

Chapter 8

On the Control of Unstable Objects: The Dynamics of Human Stick Balancing

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Introduction

Objects that we control and interact with are often unstable. Riding a bicycle, balancing a tray of food, maintaining the oscillations of a hula-hoop, and even standing upright are exemplary tasks that require the control of an unstable object. Although it is difficult to characterize the physics of complex object interactions, we are adept at learning and performing these tasks in everyday life. Unstable objects require carefully assembled control mechanisms because, by definition, the object must be stabilized through the interaction between the human control and the intrinsic object dynamics. Additionally, such tasks demand extremely precise control because error can elicit abrupt and irrevocable changes in the performance (Balasubramaniam and Turvey 2004; Cluff et al. 2008).

Although much is known about human motor control and object manipulation in predictable systems (when the mapping between actions and their consequences is straightforward), much less is understood about unstable object control. This is largely because the dominant research focus has been on characterizing the task and context-dependent attributes of firmly grasped, rigid object control (Imamizu et al. 2003; Milner et al. 2006). Although an extensive literature has focused on adaptation to novel mechanical loads, few studies have considered how we learn to control unstable objects. As a result, there are a number of important questions that remain in motor control research: What strategies are used to control unstable objects and how are these control mechanisms learned? Are common control processes shared between interacting motor systems? Do these control mechanisms involve predictive internal forward models?

In this review article, I use a stick-balancing task as a paradigmatic example to investigate control mechanisms and skill acquisition in relation to unstable object control. The stick-balancing task imposes a complex control problem that involves

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maintaining an inverted pendulum in dynamic equilibrium at the finger tip. First, the number of degrees of freedom that needs to be controlled far exceeds the dimensions of the task. Although the stick moves freely in three spatial dimensions, a large number of body segments have been coordinated in order to keep the stick upright and stable. Second, and more important, as the stick is allowed to pivot freely, the effect of forces applied at the fingertip depends on the angular state of the stick (i.e., position and velocity). Small errors in the estimation and detection of state-specific information could translate to a serious loss of performance stability.

The inverted pendulum control problem has been the object of study in control systems engineering and human motor control (Narendra and Annaswamy 1986). Previous studies have generated a number of important insights on the dynamical and neural control processes involved (Treffner and Kelso 1999; Foo et al. 2000; Mah and Mussa-Ivaldi 2003a, b; Cabrera et al. 2006), which fall under the general classification of two theories: internal model and intermittent feedback control. In the following section, I review the two theoretical frameworks, as they pertain to stick balancing in detail, before describing recent work from our laboratory on this topic.

Issues in Studying Unstable Object Dynamics

Internal Forward Model-Based Control

A large body of evidence in human reaching tasks suggests that humans develop internal models to produce the systematic forces required to deal with force-field perturbations (Lackner and DiZio 1994; Shadmehr and Mussa-Ivaldi 1994). Following the seminal work of Wolpert et al. (1995), an important theoretical development is that the brain acquires and uses an internal model that encodes the physical properties of our limbs (Singh and Scott 2003; Kurtzer et al. 2008), environment, and manipulated objects. In particular, object manipulation tasks (Ahmed et al. 2008) have suggested the existence of an internal model that captures the relationship between forces applied to an object and its ensuing movement. Further, Mussa-Ivaldi and colleagues have shown that the relationship between applied force and motion can be learned in the absence of upper limb movement (Mah and Mussa-Ivaldi 2003a). Once such a model is acquired, it can be generalized to novel limb configurations, but such a model does not transfer to objects with different dynamics (Mah and Mussa-Ivaldi 2003b). The general conclusion from these studies is that the control of objects requires knowledge of the physical properties of the object. In the context of stick balancing, these results imply that the successful control of an unstable stick requires object-specific knowledge which is acquired and maintained by the upper limb movements, the sensory consequences of these movements, and the resulting stick motion.

A question of interest in this review is: are internal models required to balance an inverted pendulum? The internal model approach would predict that the stick-balancing task could be performed by predicting sensory information about the

inverted pendulum's angular position and velocity. In much of the recent work on internal models in motor control, a major theoretical point has been that sensory signals that provide state information about the stick (position and velocity) are influenced by noise (for review, see Faisal et al. 2008) and time delay. In the wake of sensory uncertainty and time delay, it has been argued that internal models can be used to estimate the state of the body, environment, and manipulated objects. Such models are acquired and maintained by combining efference copies of motor commands and sensory feedback of the movements to predict the sensory consequences of movements (Wolpert et al. 1998). State estimates are generated using principles to minimize uncertainty via a Kalman filter (Kalman 1960) that uses internal feedback based on the motor command and sensory feedback in conjunction with a model of the motor system.

In a recent study, Mehta and Schaal (2002) examined internal models in the visuomotor control of stick balancing. They found that subjects could successfully balance a stick even in the absence of visual information (in blank-out trials lasting up to 600 ms) and in the absence of force feedback about the stick's state. They concluded that the central nervous system (CNS) uses a forward model to control the stick, but were unable to show the form of model-based control used in stick balancing (Mehta and Schaal 2002). It is possible that this was due to the limitations of a Kalman filter based state estimation mechanism for handling the type of statistical distributions seen in stick balancing (Cluff and Balasubramaniam 2009). Although I do not take up the issue of state estimation directly in this review, I highlight a few caveats about using internal models on the basis of Kalman filter based observer models.

Intermittency and Dynamical Systems Accounts of Stick Balancing

An alternative approach to the internal model account has been developed by Milton et al. (2009). According to these authors, continuous balance control does not adequately describe the behavioral strategies used to control unstable objects. They argue that the difficulty of controlling an inverted pendulum arises due to limitations in simultaneously processing noisy time-delayed feedback while specifying controlled motor responses (Milton et al. 2009). They have contested the viability of continuous model-based control following experimental evidence showing that intermittent rather than continuous control strategies are used in stick-balancing tasks in the context of feedback uncertainty and delay (Loram et al. 2006; Milton et al. 2009; Gawthrop et al. 2011).

In recent years, Cabrera and Milton (2002, 2004a) have shown that stick balancing shows characteristics of intermittent control. They observed that stick displacements exhibit alternating small and large amplitude excursions with frequency. Two important power-law relationships can be seen here. First, the power spectrum of stick fluctuations follows a $-1/2$ power law. When the laminar phases were analyzed, the distribution revealed a $-3/2$ power law. Cabrera and Milton (2002) observed

that corrective stick movements were performed at all time scales; the modal ones occurring at time intervals that are shorter than sensorimotor delays in human voluntary movement (~ 100 ms). Evidence for intermittent control mechanisms have since been reported for the manual control of unstable virtual load (Loram et al. 2009). Further, Gawthrop et al. 2011, have successfully modeled the intermittent control strategy employing ballistic control forces that operate when the angular deviations of a stick exceed specific thresholds. Such a discontinuous control mechanism reflects the usage of short time scale, stochastic forcing of objects when they cross set-point stability boundaries (Cabrera and Milton 2002, 2004a).

It is of interest to note that stick-balancing time is inversely related to the weight and height of the stick. Lighter and shorter sticks are more difficult to control. Periodic vibrations, even shaking an object with the other hand while balancing a stick, help to stabilize performance. These observations suggest that intermittent control could be related to feedback uncertainty, time delay, and interactions between the two. However, the adaptive nature of intermittent control has yet not been explored. It is likely that a combination of the stochastic processes underlying basic hand position and feedback control processes generate intermittency in stick-balancing control (Wolpert et al. 1992; Treffner and Kelso 1999). In this review, I focus on quantifying such intermittent dynamics in stick balancing and accompanying posture control mechanisms.

Task-Specific Control of Upright Posture

It is important to consider the context and task environment in stick balancing. The task of balancing the stick takes place against an almost constant backdrop of the control of upright stance. In the following, I describe recent developments in standing balance control that have contributed to our understanding of stick balancing and the control of unstable objects in general.

Upright posture is stabilized by activity in distributed muscle groups that is scaled to the magnitude and the direction of self-generated and environmental forces (Ting and Macpherson 2005). Despite the complexity of the neural mechanisms involved in postural control, the mechanical basis of standing balance is to maintain (the vertical projection of) the center of mass within a support surface. Posture control is typically studied using time-varying properties of the body's center of pressure (COP). To the extent this equilibrium requirement is satisfied, the postural system appears to be recruited to facilitate goal-directed behavior. An emerging argument, pioneered by Stoffregen and colleagues, is that the diversity of voluntary control is inseparable from the postural mechanisms that support behavior (Riccio and Stoffregen 1988; Marin et al. 1999; Stoffregen et al. 1999; Stoffregen et al. 2000). Recent studies have shown that postural sway helps to facilitate the performance of tasks that are superordinate to the task of maintaining upright balance. This has been demonstrated in the context of light touch (Riley et al. 1999) and precision aiming (Balasubramaniam et al. 2000).

The analysis of postural fluctuations has revealed the interplay between stochastic and closed-loop feedback correction processes, as seen in the multiscale analysis of stick balancing. Postural fluctuations have been modeled widely using a dual timescale model (Collins and DeLuca 1994, 1995; Zatsiorsky and Duarte 1999). However, standing balance is flexible enough to be entrained by an external stimulus (Marin et al. 1999) and robust in the context of visual feedback delays (Boulet et al. 2010). Other studies have revealed task- and context-specific control of posture (Jeka et al. 2000; Kiemel et al. 2002; Peterka and Loughlin 2004). Other findings, however, imply an intimate functional link between posture and upper limb control (Ahmed and Wolpert 2009) that extends beyond the instability of standing balance (Balasubramaniam and Wing 2002), suggesting that a common predictive mechanism might underlie the control of both systems (Flanagan and Wing 1997). In this review, I will look at the interaction between the postural system and stick-balancing dynamics. In particular, I will examine how task parameters influence the control system underlying the two.

Perspectives in Motor Learning

Stick balancing does not come easy. Learning to balance an unstable object requires mastery of the degrees of freedom of the body and an understanding of the physical dynamics of the object. In this section, I will review how scientists have approached the issue of skill acquisition in recent years. The motor learning literature may be divided into (at least) two distinct approaches: sensorimotor adaptation and coordination dynamics.

Sensorimotor adaptation paradigms have been used to study how motor commands are modified in the wake of changing environments (Lackner and DiZio 1994; Shadmehr and Mussa-Ivaldi 1994). In this approach, learning has been argued to reflect an optimal parameter estimation process that serves to reduce error. Anticipatory change in reaching kinematics has been documented extensively in force-field adaptation studies, leading to important discoveries about trial-to-trial learning, consolidation, and interference. Imaging studies have revealed that the cerebellum (Imamizu et al. 2003) and basal ganglia (Seidler et al. 2001) are strongly implicated in sensorimotor adaptation and the modification of motor commands in changing environments. Although the sensorimotor adaptation paradigms have contributed to our understanding of learning movement trajectories, there have been few studies that have investigated the role of the interaction between the multielement structure of the body (and its many degrees of freedom) and various subsystems as a function of learning.

The coordination dynamics perspective offers a powerful framework to investigate the organization, stability, and control of voluntary movement. The largest successes of this perspective have been in quantifying the acquisition of bimanual coordination patterns. In coordination dynamics, the focus of research has been on learning induced changes in the spatio-temporal properties of a system, characterized by an order parameter (Zanone and Kelso 1992). In this approach, changes in an abstract

parameter are believed to reflect dynamical events unfolding at multiple time scales (such as relative phase between two limbs). Learning has been described by the evolution of the topological properties that characterize body segment relationships and systematic changes in the recruitment and patterning of multiple degrees of freedom (Vereijken et al. 1992).

Given the number of degrees of freedom that have to be coordinated in complex motor learning situations, interactions between motor subsystems have also been a key part in dynamical approaches to motor learning. Following the seminal work of Bernstein (1967), Newell et al. (2001) have suggested that motor learning is instantiated by the evolving coordination of interacting motor subsystems. Their model distinguishes between three hierarchical levels of the motor system ranging from (1) individual effectors that operate and evolve within effector systems (e.g., individual muscles, segments, or joints) to (2) coordinative relationships between motor subsystems (e.g., posture and upper limb movement patterns) that interact to produce and stabilize (3) outcome performance. Newell et al. (2001) have proposed that such specialized motor subsystems are organized hierarchically. Such subsystems are assembled into functional units that support outcome performance. In this review, I will employ the ideas that have evolved from the motor learning literature, specifically related to the spatio-temporal properties and control of degrees of freedom, to describe skill acquisition in stick balancing.

Issues at Hand for Stick Balancing

It is, thus, evident that task- and context-specific control mechanisms are common features of posture and upper limb control. I posit that object manipulation skills in the task of balancing an unstable object, like a stick at the fingertip, are established through these common learning and control mechanisms governing these subsystems. I ask the following four questions. (1) How do we learn to control unstable objects? (2) Are stick-balancing dynamics intermittent and if so how can we quantify this intermittency? (3) Are distinct motor systems, such as the control of individual joints, posture, and the upper limb, linked through common learning and control processes? (4) What is the role of higher cognitive and attentional processes in the acquisition and maintenance of the stick-balancing skill?

Spatio-temporal Dynamics of Stick Balancing

The objective of our first study (Cluff and Balasubramaniam 2009) was to determine if the power-law scaling in stick balancing (Cabrera and Milton 2004a, b), described in the section above, is dependent on motor learning.

In order to test this idea, participants balanced a wooden dowel with length 62 cm, diameter 0.635 cm, and mass 50 g in two experimental conditions: sitting and standing. Sitting trials were performed with subjects seated comfortably in a chair at the

subjects' preferred seat height. The subjects were required to balance the pole with their back remaining in contact with the seat. In the standing condition, subjects performed pole balancing with their feet approximately shoulder-width apart, but were able to move their upper body while maintaining a stationary stance.

Participants learned to balance a small cylindrical stick on their fingertip over a 2-week period. Data collection was performed on the first day, followed by subsequent data collection every fourth day. The subjects performed 30 min of daily practice between data collection sessions (15 min per condition), which was distributed between conditions according to their preference. We avoided confounding learning effects by counterbalancing the order of conditions across subjects. Motion capture was performed with eight VICON MX-40 + infrared cameras sampled at 500 Hz (Denver, CO, USA). We tracked pole motion in three-dimensions using two markers affixed to the top and bottom on the pole.

We computed the Euclidean finger tip speed $s(t)$ and the detrended speed, Δs . For the probability of a given step size, we computed $P(\Delta s, \Delta t)$ by plotting histograms with bin size set to 1 mm/s. To determine whether the probability of a given step size was influenced by the time between observations, Δt , we decimated $\Delta s(t)$ on a logarithmic scale by factors 1–1,000. We plotted the probability of return (i.e., the probability of zero change in fingertip speed between observations), $P(0, \Delta t)$, as a function of Δt . The power-law exponent α was computed by regressing $P(0, \Delta t)$ onto Δt on a log-log scale. Figure 8.1a shows the distribution of $P(\Delta s, \Delta t)$ for the sitting and the standing conditions. The purposes of this study were two-fold: first, to determine whether the decay exponent for the probability of a given step size, α , changed with learning, and second, to determine whether α varied in a sitting versus standing condition.

As subjects learned the mean balancing time increased, unequivocally suggesting that they were getting better at the task. Figure 8.1b shows the change in the value of the power-law exponent across sessions of learning. A careful look at Fig. 8.1 reveals that the values of α range from 0 to 2 (i.e., $0 < \alpha < 2$), suggesting that stick-balancing dynamics are Lévy-distributed, a finding previously reported by Milton et al. (2004). The Lévy process can be characterized as an unbounded and unconstrained random walk. The unbounded, asymptotic character of the Lévy distribution results in an infinitely variant process, resulting in the absence of the first and second statistical moments. Figure 8.1 also reveals that the distribution broadens with learning, this corresponds to a smaller decay in the probability for large step sizes. Behaviorally, this is manifested as tolerance to stochastic processes: the participant becomes more tolerant to large changes in fingertip speed with increasing task proficiency.

Our results demonstrate that motor learning results in increased tolerance for large stick displacements. The decay exponent α was influenced by learning, becoming significantly smaller with experience and resulting in less severe decay in the probability for a given velocity step size, $P(\Delta s, \Delta t)$. Moreover, the decay exponent α for $P(\Delta s, \Delta t)$ was greater in a sitting versus standing condition. Our results show conspicuously that both decay exponents and truncation change with learning, resulting in an increased tolerance to large fingertip excursions in pole balancing.

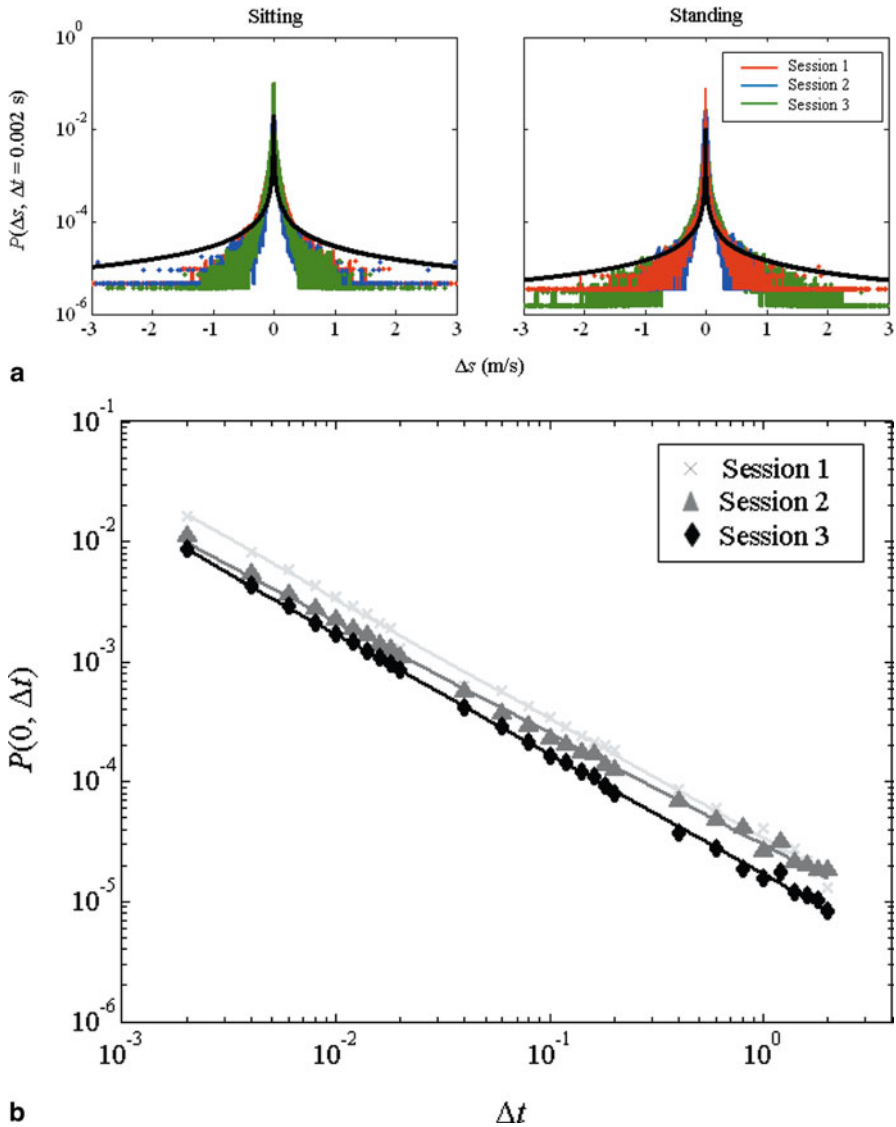


Fig. 8.1 *Top-panel*: Session 1; blue: session 2; green: session 3. Solid black line represents theoretical Lévy distribution with **a** $\alpha = 0.95$ and scale parameter $\gamma = 0.03$, **b** $\alpha = 0.98$ and scale parameter $\gamma = 0.025$. The overlaid theoretical Lévy distribution demonstrates both decay exponent α and truncation change with learning in the standing condition. *Bottom panel*: $P(0, \Delta t)$ follows a power-law distribution for $\Delta t = 0.002$ to 2 s, in the sitting condition. (Reprinted with permission from Cluff et al. 2009, Public Library of Science)

Our results that stick-balancing trajectories (probability of finger tip speed change over time interval) are Lévy-distributed, raises important concerns about hypothesized control mechanisms that are based on predictive internal models that employ

Kalman filters (Mehta and Schaal 2002). Lévy processes are indicative of nonpredictive search processes or foraging. Moreover, a conventional Kalman filter assumes additive Gaussian processes and measurement noise. It is unlikely that a technique using conventional Kalman filters can be successfully used to model systems with multiplicative noise that yields power-law distributed variables.

In summary, this study has demonstrated that learning, which reflects changes between the dynamics of passive and predictive mechanisms, can be captured by changes in ensemble statistical distributions that capture the spatio-temporal properties in stick balancing.

Quantifying the Intermittency in Stick-Balancing Dynamics

In the previous section, I reported on the nature of Lévy distributions and power-law scaling seen in stick balancing. The question that remains is what kind of control mechanisms are implicated in seeing such a distribution. One interesting possibility that this observation raises is the presence of intermittent corrections at multiple time scales. Previous work by Milton et al. (2004) has shown that power-law scaling was also evident in the laminar phases (time intervals) for successive corrective movements, demonstrating that corrective movements were intermittent. In confirmation of intermittent control, behavioral data demonstrated that 98 % of corrective movements were shorter than our sensory processing delays (~ 100 ms). Numerical analyses have since demonstrated that balance is facilitated in time-delayed stochastic systems, provided the system is tuned near a stability boundary. In this case, control could result from stochastic processes that force the fingertip trajectory back and forth across stability boundaries. It is often argued that intermittent control might be favored to continuous estimation in stochastic, time-delayed systems as the computational burden incurred by the CNS is minimized (Milton et al. 2008).

The first goal of our next study (Cluff et al. 2009) was to perform a detailed investigation of the Lévy-distributed dynamics of stick-balancing fingertip trajectories and test for the presence of intermittent control mechanisms. To investigate this, we applied recurrence quantification analysis (RQA) to the fingertip displacement time series recorded during stick balancing (Webber and Zbilut 1992). An objective of this study was to quantify the intermittency seen in stick balancing and the changes accompanying learning. Intermittent systems are characterized by two distinct states, “off”: a period over which dynamical variables are approximately constant and “on”: where sudden, intermittent bursting of activity can be seen. In such systems, when the dynamical variable remains within a certain threshold bound it is quiescent. When the threshold bound is crossed, the system transitions from the “off” to “on” state, where a burst of activity might be seen.

The earlier section summarized the work that showed that individuals became tolerant of large amplitude fingertip displacements with pole balancing experience. This tolerance reflects an increased robustness to perturbations, a form of dynamical

stability we sought to quantify. In addition, RQA provides a method for quantifying change in the degree of relative determinism versus stochasticity (*%DET*), robustness to perturbations (*Lmax*), nonstationarity (*TREND*) all embedded in pole-balancing fingertip dynamics—a characteristic of the dynamics that might be expected to change over the course of learning (cf. Riley et al. 1999; Balasubramaniam et al. 2000; Balasubramaniam and Turvey 2004). Finally, RQA provides a set of measures capable of indexing intermittency in the control enacted in pole balancing, including *%LAM*, *vmax*, and *TTIME*.

Recall that in the earlier section, we reported significant differences in learning the stick-balancing task in the sitting and the standing conditions (Cluff and Balasubramaniam 2009). A key objective of this study was to assess the nature of the difference between the sitting and standing condition. We reasoned that the availability of greater number of biomechanical degrees of freedom in standing greatly contributed to the better acquisition of the stick-balancing skill in that condition. Earlier work has shown that learning can change the orderly recruitment of degrees of freedom into organized coordinative structures, in a manner that would facilitate performance (Bernstein 1967; Vereijken et al. 1992).

As with the previous study reported in the section, Spatio-temporal Dynamics of Stick Balancing, subjects learned to balance a stick in sitting and standing conditions. We analyzed the stick-balancing displacement time-series data using RQA. Results 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 that temporal correlation in fingertip displacement series decreased with experience. Therefore, as participants became more experienced in balancing, the trajectories in the reconstructed phase space were less likely to repeat. Figure 8.2 summarizes the findings on recurrence rate as a function of learning for the sitting and the standing conditions.

Our results also demonstrated that Laminarity index (*%LAM*), and trapping time (*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 was more intermittent for the standing condition. 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 passive motor control dynamics and corrects for pole excursions only when these displacements threaten stability. Such a mechanism is often termed “drift and correct,” following the work of Milton et al. (2004).

In summary, we have shown that learning resulted in greater stability of stick movement trajectories (resistance to perturbation); although they showed a greater tendency to return to the same areas of the reconstructed phase space. The availability of greater degrees of freedom in standing resulted in intermittent dynamics

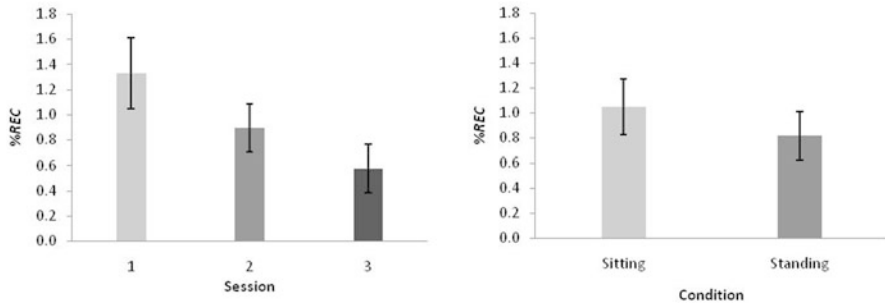


Fig. 8.2 %REC was moderated by learning and a condition effect. **a** %REC was dependent on a learning effect, decreasing progressively from the first through third experimental session. **b** %REC was dependent on a condition effect, with %REC greater in the sitting relative to standing condition, which reveals greater tendency for the dynamic to visit local neighborhoods in phase space in this condition. (Reprinted with permission from Cluff et al. 2009 @ Elsevier)

at the fingertip and suggested the role of the recruited “coordinative structures” in minimizing the computational burden on the CNS.

Task-Specific Coupling Between Posture and Hand

As mentioned in an earlier section, stick balancing takes place on top of the usual balancing and cognitive demands placed on the standing performer. Our results have also shown overwhelmingly that standing actively contributes to stick-balancing expertise and the intermittent control mechanisms that are characteristic of learned performance. Thus, a natural question to study would be: what are the interactions between the body’s COP and stick trajectories when an actor learns the task of stick balancing. Cluff et al. (2011) examined this relationship and coupling between hand and postural displacements during stick balancing.

In this study, participants learned to balance a cylindrical wooden stick on their index finger while standing in an upright posture. Learning was quantified over four experimental sessions. Data collection sessions took place every fifth day and were about 90 min in duration. Subjects performed 30 min of daily practice between experimental sessions. RQA analyses were performed separately on hand and postural displacements. Cross-RQA (CRQA) was performed to study the co-time evolution and relationship between postural and hand displacements as subjects learned the task. We hypothesized, following the work of Newell et al. (2001) that we reviewed earlier, that learning would involve a reorganization of postural control to support stick performance.

In line with our previous studies, finger trajectories became more discontinuous with learning. But we also noted similar changes in the COP time series, suggesting that postural sway was indeed facilitating the performance of the “suprapostural” task of stick balancing. As summarized in an earlier section, this is consistent with

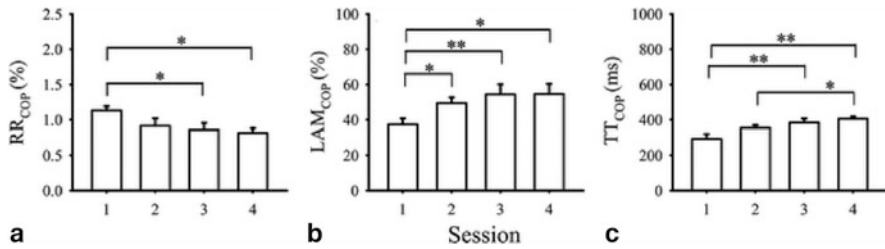


Fig. 8.3 Coupling strength and dynamical properties of the finger–COP (F–COP) interaction. **a** Recurrence rate (RR) of coupled F–COP trajectories by session. An increase in RR_{F-COP} reflects the tendency for collective control over finger and COP displacements. **b** LAM_{F-COP} measures transitions between coupled and uncoupled F–COP trajectories. Greater LAM_{F-COP} reflects an increase in the density of coupled F–COP trajectory segments. **c** Average length of coupled F–COP trajectories by session (TT_{F-COP} ; unit: ms). Error bars are the within-subjects standard error of the mean (SEM). * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$. (Reprinted with permission from Cluff et al. 2011 @ Springer)

previous work suggesting a facilitatory role for postural fluctuations (Balasubramaniam et al. 2000; Stoffregen et al. 1999, 2000). As seen in Fig. 8.3, we also demonstrated that the coupling strength between posture and hand displacement underwent substantial changes as a function of learning. Specifically, CRQA revealed that cross-recurrence, laminarity, and trapping time systematically changed with learning. Learning progressively stabilized the coupling between the upper limb and postural subsystems. In the following, we make the case that this progressive change in coupling emerged from the development of a hierarchical control system that can seamlessly switch between controlling the upper limb and postural systems (Newell et al. 2001).

According to the seminal motor learning model of Newell et al. (2001), individual subsystems become coupled to structural coordinative relationships to support performance. In this experiment, we showed the emergence of such coupling with learning. The improvement in performance can be attributed to two processes (1) at the level of individual subsystems (seen in learning sessions 1 and 2): decreases in regularity and discontinuity and (2) the lengthened coupling of the finger and COP displacements in the third learning session. Interpreting these results in the context of the model of Newell et al., one could argue that early learning changed the organization of individual subsystems and later learning influenced their coordinative relationship.

The increased coordination between the postural and finger subsystems could be due to either anticipatory (Flanagan and Wing 1997) or reactive mechanisms. We make the case that COP and finger displacement were controlled by a hierarchical system that was able to switch intermittently between individual and collective control of the subsystems in question. Future work should carefully examine how the individual biomechanical degrees of freedom of the hand and the postural system come together in a constrained way to achieve this functional coupling. We are presently engaged in research that would enable a comparison between end-effector

analyses (such as the ones presented here) and the contribution of the many redundant degrees of freedom at the disposal of the CNS to the statistical properties of the end effectors during unstable object manipulation.

Attention and Task Performance

In the previous sections, I have looked at the changing landscape of control mechanisms that accompany motor learning in stick balancing. We have also seen in the preceding section about the nature of interactions between posture and hand displacements that reveal a hierarchical control structure. In recent years, several studies contributed to a generalized theory of attentional influences on motor performance (see, Wulf and Prinz 2001, for review). Other work has also examined the function of attention as being a deterrent to successful task performance (Beilock et al. 2002; Beilock et al. 2008; Beilock et al. 2008). Stemming from this research, the “constrained action” theory proposes that attention devoted to movement execution interrupts the automaticity of performance (Wulf et al. 2001). Performance, defined as the statistical stability or variability of motor execution, is dependent on whether attention is devoted to motor execution or outcome. As a test of the constrained action theory, Cluff et al. (2010), asked if specific task instructions would influence the way skilled practitioners carry out the stick-balancing task.

We employed six experimental conditions. (1) Posture baseline condition (P): quiet standing task for 30 s with no explicit instructions. (2) Posture-cognitive dual-task (P-CDT) condition: subjects performed upright standing while performing a silent, serial arithmetic task. (3) Posture-stick balancing (P-SB): subjects balanced the stick in upright stance without specific attentional instructions. (4) P-SB external focus condition (P-SBEXT): subjects were instructed to “minimize deviations of the stick from the vertical.” (5) P-SB internal focus condition (P-SBINT): subjects were instructed to “focus on minimizing hand and finger movement.” (6) P-SB-CDT: subjects performed a CDT while standing and balancing a stick. The methods used in this experiment are reported from Cluff et al. (2010).

We hypothesized that both postural and suprapostural components of the stick-balancing task would be stabilized by a task-irrelevant external focus of attention (P-SB-CDT). We predicted that an internal focus of attention would compromise dynamical stability in the stick-balancing task, resulting in variable COP and FINGER trajectories. In confirmation of the hypothesis, FINGER and COP trajectories were least variable when participants partitioned attentional resources between stick-balancing and cognitive task components, corresponding to an external, task-irrelevant focus (P-SB-CDT). In contrast, COP and FINGER displacements were least stable when the focus of attention was internal. Performance stability for the external, task-relevant condition was similar to control performance (P-SB). Figure 8.4 summarizes this effect.

It is interesting to note that our results did not directly support the constrained action theory proposed by Wulf et al. (2001). According to this theory, performance

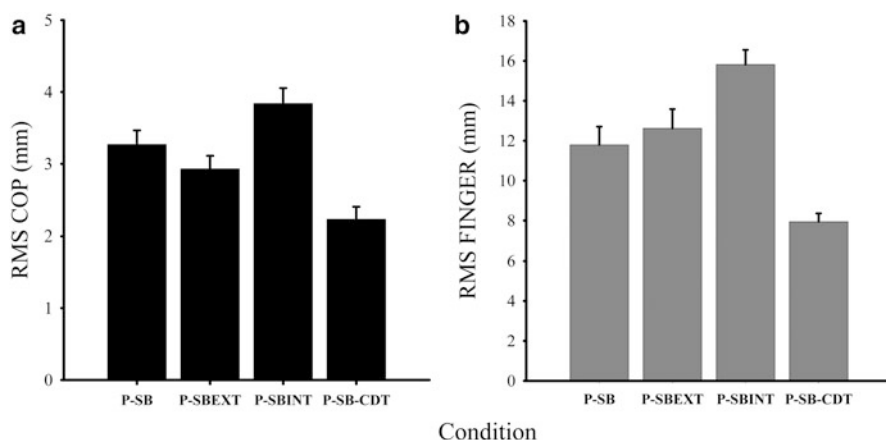


Fig. 8.4 The statistical stability of postural and suprapostural performance is dependent on focus of attention for balancing. COP and fingertip trajectories were least variable when stick balancing was performed with a concomitant cognitive load. **a** RMS COP and **b** RMS FINGER were reduced in the P-SB-CDT. Of particular interest was the stabilizing effect of cognitive load for stick-balancing performance. Finger trajectories were approximately half as variable in P-SB-CDT relative to other conditions. *Error bars* represent ± 1 SEM. (Reprinted with permission from Cluff et al. 2010 @ Springer)

variability is decreased, accompanied by increased frequency components when the attentional focus is external (minimizing movement of the stick). And conversely, performance variability is increased when attentional focus is internal (focus on minimizing finger displacements) with a slower frequency component dominating. Our data did not confirm these predictions. However, we showed that greatest reduction in performance variability was seen when performing a CDT, thus, taking the attentional focus away from the task of standing upright and concurrently balancing the stick.

It is important to underscore that previous studies of attentional focus did not deal with situations where there was an indistinct perceptual boundary between the body and the object being controlled. As originally noted by Gibson and later by investigators that study human and primate tool-use, handheld objects are often perceived as extensions of the body itself. This phenomenon, also known as exproprioception, needs to be considered in the context of the constrained action theory, proposed by Wulf and colleagues. Our results also showed that focusing on activity irrelevant to the physical task at hand (performing the concurrent cognitive task) was most beneficial to performance.

Note that all the participants in this study were skilled, having learned the stick-balancing task successfully. It is important to consider focus of attention in the context of Bernstein's ideas on expertise and its development. Although actors focus on moving body parts in the early stages of skill acquisition, attention shifts to wielded objects in the advanced stages of skill (Bernstein 1967). Advanced tennis players tend to focus on the ball or end point of the trajectory for a successful return, rather than the racquet or limb. In the stick-balancing case, there is no clear boundary between

where one ends and the other begins. Therefore, it is likely that stick balancers at earlier stages of skill acquisition show stronger differences as a function of attentional focus. Following this study, one could predict that task-irrelevant focus would not benefit less experienced stick balancers (Milton et al. 2008).

General Discussion

Goal-directed motor tasks commonly require the use of objects, tools, and implements to interact with our environment. Dynamic object interactions can vary in terms of the rigidity, geometry, and stability of manipulated objects, yet, we formulate adaptive motor responses that accommodate differences in the task, context, and object mechanics. Knowledge of the underlying control mechanisms and learning processes is imperative for understanding the basis of skilled object manipulation. The four studies presented in this review chapter used an inverted pendulum (i.e., stick) balancing paradigm to investigate skill acquisition and elaborate the task- and context-dependent attributes of unstable object control.

In the first study, we evaluated the statistics of the spatio-temporal properties of stick displacement (Cluff and Balasubramaniam 2009). After establishing that learning resulted in a systematic increase of balancing time, we fit our data to theoretical Lévy distributions. Results showed the probability of fingertip speed increase over analyzed time scales was Lévy-distributed and that this distribution changed with learning. Essentially, motor learning caused systematic increase in the prevalence of upper limb displacements in the standing condition, a feature less visible in seated subjects.

Motivated in part by the observations of Cabrera and Milton (2002) that angular stick fluctuations occur on timescales shorter than estimated voluntary control delays (~ 100 ms) and show amplitude variations that are characteristic of on-off intermittency, we quantified the nature of this intermittency using modern analytic tools based on a numerical phase space reconstruction method (RQA). Provided that angular stick fluctuations are intermittent, we hypothesized that upper limb displacements would be composed of two independent timescale components differentiated by their correlative properties. We additionally hypothesized that the temporal structure of upper limb corrections would be modulated by the balancing context. We used a numerical phase space reconstruction method (cf. Webber and Zbilut 1992; Marwan et al. 2007) to determine whether the switching time to feedback control was dependent on motor learning and the balancing context. We demonstrated (Cluff et al. 2009) that upper limb displacements are indeed composed of two independent timescale components: a fast stochastic component and slow closed-loop feedback control. Our results revealed that the discontinuity, stability, and regularity of upper limb displacements changed systematically across training sessions. Another important finding was the differential control evoked by changes in the balancing context. We found that the average time interval between upper limb corrections was substantially shorter for the seated balance.

Our studies raise important concerns for studies that employ the Kalman filter algorithm (Kalman 1960), commonly seen in studying systems with assumed motor and sensory noise. The limitation of the Kalman filter is that it is designed to handle Gaussian-distributed additive noise. I believe that the discovery of Lévy distributions in fingertip displacements questions the validity of using control models used by Mehta and Schaal (2002). I strongly suggest the use of suitable estimation algorithms (Gordon et al. 2006; Sinha et al. 2007) that are designed to be sensitive to Lévy distributions. Although it is well established that variability in muscle force production increases with movement amplitude, state-dependent motor noise is commonly assumed to be negligible (for review, see Todorov 2005). Future studies should carefully consider the role of stochasticity in the CNS in the development of state estimation models.

Complex motor tasks often involve the coordination of posture and voluntary arm movements. In the third study, we performed an innovative analysis that investigated the learning-dependent coupling of posture and upper limb dynamics (cf. Marwan et al. 2007). We interpreted our results from the perspective of a hierarchical learning model (Newell et al. 2001) and this study was among the first to quantify learning and control at multiple levels of the motor system. Our results corroborated the model of Newell et al. (2001) and demonstrated that skill acquisition involved two independent learning processes. First, we found that posture and upper limb control were governed by intermittent balancing strategies and that the time interval between corrections increased systematically across the investigated training period. The second learning effect involved the incremental occurrence and lengthened the coupling of correlated posture-upper limb trajectories.

Thus, I can make the case in which posture-upper limb coordination is contingent on a state-dependent (de)coupling mechanism. I have additionally proposed that the abrupt decoupling of posture-upper limb trajectories is caused by the instability of subsystem dynamics. Our rationale is supported by the observation that human feedback parameters are often tuned near instability. Thus, we anticipate that perturbing forces applied to the tip of the stick would induce the abrupt dissociation of posture-upper limb coupling to enable independent subsystem corrections. State-dependent posture-upper limb coupling is a plausible control mechanism and is similar to the spontaneous recruitment of body segments that has been shown to intermittently stabilize intereffector coordination (Buchanan and Kelso 1999).

Finally, I tested the constrained action theory (Wulf and Prinz 2001) using explicit attentional manipulations during unstable object control. Performance variability increased irrespective of whether participants focused on minimizing fingertip or stick displacements. Thus, explicit instruction (relevant to the task at hand), increased task variability and was in fact counterproductive (Beilock et al. 2002, 2008; Beilock et al. 2008). However, the performance of a task-irrelevant cognitive task reduced performance variability of both stick-balancing and COP displacements. The critical time for switching to corrective movements also increased for both outcome and execution-oriented attentional manipulations. It is likely that participants shifted to a slower and possibly more conscious corrective mechanism. Note that the general failure to support the constrained action theory might have been due to

the fact that our participants were expert stick balancers. Novice subjects are more likely to be influenced by this manipulation (Beilock et al. 2002) since they lack specific knowledge about the interaction between limb and object dynamics. Such participants might gain more from outcome-oriented feedback (Todorov et al. 1997; Malone and Bastian 2010).

The stick-balancing problem is thus a rich problem that provides the opportunity to explore a variety of issues in motor control and learning. By employing techniques that have borrowed from statistical mechanics, we have established how task-specific changes can be observed at different spatial and temporal scales as a person learns to master this complex task. Future research should reveal the role of multiple joints and the collective error correction formed to solve the stick's dynamics and experimentation that involves manipulating the physical dynamics of the stick itself. This research will further add to our understanding of the complex interactions between the task, actor, and environment during the acquisition and performance of unstable object manipulation.

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