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Dynamic stability differences in fall-prone and healthy adults

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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.

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

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(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 (Leipholz, 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

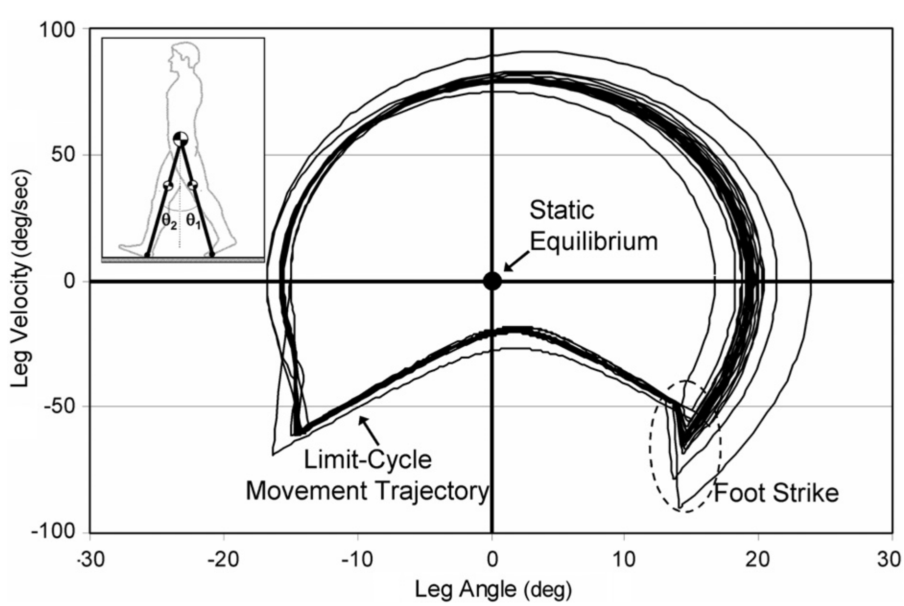

Fig. 1. Simulation of two-segment passive dynamic walker (inset) demonstrates limit-cycle dynamics (Granata and Lockhart, 2006; McGeer, 1990). The stable dynamic orbit never intersects a static balance configuration at the origin. Notice how disturbances are attracted toward a common stable orbit. Poincare 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 calcaneous and ASIS markers were analyzed.

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.

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 $q_i = [x_{i,\mathrm{Rt}}, y_{i,\mathrm{Rt}}, z_{i,\mathrm{Rt}}, \dot{x}_{i,\mathrm{Rt}}, \dot{y}_{i,\mathrm{Rt}}, \dot{z}_{i,\mathrm{Rt}}, x_{i,\mathrm{Lt}}, y_{i,\mathrm{Lt}}, z_{i,\mathrm{Lt}}, \dot{x}_{i,\mathrm{Lt}}, \dot{y}_{i,\mathrm{Lt}}, \dot{z}_{i,\mathrm{Lt}}]$ at each foot-strike event, $i = 1 \ldots n$, 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 $i+1$

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

The function $f(\ldots)$ 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)

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

$\nabla f(q_i)$ 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, $\boldsymbol{J}_f$. 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 $i = 1 \ldots n$

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

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 $j = 1 \ldots n-1$. The Jacobian matrix, $\boldsymbol{J}_f$, is readily computed from the linear least-square fit of

$$\delta Q_{j+1} = \boldsymbol{J}_f \delta Q_j, \tag{4}$$

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 $\boldsymbol{J}_f$ 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

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

where k is the number of generalized coordinates $k = 1 \ldots 12$. 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 $p < 0.05$.

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
Maximal Floquet coefficients			
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)
Average Floquet coefficients			
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 $p < 0.05$.

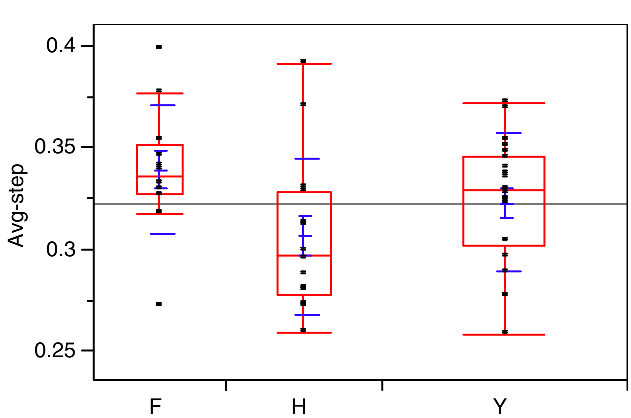

Fig. 2. Overall mean (solid line at 0.322), individual subject mean values (brief vertical lines), quartile (box) and standard deviation of the mean Floquet multiplier computed from stride differences in the dynamic state at foot-strike. The fall-prone elderly demonstrated poorer dynamic stability of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

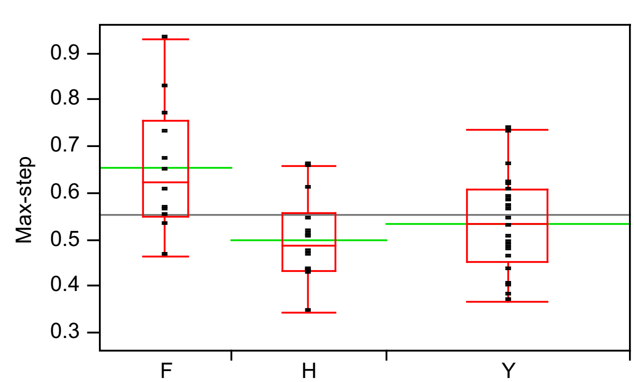

Fig. 3. Overall mean (solid line at 0.552), quartile (box) and standard deviation of the maximum Floquet multiplier computed from stride differences in the dynamic state at foot-strike. The fall-prone elderly demonstrated poorer dynamic stability of walking then the healthy old and young adults.

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 Poincare 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 mechanical 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.

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