Is slow walking more stable?

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A B S T R A C T

Several efforts have been made to study gait stability using measures derived from nonlinear time-series analysis. The maximum finite time Lyapunov exponent ($\lambda_{\text{max}}$) quantifies how a system responds to an infinitesimally small perturbation. Recent studies suggested that slow walking leads to lower $\lambda_{\text{max}}$ 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 ($\lambda_{\text{short}}$ and $\lambda_{\text{long}}$), and mean standard deviation (MeanSD) were calculated. $\lambda_{\text{short}}$ 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. $\lambda_{\text{long}}$ 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 $\lambda_{\text{l}}$ and MeanSD were found for all directions, while $\lambda_{\text{ML}}$ and MeanSD were correlated negatively in the AP direction. The different effects of walking speed on $\lambda_{\text{short}}$ and $\lambda_{\text{long}}$ 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 $\lambda_{\text{short}}$ 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 ($\lambda_{\text{max}}$), 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, $\lambda_{\text{max}}$ should be $\leq 0$, implying that infinitesimally close trajectories will, on average, not diverge. Positive values of $\lambda_{\text{max}}$ imply that such trajectories will on average diverge, indicating less stable patterns. In most gait research, two values of $\lambda_{\text{max}}$ are reported (Fig. 1): one reflecting how the system responds over a shorter time period (often 1 stride cycle, termed $\lambda_{\text{s}}$) and the other reflecting how the system responds over a longer time period (usually 4–10 stride cycles, termed $\lambda_{\text{l}}$).

Several recent studies have examined the effects of walking speed on local dynamic stability (Dingwell and Marin, 2006;...
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 $\lambda_{\text{max}}$ (Bruinj 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 $\lambda_{\text{max}}$. Accordingly, England and Granata (2007) estimated $\lambda_{\text{s}}$ for the same number of strides for all walking speeds, but instead of expressing $\lambda_{\text{s}}$ as $\lambda_{\text{s}}$ per stride ($\lambda_{\text{s-stride}}$), which would appear appropriate (Dingwell and Cusumano, 2000; Dingwell et al., 2001; Dingwell and Marin, 2006; Kang and Dingwell, 2006b), they estimated $\lambda_{\text{s}}$ per second ($\lambda_{\text{s-second}}$), and thus introduced an unwanted dependency of $\lambda_{\text{s}}$ 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 Schoner, 1999). Based on a previous methodological study (Brujin 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. $\lambda_s$ versus $\lambda_L$).

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 (Biorstr Giant™, 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 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

$$S(t) = \{q(t), q(t + \tau), \ldots, q(t + d_E - 1 + \tau)\}$$

with $S(t)$ representing the $d_E$-dimensional state vector, $q(t)$ the original 1-dimensional data, $\tau$ 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

$$y(i) = \frac{1}{N} \sum_{j} \ln(d_E(i,j))$$

where $d_E(i,j)$ represents the Euclidean distance between the jth pair of nearest neighbours after i discrete time steps (i.e. $d_E(t)$) and ($\ldots$) 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, $\lambda_s$-stride, see Fig. 1) and from 400 to 1000 samples (approximately 4–10 strides, $\lambda_L$-stride). We chose to estimate $\lambda_s$-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 $\lambda_s$-stride were observed for the different movement directions (Fig. 2, top panel). In the AP direction, $\lambda_s$-stride decreased with increasing walking speed, with a significant linear component for the effect of speed (Table 1, upper panel). In the ML direction, $\lambda_s$-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, $\lambda_s$-stride increased with increasing walking speed, again with significant linear and quadratic components for the effect of speed.

As was the case for $\lambda_s$-stride, different effects of walking speed on $\lambda_L$-stride were observed for the different directions (Fig. 2, bottom panel). $\lambda_L$-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, $\lambda_L$-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 $\lambda_s$-stride, for all directions (Fig. 3). A consistent relationship between $\lambda_s$-stride and MeanSD was found for all directions, with higher $\lambda_s$-stride Coinciding with higher MeanSD (Table 2). For $\lambda_L$-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.

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

Furthermore, we found a consistent relationship between $\lambda_S$-stride and MeanSD, with higher $\lambda_S$-stride coinciding with higher MeanSD. No consistent relationship was found between $\lambda_L$-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 $\lambda_S$-stride and $\lambda_L$-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

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*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; England and Granata, 2007), who reported that actual walking speeds and cadences were not reported. Thus, 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 (Brujin 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(divergence)/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(divergence)/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.

### 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 (Brujin 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(divergence)/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(divergence)/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.

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### Table 2

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<th>MeanSD</th>
<th>b (s.e.)</th>
<th>P</th>
</tr>
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<tr>
<td>L-stride</td>
<td>AP</td>
<td>19.191</td>
<td>(2.573)</td>
</tr>
<tr>
<td></td>
<td>ML</td>
<td>8.308</td>
<td>(3.292)</td>
</tr>
<tr>
<td></td>
<td>VT</td>
<td>27.576</td>
<td>(5.838)</td>
</tr>
<tr>
<td>S-stride</td>
<td>AP</td>
<td>-1.119</td>
<td>(0.360)</td>
</tr>
<tr>
<td></td>
<td>ML</td>
<td>-0.319</td>
<td>(0.233)</td>
</tr>
<tr>
<td></td>
<td>VT</td>
<td>0.355</td>
<td>(0.336)</td>
</tr>
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Models used are MeanSD = a + b \times L-stride, and MeanSD = a + b \times S-stride. 

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.
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 L–stride and the decrease in A–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 L–stride and A–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 L–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 indicator 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 L–stride and MeanSD. All in all, the exact correspondence between L–stride and MeanSD remains unclear, and deserving of further study. The fact that we found no consistent relationship between L–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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