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Movement Variability in the Golf Swing: Theoretical, Methodological, and Practical Issues

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Movement variability in the golf swing has recently been identified as a priority for future research in golf science (e.g., Farrally et al., 2003; Wallace, Kingston, Strangewood, & Kenny, 2008; Williams & Sih, 2002). Although this ubiquitous aspect of golf performance has featured in previous empirical investigations of the golf swing, it has tended to be subordinate and studied as an adjunct to other more conventional research questions. Furthermore, it has been interpreted largely within an information-processing theoretical framework[1] (e.g., Abernethy, Neal, Moran, & Parker, 1990; Neal, Abernethy, Moran, & Parker, 1990) and has typically been treated as an operational measure (e.g., standard deviation) rather than a theoretical construct worthy of research attention in its own right.

The recent application of concepts and tools from dynamical systems theory[2] to analyses of human movement, however, has prompted golf scientists to pay much closer attention to this omnipresent feature of the golf swing (e.g., Knight, 2004). Several empirical investigations published recently (e.g., Bradshaw et al., 2009; Kenny, Wallace, & Otto, 2008) have adopted movement variability as their main focus, but their inherent limitations have generally prevented them from making more of a substantive contribution to the literature. In this paper, I briefly comment on the main issues arising from these studies and highlight some more general topics requiring attention in this important area of study.

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Theoretical Issues

An important theoretical issue worthy of careful consideration is the relationship between movement variability and noise. Bradshaw et al. (2009) appeared to use the terms "variability" and "noise" synonymously, despite a plethora of theoretical and empirical studies published over the past two decades suggesting that variability and noise may not necessarily be equivalent (e.g., Newell, Deutsch, Sosnoff, & Mayer-Kress, 2006; Slifkin & Newell, 1998). Traditionally, movement variability has been interpreted as a negative by-product of random noise in the central nervous system that should be reduced or removed (e.g., Faisal, Selen, & Wolpert, 2008; Harris & Wolpert, 1998; van Beers, Haggard, & Wolpert, 2004). However, more recently, it has been suggested that variability observed in motor output may not necessarily be a reflection of unwanted noise or error in the movement system and that it may afford the movement system great flexibility and adaptability (e.g., Newell & James, 2008; Newell & Slifkin, 1998; Riley & Turvey, 2002). This is not to say that noise does not contribute, at least in part, to movement variability (see the "Methodological Issues" section below for a brief discussion of dynamical noise) or that all noise is detrimental to performance (see Davids, Shuttleworth, Button, Renshaw, & Glazier, 2004, for a full discussion of the potential benefits of stochastic resonance[3] to sensorimotor functioning). Likewise, it does not mean that all variability is beneficial to motor performance. Future research needs to establish the exact relationship between variability and noise and their respective contribution to the attainment of task goals. Innovative approaches to data analysis, such as principal component analysis (e.g., Daffertshofer, Lamoth, Meijer, & Beek, 2004) and uncontrolled manifold analysis (e.g., Scholz & Schöner, 1999), might be useful in achieving this research aim.

Another important and related theoretical issue regarding movement variability in the golf swing is the type of variability being examined. A clear distinction needs to be made between variability in the underlying movement dynamics (coordination patterns) and variability in the movement or task outcome (Newell & Corcos, 1993). However, to date, this distinction has not been well defined in the golf-related scientific literature. For example, Kenny et al. (2008) initially set out to examine movement variability in the underlying movement dynamics of the golf swing, but ended up simply reporting variability of impact (clubhead velocity, launch angle, and ball spin) and outcome parameters (carry distance and lateral dispersion). Likewise, Bradshaw et al. (2009) reported variability of various arbitrary kinematic variables (e.g., stance width, ball position, trunk angle and rotation, club shaft angle) at various times throughout the golf swing (address, half backswing, top of backswing, and ball contact).

A major problem with focusing solely on outcome measures is that the same outcome measure can be produced by a seemingly infinite number of different movement patterns. Indeed, this phenomenon, known as motor equivalence, has been demonstrated in a multitude of different motor tasks, including hammering a chisel (Bernstein, 1967), gun shooting (Arutyunyan, Gurfinkel, & Mirskii, 1968), and point-to-point reaching (Marasso, 1981). Furthermore, in their synthesis of recent experimental findings, Newell and James (2008) concluded that, in many motor tasks, the amount of variability in the movement outcome is inversely related to the amount of variability in the underlying movement dynamics that produce that outcome (i.e., low variability in the movement outcome is often accompanied by high variability in movement dynamics and vice versa).

Clearly, absolute invariance at the point of impact between the center of percussion (the “sweetspot”) of the golf club and the golf ball is highly desirable, but further research is required to establish how variable the underlying movement dynamics are, how this variability changes during different phases of the golf swing, and whether more skilled golfers are more or less variable than less skilled golfers. As discussed in the next section, recent developments in motion analysis technology have an important role to play in this investigative endeavor, as does emerging technology such as the TrackMan system (Trackman A/S, Denmark), which enables the three-dimensional path of the club to be accurately tracked throughout the swing in real time.

Methodological Issues

Distinguishing between movement variability and measurement noise is a major methodological issue facing golf scientists when investigating movement variability in the golf swing. Measurement noise arises from errors introduced and propagated during data acquisition and analysis and is independent of, and additive to, the signal representing the movement dynamics (van Emmerik, Hamill, & McDermott, 2005). Because measurement noise is a ubiquitous feature of a biomechanical time series, it is important that golf scientists minimize it at its source, or at least thoroughly evaluate its influence on higher-order derivative calculations and the subsequent mapping of movement trajectories in different control spaces (see McGinnis & Newell, 1982).

Selecting an appropriate motion analysis system is an important first step in minimizing measurement noise. Although no system is perfect, it is advisable for golf scientists to select the automated, marker-based, motion analysis system with the highest resolution, such as Vicon MX (Vicon, Oxford, UK) or MAC Raptor-4 (Motion Analysis Corporation, Santa Rosa, CA), to acquire sufficiently large and accurate time-continuous data sets to construct variable-variable plots (e.g., angle-angle plots, phase-plane portraits) and apply various coordination (e.g., continuous relative phase, cross-correlation, vector coding) and variability measures (e.g., standard deviation, coefficient of variation, normalized root-mean-square, transentropy; e.g., Kurz & Stergiou, 2004; Hamill, Haddad, & McDermott, 2000; Wheat & Glazier, 2006). There have been conflicting reports regarding the suitability of manual, image-based, motion analysis systems for analyzing movement variability (e.g., Bartlett, Bussey, & Flyger, 2006; Salo & Grimshaw, 1998), but ultimately it is the responsibility of the scientist to exercise due diligence. Software applications, such as Quintic (Quintic Consultancy Ltd., Coventry, UK) and siliconCOACH (siliconCOACH, Dunedin, NZ), which was used by Bradshaw et al. (2009), are excellent for planar semiquantitative analyses and frame-by-frame or split-screen video playback, but they are no substitute for purpose-built, image-based or marker-based, motion analysis systems and should not be used for analyses of movement variability. Not only are the digitizing resolutions of these software packages limited owing to there being no subpixel cursor, their reconstruction routines are typically based on simple linear-scaling techniques, which have been shown to be inferior to direct linear-transformation procedures (Brewin & Kerwin, 2003).

After data have been collected, it is customary in biomechanics to remove measurement error from time series data by using established smoothing and conditioning techniques (e.g., Wood, 1982). However, extreme caution must be applied when performing this task, because, in addition to measurement noise, biomechanical time-series data contain dynamical noise, which is generated by underlying nonlinearities in the system and is an integral part of the signal that needs preserving (van Emmerik et al., 2005). Although it is possible to separate measurement noise from dynamical noise (e.g., Siefert, Kittel, Friedrich, & Peinke, 2003), the methods appear to be nontrivial. Consequently, some investigators performing dynamical systems analyses (e.g., Buzzi, Stergiou, Kurz, Hageman, & Heidel, 2003) have opted not to apply any data smoothing and conditioning techniques to avoid omitting important data, while others (e.g., Hamill, van Emmerik, Heiderscheit, & Li, 1999) have applied digital filters but have used higher cutoff frequencies than are habitually used in biomechanics, presumably to avoid removing some of the dynamical noise component.

There have been attempts to separate movement variability and measurement noise using statistical analyses. For example, Bradshaw et al. (2009) adopted a technique that involved subtracting the standard error of the mean (SEM% = $[(SD/\sqrt{n})/M] \times 100$) from the coefficient of variation (CV% = $SD/M \times 100$) of a series of performance-related kinematic variables over repeated golf swings (SEM% was used to estimate measurement noise, whereas CV% represented the summation of measurement noise and movement variability). However, despite having previously been used by the authors to examine movement variability in sprint starts (see Bradshaw, Maulder, & Keogh, 2007), this procedure appears to be flawed, because the SEM% was calculated from repeated performance trials *not* repeated measurements of the same performance trial. By using measurements obtained from repeated performance trials, SEM% will contain varying proportions of movement variability and measurement error, whereas SEM% in repeated measurements of the same performance trial can only be measurement error.

Practical Issues

Following Knight (2004), Bradshaw et al. (2009) argued that golfers should seek to learn a variety of movement solutions rather than attempt to develop absolute invariance in their golf swings over repeated performance trials, presumably to facilitate more reliable performance when confronted by fluctuations of internal and external factors. Although not explicitly identified by Bradshaw et al. (2009), the constraints framework outlined by Newell (1986) might be useful in a discourse of how variable movement solutions could be achieved in golf. According to Newell (1986), movement patterns are an emergent property of the confluence of organismic (e.g., age, strength, flexibility, fatigue, anxiety, intentions), environmental (e.g., weather conditions, temperature, acoustic information, surface conditions) and task constraints (e.g., goals, rules, equipment) impinging on the performer (see Glazier & Davids, 2005, for the specific application of this model to the golf swing). An important implication of this constraints framework is that large amounts of repetitive practice under approximately the same set of constraints might not be the best strategy for golfers to adopt. Indeed, to prevent the golf swing from becoming too rigid and overly stable, golfers might benefit from undertaking practice sessions involving the systematic manipulation of key constraints (see chapter 7 of Davids, Button, & Bennett, 2008, for a discussion of how to structure practice environments from a constraints-led perspective). This approach would encourage what Bernstein (1967, p. 134) described as "repetition without repetition" (i.e., the development of a stable but flexible golf swing), thus facilitating greater consistency and precision of ball striking in a wider variety of performance contexts.

Conclusion

Movement variability in the golf swing has been targeted by golf scientists as a priority for future research. However, for this research to make a substantive contribution, greater consideration of the theoretical, methodological, and practical issues outlined in this paper is required. Greater emphasis needs to be given to the relationship between variability and noise, and greater distinction needs to be made between variability in movement dynamics and variability in the movement outcome. Golf scientists are now well placed to examine these issues because of the emergence of analytical tools and concepts from dynamical systems theory and developments in motion analysis and launch monitor technologies.

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Notes

1. The information processing theoretical approach to motor behavior conceptualizes the human body as a deterministic machine finitely controlled via sensory feedback loops by a capacity-limited microcomputer acting as the brain. Once perceptual information has been picked up by sensory receptors, it is embellished by memorial processes, and a program, plan, or schema containing a prescription of the desired movement response, including details about the duration, magnitude, and relative timing of muscle activation characteristics, is initiated. The ensuing motor patterns are typically invariant or show a conspicuous tendency toward invariance, and any variability is deemed to be noise or error that should be minimized or eliminated.
2. The dynamical systems theoretical approach to motor behavior conceptualizes the human body as a highly complex, nonlinear neurobiological system. This approach suggests that pattern formation among the many interacting component parts or degrees of freedom comprising the human body does not depend on anthropomorphic concepts such as programs, plans and schemas but, rather, emergent processes of physical self-organization inherent in all complex systems in nature and constraints that define the operational boundaries of the system. The development of functional coordinative states or attractor states facilitates the production of stable but flexible motor solutions, which are essential for successful attainment of task goals in dynamic performance environments.
3. Stochastic resonance has been defined as a noise induced rise in the signal-to-noise ratio of an information signal within a nonlinear system (Dykman & McClintock, 1998). The addition of an intermediate level of background random noise (electrical or mechanical) has been shown repeatedly to enhance the detection and transmission of neural signals in the sensorimotor system. For example, Collins, Imhoff, and Grigg (1996) reported that detecting weak local indentations to the tip of the finger is greatly enhanced by the presence of superimposed noise. Moreover, Priplata, Niemi, Harry, Lipsitz, and Collins (2002) demonstrated that postural control could be enhanced by the application of subsensory mechanical noise to the feet.

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