

A Nonlinear Analysis of Movement Variability: Stability in a Sit to a Stand

by

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## ABSTRACT

The human body is a complex system comprised of many parts that can coordinate in a variety of ways to produce controlled action. This creates a challenge for researchers and clinicians in the treatment of variability in motor control. The current study aims at testing the utility of a nonlinear analysis measure – the Largest Lyapunov exponent ( $\lambda_1$ ) – in a whole body movement. Experiment 1 examined this measure, in comparison to traditional linear measure (standard deviation), by having participants perform a sit-to-stand (STS) task on platforms that were either stable or unstable. Results supported the notion that the Lyapunov measure characterized controlled/stable movement across the body more accurately than the traditional standard deviation (SD) measure. Experiment 2 tested this analysis further by presenting participants with an auditory perturbation during performance of the same STS task. Results showed that both the Lyapunov and SD measures failed to detect the perturbation. However, the auditory perturbation may not have been an appropriate perturbation. Limitations of Experiment 2 are discussed, as well as directions for future study.

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## **A Nonlinear Analysis of Movement Variability: Stability in a Sit to a Stand**

The complexity of the movement system is reflected in the variability of human performance and the nonlinear manner in which skills and movement characteristics change over time. The human body is a multi-joint system that must be positioned and controlled in a complex manner in order to perform skillful actions. Consider, for example, a whole body task such as transitioning from a sitting position to an upright standing position (sit-to-stand). A large number of joints and muscles, across the entire body, must coordinate in order to rise from the chair and maintain balance. There must be sufficient leg strength and coordination to transfer the momentum of the upper body forward and upward to maintain an upright position in the face of gravity or surface instabilities (Riley, Schenkman, Mann, & Hodge, 1991). To make the task more complicated, there is inherent variability in biological systems (Harbourne & Stergiou, 2009) that has the potential to make a control strategy more challenging than if it were to occur in a system without noise. How such variable movements are stabilized and coordinated during the task is still largely unknown. The main focus of the current study is to examine movement variability in a sit-to-stand task using a nonlinear method that may provide a better understanding of the role of variability in motor control.

### **Bernstein's Degrees of Freedom**

Russian physiologist Nicolai Bernstein (Bernstein, 1967) characterized the complexity of the human body with what came to be known as the *degrees of freedom problem*. As Bernstein described, multiple degrees of freedom of the body, including joints, muscles, and the nervous system, combine with external forces during movement to produce an infinite number of patterns and strategies to accomplish a given task.

Bernstein was interested in how the nervous system organizes control of the many mechanical degrees of freedom in order to achieve stable movement patterns. Bernstein described motor learning as consisting of *freezing* and *unfreezing* of relevant degrees of freedom. Harbourne and Stergiou (2009) illustrated this with a tightrope walking example: the novice's first attempts at balancing are characterized by a wide-range of movements of the walker's center of pressure (CoP) and body segments. The novice tries many different strategies that may involve freezing and unfreezing of the body's degrees of freedom in order to balance. Those early attempts to balance on the tightrope are highly variable but somewhat random and unstructured. That unstructured variability is revealed as variations in kinematic, CoP movement, and center-of-mass measures and can be captured by traditional summary measures such as SD. Adjustments in movement become more finely-tuned and the tightrope walker exhibits stable yet flexible strategies for maintaining balance over the course of practice. Variability in the adjustments that the tightrope walker makes to disturbances on the line are more controlled and structured. That structured variability is not distinguished from unstructured variability by traditional summary measures and motivates the need for a different assessment of movement variability. In the current paper, we explore the utility of the largest Lyapunov Exponent ( $\lambda_1$ ).

### **Variability in Movement**

The control of movement variability and changes due to development or learning have been the focus of studies on reaching (Feldman & Levine, 1995; Flash & Hogan, 1985; Haggard, Hutchinson, & Stein, 1990; Won & Hogan, 1995), pointing (Morasso, 1981; Tseng, Scholz, & Schöner, 2002), grasping (Cole & Abbs, 1986), writing (Viviani

& Terzuolo, 1980; Wright, 1993), pistol shooting (Scholz, Schöner, & Latash, 2000), bimanual coordination (Domkin, Laczko, Jaric, Johansson, & Latash, 2002), locomotion (MacKinnon & Winter, 1993; Winter, 1995), speech (Gracco & Abbs, 1986), and postural sway (Balasubramaniam, Riley, & Turvey, 2000). Variability is inherent within all biological systems, as illustrated by Harbourne and Stergiou (2009) when they point out that footprints from a person walking through sand or snow never repeat exactly. The differences in stride length and foot placement width reflect the variability from step to step in a continuous cycle of movement. During quiet standing, we sway around a central equilibrium point without ever remaining exactly still, yet we maintain an upright orientation.

Traditional perspectives in the motor control literature have followed a reductionist approach, whereby decreased movement variability is associated with an increase in motor control or skill (van Emmerik & van Wegen, 2002). The common tools used to assess motor learning have been to use summary statistics, such as: range, SD, length of movement path, average radial area, etc. (Gibbons, Amazeen, & Likens, *under review*; Kirby, Price, & MacLeod, 1987; Schmidt & Lee, 2005). Movement variability is then assessed across multiple repetitions of a task over time. The assumed linear relationship is straightforward for some actions: as an individual becomes more skilled in the action, the movement becomes more efficient and accurate, and thusly variability decreases. In the literature on postural control the same assumption with postural sway and stability has been applied. The more movement of an individual's CoP trajectory during quiet standing indicates a higher degree of instability (van Wegen, van Emmerik, & Riccio, 2002). In the literature on postural control and aging, the typical finding is that



older adults exhibit larger CoP path lengths and greater variability than younger adults. The common conclusion is that older adults are less stable and therefore are at-risk of injury. In these assessments of variability in movement, variability is treated as either random error or noise the system (Glass & Mackey, 1988). However, there is mounting evidence of the importance of variability in movement, which reveals variation not as error but as necessary for function. In the literature on locomotion, reduced variability in the coordination dynamics of the limbs has been associated with an inability to transition from one movement pattern to another in patients with Parkinson's disease (van Emmerik, Wagenaar, Winogrodzka, & Wolters, 1999). In literature on postural control, it has been shown that healthy individuals with no balance disorders can exhibit long CoP path lengths with high variability, but would not be diagnosed with injury or a balance disorder (Hughes, Duncan, Rose, Chandler, & Studenski, 1996; Palmieri, Ingersoll, Stone, & Krause, 2002). In other words, large variability in movement does not necessarily mean a loss of motor control. This functional treatment of variability presents a challenge to researchers and clinicians of distinguishing movement variability that corresponds to impairment or injury, and movement variability that corresponds to skillful action. Traditional assumptions and measures of variability provide insights only into the amount of variability in the system and not aspects of control or stability of the movement, such as the structure of variability.

Nonlinear analysis offers a way to characterize qualitative changes in the dynamics of complex systems, including the human postural system (Ladislao & Fioretti, 2007; Murata & Iwase, 1998; Sasaki, Gagey, Ouaknine, Martinerie, Le Van Quyen, Toupet, & L'Heritier, 2001; Yamada, 1995). It is well known that the postural system is

characterized by nonlinearities due to elastic and damping properties of muscles and nonlinear feedback control in the nervous system (Błaszczyk & Klonowski, 2001). It is that combination of elastic and damping that allows for controlled sway. Nonlinear measures, such as the largest Lyapunov exponent ( $\lambda_1$ ), take into account inherent nonlinearities by examine the structure, or complexity, of variability over time. Negative  $\lambda_1$  reveals the presence of stable dynamics without any chaotic component. That result is unlikely in postural research because it indicates minimal or nonexistent sway. Positive  $\lambda_1$  reveals the presence of some chaotic component that temporarily pushes the system away from equilibrium. If the overall dynamics are stable, then this temporary push is countered by returns to equilibrium. Yamada (1995) demonstrated positive  $\lambda_1$  for postural sway using only stabilogram data during a quiet standing task.

Since the seminal work of Yamada (1995),  $\lambda_1$  has been examined further in posture research to examine the chaotic behavior of different postures. Murata and Iwase (1998) examined sway behavior as individuals stood in either a one-footed or two-footed stance with eyes opened and closed. Not surprisingly, more chaotic postural sway was observed for one-footed stance, a result that was interpreted as increased postural instability. Similar results have been reported in clinical studies. Adults with Parkinson's disease exhibited larger  $\lambda_1$  values in the maintenance of upright stance than healthy adults (Fioretti, Guidi, Ladislao, & Ghetti, 2004).  $\lambda_1$  has been used as a diagnostic tool for healthy infants and infants with cerebral palsy (Harbourne, Deffeyes, De Jong, Stuberg, Kyvelidou, & Stergiou, 2007). It has also been used to track changes in motor control in patients recovering from stroke (Roerdink, De Haart, Daffertshofer, Donker, Geurts, & Beek, 2006). The values of  $\lambda_1$  that have been reported in quiet

standing tasks for healthy individuals have been approximately  $0 < \lambda_1 < 1.45$  (Ladislao & Fioretti, 2007; Murata & Iwase, 1998; Yamada, 1995). In a quiet standing task for patients recovering from stroke, the reported  $\lambda_1$  values have been greater than 2 (Roerdink, De Haart, Daffertshofer, Donker, Geurts, & Beek, 2006). These reported values have begun to suggest a range of values that represent a healthy degree of structured variability, or chaos, within the system. A system with too little variability is static and unable to adapt to required changes. A system with too much variability is too chaotic and unable to stabilize into any patterns of control.

Although the use of  $\lambda_1$  in posture research has been promising, the postural sway data that was analyzed was limited in its information about movement of the entire body. Stabilogram data, such as CoP displacement, is a summary measure that captures changing reactive forces under the feet as registered by a force platform. The CoP measure does not provide information about movements of different segments of the body. The current study will examine  $\lambda_1$  measures, at the kinematic level, across multiple points on the upper and lower body as participants engage in a sit-to-stand task (STS).

The benefit of using the STS in the current study, as opposed the commonly used quiet standing task in the posture research, is that it provides a more representative task of the kind experienced in real life. The quiet standing tasks that are commonly used involve an individual standing upright without locomotion. This task does not take into account that upright posture is rarely an isolated task (van Emmerik & van Wegen, 2002). Van Emmerik and van Wegen (2002) make the point that the maintenance of upright posture is often nested within other task goals (e.g. opening doors, picking up objects,

catching a ball, etc.). The STS task is a whole body movement task that is a fundamental activity of experienced daily.

### **Current Study**

The current study was designed to examine whether  $\lambda_1$  can be used as a measure of stability in upper and lower body movement during performance of a STS task. Similar to the methods of Scholz and Schöner (1999), the STS task will require participants to transition from a seated position to an upright standing position.  $\lambda_1$  will be calculated at each of the three stages of this task (sitting, transition, standing) to assess changes in movement stability. Just as the expert tightrope walker is expected to exhibit structured and controlled movements, all of the participants in the current study are expected to have plenty of everyday experience in standing up from a seated position. Therefore, movements across the body should be stable and controlled, as indicated by near-zero  $\lambda_1$  values. To reduce expertise in this task, participants will also perform the STS task on a shaky, unstable platform. Figure 1 shows general predictions for  $\lambda_1$  values for the upper (A) and lower body (B) across the three stages of the STS task. Movements are expected to be stable, indicated by negative  $\lambda_1$  values, as participants are sitting down and slightly chaotic during the standing stage of the task. The hypothesis that movement should exhibit slightly larger  $\lambda_1$  values during upright stance is based on positive, near-zero  $\lambda_1$  values reported in posture research that has used  $\lambda_1$  on healthy participants during quiet standing tasks (Ladislao & Fioretti, 2007; Murata & Iwase, 1999; Yamada, 1995). In order to transition from a seated position to a standing position, posture must temporarily destabilize. That destabilization should be captured by a larger positive  $\lambda_1$  value at the transition stage than during the sitting and standing stages. Because an

upright stance is achieved by maintaining the CoP within the BoS, the movement of the upper body is expected to be more stable than the lower body. Finally,  $\lambda_1$  is expected to be larger (more positive) overall on the unstable platform for both the upper and lower body segments. In the second experiment, a perturbation will be used to probe stability in all three stages. The effect of the perturbation is expected to correspond inversely to stability: less stable postures will be disrupted more than more stable postures. Therefore, it is expected that the perturbation will have the largest effect during the transition stage of the task.

## **Experiment 1 Methods**

### **Participants**

Twenty-two introductory psychology students (14 females, 8 males; mean age 19.5 yrs.; mean height 170.1 cm; mean weight 69.1 kg) participated in this study in exchange for course credit. Participants did not report any musculoskeletal or neurological disorders, and informed consent was obtained prior to participation in the study. Data from two participants were removed from the analysis because of equipment failure. All participants were treated in accordance with the ethical guidelines of the American Psychological Association.

### **Apparatus**

An Optotrak 3D-Investigator (Northern Digital Inc., Waterloo, Canada) was used to collect movement data at seven locations along the right side of the body: head, shoulder, elbow, wrist, hip, knee, and ankle. An eighth marker was also fixed on the balance board. Infrared markers were attached using double-sided adhesive tape. The movement of the markers was registered at 250 Hz in three dimensions.

Participants performed the task on a Fitterfirst Professional Rocker Board (Fitter International Inc., Calgary, Canada). The square platform measures 50.8cm wide and 10.92 cm tall. The platform allows movement in one direction (e.g. like a seesaw) relative to the orientation on the ground. In the current study, the platform was positioned to allow for tilt only in the sagittal plane (i.e. side-to-side direction). Figure 2 depicts the two platform conditions used in the current study. To stabilize the platform in the stable conditions (Fig. 2 *left*), four wooden blocks were placed under the corners so that the platform could not tilt. In the unstable condition, the wooden blocks were removed (Fig. 2 *right*) to allow the platform to tilt.

### **Design**

The three factors in the repeated measures analysis of variance for  $\lambda_1$  and SD of ML movement were (1) the upper and lower halves of the body; (2) the platform condition (stable and unstable); and (3) the stages of the task (sit, transition, and stand). Vertical movement was examined to identify the three task stages in the data.

### **Procedure**

Participants were instructed to arrive wearing form-fitting gym clothes so that the body's movements could be measured accurately. All participants were asked to perform the task barefoot. If participants did not arrive wearing the appropriate attire, then the experimenters provided them with clean gym clothes.

Participants sat on a chair measuring 0.51 m in height, with the right side of their body facing the camera. Participants were instructed to sit upright and place their hands on the thighs and both feet on the platform in front of the chair. They were asked to remain as still as possible in preparation to stand. The feet were positioned

symmetrically at approximately shoulder width apart. Following STS protocol of previous studies, participants were instructed to not use their arms to push off of their legs or chair in order to rise from the chair (Greve, Zijlstra, Hortobágyi, & Bongers, 2013; Scholz & Schöner, 1999). They were asked to fixate on a 2 cm square target placed directly in front of them, at standing eye-level, throughout the task. Prior to data collection, participants were asked to perform the task twice in the unstable condition to verify that they could perform the task without discomfort. After that pre-trial period, the infrared markers were attached to the body to begin experimental trials.

For any given trial, participants initiated data collection by indicating readiness to begin the trial. After approximately 10 seconds, a verbal “GO” signal was given as a signal to stand. Participants stood at a self-chosen speed and remained standing for the duration of the 30 second trial. They then returned to the seated position in preparation for the start of the next trial. Participants performed 10 trials in each of the two platform conditions (stable, unstable) in a randomized order for a total of 20 trials. They were allowed to rest between trials. The experimental session was approximately 35 minutes in duration.

### **Analysis**

Marker occlusion (i.e. missing data) was problematic at the hip, elbow, wrist, and board markers. Occlusion was not observed prior to the experimental trials but was a consistent problem during data collection. Because we wanted participants to move as natural as possible, we chose not to further constrain movement during the task and only analyzed data collected at the head, shoulder, knee, and ankle locations.

The three distinct stages (sit, transition, stand) of the task needed to be identified, from the entire movement time series, so that our analyses could be performed on each stage. The vertical movement of the shoulder marker was used to identify the moment within the trial, and duration, that the participants rose from the chair and achieved an upright stance (i.e. the transition stage). The time between the onset and cessation of vertical movement was considered to be the transition stage. From the identified transition stage, window sizes of approximate length were used, before and after the transition, to identify the sitting and standing stages, respectively.

Stability analysis was performed on the three stages of the task using the time-delayed method of attractor reconstruction (Taken, 1981). Using this time-delayed method, the reconstructed attractor will have the same topological properties as the original one. From the reconstructed attractor the dynamical stability of the signal can be calculated. See the Appendix for the details of the methods used to calculate  $\lambda_1$ . The output was a  $\lambda_1$  measure for each marker location at each of the three task stages within one trial. The  $\lambda_1$  values from the two upper (head and shoulder) and two lower (knee and ankle) body locations averaged to create an overall  $\lambda_1$  measure for the upper and lower body.

Standard deviation was calculated over the same identified stages of the task in which the stability analysis was performed. The same steps were performed to create an upper and lower body SD measure.

## **Experiment 1 Results**

Figure 3 depicts the average transition times across participants in each of the platform conditions. As expected, transition times were shorter in the stable condition



(avg. = 3.1 sec.) than in the unstable condition (avg. = 4.2 sec.). A dependent variable *t*-test was performed to confirm that transition times difference between the two conditions was significant,  $t(21) = -8.57, p < 0.001$ . The observed transition times are slightly longer than previous work using the STS task. Greve et al. (2013) reported transition times of 1.71 and 1.78 seconds for young and elderly adults, respectively. This difference in the current transition times to previous work could be because the restricted surface area of the platform used in the current study compared to no platform in previous methods. Transition times were determined by applying a wavelet transform to identify the duration of the vertical movement.

Figure 4 depicts time series from a representative participant of the body's vertical movement as the individual transitioned from a seated position to a standing position on a stable (Fig. 4A) and unstable platform (Fig. 4B). The three stages of the task can be clearly seen in the raw time series. Both graphs in Figure 4 show minimal movement over approximately the first 10 seconds (i.e. sitting stage), followed by an upward trajectory (i.e. transition stage) and eventual halting as the participant achieved an upright position (i.e. standing stage). Not surprisingly, there is more movement across the body in the unstable than stable condition, given that the platform could tilt up and down as the participants balanced on it.

Figure 5 depicts ML movement for those same two trials. Movement towards the bottom of the figure corresponds to movement to the right, or away from the camera. Variability increased dramatically in the stable condition (Fig. 5A) only during the transition stage, when participants were in the process of standing. In contrast, ML

movement was extremely variable in the unstable condition (Fig. 5B) during both the transition and the attempt to stand on the unstable platform.

### **Largest Lyapunov Exponent**

Figure 6 depicts the averaged  $\lambda_1$  values for the upper (Fig. 6A) and lower body (Fig. 6B) across the three stages of the task for both the stable (solid line) and unstable (dashed line) platforms. One trend is nearly identical for the upper and lower body:  $\lambda_1$  is larger at the transition stage than at the sitting or standing stages.  $\lambda_1$  appears to vary more across stages for the upper body than for the lower body. A repeated measures analysis of variance revealed a significant 3-way interaction between body  $\times$  platform  $\times$  stage,  $F(2, 42) = 5.14, p = 0.027, \eta_p^2 = 0.313$ . All of the 2-way interactions were significant: body  $\times$  platform,  $F(1, 21) = 4.86, p = 0.039, \eta_p^2 = 0.188$ ; body  $\times$  stage,  $F(2, 42) = 27.77, p < 0.001, \eta_p^2 = 0.570$ ; and platform  $\times$  stage,  $F(2, 42) = 4.95, p = 0.012, \eta_p^2 = 0.191$ . There were two significant main effects: body,  $F(1, 21) = 4.74, p = 0.041, \eta_p^2 = 0.184$ ; and stage,  $F(2, 24) = 49.20, p < 0.001, \eta_p^2 = 0.701$ . To determine whether  $\lambda_1$  changed significantly across stages of the task, a series of simple effects and contrasts were conducted.  $\lambda_1$  for the upper body on the stable and unstable platform changed significantly across stages ( $F(2, 42) = 48.67, p < 0.001, \eta_p^2 = 0.698$ ; and  $F(2, 42) = 20.27, p < 0.001, \eta_p^2 = 0.491$ , respectively).  $\lambda_1$  at the transition stage was significantly larger than the sitting stage on the stable platform,  $F(1, 21) = 54.46, p < 0.001, \eta_p^2 = 0.721$ , and unstable platform condition,  $F(1, 21) = 141.79, p < 0.001, \eta_p^2 = 0.871$ .  $\lambda_1$  was significantly smaller at the standing stage than at the transition stage for the stable platform ( $F(1, 21) = 107.84, p < 0.001, \eta_p^2 = 0.837$ ) and unstable platform ( $F(1, 21) = 18.74, p < 0.001, \eta_p^2 = 0.472$ ).

Lower body  $\lambda_1$  (Fig. 6B) followed similar trends. Simple effects showed a significant change in  $\lambda_1$  across the stages of the task on both the stable platform ( $F(2, 42) = 6.94, p = 0.002, \eta_p^2 = 0.248$ ) and unstable platform ( $F(2, 42) = 7.46, p = 0.002, \eta_p^2 = 0.262$ ). For both the stable and unstable platform conditions, larger  $\lambda_1$  were observed at the transition than at the sitting and standing stages. On the stable platform,  $\lambda_1$  was significantly larger than both the sitting and standing stages ( $F(1, 21) = 8.60, p = 0.008, \eta_p^2 = 0.290$ ; and  $F(1, 21) = 7.08, p = 0.015, \eta_p^2 = 0.252$ ) This result supports the expected change that  $\lambda_1$  would be larger at the transition stage than at the sitting and standing stages. The contrast between  $\lambda_1$  at the sitting and standing stage revealed no significant difference. This suggests that, just like the upper body, participant movements were as stable when standing on a rigid surface as when sitting in a chair. On the unstable platform,  $\lambda_1$  at the transition stage was significantly larger than at the sitting stage,  $F(1, 21) = 29.16, p < 0.001, \eta_p^2 = 0.581$ . However, unlike the stable platform,  $\lambda_1$  did not significantly decrease from the transition stage to the standing stage.

Contrasts were performed to compare differences in  $\lambda_1$  between the upper and lower body at each stage of the task for the two platform conditions. Differences in upper and lower body during the sitting stage were not significant for the stable platform ( $F(1, 21) = 2.13, p = 0.23, \eta_p^2 = 0.011$ ), but were significant for the unstable platform ( $F(1, 21) = 5.51, p = 0.02, \eta_p^2 = 0.211$ ), whereby  $\lambda_1$  was significantly lower for the upper body. During the transition stage of the task  $\lambda_1$  were significantly larger for the upper body than lower body for both stable and unstable platform conditions ( $F(1, 21) = 47.89, p < 0.001, \eta_p^2 = 0.781$ ; and  $F(1, 21) = 38.13, p < 0.001, \eta_p^2 = 0.624$ , respectively). At

the standing stage of the task there were no significant differences for either platform condition.

### **Standard Deviation**

Averaged SD measures are depicted in Figure 7 for the upper (A) and lower body (B) across the same stages within the task. Similar to  $\lambda_1$ , SD changed across stages of the task differently for the upper and lower body. Overall larger deviation measures were observed in the upper body than the lower body. Within the trial there is also a difference in SD as a function of platform condition, whereby larger values were observed overall for the unstable platform than on the stable platform. A repeated measures analysis of variance revealed significance for the 3-way interaction between body  $\times$  platform  $\times$  stage,  $F(2, 42) = 9.74, p < 0.001, \eta_p^2 = 0.317$ . All 2-way interactions were significant: body  $\times$  platform,  $F(1, 21) = 14.39, p < 0.001, \eta_p^2 = 0.407$ ; body  $\times$  stage,  $F(2, 42) = 9.86, p < 0.001, \eta_p^2 = 0.319$ ; and platform  $\times$  stage,  $F(2, 42) = 32.56, p < 0.001, \eta_p^2 = 0.608$ . All three main effects were significant: body,  $F(1, 21) = 25.5, p < 0.001, \eta_p^2 = 0.548$ ; platform,  $F(1, 21) = 41.58, p < 0.001, \eta_p^2 = 0.664$ ; and stage,  $F(2, 42) = 142.15, p < 0.001, \eta_p^2 = 0.871$ . Simple effects tests were conducted to determine whether SD significantly changed across the stages of the task. As expected from examining the trends in the upper body, there was a significant change in movement variability across the stages for both the stable and unstable platform ( $F(2, 42) = 60.21, p < 0.001, \eta_p^2 = 0.741$ ; and  $F(2, 42) = 51.84, p < 0.001, \eta_p^2 = 0.712$ , respectively). Follow-up contrasts were conducted to significant changes between stages of the task. The upper body (Fig. 7 A), on the stable platform, SD was significantly larger at the transition stage than at the sit,  $F(1, 21) = 128.92, p < 0.001, \eta_p^2 = 0.747$ , and was significantly larger than

at standing stage,  $F(1, 21) = 95.00, p < 0.001, \eta_p^2 = 0.819$ . On the stable platform the deviation measures decreased slightly as upright stance was achieved. On the unstable platform the deviation measures did not significantly decrease from the transition period ( $F(1, 21) = 0.51, p = 0.482, \eta_p^2 = 0.024$ ). Movement variability did not decrease at the standing stage on the unstable platform to the same degree as the stable platform.

Movement variability for the lower body (Fig. 7B) was found to be very similar to the results of the upper body. Simple effects revealed a significant change in SD across the stages of the task for the stable,  $F(2, 42) = 62.24, p < 0.001, \eta_p^2 = 0.747$ , and unstable platform,  $F(2, 42) = 111.59, p < 0.001, \eta_p^2 = 0.842$ . On the stable platform, SD was larger at the transition stage than at the sit,  $F(1, 21) = 62.77, p < 0.001, \eta_p^2 = 0.749$ , and at the standing stage,  $F(1, 21) = 70.43, p < 0.001, \eta_p^2 = 0.770$ . SD at the sitting and standing stages were not significantly different,  $F(1, 21) = 0.11, p = 0.743, \eta_p^2 = 0.005$ . Similar to the stable platform, SD on the unstable platform was significantly larger at the transition stage than at the sit,  $F(1, 21) = 172.36, p < 0.001, \eta_p^2 = 0.891$ , and at the standing stage,  $F(1, 21) = 50.45, p < 0.001, \eta_p^2 = 0.706$ . However, unlike on the stable platform, SD was larger during the standing stage than at the sitting stage,  $F(1, 21) = 97.33, p < 0.001, \eta_p^2 = 0.822$ .

### **Experiment 1 Discussion**

Largest Lyapunov exponents were used to evaluate the stability of the upper and lower body ML movement as participants performed the STS task on stable and unstable platforms. The motivation for the current study comes from the posture research that has applied  $\lambda_1$  to stabilogram data during quiet standing task (e.g. Ladislao & Fioretti, 2007; Murata & Iwase, 1998; Yamada, 1995), however the current study seeks to expand the

utility of  $\lambda_1$  to movements across the body during a whole body movement task. It was first hypothesized that ML movement would be more stable, represented by smaller  $\lambda_1$ , during the sitting and standing stages of the task, and that  $\lambda_1$  would increase at the transition stage. Second, movement of the upper body was expected to be more stable than lower body movement. Third, movement on the stable platform was expected to be more stable, overall, relative to the unstable platform.

### **Stages of the STS task**

Results support the hypothesis that the least stable movement would be observed during the transition stage of the task. Figure 6 show the larger  $\lambda_1$  values observed during the the transition stage compared to the seated and standing stages in both platform conditions. The larger  $\lambda_1$  observed at the transition stage suggests that  $\lambda_1$  was able to capture the instability of movement as participants transitioned from one stable configuration (sitting) to another (standing).  $\lambda_1$  for both the sitting and standing stages decrease to similar values, indicating that movement in the sitting and standing stages of the task were more stable behaviors. To my knowledge this is the first study that has applied Lyapunov measures to whole body movement in a STS task, and so the support that transitional stages should be less stable in the STS task cannot found. However, the observance of larger  $\lambda_1$  during the transition is consistent with research on interlimb motor coordination that has observed large and positive  $\lambda_1$  during transitions between antiphase and inphase patterns of coordination (Amazeen, Amazeen, & Turvey, 1998; Kelso, 1984). In the current study the sitting and standing stages were expected to exhibit relatively more stable patterns of movement due to the participants' expert abilities to sit and stand upright respectively. Both the upper and lower body plots in

Figure 6 show similar  $\lambda_1$  overall at the beginning and end stages across both platforms. This indicates that ML movement was just as stable while participants were seated in a chair as when they were standing upright.

One unexpected artifact in the data was the larger  $\lambda_1$  observed for the upper body during the sitting stage on the stable platform than the unstable platform (Fig. 6A). It was expected that  $\lambda_1$  for both platforms would be identical during the sitting stage because the stability of movement should not have been effected by the platform. Further examination is required to determine why there was a difference in platform conditions at the sitting stage.

### **Upper and Lower Body Movement**

Upper and lower body ML movements exhibited similar trends across the stages of the task, however  $\lambda_1$  differed slightly in across platform conditions and stages of the task. The larger  $\lambda_1$  for the upper body during the transition stage suggest that participants are stabilizing lower body movements more as they shift the mass of the upper body upwards and forwards in order to achieve upright stance. Not surprisingly the observed behavior in upper and lower body movement is similar in both platform conditions because this objective is the same – lower body stabilizes as upper body is displaced in order achieve an upright standing position. Once standing, ML movement stabilizes for both upper and lower body to a similar degree as when seated in the stable platform condition, but not unstable platform condition. For the lower body on the unstable platform  $\lambda_1$  remains unchanged from the transition stage. Less stable movement at the lower body seems reasonable on the unstable platform because the lower body is closer in

contact to the platform, therefore if the platform is unstable then there will naturally be more movement that may not stabilize completely.

### **Stable vs. Unstable Platform**

The hypothesis that movement in the unstable condition would be less stable overall on the unstable platform than the stable platform was not fully supported by  $\lambda_1$ . Across all stages of the task,  $\lambda_1$  was similar across platform conditions for both the upper and lower body, except for the counterintuitive difference in upper body during the sitting stage, and lower body at the standing stage that have already been discussed. It is apparent from the plots in Figure 6 that ML movement is not less stable overall on the unstable platform. Though these results are unexpected, the result may suggest that the unstable platform condition was not significantly challenging, and instead participants were able to perform the task in either condition with similar ease. This possibility raises an interesting question of why participants were able to perform this movement task similarly in both conditions, or what aspects of movement were different but did not affect stability measures? The main focus of the current study was to assess the utility of  $\lambda_1$  in comparison to traditional measures of performance stability.

SD measures in Figure 7 depict trends similar to  $\lambda_1$ , however interpretations of movement stability are not as apparent. For both upper and lower body, variability in ML movement was minimal while participants were seated, increased significantly during the transition, and decreased slightly during standing. More variability was observed on the unstable platform than stable platform overall. Examining the difference in movement variability between platform conditions, traditional interpretations of increased variability may identify participants as less stable overall on the unstable



platform condition. However,  $\lambda_1$  measures depicted in Figure 6 would indicate little differences in stability across platform conditions. If we assume that all participants are expert sit-to-standers, then performance in the stable platform condition can be interpreted as baseline performance. Assessing performance using traditional measures, one may conclude that all motor control degraded on the unstable platform.

Alternatively, performance assessments using  $\lambda_1$  indicate that motor control was comparable in both platform conditions. As mentioned previously, all of the participants were able to perform the task in the unstable condition without observable difficulty, and so  $\lambda_1$  may provide a more detailed assessment of movement stability.

The current study focused on the application of  $\lambda_1$  measure in a whole body movement task. In this study  $\lambda_1$  measure distinguished stable and unstable stages of the task, as well as showed differences in stable movement across the upper and lower body at different stages of the task, suggesting that control of movement shifts across body segments as participants move from a seated position to a standing position. Overall performance differences were not as clear between the stable and unstable platform conditions, which suggests that executed the STS task similarly both platform conditions. Future work is needed to further investigate the functional use of  $\lambda_1$  measure in movement tasks.

## **Experiment 2**

The focus of the second experiment was to perturb movement stability during the same STS task. Given the use of  $\lambda_1$  to assess stability in movement during the STS task, the next logical step is to intentionally perturb task performance to examine whether changes in performance correspond to changes in  $\lambda_1$  measure. In Experiment 2, an

auditory stimulus was used to perturb postural sway at each of the three stages of the task: during the sit; during the transition; and during the stand. Research that has investigated the influence of stationary acoustic stimulation on postural sway is limited (e.g. Petersen, Magnusson, Johansson, Åkesson, & Fransson, 1995; Russolo, 2002), and the reported effects have been random. The current hypothesis is that the auditory perturbation will have a larger effect on a more unstable system. Based on the results in Experiment 1, participants were least stable during the transition stage (indicated by a larger positive  $\lambda_1$  value), thusly the effect of the perturbation is expected to be largest at the transition stage. That effect will take the form of a larger  $\lambda_1$  when the perturbation is presented compared to when the perturbation is absent. Basis for this hypothesis comes from the team coordination dynamics literature where unexpected perturbations in a team piloting task resulted in less adaptability for teams characterized as unstable (Gorman, Amazeen, & Cooke, 2010). Conversely, stable teams were more adaptive and better able to recover from the perturbation.

## **Experiment 2 Methods**

### **Participants**

Ten introductory psychology students (5 females, 5 males; mean age 19.4 yrs.; mean height 173.8 cm; mean weight 68.4 kg) participated in this study in exchange for course credit. None of the participants reported any musculoskeletal or neurological disorders, and informed consent was obtained prior to participation in the study. All participants were treated in accordance with the ethical guidelines of the American Psychological Association.

## **Apparatus**

The same materials and techniques were used for data collection as in Experiment 1. Based on the observation that all participants in Experiment 1 were able to perform the STS task on the unstable platform without difficulty, only the unstable platform condition was used in Experiment 2.

The auditory perturbation used in the current study was a single strike to an orchestral Chinese-style crash cymbal. The experimenter held a 12” Wuhan crash cymbal in one hand and struck the cymbal with a standard drumstick held in the other hand. All of the participants verbally reported that the noise from the cymbal was jarring and unpleasant.

## **Design**

The three factors in the repeated measures analysis of variance for  $\lambda_1$  and SD of ML movement were (1) the upper and lower halves of the body; (2) the stages of the task (sit, transition, and stand); and (3) the onset of the perturbation (none, during the sit, during the transition, and during the stand).

## **Procedure**

Experimental procedure was the same as Experiment 1 with the exception of the perturbation. The experimenter was positioned out of the view from participants so that the inclusion and timing of the perturbation was unknown to the participant. The perturbation was presented at one of the three stages of the trial (during the sit, during the transition, or during the stand) or not at all. When the perturbation was presented during the sitting stage the experimenter struck the cymbal approximately 2 seconds before the verbal “stand” command. When the perturbation was presented during the transition

stage, the cymbal was struck after the participant initiated the stand. When the perturbation was presented during the standing stage, the cymbal was struck approximately 2 seconds after the participant reached an upright standing position. The experiment consisted of 30 trials. Eight perturbation trials were performed for each of the three stages (sit, transition, stand). Six trials contained no auditory perturbation. Trials were performed in a randomized order. The experimental session was approximately 50 minutes in duration.

### **Analysis**

Movement data was analyzed following identical procedures from Experiment 1 in order to obtain  $\lambda_1$  and SD measures for the upper and lower body.

### **Experiment 2 Results**

Figure 8 is a raw time series of ML movement, over an entire trial length, at the head location. This sample time series is on a trial when the perturbation was presented during the transition stage of the STS task. The *shaded area* indicates when the auditory perturbation was presented. Notice that no sudden, or unusual, disruptions appear in the movement trajectory during the perturbation period, above what is to be expected during performance of the task. This initial examination of the raw movement series suggest that the auditory perturbation may not have been sufficient to disrupt task performance, and subsequent  $\lambda_1$  and SD measures will not show a perturbation effect.

### **Largest Lyapunov Exponent**

Figure 9 shows the average  $\lambda_1$  values for the upper (A) and lower body (B) at each stages of a trial and across all 4 perturbation conditions (none, at sit, at transition, at stand). A repeated measures analysis of variance revealed a significant 3-way interaction

for body  $\times$  stage  $\times$  sound,  $F(6, 54) = 2.48, p = 0.034, \eta_p^2 = 0.216$ . The only significant 2-way interaction was between body  $\times$  stage,  $F(2, 18) = 8.12, p = 0.003, \eta_p^2 = 0.474$ . Only the main effect of stage was significant,  $F(2, 18) = 36.18, p < 0.001, \eta_p^2 = 0.801$ .

Examining the 3-way interaction in Figure 8 there is not a clear distinction between trials with the perturbations and trials without the perturbation. Additionally, all of the perturbation trials contain  $\lambda_1$  across all stages of the task, and not just the stage in which the perturbation was included. To simplify the results, the difference in  $\lambda_1$  was calculated for each stage of the task in which no perturbation was presented to when the perturbation was presented at that particular stage. Figure 10 shows the difference values for the upper (A) and lower body (B). Positive difference values indicate that  $\lambda_1$  were larger when no perturbation was presented, and negative difference values indicate larger  $\lambda_1$  when the perturbation was presented. Positive difference values would contrast the hypothesis that movement should be more stable when no perturbation was presented. Difference values of zero would indicate no difference in  $\lambda_1$  with and without the perturbation.

A repeated-measures analysis of variance was performed on the difference values for the upper and lower body at each stage of the task. The analysis of variance did not reveal significant effects for the 2-way interaction of body  $\times$  stage,  $F(2, 18) = 2.12, p = 0.149, \eta_p^2 = 0.191$ , nor significant main effects of body and stage,  $F(1, 9) = 0.01, p = 0.919, \eta_p^2 = 0.001, F(2, 18) = 2.67, p = 0.097, \eta_p^2 = 0.228$ , respectively.

For the upper body (Fig 10A), participants had lower  $\lambda_1$  (i.e. closer to zero) when the perturbation was presented during the sit and transition stages of the task, compared to the sit and transition stages when there was no perturbation. In other words, upper

body movement was less chaotic when a perturbation was presented than when no perturbation was presented. Movement in the lower body (Fig. 10B) exhibited similar trends in difference values: the difference values are more positive than negative, indicating that movement was less stable when no perturbation was present. The difference values observed for both the upper and lower body contradict the hypothesis that  $\lambda_1$  would be lower when the perturbation was not presented than when the perturbation was presented.

### **Standard Deviation**

SD also showed null results with regard to the effect of the auditory perturbation. Figure 11 depicts averaged SD for the upper (A) and lower body (B) at each stage of the task. A repeated-measures analysis of variance revealed a significant 2-way interaction between body  $\times$  stage,  $F(2, 18) = 9.32, p = 0.002, \eta_p^2 = 0.510$ . Main effects for body and stage were also significant,  $F(1, 9) = 8.45, p = 0.017, \eta_p^2 = 0.484$ , and  $F(2, 18) = 98.12, p < 0.001, \eta_p^2 = 0.916$ , respectively. None of the interactions or main effects of the perturbation were significant. Examining the different perturbation conditions, for both upper and lower body in Figure 11, there is no difference in deviation values across conditions.

Differencing SD in the same manner as  $\lambda_1$  revealed the same null effect of the perturbation. To reduce the number of figures and depiction of null results those figures are not included.

Results from  $\lambda_1$  and SD measures indicated that the auditory perturbation used in the current study was not sufficient to perturb performance in the task. In the task of

moving from a seated position to a standing position, auditory perturbations do not appear to effect the performance of the task.

### **Experiment 2 Discussion**

The main focus of Experiment 2 was to assess whether changes in  $\lambda_1$  measure correspond to changes in movement from a perturbation. The perturbation was an auditory perturbation (a drum stick striking a cymbal) presented at each stage of the task (sit, transition, stand). The auditory perturbation was expected to destabilize movement at each stage of the task compared to a control condition in which the perturbation was not presented. This effect of the perturbation would be indicated by larger  $\lambda_1$  values than in the control condition. The results from the current study replicated results from Experiment 1 with regard to the interaction effect between stage and platform, however the auditory perturbation had no effect on movement stability, and therefore the  $\lambda_1$  measure was largely unchanged from the control conditions.

The general trend of  $\lambda_1$  values of the current study replicated the findings from the unstable condition in Experiment 1:  $\lambda_1$  values were larger at the transition stage than at the sitting and standing stages of the task; and larger changes in  $\lambda_1$  values were observed for the upper body relative to the lower body. The replication of the results across both studies support the continuing interpretation that more positive  $\lambda_1$  values are interpreted as increased movement instability. Instability is highest during the transition, and more dramatic changes to instability are observed at the upper body than the lower body. In the remainder of this Discussion, limitations of this study will be considered that may have led to the null perturbation effects.

## Limitations

The window size of each stage, over which  $\lambda_1$  is calculated, may have been too large to detect the effects of the perturbation. Similar to the methods used in Experiment 1,  $\lambda_1$  measure was calculated over a duration of approximately 3-4 seconds in each stage of the task. In each of those 3-4 second windows, the perturbation was only presented for approximately 1-2 seconds. One limitation of calculating  $\lambda_1$  measures is that the length of the time series needs to be long enough in order to accurately reconstruct the behavior of the system as it evolves (Kantz & Schreiber, 2004). The evolution of the systems behavior cannot be accurately represented if the time series is too short and subsequently can result in less reliable estimates (Gorman, Hessler, Amazeen, Cooke, & Shupe, 2012). The window sizes, in the current study, were not shortened to the duration of the perturbation in order to calculate more reliable estimates. Because the duration of the perturbation was nearly half the length of the window size, the effect of the perturbation could have been smothered, and therefore showed no change in  $\lambda_1$ . If the window size was too large then the perturbation should be seen in the raw time series itself, however examination of the time series in which the perturbation was present showed no distinguishable effects of the perturbation. An alternative explanation is that auditory perturbation has no effect on the postural system.

Control of the human postural system is widely understood to come from integrated feedback from three main sensory systems: somatosensory, visual, and vestibular (Massion, 1994; Nashner, 1970). Somatosensory input refers to the feedback from muscles and joints that provides information of body's orientation in the vertical plane. The visual system provides input from the visual organs that provides information



of the body's orientation and movement with respect to the environment. The vestibular system provides angular acceleration in space from the sensors located in the inner ear. The current perspective is that the control of posture is largely due to multisensory feedback, rather than selectively across sensory systems (Balasubramaniam & Wing, 2002). Each sensory system can play more or less of a role depending on the context. When input from the visual system is removed or impaired (e.g. wearing a blindfold or standing in dark, respectively) during a balance task, for example, sway will increase. However, allowing a light active touch to an external object reduces postural sway to the same levels that are observed when participants are allowed visual input (Riley, Wong, Mitra, & Turvey, 1997). The sensory input from the muscles during a light active touch becomes relatively more important when vision is excluded. Impairments to one or more sensory input can be compensated for in order to stabilize posture. The dynamic and flexible nature of the sensory inputs on postural control are a likely explanation for why a single perturbation may not be sufficient enough to elicit a response. In the current study, there were no sensory impairments during the task, and so the auditory perturbation, though startling to participants, may have been too weak. Additionally, the auditory perturbation did not have a direct influence on the somatosensory, visual, and/or vestibular sensory organs.

Future research could use perturbations that have a known effect on postural control. Several studies have indicated an affect between postural control and cognitive performance (Woollacott, & Shumway-Cook, 2002). Performance on two memory tasks while participants they were sitting down or standing in a tandem fashion (i.e. heel-to-toe) showed significantly worse recall performance when standing feet in line. Other

studies have found that sentence completion and visual perceptual matching affect postural stability (Shumway-Cook, Woollacott, Kerns, & Baldwin, 1997). The general theory behind the interaction between posture and cognition is attributed to competition for finite attentional capacity: attentional demands on a cognitive task will sacrifice the attentional demands necessary for stable movement. The current researchers are seeking to implement a cognitive task during performance of the STS task to provide a more appropriate perturbation and therefore a better assessment of changes in stability measures.

Overall the results from Experiment 2 failed to assess responses to perturbations in  $\lambda_1$  and SD measures. The effects of auditory perturbations on the postural system have not been examined previously, and subsequently there is no experimental evidence that suggest that it should affect movement stability.

### **General Discussion**

The results from the current study are consistent with a growing body of literature that stresses the functional aspects of variability in motor control. The current study specifically sought to examine the utility of applying stability analysis to movement as participants performed a STS task. Bernstein (1967) articulated the importance of accurately interpreting the source of motor variability when he observed that the human body can coordinates, in an infinite number of ways, to perform any given action. Over the course of learning, movement variability changes in systematic ways as strategies are discovered and degrees of freedom are frozen and unfrozen. After expertise of an action is achieved, variability serves an alternative purpose of allowing an individual to be flexible and adaptive in response to perturbations. Treating variability as functional to

motor control is contrasted with a traditional perspective, in which decreased variability is universally associated with stable movements, competent motor learning, and skilled performance. Changes in motor control, due to aging, injury, or disease, cannot be determined solely by increased variability (Stergiou & Decker, 2011; van Emmerik & van Wegen, 2002). The use of nonlinear analysis may provide methods to distinguish “healthy” from “unhealthy” variability by examining the temporal structure of variability.

The current study builds on previous research that has begun to characterize motor variability in postural sway, using techniques from nonlinear analysis, that is indicative of healthy systems. Values in the range of  $0 < \lambda_1 < 1.45$  have been observed for healthy individuals, and larger  $\lambda_1$  values observed for individuals with various motor impairments, during quiet standing tasks (Ladisloa & Fioretti, 2007; Murata & Iwase, 1998; Roerdink et al., 2006; Yamada, 1995). The values observed in the current study are promising because they fall within the range of values reported for a stable upright posture in healthy individuals. Participants in the current studies consisted of all similarly healthy, young adults, and so the current results support the observation of lower, near-zero values during upright stance. These findings support proposal of a critical range of  $\lambda_1$  values that can be used for diagnostic purposes in a variety of clinical settings. The responsibility of this line of research is to identify the potential boundaries of  $\lambda_1$  values in which healthy behavior resides.

### **Applications**

Accurate methods and tools that can incorporate the inherent variability of the system is necessary in the clinical setting. Studies that have implemented nonlinear analyses in posture and other types of motor control have begun to show the importance

of variability in normal health, as well as begun to identify optimal from suboptimal variability. Improved diagnostic tools can better assess patients that may be at-risk for injury due to aging, disease, and injury (Stergiou, Harbourne, & Cavanaugh, 2006). For the treatment of balance-impaired populations, or physical rehabilitation methods, this notion can have a large impact: instead of focusing on the reduction of movement variability, treatment could be aimed at increasing adaptability by emphasizing exploratory actions.

Real-time monitoring during motor learning, development, or rehabilitation, can also provide researchers and clinicians direct feedback of patient behavior. Real-time analysis of the  $\lambda_1$  measure has been successful in team coordination research. Gorman, Hessler, Amazeen, Cooke, and Shope (2012) successfully observed changes in team performance to experimentally induced perturbations during the actual team performance. Similar analyses would allow researchers to remove perturbations in a timely fashion in order to stabilize the current behavioral state, or to administer additional perturbations that shift the unstable behavior into a new, more desirable state.

## **Conclusions**

Variability in human movement should not be perceived as detrimental to function and skill, but should be examined for its functional role. The  $\lambda_1$  measure used in the current study reveals complexity and stability that is inherent in normal variability; indicating features of motor control that are important for researchers and clinicians to measure and implement in intervention. The concepts of variability and chaotic variations, along with the advanced tools used to measure these concepts, allow for new research avenues in movement dysfunction and pathology. Far from being a source of

error, evidence supports the necessity of an optimal state of variability for health and functional movement. Concepts of and methods used for nonlinear dynamics offer significant application possibilities to guide rehabilitation practice and research in human movement.

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APPENDIX A  
ATTRACTOR RECONSTRUCTION

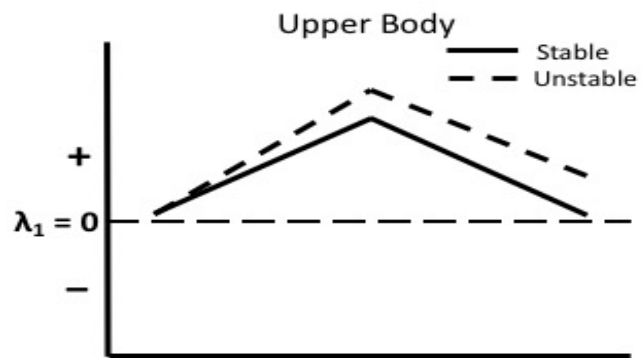
Taken's theorem (1981) states that the phase space of an attractor, and the dynamics of the system, can be reconstructed using time-delayed embedding from the original scalar vector. The main tasks are to determine the appropriate time delay ( $\tau$ ) and embedding dimensions ( $d_E$ ) on which to reconstruct the attractor. To begin, we need to select an appropriate  $\tau$  where points from the original vector,  $x(t)$ , are maximally different from the lagged vectors,  $x(t - \tau)$ ,  $x(t - 2\tau)$ , etc. The  $\tau$  parameter was estimated using the first-zero crossing of the autocorrelation function (Kaplan & Glass, 2012). The first-zero crossing is the time-delay where the original and lagged vectors share no correlation with each other. With the estimated  $\tau$ , we next select the appropriate number of embedding dimensions,  $d_E$ , to 'unfold' the vectors onto that appropriately display the attractor dynamics. The selection of  $d_E$  followed the 'false nearest neighbors' method outlined in Rosenstein, Collins, and De Luca (1993). The false nearest-neighbors method provides a percentage measure of close neighboring points in a given dimension that remain near neighbors in the next highest dimension. The  $d_E$  must be sufficiently large enough to minimize false nearest neighbors. Rosenstein, Collins, and De Luca (1993) state that the first  $d_E$  where the percentage of false nearest neighbors drops below 10% is a sufficient to represent the system's dynamics. Once the behavior of the system is appropriately reconstructed in phase space, the behavior of the system can be characterized by the largest Lyapunov exponent.

The method for estimating  $\lambda_1$  for the reconstructed attractor followed the standard procedure from Kantz and Schreiber (2004). To measure the maximal exponential rate of divergence of the attractor's dynamics (i.e. an overall stability measure), we begin by selecting two initially close-neighbor points,  $Y(i)$  and  $Y(j)$ . At  $t_0$  there is minimal

Euclidean distance between these two points,  $\delta_0 = |Y(i) - Y(j)|$ . We then measure the change in distance between these two points as they evolve over time,  $\delta_{\Delta t} = |Y(i + \Delta t) - Y(j + \Delta t)|$ . The exponential rate of divergence of the trajectories over time ( $\delta_0$  to  $\delta_{\Delta t}$ ) is given by  $\delta_{\Delta t} = \delta_0 e^{\lambda_1 \Delta t}$ . Taking the natural logarithm of both sides and rewriting the equation in linear form results in  $\ln(\delta_{\Delta t}) = \ln(\delta_0) + \lambda_1(\Delta t)$ . This linear equation represents a set of lines over all near-neighbor trajectories with slopes proportional to  $\lambda_1$ . The least-squares slope of the average line is the estimate of  $\lambda_1$  (Kantz & Schreiber, 2004).

Figure. 1

A



B

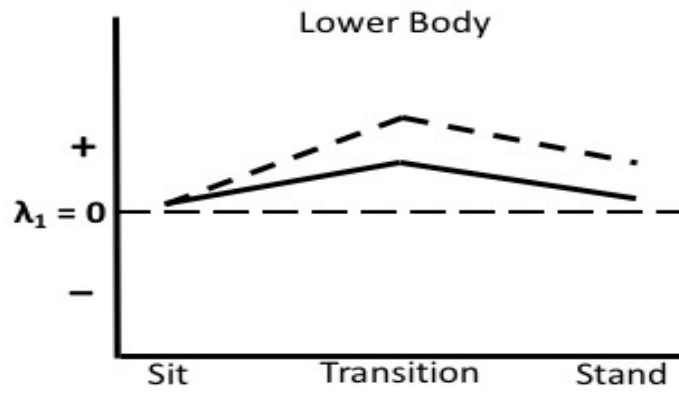


Figure. 2

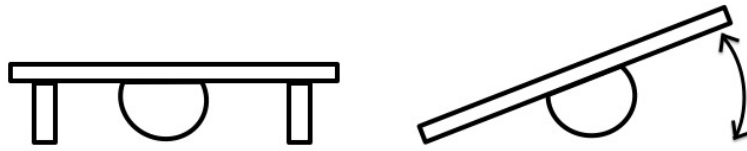


Figure. 3

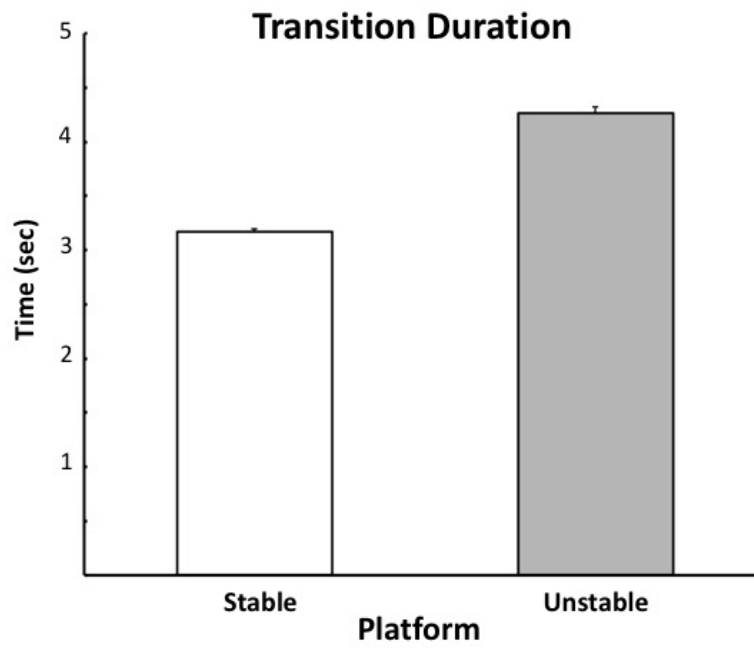
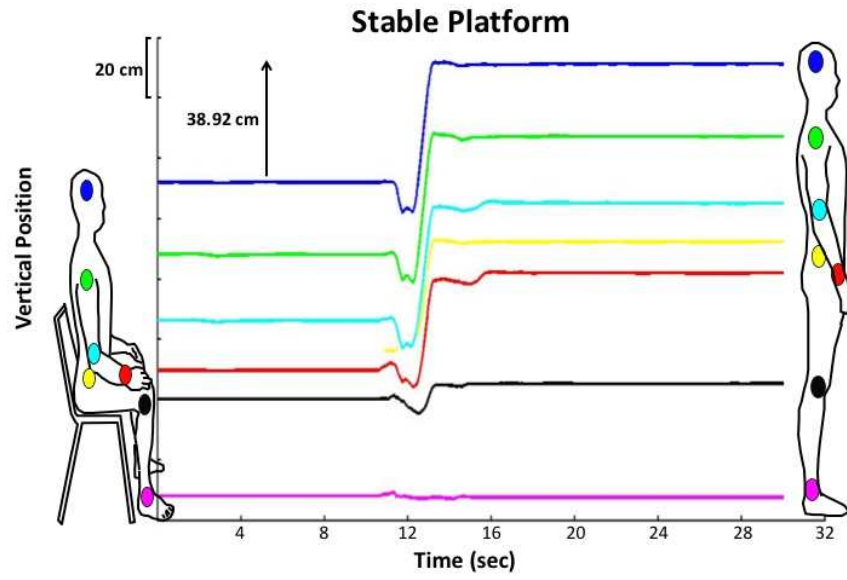




Figure. 4

A



B

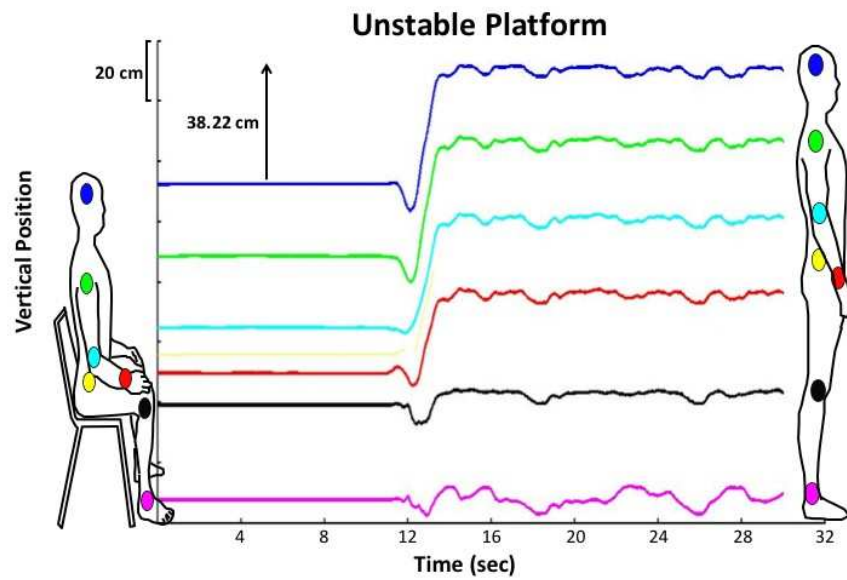
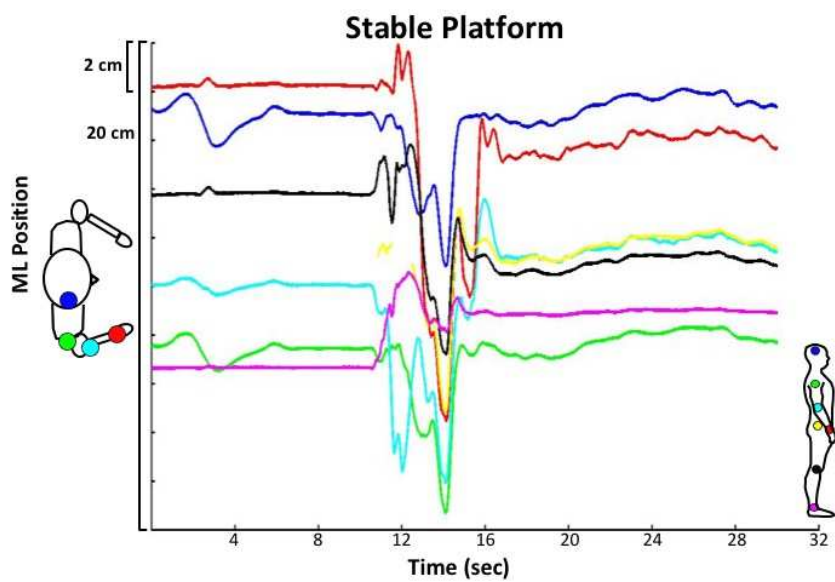


Figure. 5

A



B

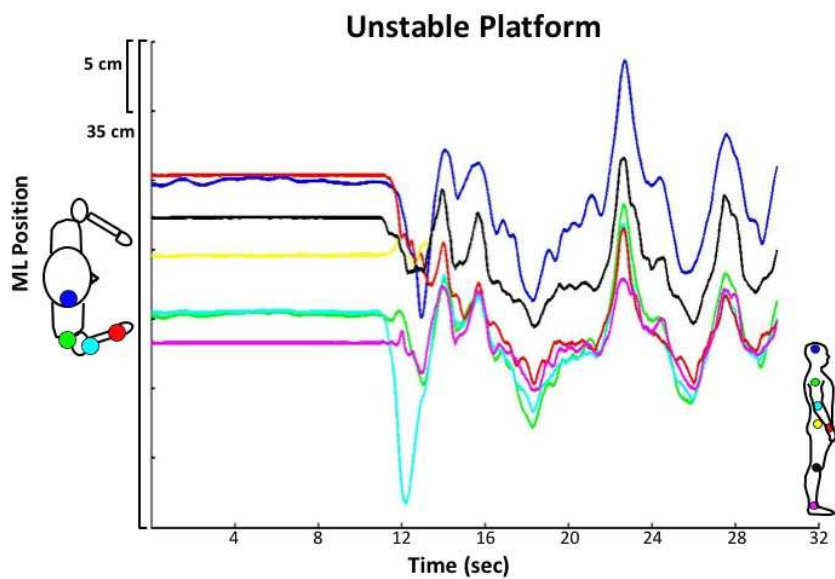
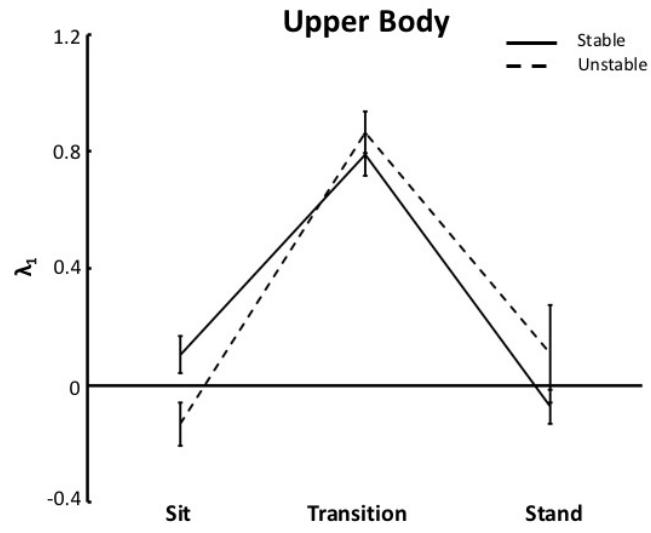


Figure. 6

A



B

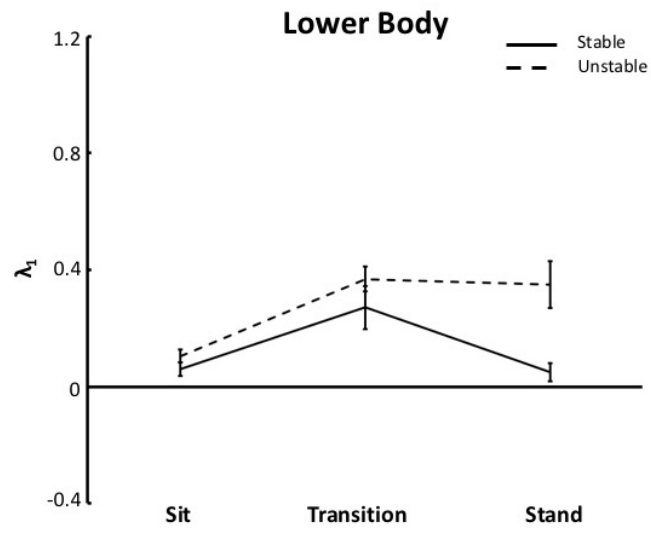
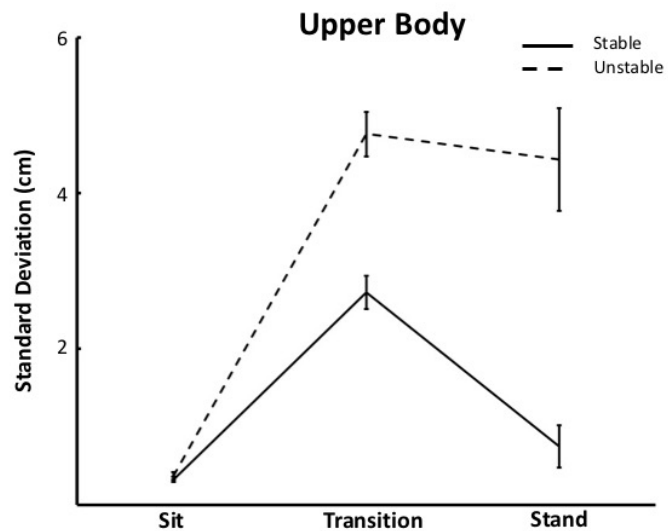


Figure. 7

A



B

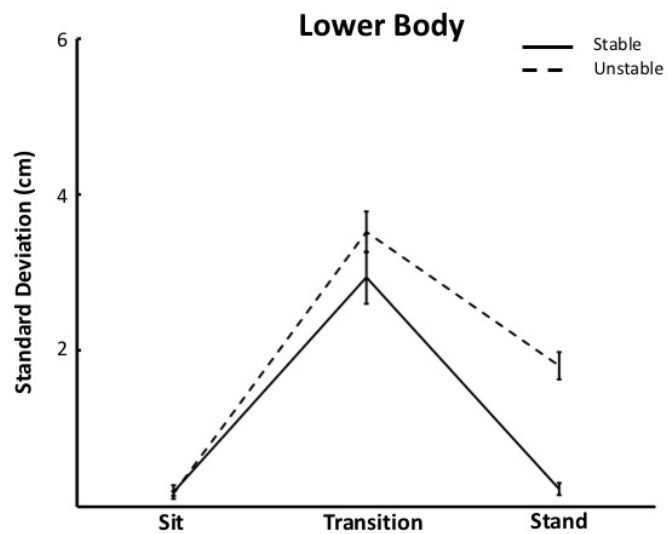


Figure. 8

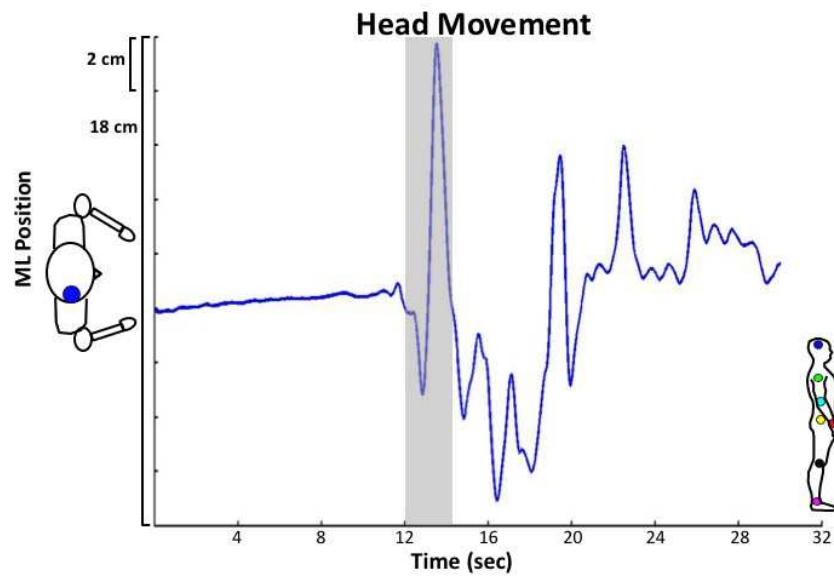
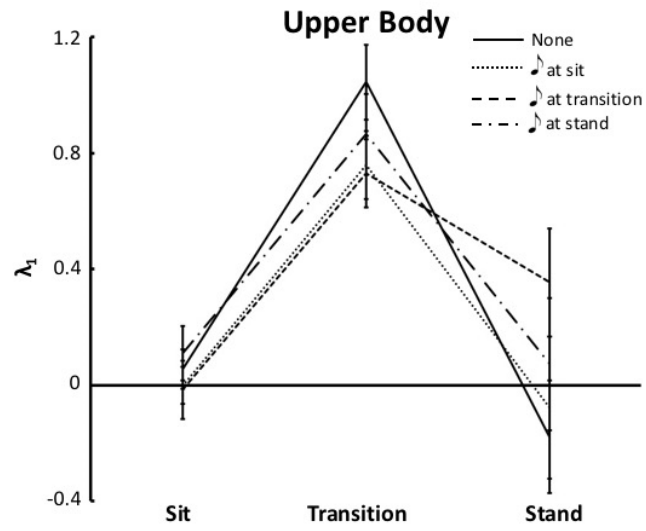


Figure. 9

A



B

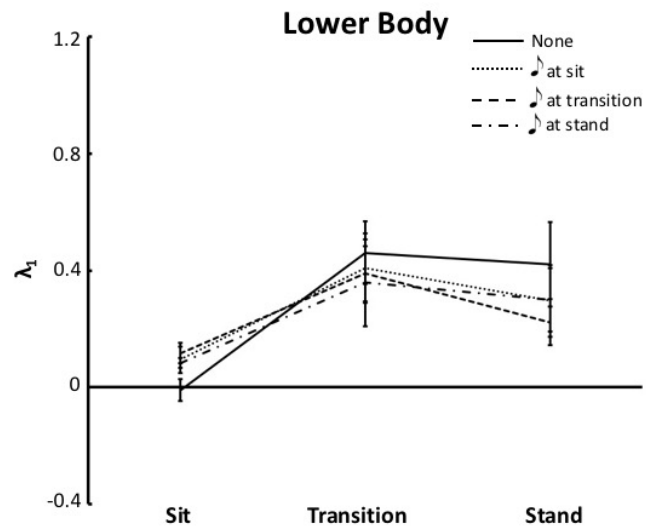
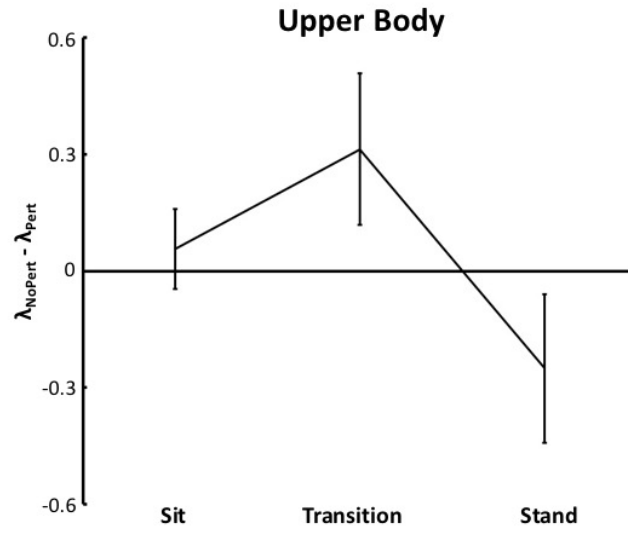


Figure. 10

A



B

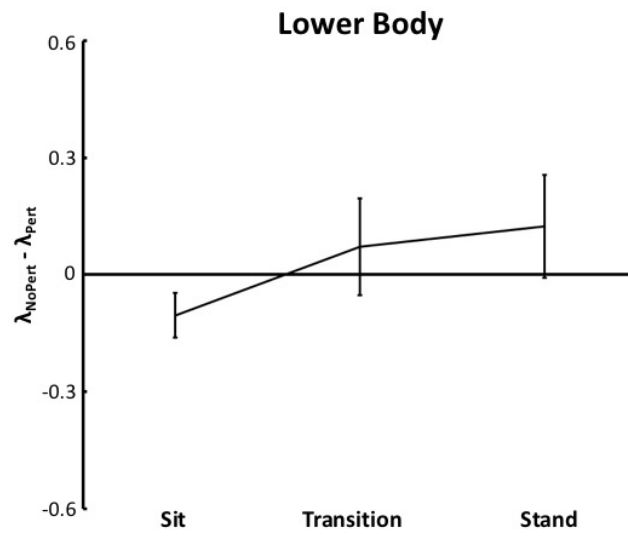
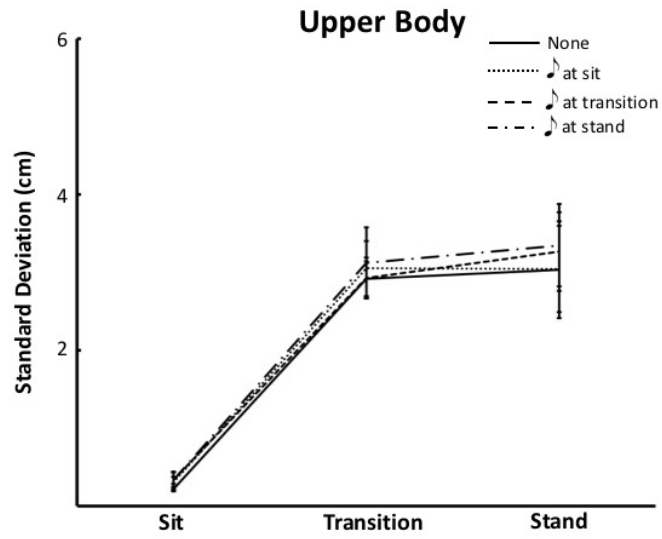


Figure. 11

A



B

