The Repeatability of Stride Time Variability, Regularity and Long-range Correlations

Abstract

Background: Detrended fluctuation analysis (DFA) and sample entropy (SE) measure the long-term correlations and regularity of gait patterns, respectively, having previously been used to identify participants at risk of falling, previous history of injury, or patients with motor diseases. Since these measures are more sensitive to gait impairment than linear measures (e.g., the standard deviation [SD] of stride time), they can be potentially used in military medicine to identify soldiers at risk of injury. However, clinometric properties are yet to be established.

Research Question: What is the repeatability of DFA, SE, and traditional linear measures of stride time variability (SD and coefficient of variation [CV]) under various load and speed constraints?

Methods: Fourteen Australian Army trainee soldiers (age: 25.6 ± 5.9 y, height: 1.74 ± 0.08 m, body mass: 77.2 ± 15.1 kg, service: 1.5 ± 1.8 y) attended three sessions over two weeks, completing four 12-minute walking trials on an instrumented treadmill in each session. Participants walked with a combination of 0 kg or 23 kg loads at a self-selected or 5.5 km/h speed. Heel contacts from the right foot were identified using treadmill-embedded force plates. From 512 stride time intervals, linear (SD and CV), and non-linear (DFA and SE) measures were obtained. To assess the between-session repeatability, intraclass correlations (ICC 2,1) were employed.

Results and Significance: There was poor-to-moderate repeatability for the SD (ICC: 0.357 - 0.545) and CV (ICC: 0.371 - 0.529). DFA showed poor-to-moderate repeatability (ICC: 0.013 - 0.504), while SE had poor repeatability (ICC: 0.133 - 0.226). Previous studies have shown that differences of > 0.19 in DFA and > 0.66 in SE can differentiate between healthy and pathological gait. These values are greater than this study's reported standard error of measurement, indicating that clinically meaningful changes may still be detectable despite low repeatability.

Keywords: variability, regularity, stride, repeatability, load-carriage, test-retest, reliability

Introduction

The physical demands of load carriage are associated with an increased risk of musculoskeletal injuries in Australian military personnel [1]. Recognising biomechanical changes due to load carriage is crucial to understanding the underlying mechanisms of injury risk and informing training protocols that may prevent such injuries. Increasing evidence suggests that changes in dynamic behaviour, such as altered stride time fluctuations, may be able to identify otherwise undetectable injury or disease-related changes in walking patterns [2]. In this regard, using these biomechanical markers could be more appropriate for evaluating military load carriage and potentially be more sensitive in detecting increases in injury risk than traditional measures.

Stride time is one of the fundamental temporal characteristics and the final output of walking [3, 4]. It is believed to represent the control of the rhythmic stepping mechanism and reflect locomotive health [5]. Traditional linear measures of stride time variability, such as the coefficient of variation (CV) and the standard deviation (SD), can provide some insight into an individual's health [6]. For example, linear measures (e.g. CV) can predict the risk of falling in Parkinson's and multiple sclerosis disease [7, 8] and are influenced by ageing and dementia [9]. Although sensitive to disease, linear measures may not be sensitive enough to distinguish walking changes owing to imposed external constraints that may lead to injury in a healthy individual [10, 11]. This could be because linear measures assume that variations in stride time are unrelated to each other, but research has proven this assumption to be incorrect [10, 12]. Through examining the magnitude of variation, linear measures ignore the temporal structures that may exist [13]. A better way to understand the dependency of continuous stride events (dynamic behaviour) is by utilising non-linear measures such as detrended fluctuation analysis (DFA) and sample entropy (SE). These measures capture the structure of a time series, providing insight into the evolution of movement [14].

DFA can be used to examine stride-time variability over time by quantifying the degree of self-similarity through a scaling exponent (DFA alpha) [15, 16]. The DFA alpha statistically estimates the persistence or anti-persistence of a time series, determining if variations are followed by variations in the same or opposite directions, respectively [17]. SE assesses how similar consecutive stride variations are to each other, with a greater value representing more unpredictability or irregularity in a stride time signal [18]. DFA and SE have been found to be more sensitive than linear measures in identifying falls risk in older adults, neuromuscular diseases, and injury [3, 19, 20]. Most non-linear stride time research has explored the use of

DFA and SE to identify between-group differences [21, 22], and prospective (longitudinal) studies to explore the prognostic capabilities of these measures still need to be completed.

It is proposed that DFA and SE can offer a different and perhaps more sensitive insight into the dynamic behaviour changes associated with injury risk during military marching, however, previous studies have shown that the repeatability of these measures ranges from poor to good [21, 23-25]. Previous research has been limited to adult and elderly populations, and the repeatability of these measures is yet to be studied when walking under physical constraints (e.g. load carriage). Determining whether DFA and SE can be employed as markers of injury risk and/or outcome measures in preventive interventions during military training is crucial. Therefore, this study aimed to determine the between-session repeatability of linear and non-linear stride-time variability measures under different loads and speed conditions.

Methods

Participants

Fourteen Australian Army trainee soldiers (age: 25.6 ± 5.9 y, height: 1.74 ± 0.08 m, body mass: 77.2 ± 15.1 kg, service: 1.5 ± 1.8 y) participated in the study. Each participant was free of neuromusculoskeletal injury for at least six months prior to participating. All participants provided written, informed consent to ethical procedures, which were approved by the XXX (Ethics protocol #XXX) and reciprocally approved by XXX (Ethics protocol # XXX).

Experimental Overview

The research design of this study was part of a broader investigation aimed at exploring various biomechanical and physiological aspects of load carriage [26]. Participants attended three sessions over the course of three weeks. In each session, participants completed four 12-minute walking trials on an AMTI Compact Tandem Force-Sensing Treadmill (AMTI, Watertown, MA, USA) whilst holding a 3.2 kg replica F88-Austeyr rifle and wearing 2-kg military boots with loose active clothing. Trials were conducted at two speeds: self-selected (SS) and 5.5 km/h, with two different loads: 0 kg and 23 kg. The external load was applied via a weighted vest (consisting of 10 kg in the front and 6 kg in the back). The remaining load consisted of a METAMAX 3B system and a Polar heart rate monitor, both included as part of a larger research design.

In the first session, the self-selected speed for each load was determined. A participant was instructed that their SS speed was “How fast you would walk from point A to point B.” To

begin, participants completed two minutes of walking on the instrumented AMTI treadmill to familiarise themselves with treadmill walking. Then to determine SS speed, the treadmill was set to 4.0 km/h and was increased by 0.1 km/h every 10 s. The participant verbally indicated when they believed they had reached their SS speed. The treadmill speed was then increased to 6.0 hm/h before being decreased by 0.1 km/h every 10 s until the participant verbally indicated they had reached their SS speed. The two recorded speeds were averaged to find the SS speed of the participant under the specific load.

At the beginning of the walking trials in each session, participants were instructed to walk in the middle of the treadmill for the entire period. The trials were performed with no audible or visual stimulus. To reduce the chance of fatigue, participants were given 12-minute rest periods in-between trials.

Data Analysis

Force and centre of pressure (COP) data (1000 Hz) were collected from the treadmill via Vicon Nexus software (v. 2.14, Vicon Motion Systems Ltd., Oxford, UK) and imported into MATLAB 2021a [27] for post-processing. Participants did not consistently maintain one foot on a single force plate while walking. Previous research by Verkerke and colleagues [28] has supported the use of COP to determine left and right heel contacts. Therefore, to calculate heel contacts, a second-order low-pass Butterworth filter (50 Hz), was applied to the force data with the antero-posterior (AP) COP used to calculate heel-contact times. A heel contact was determined when the AP COP shifted from a posterior to an anterior direction with MATLAB's "findpeaks" function used to identify each time this occurred over the walk. Medio-lateral (ML) COP was used to determine whether the first heel-contact was from the left or right heel using the first three seconds of a trial with the "findpeaks" function identifying the first occurrence. After removing heel-contact times within the first 20 s to eliminate the effects of gait initiation, the middle 513 consecutive right heel-contacts (512 stride times) were selected. This number has been recommended as the minimum to quantify non-linear measures reliably [29]. To assess linear variability, the coefficient of variation (CV) and the standard deviation (SD) were calculated in RStudio [30] and to examine non-linear variability and regularity, DFA and SE were calculated in MATLAB [27]. DFA alpha scaling exponents were calculated using an average evenly spaced windows method, which has been shown to increase the precision of the DFA alpha [15]. The window size range was set from nmin = 4 to nmax = N/9 (57) with k (21) estimated using the method described by Liddy and Haddad [31]. SE was calculated following Richman and Moorman's [32] method with parameters r = 0.2 (tolerance ratio) and

m = 2 (vector length). SE is the negative logarithm of the conditional probability that two sets of data points of length m remain similar at the next point m+1 within a tolerance of r [33].

Statistical Analysis

Eight observations were identified as outliers using boxplots. Any values above Q3 (the third quartile) plus 1.5 times the interquartile range (IQR), or below Q1 (the first quartile) minus 1.5 times the IQR, were classified as an outlier and removed [34]. All measures were confirmed as normally distributed via Shapiro-Wilk's normality test, and Levene's test confirmed there was homogeneity of variances ($p > .05$). To explore the between-session repeatability, the intraclass correlation (ICC) was calculated using a two-way random-effects model ICC (2,1) for each measure and each speed and load condition using the Irr package [35] in Rstudio [30]. In accordance with Koo and Li [36], ICC values were classified as: poor (< 0.5), moderate (0.5 - 0.75), good (0.75 - 0.9) or excellent (> 0.9). Additionally, a one-way analysis of variance (ANOVA) was conducted to determine if the means of each measure were statistically different between each session for each speed and load condition. As a convenience sample was used in this study, a sensitivity analysis was performed using G*Power. For the input parameters of: $\alpha = .05$, Power = 0.8, sample size = 14. The analysis revealed that an effect size (r) of 0.204 was required for a correlation analysis to achieve statistical significance. Additionally, for an ANOVA, an effect size of 0.95 (η^2) was determined to be necessary to yield statistically significant results. Standard error of measure (SEM) and minimal detected change (MDC) were calculated using formulas outlined by Weir [37].

Results

A total of 168 trials were collected. Several factors contributed to the decrease in the number of trials included in the analysis. One participant did not attend follow-up sessions due to an unrelated injury, and several others did not complete all required conditions due to availability, while some trials were removed from the analysis due to technical issues such as software crashes. Where trials were removed, participants' corresponding trials from the remaining sessions were also excluded from the results. The number of participants included for each speed and load is shown in Table 1. The participants' average SS walking speed was 4.95 ± 0.22 km/h (mean ± SD). Table 1 displays the summary statistics of all stride time measures (DFA, SE, SD, CV) over the three sessions for each speed and load condition. Table 2 shows the mean difference between each session and ANOVA results (one-way) for each measure and each condition. No significant effect of session was identified for any variable (p >.05). Table 3 summarises the between-session repeatability (ICC 2,1) of each measure and each condition over the three sessions. Poor-to-moderate repeatability was demonstrated for SD (ICC: 0.357 - 0.545), CV (ICC: 0.371 - 0.529), and DFA (ICC: 0.013 - 0.504). Poor repeatability was shown for SE (ICC: 0.133 - 0.226).

Table 1: Summary statistics (mean [95% confidence intervals (CI)] of the standard deviation (SD), coefficient of variation (CV) and standard error of the mean (SEM) of stride time mean, linear (SD, CV) and non-linear (DFA, SE) measures of stride time variability for each walking speed and load combination.

Measure	Speed	Load (kg)	Participants	Mean	SD	CV (%)	SEM
DFA (α)	Self-selected	0	11	0.839 [0.784, 0.894]	0.059 [0.034, 0.085]	7.092 [4.172, 10.013]	0.034 [0.020, 0.049]
	Self-selected	23	14	0.826 [0.786, 0.866]	0.083 [0.052, 0.114]	10.077 [6.365, 13.788]	0.048 [0.030, 0.066]
	5.5 km/h	0	13	0.882 [0.840, 0.926]	0.103 [0.065, 0.142]	11.679 [7.308, 16.050]	0.060 [0.037, 0.082]
	5.5 km/h	23	13	0.804 [0.756, 0.852]	0.069 [0.045, 0.093]	8.636 [5.665, 11.607]	0.040 [0.026, 0.054]
Sample Entropy (S)	Self-selected	0	14	1.78 [1.68, 1.88]	0.19 [0.12, 0.25]	10.88 [6.66, 15.10]	0.11 [0.07, 0.15]
	Self-selected	23	14	1.85 [1.77, 1.92]	0.16 [0.12, 0.21]	9.08 [6.19, 11.97]	0.10 [0.06, 0.12]
	5.5 km/h	0	13	1.85 [1.78, 1.91]	0.17 [0.09, 0.26]	9.42 [4.88, 13.95]	0.10 [0.05, 0.15]
	5.5 km/h	23	12	1.90 [1.81, 1.98]	0.16 [0.10, 0.22]	8.75 [5.50, 12.00]	0.09 [0.06, 0.13]
SD (ms)	Self-selected	0	13	17.1 [14.1, 20.2]	4.4 [2.1, 6.6]	23.1 [13.1, 33.1]	2.5 [1.2, 3.8]
	Self-selected	23	14	17.3 [14.9, 19.6]	3.0 [1.7, 4.2]	16.2 [11.0, 21.3]	1.7 [1.0, 2.4]
	5.5 km/h	0	11	14.3 [12.4, 16.2]	1.9 [1.1, 2.8]	13.5 [7.1, 20.0]	1.1 [0.6, 1.6]
	5.5 km/h	23	12	13.4 [12.2, 14.7]	1.8 [1.1, 2.5]	13.0 [8.9, 17.0]	1.0 [0.7, 1.4]
CV (%)	Self-selected	0	14	1.6 [1.4, 1.9]	0.4 [0.2, 0.6]	22.7 [13.4, 32.1]	0.2 [0.1, 0.3]
	Self-selected	23	14	1.6 [1.4, 1.8]	0.3 [0.2, 0.4]	16.0 [10.9, 21.1]	0.2 [0.1, 0.2]
	5.5 km/h	0	12	1.4 [1.2, 1.6]	0.2 [0.1, 0.3]	15.1 [8.2, 22.0]	0.1 [0.1, 0.2]
	5.5 km/h	23	12	1.3 [1.2, 1.4]	0.2 [0.1, 0.2]	12.8 [8.9, 16.7]	0.1 [0.1, 0.1]

Table 2: ANOVA results and mean difference [95% confidence interval (CI)] between each session of the linear (SD, CV) and non-linear (DFA, SE) measures of stride time variability for each speed and load combination.

		ANOVA Model			Mean Session Difference [95%CI]		
Measure	**Speed**	**Load (kg)**	***F* statistic**	***p* value**	**Session 1 VS 2**	**Session 1 VS 3**	**Session 2 VS 3**
DFA (α)	Self-selected	0	0.024	0.976	0.004 [-0.221, 0.230]	0.009 [-0.212, 0.23]	0.005 [-0.145, 0.155]
	Self-selected	23	1.785	0.181	0.003 [-0.304,0.310]	0.065 [-0.208, 0.338]	0.062 [-0.122,0.246]
	5.5 km/hr	0	1.071	0.353	-0.034 [-0.391,0.324]	0.036 [-0.301, 0.372]	0.069 [-0.23, 0.370]
	5.5 km/hr	23	0.678	0.514	0.029 [-0.187, 0.246]	-0.017 [-0.250, 0.216]	-0.046 [-0.249, 0.157]
Sample Entropy (S)	Self-selected	0	2.028	0.093	-0.02 [-0.70, 0.66]	-0.19 [-0.68, 0.31]	-0.16 [-0.62, 0.29]
	Self-selected	23	1.645	0.126	-0.15 [-0.56, 0.27]	-0.10 [-0.63, 0.43]	0.04 [-0.44, 0.52]
	5.5 km/hr	0	0.635	0.953	0.00 [-0.68, 0.68]	-0.02 [-0.62, 0.58]	-0.02 [-0.66, 0.61]
	5.5 km/hr	23	1.425	0.934	-0.02 [-0.51, 0.47]	0.01 [-0.52, 0.54]	0.03 [-0.56, 0.62]
SD (ms)	Self-selected	0	0.467	0.631	0.7 [-17.4, 18.8]	3.5 [-12.238, 19.165]	2.8 [-9.3, 14.8]
	Self-selected	23	0.786	0.463	1.9 [-8.5, 12.3]	2.1 [-8.729, 12.920]	0.3 [-7.7, 8.0]
	5.5 km/hr	0	0.261	0.772	1.0 [-3.5, 5.4]	0.1 [-7.945, 8.136]	-0.9 [-7.2, 5.5]
	5.5 km/hr	23	0.972	0.389	1.314 [-4.8, 7.5]	0.1 [-4.393, 4.635]	-1.2 [-7.3, 4.9]
CV (%)	Self-selected	0	0.400	0.673	0.1 [-1.6, 1.8]	0.3 [-1.0, 1.6]	0.2 [-1.0, 1.3]
	Self-selected	23	0.791	0.460	0.2 [-0.8, 1.1]	0.2 [-0.8, 1.2]	0.0 [-0.711, 0.7]
	5.5 km/hr	0	0.500	0.611	0.1 [-0.3, 0.5]	0.0 [-0.8, 0.8]	-0.1 [-0.839, 0.6]
	5.5 km/hr	23	1.063	0.357	0.1 [-0.4, 0.7]	0.0 [-0.4, 0.4]	-0.1 [-0.7, 0.5]

Table *3*: Intraclass correlation coefficients [95% confidence intervals (CI)], standard error of measurement (SEM) and minimal detected change (MDC) for the linear (SD, CV) and non-linear (DFA, SE) measures of stride time for each speed and load combination.

Measures	Speed	Load (kg)	ICC [95%CI]	SEM	MDC
DFA (α)	Self-selected	0	0.504 [0.118, 0.813]	0.053	0.146
	Self-selected	23	0.165 [0.000, 0.531]	0.076	0.210
	5.5 km/hr	0	0.013 [0.000, 0.414]	0.103	0.284
	5.5 km/hr	23	0.406 [0.071, 0.730]	0.053	0.148
Sample Entropy (S)	Self-selected	0	0.226 [0.000, 0.577]	0.164	0.454
	Self-selected	23	0.161 [0.000, 0.525]	0.150	0.416
	5.5 km/hr	0	0.151 [0.000, 0.248]	0.161	0.445
	5.5 km/hr	23	0.133 [0.000, 0.562]	0.152	0.421
SD (ms)	Self-selected	0	0.485 [0.149, 0.777]	3.136	8.693
	Self-selected	23	0.477 [0.160, 0.762]	2.143	5.940
	5.5 km/hr	0	0.545 [0.181, 0.831]	1.639	4.543
	5.5 km/hr	23	0.357 [0.019, 0.711]	1.449	4.017
CV (%)	Self-selected	0	0.501 [0.179, 0.778]	0.283	0.783
	Self-selected	23	0.489 [0.173, 0.769]	0.195	0.542
	5.5 km/hr	0	0.529 [0.187, 0.811]	0.142	0.394
	5.5 km/hr	23	0.371 [0.033, 0.718]	0.137	0.378

Discussion

This study examined the between-session repeatability of linear (SD and CV) and non-linear (DFA and SE) measures of stride-time variability during treadmill walking over three sessions under various load and speed conditions. In agreement with previous research for linear measures, there was poor-to-moderate repeatability for the SD (ICC: 0.357 - 0.545) and the CV (ICC: 0.371 - 0.529) [25, 38]. DFA showed moderate-to-poor repeatability (ICC: 0.013 - 0.504), while SE had poor repeatability (ICC: 0.133 - 0.226). Interestingly, despite varying ICC values, no significant effect of session was identified for any measure by the one-way repeated measure ANOVAs, suggesting a random but not systematic difference between sessions.

DFA mean values were > 0.5 and consistent with persistent stride fluctuations previously reported for healthy individuals [14]. This was expected as the observed sample was from a healthy cohort of trainee soldiers. The DFA alpha demonstrated moderate-to-poor repeatability, which aligns with previous research in healthy and older adults as well as Parkinson's affected populations' [38-40]. Although previous studies that have employed a single trial have shown good repeatability [21, 24, 41-43], they utilised different methodologies (e.g., motion capture [42, 43]), tasks (e.g., running [41]) and/or populations (e.g., multiple sclerosis [21]). For example, Raffalt and colleagues [44] included fewer sessions (n = 2), reduced walk time (5 min), fewer strides (< 500), and utilised Peng's original DFA calculation [45]. In contrast, the current study included > 500 strides over three sessions and employed the average evenly spaced windows method [31]. The latter parameters were selected to improve DFA-alpha precision, as suggested by Ravi et al. [46]. Methodological differences in the number of strides and sessions may account for the comparatively lower repeatability for DFA when compared with previously published data.

The results showed that SE had low repeatability, supporting previous studies conducted on healthy older adults and those with osteoarthritis [21, 42]. It is difficult to compare the SE values found in this study with previous research due to the dependence of SE on the number of data points, sample rate, and parameters used (m and r) [47]. Establishing a standard method for recording and reporting SE for stride time seems necessary if clinometric values are to be established in the future. It is worth mentioning that the observed low repeatability in non-linear measures is likely a result of them having high sensitivity and exploring the temporal structure of stride time variability as opposed to quantifying its magnitude (linear measures). Despite the poor observed repeatability for non-linear measures, previous studies have shown that differences of >

0.19 in DFA [48] and > 0.66 in SE values [49] can differentiate between healthy and impaired walking. These differences exceed the highest reported SEM for DFA (0.103) and SE (0.164). However, it's worth noting that the highest reported MDC for DFA (0.284) was higher than these thresholds. This was observed carrying a load (23 kg) and walking at a greater speed (5.5 km/h), while the aforementioned studies were performed with no load and at a reduced speed (~ 4.5 km/h). This study's results, when walking at a similar speed of approximately 5.0 km/h (SS) with no load, showed a lower DFA MDC (0.146), confirming the results of previous studies. Nonetheless, our results demonstrate that non-linear measures had a small variation of less than 10% between sessions and suggests that prospective research could utilise this observation to identify meaningful changes. These changes are therefore likely to be detected using the present methods, yet careful interpretations should be drawn around differences that are close to cut-off values [50].

The results of this study may have been affected by its limitations. For the majority of measures, there was low between-subject variation, as indicated by the small standard deviations (Table 1). This may have led to lower observed ICC values and wider confidence intervals (Table 3). Increasing the sample size could have helped to address these issues. Unfortunately, as a convenience sample was used, the sample size was restricted and then further reduced due to participant availability and technical issues such as software crashes. Research shows that walking on a treadmill can decrease the statistical persistence of stride time patterns [51]. Therefore, the results of this study may not apply to overground walking where changes in incline, terrain, and speed may lower repeatability. Although sufficiently long rest periods were allowed in between trials and sessions to avoid fatigue, the randomisation of conditions associated with the larger research program may have contributed to between-session differences. While not demonstrated in walking, it has been shown that statistical persistence in stride time can decrease over a prolonged run, believed to be a result of fatigue and runners having to regulate their running pattern [19].

Conclusion

This study examined the between-session repeatability of linear (SD and CV) and non-linear (DFA and SE) measures of stride-time variability during treadmill walking. It was novel as it utilised a military population and included a military-specific load and speed. It was found that both linear and non-linear measures demonstrated poor-to-moderate repeatability. Despite this,

when comparing the repeatability to stride-time variability changes reported to distinguish groups of Parkinson's patients or older adults [48, 49] these measures still have utility to effectively identify disparities between healthy and impaired walking patterns. The use of non-linear measures, as reported in this study, are likely to be repeatable enough to detect changes in stride-time variability due to military-specific task constraints. Future research should determine the effect of these task constraints on non-linear measures of stride time variability and other intrinsic factors such as fatigue and injury.

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