Evaluation of the threshold of stability for the human spine

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ABSTRACT

The threshold of stability (ToS) is introduced as a new tool for evaluating spinal stability. Current methods have evaluated the magnitude of spinal kinematic variability, stability diffusion, or Lyapunov exponents. This present method differs by modifying task difficulty to obtain a critical value delineating regions of stability and instability. Conceptually, as task difficulty increases, kinematic variability of the system increases and the basin of stability decreases. When kinematic variability exceeds the basin of stability, stability cannot be maintained over time. This concept is first illustrated using a mathematical model, from which an effective potential function was calculated to show the relationships among kinematic variability, the basin of stability, and task difficulty. In addition, an experiment was performed to evaluate the sensitivity of the ToS to changes in postural control using visual feedback as a control variable. The ToS was found to be more sensitive than the Lyapunov exponent to removal of visual feedback, suggesting it may have use as a diagnostic indicator (e.g. for low back pain). Furthermore, this new method has an additional advantage in which minimal instrumentation is needed. Its simplicity, sensitivity, and low cost suggest that the ToS has potential as a diagnostic or prognostic tool in a clinical setting.

1. Introduction

The term spinal stability may be used to describe the ability of the spine, paraspinal ligaments, core musculature, and neuro-muscular control system to maintain an upright posture. As argued by several researchers (Dieën et al., 2003; Panjabi, 2003; Granata et al., 2004) loss of spinal stability may lead to excessive strain of paraspinal tissues and thereby be a potential cause of low back pain (LBP). There is no consensus on the definition of spinal stability (Reeves et al., 2007). However in biomechanics, diverse parameters have been developed as indicators of system stability or robustness. Kinematic variability (KV) has commonly been used to quantify stability (Overstall et al., 1977; Fernie et al., 1982; Prieto et al., 1996; Blaszczyk, 2008), and is based on the assumption that more robust systems will be able to more effectively reduce system variability. Some of these KV parameters include displacement, standard deviation, RMS area, and path velocity of the center of mass (COM) or center of pressure (COP). In addition, stability diffusion analysis (Collins and De Luca, 1993;

Cholewicki et al., 2000; Hsiao-Wecksler et al., 2003) and Lyapunov stability (Dingwell et al., 2000; England and Granata, 2007; Lee and Granata, 2008) have been used to quantify stability, based on the rate of separation and the divergence of state trajectories, respectively. Higher diffusion or divergence rates are indicators of a less robust system.

All of these existing methods evaluate system performance at a fixed level of task difficulty. An alternative approach is presented and evaluated herein, involving explicit manipulation of task difficulty. The basic premise is that increasing task difficulty will have two effects. First, KV of the system will increase, indicating that the participant will explore a larger region of state space. Second, the size of the basin of stability (stable region of state space) will decrease, reducing the area of stable system behavior. When KV goes beyond the boundary of the basin of stability, the system will exhibit unstable behavior (Fig. 1). Based on this premise, a new metric is introduced, the threshold of stability (ToS). ToS is defined as the maximum task difficulty in which stability can be maintained, and is found by increasing task difficulty until KV lies just within the boundary of the basin of stability.

The purpose of this study was to develop the ToS and to evaluate its potential to serve as a quantitative indicator for spinal stability. It was hypothesized that the ToS would be able to detect changes in spinal stability induced by removal of visual feedback
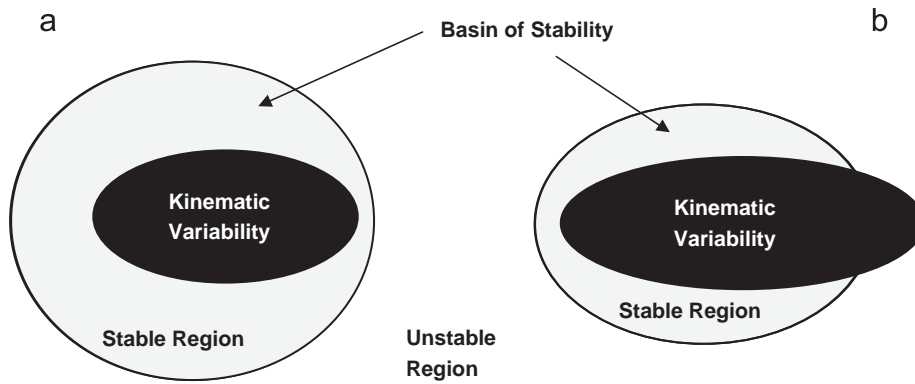
Fig. 1. Schematic diagrams of the state space. (a) If kinematic variability (KV) is fully within the stable region, the system is stable. As task difficulty increases, the KV increases while the basin of stability shrinks. (b) If the range of KV extends beyond the boundary of the stable region in state space, the system will become unstable.

during unstable sitting tests. In addition, the theoretical basis for the ToS was evaluated using a mathematical model of unstable sitting.

2. Methods

2.1. Overview of experiment

The wobble chair (Fig. 2a) is an unstable seat apparatus used to evaluate spinal stability based on the apparatus developed by Cholewicki et al. (2000) and used in several subsequent studies (Cholewicki et al., 2000; Tanaka and Granata, 2007; Lee and Granata, 2008; Lee et al., 2008; Slota et al., 2008). The seat pivots on a central low-friction ball joint, and adjustable springs are positioned at the front, back, left, and right of center. Moving these springs closer to the center decreases the restorative moment applied to the seat, thereby increasing task difficulty. Although full medial–lateral (ML) and anterior–posterior (AP) motion is possible, large ML spring distances were employed here to limit movements outside the sagittal plane.

During unstable sitting tests, postural control was challenged to determine the maximum task difficulty (smallest AP spring spacing) at which stability could be achieved (i.e. the ToS). Sensitivity of this new approach was determined with respect to the presence or absence of visual feedback (eyes open or closed) and was compared with an alternative measure of local dynamic stability (state-space averaged maximum Lyapunov exponent). Visual feedback, a known component of balance control (Jacobson et al., 1993; Herdman, 2007), was selected as an independent variable because it was easily altered and has been shown to have a substantial influence on the outcome of balance control tests (Roerdink et al., 2006; Blaszczyk, 2008). Moreover, it allowed within-subjects comparisons to be made with associated improvements in effect estimation.

2.2. Mathematical model

A simple inverted pendulum model (Fig. 2b) was developed to represent the seated balance test apparatus (Fig. 2a) (Tanaka, 2008). It included a concentrated body mass (m) and a massless segment length (h). Stabilizing springs with a spring constant k are located a distance d from the pivot point. Task difficulty is increased by reducing the distance of the springs from the central pivot point. The model also included a limited gain proportional-derivative controller to simulate neuromuscular control,

$$C(\theta, \dot{\theta}) = G_d\dot{\theta} + \begin{cases} G_p\theta & \text{if } |\theta| < \theta_{cr} \\ T_{p\,max} & \text{otherwise} \end{cases} \qquad (1)$$

where G_d is the derivative gain constant, $\theta_{cr} = T_{pmax}/G_p$ the smallest angle at which the maximum gain is achieved, G_p the proportional gain constant, and T_{pmax} the maximum value of proportional torque. Physiologically, T_{pmax} represents the fact that muscle strength is limited. The final component of the model was system noise that occurs naturally and may result from disturbances induced by breathing, heartbeat, muscle twitches, inaccurate muscle recruitment or other underlying stochastic processes (Collins and De Luca, 1993; Delignieres et al., 2003; Bottaro et al., 2005). These random disturbances were modeled as perturbation energy, E (0.1 J). Lagrange's equation was used to determine the equation of motion for the inverted pendulum, $mh^2\ddot{\theta} - mgh \sin \theta = \tau$, where θ, $\dot{\theta}$, and g are the rotation angle, angular acceleration, and acceleration of gravity, respectively. The parameter τ represents the combined torques resulting from the springs, controller, and perturbation energy. Combining these components yields

the governing differential equation

$$\ddot{\theta} = \frac{mgh \sin \theta - kd^2 \sin \theta - C(\theta, \dot{\theta}) + E}{mh^2} \qquad (2)$$

where θ is the angular velocity. Gravity, springs, and the proportional component of the controller all contribute to the potential energy of the system. These components can be combined to generate an effective potential energy function, V_{eff}, by integrating the terms with respect to θ yielding,

$$V_{eff} = -mgh(\cos \theta - 1) + kd^2(\cos \theta - 1) + \begin{cases} \frac{1}{2}G_p\theta^2 & \text{if } |\theta| < \theta_{cr} \\ \frac{1}{2}G_p\theta_{cr}^2 + T_{p\,max}(|\theta| - \theta_{cr}) & \text{otherwise} \end{cases} \qquad (3)$$

Using model parameters for a typical adult male (Table 1), a mathematical model of the potential function was developed using MATLAB® software (Math-Works; Natick, MA).

2.3. Participants and experimental protocol

Eight adults from the university and surrounding area participated in the study (five male and three female). Mean (SD) body mass, stature, and age were 71(13) kg, 174(15) cm, and 27(5) years, respectively. All participants were asymptomatic for LBP at the time of testing and reported no history of spinal surgery or back disorders. Prior to beginning the tests described below, participants completed an informed consent procedure approved by the Institutional Review Board at Virginia Tech.

Before stability testing was performed, the gravitational gradient (∇G) for each subject was found using previously developed methods (Tanaka and Granata, 2007; Lee and Granata, 2008; Slota et al., 2008). Briefly, ∇G is a measure of the mass and weight distribution of an individual given by,

$$\nabla G = \frac{\partial}{\partial \bar{\theta}_S}\bar{M}_g(\bar{\theta}_S, \bar{\theta}_T), \qquad (4)$$

where $\bar{M}_g$ is the gravitational moment, and $\bar{\theta}_S$ and $\bar{\theta}_T\theta_T^-$ are the 2-D (sagittal plane) angles of the seat and torso, respectively. Neutral stability is achieved when moments generated by the springs equilibrate the gravitational gradient (i.e. a spring setting of 100% ∇G).

During experimental trials, participants were instructed to sit on the wobble chair with arms crossed in front of the body while attempting to maintain an upright balanced posture for 60 s. Five practice trials were performed to reduce learning effects (Lee and Granata, 2008). Trials were performed in each visual feedback condition (eyes open or closed); the order of visual feedback condition was balanced across participants. A rest period of at least 1 min was provided between trials to avoid mental and physical fatigue. Sensors (MTx, Xsens Technologies; Enschede, The Netherlands) attached to the base of the seat and on the dorsal aspect of the thorax (T5 level) were used to measure (at 100 Hz) the respective angles. Participants were visually monitored to determine if the seat made contact with the base, where such contact indicated instability and a 'failing' trial.

Testing began with respective initial spring settings of 80% and 100% ∇G in the AP and ML directions. Following each trial, the AP spring distance was adjusted. Initially, if the participant maintained stability within 4° of the center, the spring setting was reduced by 20% ∇G. If the participant was able to maintain stability, but not within 4° of the center, the spring setting was reduced by 10% ∇G. If the participant became unstable as indicated by making base contact (failed) the spring setting was increased by 5% ∇G. This method quickly adjusted the task difficulty to the approximate threshold value. The first failed trial was used as an indicator that an approximate value of the ToS was found. Subsequent passing
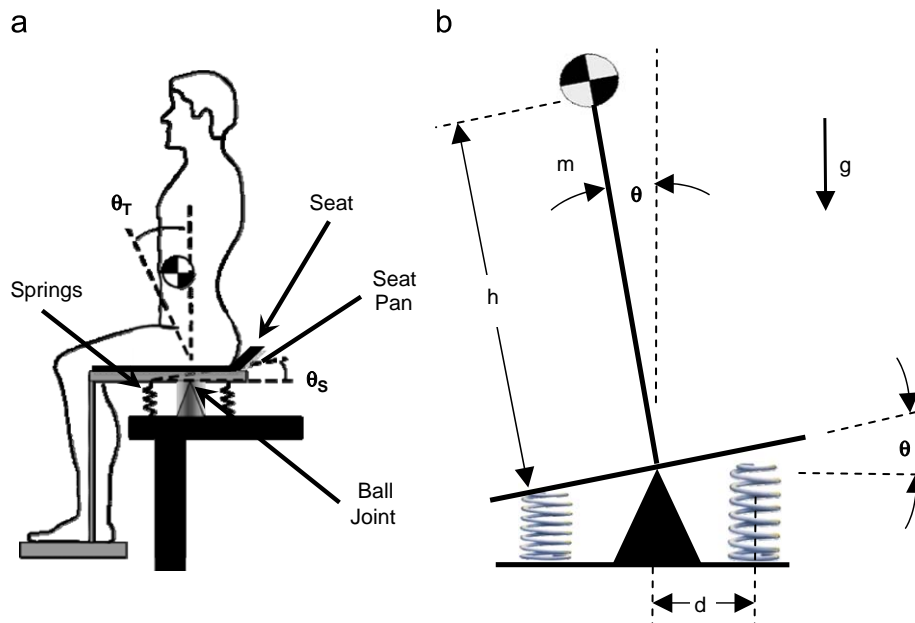
Fig. 2. Experimental and model configuration. (a) The wobble chair is a seated stability test apparatus where movement of the lumbar spine is used to maintain balance (adapted from (Cholewicki et al., 2000; Tanaka and Granata, 2007)). (b) A simple model of the wobble chair consists of a planar inverted pendulum with concentrated mass, stabilizing springs and a limited gain controller.

Table 1
Model parameters.

Parameter	Value	Description
m	69 kg	Typical body mass
g	9.81 m/s^2	Acceleration of gravity
h	43 cm	Calculated from ∇G
k	10,900 N/m	Wobble chair springs
d	10.35 cm	Half force plate width
G_d	1 Nm/(rad/s)	Derivative gain
G_p	190 Nm/rad	Proportional gain
T_{pmax}	14.5 Nm	Max proportional gain
E	0.1 J	Perturbation energy

Eyes Open

Spring Setting (∇G)	40%	45%	50%
Number of passing trials		2	2
Number of failing trials	2	1	
Spring setting result	fail	pass	pass

Eyes Closed

Spring Setting (∇G)	50%	55%	60%	65%
Number of passing trials		1	1	1
Number of failing trials	1	2	2	
Spring setting result	fail	fail	fail	pass

Fig. 3. Determining the threshold of stability (ToS). Multiple trials were conducted for each participant at different spring settings. Typical results for a participant are shown. The ToS was found by locating the lowest passing spring setting. In this case, the ToS was 45% ∇G for eyes open and 65% ∇G for eyes closed.

(failing) trials reduced (increased) the spring setting by 5% ∇G. This method was designed to concentrate data collection around the threshold of stability.

2.4. Analysis

Threshold of stability was determined through evaluation of the test results at each spring setting (Fig. 3). The number of passing and failing trials at each spring setting was tallied. When both passing and failing trials existed at a given spring setting, the majority result was assigned to that spring setting. If upon completing eight trials a clear separation existed between passing and failing spring settings, testing was concluded. However, if the number of passing and failing trials was equal at a given level, additional trials were performed until a definitive outcome was obtained.

For purposes of comparison with the ToS, the maximum Lyapunov exponent (λ_{max}) was determined; λ_{max} is a measure of local stability that quantifies the mean rate of divergence with respect to an equilibrium state (Wolf et al., 1985; Rosenstein et al., 1993). Well established methods were used to generate the state vector, filter data, and calculate λ_{max} (England and Granata, 2007; Tanaka and Granata, 2007; Lee and Granata, 2008; Tanaka, 2008).

Paired t-tests were used to assess the sensitivity of both the ToS and λ_{max} to the manipulation of visual feedback. Since λ_{max} was determined at the ToS, which varied between subjects and visual conditions, an additional analysis of covariance (ANCOVA) was performed (with ToS and visual condition as independent variables). A value of $p < 0.05$ was used as the criterion for significance.

3. Results

3.1. Model results

The effective potential function (V_{eff}) had a basin of stability between $\pm 5.72°$ at a task difficulty of 50% ∇G (Fig. 4). System states within this region were attracted toward the vertical equilibrium position as a result of the stabilizing springs and the controller. Beyond the basin of stability, trajectories were drawn away from the vertical position due to the dominating gravitational gradient (and were thus unstable).

To develop an understanding of the effects of task difficulty on system behavior, V_{eff} was determined for various levels of difficulty (Fig. 5). Increasing task difficulty increased KV and decreased the basin of stability. The intersection of the curves (44.7% ∇G, 5.16°) separates stable from unstable system behavior ($E = 0.1$ J). Increasing perturbation energy moves the transition point separating stable and unstable behavior to the right.

The effects of task difficulty on KV and the size of the basin of stability are shown in Fig. 6. In particular, the size of the basin of stability decreased with increasing task difficulty, consistent with the original premise. Furthermore, KV increased with increased task difficulty as predicted. As expected, reducing perturbation energy decreased KV, but had no impact on the basin of stability size.
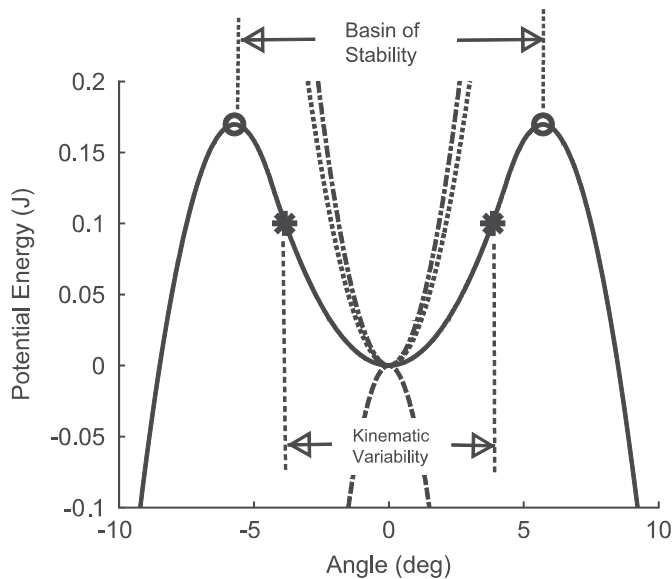
Fig. 4. Components of the effective potential function. Components that contribute to the effective potential function (solid line) include the gravitational gradient (dashed line), the stabilizing springs (dotted line) and the proportional component of the control (dot–dash line). System states within the basin of stability ($\pm 5.72^\circ$) may be able to escape given sufficiently large perturbation energy (E). For an arbitrary $E = 0.1$ J, KV remained within $\pm 3.86^\circ$. At this level of E, the system was stable since KV did not exceed the boundary of the basin of stability. However, if E exceeds the maximum value of the effective potential function (0.170 J) for this task difficulty (50% ∇G), it is possible to achieve system states outside the basin of stability. Over time, this system may exhibit unstable behavior.

Different people will have varying factors that influence the capability of the control system. One of these factors is muscle strength, which may be modeled by modifying the G_p and T_{pmax} (Fig. 7). Reducing G_p and T_{pmax} values decreased the boundary of the basin of stability and increases kinematic variability. Indeed, these two factors had a net effect of increasing the ToS.

3.2. Experimental results

For the ToS (Fig. 8), mean (SD) values for eyes open and closed were 36 (6.4)% ∇G and 51 (7.4)% ∇G, respectively. This difference of ~15% was significant ($t = 11.2$; $p = .0001$). In contrast, the effect of visual condition on λ_{max} was not significant ($t = 0.786$; $p = .46$), and mean values for eyes open and closed were 0.40 (0.18) and 0.47 (0.20), respectively. The effect of visual feedback condition on λ_{max} was similarly non-significant ($p = .71$) in the covariate analysis.

4. Discussion

In this study, the threshold of stability was developed and evaluated as an indicator for spinal stability. The theoretical analysis verified the premise that KV increases and the size of the basin of stability decreases with increasing task difficulty. Experimentally, the ToS was shown to be sensitive to differences in visual acuity, a factor known to influence postural stability. Hence, support for the ToS method was provided both theoretically and experimentally.

To understand why KV increases with increasing task difficulty, consider the source of perturbation energy. Naturally occurring perturbations resulting from a variety of natural random processes are expected to be independent of task difficulty. By examining V_{eff} at a set value of E, KV was observed to increase as
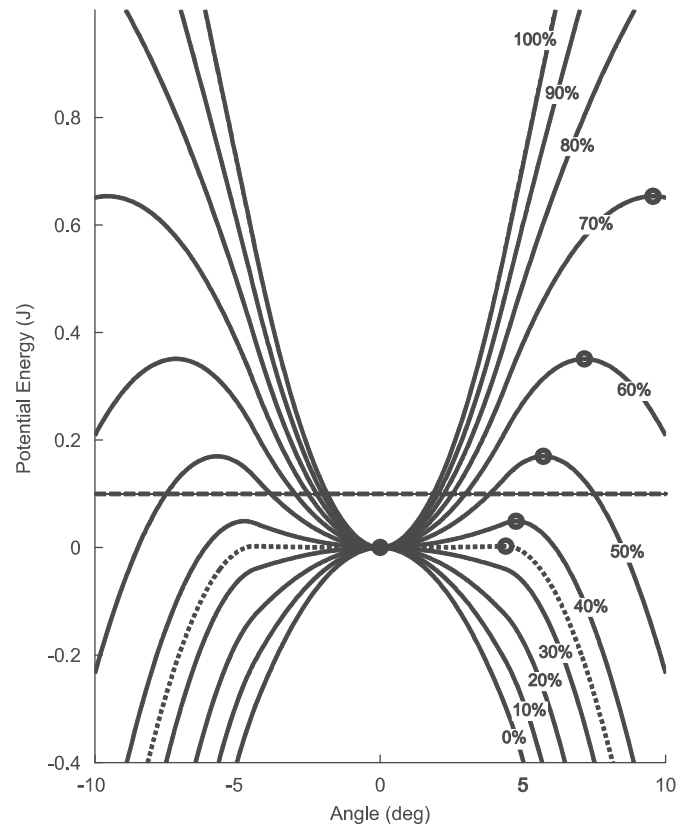

Fig. 5. Sensitivity of the effective potential function to spring setting. The V_{eff} indicated that for the four most difficult spring settings (0–30% ∇G) were globally unstable, with a local maximum existing exclusively at the vertical equilibrium point (0, 0). At a spring setting of 35% ∇G, a basin of stability (circles) formed around the vertical equilibrium position ($\pm 4.40^\circ$). The system displayed low robustness to small perturbations could induce instability. For $E = 0.1$ J (dashed line), the energy exceeded the maximum energy of the effective potential function (0.003 J). Thus, KV was not bounded by the potential function and could become large. When the task difficulty was decreased to 50% ∇G, the system became more robust, with the peak of V_{eff} increasing to 0.170 J. At this task difficulty, E was less than the peak value of V_{eff} and perturbations lacked sufficient energy to escape the potential function. Thus, KV was contained within the basin of stability and the system was stable.

the spring stiffness decreased. This increase in KV was caused by a decrease in the gradient (slope) of V_{eff}. KV continued to increase gradually until the ToS was reached, and further increases in task difficulty lowered the magnitude of V_{eff} below E. As a result, the system became unstable which greatly increased KV.

Our finding that KV increases with task difficulty is consistent with previous studies of standing postural sway that showed the area (Vuillerme et al., 2005), sway range, and variability (Teasdale et al., 1991) of the center of pressure to increase when standing on a compliant surface, typically a foam pad. It may be argued that standing on a foam pad increases KV due to decreased proprioceptive feedback rather than increased task difficulty. Granted, the foam pad decreases local pressures and may reduce proprioception. However, the compliance of the pad also acts as a spring between the controlling force applied by the foot and the reaction support that effectively increases task difficulty. Indeed, similar results were observed when standing on a thin wooden plate over a foam pad (Cornilleau-Peres et al., 2005). In this example, the plate effectively restored proprioception yet maintained the increased task difficulty caused by reduced coupling between the control and support.

The basin of stability is defined as a stable region in state space where trajectories will remain in the neighborhood over time. Unlike globally stable systems that attract trajectories regardless of
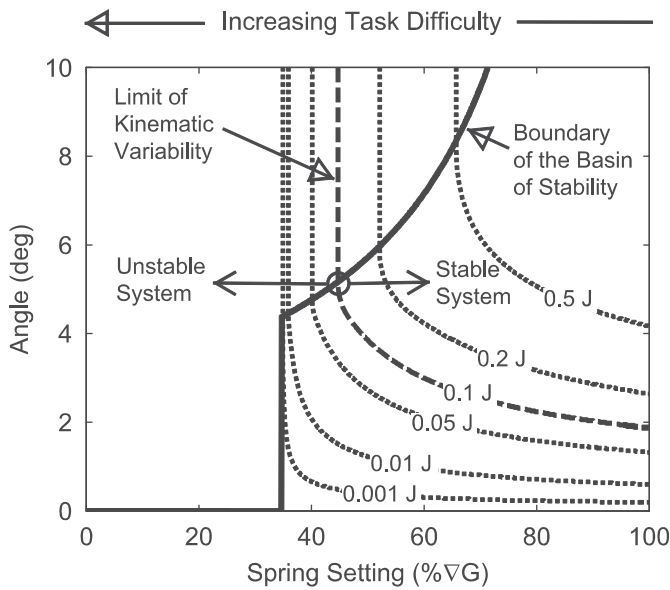
Fig. 6. Sensitivity of the ToS to changes in perturbation energy and stability regions. Three distinct regions were observed. First, a globally unstable region was present as spring settings below 34.7% ∇G where no basin of stability existed. The ToS occurred at the intersection (44.7% ∇G, 5.16°) of the KV (dashed line) and the basin of stability (solid line) curves. Second, a stable region was present for spring settings greater than the ToS (44.7% ∇G) where KV was within the boundary of the basin of stability. In the third region (between 34.7 and 44.7% ∇G) it was possible for the system to exhibit both stable and unstable behavior. Yet, over time the system will become unstable, since the range of KV exceeds the boundary of the basin of stability. For this system KV increased sharply indicating little stable behavior in this region and quickly transitions from stable to unstable behavior at the ToS.
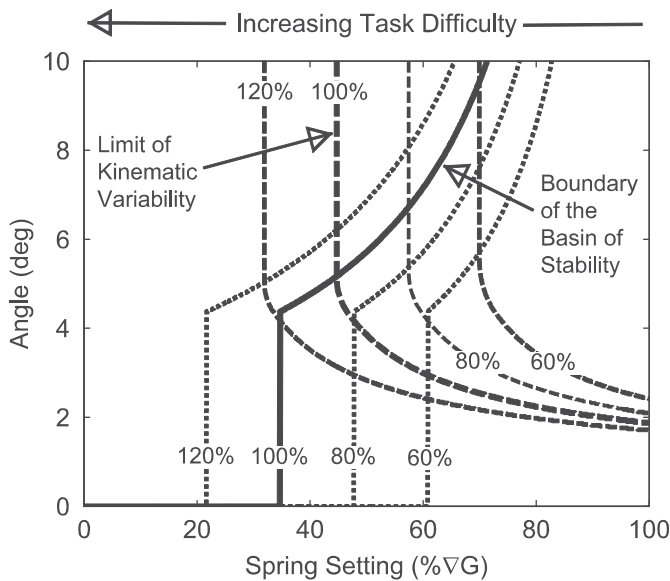

Fig. 7. Sensitivity of the ToS to simulated changes in muscle strength. Reduced muscle strength may be modeled as a decrease in G_p and T_{pmax}. At the modeled value of G_p and T_{pmax}, the ToS was 44.7% ∇G as indicated by the intersection of the KV (bold dashed line) and the basin of stability (solid line) curves labeled 100%. Decreasing G_p and T_{pmax} to 80% of their original values resulted in an increase in the ToS to 57.4% ∇G. A similar trend was observed for 60% (ToS = 69.9% ∇G) and 120% (ToS = 31.9% ∇G) muscle strength.

of their position or velocity, systems with a basin of stability only retain trajectories within the boundaries of the basin (i.e. a limited range of positions and velocities, a.k.a. states). The mathematical model showed that higher task difficulty (lower gradient of V_{eff})

resulted in a smaller basin of stability size. A transition between stable and unstable behavior occurs when the stabilizing contributions equal the destabilizing contributions. This transition forms the boundary of the basin of stability. As the spring stiffness decreased, its stabilizing contribution to V_{eff} also decreased reducing its contribution to V_{eff} at any given angle, θ. This reduction in stabilizing contributions reduced the angle where this transition occurred effectively reducing the size of the basin of stability.

The experimental results presented herein showed the basin of stability size to decrease with increasing task difficulty. This outcome is consistent with a previous standing postural sway experiment where participants leaned forward to a maximum stable angle using only the ankle joint and rotated in a circular direction to experimentally define the stability boundary (Cornilleau-Peres et al., 2005). Task difficulty was increased by performing the task while standing on a thin wooden plate covering a foam pad. Importantly, this experiment showed the basin of stability to decrease with task difficulty when evaluated in configuration space (position but not velocity).

Another aspect of our method that differentiates it from previous methods is the application of task difficulty as an independent variable. Altering task difficulty is inherently different, because it actively changes the system (i.e. "plant" in control theory) to determine the performance on the controller. This difference may not be an overall improvement over previous methods, but its use may allow a difference to be detected that would otherwise be missed using traditional approaches.

Fundamentally, one of the strengths of the ToS is that it identifies a transition between two distinctly different types of behavior (i.e. stable and unstable). For the mathematical model evaluated herein, the transition is sharp, indicating that the method is relatively insensitive to variability. This sharp transition was also observed in the wobble chair experiments, but with less consistency. This inconsistency may be attributed to an increase in degrees of freedom of the actual system and an increased complexity of human neuromuscular control relative to the PD control used in the model. Nevertheless, despite these inconsistencies and a small sample size, we demonstrated that the ToS was sensitive to differences in the balance control system. In addition, ToS was also found to be more sensitive than Lyapunov stability which did not show significant differences.

One limitation of this study was the choice of mathematical model that consisted of a single inverted pendulum with stabilizing springs and PD control. A potentially more accurate model would consist of a double inverted pendulum with segments representing the lower and upper body and a pin joint at the lumbar spine. This type of model would more closely represent the actual experimental configuration but at the expense of increasing model complexity. Since the purpose of our model was to illustrate a theoretical concept, the authors felt the less complex model would effectively fulfill the purpose.

Ultimately, the ToS may be useful in the future as a diagnostic tool in a clinical setting. Specifically, ToS could be used to indicate patients who have low back pain because of instability allowing appropriate treatments to be prescribed. Although electronics were used in this study to determine the Lyapunov exponents, they were not needed to find the threshold of stability. Furthermore, the ∇G for each participant could be approximated using anthropometric parameters. Thus, the simplicity, sensitivity, and low cost of this method may make it suitable for evaluating spinal stability of LBP patients in a clinical practice.

Overall, a new method, ToS, was developed for evaluating spinal stability. This new method was theoretically and experimentally evaluated. Results indicated that the method has a sound theoretical foundation and is sensitive to differences using a small
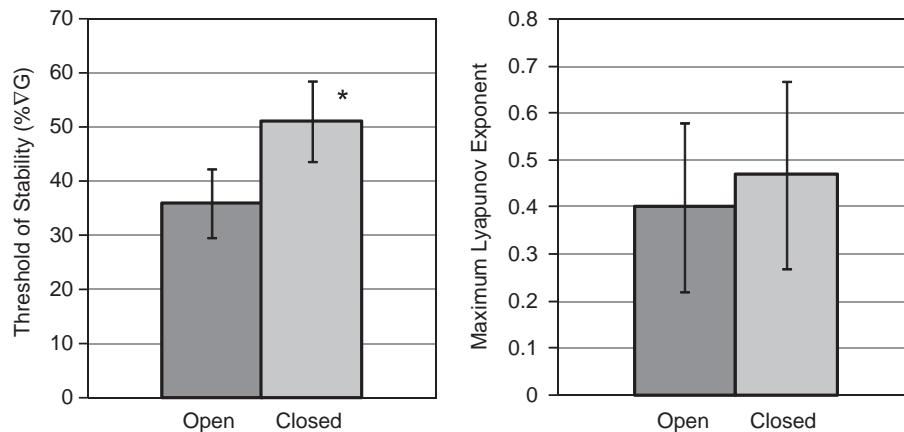
Fig. 8. Effects of visual feedback (eyes open vs. closed) on the threshold of stability (left) and maximum Lyapunov exponent (right). Values are means (SD), and the symbol * indicates a significant effect of visual feedback.

number of samples. Future applications for the ToS method might include its use as a diagnostic tool for evaluating spinal stability associated with LBP.

Conflict of interest

The authors declare that there are no conflicts of interest associated with this research.

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