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Local Dynamic Stability Versus Kinematic Variability of Continuous Overground and Treadmill Walking

This study quantified the relationships between local dynamic stability and variability during continuous overground and treadmill walking. Stride-to-stride standard deviations were computed from temporal and kinematic data. Maximum finite-time Lyapunov exponents were estimated to quantify local dynamic stability. Local stability of gait kinematics was shown to be achieved over multiple consecutive strides. Traditional measures of variability poorly predicted local stability. Treadmill walking was associated with significant changes in both variability and local stability. Thus, motorized treadmills may produce misleading or erroneous results in situations where changes in neuromuscular control are likely to affect the variability and/or stability of locomotion.
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1 Introduction

Human gait is typically analyzed by normalizing and averaging together data from a number of isolated and independent strides. This approach, however, is not well suited to addressing the fundamental control task of locomotion: that of maintaining dynamic stability. Focusing on the events that occur during an average stride implicitly assumes that each stride of locomotion is generated independently of past and future strides and that stride-to-stride variations are random. However, stride-to-stride variations in muscle force-time histories in cats are systematically related to step cycle durations [1]. In continuous human walking, consecutive stride times are correlated over a wide range of time scales [2] and kinematic fluctuations are statistically distinguishable from linearly correlated Gaussian noise [3]. Furthermore, passive dynamic walking machines can exhibit chaotic behavior [4,5], producing nonrepeating but globally stable walking patterns of deterministic origin. Thus, a complete description of locomotor control requires an understanding not only of how a single stride is generated, but also of how movements are controlled from one stride to the next.

To understand how stability is maintained during locomotion, quantitative measures of dynamic stability are needed. Several authors have proposed ''indices of stability'' that quantify various aspects of locomotor variability [6–8]. Indeed, increases in locomotor variability have been associated with increased fall risk in the elderly [9] and with degenerative basal ganglia disorders [10]. However, while variability is often equated with stability, there is little foundation for this assumption. Standard deviations only quantify the average differences between strides, independent of the temporal order in which strides occur. Such measures contain no information about how the locomotor control system responds to perturbations either within or across strides. This suggests that more precise definitions of dynamic stability are required [3].

In the present context, ''stability'' is defined as the sensitivity of a dynamic system to perturbations. ''Global stability'' refers to the ability of the system to accommodate finite perturbations (which might occur during a slip or trip). ''Local stability'' refers to the sensitivity of the system to infinitesimal perturbations. The natural fluctuations that occur during locomotion reflect precisely these types of local perturbations. It is presumably the effects of such infinitesimal perturbations that measures of gait variability are attempting to quantify. The locomotor control system must adjust for such perturbations at least within the current stride, and possibly across subsequent strides. The first goal of the present study was to demonstrate that the processes responsible for maintaining local stability of walking act across multiple consecutive strides of gait. It was hypothesized that measures of local dynamic stability would quantify fundamentally different aspects of locomotor control than traditional measures of variability.

The notion of directly quantifying local stability from experimental data is not entirely new. Floquet multipliers were used to quantify stride-to-stride local stability in healthy subjects and post-polio patients [11,12]. However, Floquet theory assumes exactly periodic motion, which is not entirely valid for human walking [2,3]. The present study quantified local stability by estimating maximum finite-time Lyapunov exponents, which are similar to Floquet multipliers, but do not require the assumption of periodicity.

To make a proper estimate of finite-time Lyapunov exponents experimentally, it is necessary to collect time series data for a large number of consecutive strides of gait. Motorized treadmills could be useful in this regard because they allow many consecutive strides to be sampled using existing gait analysis technologies. However, the validity of comparing treadmill and overground locomotion has been an issue of debate for many years. Treadmill locomotion has been associated with shorter stride lengths, increased cadences [13,14], and changes in walking kinematics [15] and ground reaction forces [16]. However, several studies have reported minimal or no differences between the two tasks for similar variables [13–15]. There are no theoretical mechanical differences between walking on an ideal treadmill (i.e., rigid surface and constant belt speed) and walking overground [17]. Experimentally, however, intrastride variations in instantaneous treadmill belt speed can alter locomotor kinematics [18,19]. More importantly for the present context, several studies have

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suggested that treadmills may artificially reduce the natural variability of locomotor patterns [20,15,21]. It was therefore hypothesized that, compared to overground walking, walking on a motorized treadmill would reduce stride-to-stride variability and would also reduce the sensitivity of the locomotor system to local perturbations, thereby stabilizing locomotor kinematics.

2 Methods

2.1 Experimental Procedures. Ten healthy subjects (5 males and 5 females; mean age $=27.10\pm3.25$ yr; height $=1.71\pm0.09$ m; and weight $=64.85\pm12.47$ kg) gave informed consent before participating. Each subject underwent a screening exam (health history, height, weight, blood pressure, and lower extremity passive ranges of motion) to rule out any history of medications, illnesses, surgeries, or other injuries that may have affected their gait.

A self-contained programmable "DataLogger" collected kinematic data during continuous walking. The DataLogger was based on Tattletale Model 8 hardware (Onset Computer, Inc., Pocasset, MA), which incorporated a microprocessor and 8-channel 12-bit A/D converter, interfaced to a 15 Mb Flash RAM card. The DataLogger was attached to a lightweight (<2.5 kg) harness that did not interfere with normal walking (Fig. 1). Strain gage electrogoniometers (Penny & Giles, Inc., Santa Monica, CA) measured sagittal plane motions of the hip, knee, and ankle joints of the right leg. A tri-axial accelerometer constructed from three uniaxial accelerometers (Kistler Instrument Corp., Amherst, NY) was mounted at the base of the sternum to measure three-dimensional movements of the upper body.

Subjects wore standardized walking shoes and completed a ten-minute acclimatization period on the treadmill at their self-selected speed before being outfitted with the DataLogger instrumentation. Overground (OG) walking trials were performed first. Each subject walked around an approximately 7 m wide and 200 m long level indoor walking track at his/her own self-selected walking speed and was instructed "to walk in as consistent a manner as possible." The total distance walked was measured with a rolling measuring wheel to calculate each subject's average walking speed. Subjects rested five minutes before walking on the treadmill (TM) at their average overground speed. Data were collected for 10 continuous minutes at 66.67 Hz under both conditions.

2.2 Quantifying Variability. Start and end times for each stride were defined as that point in time corresponding to maximum knee extension just prior to heel strike. Average walking speeds and stride lengths were calculated by dividing the total distance walked by ten minutes and by the total number of strides, respectively. Average stride times and standard deviations of stride times were calculated from the individual stride times extracted from the continuous time series data. These data were analyzed using a two-factor (Subject×Condition) balanced analysis of variance (ANOVA) for randomized block design.

For each time series, thirty consecutive strides of data were extracted from each of the 1st, 5th, and 10th minutes of each trial. Data for each stride were time-normalized to 100 samples (100 percent). The re-sampled data were pooled across strides to compute stride-to-stride standard deviations ($SD(i)\ \forall\ i \in[1\text{ percent},\ldots,100\text{ percent}]$). Mean ($\text{MeanSD}=\langle SD(i)\rangle$, where $\langle\cdot\rangle$ denotes the average across all i) and maximum ($\text{MaxSD}=\max[SD(i)]$) standard deviations were computed for each time series for each subject. Data for each variable were analyzed using a three-factor (Subject×Condition×Observation) balanced ANOVA for randomized block design.

2.3 Quantifying Local Dynamic Stability. Nonlinear time series methods quantified local dynamic stability based on state space representations of each time series [3]. A valid state space is any vector space containing a sufficient number of independent coordinates to define the state of the system unequivocally at any point in time. An appropriate state space can be reconstructed from a single time series using the original data and its time-delayed copies [22,23]:

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

where $\mathrm{X}(t)$ is the d_E-dimensional state vector, $x(t)$ are the original data, T is the time delay, and d_E is the embedding dimension (Figs. 2(*A*) and 2(*B*)). Time delays were calculated from the first minimum of the Average Mutual Information (AMI) function [24], which evaluates the amount of information (in bits) shared

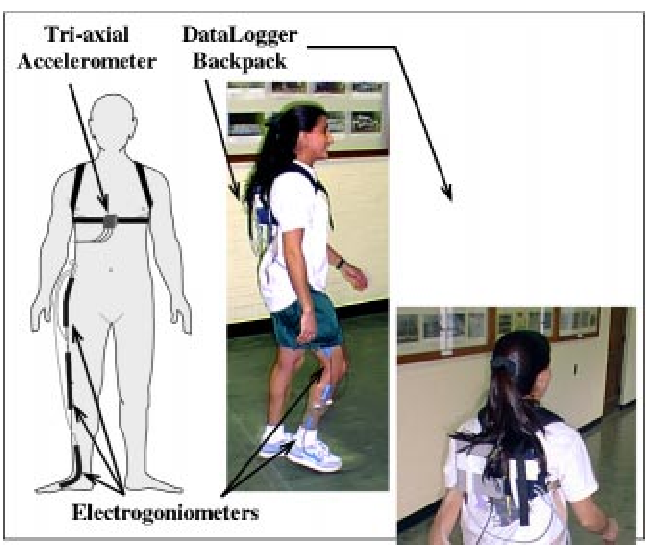

Fig. 1 Set-up of DataLogger data collection instrumentation

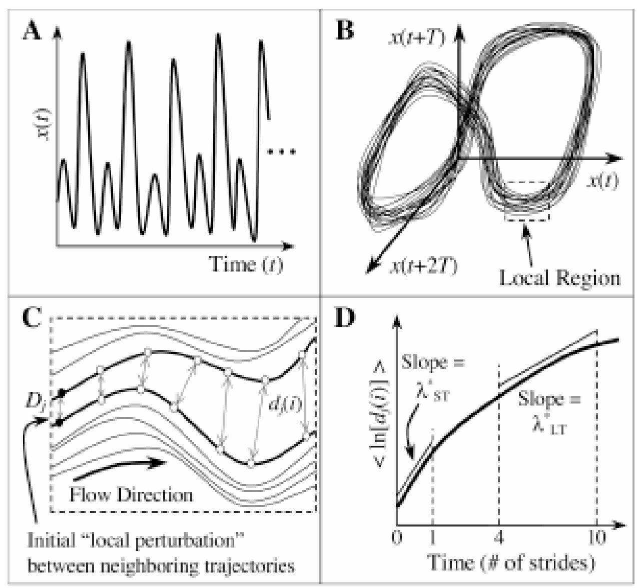

Fig. 2 Schematic representation of local stability analysis. (*A*) original time series data, $x(t)$; (*B*) data embedded in a global 3-dimensional state space, $\mathrm{X}(t)=[x(t),x(t+T),x(t+2T)]$, with a local region outlined; (*C*) close-up view of the local region outlined in (*B*) showing divergence of neighboring trajectories resulting from local perturbations to the system; (*D*) average logarithmic divergence of neighboring trajectories, indicating the calculation of the short-term (λ^*_{ST}) and long-term (λ^*_{LT}) finite-time Lyapunov exponents as the slopes of these curves in the ranges between 0 and 1 stride and between 4 and 10 strides, respectively.

between two data sets over a range of time delays (analogous to a nonlinear autocorrelation function). Choosing the first minimum of the AMI provides adjacent delay coordinates with a minimum of shared information.

Embedding dimensions were computed from a Global False Nearest Neighbors (GFNN) analysis [25], which compares the distances between neighboring trajectories in the reconstructed state space at successively higher dimensions. Overlapping trajectories in dimension d_i that are distinguished in d_{i+1} constitute ''false neighbors'' in d_i. As the state space is expanded (i.e., as i increases), d_E is chosen where the total percentage of false neighbors approaches zero, thus providing a sufficient number of coordinates to define the system state at all points in time. In the present study, GFNN analysis indicated an appropriate embedding dimension of $d_E=5$ for all time series [3].

Local perturbations to the system result in small displacements that appear as neighboring trajectories in state space (Fig. 2(*C*)). Lyapunov exponents quantify the average exponential rate of divergence of these initially neighboring trajectories, and thus provide a direct measure of local dynamic stability [26,27]. The maximum Lyapunov exponent (λ_1) can be defined using:

$$d(t)=De^{\lambda_1 t} \tag{2}$$

where $d(t)$ is the mean Euclidean distance between neighboring trajectories in state space at time t and D is the initial average separation between neighboring trajectories. Thus, λ_1 is defined in the dual limit as $t\rightarrow\infty$ and $D\rightarrow 0$ in Eq. (2).

However, because experimental time series are finite in length, true Lyapunov exponents cannot be computed reliably. Therefore, a previously published algorithm ([26]; Totts Gap Medical Institute, Bangor, PA) provided estimates of the maximum *finite-time* Lyapunov exponents (λ^*) for each embedded time series [3]. Following from Eq. (2) and taking the log of both sides, λ^* was defined from:

$$\ln[d_j(i)]\approx\lambda^*(i\Delta t)+\ln[D_j] \tag{3}$$

where $d_j(i)$ was the Euclidean distance between the jth pair of nearest neighbors after i discrete time steps (i.e., $i\Delta t$ seconds). Euclidean distances between neighboring trajectories in state space were calculated as a function of time and averaged over all original pairs of nearest neighbors. The λ^* were estimated from the slopes of linear fits to curves defined by:

$$y(i)=\frac{1}{\Delta t}\langle\ln[d_j(i)]\rangle \tag{4}$$

where $\langle\cdot\rangle$ denotes the average over all values of j (Fig. 2(*D*); [26]).

Since each subject exhibited a different average stride time, the time axes of these curves were rescaled by multiplying by the average stride frequency for each subject. Estimates of λ^* were calculated over two different time scales. Short-term exponents (λ^*_{ST}) were computed between 0 and 1 stride and long-term exponents (λ^*_{LT}) were computed between 4 and 10 strides (Fig. 2(*D*)). Because this algorithm was shown to be robust for small data sets [26], each ten-minute time series was first divided into five two-minute intervals to compute both within- and between-subject variances in the λ^* estimates. A three-factor (Subject$\times$Condition $\times$Interval) balanced ANOVA for randomized block design was used to evaluate differences in λ^* for each time series.

2.4 Variability Versus Local Dynamic Stability. Single averaged values of each measure of variability (MeanSD and MaxSD) and local dynamic stability (λ^*_{ST} and λ^*_{LT}) were computed for each subject. For each of the six time series examined, Pearson product moment correlation coefficients (r^2) were computed between each variability and local dynamic stability measure to determine if these measures were linearly related.

3 Results

3.1 Overall Gait Characteristics. Average walking speeds were not significantly different between the two conditions ($p=0.202$). There were trends toward decreased average stride length ($p=0.065$) and average stride time ($p=0.092$) for TM walking compared to OG walking (Fig. 3), consistent with previous reports [13,14]. Standard deviations for individual stride times were significantly reduced during TM walking compared to OG walking ($p=0.016$; Fig. 3).

3.2 Stride-to-Stride Kinematic Variability. MeanSD and MaxSD values for upper body accelerations were generally

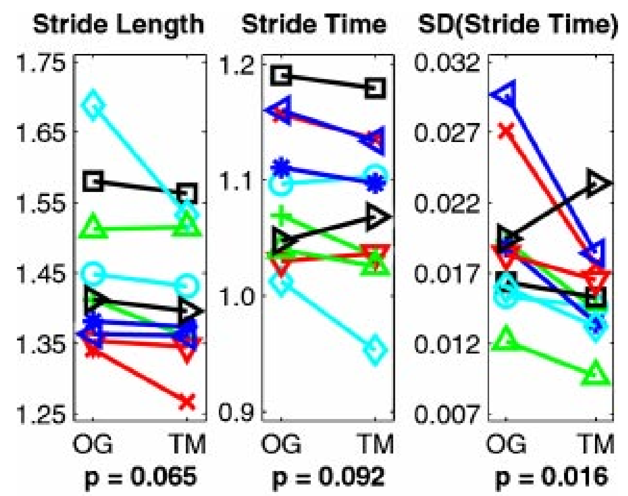

Fig. 3 Average stride lengths (m), average stride times (s), and standard deviations of stride times (s) between OG and TM walking. Each line represents average results for one subject. ANOVA *p*-values for Condition effects are shown below each graph.

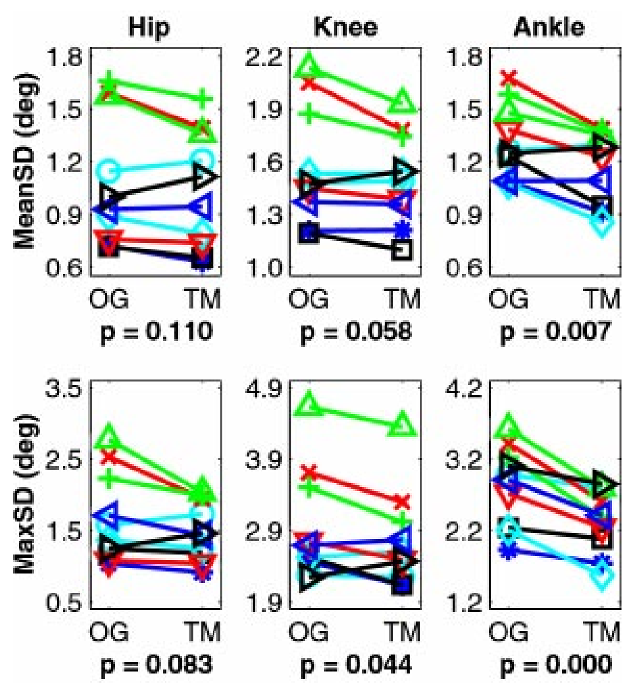

Fig. 4 Mean and maximum joint angle standard deviations for OG and TM walking. Each line represents average results for one subject. ANOVA *p*-values for Condition effects are shown for each comparison.

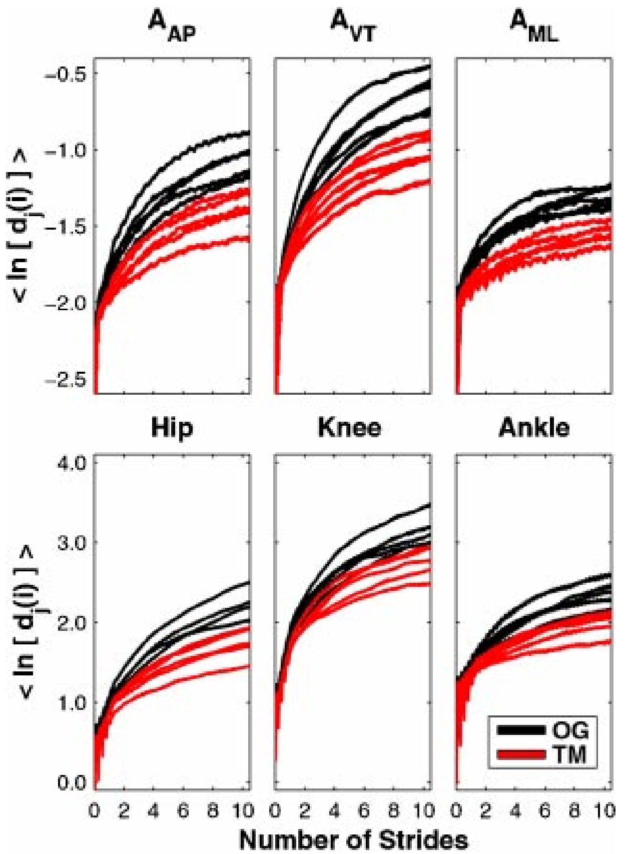

Fig. 5 Representative plots of the average logarithmic divergence, $\langle \ln[d_j(i)] \rangle$, as a function of normalized time for a typical subject for both OG and TM walking for all six sets of time series data. Within each subplot, five curves are drawn for each condition; one for each of the five two-minute intervals of data analyzed. Short-term (λ^*_{ST}) and long-term (λ^*_{LT}) finite-time Lyapunov exponents were computed from each curve as described in Fig. 2. Similar results were obtained for all subjects.

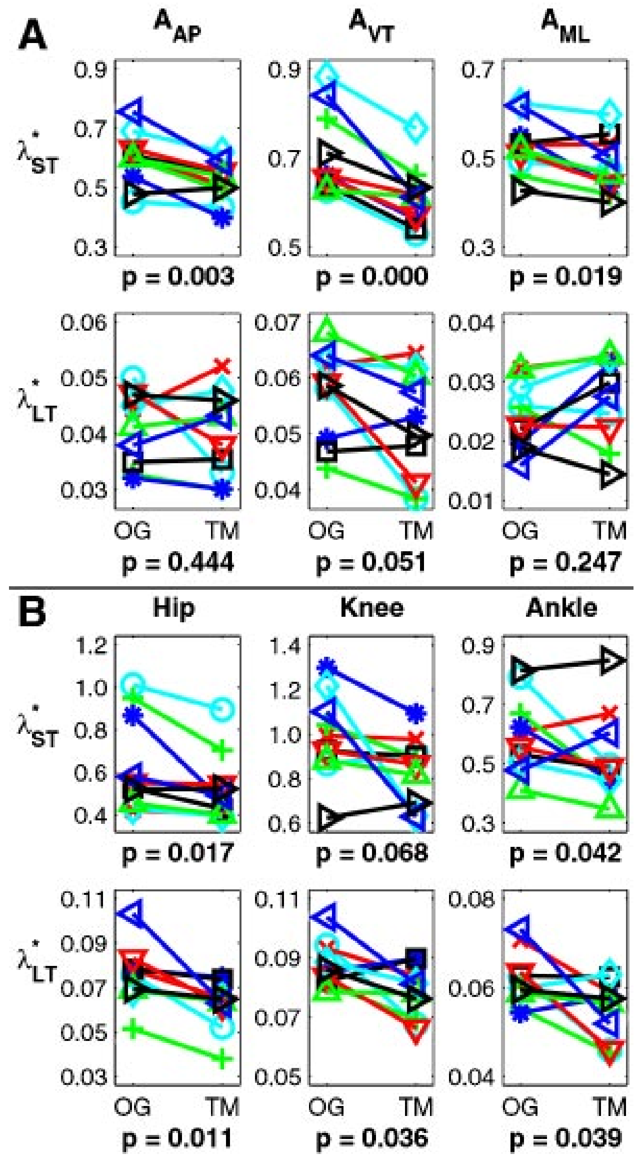

Fig. 6 Short-term (λ^*_{ST}) and long-term (λ^*_{LT}) finite-time Lyapunov exponents ($\langle \ln[d_j(i)] \rangle$/*Stride*) for (*A*) upper body accelerations and (*B*) lower extremity kinematics. Each line represents average results for one subject. ANOVA *p*-values for differences between OG and TM walking are shown below each comparison.

greater for OG walking than for TM walking. However, this trend was only statistically significant for MeanSD of anterior–posterior accelerations (A_{AP}; $p=0.010$). For lower extremity kinematics (Fig. 4), standard deviations were greater for OG walking than for TM walking for nearly all subjects and three of these comparisons were statistically significant. Additionally, these differences systematically became more significant from the proximal to the more distal joints (hip versus knee versus ankle). Thus, TM walking significantly reduced kinematic variability, predominantly at the distal lower extremity.

3.3 Local Dynamic Stability. Local perturbations, on average, produced continued divergence of neighboring trajectories for more than ten strides (Fig. 5). Furthermore, this divergence was consistently attenuated during TM walking, a trend that was confirmed by statistical analysis. TM walking resulted in statistically significant reductions for most λ^*_{ST} and λ^*_{LT} exponents for both upper body accelerations and lower extremity kinematics (Fig. 6). Thus, TM walking led to more locally stable movements of both the lower extremity and upper body.

3.4 Correlations Between Variability and Local Dynamic Stability. Correlation coefficients (r^2) between variability and local dynamic stability measures (Table 1) were mostly weak ($r^2 < 31$ percent), many of them were negative, and statistically significant results were obtained for only 4 of the 24 correlations computed. These results confirm that measures of stride-to-stride variability are poor indicators of local dynamic stability.

4 Discussion

Traditional approaches to gait analysis have generally assumed that locomotor control can be described in terms of the events that occur during a single stride. Gait stability is described in terms of statistical variations between independently sampled strides. The purposes of the present study were to demonstrate that the processes involved in controlling locomotor stability act over multiple consecutive strides of gait, to determine if measures of variability reliably quantify local dynamic stability, and to determine whether walking on a motorized treadmill significantly alters these processes.

Figure 5 demonstrates that, on average, local perturbations continued to affect kinematic trajectories at least 10 strides after the initial perturbation. Had these effects been confined to a single

Table 1 Correlation coefficients (r^2) between measures of variability (MeanSD and MaxSD) and local dynamic stability (λ^*_{ST} and λ^*_{LT}) for each of the six time series examined. Values marked with a (*) indicate statistically significant ($p<0.05$) correlations.

Upper Body Correlations (r^2)		
	MeanSD - A_{AP}	MaxSD - A_{AP}
λ^*_{ST} - A_{AP}	0.0004	0.0029
λ^*_{LT} - A_{AP}	0.1318	**0.1998 ***
	MeanSD - A_{VT}	MaxSD - A_{VT}
λ^*_{ST} - A_{VT}	- 0.0392	**- 0.1989 ***
λ^*_{LT} - A_{VT}	0.0365	0.0104
	MeanSD - A_{ML}	MaxSD - A_{ML}
λ^*_{ST} - A_{ML}	- 0.0022	0.0213
λ^*_{LT} - A_{ML}	0.1656	0.1030
Lower Extremity Correlations (r^2)		
	MeanSD - Hip	MaxSD - Hip
λ^*_{ST} - Hip	0.1043	0.0225
λ^*_{LT} - Hip	**- 0.2362 ***	- 0.0724
	MeanSD - Knee	MaxSD - Knee
λ^*_{ST} - Knee	- 0.0020	0.0061
λ^*_{LT} - Knee	- 0.0123	- 0.0016
	MeanSD - Ankle	MaxSD - Ankle
λ^*_{ST} - Ankle	0.1552	**0.3080 ***
λ^*_{LT} - Ankle	- 0.0004	0.0552

stride, these divergence curves would have saturated (i.e., leveled off) after one stride. Traditional measures of variability, which only provide estimates of the average magnitude of variations across strides, are therefore insufficient to characterize the local dynamic stability properties of locomotor behavior. This finding is supported by the general lack of correlation between the standard deviations and λ^* exponents examined in this study (Table 1). In fact, while there were no differences in upper body variability between OG and TM walking, highly significant differences were obtained for the λ^*_{ST} exponents of upper body accelerations (Fig. 6). This notion that variability cannot adequately quantify stability was further substantiated by the results of a companion study in which patients with diabetic neuropathy simultaneously exhibited increased variability [28], but decreased λ^*_{LT} exponents [29] compared to matched controls. Thus, measurements of stride-to-stride variability and local dynamic stability quantify fundamentally different aspects of locomotor behavior. Furthermore, the behavior of the locomotor system must be examined across multiple consecutive strides to characterize locomotor stability properly.

If proper assessment of local stability requires the examination of continuous locomotion, then it becomes equally important to know if having subjects walk on a motorized treadmill significantly alters their local stability. In the present study, TM walking was associated with small, but in some cases statistically significant, reductions in variability and improvements in local dynamic stability compared to OG walking. These results confirm previous findings of reduced variability during treadmill locomotion [20,13,21], and suggest that treadmills should not be used to study locomotion in certain circumstances. For example, differences in kinematic variability between patients with diabetic neuropathy and matched controls were not significant when subjects walked on a motorized treadmill [21]. However, these differences became significant when a similar cohort of subjects walked over level ground [28]. Thus, motorized treadmills may produce misleading or erroneous results, especially in situations where changes in neuromuscular control are likely to result in changes in the variability and/or stability of locomotion. Examples of similar situations would include the elderly [9] and patients with degenerative neurological disorders [10], among others.

This study has demonstrated that motorized treadmills can significantly affect the variability and local stability of gait. However, the underlying causes of these differences remain less clear. On one hand, the motorized treadmill imposed a constant nominal speed on the subjects and constrained them to walk along a much narrower and straighter path than during OG trials. On the other hand, other differences between the two walking conditions may also have contributed to the present findings. If the turns made by subjects during OG trials were sufficiently abrupt, these might have led to increased variability in the OG trials. However, these turns would also have produced consistent nonstationarities in the data and further analyses revealed no evidence of such nonstationarities [3]. The differences found were likely due at least in part to intrastride fluctuations in treadmill belt speed [18,19], since any attenuation of force occurring at heel strike would have dampened variations. Unfortunately, it was not possible to measure instantaneous belt speed in the present study, and Savelberg et al. [19] did not discuss the effects of belt speed variations on gait variability. Similarly, locomotion patterns may have been affected by differences in mechanical compliance between the walking surfaces of the treadmill and the indoor track. It has also been hypothesized that locomotor control during treadmill walking may be significantly affected by changes in visual and vestibular perceptual information [17,14]. Regardless of whether the differences between OG and TM walking resulted from modifications in neuromuscular control, changes in mechanical constraints, or both, it is clear that treadmills can alter the variability and local stability properties of locomotion and potentially lead to misleading conclusions.

5 Conclusions

This study quantified the relationship between local dynamic stability and variability of locomotor kinematics during overground and treadmill walking. Results demonstrated that local stability of gait kinematics is achieved over multiple consecutive strides of gait. Furthermore, the λ^* exponents computed in this study quantified fundamentally different aspects of locomotor behavior than traditional measures of variability. It is proposed that because these measures specifically quantify the sensitivity of the locomotor system to local perturbations, they are more relevant for examining the neuromuscular control of balance and stability during locomotion. Results further demonstrated that TM walking was associated with significant reductions in locomotor variability, primarily at the distal lower extremity, and with significant improvements in local dynamic stability. It is concluded that, especially in cases where differences in locomotor control may produce changes in the variability and/or local stability of locomotion, such differences may be masked by having subjects walk on motorized treadmills.

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