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Dynamical structure of hand trajectories during pole balancing

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ABSTRACT

We studied the dynamics of fingertip displacement series in human pole balancing using recurrence quantification analysis (RQA). The purpose of this research was to determine how the dynamical structure of fingertip fluctuations evolved with learning. Learning was accompanied by increased stability of movement trajectories in spite of a reduced tendency for movement trajectories to recur. Task manipulations, on the other hand, resulted in more intermittent fingertip dynamics, which suggests that individuals were more tolerant of random fingertip displacements when the task was performed while sitting relative to standing. Such a strategy would minimize the computational burden associated with maintaining pole stability.

Complex perceptual-motor tasks such as pole balancing have generated empirical and theoretical interest because they are representative of how the CNS interacts with and controls unstable objects [4–6,9,16]. Two opinions have emerged regarding control for the pole balancing task.

Computational approaches have been used to argue the CNS employs forward models to ensure the pole remains upright. The premise is that predictive control can help circumvent sensorimotor processing delays to produce low latency movements required for controlling the pole's angle [16]. Such predictive mechanisms have been described in the wake of sensory uncertainty using internal forward models [30]. Alternatively, the stability of pole dynamics may emerge as a consequence of the stochastic properties of motor control [4]. In support of this argument, behavioral data have shown that 98% of fingertip movements are on timescales shorter than sensory processing delays. Numerical analyses subsequently demonstrated that balance can be facilitated in time-delayed stochastic systems provided the dynamics are tuned such that stochastic displacements force the fingertip trajectory back and forth across stability boundaries [5,6]. Accordingly, intermittent control might be favorable for stochastic, time-delayed systems since the computational burden is minimized [17].

In support of the latter argument, we previously quantified decay exponents (α) and truncation for the distribution of fingertip speed changes in pole balancing [8]. Successive differences in fingertip speed were shown to be Lévy distributed. Learning, which was quantified behaviorally as an increase in balancing time, resulted in reduced decay for the probability of large speed steps [8]. The observed decrease in the α-parameter of the Lévy distribution reflects tolerance to fluctuations in the position of the pole over the course of learning. In other words, following extensive practice, large excursions of the fingertip are probabilistically rare, but enacted more frequently than early in learning. These large amplitude corrections are initiated only when stability is threatened, as opposed to early in the course of learning, when large fingertip excursions are performed more continuously. These findings effectively demonstrated that learning may be characterized by changes in the statistical properties of movement kinematics.

The first goal of the present study was to provide a detailed profile of the Lévy-distributed dynamics of pole-balancing fingertip trajectories over the course of learning. We applied recurrence quantification analysis to time series of fingertip trajectories recorded during pole-balancing (RQA) [28,29] to substantiate the link between the gross statistical properties of movements and the time series dynamics of individual performances. This study was motivated by previous work [8], which found that individuals were more tolerant of large amplitude fingertip displacements with pole balancing experience. This tolerance reflects an increased robustness to perturbations, a form of dynamical stability that is captured by the RQA variable L_{max} (this and the other RQA variables mentioned here are described in detail below). Therefore, we predicted that L_{max} would increase over the course of learning and would reflect sensorimotor skill acquisition. The increase in the relative frequency of large fingertip excursions that accompanies learning might also be reflected in the magnitude of the variable

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TREND, which measures nonstationarity. In addition, RQA provides a method for quantifying change in the degree of relative determinism versus stochasticity (*%DET*) embedded in pole-balancing fingertip dynamics, a characteristic of the dynamics that might be expected to change over the course of learning [cf. 18,1,2,23]. Finally, RQA provides a set of measures capable of indexing intermittency in the control enacted in pole-balancing, including *%LAM*, $\upsilon_{\max}$, and *TTIME*.

The second goal of this study was to determine the effects of available biomechanical degrees of freedom (*df*) for balancing. Previous findings demonstrated that learning is accompanied by a progressive recruitment of mechanical degrees of freedom that parallels the development of motor expertise [25–27]. These findings follow from Bernstein's stages of motor learning, whereby early learning is most aptly characterized by constraining degrees of freedom and eliminating motor redundancy. Effectively, constraining degrees of freedom translates to more readily manageable, rigid patterns of movement. Practice tends to release restrictions, as degrees of freedom become organized in a coordinative unit whereby reactive forces of the task dynamics are exploited [3].

Quantifying time series dynamics: RQA is a nonlinear time series analysis that quantifies several dimensions of the time evolution of a signal. Importantly, RQA makes no assumptions about the statistical distribution or stationarity of time series, and furthermore, is suited for the analysis of brief time series. For detailed reviews of RQA including practical tutorials see [13,20,28].

The first step in RQA is to determine how frequently the movement trajectory revisits locations in reconstructed phase space (i.e., how frequently states recur). This is captured by the RQA variable *%REC*. Reductions in *%REC* reflect a decrease in the regularity of the system behavior—the system less frequently revisits states that it previously visited. The patterns of recurrence can then be used to quantify the dynamical structure of the time series as characterized by the following RQA variables.

%DET is the percentage of recurrent points that form diagonal lines in the recurrence plot of minimal length $l_{\min}$. The rationale for *%DET* is that un- or weakly correlated stochastic processes (probabilistically) elicit many isolated recurrent points. Deterministic dynamics, however, manifest as longer diagonals and fewer isolated recurrent points [13]. As such, *%DET* reflects the deterministic (predictable) structure of the dynamics.

The maximum length of diagonal lines in the recurrence plot, excluding the main diagonal (where $i = j$ and the distance between points is by definition zero) defines the $L_{\max}$ parameter. $L_{\max}$ is inversely proportional to divergence and thereby quantifies the dynamic's robustness to perturbation (or to a change in initial conditions), since it approximates the lowest limit of the sum of positive Lyapunov exponents [10,24,31].

Entropy (*ENT*) is the Shannon entropy for the frequency distribution of diagonal line lengths. The *ENT* parameter quantifies complexity in the deterministic structure embedded in the signal [29]. Greater values of *ENT* indicate increased complexity (i.e., for uncorrelated noise, *ENT* is small, indicating low complexity).

Laminarity (*%LAM*) is analogous to *%DET* but measures the percentage of recurrent points forming vertical (with minimum length $\upsilon_{\min}$) rather than diagonal lines. *%LAM* quantifies the local time relationship between close trajectory segments [14,15]. *%LAM* demarcates time intervals during which the system's state is relatively constant compared to intervals of sudden bursts of activity, a hallmark of intermittent systems [13,14]. Recently, Kuznetsov and Riley (submitted) used *%LAM* to distinguish between force production tasks where feedback modulated the intermittency of the enacted control.

Directly related to the *%LAM* parameter is the trapping time (*TTIME*), which quantifies the average length of vertical structures in the recurrence matrix. *TTIME* estimates the mean time (samples) the system abides at a specific state; the average time for which the state is trapped. The final measure which considers vertical line structures from the recurrence matrix is the maximal length of vertical lines, $\upsilon_{\max}$, which is analogous to the $L_{\max}$ measure for diagonal line structures.

In this study we present a reanalysis of data collected for a pole-balancing learning study [8]. Previously the fingertip trajectory data were examined to determine how the statistical properties of pole-balancing kinematics were influenced by learning [8]. Participants learned to pole balance over four experimental sessions that spanned two weeks. Balancing performance improved progressively over the course of learning, as evidenced by an increase in the average time spent balancing in each trial. Task constraints, which were imposed by constraining available biomechanical degrees of freedom for balancing, also influenced performance. In this regard, balancing was facilitated by the availability of biomechanical degrees of freedom, i.e., in the standing relative to sitting condition. Sensorimotor skill acquisition led to changes in the decay parameter for the probability of fingertip speed step sizes, which translated to tolerance for large amplitude, noisy pole displacements. In this experiment we pursue a different aim, employing RQA to determine whether the evolution of fingertip displacement dynamics was moderated by learning or task-level constraints imposed for balancing (reduced biomechanical *df* for balancing).

Six healthy subjects (2 males, aged 26–28 years; 4 females, aged 23–27 years) participated in this research. Subjects were members of the Sensorimotor Neuroscience Laboratory. Participants had normal or corrected to normal vision and were free of neuromuscular and musculoskeletal disorders at the time of collection. All procedures were performed in accordance with the Declaration of Helsinki. The protocol was approved by the McMaster University institutional review board and subjects provided written informed consent prior to experimentation.

Motion capture was performed with 8 VICON MX-40+ infrared cameras sampled at 500 Hz (Denver, CO, USA). Three dimensional pole kinematics were recorded using two spherical reflective markers (14 mm diameter) affixed to the top and bottom of the pole with double-sided adhesive. Data acquisition was performed with the Workstation software (v4.6). Marker trajectories were processed offline and exported for subsequent analysis.

Subjects balanced a wooden dowel (length 62 cm, diameter 0.635 cm, mass 50 g) in two experimental conditions: sitting and standing. Sitting trials were performed with subjects seated comfortably in a chair at their preferred seat height. Subjects were instructed to maintain contact with the backrest. In the standing condition, subjects balanced with feet approximately shoulder-width apart and were free to move the upper body while keeping the feet stationary. When foot movement occurred, the trial was excluded from subsequent analysis.

This study employed a learning protocol. Subjects learned to pole balance over a two-week period. Data collection occurred on the first day, followed by collection every fourth day. At each session, subjects performed 10 trials for each experimental condition. The presentation of conditions was blocked and counterbalanced across subjects. Subjects practiced pole balancing for 30 min per day (15 min per condition) between experimental sessions, distributed according to their preference. We did not enforce a predetermined learning regimen (i.e., massed vs. distributed practice).

RQA was implemented with the RQA software suite (v13.1; Webber 2009). We determined the embedding delay (τ) and dimension (D_e) from a representative sample of trials using average mutual information (AMI) and false nearest neighbors (FNN) analysis, respectively. The embedding delay (τ) was the first minimum of AMI for the finger displacement series. The embedding dimension D_e was the dimension at which FNN were minimum (1%

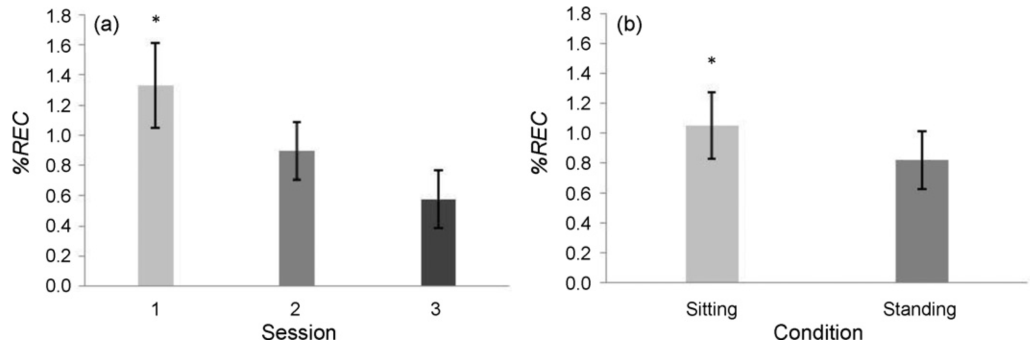

Fig. 1. *%REC* was moderated by learning and a condition effect. (a) *%REC* was dependent on a learning effect, decreasing progressively from the first through third experimental session. (b) *%REC* was dependent on a condition effect, with *%REC* greater in the sitting relative to standing condition, which reveals greater tendency for the dynamic to visit local neighborhoods in phase space in this condition.

considered acceptable), which signifies the attractor has been sufficiently unfolded. The embedding delay parameters ranged from 34 to 108 samples, whereas the embedding dimensions ranged from 3 to 7. We used the median embedding delay $\tau = 62$ samples and dimension $D_e = 5$ for RQA. The *line* parameter, which specifies the number of successive points defining a line segment, was set to 5. We chose the more conservative *line* parameter to avoid saturation of *%DET* and a subsequent ceiling effect. The distance matrix was computed from the Euclidean distance between points, with the threshold for neighborliness, the radius ε, set to 10% of the mean distance between points. RQA was performed for fingertip series in both the *x*- and *y*-axes. Results for sagittal plane (*y*-axis) fingertip trajectories are reported here. Analysis of the coronal plane (*x*-axis) displacements yielded nearly identical results.

Dependent variables were contrasted with session (3) and condition (2) as independent factors using separate 3×2 ANOVAs with repeated-measures. Post hoc analyses were performed with Bonferonni corrections. The significance level for statistical contrasts was .05. Only significant effects are reported.

%REC (Fig. 1) was dependent on learning, $F(2,10) = 12.751$, $p < .01$, with *%REC* significantly greater in Session 1 ($M = 1.327$, $SE = 0.281$) relative to Session 3 ($M = 0.575$, $SE = 0.191$), $p < .05$, whereas *%REC* was not different between Session 1 and 2 ($M = 1.244$, $SE = 0.241$). *%REC* was also larger in the second ($M = 0.896$, $SE = 0.189$) relative to third session, $p = .008$.

$L_{\max}$ (Fig. 2) was influenced by learning, $F(2,10) = 9.100$, $p < .01$. $L_{\max}$ was significantly larger at the outset ($M = 2356.60$, $SE = 434.76$) relative to both the first ($M = 1619.36$, $SE = 376.05$) and second sessions ($M = 1354.86$, $SE = 267.73$). $L_{\max}$ was also dependent on condition, $F(1,5) = 4.980$, $p < .05$, with greater maximum diagonal line length in the standing ($M = 2270.85$, $SE = 420.19$) relative to sitting ($M = 1403.02$, $SE = 277.72$) condition. There was also a significant interaction, however, $F(2,10) = 5.386$, $p < .05$. The interaction showed that $L_{\max}$ was similar between conditions at the outset, but increased disproportionately in the standing relative to sitting condition thereafter. Following learning, the dynamical stability of fingertip movements was greater when the task was performed while standing.

ENT was dependent on the condition for balancing, $F(1,5) = 27.968$, $p < .01$. *ENT* was significantly greater in the standing ($M = 4.71$, $SE = 0.12$) relative to sitting ($M = 4.18$, $SE = 0.21$) condition.

Fingertip displacement series were nonstationary in the pole balancing task, *TREND* was dependent on condition, $F(1,5) = 7.59$, $p < .05$. Nonstationarity was greater in the sitting ($M = -18.75$, $SE = 8.08$) relative to standing condition ($M = -8.13$, $SE = 4.43$).

%LAM was influenced by condition, $F(1,5) = 20.32$, $p < .001$, with significantly greater *%LAM* in the standing ($M = 55.51$, $SE = 4.16$) relative to sitting ($M = 35.70$, $SE = 4.16$) condition. $v_{\max}$ was also dependent on condition, $F(1,5) = 106.57$, $p < .001$, with significantly greater vertical line length in the standing ($M = 21.94$, $SE = 1.88$) relative to sitting condition ($M = 14.65$, $SE = 2.26$), $p < .01$. In addition, *TTIME* was dependent on condition, $F(1,5) = 32.60$, $p < .01$. *TTIME* was significantly greater in the standing ($M = 7.35$, $SE = 0.37$) relative to sitting condition ($M = 6.05$, $SE = 0.41$). Taken together, the latter three results indicate more intermittent control when the task is performed while standing.

The primary purpose of this research was to determine how fingertip dynamics were influenced by learning in the pole-balancing task. This study follows from previous work carried out in our laboratory [8]. RQA revealed a number of changes in the dynamics of fingertip displacements that occurred over the course of learning. RQA also revealed a number of effects related to the availability of biomechanical degrees of freedom for task performance.

%REC is a measure of temporal correlation. It reflects the tendency for points that over time return to the same local neighborhood of the reconstructed phase space. *%REC* decreased progressively with learning, suggesting the temporal correlation in fingertip displacement series decreased with experience. Therefore, as participants became more experienced in balancing,

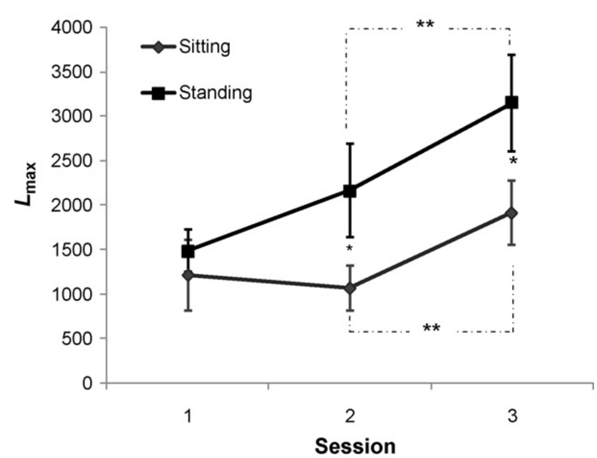

Fig. 2. $L_{\max}$ was influenced idiosyncratically by learning and condition. At the outset, $L_{\max}$ was similar, which suggests that prior to any sensorimotor skill acquisition the dynamic was equistable between conditions. However, with the development of expertise, $L_{\max}$ increased disproportionately in the standing relative to sitting condition. The stability of the dynamic increased nearly linearly with experience, culminating in relatively more stable fingertip dynamics in the standing condition. $L_{\max}$ and therefore dynamical stability of fingertip trajectories was greater in the standing relative to sitting condition during the second and third sessions. In both conditions, dynamical stability increased from second to third sessions. $^{*}p < .05$; $^{**}p < .01$.

trajectories in the reconstructed phase space were less likely to repeat.

L_{max} is the maximum diagonal line length in the recurrence matrix (aside from the main diagonal, when $i = j$) and is proportional to the maximum positive Lyapunov exponent [24]. L_{max} thereby quantifies the stability of the underlying dynamics. In this experiment, L_{max} increased with learning, reflecting sensorimotor skill acquisition, but the interaction was such that the learning effect for L_{max} varied idiosyncratically across conditions. The relative stability of pole-balancing fingertip dynamics was equal prior to experience, however, with learning L_{max} increased disproportionately for the standing balance condition. Effectively, the difference in stability suggests the availability of biomechanical degrees of freedom affected the pole balancing dynamics. This result supplements previous findings whereby performance in the pole balancing task saw an overall improvement with learning but was greater in the standing condition.

Therefore, over the course of learning, fingertip displacement trajectories were less likely to repeat, overall, but repeating values in the trajectories tended to occur as longer strings of recurrent points. Several previous studies have employed dynamical measures to characterize motor skill acquisition. Those studies have revealed findings such as reduced movement system variability over the course of learning [7,11,18,19]. Mitra et al. [18] also demonstrated that continued skill refinement led to further decreases in dynamical noise, which endured after system dimensionality had stabilized. Broadly speaking, motor learning appears to involve the establishment and refinement of stable dynamical structure underlying movement trajectories. Moreover, that the stability of fingertip dynamics followed different learning trajectories suggests the availability of biomechanical degrees of freedom influenced the dynamical stability of fingertip displacements during pole balancing. These results suggest control proffers from motor abundancy that accompanies biomechanical degrees of freedom [3,12,21,22]. That is, the flexibility of abundant motor solutions manifests as an increase in the stability of fingertip dynamics.

ENT, a measure of the complexity of the deterministic structure in the time series, was also greater in the standing relative to sitting condition, while *TREND* magnitude was greater in the sitting relative to standing condition. The addition of biomechanical degrees of freedom for control led to more stationary yet complex dynamics of fingertip displacement. These results complement previous work [8], which considered how the macroscopic variability of fingertip fluctuations in pole balancing was influenced by biomechanical degrees of freedom available for balancing. Taking the results of these studies together, the increased variability in fingertip fluctuation magnitudes and L_{max} in the standing condition translate to increased probability for varied segment lengths, which is reflected as increased complexity by the *ENT* variable.

Our results demonstrate that *%LAM*, v_{max}, and *TTIME*, which index intermittency in the dynamics, were all larger in the standing relative to sitting condition. Collectively, these results suggest that the underlying control strategy in the standing condition is more intermittent, obviated by the relative amount of laminar phases in the observed dynamics. In other words, the system's propensity for intermittency was observed in relatively longer phases whereby the fingertip position was approximately constant. These results are consistent with a control mechanism that capitalizes on the passive dynamics of the pole, and subsequently corrects for pole excursions only when these displacements threaten stability.

Intermittent systems exhibit two distinct phenomenological states. In the "off" state, the dynamics are approximately constant over various time intervals. In the pole balancing task, the "off" state is reflected by time periods where the fingertip position remains approximately constant. Conversely, the "on" state is characterized by intermittent bursting of the dynamical variable, which in the pole balancing task is manifest as rapid, large amplitude corrective finger displacements. Intermittency requires the dynamics be invariant within specific bounds, so that in the pole balancing task, corrective movements are enacted only when pole excursions threaten stability.

In summary, condition contrasts revealed drastic differences with regards to how task manipulations resulted in different dynamics. The *%LAM*, v_{max} and *TTIME* variables from RQA revealed that fingertip fluctuations were more intermittent in the standing condition. Intermittency in the dynamics reflects greater relative contribution from small amplitude, random fluctuations on fast timescales (passive vs. active dynamics).

In summary, these results both corroborate and extend previous work, which demonstrated that skill acquisition in the pole balancing task is reflected by the statistical properties of fingertip movement kinematics. The primary motivation for this research was to determine how the dynamical structure of fingertip fluctuations evolved with learning, and moreover, to determine how this might have contributed to improved balancing performance. To address this purpose, the previous data were reanalyzed using recurrence quantification analysis (RQA) which provided significant insight on the dynamical changes that accompanied learning and furthermore, how the dynamics of fingertip fluctuations varied in response to manipulations of the number of biomechanical degrees of freedom available to contribute to balancing. Learning was accompanied by increased stability of movement trajectories in spite of a reduced tendency for movement trajectories to recur. Task manipulations, on the other hand, resulted in more intermittent fingertip dynamics, which suggests that individuals were more tolerant of random fingertip displacements when the task was performed while sitting relative to standing. Such a strategy would minimize the computational burden associated with maintaining pole stability.

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