Limit cycle dynamics of the gymnastics longswing

Domenico Vicinanza[a], Genevieve K. R. Williams[b], Lee Smith[c], Gareth Irwin[d], Karl M. Newell[e]

[a]Department of Computing and Technology, Anglia Ruskin University, Cambridge, UK, email: domenico.vicinanza@anglia.ac.uk

[b]School of Sport and Health Sciences, University of Exeter, UK, email: g.k.r.williams@exeter.ac.uk

[c]Cabridge Centre for Sport and Exercise Science, Anglia Ruskin University, Cambridge, UK, email: lee.smith@anglia.ac.uk

[d]School of Sport, Cardiff Metropolitan University, Cardiff, UK, email: girwin@cardiffmet.ac.uk

[e]Department of Kinesiology, University of Georgia, Athens, USA, email: kmn1@uga.edu

Corresponding Author Details:

Dr Domenico Vicinanza

Email: domenico.vicinanza@anglia.ac.uk

Anglia Ruskin University

COM307 Compass House

East Road

Cambridge, Cambridgeshire, CB1 1PT, UK

Abstract

The purpose of the study was to examine the macroscopic dynamics of the longswing through a limit cycle analysis of the motion of the center of mass (CM) as a function of skill level. One elite international, five release and re-grasp, five non-release and re-grasp, and five novice gymnasts each performed four consecutive longswings on a high bar. Kinematic data were collected to facilitate the calculation of the center of mass position of the performer during swinging. The attractor dynamic was very close to a one-dimensional limit cycle for the elite (D=1.18) but higher for the release and re-grasp ($D = 1.35 \pm 0.06$), non-release and re-grasp ($D = 1.37 \pm 0.07$). The novice dynamic was characterized by a two-dimensional limit cycle ($D = 2.49 \pm 0.28$) that also had more variability and lower determinism. In the frequency domain, Inharmonicity was lower and the Q factor higher as a function of increased skill level. The findings show that the dynamical degrees of freedom of the CM in the skilled performance were reduced compared to those of novices and represented a more efficient and predictive, rather than exploratory, technique.

188 words

KEY WORDS: dynamical systems, variability, motor control, collective variable, biomechanics, gymnastics

1.0 Introduction

The concepts of thermodynamics and self-organization have underpinned the introduction of dynamical systems approaches to further of understanding movement coordination, control and skill (Kelso, 1995; Kugler & Turvey, 1987; Kugler, Kelso, & Turvey, 1980; Lipsitz & Goldberger, 1992). Dynamical approaches seek low dimensional solutions to capture the global macroscopic movement dynamics of the complex multi-segment musculoskeletal system in action. Macroscopic coordination dynamics in motor control has typically been limited to the consideration of relations between two limb segment oscillators through measures of relative phase and vector coding (Haken, Kelso, & Bunz, 1985; van Emmerik, Ducharme, Amanda, & Hamill, 2016). However, Bernstein's (1967) problem was to understand how the many degrees of freedom (DF) of the system are organized so as to master the redundancy of the system: a multivariate challenge that requires a theoretical and experimental strategy to decompose the contribution to system control of the many degrees of freedom (DF) in whole-body action.

A common but underdeveloped thread of theorizing in systems approaches to motor control is the idea that macroscopic variable(s) capture the global structural integrity of the movement in action. Gel'fand and Tsetlin (1962), in an early systems approach, sought a determination of the qualitative structural relations by distinguishing essential variables from the nonessential variables, where the latter were hypothesized to play primarily a scaling role in a movement coordination pattern (see Kugler et al., 1980). The coordination dynamics framework has a macroscopic qualitative variable in movement dynamics fulfilled by an order parameter of relative phase in the bimanual task (Haken et al., 1985; Kelso, 1995). The term collective variable (that we use here) has also been invoked as synonymous to the order parameter in capturing the macroscopic dynamics (Kelso, 1995; Mitra, Amazeen, & Turvey, 1998; Schöner, Zanone, & Kelso, 1992).

In the coordination dynamics framework, it is assumed that mechanical DF of joint space are working to preserve (and are reciprocally preserved by) the dynamic characteristics of the collective variable in the context of a successful performance of the action (Kelso, 1995). To date, investigation of the construct of collective variables for complex multi-variable human movement has been largely limited to the 2 DF bimanual task. The unpacking of the collective variable in whole-body motion DF tasks is a more difficult challenge. It has been approached through a priori theorizing (or just a hunch) of a biomechanically relevant global dynamical variable (e.g., a particular relative phase) or post hoc decomposition of a set of movement variables through principal component analysis (PCA).

Bernstein (1967) proposed 3 progressive stages of learning that reflect the changing organization of the joint space DFs: namely, freezing, freeing and exploiting reactive forces. Several studies have provided experimental support for the freezing and freeing of the joint space degrees of freedom with learning (Newell, 1991; Newell, Broderick, Deutsch, & Slifkin, 2003; Vereijken, van Emmerik, Whiting, & Newell, 1992). There does not appear to be a single strategy to change in learning as the emergent pathway in the adaptive organization of the torso and limbs in action is strongly influenced by the particulars of the task constraints (Newell & McDonald, 1994).

However there has been much debate as to what the DF of movement organization represent in motor control, for example mechanical or dynamical variables (Latash, 2010; Newell & Vaillancourt, 2001). In addition, research has shown that depending on the task constraints and intrinsic dynamics the functional DF of the attractor dynamic can either increase or decrease with learning (Newell & Vaillancourt, 2001; Newell et al., 2003). It can be suggested from a dynamical systems theory perspective, the order of the collective variable reflects the amount of determinism that may relate to how the movement is 'controlled' and the efficiency in the movement will all be key aspects for understanding skill development.

The longswing on the high bar (Figure 1) involves the rotation of the performer about the high bar in the sagittal plane. The longswing is a fundamental skill that underpins the development of more complex high bar skills. The biomechanics of the joint motions in the longswing as a function of skill level has been extensively studied (Busquets et al., 2011, 2013a,b, 2016; Williams et al., 2012; 2015a,b; 2016). However, from a dynamical perspective, the longswing has an implicit limit cycle demand in the task constraints, where consecutive rotations are sustained via the input of energy in each cycle. Further evidence to support the use of an angular position-angular velocity (phase space) representation of the skill is found in forward dynamics models. These consider the angular velocity of the center of mass (CM) of the performer about the bar as the key outcome measure (Hiley & Yeadon, 2016; 2014): suggesting that it is a macroscopic dynamical variable. Therefore, the dynamics of the CM could provide evidence of skill level in line with the dimensionality and deterministic properties of that limit cycle dynamic (see Goldfield, Kay & Warren (1993) for a related developmental oscillatory movement example).

———- Figure 1 ———-

The aim of this study was to investigate the limit cycle dynamics of the motion of CM during the longswing on the high bar as a function of the performer's skill level. It was anticipated that oscillatory properties of the dynamics of the CM would provide a signature of the macroscopic structure of the longswing skill that was not forthcoming from the standard biomechanical kinematic and kinetic analyses of joint motions (Williams et al., 2012, 2015a,b, 2016; Busquets et al., 2011, 2013a,b, 2016). A central determination was the correlation dimension of the attractor dynamic of the CM to examine the proposition that the functional DoF of a macroscopic variable of the system output is reduced with practice and skill level (Bernstein, 1967; Mitra et al., 1998). The phase plane characterization was supplemented with time (recurrent quantification analysis - RQA) and frequency (spectral and harmonic analysis) analysis of the motion of the CM to provide further insights to the macroscopic dynamics of the longswing. The analysis approach taken here with the set of dynamical analyses of CM is a mixture of descriptive and inferential statistics given the small and different number of participants in each skill group.

2.0 Methods

2.1 Participants

Prior to the onset of the study, approval was gained from the Cardiff Metropolitan University Ethics committee. Sixteen male participants: one elite international GB Squad gymnast (age: 23 years, mass: 70.9 kg and stature: 1.73 m), two intermediate groups n = 5, able to perform release and regrasp skills (junior elite) gymnasts (mean ± SD age: 14 ± 2.5, mass 44 ± 9, height 1.55 ± 10), and non release and regrasp skills (junior national) gymnasts (mean ± SD age: 12 ± 3, mass 42 ± 10, height 1.50 ± 10), and five novice gymnasts who had practiced for 6 weeks to perform the longswing (mean age 24 ± 4 years, mass 69 ± 4 kg, height 1.74 ± 0.10 m), gave voluntary informed written consent to take part in this study. The longswing performance here of the novice was after 7 weeks of structured practice where they could complete a circle on the highbar. Typically, of course, an unpracticed participant in the longswing cannot complete a longswing circle. Hence, we are not examining the novice at the very initial stage of practice.

Anthropometric data were obtained using the digital image technique (Gittoes, Bezodis, & Wilson, 2009; Canon EOS400D SLR, Japan) facilitating the calculation of individual-specific body segment masses (Yeadon, 1990) geometric inertia model. Each participant performed a series of four longswings while looped to the high bar. Unilateral kinematic data were collected using an automated 3D motion capture system (CODA) sampling at 100 Hz. Two CX1 CODA scanners (CODAmotion, Charnwood Dynamics Ltd, UK) provided a field of view exceeding 2.5 m around the center of the bar. Active markers were placed on the lateral aspect of each participant's right side at the estimated center of rotation of the shoulder and the elbow, at the mid forearm, greater trochanter, femoral condyle, lateral malleolus, fifth metatarsophalangeal and the center of the underside of the bar.

2.2 Data Processing:

Raw marker data in the horizontal and vertical directions were identified from 3D CODA output, and all subsequent analyses took place using customized code written in R (http://www.r-project.org). The angular orientation of the gymnast about the bar was described by the circle angle; defined by the mass center to bar vector with respect to the vertical rotating anti-clockwise 0° and 360° saw the CM of the performer above the bar (in handstand) (see Figure 1).

2.3 Data Analysis

Poincare plots: Poincaré maps are computed taking the Takens' vectors as the continuous trajectory in the phase space (Kantz & Schrieber, 2004). Takens' theorem states that reconstructed system is equivalent (there is a topological isomorphism) to the original dynamical system that is generated by the observed time series. The n-th Takens' vector is defined as:

T[n]=time.series[n],time.series[n+timeLag],...time.series[n+m*timeLag] (1)

The Takens' vectors were built from the angular velocity time series, time lagged by 18 points and embedded in a 3-dimensional space (Kennel, Brown & Abarbanel, 1992). The time lag was calculated using time delayed mutual information (TDMI), as suggested by Fraser and Swinney (1986). Unlike the autocorrelation function, the mutual information takes into account also nonlinear correlations, making it a suitable choice for non-linear dynamical systems.

Correlation Dimension (CD): Correlation dimension was estimated using the Grassberger and Procaccia algorithm (Grassberger & Procaccia, 1983a, b). This is the most common measure of fractal dimension and it has been used to evaluate the dimensionality of the ωCM limit cycle embedded in the phase space.

Determinism (DET): Determinism, calculated through recurrence quantification analysis (RQA; Webber & Zbilut, 1996), was used to explore stability and structure of the non-linear dynamic of the ωCM within the series of repetitions in the phase space. Both Poincare and RQA analysis are tools to study the capacity of a system to return to the same status within a certain margin, revealing structures not easily detectable in the original state space, helping identify the existence of attractors, and revealing the self-similarity present in fractal systems (van Emmerik et al., 2016; van Mourik, Daffertshofer, & Beek).

Determinism (DET) was calculated over a length of 10 points and radius r = 0.1, to measure the proportion of recurrent points forming diagonal line structures in the RQA. The designation of determinism comes from repeating or deterministic patterns in the dynamic. Periodic signals (e.g. sine waves) will give very long diagonal lines, chaotic signals (e.g., Hénon attractor) will give very short diagonal lines, and stochastic signals (e.g. random numbers) will give no diagonal lines at all (unless parameter RADIUS is set too high).

Phase space: Angular velocity of the center of mass (ωCM) was interpolated in 1° increments of rotation about the bar and presented as a polar plot (see Figure 3). For this analysis, kinematic data were filtered by way of a fourth-order low-pass Butterworth filter, cut-off frequency 10 Hz (Winter, 2005). Variability of ωCM over the four swings at each degree in the circle was calculated based on the standard deviation (SD). Average variability during the whole swing and in each quartile was calculated.

Frequency analysis: A frequency analysis was performed on the raw (not interpolated) ωCM data using the seewave package (http://rug.mnhn.fr/seewave/) to perform Fast Fourier Transform with 216 point moving Hanning window with no overlap. Discrete variables; base frequency, Q Factor, Inharmonicity Index and Simpson Entropy were calculated from the Fourier spectra. Base frequency was the fundamental frequency peak in the spectrum. The Q Factor was calculated based on the Q function in seewave and was the resonance quality factor at -3 dB level. Inharmonicity Index, calculated based as the average of the exponential of the deviation of a peak from a perfectly harmonic spectrum (Equation 2), is a quantitative description of how the spectrum was deviating from a perfect harmonic, where 0 is a purely harmonic spectrum as the overtones are integer multiples of a fundamental frequency.

$$I = \frac{\sum_i e^{|f_i/f_1 - i|}}{N} - 1 \qquad (2)$$

where I is the Inharmonicity Index, N is the number of spectral components, f_i is the frequency of the i-th peak in the spectrum, and f_1 is the fundamental frequency (Williams & Vicinanza, *minor revisions*).

Finally we can define a Spectral Structure Index as the ratio between the Q Factor and the Inharmonicity Index. Larger values of the Spectral Structure Index are associated to highly resonant oscillatory dynamics, smaller values represent less resonant dynamics with broader frequency ranges and more significant contributions from inharmonic components.

3.1 Results

3.1.1 Poincare Plots and Correlation Dimension

Poincare plots (Figure 2) show the limit cycle dynamics through a closed trajectory in the phase space. The cross section of this trajectory is almost one-dimensional for the elite (CD = 1.18), but two-dimensional for novices (Table 1). A significant difference was observed between the intermediate groups and the novice group (No release regrasp/Novices: $F(1,8)= 77.27$, $p=2.2e-05$, Release regrasp/Novices: $F(1,8)=81.13$, $p=1.84e-05$). There was no significant difference between the two intermediate groups ($F(1,8)=0.33$, $p=0.582$). Position divergence can clearly be seen, particularly around the top right of the maps for novice and intermediates, that is relatively more stable for the elite gymnast. That the Poincare plot covers a larger area for the intermediate and novice participants implies that more energy is involved in the system.

-——— Insert Figure 2 around here ———-

-——— Insert Table 1 around here ———-

3.1.2 Recurrence Plots and Determinism

Recurrence plots revealed the non-linear variability, or recurrence, in the Poincare plots. Solid diagonal lines for the elite participant reflect high recurrence rate in the phase space over swings. Lower recurrence was shown for the novices through the ‘feathered’ appearance of the diagonal lines (Figure 3).

-——— Insert Figure 3 around here ———-

Determinism was higher for more skilled participants (Table 1). A significant difference was observed between the intermediate groups and the novice group (No release regrasp/Novices: $F(1,8)= 7.459$, $p= 0.0258$; Release regrasp/Novices: $F(1,8)= 6.336$, $p= 0.036$). The difference between the two intermediate groups was not significant ($F(1,8)= 0.449$, $p= 0.522$).

3.1.3 Phase Space Plots

Phase space plots (Figure 4) show that the ωCM was smoother, more symmetrical, and more consistent for the elite and intermediate gymnasts, when compared to the novice gymnasts. Maximum ωCM was higher for the novice gymnasts, suggesting a less efficient longswing.

-——— Insert Figure 4 around here ———-

Variability of the ωCM was on average higher during the whole swing and during all quadrants of the swing for the novice group, compared to the intermediate gymnast groups, where the elite gymnast had the lowest variability in ωCM between swings (see Figure 4; Table 2). The release and regrasp group had significantly lower variability for the whole swing compared to novices ($F(1,8)= 6.186$, $p=0.0377$). In quartile 1, all groups were significantly different from each other, with the novice group being the most variable and the release and regrasp group being the least (No release regrasp/release regrasp: $F(1,8) = 20.29$, $p = 0.00199$; No release regrasp/Novices: $F(1,8) = 9.932$, $p = 0.0136$; Release regrasp/Novices: $F(1,8) = 5.283$, $p = 0.0506$). In quartile 2, the intermediate groups had significantly less variability than the novice group (No release regrasp/release regrasp: $F(1,8) = 0.126$, $p = 0.732$; No release regrasp/Novices: $F(1,8) = 8.5$, $p = 0.0194$; Release regrasp/Novices: $F(1,8) = 6.118$, $p = 0.0385$). No significant differences between groups were observed in quartiles 3 and 4 (Quartile3: No release regrasp/release regrasp: $F(1,8) = 0.045$, $p = 0.837$; No release regrasp/Novices: $F(1,8) = 4.148$, $p = 0.0761$; Release regrasp/Novices: $F(1,8) = 3.425$, $p = 0.101$. Quartile4: No release regrasp/release regrasp: $F(1,8) = 0.026$, $p = 0.876$; No release regrasp/Novices: $F(1,8) = 0.277$, $p = 0.613$; Release regrasp/Novices: $F(1,8) = 0.591$, $p = 0.464$).

3.1.4 Frequency Analysis

The elite gymnast had the most harmonic spectrum for the ωCM, while all of the novices had the least harmonic spectrum (Table 3). Intermediate groups had significantly lower Inharmonicity than the novice group (No release regrasp/Novices: $F(1,8) = 26.87$, $p = 0.000839$; Release regrasp/Novices: $F(1,8) = 40.83$, $p = 0.000211$), and the release and regrasp group had significantly lower Inharmonicity than the No release and regrasp group ($F(1,8) = 9.966$, $p = 0.0135$).

The Q factor was higher for elite and intermediate gymnasts compared to novices (No release regrasp/Novices: $F(1,8) = 35.14$, $p = 0.00035$; Release regrasp/Novices: $F(1,8) = 32.62$, $p = 0.000449$).

The spectral structure index was significantly higher for the elite and the release and regrasp group, compared to No release and regrasp and novice groups (No release regrasp/release regrasp: $F(1,8) = 8.619$, $p = 0.0188$; No release regrasp/Novices: $F(1,8) = 15.27$, $p = 0.0045$; Release regrasp/Novices: $F(1,8) = 63.27$, $p = 4.55e\text{-}05$).

——— Insert Figure 5, and Table 3 around here ———-

4.0 Discussion

The aim of this study was to investigate the limit cycle dynamics of the motion of CM during the longswing on high bar as a function of skill level. Since the performers can all satisfy the biomechanical demands of the task, the goal is reproducibility and efficiency in the action, and we can assume that this is the product of practice. The limit cycle (based on the angular displacement and angular velocity of the CM) provided a dynamical signature of the macroscopic structure of the longswing skill that complements the standard biomechanical analysis of joint motions (Busquet et al., 2011, 2013a,b; Williams et al., 2012, 2015a,b, 2016) and provides evidence to support dynamical systems models of the DF problem in motor skill acquisition (Bernstein, 1967; Newell, 1985).

Overall, the structure of the limit cycle had a higher dimension, was less variable (quantified by SD), and was reflected by a less harmonic and resonant, less mechanically efficiency, oscillator for novice participants compared to intermediate and elite. The analysis confirmed limit cycle behaviour of the CM during the longswing via the closed trajectory in the state space. Extending previous work on the biomechanics of the longswing (Busquets et al., 2011, 2013a,b, 2016; Williams et al., 2012; 2015a,b; 2016), the limit cycle is present due to the non-conservative gymnast-bar system that required a systemic injection of energy to preserve oscillations. If, for example, the frictionless gymnast moved about the bar as a stiff rod - a point attractor dynamic would have been observed.

Exploring the structure of this limit cycle, the correlation dimension provided evidence that dynamical DF underpinning skilled performance is lower than that of the less skilled and particularly the novices. Correlation dimension quantified an attractor close to a one-dimensional limit cycle for the elite (CD=1.15) and the intermediate (range CD=1.27-1.45) gymnasts, while the novice dynamic was in the order of 2 dimensions (range CD = 2.05-2.72). Previous studies have provided support for a reduction in dynamical DoF with skill learning (Mitra et al., 1998; Newell & Vaillancourt, 2001; Newell et al., 2003; Vereijken et al., 1992) as well as breaks in recurrence (Eckmann, Kamphorst & Ruelle, 1987). However, it should be noted that lower dimensions in skilled or healthy states have been predicted for cyclic tasks, whereas the demands of a point attractor task have been associated with higher dimensional attractors in the less skilled (Vaillancourt and Newell, 2002).

While more variability and irregular behaviour was present for novices, the limit cycle structure provides evidence given the relatively lower dimension (CD=2.05-2.72) than that of a random white noise profile (CD tending to infinite - uncorrelated random process). To explore further, Poincare plots and determinism through recurrence quantification analysis (RQA) were used to quantify self-similarity present in the system (stability and structure) within the series of repetitions in the phase space. Determinism (DET), the reproducibility of the signal, was higher for intermediate groups (release and regrasp 0.68 +- 0.05 %; non release and regrasp group 0.71 +- 0.7 %) compared to novices (0.43 +- 0.21%), suggesting that more of the data fell in the region of stochastics for novice participants. Since the novice DET is lower, it is suggested that the fewer shorter range local correlation provide evidence for a ‘reactive’ rather than ‘predictive’ technique, where changes in one part of the circle are not associated with previous or future changes.

The elite gymnast on the other hand, shows a higher determinism, suggesting that predictive adjustments are made. The lower dimension of the limit cycle as a function of advanced skill level is consistent with the long held position on motor skill acquisition that with practice there is a shift in emphasis of control from peripheral to central sources (Pew, 1966). In this view, the movement trajectory becomes more predictive and efficient with fewer perceptually based corrections of the movement trajectory as a function of practice; an interpretation that would also lead to a lower correlation dimension. However, given the lack of experimental manipulations here beyond practice and skill level, we are not in a position to interpret the change in dimension of the limit cycle dynamics in this way, though as noted it is consistent with it. Together these findings provide evidence to support performers reaching the learning stage of control (Newell, 1985) and reducing dynamical degrees of freedom (Bernstein, 1967) during learning. This analysis also highlights the importance of future dynamical analysis of skill learning considering the notions of predictive and reactive phenomena in task dynamics.

4.1 Variability

Variability, and its functionality, is a notion being explored in human movement science (Newell & Corcos, 1993; Newell & McDonald, 1994). Evidence is being accrued that will enable greater understanding of the 'level' of variability associated with skilled and unskilled performance, and how this changes across different levels of the system. The current data provide evidence that variability of a macroscopic variable is on average lower during the longswing skill for the more skilled participants compared to novices. However, it is also clear that while the amount of variability is significantly lower in some quartiles of the circle (1st and 2nd), this difference is reduced in the latter half of the circle that does not provide statistically significant results for more skilled groups compared to novices.

Lower kinematic variability in the time domain for more skilled participants is consistent with the findings of previous literature, where a 'U' shaped association between variability in joint coordination variables and skill level (from novice, through intermediate, to elite) has been found. However, it should be highlighted that the level and measure of the system will capture different aspects of variability. For example, for higher skill levels, variability is likely to be low in higher order variables that are associated with performance outcome, but may again be high in variables, or combinations of variables that are associated with underpinning mechanical degrees of freedom (Wilson et al., 2006; Arutyunyan, Gurfinkel & Mirskii, 1968). Therefore, fundamental questions about the functional nature of variability for both novices, facilitating exploration of their environment, and skilled performers, maintaining overarching stability, are again highlighted. Longitudinal studies are required to further understand the association of technique variability to performance outcome variability, as well as the addition of modelling approaches (Hiley & Yeadon, 2014).

4.2 Frequency

We used RQA and Poincare to introduced the concept of recurrence and periodicity. Extending the analysis to the frequency domain the periodic structure of the CM angular velocity behaviour was investigated. From a quantitative perspective, the measures of Q and Inharmonicity provide a description of the profile of the spectrum, rather than a statistical breakdown of its content, showing that the movement of the ωCM was described by a largely harmonic and resonant oscillator. Specifically, elite swinging was described by a more harmonic combination of oscillations that has a stronger resonance than novice swinging.

A fundamentally harmonic structure was identified for the elite and skilled swings, suggesting that the macroscopic variable was dominated by changes that were at integer multiples of the swing frequency. Thus, the external drivers, the flexion and extension actions at the hips and shoulders, were occurring very close to harmonics of the resonant frequency in order to maximise the energy that the swing absorbs (Goldfield et al., 1993). For novices, harmonics were significantly weaker (I = 0.25 +- 0.08) than for skilled participants (release and regrasp group I = 0.03 +- 0.01; non release and regrasp group I = 0.06 +- 0.02), suggesting that greater Inharmonicity is a characteristic of low skill level and, a less mechanically efficient swinging action.

The resonance quality (Q) was significantly lower for novices compared to skilled performers, and was highest for the elite gymnast, showing a lower dispersion of frequencies around peaks in the amplitude. Therefore, the novice technique was characterised by a more complex action not yet tuned to the task dynamic. Higher resonance suggests that, mechanically, the system is more 'tuned'; phase coherent, efficient, and less susceptible to perturbations for skilled participants. The concept of stability is explored by van Emmerik et al (2016) who suggest that movement across an attractor landscape finds regions of stable states throughout the learning period.

From a motor control perspective, Inharmonicity can be considered a measure of complexity (Lipsitz & Goldberger, 1992); the closer to 0 the Inharmonicity, the more harmonic, hence simpler is the global dynamic. Inharmonic components suggest multiple oscillators that could be considered to be manifest through active degrees of freedom. Based on this proposition, the more inharmonic spectrum provides support for the greater dynamical degrees of freedom that characterise novice performance compared to skilled performance for the longswing task. Von Holst and Mittelstaedt (1950, 1973) suggested that integer or phase coherent frequencies were not the only functional relations that could exist in nature. However, oscillations independent of the base frequency suggest a less mechanically efficient action, which in line with previous biomechanical work on the mechanical efficiency of skill learning (Williams et al., 2015), that showed novices are less mechanically efficient that more skilled participants.

Efficiency is the last stage of motor learning models (Bernstein, 1967; Newell, 1985; Sparrow & Newell, 1998) and while an indirect measurement of bio-mechanical efficiency, the oscillatory properties of the centre of mass velocity provide evidence that the elite followed by the intermediate gymnasts were more mechanically efficient than the novices.

Overall, the frequency analysis of the phase plane dynamics highlights the concepts of complexity, stability and efficiency in a novel way.

5.0 Concluding Comments

The analyses of the CM motion have revealed its limit cycle dynamic structure as a function of skill level. The findings show that the dynamical degrees of freedom of the CM in the skilled performance were reduced compared to those of novices and represented a more efficient and predictive, rather than exploratory, technique. The motion of the CM is that of a macroscopic variable that acts in a manner consistent with the expectations of a collective variable (Kelso, 1995), the direct association of which requires further study.

References

Arutyunyan, G. H., Gurfinkel, V. S., & Mirskii, M. L. (1968). Investigation of aiming at a target. *Biophysics, 13*, 536–538.

Bernstein, N. (1967). *The co-ordination and regulation of movements.* New York: Pergamon.

Busquets A., Marina M., & Angulo-Barroso R. M. (2013a) Changes in motor strategies across age performing a longswing on the high bar. *Research Quarterly for Exercise and Sport, 84,* 353-362.

Busquets A., Marina M., Irurtia A., & Angulo-Barroso R.M. (2013b) Coordination Analysis Reveals Differences in Motor Strategies for the High Bar Longswing among Novice Adults. *PLoS One, 8*, e67491.

Busquets A., Marina M., Irurtia A., Ranz D., & Angulo-Barroso R. M. (2011) High bar swing performance in novice adults: effects of practice and talent. *Research Quarterly for Exercise and Sport, 82*, 9-20.

Busquets, B. A., Marina, M., Davids, K., & Angulo-Barroso, R. (2016). Differing Roles of Functional Movement Variability as Experience Increases in Gymnastics. Journal of sports science & medicine. 15. 268-276.

Eckmann, J. P., Kamphorst, S. O., Ruelle, D. (1987). Recurrence plots of Dynamical systems. *Europhysics Letters, 5*(9), 973–977. doi:10.1209/0295-5075/4/9/004.

Fraser, A. M., & Swinney, H. L. (1986). Independent coordinates for strange attractors from mutual information. *Physics Reviews, A 33*, 1134.

Gel'fand, I. N., & Tsetlin, M. L. (1962). Some methods of control for complex systems. *Russian Mathematics Surveys, 17*(1), 95–117.

Gittoes, M. J., Bezodis, I. N., & Wilson, C. (2009). An image-based approach to obtaining anthropometric measurements for inertia modelling. *Journal of Applied Biomechanics, 25*(3), 265-270. DOI: https://doi.org/10.1123/jab.25.3.265

Goldfield, E., Kay, B., & Warren, W. (1993). Infant bouncing: The assembly and tuning of an action system. *Child Development, 64,* 1128–1142.

Grassberger, P., & Procaccia, I. (1983a). Characterization of strange attractors. *Physical Review Letters, 50,* 346–349.

Grassberger, P., & Procaccia, I. (1983b). Measuring the strangeness of strange attractors. *Physica D, 9,* 189–208.

Haken, H., Kelso, J. A. S., & Bunz, H. (1985). A theoretical model of phase transitions in human hand movements. *Biological Cybernetics, 51,* 347-356.

Hiley, M.J. and Yeadon, M.R. (2014). Determining the solution space for a co-ordinated whole body movement in a noisy environment: application to the upstart in gymnastics, Journal of Applied Biomechanics, 30, 508-513.

Hiley, M.J. and Yeadon, M.R. (2016). Investigating optimal technique in the presence of motor system noise: application to the double layout somersault dismount on high bar, *Journal of Sport Science, 34*(5), 440-449.

Jordan, M. I. (1996). Computational aspects of motor control and motor learning. *Handbook of Perception and Action, 2,* 71-120. DOI: https://doi.org/10.1016/S0167-9457(97)00023-7

Kantz, H., & Schreiber, T. (2004). Nonlinear time series analysis. Cambridge: Cambridge University Press.

Kelso, J. A. S. (1995). Dynamic patterns: *The self organization of brain and behavior.* Cambridge, MA: The MIT Press.

Kennel, M. B., Brown, R., & Abarbanel, H.D.I. (1992). Determining minimum embedding dimension using a geometrical construction. *Physical Review A, 45,* 3403-3411. Doi:

http://dx.doi.org/10.1103/PhysRevA.45.3403.

Kugler, P. N., & Turvey, M. T. (1987). *Information, natural law, and the self-assembly of rhythmic movement.* Hillsdale, N.J.: Erlbaum Associates.

Kugler, P. N., Kelso, J. A. S., & Turvey, M. T. (1980). On the concept of coordinative structures as dissipative structures. I. Theoretical lines of 191 convergence. In G. E. Stelmach (Ed.), Tutorials in motor behavior. Amsterdam: North-Holland.

Latash, M. L. (2010). Two archetypes of motor control research. *Motor Control, 14*(3), e41-e53. DOI: https://doi.org/10.1123/mcj.14.3.e41

Lipsitz, L. A., & Goldberger, A. L. (1992). Loss of 'complexity' and aging. Potential applications of fractals and chaos theory to senescence. *JAMA, 267*(13), 1806-1809.

Mitra, S., Amazeen, P. G., & Turvey, M. T. (1998). Intermediate motor learning as decreasing active (dynamical) degrees of freedom. Human Movement Science, 17(1), 17-65.

Newell, K. M. (1985). *Coordination, control and skill.* In Differing Perspectives in Motor Learning, Memory, and Control, ed. D. Goodman, R. B. Wilberg, I. M. Franks, Amsterdam: Elsevier, 295-317.

Newell, K. M. (1991). Motor skill acquisition. *Annual Review of Psychology, 42*, 213-237. https://doi.org/10.1146/annurev.ps.42.020191.001241

Newell, K. M. & Corcos, D. M. (1993). *Variability and motor control.* Human Kinetics Publishers. Champaign.

Newell, K. M., & McDonald, P. V. (1994). Information, coordination modes and control in a prehensile force task. Human Movement Science, 13(3), 375-391. DOI: https://doi.org/10.1016/0167-9457(94)90046-9

Newell, K. M., & Vaillancourt, D. E. (2001). Dimensional change in motor learning. *Human Movement Science, 20,* 695-715. DOI: 10.1016/S0167-9457(01)00073-2

Newell, K. M., Broderick, M. P., Deutsch, K. M., & Slifkin, A. B. (2003). Task goals and change in dynamical degrees of freedom with motor learning. *Journal of Experimental Psychology: Human Perception and Performance, 29*(2), 379-387. DOI: http://dx.doi.org/10.1037/0096-1523.29.2.379

Schöner, G., Zanone, P. G., & Kelso, J. A., (1992). Learning as change of coordination dynamics: theory and experiment. *Journal of Motor Behavior, 24*(1), 29-48.

Sparrow, W. A., & Newell, K. M. (1998). Metabolic energy expenditure and the regulation of movement economy. *Psychonomic Bulletin and Review, 5*, 173-196.

Vaillancourt, D. E., & Newell, K. M. (2002). Changing complexity in human behavior and physiology through aging and disease. *Neurobiology of Aging, 23*(1), 1-11. DOI: https://doi.org/10.1016/S0197-4580(01)00247-0

van Emmerik, R. E. A., Ducharme, S. W., Amanda, A. C., & Hamill, J. (2016). Comparing dynamical systems concepts and techniques for biomechanical analysis. *Journal of Sport and Health Science*, *5*(1), 3-13.

van Mourik, A.M., Daffertshofer, A. & Beek, P.J. (2005). Deterministic and stochastic features of rhythmic human movement. *Biological Cybernetics, 94*, 233-244. DOI: https://doi.org/10.1007/s00422-005-0041-9

Vereijken, B., van Emmerik, R. E. A., Whiting, H. T. A., & Newell, K. M. (1992). Free(z)ing degrees of freedom in skill acquisition. *Journal of Motor Behavior, 24,* 133-142. DOI: http://dx.doi.org/10.1080/00222895.1992.9941608

Von Holst, E., & Mittelstaedt, H. (1950/1973). Daz Reafferezprincip. Wechselwirkungen zwischen Zentralnerven-system und Peripherie. *Naturwissenschaften, 37,* 467–476. The reafference principle. In: *The behavioral physiology of animals and man. The collected papers of Erich von Holst.* Martin R (translator) University of Miami Press, Coral Gables, Florida, pp 139–173.

Webber C. L., Jr., & Zbilut J. P. (1996). *Assessing deterministic structures in physiological systems using recurrence plot strategies.* In: Bioengineering Approaches to Pulmonary Physiology and Medicine, Ed. Khoo M. C. K., editor. New York, NY: Plenum Press, 137–148.

Williams, G. K. R. & Vicinanza, D. (In press). Coordination in gait: Demonstration of a spectral approach. *Journal of Sport Sciences.*

Williams, G. K. R., Irwin, G., Kerwin, D. G., & Newell, K. M. (2015b). Biomechanical energetic analysis of technique during learning the longswing on the high bar. *Journal of Sports Sciences, 33*(13), 1376-1387. DOI: http://dx.doi.org/10.1080/02640414.2014.990484

Williams, G. K., Irwin, G., Kerwin, D. G., & Newell, K. M. (2015a). Changes in joint kinetics during learning the longswing on high bar. *Journal of Sports Sciences, 33*(1), 29-38. DOI: http://dx.doi.org/10.1080/02640414.2014.921831

Williams, G. K., Irwin, G., Kerwin, D. G., Hamill, J., Van Emmerik, R. E., & Newell, K. M. (2016). Coordination as a function of skill level in the gymnastics longswing. *Journal of Sports Sciences, 34*(5), 429-439. DOI: http://dx.doi.org/10.1080/02640414.2015.1057209

Williams, G., Irwin, G., Kerwin, D. G., & Newell, K. M. (2012). Kinematic changes during learning the longswing on high bar. Sports Biomechanics, 11(1), 20-33. DOI: http://dx.doi.org/10.1080/14763141.2011.637120

Winter, D. A. (2005). *Biomechanics and motor control of human movement.* Hoboken, NJ: Wiley.

Wilson, C., Simpson, S. E., Van Emmerik, R. E., & Hamill, J. (2008). Coordination variability and skill development in expert triple jumpers. *Sports Biomechanics, 7*(1), 2-9. DOI: http://dx.doi.org/10.1080/14763140701682983

Yeadon, M. R. (1990). The simulation of aerial movement—II. A mathematical inertia model of the human body. Journal of biomechanics, 23(1), 67-74. DOI https://doi.org/10.1016/0021-9290(90)90370-I

List of Tables

Table 1. Correlation dimension and determinism as a function of skill level.

Table 2. Variability (SD) as a function of skill level for the whole swing and across each quartile of the swing.

Table 3. Frequency properties as a function of skill level.

List of figures

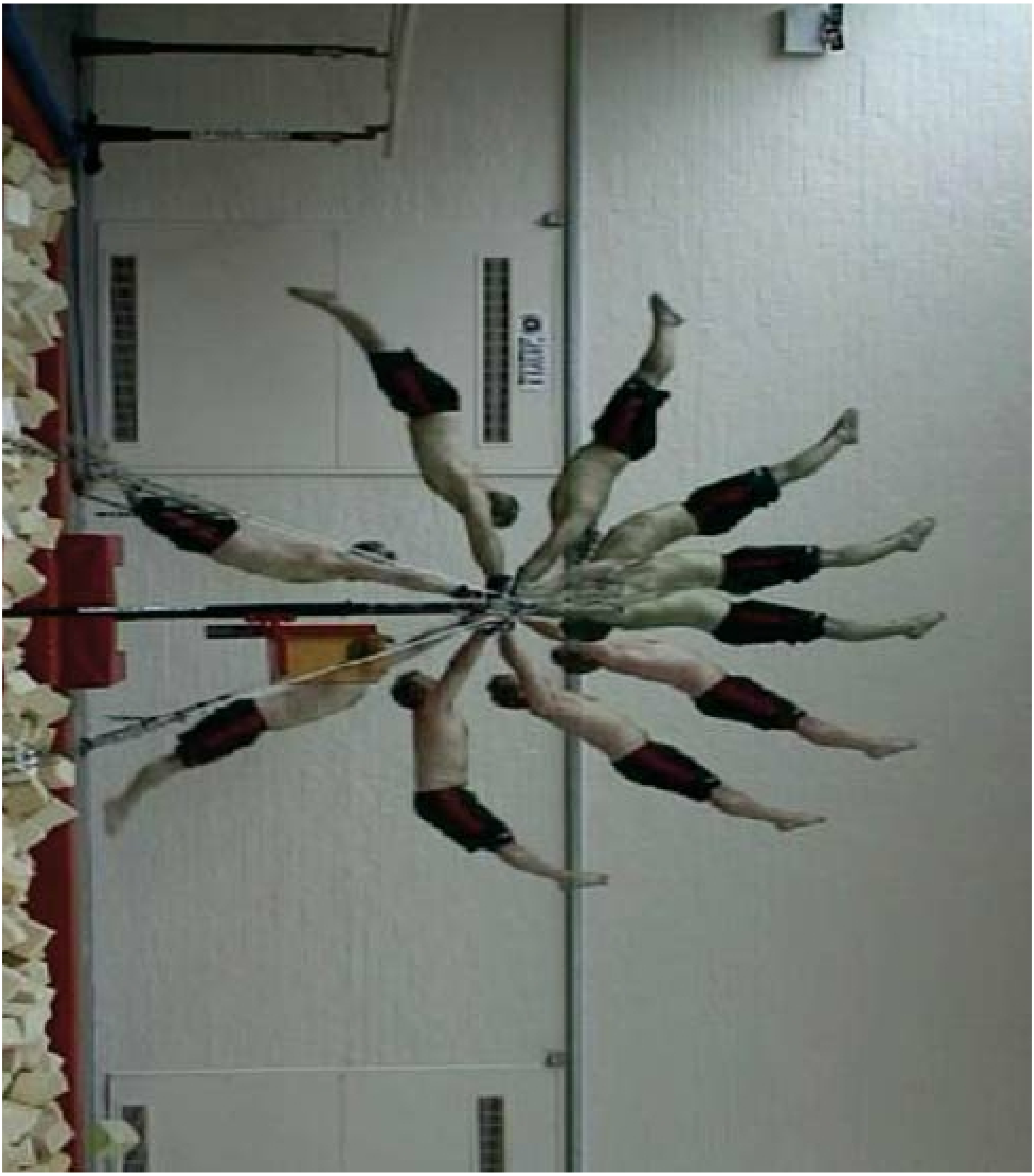
Figure 1. Representation of a performer completing a longswing on high bar. The performer is at 0 and 360□ when in handstand above the bar.

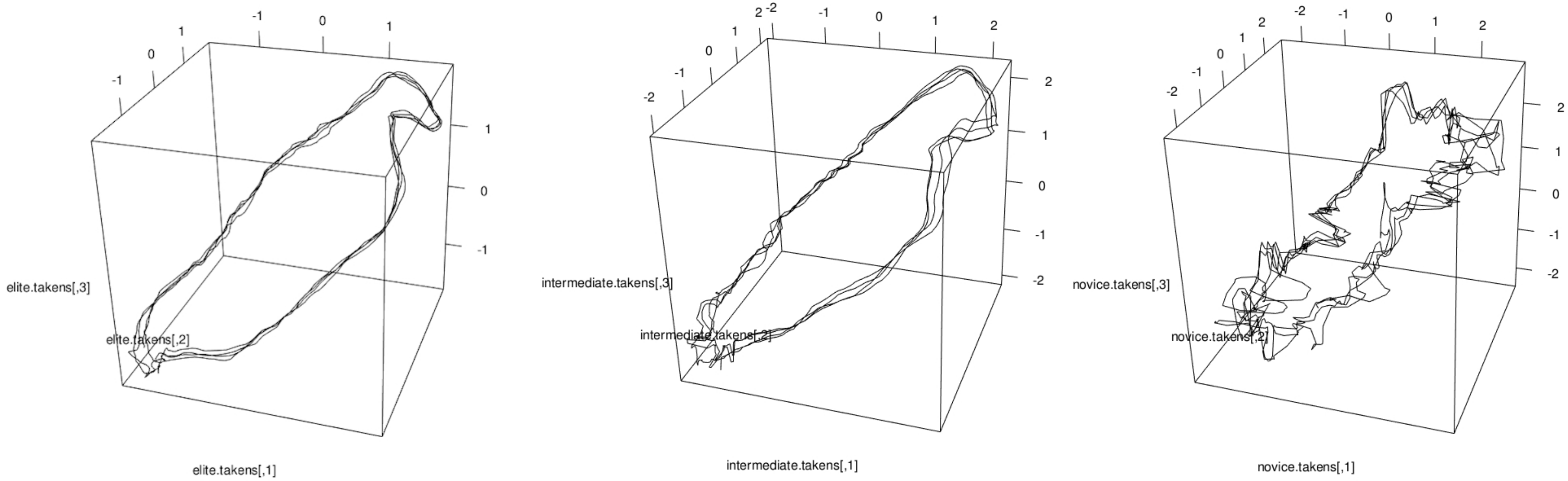
Figure 2. Poincare plot for elite (left), and a representative intermediate (middle) and novice (right) participant.

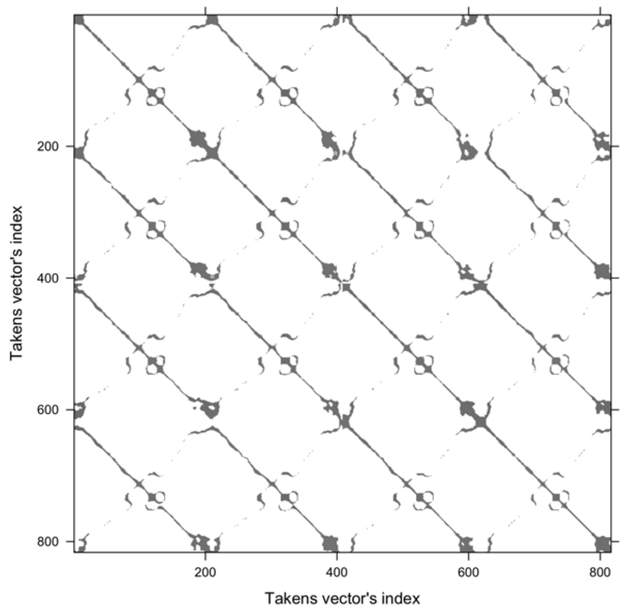
Figure 3. Recurrence plots for elite (left), and a representative intermediate (middle) and novice (right).

Figure 4: Polar plot of the centre of mass angular velocity (ωCM; x-axis) in the circle (y-axis) for four consecutive longswings by an elite gymnast (solid black line), intermediate gymnast (solid grey line) and novice (dashed black line).

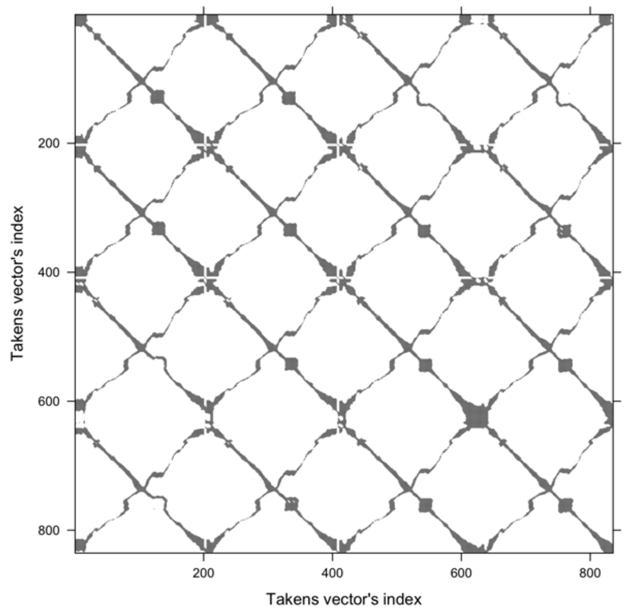
Figure 5. Normalised (to swing) frequency spectrum of the center of mass angular velocity (ωCM) for an elite gymnast (solid black line), intermediate gymnast (solid grey line) and novice (dashed black line).



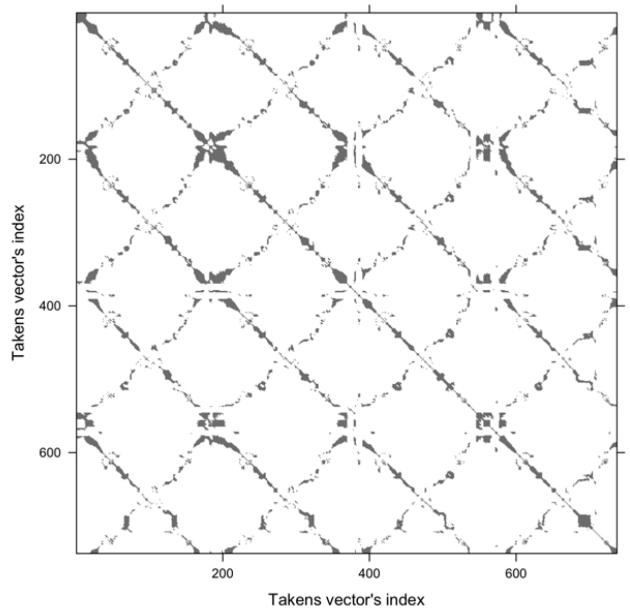

elite.takens[,3]
elite.takens[,2]
elite.takens[,1]
intermediate.takens[,3]
intermediate.takens[,2]
intermediate.takens[,1]
novice.takens[,3]
novice.takens[,2]
novice.takens[,1]



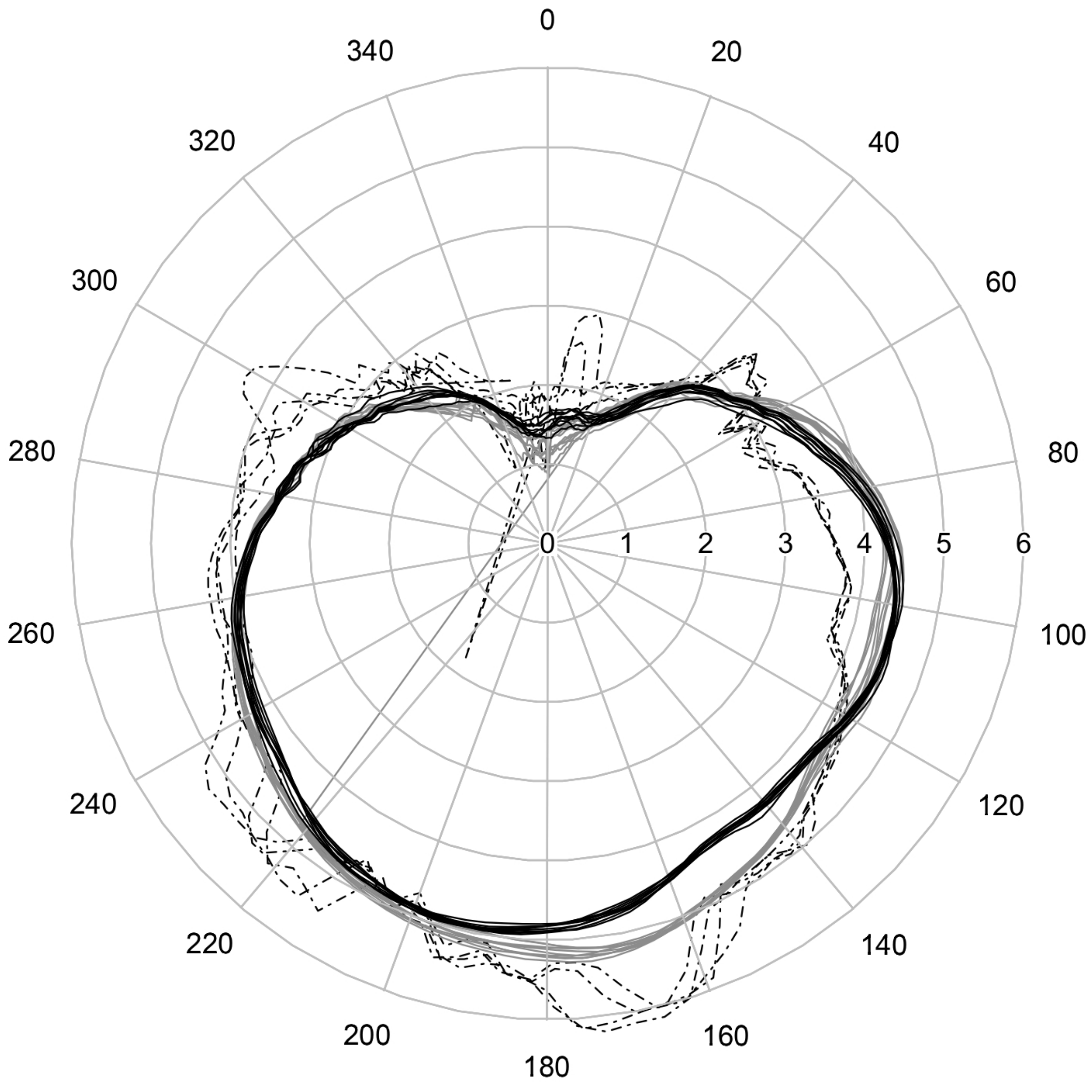
Takens vector's index
200
400
600
800
Takens vector's index

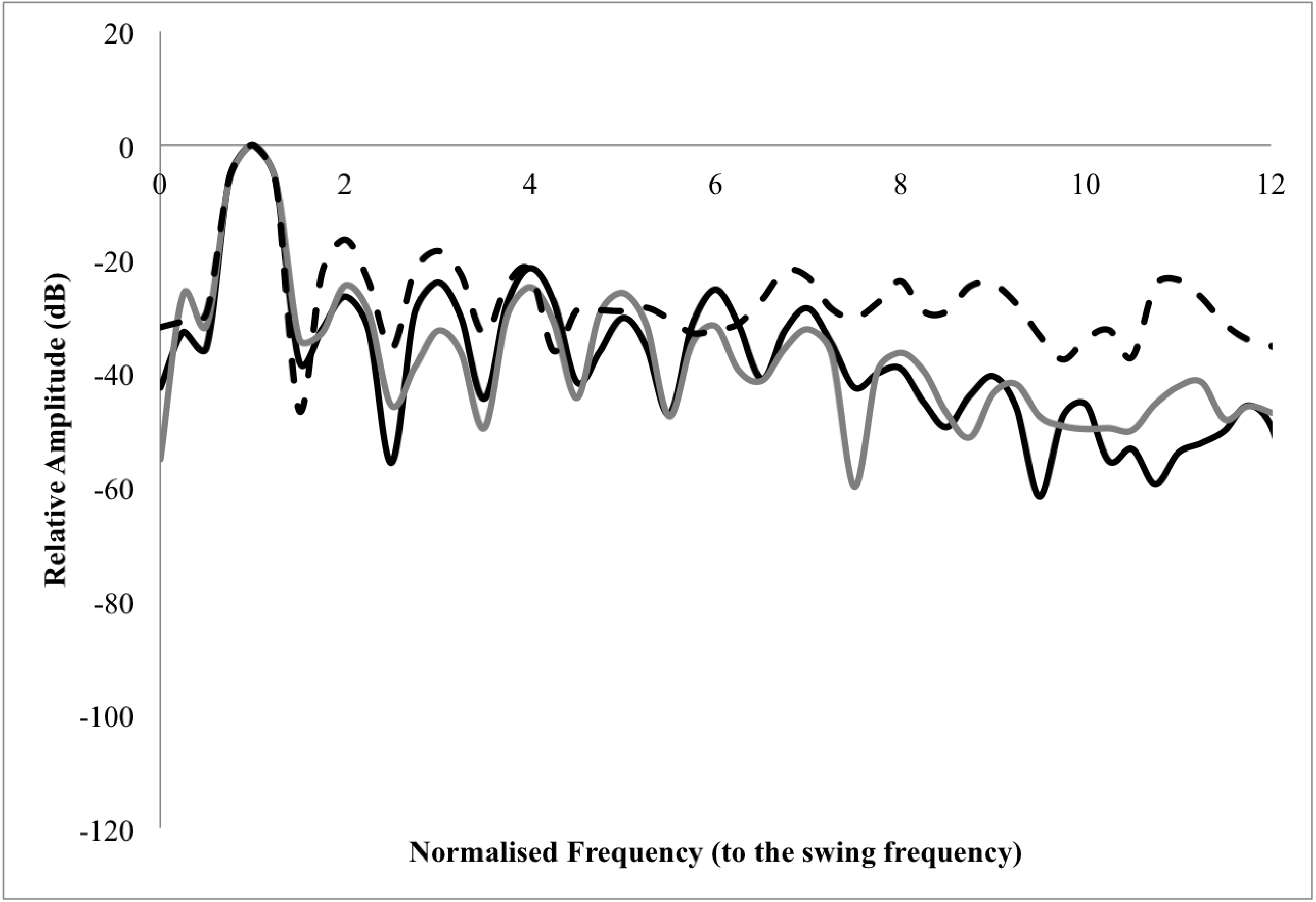


Takens vector's index
200
400
600
800
Takens vector's index



Takens vector's index
200
400
600
Takens vector's index


0
20
40
60
80
100
120
140
160
180
200
220
240
260
280
300
320
340
0
1
2
3
4
5
6



Relative Amplitude (dB)
20
0
-20
-40
-60
-80
-100
-120
0
2
4
6
8
10
12
Normalised Frequency (to the swing frequency)

Table 1. Correlation dimension and determinism as a function of skill level.

Group	Correlation Dimension Mean ± SD	Determinism Mean ± SD
Elite	1.18	0.7
Release Group	1.348 ± 0.06	0.68 ± 0.05
Non Release Group	1.372 ± 0.07	0.64 ± 0.16
Novices	2.488 ± 0.28	0.44 ± 0.25

Table 2. Variability (SD) as a function of skill level for the whole swing and across each quartile of the swing.

	Swing Variability Mean ± SD				
	Whole swing	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Elite	2.12	1.93	1.76	1.92	2.39
Release Group	5.17 ± 0.67	4.82 ± 0.25	3.68 ± 1.67	4.93 ± 2.44	7.27 ± 2.66
Non Release Group	5.44 ± 1.99	3.73 ± 0.48	3.31 ± 1.61	5.19 ± 1.33	7.58 ± 3.50
Novices	7.77 ± 2.24	7.62 ± 2.72	6.08 ± 1.39	7.95 ± 2.73	8.70 ± 3.21

Table 3. Frequency properties as a function of skill level.

Frequency Analysis			
Group	Inharmonicity	Q	SSI
Elite	0.03	4.09	136.30
Release Group	0.03 ± 0.01	3.90 ± 0.10	155.15 ± 53.29
Non Release Group	0.06 ± 0.02	3.97 ± 0.14	71.58 ± 34.58
Novices	0.25 ± 0.08	2.64 ± 0.48	11.04 ± 2.21