On the Use of Sample Entropy and Quantized Dynamical Entropy of Human Gait Signals as Biomarkers of Increased Fall Risk: Experimental Data Analysis

by

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Abstract

Identifying people who are at risk of fall during walking is crucial. The objective of this thesis is to comprehensively evaluate the application of two selected entropy measures, sample entropy (SampEn) and quantized dynamical entropy (QDE), as biomarkers of increased fall risk when applied to whole gait signals. SampEn is the most used entropy measure in human gait studies and QDE has the robustness of SampEn to noise but offers a superior computational performance. The first study further investigates the viability of SampEn and QDE along with choosing the signal which best discriminates between young healthy adults and elderly fallers as well as between walk only and dual-task walking condition. The results suggest that, amongst the five different signals representing trunk motion, leg motion, and the center of pressure of feet displacement, the center of pressure in the mediolateral direction (ML COP-D) is the best signal. The second study establishes the sensitivity of the SampEn and QDE of the ML COP-D signal to two preprocessing methods and to variant values of template size, tolerance size, and sampling rate. The results suggest that SampEn and QDE benefit from a relative consistency across variant parameter values, showing a significant increase from walk only to dual-task walking condition, especially when signals are low-pass filtered.

Finally, the correlation of SampEn and QDE with two other families of gait measures (i.e., variability measures and the short-term largest Lyapunov exponent [LLE] measure), which have been used for gait stability assessment, is investigated. Two difficulty levels for the secondary visuomotor cognitive games are used. The results show that all gait measures increase due to dual-tasking, except for the short-term LLE which increases significantly only during the easy game.

Additionally, these measures are not sensitive to the degree of difficulty of the secondary tasks. This is along with a poorer task performance when participants perform the secondary task while walking as compared to stationary standing. Only one variability measure, dispersion of foot placement in the mediolateral direction, is positively correlated with SampEn and QDE. Overall, the SampEn and QDE of whole gait signals show a great potential to serve as biomarkers of increased fall risk because they consider both inter-stride and intra-stride information of human gait cycles and are able to discriminate between different walking conditions.

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To my best friend,

With all my love,

To Mohammad!

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ANOVA	Analysis of Variance
AP	Anteroposterior
AP COP-D	Center of Pressure Displacement in AP Direction
AP trunk-LA	Trunk Linear Acceleration in AP Direction
AP-Drift	COV of Drifts in AP Direction
ApEn	Approximate Entropy
BOS	Base of Support
COM	Center of Mass
COP	Center of Pressure
COP-D	Center of Pressure Displacement
COV	Coefficient of Variance
COV-SL	COV of Step Length
COV-ST	COV of Step Time
COV-SW	COV of Step Width
COV-SwT	COV of Swing Time
D	Decimation
DFA	Detrended Fluctuation Analysis
D-R	Decimation and Resampling
DT	Dual-Task
FD	Filtering-Downsampling
FD-R	Filtering-Downsampling and Resampling
IMM	Inertial Motion Monitors
LLE	Largest Lyapunov Exponent
ML	Mediolateral Direction
ML COP-D	Center of Pressure Displacement in ML Direction
ML shank-AV	Shank Angular Velocity in ML Direction
ML trunk-LA	Trunk Linear Acceleration in ML Direction
ML-Drift	COV of Drifts in ML Direction
MSE	Multi-Scale Sample Entropy
QDE	Quantized Dynamical Entropy
SampEn	Sample Entropy
SD	Standard Deviation
SEM	Standard Error of the Means

VCG	Visuomotor Cognitive Game
VCG1	Easy Visuomotor Cognitive Game
VCG2	Difficult Visuomotor Cognitive Game
WO	Walk Only

List of Symbols

d	Embedding Dimension
f	Downsampling Factor
m	Template Size
N	Data Length
r	Tolerance Size
T	Time Delay
λ_s	Short-term Largest Lyapunov Exponent
λ_L	Long-term Largest Lyapunov Exponent

Chapter 1

Introduction

1.1 Motivation

Falls, which mostly occur during human ambulation (including walking, turning, and standing), have devastating consequences [1]. One common cause of falls is neurological and physical impairment due to aging. The ability to walk declines as people age and especially when they become cognitively impaired. Complications in gait initiation, reduction of gait speed, and altered gait posture, such as forward lean and loss of gait symmetry, are some changes that may occur as people age [2]. These changes may accumulate over time and lead to fall [3].

Falls in older adults cause physical injury, health service use, and fear of fall. The fear of fall causes a decline in physical activity and social participation after falling. These may lead to a further decline in overall physical and mental health conditions of older adults (e.g., depression, higher medication use, and atrophy) [4].

Furthermore, the world's population is getting older and in 2050, more than 20 percent of the population will be aged 80 years or over as compared to 14 percent in 2015 [5]. A decrease in the number of falls will decrease the costs of healthcare dramatically. These expenses are because of many factors, such as treatments in emergency departments, hospitalization because of injuries, nursing home cares, and other long-term effects such as future fear of fall, which cause people to be dependant on others and have less life quality.

Although elderly adults are at higher risks of fall, young and middle-aged adults experience high incidents of falls too. Gait impairments along with accidental or environmental reasons are the leading causes of falls among these two age groups [1]. In addition, performing attention-demanding tasks while walking may affect normal gait of all age groups and lead to fall [6]. Overcoming perturbations and obstacles because of internal and external sources (e.g., bumps in the roads, slippery ground, talking on the phone, etc.) is an example of such attention-demanding tasks.

Given the observations discussed above, identifying people at risk of fall is a matter of great importance and will benefit both individuals and society. Individuals who are assessed and diagnosed with a high risk of fall can get supervised rehabilitating exercises to enhance their ambulation and confidence, and decrease their future possible falls. Furthermore, if the measure could identify persons who are not fallers (at high risk of fall) yet, but may become fallers in a few years, then preventive care planning could benefit them far ahead of time.

Typical fall risk assessment tools are recording falls history (i.e., the number of falls in the past few months), Timed Up and Go test (i.e., time to rise from a chair without using arms, walk 3 meters then turn and return to the chair), Dynamic Gait index (i.e., the ability to modify gait in response to task demands changes), and recording some other symptoms (e.g., collecting Orthostatic vital signs while supine and again while standing) [7]. Although these assessments are very valuable, they lack precise quantitative monitoring [8].

Several attempts have been made to characterize human gait and find a biomarker for the incident of fall. Human gait signal analysis has been widely used to attain this objective [9], and linear and nonlinear dynamics measures' association with fall risk have been studied to some extent. Variability measures [10], the short-term largest Lyapunov exponent (LLE) measure [11], and entropy measures [12] are among the measures that have shown promising results when discriminating between different walking conditions. Variability measures and the short-term LLE have been shown to outperform other existing gait measures in a comprehensive review in which entropy measures were excluded [9]. However, variability measures disregard intra-stride information and the short-term LLE does not look at the entire time series and examines only the degree of divergence of the neighboring points over a short period of time. Entropy measures have the advantage over these two families of gait measures if applied to whole gait signals because both inter-stride and intra-stride information are considered. Even though a great effort has been made, further investigation and more rigorous methodologies are needed [9], [13]. Firstly, these measures have produced inconsistent results stemmed from various underlying reasons. Using variant experimental protocols (e.g., treadmill vs. overground walking or fixed vs. preferred walking speed) and collecting various human gait signals (e.g., trunk linear acceleration and knee joint angle) are examples of those reasons. Secondly, several measures have been applied to inter-stride spatio-temporal gait signals, such as step time signal. This type of approach neglects intra-stride fluctuations that vary from one stride to the next and contain valuable information about the control mechanism of human gait.

The use of entropy measures and their application to whole gait signals (as opposed to inter-stride spatio-temporal gait signals) could potentially be a solution to this problem. Although there are a few studies that have applied entropy measures to whole gait signals [12], [14]–[16], several questions are unanswered and their viability needs further investigation. It is important to find out whether these measures are able to discriminate between different walking conditions, for example, between young healthy adults and elderly fallers and between walk only (WO) and dual-task (DT) walking conditions. Despite a few attempts to answer this question, inconsistencies in the results hinder the application of entropy measures as biomarkers of increased fall risk. Therefore, it is beneficial to further investigate the viability of these measures along with comparing and contrasting the use of various human gait signals. In addition, entropy measures have been applied to segmented and normalized human gait signals rather than whole gait signals [12]. Studying the effect of this preprocessing could elicit further understanding of intra-stride information. Furthermore, entropy measures require predefined parameter values, and a thorough search of the relevant literature yielded no related article investigating the sensitivity of these measures to variant parameter values when applied to whole gait signals. Therefore, a systematic methodological study should be undertaken to address this issue. Finally, the correlation of entropy measures with other gait stability measures is not clear. Therefore, a direct comparison should be concerned with this problem.

1.2 Objectives

The main objective of this study is to investigate the efficacy of two entropy measures, sample entropy (SampEn) and quantized dynamical entropy (QDE), to act as biomarkers of increased fall risk when applied to "whole" gait time series. Whole gait signals are the entire time series data obtained from force or inertial sensors. These two measures are selected based on a previous research [12], in which SampEn and QDE were recommended for human gait analysis. SampEn, as the most used entropy measures in human gat studies, has been applied to both stride interval times series and whole gait signals [12], [15]–[18]. QDE has the robustness of SampEn to noise and at the same time is computationally more efficient [12], [18]. If the discriminatory ability of these two measures is shown to be similar, QDE can be chosen as a viable alternative to SampEn because of its superior computational efficiency. The specific objectives addressed in this study are listed below:

(1) To investigate the discriminatory ability of the SampEn and QDE of five human gait signals (as both whole and segmented signals) during treadmill walking between two age groups (i.e., young healthy and elderly fallers) and between two walking conditions (i.e., WO and DT walking condition).

    Hypothesis I: Aging and dual-tasking will have an increasing effect on both SampEn and QDE of whole and segmented signals when controlling for the confounding effect of speed.

    Hypothesis II: The performance of SampEn and QDE will be different across different human gait signals.

    Hypothesis III: Using segmented and normalized signals instead of whole gait signals will result in different outcomes with respect to the discriminatory ability of SampEn and QDE.

(2) To study the sensitivity of SampEn and QDE to variant parameter values and preprocessing methods when applied to whole gait signals. The outcomes will be a guideline for proper implementation of SampEn and QDE when applied to whole gait signals.

(3) To determine whether SampEn and QDE are correlated with two other gait stability measures (i.e., variability measures and the short-term LLE) and whether these measures are sensitive to the difficulty level of secondary tasks. This could shed some light on where entropy measures stand among commonly used measures of gait stability.

Hypothesis IV: All gait measures will increase because of dual-tasking and the increase will be proportional to the difficulty of the secondary tasks.

Hypothesis V: The entropy measures, variability measures, and the short-term LLE will not be highly correlated.

Hypothesis VI: Task performance will deteriorate during dual-task walking as compared to stationary standing.

To achieve the first objective, an experiment was designed where participants (young and older adults) walked on a treadmill at a fixed speed and under walk only and dual-task walking conditions. Five different gait signals were recorded and were used to calculate SampEn and QDE. Statistical analyses were employed to investigate the discriminatory ability of these two entropy measures when applied to whole gait signals and to select the best signal. To meet the second and third objectives, another experiment was designed, and the signal selected in the previous step was collected. The sensitivity of SampEn and QDE to variant parameters, low-pass filtering, and resampling was explored via statistical analyses. Finally, the correlation of these two measures with two other gait stability measures was determined.

1.3 Thesis Outline

Chapter 2 provides an overview of human gait and related terminology, fall-provoking conditions, current human gait measures, and the reason why entropy measures of whole gait signals are worth further investigations. Chapter 3 details the methodology and experimental approach used in this study including an explanation of sample entropy, quantized dynamical entropy, and two other families of gait measures (variability measure and the short-term LLE). This is followed by describing data collection and secondary visuomotor cognitive games. In Chapter 4, the discriminatory ability of SampEn and QDE is investigated by analyzing the effect of aging and dual-tasking across 5 various human gait signals. The selected human signal from Chapter 4 is used in Chapter 5 to thoroughly investigate the sensitivity of SampEn and QDE to variant parameter values and preprocessing methods. Chapter 6 focuses on the secondary task performance along with investigating the correlation between entropy measures (SampEn and QDE) and two other families of gait measures (variability measure and the short-term LLE). Finally, Chapter 7 summarizes the contributions made in this thesis, important findings, and direction for future work.

Chapter 2

Background

In this chapter, first, a brief description of human gait will be presented. This will be followed by a literature review on human gait measures. Finally, the research gaps will be outlined.

2.1 Human Gait and Fall-Provoking Conditions

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 [19]: first by a feedforward control system to maintain control over the position and motion of the body's center of mass (COM) within the moving base of support (BOS); second by a feedback control system to restore stability in response to a sudden perturbation or movement error (i.e., unexpected deviation from a planned movement) and to avoid falling. This sophisticated control system prevents falling during each stride where the COM of the body is outside of the BOS for a fraction of stride.

The human gait cycle is the time interval between two successive incidences of quite repetitive events. It starts with the initial heel contact of the right foot with the ground denoting the beginning of the stance phase of the right foot. This incident coincides with the toe-off of the left foot which is the beginning of the swing phase of the left foot. These occurrences repeat for each foot with a half cycle delay. At the beginning and at the end of the stance phase of each foot, there is a period when both feet are in contact with the ground. This period of the gait cycle is called the double support phase. The rest of the stance phase, when only one foot is in contact with the ground, is called the single support phase of that foot (see Figure 2-1). One stride (gait cycle) consists of two steps, left and right. And each step consists of one swing and one stance phase.

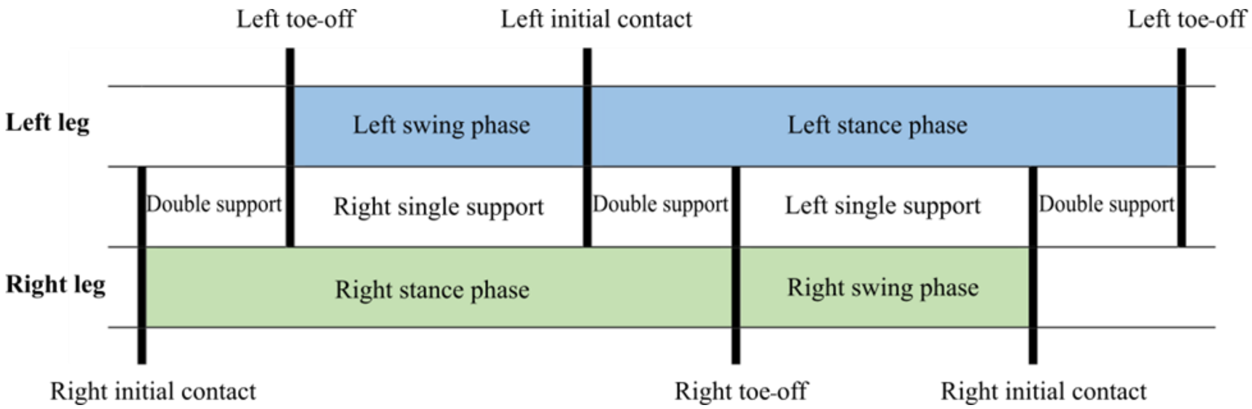


Figure 2-1: Human gait cycle phases, starting with right foot initial contact.

Although each gait cycle seems to be a repetition of its previous cycle, many parameters change from one stride to another. This includes, but is not limited to, stride length, stride time, stride width, and intra-stride fluctuations. Stride-to-stride fluctuations of a healthy young adult walking in a straight line are relatively small and are on the order of just a few percent [10].

Various quantitative measures have been proposed for gait assessment. These measures have been studied when comparing normal walking to that of people who are at a greater risk of fall. Examples of such walking conditions pertain to older adults who have had repetitive falls [3], [20], [21], people who are engaged in a secondary motor-cognitive task while walking [12], [22]–[25], and finally people with diseases that affect their gait (e.g., Parkinson [26], [27] and peripheral neuropathy [28], [29]). In this thesis, the first two fall-provoking conditions (aging and dual-tasking) are investigated.

Dual-task walking imposes a great risk of fall not only on senior adults but also on young healthy population [6], [30], [31]. According to the strategy of “posture first”, people prioritize gait over the secondary cognitive or motor task if they sense a threat to their stability [32]. This implies that under DT walking condition, the performance of the secondary task would decrease, while gait stability would remain intact. However, when the secondary task becomes more complex and a higher degree of attention is required for its success, it is highly likely to see a poorer performance on both gait and secondary tasks [33]. Therefore, it is essential to quantify both gait and secondary task performance in order to be able to understand the prioritization and control mechanism of dual-tasking.

Most of the secondary tasks used in the literature, such as verbal fluency [6], number subtraction [34], and the Stroop test [35], have a low ceiling effect which means they reach their maximum effect very fast, and will no longer affect human gait significantly. They also do not consider visuomotor processing. To overcome these limitations, Szturm et al. [36] have developed a computer game-based DT assessment platform. This platform consists of an instrumented treadmill, visuomotor cognitive computer games displayed on a computer monitor, and a motion-sensing mouse attached to a plastic headband allowing for hands-free interaction with computer games. This DT assessment platform, which is used in this thesis, is a very good choice for the study of the effectiveness of a gait measure [37].

2.2 Human Gait Measures

Human gait has a sufficient resilience to perturbations and it is very difficult to determine how close the complex human gait is to shift from a stable to an unstable state. From the biomechanical perspective, instability and falls occur when the projection of the COM falls out of the BOS [38] and no action is taken to restore stability. This resembles large perturbations being exerted on the gait. Assessing gait stability from the biomechanical perspective (e.g., using the margin of stability measure [39] while considering the position and velocity of the COM) is almost inaccessible during gait because of data collection procedures. In order to get usable data, several cameras and markers are required, and also a cumbersome amount of post-processing is needed. Even though there are some methods that can calculate the COM indirectly, their validity has not been tested yet [40].

Alternately, analysis of time series obtained during walking has been shown to be potential candidates for human gait studies. Conventional average stride (or step) variables were the very first features that were extracted during human gait. Stride (or step) length, stride (or step) width, stride (or step) time, swing time, and double-support time have been used to discriminate between faller and non-fallers, and between different DT conditions. Gehlsen et al. [41] identified the step frequency, stance time, swing time, double support time, step length, heel width, heel height, and toe height of two groups using camera equipment while participants walked on a motorized treadmill at a fixed speed. None of the aforementioned variables showed any significant change between non-fallers and fallers. Their results were confirmed by Feltner et al. [42] who studied stride length, step length, step width, stride time, step time, single support time, and swing time.

These variables were computed using the sagittal and frontal view videotapes of participants walking on a carpeted floor of 8.2 m. They found that none of the variables could distinguish between the retrospective fallers and non-fallers or could predict the prospective falls. On the other hand, Imms et al. [43] reported a significant decrease in velocity and stride length from fallers to non-fallers and no significant change of double support time. Maki [44] computed spatial and temporal gait parameters, from digitized footprints and footswitches, along with their variabilities. He reported that decreased stride length, reduced speed, and increased double support time were not indicative of falling but were associated with the fear of fall as stabilizing adaptations. However, stride-to-stride variability in stride length, speed, and double support time increased with fall risk. These variables are defined as standard deviation (SD) or coefficient of variance (COV) of the mean (SD divided by mean). Unlike average variables, they take into account inter-stride variabilities that are very fundamental to human gait. To that point, these variabilities had been considered as system noise and had been neglected [10]. A prospective study of swing and stride time on community-living older adults by Hausdorff et al. [20] showed that variability of temporal variables is also capable of predicting future falls while the mean gait speed and Timed Up and Go did not show significant changes. In their study, footswitches (force-sensitive insoles) were used to collect swing and stride time data while participants walked at their normal pace on level ground. These results suggested that the variability measures might be more sensitive than the average of gait parameters to the elevated risk of fall. These measures may reflect the inconsistency in the ability of the neuromuscular control system for gait regulation and maintaining a steady state walking pattern. This interpretation of variability measures could associate them with gait stability and fall risk [10].

The results of the variability measures are not always consistent with the aforementioned ones (i.e., increased variability with increased fall risk). Brach et al. [45] reported that only extreme step width variability (too much or too little) was associated with retrospective fall risk and step length, stance time, and step time variability did not distinguish fallers from non-fallers. This observation was only made for participants who walked faster than 1 m/s on ground level.

The detrended fluctuation analysis (DFA) of stride interval gait parameters has also been investigated as a potential human gait measure [46]. To calculate the scaling exponent from stride interval time series (e.g., stride time) using DFA, the data is integrated first. This is followed by fitting a line to the data in windows of size n. The average fluctuation of the data around the fitted line, $f(n)$, is calculated for various n values. Finally, the slope of the fitted line to the log-log plot of $f(n)$ versus n is the scaling exponent (α). Values of $0.5 < \alpha < 1.0$ have been reported for human gait showing the presence of positive long-range correlations. Herman et al. [47] tested the ability of long-range correlations to discriminate between fallers and non-fallers. They asked participants to walk on the level ground and collected stride time data using force sensitive insoles. Their results showed a significant increase in DFA scaling exponent from the non-faller control group to fallers along with a significant increase in stride time variability.

Even though these measures have shown potential in discriminating between different walking conditions and have addressed many clinical questions about human gait, they have ignored the inherent dynamical nature of locomotion. The disregarded intra-stride information, which changes from one stride to the next, represents important passive and active gait control process. Therefore, researches started to investigate various time series analyses adopted from nonlinear dynamics to incorporate intra-stride information into their investigation.

Hurmuzlu et al. [48] adopted the Floquet multipliers from robotic gait analysis to assess the orbital dynamic stability of human locomotion from kinematic data recorded during walking. This measure simply quantifies the resilience of the gait patterns when subjected to disturbances and it assumes that kinematic data is strictly periodic. Even though the assumption of periodicity is necessary for the calculation of the Floquet multipliers, it is not a correct assumption for human gait since there are fluctuations from one stride to the next [9]. Nevertheless, it is quantified by calculating the magnitude of the maximum Floquet multiplier which is the rate of convergence/divergence from a limit cycle because of small perturbations from one gait cycle to the next [49]. A pilot study by Granata et al. [50] reported a significant increase in the maximum Floquet multipliers from healthy young and healthy older participants to fall-prone older adults. Data used in this study was based on the relative position and velocity data of the COP with respect to the COM from a critically small sample size.

Dingwell et al. [11], [51] were the first researchers who used the method of the largest Lyapunov exponent or LLE to analyze the local dynamic stability of human walking kinematics. This outcome measure quantifies the average logarithmic rate of divergence of neighboring trajectories - of the reconstructed state-space from a single time series of a nonlinear system - after small perturbations. In this measure, each state may be regarded as a small perturbation of the other states [9]. The larger values of the LLE is indicative of more local instability [11]. It is calculated as the slope of the mean divergence curve over 0 to 0.5 (or 1) stride [52] or over 4-10 strides [11]. The former one is called the short-term LLE (λ_s) and the latter one is called the long-term LLE (λ_L). Typical biological signals used to compute the short-term LLE are upper and lower trunk linear acceleration (trunk-LA) and linear velocity collected during overground and treadmill walking [53]–[56]. Recently, the short-term LLE of the center of pressure (COP) trajectory has also been shown to successfully distinguish between normal and auditory cueing walking conditions [57]. Lockhart et al. [58] reported a significant increase in the short-term LLE from healthy young and healthy older adults to fall-prone older adults. The short-term LLE was calculated from lower trunk-LA signal in the anteroposterior (AP) direction while participants walked on a treadmill at a preferred walking speed. Similar results were reported by Toebes et al. [59] where the short-term LLE and not the long-term LLE of upper trunk-LA was positively associated with fall risk when participants walked at a fixed speed on a treadmill. However, by considering only few steps when studying the divergence of system's trajectory, the short-term LLE is not capable of predicting the global stability of human gait.

Researches have also explored the viability of using entropy measures for the purpose of fall risk detection [12], [16], [17], [60]. Entropy measures are inherently representing the difficultness of describing the patterns of systems trajectory [61]. The terms unpredictability, irregularity, and complexity have been used to reflect this idea [62], [63]. Larger entropy values indicate less regularity or predictability in a time series [64]. Various entropy measures have been proposed based on Shannon's entropy [65] and its successor method, approximate entropy (ApEn). ApEn was developed to enable using Kolmogorov-Saini entropy [66] for complexity analysis of experimental time series. A drawback of ApEn was its bias toward regularity caused by self-counting when finding similar templates. Consequently, sample entropy or SampEn was introduced to avoid self-counting [67]. Recently, quantized dynamical entropy or QDE [12] was proposed, which has the robustness of SampEn and a superior computational performance. Multi-scale sample entropy (MSE) [17] was also introduced to examine the regularity of signals at different temporal scales. Even though single-scale measures are not capable of revealing hidden information in self-affine sequences, they have a lot to offer and are adequate for the purpose of single-scale comparison [61].

Entropy measures have been applied to both spatio-temporal cycle-to-cycle gait parameters and “whole” gait signals. Whole gait signals are the entire time series data obtained from force or inertial sensors. Applying entropy measures to the whole signal of motion or force reveals important information about the regularity of human gait signals [15], [60]. In other words, when analyzing whole data, inter-stride and intra-stride dynamical features are evaluated while analyzing inter-stride spatio-temporal gait signals neglects intra-stride information.

The first study that applied entropy measures to study human gait dynamics was conducted by Arif et al. [68] in 2002. Their results showed that ApEn of the mediolateral (ML) linear acceleration of the center of gravity increased significantly from young adults to older adults. However, in that study participants had synchronized their cadence with the tempo of a metronome. As a result, it was not a comparison of normal walking of the two groups. Costa et al. [17] applied MSE to stride time signal and compared slow, normal, and fast walking of healthy young adults, and reported that a metronomically-paced walking destroyed the correlations among the stride intervals. Bisi et al. [15] further applied MSE to trunk-LA signal (AP and vertical directions) obtained from participants of different age groups (toddlers to older adults). Participants walked overground at their self-selected speed in a corridor longer than 12 *m* that resulted in the collection of 10 consecutive strides. Their results showed that MSE changes with respect to aging. In another study by Ihlen et al. [16], the values of a modified MSE of trunk-LA in the ML direction were higher for non-fallers compared to those values of fallers at all scale levels. However, in this study, the overground walking speed, which is a confounding factor and has been reported to be lower for fallers [44], was not controlled. Additionally, there was no abrupt change in the results across different scales as suggested by Costa et al. [17]. Leverick et al. reported that the value of four different entropy measures, including SampEn and QDE, were higher for older adults as compared to young healthy adults. In this study, the center of pressure displacement in the ML direction (ML COP-D) was collected during fixed speed treadmill walking and was segmented and normalized (amplitude and gait cycle) before calculating SampEn and QDE.

A comprehensive review by Bruijn et al. [9] on the validity of different proposed gait measures for gait stability assessment concluded that variability measures and the short-term LLE outperform other existing gait measures. The validity of entropy measures based on the same criteria was shown by Leverick et al. [12].

These three families of measures (i.e., variability measures, the short-term LLE, and entropy measures) have also shown different and to some extent contradictory results when they were used to compare WO to DT walking condition. For young healthy adults, a significant increase in variability measures (e.g., stride time variability [31] and stride width variability [22]), the short-term LLE [23], and entropy measures [69] have been reported during DT walking. Whereas no significant change in variability measures (e.g., stride length variability [31], swing time variability [70], and stride time variability [71]), the short-term LLE [24], and entropy measures [12], [23] have also been reported as a result of dual-tasking. Moreover, a significant decrease in step width variability [72] has also been reported. Since these studies have had different protocols and task conditions, and have used different biological signals, a comparison would be difficult to make.

Hence, a direct comparison would be beneficial and would help understand how each measure is affected by dual-tasking.

A few studies have investigated how variant parameters would affect entropy measures of short [73] and long [74] time series when using spatio-temporal gait variables. It was shown that entropy measures are dependent on the combination of template size and tolerance size, and not on data length [73], [74]. However, no study has investigated the effect of parameter selection on the SampEn and QDE of human gait whole signals over an appropriate number of continuous strides. During continuous, steady-state gait, these signals are similar in nature with a few dominant frequencies and have consistent fluctuations from one stride to the next. Considering the increasing use of these measures in analyzing human gait whole signals, it is essential to investigate how parameter selection would affect the outcomes. The importance of this investigation stems from the fact that parameter selection for calculating the SampEn and QDE of whole gait signals, in many studies, is based on those that have analyzed inter-stride gait variables [75], [76].

Most studies, which have examined the effect of aging or dual-tasking on human gait, use self-paced walking and do not control the gait speed. Self-paced walking results in different walking speeds and, therefore, each walking condition will have a different average number of data points per stride. It has been shown that gait speed is significantly reduced during DT walking compared to WO trials [77] and it has been reported that speed has a significant effect on the measures of dynamical systems, such as the LLE [78]–[80]. Moreover, researchers have used different sampling frequencies when collecting target whole signals, which, in turn, have resulted in a different average number of data points per stride. It is unknown whether a different average number of data points per stride caused by varying walking speed or sampling rate would affect

SampEn. Furthermore, many researchers have opted to apply SampEn, or other entropy measures, to raw unfiltered signals [12], [76], [81] to avoid losing or altering information because of filtering. While others have filtered the high-frequency components of trunk-LA signal using a cut-off frequency of 20 Hz [82], [83]. Therefore, investigating the effect of filtering would also be beneficial.

2.3 Summary and Research Gaps

Although a great effort has been made to characterize human gait, there are still some remaining research questions. This thesis addresses these research gaps as articulated below:

1- There are no studies using entropy measures comparing and contrasting trunk motion, leg motion, and the center of foot pressure during different walking conditions. It is important to study the behavior of these signals with aging and dual-tasking as they have different control mechanisms.

2- Leverick et al. [12] proposed segmenting and normalizing human gait cycles before calculating entropy measures. It is important to compare it to the non-segmented and non-normalized signal, and to examine the effect of segmenting and normalizing on entropy measures.

3- SampEn and QDE have shown to be more promising amongst other proposed entropy measures [12]. However, their sensitivity to variant parameter values and to different preprocessing methods has not been studied yet. The majority of studies that have applied entropy measures to whole gait signals have chosen the methodological details based on the works that have analyzed inter-stride spatio-temporal gait variables [75], [76]. Therefore, it is of paramount importance to investigate the sensitivity of SampEn and QDE to variant parameter values (i.e., template size, tolerance size, and sampling rate) and to two preprocessing methods (i.e., resampling signals to have the same average number of data points per stride and low-pass filtering).

4- The correlation between these two measures (SampEn and QDE) and two other families of gait stability measures (i.e., variability and local dynamic stability measures) is not known since no direct comparison is available in the literature.

5- Task prioritization and sensitivity of gait measures to the difficulty level of the secondary visuomotor cognitive tasks could be further examined using the DT assessment platform proposed by Szturm et al. [36]. The visuomotor cognitive tasks employed in the present study are cognitively demanding and at the same time, gait speed and walking surface conditions can be controlled by means of using a treadmill.

Chapter 3

Methodology and Experimental Approach

In this chapter, the methodology and experimental approach used in this thesis are explained. First, the secondary visuomotor cognitive games will be described. Next, the data collection, which consists of two sets, will be presented. Finally, the calculation procedure of the three families of gait measures (i.e., entropy measures, the short-term LLE measure, and variability measures) used in this work will be presented.

3.1 Visuomotor Cognitive Games

The goal of visuomotor cognitive games (VCG) is to move a game paddle horizontally to interact with the moving game objects. The game objects are categorized as designated targets or designated distractors, with the shape of a soccer ball and a dotted sphere, respectively. They appear at random locations at the top of the display every 2 seconds and move diagonally toward the bottom of the display. In response to each "game event" (target appearance), participants produce a head rotation (i.e., rotation of the motion-sensing mouse) to move the game paddle (left/right) and catch the target objects as well as avoid the distractors [69], [84]. Two difficulty levels of VCG are tested in this thesis. The easy one (VCG1) has only one target and one distractor. The difficult one (VCG2) consists of one target and two distractors of different shapes (i.e., dotted sphere and clock) and they appear much faster and the paddle size is smaller compared to VCG1 (see Figure 3-1).

Figure 3-1: Visuomotor cognitive games: **(A)** VCG1 (easy game) and **(B)** VCG2 (difficult game). The yellow game paddle is moved by head rotations to catch the target objects (soccer ball) and avoid the distractors (dotted sphere and clock).

3.2 Data Collection

Two sets of data collection are used in this thesis, the first one is only used in Chapter 4 while the second one is used in Chapters 5 and 6, both described below.

In the present study, a computer game-based treadmill platform, developed and validated by Szturm and colleagues, was used for data collection [36]. Although overground walking condition or walking at a self-selected gait speed is the true free-running daily life condition, treadmill walking at a fixed speed may limit the number of influencing variables when interpreting the results of gait analysis. Gait variables are significantly influenced by walking speed, and reducing gait speed is a highly consistent strategy to overcome gait instability [78], [80]. In other words, as people engage themselves in a secondary task, they might slow down as a control strategy and they become more cautious as well. This is observed in almost all dual-task gait studies when participants walk over the ground at their self-selected speed [77]. To avoid participants undertaking this strategy, it is necessary to control their speed by using a treadmill. Participants can walk at the same speed they feel comfortable walking and performing secondary tasks despite some restrictions imposed on their gait by the treadmill. In addition, treadmill walking is an efficient method to collect data from several consecutive strides. It has also been reported [80] that there was no significant difference of the ML trunk-LA SampEn between daily life overground and treadmill walking of older adults where the gait speed was matched.

During all walking trials, participants viewed an 80 cm computer monitor positioned 1 meter away at eye level. During 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 cognitive game activities, a commercial motion-sensing wireless mouse (Elite mouse, SMK Electronics, USA) was mounted on a plastic headband worn by each participant (see Figure 3-2). Therefore, during walking, the head rotation was used to control the motion of a computer cursor. Participants were asked not to intentionally prioritize either their gait or the secondary task. Test protocols were defined based on a series of experiments conducted by Szturm and colleagues [12], [84] in which test-retest reliability and validity of dual-task assessment platform have been extensively investigated and reported.

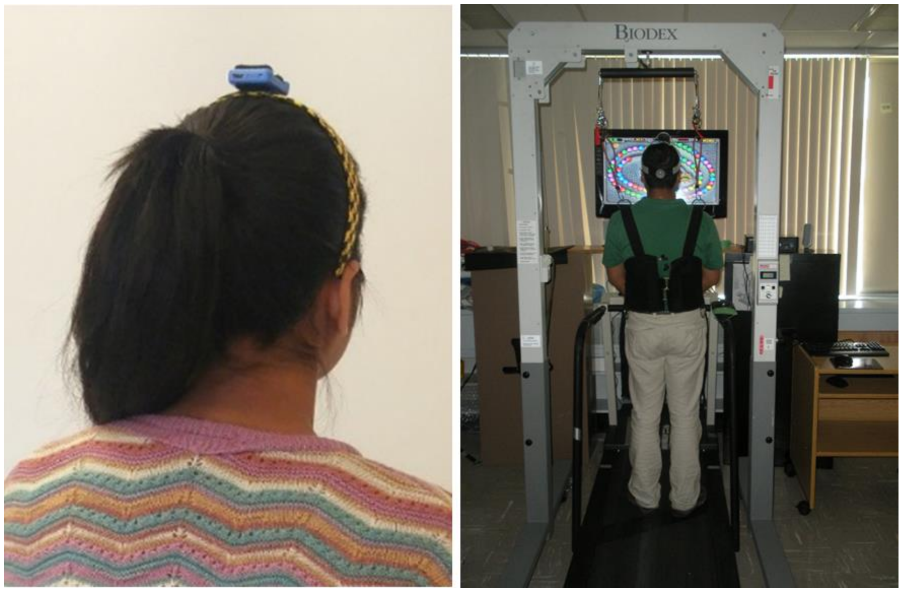


Figure 3-2: Dual-task assessment treadmill workstation and motion-sensing mouse.

3.2.1 First Dataset

For the first dataset, a total of 40 subjects, including 20 healthy young adults (3 females, 20-36 years old) and 20 older adults (12 females, 70-85 years old) were recruited. The elderly group was able to walk 400 meters without walking aid and had experienced one or more falls in the past 12 months (elderly fallers). They had adequate hearing and vision to perform the computer game activities. The study was approved by the University of Manitoba human research ethics committee and all participants signed the informed consent form. This dataset was used in Chapter 4.

Participants were asked to walk on a standard treadmill under two different walking conditions;

a) Walk only trial of 45 seconds at a speed of 0.8 m/s, and

b) Walking while performing the VCG1 task for 45 seconds at 0.8 m/s.

Forty seconds of each walking trial is used in this analysis. During treadmill walking trials, the following five signals were recorded: the center of pressure displacement (COP-D) in the ML and AP directions (ML/AP COP-D), trunk linear acceleration in the ML and AP directions (ML/AP trunk-LA), and shank angular velocity (shank-AV) in the ML direction (ML shank-AV). A standard treadmill equipped with a pressure mat (Vista Medical Ltd., Canada) underneath the belt was used to collect the COP migration at a sampling frequency of 60 Hz. Two miniaturized inertial motion monitors (IMM) (NexGen Ergonomics, Canada) were used to record trunk-LA and shank-AV at a sampling frequency of 128 Hz (see Figure 3-3). Straps were used to secure the IMMs to the sternum and the lower shank (2 cm above lateral malleolus).

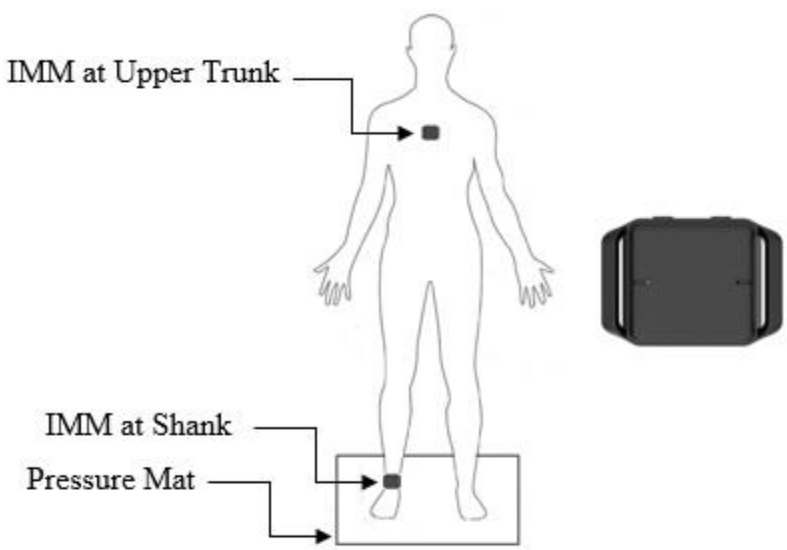


Figure 3-3: Locations of inertial motion monitors. The image of IMM is reproduced with permission from NexGen Ergonomics Inc., http://www.nexgenergo.com [84].

3.2.2 Second Dataset

For the second dataset, a convenience sample of 29 healthy young participants (8 females, 28.3 ± 2.7 years, 173.4 ± 8.8 cm, 69.7 ± 14.2 kg, mean ± SD) was recruited. They were screened to ensure that no participant had any illnesses, neuromuscular injuries or previous surgeries that might 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. This dataset was used in Chapters 5 and 6.

Participants were asked to walk on an instrumented Bertec treadmill (Bertec Corporation, Columbus, Ohio, USA) (see Figure 3-4) under four different walking conditions;

a) Walk only trial of 1 minute at a speed of 1.0 m/s, and
b) Walking while performing the VCG1 task (see Section 3.1) for 1 minute,
c) Walking while performing the VCG2 task (see Section 3.1) for 1 minute,
d) Walk only trial of 1 minute at a speed of 1.3 m/s (WO-1.3).

Forty seconds of each walking trial is used in this analysis. The ML COP-D signal was calculated from the force and moment components sampled at 1000 Hz. Additionally, 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 task performance.

Figure 3-4: Dual-task assessment treadmill workstation using Bertec treadmill.

3.3 Gait Measures

Three different families of gait measures have been used in this thesis (i.e., entropy measures, the short-term LLE, and inter-stride spatio-temporal gait variability measures). SampEn and QDE were used in Chapters 4 to 6 while other gait measures were only used in Chapter 6 for a direct comparison with entropy measures. The short-term LLE and variability measures have often been used to study human gait, and they have been shown to better assess human gait stability [9]. For example, Dingwell et al. [24] analyzed the short-term LLE of the upper trunk linear velocity signals and the results showed that performing the Stroop test did not have any significant effect on human gait local dynamic stability.

SampEn (or a modified version, such as MSE) has often been used to study inter-stride gait variable time series [17]. While this approach led to some important findings, it does not include intra-stride fluctuations that contain important information about the gait control mechanism. Few studies have investigated the direct relationship between SampEn and whole gait signals such as trunk-LA time series. Ihlen et al. [16] used a modified MSE measure with ML trunk-LA and showed that the values were higher for non-fallers compared to those values of fallers at all scale levels. The overground walking speed, a confounding factor reported to be lower for fallers [44], was not controlled in their study. On the other hand, the SampEn and QDE of the segmented and normalized ML COP-D (collected during treadmill walking trials) were used by Leverick et al. [12] and their results showed that these two measures could discriminate between fallers and young healthy adults showing significant larger values for fallers.

In the following sections, the calculation procedure of SampEn, QDE, the short-term LLE, and variability measures are presented.

3.3.1 Sample Entropy Measure

The SampEn (m, r, N) of a dataset of length N 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 [67]. The calculation procedure of SampEn is as follows:

Consider a time series of length N given below:

$$X = \{x(1), x(2), \dots, x(N)\} \; or \; X = \{x(j) \colon 1 \leq j \leq N\} \quad (3\text{-}1)$$

The value for template size (m) is chosen to construct series of pairs, size m as:

$$X_m(i) = \{x(i+k): 0 \le k \le m-1\}, 1 \le i \le N-m+1 \tag{3-2}$$

Next, matching templates are found by comparing their Chebyshev distance (denoted as $\mathrm{d}|.|$) to a pre-determined threshold size (r) while excluding self-comparison. Next, the variable B_i, which is the number of pairs satisfying the aforementioned criteria, is built.

$$B_i^m(\mathrm{r}) = \frac{1}{N-m-1}\ (\#\ \mathrm{of}\ \mathrm{d}|X_m(i) - X_m(j)|\ \le r,\ where\ j = 1{:}\, N-m\ \&\ i \ne j) \tag{3-3}$$

$$\mathrm{d}|X_m(i) - X_m(j)| = \max\{|x(i+k) - x(j+k)|: 0 \le k \le m-1\} \tag{3-4}$$

Next, $B^m(r)$ is defined as:

$$B^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} B_i^m(r) \tag{3-5}$$

This process is repeated for $m+1$ and r to form $A^m(r)$:

$$A_i^m(\mathrm{r}) = \frac{1}{N-m-1}\ (\#\ \mathrm{of}\ \mathrm{d}|X_{m+1}(i) - X_{m+1}(j)| \le r), \text{ where } j = 1{:}\, N-m\ \&\ i \ne j \tag{3-6}$$

$$A^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} A_i^m(r) \tag{3-7}$$

Lastly, SampEn [67] is calculated based on $B^m(r)$ and $A^m(r)$ as

$$\mathrm{SampEn}(m, r, N) = -\ln\frac{A^m(r)}{B^m(r)} \tag{3-8}$$

where m, r and N are the template size (i.e., the length of template vector), tolerance size and the length of time series, respectively.

3.3.2 Quantized Dynamical Entropy Measure

The QDE (m, r, N) of a dataset is based on the definition of Shannon's entropy and measures the abundance of its dynamical features [12]. QDE is based on coarse quantization and vector identifiers [18]. The calculation procedure of QDE is as follows:

Consider a time series as:

$$X = \{x(1), x(2), \dots, x(N)\} \text{ or } X = \{x(j): 1 \le j \le N\} \tag{3-9}$$

The quantized time series is constructed using a positive tolerance size (r) and the floor function. The floor function $\lfloor x \rfloor$ gives the largest integer less than or equal to x. This process converts time series into quantized bins with various sizes, X_q:

$$X_q = \left\lfloor \frac{X - \inf(X)}{r} \right\rfloor \tag{3-10}$$

As a result, a quantized time series, all as whole numbers, is built:

$$X_q(i) \in \mathbb{N}^0, \mathrm{i} = 1, 2, \dots, \mathrm{N} \tag{3-11}$$

Then pairs of neighboring points having a template size m are constructed:

$$\{x_q(i), x_q(i+1), \dots, x_q(i+m-1)\} \text{ where } 1 \le i \le N - m + 1 \tag{3-12}$$

Next, vector identifiers are defined as:

$$\varphi_i = [x_q(i), x_q(i+1), \dots, x_q(i+m-1)] \tag{3-13}$$

Next, the number of occurrences of each identifier is defined:

$$Q(\varphi_i) = \#\{ 1 \le i \le N - m + 1, [x_q(i), x_q(i+1), \dots, x_q(i+m-1)] \in \varphi_i\} \tag{3-14}$$

By defining the relative frequency of identifiers as below, the probability of encountering a given identifier is:

$$P(\varphi_i) = \frac{\mathrm{Q}(\varphi_i)}{N - m + 1} \tag{3-15}$$

Next, $H(m, r)$ is defined based on Shannon's entropy as:

$$H(m, r) = -\sum_{\varphi} P(\varphi_i) \log_2 P(\varphi_i) \tag{3-16}$$

Where using a binary logarithm causes the units of $H(m, r)$ to be bits. In the end, the QDE per symbol is defined as follows:

$$\mathrm{QDE} = \frac{H}{m} \tag{3-17}$$

For these entropy measures, values near zero imply more regular signals.

3.3.3 Short-Term Largest Lyapunov Exponent Measure

The sensitivity of a dissipative and globally stable dynamical system to initial conditions is quantified by the Lyapunov exponents. The presence of a positive exponent is sufficient to claim local instability in a particular direction. That being said, the sum across the entire spectrum, however, is negative. It has also been stated that two randomly chosen initial conditions will diverge exponentially at a rate given by the largest Lyapunov exponent or LLE since exponential growth in that direction quickly dominates the growth along the other Lyapunov directions [85]. The calculation process of the LLE from an experimental time series is as follows:

Consider a time series of length N as equation (3-1), $X = \{x(1), x(2), \ldots, x(N)\}$. In order to calculate LLE [85], first, the attractor dynamics of the single time series should be reconstructed using the method of delays [86] with a time delay (T) (see Section 3.3.3.1) and an embedding dimension (d) (see Section 3.3.3.2) as $\boldsymbol{X}$,

$$\boldsymbol{X} = (\boldsymbol{X}_1\ \boldsymbol{X}_2\ \ldots\ \boldsymbol{X}_M)^T \tag{3-18}$$

where $M = N - (d-1)T$. The rows of $\boldsymbol{X}$ are the state-space vectors defined as $\boldsymbol{X_i}$ at discrete time i:

$$\boldsymbol{X}_i(d) = [x(i)\ \ x(i+T)\ \ldots\ \ x(i+(d-1)T)] \tag{3-19}$$

After reconstructing the dynamics, the initial distance from the nearest neighbor of each point on the trajectory is located as:

$$\mathrm{d}_j(0) = \min_{x_{\hat{j}}} \left\| \boldsymbol{X}_j - \boldsymbol{X}_{\hat{j}} \right\| \tag{3-20}$$

where $\|.\|$ denotes the Euclidean norm (i.e., positive Euclidean distance). An additional constraint that nearest neighbors should have is a separation greater than the mean period of the time series:

$$|j - \hat{j}| > \text{mean period} \tag{3-21}$$

The next step is to consider the desired maximum iteration and measure the average separation of neighbors by calculating the distance between successive points of neighbors for each iteration from 0 to the maximum iteration. Finally, a least-squares fit to the average line, which is the plot of average separation values versus iteration values, will be the LLE:

$$y(i) = \frac{1}{\Delta t} \langle \ln \mathrm{d}_j(i) \rangle \tag{3-22}$$

For human gait signals, two regions of the average line are recommended for this purpose. The first one is over the first stride (or step) and is called the short-term LLE or λ_s [78]. The second one is over the 4-10 strides and is called the long-term LLE or λ_L[11].

3.3.3.1 Time Delay

The first minimum of average mutual information [87] has been proposed to calculate T. Given two time series $X = \{x(1), x(2), \dots, x(N - Lag)\}$ and $Y = \{y(1), y(2), \dots, y(N - Lag)\}$ where $y_i = x_{i+Lag}$. The mutual information $I(X_i, X_{i+Lag})$ is calculated as a function of Lag using the following equation:

$$I(X,Y) = \sum_{i=1}^{N_X} \sum_{j=1}^{N_Y} P_{XY}(i,j) \log_2 \left\{ \frac{P_{XY}(i,j)}{P_X(i)P_Y(j)} \right\} \tag{3-23}$$

where $P_X(i)$ and $P_Y(j)$ are the occupation probability of the i-th and j-th bin, N_X and N_Y are the numbers of elements, and $P_{XY}(i,j)$ is the joint probability distribution. The first minimum in then considered as the time delay for the desired state-space reconstruction.

3.3.3.2 Embedding Dimension

In order to obtain the proper embedding dimension, d, Cao [88] proposed a practical method for its calculation using a known time delay. This method is based on the false neighbors [89] and is calculated as follows:

Consider the reconstructed state-space of the time series of equation (3-1) as equations (3-18) and (3-19). Then $a(i,d)$ is defined as below:

$$a(i,d) = \frac{\left\| X_i(d+1) - X_{n(i,d)}(d+1) \right\|}{\left\| X_i(d) - X_{n(i.d)}(d) \right\|} \text{ ,where } i = 1,2, \dots, N - dT \tag{3-24}$$

In Equation (3-24), $X_i(d+1)$ is the i-th reconstructed vector with embedding dimension $d + 1$ and $n(i + d)$ is an integer such that $X_{n(i.d)}(d)$ is the nearest neighbor of $X_i(d)$ in the

d-dimensional reconstructed state-space. If d is the true embedding dimension of the system, then any two points which stay close in the d-dimensional reconstructed state-space will remain close in the $(d+1)$-dimensional reconstructed state-space. Such a pair of points is called true neighbors. In order to find the true embedding dimension, $E(d)$ and $E1(d)$ are defined as below:

$$E(d) = \frac{1}{N-dT} \sum_{i=1}^{N-dT} a(i,d) \tag{3-25}$$

$$E1(d) = \frac{E(d+1)}{E(d)} \tag{3-26}$$

For an attractor, $E1(d)$ stops changing when d is greater than some value, d_0. Then $d_0 + 1$ is the minimum embedding dimension of the time series required to construct the state-space. Cao [88] also defined parameters $E^*(d)$and $E2(d)$ as follows:

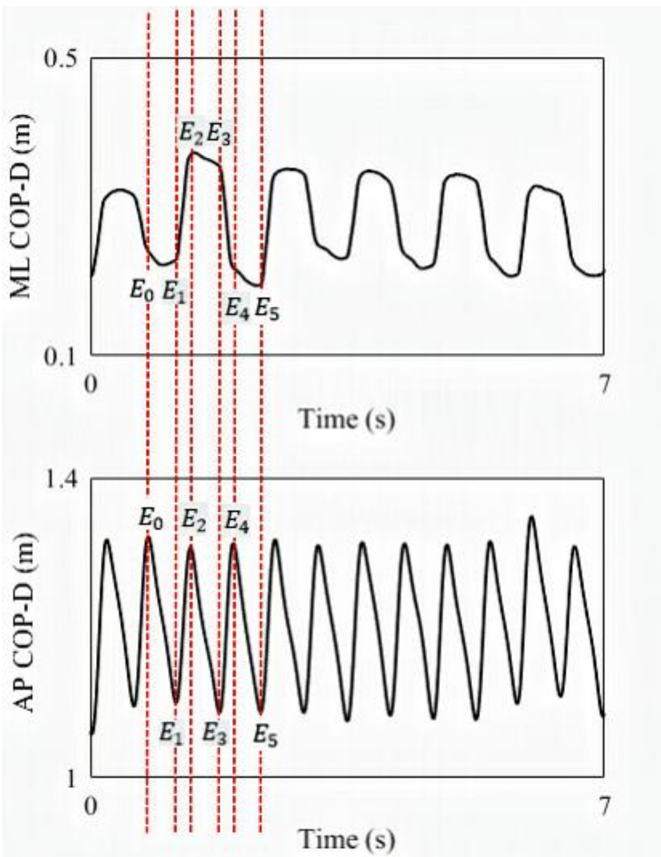
$$E^*(d) = \frac{1}{N-dT} \sum_{i=1}^{N-dT} \left| x_{i+dT} - x_{n(i,d)+dT} \right| \tag{3-27}$$

$$E2(d) = \frac{E^*(d+1)}{E^*(d)} \tag{3-28}$$

For random data, $E2(d)$ will be equal to 1 for any values of d as any future values are independent of the past values. On the other hand, for a deterministic data, it has some values other than 1 for some d's.

3.3.4 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. Step time, step width, step length, and swing time are the most commonly used parameters. 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). Figure 3-5 shows the incidents of toe-off and heel contacts, and defines spatio-temporal gait variables on both ML and AP COP-D signals.



E_1 & E_5: Left heel contact

E_2: Right toe-off

E_3: Right heel contact

E_4: Right toe-off

Spatial parameter in AP direction:

$E_2 - E_3$: Right step length

$E_4 - E_5$: Left step length

Spatial parameter in ML direction:

$E_1 - E_3$: Left step width

$E_3 - E_5$: Right step width

Temporal parameters

$E_0 - E_1$: Left swing time

$E_2 - E_3$: Right swing time

$E_1 - E_3$: Left step time

$E_3 - E_5$: Right step time

Figure 3-5: Spatio-temporal gait parameter definitions.

Chapter 4

Discriminatory Ability of SampEn and QDE

In this chapter[1], the viability of using SampEn and QDE to characterize human locomotor performance is further examined across DT (VCG1) walking condition and as a function of aging. Dual-tasking and aging are both known to negatively affect gait control. Results on both whole gait signals and segmented/normalized time series are presented. Five different signals are used for the sake of comparison and choosing the signal that best discriminates between different walking conditions. The first dataset (see Section 3.2.1) was used in this chapter.

4.1 Data Analysis

SampEn and QDE were calculated from both raw unfiltered data and segmented and normalized time series of 5 recorded ML/AP COP-D, ML/AP Trunk-LA, and ML Shank-AV signals. Forty seconds of data was used after discarding approximately the first 4 strides. The raw time series data of the AP/ML COP-D for 4 strides are presented in Figure 4-1 and on the right, their respective segmented and normalized signals for several gait cycles are presented. Segmenting AP/ML COP-

[1] The results of this chapter have been published in [69].

D was based on the maxima values of the AP COP-D signal denoting the beginning of the single support phase of one leg and toe-off of the other leg. Odd-numbered (or even-numbered) time indices were used to segment data into individual gait cycles as the time from the toe-off of one leg to the next toe-off of the same leg. Time normalizing of each gait cycle was performed by resampling gait cycle segments to the average number of data points. The amplitude of the COP-D was also normalized to values between 0 to 1.

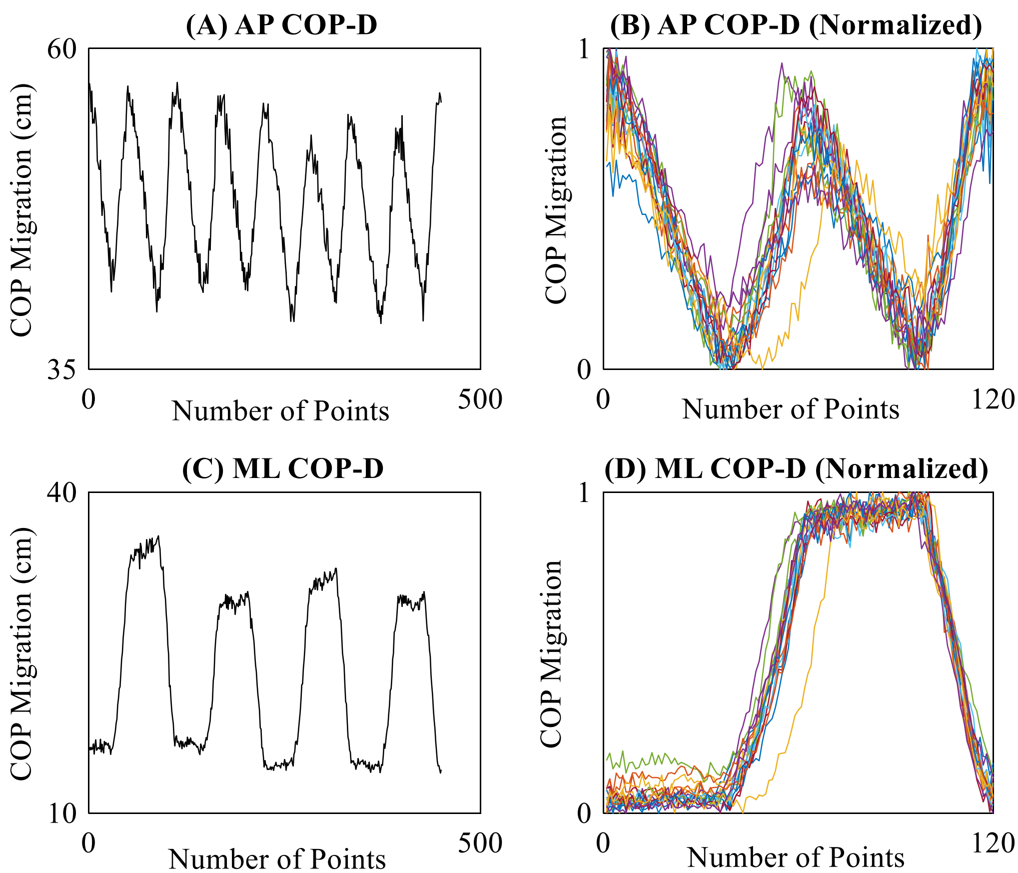


Figure 4-1: Segmenting and normalizing: **(A)** AP COP-D, **(B)** AP COP-D (Normalized), **(C)** ML COP-D, and **(D)** ML COP-D (Normalized). On the left, the raw time series data of the AP/ML COP-D for 4 strides and on the right, their respective segmented and normalized signals for several gait cycles are presented.

The raw time series data of ML shank-AV and ML/AP trunk-LA for 4 strides are presented in Figure 4-2, and on the right, their respective segmented and normalized signals for several gait cycles are presented. Segmenting these three signals was based on the minima of ML shank-AV signal denoting the instant of the toe-off of one leg. These time indices were used to segment the data into individual strides. Segmented data were spatially and temporally normalized similar to the COP-D signals.

The majority of approaches and 5 signals had a decreasing trend with increasing template size, m. Parameter m (see Sections 3.3.1 and 3.3.2) was selected as 6 for further analysis based on the parametric study on where the curves plateaued or where they had the most common highest sensitivity to changes in gait dynamics.

In the case of studying whole data, data length was fixed to 2500 data points for COP-D and 5200 data points for IMM signals equivalent to about 30 strides. However, segmenting and normalizing resulted in having slightly different data length for subjects. A length convergence test was performed on the ML trunk-LA signal of older age group with 20 subjects, where a convergence criterion was %1. The Length was changed from 60 to 2400 with steps of 60 points. As shown in Figure 4-3, as m increased, SampEn converged at higher values of data length, N. Given m=6, convergence criteria met at N=960, which is considerably smaller than the data length of all subjects.

Tolerance size, r, was selected based on literature as 0.2 of the average SD [12], [67] of the whole data of all subjects, and for segmented data series, it was the average SD of the signals [12].

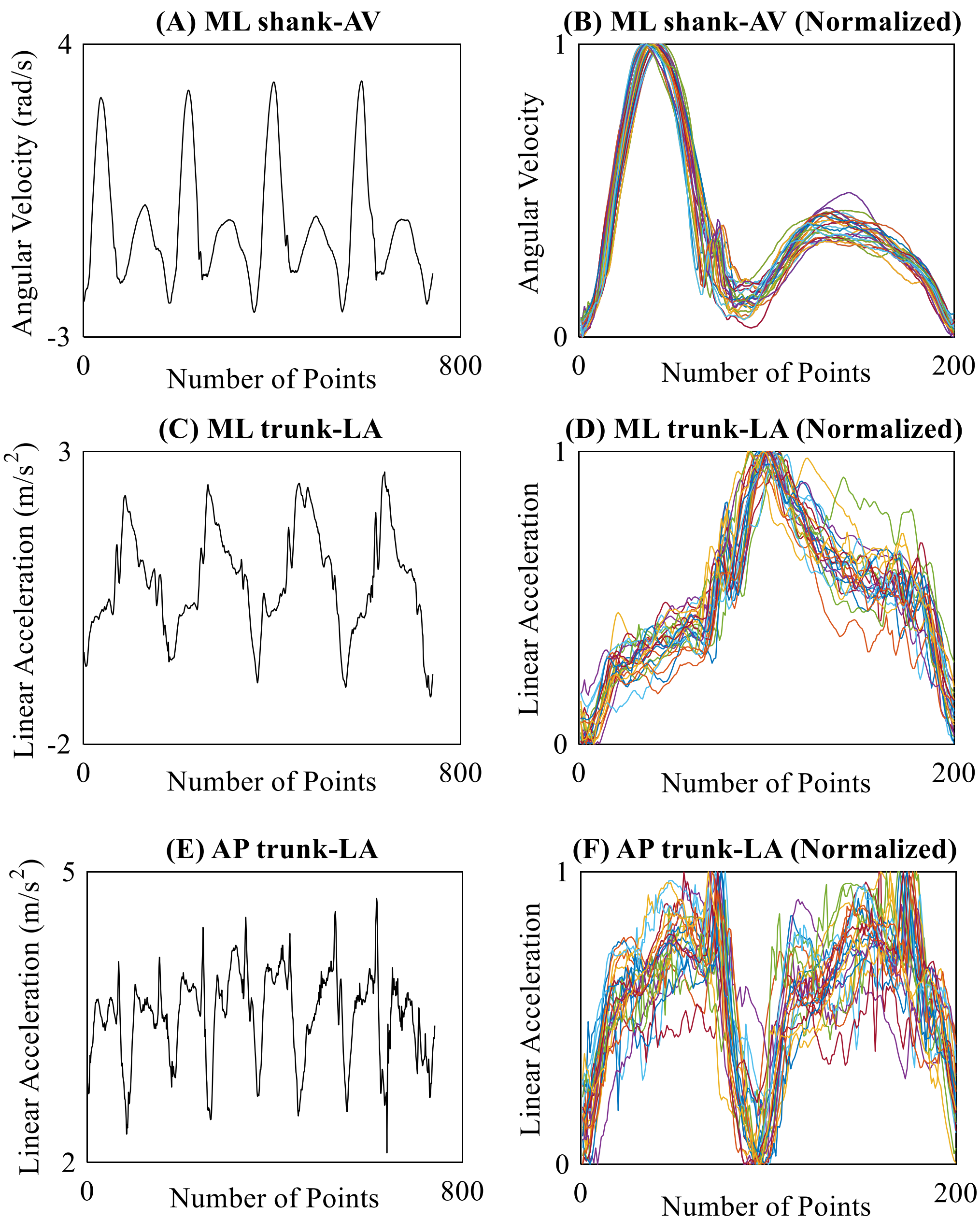


Figure 4-2: Segmenting and normalizing: **(A)** ML shank-AV, **(B)** ML shank-AV (Normalized), **(C)** ML trunk-LA, **(D)** ML trunk-LA (Normalized), **(E)** AP trunk-LA, and **(F)** AP trunk-LA (Normalized). On the left, the raw time series data of the IMM signals for 4 strides and on the right, their respective segmented and normalized signals for several gait cycles are presented.

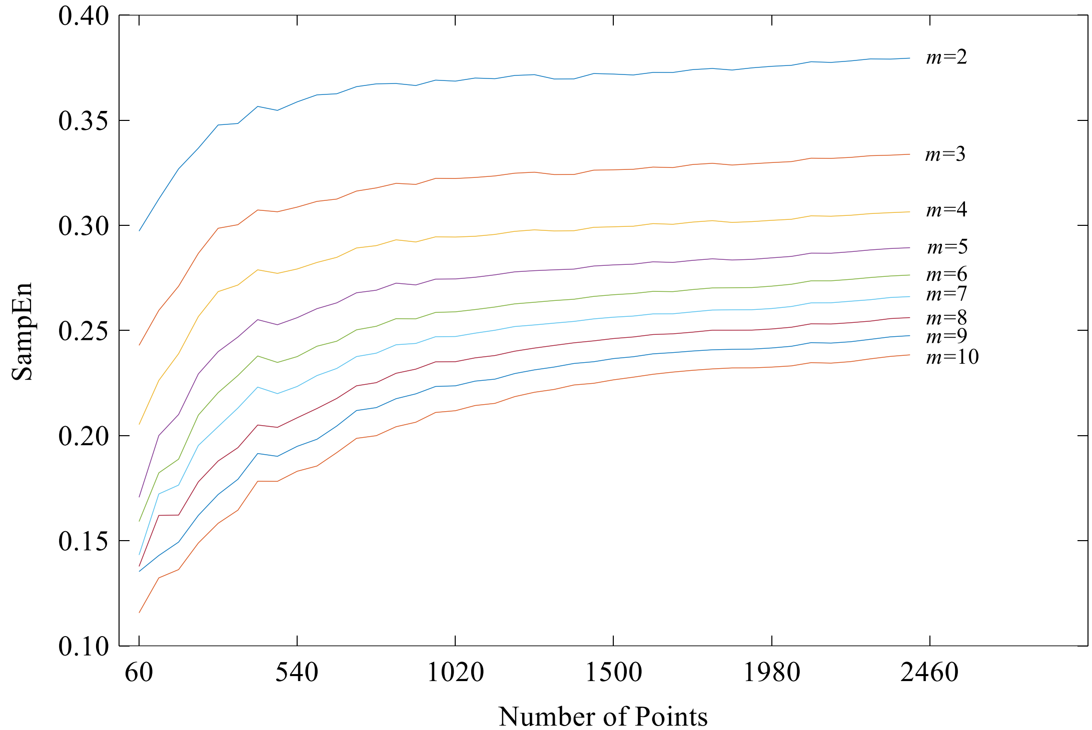


Figure 4-3: Data length convergence test for a various range of template sizes, *m*. The ML trunk-LA signal of older age group was used.

4.2 Statistical Analysis

A two-way (mixed repeated measures analysis of variance (ANOVA) was used to examine the main and interaction effects of task condition (i.e., WO and DT walking condition) and age (i.e., young and older age groups) on QDE and SampEn for each of the five gait signals. Further pairwise comparisons were performed to examine the effects of task condition for each age group. Normality of dataset was checked using the Shapiro-Wilk normality test and they were normally distributed. In all tests, a *p*-value less than 0.05 was considered significant. Statistical analysis was performed using SPSS software version 20 and MATLAB R2014a.

4.3 Results

Statistical results of the effects of aging and DT on human gait signal regularity for each approach are presented in Figure 4-4, Figure 4-5, Figure 4-6, and Figure 4-7; SampEn whole data, QDE whole data, SampEn segmented data, and QDE segmented data. The group means and standard error of the means (SEM) are also presented in bar graphs. Statistical analysis revealed significant main effects of both aging and DT. No significant interaction effect was observed for any of dependent variables. A significant increase in entropy values with aging was observed for all four approaches for the ML/AP COP-D, ML shank-AV, and ML Trunk-LA. No significant age effect was observed for the entropy of AP trunk-LA.

For analysis of whole signals, there was a significant increase in SampEn from WO to DT walking trials but only for the ML COP-D (p<0.001). This was the case for both age groups. For analysis of whole signals, there was a significant increase in QDE from WO to DT walking trials for the ML COP-D (p<0.001). This was the case for both age groups. There was also a significant increase in the QDE of ML shank-AV (p<0.05) during DT walking trials, but this was only seen in the older age group. No significant effect of dual-tasking on entropy values was observed for the trunk-LA.

As compared to whole signals, for analysis of segmented data signals, there were far more significant changes in both SampEn and QDE between WO and DT walking condition. There was a significant increase in SampEn from WO to DT walking trials for all except one signal in the young age group; ML COP-D (p<0.005), AP COP-D (p<0.05), ML trunk-LA (p<0.005), and AP trunk-LA (p<0.005). The only exception was ML shank-AV. A similar increase in the SampEn of segmented data from WO to DT walking trials was observed in the older age group; ML COP-D

($p<0.001$), AP COP-D ($p<0.05$), AP trunk-LA ($p<0.05$), and ML shank-AV ($p<0.01$). The only exception was ML trunk-LA.

The results for the QDE of segmented data in the young age group were the same as those of SampEn; a significant increase in QDE from WO to DT condition for; ML COP-D ($p<0.005$), AP COP-D ($p<0.05$), ML trunk-LA ($p<0.005$), and AP trunk-LA ($p<0.005$). For the older age group, there was a significant increase in QDE for only three of the five signals; ML COP-D ($p<0.001$), AP trunk-LA ($p<0.05$), and ML shank-AV ($p<0.01$).

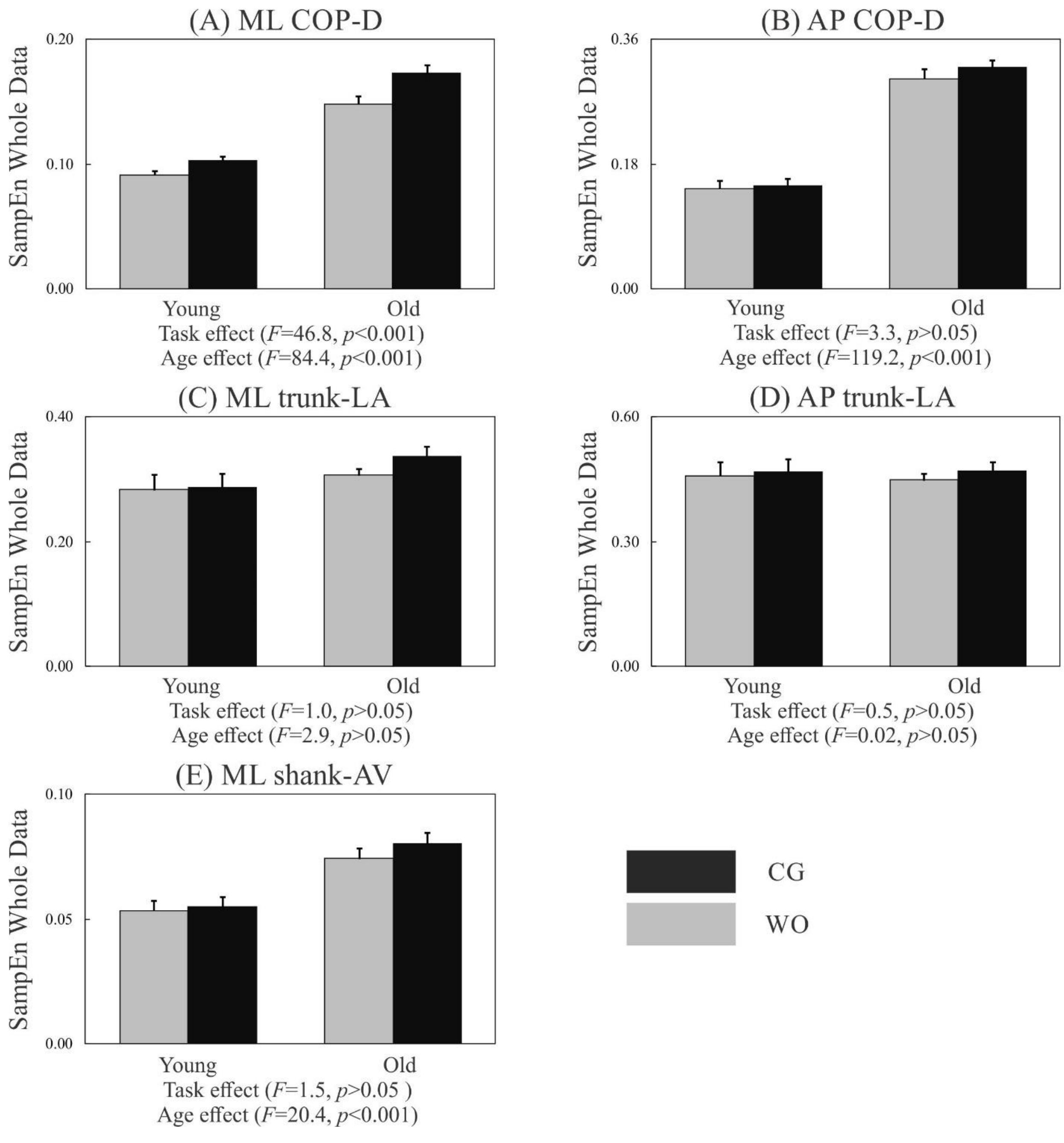


Figure 4-4: Group means and SEM of SampEn (unitless) of whole data along with the results of statistical analysis (*F*-statistics and *p*-values) representing age and DT effects: **(A)** ML COP-D, **(B)** AP COP-D, **(C)** ML trunk-LA, **(D)** AP trunk-LA, and **(E)** ML shank-AV

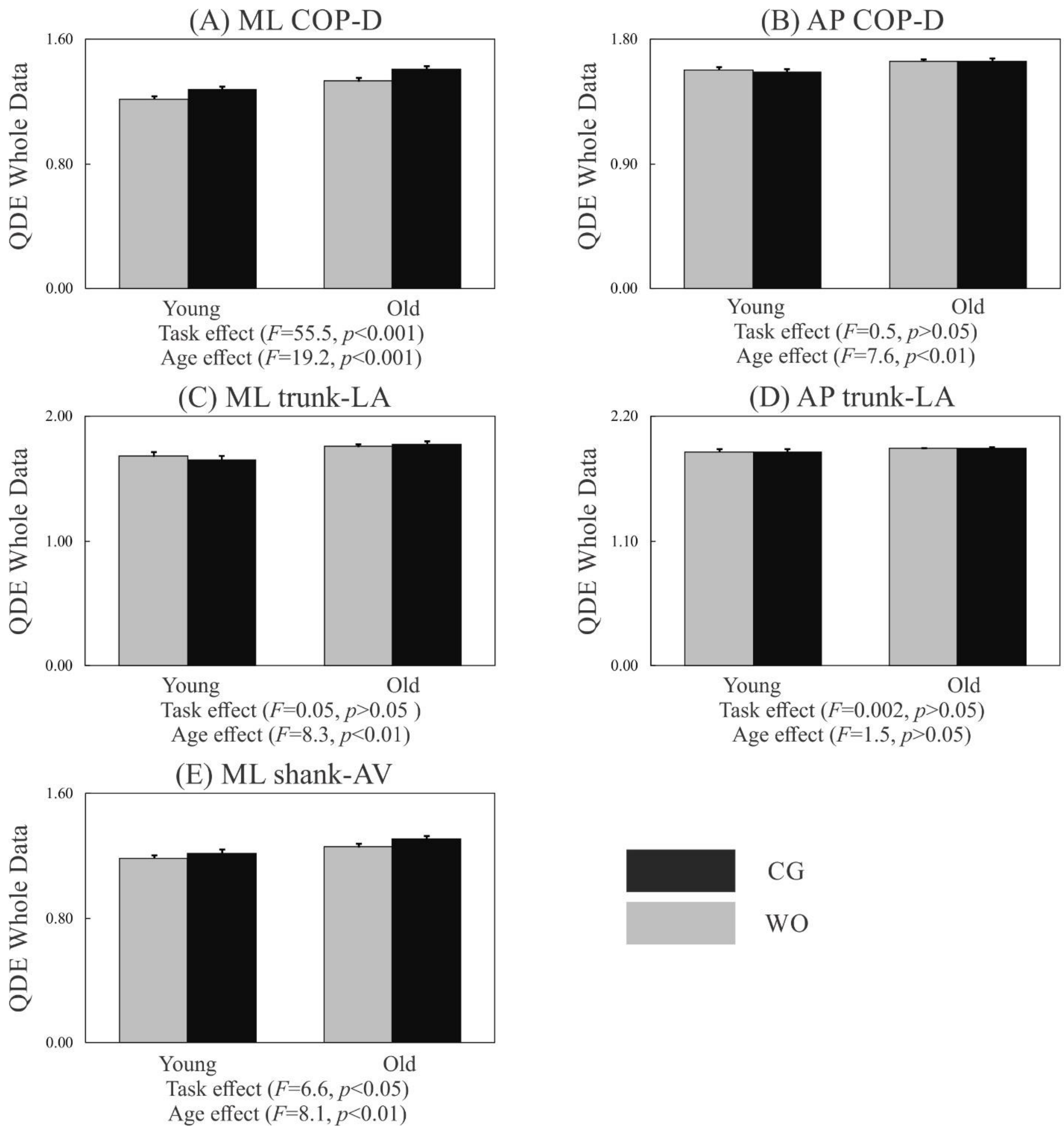


Figure 4-5: Group means and SEM of QDE (unitless) of whole data along with the results of statistical analysis (*F*-statistics and *p*-values) representing age and DT effects: **(A)** ML COP-D, **(B)** AP COP-D, **(C)** ML trunk-LA, **(D)** AP trunk-LA, and **(E)** ML shank-AV

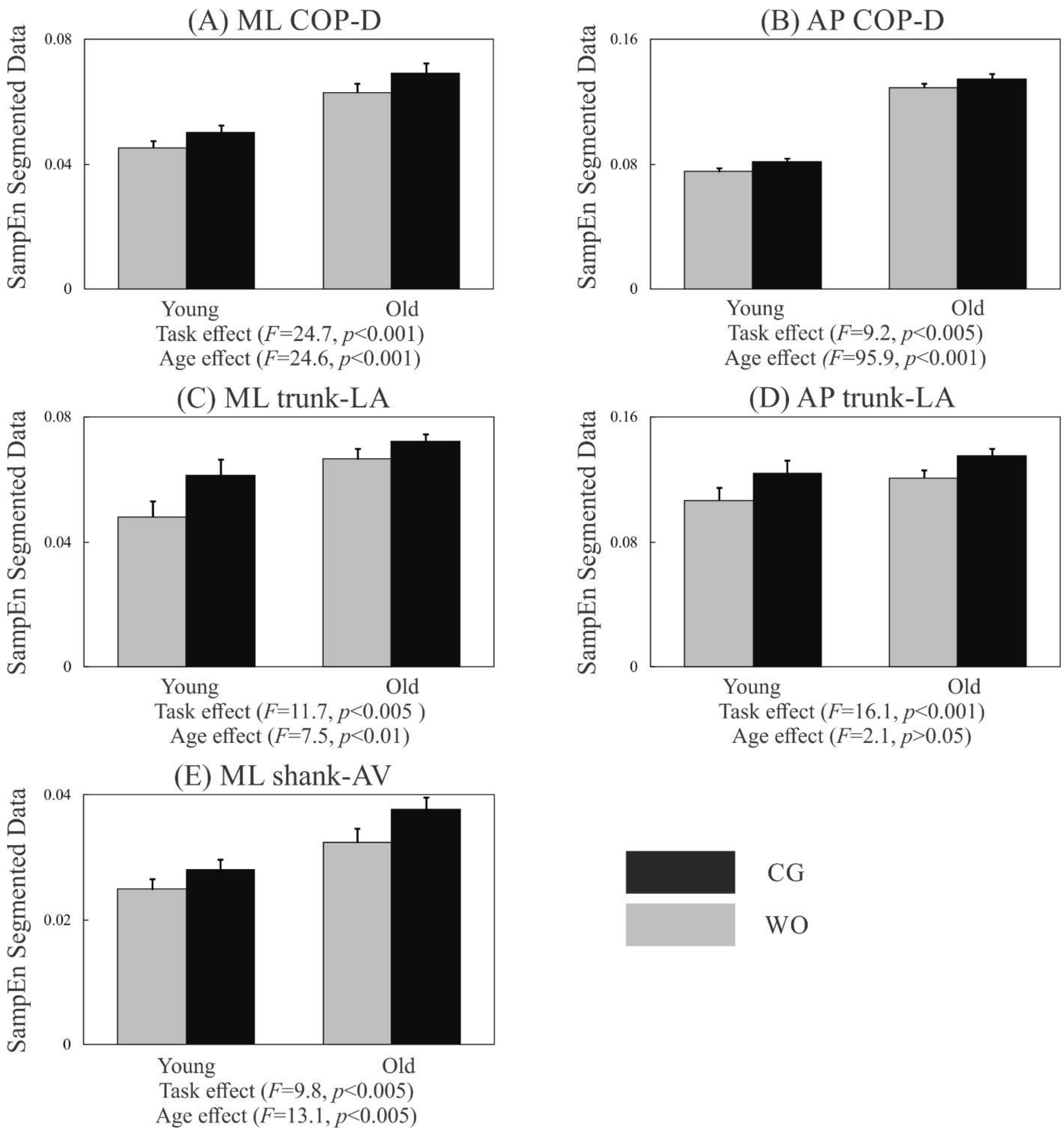


Figure 4-6: Group means and SEM of SampEn (unitless) of segmented data along with the results of statistical analysis (*F*-statistics and *p*-values) representing age and DT effects: **(A)** ML COP-D, **(B)** AP COP-D, **(C)** ML trunk-LA, **(D)** AP trunk-LA, and **(E)** ML shank-AV

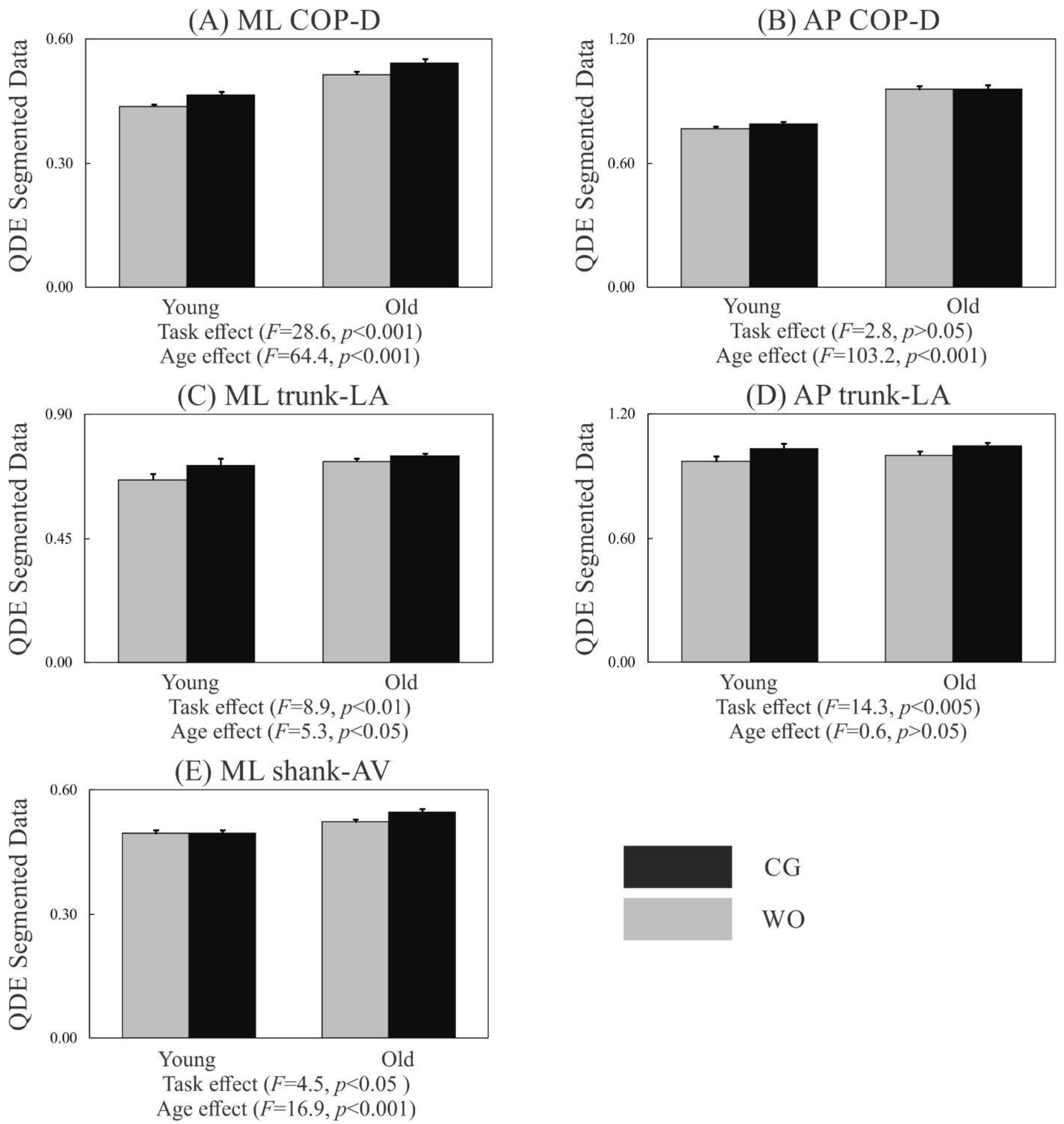


Figure 4-7: Group means and SEM of QDE (unitless) of segmented data along with the results of statistical analysis (F-statistics and p-values) representing age and DT effects: **(A)** ML COP-D, **(B)** AP COP-D, **(C)** ML trunk-LA, **(D)** AP trunk-LA, and **(E)** ML shank-AV

4.4 Discussion

The present study investigated the effects of aging and increased information processing load on the entropy of various gait signals representing trunk motion, leg motion, and the COP migration. Both QDE and SampEn significantly increased with age and when performing a secondary visuomotor cognitive task. Steady-state gait signals are intrinsically periodic with consistent fluctuation from stride to stride. It can be argued that when human gait is disrupted by performing a secondary task or negatively affected by aging or diseases, these fluctuations would change. The unplanned fluctuations might increase during walking under challenging conditions known to cause gait disturbances and stumbles [90]. The increased fluctuations would, therefore, cause an increase in SampEn and QDE. Segmented and normalized data was more affected by the addition of a secondary task as compared to analysis using the whole data. Amongst different gait signals examined, the ML COP-D was the only one to exhibit a significant increase in irregularity with age and DT conditions for both QDE and SampEn, and for both segmented and whole data.

The present findings demonstrated a significant increase in irregularity of the segmented gait signals when dual-tasking. An increase in entropy during DT treadmill walking was only seen in a few cases when using whole gait signals (i.e., ML COP-D and ML shank-AV). Segmenting gait signals into individual gait cycles and normalizing them by cycle time period and amplitude works similarly to detrending the signal by minimizing or eliminating inter-stride correlations of the signal [12]. Therefore, it would help reveal changes hidden by variations because of drifts. For example, a significant increase in the regularity of the segmented trunk-LA signal from WO to DT walking trials was observed for both QDE and SampEn, whereas, no change was observed when the analysis was performed using the whole trunk-LA data. Inter-stride features would reflect the gait history and the operation of the central locomotor pattern generator. Whereas intra-stride features would reflect the moment-to-moment behavior within each stance-swing phase, such as limb loading, single limb support dynamics, the center of body mass deceleration and acceleration, the accuracy of leg swing, etc. These processes are of relatively short duration (i.e., 70-100 milliseconds) to accept the total body's COM from heel contact, and a similar time period to decelerate lateral motion of the total body's COM in single limb support, and the reverse in push off. Errors or disruption in any of these processes would result in gait instability and the need to reset locomotor rhythm and movement amplitude [91]. Note that temporal stride interval measures have also been used to examine gait performance [92]. It was reported that older adults with higher activity level exhibited a more irregular stride time series pattern during WO trials. However, analysis based on only inter-stride information does not take into consideration the information within each stride. The analysis which considers intra-stride dynamical features is important in understanding how different factors can impact human gait function.

The present results are consistent with previous studies in which an increase in the entropy of the COP migration with age and while performing a concurrent cognitive task [12], and an increase in the entropy of trunk-LA in fallers as compared to non-fallers [60] were reported. A decrease in the entropy of trunk-LA in fallers as compared to non-fallers [16] during overground walking have also been reported. However, in that study, many important factors were uncontrolled such as gait speed and walking surface. Slowing down is an effective method that peoples, especially those who are at risk of fall, acquire to avoid losing stability. The difference in entropy between fallers and non-fallers could be because of a difference in gait speed, that is, fallers might have walked slower outdoors than the non-fallers because of fear of falling. It should be noted that a young healthy adult can successfully manage or cope with many different complex and novel situations, maintain control of body movements, and restore stability. When older adults or individuals who have a reduced capacity and adaptability to perturbations (either external and internal) are forced to keep up with a specific speed (i.e., not able to slow down as a control strategy), then signal irregularity may increase because of an increase in movement variation or general lack of timely compensatory responses and as a consequence increased motion. This is consistent with the theory of bidirectional change in complexity of control systems with oscillating intrinsic dynamics. In these type of systems, increased fluctuation around the rhythmical pattern of the trajectory increases the system complexity [90]. Moreover, a significant increase in the SampEn of lower trunk-LA in the AP direction during overground dual-tasking in older adults has been reported by Lamoth et al. [82]. It might suggest that the no significant change of the whole data entropy values of AP trunk-LA in our study is mainly due to treadmill walking which forces the participants to keep up with the fixed speed in the AP direction. However, it should also be noted that a significant decrease in gait speed during DT walking condition as compared to WO condition was also observed [82]. A similar study by Bisi et al. [93] also examined the effects of dual-tasking on the SampEn of lower trunk-LA obtained from overground walking trials of adolescents. Their results showed no significant effect of cognitive load on SampEn and the values of self-selected gait speed were not reported during WO and DT walking condition. In those three studies [4-5, 39], participants performed the tasks overground and at their self-selected speed that is the free-running walking condition. However, uncontrolled gait speed, along with the desired parameters, might have influenced the entropy values.

Another main finding of the present study was that the effects of age and DT condition on signal regularity differed among the five gait signals which included trunk and shank body segments, the COP migration, as well as both AP and ML directions of motion. The young age group did not show any significant changes in SampEn or QDE at shank segment while performing cognitive games, whereas the older age group exhibited significant increases while performing the secondary task. This would indicate that the control of swing phase during more challenging tasks is affected by age. Throughout the swing phase, only one foot is bearing body weight and the center of body mass is moving away from the base of support, hence, the velocity control of the swinging leg becomes important. The fact that AP trunk-LA did not show any age effect could be because of walking on a treadmill at a constant speed and therefore more or less in the same location in space. In addition, previous studies have shown that human gait is more sensitive in the ML direction regardless of the direction of perturbations [94] especially amongst older adults who are prone to fall [95]. The results of the present study are consistent with the previous findings and demonstrate that gait disturbances are most likely to be observed in the ML direction. SampEn and QDE of the ML COP-D, either whole or segmented data was the best signal to capture the age and DT effects. The ML COP-D was able to better represent the slightest within-stride changes comprising both stance and swing phases along with the transitions. These transitions are critical points where instability cannot be resolved easily.

Two possible limitations should be considered when interpreting the results of this study. First, the present visuomotor DT involves both head rotation and cognitive processing. The current method cannot exclude any intersegmental mechanical effects of the head rotation that may cause the gait changes observed between WO and DT walking trials, and changes could be because of both factors. However, head rotations during dual-tasking were relatively small and slow. The majority of head rotations for paddle movements, which occurred every 2 seconds, were less than 20 degrees and movement duration was about 200-400 milliseconds. Based on a preliminary data, the SampEn of the whole data ML COP-D slightly decreased when participants rotated their head (up to 20 degrees) in synchrony with a cyclic motion of a target on the screen. Also, a previous study [96] has examined the effects of head rotation on the COP migration while open loop tracking a moving visual target (up to 25 degrees) on a treadmill. The results demonstrated a very small COP deviation from the midline when participants performed the tracking task with head rotation. Second, all tasks were performed while participants walked on a treadmill. Although treadmill walking is an efficient method to collect data from several strides, previous studies have shown that it may alter some characteristics of gait, such as local dynamic stability and variability [11]. However, it was necessary for the current study to perform the tests on a treadmill to collect lengthy data and to limit the number of factors influencing gait by fixing the walking speed.

4.5 Summary

This chapter demonstrated that both aging and dual-tasking had a significant increasing effect on SampEn and QDE of whole gait signals. In addition, the results of this study suggest that the method of segmenting and normalizing could be beneficial when intra-stride changes are of interest. The results also demonstrated that, in a fixed-speed treadmill walking condition, the ML COP-D is more capable of capturing changes caused by aging and dual-tasking than AP COP-D, ML/AP trunk-LA, and ML shank-LA. This was true for both SampEn and QDE and while analyzing both whole data and segmented/normalized data. Previous studies had only investigated one signal, such as trunk linear acceleration [16] or ML COP-D [12], and had reported inconsistent results. In this chapter, a more comprehensive investigation has been conducted by considering 5 different signals and including both whole and segmented signals. This resulted in selecting the best signal for entropy measures and increased the knowledge base of the impact of segmenting signals. In the next chapter, the sensitivity of the SampEn and QDE of the ML COP-D to variant values of template size, tolerance size, and sampling rate and to two preprocessing methods will be thoroughly investigated.

Chapter 5

Systematic Study on SampEn and QDE for Whole Gait Signals

The first objective of this chapter[2] is to systematically examine the sensitivity of the SampEn and QDE of the ML COP-D signals, obtained during treadmill walking, to variant values of template size, tolerance size, and sampling rate. The second objective is to determine the effects of the choice of low-pass filtering and data resampling (i.e., to have the same average number of data points per stride) on the SampEn and QDE of the ML COP-D signals. Discriminatory ability of SampEn and QDE is examined through comparing WO to DT (VCG1) walking condition. The second dataset (see Section 3.2.2) was used in this chapter.

5.1 Data Analysis

This chapter consists of two parts. In the first part, the sensitivity of SampEn and QDE to changing template size, tolerance size, and sampling rate is investigated when comparing WO to DT walking

[2] The results of this chapter have been published in [106].

condition. Two methods were used to downsample signals from 1000 Hz to lower sampling rates (see Table 5-1). The goal was to downsample signals by factors of 1, 2, 4, 8, 16, and 32. The first method, decimation (D) by a factor of *f*, used an eighth-order low-pass Chebyshev Type I filter, which filtered the signal in forward and reverse directions to remove phase distortions, and then selected every *f*-th point. The filter had a normalized cut-off frequency of $0.8/f$. This method was chosen to avoid aliasing distortion that might occur by simply downsampling the signal.

The second method, filtering-downsampling (FD) by a factor of *f*, used a second-order Butterworth low-pass filter [97]–[99] with a cut-off frequency of 30 Hz, and then downsampled the signal by a factor of *f*. Butterworth low-pass filter is the most common filter used in the literature to reduce the effects of noise [99] along with maintaining the variability in the lower range frequencies where the musculoskeletal motion occurs [97].

A nonparametric power spectral density or PSD estimator, Welch's algorithm, was used to obtain the cut-off frequency. The PSD of a signal describes the power present in the signal as a function of frequency, per unit frequency. The dominant peak was at 0.89±0.06 Hz (mean ± SD) for WO, 0.91 ± 0.06 for DT, and 0.99 ± 0.06 for WO-1.3. The last peak before the noise floor occurred in the 8-15 Hz frequency range (See Figure 5-1). Therefore, 15 Hz was considered as the highest frequency component and 30 Hz was used as the cut-off frequency.

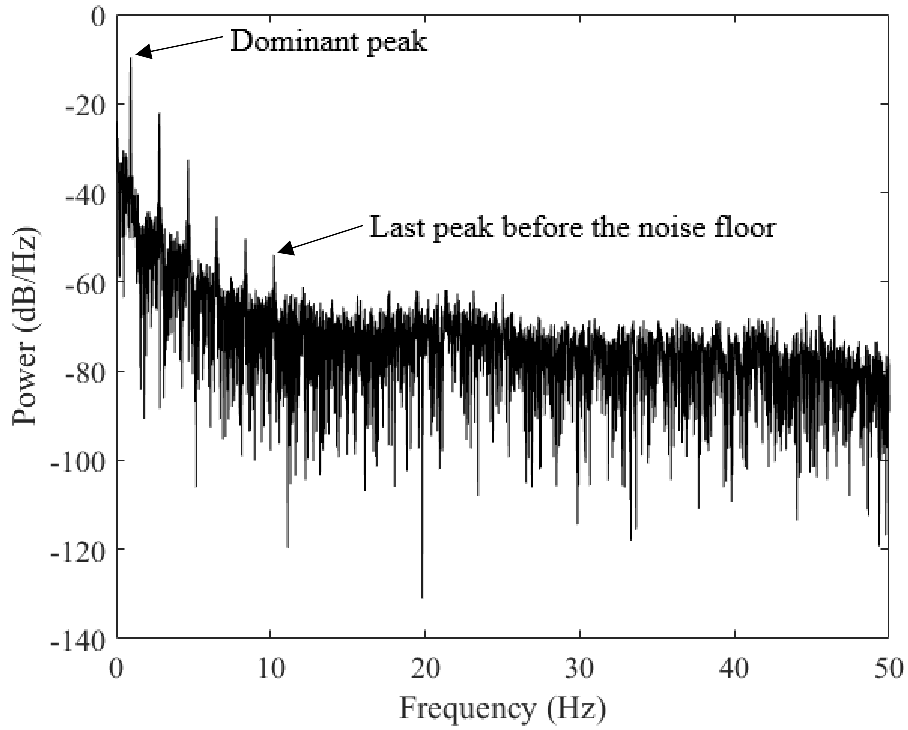


Figure 5-1: Power spectral density of the ML COP-D signal obtained from one of the participants along with showing the dominant peak and the last peak before the noise floor.

Table 5-1: Summary of downsampling factors (*f*), sampling rates and cut-off frequency for decimation and filtering-downsampling methods.

f	Sampling rate (Hz)	Cut-off frequency (Hz)	
		Decimation	Filtering-Downsampling
1	1000	800	30
2	500	400	30
4	250	200	30
8	125	100	30
16	62	50	30
32	31	25	30

The two methods yielded approximately the same results with respect to the low-pass filtering for $f = 32$ because of a similar cut-off frequency. Therefore, the first five *f* values could shed light on the effects of low-pass filtering prior to the calculation of SampEn and QDE.

SampEn and QDE were calculated using all combinations of template size values ($m = 2, 4, 6, 8, \text{and } 10$) tolerance size values ($r = 0.2\ and\ 0.3 \times$SD of all time series), and downsampling factor values ($f = 1, 2, 4, 8, 16,\ \text{and } 32$) and for both decimated and filtered-downsampled signals of WO and DT walking condition. The present investigation was based on more *m* and *f* values in the selected ranges. However, the necessity for statistical analysis with the purpose of studying the discriminatory ability of SampEn and QDE led to choosing fewer parameter values (i.e., levels within a factor); for example, five levels versus nine levels for template size (m=2~10). In a previous study [73], $m = 2$,3,4 were tested when SampEn was applied to the inter-stride spatio-temporal gait variables. The present work included more *m* values to study the SampEn and QDE of the entire gait signals and not just times at heel strike or step distances. It was hypothesized that larger *m* values could better discern changes when there is a much greater number of data points per gait cycle or stride. Additionally, unlike ApEn, SampEn decreases almost monotonically with increasing *r* value [67], [73] and 0.1-0.3 times the SD has been suggested for inter-stride spatio-temporal gait variables [73]. The current analysis was based on $r = 0.1 \times SD, r = 0.2 \times SD,$ and $r = 0.3 \times SD$. However, when the parameter value $r = 0.1 \times SD$ was used, many SampEn and QDE values converged to infinity. Therefore, this level was not included in the results. Large *r* values were not included because they result in much smaller SampEn and QDE values for each condition (i.e., more matched templates), which diminish the discriminatory ability of SampEn.

In the second part of this chapter, the effects of low-pass filtering and resampling, to have the same average number of data points per stride, is investigated. The SampEn and QDE of the ML COP-D signal of WO, DT, and WO-1.3 (see Figure 5-2) were calculated using $m = 4, r = 0.2 \times SD$ and $f = 8$ (based on the results of the first part).

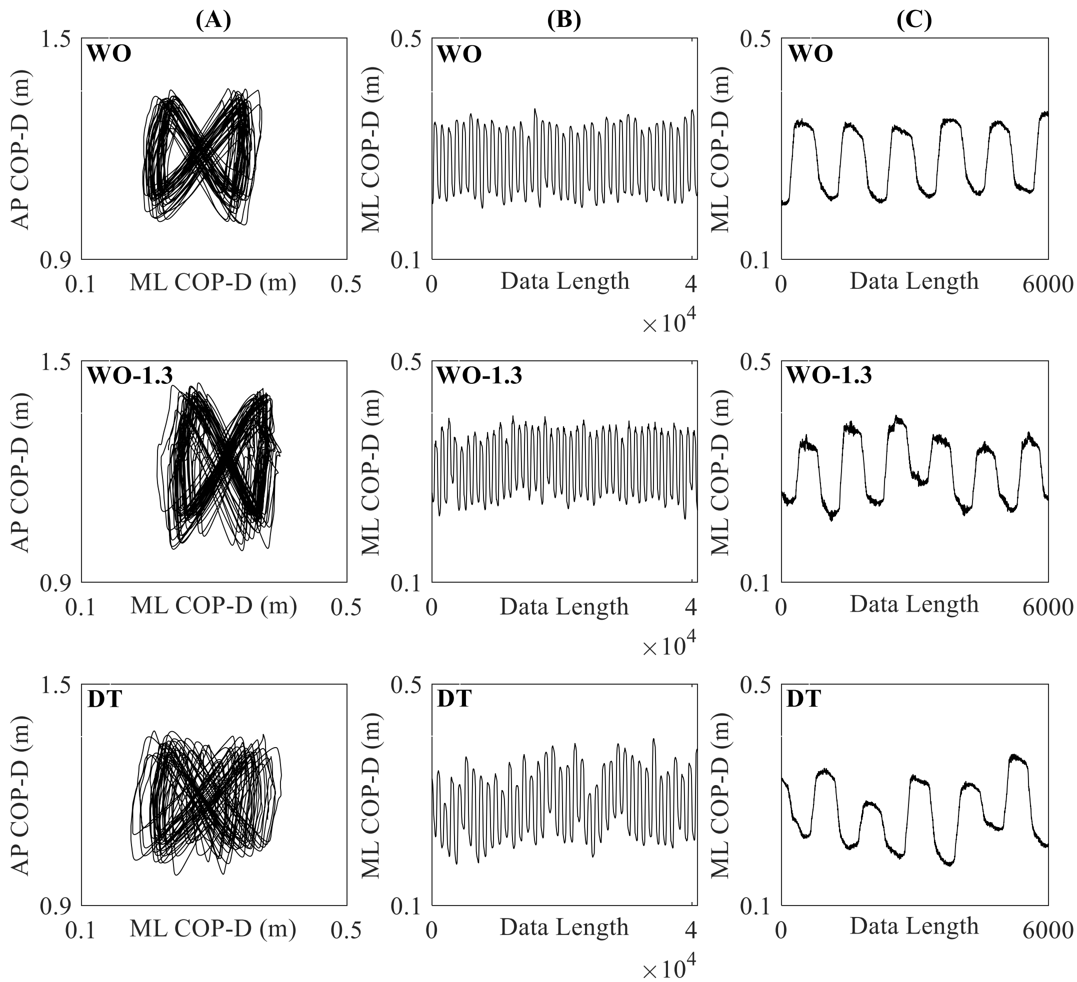


Figure 5-2: Trajectory of COP migration under WO (top), WO-1.3 (middle), and DT (bottom) conditions: **(A)** low-pass filtered trajectory of COP migration displayed as AP COP-D vs. ML COP-D, the butterfly pattern is less visible during DT condition **(B)** low-pass filtered ML COP-D , drifting in ML direction is noticeable during DT condition **(C)** several strides of unfiltered ML COP-D, vibrational noise is increased during WO-1.3 condition

Four methods of preprocessing were used for each condition;

- decimation (D),
- decimation and resampling (D-R),
- filtering-downsampling (FD) and,
- filtering-downsampling and resampling (FD-R).

The average number of data points per stride for WO, DT, and WO-1.3 were 142,140, and 128, respectively. Therefore, 30 strides of each time series were resampled so that all of the signals would have an average of 142 data points per stride.

5.2 Statistical Analysis

In the first part of this study, there were 4 factors of within-subject repeated measures, which were 2 levels of walking condition (WO and DT), 2 levels of r, 6 levels of f, and 5 levels of m. The following steps were taken to perform the statistical analysis separately for both decimated and filtered-downsampled signals and Separately for SampEn and QDE.

i. A two-factor repeated measures ANOVA (walking condition*m) was performed at each f level while considering the first tolerance level.
ii. A two-factor repeated measures ANOVA (walking condition*m) was performed at each f level while considering the second tolerance level.
iii. A two-factor repeated measures ANOVA (walking condition*f) was performed at each m level while considering the first tolerance level.

iv. A two-factor repeated measures ANOVA (walking condition**f*) was performed at each *m* level while considering the second tolerance level.

v. Post hoc pairwise comparisons with Bonferroni correction were performed to examine the effects of dual-tasking at each level.

vi. Finally, a two-factor (walking condition**r*) repeated measures ANOVA was performed at fixed m=4 and f=8 values, which were chosen based on the previous step's statistical results.

In the second part of this study, two two-factor within-subject ANOVAs were used to examine the main and interaction effects of the following factors on SampEn and QDE separately;

- walking condition (WO versus DT) and preprocessing method (D, D-R, FD, FD-R)
- gait speed (1.0 m/s versus 1.3 m/s) and preprocessing method (D, D-R, FD, FD-R)

Normality of all dependent variables was checked using the Shapiro-Wilk normality test. Results confirmed that the data were normally distributed. Statistical analysis was performed using SPSS software version 24. A *p*-value less than 0.05 was considered significant. A Bonferroni correction was used in the software for multiple comparisons.

5.3 Results of SampEn

The results of the main and interaction effects of walking condition (WO and DT), template size *m*, and downsampling factor *f* at each tolerance size *r* value are presented in Table 5-2 and Table 5-3. In addition, the results of the pairwise comparisons of the significant main effects of walking condition are presented in Table 5-4. The detailed results for each downsampling method are presented in the following sections followed by the results of the effects of preprocessing methods.

For the vast majority of the combinations of parameter values, the SampEn of the ML COP-D during DT walking was significantly larger than that of WO. In general, SampEn decreased as m increased, as r increased and as f factor decreased (i.e., as sampling rate increased or as the number of points per stride increased). However, there were a few exceptions which will be discussed further.

Table 5-2: Main and interaction effects (p-values) of "walking condition (W-C)*f" on SampEn at each r and m value for filtered-downsampled and decimated ML COP-D. The two conditions are WO and DT. p-values in bold indicate a significant difference.

		W-C	f	W-C *f			W-C	f	W-C *f
	m=2	**<0.001**	**<0.001**	**<0.001**		m=2	**0.009**	**<0.001**	**<0.001**
	m=4	**<0.001**	**<0.001**	**0.006**		m=4	**0.009**	**<0.001**	**<0.001**
FD $r = 0.2 \times SD$	m=6	**0.001**	**<0.001**	0.123	D $r = 0.2 \times SD$	m=6	**0.021**	**<0.001**	**0.023**
	m=8	**0.004**	**<0.001**	0.334		m=8	**0.037**	**<0.001**	0.070
	m=10	**0.020**	**<0.001**	0.421		m=10	0.075	**<0.001**	0.211
		W-C	f	W-C *f			W-C	f	W-C *f
	m =2	**<0.001**	**<0.001**	**<0.001**		m=2	**0.008**	**<0.001**	**<0.001**
	m=4	**<0.001**	**<0.001**	**<0.001**		m=4	**0.001**	**<0.001**	**<0.001**
FD $r = 0.3 \times SD$	m=6	**0.002**	**<0.001**	0.080	D $r = 0.3 \times SD$	m=6	**0.015**	**<0.001**	**0.034**
	m=8	**0.006**	**<0.001**	0.232		m=8	**0.032**	**<0.001**	0.154
	m=10	**0.020**	**<0.001**	0.387		m=10	0.068	**<0.001**	0.279

Table 5-3**:** Main and interaction effects (p-values) of "walking condition (W-C)*m" on SampEn at each r and f value for filtered-downsampled and decimated ML COP-D. The two conditions are WO and DT. p-values in bold indicate a significant difference.

		W-C	m	W-C *m			W-C	m	W-C *m
	f=1	**0.007**	**<0.001**	**0.001**		f=1	0.094	**<0.001**	**0.004**
	f=2	**0.002**	**<0.001**	**0.007**		f=2	0.806	**<0.001**	**0.000**
FD $r = 0.2 \times SD$	f=4	**<0.001**	**<0.001**	0.128	D $r = 0.2 \times SD$	f=4	**0.049**	**<0.001**	0.176
	f=8	**<0.001**	**<0.001**	**0.015**		f=8	**0.008**	**<0.001**	0.145
	f=16	**<0.001**	**<0.001**	**0.002**		f=16	**0.001**	**<0.001**	**0.003**
	f=32	**0.007**	**<0.001**	0.070		f=32	**0.005**	**<0.001**	0.114
		W-C	m	W-C*m			W-C	m	W-C*m
	f=1	**0.011**	**<0.001**	**0.010**		f=1	0.329	**<0.001**	**0.044**
	f=2	**0.006**	**<0.001**	**0.000**		f=2	0.938	**<0.001**	**<0.001**
FD $r = 0.3 \times SD$	f=4	**0.001**	**<0.001**	0.170	D $r = 0.3 \times SD$	f=4	**0.049**	**<0.001**	**0.020**
	f=8	**<0.001**	**<0.001**	0.062		f=8	**0.006**	**<0.001**	0.178
	f=16	**<0.001**	**<0.001**	**0.002**		f=16	**0.001**	**<0.001**	**0.004**
	f=32	**0.005**	**<0.001**	**0.006**		f=32	**0.005**	**<0.001**	**0.010**

Table 5-4: Pairwise comparisons of “walking condition*m” for SampEn at each r and f value for filtered-downsampled and decimated ML COP-D. The two conditions are WO and DT. p-values in bold indicate a significant difference.

		Pairwise Comparisons (p-values)			
		$r = 0.2 \times SD$		$r = 0.3 \times SD$	
		FD	D	FD	D
f=1	m=2	**0.008**	-	**0.012**	-
	m=4	**0.008**		**0.012**	
	m=6	**0.008**		**0.011**	
	m=8	**0.008**		**0.011**	
	m=10	**0.004**		**0.011**	
f=2	m=2	**0.008**	-	**0.012**	-
	m=4	**0.008**		**0.011**	
	m=6	**0.002**		**0.011**	
	m=8	**0.001**		**0.005**	
	m=10	**<0.001**		**0.002**	
f=4	m=2	**0.008**	0.568	**0.011**	0.578
	m=4	**0.001**	**0.042**	**0.006**	0.130
	m=6	**<0.001**	**0.011**	**0.001**	**0.018**
	m=8	**0.002**	**0.035**	**0.001**	**0.007**
	m=10	**0.002**	0.058	**0.001**	**0.008**
f=8	m=2	**0.002**	**0.042**	**0.008**	0.127
	m=4	**0.001**	**0.013**	**0.001**	**0.005**
	m=6	**0.002**	**0.041**	**0.001**	**0.010**
	m=8	**0.001**	**0.008**	**<0.001**	**0.003**
	m=10	**0.001**	**0.015**	**<0.001**	**0.002**
f=16	m=2	**<0.001**	**0.001**	**0.001**	**0.002**
	m=4	**0.001**	**0.002**	**<0.001**	**0.001**
	m=6	**0.001**	**0.007**	**<0.001**	**0.002**
	m=8	**0.010**	**0.049**	**0.004**	**0.014**
	m=10	0.052	0.181	**0.042**	0.102
f=32	m=2	**<0.001**	**0.001**	**<0.001**	**<0.001**
	m=4	**0.004**	**0.004**	**0.001**	**0.001**
	m=6	0.051	**0.037**	0.069	0.066
	m=8	0.138	0.105	0.143	0.156
	m=10	0.224	0.154	0.220	0.211

5.3.1 Sensitivity to Variant Parameter Values for Filtering-Downsampling

Figure 5-3 and Figure 5-4 show the effects of changing f and m values on the SampEn of the filtered-downsampled signals at $r = 0.2 \times SD$. The figures are virtually the same as those of $r = 0.3 \times SD$. The statistical results are also reported in Tables 5-2 to 5-4. A statistically significant interaction was found between walking condition and *f* at $m = 2$ and $m = 4$ for both tolerance values. Since the direction of the changes of SampEn with increasing *f* was increasing for both walking conditions, the interaction effects would signify a difference in the rate of the changes between levels. A statistically significant interaction was found between walking condition and *m* at all *f* values except for; a) $f = 4$ and $f = 32$ for $r = 0.2 \times SD$ and b) $f = 4$ and $f = 8$ for $r = 0.3 \times SD$. At each *f* value, the direction of the changes of the SampEn of WO, with respect to *m*, was similar to those of DT. The two-factor repeated measures of the ANOVA of "walking condition**r*" showed that there was no significant interaction between the walking condition and the *r* value (p=0.813). However, there was a statistically significant decrease in SampEn with increasing *r* value (p<0.001). At each *r* value, the SampEn of DT was statistically significantly greater than that of WO (p<0.001).

For all *m* values, there was a statistically significant main effect of walking condition and *f* value on SampEn. Similarly, for all *f* values, there was a statistically significant main effect of walking condition and *m* value on SampEn. SampEn significantly increased from WO to DT for most combinations of *r, m,* and *f* values except for; a) 4 out of 30 combinations of *f* and *m* values for $r = 0.2 \times SD$ and b) 3 out of 30 combinations for $r = 0.3 \times SD$. Nevertheless, for these exceptions, there was a trend of increased SampEn from WO to DT. Based on the statistical analysis, the increasing effect of dual-tasking on the SampEn of the ML COP-D signal can be captured for most combinations of r, m, and f values. The only exceptions are $m = 10$ for $f = 16$ and $m = 6, 8, 10$ for $f = 32$.

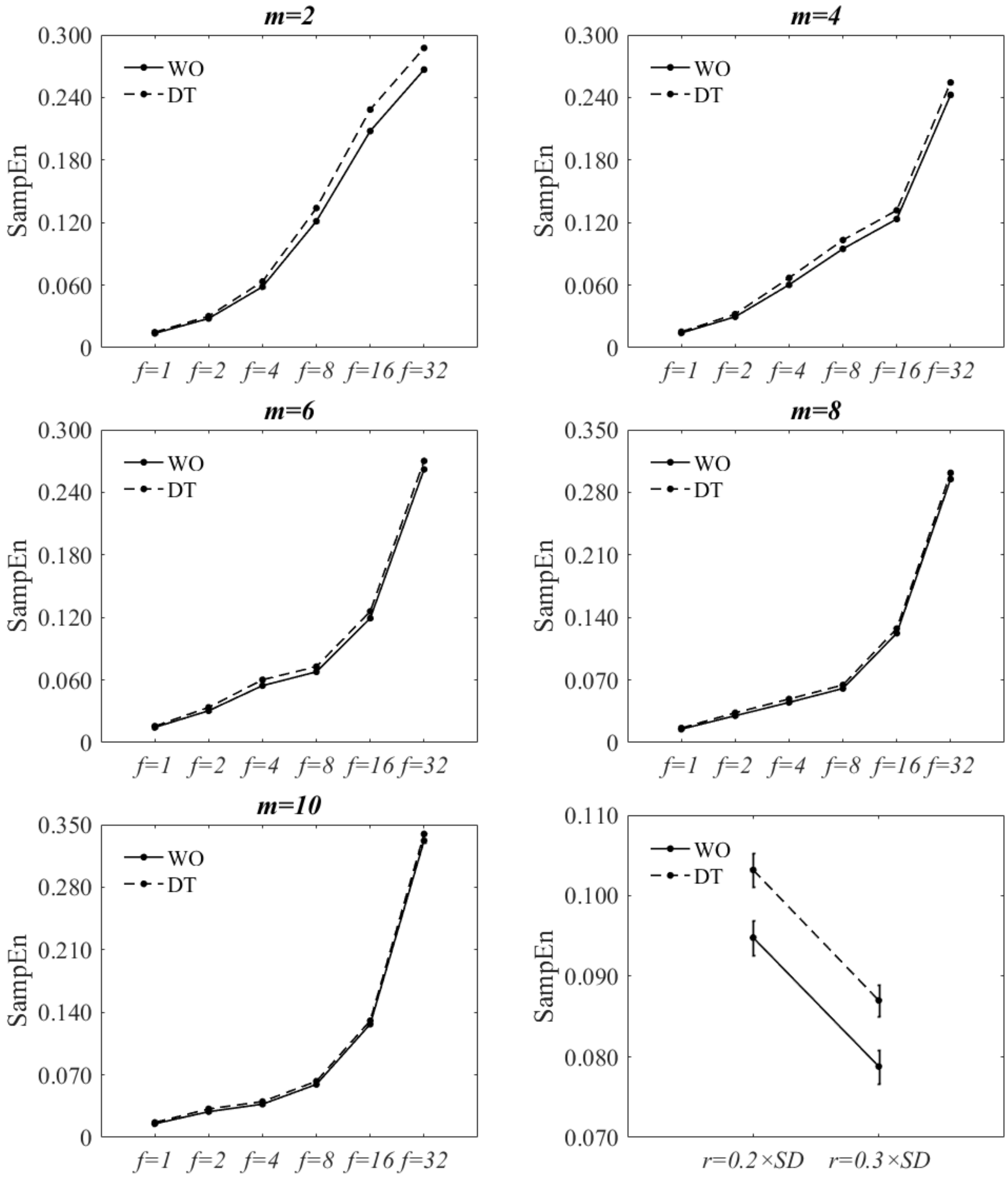


Figure 5-3: Effects of changing f on SampEn of WO and DT at each m value at $r = 0.2 \times SD$ for filtered-downsampled ML COP-D. Bottom-right: Effects of r on SampEn at $f = 8$ and $m = 4$. Error bars reflect SEM.

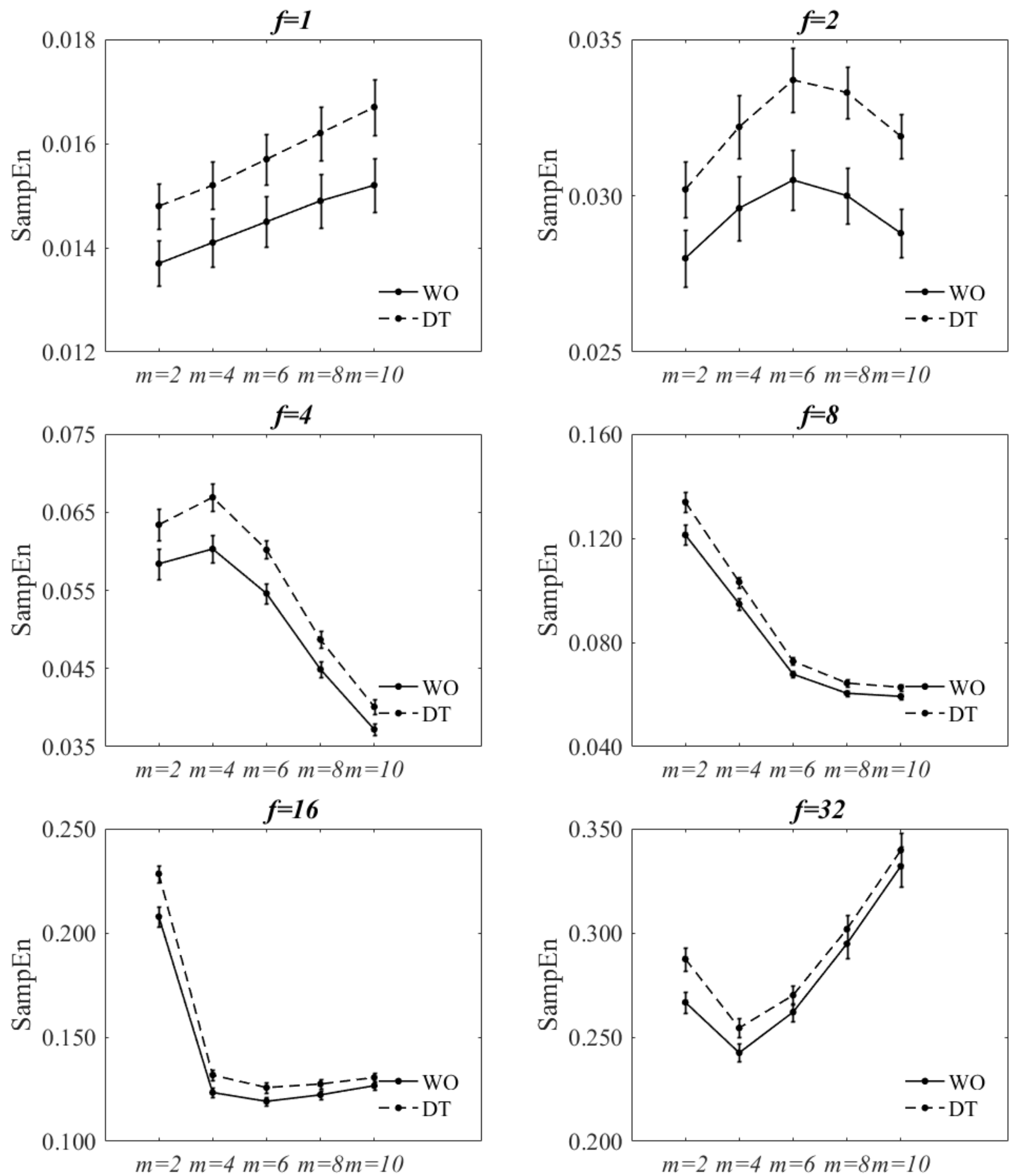


Figure 5-4: Effects of changing m on SampEn of WO and DT at each f value at $r = 0.2 \times SD$ for filtered-downsampled ML COP-D. Error bars reflect SEM.

5.3.2 Sensitivity to Variant Parameter Values for Decimation

Figure 5-5 and Figure 5-6 show the effects of changing *f* and m values on the SampEn of decimated signals at $r = 0.2 \times SD$. The figures are virtually the same as those of $r = 0.3 \times SD$. The statistical results are also reported in Tables 5-2 to 5-4. A statistically significant interaction was found between walking condition and f at $m = 2$, $m = 4$, and $m = 6$ for both tolerance values. The direction of the changes of SampEn with increasing f was increasing for both tasks. A statistically significant interaction was found between walking condition and m at all f values except for; a) $f = 4$, $f = 8$ and $f = 32$ for $r = 0.2 \times SD$ and b) $f = 8$ for $r = 0.3 \times SD$. At each *f* value, the direction of changes of the SampEn of WO, with respect to *m*, was the same to those of DT. The two-factor repeated measures of the ANOVA of "walking condition*r" showed that there was no significant interaction between the walking condition and the *r* value (p=0.980). However, there was a statistically significant decrease in SampEn with increasing *r* value (p=0.001). At each *r* value, the SampEn of DT was statistically significantly greater than that of WO (p<0.001)

For all m values, there was a statistically significant main effect of walking condition (except for $m = 10$) and *f* values on SampEn. And for all *f* values, there was a statistically significant main effect of walking condition (except for $f = 1$ and $f = 2$) and m values on SampEn. SampEn significantly increased from WO to DT for most combinations of *m*, *r and f* (4, 8, 16 and 32) values with a few exceptions; smaller m values at $f = 4$ and larger m values at $f = 16$ and $f = 32$. Nevertheless, SampEn was seen to increase from WO to DT for those exceptions.

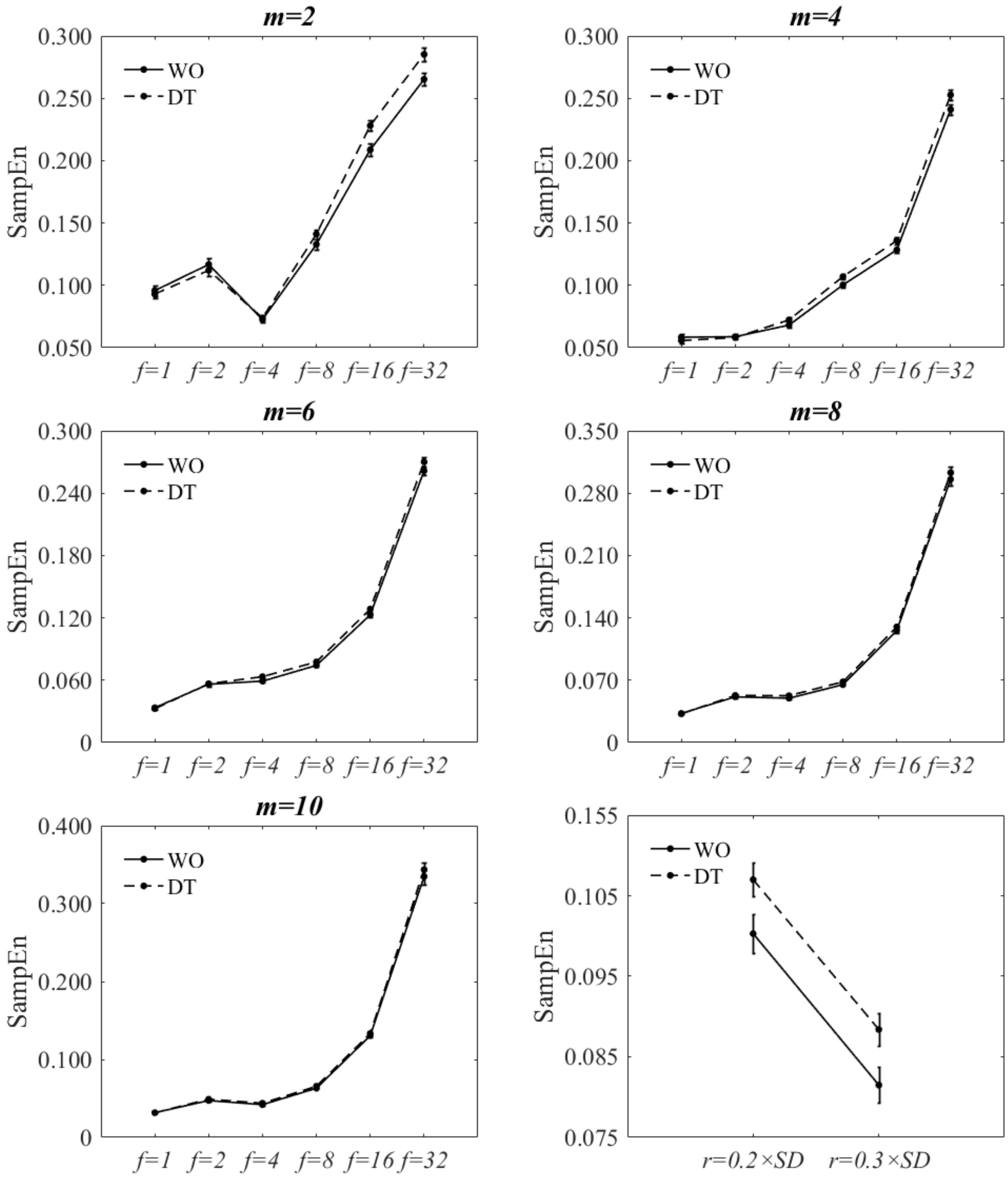


Figure 5-5: Effects of changing f on SampEn of WO and DT at each m value at $r = 0.2 \times SD$ for decimated ML COP-D. Bottom-right: Effects of r on SampEn at $f = 8$ and $m = 4$. Error bars reflect SEM.

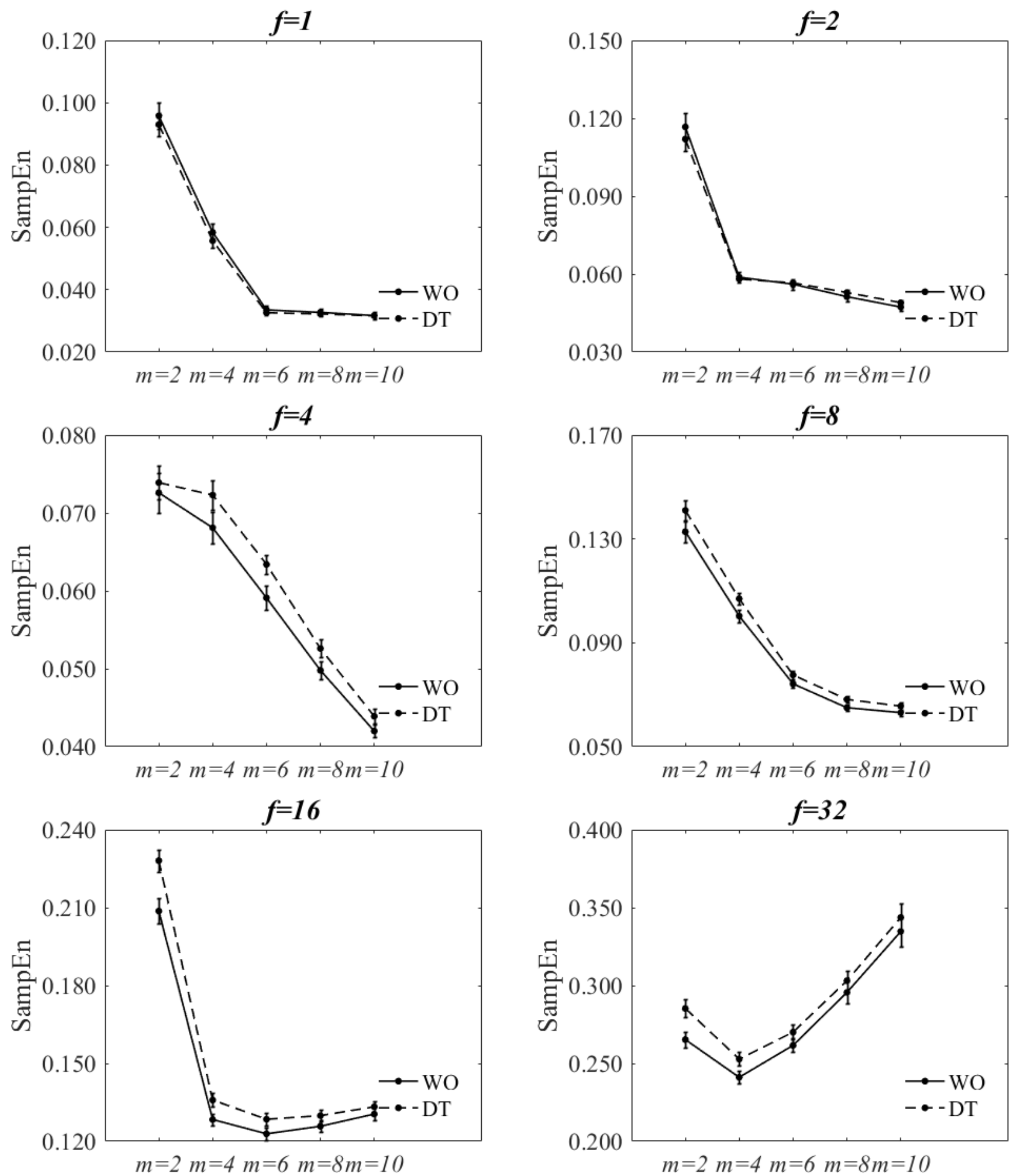


Figure 5-6: Effects of changing m on SampEn of WO and DT at each f value at $r = 0.2 \times SD$ for decimated ML COP-D. Error bars reflect SEM.

5.3.3 Effects of Preprocessing Methods

The descriptive and statistical results of the walking condition (WO versus DT), walking speed (1.0 m/s versus 1.3 m/s), and preprocessing method (D, D-R, FD, FD-R) on SampEn for the combination of $f = 8$, $m = 4$, and $r = 0.2 \times SD$ are presented in Figure 5-7 and Table 5-5. There was a significant interaction effect of walking speed and method, while no significant interaction of walking condition and method was found. In addition, all three walking condition, speed, and method had a significant main effect on SampEn (see Table 5-5). The results revealed that resampling signals to have a larger average number of data points per stride had a decreasing effect on the SampEn of WO-1.3 signals (see Figure 5-7). However, there was no significant effect of resampling on the SampEn of DT and WO signals. The only exception was the significant decrease in the SampEn of WO from FD to FD-R (see Table 5-5). In addition, SampEn significantly decreased when filtering the high-frequency components (see Figure 5-7). Furthermore, SampEn increased significantly from WO to DT when using all four methods. Finally, there was a significant increase in SampEn with increasing walking speed (WO to WO-1.3) only when using decimation or decimation-and-resampling (see Table 5-5).

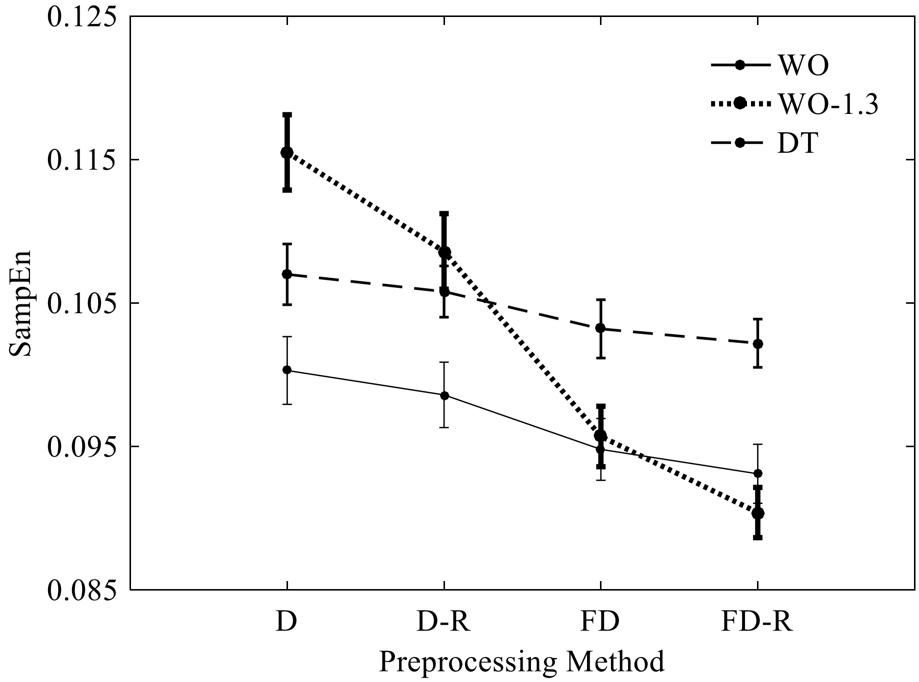


Figure 5-7: Effects of different preprocessing methods on SampEn of ML COP-D signal of WO, DT and WO-1.3 conditions for the combination of $f = 8$, $m = 4$ and $r = 0.2 \times SD$. Error bars reflect SEM.

Table 5-5: Statistical results of walking condition (WO and DT), walking speed (1.0 m/s and 1.3 m/s), and preprocessing method (D, D-R, FD, and FD-R) on SampEn of ML COP-D for the combination of $f = 8$, $m = 4$ and $r = 0.2 \times SD$.The top section presents main and interaction effects. The middle section presents the pairwise comparisons between preprocessing methods for each walking condition (WO, WO-1.3, and DT). The bottom section presents pairwise comparisons between walking conditions for each preprocessing method. *p*-values in bold indicate a significant difference.

Main and Interaction Effects (*p*-values)			
	Condition/Speed	Method	Interaction
WO vs. WO-1.3	**0.017**	**<0.001**	**<0.001**
WO vs. DT	**0.002**	**<0.001**	0.057
Pairwise Comparisons (*p*-values)			
	D vs. D-R	D vs. FD	FD vs. FD-R
WO	0.104	**<0.001**	**0.042**
WO-1.3	**<0.001**	**<0.001**	**<0.001**
DT	0.981	**<0.001**	1.000
Method	WO vs. WO-1.3	WO vs. DT	
D	**<0.001**	**0.013**	
D-R	**0.001**	**0.006**	
FD	0.701	**0.001**	
FD-R	0.225	**<0.001**	

5.4 Results of QDE

The results of the main and interaction effects of the walking condition (WO and DT), *m* and *f* at each *r* value are presented in Table 5-6 and Table 5-7. In addition, the results of the pairwise comparisons of the significant main effects of the walking condition are presented in Table 5-8. The detailed results for each downsampling method are presented in the following sections followed by the results of the effects of the preprocessing methods. For the vast majority of combinations of parameter values, the QDE of the ML COP-D during DT walking was significantly larger than that of WO. In general, QDE decreased as *m* increased, as *r* increased and as *f* factor decreased (i.e., as sampling rate increased or as the number of points per stride increased). However, there were a few exceptions which will be discussed further.

Table 5-6: Main and interaction effects (p-values) of "walking condition (W-C)*f" on QDE at each r and m value for filtered-downsampled and decimated ML COP-D. The two conditions are WO and DT. p-values in bold indicate a significant difference.

		W-C	f	W-C *f			W-C	f	W-C *f
FD $r = 0.2 \times SD$	m=2	**0.001**	**<0.001**	**0.001**	D $r = 0.2 \times SD$	m=2	**0.004**	**<0.001**	**0.001**
	m=4	**0.001**	**<0.001**	**<0.001**		m=4	**0.034**	**<0.001**	**<0.001**
	m=6	**0.002**	**<0.001**	**0.002**		m=6	0.116	**<0.001**	**0.005**
	m=8	**0.002**	**<0.001**	**0.007**		m=8	0.262	**<0.001**	0.058
	m=10	**0.002**	**<0.001**	**0.005**		m=10	0.437	**<0.001**	0.224
		W-C	f	W-C *f			W-C	f	W-C *f
FD $r = 0.3 \times SD$	m =2	**0.001**	**<0.001**	**0.006**	D $r = 0.3 \times SD$	m=2	**0.002**	**<0.001**	**0.009**
	m=4	**0.002**	**<0.001**	**<0.001**		m=4	**0.01**	**<0.001**	**0.002**
	m=6	**0.003**	**<0.001**	**0.001**		m=6	**0.024**	**<0.001**	**0.004**
	m=8	**0.003**	**<0.001**	**0.006**		m=8	**0.049**	**<0.001**	**0.026**
	m=10	**0.004**	**<0.001**	**0.020**		m=10	0.080	**<0.001**	0.134

Table 5-7: Main and interaction effects (p-values) of "walking condition (W-C)*m" on QDE at each r and f value for filtered-downsampled and decimated ML COP-D. The two conditions are WO and DT. p-values in bold indicate a significant difference.

		W-C	m	W-C *m			W-C	m	W-C *m
FD $r = 0.2 \times SD$	f=1	**0.003**	**<0.001**	**<0.001**	D $r = 0.2 \times SD$	f=1	**0.016**	**<0.001**	**<0.001**
	f=2	**0.004**	**<0.001**	**<0.001**		f=2	0.108	**<0.001**	**<0.001**
	f=4	**0.003**	**<0.001**	**0.001**		f=4	0.240	**<0.001**	**<0.001**
	f=8	**0.001**	**<0.001**	**0.004**		f=8	0.155	**<0.001**	**0.002**
	f=16	**0.001**	**<0.001**	**0.004**		f=16	**0.014**	**<0.001**	**0.005**
	f=32	**<0.001**	**<0.001**	**0.001**		f=32	**0.001**	**<0.001**	**0.002**
		W-C	m	W-C*m			W-C	m	W-C*m
FD $r = 0.3 \times SD$	f=1	**0.002**	**<0.001**	**<0.001**	D $r = 0.3 \times SD$	f=1	**0.002**	**<0.001**	**<0.001**
	f=2	**0.004**	**<0.001**	**<0.001**		f=2	**0.020**	**<0.001**	**<0.001**
	f=4	**0.004**	**<0.001**	**0.001**		f=4	0.127	**<0.001**	**<0.001**
	f=8	**0.003**	**<0.001**	**0.002**		f=8	0.053	**<0.001**	**0.001**
	f=16	**0.001**	**<0.001**	**0.004**		f=16	**0.013**	**<0.001**	**0.007**
	f=32	**0.001**	**<0.001**	**0.002**		f=32	**0.001**	**<0.001**	**0.002**

Table 5-8: Pairwise comparisons of "walking condition*m" for QDE at each r and f value for filtered-downsampled and decimated ML COP-D. The two conditions are WO and DT. p-values in bold indicate a significant difference.

		Pairwise Comparisons (p-values)			
		$r = 0.2 \times SD$		$r = 0.3 \times SD$	
		FD	D	FD	D
f=1	m=2	**0.001**	**0.001**	**0.001**	**<0.001**
	m=4	**0.002**	**0.009**	**0.002**	**0.001**
	m=6	**0.006**	0.079	**0.004**	**0.006**
	m=8	**0.011**	0.235	**0.007**	**0.022**
	m=10	**0.018**	0.431	**0.012**	0.053
f=2	m=2	**0.001**		**0.001**	**0.001**
	m=4	**0.005**		**0.004**	**0.017**
	m=6	**0.010**	-	**0.009**	0.084
	m=8	**0.013**		**0.015**	0.191
	m=10	**0.012**		**0.020**	0.275
f=4	m=2	**0.002**		**0.001**	
	m=4	**0.005**		**0.006**	
	m=6	**0.005**	-	**0.009**	-
	m=8	**0.003**		**0.009**	
	m=10	**0.003**		**0.008**	
f=8	m=2	**0.002**		**0.002**	
	m=4	**0.002**		**0.005**	
	m=6	**0.001**	**-**	**0.004**	-
	m=8	**0.001**		**0.004**	
	m=10	**0.001**		**0.003**	
f=16	m=2	**0.002**	**0.006**	**0.002**	**0.007**
	m=4	**0.001**	**0.025**	**0.001**	**0.007**
	m=6	**<0.001**	**0.022**	**0.001**	**0.023**
	m=8	**0.001**	**0.034**	**0.001**	**0.018**
	m=10	**0.001**	0.060	**0.001**	**0.022**
f=32	m=2	**0.001**	**0.002**	**0.001**	**0.001**
	m=4	**<0.001**	**0.001**	**0.001**	**<0.001**
	m=6	**0.001**	**0.001**	**0.001**	**<0.001**
	m=8	**0.001**	**0.004**	**0.001**	**0.001**
	m=10	**0.003**	**0.009**	**0.003**	**0.002**

5.4.1 Sensitivity to Variant Parameter Values for Filtering-Downsampling

Figure 5-8 and Figure 5-9 show the effects of changing f and m values on the QDE of filtered-downsampled signals at $r = 0.2 \times SD$. The figures are virtually the same as those of $r = 0.3 \times SD$. The statistical results are also reported in Tables 5-6 to 5-8. A statistically significant interaction was found between walking condition and *f* at all *m* values for both tolerance values. Since the direction of the changes of QDE with increasing *f* was increasing for both walking conditions, the interaction effect would signify a difference in the rate of the changes between levels. A statistically significant interaction was found between walking condition and *m* at all *f* values. At each *f* value, the direction of the changes of the QDE of WO, with respect to *m*, was similar to those of DT. The two-factor repeated measures of the ANOVA of "walking condition*r*" showed that there was a significant interaction between the walking condition and the *r* value (p=0.023). Additionally, there was a statistically significant decrease in QDE with increasing *r* value (p<0.001). At each *r* value, the QDE of DT was statistically significantly greater than that of WO (p=0.003).

For all *m* values, there was a statistically significant main effect of walking condition and *f* value on QDE. Similarly, for all *f* values, there was a statistically significant main effect of walking condition and *m* value on QDE. QDE significantly increased from WO to DT for all combinations of *r*, *m*, and *f* values. Based on the statistical analysis, the increasing effect of dual-tasking on the QDE of the ML COP-D signal can be captured for all combinations of *r*, *m*, and *f* values.

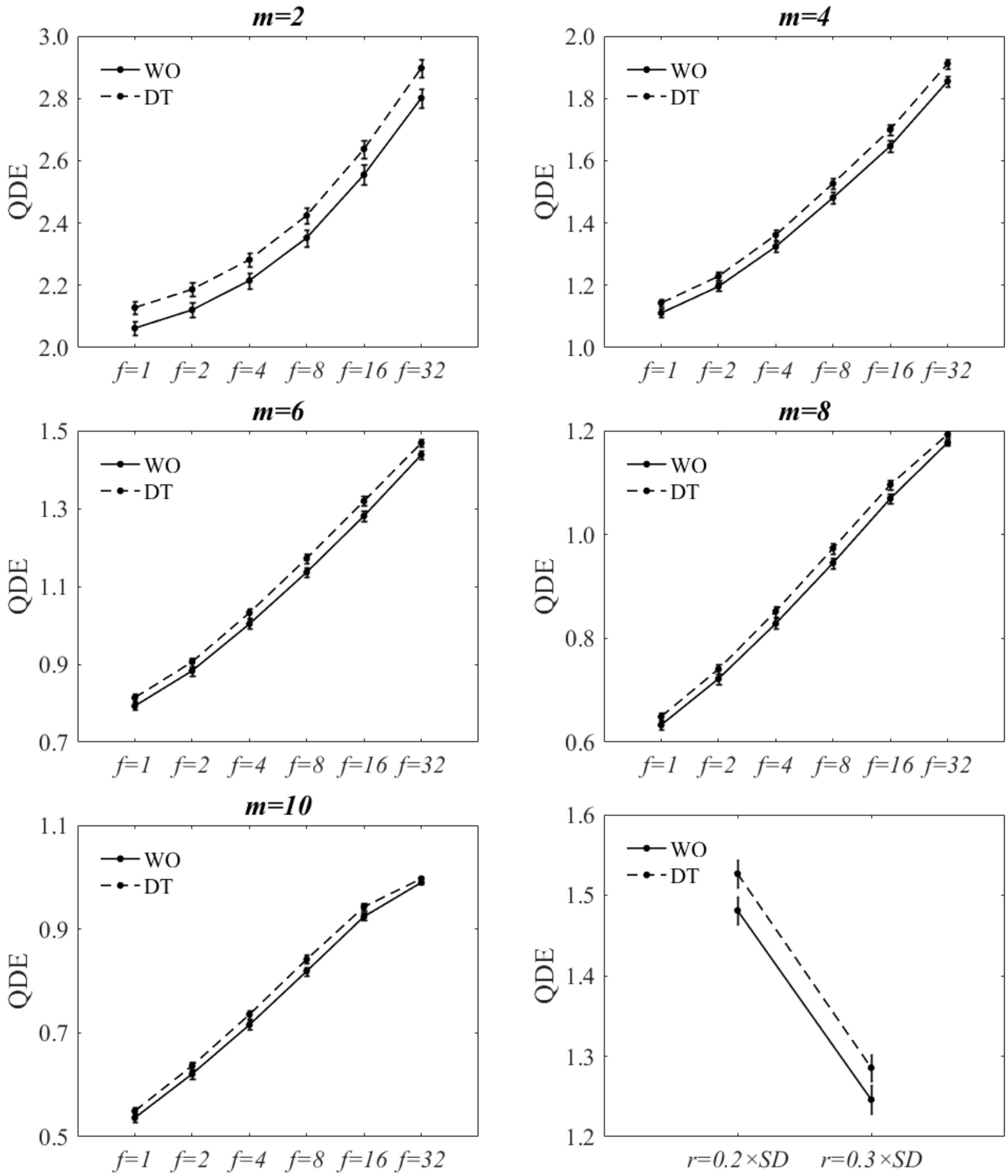


Figure 5-8: Effects of changing f on QDE of WO and DT at each m value at $r = 0.2 \times SD$ for filtered-downsampled ML COP-D. Bottom-right: Effects of r on QDE at $f = 8$ and $m = 4$. Error bars reflect SEM.

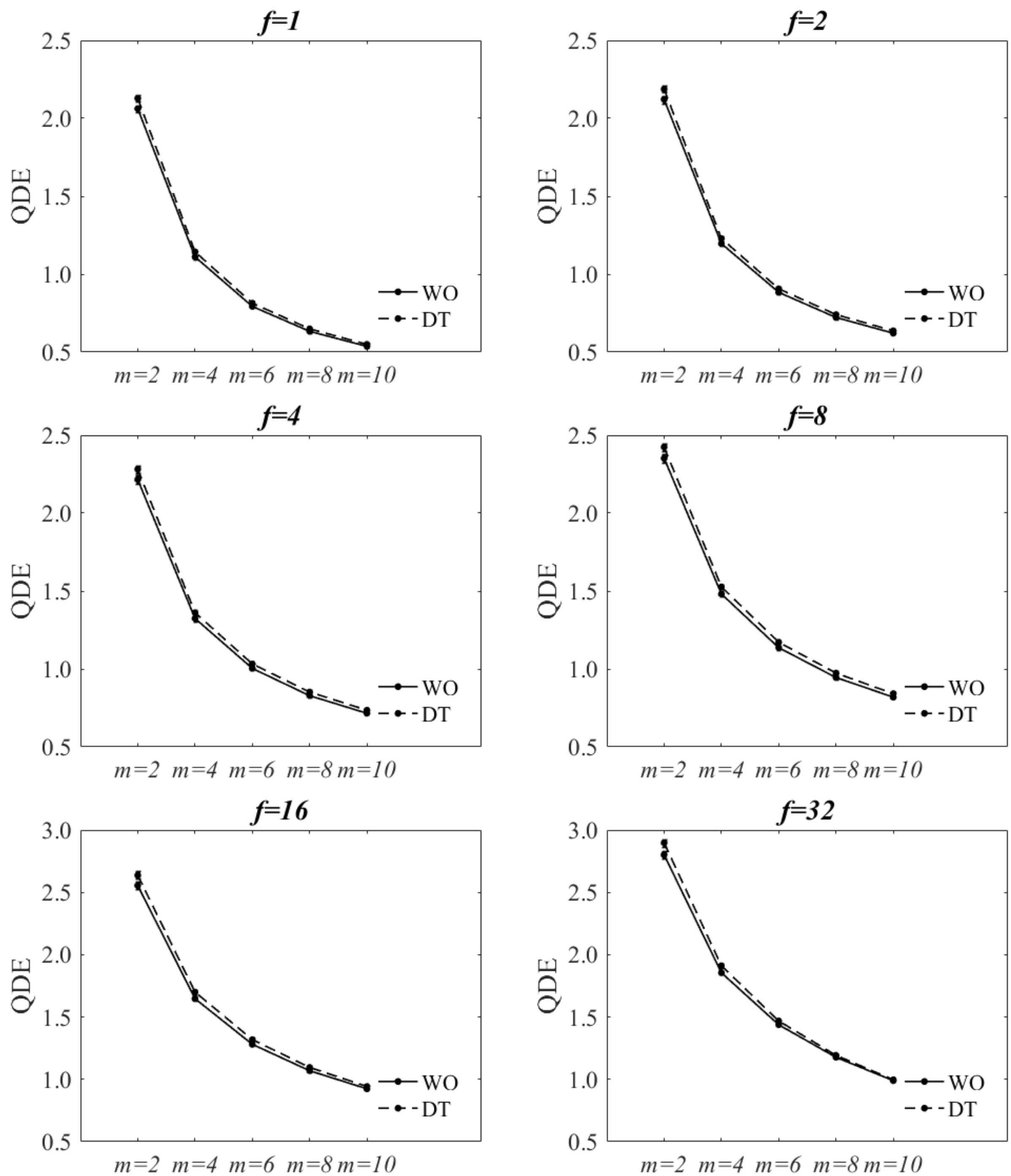


Figure 5-9: Effects of changing m on QDE of WO and DT at each f value at $r = 0.2 \times SD$ for filtered-downsampled ML COP-D. Error bars reflect SEM.

5.4.2 Sensitivity to Variant Parameter Values for Decimation

Figure 5-10 and Figure 5-11 show the effects of changing *f* and *m* values on the QDE of decimated signals at $r = 0.2 \times SD$. The figures are virtually the same as those of $r = 0.3 \times SD$. The statistical results are also reported in Tables 5-6 to 5-8. A statistically significant interaction was found between walking condition and f at $m = 2{\sim}6$ for $r = 0.2 \times SD$ and $m = 2{\sim}8$ for $r = 0.3 \times SD$. The direction of the changes of QDE with increasing *f* was the same for both tasks. A statistically significant interaction was found between walking condition and m at all *f* values. At each *f* value, the direction of changes of the QDE of WO, with respect to *m*, was the same as those of DT. The two-factor repeated measures of the ANOVA of "walking condition*r" showed that there was no significant interaction between the walking condition and the r value (p=0.094). However, there was a statistically significant decrease in QDE with increasing *r* value (p<0.001). At each r value, the QDE of DT did not show any significant change from the QDE of WO (p=0.001).

For a few m values, there was a statistically significant main effect of walking condition ($m = 2{\sim}4$ for $r = 0.2 \times SD$ and $m = 2{\sim}8$ for $r = 0.3 \times SD$) on QDE. However, for all *m* values, there was a statistically significant main effect of *f* values on QDE. And for all *f* values, there was a statistically significant main effect of *m* value QDE. However, only at $f = 1{,}16$ and 32 for $r = 0.2 \times SD$ and $f = 1, 2, 16$ and 32 for $r = 0.3 \times SD$, there was a significant effect of walking condition on QDE. QDE significantly increased from WO to DT for only a few combinations of m, r, and *f* (16 and 32) values.

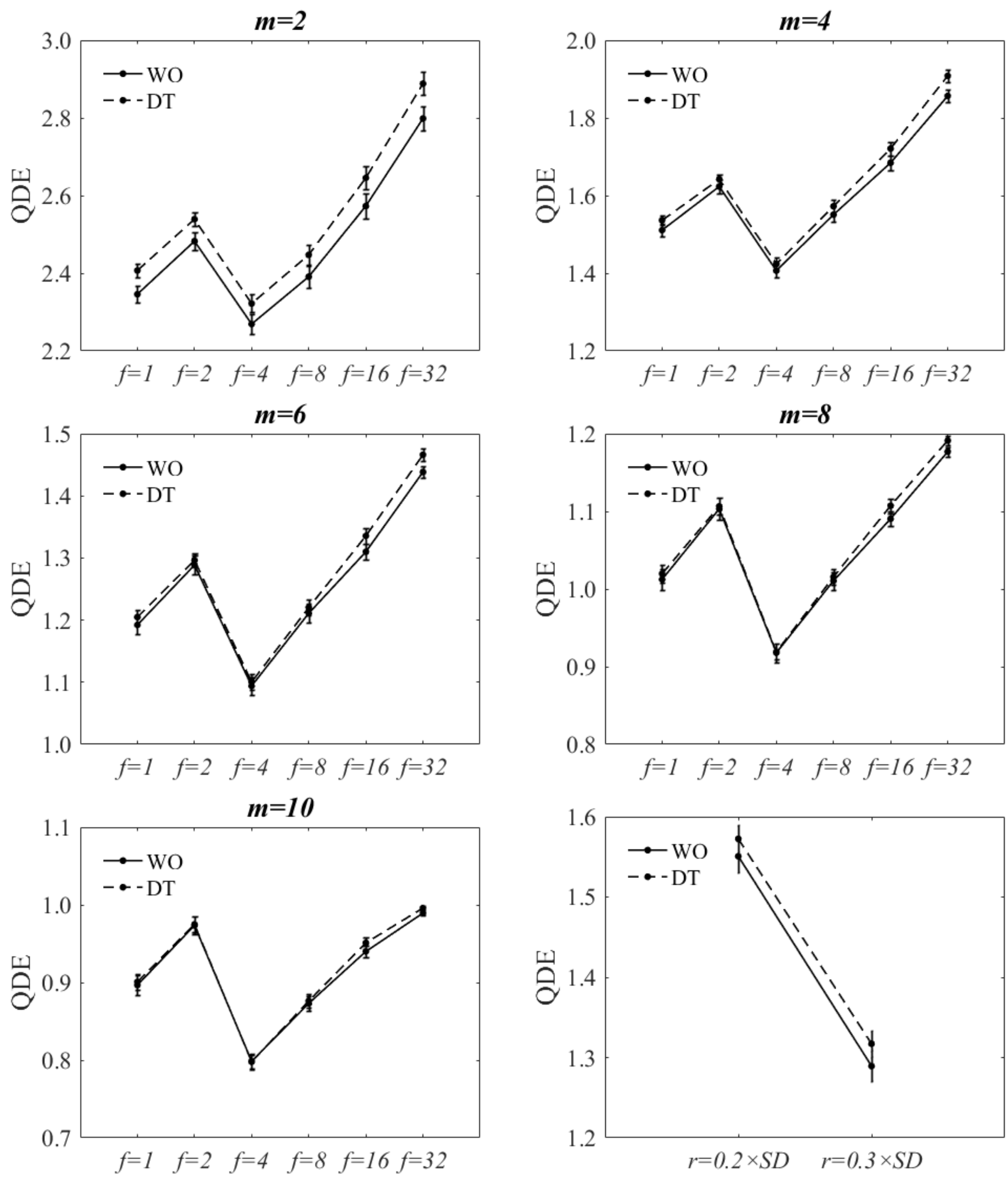


Figure 5-10: Effects of changing f on QDE of WO and DT at each m value at $r = 0.2 \times SD$ for decimated ML COP-D. Bottom-right: Effects of r on QDE at $f = 8$ and $m = 4$. Error bars reflect SEM.

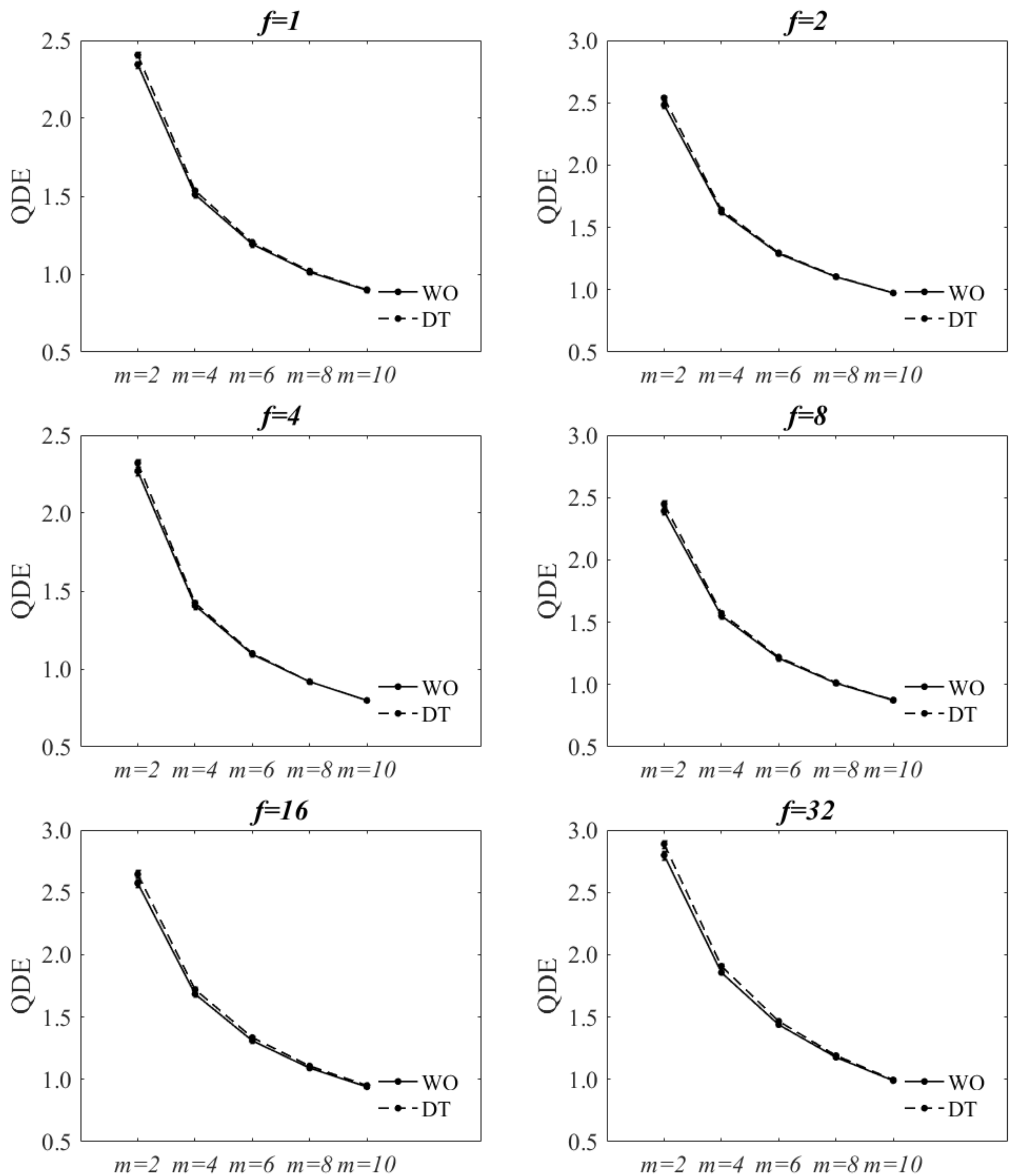


Figure 5-11: Effects of changing m on QDE of WO and DT at each f value at $r = 0.2 \times SD$ for decimated ML COP-D. Error bars reflect SEM.

5.4.3 Effects of Preprocessing Methods

The descriptive and statistical results of the walking condition (WO versus DT), walking speed (1.0 m/s versus 1.3 m/s), and preprocessing method (D, D-R, FD, FD-R) on QDE for the combination of $f = 8$, $m = 4$, and $r = 0.2 \times SD$ are presented in Figure 5-12 and Table 5-9. There was a significant interaction effect of walking speed and method. Likewise, there was a significant interaction effect of walking condition and method. In addition, walking condition, speed and method had a significant main effect on QDE (see Table 5-9). The results revealed that resampling signals to have a fixed average number of data points per stride had a decreasing effect on the QDE of WO-1.3 and WO signals (see Figure 5-12). However, there was no significant effect of resampling on the QDE of DT signals (see Table 5-9). In addition, QDE significantly decreased when filtering the high-frequency components (see Figure 5-12). Furthermore, QDE increased significantly from WO to DT only after filtering the high-frequency components. Finally, there was a significant increase in QDE with increasing walking speed (from WO to WO-1.3) except for FD-R (see Table 5-9).

Table 5-9: Statistical results of walking condition (WO and DT), walking speed (1.0 m/s and 1.3 m/s), and preprocessing method (D, D-R, FD, and FD-R) on QDE of ML COP-D for the combination of $f = 8$, $m = 4$ and $r = 0.2 \times SD$. The top section presents main and interaction effects. The middle section presents the pairwise comparisons between preprocessing methods for each walking condition (WO, WO-1.3, and DT). The bottom section presents pairwise comparisons between walking conditions for each preprocessing method. p-values in bold indicate a significant difference.

Main and Interaction Effects (p-values)			
	Condition/Speed	Method	Interaction
WO vs. WO-1.3	**<0.001**	**<0.001**	**<0.001**
WO vs. DT	**0.019**	**<0.001**	**<0.001**
Pairwise Comparisons (p-values)			
	D vs. D-R	D vs. FD	FD vs. FD-R
WO	**0.029**	**<0.001**	**0.029**
WO-1.3	**<0.001**	**<0.001**	**<0.001**
DT	0.307	**<0.001**	0.152
Method	WO vs. WO-1.3	WO vs. DT	
D	**<0.001**	0.177	
D-R	**<0.001**	0.116	
FD	**0.049**	**0.002**	
FD-R	0.784	**0.002**	

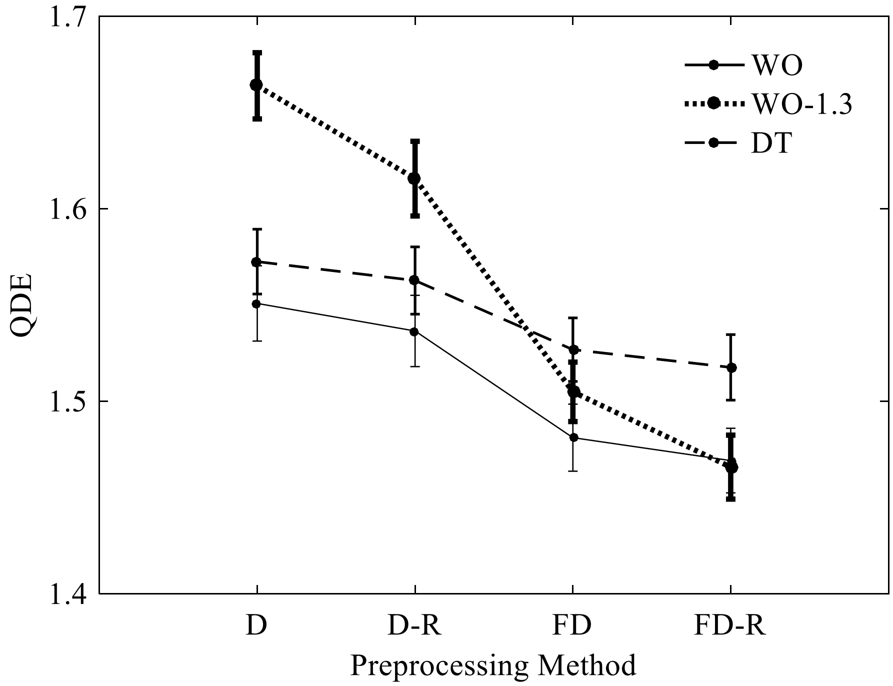


Figure 5-12: Effects of different preprocessing methods on QDE of ML COP-D signal of WO, DT and WO-1.3 conditions for the combination of $f = 8, m = 4,$ and $r = 0.2 \times SD$; Error bars reflect SEM.

5.5 Discussion

The results of this study showed that the SampEn and QDE of the ML COP-D signal increases as participants perform a concurrent cognitive task while walking. Another study has reported that the SampEn of trunk-LA signal was smaller in older adults who had reported a fall versus non-fallers when tested during overground walking [16]. However, in that study, speed was not controlled. Reducing one's walking speed is a consistent strategy to manage threats to balance and when attending to concurrent cognitive tasks. In this regard, a main finding of the present study was that walking speed had a significant effect on the SampEn and QDE of the ML COP-D signal.

One reason is an increase in vibrational noise of the treadmill-mounted force plate at higher walking speeds. Increased noise will cause an increase in SampEn and QDE. This problem can be solved by preprocessing the signal using a low-pass filter to eliminate high-frequency vibrational noise. Another issue when comparing signals collected at different speeds is that stride time will be reduced as speed increases and therefore the number of data points per stride will be reduced. The present results of the effects of different f values on SampEn and QDE demonstrated that these measures increased as the number of data points per stride decreased. One method to deal with this issue is to resample the signals so that the average number of data points per stride would be the same across different walking speeds. Based on these findings, it is important to control the walking speed when comparing the SampEn and QDE of gait signal between WO and DT conditions; since people, especially older adults, slow down when they perform a secondary task [34], [100].

The results of this study suggest that SampEn and QDE benefit from a relative consistency (a significant increase from WO to DT) across different combinations of the variant values of m, r, and f. For chaotic signals like Mackey-Glass system, which resemble periodic time series, entropy values decrease with increasing m value [101]. In the present study, there was a decreasing trend of the QDE of the ML COP-D signal with increasing m. However, for SampEn, there were exceptions and the values plateaued only at $m = 4$ for $f = 16$. With respect to changes in template size at higher sampling rates, SampEn showed an increasing trend with increasing m. A possible reason for this behavior may be related to the strong periodicity of the signal. To overcome this, larger template sizes might be chosen for signals collected at higher sampling rates. A similar issue exists for lower sampling rates where SampEn values increased with increasing m, but only after a specific *m* value. This suggests that smaller *m* values should be chosen for lower sampling rates. The difference between SampEn and QDE with respect to their changes with *m* values 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. The two tolerance sizes performed similarly since the smaller one was already larger than the noise level of the signal. This study was not designed to investigate the effects of data length on SampEn and QDE. Nevertheless, the SampEn and QDE of whole signals plateau after a few strides [69] and it has been shown that 30 strides are sufficient to calculate the SampEn and QDE of whole gait signals [12].

There are three limitations to this study. First, the sample size of the current study (29 participants). This led to performing several 2-factor repeated measures ANOVAs instead of, for example, two 3-factor repeated measures ANOVAs. A much larger sample size would be more appropriate to study the effects of four factors each with many levels. Second, this study examined the discriminatory ability of SampEn and QDE by only comparing WO to DT conditions. Several other factors, such as aging, should be considered to generalize the results of this study. Finally, only SampEn and QDE, which are single-scale entropy measures, were studied. Multi-scale SampEn and QDE analysis [17] or modified SampEn and QDE analysis (i.e., incorporating a time delay greater than one) [102] would likely yield important findings.

5.6 Summary

The goal of this investigation was to identify the sensitivity of SampEn and QDE to variant values of parameters (i.e., template size, tolerance size, and sampling rate) and two preprocessing methods when applied to the ML COP-D signal obtained during treadmill walking under WO and DT conditions. There were two main observations in this study. First, the SampEn and QDE of the ML COP-D maintained the directional difference between two walking conditions across variant parameter values, showing a significant increase from WO to DT walking condition, especially when a low-pass filter with a cut-off frequency of 30 Hz was applied to the signals. This finding is in agreement with the previous studies [12], [60], [69]. For filtered-downsampled MLCOP-D, the combinations of large template sizes (i.e., m=6, 8, and 10) and large downsampling factors (i.e., f= 16 and 32) were the exceptions for SampEn, where no significant increase was observed. For decimated ML COP-D, only a few combinations were able to distinguish WO from DT walking condition (i.e., combinations of f=4, 8, and 16 and variant m values for SampEn and combinations of f=16 and 32 and variant m values for QDE). Second, the results demonstrated that walking speed should be controlled when studying the effects of another factor, such as adding a cognitive task. Based on the results of this study, it is recommended to use a low-pass filter prior to the calculation of the QDE and SampEn of the ML COP-D. In addition, a sampling rate of 125 Hz or 62 Hz with template size of 2~6 and tolerance size of 0.2 times the SD of the entire time series is recommended for the SampEn and QDE of the ML COP-D signal. For studies testing overground walking where speed is difficult to control, an integer number of strides should be resampled so that the average number of data points per stride remains the same. In the next chapter, the correlation of the SampEn and QDE of the ML COP-D with two other families of gait measures (i.e., variability measures and the short-term LLE) will be investigated. In addition, the sensitivity of these measures to the degree of difficulty of the secondary tasks will be studied.

Chapter 6

SampEn and QDE as Gait Stability Measures

The work in this chapter expands upon the previous studies [12], [69] by investigating the correlation of the SampEn and QDE of the ML COP-D with two other families of gait measures (i.e., variability measures and the short-term LLE) that reflect human gait stability [9]. To do this, the effects of DT treadmill walking on the select spatio-temporal gait variables, the short-term LLE, and entropy measures derived from the ML COP-D signal of young healthy adults are studied. The DT cost for each measure was computed before the correlation analysis. In addition, the effects of physical demands on the performance of the secondary cognitive games are determined. The performance of two visuomotor cognitive tasks (i.e., easy and difficult) was quantified during standing (single-task condition) and while treadmill walking (DT condition). It is hypothesized that (a) all gait measures would increase as a result of dual-tasking and the increase would be proportional to the difficulty level of the secondary task, (b) the entropy measures, variability measures, and the short-term LLE would not be highly correlated and (c) there would be a significant decrease in cognitive task performance during treadmill walking as compared to stationary standing. The second dataset (see Section 3.2.2) is used in this chapter.

6.1 Task Performance Measures

Figure 6-1 shows a single movement trajectory and the sorted game responses of a participant to the game events of the VCG task. Three measures were used to compare stationary standing single-task and dual-task performances. These measures were calculated based on the medium amplitude movements (30%-66% of the display width) of the paddle, which were the majority of the game events. The first one was the movement time that 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 success rate that is the percentage of the total number of target objects that were caught. The third measure was the movement variance that is the average of the SD 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 considered for further analysis.

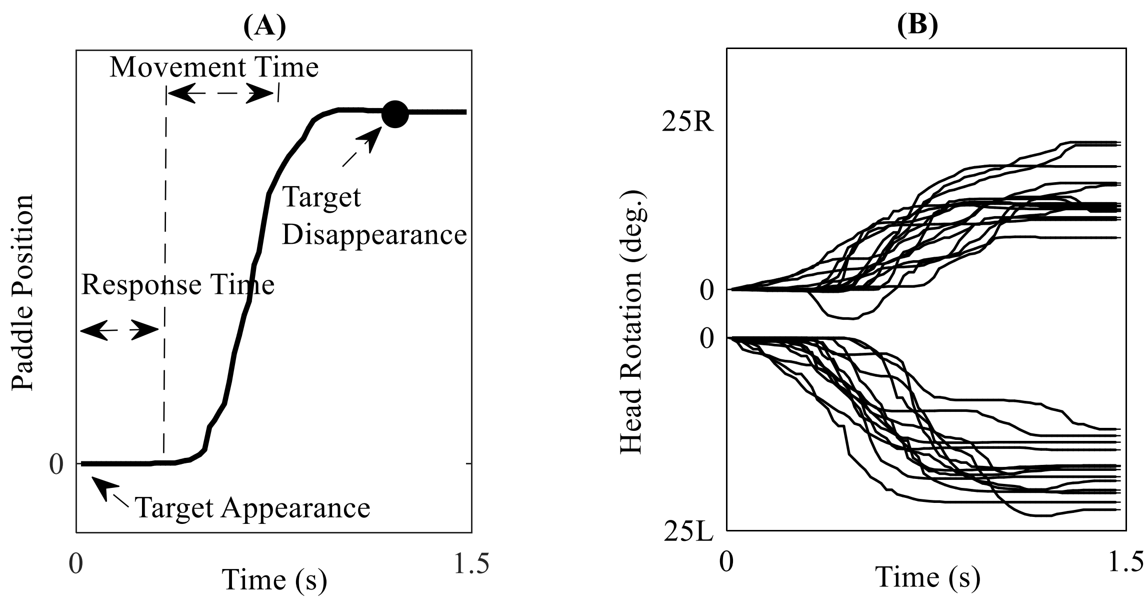


Figure 6-1: Secondary visuomotor cognitive games: **(A)** single movement trajectory of the visuomotor cognitive game, VCG, representing target appearance, response time, movement time, and target disappearance, (**B**) sorted left/right movement trajectories of visuomotor cognitive game, VCG.

6.2 Data Analysis

The ML COP-D and AP COP-D signals that were collected at 1000 Hz were low-pass filtered with a cut-off frequency of 30 Hz and downsampled to 125 Hz. Forty seconds of data was used after discarding approximately the first 4 strides. The analysis was based on at least 30 consecutive strides [12], [97], [103], [104] during WO trials and when performing two visuomotor cognitive tasks of increasing difficulty (VCG1 and VCG2).

6.2.1 SampEn and QDE

For entropy measures, even though a wide range of 10-250 stride has been used in the literature [12], [55], [69], [76], [82], [100], [105], 30 strides has been shown to be sufficient [12], [103] and was used in this study as well. A template size of 4 and a tolerance size of 0.2 times the SD of all time series were used based on the results of the previous chapter [106].

6.2.2 Short-term Largest Lyapunov Exponent

In Section 3.3.3, a brief description of the short-term LLE calculation was provided. Here, the procedure of obtaining the short-term LLE from the ML COP-D is explained. For the short-term LLE, one study [52] has recommended a relatively long experimental time series (150 strides) to obtain statistically reliable results. However, other studies have reported that as few as 10 [103] or 35 [104] strides produce statistically reliable results. As a result, and in order to remain consistent with entropy analysis, 30 strides were used to calculate the short-term LLE.

Since the number of strides between participants was different, all signals were normalized to have the same $30 \times 142 = 4260$ data points, where 142 was the average number of data points per stride [97]. Next, the minimum average mutual information was used to calculate the time delay (see Figure 6-2). A range of 19-39 was obtained for time delay from different signals, where the median 30 was selected for future analysis [56]. However, the value based on this method did not result in a straight line required for the short-term LLE. As a result, a time delay of 15 was selected which is approximately 10% of the average stride time, as suggested by England et al. [97].

Cao's method [88] was used to find the true embedding dimension. Figure 6-3 shows both *E1* and *E2* plots (see Section 3.3.3.2) using $T = 15$. *E1* stopped changing at $d = 5$. Therefore, $d = 5$ was chosen 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 [56], [57], [107]. In addition, there were some d's where *E2* was not 1. This suggests that this single experimental time series is a deterministic signal and not a stochastic one [88].

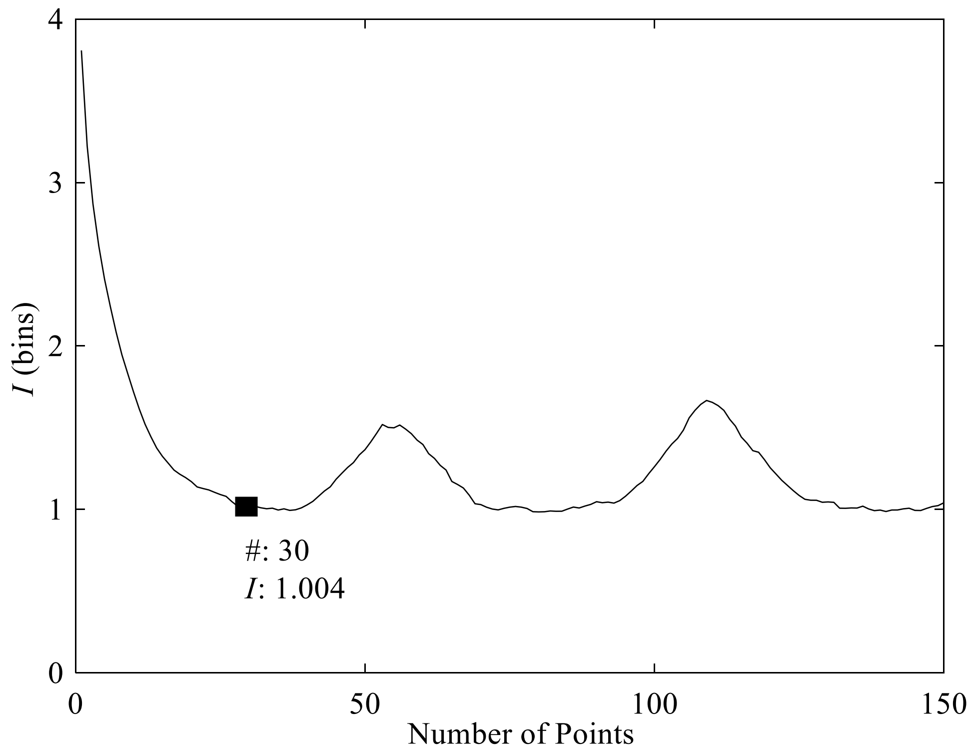


Figure 6-2: First minimum of average mutual information, I, of ML COP-D signal occurring at time delay of 30.

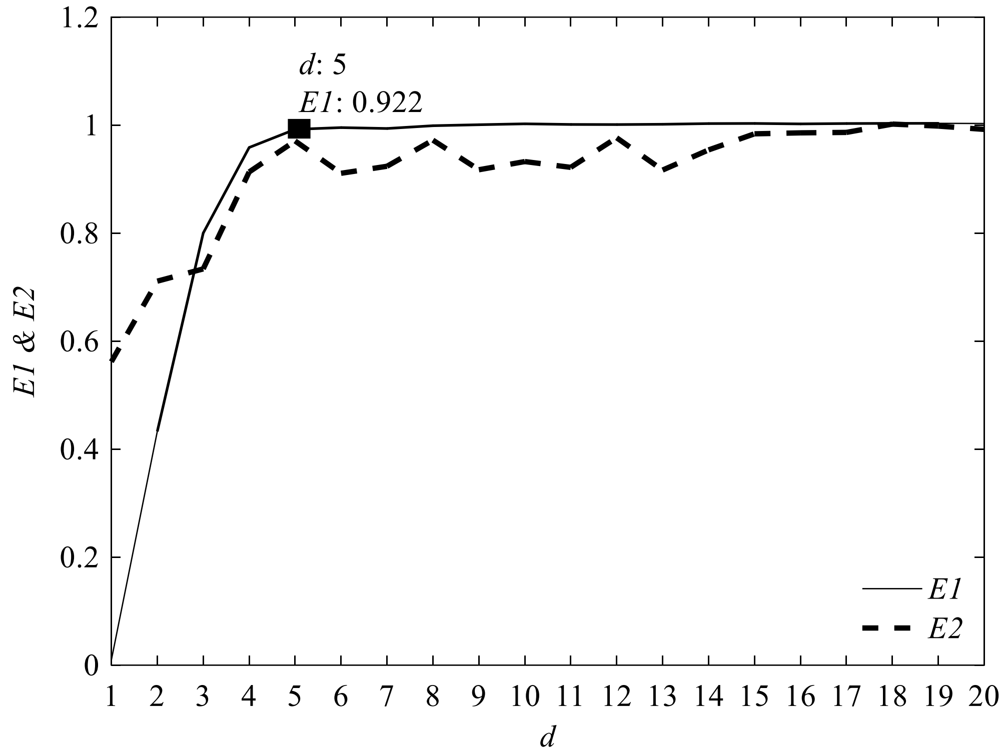


Figure 6-3: *E1* and *E2* values for different *m* values using the time delay of 15. *E1* stops changing at *d*=5 and there are some *d*'s where *E2* is not 1.

With an embedding dimension of 5 and a time delay of 15, the proper state-space was constructed from the ML COP-D signal. Figure 6-4 (A-B) shows 4 strides of filtered ML COP-D and a three-dimensional reconstructed state-space using a time delay of 15. Next, true neighbors were found with a constraint of a mean period of 142 (i.e., the average number of data points per stride). The average divergence, then, was found between successive points for an iteration of $142 \times 4 = 568$. Finally, λ_s was calculated as the tangent to the average rate of divergence over 0-0.5 stride (see Figure 6-4 (C))[97].

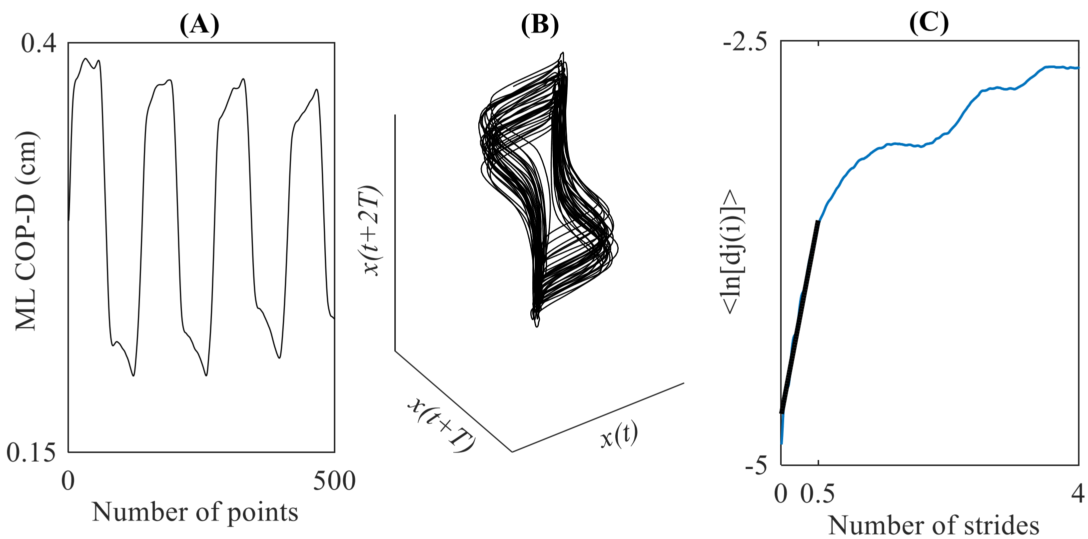


Figure 6-4: Calculation process of short-term largest Lyapunov exponent, λ_s: **(A)** 4 strides of ML COP-D; **(B)** 3D state-space reconstruction with the time delay of 15, **(C)** slope of mean divergence curve $\langle \ln d_j(i) \rangle$ over 0 to 0.5 stride.

6.2.3 Average and COV of Step Variables

- The variability measures that were used in this study were as follows:
  a) 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)

There was no statistically significant difference between the even and odd steps of these values. Therefore, the odd steps were only considered for subsequent analysis.

e) COV of the drifts in ML and AP directions (ML/AP-Drift): These were calculated from the SD of all heel contact position values of each leg divided by the average of all these values. A statistically significant difference was found between even and odd steps in the ML direction; therefore, both values would be considered for analysis. However, there was no statistically significant difference between even and odd steps in the AP direction. Therefore, only odd steps were considered for subsequent analysis.

6.3 Statistical Analysis

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 performed. A *p*-value less than 0.05 was considered significant for all tests except for multiple comparisons, 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 analysis.

6.4 Results

The descriptive and statistical results of the visuomotor cognitive games' performance measures are presented in Figure 6-5. For both VCG tasks, success rate decreased significantly, and movement variance increased significantly from standing to DT walking conditions. There was no significant change in average movement time from standing to DT walking conditions. Post hoc pairwise comparisons showed 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 Figure 6-6 and Figure 6-7. More specifically, the results of the SampEn, QDE, λ_s, COV-SL, ML-Drift (even), and ML-Drift (odd) are presented in Figure 6-6. The results of COV-ST, COV-SW, COV-SwT, and AP-Drift are presented in Figure 6-7. As presented in Table 6-1 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 WO. 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 Figure 6-6, 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 ($r = 0.401\sim0.549, p < 0.05$ and $r = 0.634\sim0.844, p < 0.001$, respectively). In addition, COV-SL was significantly correlated with COV-ST ($r = 0.628\sim0.826, p < 0.001$), COV-SW ($r = 0.381\sim0.504, p < 0.005$) and COV-SwT ($r = 0.699\sim0.822, p < 0.001$). Finally, COV-ST was significantly correlated with COV-SwT ($r = 0.904\sim0.926, p < 0.001$).

Table 6-1: Main effect (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	$\boldsymbol{F = 17.149}$	$\boldsymbol{< 0.001}$	$\boldsymbol{t = 3.723}$, $\boldsymbol{p = 0.001}$	$\boldsymbol{t = 5.474}$, $\boldsymbol{p < 0.001}$	$t = 1.739$, $p = 0.093$
QDE	$\boldsymbol{F = 15.378}$	$\boldsymbol{< 0.001}$	$\boldsymbol{t = 3.481}$, $\boldsymbol{p = 0.002}$	$\boldsymbol{t = 4.566}$, $\boldsymbol{p < 0.001}$	$t = 2.485$, $p = 0.019$
λ_s	$\boldsymbol{F = 4.580}$	$\boldsymbol{0.014}$	$\boldsymbol{t = 3.011}$, $\boldsymbol{p = 0.005}$	$t = 1.853$, $p = 0.074$	$t = 1.051$, $p = 0.302$
COV-SL	$\boldsymbol{F = 13.186}$	$\boldsymbol{< 0.001}$	$\boldsymbol{t = 3.449}$, $\boldsymbol{p = 0.002}$	$\boldsymbol{t = 4.262}$, $\boldsymbol{p < 0.001}$	$t = 2.086$, $p = 0.046$
COV-ST	$\boldsymbol{\chi^2 = 15.379}$	$\boldsymbol{< 0.001}$	$\boldsymbol{z = 3.211}$, $\boldsymbol{p = 0.001}$	$\boldsymbol{z = 3.341}$, $\boldsymbol{p = 0.001}$	$z = 0.811$, $p = 0.417$
COV-SwT	$\boldsymbol{\chi^2 = 17.034}$	$\boldsymbol{< 0.001}$	$\boldsymbol{z = 3.341}$, $\boldsymbol{p = 0.001}$	$\boldsymbol{z = 3.795}$, $\boldsymbol{p < 0.001}$	$z = 0.9632$, $p = 0.336$
COV-SW	$\boldsymbol{\chi^2 = 19.241}$	$\boldsymbol{< 0.001}$	$\boldsymbol{z = 3.168}$, $\boldsymbol{p = 0.002}$	$\boldsymbol{z = 3.730}$, $\boldsymbol{p < 0.001}$	$\boldsymbol{z = 2.411}$, $\boldsymbol{p = 0.016}$
ML-Drift (odd)	$\boldsymbol{F = 10.318}$	$\boldsymbol{< 0.001}$	$\boldsymbol{t = 3.635}$, $\boldsymbol{p = 0.001}$	$\boldsymbol{t = 3.841}$, $\boldsymbol{p = 0.001}$	$t = 1.251$, $p = 0.221$
ML-Drift (even)	$\boldsymbol{F = 23.472}$	$\boldsymbol{< 0.001}$	$\boldsymbol{t = 5.050}$, $\boldsymbol{p < 0.001}$	$\boldsymbol{t = 5.940}$, $\boldsymbol{p < 0.001}$	$t = 2.447$, $p = 0.021$
AP-Drift	$\boldsymbol{\chi^2 = 13.517}$	$\boldsymbol{0.001}$	$\boldsymbol{z = 3.146}$, $\boldsymbol{p = 0.002}$	$\boldsymbol{z = 3.060}$, $\boldsymbol{p = 0.002}$	$z = 0.011$, $p = 0.991$

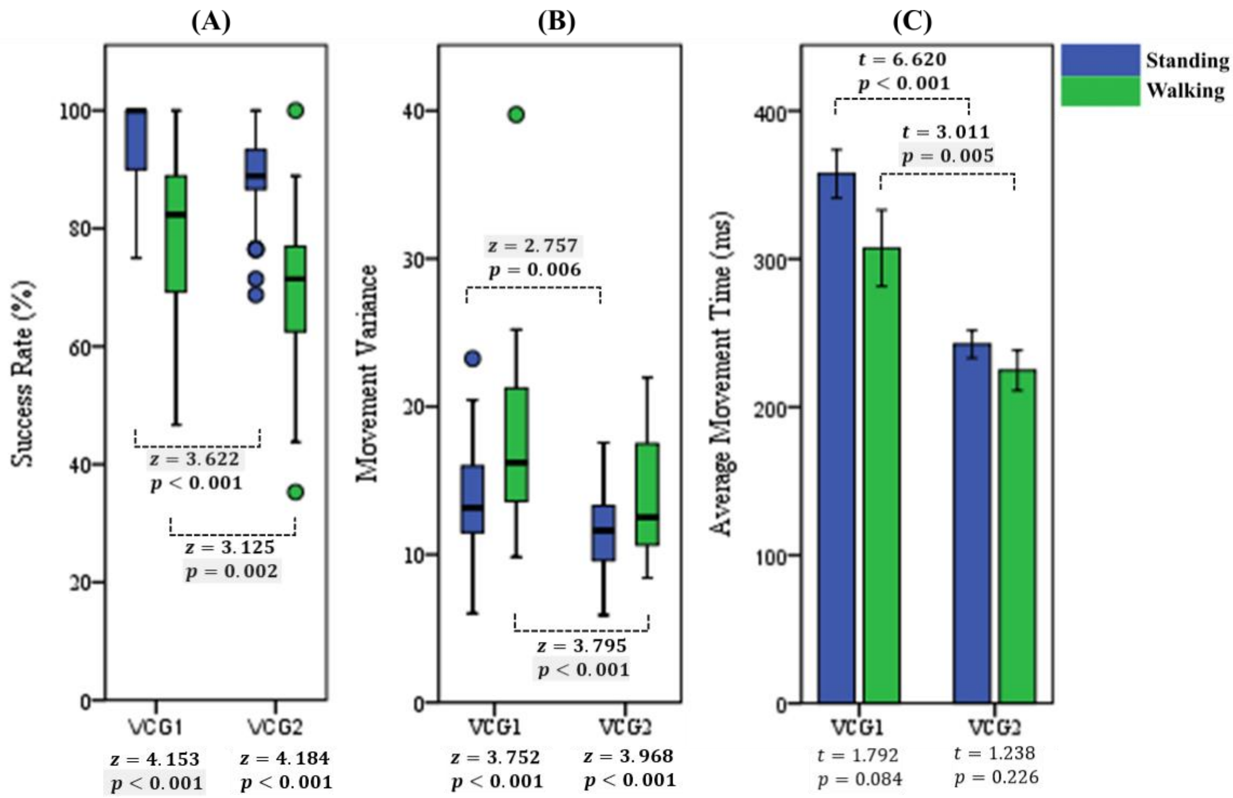


Figure 6-5: Descriptive and statistical results of task performance measures: **(A)** group medians and inter-quartile ranges of success rate (%), **(B)** group medians and inter-quartile ranges of movement variance, **(C)** group means and SEM of average movement time (ms). The results of pairwise comparisons between standing and walking conditions for each VCG game are presented under x-axis labels. The results of 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: $p < 0.05/4 = 0.013$).

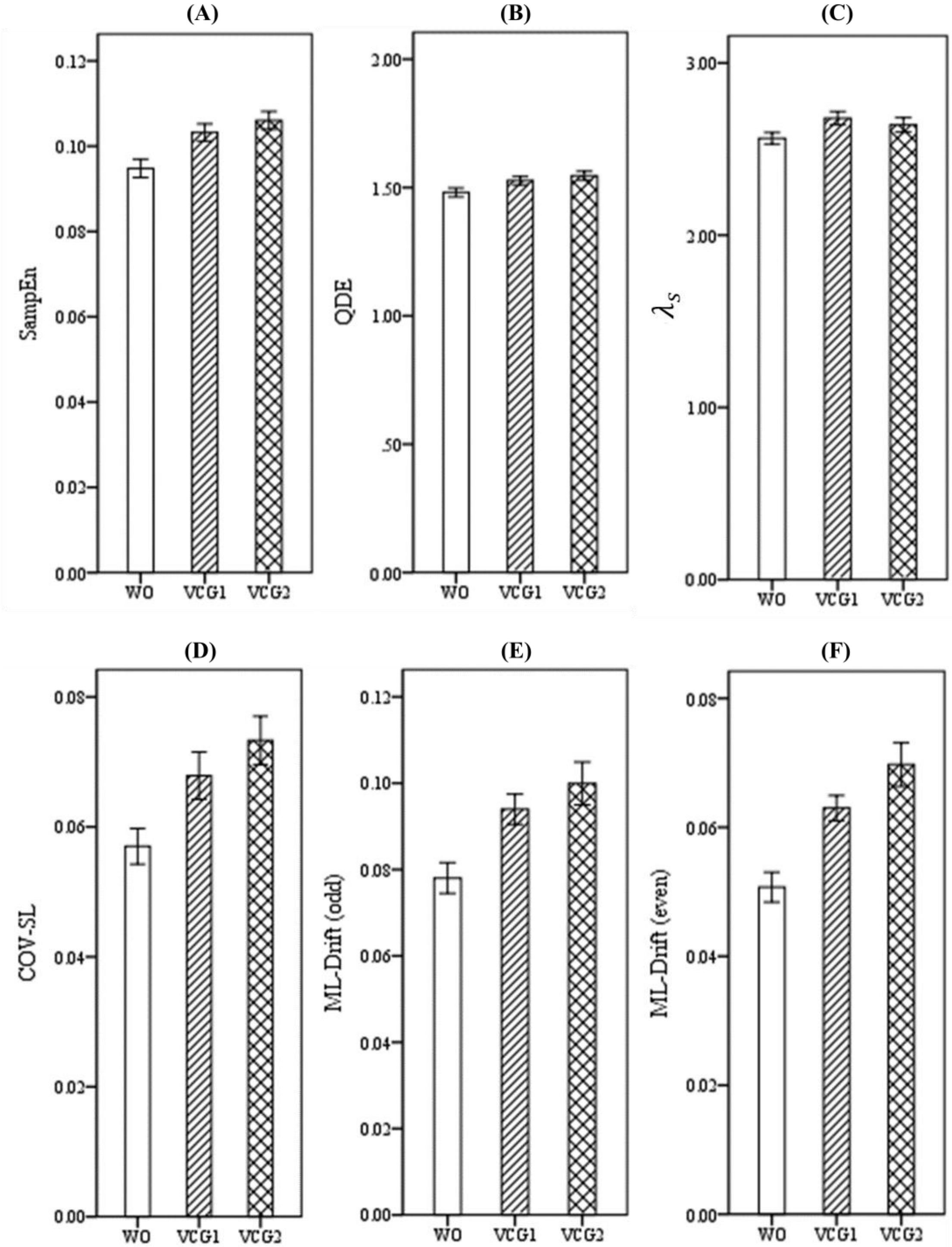


Figure 6-6: Group means and SEM of: (**A**) SampEn, (**B**) QDE, (**C**) λ_S, (**D**) COV-SL, (**E**) ML-Drift (odd), and (**F**) ML-Drift (even), under WO, VCG1 and VCG2 walking conditions.

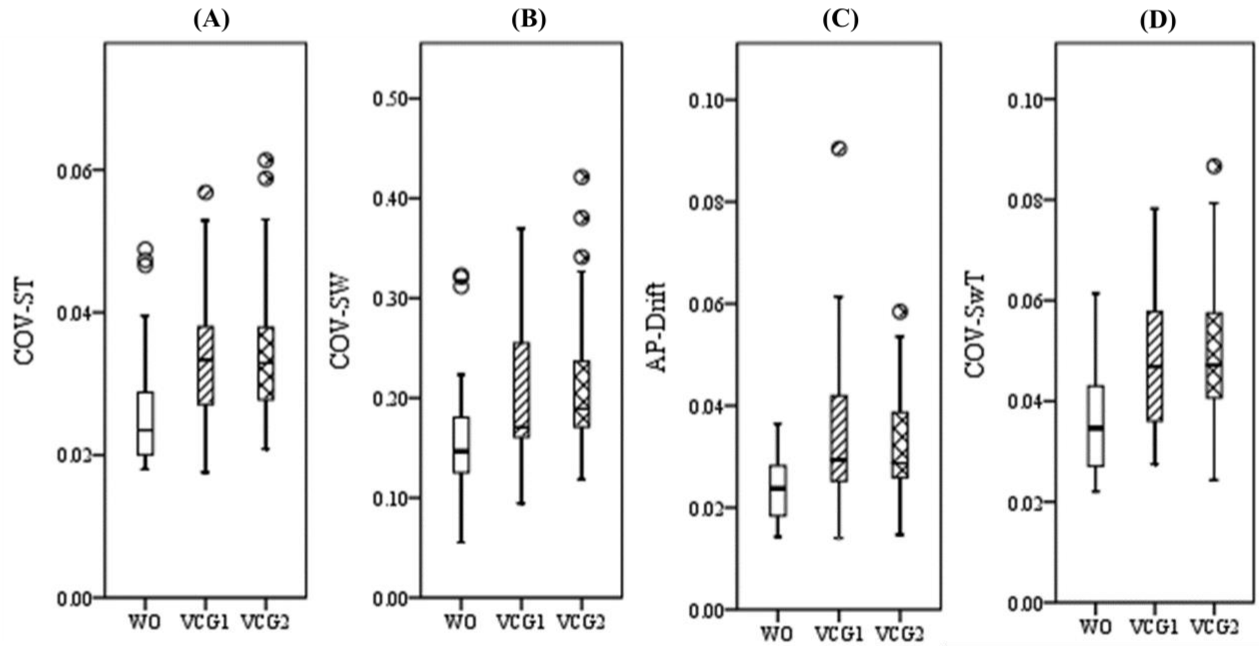


Figure 6-7: Group medians and inter-quartile ranges of: (**A**) COV-ST, (**B**) COV-SW, (**C**) AP-Drift, and **(D)** COV-SwT under WO, VCG1 and VCG2 walking conditions

6.5 Discussion

The main purpose of the present study was to compare the gait variability measures, entropy measures, and the short-term LLE 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 WO to both DT walking tasks (VCG1 and VCG2). However, the short-term LLE increased when performing the VCG1 task and not the VCG2 task. It is not clear why participants opted to prioritize their local stability when performing the more difficult VCG2 task. Nonetheless, during VCG2, participants' gait was more variable and more irregular than WO. There was a trend of increased gait variability and entropy measures from

VCG1 to VCG2, although these changes did not reach the significance level. In other words, the gait measures examined in the present study were more sensitive to changes from WO to DT 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, Other studies [12], [23] did not observe an increase in the SampEn of various gait time series 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. [12] in which no distractors were used and movement trajectories were predictable (i.e., straight vertical paths). There are a number of differences between texting used in the study of Magnani et al. [23] and visuomotor cognitive tasks used in the present study. In addition, Magnani et al. [23] computed SampEn from trunk linear velocity time series. In this regard, a previous study has reported no significant change in the SampEn of trunk-LA between WO and DT, whereas a significant increase in the SampEn of the ML COP-D was observed [69].

The visuomotor cognitive games used in the current study required continuous visual observation, tracking of the moving visual objects, and timely precise head rotations in order to move the game paddle to 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. Therefore, both gait and visuomotor cognitive tasks' performance measures are required as fall risk biomarkers.

Variability measures have been associated with instability. However, the cause-and-effect relationship between the two has been challenged. Dingwell et al. [24] re-analyzed the data from a previous study [72] in which 15 healthy young adults walked on a treadmill at their self-selected speed under two walking conditions (i.e., WO 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 contain valuable information about the gait control mechanism. On the other hand, the short-term LLE reflects how the system responds to small perturbations as it examines the degree of divergence of two neighboring points over a period of one step. Additionally, SampEn and QDE compare each template to all other templates throughout the entire time series and identify ones that match. These differences in the features of the gait time series that are quantified by the three different methods are in agreement with the notion that local dynamic stability defined by the short-term LLE is not synonymous with regularity defined by entropy measures or either stride-to-stride variability [13].

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 LLE. 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 [108]. This is consistent with previous research findings of the increased demands on mediolateral stability during visual perturbations [108]–[111].

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 DT interference effects were due to added information processing load or due to head rotations. Nonetheless, a previous study [96] has reported 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.

6.6 Summary

The main purpose of this chapter was to study the correlation between entropy measures (SampEn and QDE) and two other families of gait measures (i.e., variability measures and the short-term LLE). It was shown that entropy measures, the short-term LLE 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 the ML-Drift measure. Therefore, a combination of these measures could elicit information on inter-stride and intra-stride changes due to dual-tasking. Furthermore, no measure was sensitive to the degree of difficulty of the secondary cognitive games. In addition to DT interference effects on gait, there was a significant decrease in performance measures of the cognitive games during walking as compared to standing.

Chapter 7

Conclusions

This thesis evaluated the viability of using sample entropy and quantized dynamical entropy measures of whole gait signals as biomarkers of increased fall risk. A few previous studies have investigated the effect of aging and dual-tasking on these two measures [12], [15]–[17]. However, they have reported inconsistent or contradictory results because of two possible reasons. First, they have used different test protocols regarding control for gait speed, different biological signals, and different secondary tasks. Second, they have disregarded either intra-stride or inter-stride information. In this thesis, a dual-task assessment treadmill platform was used to enable performing different tasks, including dual-task walking while playing visuomotor secondary tasks, at a fixed yet comfortable speed. Whole gait signals were collected using inertial motion monitors and pressure mats and were used to calculate entropy measures. SampEn and QDE of whole gait signals successfully distinguished between young and older faller adults as well as between walk only and dual-task walking condition. All the objectives for this thesis (see Section 1.2) were met and the contributions made are listed below. In summary, it has been shown that SampEn and QDE of the center of pressure in the mediolateral direction are great candidates for assessing fall risk if the confounding effect of speed is avoided. They also represent a different aspect of human gait control mechanism than the one reflected by variability measures or the short-term LLE. Finally, these two measures produced similar results in terms of discriminatory ability, sensitivity to parameter selection and preprocessing methods, and correlation with other families of gait measures. Therefore, QDE could be a viable alternative candidate for future studies to identify individuals at risk of fall as it is computationally more efficient.

7.1 Contributions of this Thesis

This thesis made a number of original contributions listed below:

1. This research increased the knowledge base of the discriminatory ability of SampEn and QDE by examining the first three hypotheses of this thesis (see Section 1.2). Confirming the first hypothesis, it was shown that the SampEn and QDE of whole gait signals significantly increased with age and when dual-tasking when controlling for the confounding effect of speed. Human gait is likely to be disrupted by performing a secondary visuomotor cognitive task or negatively affected by aging and therefore unplanned inter-stride and intra-stride fluctuations increase. This would result in a more irregular and more unpredictable signal that would result in larger SampEn and QDE values. The second hypothesis was supported by showing that the discriminatory ability of the SampEn and QDE of whole gait signals differed among different signals. This observation indicates that each gait signal is a unique representation of human gait control process. Moreover, only when calculated from the ML COP-D signal, SampEn and QDE measures could detect both aging and DT effects. The superiority of the ML COP-D signal in terms of better distinguishing different walking conditions as well as the unobtrusive nature of its collection make it a great candidate for future studies which use entropy measures. The third hypothesis was also verified by showing that segmenting and

normalizing whole gait signals before calculating SampEn and QDE measures helped better discriminate between WO and DT conditions when using trunk-LA signal. This procedure removed inter-stride correlations and helped reveal changes hidden by variations because of drifts.

2. Although a few studies have investigated the proper implementation of entropy measures when applied to stride interval time series [73], [74], there are no studies for whole gait signals. Therefore, for the first time, a comprehensive methodological study was conducted on the sensitivity of the SampEn and QDE of the ML COP-D to variant parameter values and preprocessing methods. It was shown that these measures produce a consistent result showing a significant increase from WO to DT conditions. SampEn and QDE decreased as tolerance size, template size, and the average number of points per stride increased. The few exceptions were mixed results of SampEn with increasing template size and mixed results of QDE with increasing the average number of points per stride. It was also shown that gait speed had a significant effect on the SampEn and QDE of the ML COP-D signal for two reasons. The first reason was an increase in vibrational noise of collected signals at higher speeds. And the second one was the variant average number of data points per stride of the gait signal when comparing signals collected at different speeds. The first issue can be avoided by low-pass filtering the signal. The second issue can be resolved by resampling signals so that all signals have the same average number of data points per stride without eliminating inter-stride correlations. The results of this methodological study can be used as a guideline for proper implementation of SampEn and QDE when using whole gait signals. Furthermore, these results highlight the confounding effect of walking

speed on these two measures and the importance of avoiding it by either fixing the speed or resampling the signals to have the same average number of data points per stride.

3. The correlation analysis between entropy measures (SampEn and QDE) and two other families of gait measures (i.e., variability measures and the short-term LLE) commonly used in the literature was carried out. All measures were calculated from the ML COP-D signal collected during treadmill walking under WO and DT walking conditions of different difficulty level. The results partially confirmed the fourth hypothesis showing that SampEn, QDE, and variability measures increased significantly due to dual-tasking and the increase was proportional to the difficulty level of the secondary task. However, the difference between two dual-task conditions did not reach the significance level. The fifth hypothesis was also partially confirmed as the results showed that the three families of gait measures were not highly correlated except for the newly introduced drift measure in the ML direction which was highly correlated with SampEn and QDE. These results indicated that various measures proposed for gait analysis are indeed representing different aspects of human gait control mechanism.
4. The sixth hypothesis was tested by analyzing the results of gait measures (i.e., entropy measures, the short-term LLE, and variability measures) and task performance measures side by side. Additionally, two visuomotor cognitive tasks were used to investigate the sensitivity of these measures to the difficulty level of the secondary tasks. A poorer task performance was observed from single-task condition to DT walking conditions. This was along with more irregular signals (i.e., larger SampEn and QDE), larger spatio-temporal gait variability, and larger short-term LLE (only for the easy task). This observation

indicated that gait and task performance were both affected by dual-tasking when there was no intentional prioritization. Furthermore, these measures were not sensitive to the degree of difficulty of the secondary tasks.

7.2 Future Work

Several unanswered questions were addressed in this thesis and the outcomes paved the way for further studies in this area. A list of possible future work is mentioned below:

1. This thesis studied two fall-provoking conditions which are aging and dual-tasking. Other important factors, such as Parkinson's disease, that can result in falls should be investigated to further examine the discriminatory ability of SampEn and QDE. Furthermore, it is indispensable to examine the effectiveness of these two measures when comparing non-faller older adults to faller elderlies.
2. A previous study [12] assessed the test-retest reliability of the SampEn and QDE of segmented and normalized ML COP-D for the older population. The results showed that these two measures exhibited sufficiently strong test-retest reliability. It is, therefore, recommended to further examine the repeatability or test-retest reliability [104] of these measures when applied to whole gait signals.
3. It is recommended to perform a prospective study in which the effects of DT rehabilitation are investigated. The values of SampEn and QDE alongside the task performance measures should be evaluated before and after the treatment. This might reveal if the treatment is

able to improve gait or task performance and whether these measures are able to detect the differences.

4. Multi-scale SampEn has been used to some extent with trunk-LA signal [16], however, the results have not shown any abrupt changes across different time scales. The results presented in this thesis suggest that the ML COP-D is a better choice for human gait analysis. Therefore, investigation of the multi-scale SampEn and multi-scale QDE of the ML COP-D should yield important findings.
5. In the majority of studies (including this thesis) that have used either single- or multi-scale entropy measures, a time delay of one has been used when constructing the templates. These studies have shown promising results discriminating between different conditions. However, incorporating a time delay greater than one (previously applied to heartbeat interval time series [102]) could yield important findings. Comparing the procedure taken in this thesis with the one in which a time delay greater than one is used would be beneficial.
6. Throughout this thesis, SampEn and QDE were applied to single signals after constructing the templates. Nevertheless, considering only one single signal as a representation of human gait is oversimplifying this complex system. A further step towards a better understanding of this complex system could be studying multiple signals by means of methods similar to entropy measures. For example, the effects of dual-tasking or aging on human gait COP-D in both ML and AP directions could be investigated using the correlation dimension.

7. It is highly recommended to further examine the increasing relationship between fall risk and entropy measures. For this purpose, future studies should include more experiments with the aim of incrementally increasing fall risk and study its relationship with entropy measures. Furthermore, by recruiting more participants with a more diverse range of fall risk, a threshold of SampEn and QDE indicating a higher risk of fall can be developed.
8. In this thesis, participants performed the tests while walking on a treadmill at a fixed speed. Although treadmill walking does not equate overground walking, it was necessary to control for speed to investigate the effect of aging and dual-tasking on SampEn and QDE. Future studies could explore the correlation between overground walking and treadmill walking in this context.

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Publications

Refereed journal publications:

S. Ahmadi, C. Wu, N. Sepehri, A. Kantikar, M. Nankar, and T. Szturm, “The effects of aging and dual tasking on human gait complexity during treadmill walking: a comparative study using quantized dynamical entropy and sample entropy,” J. Biomech. Eng., vol. 140, no. 1, p. 011006, 2018.

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Paper under review:

S. Ahmadi, N. Sepehri, C. W, and T. Szturm, “Comparison of Selected Measures of Gait Stability Derived from Center of Pressure Displacement Signal during Single and Dual-task Treadmill Walking”

Conference proceedings:

S. Ahmadi, N. Sepehri, C. Wu, and T. Szturm, “Effect of Dual-task Walking on Complexity and Stability of Center of Pressure Displacement”, 20th Biennial Meeting of the Canadian Society of Biomechanics, August 2018.

S. Ahmadi, C. Wu, N. Sepehri, and T. Szturm, “On the Implementation of Sample Entropy to Quantify Gait Performance”, 40th Annual meeting of American Society of Biomechanics, August 2016.