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Stability of Dynamic Trunk Movement

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Abstract

Study Design.—Nonlinear systems analyses of trunk kinematics were performed to estimate control of dynamic stability during repetitive flexion and extension movements.

Objective.—Determine whether movement pace and movement direction of dynamic trunk flexion and extension influence control of local dynamic stability.

Summary of Background Data.—Spinal stability has been previously characterized in static, but not in dynamic movements. Biomechanical models make inferences about static spinal stability, but existing analyses provide limited insight into stability of dynamic movement. Stability during dynamic movements can be estimated from Lyapunov analyses of empirical data.

Methods.—There were 20 healthy subjects who performed repetitive trunk flexion and extension movements at 20 and 40 cycles per minute. Maximum Lyapunov exponents describing the expansion of the kinematic state-space were calculated from the measured trunk kinematics to estimate stability of the dynamic system.

Results.—The complexity of torso movement dynamics required at least 5 embedded dimensions, which suggests that stability components of lumbar lordosis may be empirically measurable in addition to global stability of trunk dynamics. Repeated trajectories from fast paced movements diverged more quickly than slower movement, indicating that local dynamic stability is limited in fast movements. Movements in the midsagittal plane showed higher multidimensional kinematic divergence than asymmetric movements.

Conclusion.—Nonlinear dynamic systems analyses were successfully applied to empirically measured data, which were used to characterize the neuromuscular control of stability during repetitive dynamic trunk movements. Movement pace and movement direction influenced the control of spinal stability. These stability assessment techniques are recommended for improved workplace design and the clinical assessment of spinal stability in patients with low back pain.

Keywords

spine; stability; dynamics; neuromuscular control

Neuromuscular control of spinal stability has been characterized in static, but not in dynamic movement tasks. Stability is defined as the ability to maintain intervertebral and global torso equilibrium, despite the presence of small mechanical disturbances and/or small neuromuscular

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control errors. Research indicates that 3 subsystems contribute to spinal stability.¹ One is the passive contributions from the spinal ligaments, discs, and bone. The second is the steady-state active muscle recruitment contribution to spinal stability. Third is the neural feedback system that includes active and voluntary responses. Biomechanical models describe how factors, including muscle recruitment, spinal posture, and external load, contribute to the potential energy of the musculoskeletal system,²⁻⁴ which is important because static stability is achieved when the equilibrium posture of the spine is also a state of minimum potential energy.⁵

Although these models have been applied to data collected during movement tasks,^{6,7} they ignore the role of kinetic energy. Therefore, when investigating the stability of dynamic movements, existing models are limited by 2 factors. First, existing models do not yet account for the energy of movement dynamics. Second, they ignore the role of the time-dependent dynamic neural feedback for the control of spinal stability. Empirical estimates of stability are an alternative to biomechanical modeling and may contribute valuable insight regarding control of spinal stability during dynamic movement tasks.

Stability can be estimated from the time-dependent behavior of kinematic variance. Empirical estimates of torso stability have been recorded while subjects maintained steady-state seated balance on a wobbly chair.⁸ The equilibrium state during that study was a zero-velocity, upright seated posture. However, small biomechanical or neuromotor disturbances continuously perturb the system, causing kinematic variance. Consequently, torso posture and velocity were rarely identical to the equilibrium state.⁹ The neuromuscular controller maintains postural stability by actively working to return the disturbed posture toward the equilibrium state.¹⁰ Therefore, stability can be observed when the measured kinematics appears to be attracted toward the posture of static equilibrium.¹¹ A similar approach can be applied to record stabilizing control of dynamic movements.

During repetitive dynamic trunk flexion-extension movements, it is reasonable to assume that the kinematics of each cycle could be similar to every other cycle (*i.e.*, the target trajectory).¹² Kinematic variance about this target trajectory is the manifestation of stochastic disturbances and control errors during the movement process. At any given time, the multidimensional kinematic variance can be represented as an n -dimensional sphere, where the volume of the sphere describes the magnitude of the kinematic dispersion, and n is the number of state variables.¹³ Measurable state variables include the trunk angles and velocities in each recorded dimension. Neuromuscular response to the kinematic perturbations will cause the movement dynamics to be attracted toward the target trajectory.

Therefore, as time (t) progresses, the n -dimensional sphere of kinematic variance evolves into an ellipsoid, whose principle axes contract (or expand) at rates described by Lyapunov exponents.¹⁴ One Lyapunov exponent exists for every movement dimension, which can be arranged in order of most rapidly expanding to most rapidly contracting, $\lambda_1 > \lambda_2 > \dots > \lambda_n$. A system is stable when the sum of these exponents is negative (*i.e.*, the rate of contraction is higher than the rate of expansion). It is noteworthy that it is necessary to quantify the time-dependent behavior of kinematic variability when investigating stability. However, calculation of the full Lyapunov spectrum from experimental data is exceedingly difficult. These calculations may be simplified greatly by realizing that 2 randomly selected initial trajectories should diverge, on average, at a rate determined by the largest Lyapunov exponent, λ_{Max} .¹⁴ Calculation of λ_{Max} is relatively easy and can be used to investigate the role of movement dynamics in neuromuscular control of spinal stability.

The goal of this study was to implement Lyapunov analyses to assess stabilizing control during dynamic trunk movement. These analyses were used to test whether movement rate and direction affect stability. Epidemiologic data suggest that the risk of low back injury is related

to the dynamic movement rate during repetitive trunk flexion tasks.^{15,16} Therefore, we hypothesized that during repetitive trunk flexion-extension movement, dynamic stability may decrease with an increased pace of cyclic movement. Existing evidence further suggests that the risk of low back injury is increased when trunk movements include nonsagittal movement components.¹⁷ Thus, we also hypothesized that movements in the midsagittal plane may be more stable than asymmetric movement trajectories (*i.e.*, movements that include components in both the sagittal and transverse planes).

Methods

Experimental Procedures. There were 20 subjects who performed repetitive dynamic trunk flexion and extension movements. Subjects included 8 males and 12 females, with no self-reported history of low back pain (Table 1). Participants provided informed consent approved by the Virginia Tech institutional review board before participation in the study.

The experiment required subjects to perform continuously repeated trunk flexion and extension movements (Figure 1). They were required to touch targets with their hands held together. Targets were located at pre-specified locations similar to methods described by Thomas *et al.*¹⁸ One target was placed at shoulder height in the anterior sagittal midline so that the target could be reached when standing upright with the arms horizontally extended. A second target was placed in the sagittal midline, 50 cm anterior to the knee. Subjects were required to touch the upper target followed by the lower target and continuously repeat this motion throughout the duration of each experimental trial. Asymmetric trials were recorded in which the upper target was moved to the right and the lower target to the left to induce a nominal 45° axial rotation of the torso at the upper and lower targets. Movements during these trials thus included torso flexion and left twist.

Separate trials were conducted in which the targets were placed to require flexion and right twist. Each target was touched synchronous with a periodic tone from a metronome to establish the movement pace, 20 and 40 cycles per minute. To ensure 30 movement cycles per trial, the slow paced trials were 90 seconds in duration, while the fast paced trials were 45 seconds in duration. Although all movement cycles of each trial were recorded, only the middle 15 cycles were analyzed to ensure steady-state movement behavior. Subjects were allowed to practice the movements until they were comfortable with the movement trajectory and movement pace before data collection of each trial. Experimental conditions were presented in randomized order, with at least 2 minutes rest between trials.

Upper-body kinematic data were recorded from electromagnetic motion sensors that were secured by double-sided tape over the vertebral processes of the T10 and S1 (Ascension Technology Corp., Burlington, VT). Trunk angles were computed by 3-dimensional Euler rotation matrices recorded from the T10 sensor, with respect to the S1 sensor at a sample rate of 100 Hz. Following data collection, the kinematic data were filtered with a 10 Hz, low-pass, second-order Butterworth filter in preparation for calculation of dynamic stability. The number of data samples per cycle can influence the estimate of stability.¹⁹ Therefore, the data were resampled in software to obtain 4500 data samples per 15 movement cycles. It is noteworthy that this process provides a mean value of 300 samples per cycle on average, but cycle-to-cycle variability in movement duration was retained. Expansion of kinematic variability in 1 dimension may be compensated by contraction in another dimension. Thus, stability analyses were performed on the Euclidean norm (*i.e.*, square root of the sum of squares) of the 3 trunk angles recorded at each time.

Calculating Dynamic Stability. Local dynamic stability of the trunk flexion-extension movement was computed from the maximum finite-time Lyapunov exponent, λ_{Max} . Complex

dynamic systems must be represented with a higher number of dimensions than simple systems. However, the recorded data were 1-dimensional, time-series, column vectors, $x(t)$, representing the Euclidean norm of the trunk angles. One typical method of creating an n -dimensional state-space from scalar data is by method of delays,

$$y(t) = [x(t), x(t+T_d), x(t+2T_d), \dots, x(t+(n-1)T_d)]$$

where $x(t)$ is the original scalar data of trunk movement, n is the number of reconstruction dimensions, and T_d is a constant time delay (Figure 2). This embeds information related to finite-difference estimation of velocity, acceleration, *etc.* Several methods exist for calculation of the reconstruction delay, T_d . These methods include time delays estimated from the Average Mutual Information function,²⁰ the time it takes for the autocorrelation function to decrease to a pre-specified fraction of its initial value,²¹ and time delays that maximize the space filled by the n -dimensional reconstructed signal.¹⁹

There is no consensus on which method provides optimal results. To ensure that all trials were analyzed similarly, a constant T_d of 30 samples (10% of the length of the average cycle) was used for all trials based on autocorrelation assessment described previously. The number of reconstruction dimensions was determined from a Global False Nearest Neighbors analyses¹⁴ and revealed that an embedding dimension of $n = 5$ was appropriate for the analyzed data. False nearest neighbors are defined as sets of points that are very close to each other at dimension $n = k$, but not at $n = k + 1$. This method incrementally increases n until the number of false nearest-neighbors approaches zero.

Maximum finite-time Lyapunov exponents were calculated from the distance, $d_i(t)$, between nearest neighbors in the reconstructed state-space, $Y(t)$. Nearest neighbors were found by selecting data points from separate cycles that are closest to each other in the reconstructed state-space (Figure 2). If repeated movement cycles were kinematically identical, then an illustration of the trajectories would plot each cycle on top of the others. In this condition, the distance between nearest neighbors, $d_i(t)$, would be zero for all pairs of nearest neighbors, i . However, in the empirically measured data, the distance between nearest neighbors, $d_i(t)$, was more than zero. Therefore, there are clearly kinematic disturbances and/or chaotic behaviors observable in the data. The distance between all nearest neighbors was tracked forward in time, t . Because the growth in the least stable dimension quickly dominates expansion of the n -dimensional sphere of kinematic variance, randomly selected initial trajectories should diverge, on average, at a rate determined by the largest Lyapunov exponent, λ_{Max} .¹⁴ Therefore, the maximum Lyapunov exponent, λ_{Max} , was approximated as the slope of the linear best-fit line created by the equation,

$$y(t) = \frac{1}{\Delta t} \langle \ln d_i(t) \rangle$$

where $\langle \ln d_i(t) \rangle$ represents the average logarithm of displacement, $d_i(t)$, for all pairs of nearest neighbors, i , throughout a time span, $t = 0$ to $t = 1$ cycles (Figure 3). Stability is thereby calculated as λ_{Max} , which is the rate of divergence of initially neighboring trajectories.

Statistical analyses were performed to determine the effect of movement pace and asymmetry on the neuromuscular control of dynamic stability. Preliminary analyses revealed no significant differences in λ_{Max} during asymmetric right-to-left *versus* left-to-right trials for the number of subjects studies ($P = 0.437$, $F = 0.617$). Therefore, data from the 2 asymmetric conditions were pooled for statistical analyses. Independent variables of movement pace (slow, fast) and asymmetry (midsagittal, asymmetric) were treated as within-subject effects in a 2-factor

repeated measures analysis of variance. Analyses were performed using commercial software (Statsoft, Inc., Tulsa OK) using a significance level of $\alpha < 0.05$.

Results

Maximum finite-time Lyapunov exponents, λ_{Max} , were calculated to estimate the neuromuscular control of stability during repeated dynamic trunk flexion-extension movements (Figure 4). A significant main effect for movement pace ($P < 0.001$, $F[1,19] = 929.9$) was observed. Mean values during repetitive trunk movement at 20 cycles per minute were $\lambda_{\text{Max}} = 0.397$ (standard deviation [SD] 0.062), whereas when moving at 40 cycles per minute $\lambda_{\text{Max}} = 0.846$ (SD 0.098). Recall that larger values of λ_{Max} represent more rapidly diverging dynamics and are considered less stable. Results suggest the value of the λ_{Max} during the fast trials were more than twice the level recorded during slow dynamic movement. However, it would be incorrect to infer from this that the slow movement was twice as stable unless the complete Lyapunov spectrum was computed. Nonetheless, it can be concluded that the neuromuscular control of dynamic stability declined significantly with increased movement rate.

A significant main effect for movement asymmetry was observed ($P < 0.001$, $F[1,19] = 28.5$). Sagittally symmetric movements were associated with higher λ_{Max} than asymmetric trials, mean 0.665 (SD 0.256) and mean 0.579 (SD 0.218), respectively. A pace-by-asymmetry interaction ($P < 0.018$, $F[1,19] = 6.69$) revealed that the difference between slow and fast conditions was attenuated in the asymmetric movement (Figure 4). Nonetheless, the difference between slow and fast movements was statistically significant ($P < 0.001$) in both symmetric and asymmetric movement conditions.

Discussion

Musculoskeletal low back injuries are often associated with dynamic trunk flexion.¹⁵ Studies show that movement velocity influences torso muscle recruitment and cocontraction, thereby contributing to higher spinal load during fast paced lifting movements than during slow movements.²² It is unclear why cocontraction might be increased during fast movement. However, static^{23,24} and quasi-static²⁵ analyses of lifting exertions suggest that cocontraction may be recruited, in part, to augment spinal stability. Reduced spinal stability combined with increased spinal compression may contribute to the risk associated with dynamic trunk flexion. Although spinal stability has been estimated in static conditions,⁴ we are unaware of any previous studies to quantify the neuromuscular control of stability during dynamic trunk movements. Therefore, the goal of this study was to determine whether the rate of movement influences stability during dynamic trunk flexion and extension tasks.

Neuromuscular control of stability declined with movement pace. Several factors may contribute this behavior. First, momentum increases with movement velocity, thereby requiring more neuromuscular effort to control and attenuate kinematic disturbances. Second, torso muscle activity and cocontraction increase with trunk velocity and acceleration.^{26,27} Modulation of muscle forces when muscle activity is high requires the recruitment of large motor units, thereby limiting finemotor control during fast paced movements. Finally, fast dynamic movements reduce the allowable time for neuromuscular corrections, which suggests increased delay in the active recruitment and neural feedback relative to the movement trajectory. Feedback delay is well recognized as a destabilizing factor in control systems.²⁸ The Fitt law of motor control²⁹ suggests that higher kinematic errors may be expected when movement pace is fast. Therefore, it is not surprising that neuro-control of dynamic stability was compromised during the fast dynamic movement tasks.

Movements in the midsagittal plane were less stable than when moving in a combined sagittal and twist trajectory. This contradicted our second hypothesis but may not be surprising when one considers the neuromuscular control of these tasks. Published surface electromyogram measurements suggest higher recruitment and coactivation of the internal and external oblique muscle groups during asymmetric tasks.^{30,31} This recruitment is necessary to control the asymmetric tasks, whereas activation of these muscles is less critical when moving in the midsagittal plane. Todorov and Jordan³² showed that an optimal movement strategy may allow variability in redundant, task-irrelevant dimensions (*e.g.*, kinematic variability in the transverse plane during midsagittal movement). Simultaneous movement in both the sagittal and transverse planes imposed constraints, increased control was required, as documented by smaller values of λ_{Max} .

Further research is necessary to investigate how asymmetric trajectories influence the control of dynamic movement. Specifically, the asymmetric movement in our protocol resulted in movements that crossed the midsagittal plane (*i.e.*, each movement included rotation from left twist to right twist postures and *vice versa*). Moreover, the movement tasks did not require handling of an external load. Representation of epidemiologic results should investigate stability when the movement is confined to the left half-plane or right half-plane and with a load in the hands. Nonetheless, results show that neuromuscular control patterns associated with asymmetric movement trajectories significantly influence dynamic stability.

Understanding the meaning of the λ_{Max} coefficient is important when interpreting the results. During static postural tasks, the neuromuscular response to a kinematic perturbation will cause the system to return toward the equilibrium state.¹⁰ Likewise, during dynamic torso flexion and extension tasks, the stabilizing neuromuscular control system will cause the movement dynamics to be attracted toward the target movement trajectory. Recall that the existence of an attractor trajectory representing a globally stable system is guaranteed when the sum of the complete spectrum of Lyapunov exponents is negative (*i.e.*, the rate of kinematic error contraction is higher than the rate of expansion).

Clearly, in our study, the torso was stable for all experimental conditions because there were no unbounded movements or injuries. Therefore, we conclude that the sum of exponents was negative. However, the goal of the study was to determine whether specific dynamic movement conditions were more or less stable than others. The maximum Lyapunov exponent, λ_{Max} , characterizes the maximum time rate of expansion for the n -dimensional sphere that describes kinematic variability. In other words, this value represents the least stable aspect of the movement dynamics.¹⁴

Consequently, it was logical to investigate the maximum Lyapunov exponent, λ_{Max} , because it provides insight into the dynamic behavior of the musculoskeletal system, and it is mathematically feasible to estimate this coefficient from empirical data. We hope to pursue further studies that will attempt to estimate the full Lyapunov spectrum to provide more insight into the neuromuscular control of the spine. Moreover, future studies should investigate the nature of the maximum Lyapunov exponent, λ_{Max} , in individual subjects. It represents local instability in a particular direction, thereby providing potential insight into the weakest control direction. It may be useful to identify which kinematic dimensions are well controlled and which are poorly controlled in individual patients for optimized prophylactic intervention or for design of individual-specific injury rehabilitation.

An additional interesting result was the reconstruction dimension $n = 5$. The reconstruction dimension provides insight into the complexity of the neuromuscular dynamics. Recall that the kinematics was represented as a 1-dimensional Euclidean norm vector of the trunk angles. Nonetheless, analyses revealed that the data must include at least 5 reconstructed dimensions

to represent adequately the dynamic system. We would not have been surprised with $n = 3$ when one recognizes that the trunk moved in 3 dimensions. A value of at least $n = 3$ is predicted by Takens' theorem.³³ However, the requirement of larger values ($n = 5$) suggests that multidimensional spinal curvature may have contributed to the results, which may indicate that the analyses were sensitive to effects from spinal lordosis movement in addition to the global trunk dynamics. Previous studies indicate that neuromuscular deficits in patients with low back pain are revealed most effectively in complex dynamic tasks.³⁴ Whether the complexity of neuromuscular control changes with movement task design, and whether it is related to injury and efficacy of rehabilitation should be investigated in future research.

Conclusions

Nonlinear dynamic systems analyses were applied to empirically recorded repetitive dynamic trunk movements. These analyses characterize the neuromuscular control of stability during dynamic movements. Results show that both movement pace and movement asymmetry influence the control of spinal stability. Continued development of these stability assessment techniques are recommended for improved workplace design and clinical assessment of spinal stability in patients with low back pain.

Key Points

- Nonlinear dynamic systems analyses can be used to quantify neuromuscular control of spinal stability of repetitive dynamic torso flexion movements.
- Lyapunov exponents from measured trunk kinematics show that stability declines with the rate of flexion-extension movement and is influenced by movement asymmetry.
- Embedding dimensions higher than expected show that the movement dynamics in the trunk are more complex than previously considered.

References

1. Panjabi MM. The stabilizing system of the spine. Part I Function, dysfunction, adaptation and enhancement. *J Spinal Disord* 1992;5:383–9. [PubMed: 1490034]
2. Bergmark A. Stability of the lumbar spine: A study in mechanical engineering. *Acta Orthop Scand Suppl* 1989;230:1–54. [PubMed: 2658468]
3. Gardner-Morse MG, Stokes IAF, Laible JP. Role of muscles in lumbar stability in maximum extension efforts. *J Orthop Res* 1995;13:802–8. [PubMed: 7472760]
4. Granata KP, Wilson SE. Trunk posture and spinal stability. *J Biomech* 2001;16:650–9.
5. Thompson, JMT.; Hunt, GW. Elastic instability phenomena. John Wiley & Sons; New York, NY: 1984. The general conservative theory; p. 1-26.
6. Cholewicki J, McGill SM. Mechanical stability on the in vivo lumbar spine: Implications for injury and chronic low back pain. *Clin Biomech (Bristol, Avon)* 1996;11:1–15.
7. Van Dieen JH, Cholewicki J, Radebold A. Trunk muscle recruitment patterns in patients with low back pain enhance the stability of the lumbar spine. *Spine* 2003;28:834–41. [PubMed: 12698129]
8. Cholewicki J, Polzhofer GA, Radebold A. Postural control of trunk during unstable sitting. *J Biomech* 2000;22:1733–7. [PubMed: 11006402]
9. Hodges PW, Gurfinkel VS, Brumagne S, et al. Coexistence of stability and mobility in postural control: Evidence from postural compensation for respiration. *Exp Brain Res* 2002;144:293–302. [PubMed: 12021811]
10. Peterka RJ. Simplifying the complexities of maintaining balance. *IEEE Eng Med Biol Mag* 2003;22:63–8. [PubMed: 12733461]
11. Collins JJ, DeLuca CJ. Open-loop and closed-loop control of posture: A random-walk analysis of center of pressure. *Exp Brain Res* 1993;95:308–18. [PubMed: 8224055]

12. Dingwell JB, Cusumano JP. Nonlinear time series analysis of normal and pathological human walking. *Chaos* 2000;10:848–63. [PubMed: 12779434]
13. Leipholtz, H. *Stability Theory. An Introduction to the Stability of Dynamic Systems and Rigid Bodies.* John Wiley & Sons; New York, NY: 1987.
14. Rosenstein MT, Collins JJ, Deluca CJ. A practical method for calculating largest Lyapunov exponents from small data sets. *Physica D* 1993;65:117–34.
15. National Research Council. *Musculoskeletal Disorders and the Workplace.* National Academy Press; Washington, DC: 2001.
16. Marras WS, Lavender SA, Leurgans S, et al. Biomechanical risk factors for occupationally related low back disorder risk. *Ergonomics* 1995;38:377–410. [PubMed: 7895740]
17. Fathallah FA, Marras WS, Parnianpour M. The role of complex, simultaneous trunk motions in the risk of occupation-related low back disorders. *Spine* 1998;23:1035–42. [PubMed: 9589543]
18. Thomas JS, Corcos DM, Hasan Z. Effect of movement speed on limb segment motions for reaching from a standing position. *Exp Brain Res* 2003;148:377–87. [PubMed: 12541148]
19. Rosenstein MT, Collins JJ, Deluca CJ. Reconstruction expansion as a geometry-based framework for choosing proper delay times. *Physica D* 1994;73:82–98.
20. Fraser AM, Swinney HL. Independent coordinates for strange attractors from mutual information. *Phys Rev A* 1986;33:1134–40. [PubMed: 9896728]
21. Albano AM, Muench J, Schwartz C, et al. Singular-value decomposition and the Grassberger-Procaccia algorithm. *Phys Rev A* 1988;38:3017–26. [PubMed: 9900718]
22. Granata KP, Marras WS. The influence of trunk muscle coactivity upon dynamic spinal loads. *Spine* 1995;20:913–9. [PubMed: 7644956]
23. Granata KP, Orishimo K. Response of trunk muscle coactivation to changes in spinal stability. *J Biomech* 2001;34:1117–23. [PubMed: 11506782]
24. Gardner-Morse MG, Stokes IAF. The effects of abdominal muscle coactivation on lumbar spine stability. *Spine* 1998;23:86–92. [PubMed: 9460158]
25. Cholewicki J, Panjabi MM, Khachatryan A. Stabilizing function of trunk flexor-extensor muscles around a neutral spine posture. *Spine* 1997;22:2207–12. [PubMed: 9346140]
26. Marras WS, Mirka GA. Electromyographic studies of the lumbar trunk musculature during the generation of low-level trunk acceleration. *J Orthop Res* 1993;11:811–7. [PubMed: 8283325]
27. Dolan P, Adams MA. The relation between EMG activity and extensor moment generation in the erector spinae muscles during bending and lifting activities. *J Biomech* 1993;26:513–22. [PubMed: 8478353]
28. Ogata, K. *Modern Control Engineering.* Vol. 4th ed.. Prentice Hall; Upper Saddle River, NJ: 2002.
29. Fitts PM. The information capacity of the human motor system in controlling the amplitude of movement. *J Exp Psychol* 1954;47:381–91. [PubMed: 13174710]
30. Lavender SA, Tsuang YH, Hafezi A, et al. Coactivation of the trunk muscles during asymmetric loading of the torso. *Hum Factors* 1992;34:239–47. [PubMed: 1601434]
31. Granata KP, Marras WS. An EMG-assisted model of loads on the lumbar spine during asymmetric trunk extensions. *J Biomech* 1993;26:1429–38. [PubMed: 8308047]
32. Todorov E, Jordan MI. Optimal feedback control as a theory of motor coordination. *Nat Neurosci* 2002;5:1226–35. [PubMed: 12404008]
33. Takens, F. Detecting strange attractors in turbulence. In: Young, L-S., editor. *Dynamical Systems and Turbulence.* Springer; New York, NY: 1981. p. 366-81.
34. Radebold A, Cholewicki J, Polzhofer GA, et al. Impaired postural control of the lumbar spine is associated with delayed muscle response times in patients with chronic idiopathic low back pain. *Spine* 2001;26:724–30. [PubMed: 11295888]

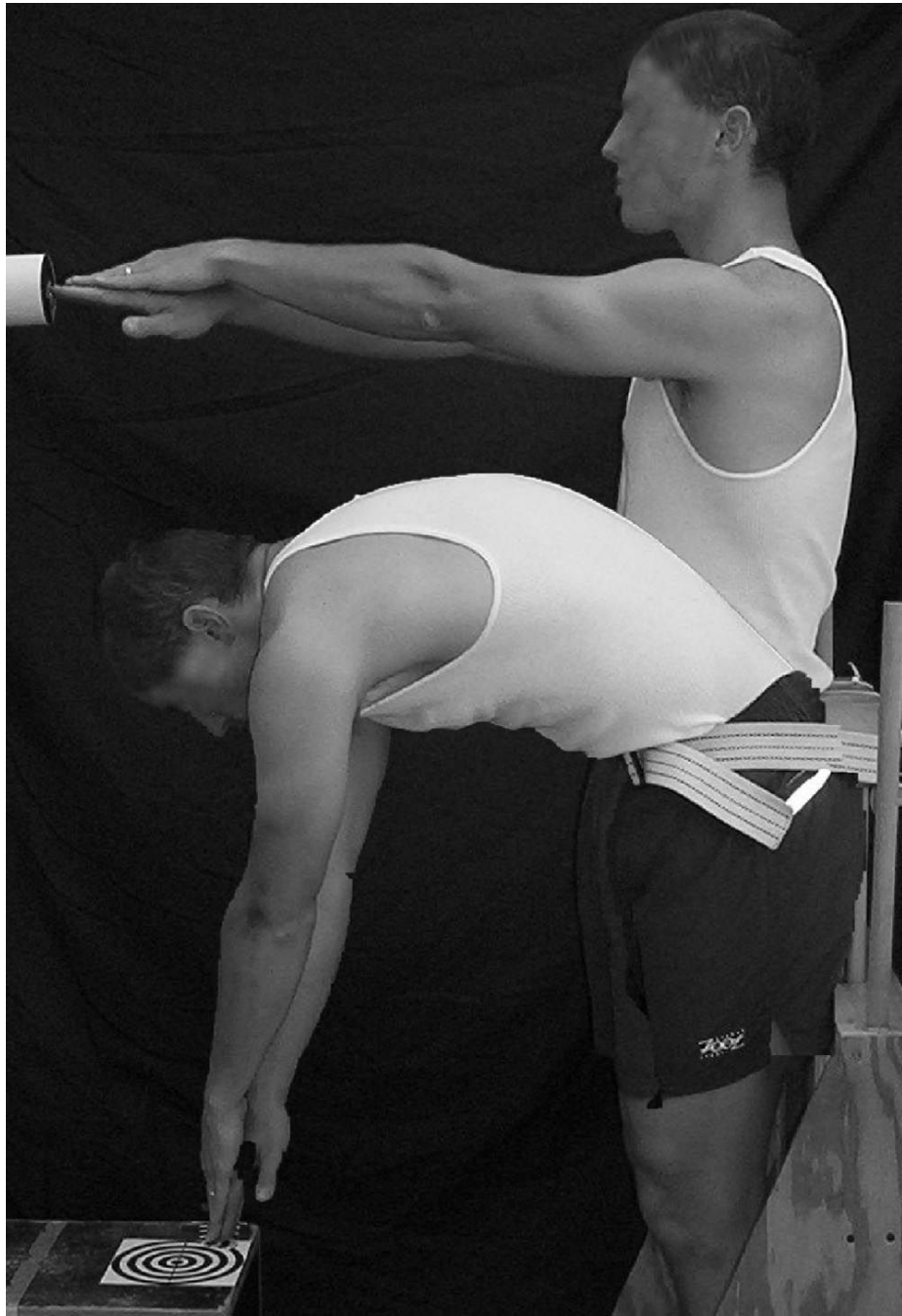


Figure 1.
Experimental setup of the targeted movement task.

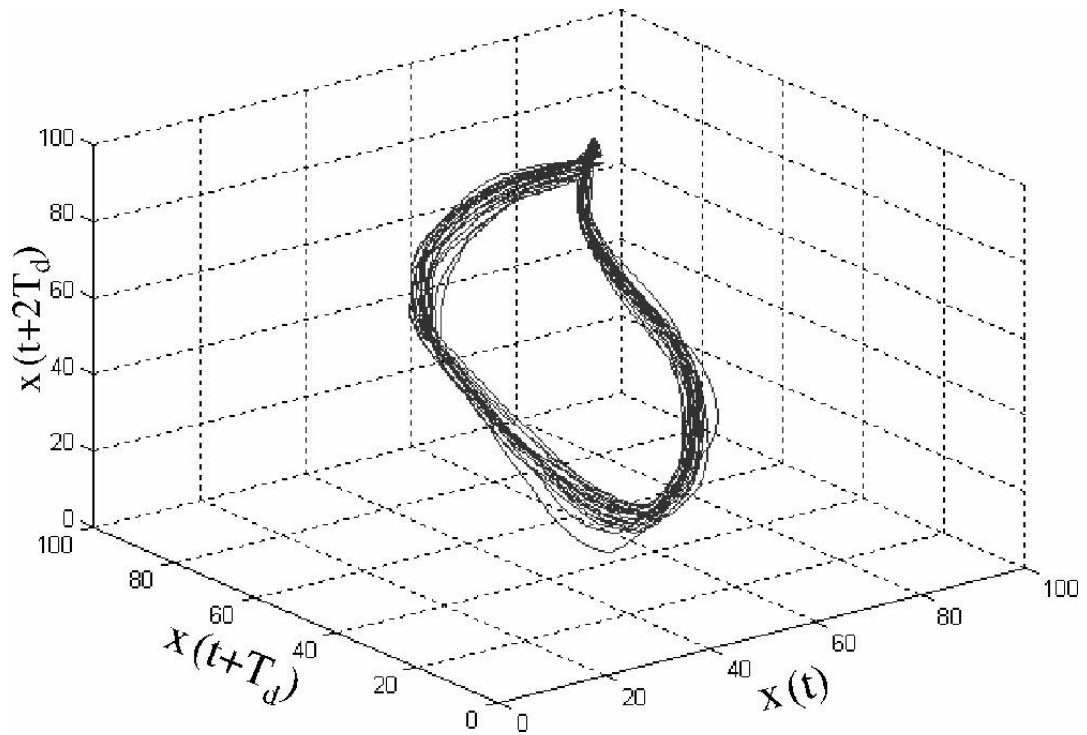


Figure 2. Example of a reconstructed movement trajectory with $n = 3$ state-space dimensions. Although the movement data were analyzed with $n = 5$, 3 embedding dimension is the largest that can be illustrated.

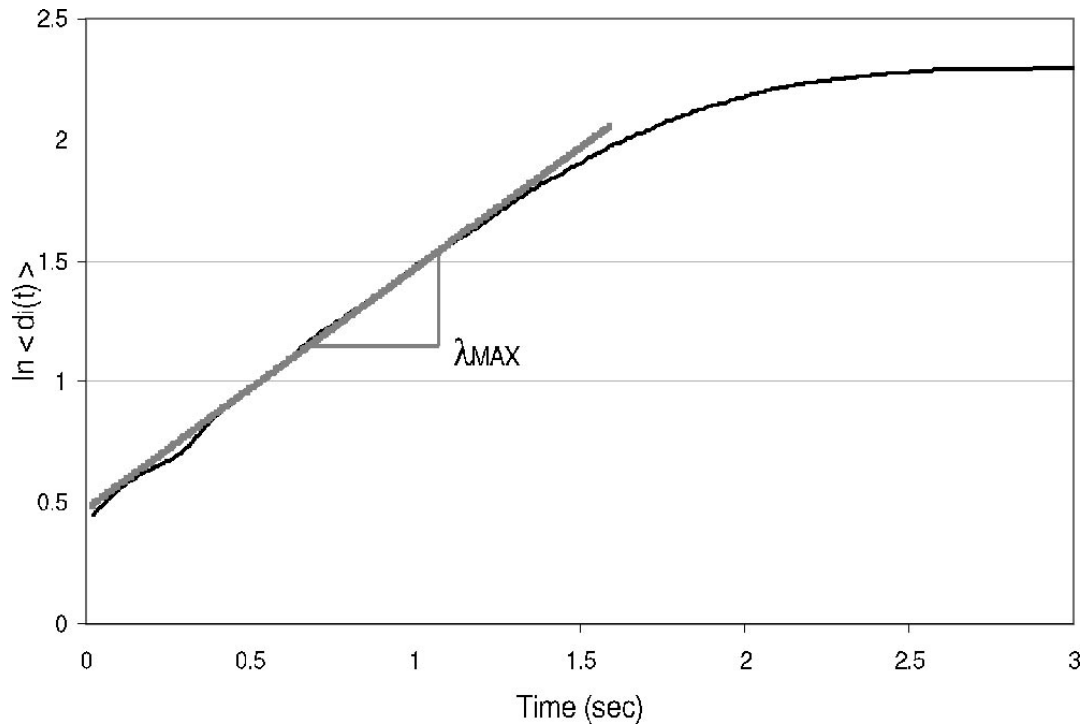


Figure 3. Typical plot of the state-space expansion with time. The dashed line represents the best-fit line between $t = 0:1$ cycles (with a cycle length of approximately 1.5 seconds for this trial). The slope of this best-fit line was used to represent the state-space expansion, *i.e.* local dynamic stability of the task.

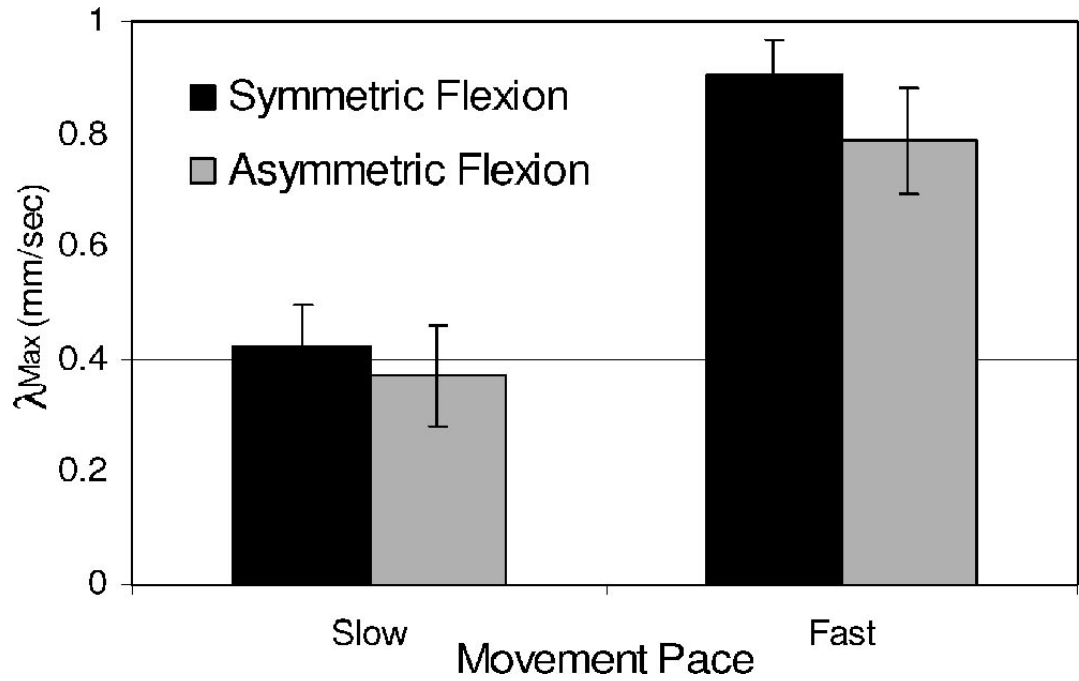


Figure 4. λ_{Max} values were greater during fast paced movement trials than slow paced cyclic movement. Values were also greater during asymmetric movement tasks than during sagittal midplane movements. Larger values of λ_{Max} represent more chaotic, *i.e.* less stable, movement dynamics.

Table 1

Subject Demographics and Anthropometry

	Subjects	
	Male	Female
No.	8	12
Mean age (SD)	23.8 ys (2.3)	21.5 ys (2.6)
Mean height (SD) *	183.5 cm (3.8)	164.5 cm (5.3)
Mean body mass (SD) *	83.9 kg (12.8)	61.2 kg (7.5)

SD indicates standard deviation.

* Significant difference between genders.