DYNAMICS OF HANDSTAND BALANCE

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The purpose of this study was to identify parameters that are associated with more successful motor control during handstand performance. For two groups of gymnasts, ‘less skilled’, who were able to hold handstands for 4 to 6s, and ‘more skilled’, who held handstands in excess of 10s, centre of mass (CoM) and centre of pressure (CoP) motion during the initial 3s of the handstand stability phase were analysed, as well as the 6 to 9s stabilised period for the more skilled gymnasts (balance phase). Time-space, time-frequency, CoM-CoP coherence, Hurst Exponent and CoM-CoP causality were investigated in anterior-posterior (AP) and medio-lateral (ML) directions. Characteristics of CoM and CoP for more and less skilled gymnasts were found to be directionally dependent (AP and ML). Nonlinear and frequency domain measures distinguished skill levels to a greater extent than time-space domain measures. The study findings shed light on the subtleties and complexities of the mechanics and dynamics that define CoM and CoP relations with increased skill level, that add to both basic and applied understanding.

KEYWORDS: nonlinear dynamics, motor control, inverted posture

INTRODUCTION: A handstand is defined as the act of holding the body in an inverted vertical stance with the hands in contact with the support surface. The common goal of preserving balance with respect to gravity presents different challenges when balancing on two arms instead of legs, due to different biomechanical structures, a higher centre of mass (CoM) and smaller surface area. The performance of a handstand requires simulation of the basic human action of upright posture which creates an interesting landscape for the study of motor control. Handstand balance is controlled by subtle changes of hand pressure and limb actions to control whole-body posture. Biomechanical analyses used to further understanding of handstand balance mechanisms have examined individual and coordinated joint motions in the anterior-posterior (AP) direction, primarily at the hips, shoulders and wrists (Kerwin and Trewartha, 2001), and basic CoP motion in AP and medio-lateral (ML) (Slobounov and Newell, 1996). More comprehensive analyses of upright balance (standing) have been centred on macroscopic variables such as the CoM and centre of pressure (CoP), however, the roles of these variables are yet to be investigated in handstand balancing.

Independent analyses of CoM and CoP in both AP and ML directions during upright stance has provided valuable insight into balance strategies and their underlying motor control mechanisms. Furthermore, Newell and colleagues highlighted CoM-CoP relations as a promising candidate collective variable candidate in upright posture, since they were able to see phase transitions with different foot placements, or different oscillatory properties of a platform (Ko et al., 2014). Investigation of the linear interactions of the complex non-stationary time-series, for example, through coherence analysis, may therefore provide essential insight to assist understanding of how individuals successfully balance during the handstand.

Fundamental understanding of linear CoM and CoP interactions may be built upon through our knowledge that biological processes are characterised by complex nonlinear dynamics (Walleczek, 2000), organised within spatial and temporal domains. The nonlinear analysis of
CoM and CoP dynamics can be used to further understanding of signal complexities and the fine-grained characteristics of mechanisms involved in the control of posture (Isableu et al., 2017). Therefore, the aim of this work was to quantify characteristics of CoM and CoP motion during handstand balance. The purpose was to identify parameters that are associated with more successful motor control during handstand performance.

METHODS: Participants: Competitive female artistic gymnasts who trained regularly at a national level were recruited for the study (mean age = 10 ± 1 years, height = 1.37 ± 0.09 m, mass = 31.5 ± 2.9 kg, training duration = 5 ± 2 years, training frequency = 20 ± 5 hours/week).

Protocol: Each gymnast performed 20 handstand trials of up to 20s. Kinematic data were recorded using four CODA motion Cx1 units (Charnwood Dynamics Ltd., Leicestershire, UK) and 48 markers (100 Hz), synchronised with ground reaction forces data from a Kistler force plate (1000 Hz; 9287BA, Kistler, Switzerland). Data analysis: The start of the hand balance phase was defined when the minimum sagittal distance between the left and right feet was reached. During the initial 3s of the handstand (stabilising phase) the CoM and CoP were analysed for two groups of gymnasts: less skilled (n = 5), who were able to hold handstands between 4 and 6s and more skilled (n = 5), who held handstands in excess of 10s. In addition, the 6-9s period of more skilled trials were analysed (balance phase). Whole-body CoM was calculated using 13-segment models along with CoP data which were calculated in Visual 3D software (v6, C-motion, Inc., Rockville, MD) for three trials per gymnast.

AP and ML components of CoM and CoP were analysed in the time and frequency domains, in addition to CoM-CoP coherence analysis (Fig. 1). Displacements and velocities (time domain) were analysed in addition to CoM and CoP power < and > 0.4 Hz and cross wavelet coherence across a frequency spectrum of 1.4 to 100 Hz (frequency domain). Hurst exponent (H) analysis of CoM and CoP signals was then undertaken in addition to AP and ML CoP-CoM causality analysis. Coherence difference between groups were considered using t-tests within Statistical Parametric Mapping (SPM) software. A multiple stepwise regression was undertaken to establish the model with greatest contribution to overall hand balance time.

RESULTS: During the stabilising phase, both groups (less and more skilled) had greater AP and ML displacements of CoM and CoP than was found during the balance phase. The more skilled gymnasts consistently used greater CoP instantaneous velocity than the balance phase (p<0.05), compared to the less skilled gymnasts where velocity differed significantly from the balance phase in the anterior direction only.

More skilled gymnasts had greater ML CoP power at frequencies above 0.4 Hz than less skilled gymnasts (22.31% difference; p = 0.007). Cross wavelet coherence analyses revealed areas of high common power between CoM and CoP (Figure 2). Less and more skilled gymnasts’ CoM-CoP peak coherence differed significantly between approximately 1.95 and 2.90 Hz for AP and ML. More skilled had lower coherence in AP (p = 0.008), but higher coherence in the ML than the less skilled gymnasts (p = 0.004).
Figure 2: Statistical parametric mapping (SPM) outcomes for significant peak CoM-CoP coherence values. Solid line = less skilled, black dash = skilled, black dotted = skilled stability. Shading = sig diff in SPM between skilled and less skilled. Scale = value/100.

For the more skilled group, H outputs revealed weaker long range correlations within the AP CoM signals and the ML CoP signals compared to less skilled (0.05 and 0.07, respectively, Table 1). Significantly stronger long range ML CoM and AP CoP correlations were additionally identified for the less skilled group compared with balance phase (0.06 and 0.13 differences, respectively). CoP was found to drive CoM in all groups (Table 2). An actual driver, where the maximum delay was negative, existed in between 60% and 94% of trials. Of the trials for which an actual driver existed, more skilled gymnasts had a significantly weaker CoP-CoM causal link in AP compared to less skilled (0.02 difference).

When considered by way of a stepwise multiple regression, ML CoP H and ML CoP Power < 0.4 collectively explained 63% of handstand stability time ($R^2 = 0.629$, $P < 0.001$).

Table 1: CoM and CoP Hurst exponent outputs for each group where $ab = \text{sig diff between less and more skilled}$, $ac = \text{sig diff between less skilled and balance phase}$.

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<thead>
<tr>
<th></th>
<th>CoM</th>
<th></th>
<th>CoP</th>
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<tbody>
<tr>
<td></td>
<td>Less skilled</td>
<td>More skilled</td>
<td>Balance</td>
</tr>
<tr>
<td>AP H</td>
<td>0.92±0.04$^{ab,ac}$</td>
<td>0.87±0.05$^b$</td>
<td>0.88±0.06$^{ac}$</td>
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<tr>
<td></td>
<td>0.74±0.06$^{ac}$</td>
<td>0.73±0.06$^{bc}$</td>
<td>0.61±0.03$^{ac,bc}$</td>
</tr>
<tr>
<td>ML H</td>
<td>0.94±0.04$^{ac}$</td>
<td>0.91±0.05</td>
<td>0.88±0.06$^{ac}$</td>
</tr>
<tr>
<td></td>
<td>0.77±0.05$^{ab}$</td>
<td>0.70±0.07$^{ab}$</td>
<td>0.74±0.03</td>
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Table 2: Number of trials for which an actual driver existed and CoP to CoM causality for AP and ML. $ab = \text{sig diff between less and more skilled}$.

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<tr>
<th>Actual Driver Trials</th>
<th>CoP $\rightarrow$ CoM</th>
<th>Balance</th>
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<tr>
<td></td>
<td>Less skilled</td>
<td>More skilled</td>
</tr>
<tr>
<td>AP Causality</td>
<td>0.98±0.02$^{ab}$</td>
<td>0.96±0.03$^{ab}$</td>
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<tr>
<td>Actual Driver Trials (ML)</td>
<td>60%</td>
<td>74%</td>
</tr>
<tr>
<td>ML Causality</td>
<td>0.97±0.05</td>
<td>0.98±0.03</td>
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DISCUSSION: The study aimed to quantify characteristics of successful handstand balance in CoM and CoP for AP and ML using linear and nonlinear measures. For two groups of gymnasts, less skilled who were able to hold handstands for 4 to 6s and more skilled who held handstands in excess of 10s. CoM and CoP motion during the initial 3s of the stability phase were analysed as well as the 6 to 9s balance phase for the more skilled gymnasts. Characteristics of CoM and CoP for more and less skilled gymnasts were found to be directionally dependent (AP and ML). Nonlinear and frequency domain measures highlighted the difference between skill level to a greater extent than time-space domain measures.
In the AP direction, a key finding of the study was that in the stabilising phase the more skilled gymnasts had a significantly lower causal drive from CoP to CoM, compared to the less skilled. Underpinning a weaker causal link, more skilled gymnasts had lower AP coherence at 1.95 and 2.9 Hz. Additionally, with a lower H output, the more skilled gymnasts’ CoM in AP was less repetitive and predictable than that of the less skilled. Overall, we interpret these results to suggest that the more skilled gymnasts had ‘freed’ the association between the CoM and CoP in the AP direction, whereas the less skilled had ‘locked’ these into coherence. This suggests skilled performance is characterised by subtleties that define the relations of CoM and CoP in a more independent and complex way in the AP direction.

When considering the ML direction, a driver from CoP to CoM was evident in 94% of trials during the balance phase and 74% of cases for the more successful gymnasts during the stabilising phase, compared to 60% in the less skilled gymnasts. The trend of greater ML CoP to CoM drive in the most stable conditions suggests that this mechanism is important for high level, long lasting handstands. A key question is whether this strategy is a more effective and efficient way of controlling the system, which might be associated with anticipatory rather than reactive control. Higher ML coherence for more skilled compared to less skilled shows a dominant mechanical coupling between CoM and CoP to be favourable in ML. Exploitation of the mechanical coupling where the potential range of motion isn’t so strongly constrained (i.e. the BoS is larger for ML than AP), suggests that skilled performance is about exploiting the best use of mechanical and dynamical associations that results in the most effective and efficient performance. In addition, more skilled gymnasts had higher CoP power at higher frequencies in the ML, compared to the less skilled gymnasts who had slower moving oscillations which had less drive of, and coherence with, the CoM oscillation. As within AP, the significantly lower H in ML of CoP for the more skilled, compared to the less skilled gymnasts shows a more complex signal. In summary, in the ML CoP the more skilled gymnasts have a faster oscillating, less predictable signal, which in more cases was dynamically driving the CoM, and was more mechanically coherent with the CoM than the less skilled gymnasts.

Regression analysis showed for the more skilled gymnasts, 63% of hand balance time was able to be explained by H (lower) and <0.4 Hz frequency (more above 0.4 Hz) in ML. Therefore, frequency domain and non-linear methods may be better able to discriminate between skilled and less skilled handstand performance.

CONCLUSION: Nonlinear dynamics analyses has provided new perspectives for understanding characteristics of CoM and CoP in handstand balancing. Specifically, this work highlights the importance of analysing ML in addition to AP, as has previously been the favoured approach, and the distinguishing features of both directional components in relation to skill level. Complexity has been found to relate to the constraints of the mechanics in ML and AP for the more skilled gymnasts compared to the less skilled, furthering discussion on directionality of complexity with skill level (King et al., 2012). Finally, the work demonstrates the application of causality to understand the dynamics of mechanically linked variables.

REFERENCES