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Measures of dynamic stability: Detecting differences between walking overground and on a compliant surface

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ABSTRACT

Numerous measures of dynamic stability have been proposed to gauge fall risk in the elderly, including stride interval variability and variability of the center of mass. However, these measures have been deemed inadequate because they do not take into account temporal information. Therefore, research on the measurement of dynamic stability has turned to other analysis methods such as stride interval dynamics and the maximum Lyapunov exponent. Stride interval dynamics reflect the statistical persistence of an individual's stride interval time series and the Lyapunov exponent quantifies local dynamic stability – the sensitivity of the system to infinitesimal perturbations. In this study, we compare the ability of these measurement tools to detect changes between overground and compliant-surface walking, a condition known to affect stability, to determine their aptness as measures of dynamic stability. Fourteen able-bodied participants completed three 15 min walks, two overground and one on a compliant surface. Our results show that the Lyapunov exponent may be more sensitive to gait changes than stride interval dynamics and gait variability measures.

1. Introduction

Falls are a major cause of morbidity and mortality in older adults (Hausdorff, Rios, & Edelberg, 2001; Hill, Schwarz, Flicker, & Carroll, 1999; Kannus et al., 1999). For the elderly population, up to 70% of these falls occur during walking (Cali & Kiel, 1995; Menz, Lord, & Fitzpatrick, 2003; Norton,

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Campbell, Lee-Joe, Robinson, & Butler, 1997), often leading to hip fractures and subsequent hospitalization (Hausdorff et al., 2001). It is therefore important to screen for high-risk individuals so that interventions can be put in place to prevent falls. One method of gauging fall risk is to quantify dynamic stability – the ability to maintain balance during locomotion.

Two examples of traditional measures of dynamic stability are stride interval variability (Hausdorff, Edelberg, Mitchell, Goldberger, & Wei, 1997; Hausdorff et al., 2001) and the variability of the center of mass, as quantified by the root-mean-square (RMS) of lower trunk accelerations (Moe-Nilssen, 1998a). The term gait variability will be used to refer to these two measures. In recent literature, it has been suggested that these measures are inadequate because they do not take into consideration temporal information (Buzzi & Ulrich, 2004; England & Granata, 2007). Measures of gait variability assume statistical independence of data points and hence, previous states of the locomotor system are ignored (Buzzi & Ulrich, 2004). Therefore, research on the measurement of dynamic stability has recently focused on other analysis methods in an attempt to quantify temporal fluctuations in gait and provide further insight into the locomotor control system (Bruijn, van Dieën, Meijer, & Beek, 2009a; Buzzi & Ulrich, 2004; Chang, Shaikh, & Chau, 2009; Dingwell & Cusumano, 2000; Dingwell, Cusumano, Cavanagh, & Sternad, 2001; England & Granata, 2007; Gates & Dingwell, 2007; Hausdorff, Cudkowicz, Firtion, Wei, & Goldberger, 1998; Hausdorff, Mitchell, et al., 1997; Hausdorff et al., 1996; Jordan, Challis, Cusumano, & Newell 2009; Jordan, Challis, & Newell, 2007; West & Griffin, 1999). Stride interval dynamics and the maximum Lyapunov exponent are two such analysis methods. Collectively, these two measures will be referred to as an individual's gait dynamics.

Stride interval dynamics is the statistical persistence of the temporal fluctuations within an individual's stride interval time series as measured by α, a scaling exponent quantified by detrended fluctuation analysis (DFA) (Chang et al., 2009). Unlike measures of gait variability, DFA does not assume statistical independence and attempts to quantify the degree of correlation within a data set. Hausdorff et al. discovered that the temporal structure of stride-to-stride fluctuations are significantly different between able-bodied individuals ($\alpha \sim 0.8$–1.0) and patients with Parkinson's and Huntington's diseases who typically present with lower α values (Hausdorff, Mitchell, et al., 1997; Hausdorff et al., 1996, 2000). Herman et al. revealed that the statistical persistence of stride interval fluctuations could distinguish fallers from non-fallers (Herman, Giladi, Gurevich, & Hausdorff, 2005), whereas stride interval variability failed to do so. Thus, this measure may provide insight into the neuromuscular control system. Furthermore, stride interval dynamics were found to be influenced by gait speed (Jordan et al., 2007) and the use of a handrail during treadmill walking (Chang et al., 2009). Taken all together, stride interval dynamics intrinsic to natural gait seem to be influenced by the ability of the locomotor system to maintain dynamic stability. Lower α values (i.e., $\alpha \approx 0.5$) seem to be indicative of dynamic instability. However, the interpretation of higher values (i.e., $\alpha > 0.5$) is still unclear since children, whose gait dynamics are yet to reach full maturity, exhibit higher values than young able-bodied adults (Hausdorff, Zemany, Peng, & Goldberger, 1999), and faster and slower walking paces yield higher values than preferred walking paces (Jordan et al., 2007).

The maximum Lyapunov exponent quantifies local dynamic stability – the sensitivity of the system to infinitesimal perturbations (Dingwell et al., 2001). Dingwell et al. (2001) presumed that it is these perturbations that traditional gait variability measures are attempting to quantify. Since this method entails measuring the divergence of movement trajectories at multiple instances in time, it provides a more encompassing analysis of the temporal fluctuations in the locomotor system's stability than traditional measures. Hence, in contrast to DFA which assumes an underlying stochastic process, this method assumes that the process is deterministic. Recent studies have shown that the Lyapunov exponent is influenced by gait speed (Dingwell & Marin, 2006; England & Granata, 2007; Kang & Dingwell, 2008). Generally, local dynamic stability was shown to be enhanced at slower speeds (Dingwell & Marin, 2006; England & Granata, 2007; Kang & Dingwell, 2008), however a more recent study suggests that slow walking may not be necessarily more stable (Bruijn et al., 2009a). Buzzi and Ulrich (2004) showed that children with Down syndrome exhibited decreased local dynamic stability. In addition, Lockhart and Liu (2008) found that fall-prone elderly individuals exhibited significantly lower local dynamic stability than their healthy control counterparts.

Stride interval variability, RMS of lower trunk accelerations, stride interval dynamics, and the Lyapunov exponent have all been individually employed to quantify dynamic stability. However, as outlined above, they each have very different underlying assumptions about processes generating the time series data. Hence, an analysis contrasting the different methods may be particularly enlightening. Although Bruijn, van Dieën, Meijer, and Beek (2009b) performed an elaborate analysis to test the ability of the Lyapunov exponent to detect changes in walking conditions, a study to compare the ability of all these measures to detect changes in dynamic stability has not been performed to date. Thus, in this study, we compare the ability of each measure to detect changes between walking overground and walking on a compliant surface for able-bodied individuals to determine their aptness as measures of dynamic stability.

2. Methods

2.1. Participants

Fourteen able-bodied adult participants (five male, nine female) were recruited from the Bloorview Research Institute at Bloorview Kids Rehab in Toronto as a convenience sample. Participants had normal or corrected-to-normal vision and were all right-foot dominant. All participants had no self-reported musculoskeletal or neurological disorders that could affect their gait performance. Mean age was 25.2 ± 3.0 (*SD*) years. Mean height and mass were 1.69 ± 0.09 (*SD*) m and 64.9 ± 12.7 (SD) kg, respectively. The study was approved by the Research Ethics Board of Bloorview Kids Rehab, Toronto, Canada. All participants provided informed written consent prior to participation in the study.

2.2. Apparatus

Two ultra-thin, force-sensitive resistors (FSRs; models #402 and #406, Interlink Electronics, California, USA) were used to capture the time of heel-strike and toe-off events. The FSRs were adhered below the participant's right shoe insole: the circular FSR (model #402, diameter: 0.5 in.) was placed underneath the heel of the foot and the square FSR (model #406, side: 1.5 in.) was placed underneath the ball of the foot (head of 1st metatarsal).

Linear accelerations of the lower trunk were measured along three orthogonal axes (anterio-posterior, medio-lateral, and vertical) with a tri-axial capacitive micromachined accelerometer (model MMA7260Q, Freescale Semiconductor, Texas, USA) set to a sensitivity range of ±1.5 g. The accelerometer was fixated onto an adjustable belt with Velcro™. The accelerometer was then placed snuggly over the L3 segment of the lumbar spine, close to the standing center of mass, and the belt was firmly tightened and additionally clipped in place to ensure it did not loosen during the walking trials.

The FSRs and accelerometer were connected to a customized, battery-operated portable datalogger containing an R-Engine-A processor board (Tern Inc., California, USA). The signals were sampled at 200 Hz and stored in a 128 MB CompactFlash card. The datalogger was carried in a custom-made small backpack firmly fitted to the participant, taking care not to interfere with natural gait movements. The entire apparatus weighed 720 g.

2.3. Protocol design

Participants walked in three consecutive trials, each for 15 min on a circular track (circumference: 34 m, walkway width: 1.2 m). The sequence of walking trials was as follows: (1) overground walking, (2) walking on soft collegiate gym mats (QUED, Quebec, Canada), and (3) overground walking again. The purpose of the third trial was to examine if gait dynamics were affected from recently walking on a compliant surface. The collegiate gym mats were made of 2.2 lb., 100ILD 2″ thick polyurethane foam reinforced by a 18 oz. fire resistant vinyl covering. The mats were fixed together with 2″ wide velcro fasteners.

Participants walked at a self-selected comfortable walking speed via instruction to "walk at a comfortable pace". The participants were given a 2 min practice period before each walking trial for the purpose of familiarization. Participants were given 5 min to rest between trials.

2.4. Assessment of gait dynamics

The stride interval time series was extracted from the footswitch data by employing a probabilistic stride interval extraction algorithm that locates the initial time of heel strikes through changes in magnitude and slope of the force (Chau & Rizvi, 2002). To minimize "start-up" effects, the first 15 s of the stride interval time series was excluded from analysis. Since the mean number of strides was decreased on the compliant surface condition compared to the overground conditions, the stride number of the overground conditions was trimmed to the number of strides in the compliant condition for each participant by truncating strides from the end of the stride interval time series.

Subsequently, detrended fluctuation analysis was applied to the stride interval time series to quantify its temporal dynamics. This analysis forms an accumulated sum of the time series which is sectioned into a number of window sizes. The window sizes used were 16 to $N/9$, where N is the total number of data points in the time series. This range was chosen because empirical findings reveal that it gives a stable estimate of the scaling exponent α (Damouras, Chang, Sejdić, & Chau, 2010). Subsequently, the log of the average size of the fluctuation at each window size is plotted against the log of the window size. The slope of this line yields α. Detrended fluctuation analysis has proven useful in detecting the degree of correlation in highly non-stationary physiological data (Herman et al., 2005). The spurious detection of correlations that are artifacts of non-stationarities is also avoided with DFA (Herman et al., 2005). Methodological details regarding DFA can be found in Chau (2001), Goldberger et al. (2002), Hausdorff et al. (1996), and Hausdorff, Mitchell, et al. (1997). However, it is worthwhile to point out that $\alpha = 0.5$ indicates a completely uncorrelated process (i.e., white noise); $0.5 < \alpha < 1.0$ is indicative of statistical persistence; $\alpha < 0.5$ indicates statistical anti-persistence.

Mean walking speed was calculated by multiplying the number of completed laps by the circumference of the circular track and dividing by time elapsed for those laps. Mean stride length was calculated by dividing the total distance by the number strides taken. Stride interval variability was calculated by determining the coefficient of variation (SD/mean $\times$ 100%) of the extracted stride interval time series (Hausdorff et al., 2001; Maki, 1997).

2.5. Accelerometry

The accelerometer was statically calibrated against gravity by positioning each of the sensing axes perpendicular to the horizontal surface, first pointing up, and then down, to estimate the ±1 g values. The statically calibrated acceleration signals were subsequently corrected for tilt by utilizing an approximation algorithm derived by Moe-Nilssen (1998a). Since the acceleration signals were transformed to give a mean of zero due to the correction for tilt, the acceleration RMS is essentially the standard deviation of the signal.

2.6. Maximum Lyapunov exponent

Local stability, quantified by the maximum Lyapunov exponent, is defined as the sensitivity of the system to small perturbations and its dependence on initial conditions (Dingwell & Cusumano, 2000; Rosenstein, Collins, & DeLuca, 1993). The exponent quantifies the exponential rate of divergence of adjacent trajectories in phase space. The proximity of adjacent paths is indicative of local stability and hence, the lower the Lyapunov exponent, the more stable the system.

To estimate the Lyapunov exponent for the considered series, we used the approach outlined in Dingwell and Cusumano (2000) and Rosenstein et al. (1993). The method is based on the assumption that 1-D measurements contain sufficient information about the underlying dynamics of the system. Using these measurements we can reconstruct a multi-dimensional state space via a so-called time-delayed coordinate approach (Rosenstein et al., 1993). The approach requires estimation of two parameters, minimum embedding dimension (d_E) and time delay (Rosenstein et al., 1993).

In the present study, the time delay was estimated by using the autocorrelation function (Rosenstein et al., 1993), while the estimation of the embedding dimension was performed using the global false nearest neighbor analysis (Kennel, Brown, & Abarbanel, 1992). Our numerical analysis indicated that the average number of embedding dimensions was equal to five. Similar results were observed in previous gait studies (Dingwell & Cusumano, 2000; Dingwell et al., 2001); hence, we used $d_E = 5$ for all of our analyses. Upon successful estimation of these two parameters, we proceeded with the calculation of the largest Lyapunov exponent.

In particular, the exponent was calculated as the slope of the average logarithmic divergence of the neighboring trajectories in the state space (Dingwell & Cusumano, 2000; Dingwell et al., 2001; Rosenstein et al., 1993). Using the procedure outlined in Dingwell et al. (2001), we calculated short-term exponents (λ_{ST}) and long-term exponents (λ_{LT}). λ_{ST} was calculated as the slope of the average logarithmic divergence between 0 and 1 stride, while λ_{LT} represents the slope of the average logarithmic divergence between 4 and 10 strides. The *x*-axis of the divergence curve was in stride cycles. It should be mentioned that because this algorithm was shown to be robust for small data sets (Rosenstein et al., 1993), each series was divided into segments with equal number of strides (in this case, 100 strides). Hence, the reported λ values represent average values (Dingwell & Cusumano, 2000; Dingwell et al., 2001).

2.7. Statistics

After checking assumptions of normality and homoscedasticity, either a one-way ANOVA or Kruskal–Wallis test was used to determine significant differences between the three walking trials for the scaling exponents, mean stride interval, mean stride length, gait speed, stride interval variability, RMS of the accelerations, and Lyapunov exponents. Subsequently, pairwise comparisons between groups employed the paired *t*-test or Mann–Whitney *U*-test. The intraclass correlation coefficient $(-1, 1)$ was used to quantify the agreement between the α values derived from the stride interval time series of heel-strikes and toe-offs. A *p*-value of .05 (two-tailed) was adjusted by the Bonferroni correction to yield a stricter significance level of .0167 for determining pairwise group differences. Statistical analysis was performed using MATLAB for Windows (The MathWorks, version R2008a).

3. Results

Stride interval variability was not significantly different between the first overground walk (OG1) and walking on the compliant surface (CS) ($p > .3$) (Table 1). However, the stride interval variability of the second overground walk (OG2) was significantly decreased compared to the CS condition ($p < .01$). Gait speed was slightly lower on the compliant surface (Table 1), though it was not significantly different from OG1 ($p > .3$) or OG2 ($p > .2$). The mean stride interval and mean stride length were both significantly longer ($p < .003$ and $p < .0001$, respectively) on the CS condition as compared to both overground walks (Fig. 1).

Table 1
Gait parameters and stride interval dynamics of able-bodied participants during the three walking conditions.

	OG1	CS	OG2
Gait speed (m/s)	1.27 ± 0.21	1.24 ± 0.22	1.27 ± 0.19
Stride interval variability – *CV* (%)	1.84 ± 0.76	1.96 ± 0.62	1.41 ± 0.36[†]
Scaling exponent (α) – Heel	0.97 ± 0.14	0.92 ± 0.17	0.96 ± 0.12
Scaling exponent (α) – Toe	0.97 ± 0.14	0.91 ± 0.16	0.97 ± 0.12

Values are means ± *SD*; *CV*: coefficient of variation.
OG1: First overground walk, CS: Compliant surface, OG2: Second overground walk.
[†] $p < .0167$ for pairwise comparison with the CS condition.

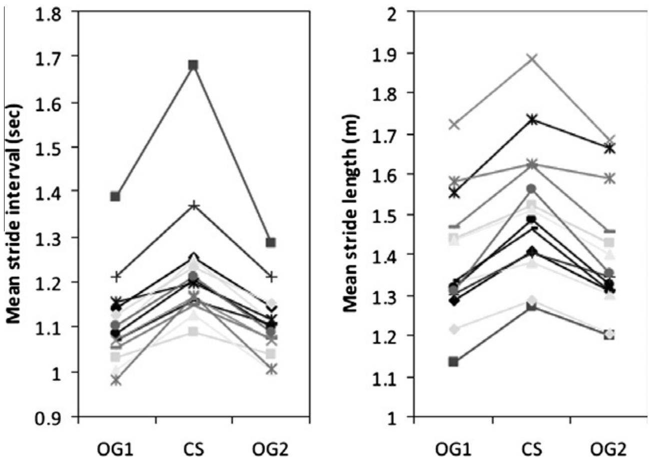

Fig. 1. Comparison of mean stride interval (sec) and mean stride length (m) during OG1, CS and OG2. Each line represents one participant. The mean stride interval and mean stride length in the CS condition were both significantly longer ($p < 0.003$ and $p < 0.0001$, respectively) than the OG conditions.

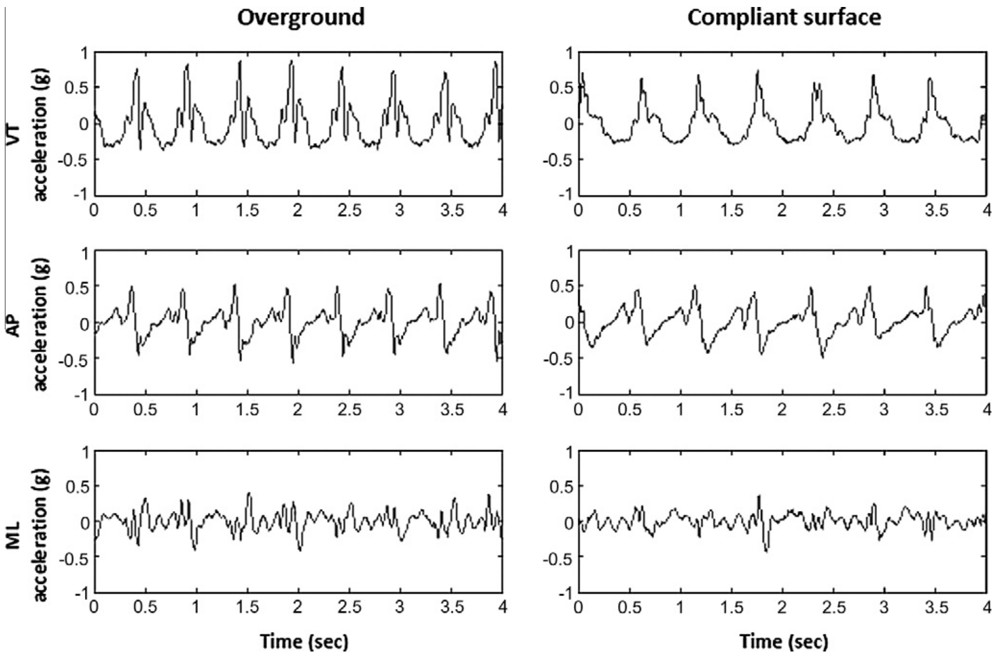

Fig. 2. Typical raw lower trunk accelerations in the VT, AP and ML axes during overground walking (left) and walking on a compliant surface (right) for an able-bodied young adult.

Plots of typical lower trunk accelerations in the vertical (VT), anterio-posterior (AP), and medio-lateral (ML) directions during each of the three walking conditions are shown in Fig. 2. The RMS AP acceleration for the first overground walk, OG1, was significantly different ($p < .004$) from that of the CS condition (Table 2). The RMS ML acceleration of the second overground walk, OG2, was also

Table 2
Mean RMS of lower trunk accelerations.

	OG1	CS	OG2
Anterio-posterior	1.76 ± 0.27†	1.91 ± 0.26	1.83 ± 0.19
Medio-lateral	1.31 ± 0.44	1.19 ± 0.32	1.39 ± 0.44†
Vertical	2.32 ± 0.65	2.19 ± 0.56	2.38 ± 0.64

Values are means ± $SD \times 10^{-1}$ g.
† $p < .0167$ for pairwise comparison with the CS condition.

significantly different from that of the CS condition ($p < .002$). No other significant differences were found between CS and OG1 or OG2 RMS values.

The scaling exponent α, when measured with the heel or toe FSR, did not show a significant difference ($p > .1$) between any of the three walking conditions (Table 1). The intraclass correlation coefficient revealed that the α derived from heel and toe FSR signals of each participant were in high agreement ($ICC > .98$ and $p < .0001$ for all three conditions). Computation of the scaling exponent using the typical window size range of 4 to N/4 yielded similar results.

The λ_{LT} showed a significant difference between CS and both OG conditions for ML ($p < .001$) and VT ($p < .015$) trunk accelerations (Fig. 3). The λ_{LT} values of the AP trunk acceleration (A_{AP}) signal and the

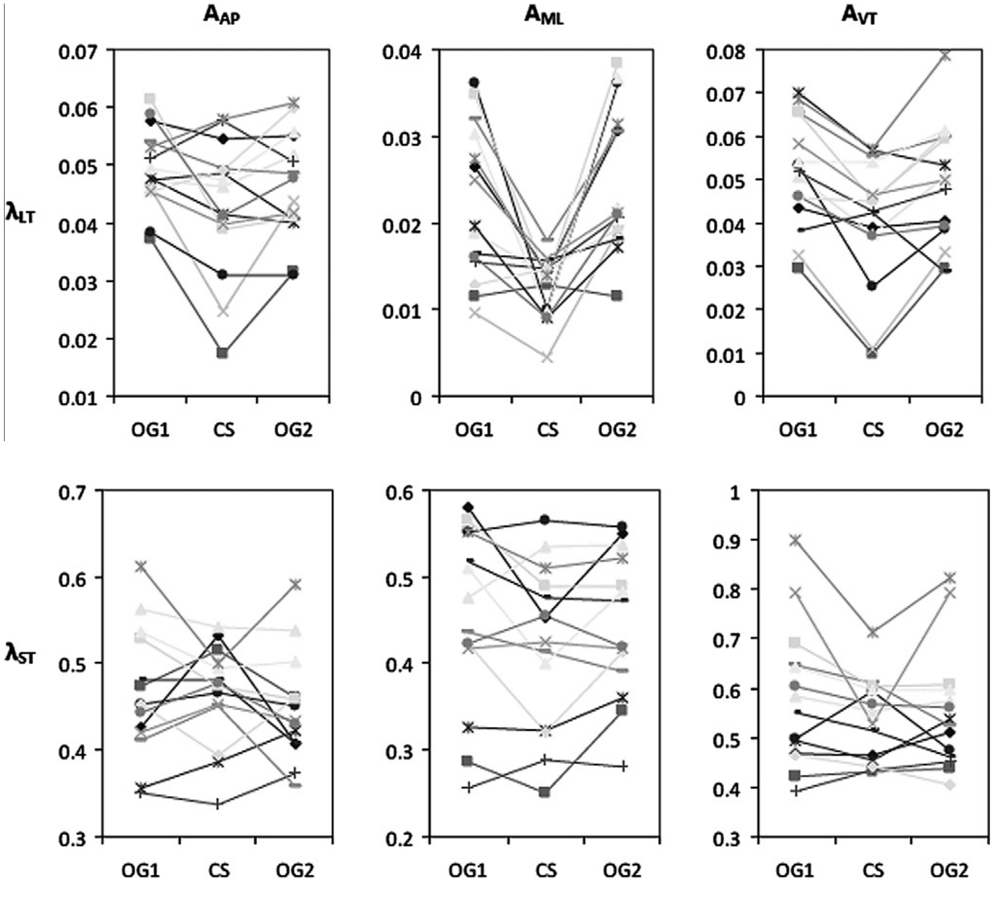

Fig. 3. Long-term and short-term Lyapunov exponents in the anterio-posterior (A_{AP}), medio-lateral (A_{ML}) and vertical (A_V) directions. Each line represents one participant.

λ_{ST} values for all three trunk acceleration signals did not show any significant differences between the CS condition and OG1 or OG2 ($p > .05$).

4. Discussion

In this study, we examined the changes in stride interval variability, RMS of lower trunk accelerations, stride interval dynamics as measured by DFA, and maximum Lyapunov exponents of lower trunk accelerations in able-bodied young adults between overground walking and walking on a compliant surface. The key result was that only λ_{LT} of the ML and VT trunk accelerations could consistently differentiate between OG and CS conditions.

Previous research showed that stride interval variability can distinguish fallers from non-fallers (Hausdorff, Edelberg, et al., 1997; Hausdorff et al., 2001). However, more recently it has been shown that nonlinear analysis methods, such as DFA may be more sensitive to changes in an individual's stability (Chang et al., 2009; Herman et al., 2005). Perhaps the capacity of stride interval variability to differentiate among different patterns is limited because it treats each gait cycle independently (Buzzi & Ulrich, 2004). Stride interval variability does not take into consideration temporal correlations or point-to-point fluctuations in movement trajectories, which provide insight into the control of the neuromuscular system. Thus, unsurprisingly, in the present study, stride interval variability did not show a significant difference between OG1 and the CS condition. However, a decrease in variability was observed in OG2 possibly due to a transfer effect from recently walking on a compliant surface.

The center of mass (COM) has been described as a global indicator of balance (Moe-Nilssen, 1998b; Winter, 1995). Typically, higher RMS accelerations are associated with walking instability (Menz et al., 2003; Moe-Nilssen, 1998b). However, the RMS accelerations in the present study were unable to consistently distinguish between OG and CS conditions. Able-bodied individuals are known to employ numerous biomechanical strategies to adapt to walking on a compliant surface (MacLellan & Patla, 2006; Marigold & Patla, 2005). Marigold and Patla (2005) revealed that flexion of the knee was increased to maintain toe clearance and that peak vertical COM was lower when walking on a compliant surface than when walking overground. This lowering of the vertical COM peak provides a more stable posture (MacLellan & Patla, 2006). Subsequently, MacLellan and Patla (2006) showed that step width, step length, and step time all increased when walking on a compliant surface as a compensatory reaction to widen the base of support and provide better control of the COM. These proactive and reactive motor control adaptations may have contributed to attenuations in COM accelerations on the compliant surface in the present study.

Although stride interval dynamics have the capacity to distinguish between able-bodied controls and individuals with Parkinson's disease and Huntington's disease (Hausdorff, Cudkowicz, Firtion, Wei, & Goldberger, 1998; Hausdorff, Mitchell, et al., 1997; Hausdorff et al., 2000), and fallers from non-fallers in patients with higher-level gait disorders (Herman et al., 2005), it could not distinguish overground walking from walking on a compliant surface for able-bodied individuals. Similarly, Gates and Dingwell (2007) found that stride interval dynamics were not significantly altered between patients with peripheral neuropathy and controls.

In addition, the scaling exponents of the toe-off time series were in high agreement with the scaling exponents derived from the heel-strike time series. This finding shows that scaling exponents derived from toe-off time series can be used as an alternative measure for stride interval dynamics. This is especially important for studies involving children with cerebral palsy who commonly have equinus (i.e. heavy-toed gait) (Gage, 1991).

The λ_{LT} of the ML and VT lower trunk accelerations were significantly decreased on the compliant surface as compared to both OG conditions. Although this seems counterintuitive, Dingwell and Cusumano (2000) also reported that individuals with peripheral neuropathy exhibited lower λ_{LT} values for upper body accelerations than control subjects. They proposed that this improvement in local dynamic stability was attributed to a decrease in gait speed (Dingwell & Cusumano, 2000). However, in our study, gait speed decreased only slightly on the CS condition, but not significantly. Post hoc ANOVA analysis revealed that the change in stride interval during the compliant surface condition may be a covariate influencing λ_{LT} in the ML and VT directions. This suggests that increased mean stride intervals may have possibly contributed to the decreased λ_{LT} value. Another possible covariate is increased cautiousness, resulting in a conscious compensatory response that may in turn enhance local dynamic stability (Lee & Hidler, 2008; Prokop, Schubert, & Berger, 1997; Stolze et al., 1997). It would be enlightening if future studies investigate the local dynamic stability of elderly individuals with fear of falling.

This study demonstrated that walking on a compliant surface can be distinguished from overground walking by the maximum Lyapunov exponent. Stride interval variability, RMS trunk accelerations and stride interval dynamics seem to be less sensitive to changes in surface compliance. The inability of gait variability measures (i.e., stride interval variability and RMS trunk accelerations) to distinguish between overground walking and walking on a compliant surface further supports the widely accepted notion that traditional measures of variability are inadequate to quantify dynamic stability (Buzzi & Ulrich, 2004; Dingwell & Cusumano, 2000; Dingwell et al., 2001; England & Granata, 2007; Lockhart & Liu, 2008). Walking is a dynamic condition and thus measures should reflect both time and movement (England & Granata, 2007).

We recognize that stride interval dynamics quantifies temporal fluctuations (time component) in an individual's stride interval time series (kinematic component). However, it seems that temporally correlated strides are generated regardless of the system's local dynamic stability. As a note, the resulting scaling exponents in this study were considerably higher than previous studies investigating stride interval dynamics (Frenkel-Toledo et al., 2005; Hausdorff et al., 1996, 2000; Hausdorff, Mitchell et al., 1997; Herman et al., 2005; Jordan et al., 2007). This increase in α values might be attributed to a repetitive, circular walking of participants around the mats. Similar behavior has been observed in the analysis of grip forces exerted during different drawing or handwriting tasks (Fernandes & Chau, 2008). In particular, higher α values were observed while participants conducted a repetitive circle-drawing task as opposed to a linear handwriting task.

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