Characteristics of Stride Behavior During Treadmill Walking and Stationary Stepping

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Abstract:

Much has been learned about the characteristics of gait in overground and treadmill walking. However, there are many contexts in which overground or treadmill walking might not be possible, such as in home-based physical therapy. In those cases, a surrogate task to index gait behavior would be a valuable tool. Thus, the purpose of this study was to evaluate the stride behavior characteristics of stationary stepping compared with treadmill walking. Healthy young adults (N = 10) preformed two 15-minute tasks: (1) treadmill walking and (2) stationary stepping. Several stride behavior characteristics were recorded, including the number of strides taken, minimum and maximum knee angle, stride interval mean, stride interval standard deviation, and detrended fluctuation analysis (DFA) alpha of the stride interval time series. The results showed that stride behavior was similar between tasks when examined at the group level. However, when individual level analyses were used to examine the reliability of each metric between tasks, poor reliability was observed in most metrics, indicating that stationary stepping may not be an appropriate surrogate task for overground or treadmill walking. These results are discussed in the context of a gait dynamics framework, with attention to task constraints that may have influenced the findings.

Keywords: gait | locomotion | dynamics | detrended fluctuation analysis

Article:

Walking is a fundamental motor task that is influenced by numerous interacting systems. For example, sensory information from auditory and visual sources are integrated to control hundreds of muscles and bones to produce coordinated movement.[1] The interaction of systems and multiple degrees of freedom causes every stride to be slightly varied from the preceding stride, a phenomenon that has been reported for more than a century.[2] The variability from stride to stride has traditionally been used as a marker of motor imprecision, a notion supported by the fact that many clinical or developing populations exhibit increased variability in their stride-to-stride intervals compared with young healthy adults.[3–5] The traditional approach to examine gait variability is to quantify the magnitude of variability (ie, standard deviation) in variables such as stride time, stride length, or step width. However, gait behavior evolves over time, a characteristic that the magnitude of variability is ill suited to quantify. An alternative approach, using a dynamics framework, quantifies the structure of variability by indexing dynamic patterns within the behavior. These dynamic patterns are indicative of the stereotypy exhibited over time, which has been linked to the functionality of a system.[6] The characteristics of these patterns fall on a continuum, with constrained and rigid behavior on one end and unconstrained and random behavior on the other end.[7–9] A healthy, functional system falls in the middle of the continuum, exhibiting an underlying structure with adaptive variation as needed. However, pathology or natural aging can cause a shift in behavior toward either end of the continuum, reflecting a decline in functionality. Thus, metrics that quantify the structure of variability in gait behavior might be used to index a patient's locomotor ability before an intervention or to track their progress.[7,10,11]

A variety of metrics quantifying the structure of variability in gait have been employed over the past two decades (see Rhea and Kiefer[11] and Bravi, Longtin, and Seely[12] for a review). These have included analyses such as Lyapunov exponent, Floquet index, and recurrence quantification analysis. Many studies examining the structure of variability in stride-to-stride behavior have used overground walking as their gait task.[13–16] These studies showed that self-similar patterns are present across multiple time scales, termed long-range correlations, in stride-to-stride variability; this indicates that gait variability was not simply a random consequence of an imprecise motor system. Importantly, the patterns must be provided adequate time to emerge, so taking a small sample size of gait behavior (< 600 strides) is likely to return inconsistent and possibly inaccurate results when employing structure of variability analyses on stride timing behavior.[17] In overground walking, decelerations and accelerations from turning can alter gait behavior, so a large space such as a track, gymnasium, or open corridor is required to study the structure of the stride-to-stride variability. Alternatively, a treadmill can be used to record stride-to-stride behavior, which is advantageous because it requires less space and no turning to obtain the required number of strides. While slight differences are observed in stride-to-stride behavior between overground and treadmill walking, these differences are negligible when comparing the long-range correlations within gait behavior,[18] allowing researchers to employ both overground walking and treadmill walking to examine the dynamic nature of gait behavior.

While it has been encouraging to learn that treadmill walking exhibits behavior similar to overground walking, a treadmill is not available in all settings. For example, many clinics have only one or two treadmills, which limits the number of patients that can be tested at a time. Many home-based physical therapists may not have a treadmill at all, which is also true for many military medics at medical facilities in theater. Because the motor behavior field is moving toward the use of structure of variability metrics of gait behavior to identify patients' motor ability,[7,10,11,19] these metrics may be used in the future by clinical professionals as a complement to current clinical assessments. Furthermore, because stride-to-stride variability metrics are currently constrained to overground walking or treadmill walking tasks, a number of clinical cohorts that do not have access to large open spaces or treadmills will not be assessed using current protocols.

To close this gap, other tasks that can index the functionality of a person's locomotor system should be considered. The ideal task should exhibit similar dynamic properties (ie, long-range correlations) as overground or treadmill walking and be suitable for environments where a large space or treadmill is not available. Because a hallmark of a functional motor control system is the presence of long-range correlations (as observed in gait, posture, finger tapping, and arm oscillations),[10,20–22] it is plausible that a surrogate task that is similar to overground or treadmill walking could capture the dynamic properties of gait behavior.

The purpose of this study was to determine if stationary stepping exhibited similar characteristics in stride behavior compared with treadmill walking. The variables describing stride behavior characteristics were the number of strides taken, maximum knee angle, minimum knee angle, stride interval mean, stride interval standard deviation, and the structure of variability within the stride interval time series, which was assessed with detrended fluctuation analysis (DFA).[23] The mean, reliability, and level of agreement of each metric were compared between the two tasks. It was hypothesized that no differences would be observed in the mean of each variable between tasks and a strong relationship (both correlation and level of agreement) between tasks would be observed for each variable. An exploratory, second purpose of this study was to examine the relation between each metric within the same task. Previous research has shown that the number of strides taken within a trial can influence the structure of variability,[24] so our goal was to extend this analysis to examine the relation among other gait metrics within a trial. Given the exploratory nature of the second purpose, no a priori hypotheses were developed. Thus, this study was constructed to not only determine if similar characteristics in stride behavior emerged in treadmill walking and stationary stepping, but also allow us to further probe how gait metrics within a trial may be related to each other, providing further insight into locomotor control.

Methods

Participants

Ten young healthy adults (2 males and 8 females; 21.1 ± 0.3 y; 1.70 ± 0.10 m; 63.2 ± 12.2 kg) participated. All procedures were approved by the local institutional review board and all participants signed an informed consent form. All participants were screened to ensure they did not have any neurological disorders or injuries that would preclude them from walking normally.

Procedure

All participants performed two 15-minute tasks in randomized order: treadmill walking and stationary stepping. Before data collection, the participants found their self-selected speed (1.1 ±

0.2 m/s) while walking on a treadmill for approximately 60 seconds. Participants' self-selected speed was used during their treadmill walking trial, and they were told to match their stationary stepping cadence to their self-selected speed on the treadmill to the best of their ability. Kinematic data of the lower limbs were recorded during each task using reflective markers recorded at 200 Hz (Qualisys, Gothenburg, Sweden). Markers placed on the midthigh, lateral femoral epicondyle, and midshank were used to calculate the sagittal plane knee angle during each task. Outliers were accounted for by removing the 99th and 1st percentile data points from all data.

The dependent variables derived from the knee angle trajectory were: (1) the number of strides taken, (2) maximum knee angle, and (3) minimum knee angle. In addition, the time between peak knee flexion was calculated for the right limb, resulting in a fourth dependent variable, stride interval time. As previously discussed, the variability in stride-to-stride intervals is informative of the functional capacity of the locomotor system. Thus, stride interval variability was quantified in two ways. First, the magnitude of variability in the stride interval time series was quantified using a standard deviation calculation. Second, the structure of variability in the stride interval time series was calculated using DFA, which provides a way to index long-range correlations in a system. The methodological details of DFA have been previously published [13,23] and the computational details are provided in "Appendix A." DFA provides an a metric, which corresponds to the strength of the long-range correlations. Most human physiological systems exhibit a DFA α between .5 and 1.0, with lower values indicating weaker long-range correlations and vice versa. DFA α in the stride-to-stride behavior of young healthy adults is typically around .75 and deviation from this value has been interpreted as a reflection of decreased locomotor function.[7,10]

Statistics

Summary statistics of the two tasks were compared, including the number of strides taken, the maximum and minimum of the knee angle (0° = full extension; > 0° = flexion), mean stride interval, and standard deviation of the stride interval. In addition, the structure of variability of stride intervals was compared between the two tasks using DFA α. To test group mean differences and reliability, separate paired sample *t* tests and Pearson correlation coefficients, respectively, were calculated with IBM SPSS Statistics Package (Version 18; IBM Corporation, New York) ($P < .05$). We were primarily interested in determining if the two tasks exhibited similar characteristics, so the paired *t* test was used to compare the same metric between tasks. We were also interested in determining if there was a relation between metrics, so Pearson correlation coefficients were calculated. The motivation behind these correlational analyses was two-fold. First, we aimed to determine if similar gait characteristics were observed between the tasks. To address this question, correlation coefficients were computed by comparing all metrics in one task to all metrics in the second task (eg, comparing stride interval mean during treadmill walking to stride interval mean during stationary stepping). Second, we aimed to determine if metrics within the same task were related. To address this question, correlation coefficients were computed by comparing all metrics within the same task to each other (eg, relation between number of strides and DFA α in treadmill walking).

Because a large distribution of scores can inflate Pearson correlations, 95% limits of agreement (LOA) were also employed. Ninety-five percent LOA is a method to compare the consistency of a single metric across multiple measurements or between two metrics by determining the range of values in which the mean difference between two observations falls within a set threshold (95% confidence interval or 1.96 standard deviations). LOA is not dependent on sample characteristics, so it provides an unbiased estimate of the systematic bias when comparing a metric between tasks.[25] In the current study, 95% LOA was employed by determining the mean difference within a metric across the two tasks (treadmill walking and stationary stepping), which is interpreted as the systemic bias between measurements. The mean difference is often considered in relation to the mean value of the measurement from the standard task (treadmill walking in the case of the current study). For example, if the mean value for a metric was 105 during treadmill walking and 115 during stationary stepping, then the mean difference (ie, systematic bias) would be 10. Relative to the treadmill value, this metric would have a systematic bias of 9.5% (10/105). For this study, systematic biases > 10% are considered large, 5% to 10% are considered moderate, and < 5% are small; although it should be noted that there is not a consensus as to what constitutes a large, moderate, or small systematic bias in the gait literature. Systematic shifts in the metrics can also be visualized using 95% LOA plots, which were calculated and depicted using Bland–Altman plots (MedCalc Statistical Software, Version 12.2.1.0; MedCalc, Ostend, Belgium). Ninety-five percent LOA also identifies the range of data that falls within 1.96 standard deviations, which is interpreted as the random error between measurements. Two measurements that are highly reliable would exhibit a 95% LOA near 0 ± 0, with the first number indicating the systematic bias and the second number indicating the random error.

Table 1 Descriptive statistics and 95% LOA for each dependent variable

	Treadmill Walking	**Stationary Stepping**		
Dependent Variable	**Mean ± SD**	**Mean ± SD** *t*	**Test**	**95% LOA**
Number of strides	802 ± 77.5	822.5 ± 141.6	*P* = .614	–20.5 ± 248.3
Maximum knee angle (°)	64.2 ± 6.3	72.8 ± 10.7	*P* = .067	–8.6 ± 25.6
Minimum knee angle (°)	6.4 ± 6.2	6.5 ± 6.1	*P* = .891	–.1 ± 4.2
Stride interval mean (s)	1.13 ± .11	1.11 ± .22	*P* = .768	.02 ± .35
Stride interval standard	.02 ± .01	.07 ± .03	*P* = .002a	–.05 ± .07

deviation (s)				
DFA α	.72 ± .05	.79 ± .18	*P* = .303	–.07 ± .39

Abbreviations: LOA, limits of agreement; SD, standard deviation; DFA α, detrended fluctuation analysis alpha. [a] Significant difference between tasks

Results

Minimal group differences in the summary statistics and the structure of variability were observed between treadmill walking and stationary stepping (Table 1). Stride interval behavior for one participant is plotted for comparison purposes (Figure 1). The number of strides taken was not different between tasks, $t(9) = .52$, $P = .614$. No significant differences were observed between tasks for the maximum knee angle, $t(9) = 2.08$, $P = .067$; minimum knee angle, $t(9) = .14$, $P = .891$; or mean stride interval time, $t(9) = –.30$, $P = .768$. However, a greater stride interval variability magnitude was observed in the stationary stepping compared with the treadmill walking task, $t(9) = 4.30$, $P = .002$. No significant differences were observed in the DFA α values between the two tasks, $t(9) = 1.10$, $P = .303$.

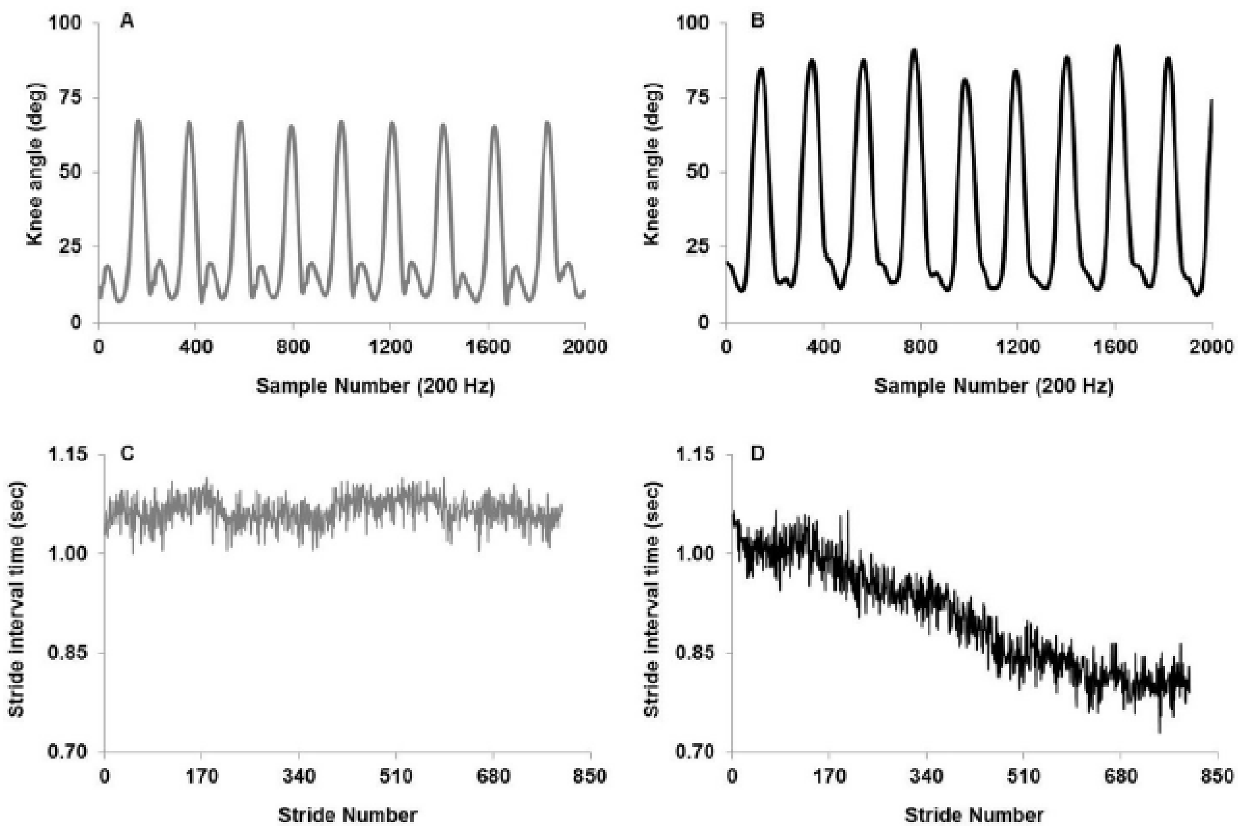

Figure 1 — Knee angle trajectory over 10 seconds during (A) treadmill walking and (B) stationary stepping as well as the stride interval time series over the entire 15-minute trial during (C) treadmill walking and (D) stationary stepping for one participant.

The reliability analysis for each metric between tasks showed similarity in knee kinematics, but no other variables (Table 2). A strong positive correlation was observed between minimum knee angle in the stationary stepping task and minimum knee angle in the treadmill walking task, $r(10) = .94$, $P < .001$. When comparing the minimum knee angle in stationary stepping to the maximum knee angle in treadmill walking, a moderate correlation was observed, $r(10) = .65$, $P = .043$. No other significant correlations were observed (all $P > .05$).

To compare the level of agreement (consistency) of the same metric between tasks, 95% LOA were computed (Table 1) and displayed in Bland–Altman plots (Figure 2). A large systematic bias (> 10%) was observed for the maximum knee angle and stride interval standard deviation. A moderate systematic bias (9.7%) was observed for DFA α and low systematic bias (< 2%) was observed for the minimum knee angle and stride interval mean. In the stationary stepping task, participants tended to increase their maximum knee flexion angle by 8.6°, increase their stride interval variability by .05 seconds, and produce an increased DFA α of .07 relative to treadmill walking. Importantly, the random error for each metric was high relative to the mean, indicating that a large range of values within each metric was observed.

Lastly, when examining each metric within the same task, the data showed a series of positive and negative correlations (Table 2). For the stationary stepping task, a strong positive correlation was observed between the standard deviation of the stride interval and DFA α, $r(10) = .81$, $P = .005$, as well as the number of strides and DFA α, $r(10) = .69$, $P = .027$. A strong negative correlation was observed in between the number of strides and mean stride interval, $r(10) = –.95$, $P < .001$. For treadmill walking, a strong positive correlation was also observed between minimum knee angle and maximum knee angle, $r(10) = .78$, $P = .008$, as well as mean stride interval and standard deviation of the stride interval, $r(10) = .70$, $P = .025$. Strong negative correlations were observed between mean stride interval time and number of strides, $r(10) = –.99$, $P < .001$, standard deviation of the stride interval and number of strides, $r(10) = –.73$, $P = .018$, and standard deviation of the stride interval and minimum knee angle, $r(10) = –.70$, $P = .025$.

Discussion

This project compared the stride-to-stride behavior during treadmill walking versus stationary stepping. Three unique contributions to the literature were identified: (1) Similar group level gait characteristics were observed in treadmill walking and stationary stepping; (2) despite group similarities between the tasks, individuals displayed poor reliability between tasks for most metrics, suggesting they adopted different strategies between tasks; and (3) treadmill walking is more constrained that stationary stepping. The results are discussed in the context of a gait dynamics framework and how performing the two tasks differently may have influenced the observed behavior.

The dynamic patterns of behavior exhibited by healthy systems exhibit a characteristic called long-range correlation, an indication that similar patterns are repeated over short- and long-time scales.

These patterns were first observed in DNA nucleotides,[23] but have since been observed in cardiac behavior, gait, posture, finger tapping, and arm oscillations.[6,10,20–22,26] Because these patterns are observed across healthy, adaptive systems, we hypothesized that a task similar to treadmill and overground walking, such as stationary stepping, would also share the same dynamic properties. To test this hypothesis, we examined the stride characteristics to determine if the two tasks were performed similarly. Because no differences between tasks were observed in the number of strides taken, maximum or minimum knee angle, mean stride time, or the structure of stride interval variability, it is reasonable to suggest that the two tasks were similar in nature (Table 1). However, the magnitude of stride interval variability was higher in the stationary stepping task (Figure 1). The participants were asked to constrain their stationary stepping cadence to their treadmill walking cadence. However, they were not given an auditory or visual stimulus in which to synchronize before or during the stationary stepping activity. In the case of one participant (Figure 1), the stride interval time during stationary stepping started out near the same time as their treadmill walking stride time interval (~1.05 s); but the participant drifted toward a faster stride time interval throughout the stationary stepping task, accounting for the higher magnitude of variability across the stride interval time series.

Table 2 Between and within task correlations among dependent variables

Task	Dependent Variable	Number of Strides	Maximum Knee Angle (°)	Minimum Knee Angle (°)	Stride Interval Mean (s)	Stride Interval Standard Deviation (s)	DFA α
		Between Task Correlations					
		Task: Treadmill Walking					
Stationary Stepping	Number of strides	.49	.14	−.05	−.54	−.21	.22
	Maximum knee angle (°)	.03	−.17	−.28	−.11	.31	.23
	Minimum knee angle (°)	.31	.65[a]	.94[b]	−.23	−.63	.23
	Stride interval mean (s)	−.54	−.11	.12	.61	.19	−.27
	Stride interval standard deviation (s)	−.19	−.03	−.11	.13	−.04	−.25
	DFA α	.03	.32	.07	−.07	−.28	−.17
		Within Task Correlations					
		Task: Treadmill Walking					
Task	**Dependent Variable**	**Number of Strides**	**Maximum Knee Angle (°)**	**Minimum Knee Angle (°)**	**Stride Interval Mean (s)**	**Stride Interval Standard Deviation (s)**	**DFA α**
Treadmill Walking	Number of strides		.24	.48	−.99[b]	−.73[a]	.34
	Maximum knee angle (°)			.78[b]	−.19	−.40	.54
	Minimum knee angle (°)				−.40	−.70[a]	.41
	Stride interval mean (s)					.70[a]	−.31
	Stride interval standard deviation (s)						.03
	DFA α						
		Task: Stationary Stepping					
Stationary Stepping	Number of strides		.30	−.10	−.95[b]	.51	.69[a]
	Maximum knee angle (°)			−.30	−.34	.27	.06
	Minimum knee angle (°)				.23	.10	.12
	Stride interval mean (s)					−.39	−.56
	Stride interval standard deviation (s)						.81[b]
	DFA α						

Abbreviation: DFA α, detrended fluctuation analysis alpha. [a] $P < .05$; b $P < .01$.

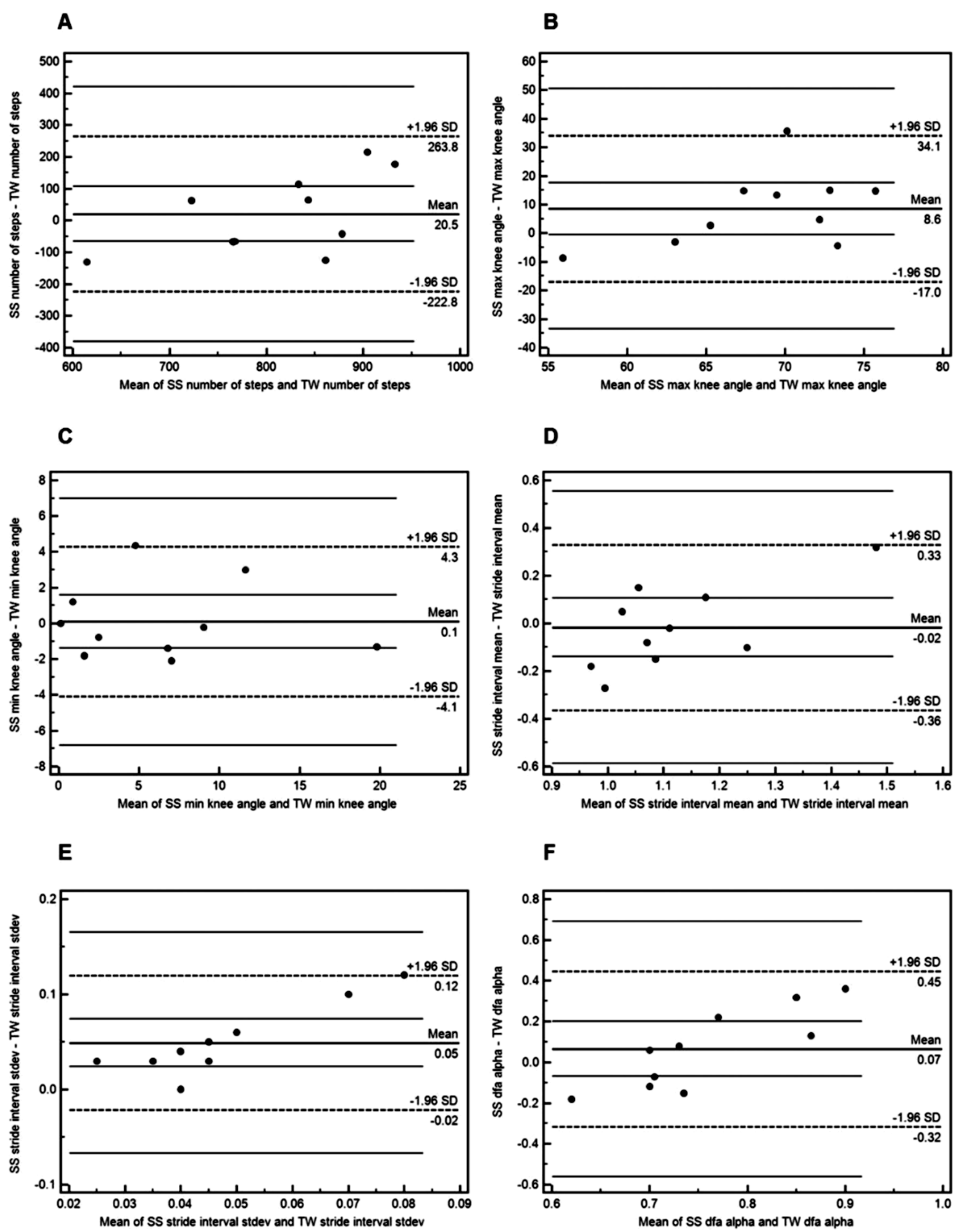

Figure 2 — Bland–Altman plots to illustrate the 95% limits of agreement (LOA) analysis for (A) the number of steps, (B) maximum knee angle, (C)

minimum knee angle, (D) stride time mean, (E) stride time standard deviation, and (F) DFA α of the stride interval time series. Data for each subject is plotted, with the x-axis exhibiting the mean of each metric for treadmill walking (TW) and stationary stepping (SS), and the y-axis exhibiting the difference between the SS and TW mean for each metric. The mean illustrated on each panel indicates the systematic bias between tasks, while the ±1.96 standard deviations indicate the random error.

Although minimal differences were observed when comparing the group mean of each metric between tasks, a more appropriate analysis given the purpose of this study was to examine the relatedness of each metric between tasks. This was accomplished in two ways. First, Pearson correlation coefficients were calculated for each metric between tasks (Table 2). If each task elicited similar behavior, then moderate to high correlations would be expected when comparing each metric between tasks. Only the minimum knee angle was correlated with itself between tasks ($r = .94$), indicating that the participants extended their lower limbs similarly between the two tasks. This finding is reasonable because minimal differences between the two tasks would be expected when the knee is fully extended and thus this variable provides nominal information about the similarities in behavior between treadmill walking and stationary stepping. The nonsignificant correlation of maximum knee angle between tasks suggests that different strategies were adopted between tasks, which is also highlighted when examining the mean and standard deviation of maximum knee angle in treadmill walking (64.2 ± 6.3°) and stationary stepping (72.8 ± 10.7°). All other metrics were not significantly correlated with themselves between tasks, suggesting that the two tasks elicited different behaviors. Using the means, standard deviations, and correlations of each variable between tasks, the following sample size would be needed to show significant differences between tasks: number of strides (N = 730), maximum knee angle (N = 34), minimum knee angle (N = 5913), stride interval mean (N = 1009), stride interval standard deviation (N = 8), and DFA α (N = 103). Reliability was also examined using 95% LOA analysis (Table 1). A large systematic bias was observed in the maximum knee angle and stride interval magnitude, suggesting that participants exhibited a more flexed knee and greater magnitude in their stride interval variability during the stationary stepping task. A moderate systematic bias was observed in DFA α, showing that the stationary stepping task elicited consistently stronger long-range correlations than the treadmill walking task. Furthermore, the random error for all metrics between tasks was relatively high. Taken together, these findings indicate that stride interval characteristics at the individual level differ between tasks, even though group level analyses of most metrics showed no differences.

These observations may be explained by the unconstrained nature of the stationary stepping task. Constraints have long been known to influence a task's behavior.[1,27,28] In fact, simply changing the instructions within the same task has been shown to alter characteristics of the behavior.[29] During treadmill walking in the current study, participants were physically constrained by the limitations of the treadmill's geometry and speed to not fall. During the stationary stepping task, two verbal constraints were imposed: (1) Maintain the same cadence as treadmill walking and (2) stay in the same general location. However, there was no penalty (ie, a fall) for not adhering to the verbal constraints, nor was feedback provided if the participants started altering their stride interval time or their stepping location. Follow-up analyses confirmed that the participants did drift in both stride interval time (Figure 1) and location. Interestingly, a similar stride interval time was observed between tasks, even though participants increased their maximum knee angle by 8.6° in the stationary stepping task. Because the minimum knee angle was similar between tasks, this indicates a greater range of motion over the same time interval during stationary stepping; an observation that may account for the increased magnitude of variability in the stride interval time. Although a similar number of actions (ie, strides) were observed in the two tasks over the 15-minute trial duration, the unconstrained nature of the stationary stepping task may have accounted for the different behavior observed in the two tasks.

A secondary purpose of this study was to examine the relation between different metrics of behavior within the same task (Table 2). The examined metrics exhibited minimal relation to each other within the same task, indicating that unique characteristics are indexed with each metric. Previous research has shown that stride number can influence stride interval DFA α,[24] a finding that was observed during stationary stepping but not during treadmill walking. This inconsistency could be due to the variation in stride number between tasks (treadmill walking: 802.0 ± 77.5; stationary stepping: 822.5 ± 146.6), which was temporally constrained due to the 15-minute trials. The previous study examined DFA α over a much larger range of strides (from 256 to approximately 900), which may explain their reported relation between stride number and DFA α during treadmill walking.[24] It is also interesting to note that stride interval standard deviation and DFA α were not correlated during treadmill walking. Both metrics index the variability, with standard deviation quantifying the magnitude of the variability and DFA α quantifying the structure of the variability. This finding supports previous work showing that the magnitude and structure of the variability within a system's behavior can fluctuate independently.[6,7,26]

There are a number of limitations that restrict the interpretation of our data. First, a relatively small sample size (N = 10) was used to derive the relation of gait characteristics between treadmill walking and stationary stepping. Future research in this area should include a larger sample size so that a more representative range of locomotor behaviors can be indexed. Second, the different behaviors adopted between tasks could be due to different constraints that were imposed. Future research should monitor the cadence and spatial location when performing the two tasks to determine how imposing similar constrains affects task behavior.

In sum, the current study showed that similar characteristics of stride interval behavior at the group level are observed between treadmill walking and stationary stepping. However, minimal reliability of the metrics between tasks was observed when examined at the individual level, suggesting that unconstrained stationary stepping may not be an appropriate surrogate task for treadmill walking. Future research should further explore how constraints may influence task behavior and continue to develop surrogate tasks to index gait behavior in a variety of environmental contexts.

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Appendix A

Computational Details of DFA

The stride interval time series is first integrated by subtracting the mean from every data point via the following equation:

$$y(k) = \sum_{i=1}^{k} \left[S(i) - S_{ave} \right], \qquad (1)$$

where *S*(*i*) is the *i*th stride number and *Save* is the average stride interval. The integrated time series *y(k)* is then portioned into boxes that consist of an equal number of data points, and a trend line is fit to the data contained within each box. Next, the local trend is removed from each box and the remaining fluctuations (*F*[*n*]) are quantified using the root-mean-square method:

$$F(n) = \sqrt{\tfrac{1}{N} \sum_{k=1}^{N} \left[y(k) - y_n(k) \right]^2}. \qquad (2)$$

This process is iterated across box sizes of increasing size that typically range from 4 data points long to a maximum length of one-quarter of the entire time series length. The root-mean-square of the detrended fluctuations at each box length is then plotted on a log-log plot and a least squares line indexes the slope of the data. This slope corresponds to the DFA alpha *(*α*)* value, and is a measure of the strength of the long-range correlations. DFA α typically ranges from .5 to 1.0 in human stride intervals, with values tending toward .5 indicating weaker long-range correlations (ie, more random behavior) and values tending toward 1.0 indicating stronger long-range correlations (ie, more patterned behavior). Healthy human gait typically exhibits a DFA $\alpha \approx .75$.