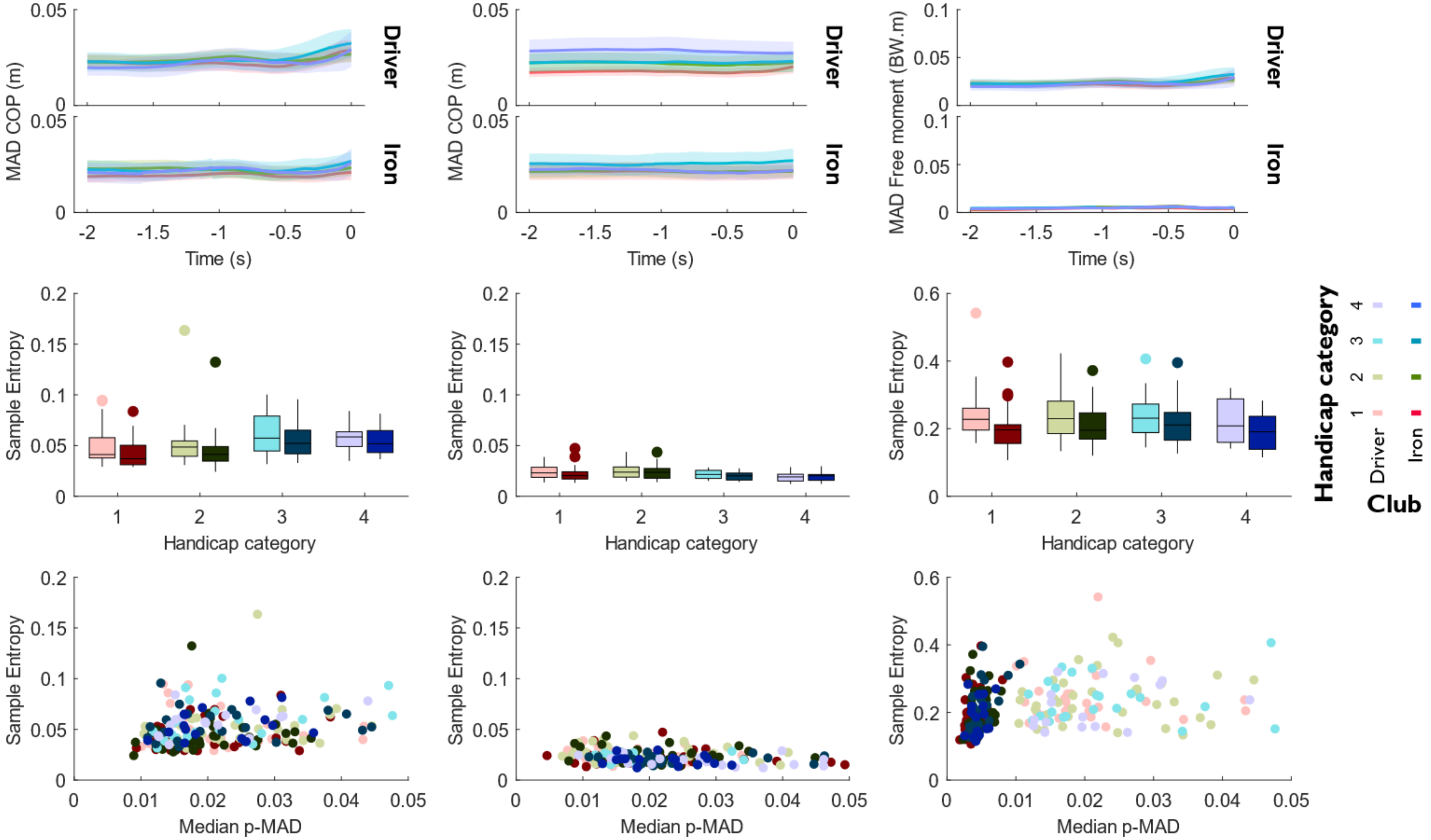


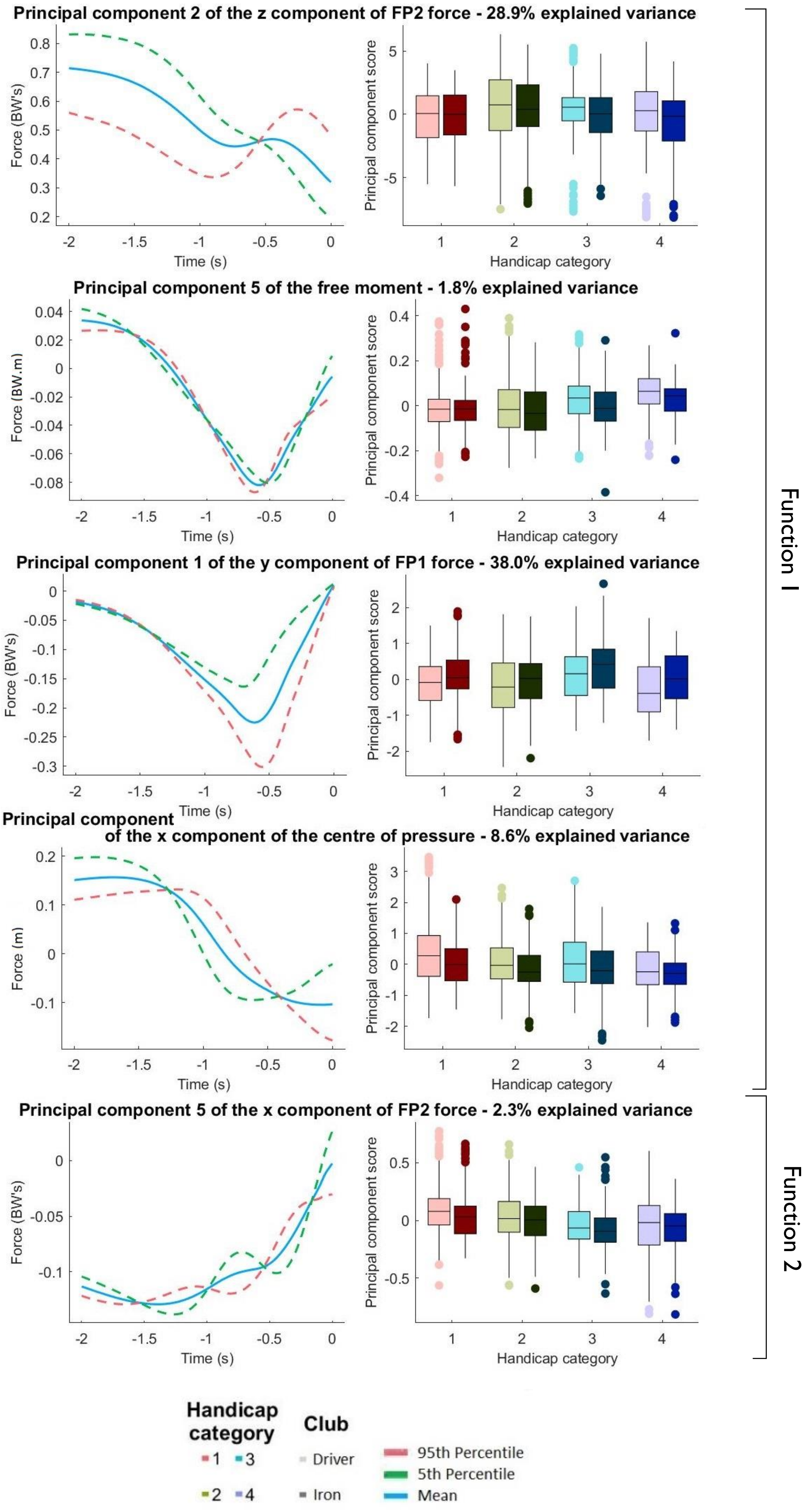
Figure 5.17. Centre of pressure and free moment median absolute deviation trajectories, sample entropy and sample entropy against average variability for golfers in the four handicap categories.

Statistically significant differences between the handicap categories were also indicated in the sample entropy of the ground reaction force variables ($V = 0.38, F(36,585) = 2.36, p < 0.01$). The follow-up discriminant analysis revealed three discriminant functions explaining 62.0%, 29.2% and 8.8% of the variance (*canonical* $R^2 = 0.47, 0.34$ and 0.20 respectively). In combination the functions significantly differentiated the groups ($\Lambda = 0.66, \chi^2(36) = 83.01, p < 0.01$) but did not differentiate between the groups on removal of the first function ($\Lambda = 0.85, \chi^2(22) = 33.07, p = 0.06$). The correlations between the outcome variables and the first discriminant function indicated that the free moment, FS Y and Z component and the FP1 and FP2 Y component loaded positively onto this function. The correlations were as follows: free moment ($r = 0.52$), the FS force ($r = 0.40$ and 0.38 for the Y and Z components respectively), the Y component of FP1 and FP2 force ($r = 0.44$ and 0.35 respectively). The function differentiated Category 1 golfers from Category 2 golfers and Categories 3 and 4, with each group displaying progressively larger values in this function. Category 1 golfers displayed lower sample entropy in the specified components of ground reaction force compared to golfers in Categories 2, 3 and 4. Category 2 golfers displayed lower sample entropy in the specified components of ground reaction force than Categories 3 and 4 but higher than Category 1. The maximum median difference in the sample entropy of the ground reaction forces between the groups was 0.006, 0.006 and 0.028 for the X, Y and Z components of ground reaction force, 0.016 and 0.004 for the X and Y components of centre of pressure, and 0.026 for the free moment. The Pearson's correlation coefficients for the average variability and the sample entropy were between 0.14 and 0.54 for the driver club and 0.28 and 0.59 for the iron club, indicating low to moderate correlation.

There were statistically significant differences indicated in the average variability of ground reaction force variables between the driver and iron club ($V = 0.88, F(12,195) = 116.17, p < 0.01$), but not in the sample entropy between the clubs ($V = 0.07, F(12,195) = 1.22, p = 0.27$). The follow-up analysis on the average median absolute deviation of the ground reaction force variables indicated that a single function was able to explain 100% of the variance in the data (*canonical* $R^2 = 0.94$) and significantly differentiated between the two clubs ($\Lambda = 0.12, \chi^2(12) = 8419.58, p < 0.01$). The Z component of FP1 and FP2 force loaded negatively on this function ($r = -0.43$ and -0.49 respectively) and the free moment loaded positively ($r = 0.49$). Since the driver club displayed greater value in this function on average, the Z component of left foot and right foot force were generally less variable with the driver club and the free moment was generally more variable.

There were also statistically significant differences between the males and females in the average variability ($V = 0.14, F(12,195) = 2.53, p < 0.01$) and the sample entropy ($V = 0.33, F(12,195) = 7.95, p < 0.01$) of ground reaction force variables. Follow-up discriminant analysis indicated one function which discriminated 100% of the variance (*canonical* R^2 *of* *0.37* and *0.57* for the magnitude and structure of variability respectively). The discriminant functions significantly differentiated between male and female golfers in the magnitude ($\Lambda = 0.87, \chi^2(12) = 28.96, p < 0.01$) and structure of variability ($\Lambda = 0.67, \chi^2(12) = 79.68, p < 0.01$). Focusing on the magnitude of variability, the correlations showed that the X and Y components of FP1 force ($r = -0.49$ and -0.24), the X and Y components of FP2 force ($r = -0.50$ and -0.47) and the Y and Z components of FS force ($r = -0.23$ and -0.28) loaded most highly on this function. Since the average value in this function was higher in male golfers, the discriminant function analysis indicated that male golfers generally displayed less variability in the X and Y components of left foot and right foot force and in the Y and Z components of the total force. The correlations for the structure of variability indicated that the free moment ($r = 0.41$) and the y component of the centre of pressure ($r = -0.29$) loaded most on this function. Female golfers displayed a higher average value in this function which indicates that female golfers displayed greater sample entropy in the free moment and lower sample entropy in the Y component of centre of pressure when compared to male golfers.

Regarding the principal components analysis, statistically significant differences were indicated in the principal components scores describing 90% of the variance in the ground reaction force, centre of pressure and free moment trajectories between the four handicap categories ($V = 1.71, F(273,6906) = 33.67, p < 0.01$). Follow-up discriminant analysis found three discriminant functions which accounted for 56.2, 26.6 and 17.3% of the variance in the data (*canonical* $R^2 = 0.80, 0.68$ and *0.60 respectively*). The functions significantly differentiated between the handicap categories together ($\Lambda = 0.12, \chi^2(207) = 4946.55, p < 0.01$), and on removal of the first ($\Lambda = 0.35, \chi^2(136) = 2506.82, p < 0.01$) and second ($\Lambda = 0.64, \chi^2(67) = 1045.40, p < 0.01$) functions. The first function differentiated between golfers in Categories 1 and 2, and those in Categories 3 and 4. Category 1 and Category 2 golfers displayed higher values in this function on average. The second function differentiated Category 1 and Category 3 golfers, with Category 2 and Category 4 golfers displaying progressively higher values in this function. The third function differentiated between golfers in Categories 1 and 4, and those in Categories 2 and 3. Category 2 and Category 3 golfers displayed higher values in this function on average. For first function, an inspection of the loadings showed that the second principal component of the Z component of FP2 force ($r = -0.25$), the fifth principal component of the free moment ($r = 0.21$), the first principal component of the Y component of FP1 force ($r = 0.21$) and the third principal component of the X component of the centre of pressure ($r = 0.21$) loaded most highly onto this function. For the second function, the fifth principal component of the X component of the FP2 force ($r = 0.27$) loaded most highly onto this function. For the third function, the second principal component of the Z component of FS force ($r = -0.28$), the eight principal component of the Z component of FP2 force ($r = 0.27$), the second principal component of the X component of FP1 force and FP2 force ($r = -0.26$ and 0.24 respectively) and the fifth principal component of the Z component of FP2 force ($r = 0.22$) loaded most highly onto this function. The single component reconstruction illustrates the features which these principal components represent in the trajectories (Figure 5.18). Inspection of the principal component scores for these components suggested that the differences indicated by the discriminant analysis were not clear.



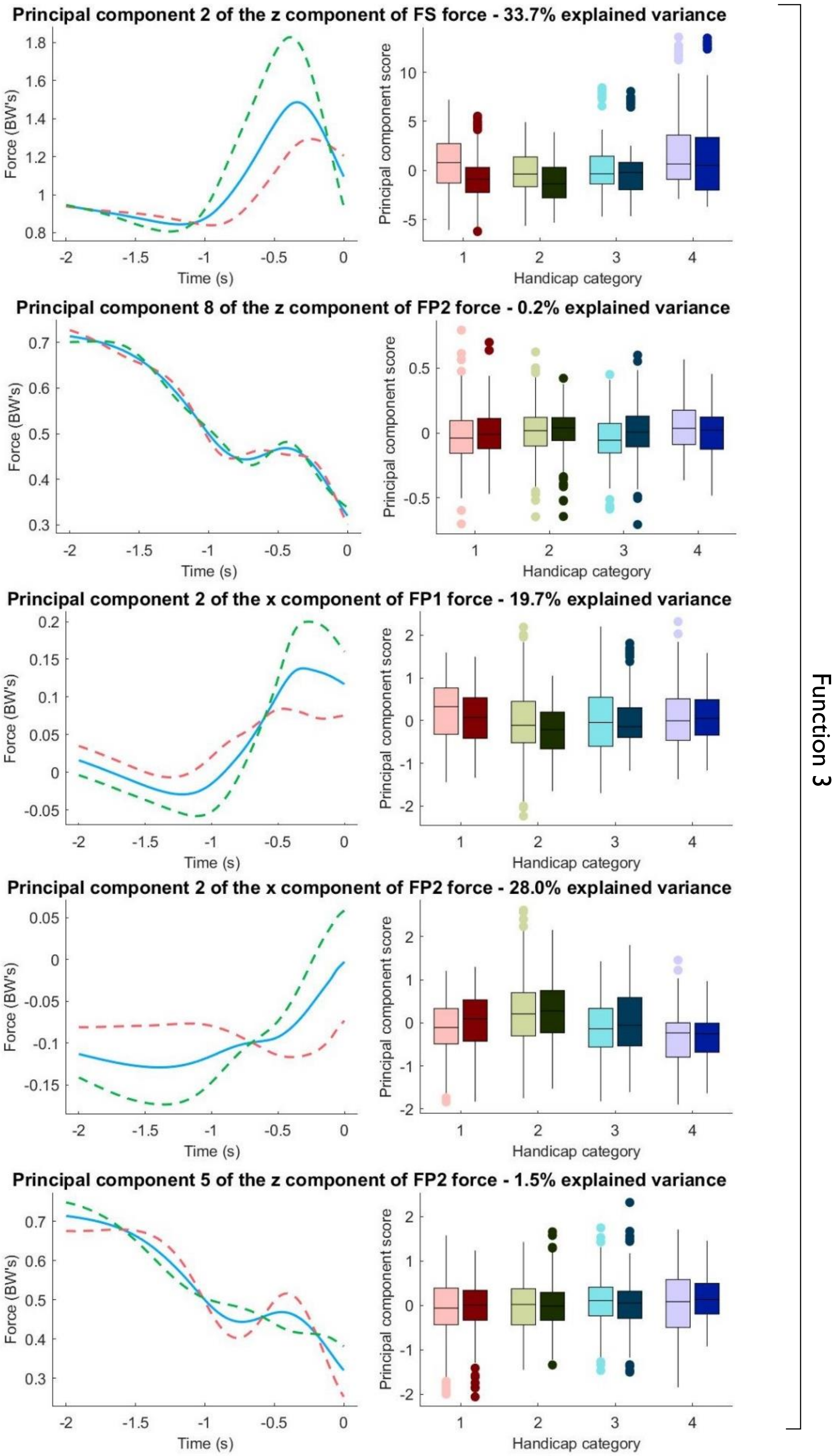
Principal component 2 of the z component of FP2 force - 28.9% explained variance

Principal component 5 of the free moment - 1.8% explained variance

Principal component 1 of the y component of FP1 force - 38.0% explained variance

Principal component of the x component of the centre of pressure - 8.6% explained variance

Principal component 5 of the x component of FP2 force - 2.3% explained variance


Principal component 2 of the z component of FS force - 33.7% explained variance

Principal component 8 of the z component of FP2 force - 0.2% explained variance

Principal component 2 of the x component of FP1 force - 19.7% explained variance

Principal component 2 of the x component of FP2 force - 28.0% explained variance

Principal component 5 of the z component of FP2 force - 1.5% explained variance

Figure 5.18. Single component reconstruction plots for the principal components identified as displaying differences between the golfers in the four handicap categories.

There were statistically significant differences in the principal components scores between the two clubs used ($V = 0.70, F(91,2302) = 58.02, p < 0.01$). Follow-up discriminant analysis found a single discriminant function which accounted for 100% of the variance in the data (*canonical* $R^2 = 0.77$). This function significantly differentiated between the two clubs ($\Lambda = 0.40, \chi^2(65) = 2107.15, p < 0.01$) and the driver club had lower values in this function on average. Inspecting the loadings showed that the fourth principal component of the Y component of FP2 force ($r = -0.33$), the first principal component of the Y component of the centre of pressure ($r = 0.27$) and the second principal component of the X component of FP2 force ($r = 0.22$) loaded most highly onto this function. The fourth principal component of the Y component of FP2 force explained 5.2% of the variance in the trajectory and primarily described a smaller and earlier peak in the ground reaction force. Driver shots showed a larger expression of this principal component. The first principal component of the Y component of the centre of pressure explained 88.6% of the variance in the trajectory and primarily described a shift in trajectory. Iron shots showed a larger expression of this principal component and the Y component of centre of pressure was closer to the ball with iron clubs. The second principal component of the X component of FP2 force explained 28.0% of the variance in the trajectory and primarily described a more negative ground reaction force in the first half of the swing and a larger shift toward a positive ground reaction force in the second half of the swing. Driver shots showed a larger expression of this principal component.

Regression analysis indicated that the variability in ground reaction force, centre of pressure and free moment was not significantly better than a constant model at predicting the variability of total length ($r^2 = 0.09, F(12,195) = 1.53, p = 0.12$) but was significantly better than a constant model at predicting the variability of shot angle ($r^2 = 0.12, F(12,195) = 2.16, p = 0.02$). However, this model was not a good fit for the data as indicated by the small amount of overall variance explained by the model. The structure of the variability in the ground reaction force, centre of pressure and free moment was also not significantly better than a constant model at predicting the variability of total length ($r^2 = 0.04, F(12,195) = 0.65, p = 0.80$) or shot angle ($r^2 = 0.06, F(12,195) = 1.04, p = 0.41$). A regression model with the principal component scores explaining 90% of the variance in the ground reaction force, centre of pressure and free moment variables was significantly better than a constant model at predicting the variability in total length ($r^2 = 0.70, F(86,2306) = 63.19, p < 0.01$) and shot angle ($r^2 =$

0.11, F(86,2306) = 3.27, p < 0.01). The regression model with shot angle as an outcome variable was able to predict only a small amount of the variance in the data but the regression model with total length as an outcome was able to predict a relatively large amount of the variance in the data.

D. Discussion

The pointwise-median absolute deviation trajectories for all participants indicated that the variability of ground reaction force increased through the swing. This pattern was most prominent during the downswing and largest in the vertical component of the ground reaction force. This pattern was not observed in the free moment or centre of pressure data during the swing; the variability in these trajectories remained relatively consistent throughout the swing. The multiple single-subject investigation found the same pattern of increasing variability of ground reaction force during the downswing, and noted that this pattern is opposite to the pattern of decreasing variability observed in hand (Horan et al., 2011) or clubhead trajectories (Morrison et al., 2016). Since the variability of the hand and clubhead trajectories are more closely linked to the variability in the clubhead trajectory, it is possible that the increase in variability of ground reaction force is an indication of compensatory variability occurring in other parts of the system. The uncontrolled manifold hypothesis states that the certain variables can vary to maintain consistency in task important variables. The increase in variability of the ground reaction force during the downswing, could reflect a release of control by the movement system to facilitate greater control over segments which have a direct impact on the clubhead trajectory toward impact.

The overall variability of ground reaction force was relatively low; The maximum variability of ground reaction force during the downswing was under 0.1 bodyweights for all handicap categories. In general, there was a trend for the lower handicap golfers to display lower variability in the ground reaction force throughout the swing with both the iron and driver clubs. However, regression analysis did not indicate a strong relationship between the variability of ground reaction force variables and the variability of shot outcome and the size of differences between the groups was generally small. It is not clear that decreased variability in ground reaction force is beneficial to the golfer, or a trait which is generally shared by low handicap golfers. There were also differences in the magnitude of variability between the two clubs; in general, the vertical ground reaction force was less variable with the driver club swings and the free moment was generally more variable with iron club swings. Whilst the task set to the golfers with both clubs was the same, the difference in variability between the two clubs could indicate that the different clubs place different demands on the golfer such that different movement patterns are necessary to consistently meet the task demands, but these differences were also small.

In the multiple single-subject investigation, the highest skilled golfer displayed higher sample entropy and cross-sample entropy than the two other golfers. That is, variations in ground reaction force were less predictable. However, the highest skilled golfers in this investigation generally displayed the lowest sample entropy in many of the force variables, suggesting that the ground reaction force of higher skilled golfers had lower variability and greater predictability than that of lower skilled golfers. Indeed, Pearson's correlation coefficients showed moderate to strong relationships between the average variability and the sample entropy of the ground reaction force variables. However, the fixed tolerance value lends the sample entropy algorithm to finding a greater number of matches in a signal which has lower overall variability. Whilst the most common finding in the extant literature is of an inverted U relationship between the structure of variability and performance, with extremely structured or unstructured patterns indicative of worse performance (Newell and Slifkin, 1998), the ideal structure of variability in the golf swing is unknown. As with the magnitude of variability, the structure of variability in the ground reaction force was not strongly related to the variability in shot outcome.

The principal components analysis highlighted inter-individual differences in ground reaction force, centre of pressure and free moment trajectories between the participants. Differences between the handicap category groups were small and there were no compelling differences which separated the golfers. Previous research has found differences between differently skilled golfers in the ground reaction force trajectories (Lynn et al., 2012) but the participants studied were from two highly different groups, whereas the participants in this investigation were spread across a range of handicaps. This could reduce the investigations ability to detect differences between golfers with at the extremes of handicap. Rather, this investigation suggests that there are several features which describe the ground reaction force, centre of pressure and free moment trajectories which are not different between differently skilled golfers.

5.4.4. Intra-individual variability in club kinematics of a large group of differently skilled golfers with driver and iron clubs.

A. Introduction

The multiple-single subject investigation found statistically significant differences in the magnitude and structure of variability in the kinematics of the golf swing, but the size of these differences was small, and it was hypothesised that these differences were reflective of the specific individuals studied; not more widely generalisable. This investigation chose to focus on the variability of ground reaction forces as an indication of movement variability, due to the significantly simpler testing set-up required. However, the placement of markers on the club facilitated an examination of the global club kinematics and the variability of global club angle during the golf swing. The aim of this section of the investigation was to examine the magnitude and structure of variability the club kinematics of a large group of golfers.

B. Methods

The global club angle was calculated as the YXZ Cardan angle between the shaft coordinate system and the global coordinate system. Additional markers placed away from the shaft axis were not used in this investigation, as participants feedback indicated that they were a distraction during the multiple-single subject investigation. This means that only the first two rotations in the sequence have meaning, as the third is defined arbitrarily and not tracked. The rotations of the club about the long axis of the shaft were therefore not measured in this investigation. Analysis of the global club angle followed the procedures described for the analysis of ground reaction force in Section 5.4.3. These procedures included trajectory alignment and trimming, construction of a pointwise-median absolute deviation trajectory, calculation of sample entropy (tolerance, $r = 0.9°$), principal components analysis, statistical hypothesis testing and multiple regression.

C. Results

The club angle trajectories, pointwise-median absolute deviation trajectories and sample entropy are displayed in Figure 5.19. Statistically significant differences between the handicap categories in the median pointwise-median absolute deviation of the club angle were indicated by a MANOVA and Pillai's trace statistic ($V = 0.25, F(6,408) =$

9.74, $p < 0.01$). The MANOVA was followed up with discriminant analysis which revealed two discriminant functions explaining 98.9% and 1.1% of the variance (*canonical* $R^2 = 0.50$ and 0.06 respectively). In combination these functions significantly differentiated the groups ($\Lambda = 0.75$, $\chi^2(6) = 58.60$, $p < 0.01$) but did not differentiate between the groups on removal of the first function ($\Lambda = 0.99$, $\chi^2(2) = 0.77$ $p = 0.68$). The first function differentiated all handicap category groups from each other, with Category 1 golfers displaying the lowest average value and the average value increasing for subsequent categories. Category 1 golfers displayed the lowest variability in global club angle and the variability in global club angle increased for the higher handicap category groups. The maximum median difference in average variability between handicap groups was 0.70° and 1.10° for the X and Y components of the global club angle respectively.

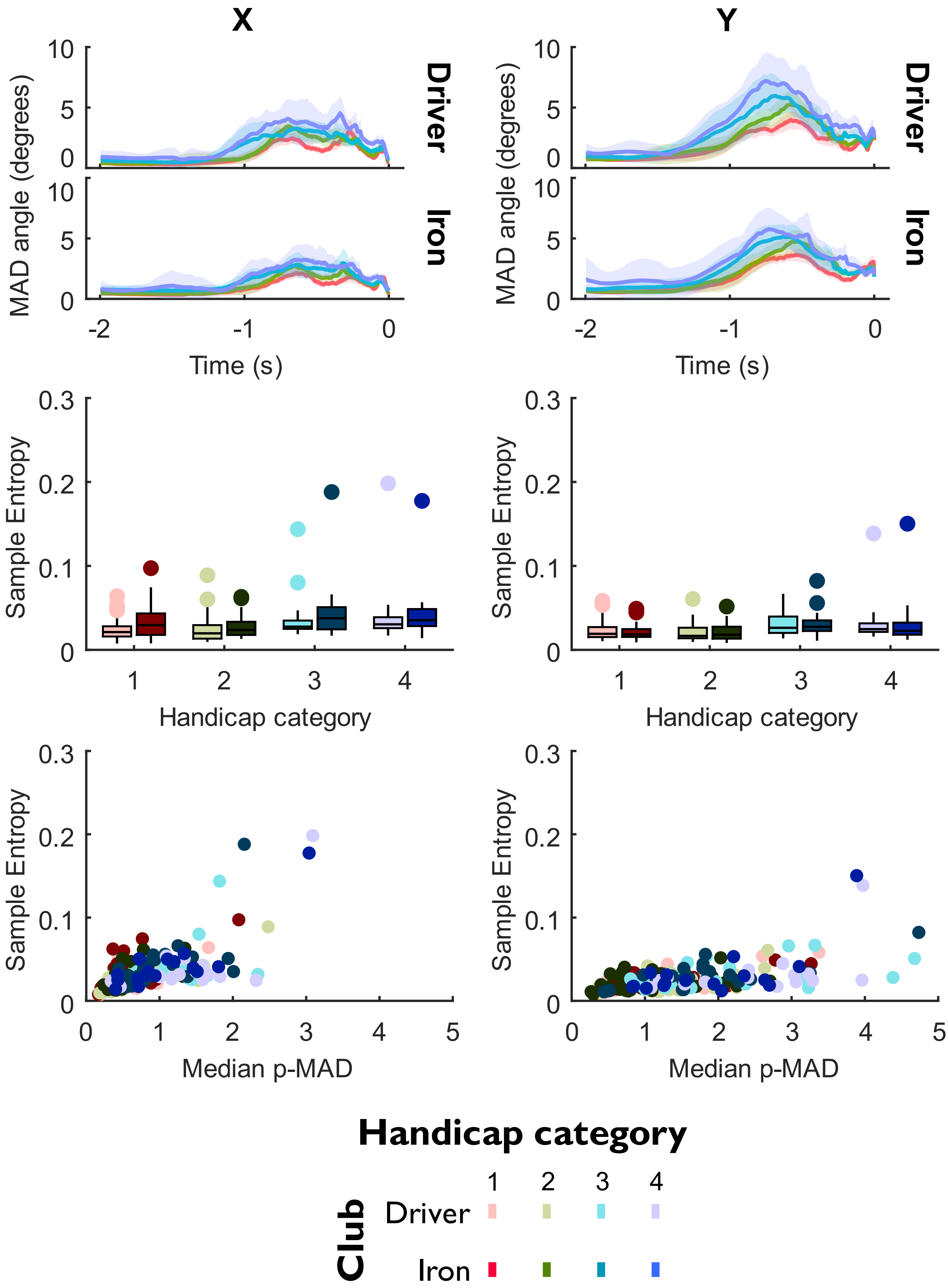


Figure 5.19. Global club angle median absolute deviation trajectories, sample entropy and sample entropy against average variability for golfers in the four handicap categories.

There were also statistically significant differences between the handicap categories in the sample entropy of the global club angle (*$V = 0.08$, $F(4,408) = 2.85$, $p = 0.01$*). The follow-up discriminant analysis revealed two discriminant functions explaining 92.5% and 7.5% of the variance (*canonical $R^2 = 0.27$* and *0.08* respectively). In combination these functions significantly differentiated the groups (*$\Lambda = 0.92$, $\chi^2(6) = 17.02$, $p = 0.01$*) but did not differentiate between the groups on removal of the first function (*$\Lambda = 0.99$, $\chi^2(2) = 1.32$, $p = 0.52$*). The correlations between the outcome variables and the first discriminant function indicated that sample entropy of the Y component of the global club angle loaded more highly onto this function than the X component (*$r = 0.86$* and *0.20* respectively). The function differentiated Categories 1 and 2 from Categories 3 and 4, with Category 3 and Category 4 golfers displaying larger average values in this function. Category 1 and Category 2 golfers displayed lower sample entropy in the global club angle compared to Category 3 and Category 4 golfers. The maximum median difference in sample entropy between handicap groups was 0.009 and 0.009 for the X and Y components of the global club angle respectively. The correlations between average variability and sample entropy were 0.66 and 0.57 with the driver and 0.72 and 0.61 with the iron for the X and Y components of global club angle respectively.

Regression analysis indicated that the average variability in global club angle was significantly better than a constant model at predicting the variability of total length (*$r^2 = 0.09$, $F(2,205) = 10.23$, $p < 0.01$*) and shot angle (*$r^2 = 0.08$, $F(2,205) = 8.47$, $p < 0.01$*). However, the models were not a good fit for the data as only a small amount of overall variance was explained by the model. The structure of the variability in the global club angle was not significantly better than a constant model at predicting the variability of total length (*$r^2 = 0.01$ $F(12,205) = 0.47$, $p = 0.62$*) or shot angle (*$r^2 = 0.03$, $F(2,205) = 2.82$, $p = 0.06$*).

D. Discussion

Whilst the variability of the centre of pressure tended to remain constant throughout the swing and the variability of the ground reaction forces tended to increase in the second prior to impact; the variability of global club angle tended to increase through the backswing to a maximum about 0.6-0.8 seconds prior to impact. The variability of the global club angle then decreased until impact. Similar patterns have been reported in the literature; Morrison, McGrath and Wallace (2014) found that clubhead variability increased through the backswing and decreased during the downswing, a finding also reported by Horan, Evans and Kavanagh (2011). The general patterns of club angle variability appear to be shared by golfers of all skill levels, with higher skilled golfers able to maintain a lower variability throughout the swing and at impact. The average variability and the sample entropy of global club angle were lower in the lower handicap groups, compared to the higher handicap groups and the correlations between the magnitude and structure of variability were moderate. However, neither the magnitude or structure of variability were able to explain a significant proportion of the variability in shot outcome. These results are similar to those observed in the ground reaction force data, although the relationship between skill and global club angle variability during the swing are less surprising given the existing literature regarding the clubhead (Morrison et al., 2014) and hand variability (Horan et al., 2011). It appears there is a reduction in the variability of segments which influence the clubhead variability during the downswing to attain low clubhead presentation variability at impact. This relationship has been observed in this investigation and in the existing literature.

5.5. Summary of cross-sectional investigation of the intra-individual variability of a large group of differently skilled golfers

5.5.1. Section objectives

This section presents a summary and general discussion of the results from the preceding sub-sections of the investigation. In this section, the results will be considered jointly and the relationships between variables in different sub-investigations will be discussed.

5.5.2. Summary

The data presented in this investigation presents compelling evidence that the variability in shot outcome, ball launch and clubhead presentation variables is lower in highly skilled golfers than in lower skilled golfers. The investigation extended previous research, which focused on shots with the driver (Betzler et al., 2012), to include shots with an iron club. Similar patterns were observed with both clubs but the correlations in the variability between the driver and iron club were moderate at best. Thus, whilst more highly skilled golfers were generally less variable in outcome measures, variability with the driver was not a particularly good predictor for their variability with the iron club.

In general, there was support for the lowest handicap golfers displaying the lowest variability in the address variables, the ground reaction force and the global club angle, but not in the centre of pressure or free moment. However, the differences between the handicap groups were small and there was a large amount of inter-individual variability in movement variability. Whilst lower handicap golfers generally displayed lower variability in many of the variables, there was a large amount of overlap between the groups. Furthermore, the relationships between movement and outcome variability were weak and there was no clear evidence that low movement variability was necessary to achieve low outcome variability. Indeed, there were participants with low movement variability but high outcome variability and vice-versa. This is not to say that no such relationship exists, but the methods used in this investigation did not provide strong evidence of a relationship.

Individual specific patterns were evident in all areas of the investigation and these patterns did not appear to be related to the skill of the golfer. There was a wide range of physical characteristics, age and skill levels displayed by the golfers in this investigation and the golfer's movements tended to be equally heterogeneous. Using two highly different groups, such as a high skilled and a low skilled group of similar golfers, may provide the investigation with greater power to find differences between the groups, but such groups do not provide the rich knowledge which comes from the study of a breadth of golfers.

5.6. Chapter summary

This chapter presented a cross-sectional investigation of many amateur golfers with a range of skill levels, hitting full golf shots with two different clubs. A comprehensive analysis of shot outcome, address position and ground reaction force kinetics were presented. In agreement with existing literature, the highest skill golfers displayed the lowest variability in shot outcome, ball launch and clubhead presentation variables, but the variability with a driver club was not highly correlated with variability with the driver club. For variables concerned with the variability of movement, the higher skilled groups of golfers were less variable than the lower skilled groups in several variables, but there were also variables where the variability did not appear to differ between groups. Furthermore, differences between the groups were small and there was a large amount of inter-individual variation and cross-over between the skill groups. It was therefore not clear that a reduction in movement variability was related to reduced outcome variability or an unrelated trait generally shared by the better golfers in this investigation.

6. Discussion and summary

6.1. Chapter objectives

The chapter will discuss the research questions studied in this thesis with reference to the data collected and existing literature, address the limitations of the research, and suggest possible future research.

6.2. Research overview

The main objective of the research was to characterise variability in the golf swing and how this may differ in relation to other factors. As such, it may first help to characterise the experimental work conducted in relation to Equation 2.1:

$$V_T = V_{nl} + V_{eb} + V_{em}$$

Initial work considered the methods, as these have the potential to influence the results and their interpretation (James, 2004). Existing literature and investigations which attempted to minimise other sources of variability were used to estimate the variability relating to the measurement error (Vem). Later investigations considered only the total variability (VT), but this understanding of the potential magnitude of measurement error provides context to these results.

The multiple-single subject investigation did not aim to provide generalisable results, instead guiding the development of a cohort investigation which considered many golfers. The study recruited 104 golfers, more than 95% of the studies published in the journal Sports Biomechanics between 1985 and 2014 (Vagenas et al., 2018), and considered many facets of the variability of the golf swing. This is a large contribution to the scientific literature considering movement and outcome variability in the golf swing and allowed significant insight into the research questions posed in this thesis.

6.3. Intra-individual variability and golfing skill

How does intra-individual variability in the golf swing relate to golfing skill?

To understand the relation to golfing skill, it is necessary to clearly understand how skill is defined. Research has used several methods to categorise differently skilled participants, including competition level (Schorer et al., 2007), a performance test

(Robins et al., 2008) and task performance (Verhoeven and Newell, 2016), but handicap remains the most common measure in golf research. Skill was indicated in this thesis by two measures; handicap, a general indicator of potential scoring, and shot score, a specific measure of task performance. Generally, analysis in this thesis was performed according to the CONGU handicap categories, as this makes comparison to existing literature easiest, but other methods could lead to alternative interpretations. Whilst the lowest handicap golfers generally had the highest task performance, the relationship between task performance and handicap was weak ($|r| < 0.26$) and there was overlap in performance between handicap category groups.

Using handicap as an indication of golfing skill, the finding with the largest effect size was that golfers in the higher handicap category groups displayed significantly more variability in shot outcome, ball launch and clubhead presentation variables than golfers in the lower handicap category groups. This result is well documented in existing literature in golf (Betzler et al., 2012), and reduced outcome variability in higher skilled performers is also a common finding in wider research (Preatoni et al., 2013). Novel to this thesis was the concurrent measurements of outcome and movement variables, but differences in other variables, such as the variability of address position, kinematics or kinetics, were much smaller than in the outcome variables.

6.4. Variability of movement and outcome

Is the relationship between intra-individual variability of movement and golfing skill different to the relationship between intra-individual variability of outcome and golfing skill?

Wider research has indicated that the relationship between variability and skill may depend on the variable studied, and whether that variable concerns the outcome or the movement (Preatoni et al., 2013). There is a large body of evidence investigating the variability of outcome measures in the golf swing, including the differences observed in the shot outcome, ball launch and clubhead presentation variables observed in this thesis, and it seems clear that outcome variability decreases with increasing skill. In contrast, there is less research which considers movement variability in the golf swing and the relationships are somewhat less clear.

The most compelling research on movement variability in the golf swing considers the clubhead; clubhead variability tends to peak during the backswing and decrease during the downswing toward impact (Horan et al., 2011; Morrison et al., 2016; Tucker et al., 2013). The variability of the clubhead was not examined in this thesis, but similar patterns in the variability of the global club angle were observed. This is unsurprising as they are measurements of the same object, although the club shaft flexes during the swing. Variation in club movement during the backswing seems to necessitate a decrease in variability during the downswing, which funnel the club movement toward consistency at impact. This decrease was observed for all levels of golfer, suggesting that this pattern of variability has more utility than maintaining consistency throughout the swing, but the lowest handicap golfers also displayed lower average variability, suggesting that consistency throughout the swing remains favourable. The pattern of variability may also be related to the dynamics of the movement, as variability is highest at the top of the backswing, where clubhead speed is lowest, and decreases in the downswing as clubhead speed increases.

Patterns in the variability of address position and swing timing are less clear. The variability of address has been the subject of some research (Bradshaw et al., 2009; Langdown et al., 2013a), but existing findings have been mixed. Data in this thesis found lower handicap golfers to have lower variability in all address variables studied, but differences in variability tended to be small and relationships between address position variability and shot outcome were weak. Lower variability in address did not appear to be a determinant of outcome consistency, and it is not clear that it is desirable; despite being a characteristic generally shared by lower handicap golfers. The small amount of research into the variability of swing timing is also inconclusive, with some suggestions that the variability of swing timing in highly skilled golfers is low (Corke, 2015). In this thesis, swing timing variability was higher in the Category 4 golfers, but the difference was small. As backswing time variability was also larger than downswing time variability, it could be that differences in timing variability are caused by differences in the speed of the club rather than reflecting strategies which enable outcome consistency. Furthermore, relationships between swing timing variability and outcome variability were weak and, it does not appear as though the variability in swing timing is an important consideration for ensuring outcome consistency.

The intra-individual variability of ground reaction forces during the golf swing had been the subject of little previous research, but a pattern of increasing variability prior to impact was consistently observed in this thesis. This finding, coupled with the decrease in variability of the club angle during the downswing and the consistency of the clubhead at impact, provides indirect evidence for compensatory variability during the swing. Increased variability in ground reaction force suggests slight differences in movement from swing to swing. These differences could be compensatory movements which enable outcome consistency but could also be movements unimportant to the outcome. Since the variability of ground reaction force was generally lower in the lower handicap golfers, it appears that movement consistency may still play a role in ensuring outcome consistency; although differences were small and there was a large amount of overlap between the handicap groups. Overall, the data suggests that both movement consistency and compensatory variability are possible strategies for achieving outcome consistency and may be individual specific.

To summarise, there is a clear relationship between outcome variability and skill, but the relationship between movement variability and skill is less clear and dependent on the variables being studied. However, there are interesting patterns of variability in the club movement and ground reaction force which might indicate the presence of compensatory coordination.

6.5. Magnitude and structure of variability

Is the relationship between the magnitude of intra-individual variability and golfing skill different to the relationship between the structure of intra-individual variability and golfing skill?

Theoretically, it is important to consider both the structure and magnitude of variability but, there were no clear differences in the structure of variability between the handicap groups. Whilst differences were observed in the structure of ground reaction force variability, indicated by the sample entropy, these were small and could have been related to differences in the magnitude of variability rather than different movement strategies. This examination of the structure of variability was novel in golf biomechanics research and, although differences between the handicap categories would have been more striking, the lack of a clear difference is an interesting finding. The findings are specific to the methods used, which may not be sensitive to differences. The use of novel methods has increased understanding of variability the golf swing (for example, Morrison et al., 2016; Sweeny et al., 2014; Tucker et al., 2013) and should be encouraged to further increase understanding of the structure of variability in the golf swing.

6.6. Inter-session variability

How does intra-individual variability in the golf swing differ between repeated testing sessions?

There were no clear patterns in the inter-session variability; rather the five golfers displayed generally similar amounts of inter-session variability. Variability was generally more stable than the average value between sessions, but both showed some inter-session differences which were generally larger than the intra-session variability. These findings are in broad agreement with existing literature (Corke, 2015) but research in this area is limited. Ideally, this research would have been continued throughout the thesis, but the recruitment of many participants was prioritised in the later investigation. Nonetheless, the multiple single-subject investigation provides a useful starting point for further research into the inter-session variability in the golf swing. This research would be beneficial to the biomechanics community because the inter-session variability provides context in which differences in traditional biomechanical investigations can be interpreted.

6.7. Variability with iron and driver clubs

How does intra-individual variability in the golf swing differ with different golf clubs?

Most research into variability in the golf swing utilised a driver club, but this thesis extended research by considering variability with two clubs. A thorough description of variability with an iron club had not been previously presented in the literature but, in general, patterns of variability observed with the driver and the 5-iron club were similar throughout across all variables studied. This thesis also extended research by considering variability with both clubs in the same session; allowing the relationship between the clubs to be considered. Interestingly, this relationship was not particularly strong ($r < 0.5$). For example, lower handicap golfers tended to be the least variable in outcome with both clubs but an individual's variability with the driver was not a good indicator of an individual's variability with the iron club. Interestingly, the task set to the golfers remained the same with both clubs, so it is unclear if variability in the golf swing is more strongly related to the task, rather than the club.

6.8. Additional findings

Throughout the research, inter-individual variability was ubiquitous, and these differences were generally greater in magnitude than intra-individual variability. In comparison to the range of movement patterns displayed, participants were relatively consistent in repeating their own signature movement patterns. It was not the purpose of this research to separate golfers into groups based on their movement patterns, as has been done in previous investigations (for example, Ball and Best, 2007) and, if possible, it is not clear that such classification would provide meaningful information. Whilst this could be a potential avenue for further research, the data collected suggests that golfers have the characteristic of continua, rather than distinct groups, and discretising these differences into groups may not aid in understanding. Indeed, there was overlap between the handicap category groups in most observed differences. These inter-individual differences make hypotheses around compensatory variability difficult, as the structures in which compensatory variability may occur, or the characteristics of this variability, could be individual specific.

Whilst not an applied body of research, there are interesting implications for practice contained in this thesis. The data highlights both inter- and intra-individual variability in the golfers studied, suggesting that there is no single perfect swing, or indeed one perfect swing for everyone. Rather than a focus on the movement, an individual's swing should be evaluated based on its outcome. Coaches and practitioners could aid golfers to develop individual movement patterns with a focus on consistent outcomes, instead of coaching specific features of the movement. Appendix E contains tables with the average shot outcome, ball launch, clubhead presentation, address and swing timing for the different handicap categories which may be an interesting reference for practitioners. Although the values should not be considered optimum, they provide an indication of the approximate value and variability for amateur golfers with both a 5-iron and driver.

6.9. Limitations and recommendations for future work

Although the programme of work has contributed significantly to the literature, the limitations of the work should be acknowledged and considered in the planning of future research. Firstly, the investigations contained within this thesis were primarily descriptive, and cannot infer causality. Whilst descriptive research remains an essential step in the development of innovative hypotheses and interventions (Bishop, 2008), it is not possible to suggest that a change toward the movement or movement variability displayed by the lower handicap golfers would result in increased performance. Future applied research could consider whether an intervention could decrease the outcome variability of a group of golfers and whether a decrease in outcome variability was associated with a decrease in movement variability. Alternatively, a longitudinal investigation, where golfers are tested several times over a long period, could investigate if changes in movement or outcome variability are related to changes in handicap or task performance. Future work could also consider differences in variability between injured and uninjured golfers, as has been considered in running gait (Heiderscheit et al., 2002), but difficulties controlling for injury characteristics and golfing skill might make this research practically difficult.

The characteristics of the golfers studied are another potential limitation of the research because, whilst the golfers covered the range of CONGU handicap categories, they do not represent the range of possible skills. Research which includes both professional and novice golfers would prove useful in extending the research to a broader skill range than was considered in this investigation. Including golfers with extremely high or low skill could help to discover patterns which were not evident in this research and could be particularly revealing if a U-shaped relationship between movement variability and skill exists. This relationship has been observed in wider literature (Wilson et al., 2008) but not in the golf swing. However, recruiting participants with the desired skills could be difficult because professional golfers are fewer in number and extremely novice golfers tend to be unwilling to volunteer for scientific research. Both the cohort study and previous work by Betzler et al. (2012) recruited a large group of golfers which was biased toward male golfers in handicap category 2; this seems to be the easiest group to recruit.

The ecological validity of the results is somewhat unknown, since it is not possible to quantify the differences between the data collected and on-course performance. It may be interesting to consider varying the task set to the golfers in future research, since movement variability is inherently linked to constraints (Davids et al., 2003). The task in this thesis was consistent with both clubs, but golfers face a variety of tasks during a round of golf and the relative value of accuracy and distance varies from shot to shot. Outside of research into the putting stroke, research has generally failed to consider tasks where accuracy is the primary concern. It could be hypothesised that the number of potential movement solutions declines as the participant approaches their maximum shot distance and expected that movement variability would be greater in a shot for accuracy compared to distance. Research could consider the variability of shots with a short iron toward an easily reachable target and investigate whether the movement solutions adopted are more variable than those observed in this thesis.

Compensatory variability has been observed in several movements, including table tennis (Bootsma and van Wieringen, 1990), basketball free-throw (Robins et al., 2008), targeted throwing (Muller and Sternad, 2004) and pistol shooting (Arutyunyan et al., 1969) but, because the golf swing is a full body movement with a large number of mechanical degrees of freedom, it is unclear where compensatory variability would manifest. Indirect evidence for compensatory variability exists in the literature (for example Sweeny et al., 2014) and in this thesis, but future research is necessary to achieve a greater understanding of compensatory variability. Since the hand trajectory displays a reduction in variability in the downswing, like that observed in the clubhead (Horan et al., 2011), there is a basis to begin investigations into compensatory variability with the movement of the arms. Whilst the multiple single-subject investigation did not provide evidence of compensatory variability in the arm movements, future investigations could utilise novel measures, such as continuous relative phase (Lamb and Stöckl, 2014) or vector coding (Needham et al., 2015). Another interesting starting point could be to consider the potential for a proximal to distal increase in variability, as this has been observed in the other movements and might be linked to compensatory variability (Robins et al., 2008; Wagner et al., 2012; Whiteside et al., 2013). Ultimately, further exploratory work is required, possibly utilising a multiple single-subject research design, before larger group-based studies of compensatory coordination can provide meaningful results.

Movement and outcome variability of the golf swing of amateur golfers with driver and iron clubs

There is variability in all human movement, even that of expert performers

Variability is not necessarily a sign of error

There is a lack of research into variability in the golf swing

Driver Iron

Variability in handwriting

Results

Size of effect

Large

Lower handicap golfers display lower variability in:
Shot outcomes, ball launch and clubhead presentation

Decrease in variability of club angle and increase in variability of ground reaction force during the downswing displayed by all handicap groups

Small

Low handicap golfers display lower variability in address position but there is a large overlap between groups and a weak relationship with outcome variability

Lower handicap golfers display lower variability in club angle and ground reaction force during the whole swing
Inter-individual differences are generally larger than intra-individual variability

No strong relationship in the variability with the driver and iron club

None

No clear differences in:
- The variability of swing timing
- The structure of variability in any variable
- Between-session variability but this is generally larger than the within-session variability

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R&A

Figure 6.1. Summary of thesis findings

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Appendices

A. Marker locations and definitions of landmarks, segments and joint angles in the kinematic model for the multiple single-subject investigation.

Table A.1. Anatomical description of marker locations for markers tracked by the full body optical motion capture system.

Marker	Positioning
HdF	Middle of forehead - on hat
HdL/HdR	Approximately 1.5cm anterior to the top of the ears - on hat
C7	Spinous process of the 7th cervical vertebrae
Stn*	Sternal notch
Xph*	Xiphoid process
LThor/RThor	Approximately 5cm inferior and lateral of the C7 marker
LASIS/RASIS	Superior to the anterior superior iliac spine - on Velcro belt
LPSIS/RPSIS	Superior to the posterior superior iliac spine - on Velcro belt
LAS/RPS	Lateral aspect of coracoid Process
LSS/RSS	Superior aspect of acromion Process
LPS/RPS	Ventral aspect of coracoid Process
LBi/RBi	Anterior border of deltoid and biceps brachii
LTri/RTri	Posterior border of deltoid and biceps brachii
LLE/RLE	Lateral epicondyle of the elbow
RME*/LME*	Medial epicondyle of the elbow
LUP/RUP	Approximately 5cm distal from the olecranon along the ulnar border
LUD/RUD	Approximately 10cm distal from the olecranon along the ulnar border
LWTC/RWTC	Approximately 4cm proximal of the wrist on the central dorsal aspect of the forearm
LWTL/RWTL	Approximately 4cm proximal and 3cm lateral of the LWTC marker
LWTM/RWTM	Approximately 4cm proximal and 3cm medial of the LWTC marker
LLW/RLW	Radial styloid of the wrist
LMW*/RMW*	Ulna styloid of the wrist
LCH*/RCH*	Approximately 5cm distal of the wrist on the central dorsal aspect of the hand
LLH*/RLH*	Between the 2nd and 3rd metacarpophalangeal joints on the dorsal aspect of the hand
LMH*/RMH*	Between the 4th and 5th metacarpophalangeal joints on the dorsal aspect of the hand
LTHP/RTHP	Approximately 15cm proximal and 3cm posterior of the LLK marker
LTHD/RTHD	Approximately 12cm proximal and 3cm anterior of the LLK marker

LLK/RLK	Lateral condyle of the knee
LMK*/RMK*	Medial condyle of the knee
LTT/RTT	Tibial tuberosity
LLA/RLA	Lateral malleolus of the ankle
LMA/RMA	Medial malleolus of the ankle
LH/RH	Superior to the posterior aspect of the calcaneus on the shoe
L1MT/R1MT	Superior to the 1st metatarsophalangeal joint - on the shoe
L2MT/R2MT	Superior to the 2nd metatarsophalangeal joint - on the shoe
L5MT/R5MT	Superior to the 5th metatarsophalangeal joint - on the shoe
Shaft Top	Retroreflective tape approximately 2cm distal of the grip
Shaft Front/Shaft Rear	19mm diameter spherical markers on the ends of a 10cm rod secured equidistant to the Shaft Top and Shaft Centre markers
Shaft Centre	Retroreflective tape approximately 20cm distal of the grip
Shaft Bottom	Retroreflective tape approximately 2cm proximal of the ferrule

* Marker removed after functional joint trials completed

Table A.2. Definition of virtual landmarks used to define the kinematic model.

Landmark	Definition
HeadDist	The HdF marker projected onto the line which passes through the ThoraxProx and ThoraxDist landmarks
HeadCentre	The HeadDist marker shifted an arbitrary distance (0.27m) along the line which passes through HeadDist, ThoraxProx and ThoraxDist
ThoraxProx	The Xph marker projected onto the line which passes through the ThoraxDist and PelvisMid Landmarks
ThoraxDist	The midpoint of the line connecting the C7 and Stn markers
ThoraxY	The ThoraxDist landmark shifted an arbitrary distance (0.06m) perpendicular to the plane which passes through ThoraxDist, ThoraxProx and C7 (to the right)
PelvisMid	The midpoint of the line connecting the PelvisAnt and PelvisPost landmarks
PelvisAnt	The midpoint of the line connecting the LASIS and RASIS markers
PelvisPost	The midpoint of the line connecting the LPSIS and RPSIS markers
PelvisZ	The PelvisAnt landmark shifted an arbitrary distance (0.06m) perpendicular to the plane which passes through PelvisAnt, PelvisProx and RASIS (downwards)
MidScap	The Stn marker projected onto the line which passes through the PelvisPost landmark and C7 marker
Left/Right ScapulaX	The MidScap landmark shifted an arbitrary distance (0.06m) perpendicular to the line which passes through MidScap and L/RPS on the plane which includes the line and the ThoraxY landmark (forwards)
Func Left/Right Shoulder	Landmark created at centre of rotation from functional joint trial
Left/Right MidElbow	The midpoint of the line connecting the L/RLE and L/RME markers
Func Left/Right Elbow	Landmark created at centre of rotation from functional joint trial
Func Left/Right Elbow_X	Landmark created along joint axis from functional joint trial

Func Left/Right MidElbow	The L/R MidElbow marker projected onto the line which passes through the Func L/R Elbow and Func L/R Elbow_X landmarks
Func Left/Right Wrist	Landmark created at centre of rotation from functional joint trial
Left/Right Ulna Y	The Func L/R MidElbow landmark shifted an arbitrary distance (0.06m) perpendicular to the plane which passes through Func L/R MidElbow, Func L/R Elbow_X and L/RMW (forwards)
Func L/R R-U	Landmark created at centre of rotation from functional joint trial
Func L/R R-U_X	Landmark created along joint axis from functional joint trial
L/R Radius Elbow	The L/R MidElbow marker projected onto the line which passes through the Func L/R R-U and Func L/R R-U_X landmarks
L/R RadiusY	The L/R Radius Elbow landmark shifted an arbitrary distance (0.06m) perpendicular to the plane which passes through L/R Radius Elbow, L/RLW and L/RMW (forwards)
Func L/R Hip	Landmark created at centre of rotation from functional joint trial
L/R MidKnee	The midpoint of the line connecting the L/RLK and L/RMK markers
Func L/R Knee	Landmark created at centre of rotation from functional joint trial
Func L/R Knee_X	Landmark created along joint axis from functional joint trial
Func L/R MidKnee	The L/R MidKnee marker projected onto the line which passes through the Func L/R Knee and Func L/R Knee_X landmarks
Func L/R Ankle	Landmark created at centre of rotation from functional joint trial

Table A.3. Definition of segments included in the kinematic model.

Segment	Origin	X-axis	Y-axis	Z-axis	Tracking targets
Head	HeadDist	The line connecting the HeadDist landmark with the HdF marker, pointing forwards	The line which is mutually perpendicular to the X and Z axes, pointing right	The line connecting the HeadCentre and HeadDist landmarks, pointing upwards	HdF, HdL, HdR
Thorax/Ab	ThoraxDist	The line which is mutually perpendicular to the Y and Z axes, pointing forwards	The line connecting the ThoraxDist and ThoraxY landmarks, pointing right	The line connecting the ThoraxProx and ThoraxDist landmarks, pointing upwards	C7, LThor, RThor
Pelvis	PelvisAnt	The line which is mutually perpendicular to the Y and Z axes, pointing forwards	The line connecting the PelvisAnt landmark with the RASIS marker, pointing right	The line connecting the PelvisAnt and PelvisZ landmarks, pointing upwards	LASIS, LPSIS, RASIS, RPSIS
Right/Left Upper Arm	Func Left/Right Shoulder	The line perpendicular to the Z-axis and laying in the plane formed by the Z-axis and the L/RMW marker when arms bent at 90°, pointing forwards	The line which is mutually perpendicular to the X and Z axes, pointing right	The line connecting the Func L/R Shoulder and Func L/R MidElbow landmarks, pointing upwards	L/RBi, L/Rtri, L/RLE
Right/Left Forearm	Func Left/Right MidElbow	The line which is mutually perpendicular to the Y and Z axes, pointing forwards	The line connecting the Func L/R Wrist landmark with the L/RMW marker, pointing right	The line connecting the Func L/R MidElbow and Func L/R Wrist landmarks, pointing upwards	L/RWTC, L/RWTL, L/RWTM

Right/Left Thigh	Func Left/Right Hip	The line which is mutually perpendicular to the Y and Z axes, pointing forwards	The line perpendicular to the Z-axis and laying in the plane formed by the Z-axis and the Func L/R Knee_X landmark in neutral stance, pointing right	The line connecting the Func L/R Hip and Func L/R MidKnee landmarks, pointing upwards	L/RTHP, L/RTHD, L/RLK
Right/Left Shank	Func L/R MidKnee	The line which is mutually perpendicular to the Y and Z axes, pointing forwards	The line perpendicular to the Z-axis and laying in the plane formed by the Z-axis and the L/RLA landmark in neutral stance, pointing right	The line connecting the Func L/R MidKnee and Func L/R Ankle landmarks, pointing upwards	L/RTT, L/RLA, L/RMA
Right/Left Foot	Func L/R Ankle	The line perpendicular to the Z-axis and laying in the plane formed by the Z-axis and the global Z-axis, pointing upwards	The line which is mutually perpendicular to the X and Z axes, pointing right	The line connecting the Func L/R Ankle landmark and the L/R2MT marker, pointing backwards	L/RH, L/R1MT, L/R2MT, L/R5MT
Shaft	Shaft Top	The line which is mutually perpendicular to the Y and Z axes, pointing forwards	The line perpendicular to the Z-axis and laying in the plane formed by the Z-axis and the Shaft Front marker, pointing right	The line connecting the Shaft Top and Shaft Centre landmarks, pointing upwards	Shaft Top, Shaft Front, Shaft Rear, Shaft Centre, Shaft Bottom

Table A.4. Definition of joint angles calculated from the kinematic model.

Joint angle	Segment	Reference segment	Rotation sequence
Pelvis-torso	Pelvis	Thorax/Ab	ZYX
Neck	Thorax/Ab	Head	ZYX
Shoulder (L + R)	Upper arm (L + R)	Thorax/Ab	YXY
Elbow (L + R)	Forearm (L + R)	Upper arm (L + R)	ZXY
Wrist (L + R)	Shaft	Forearm (L + R)	YZY
Ankle angle (L + R)	Foot (L + R)	Shank (L + R)	YZY
Knee angle (L + R)	Shank (L + R)	Thigh (L + R)	ZXY
Hip angle (L + R)	Thigh (L + R)	Pelvis	ZXY
Global club angle	Shaft	Lab	YXZ

B. Effect of changing constant on the shot score variable.

The shot score variable described in the thesis penalised deviation from the target line using a quadratic function with a constant (Equation 4.1). The effect of changing this constant is shown in FIG for different constant values and FIG for the same constant (1/5000) but different total shot length. The chosen constant, 1/5000, was selected as it resulted in a qualitatively acceptable penalty for deviation from the target line.

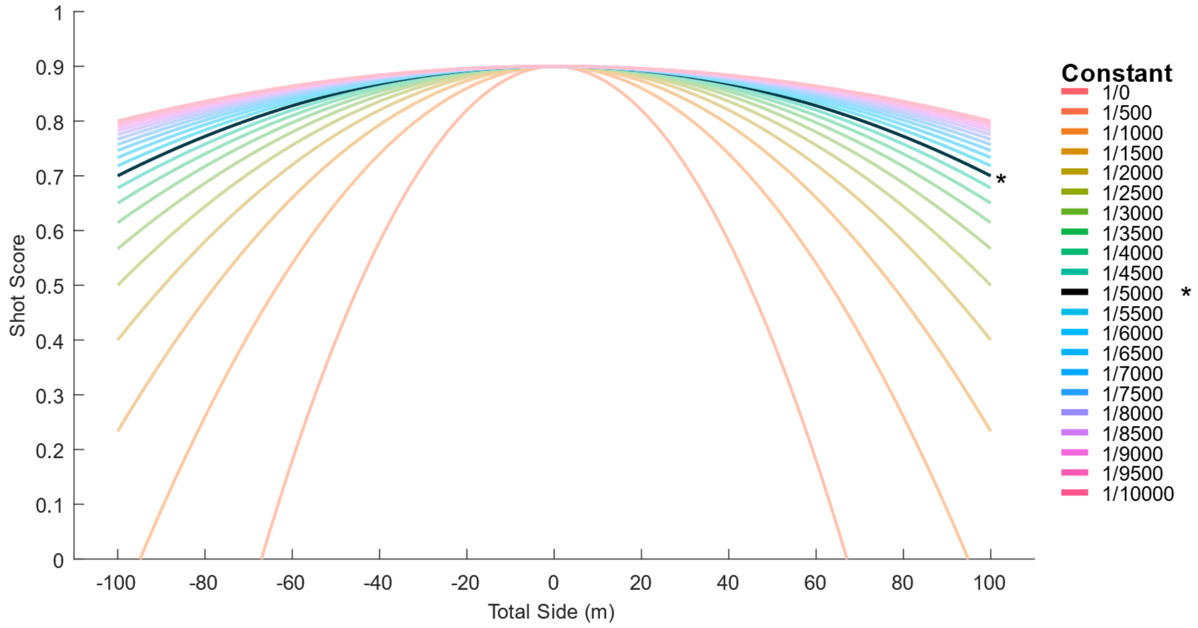

Figure B.1. The effect of changing the shot score constant for shots with different deviation from the target line (total side).

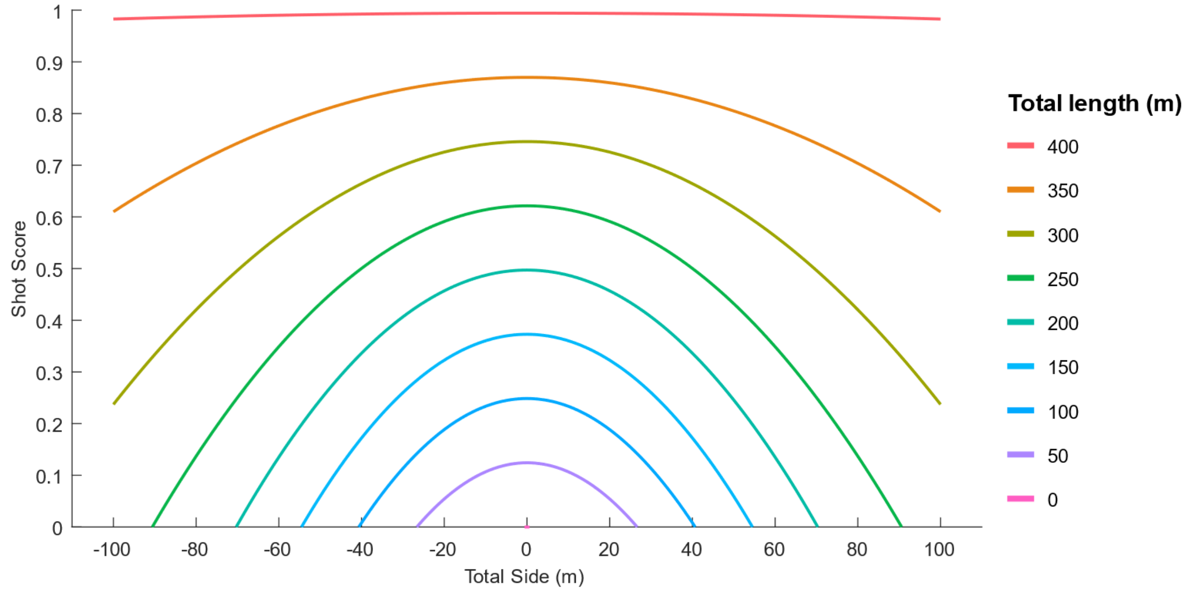

Figure B.2. The shot score for shots of different total length and total side (reference distance = 402.3 m).

C. Full results tables from multiple single-subject investigation.

Table C.1. Median, median absolute deviation (MAD) and outliers for the shot outcome variables in the multiple single-subject investigation.

Driver		No. Shots (discarded)	Carry length (m)			Carry side (m)			Total length (m)			Total side (m)		
			Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	10 (0)	146.4	7.5	0	10.0	6.6	0	162.9	7.0	0	9.4	7.0	0
	Session 2	10 (2)	141.6	7.6	0	18.4	1.2	4	156.5	7.4	0	19.0	1.5	3
	Session 3	10 (1)	130.3	6.4	0	15.0	4.6	1	147.1	3.7	2	16.4	5.4	1
Participant 2 Handicap = 8	Session 1	10 (2)	211.7	4.7	0	14.3	15.6	0	228.0	4.2	1	13.0	16.0	0
	Session 2	10 (1)	227.8	9.1	0	-1.8	10.3	0	254.8	8.3	1	-4.4	13.0	0
	Session 3	10 (2)	220.9	7.2	0	-7.5	12.3	0	243.5	3.9	0	-9.8	13.8	0
Participant 3 Handicap = 22	Session 1	10 (0)	164.3	5.9	1	19.8	7.3	0	184.8	7.1	0	22.7	6.9	0
	Session 2	10 (0)	147.4	10.1	0	7.5	3.8	0	167.7	9.3	0	10.1	4.2	0
	Session 3	10 (0)	158.5	9.9	0	5.9	7.7	1	177.5	11.7	0	8.0	7.5	0
Participant 4 Handicap = 18	Session 1	10 (0)	173.8	5.8	1	-3.6	9.2	0	189.6	3.5	0	-4.1	9.7	0
	Session 2	10 (0)	176.7	7.1	0	4.6	9.1	0	185.9	8.0	0	4.4	8.8	0
	Session 3	10 (0)	192.6	2.6	1	-1.9	6.9	1	207.2	4.4	2	-2.2	7.6	1
Participant 5 Handicap = 4	Session 1	10 (0)	197.6	3.0	0	4.4	2.6	0	224.1	3.6	0	2.8	4.5	0
	Session 2	10 (3)	198.0	2.6	0	6.9	9.6	0	220.6	3.3	0	4.3	10.8	0
	Session 3	10 (0)	203.7	3.0	1	1.6	6.1	0	234.0	6.4	1	-0.1	6.4	0

		Shot angle (°)			Shot score			Subjective rating (0-5)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	1.5	0.1	1	0.39	0.03	0	3.5	0.0	1
	Session 2	1.4	0.0	2	0.34	0.04	2	3.0	0.5	0
	Session 3	1.5	0.0	1	0.33	0.03	1	3.0	0.5	0
Participant 2 Handicap = 8	Session 1	1.5	0.1	0	0.53	0.03	0	4.0	0.5	0
	Session 2	0.0	1.5	0	0.62	0.03	0	3.8	0.8	0
	Session 3	-1.4	0.1	0	0.59	0.01	1	4.0	0.5	0
Participant 3 Handicap = 22	Session 1	1.4	0.0	0	0.40	0.03	0	3.0	0.0	2
	Session 2	1.5	0.0	1	0.40	0.03	1	3.0	1.0	0
	Session 3	1.5	0.1	0	0.44	0.05	0	3.0	0.5	0
Participant 4 Handicap = 18	Session 1	-1.5	0.1	0	0.45	0.01	0	3.0	1.0	0
	Session 2	1.5	0.1	0	0.44	0.02	0	3.5	0.5	0
	Session 3	-1.5	0.1	0	0.50	0.02	1	4.0	0.5	0
Participant 5 Handicap = 4	Session 1	1.5	0.0	0	0.55	0.01	0	3.3	0.5	0
	Session 2	1.5	0.1	0	0.54	0.01	1	3.0	0.0	0
	Session 3	0.0	1.5	0	0.57	0.01	1	4.0	0.3	2

Iron		No. Shots	Carry length (m)			Carry side (m)			Total length (m)			Total side (m)		
		(discarded)	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	10 (1)	116.2	9.2	0	4.3	3.4	0	131.2	9.4	0	3.9	3.7	1
	Session 2	10 (1)	120.5	3.6	0	13.0	5.4	0	131.9	6.8	0	13.0	6.1	0
	Session 3	10 (0)	107.3	1.6	2	7.5	6.6	0	119.9	4.6	0	7.5	6.5	0
Participant 2 Handicap = 8	Session 1	10 (0)	172.8	1.7	2	1.5	7.1	0	187.2	2.9	1	-0.6	8.0	0
	Session 2	10 (1)	170.4	8.0	0	-1.8	4.4	1	191.7	7.7	0	-4.5	4.3	1
	Session 3	10 (2)	176.7	3.7	0	-0.5	4.6	0	190.4	4.2	0	-1.7	4.8	0
Participant 3 Handicap = 22	Session 1	10 (1)	124.4	11.4	1	2.8	8.0	0	137.9	12.1	0	3.2	9.3	0
	Session 2	10 (0)	128.0	3.3	0	8.0	4.7	0	140.5	3.3	1	8.5	4.7	0
	Session 3	10 (0)	127.2	11.9	0	0.2	2.1	3	138.3	11.7	0	0.8	2.1	3
Participant 4 Handicap = 18	Session 1	10 (0)	132.9	3.3	0	-0.1	7.8	0	137.8	3.5	0	-0.3	7.5	0
	Session 2	10 (2)	132.3	3.9	0	-3.8	13.2	0	136.0	4.3	0	-4.0	13.2	0
	Session 3	10 (1)	128.6	4.1	0	-2.8	6.9	0	133.5	6.0	0	-3.2	6.9	0
Participant 5 Handicap = 4	Session 1	10 (1)	157.8	2.4	2	1.0	5.3	0	172.6	3.8	0	0.1	5.8	0
	Session 2	10 (2)	158.4	3.6	1	-2.6	4.7	0	172.7	4.2	1	-3.5	5.4	0
	Session 3	10 (1)	159.3	6.8	0	4.7	5.4	0	176.4	9.1	0	3.8	5.8	0

		Shot angle (°)			Shot score			Subjective rating (0-5)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	1.5	0.1	2	0.45	0.04	1	2.5	0.5	0
	Session 2	1.5	0.1	0	0.44	0.04	0	3.0	0.5	0
	Session 3	1.5	0.1	1	0.42	0.02	0	2.5	0.5	0
Participant 2 Handicap = 8	Session 1	0.0	1.5	0	0.65	0.02	0	3.5	0.5	0
	Session 2	-1.5	0.0	0	0.67	0.03	0	3.5	0.5	0
	Session 3	-1.5	0.0	0	0.66	0.02	1	4.0	0.0	2
Participant 3 Handicap = 22	Session 1	1.4	0.1	0	0.48	0.05	0	3.0	1.0	0
	Session 2	1.5	0.0	0	0.48	0.01	1	3.0	0.0	0
	Session 3	1.5	0.1	0	0.48	0.05	0	3.0	1.0	0
Participant 4 Handicap = 18	Session 1	0.1	1.5	0	0.47	0.02	0	3.0	1.0	0
	Session 2	-1.4	0.1	0	0.47	0.02	0	3.0	0.0	4
	Session 3	-1.5	0.1	0	0.47	0.02	0	3.0	1.0	0
Participant 5 Handicap = 4	Session 1	0.0	1.5	0	0.60	0.02	0	3.0	0.3	1
	Session 2	-1.5	0.1	0	0.60	0.01	1	3.3	0.8	0
	Session 3	1.5	0.0	0	0.62	0.03	0	3.5	0.5	0

Table C.2. Median, median absolute deviation (MAD) and outliers for the ball launch variables in the multiple single-subject investigation.

Driver		Ball speed ($m \cdot s^{-1}$)			Efficiency			Launch angle (°)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	48.6	0.6	0	1.42	0.01	0	17.6	1.4	1
	Session 2	49.2	0.8	0	1.41	0.01	0	17.6	2.2	0
	Session 3	47.6	0.6	1	1.41	0.01	1	17.3	1.8	2
Participant 2 Handicap = 8	Session 1	66.8	0.8	0	1.44	0.01	1	9.6	1.4	0
	Session 2	68.6	0.7	1	1.45	0.01	0	10.8	1.2	0
	Session 3	69.2	0.8	0	1.45	0.01	0	8.5	1.7	0
Participant 3 Handicap = 22	Session 1	55.0	0.8	1	1.40	0.02	1	13.8	1.3	0
	Session 2	52.2	0.8	0	1.36	0.03	0	14.1	2.0	0
	Session 3	54.3	0.8	0	1.41	0.02	0	11.5	1.2	0
Participant 4 Handicap = 18	Session 1	58.5	0.8	0	1.43	0.02	0	11.5	2.1	0
	Session 2	58.5	0.8	0	1.43	0.02	0	14.4	0.5	2
	Session 3	59.5	0.6	1	1.46	0.01	1	15.4	1.1	1
Participant 5 Handicap = 4	Session 1	62.9	0.5	0	1.48	0.01	0	11.6	1.0	0
	Session 2	62.6	0.2	1	1.47	0.01	1	12.3	1.2	0
	Session 3	62.9	0.6	1	1.47	0.01	1	12.3	1.0	0

		Launch direction (°)			Spin rate (rad·s^{-1})			Spin axis (°)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	3.2	1.9	0	399	36	0	1.5	3.1	0
	Session 2	5.7	2.0	0	444	25	1	4.7	1.9	0
	Session 3	5.0	2.5	0	392	73	0	5.7	5.0	0
Participant 2 Handicap = 8	Session 1	6.1	3.1	0	368	36	0	-5.7	5.5	0
	Session 2	6.4	1.2	0	312	37	0	-9.3	6.1	0
	Session 3	4.4	1.4	1	340	34	0	-10.0	6.0	0
Participant 3 Handicap = 22	Session 1	-0.3	2.4	0	365	51	0	14.1	2.0	0
	Session 2	-3.3	1.5	0	389	32	1	15.9	3.5	0
	Session 3	-5.5	1.5	0	351	54	0	13.4	2.9	0
Participant 4 Handicap = 18	Session 1	0.4	1.1	0	327	19	2	-1.7	3.8	0
	Session 2	0.8	1.3	0	357	36	0	0.4	4.2	0
	Session 3	2.0	2.3	0	295	11	3	-4.0	4.9	2
Participant 5 Handicap = 4	Session 1	4.4	1.3	0	253	14	0	-6.2	6.4	0
	Session 2	5.1	1.2	1	264	21	1	-3.7	3.5	0
	Session 3	2.5	2.1	0	250	28	0	-2.6	4.2	0

Iron		Ball speed ($m \cdot s^{-1}$)			Efficiency			Launch angle (°)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1	Session 1	41.8	1.3	0	1.38	0.04	0	22.3	1.1	0
Handicap = 13	Session 2	43.5	0.9	0	1.39	0.03	0	22.3	1.4	0
	Session 3	40.6	0.2	3	1.35	0.02	2	21.1	1.8	0
Participant 2	Session 1	57.1	0.9	1	1.41	0.01	1	12.4	1.1	0
Handicap = 8	Session 2	56.2	1.1	0	1.41	0.03	0	13.8	1.5	1
	Session 3	58.5	0.7	1	1.45	0.01	1	12.5	0.4	2
Participant 3	Session 1	46.6	1.6	1	1.35	0.07	1	17.4	1.3	0
Handicap = 22	Session 2	46.0	0.6	1	1.36	0.02	0	21.5	1.1	0
	Session 3	45.8	2.5	0	1.36	0.06	0	21.5	1.3	0
Participant 4	Session 1	48.6	1.0	0	1.42	0.02	0	20.1	0.4	1
Handicap = 18	Session 2	49.4	0.2	1	1.43	0.01	2	20.3	0.9	0
	Session 3	47.1	0.8	0	1.38	0.03	0	21.3	1.0	0
Participant 5	Session 1	53.8	0.8	1	1.46	0.02	0	12.7	0.8	0
Handicap = 4	Session 2	53.0	0.2	1	1.46	0.01	1	12.8	0.4	1
	Session 3	53.0	0.8	0	1.45	0.02	0	13.9	0.9	0

		Launch direction (°)			Spin rate (rad·s^{-1})			Spin axis (°)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1	Session 1	5.7	2.5	0	453	42	0	-2.7	4.4	1
Handicap = 13	Session 2	7.3	2.3	0	510	32	0	-0.3	3.6	0
	Session 3	4.5	2.8	0	450	17	0	-0.9	2.6	2
Participant 2	Session 1	9.9	0.9	2	458	6	2	-13.2	2.9	0
Handicap = 8	Session 2	8.2	0.7	0	453	14	0	-13.9	4.7	0
	Session 3	8.3	0.9	0	454	11	2	-15.4	3.1	0
Participant 3	Session 1	-1.2	1.9	0	563	49	0	4.6	4.5	0
Handicap = 22	Session 2	-1.0	1.6	0	546	61	0	7.7	2.4	0
	Session 3	-4.9	1.7	0	555	43	0	6.1	3.0	0
Participant 4	Session 1	3.5	0.8	1	505	13	0	-4.3	3.3	0
Handicap = 18	Session 2	2.8	1.4	0	487	37	0	-5.1	5.4	0
	Session 3	2.8	1.2	0	468	54	0	-5.3	3.3	0
Participant 5	Session 1	5.4	1.4	0	437	23	0	-8.2	4.9	0
Handicap = 4	Session 2	5.1	0.5	0	425	13	1	-9.0	4.2	0
	Session 3	4.8	0.5	2	456	19	0	-4.1	0.8	4

Table C.3. Median, median absolute deviation (MAD) and outliers for the clubhead presentation variables in the multiple single-subject investigation.

Driver		Clubhead speed (m·s^{-1})			Attack angle (°)			Path angle (°)			Face angle (°)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	33.8	0.5	0	5.3	0.6	1	1.7	1.2	0	8.8	3.5	0
	Session 2	34.8	0.4	0	5.6	0.4	0	2.4	0.7	0	11.5	2.7	0
	Session 3	33.9	0.3	0	6.8	1.1	0	2.4	1.3	0	9.5	2.4	1
Participant 2 Handicap = 8	Session 1	46.3	0.4	1	2.3	0.3	0	5.1	1.0	0	4.1	1.8	0
	Session 2	47.4	0.2	1	2.3	0.5	1	6.8	0.7	0	3.6	0.7	0
	Session 3	47.5	0.2	0	2.5	0.6	0	7.7	1.1	0	4.7	2.2	0
Participant 3 Handicap = 22	Session 1	39.4	0.2	0	1.1	0.3	1	1.3	1.3	0	8.1	2.0	0
	Session 2	38.4	0.2	0	-0.1	0.4	1	-3.2	1.0	0	5.3	2.0	0
	Session 3	38.7	0.2	1	0.5	0.4	0	-3.3	1.0	0	4.0	2.6	0
Participant 4 Handicap = 18	Session 1	40.8	0.2	0	7.1	0.3	0	4.0	0.5	0	3.9	1.1	0
	Session 2	40.6	0.3	0	7.6	0.6	0	4.4	0.4	0	5.3	2.0	0
	Session 3	40.9	0.3	0	7.8	0.4	0	5.4	0.4	0	4.6	1.4	1
Participant 5 Handicap = 4	Session 1	42.6	0.2	0	5.6	0.6	0	5.7	0.9	0	3.3	1.0	0
	Session 2	42.2	0.1	0	6.2	0.3	0	4.1	0.2	3	3.3	1.4	0
	Session 3	42.8	0.2	0	4.6	0.3	1	4.1	1.0	0	3.5	1.3	0

		Effective loft (°)			Effective lie (°)			Horizontal impact location (mm)			Vertical impact location (mm)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	21.8	1.8	1	9.7	0.5	0	-3.9	7.1	0	-7.3	5.7	0
	Session 2	22.0	0.8	0	8.5	0.6	0	2.5	7.9	0	-12.2	3.5	0
	Session 3	22.1	1.7	1	7.7	0.9	0	-0.2	10.0	1	-14.0	7.4	0
Participant 2 Handicap = 8	Session 1	12.6	0.9	0	2.8	1.9	0	-10.2	4.6	1	-11.1	3.6	2
	Session 2	12.4	1.5	0	0.8	0.5	3	-10.4	8.8	0	-2.7	4.9	0
	Session 3	11.7	1.8	0	2.0	1.4	0	-8.3	9.5	0	-8.1	3.7	0
Participant 3 Handicap = 22	Session 1	15.1	1.3	1	6.4	0.6	1	15.6	6.3	1	5.1	3.5	1
	Session 2	15.7	0.9	2	7.1	0.5	0	21.1	9.4	0	8.1	6.2	0
	Session 3	14.8	1.8	0	8.2	0.5	0	14.2	9.8	0	-1.7	3.3	0
Participant 4 Handicap = 18	Session 1	18.3	0.9	1	6.1	0.9	0	9.9	4.6	0	-15.7	4.0	0
	Session 2	18.5	1.8	0	5.7	0.6	0	6.5	6.1	0	-9.6	3.7	0
	Session 3	17.5	0.7	1	6.4	0.9	0	2.7	2.8	3	-5.4	4.8	0
Participant 5 Handicap = 4	Session 1	12.5	0.8	0	0.7	0.5	0	-4.4	9.0	0	-4.7	2.1	0
	Session 2	14.5	1.0	0	0.3	0.3	1	-5.6	4.9	0	-3.7	3.1	1
	Session 3	12.7	0.5	1	0.8	0.3	1	-2.6	4.7	0	-1.3	5.5	0

Iron		Clubhead speed ($m \cdot s^{-1}$)			Attack angle (°)			Path angle (°)			Face angle (°)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	30.4	0.3	0	1.9	0.2	0	7.0	0.4	1	6.3	2.8	0
	Session 2	31.0	0.2	0	2.1	0.6	0	7.1	1.3	0	8.7	2.1	0
	Session 3	30.2	0.3	0	1.9	0.3	2	6.5	0.9	0	5.9	2.6	0
Participant 2 Handicap = 8	Session 1	40.5	0.3	0	-2.2	0.6	2	12.0	1.2	0	4.2	0.8	1
	Session 2	40.3	0.3	0	-2.0	1.1	0	13.5	0.7	0	4.9	0.7	0
	Session 3	40.4	0.2	1	-2.5	0.3	1	13.9	1.0	0	6.4	1.4	0
Participant 3 Handicap = 22	Session 1	34.1	0.3	0	-0.3	0.5	0	-1.4	0.9	0	1.4	2.6	0
	Session 2	33.7	0.2	0	-0.4	0.4	0	-5.2	0.9	0	1.0	1.9	0
	Session 3	33.8	0.1	1	0.2	0.3	0	-4.3	0.5	0	-0.5	1.5	0
Participant 4 Handicap = 18	Session 1	34.7	0.1	0	2.5	0.5	1	6.3	0.4	1	4.7	1.7	0
	Session 2	34.6	0.2	0	2.6	0.6	0	6.3	0.8	0	3.9	1.9	0
	Session 3	34.2	0.6	0	3.1	0.6	2	7.5	0.5	1	5.0	2.1	0
Participant 5 Handicap = 4	Session 1	36.8	0.2	0	-3.0	0.6	0	6.6	0.9	0	3.7	1.2	0
	Session 2	36.4	0.3	0	-2.7	0.3	0	5.8	1.0	0	2.8	0.8	0
	Session 3	36.8	0.2	0	-2.9	0.5	0	5.7	0.6	1	4.9	0.9	0

		Effective loft (°)			Effective lie (°)			Horizontal impact location (mm)			Vertical impact location (mm)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	27.8	0.9	0	0.1	0.8	0	10.6	4.7	0	-2.8	8.3	0
	Session 2	30.0	1.3	0	-0.3	0.5	0	6.6	1.5	3	-10.4	4.5	0
	Session 3	28.6	1.5	0	-0.4	0.8	0	2.9	4.2	0	-16.9	2.2	1
Participant 2 Handicap = 8	Session 1	21.4	1.3	0	-7.6	0.9	0	-18.6	3.7	0	-12.4	3.3	0
	Session 2	21.3	1.3	0	-9.0	0.7	0	-16.5	2.3	1	-2.7	3.9	0
	Session 3	22.1	1.6	0	-7.3	1.1	0	-5.9	4.3	1	-8.7	2.7	0
Participant 3 Handicap = 22	Session 1	24.4	1.6	0	-2.4	1.0	0	3.0	9.4	0	-11.5	1.7	3
	Session 2	28.0	1.4	0	-0.4	0.9	0	7.2	4.8	0	-4.1	3.7	0
	Session 3	27.2	1.2	0	-0.8	0.5	0	9.0	4.3	1	-0.3	6.4	0
Participant 4 Handicap = 18	Session 1	26.5	0.9	0	-1.2	0.3	0	6.4	3.9	0	-9.9	4.6	0
	Session 2	25.7	1.6	0	-1.9	0.7	0	5.6	4.4	0	-5.0	2.4	0
	Session 3	26.8	1.8	0	0.8	0.5	0	11.2	5.6	0	1.1	4.3	0
Participant 5 Handicap = 4	Session 1	18.1	1.1	1	-4.3	1.0	0	0.4	4.4	1	-7.1	2.2	1
	Session 2	19.1	1.1	1	-4.1	0.8	1	0.8	4.6	0	-5.9	2.2	0
	Session 3	18.6	1.0	0	-4.3	0.3	1	-7.9	4.0	0	-5.5	2.2	0

Table C.4. Median, median absolute deviation (MAD) and outliers for the stance position and alignment variables in the multiple single-subject investigation.

Driver		Stance width (m)			Stance width %			Stance depth (m)			Ball position (m)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	0.52	0.01	0	127.7	2.6	0	0.84	0.01	2	0.03	0.01	0
	Session 2	0.52	0.01	0	128.1	1.2	0	0.88	0.01	0	0.08	0.01	0
	Session 3	0.53	0.01	0	131.6	3.8	0	0.84	0.00	0	0.01	0.00	0
Participant 2 Handicap = 8	Session 1	0.52	0.01	1	126.1	1.5	1	0.88	0.01	1	0.01	0.00	1
	Session 2	0.54	0.01	0	139.7	2.4	0	0.88	0.00	0	0.05	0.02	0
	Session 3	0.54	0.01	1	139.8	2.3	1	0.87	0.01	0	0.05	0.02	0
Participant 3 Handicap = 22	Session 1	0.41	0.01	0	121.5	3.7	0	0.92	0.01	0	0.07	0.03	0
	Session 2	0.37	0.01	0	106.5	3.6	0	0.94	0.00	1	0.15	0.02	0
	Session 3	0.37	0.00	1	108.2	0.4	1	0.96	0.01	0	0.11	0.01	0
Participant 4 Handicap = 18	Session 1	0.57	0.01	0	167.2	2.3	0	1.00	0.01	0	0.05	0.02	0
	Session 2	0.58	0.00	3	158.0	0.9	1	1.01	0.01	0	0.08	0.01	1
	Session 3	0.55	0.01	2	154.4	3.5	2	1.01	0.01	0	0.04	0.02	0
Participant 5 Handicap = 4	Session 1	0.62	0.01	0	157.6	3.9	0	0.94	0.00	0	0.12	0.01	1
	Session 2	0.61	0.01	0	154.5	2.9	0	0.91	0.01	0	0.07	0.00	1
	Session 3	0.60	0.01	0	149.5	2.8	0	0.90	0.01	0	0.07	0.01	0

		Torso rotation angle (°)			Pelvis rotation angle (°)			Feet alignment angle (°)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	-0.6	0.7	1	-2.9	0.6	2	4.9	0.8	0
	Session 2	8.0	0.7	0	-4.9	0.7	0	4.5	0.7	0
	Session 3	7.0	1.0	0	-3.1	1.4	0	5.0	0.6	0
Participant 2 Handicap = 8	Session 1	18.4	0.4	0	-10.6	6.3	0	0.2	0.7	1
	Session 2	14.4	1.6	1	-16.1	2.3	1	2.8	0.9	0
	Session 3	19.6	0.9	1	-10.0	4.5	1	1.9	0.8	0
Participant 3 Handicap = 22	Session 1	12.4	1.4	0	-5.9	1.0	0	-2.7	1.4	0
	Session 2	19.5	0.8	0	-2.5	0.3	1	-7.8	0.5	1
	Session 3	20.4	0.8	0	-3.0	1.9	0	-9.1	1.6	0
Participant 4 Handicap = 18	Session 1	11.9	0.6	0	-6.1	0.9	1	3.2	1.0	0
	Session 2	15.9	0.7	0	-4.9	1.4	0	2.4	0.6	1
	Session 3	13.8	0.5	2	-2.0	1.4	1	3.6	1.3	0
Participant 5 Handicap = 4	Session 1	25.4	0.6	0	6.8	0.4	0	-5.1	0.6	0
	Session 2	25.4	0.5	0	2.6	1.0	0	-3.5	0.8	0
	Session 3	24.1	0.4	0	7.6	0.8	0	-4.5	0.8	0

Iron		Stance width (m)			Stance width %			Stance depth (m)			Ball position (m)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	0.45	0.01	1	111.1	3.0	1	0.59	0.01	0	0.14	0.01	0
	Session 2	0.45	0.00	0	112.0	0.8	0	0.71	0.01	0	0.25	0.01	0
	Session 3	0.46	0.01	0	114.5	2.3	0	0.61	0.01	0	0.11	0.02	0
Participant 2 Handicap = 8	Session 1	0.44	0.00	2	107.3	0.9	2	0.61	0.01	0	0.09	0.01	0
	Session 2	0.45	0.01	0	116.5	2.6	0	0.60	0.01	0	0.17	0.01	0
	Session 3	0.46	0.01	0	118.7	3.4	0	0.59	0.01	0	0.19	0.01	0
Participant 3 Handicap = 22	Session 1	0.35	0.01	0	105.8	1.5	0	0.70	0.01	0	0.11	0.01	0
	Session 2	0.32	0.01	0	92.6	3.3	0	0.70	0.01	0	0.14	0.01	0
	Session 3	0.31	0.00	0	93.0	1.3	0	0.70	0.01	0	0.12	0.02	0
Participant 4 Handicap = 18	Session 1	0.53	0.01	0	154.1	2.2	0	0.74	0.01	0	0.17	0.00	0
	Session 2	0.53	0.01	0	144.9	3.3	0	0.74	0.01	0	0.17	0.01	0
	Session 3	0.51	0.01	2	145.0	2.4	2	0.74	0.00	0	0.16	0.01	0
Participant 5 Handicap = 4	Session 1	0.54	0.01	0	138.2	2.9	0	0.68	0.01	0	0.24	0.01	0
	Session 2	0.53	0.01	0	134.6	1.5	0	0.65	0.00	1	0.20	0.01	0
	Session 3	0.52	0.01	0	131.4	1.8	0	0.65	0.00	0	0.20	0.00	1

		Torso rotation angle (°)			Pelvis rotation angle (°)			Feet alignment angle (°)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	-4.2	1.0	1	-4.8	0.8	1	3.3	0.9	0
	Session 2	7.9	1.1	0	-7.3	2.5	0	1.4	0.4	1
	Session 3	7.3	1.2	0	-3.0	0.8	0	3.4	0.7	0
Participant 2 Handicap = 8	Session 1	13.2	0.9	0	-21.3	4.2	0	-1.1	0.6	0
	Session 2	10.5	1.5	0	-23.1	2.8	0	1.4	0.6	1
	Session 3	13.5	0.8	0	-16.6	2.6	0	-0.6	0.5	0
Participant 3 Handicap = 22	Session 1	20.4	0.9	0	-3.2	1.8	0	-6.6	1.5	0
	Session 2	25.3	0.8	0	1.0	0.8	0	-10.8	0.7	0
	Session 3	24.6	0.6	0	-1.7	1.2	0	-12.5	0.6	3
Participant 4 Handicap = 18	Session 1	7.9	0.3	0	-5.2	1.2	1	3.2	0.7	0
	Session 2	10.5	0.6	1	-6.8	0.6	1	3.5	0.9	0
	Session 3	7.6	0.9	1	-0.1	2.9	1	3.3	0.9	0
Participant 5 Handicap = 4	Session 1	21.5	0.5	0	7.2	0.5	0	-4.2	0.9	0
	Session 2	21.9	0.6	1	1.1	0.2	2	-1.9	0.5	0
	Session 3	22.1	0.9	0	6.1	0.2	3	-3.3	0.4	1

Table C.5. Median, median absolute deviation (MAD) and outliers for the swing timing variables in the multiple single-subject investigation.

Driver		Backswing (s)			Downswing (s)		
		Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	0.81	0.017	0	0.23	0.017	0
	Session 2	0.75	0.013	1	0.20	0.021	0
	Session 3	0.76	0.014	1	0.24	0.008	1
Participant 2 Handicap = 8	Session 1	0.90	0.041	0	0.24	0.011	0
	Session 2	0.77	0.038	0	0.24	0.024	0
	Session 3	0.86	0.051	1	0.25	0.003	0
Participant 3 Handicap = 22	Session 1	0.81	0.022	0	0.29	0.007	2
	Session 2	0.78	0.020	0	0.31	0.003	0
	Session 3	0.78	0.022	0	0.32	0.008	0
Participant 4 Handicap = 18	Session 1	0.94	0.014	0	0.29	0.003	1
	Session 2	0.93	0.015	1	0.29	0.003	0
	Session 3	0.94	0.035	0	0.28	0.007	0
Participant 5 Handicap = 4	Session 1	0.82	0.018	1	0.28	0.004	0
	Session 2	0.82	0.008	1	0.28	0.005	0
	Session 3	0.84	0.025	2	0.28	0.005	0

		Early-backswing (s)			Mid-backswing (s)			Late-backswing (s)			Early-downswing (s)			Mid-downswing (s)			Late-downswing (s)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	0.40	0.014	0	0.21	0.002	4	0.19	0.008	0	0.10	0.019	0	0.07	0.002	0	0.06	0.002	0
	Session 2	0.36	0.013	0	0.19	0.006	1	0.20	0.017	0	0.08	0.019	0	0.06	0.000	3	0.06	0.001	0
	Session 3	0.37	0.015	0	0.20	0.007	1	0.18	0.004	1	0.12	0.003	2	0.07	0.004	0	0.06	0.001	3
Participant 2 Handicap = 8	Session 1	0.49	0.026	0	0.18	0.006	0	0.21	0.001	4	0.14	0.006	0	0.06	0.002	0	0.04	0.001	1
	Session 2	0.38	0.016	1	0.18	0.010	0	0.22	0.006	0	0.13	0.025	0	0.06	0.004	0	0.05	0.011	0
	Session 3	0.44	0.033	1	0.19	0.011	0	0.23	0.012	0	0.15	0.005	0	0.06	0.001	0	0.04	0.002	1
Participant 3 Handicap = 22	Session 1	0.41	0.013	0	0.27	0.009	0	0.14	0.017	0	0.08	0.011	0	0.14	0.007	0	0.06	0.002	0
	Session 2	0.40	0.013	0	0.25	0.004	1	0.15	0.005	0	0.14	0.003	0	0.13	0.003	1	0.05	0.001	0
	Session 3	0.39	0.007	0	0.24	0.004	0	0.14	0.010	1	0.14	0.007	1	0.13	0.004	0	0.05	0.001	0
Participant 4 Handicap = 18	Session 1	0.54	0.010	0	0.22	0.004	0	0.19	0.009	0	0.14	0.005	0	0.09	0.001	2	0.05	0.001	1
	Session 2	0.53	0.017	1	0.21	0.007	0	0.19	0.004	0	0.15	0.004	1	0.09	0.002	0	0.05	0.001	0
	Session 3	0.53	0.026	0	0.22	0.008	0	0.18	0.014	0	0.15	0.012	0	0.09	0.005	0	0.05	0.001	0
Participant 5 Handicap = 4	Session 1	0.42	0.008	1	0.18	0.006	0	0.22	0.004	0	0.16	0.005	0	0.06	0.000	3	0.05	0.001	0
	Session 2	0.42	0.007	1	0.18	0.004	0	0.22	0.006	0	0.16	0.004	0	0.06	0.000	1	0.05	0.001	0
	Session 3	0.44	0.013	2	0.18	0.007	0	0.22	0.007	0	0.16	0.004	0	0.06	0.000	3	0.05	0.001	0

Iron		Backswing (s)			Downswing (s)		
		Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	0.72	0.010	1	0.27	0.004	0
	Session 2	0.70	0.010	0	0.25	0.007	0
	Session 3	0.75	0.020	0	0.26	0.010	0
Participant 2 Handicap = 8	Session 1	0.90	0.039	0	0.26	0.002	1
	Session 2	0.75	0.036	0	0.25	0.007	1
	Session 3	0.77	0.033	0	0.26	0.009	0
Participant 3 Handicap = 22	Session 1	0.78	0.014	1	0.29	0.004	2
	Session 2	0.75	0.021	0	0.30	0.006	0
	Session 3	0.77	0.040	0	0.31	0.003	1
Participant 4 Handicap = 18	Session 1	0.89	0.004	0	0.30	0.006	0
	Session 2	0.89	0.004	3	0.30	0.006	0
	Session 3	0.92	0.013	2	0.30	0.004	0
Participant 5 Handicap = 4	Session 1	0.80	0.010	0	0.26	0.002	2
	Session 2	0.79	0.011	0	0.27	0.005	0
	Session 3	0.79	0.005	0	0.27	0.005	0

		Early-backswing (s)			Mid-backswing (s)			Late-backswing (s)			Early-downswing (s)			Mid-downswing (s)			Late-downswing (s)		
		Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers	Median	MAD	Outliers
Participant 1 Handicap = 13	Session 1	0.33	0.004	0	0.23	0.006	1	0.16	0.005	0	0.12	0.003	0	0.09	0.003	0	0.06	0.002	0
	Session 2	0.32	0.009	0	0.22	0.006	0	0.16	0.007	0	0.10	0.008	0	0.08	0.003	0	0.06	0.001	0
	Session 3	0.35	0.014	1	0.23	0.008	0	0.18	0.010	0	0.12	0.007	0	0.08	0.002	1	0.06	0.003	0
Participant 2 Handicap = 8	Session 1	0.50	0.033	1	0.22	0.004	1	0.18	0.006	0	0.14	0.003	0	0.06	0.002	0	0.06	0.003	0
	Session 2	0.34	0.016	0	0.19	0.013	0	0.21	0.013	0	0.14	0.008	0	0.05	0.003	0	0.06	0.002	0
	Session 3	0.38	0.036	0	0.20	0.015	0	0.19	0.004	2	0.14	0.012	0	0.05	0.001	2	0.06	0.002	1
Participant 3 Handicap = 22	Session 1	0.42	0.018	0	0.26	0.011	0	0.10	0.010	0	0.08	0.012	0	0.14	0.006	0	0.08	0.003	1
	Session 2	0.39	0.021	0	0.23	0.006	1	0.14	0.006	1	0.12	0.004	2	0.11	0.006	0	0.06	0.004	0
	Session 3	0.42	0.032	0	0.22	0.014	0	0.14	0.007	0	0.13	0.004	1	0.11	0.002	1	0.07	0.003	1
Participant 4 Handicap = 18	Session 1	0.53	0.003	0	0.16	0.004	0	0.21	0.004	0	0.16	0.004	0	0.08	0.003	0	0.06	0.003	0
	Session 2	0.52	0.009	0	0.16	0.007	0	0.22	0.007	0	0.16	0.006	0	0.08	0.002	0	0.05	0.002	0
	Session 3	0.51	0.021	0	0.17	0.006	0	0.24	0.004	1	0.17	0.004	0	0.08	0.002	1	0.05	0.002	0
Participant 5 Handicap = 4	Session 1	0.39	0.006	1	0.19	0.004	1	0.22	0.003	1	0.15	0.002	2	0.06	0.001	1	0.05	0.001	0
	Session 2	0.40	0.009	0	0.18	0.004	0	0.22	0.003	1	0.16	0.005	0	0.06	0.000	0	0.05	0.001	0
	Session 3	0.40	0.007	0	0.18	0.005	0	0.22	0.005	0	0.16	0.003	0	0.06	0.002	0	0.04	0.001	1

D. Marker locations and definitions of landmarks and segments included in the kinematic model for the cross-sectional investigation

Table D.1. Anatomical description of marker locations for markers tracked by the full body optical motion capture system.

Marker	Positioning
HdF	Middle of forehead - on hat
HdL/HdR	Approximately 1.5cm anterior to the top of the ears - on hat
LH/RH	Superior to the posterior aspect of the calcaneus on the shoe
L1MT/R1MT	Superior to the 1st metatarsophalangeal joint - on the shoe
L2MT/R2MT	Superior to the 2nd metatarsophalangeal joint - on the shoe
L5MT/R5MT	Superior to the 5th metatarsophalangeal joint - on the shoe
Shaft Top	Retroreflective tape approximately 2cm distal of the grip
Shaft Centre	Retroreflective tape approximately 20cm distal of the grip
Shaft Bottom	Retroreflective tape approximately 2cm proximal of the ferrule

Table D.2. Definition of landmarks included in the kinematic model.

Landmark	Definition
HeadCentre	Halfway between the HdL and HdR markers, on the line which co the markers
Head Z	The HeadCentre landmark shifted an arbitrary distance (0.04m) vertically downward in the global coordinate system
L/R MidFoot	Halfway between the 2MT and Heel markers, on the line which connects the markers
L/R MidFoot Z	The L/R MidFoot landmark shifted an arbitrary distance (0.04m) vertically downward in the global coordinate system
Shaft X	The Shaft Centre marker shifted an arbitrary distance (0.05m) in the direction of the global X-axis

Table D.3. Definition of segments included in kinematic model.

Segment	Origin	X-axis	Y-axis	Z-axis	Tracking targets
Head	HeadCentre	The line perpendicular to the Z-axis which passes closest to the HdF marker, pointing forward	The line which is mutually perpendicular to the X and Z axes, pointing right	The line connecting the HeadCentre and HeadZ landmarks, pointing upward	HdF, HdL, HdR
Right/Left Foot	MidFoot	The line connecting the MidFoot landmark and the 2MT landmark, pointing forward	The line which is mutually perpendicular to the X and Z axes, pointing right	The line connecting the MidFoot landmark and the MidFoot Z landmark, pointing downward	L/RH, L/R1MT, L/R2MT, L/R5MT
Shaft	Shaft Top	The line which is mutually perpendicular to the Y and Z axes, pointing forward	The line connecting the Shaft Centre and Shaft X landmarks, pointing right	The line connecting the Shaft Top and Shaft Centre landmarks, pointing upward	Shaft Top, Shaft Centre, Shaft Bottom

E. Full results tables from cross-sectional investigation

Table E.1. Median, median absolute deviation (MAD) and outliers for the shot outcome variables in the cross-sectional investigation.

Driver		Carry length (m)			Carry side (m)			Total length (m)			Total side (m)			Shot angle (°)			Shot score ( )			Subjective rating ( )		
CONGU handicap category	Number of golfers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers
1	31	203.0	4.48	0.3	2.5	7.27	0.3	220.6	4.57	0.2	2.9	8.05	0.3	-0.77	2.24	0.3	0.89	0.02	0.5	4	1.0	0.06
2	35	170.1	4.89	0.6	4.3	6.95	0.2	193.0	5.81	0.6	5.6	8.28	0.2	-1.79	2.66	0.2	0.78	0.03	0.5	4	1.0	0.37
3	22	136.6	5.67	0.5	5.2	6.33	0.2	158.3	6.90	0.5	6.8	8.55	0.2	-2.74	3.27	0.3	0.70	0.03	0.5	4	1.0	0.50
4	16	96.3	6.65	0.4	6.7	4.87	0.1	127.7	8.28	0.4	8.5	6.58	0.1	-3.72	3.00	0.3	0.64	0.04	0.5	3	0.5	0.63

Iron		Carry length (m)			Carry side (m)			Total length (m)			Total side (m)			Shot angle (°)			Shot score ( )			Subjective rating ( )		
CONGU handicap category	Number of golfers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers
1	31	154.6	3.38	0.6	0.4	4.25	0.3	168.2	3.84	0.5	0.3	4.94	0.3	-0.10	1.75	0.2	0.96	0.02	0.5	3	1.0	0.42
2	35	130.3	6.86	0.7	-0.3	4.75	0.3	149.0	5.12	0.6	-0.7	5.49	0.3	0.26	2.34	0.4	0.85	0.03	0.6	4	1.0	0.11
3	22	108.1	6.10	0.3	0.3	4.16	0.2	126.3	5.74	0.5	-0.2	5.46	0.2	0.06	2.73	0.2	0.77	0.03	0.4	3	0.8	0.23
4	16	78.0	10.49	0.4	0.3	3.82	0.2	100.3	8.50	0.6	-0.6	5.85	0.2	0.31	3.47	0.1	0.70	0.05	0.6	3	0.5	0.25

Table E.2. Median, median absolute deviation (MAD) and outliers for the ball launch variables in the cross-sectional investigation.

Driver	Ball speed (m·s^{-1})			Efficiency ( )			Launch angle (°)			Launch direction (°)			Spin rate (rad·s^{-1})			Spin axis (°)		
CONGU handicap category	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers
1	63.8	0.65	0.4	1.44	0.01	0.3	11.5	1.00	0.2	0.2	1.15	0.2	344	28.6	0.5	0.0	3.55	0.4
2	57.7	0.74	0.3	1.44	0.02	0.3	11.4	1.20	0.6	0.5	1.40	0.2	299	38.8	0.4	2.2	4.10	0.3
3	49.6	0.99	0.6	1.43	0.02	0.8	11.7	1.25	0.9	0.4	1.83	0.1	280	50.6	0.5	5.3	5.98	0.2
4	42.8	1.07	0.6	1.41	0.03	0.5	10.1	2.35	0.3	1.5	2.08	0.3	358	66.5	0.5	13.9	3.60	0.2

Iron	Ball speed (m·s^{-1})			Efficiency ( )			Launch angle (°)			Launch direction (°)			Spin rate (rad·s^{-1})			Spin axis (°)		
CONGU handicap category	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers
1	52.7	0.67	0.5	1.45	0.02	0.4	13.7	0.70	0.5	1.1	0.85	0.2	484	30.4	0.5	-1.0	2.70	0.2
2	47.4	0.98	0.5	1.44	0.03	0.6	13.8	1.00	0.5	0.0	1.15	0.5	426	31.4	0.6	-0.6	3.10	0.3
3	41.3	0.96	0.6	1.44	0.03	0.4	14.6	1.00	0.7	0.0	1.80	0.1	383	66.5	0.5	-1.3	4.23	0.2
4	36.4	1.81	0.4	1.41	0.06	0.3	14.4	1.60	0.9	-0.1	2.30	0.1	362	65.9	0.3	3.6	3.85	0.1

Table E.3. Median, median absolute deviation (MAD) and outliers for the clubhead presentation variables in the cross-sectional investigation.

Driver	Club speed (m·s^{-1})			Face angle (°)			Effective loft (°)			Effective lie (°)			Path angle (°)			Attack angle (°)		
CONGU handicap category	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers
1	44.1	0.22	0.2	1.3	1.10	0.3	13.1	0.65	0.5	5.4	0.40	0.2	-1.8	0.50	0.3	0.9	0.50	0.2
2	40.4	0.27	0.2	1.4	1.65	0.2	13.4	1.00	0.3	4.7	0.45	0.4	-2.2	0.65	0.2	1.2	0.50	0.2
3	35.0	0.35	0.4	1.3	1.70	0.2	11.3	1.50	0.1	5.5	0.70	0.4	-2.4	0.70	0.3	0.5	0.70	0.4
4	31.4	0.31	0.4	2.3	2.25	0.1	13.5	1.88	0.1	6.5	0.73	0.3	-4.7	0.90	0.5	-1.8	0.85	0.4

Iron	Club speed (m·s^{-1})			Face angle (°)			Effective loft (°)			Effective lie (°)			Path angle (°)			Attack angle (°)		
CONGU handicap category	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers
1	36.4	0.20	0.3	-1.5	1.05	0.1	20.0	0.85	0.2	-1.3	0.40	0.3	-0.3	0.60	0.4	-4.5	0.40	0.2
2	33.1	0.25	0.5	-1.0	1.40	0.3	19.5	1.20	0.4	-1.8	0.50	0.2	-1.0	0.80	0.2	-2.8	0.60	0.4
3	28.5	0.29	0.6	-1.4	2.28	0.2	20.2	1.83	0.2	-2.0	0.53	0.5	-1.8	0.65	0.1	-1.5	0.78	0.1
4	26.6	0.37	0.5	-2.3	2.58	0.1	20.3	1.45	0.2	-0.3	0.85	0.1	-3.0	1.00	0.3	-1.9	1.00	0.3

Driver	Face angle rate of change (rad·s^{-1})			Attack angle rate of change (rad·s^{-1})			Path rate of change (rad·s^{-1})			Horizontal impact position (mm)			Vertical impact position (mm)		
CONGU handicap category	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers
1	0.8	0.02	0.2	0.4	0.01	0.4	-0.4	0.01	0.4	-0.2	5.00	0.3	-1.4	3.90	0.1
2	0.7	0.02	0.2	0.4	0.01	0.4	-0.4	0.01	0.3	-0.1	6.00	0.3	0.0	4.85	0.3
3	0.6	0.02	0.2	0.3	0.01	0.5	-0.3	0.01	0.5	2.3	7.28	0.0	6.4	5.73	0.1
4	0.6	0.03	0.4	0.3	0.01	0.4	-0.3	0.01	0.7	1.2	9.50	0.1	-0.2	7.55	0.1

Iron	Face angle rate of change (rad·s^{-1})			Attack angle rate of change (rad·s^{-1})			Path rate of change (rad·s^{-1})			Horizontal impact position (mm)			Vertical impact position (mm)		
CONGU handicap category	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers
1	0.8	0.02	0.3	0.5	0.01	0.4	-0.3	0.01	0.3	0.4	3.60	0.4	-12.7	3.25	0.2
2	0.7	0.02	0.6	0.4	0.01	0.7	-0.3	0.01	0.7	-3.1	5.20	0.3	-13.8	4.20	0.4
3	0.6	0.02	0.3	0.4	0.01	0.7	-0.3	0.01	0.6	-4.2	7.40	0.1	-12.0	5.55	0.0
4	0.6	0.02	0.3	0.4	0.02	0.8	-0.2	0.01	0.6	-3.4	7.58	0.2	-14.7	5.38	0.3

Table E.4. Median, median absolute deviation (MAD) and outliers for the address variables in the cross-sectional investigation.

Driver		Stance width (m)			Stance depth (m)			Ball position (m)			Feet to target line angle (°)			Foot to foot angle (°)		
CONGU handicap category	Number of golfers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers
1	31	0.56	0.007	0.3	0.93	0.005	0.4	0.12	0.010	0.1	-0.03	0.610	0.3	-28.47	1.067	0.3
2	35	0.55	0.008	0.2	0.91	0.010	0.3	0.11	0.012	0.1	-0.36	0.626	0.1	-24.23	1.284	0.2
3	22	0.54	0.010	0.1	0.93	0.008	0.2	0.14	0.015	0.3	0.44	0.751	0.1	-26.83	1.355	0.1
4	16	0.50	0.008	0.3	0.90	0.010	0.3	0.16	0.013	0.1	1.32	0.529	0.1	-22.69	1.631	0.2

Iron		Stance width (m)			Stance depth (m)			Ball position (m)			Feet to target line angle (°)			Foot to foot angle (°)		
CONGU handicap category	Number of golfers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers
1	31	0.51	0.007	0.1	0.66	0.006	0.1	0.21	0.007	0.4	1.32	0.499	0.3	-25.79	1.057	0.1
2	35	0.50	0.007	0.4	0.66	0.008	0.2	0.18	0.009	0.3	0.69	0.655	0.3	-21.30	1.139	0.3
3	22	0.51	0.009	0.2	0.67	0.009	0.1	0.20	0.009	0.3	0.53	0.578	0.3	-25.69	1.289	0.4
4	16	0.48	0.012	0.2	0.66	0.009	0.4	0.19	0.011	0.1	1.46	0.879	0.3	-22.94	1.381	0.4

Table E.5. Median, median absolute deviation (MAD) and outliers for the swing timing variables in the cross-sectional investigation.

Driver		Backswing time (s)			Downswing time (s)		
CONGU handicap category	Number of golfers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers
1	31	0.80	0.013	0.3	0.25	0.005	0.5
2	35	0.77	0.015	0.3	0.25	0.005	0.4
3	22	0.85	0.018	0.3	0.30	0.005	0.5
4	16	0.82	0.022	0.3	0.33	0.009	0.2

Iron		Backswing time (s)			Downswing time (s)		
CONGU handicap category	Number of golfers	Median	MAD	Mean no. of outliers	Median	MAD	Mean no. of outliers
1	31	0.75	0.013	0.4	0.24	0.004	0.2
2	35	0.72	0.013	0.2	0.24	0.004	0.3
3	22	0.81	0.018	0.5	0.28	0.004	0.3
4	16	0.79	0.017	0.4	0.33	0.006	0.2