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Comparison of selected measures of gait stability derived from center of pressure displacement signal during single and dual-task treadmill walking

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ABSTRACT

Steady state gait dynamics has been examined using the measures of regularity, local dynamic stability, and variability. This study investigates the relationship between these measures under increasing cognitive loads. Participants walked on an instrumented treadmill at 1 m/s under walk only and two dual-task conditions. The secondary tasks were visuomotor cognitive games (VCG) of increasing difficulty level. The center of pressure displacement in the mediolateral direction (ML COP-D) and cognitive game performance were recorded for analysis. The following measures were calculated: (1) sample entropy (SampEn) and quantized dynamical entropy (QDE) of the ML COP-D, (2) short-term largest Lyapunov exponent (LLE) of the ML COP-D, and (3) variability of inter-stride spatio-temporal gait variables. Entropy and variability measures significantly increased from walk only to both dual-task conditions. Whereas, the short-term LLE increased only during the easy VCG task. No measure was sensitive to the difficulty level of the VCG tasks. The variability of heel strike positions in the mediolateral direction was positively correlated with SampEn and QDE. However, there were no significant correlations between the short-term LLE and either variability measures or entropy measures. These findings confirm that each of these measures is representative of a different aspect of human gait dynamics.

1. Introduction

Balance is a functional term and its control during walking is a complex multi-dimensional task. The central nervous system deals with balance or gait stability requirements by two processes [1]: (a) feedforward control system to maintain control over the position and motion of the center of body mass (COM) within the moving base of support (BOS), and (b) feedback control system to restore stability in response to a sudden perturbation or movement error (i.e. unexpected deviation from a planned movement). In many studies, gait cycle variability is often used synonymously with stability [2]. For example, increased variability in step length or step time of older adults, i.e. values determined at gait cycle endpoints, is often equated with loss of gait stability [3] and associated with increased fall risk [4–6].

More recently, nonlinear analysis methods based on dynamical systems approach have been explored as possible measures of steady state gait stability [7,8]. The short-term largest Lyapunov exponent (LLE) has been reported as a measure of the local dynamic stability of human walking [9,10]. This outcome measure quantifies the average logarithmic rate of divergence of a system after small perturbations. It is calculated as the slope of the mean divergence curve at 0–0.5 strides [11]. Typical biological signals used to compute the short-term LLE are upper and lower trunk linear acceleration and linear velocity collected during overground and treadmill walking [12–16]. The short-term LLE of the center of pressure trajectory has also been shown to successfully distinguish between normal and auditory cueing walking conditions [17]. Another measure used to quantify gait stability is entropy [18]. Entropy measures represent the difficultness of describing the patterns of the trajectory of a system. A signal with few repetitive patterns would have a relatively large entropy value [19]. The terms unpredictability, irregularity, and complexity have been used to reflect this idea [20,21]. Recent studies have reported an increase in entropy of the center of pressure displacement in the mediolateral direction (ML COP-D) recorded during treadmill walking with age and dual-task (DT) walking [18,22].

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Unlike typical average step (or stride) variables used in the past, gait cycle variability considers stride-to-stride variations, which have shown a long-range correlation [23]. However, gait fluctuations are not limited only to gait cycle endpoint variations. Within each step (or stride), gait signals show complex fluctuations, which change from stride to stride. Entropy measures and the short-term LLE use whole signals and are not limited to timing or distance variables between cycle endpoints (i.e. heel strikes). Therefore, they take into account not only the inter-stride fluctuations, but also the intra-stride fluctuations, which contain crucial information on the locomotor control system [22,24].

Performing a concurrent cognitive task while walking (dual-tasking) has been reported to negatively affect human gait stability [25]. The aforementioned measures have shown different and to some extent contradictory results when they were used to study the effect of dual-tasking. The possible reason is that these studies have had different protocols and task conditions and have used different biological signals, thereby making the comparison between the available results difficult. Hence, a direct comparison would be beneficial and would help to understand how each of these measures is affected by dual-tasking. To illustrate the heterogeneity of these studies, a significant increase in variability measures (e.g. stride time variability [26] and stride width variability [27]), the short-term LLE [28] and entropy measures [22] have been reported during DT walking for young healthy adults. Conversely, no significant change in variability measures (e.g. stride length variability [26], swing time variability [29], and stride time variability [30]), the short-term LLE [31], and entropy measures [18,28] have been reported as a result of dual-tasking. Moreover, a significant decrease in step width variability [32] has also been reported.

The first objective of the current study was to compare the effects of dual-task treadmill walking and its degree of difficulty on three families of gait measures. These measures are the coefficient of variance of select spatio-temporal gait variables, the short-term LLE and entropy measures all derived from the ML COP-D signal of young healthy adults. The ML COP-D has previously been shown to discriminate between different walking conditions [17,18,22]. In the present study, a treadmill instrumented with a pressure mapping system was used to collect the ML COP-D signal. It was hypothesized that all three gait measure would increase as a result of dual-tasking and the increase would be proportional to the difficulty level of the secondary task. The second objective was to quantify the relationship among the three measures using a correlation analysis [24,33]. It has been argued that these measures represent fundamentally different aspects of systems dynamics [2]. This notion has been confirmed to some extent by showing that the local stability of trunk linear acceleration is poorly correlated to traditional measures of variability such as standard deviation of stride times when comparing continuous overground and treadmill walking [24]. With regard to the second objective, it was hypothesized that the entropy measures, variability measures and the short-term LLE would not be highly correlated. The third objective was to determine the effects of physical demands (standing versus walking) on the performance of the visuomotor cognitive games. It was hypothesized that there would be a significant decrease in cognitive task performance during treadmill walking as compared to stationary standing.

2. Methods

2.1. Subjects

A convenience sample of 29 young healthy participants (8 females, 28.3 ± 2.7 years, 69.7 ± 14.2 kg, and 173.4 ± 8.8 cm, mean ± standard deviation (SD)) were recruited. Exclusion criteria were any illnesses, neuromuscular injuries or previous surgeries that might negatively affect their balance and gait. The University of Manitoba human research ethics committee has approved the study and all participants signed the informed consent form prior to the tests. The raw data obtained for the current study has been partially used in a previous study [34].

2.2. Experimental procedure

Participants walked on an instrumented Bertec treadmill (Bertec Corporation, Columbus, Ohio, USA) at a fixed speed of 1 m/s to avoid the confounding effect of different walking speeds [26,35,36]. The belt of the treadmill incorporates a force plate measuring resultant forces and moments. The center of pressure data is then calculated from the force and moment components. Participants walked under 3 different walking conditions, each for 1 min:

(a) walk only (WO) trial,
(b) walking while performing the easy secondary visuomotor cognitive game (VCG1) task, which is described in Section 2.3,
(c) walking while performing the difficult secondary visuomotor cognitive game (VCG2) task, which is described in Section 2.3.

All participants first performed the WO trial followed by randomly presented VCG1 and VCG2 tasks. Prior to performing gait tests, participants were instructed on the computer tasks while seated. After comprehending the tasks, they performed each task while comfortably standing with a computer display at eye-level. The outcomes of these tests were used as the baseline for the task performance. During the WO trials, participants watched a scenery video to maintain gaze and head position relative to the monitor. For the purpose of hands-free interaction with the cognitive game activities, a commercial motion-sense wireless mouse (Elite mouse, SMK Electronics, USA) was mounted on a plastic headband worn by each participant. Therefore, during walking, the head rotation was used to control the motion of a computer cursor. The participants were instructed not to intentionally prioritize either their gait or the secondary tasks.

2.3. Description of secondary tasks

The goal of the visuomotor cognitive game (VCG) was to move a game paddle horizontally to interact with the moving game objects. The game objects were categorized as designated targets or designated distractors, with the shape of a soccer ball and a dotted sphere, respectively. They appeared at random locations at the top of the display every 2 s and moved diagonally toward the bottom of the display. In response to each “game event” (target appearance), participants rotated their head (i.e. rotation of the motion-sense mouse) to move the game paddle (left/right) in order to catch the target objects while avoiding the distractors [22,37]. Two difficulty levels of VCG were tested in this study. Task VCG1 had only one target and one distractor. Task VCG2 had increased difficulty and consisted of one target and two distractors of different shapes, and they appeared much faster and the paddle size was smaller compared to VCG1.

2.4. Gait measures

During walking trials, the center of pressure of foot displacement (COP-D) in the mediolateral (ML) and anteroposterior (AP) directions was collected at 1000 Hz. The signals were filtered using a second-order Butterworth low-pass filter with a cut-off frequency of 30 Hz and downsampled to 125 Hz [34]. Forty seconds of data was used after discarding data related to approximately the first 4 strides. The analysis was based on at least 30 consecutive

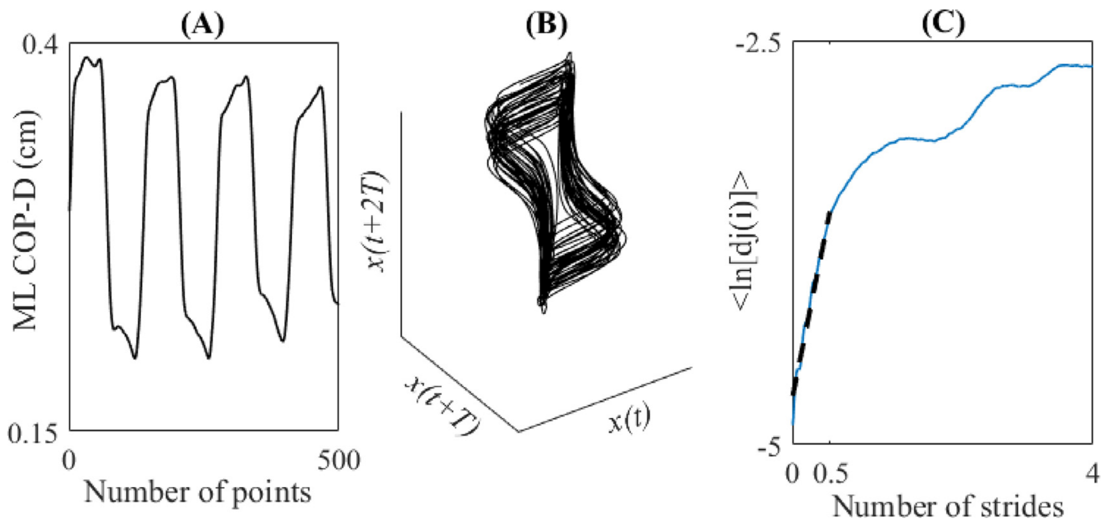

Fig. 1. Calculation process of short-term largest Lyapunov exponent, λ_s: (**A**) 4 strides of ML COP-D; (**B**) 3D state-space reconstruction with the time delay of 15; (**C**) slope of mean divergence curve of $\langle \ln d_j(i) \rangle$ over 0 to 0.5 stride.

strides, which is consistent with previous works [18,35,38,39] during WO trials and when performing two visuomotor cognitive tasks of increasing difficulty [37].

The following gait measures were calculated:

- **Sample entropy (SampEn) and quantized dynamical entropy (QDE)**: Two entropy measures were used is this study, SampEn and QDE. The SampEn of a dataset is the negative natural logarithm of the conditional probability of two successive counts of similar pairs (i.e., having Chebyshev distance less than a tolerance r) of template size m and $m+1$ without allowing self-matches [40]. The QDE of a dataset is based on the definition of Shannon's entropy and measures the abundance of its dynamical features [18]. QDE is based on coarse quantization and vector identifiers [41]. SampEn is the most common used entropy measure [40], and QDE is the most computationally efficient one [41]. The difference between SampEn and QDE is due to their inherent methodological process. For SampEn, matched templates are compared at two template size levels, m and $m+1$. However, QDE represents the abundance of dynamical features at only one template size. A template size of 4 and a tolerance size of 0.2 times the standard deviation of all time series were used based on a systematic parameter selection study [34].
- **Short-term largest Lyapunov exponent (λ_s):** Each signal was time normalized to have the same number of data points ($30 \times 142 = 4260$), where 142 was the average number of data points per stride. The minimum average mutual information method was used to calculate the time delay. A range of 19–39 was obtained from different signals, where the median 30 was selected for future analysis [15]. However, the value based on this method did not result in a straight line required for the short-term LLE [42]. As a result, a time delay of 15 was selected which is approximately 10% of the average stride time, as suggested by previous works [10,35]. Cao's method [43] was used to find the true embedding dimension which resulted in $d = 5$ as the true embedding dimension of the experimental time series ML COP-D. This is consistent with previous studies which have reported the same value for different human gait whole signals [15,17,44]. The embedding dimension of 5 and the time delay of 15 were used to reconstruct the state space and calculate λ_s (see Fig. 1) [10].
- **Variability measures:** Variability measures quantify the inter-stride spatio-temporal fluctuations around the mean value and report it as standard deviation, SD, or coefficient of variance, COV. The variability measures that were used in this study are as follows;
  a) coefficient of variance (COV) of step time (COV-ST),
  b) COV of step length (COV-SL),
  c) COV of step width (COV-SW),
  d) COV of swing time (COV-SwT)
  Step time is the time between successive heel contacts, step length is the distance between two successive heel contacts in the AP direction, step width is the distance between two successive heel contacts in the ML direction, and swing time is the time between toe-off and heel contact of each leg. Each of these parameters may be reported for right or left leg (odd or even step). In this study, there was no statistically significant difference between even and odd steps of these values. Therefore, only the odd steps were reported in the analysis.
  e) COV of the drifts in ML and AP directions (ML/AP-Drift): these were calculated from the standard deviation of all heel contact position values of each leg divided by the average of all these values. In other words, ML-Drift and AP-Drift represent the dispersion of foot placement in the ML and AP directions, respectively. A statistically significant difference was found between even and odd steps in the ML direction; therefore, both values were considered for analysis. However, in the AP direction, no statistically significant difference was found between even and odd steps and therefore, only odd steps were reported in the analysis.

2.5. Task performance measures

Fig. 2-A and 2-B show a single movement trajectory and the sorted (left/right trajectories) game responses of a participant to the game events of the VCG task. Three measures were used to compare single-task and DT performance. These measures were calculated based on the medium amplitude movements (30%–66% of the display width) of the paddle. Those medium amplitude movements were the majority of the game events. The first one was the movement time, which is the time from the beginning of the game paddle movement to the time it reaches its plateau at the point where the target disappears. The second one was the

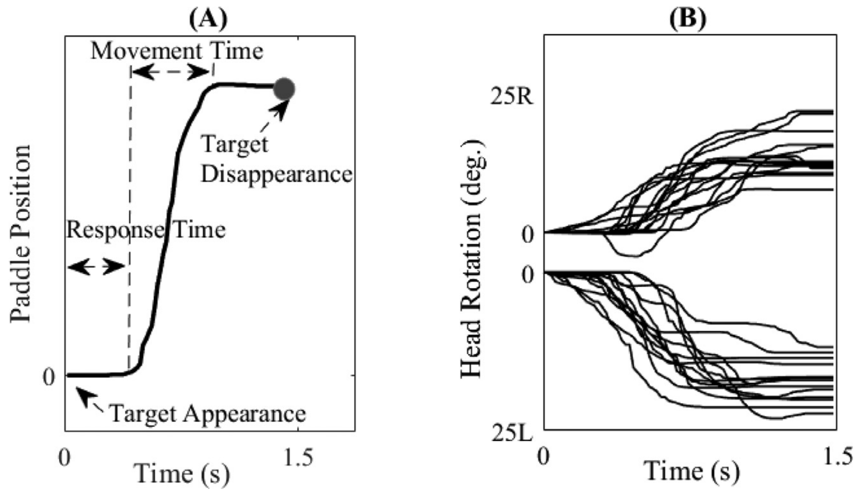

Fig. 2. Secondary visuomotor cognitive games: (**A**) single movement trajectory of the visuomotor cognitive game, VCG, representing target appearance, response time, movement time, and target disappearance; (**B**) sorted left/right movement trajectories of the visuomotor cognitive game, VCG.

success rate which is the percentage of the total number of target objects that were caught. The third measure was the movement variance which is the average of the standard deviation values of each sampled data point along the medium movement traces.

For VCG games, statistical analysis (paired sample t-test or Wilcoxon test) revealed no significant difference between the two directions. Therefore, only one direction was reported in the analysis.

2.6. Statistical analysis

The normality of datasets was checked using the Shapiro–Wilk normality test. For both gait and task performance measures, proper parametric (repeated measures ANOVA) or nonparametric (Friedman's test) statistical methods were used to investigate the main effect of the task condition. This was followed by pairwise comparisons (paired-sampled t-test or Wilcoxon test) to assess the difference between specific conditions. A Bonferroni correction was used when multiple comparisons were carried out. A p-value less than 0.05 was considered significant for all tests except for multiple comparisons of analyses where 0.05 was divided by the number of comparisons.

A Spearman's rank-order correlation was also performed to investigate the correlation between different gait measures used in this study. In order to account for the DT cost, for each gait measure, the value of WO was subtracted from that of DT condition. Pairwise comparisons between even and odd steps showed no significant difference, therefore only odd steps were used for this analysis. IBM SPSS Statistics version 24 was used for all statistical analyses.

3. Results

The descriptive and statistical results of the visuomotor cognitive games' performance measures are presented in Fig. 3. For both VCG tasks, success rate decreased significantly, and movement variance increased significantly from standing to DT walking condition. There was no significant change in average movement time from standing to DT walking condition. Additionally, there was a significant decrease in average movement time, success rate, and movement variance from VCG1 to VCG2. This was the case for both standing and DT walking conditions.

The descriptive results of the 10 gait measures for each walking condition (WO, VCG1 and VCG2) are presented in Figs. 4 and 5. More specifically, the results of SampEn, QDE, λ_s, COV-SL, ML-Drift (even), and ML-Drift (odd) are presented in Fig. 4. The results of COV-ST, COV-SW, COV-SwT, and AP-Drift are presented in Fig. 5. As presented in Table 1, there was a significant DT effect on all gait measures. Post hoc analysis revealed a significant increase in all outcome measures during the VCG1 task as compared to walk only. There was a significant increase in entropy and variability measures between WO and VCG2, but there was no significant change in λ_s between WO and VCG2. With one exception, there was no significant difference in entropy or variability measures as the cognitive task demands increased (from VCG1 to VCG2). The one exception was COV-SW which showed a significant increase ($p = 0.016$). However, as can be seen in Fig. 4, there is a consistent trend for an increase in entropy and COV gait variables between VCG1 and VCG2.

With reference to the correlation analysis, only 6 out of 36 possible correlations were found significant. SampEn and QDE were significantly correlated with ML-Drift ($r = 0.401 \sim 0.549,\ p < 0.05$ and $r = 0.634 \sim 0.844,\ p < 0.001$, respectively). In addition, COV-SL was significantly correlated with COV-ST ($r = 0.628 \sim 0.826,\ p < 0.001$), COV-SW ($r = 0.381 \sim 0.504,\ p < 0.005$), and COV-SwT ($r = 0.699 \sim 0.822,\ p < 0.001$). Finally, COV-ST was significantly correlated with COV-SwT ($r = 0.904 \sim 0.926,\ p < 0.001$).

4. Discussion

The main purpose of the present study was to compare the gait variability measures, entropy measures and local dynamic stability of the ML COP-D signal collected during treadmill walking under WO and DT conditions. The results partially confirmed our first hypothesis; variability and entropy measures increased significantly from the walk only to both DT walking tasks (VCG1 and VCG2). However, this was not the case with the short-term LLE. The present results reveal that the measure of local dynamic stability using the short-term LLE is sensitive to small deviations (internal perturbations) from a steady state but it does not detect the larger deviations due to the more demanding VCG2 task. Nonetheless, during VCG2, participants' gait was more variable and more irregular than WO. In addition, with one exception, there was no significant correlation between the three measures. This is consistent with the notion that local dynamic stability measured by short-term LLE is not synonymous with regularity presented by entropy measures or stride-to-stride variability [2].

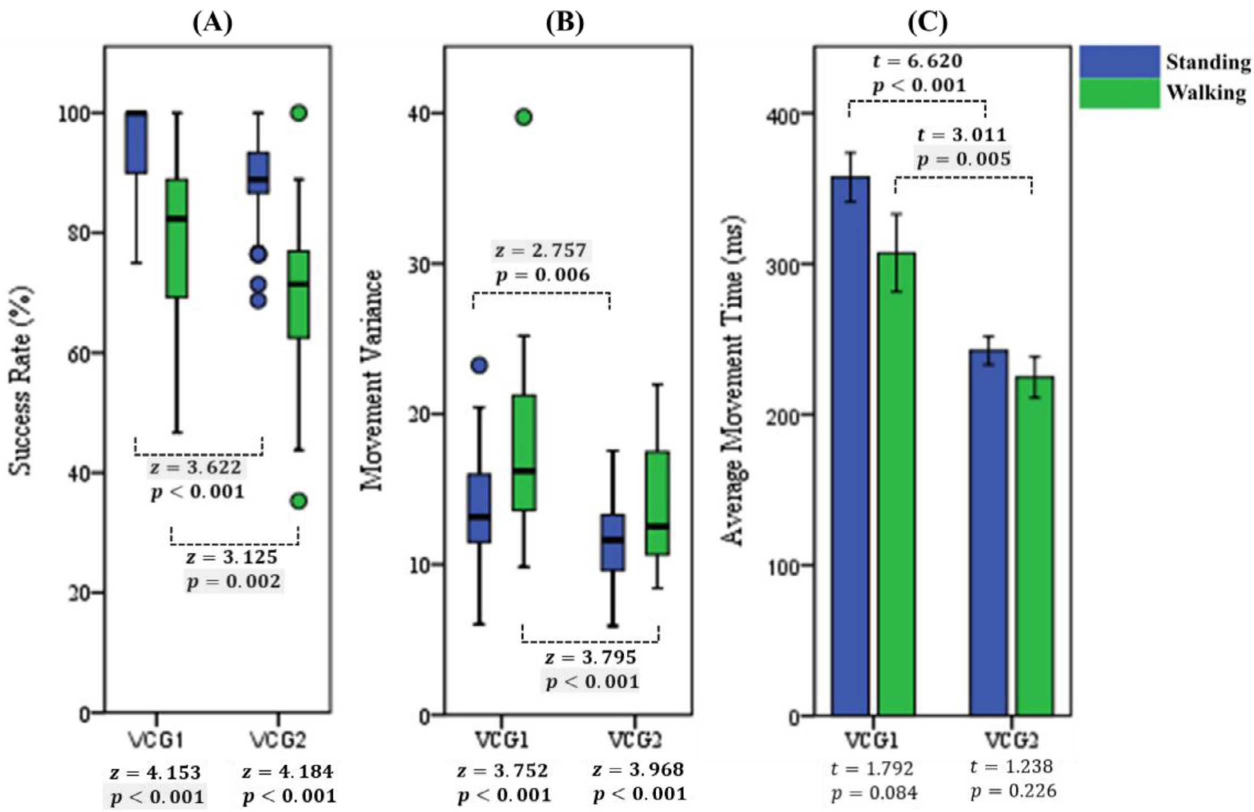

Fig. 3. Descriptive and statistical results of the task performance measures: **(A)** group medians and inter-quartile ranges of success rate (%); **(B)** group medians and inter-quartile ranges of movement variance; **(C)** group means and standard error of mean of average movement time (ms). The results of the pairwise comparisons between standing and walking condition for each VCG game are presented under x-axis labels. The results of the pairwise comparisons between VCG1 and VCG2 for each standing and walking condition are presented above/under the dashed lines. p-values in bold indicate a significant difference (significance level: $p < 0.05/4 = 0.013$).

Variability measures have been associated with instability. However, the cause-and-effect relationship between the two has been challenged. Dingwell et al. [31] re-analyzed the data from a previous study [32] in which 15 healthy young adults walked on a treadmill at their self-selected speed under two walking conditions, i.e. walk only and walking while performing a visual Stroop test. They determined that decreased step width variability did not translate to greater local dynamic stability of trunk linear velocity during DT walking condition. Variability of spatio-temporal gait variables derived from heel strike or toe-off events (gait cycle endpoints) was used to determine gait performance. However, it would not consider the features of the entire gait signal. The intra-stride dynamical features of various signals, such as trunk acceleration or COP displacement, contain valuable information about mechanisms underlying steady state gait control [45]. On the other hand, λ_s reflects how the system responds to small perturbations as it examines the degree of divergence of two neighboring points within a period of one step. In this regard, SampEn and QDE compare each template to all other templates and identify ones that match; i.e. they consider all data points and step cycles in the COP displacement time series. These differences in the features of the gait time series that are quantified by the three different methods also support the view that local dynamic stability defined by λ_s is not synonymous with regularity defined by entropy measures or either stride-to-stride variability [2]. The question of how these measures would relate to fall risk, disease severity and fall incidence will be a subject of future studies.

Another main finding of this study was that the ML-Drift measure was the only variability measure which had a significant and moderate to strong correlation with SampEn and QDE, but not with the short-term largest Lyapunov exponent. The ML-Drift measure looks at the dispersion of heel strike locations on the treadmill. The increased variability in heel strike locations in the mediolateral direction observed during DT treadmill walking might be required to match or recapture disturbances in the control of the motion of the body center of mass [46]. This is consistent with previous research findings of the increased demands on mediolateral stability during visual perturbations [46–49].

There was a trend of increased entropy measures as well as gait variability from VCG1 to VCG2, although these changes did not reach the significance level. Therefore, these gait measures were more sensitive to changes from the walk only to dual-task walking condition, than to the difference in difficulty level between VCG1 and VCG2. While the present results showed a significant DT interference effect of the visuomotor cognitive tasks on SampEn and QDE, another study [18] did not observe an increase in SampEn of ML COP-D between WO and DT treadmill walking conditions. The visuomotor cognitive tasks used in the current study were more challenging than the one used by Leverick et al. [18] in which no distractors were used and movement trajectories were predictable (i.e. straight vertical paths). Magnani et al. [28] computed SampEn from trunk linear velocity time series and reported a decrease or no change in SampEn due to dual-tasking. In this regard, a previous study has reported no significant change in SampEn of trunk linear acceleration between WO and DT, whereas a significant increase in the SampEn of the ML COP-D was observed [22]. In addition, there are a number of differences between texting used in the study of Magnani et al. [28] and the visuomotor cognitive tasks used in the present study.

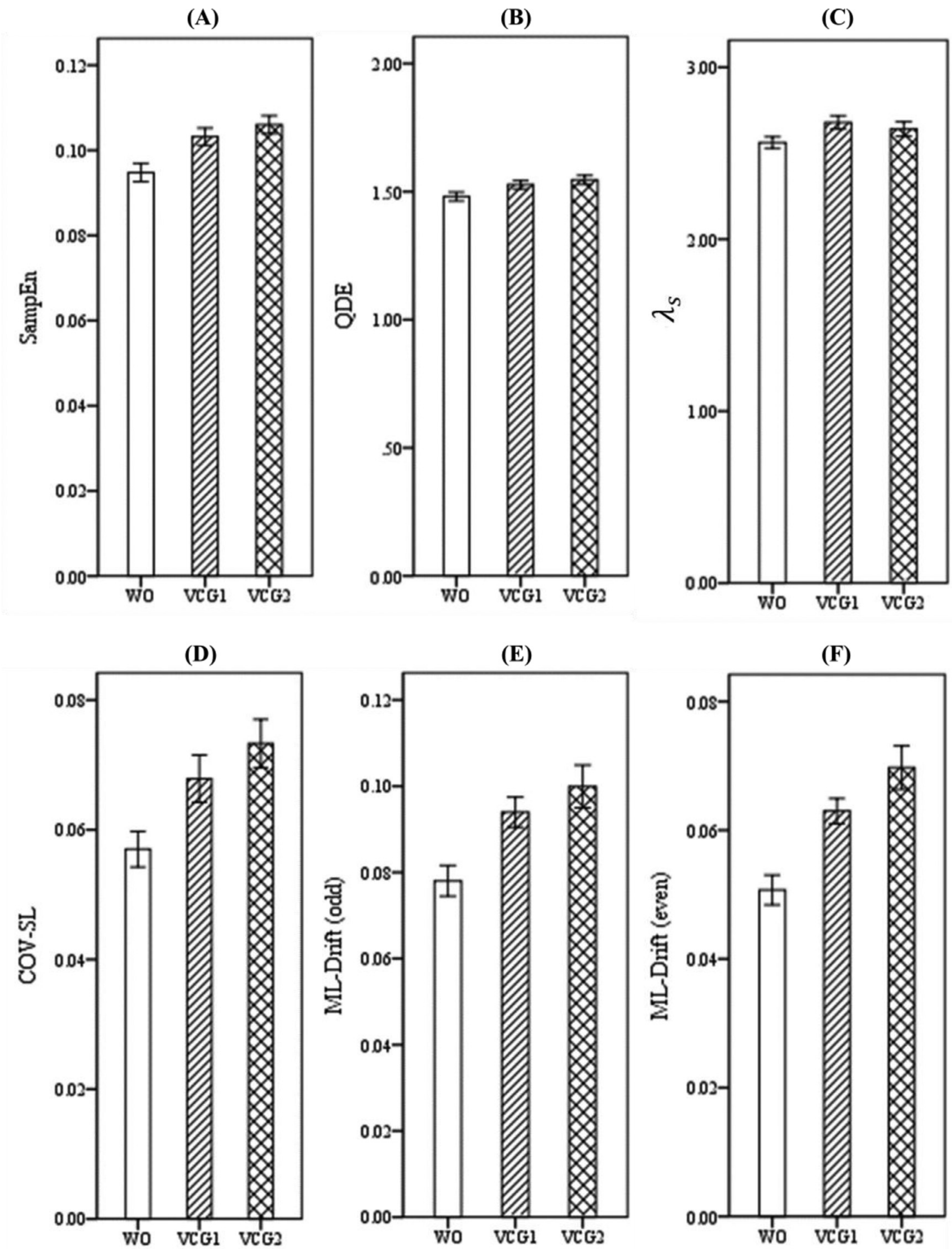

Fig. 4. Group means and standard error of mean of: (**A**) SampEn, (**B**) QDE, (**C**) λ_s, (**D**) COV-SL, (**E**) ML-Drift (odd), and (**F**) ML-Drift (even), under WO, VCG1, and VCG2 walking conditions.

The visuomotor cognitive game tasks used in the current study required continuous visual observation, tracking of the moving visual objects, and timely precise head rotations to move the game paddle and catch moving targets and avoid distractor objects. The present findings showed that in addition to significant DT effects on gait performance, visuomotor cognitive performance (i.e. success rate and movement variance) were negatively affected during treadmill walking as compared to standing. It is important to quantify both gait and cognitive task performance when identifying possible prioritization strategies and when interpreting DT interactions between cortical processes responsible for gait and those responsible for the information processing required by the cognitive tasks.

A few limitations should be considered when interpreting the results of this study. First, motor-cognitive tasks were used in this study and it is not clear to what extent the DT interference effects were due to the added information processing load or due to the head rotations. Nonetheless, a previous study [50] has re-

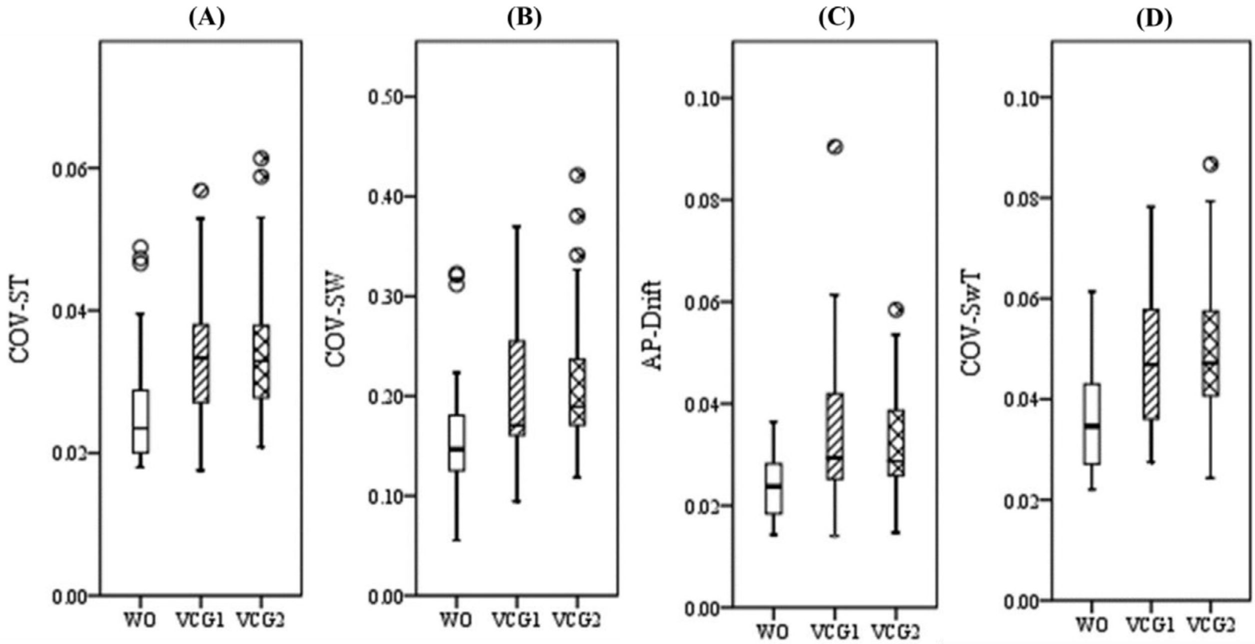

Fig. 5. Group medians and inter-quartile ranges of: (**A**) COV-ST, (**B**) COV-SW, (**C**) AP-Drift, and **(D)** COV-SwT under WO, VCG1, and VCG2 walking conditions.

Table 1
Main effects (significance level: $p < 0.05$) of task conditions on gait measures along with pairwise comparisons (significance level: $p < 0.05/3 = 0.017$). p-values in bold indicate a significant difference.

Gait Measures	Main Effect		Pairwise Comparisons		
	F or χ^2 Statistics	p-value	WO vs. VCG1	WO vs. VCG2	VCG1 vs. VCG2
SampEn	**$F = 17.149$**	**< 0.001**	**$t = 3.723$** **$p = 0.001$**	**$t = 5.474$** **$p < 0.001$**	$t = 1.739$ $p = 0.093$
QDE	**$F = 15.378$**	**< 0.001**	**$t = 3.481$** $p = 0.002$	**$t = 4.566$** **$p < 0.001$**	$t = 2.485$ $p = 0.019$
λ_s	**$F = 4.580$**	**0.014**	**$t = 3.011$** **$p = 0.005$**	**$t = 1.853$** **$p = 0.074$**	$t = 1.051$ $p = 0.302$
COV-SL	**$F = 13.186$**	**< 0.001**	**$t = 3.449$** **$p = 0.002$**	**$t = 4.262$** **$p < 0.001$**	$t = 2.086$ $p = 0.046$
COV-ST	**$\chi^2 = 15.379$**	**< 0.001**	**$z = 3.211$** **$p = 0.001$**	**$z = 3.341$** **$p = 0.001$**	$z = 0.811$ $p = 0.417$
COV-SwT	**$\chi^2 = 17.034$**	**< 0.001**	**$z = 3.341$** **$p = 0.001$**	**$z = 3.795$** **$p < 0.001$**	$z = 0.9632$ $p = 0.336$
COV-SW	**$\chi^2 = 19.241$**	**< 0.001**	**$z = 3.168$** **$p = 0.002$**	**$z = 3.730$** **$p < 0.001$**	**$z = 2.411$** **$p = 0.016$**
ML-Drift (odd)	**$F = 10.318$**	**< 0.001**	**$t = 3.635$** **$p = 0.001$**	**$t = 3.841$** **$p = 0.001$**	$t = 1.251$ $p = 0.221$
ML-Drift (even)	**$F = 23.472$**	**< 0.001**	**$t = 5.050$** **$p < 0.001$**	**$t = 5.940$** **$p < 0.001$**	$t = 2.447$ $p = 0.021$
AP-Drift	**$\chi^2 = 13.517$**	**0.00**1	**$z = 3.146$** **$p = 0.002$**	**$z = 3.060$** **$p = 0.002$**	$z = 0.011$ $p = 0.991$

ported that open loop tracking of a moving target with only head rotation, while walking on a treadmill, resulted in a very small COP deviation from the midline. Second, in the present study, the analysis was based on the data collected during treadmill walking. While treadmill walking does not equate overground walking, it was essential for this study to avoid the confounding effect of walking speed. Third, all participants walked at a fixed speed of 1 m/s. Although some studies have recommended collecting data at self-selected walking speed, 1 m/s was in the comfortable range of speed for the young healthy participants of this study. Fourth, although the order of dual-task walking conditions was randomized, all participants performed the WO trial first. Finally, while this study compared variability, entropy, and local dynamic stability measures by investigating the DT effect, prospective investigations are needed to determine how the degree to which these measures change as a function of aging, cognitive load, and physical demands relate to and predict falls.

In summary, when people engaged in a secondary visuomotor cognitive task while walking on a treadmill, both gait and cognitive performance were negatively affected. It was shown that entropy measures, the short-term largest Lyapunov exponent and variability measures were representing different aspects of human gait stability. In addition to different methods of calculation and various features of signals that these measures use, there was no significant correlation between them. The only exception was a significant correlation between entropy measures and ML-Drift measure. Therefore, a combination of these measures could elicit information on inter-stride and intra-stride changes due to dual-tasking.

Declaration of Competing Interest

The authors declare that no conflict of interests was associated with the present study.

Acknowledgement

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Ethical approval

The University of Manitoba human research ethics committee has approved the study and all participants signed the informed consent form prior to the tests. (Ethics File Number: H2016:386).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.medengphy.2019.07.018.

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