



Is slow walking more stable?

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ABSTRACT

Several efforts have been made to study gait stability using measures derived from nonlinear time-series analysis. The maximum finite time Lyapunov exponent (λ_{\max}) quantifies how a system responds to an infinitesimally small perturbation. Recent studies suggested that slow walking leads to lower λ_{\max} values, and thus is more stable than fast walking, but these studies suffer from methodological limitations. We studied the effects of walking speed on the amount of kinematic variability and stability in human walking. Trunk motions of 15 healthy volunteers were recorded in 3D during 2 min of treadmill walking at different speeds. From those time series, maximum Lyapunov exponents, indicating short-term and long-term divergence ($\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$), and mean standard deviation (MeanSD) were calculated. $\lambda_{S\text{-stride}}$ showed a linear decrease with increasing speed for forward–backward (AP) movements and quadratic effects (inverted U-shaped) for medio-lateral (ML) and up–down (VT) movements. $\lambda_{L\text{-stride}}$ showed a quadratic effect (inverted U-shaped) of walking speed for AP movements, a linear decrease for ML movements, and a linear increase for VT movements. Moreover, positive correlations between λ_S and MeanSD were found for all directions, while $\lambda_{L\text{-stride}}$ and MeanSD were correlated negatively in the AP direction. The different effects of walking speed on $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$ for the different planes suggest that slow walking is not necessarily more stable than fast walking. The absence of a consistent pattern of correlations between $\lambda_{L\text{-stride}}$ and MeanSD over the three directions suggests that variability and stability reflect, at least to a degree, different properties of the dynamics of walking.

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1. Introduction

With their high incidence and associated costs, falls form a considerable problem in modern society (Rubenstein, 2006). Consequently, there is a rapidly growing body of research on (in)stability of posture and gait in both the elderly and selected patient groups (i.e. Buzzi et al., 2003; Calandre et al., 2005; Dingwell et al., 2000, 2007; Hausdorff et al., 1996; Hurmuzlu et al., 1996; Stergiou et al., 2004).

Unfortunately, stability “...appears to have unstable definitions” (Reeves et al., 2007, p. 266, italics added). Several efforts have been made to study gait stability using measures derived from nonlinear time-series analysis (Buzzi et al., 2003; Dingwell et al., 2000, 2007; Dingwell and Marin, 2006; Hurmuzlu and Basdogan, 1994; Hurmuzlu et al., 1996; Kang and Dingwell, 2006a, b; Stergiou et al., 2004). In the current study, we focus on gait stability defined as inverse of the rate of divergence from the intended trajectory after a small perturbation. This may be quantified using the maximum finite time Lyapunov exponent

(λ_{\max}), which estimates a system's local dynamic stability (Rosenstein et al., 1993).

There are several other nonlinear methods to analyze gait stability, such as the assessment of scaling behavior of stride parameters (Hausdorff, 2005). While we acknowledge the value of such methods in view of their potential practical applications (Hausdorff, 2005; Jordan et al., 2007a), we sought to quantify stability by estimating the rate of divergence of kinematic variables within a time series, as captured by maximum time finite Lyapunov exponents. The maximum finite time Lyapunov exponent represents the average logarithmic rate of divergence of infinitesimally close trajectories, and thus indexes how a system responds to an infinitesimally small perturbation. For a process to be stable, λ_{\max} should be ≤ 0 , implying that infinitesimally close trajectories will, on average, not diverge. Positive values of λ_{\max} imply that such trajectories will on average diverge, indicating less stable patterns. In most gait research, two values of λ_{\max} are reported (Fig. 1): one reflecting how the system responds over a shorter time period (often 1 stride cycle, termed λ_S) and the other reflecting how the system responds over a longer time period (usually 4–10 stride cycles, termed λ_L).

Several recent studies have examined the effects of walking speed on local dynamic stability (Dingwell and Marin, 2006;

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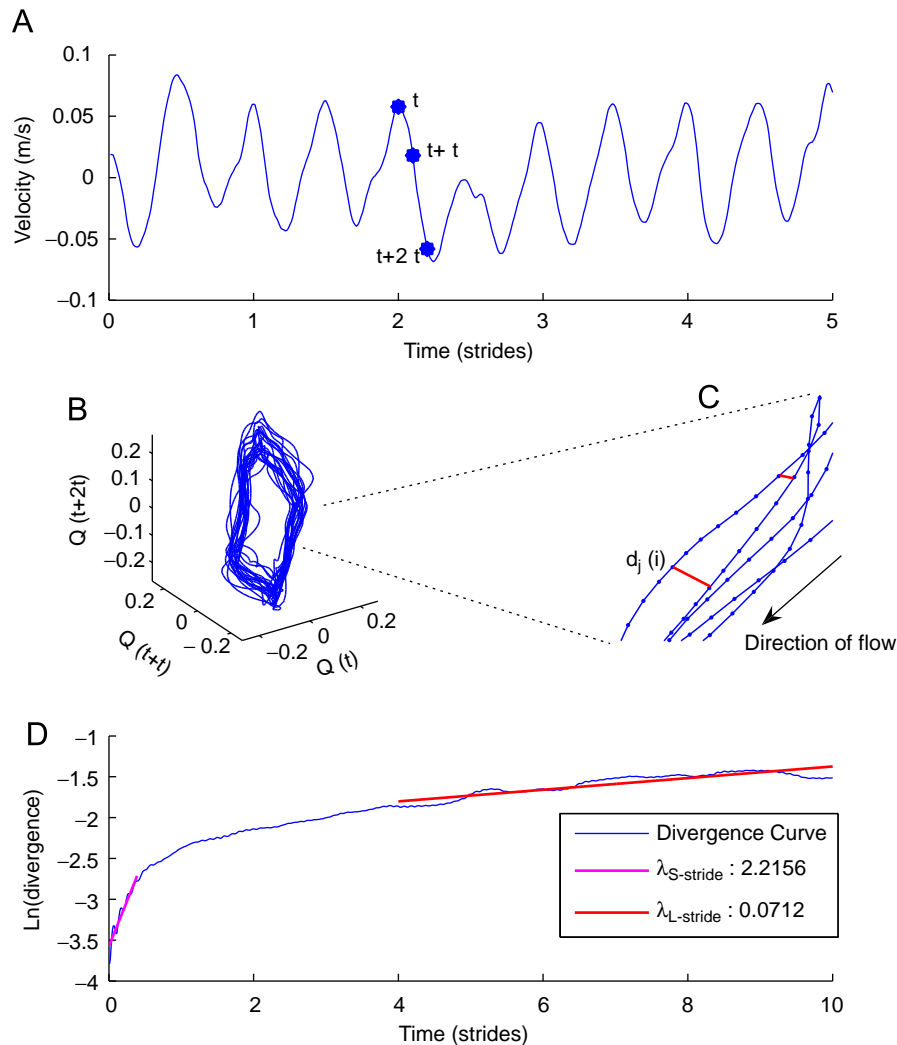


Fig. 1. Schematic representation of the calculation of maximum time finite Lyapunov exponents. (A) original velocity time-series data. (B) The 3D reconstructed state space using $S(t) = [q(t), q(t+\tau), \dots, q(t+(d_E-1)\tau)]$, where $S(t)$ is the d_E dimensional state space, constructed from the original signal $q(t)$ and copies with a delay of τ . (Note that calculations were carried out on a 5D state space, which cannot be visualized). (C) Expanded view of a section of B; for each point on the attractor, the nearest neighbour was calculated, and divergence from this point was calculated as $d_j(i)$. (D) Average logarithmic rate of divergence, from which maximum time finite Lyapunov exponents, $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$, can be calculated as the slope of the curve at 0–0.5 strides and at 4–10 strides, respectively.

England and Granata, 2007; Stergiou et al., 2004). Most of these studies suggested that slow walking is more stable than fast walking, which could explain why patients with different locomotor pathologies walk slower. This appears to stand in contrast with suggestions that passive dynamic walkers are more stable at higher walking speeds (Wisse and Schwab, 2005; Hobbelen and Wisse, 2007). Moreover, the variability of interlimb coordination during human walking has been found to decrease with increasing walking speed (Donker and Beek, 2002; Donker et al., 2001), which was interpreted to imply that stability increases with walking speed.

Thus, there are suggestions that the stability of walking increases with walking speed, but these were not confirmed when stability was defined in terms of maximum Lyapunov exponents. Actual human walking and passive dynamic walking are not the same, and variability cannot simply be equated with (in)stability (Dingwell and Marin, 2006). On the other hand, the observed effects of walking speed on local dynamic stability may (partly) reflect the consequence of methodological choices, rather than changes in stability per se. A first concern when estimating maximum finite time Lyapunov exponents from experimental

data is the length of the time-series analyzed, which is known to affect λ_{\max} (Bruijn et al., 2009; Kang and Dingwell, 2006b; Rosenstein et al., 1993). Dingwell and Marin (2006) used the same time-series length for all speeds tested. However, time series at higher speeds include more strides than time series at lower speeds, which may affect the estimate of λ_{\max} . Accordingly, England and Granata (2007) estimated λ_S for the same number of strides for all walking speeds, but instead of expressing λ_S as λ_S per stride ($\lambda_{S\text{-stride}}$), which would appear appropriate (Dingwell and Cusumano, 2000; Dingwell et al., 2001; Dingwell and Marin, 2006; Kang and Dingwell, 2006b), they estimated λ_S per second ($\lambda_{S\text{-second}}$), and thus introduced an unwanted dependency of λ_S upon stride time.

In the present study, we investigated the effects of walking speed on local dynamic stability of the trunk (operationalized as maximum Lyapunov exponents), while taking into account the methodological issues mentioned in the preceding. In doing so, we additionally addressed the relationship between local dynamic stability and the amount of variability of the trunk kinematics between strides (operationalized as mean standard deviation between strides) in human walking because this relationship is of

general interest to theories of motor control (Riley and Turvey, 2002; Scholz and Schonher, 1999). Based on a previous methodological study (Bruijn et al., 2009), we hypothesized that increasing walking speed would differentially affect local dynamic stability, depending upon plane of analysis and type of Lyapunov exponent used (i.e. λ_S versus λ_L).

2. Methods

2.1. Subjects

Fifteen healthy volunteers (4 men and 11 women, mean age 23.6 years, SD 2.9, mean weight 66.7 kg, SD 9.0, and mean height 1.74 m, SD 0.08) participated in the experiment. Exclusion criteria were any orthopaedic or neurological disorders that could interfere with gait. Subjects gave their informed consent and the local ethical committee approved the protocol before the experiment was conducted.

2.2. Procedure

A neoprene band with a cluster of three infrared light-emitting diodes (LED's) was attached to the back of the trunk (over the spine) at the level of T6 and at the right heel. The LED's were used for movement registration with an active 3D movement registration system (Optotrak[®] Northern Digital Inc., Waterloo, Ontario). Sample rate was set at 50 samples per second.

During the experiment, subjects walked on a treadmill (Biostar GiantTM, Biometrics, Almere, The Netherlands) at different speeds (from 0.62 to 1.72 m/s, in increments of 0.22 m/s). At each speed, 2 min of measurement started after 3 min of warm-up. Between speeds, subjects were allowed a break of maximum 5 min, if they felt they required one.

2.3. Calculations

2.3.1. Pre-processing

Given the difficulties associated with filtering nonlinear signals (Kantz and Schreiber, 1997; Mees and Judd, 1993), data were analyzed without filtering. To overcome non-stationarities (cf. Dingwell and Marin, 2006), the first derivative of the anterior posterior (AP), medio-lateral (ML) and vertical (VT) position time series of the average movements of the thorax markers was used to estimate the stability and variability measures of interest (see below). Since estimates of maximum finite time Lyapunov exponents may be biased by time-series length and number of strides (cf. Bruijn et al., 2009; Kang and Dingwell, 2006b), we analyzed the first 50 consecutive strides of each time series. Time series were time normalized, using a shape-preserving spline interpolation, so that each time series of 50 strides had a total length of 5000 samples (England and Granata, 2007). For the purpose of calculating normalized stride cycles, heel strikes were determined from the minimum vertical position of the average of the three heel markers.

2.3.2. Local dynamic stability

From the time-normalized time-series and their time-delayed copies, state spaces were reconstructed using

$$S(t) = [q(t), q(t + \tau), \dots, q(t + (d_E - 1)\tau)] \quad (1)$$

with $S(t)$ representing the d_E -dimensional state vector, $q(t)$ the original 1-dimensional data, τ the selected time delay and d_E the embedding dimension. An embedding dimension of $d_E = 5$ was used, because 5 dimensions proved to be sufficient to capture most of the dynamics of human walking (Dingwell and Cusumano, 2000), and because global false nearest neighbour analysis (Kennel et al., 1992) of our own data suggested that $d_E = 5$ was appropriate. Time delays were estimated using the first minimum of the average mutual information function (Fraser, 1986). We found delays ranging from 4 to 22 samples, but since all time series had the same frequency after normalization (i.e. 50 strides in 5000 samples), we used a standard embedding delay of 10 samples for all time series (cf. England and Granata, 2007).

From the thus constructed state spaces, Euclidean distances between neighbouring trajectories in state space were calculated as a function of time and averaged over all original nearest neighbour pairs to obtain the average logarithmic rate of divergence

$$y(i) = \frac{1}{\Delta t} \langle \ln(d_j(i)) \rangle \quad (2)$$

where $d_j(i)$ represents the Euclidean distance between the j th pair of nearest neighbours after i discrete time steps (i.e. $i\Delta t$) and $\langle \cdot \rangle$ denotes the average over all values of j . The slope of the resulting divergence curves provides an estimate of the maximum finite time Lyapunov exponent (Rosenstein et al., 1993). This slope was estimated for two intervals: from 0 to 50 samples (approximately 0–0.5 stride,

$\lambda_{S\text{-stride}}$, see Fig. 1) and from 400 to 1000 samples (approximately 4–10 strides, $\lambda_{L\text{-stride}}$). We chose to estimate $\lambda_{S\text{-stride}}$ from 0 to 50 samples, rather than 0–100 samples, because we noticed that the divergence curve often was clearly nonlinear after about 75 samples. All calculations were done using custom made Matlab (The MathWorks, Inc. Natick, MA) programs.

2.3.3. Variability

To quantify the amount of variability of the AP, ML and VT time series, data of each stride within a given time series were first time normalized to 101 samples (0–100%). At each percent of the stride cycle, standard deviations between strides were calculated, and then averaged over the stride cycle (MeanSD).

2.3.4. Statistical analysis

For the maximum finite time Lyapunov exponents, the effect of speed was tested using generalized estimation equations (GEE, cf. Liang and Zeger, 1986; Zeger and Liang, 1986). GEE is a regression technique that takes repeated measures (dependent observations) into account. The relationship between local dynamic stability and amount of variability was tested using this procedure. The R package for statistical analysis (<http://www.r-project.org/>, Halekoh et al., 2006) was used for all statistics, and $P < 0.05$ was considered significant.

3. Results

Some subjects did not produce enough strides at some speeds; for 0.62, 0.84, 1.5, and 1.72 m/s we had complete data sets for 14 subjects, while for 1.06 and 1.28 m/s data sets for all 15 subjects were available for analysis. Time series of an insufficient number of strides were omitted from the analysis.

3.1. Local dynamic stability

Different effects of speed on $\lambda_{S\text{-stride}}$ were observed for the different movement directions (Fig. 2, top panel). In the AP direction, $\lambda_{S\text{-stride}}$ decreased with increasing walking speed, with a significant linear component for the effect of speed (Table 1, upper panel). In the ML direction, $\lambda_{S\text{-stride}}$ somewhat increased for speeds up to 1.28 m/s, and then somewhat decrease, with significant linear and quadratic components for the effect of speed. In the VT direction, $\lambda_{S\text{-stride}}$ increased with increasing walking speed, again with significant linear and quadratic components for the effect of speed.

As was the case for $\lambda_{S\text{-stride}}$, different effects of walking speed on $\lambda_{L\text{-stride}}$ were observed for the different directions (Fig. 2, bottom panel). $\lambda_{L\text{-stride}}$ increased linearly with increasing walking speed for the AP and VT directions. These effects were significant, with a significant quadratic component for the effect of speed in the AP direction (Table 1, lower panel). For the ML direction, $\lambda_{L\text{-stride}}$ decreased linearly with increasing walking speed, and this effect was significant.

3.2. Relationship between local dynamic stability and variability

With increasing speed, MeanSD showed a pattern similar to that of $\lambda_{S\text{-stride}}$ for all directions (Fig. 3). A consistent relationship between $\lambda_{S\text{-stride}}$ and MeanSD was found for all directions, with higher $\lambda_{S\text{-stride}}$ coinciding with higher MeanSD (Table 2). For $\lambda_{L\text{-stride}}$, a weak negative relationship with MeanSD was found in the AP direction, and no relationship in the other two directions.

4. Discussion and conclusion

In the present study, we examined the effects of walking speed on local dynamic stability, taking into account methodological issues that may hamper the estimation of these measures. In doing so, we included an analysis of the relationship between local dynamic stability and amount of variability.

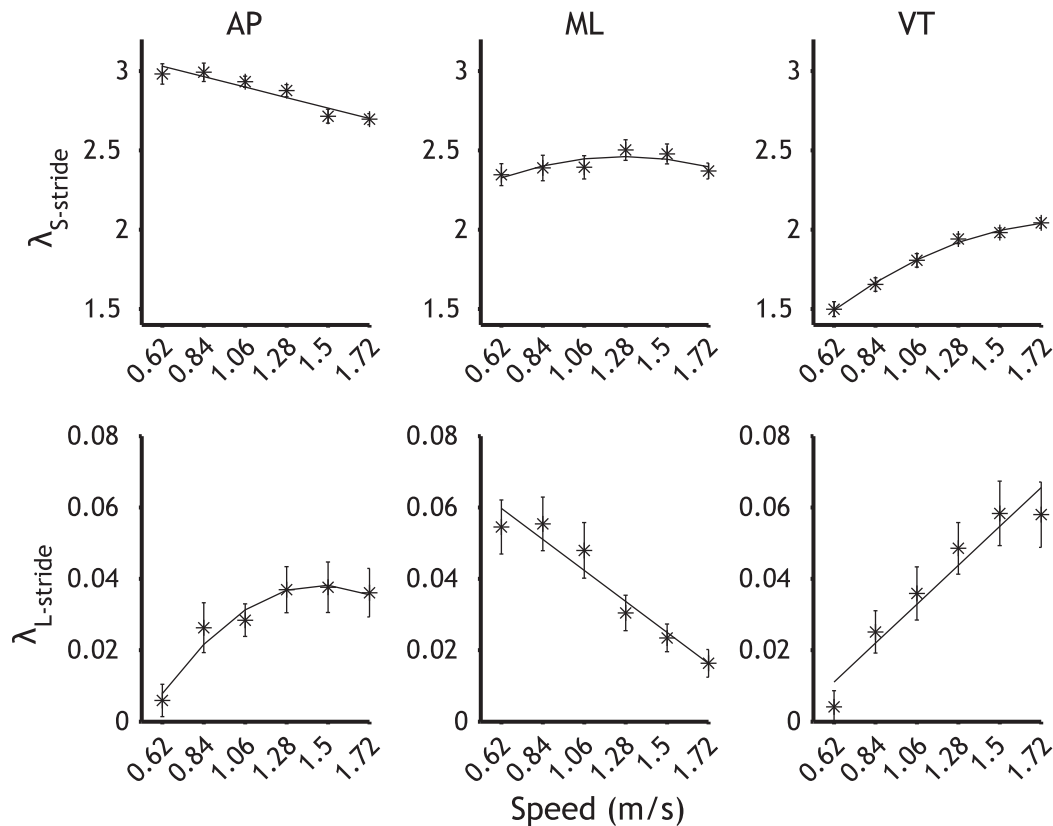


Fig. 2. The effects of walking speed on $\lambda_{S\text{-stride}}$ (top panels) and $\lambda_{L\text{-stride}}$ (bottom panels), for the anterior posterior (AP), medio-lateral (ML) and vertical (VT) directions. Lines represent the fit of the (GEE) regression model (for coefficients see Table 1). Error bars represent standard errors.

Table 1

(GEE) Regression coefficients (b and c) and their standard errors (s.e.) for the effects of walking speed on $\lambda_{S\text{-stride}}$ (upper panel) and $\lambda_{L\text{-stride}}$ (lower panel), for the anterior posterior (AP), medio-lateral (ML) and vertical (VT) directions.

		b (s.e.)	P	c (s.e.)	P
$\lambda_{S\text{-stride}}$	AP	−0.067 (0.011)*	<0.001	−0.014 (0.006)*	0.002
	ML	0.151 (0.057)*	0.008	−0.017 (0.005)*	0.019
	VT	0.260 (0.050)*	<0.001	−0.017 (0.005)*	0.019
$\lambda_{L\text{-stride}}$	AP	0.024 (0.007)*	<0.001	−0.002 (0.001)*	0.007
	ML	−0.008 (0.121)*	<0.001	<0.001	
	VT	0.011 (0.002)*	<0.001		

Models used are $\lambda_{S\text{-stride}} = a + b \times \text{speed} + c \times \text{speed}^2$ and $\lambda_{L\text{-stride}} = a + b \times \text{speed} + c \times \text{speed}^2$. The quadratic term was removed from the model if it was not significant.

* $P < 0.05$.

We found different effects of walking speed on both $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$ for the different directions of interest. For the anterior posterior direction, $\lambda_{S\text{-stride}}$ decreased with increasing speed while $\lambda_{L\text{-stride}}$ increased for speeds up to 1.5 m/s. For the medio-lateral direction, $\lambda_{S\text{-stride}}$ roughly showed an inverted U-shaped pattern, while $\lambda_{L\text{-stride}}$ showed a decrease with increasing speed. For the vertical direction, both $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$ increased markedly with increasing speed.

Furthermore, we found a consistent relationship between $\lambda_{S\text{-stride}}$ and MeanSD, with higher $\lambda_{S\text{-stride}}$ coinciding with higher MeanSD. No consistent relationship was found between $\lambda_{L\text{-stride}}$ and MeanSD.

4.1. Limitations of the present study

We estimated stability during treadmill walking, which may yield slightly lower values of maximum finite time Lyapunov exponents than overground walking (Dingwell et al., 2001). Moreover, walking speeds were not offered in random fashion, which may have influenced our results.

We used rather brief data series (50 strides), which may have limited the statistical precision of our estimates of the maximum finite time Lyapunov exponents (Bruijn et al., 2009; Kang and Dingwell, 2006b; Rosenstein et al., 1993). However, our results showed smooth linear and quadratic effects of walking speed on $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$, making it highly unlikely that the observed effects of speed resulted from chance. Moreover, our time-normalization procedure and the relatively low sample rate used in the present study (50 samples/s) implied that stride cycles at higher speeds were stretched out, which may have rendered the stability estimates less reliable. However, when we performed the same calculations without time normalization, we found similar values. Furthermore, Rosenstein's algorithm requires an adequate selection of a "linear region" (Rosenstein et al., 1993), which we set from 0 to 0.5 and from 4 to 10 strides. Since these regions (especially the short-term region) may influence the results, they should be chosen carefully. Lastly, it has been suggested that Rosenstein's algorithm does not produce valid results for periodic motion (Franca and Savi, 2001). However, walking is not strictly periodic because time series of stride intervals exhibit fractal-like fluctuations (e.g. Hausdorff et al., 1995, 1996; Jordan et al., 2007a). Moreover, even if one assumes walking to be periodic, maximum Lyapunov exponents may still provide well-defined metrics for the

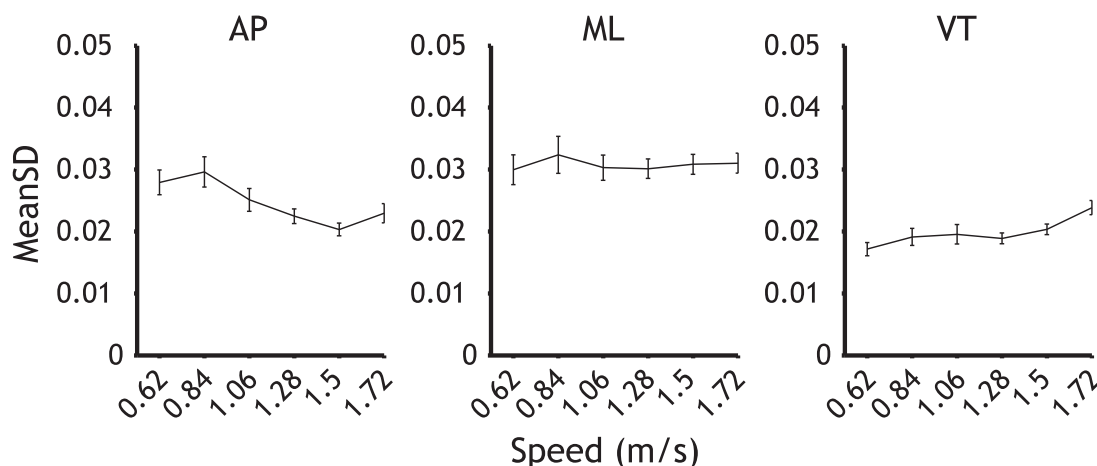


Fig. 3. The effect of walking speed on MeanSD, for the anterior posterior (AP), medio-lateral (ML) and vertical (VT) directions. Error bars represent standard errors.

Table 2

(GEE) Regression coefficients and their standard errors for the relation between stability ($\lambda_{S\text{-stride}}$, upper panel and $\lambda_{L\text{-stride}}$, lower panel) and variability (MeanSD, for the anterior posterior (AP), medio-lateral (ML) and vertical (VT) directions).

		MeanSD	
		<i>b</i> (s.e.)	<i>P</i>
$\lambda_{S\text{-stride}}$	AP	19.191 (2.573)*	<0.001
	ML	8.308 (3.292)*	0.011
	VT	27.576 (5.838)*	<0.001
$\lambda_{L\text{-stride}}$	AP	−1.119 (0.360)*	0.018
	ML	−0.319 (0.233)	0.291
	VT	0.355 (0.336)	0.171

Models used are $\text{MeanSD} = a + b \times \lambda_{S\text{-stride}}$, and $\text{MeanSD} = a + b \times \lambda_{L\text{-stride}}$.

* $P < 0.05$.

sensitivity of gait kinematics to small intrinsic perturbations (e.g. Dingwell and Kang, 2007).

It should be kept in mind that maximum finite time Lyapunov exponents quantify a dynamical system's response to infinitesimally small perturbations, not to large external perturbations (Dingwell and Cusumano, 2000; Dingwell et al., 2001, 2000; Dingwell and Marin, 2006). In this regard it is noteworthy that some recent studies (Kang and Dingwell, 2008; Lockhart and Liu, 2008) found that maximum time finite Lyapunov exponents could successfully discriminate elderly with a history of falling from elderly without such a history. However, those results may have been confounded by differences in walking speed (Lockhart and Liu, 2008) or number of strides due to differences in cadence (Kang and Dingwell, 2008). Using maximum Floquet multipliers, which like Lyapunov exponents are based on infinitesimally small perturbations, Granata and Lockhart (2008) could also discriminate between fallers and non-fallers. In this study, no potential bias due to walking speed or cadence was reported, although actual walking speeds and cadences were not reported. Thus, it remains to be established how maximum finite time Lyapunov exponents and maximum Floquet multipliers correlate with real-life perturbation resistance (i.e. common-sense notions of stability).

4.2. Local dynamic stability

The present results are different from those of Dingwell and Marin (2006) and England and Granata (2007), who reported that slow walking is more stable than fast walking. We believe that

those differences may be due to methodological differences. Firstly, while Dingwell and Marin (2006) analyzed three minutes of data at all walking speeds, we analyzed a fixed number of strides (as suggested by England and Granata (2007)). Longer time series lead to a larger maximum finite time Lyapunov exponent (Bruijn et al., 2009; Kang and Dingwell, 2006b). Choosing a fixed time interval implies that with increasing speed more strides are analyzed, implying a larger maximum Lyapunov exponent. While England and Granata (2007) recognized this problem, and analyzed knee angle time series across 30 strides at all speeds tested, they calculated maximum finite time Lyapunov exponents as $\ln(\text{divergence})/\text{second}$, which introduces a dependency upon stride time. In a study by Stergiou et al. (2004), in which the maximum finite time Lyapunov exponent of knee angle time series was estimated across 100 strides at different speeds as $\ln(\text{divergence})/\text{stride}$, no significant change with increasing speed was found. Although the methods used in the present study resemble those of Stergiou et al. (2004), we did not replicate their main results, perhaps because we analyzed thorax movements, whereas Stergiou et al. (2004) analyzed knee angle time series.

We found different effects of walking speed on walking stability for the different directions. This finding may be somewhat puzzling and appears to be in conflict with previous findings (Dingwell and Marin, 2006), but it is in line with research on changes in trunk coordination with increasing walking speed, showing different speed-dependent effects for different directions (Van Emmerik et al., 2005). As a result, no definite answer can be given to the question whether slow walking is more stable than fast walking. Recently, a new stability measure was introduced in the field of passive dynamic walking. This measure can accurately predict failure to cope with an actual perturbation of a passive dynamic walker since it: “weighs the relevance of the walker's eigenmodes with respect to actual failure modes” (Hobbelen and Wisse, 2007, pp. 7, italics added), implying that information from different sources (i.e. movements in different planes) is weighted with respect to its importance. If we assume that also in human walking some modes (or directions) are more relevant than others when coping with a perturbation, the question arises which of those directions contains the most useful information. While VT movements appear to be the least relevant in this regard, work by Hausdorff (2005) and Maki (1997) suggested that increased variability in the ML direction is a predictor of falls, which could imply that ML movements are more important than AP movements. This conclusion would be consistent with the fact that in walking the base of support is larger in the AP direction than in

the ML direction, as a result of which ML stability may be a limiting factor in balance control (see also Dean et al., 2007). If we take this as a starting point, the limited and inverted U-shaped variation of $\lambda_{S\text{-stride}}$ and the decrease in $\lambda_{L\text{-stride}}$ with increasing walking speed for the ML direction suggests that fast walking may be more stable than slow walking. It must be noted that other studies, using long range correlations as an indicator of stability, reported opposite results, with the comfortable walking speed appearing the most stable region (Jordan et al., 2007a, b). However, our conclusion that faster walking may be more stable than slow walking seems to be in agreement with the finding that the ML center of mass movements decrease with increasing walking speed (Orendurff et al., 2004), which may reflect a more stable gait. Still, the precise meaning of $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$ needs to be determined, as need the mechanism(s) underlying the walking speed effects.

4.3. Relationship between local dynamic stability and variability

Previous studies have demonstrated that stability and variability respond differently to changes in walking speed (Dingwell and Marin, 2006), and there is an ongoing effort to elucidate the relationship between stability and variability in human movement. The positive relationship between $\lambda_{S\text{-stride}}$ and MeanSD found here indicates that the rate of divergence on the short term is correlated with the amount of kinematic variability. Intuitively, this is understandable if we view the MeanSD as an indication of the spatial divergence of two nearest neighbours after one stride. Similar findings were reported in a recent study of local dynamic stability and amount of variability in a passive dynamic walker descending a bumpy slope (Su and Dingwell, 2007). Surprisingly, however, a study comparing treadmill and overground walking (Dingwell et al., 2001) failed to find consistent correlations between $\lambda_{S\text{-stride}}$ and MeanSD. All in all, the exact correspondence between $\lambda_{S\text{-stride}}$ and MeanSD remains unclear, and deserving of further study. The fact that we found no consistent relationship between $\lambda_{L\text{-stride}}$ and MeanSD (there was only a significant relationship for the AP direction) seems to confirm that measures of dynamic stability and amount of variability reflect different properties of walking dynamics (Dingwell et al., 2001, 2007; Dingwell and Marin, 2006; Dingwell et al., 2008), and may intuitively be understood from the fact that not only spatial (i.e. MeanSD), but also temporal variations (i.e. in stride times) as well as their *structure* play a role in the divergence of two points after several strides.

5. Conclusion

The present study suggests that slow walking is not necessarily more stable than fast walking in terms of local dynamic stability. Different conclusions pertain to different planes. The relationship between local dynamic stability and amount of variability observed here suggests that measures of stability and amount of variability may, at least in part, reflect different properties of the dynamics of walking. Moreover, in estimating maximum Lyapunov exponents, great caution should be exerted to avoid methodological pitfalls.

Conflict of interest statement

None of the authors of this paper have any financial and personal relationships with other people or organizations that could inappropriately influence the presented work.

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References

- Bruijn, S.M., van Dieën, J.H., Meijer, O.G., Beek, P.J., 2009. Statistical precision and sensitivity of measures of dynamic gait stability. *Journal of Neuroscience Methods* 178, 327–333.
- Buzzi, U.H., Stergiou, N., Kurz, M.J., Hageman, P.A., Heidel, J., 2003. Nonlinear dynamics indicates aging affects variability during gait. *Clinical Biomechanics* (Bristol, Avon) 18, 435–443.
- Calandre, L., Conde, I., Bermejo Pareja, F., 2005. Gait and stability disorders of the elderly. *Clinical analysis of a series of 259 patients older than 70 years. Neurologia* (Barcelona, Spain) 20, 232–239.
- Dean, J.C., Alexander, N.B., Kuo, A.D., 2007. The effect of lateral stabilization on walking in young and old adults. *IEEE Transactions on Biomedical Engineering* 54, 1919–1926.
- Dingwell, J.B., Cusumano, J.P., 2000. Nonlinear time series analysis of normal and pathological human walking. *Chaos* 10, 848–863.
- Dingwell, J.B., Cusumano, J.P., Cavanagh, P.R., Sternad, D., 2001. Local dynamic stability versus kinematic variability of continuous overground and treadmill walking. *Journal of Biomechanical Engineering* 123, 27–32.
- Dingwell, J.B., Cusumano, J.P., Sternad, D., Cavanagh, P.R., 2000. Slower speeds in patients with diabetic neuropathy lead to improved local dynamic stability of continuous overground walking. *Journal of Biomechanics* 33, 1269–1277.
- Dingwell, J.B., Gu, K.H., Marin, L.C., 2007. The effects of sensory loss and walking speed on the orbital dynamic stability of human walking. *Journal of Biomechanics* 40, 1723–1730.
- Dingwell, J.B., Kang, H.G., 2007. Differences between local and orbital dynamic stability during human walking. *Journal of Biomechanical Engineering* 129, 586–593.
- Dingwell, J.B., Marin, L.C., 2006. Kinematic variability and local dynamic stability of upper body motions when walking at different speeds. *Journal of Biomechanics* 39, 444–452.
- Dingwell, J.B., Robb, R.T., Troy, K.L., Grabiner, M.D., 2008. Effects of an attention demanding task on dynamic stability during treadmill walking. *Journal of Neuroengineering and Rehabilitation* 5, 12.
- Donker, S.F., Beek, P.J., 2002. Interlimb coordination in prosthetic walking: effects of asymmetry and walking velocity. *Acta Psychologica* 110, 265–288.
- Donker, S.F., Beek, P.J., Wagenaar, R.C., Mulder, T., 2001. Coordination between arm and leg movements during locomotion. *Journal of Motor Behavior* 33, 86–102.
- England, S.A., Granata, K.P., 2007. The influence of gait speed on local dynamic stability of walking. *Gait & Posture* 25, 172–178.
- Franca, L.F.P., Savi, M.A., 2001. Distinguishing periodic and chaotic time series obtained from an experimental nonlinear pendulum. *Nonlinear Dynamics* 26, 253–271.
- Fraser, 1986. Using mutual information to estimate metric entropy. In: Mayer-Kress, G. (Ed.), *Dimensions and Entropies in Chaotic Systems*. Springer, Berlin, pp. 82–91.
- Granata, K.P., Lockhart, T.E., 2008. Dynamic stability differences in fall-prone and healthy adults. *Journal of Electromyography and Kinesiology* 18, 172–178.
- Halekoh, U., Hojsgaard, S., Yan, J., 2006. The R package geepack for generalized estimating equations. *Journal of Statistical Software* 15.
- Hausdorff, J.M., 2005. Gait variability: methods, modeling and meaning. *Journal of Neuroengineering and Rehabilitation* 2, 19.
- Hausdorff, J.M., Peng, C.K., Ladin, Z., Wei, J.Y., Goldberger, A.L., 1995. Is walking a random walk? Evidence for long-range correlations in stride interval of human gait. *Journal of Applied Physiology* 78, 349–358.
- Hausdorff, J.M., Purdon, P.L., Peng, C.K., Ladin, Z., Wei, J.Y., Goldberger, A.L., 1996. Fractal dynamics of human gait: stability of long-range correlations in stride interval fluctuations. *Journal of Applied Physiology* 80, 1448–1457.
- Hobbelen, D.G.E., Wisse, M., 2007. A disturbance rejection measure for limit cycle walkers: the gait sensitivity norm. *IEEE Transactions on Robotics* 23, 1213–1224.
- Hurmuzlu, Y., Basdogan, C., 1994. On the measurement of dynamic stability of human locomotion. *Journal of Biomechanical Engineering* 116, 30–36.
- Hurmuzlu, Y., Basdogan, C., Stoianovici, D., 1996. Kinematics and dynamic stability of the locomotion of post-polio patients. *Journal of Biomechanical Engineering* 118, 405–411.
- Jordan, K., Challis, J.H., Newell, K.M., 2007a. Speed influences on the scaling behavior of gait cycle fluctuations during treadmill running. *Human Movement Science* 26, 87–102.
- Jordan, K., Challis, J.H., Newell, K.M., 2007b. Walking speed influences on gait cycle variability. *Gait & Posture* 26, 128–134.
- Kang, H.G., Dingwell, J.B., 2006a. A direct comparison of local dynamic stability during unperturbed standing and walking. *Experimental Brain Research* 172, 35–48.

- Kang, H.G., Dingwell, J.B., 2006b. Intra-session reliability of local dynamic stability of walking. *Gait & Posture* 24, 386–390.
- Kang, H.G., Dingwell, J.B., 2008. Effects of walking speed, strength and range of motion on gait stability in healthy older adults. *Journal of Biomechanics* 41, 2899–2905.
- Kantz, H., Schreiber, T., 1997. *Nonlinear Time Series Analysis*. Cambridge University Press, Cambridge, New York.
- Kennel, M.B., Brown, R., Abarbanel, H.D.I., 1992. Determining embedding dimension for phase-space reconstruction using a geometrical construction. *Physical Review A* 45, 3403–3411.
- Liang, K.Y., Zeger, S.L., 1986. Longitudinal data-analysis using generalized linear-models. *Biometrika* 73, 13–22.
- Lockhart, T.E., Liu, J., 2008. Differentiating fall-prone and healthy adults using local dynamic stability. *Ergonomics* 51, 1860–1872.
- Maki, B.E., 1997. Gait changes in older adults: predictors of falls or indicators of fear. *Journal of the American Geriatrics Society* 45, 313–320.
- Mees, A.I., Judd, K., 1993. Dangers of geometric filtering. *Physica D* 68, 427–436.
- Orendurff, M.S., Segal, A.D., Klute, G.K., Berge, J.S., Rohr, E.S., Kadel, N.J., 2004. The effect of walking speed on center of mass displacement. *Journal of Rehabilitation Research and Development* 41, 829–834.
- Reeves, N.P., Narendra, K.S., Cholewicki, J., 2007. Spine stability: the six blind men and the elephant. *Clinical Biomechanics* (Bristol, Avon) 22, 266–274.
- Riley, M.A., Turvey, M.T., 2002. Variability and determinism in motor behavior. *Journal of Motor Behaviour* 34, 99–125.
- Rosenstein, M.T., Collins, J.J., Deluca, C.J., 1993. A practical method for calculating largest lyapunov exponents from small data sets. *Physica D* 65, 117–134.
- Rubenstein, L.Z., 2006. Falls in older people: epidemiology, risk factors and strategies for prevention. *Age and Ageing* 35 (Suppl. 2), ii37–ii41.
- Scholz, J.P., Schoner, G., 1999. The uncontrolled manifold concept: identifying control variables for a functional task. *Experimental Brain Research* 126, 289–306.
- Stergiou, N., Moraiti, C., Giakas, G., Ristanis, S., Georgoulis, A.D., 2004. The effect of the walking speed on the stability of the anterior cruciate ligament deficient knee. *Clinical Biomechanics* (Bristol, Avon) 19, 957–963.
- Su, J.L.S., Dingwell, J.B., 2007. Dynamic stability of passive dynamic walking on an irregular surface. *Journal of Biomechanical Engineering* 129, 802–810.
- Van Emmerik, R.E., McDermott, W.J., Haddad, J.M., Van Wegen, E.E., 2005. Age-related changes in upper body adaptation to walking speed in human locomotion. *Gait & Posture* 22, 233–239.
- Wisse, M., Schwab, A.L., 2005. Skateboards, bicycles, and three-dimensional biped walking machines: velocity-dependent stability by means of lean-to-yaw coupling. *International Journal of Robotics Research* 24, 417–429.
- Zeger, S.L., Liang, K.Y., 1986. Longitudinal data analysis for discrete and continuous outcomes. *Biometrics* 42, 121–130.