LIMIT CYCLE DYNAMICS ACROSS ELITE MALE ARTISTIC GYMNASTS.

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Biological systems described by their attractor dynamics provide a method to understand the fundamental characteristics of skilled movement. Here the limit cycle dynamics of the longswing were investigated across tiers of elite men's gymnasts. Senior, junior and development elite gymnasts (N=21) performed three trials of eight consecutive longswings on high bar. Limit cycle analysis revealed a more symmetrical angular velocity of the centre of mass about the bar trajectory in phase space, higher recurrence, lower correlation dimension and lower variability for senior gymnasts suggesting a more deterministic, efficient and predictive technique. The addition of non-linear dynamics to traditional biomechanics offers complementary theoretical and coaching knowledge to movement coordination, control and skill.

KEY WORDS: attractor, dynamical systems, gymnastics, recurrence, variability

INTRODUCTION: Biological systems described by their attractor dynamics provide a method to understand the fundamental characteristics of skill and health in line with basic principles of nature such as adaptability and complexity. Since traditional biomechanics can quantify the biomechanical demands of individual skills (i.e. effective joint angles, velocities and accelerations), further understanding of skill development can be obtained through exploring system stability, movement control and how systems evolve in time. Knowledge of the control and organisation of the biomechanical determinants of performance can begin to recognise the movement dynamics required to produce continually developing dynamical responses. Through the application of non-linear dynamics, knowledge of variability, stability, flexibility and redundancy can begin to quantify the evolution of systems in time.
Dynamical systems theory has arisen as an effective approach for analysing sports performance, due to the importance placed on processes of control and coordination in movement systems (Glazier, Bartlett & Davids, 2003). Methods, such as identification of attractor states have been developed to quantify coordination and control characteristics in biological systems, including but not limited to: fixed point, limit cycle attractors and chaotic attractors (Strogatz, 2015). The decrease in the number of biomechanical degrees of freedom (DoF) of the motor system supports the development of these attractor states to describe behaviour**.** Transitions between attractors allows for adaptable, flexible and evolving motor system behaviour, promoting individual exploration of performance contexts (Negrello, 2001, p206). However, the notion of attractor states is not commonly utilised within applied analysis of full body movements yet can offer additional information to traditional biomechanics in order to further explain concepts of control and organisation.
Gymnastics provides a particularly favourable environment to analyse skill development as success is defined through the achievement of specific movement patterns outlined by the gymnastics Code of Points (FIG, 2017), whereas there can be many movement patterns utilised for success in most other sports (i.e. scoring a goal in football). From a non-linear dynamics perspective, the gymnastics longswing has the inherent characteristics of an attractor, specifically the closed trajectory features within phase space of a limit cycle, whereby repeated rotations around the bar are maintained through energy input (Vicinanza et al., 2017). Vicinanza et al. (2017) were the first to apply these methods to longswing analyses, finding that more elite gymnasts demonstrated increased mechanical efficiency during longswing performance in comparison to novice gymnasts; this work is furthering their analysis through using multiple tiers of elite gymnasts who are expected to have reached the

control stage of learning (Newell, 1985). The concept of attractor states is important for the understanding of biomechanics and movement systems as it can begin to explain how consistency and stability emerges, together with the notion of functional variability required for flexible movement behaviour. Therefore, based on the principles of biomechanics and movement dynamics, the aim of this study was to investigate the limit cycle dynamics during the high bar longswing across tiers of elite men's gymnastics.

METHODS: Participants: Prior to the onset of the study, ethical approval was gained from the University Research Ethics Committee. Seven senior elite level (age: 20 ± 3 yrs, mass: 64 ± 7 kg, stature: 1.65 ± 0.07 m), seven junior elite level (age: 15 ± 1 yrs, mass: 49 ± 9 kg, stature: 1.59 ± 0.01 m), and seven development elite level (age: 10 ± 1 yrs, mass: 31 ± 6 kg, stature: 1.24 ± 0.16 m) male artistic gymnasts gave voluntary informed consent to partake in the study. A legal parent or guardian provided informed consent for participants under the age of 18 years. Direct anthropometric measurements were obtained in line with Yeadon's (1990) inertia model. Each participant performed three trials of eight consecutive longswings whilst looped to the horizontal bar. **Data Collection and Processing:** An automated 3D motion capture system (CODAmotion, Charnwood Dynamics Ltd, Leicester, UK) sampling at 200 Hz captured unilateral kinematic data. Two CX1 scanners provided a field of view exceeding 2.5 m around the centre of the bar (see Williams et al., 2012). Active markers were fixed laterally to each participant's right side on the fifth metatarsophalangeal joint, lateral malleolus, lateral femoral condyle, greater trochanter, estimated centre of rotation of the glenohumeral joint, lateral epicondyle, mid forearm and the underside of the centre of the horizontal bar. Data were processed using a modified written code (Vicinanza et al., 2017) in R (http://www.r-project.org). Circle angle (θ_c) was distinguished by the mass centre to bar vector with respect to the horizontal, where, a θ_c of 90° and 450° defined the gymnast's centre of mass (CM) as above the bar (in handstand). Data were interpolated using a cubic spline to 1^o increments of overall θ_c about the bar. **Data Analysis:** Poincaré plots (see Kantz & Schreiber, 2004) were used to denote the CM trajectory in the phase space as an initial step to examine the presence of attractors and closed paths (Vicinanza et al., 2017). Methods from Vicinanza et al. (2017) were used to calculate Takens' (1981) vectors and estimated correlation dimension (CD). Recurrence quantification analysis and Poincare analysis were used to investigate the capability of a system to return to the same condition (Zbilut & Webber Jr., 1992; Castanié, 2006, p16). Variability of the angular velocity (ω) of the CM about the bar was generated at each degree of θ_c based on standard deviation (SD). Average variability was calculated in each quartile of the swing and across the whole swing. Quartile 1 is represented between 90°-179° of θ_c, quartile 2 as 180°-269° of θ_c, quartile 3 as 270°-359° of θ_c and quartile 4 as 360°-449° of θ_c. A one-way analysis of variance followed by a Bonferroni post hoc test, examined differences between all variables across performance levels; alpha level was set at $P \leq .05$. Statistical tests were processed using the IBM SPSS Statistics 22 Software (IBM SPSS, Inc., Chicago, IL, USA).

RESULTS & DISCUSSION: The aim of this study was to investigate the limit cycle dynamics during the high bar longswing across tiers of elite men's gymnastics. The analysis confirmed the limit cycle behaviour of the longswing in phase space, describing the repeated oscillations as a stable attractor, maintained through energy input (Vicinanza et al., 2017). Overall, the structure of the limit cycle displayed a more symmetrical ωCM trajectory in phase space, higher recurrence, lower CD and lower variability (quantified by SD) for senior elite gymnasts. Poincare plots (Figure 1) denoted the closed loop limit cycle trajectories in phase space and displayed similar trajectories across all gymnasts. However, the ωCM was smoother for senior and junior elite gymnasts, compared to the development gymnasts. Recurrence plots offer a method to visualise the periodic nature of a trajectory through a phase space (Marwan, Romano, Thiel & Kurths, 2007). White noise tends to display single dots and few diagonal lines within a recurrence plot, whereas a deterministic process has a recurrence plot with very few single dots but many diagonal lines (Eckmann, Kamphorst & Ruelle, 1987). Shorter lengths of diagonals within recurrence plots display lower recurrence rates in phase space, suggesting a less deterministic process for development gymnasts compared to senior and junior gymnasts over swings (Figure 2). The results suggest that senior elite gymnasts' limit cycle trajectories have increased recurrence of states, meaning that states are arbitrarily close and the trajectory returns to a location previously visited before, typical of deterministic dynamical systems (Riley, Balasubramaniam & Turvey, 1999).

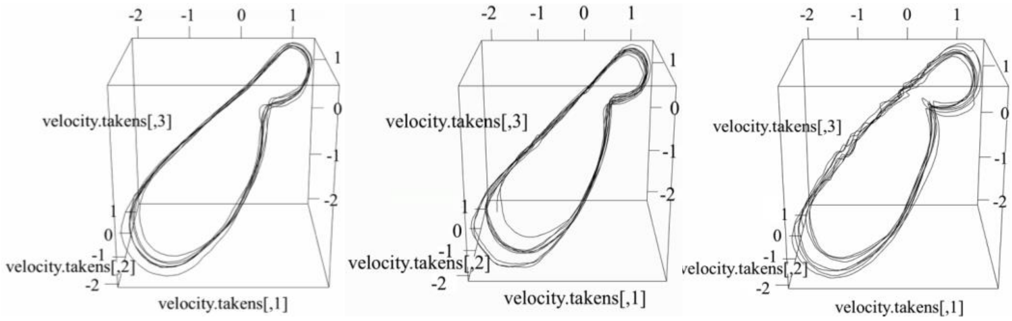

Figure 1. Poincaré plot representation of a senior (left), junior (centre) & development (right) gymnast.

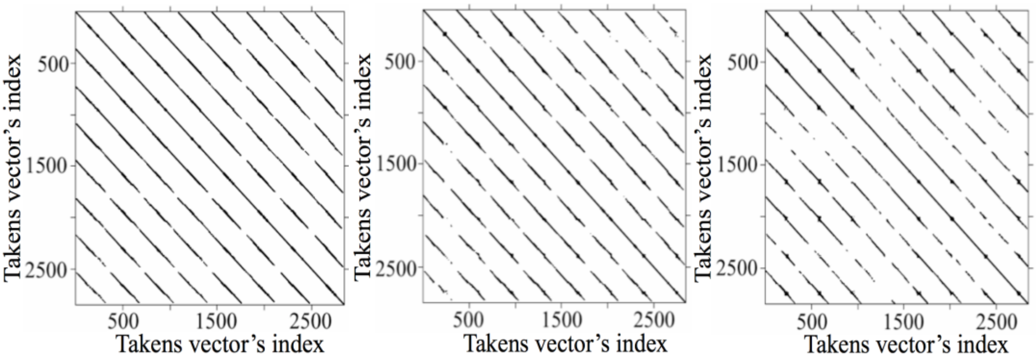

Figure 2. Senior (left), junior (centre) & development (right) gymnast recurrence plot representation.

Table 1. CD, whole longswing variability and quartile variability as a function of skill level.

	CD (mean	**Variability quantified by SD (mean ± SD)**				
Group	**± SD)**	Whole Swing	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Senior	1.1 ± 0.1	8.3 ± 2.7	8.9 ± 2.8	6.8 ± 1.4	8.4 ± 1.7	9.0 ± 3.7
Junior	1.3 ± 0.1	10.0 ± 3.7	9.8 ± 3.4	7.0 ± 2.5	11.3 ± 2.6	11.8 ± 4.0
Development	1.4 ± 0.1	13.7 ± 4.2	13.9 ± 4.8	11.0 ± 2.8	12.6 ± 3.1	17.0 ± 3.6

CD, the number of dimensions needed to capture the attractor structure of the longswing (Decoster & Mitchell, 1991), presented an attractor close to a one-dimensional limit cycle for all groups of gymnasts (1.1 ± .1, 1.3 ± .1 and 1.4 ± .1 for senior, junior and development gymnasts, respectively, Table 1). The CD of the phase space trajectory displayed significant differences between the development and senior groups and development and junior groups (both $p < 0.01$); however, no significant differences were observed between senior and junior groups ($p=0.62$). It is understood that cyclic tasks, such as the gymnastics longswing, achieved by skilled performers are predicted to display lower dimensions (Vaillancourt & Newell, 2002; Vicinanza et al., 2017). The increased skill level of participants paired with lower limit cycle dimension is consistent with the view that a shift in peripheral to central control occurs (Pew, 1966; Vicinanza et al., 2017). From this perspective, the senior elite gymnasts in this research have a more efficient and predictive movement trajectory (Vicinanza et al., 2017). These results offer further support for dynamical DoF reduction (Bernstein, 1967) as performers attain the control stage of learning (Newell, 1985). Key features of successful longswing technique have been previously identified, e.g. hip and shoulder functional phases (Yeadon & Hiley, 2000; Irwin & Kerwin, 2005), whereby in this research, the functional phase actions occur within quartile 2 and 3. Variability of the ωCM was significantly higher during the whole swing for the development group, compared to the junior and senior groups ($p < 0.01$) (Table 1). In all quartiles, significant differences were displayed between all groups ($p < 0.01$). In quartile 2, when the initial action of the functional phase occurs (Irwin & Kerwin, 2005), variability is significantly lower ($p < 0.01$) than all other quartiles across all elite groups suggesting a more consistent swing technique between 180° and 360° of circle angle. This finding is consistent with that of Hiley, Zuevsky and Yeadon (2013) who identified lower variability within the more mechanically important characteristics of successful performance in elite gymnasts compared to lower level performers. Additionally, the current research found highest values of variability in the fourth quartile. Hiley and Yeadon (2016) showed that this higher variability near the top of the circle, a less mechanically important position of the longswing, is related to the control of ωCM.

CONCLUSION: Limit cycle analysis displayed a more symmetrical ωCM trajectory in phase space, higher recurrence, lower correlation dimension and lower variability for senior elite gymnasts suggesting a more deterministic, efficient and predictive movement technique. It is proposed that the addition of non-linear dynamic methods to traditional biomechanics may offer additional theoretical and coaching knowledge into the coordination, control and organisation of a biomechanical system making training more effective, efficient and safe.

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