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Differentiating fall-prone and healthy adults using local dynamic stability

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Abstract

Variability in kinematic and spatio-temporal gait parameters has long been equated with stability and used to differentiate fallers from non-fallers. Recently, a mathematically rigorous measure of local dynamic stability has been proposed based on the non-linear dynamics theory to differentiate fallers from non-fallers. This study investigated whether the assessment of local dynamic stability can identify fall-prone elderly individuals who were unable to successfully avoid slip-induced falls. Five healthy young, four healthy elderly and four fall-prone elderly individuals participated in a walking experiment. Local dynamic stability was quantified by the maximum Lyapunov exponent. The fall-prone elderly were found to exhibit significantly lower local dynamic stability (i.e. greater sensitivity to local perturbations), as compared to their healthy counterparts. In addition to providing evidence that the increased falls of the elderly may be due to the inability to attenuate/control stride-to-stride disturbances during locomotion, the current study proposed the opportunity of using local dynamic stability as a potential indicator of risk of falling. Early identification of individuals with a higher risk of falling is important for effective fall prevention. The findings from this study suggest that local dynamic stability may be used as a potential fall predictor to differentiate fall-prone adults.

Keywords

local dynamic stability; falls; gait; risk assessment; slips and falls; locomotion; elderly falls; fall accidents

Introduction

Reducing fall accidents has been the goal of numerous researchers since the 1920s. Although much has been learned over the past few decades about the mechanism of and contributing factors to fall accidents (Lockhart 2008), fall accidents continue to represent a significant burden to society, both in terms of human suffering and economic losses (National Safety Council 2006). Fall accidents are among the most common and serious problems facing the elderly and these accidents constitute a major cause of mortality, reduced functioning and premature nursing home placement. Although modern medicine and new medical technologies offer enormous potential to improve diagnosis and treatment of many diseases, mortalities from fall accidents are steadily on the rise for the elderly (Centers for Disease Control 1999–2005). Early detection of fall-related risks is therefore critical to timely interventions prior to falling episodes (Celler *et al*. 1995).

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Before effective fall-prevention strategies can be implemented, it is important to identify those individuals subject to a higher risk of falling. A risk of falling among the elderly has been attributed to gait. The acquisition of gait characteristics during walking provides important information about limb propulsion and control and provides insight into muscle performance (Winter 1990). Furthermore, gait evaluations can be used as global indicators of stability (Scheiner *et al*. 1995). Age and disease-related degradation of an individual's ability to ambulate in a repetitive and stable manner is regarded as an apparent sign of many gait pathologies leading to falls. For example, a study investigating the gait characteristics of older adults who were hospitalised after falls suggested that individuals with greater step variability fell more often than non-fallers (Guimaraes and Isaacs 1980). Furthermore, the work of Imms and Edholm (1979) also demonstrated that gait variability is linked to falls in the elderly. Although many older adults walk without any significant mobility impairment (Bloem 1992), Nayak and Isaacs (1982) proposed that one of the effects of old age is an increased intercycle (step-to-step) variability of gait, possibly associated with the gradual deterioration of balance mechanisms, which is known to occur. Several gait characteristics including stride length (spatial) and step duration (temporal) are related to balance control. In terms of the biomechanical principle, decrease in stride length and step duration will lead to greater stability and may be regarded as compensation for instability. An increase in the variability of one or both of these parameters could indicate lack of compensation for instability and might predispose an individual to falls, especially when balance mechanisms are stressed (Hausdorff *et al*. 1997). As such, gait analyses may provide an effective tool for evaluating and quantifying gait problems associated with fall-prone individuals.

However, even with the assistance of gait analysis, objectively quantifying the risk of falls or instability remains difficult. For example, numerous studies suggest that elderly people tend to have a shorter step length and a broader walking base, which results in an increase in stance time and double support time (Winter *et al.* 1990). These gait adaptations are thought to result in a more stable or safer gait pattern. However, despite these adaptive changes, many older adults fall while walking. Furthermore, most studies using gait analysis have relied on comparisons of a limited number of specific gait characteristics (i.e. step length and step frequency, etc.) by normalising and averaging together data from a number of isolated and independent strides. This approach ignores the high degree of correlation that exists between various aspects of an individual's gait and is not well-suited to address the fundamental control task of locomotion (i.e. maintaining dynamic stability). As such, to accurately evaluate the extent of gait deviations from normal gait and associated risk of fall accidents, it is necessary to consider not only how a single stride is generated, but also how movements are controlled from one stride to the next, requiring continuous monitoring of gait (Dingwell and Cusumano 2000, Schutte *et al*. 2000).

Understanding the locomotor control can help predict future falls since motor variability could arise due to failure of the automatic stepping mechanisms. A local dynamic stability measure, which is based on the non-linear dynamic theory, has been proposed as a more precise measurement of individuals' resistance to perturbations. Using the dynamic stability concept, Dingwell and Cusumano (2000) successfully explained that individuals with pathological gait exhibited a slow-down adaptation to increase their stability and clearly demonstrated the difference between dynamic stability and conventional gait variability measurements. This dynamic stability measure was also shown to be able to detect the influences of external conditions (treadmill gait and over-ground gait) (Dingwell *et al*. 2001) and patients with and without peripheral neuropathy (Dingwell and Cusumano 2000).

Biomechanically, age and disease-related degradation of an individual's ability to ambulate in a repetitive and stable manner is linked to risk of falling and variability in kinematic and spatio-temporal gait parameters has been used to differentiate fallers from non-fallers (Maki 1997, Hausdorff *et al*. 2001, Barak *et al*. 2006). Higher variability observed in time series measurements are often considered to be indicative of higher instability and, thus, higher risk of falling. However, equating variability with stability lacks theoretical foundation (Stergiou 2004) and may fail to explain some seemingly confusing phenomena. For example, adopting a slower walking speed, which is considered to be a common practice to increase stability, is often found to be associated with higher gait variability (Dingwell *et al*. 2000). Therefore, since the early 2000s, a mathematically rigorous definition of stability, local dynamic stability, has been proposed to complement existing variability measures based on the non-linear dynamics theory (Dingwell and Cusumano 2000).

Local dynamic stability, as quantified by maximum finite-time Lyapunov exponent (maxLE), refers to the sensitivity of a dynamic system to infinitesimally small perturbations (Dingwell and Cusumano 2000). In the context of human gait, local dynamic stability measures the ability of the human neuromuscular control system to attenuate those disturbances manifested from either neuro-control errors or environmental noises (e.g. uneven floor surfaces, small obstacles, etc.). A survey of literature has shown its promising applications in various aspects of human movement research. With a slower walking speed, the diabetic neuropathic patients were found to adopt a more locally stable gait pattern, despite exhibiting a greater kinematic variability than the healthy controls (Dingwell and Cusumano 2000). By examining the local stability in both unperturbed standing and walking conditions, it was concluded that the motor control mechanisms governing static balance and dynamic balance are different (Kang and Dingwell 2006b, Roerdink *et al*. 2006). The local dynamic stability has also been successfully applied to examine the underlying dynamics of specific body segments, including the knee joint (Stergiou *et al*. 2004) and trunk segment (Granata and England 2006) and slow-time-scale physiological changes such as fatigue (Yoshino *et al*. 2004). With the evidences that support its utility, a natural question arises as to whether local dynamic stability can be used to effectively assess the risk of falling.

Unfortunately, knowledge about the link between an individual's risk of falling and local dynamic stability is insufficient and unclear. On one hand, researchers have suggested that the underlying mechanisms responsible for governing local and global stability (the response of the motor control system to much larger perturbations including slips and falls) are likely related in some manner (Dingwell and Marin 2006). If local perturbations are permitted to grow without proper attenuation, stable walking behaviour cannot be maintained and may eventually result in a fall (Granata and Lockhart 2008). A recent study (Granata and Lockhart 2008) utilising orbital dynamic stability (i.e. another local stability measure based on non-linear dynamics) successfully differentiated fall-prone individuals from healthy counterparts. Although a primary fall risk factor, ageing, was found to result in significant local instability (Buzzi *et al*. 2003), the evidence that directly relates local dynamic stability to fall-prone individuals with impaired global stability is lacking. In order to justify the utility of local dynamic stability measures in fall prevention, it becomes necessary to directly assess its capability in identifying those individuals who are deemed as unable to successfully avoid large-scale perturbations (e.g. slip-induced falls).

Therefore, the objective of this study was to investigate the capability of local dynamic stability in identifying fall-prone elderly who were unable to successfully avoid slip-induced falls. Additionally, spatio-temporal gait parameters were studied as a comparison with local stability measures. It was hypothesised that: 1) fall-prone elderly would have lower local dynamic stability (as measured by Lyapunov exponent) than their healthy counterparts; 2) the spatial-temporal gait parameters of the fall-prone elderly would also be different from those of the healthy individuals. The findings from the current study would help substantiate the utility of the local dynamic stability measure in fall-risk assessment and open the possibility of 'in-the-field' development and testing with an ambulatory monitoring system.

Methods

Participants

Five healthy young, four healthy elderly and four fall-prone elderly individuals were involved in the current study. Their anthropometric information is summarised in Table 1. Informed consent was reviewed by the Institutional Review Board (IRB) at Virginia Tech and obtained from each participant prior to data collection. Fall-prone elderly were selected based on previous slip-and-fall studies (Liu and Lockhart 2006a,b) and identified as unable to avoid slip-induced falls. Self-reported medical questionnaires also indicated they had recent histories of falling (at least one fall within 6 months).

Instrument and procedure

One dual-axial accelerometer (ADXL 203; Analog Devices, Norwood, MA, USA; range = +1.7 g, sensitivity = 1 mV/mg, noise level = 1 mVrms, frequency = 125 Hz) was placed near the right anterior superior iliac spine (ASIS). The accelerometer measurements were transmitted to a local computer via Bluetooth networking for further processing. Two infrared-reflective markers were placed bilaterally on the heels for kinematic motion capture with a six-camera ProReflex system (Qualysis Medical AB, Gothenburg, Sweden; 120 Hz). An overhead safety harness system was used to protect participants from accidentally losing balance while walking on the treadmill.

Before the data collection, each participant was allowed up to 5 min to familiarise themselves on the Parker PM treadmill (Parker Treadmill Co., Auburn, AL, USA). Sleeveless shirts, tight shorts and athletic shoes of the same type were provided to each participant. Participants selected their own preferred speeds at which they felt comfortable to swing their arms naturally without requiring the use of the handrails on the treadmill. A continuous 1-min dataset was taken by both the motion capture system and accelerometer system simultaneously.

Computation of gait parameters

Marker data were low-pass filtered (Butterworth, fourth order, 6 Hz) before further processing. The timing of heel contact was determined using the heel kinematics data with an algorithm similar to that proposed by Ghoussayni *et al*. (2004). Step duration, step length and heel contact velocity were then calculated for each participant according to a previous publication (Lockhart *et al*. 2003).

Local dynamics stability computation

Stability is defined as the ability of the neuromuscular system to maintain dynamic equilibrium of walking in the presence of kinematic and control variability and can be quantified from engineering analysis of the kinematic movement patterns and kinematic disturbances (Leipholz 1987). One quantitative measure of stability describes the rate at which kinematic variability approaches the equilibrium movement trajectory.

Local dynamic stability was quantified by the maxLE from a non-linear dynamics approach. Based on Taken's (1981) theorem, any single-dimensional time-series measurements contain sufficient information about the underlying dynamics of the system of interest and can be used to reconstruct a multi-dimensional state space via a so-called time-delayed coordinate approach. Such state space can faithfully represent the underlying characteristics (system invariants such as stability characteristics) of the dynamical system (human motor control system, in this case) under investigation. Two parameters, minimum embedding dimension (d_E) and time delay (T), are required for the time-delayed approach and can be determined via the auto mutual information approach (Cao 1997) and nearest false neighbours approach

(Abarbanel *et al*. 1993). With an initial single dimension time series data *x(t)*, the state space *X(t)* can be reconstructed as:

$$X(t)=[x(t), x(t+T), x(t+2T), \ldots, x(t+(d_E-1)T)] \quad (1)$$

The resistance of the motor control system to local perturbations, in other words local dynamic stability, can be assessed by tracking the average divergence of the neighbouring trajectories in the state space. Lyapunov exponents were used to quantify dynamic stability from the reconstructed state space *X(t)*. 'Nearest neighbours' are found by picking data points from separate strides that are closest to each other in state space. This is performed for all data points. The distance measure (*D*, see below for definition) between all of these nearest neighbours is tracked forward in time, *t*, to record time-dependent change in kinematics variability. Hence, the divergence or attenuation of kinematic variability is recorded as a function of time. These points will diverge at a rate given by the maxLE:

$$\lambda(i)=\left\langle \ln[D_j(i)]\right\rangle / \Delta t \quad (2)$$

where $D_j(i)$ is the Euclidean distance between the *j*th pair of nearest neighbours after *i* discrete time steps, Δt is the sampling period of the time series data and $\langle\cdots\rangle$ denotes the average over all values of *j*.

For experimental data, this local dynamic stability can be quantified by maxLE via linearly fitting the logarithmic rate of divergence with regard to time, based on the principle that divergence due to local perturbations will grow exponentially (Abarbanel 1996). The higher the maxLE is, the faster the divergence will grow and the worse the system's resistance to local perturbations. Consequently, higher maxLE indicates lower local dynamic stability of the human motor control system of interest (i.e. instability).

Specifically, in the current study (Figure 1), the anterior–posterior accelerometer signal close to the hip joint was first low-pass filtered using a constrained least squares finite impulse response (FIR) filter (order = 6, cut off frequency = 10 Hz). The FIR filter, instead of a regular infinite impulse response (IIR) filter, was chosen in order to avoid distorting the underlying chaotic structure of the target system (Abarbanel *et al*. 1993). For each participant, a time series dataset of 40 continuous gait cycles was extracted and re-sampled to 4000 frames. Thus, 100 frames were roughly equal to one gait cycle. This re-sampling approach was to ensure the between-subject comparison could be made on the same timescale without losing or artificially removing the cycle-to-cycle temporal variability information (England and Granata 2007). The time-delayed coordinate approach (Packard *et al*. 1980) was then used to reconstruct the state space with the embedding dimension of 5 and the time delay of 10 frames. Afterwards, Rosenstein's algorithm (Rosenstein *et al*. 1993) was applied to track the average divergences between neighbouring trajectories in the reconstructed state space. The maxLE was then calculated as the logarithmic rate of average divergence with regard to the time duration of 0 to 50 frames, which corresponded to the first gait step. Therefore, the maxLE obtained in the current study indicated the capability of the human motor control system to resist the perturbations generated within a single step.

Detailed computation can be found in a previous publication (Liu *et al*. 2008). All of the computations were performed by custom-made programs in MATLAB 7.0 (The MathWorks Inc., Natick, MA, USA) and TSTool (Merkwirth *et al*. 1997).

Statistical analysis

The current study had four dependent variables (i.e. maxLE, step length, step duration and heel contact velocity) and one independent variable (i.e. group), which had three levels (i.e. fall-prone old, FO; healthy old, HO; healthy young, HY). One-way between-subject ANOVA was performed on each of the dependent variables with group as the independent variable. A Tukey-Krammer HSD test was performed in case of significant ANOVA test results. A significance level of $p < 0.05$ was adopted for all of the tests. All of the statistical analyses were performed in JMP 7.0 (SAS Institute Inc., Cary, NC, USA).

Results

Local dynamic stability

The ensemble divergence curves, which were averaged across each group, are shown in Figure 2. According to this figure, the average divergence of the FO group during the initial step appeared much faster than that of the HY and HO groups. The ANOVA test confirmed that the maxLE was significantly influenced by group ($p = 0.0066$). A Tukey-Krammer HSD test further indicated that the maxLE of the FO group was significantly higher (approximately 20% to 31% higher) than those of HO and HY groups (Figure 3). Recall that higher maxLE indicates more rapidly diverging dynamics and thus represents lower stability. The results indicate that the fall-prone elderly were characterised as having significantly lower local dynamic stability than their healthy counterparts (i.e. higher instability).

Gait parameters

A summary of gait parameters is provided in Table 2. The ANOVA test indicated that the group had a significant effect only on step length ($p = 0.0018$). A Tukey-Krammer HSD test further revealed that the FO group had a significantly shorter step length (approximately 45% to 52% shorter) than both the HO and HY groups (Figure 4). In other words, the step lengths of the fall-prone elderly were significantly shorter than those of their healthy counterparts. Additionally, the fall-prone elderly walked significantly slower than the other two groups ($p = 0.0002$).

No significant group effects were found in heel contact velocity or step duration (Table 2).

Discussion

The objective of the current study was to provide an initial evaluation of whether local dynamic stability, as quantified by maxLE utilising a simple ambulatory monitoring accelerometer, can be used to discriminate fall-prone individuals from healthy adults. Previous studies have suggested that the results supported by the local dynamic stability measure may or may not extend to global stability, which is more directly relevant to an individual's risk of falling (Dingwell and Marin 2006). Thus, there is a need to determine whether maxLE can predict individuals' resilience to larger perturbations. Additionally, several gait parameters were compared to assess the effectiveness of these measures in differentiating the fall-prone elderly individuals. Indeed, the results from the current study indicate that measures of local dynamic stability can identify fall-prone elderly from healthy young and older adults. Specifically, the fall-prone elderly were found to be less stable than their healthy counterparts when considering local dynamic stability during treadmill walking.

The current findings are in agreement with a previous analysis (Granata and Lockhart 2008), suggesting that the stability measures derived from non-linear dynamics can be used to quantify the risk of falling. Granata and Lockhart (2008) suggested that stability describes the ability of the neuromuscular system to maintain dynamic equilibrium in the presence of kinematic and control variability. In essence, stability is maintained by active neuromuscular control. This will require both active as well as passive stiffness control (Winter *et al*. 1998, Morasso and Sanguineti 2002) and recruitment strategies of active muscles (Nielsen *et al*. 1994). The neuro-control system provides active corrective response and intrinsic joint torques to maintain dynamic equilibrium in the presence of kinematic disturbances (i.e. micro-slip, step-disturbance, neuromotor recruitment error, etc.). Attenuation of kinematic disturbances is manifested in dynamic stability measures and fall-prone individuals may be less able to attenuate the kinematic disturbances. For example, utilising maximum Floquet multiplier (a measure of orbital dynamic stability, i.e. maximum eigenvalue of the system), a previous study (Granata and Lockhart 2008) was able to differentiate fall-prone elderly from healthy adults. Similar differentiation was also evident in the current study, in which local dynamic stability calculation was applied.

It has been suggested that measures of local stability and orbital stability quantify different properties of system dynamics (Dingwell and Kang 2007). On one hand, the local dynamic stability quantifies the divergence in terms of both space and time variables. Additionally, the tracking of the divergence for a given trajectory is relative to its own neighbouring trajectory. Being the maximum value among the Lyapunov exponent spectrum in the state space, the maxLE represents the least stable aspect of the movement dynamics (Granata and England 2006). On the other hand, the orbital dynamic stability quantifies the divergence only in space. Additionally, assuming limit cycle systems, the orbital stability quantifies the tendency of the dynamic system to diverge/converge back to its (one target) trajectory in a discrete manner. In a scenario of continuous walking, the stochastic disturbances and control errors are manifested as the kinematic variability about its target trajectory. The ability of the neuromuscular response to such kinematic variability is quantified by the orbital dynamic stability. A recent study (Dingwell and Kang 2007) has shown that an individual can be both locally unstable and orbitally stable. The results from the current study and a previous study (Granata and Lockhart 2008) clearly demonstrate that both local dynamic stability and orbital dynamic stability can be used to effectively identify fall-prone individuals. Having both measures as potential candidates, an important line of future research will be to compare and determine the most robust and sensitive stability measure as the effective fall-risk predictor. For example, Floquet analysis can be made at the instance of a gait cycle to determine and quantify the system's ability to recover from the perturbation at a fixed point (e.g. at the time of heel contact, mid stance, etc.) to identify and help pinpoint where in the older adults' gait cycle instability may occur.

There are several issues to be considered when applying local dynamic stability analysis to experimental data. First is the choice of walking speed. Similar to previous research (Buzzi *et al*. 2003, Granata and Lockhart 2008), participants were allowed to walk at a preferred speed instead of a fixed speed. Walking speed was not involved in the analyses for two reasons; first, to ensure the optimal consistency of gait performances (Diedrich and Warren 1995) and to minimise any potential discomfort (Sekiya *et al*. 1997). Meanwhile, it was also argued that each preferred gait speed behaves similarly to an attractor characterised by the stable state phase (Diedrich and Warren 1995). Thus, it was posited that local dynamic stability analysis should be performed when participants walk at a preferred speed. Second, involving walking speed in the statistical model (e.g. as a covariate) was deemed inappropriate. Previous studies have found an inverse relationship between local dynamic stability and walking speed among healthy young adults (Dingwell and Marin 2006, England and Granata 2007). However, whether this relationship would hold true for fall-prone elderly and/or a mixture of population (young and elderly) has to be investigated in future studies. In fact, the current study indicated that even with a slower walking speed (Table 2), the fall-prone elderly still exhibited a significantly lower dynamic stability than healthy adults.

With regard to the regular spatio-temporal gait parameters, the current study did not observe any significant ageing effect on heel contact velocity and step duration. Similar results were also found by Lockhart and Kim (2006), who argued that it may be due to the age-related differences in fear of an upcoming slippery surface. Even though the current study did not involve any slippery surface, walking on a treadmill continuously may present itself as a challenging task for the fall-prone elderly. It is possible that they were adopting similar gait patterns in the current study. The fall-prone elderly were also found to have a significantly shorter step length than the healthy adults. Similar age-related reduction in step length was also found in the literature (Maki 1997). Additionally, it is a confirmed gait adaptation strategy when encountering a known slippery surface, so as to avoid a slip-induced fall (Lockhart *et al*. 2007). Despite these known gait adaptations, fall-prone elderly still continue to fall. Buzzi *et al.* (2003) hypothesised that one factor contributing to the increased falls due to ageing may be the inability of the elderly to compensate for the natural stride-to-stride variations present during walking. With local dynamic stability, the findings from the current study can be viewed as a support to this hypothesis. Nevertheless, since most falls were initiated by larger (global) perturbations, the connection between local dynamic stability and the ability to negotiate global perturbations has to be investigated in future studies. As such, the current study should be generalised with caution. Future studies should also investigate the direct correlation between local dynamic stability and gait parameters.

It should be noted that the findings of this study were derived from a small sample size. It is quite possible that the small but insignificant differences between the HO and HY groups would have been significant given a larger sample size. Future studies with a larger number of participants may produce more conclusive results regarding the discriminative capability of local dynamic stability measures. Additionally, many other factors (i.e. individuals' range of motion, muscle strength, peripheral sensation, etc.) may play a role in one's local stability and should be considered in future studies.

It should also be noted that, for each participant, time series data of 40 continuous gait cycles were extracted for the analysis. Although implicated (Kang and Dingwell 2006a), appropriate trial length (of a time series data) for obtaining the most reliable results for the elderly should be further investigated.

In summary, together with the aged-related spatio-temporal gait adaptations, the current study found that the fall-prone elderly had a significantly reduced local dynamic stability. In addition to providing the evidence that the increased falls of the elderly may be due to an age-related inability to attenuate/control stride-to-stride variances during locomotion, the current study proposed the possibility of using local dynamic stability as a potential predictor to assess risk of falling.

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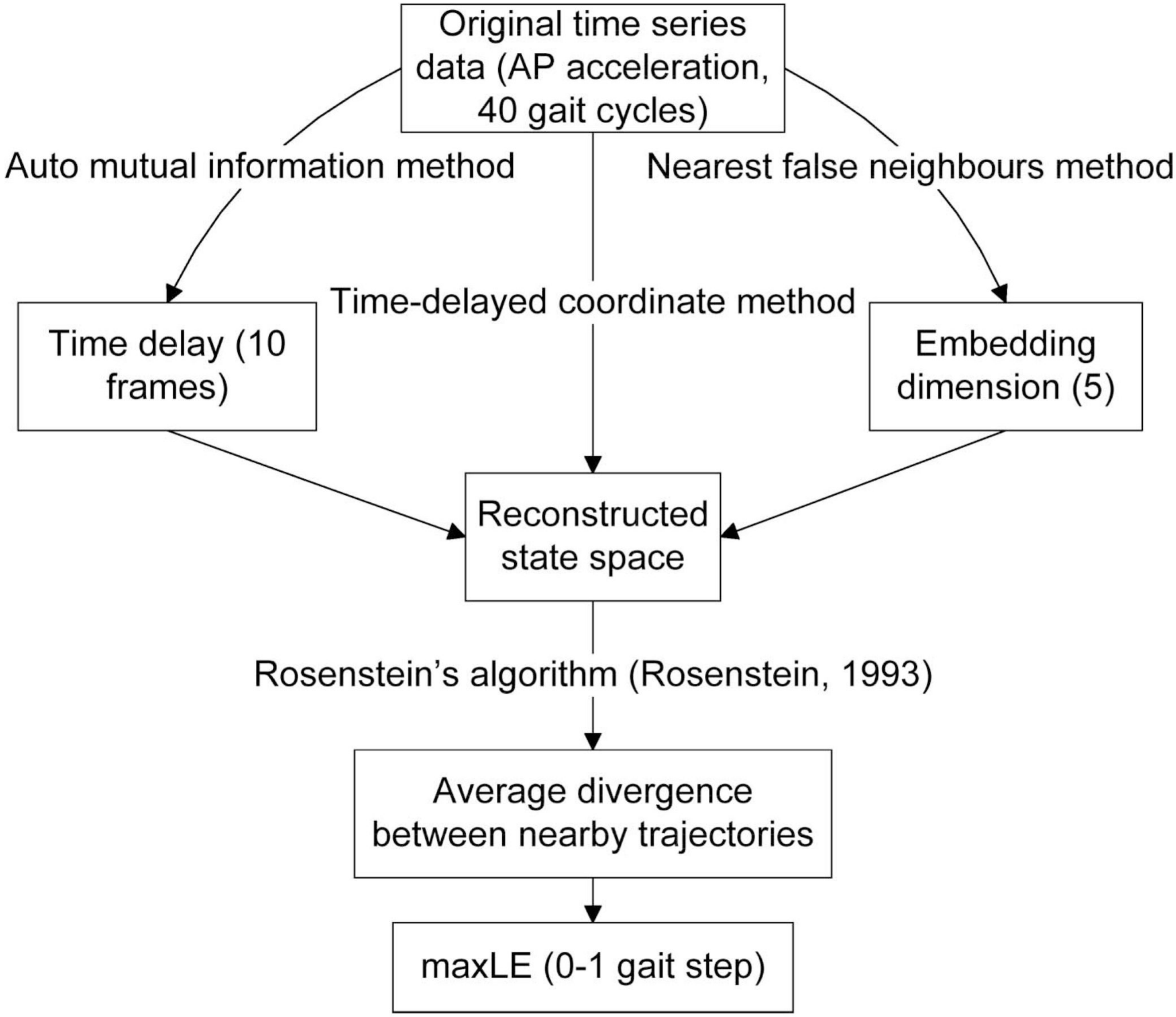

Figure 1.
Illustration of local dynamic stability computation. AP = anterior–posterior; maxLE = maximum Lyapunov exponent; 1 gait cycle = 2 gait step.

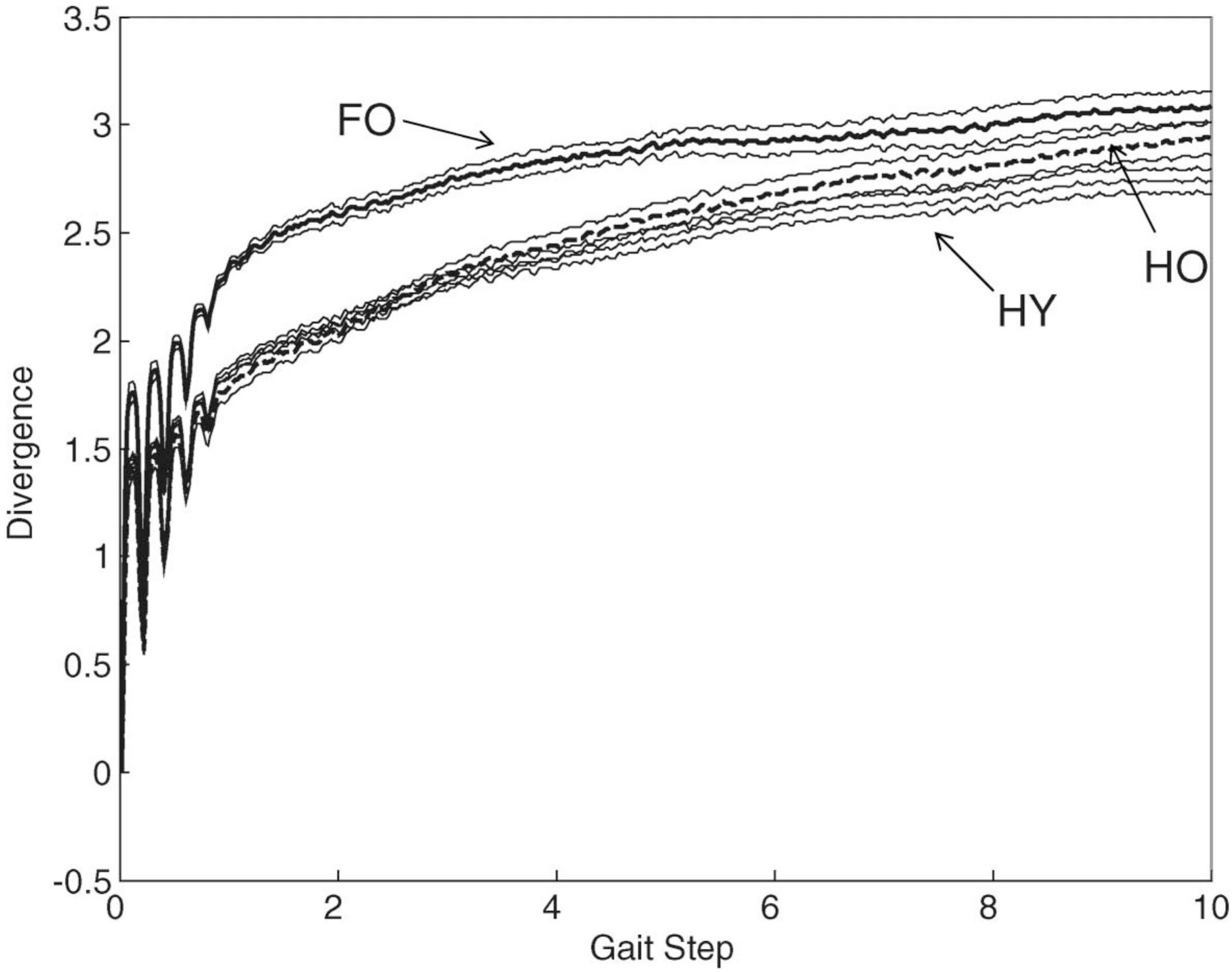

Figure 2.
Ensemble divergence curve by group. FO = fall-prone old; HO = healthy old; HY = healthy young; 1 gait step = 0.5 gait cycle; dash line around each ensemble average curve represents 1 SE.

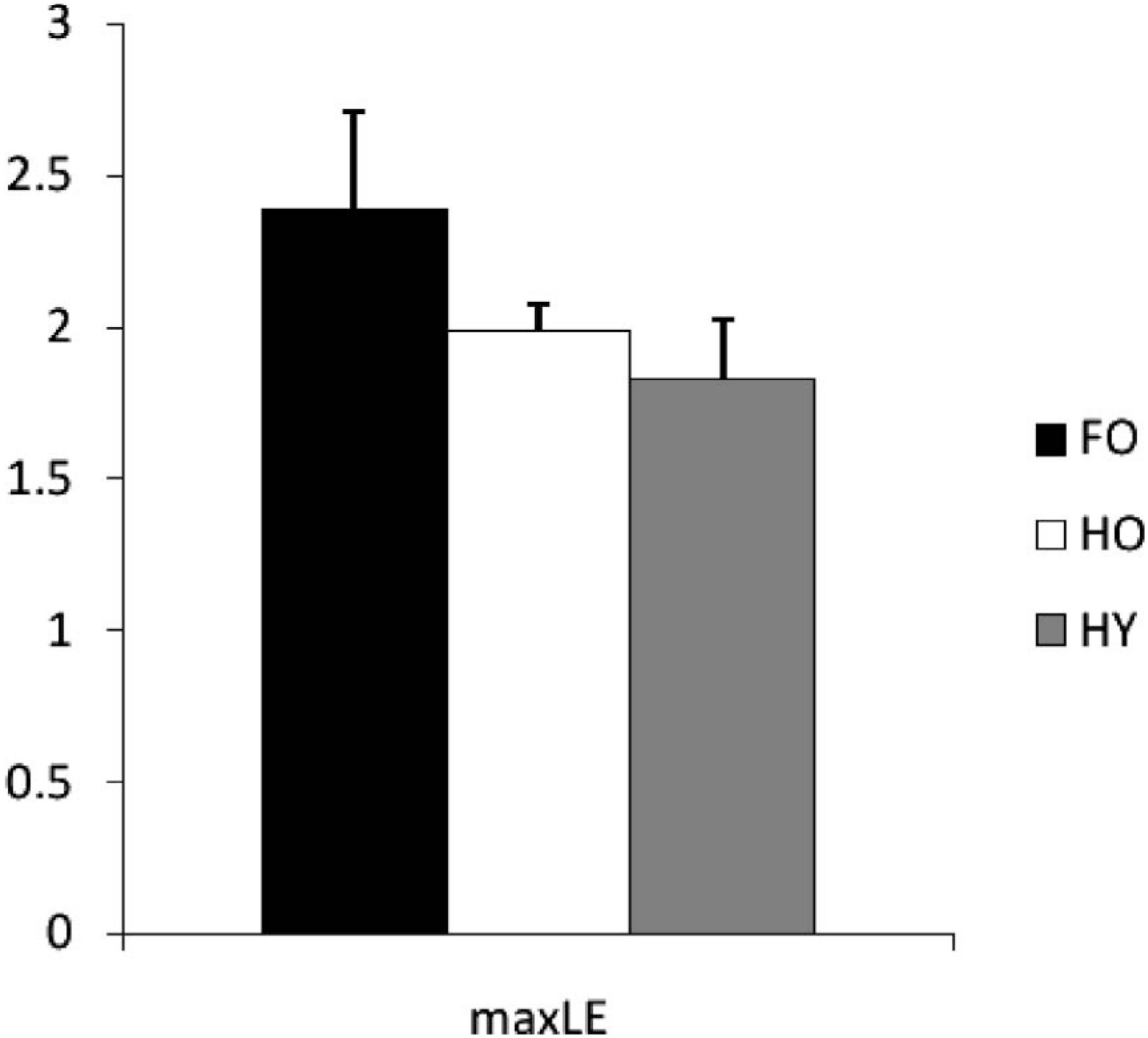

Figure 3.
Mean and SD of maximum Lyapunov exponent (maxLE) by group. FO = fall-prone old; HO = healthy old; HY = healthy young.

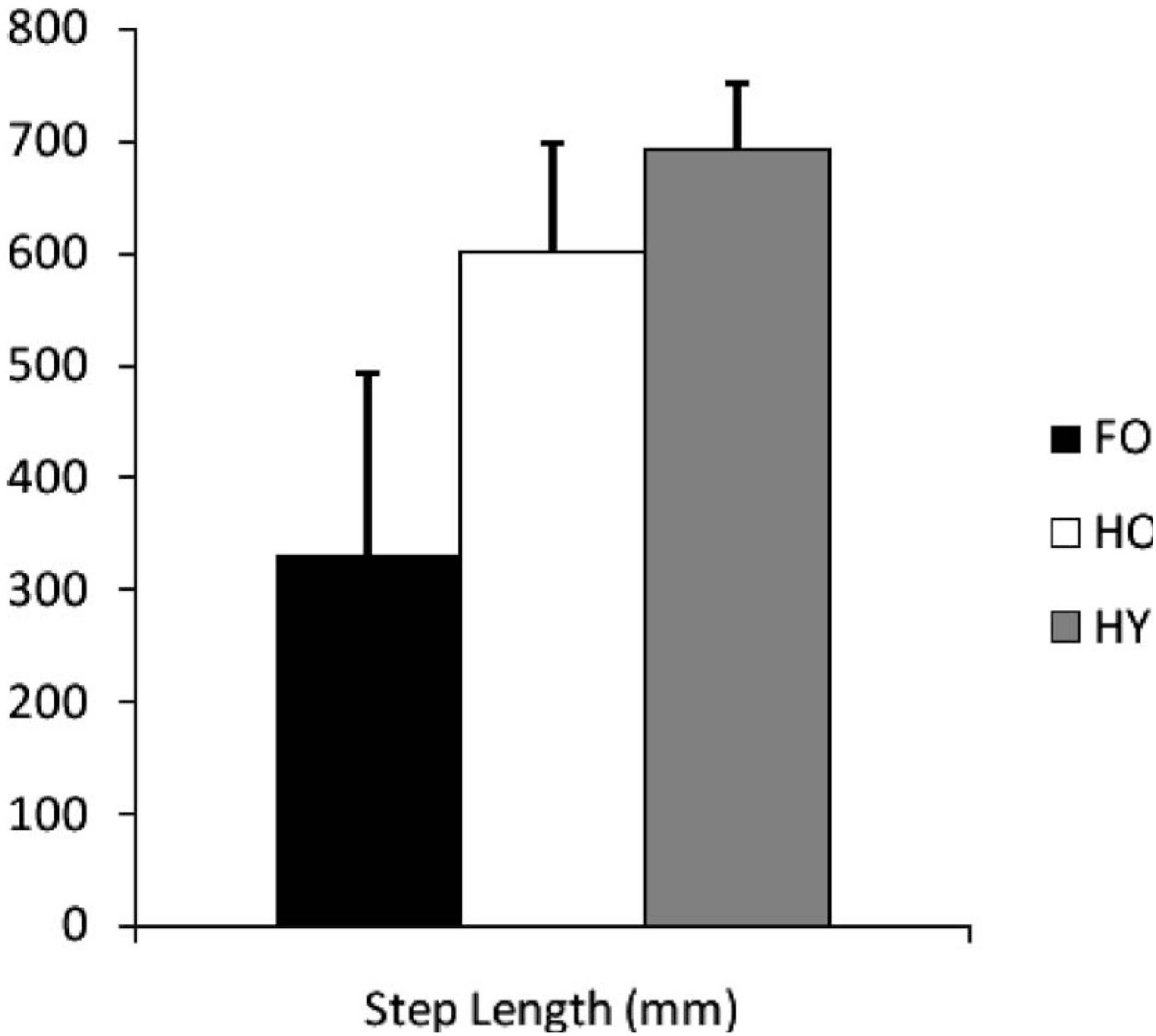

Figure 4.
Mean and SD of step length by group. FO = fall-prone old; HO = healthy old; HY = healthy young.

Table 1

Participants' anthropometric information.

Group	Age (years)		Weight (kg)		Height (cm)	
	Mean	SD	Mean	SD	Mean	SD
HY	26.4	2.3	71.0	13.6	176.8	7.4
HO	71.3	6.5	71.2	7.3	164.7	9.3
FO	71.0	3.0	88.6	10.4	172.3	10.8

HY = healthy young; HO = healthy old; FO = fall-prone old.

Table 2

Summary of gait parameters and maximum Lyapunov exponent (maxLE) by group.

	FO		HO		HY		
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	***p***
maxLE	2.39	0.32	1.99	0.08	1.83	0.19	0.0066*
Heel contact velocity (mm/s)	321.6	110.6	431.1	291.0	396.4	411.0	0.8792
Walking velocity (mm/s)	0.57	0.23	1.16	0.21	1.33	0.08	0.0002
Step length (mm)	329.5	162.4	601.3	97.2	693.6	57.0	0.0018*
Step duration (s)	1.19	0.08	1.04	0.16	1.04	0.13	0.2119

FO = fall-prone old; HO = healthy old; HY = healthy young.

* Significant when p 5 0.05.