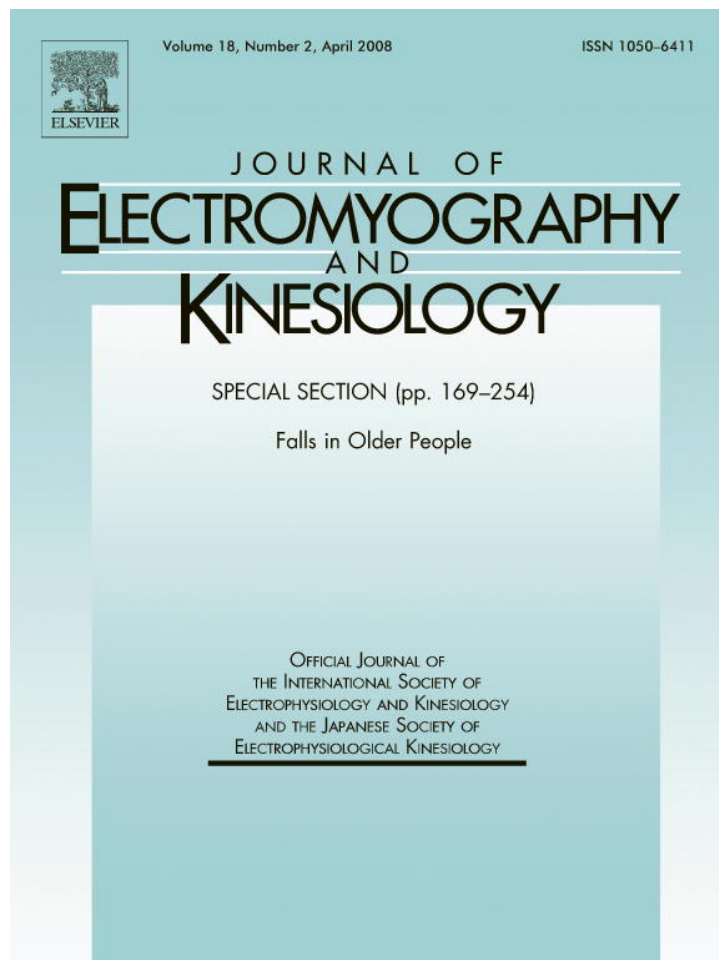




This article was published in an Elsevier journal. The attached copy is furnished to the author for non-commercial research and education use, including for instruction at the author's institution, sharing with colleagues and providing to institution administration.

Other uses, including reproduction and distribution, or selling or licensing copies, or posting to personal, institutional or third party websites are prohibited.

In most cases authors are permitted to post their version of the article (e.g. in Word or Tex form) to their personal website or institutional repository. Authors requiring further information regarding Elsevier's archiving and manuscript policies are encouraged to visit:

<http://www.elsevier.com/copyright>



ELSEVIER

Available online at www.sciencedirect.com
 ScienceDirect

Journal of Electromyography and Kinesiology 18 (2008) 172–178

JOURNAL OF
ELECTROMYOGRAPHY
AND
KINESIOLOGY

www.elsevier.com/locate/jelekin

Dynamic stability differences in fall-prone and healthy adults

Kevin P. Granata ^{a,*}, Thurmon E. Lockhart ^{b,*}

^a *Musculoskeletal Biomechanics Laboratory, Department of Engineering Science and Mechanics, School of Biomedical Engineering and Science, Virginia Polytechnic Institute and State University, Blacksburg, VA, USA*

^b *Locomotion Research Laboratory, Grado Department of Industrial and Systems Engineering, School of Biomedical Engineering and Science, Virginia Polytechnic Institute and State University, Blacksburg, VA, USA*

Received 3 January 2007; received in revised form 27 February 2007; accepted 27 February 2007

Abstract

Typical stability assessments characterize performance in standing balance despite the fact that most falls occur during dynamic activities such as walking. The objective of this study was to identify dynamic stability differences between fall-prone elderly individuals, healthy age-matched adults, and young adults. Three-dimensional video-motion analysis kinematic data were recorded for 35 contiguous steps while subjects walked on a treadmill at three speeds. From this data, we estimated the vector from the center-of-mass to the center of pressure at each foot-strike. Dynamic stability of walking was computed by methods of Poincare analyses of these vectors. Results revealed that the fall-prone group demonstrated poorer dynamic stability than the healthy elderly and young adult groups. Stability was not influenced by walking velocity, indicating that group differences in walking speed could not fully explain the differences in stability. This pilot study supports the need for future investigations using larger population samples to study fall-prone individuals using nonlinear dynamic analyses of movement kinematics.

© 2007 Published by Elsevier Ltd.

Keywords: Stability, Falls

1. Introduction

Stability is a critical component of both static standing balance and dynamic walking (Goswami et al., 1998; Hurmuzlu and Basdogan, 1994a). It is characterized by the dynamic state of a system wherein the state is the multi-dimensional posture and movement trajectories at an instant in time. This state is stable if small disturbances are attracted toward a prescribed reference point (Neyfeh and Balachandran, 2005). For example, an upright static reference state of standing posture is stable if small disturbances are attenuated in time such that the state is attracted toward the static upright state (Collins and DeLuca, 1993; Leipholz, 1987). Otherwise, a small state disturbance may grow without bound and the observed posture will sway precipitously. Hence, a kinematic trajectory is

considered Lyapunov stable if all trajectories that start sufficiently close to the reference remain close for all time (Strogatz, 2000). The reference trajectory may describe a static posture or it may describe a dynamic movement. Estimates of static stability identify individuals at greatest risk of falling (Maki et al., 1994), but there are few studies to determine whether stability of dynamic movement can identify fall-prone individuals.

Methods of clinical posturography record natural postural sway during quiet upright standing (Nashner, 1979). Others record the response to a kinetic or inertial disturbance during quiet upright standing. These assessments are performed because control of postural sway is correlated with prospective risk of falls (Maki et al., 1994). The most common techniques record the behavior of the center of pressure (CoP). Summary statistics include average or RMS distance from the geometric mean (Goldie et al., 1993; Maki et al., 1990), excursions of the CoP (Daley and Swank, 1981; Era and Heikkinen, 1985), excursion normalized per unit time, i.e. mean velocity

* Corresponding author. Tel.: +1 540 231 9088; fax: +1 540 231 3322.
E-mail address: lockhart@vt.edu (T.E. Lockhart).

* Deceased.

(Lichtenstein et al., 1990; Maki et al., 1990), or area circumscribed by the CoP trajectory (Hasan et al., 1990; Hufschmidt et al., 1980; Maki et al., 1990; Motta et al., 1991), among others. Frequency-domain estimates include a variety of summary statistics describing the spectral distribution of the CoP (Era and Heikkinen, 1985; Maki et al., 1990; Mauritz et al., 1979; Mizrahi and Susak, 1989; Motta et al., 1991). These CoP statistics are often used because they represent the generalized control forces necessary to maintain the center-of-mass (CoM) over the base-of-support (Peterka, 2003; Sliwinski et al., 2004). The relation between CoP and CoM movements provide further insight into the control of standing balance (Winter et al., 1998). However, risk of falls may also be related to dynamic performance.

The majority of fall-related injuries in the elderly occur during walking or dynamic movement tasks (Campbell et al., 1989). Walking is a dynamic condition wherein the CoM is rarely located within the base-of-support of a stance foot (MacKinnon and Winter, 1993). The walking process does not include an equilibrium state. Instead, the system must be described as a stable dynamic limit-cycle (Goswami et al., 1996). Methods of static posturography cannot be applied to limit-cycle dynamics thereby limiting predictive acuity regarding the risk associated with stability of walking. It is reasonable to assume that poor neuromuscular control in static equilibrium may indicate neuro-control limitations in dynamic tasks (Dingwell and Marin, 2006; England and Granata, 2007), but evidence from the motor control literature challenges this assumption (Winter, 1990). Therefore, assessment of dynamic walking stability may help to identify potential fallers (Granata and Lockhart, 2006). For example, evidence suggests that spatio-temporal parameters of walking, kinematic variability,

and kinetic variability of walking may discriminate between populations of fall-prone and low-risk individuals (Hausdorff et al., 1999; Masani et al., 2002; Scarborough et al., 1999; Winter, 1989). However, those analyses are based on variability and variability is not equal to dynamic stability (Dingwell et al., 2000).

Stability of human walking can be estimated from time-dependent analyses of dynamic variability (Wolf et al., 1985). For example, stable dynamic walking can be achieved when simulating a two-segment, unactuated, walking robot (McGeer, 1990) (Fig. 1 insert). Quasi-periodic behavior of the leg segment angles $[\theta_1, \theta_2]$ and velocities $[\dot{\theta}_1, \dot{\theta}_2]$ illustrates stable limit-cycle dynamics (Fig. 1), i.e. the dynamic state is attracted to an orbit that never intersects a static balance configuration at the origin. Therefore, the system can be dynamically stable but is unstable in most static postures (Coleman and Riuna, 1998). Similar behavior is observed in human locomotion but has more degrees-of-freedom than can be graphically illustrated. Disturbances to the walking trajectory are continuously manifest in human locomotion and typically recorded as kinematic variability. Analyses of the time-dependent behavior of this variability can quantify the rate at which the disturbances are attracted toward the steady-state trajectory (Leipholtz, 1987; Wolf et al., 1985). Every instant during the gait cycle need not be stable, i.e. local instability. For example, the steady-state walking trajectory of the robot simulation is locally unstable in the early phase of the cycle. Similarly, measurements of walking by Dingwell and Cusumano (2000) suggest local instability in human locomotion. However, a dynamic system can be orbitally stable despite brief local instabilities (Ali and Menzinger, 1999), i.e. the gait trajectory is stable as a whole. Orbital stability is determined by integrating local

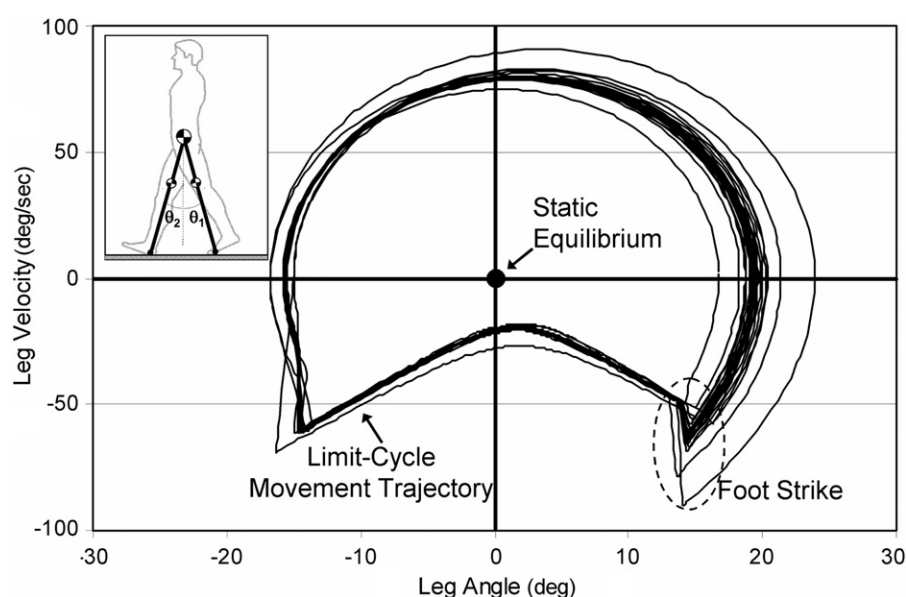


Fig. 1. Simulation of two-segment passive dynamic walker (inset) demonstrates limit-cycle dynamics (Granata and Lockhart, 2006; McGeer, 1990). The stable dynamic orbit never intersects a static balance configuration at the origin. Notice how disturbances are attracted toward a common stable orbit. Poincare analyses can be used to characterize the orbital stability (Hurmuzlu and Basdogan, 1994a).

dynamic stability over the entire gait cycle. Alternatively, it can be determined from kinematic data recorded from repetitive walking strides (Hurmuzlu and Basdogan, 1994a). Hurmuzlu et al. (1996) used Poincare analyses to quantify dynamic orbital stability of human locomotion by recording joint angles and joint angular velocities at specific cyclic events, e.g. heel contact. These nonlinear methods can be used to evaluate the dynamic walking stability of fall-prone individuals.

The goal of our ongoing research efforts are to characterize the dynamic stability of fall-prone elderly individuals versus healthy age-matched subjects. However, it is first reasonable to test in a pilot sample of subjects whether there are significant differences in dynamic stability between these subject groups. Therefore, Poincare analyses were performed to quantify the stability of the center-of-mass (CoM) with respect to the CoP at the instant of foot-strike. Controlled foot placement assures an appropriate relation between the generalized momentum of the CoM and the base-of-support (Pai and Patton, 1997; Redfern and Schumann, 1994). We hypothesized that fall-prone individuals demonstrate significantly reduced dynamic stability compared to individuals without a history of falls.

2. Methods

Twelve adult subjects participated in an experiment of dynamic walking stability. Subjects included four healthy young adults, four healthy elderly individuals, and four fall-prone elderly individuals (Table 1). Fall-prone subjects were identified by self-report medical questionnaires indicating recent histories of falling. These individuals had fallen more than two times within six months prior to the study but were uninjured at the time of the experiment. Participants provided informed consent approved by the Virginia Tech IRB before data collection.

Video-motion analyses recorded kinematics as each subject walked on a treadmill (Qualysis Medical AB, Gothenburg, Sweden, 120 Hz). Ten infrared-reflective markers were placed bilaterally over participants' bony landmarks. Marker locations included the left and right second metatarsal, calcaneus, lateral malleolus, lateral epicondyle, and anterior-superior iliac spine (ASIS). Piezoelectric sensors were attached to each heel to identify heel contact events.

Each participant walked for 5 min on a motorized treadmill to become acclimated to the system (Parker Treadmill Co., Auburn, AL). They were allowed to freely adjust the treadmill speed so as to achieve a self-selected comfortable walking speed without having to hold onto the handrails. This self-selected speed was operationally defined as 100% normal treadmill walking speed for

each participant. After completing the familiarization walking task, each subject participated in three-trials of treadmill walking at 100%, 110% and 120% of their comfortable walking speed. The walking speed conditions were presented in sequentially increasing order to assure subject confidence in all walking conditions. The duration of each trial lasted 5 min, with kinematic data recorded during the final 50 s of each trial. This assured a minimum of 35 contiguous steps were recorded. Three-dimensional position of each marker was collected and computed at the instant of foot-strike using the ProReflex motion analysis system (Qualysis, USA) and stored for data analysis. For the current study only the calcaneus and ASIS markers were analyzed.

Poincare analyses of the kinematic dispersion were performed to estimate dynamic orbital stability of each walking trial. Three-dimensional locations of a point mid-way between the ASIS and the location of the heel-markers were recorded. Although the point of the mid-ASIS location is not identical to the location of the whole body CoM, it can be used as a surrogate because this point shares similar dynamic variance as the whole body CoM. Likewise, the heel-marker is not identical to the CoP but they share similar kinematic variance at the instant of foot-strike. Three-dimensional position vectors between these surrogate CoM and CoP were recorded at the instant of foot-strike for every step. Velocity vectors of the heel-marker with respect to the mid-ASIS point were computed using methods of finite difference. Therefore, the vectors approximated the 3-D position $[x_i, y_i, z_i]$ and velocity $[\dot{x}_i, \dot{y}_i, \dot{z}_i]$ of CoP relative to CoM for each of the right (Rt) and left (Lt) leg at the instant of foot contact for each step. These were collected into a 12 element state-vector $q_i = [x_{i,Rt}, y_{i,Rt}, z_{i,Rt}, \dot{x}_{i,Rt}, \dot{y}_{i,Rt}, \dot{z}_{i,Rt}, x_{i,Lt}, y_{i,Lt}, z_{i,Lt}, \dot{x}_{i,Lt}, \dot{y}_{i,Lt}, \dot{z}_{i,Lt}]$ at each foot-strike event, $i = 1 \dots n$, where n is the number of steps.

Walking dynamics at the instant of foot-strike were represented as a nonlinear map of the state-vector at step i to the state-vector at step $i + 1$

$$q_{i+1} = f(q_i). \quad (1)$$

The function $f(\dots)$ is a 12×1 nonlinear dynamic representation of movement and describes how kinematic posture is modified in the time period between foot-strike events at steps i and $i + 1$. This is a Poincare section of the dynamic system. Response to a small disturbance δq_i of the state-vector during step i can be represented by Taylor series expansion of Eq. (1)

$$\delta q_{i+1} = \nabla f(q_i) \delta q_i \quad \text{where } \delta q_{i+1} = q_{i+1} - f(q_i), \quad (2)$$

$\nabla f(q_i)$ is the nonlinear gradient of the step function about the reference state q_i . For small disturbances typical of steady-state walking this gradient can be represented as a 12-by-12 Jacobian matrix, J_f . This Jacobian was estimated from the measured kinematic state-vectors using methods described by Hurmuzlu and Basdogan (1994a). Disturbance vectors δq_i at foot-strike of each step i , were computed from the measured data, i.e. the difference between each state-vector component at step i versus the mean value across all steps $i = 1 \dots n$

$$\delta q_i = q_i - 1/n \sum_{j=1}^n q_j. \quad (3)$$

These measured disturbances can be arranged into a 12-by- $(n - 1)$ matrix δQ_j where rows are the vector components of δq_i and the columns represent separate steps $j = 1 \dots n - 1$. The Jacobian matrix, J_f , is readily computed from the linear least-square fit of

$$\delta Q_{j+1} = J_f \delta Q_j, \quad (4)$$

Table 1
Participant's anthropometric information

Group	Age (years)	Weight (kg)	Height (cm)
HY	26.3 (2.1)	70.6 (13.2)	174.5 (7.1)
HO	71.3 (6.5)	71.2 (7.3)	164.7 (9.3)
FP	71.0 (3.0)	88.6 (10.4)	172.3 (10.8)

HY = healthy young; HO = healthy elderly; FP = fall-prone elderly.

using the pseudo-inverse routine in MATLAB (Mathworks, Natick, MA).

To assure stability of the dynamic system, variation, δq_i , must decay in time, $\delta q_{i+1} < \delta q_i$, i.e. a CoP placement error at step i decays with subsequent steps. This requires the eigenvalues of $\mathbf{J}_f$ must have a magnitude less than one (Fig. 2). These eigenvalues are called Floquet multipliers, λ_j . Recognizing that there are 12 eigenvalues per condition, Hurmuzlu and Basdogan (1994a,b) recommend characterizing stability by the mean Floquet magnitude to compare stability differences between subject groups

$$\langle \lambda \rangle = 1/2n \sum_{k=1}^{12} |\lambda_k|, \quad (5)$$

where k is the number of generalized coordinates $k = 1 \dots 12$. The condition with the largest overall value of $\langle \lambda \rangle$ is least stable. Dynamics of the system are quickly dominated by the least stable dimension of the step placement, i.e. maximum eigenvalue (Rosenstein et al., 1993). Therefore, in addition to the mean Floquet value we also recorded maximum Floquet multiplier for each subject and walking speed. The hypotheses suggest that these values will be statistically greater for fall-prone individuals than healthy adults.

Analyses of covariance were performed to investigate effects of group and walking speed. Group served as the between-subject variable (HY = healthy young, HO = healthy old, FP = fall-prone old). Although all subjects walked at 100%, 110%, and 120% of normal walking speed, these velocities were different for every subject, i.e. self-selected. Therefore, walking velocity recorded from the treadmill was treated as a covariate. Post-hoc analyses of significant effects were performed using a Tukey HSD test. Effects of step and stride stability were examined in independent analyses. Specifically, separate analyses examined the mean and maximum Floquet coefficients for: (1) left-step: left foot-strike to the subsequent right foot-strike; (2) right-step: right foot-strike to the subsequent left foot-strike; (3) stride: foot-strike to the subsequent ipsilateral foot-strike. Separate univariate analyses were performed to test for group and speed condition effects on walking velocity. All statistical analyses were performed in SAS (SAS Institute Inc., USA) using a significance level of $p < 0.05$.

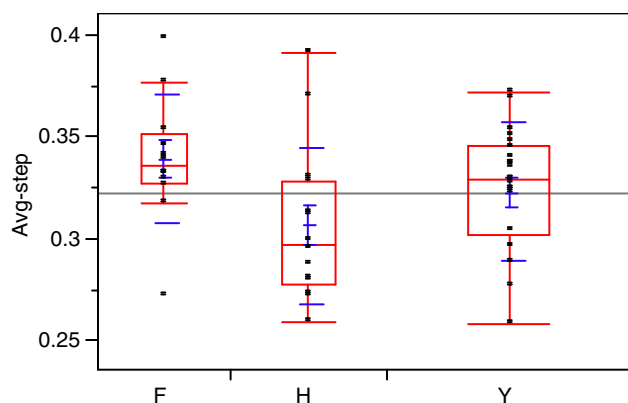


Fig. 2. Overall mean (solid line at 0.322), individual subject mean values (brief vertical lines), quartile (box) and standard deviation of the mean Floquet multiplier computed from stride differences in the dynamic state at foot-strike. The fall-prone elderly demonstrated poorer dynamic stability of walking than the healthy old and young adults.

3. Results

The elderly subjects walked slower than the young participants. There was a significant main effect of group and experimental speed conditions ($F_{(3,38)} = 10.37$, $p = 0.001$). As expected, the walking speed was significantly faster during 120% of normal walking speed than at 100% of normal walking speed ($F_{(2,38)} = 25.78$, $p = 0.001$).

When evaluating the mean Floquet multipliers there was a significant main effect of group ($F_{(2,35)} = 7.08$, $p = 0.04$) but not velocity (Table 2). This indicates a group difference in orbital stability of the CoM with respect to the CoP (Fig. 2) independent of the group differences in walking velocity. In other words, the walking velocity does not explain the group differences in stability. Post-hoc analyses indicated that the mean Floquet multiplier computed from the stride differences in foot-strike dynamics were significantly greater for the FP elderly than the healthy elderly ($p < 0.05$) and the young adults ($p < 0.05$). There was no significant difference between the healthy old and young adult groups. Values computed from stride-to-stride comparisons of measured data were significantly less ($p < 0.01$) than right-step and left-step results. There were no significant main effects of group or velocity when investigating the

Table 2
Summary of the dependent variables among three groups

Variables	Young	Healthy old	Fall-prone old
<i>Maximal Floquet coefficients</i>			
Left-step	0.648 (0.07)	0.674 (0.09)	0.716 (0.09)
Right-step	0.667 (0.07)	0.674 (0.04)	0.719 (0.11)
Stride*	0.536 (0.10)	0.501 (0.09)	0.646 (0.14)
<i>Average Floquet coefficients</i>			
Left-step	0.416 (0.03)	0.428 (0.06)	0.454 (0.05)
Right-step	0.411 (0.04)	0.403 (0.05)	0.446 (0.05)
Stride*	0.327 (0.03)	0.306 (0.03)	0.339 (0.03)

* Significant at $p < 0.05$.

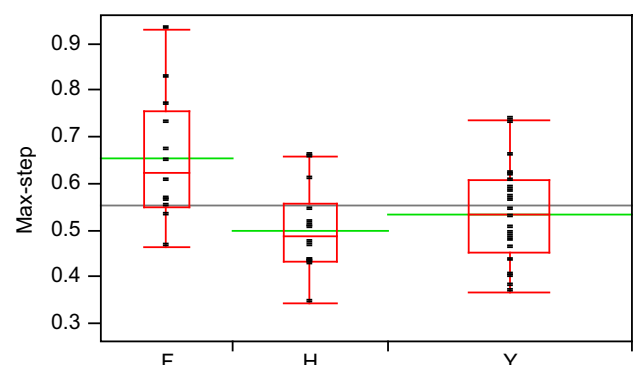


Fig. 3. Overall mean (solid line at 0.552), quartile (box) and standard deviation of the maximum Floquet multiplier computed from stride differences in the dynamic state at foot-strike. The fall-prone elderly demonstrated poorer dynamic stability of walking than the healthy old and young adults.

right-step ($F_{(2,35)} = 2.73$, $p = 0.17$). However, there was a trend toward stability differences evaluated from left-step data ($F_{(2,35)} = 5.58$, $p = 0.06$).

Results for the maximum Floquet multipliers were similar to the results for the mean Floquet multipliers (Fig. 3). Maximum Floquet multipliers computed from stride data revealed a significant main effect of group ($F_{(2,35)} = 7.35$, $p = 0.04$) but no velocity effects. Post-hoc comparison of means indicated that the maximum Floquet multipliers for the fall-prone elderly group was significantly greater than both the young ($p < 0.05$) and healthy old groups ($p < 0.05$). There was no significant difference between the healthy old and young adult groups. Average left-step ($F_{(2,35)} = 0.7$, $p = 0.54$) and right-step ($F_{(2,35)} = 2.84$, $p = 0.17$) results were not significantly influenced by group.

4. Discussion

Health and economic aspects of fall interventions necessitate the identification of and intervention for individuals at greatest risk of falling (Hill et al., 1999; National Aging Research Institute, 2000). In that regard, various measures of balance and physical functions have been proposed to identify potential fallers. The objective of this study was to provide an initial evaluation of whether dynamic stability of walking can be used to identify group differences between fall-prone individuals and healthy adults. Results demonstrated that measures of dynamic stability can differentiate fall-prone older adults from healthy young and older adults. Specifically, the fall-prone group was less stable than healthy old and young adults when considering orbital stability of treadmill walking.

The present findings are in agreement with previous results (Hausdorff et al., 2001; Tinetti et al., 1998; Wolfson et al., 1990) suggesting that stride-to-stride fluctuations may be used to characterize risk of falls. The utility of nonlinear techniques to identify the deterministic nature of motor variability within a system has been identified in previous studies (Buzzi et al., 2003; Dingwell and Cusumano, 2000). Those studies suggested that traditional linear measures mask the dynamic structure of motor variability such as the loss of the temporal variations of the gait pattern due to averaging procedures. Measures of static equilibrium during quiet standing are useful estimates of risk (Hill et al., 1999) but cannot fully characterize stability during walking wherein the majority of falls occur (Campbell et al., 1981). Nonlinear stability assessments of walking may augment traditional clinical assessments to help identify potential fallers.

To interpret the results it is useful to understand Poincaré analyses of dynamic stability. It is reasonable to assume that every walking stride could be dynamically similar to every other stride, i.e. reference trajectory. Variability in kinematic and spatio-temporal gait parameters is observed in empirical data and is associated with risk of falls (Hausdorff et al., 2001; Tinetti et al., 1998; Wolfson et al., 1990). This natural variance is attributed to mechan-

ical disturbances or neuromotor control errors. However, variability is time-linked, i.e. mechanical momentum and neuromuscular response associated with a disturbance influence the movement and disturbance amplitude at subsequent time intervals. In fact, a disturbance at a given time may influence the walking movement for many subsequent strides (Dingwell et al., 2001). If disturbances are permitted to grow without bound then walking behavior cannot be maintained; possibly resulting in a fall. Fortunately, the neuro-controller and musculoskeletal system attenuates the disturbances in order to maintain a stable walking pattern. The Floquet multiplier quantifies how a disturbance δq_i at foot-strike is attenuated at the time of a subsequent foot-strike. Results suggest that dynamic error correction is slower in the fall-prone elderly.

Elderly, balance-impaired, and fall-prone individuals walk slower than age-matched healthy older adults or young adults (Winter, 1990). Reduced walking velocity may be a compensatory behavior to maintain dynamic stability. Evidence supports the fact that local dynamic stability is influenced by walking velocity (Dingwell and Marin, 2006; England and Granata, 2007). Conversely, current results suggest that orbital dynamic stability of walking is unaffected by small changes in walking velocity in the range of 100% normal self-selected walking speed to 120% of normal speed. Dingwell et al. (2007) reports similar results, i.e. walking velocity does not affect orbital dynamic stability of walking. Thus, nonlinear dynamic stability as measured by Floquet multipliers can characterize instability in lieu of group differences in walking velocities. Analyses of covariance supported this assertion. Group differences in dynamic stability of walking were not attributable to walking velocity. This suggests that reduced walking velocity commonly observed in the elderly may not be caused by the need to enhance orbital stability. Alternative explanations for reduced walking velocity in biomechanically unstable individuals may be to facilitate detection of tripping obstacles, to limit injury severity in the event of a potential fall, etc.

Several limitations must be considered when interpreting the results. First, the data represent a pilot study with a small sample size. Our goal was to test whether larger studies of dynamic stability in fall-prone individuals are justified. Future studies will investigate larger population samples and a broader velocity range. Second, data were collected while walking on a treadmill. Subtle differences between walking on a treadmill and walking over ground may influence kinematic variability and dynamic stability (Dingwell et al., 2001; Masani et al., 2002). Third, analyses were limited to kinematics of foot-strike with respect to the CoM. Similar methods could be applied to EMG. However, myoelectric data has greater dynamic complexity than kinematics, e.g. biomechanical movement can be represented as the nonlinear convolution filter of multiple EMG signals (Zajac, 1989). Therefore, stability analyses using EMG must include much larger systems, i.e. more degrees-of-freedom to account for co-contraction and

time-delayed reflex response. Finally, theoretical developments are necessary to overcome limitations in the stability analyses. Methods assume that the reference trajectory is a period-one limit-cycle, i.e. repeats each step or stride, and that the reference trajectory is identical to the mean state-vector (Eq. (3)). Long-range correlations in stride-time data have been observed (Hausdorff et al., 1999; Hausdorff et al., 2001) that cause apparent non-deterministic noise to the Poincare section. Nonetheless, a stable attractor reference trajectory clearly exists within the gait dynamics, e.g. Floquet values were less than one. Despite empirical and fractal noise in the data, the dynamic stability analyses successfully discriminated between healthy and fall-prone subject groups.

In summary, dynamic orbital stability of the anthropometric CoM with respect to the CoP was quantified by Poincare analyses in a pilot sample of fall-prone elderly individuals and healthy adults. Although the fall-prone adults walked slower than the healthy age-matched and young adults, the mean Floquet multiplier value and maximum Floquet coefficients were significantly greater in the fall-prone group. These indicate that the fall-prone group demonstrated poorer stability of dynamic walking than the other groups. Future investigation should include larger population samples and prospective studies of fall-prone individuals using nonlinear dynamic analyses of movement kinematics.

References

- Ali F, Menzinger M. On the local stability of limit cycles. *Chaos* 1999;9(2):348–56.
- Buzzi UH, Stergiou N, Kurz MJ, Hageman PA, Heidel J. Nonlinear dynamics indicates aging affects variability during gait. *Clin Biomech (Bristol, Avon)* 2003;18(5):435–43.
- Campbell AJ, Reinken J, Allan BC, Martinez GS. Falls in old age; a frequency and related factors. *Age Aging* 1981;10:264–70.
- Campbell AJ, Borrie MJ, Spears GF. Risk factors for falls in a community-based prospective study of people 70 years and older. *J Gerontol* 1989;44:M112–7.
- Coleman M, Riuna A. An uncontrolled walking toy that cannot stand still. *Phys Rev Lett* 1998;80(16):3658–61.
- 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.
- Daley ML, Swank RL. Quantitative posturography – use in multiple-sclerosis. *IEEE Trans Biomed Eng* 1981;28(9):668–71.
- Dingwell JB, Cusumano JP. Nonlinear time series analysis of normal and pathological human walking. *Chaos* 2000;10(4):848–63.
- Dingwell JB, Marin LC. Kinematic variability and local dynamic stability of upper body motions when walking at different speeds. *J Biomech* 2006;39(3):444–52.
- Dingwell JB, Cusumano JP, Sternad D, Cavanagh PR. Slower speeds in patients with diabetic neuropathy lead to improved local dynamic stability of continuous overground walking. *J Biomech* 2000;33(10):1269–77.
- Dingwell JB, Cusumano JP, Cavanagh PR, Sternad D. Local dynamic stability versus kinematic variability of continuous overground and treadmill walking. *J Biomech Eng Trans ASME* 2001;123(1):27–32.
- Dingwell JB, Kang HG, Marin LC. The effect of sensory loss and walking speed on the orbital stability of human walking. *J Biomech* 2007;40(8):1723–30.
- England SA, Granata KP. The influence of gait speed on local dynamic stability of walking. *Gait Posture* 2007;25(2):172–8.
- Era P, Heikkinen E. Postural sway during standing and unexpected disturbance of balance in random samples of men of different ages. *J Gerontol* 1985;40(3):287–95.
- Goldie PA, Bach TM, Evans OM. Force platform measures for evaluating postural control – reliability and validity. *Arch Phys Med Rehab* 1993;70(7):510–7.
- Goswami A, Espiau B, Keramane A. Limit cycles in a passive compass gait biped and passivity-mimicking control laws. *Auton Robot* 1996;4(3):273–86.
- Goswami A, Espiau B, Thuiot BA. A study of passive gait of a compass-like biped robot: symmetry and chaos. *Intl J Robot Res* 1998;17:1282–301.
- Granata KP, Lockhart TE. Group differences among fall-prone individuals and healthy old and younger counterparts utilizing nonlinear stability measures. *J Biomech* 2006;39(Suppl 1):89.
- Hasan SS, Goldner DN, Lichtenstein MJ, Wood AJJ, Shiavi RG. Selecting a suitable biomechanics platform measure of sway. In: Paper presented at the 12th annual international conference IEEE EMBS; 1990.
- Hausdorff JM, Zeman L, Peng CK, Goldberger AL. Maturation of gait dynamics: stride-to-stride variability and its temporal organization in children. *J Appl Physiol* 1999;86(3):1040–7.
- Hausdorff JM, Rios DA, Edelberg HK. Gait variability and fall risk in community-living older adults: a 1-year prospective study. *Arch Phys Med Rehab* 2001;82(8):1050–6.
- Hill K, Schwarz J, Flicker L, Carroll S. Falls among healthy, community-dwelling older women: a prospective study of frequency, circumstances, consequences and prediction accuracy. *Aust N Z J Public Health* 1999;23:41–8.
- Hufschmidt A, Dichgans J, Mauritz KH, Hufschmidt M. Some methods and parameters of body sway quantification and their neurological applications. *Arch Psychiat Nerven* 1980;228(2):135–50.
- Hurmuzlu Y, Basdogan C. On the measurement of dynamic stability of human locomotion. *J Biomech Eng* 1994a;116:30–6.
- Hurmuzlu Y, Basdogan C. Presenting joint kinematics of human locomotion using phase plane portraits and Poincare maps. *J Biomech* 1994b;27(12):1495–9.
- Hurmuzlu Y, Basdogan C, Stoianovici D. Kinematics and dynamic stability of the locomotion of post-polio patients. *J Biomech Eng* 1996;118(3):405–11.
- Leipholtz H. Stability theory. An introduction to the stability of dynamic systems and rigid bodies. New York: John Wiley & Sons; 1987.
- Lichtenstein MJ, Burger MC, Shields SL, Shiavi RG. Comparison of biomechanics platform measures of balance and videotaped measures of gait with a clinical mobility scale in elderly women. *J Gerontol* 1990;45(2):M49–54.
- MacKinnon CD, Winter DA. Control of whole body balance in the frontal plane during human walking. *J Biomech* 1993;26(6):633–44.
- Maki BE, Holliday PJ, Fernie GR. Aging and postural control – a comparison of spontaneous-sway and induced-sway balance tests. *J Am Geriatr Soc* 1990;38(1):1–9.
- Maki BE, Holliday PJ, Topper AK. A prospective study of postural balance and risk of falling in an ambulatory and independent elderly population. *J Gerontol* 1994;49:M72–84.
- Masani K, Kouzaki M, Fukunaga T. Variability of ground reaction forces during treadmill walking. *J Appl Physiol* 2002;92(5):1885–90.
- Mauritz KH, Dichgans J, Hufschmidt A. Quantitative-analysis of stance in late cortical cerebellar atrophy of the anterior lobe and other forms of cerebellar-ataxia. *Brain* 1979;102:461–82.
- McGeer T. Passive walking with knees. In: Proc. 1990 IEEE Robotics & Automation Conference, Cincinnati, OH; 1990. p. 1640–5.
- Mizrahi J, Susak Z. Bi-lateral reactive force patterns in postural sway activity of normal subjects. *Biol Cybern* 1989;60(4):297–305.
- Motta M, Spano A, Neri M, Schillaci G, Cortelloni C, Andermarcher E, et al. The specificity and sensitivity of computerized posturography in study of postural unbalance in the elderly. *Arch Gerontol Geriatr* 1991;127–32.

- Nashner LM. Computerized dynamic posturography. In: Granit R, Pompeiano O, editors. Reflex control of posture and movement. Progress in brain research. NY: Elsevier/North Holland Biomedical Press; 1979. p. 280–307.
- National Aging Research Institute. An analysis of research on preventing falls and falls injury in older people: community, residential aged care and acute care settings. Commonwealth of Australia: Report to the commonwealth department of health and aged care injury prevention section; 2000.
- Neyfeh AH, Balachandran B. Applied nonlinear dynamics: analytical, computational and experimental methods. New York: John Wiley & Sons; 2005.
- Pai YC, Patton J. Center of mass velocity-position predictions for balance control. *J Biomech* 1997;30(4):347–54.
- Peterka RJ. Simplifying the complexities of maintaining balance. *IEEE Eng Med Biol Mag* 2003;22(2):63–8.
- Redfern MS, Schumann T. A model of foot placement during gait. *J Biomech* 1994;27(11):1339–46.
- Rosenstein MT, Collins JJ, Deluca CJ. A practical method for calculating largest Lyapunov exponents from small data sets. *Physica D* 1993;65(1–2):117–34.
- Scarborough DM, Krebs DE, Harris BA. Quadriceps muscle strength and dynamic stability in elderly persons. *Gait Posture* 1999;10(1):10–20.
- Sliwinski MM, Sisto SA, Batavia M, Chen B, Forrest GF. Dynamic stability during walking following unilateral total hip arthroplasty. *Gait Posture* 2004;19(2):141–7.
- Strogatz S. Nonlinear dynamics and chaos: with applications to physics, biology, chemistry, and engineering. 1st ed. NY: Westview Press; 2000.
- Tinetti ME, Speechley M, Ginter SF. Risk factors for falls among elderly patients living in the community. *N Eng J Med* 1998;319:1701–7.
- Winter DA. Biomechanics of normal and pathological gait: implications for understanding human locomotor control. *J Motor Behav* 1989;21(4):337–55.
- Winter DA. Biomechanics and motor control of human movement. New York: Wiley; 1990.
- Winter DA, Patla AE, Prince F, Ishac MG, Gielo-Perczak K. Stiffness control of balance in quiet standing. *J Neurophysiol* 1998;80:1211–21.
- Wolf A, Swift JB, Swinney HL, Vastano JA. Determining Lyapunov exponents from a time-series. *Physica D* 1985;16(3):285–317.

Wolfson L, Whipple R, Amerman P, Tobin JN. Gait assessment in the elderly: a gait abnormality rating scale and its relation to falls. *J Gerontol* 1990;45:M12–9.

Zajac FE. Muscle tendon: Properties, models, scaling, and application to biomechanics and motor control. *CRC Crit Rev Biomed Eng* 1989;17:354–411.



Kevin Granata is a professor in the Department of Engineering Science and Mechanics at Virginia Tech. He earned a MS in physics from Purdue University and a Ph.D. in biomechanics from The Ohio State University. Dr. Granata served as Research and Engineering Director of the Motion Analysis Laboratory at the University of Virginia where he was an Associate Professor of Orthopaedic Surgery and Biomedical Engineering. He is currently a Director of the Musculoskeletal Biomechanics Laboratory at Virginia Tech. His research

focuses on nonlinear dynamics and neuromuscular control of human movement with specific interests in musculoskeletal stability for injury prevention and rehabilitation.



Thurmon Lockhart is a human locomotion biomechanist and the Director of the Locomotion Research Laboratory at the Virginia Polytechnic Institute and State University where he is an Associate Professor of Industrial and Systems Engineering and the School of Biomedical Engineering and Science. He obtained his undergraduate and graduate degrees in Industrial Engineering from the Texas Tech University, and earned a Ph.D. with Biomechanics concentration from the same institution. His research focuses on

understanding motor control aspects of slip-induced fall accidents among workers and the older population utilizing theoretical biomechanical modeling, human factors and ergonomics, postural control, gait mechanics, and point-of-care devices to develop and implement intervention strategies to reduce fall accidents.