MONITORING GAIT COMPLEXITY IN THE WILD

VINCENZO EDOARDO DI BACCO

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ABSTRACT

Human steady-state gait exhibits subtle stride-to-stride fluctuations that produce complex patterns, termed gait complexity, which provide information about the quality of gait control and adaptive capacity of the walker. Our knowledge of gait complexity is premised on studies estimating nonlinear measures such as fractal indices and entropy within controlled walking environments, which may misrepresent gait patterns. Such measures may be more sensitive compared to traditional linear gait variability measures (e.g., stride time coefficient of variation) for detecting age-related changes in gait control and fall risk. Although wearable sensors have demonstrated valid estimates of traditional gait measures while walking in the free-living environment, research on the estimate of gait complexity is scarce. Furthermore, current wearable sensors require secure attachment to specific body locations and must be given to participants which may not be feasible for long-term monitoring. Smartphones with embedded accelerometers may be a viable option for measuring gait complexity beyond the confines of the laboratory setting and provide a true representation of gait dynamics.

Through a series of three studies, this dissertation was designed for the validation and implementation of a smartphone accelerometer system (SPAcc) to capture and compare gait dynamics during free-living walking among healthy young and older adults. Study 1 and Study 2 revealed that the SPAcc provides valid and reliable estimates of linear and nonlinear gait variability measures, similar to research-grade laboratory equipment, during both treadmill (Study 1) and overground (Study 2) walking while simply placed in the user's front pants pocket. Study 3 utilized the SPAcc to capture walking bouts throughout a two-hour free-living walking condition among young and older adults. The SPAcc-derived measures revealed greater gait variability among older, compared to young adults. Gait complexity was found to be similar

between age groups, with values greater than typical laboratory-based studies, which may suggest a more structured but adaptive stepping-strategy response due to the increased challenge associated with free-living walking. Overall, the SPAcc may be a low-cost, user-friendly, and viable option for remote monitoring of gait complexity in the free-living environment. Further work will need to determine what aspects of the environment influence gait complexity.

DEDICATION

This work is dedicated to my parents, Vincenzo and Veronica, and my dear wife, Alessandra.

Thank you for your constant love and support every step of the way.

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LIST OF ABBREVIATIONS

ABC – Activities-Specific Balance Confidence

ApEn – Approximate Entropy

BA – Bland-Altman

CI – Complexity Index

COV – Coefficient of Variation

CWT – Continuous Wavelet Transform

DFA – Detrended Fluctuation Analysis

DST – Dynamical Systems Theory

EnHL – Entropic Half-Life

FSE-I – Falls Efficacy Scale-International

FoF – Fear of Falling

FSI – Fractal Scaling Index

FSR – Force-Sensing Resistive Footswitch

ICC – Intraclass Correlation Coefficient

ISI – Inter-Stride Interval

LOA – Limits of Agreement

LOC – Loss of Complexity Hypothesis

MoCap – Motion Capture System

MSE – Multiscale Entropy

OA – Older Adult

OMV – Optimal Movement Variability

RHC – Right Heel Contact

SaEn – Sample Entropy

SD – Standard Deviation

SP – Smartphone

SPAcc – Smartphone Accelerometer System

SPD – Statistical Persistence Decay

STv – Stride Time Variability

TUGT – Timed Up and Go Test

V1 – Visit 1

V2 – Visit 2

V3 – Visit 3

xISI – Average Inter-Stride Interval

YA – Young Adult

CHAPTER 1

INTRODUCTION

1.0. General Introduction

Human gait is a remarkably periodic movement pattern that must also be appropriately flexible to accommodate a constantly changing environment as one navigates the free-living world. Walking is the primary form of locomotion and healthy functioning is paramount to numerous activities of daily living, independence, and overall quality of life (Mahlknecht et al., 2013). A cardinal sign of aging is impaired balance control during gait and is typically measured using linear variability measures which estimates the magnitude of variability around a central point. Variability can be defined as the dispersion of data points around a central value and is often calculated as the standard deviation of the parameter of interest. The amount of variability present in the gait pattern is suggested to reflect the quality of neuromuscular control, with lesser amounts of variability representing better neuromuscular control and gait stability, where stability can be defined as one's ability to maintain upright equilibrium following exposures to external or self-generated perturbations (Bruijn et al., 2013; van Emmerik et al., 2016). The opposite is also true and is suggested to increase the risk of falls for older adults. However, linear measures of variability are sometimes not sensitive enough to identify differences between population groups (i.e., faller versus non-faller adults). Through the application of nonlinear measures, rooted in Dynamical Systems Theory, researchers are able to obtain information from gait patterns by assessing how the stride pattern changes over time (i.e., from one stride to the next). By doing so, gait patterns are found to reveal a complex structure, termed gait complexity, that can provide insight into the capacity of the walker to make flexible adaptations when necessary for the maintenance of balance and forward progression, regardless of environmental constraints; putatively evaluating fall risk.

Falls are a major concern for older adults, defined as 65 years of age or older (Lappan et al., 2021), leading to serious injuries, a loss of independence, decreased quality of life, and increased mortality (Rubenstein, 2006; Sylliaas et al., 2009; Boyd and Stevens, 2009; Salari et al., 2022). With advancing age, the components comprising the gait control system begin to diminish control due to age-related physical changes in neuromuscular structures and tissues, increasing neuromuscular 'noise', leading to a diminished adaptive capacity, and ultimately increasing fall risk. Noise in this context can be defined as error or unwanted movement of lower-limb control produced during steady-state walking, or more specifically, the subtle stride-to-stride fluctuations. Traditionally, the noise in the neuromuscular system was simply ignored. However, more recently, this noise was found to contain a *hidden* structure, reflective of the health status and adaptive capacity of the system. The quantification of this structure is estimated using nonlinear measures, such as the fractal scaling index and entropy, which measures the correlation between past and future states, as well as behaviour regularity over time, respectively. The increased neuromuscular noise associated with aging is suggested to break down gait complexity, represented as either a more regular and rigid stride pattern or a more disorganized and inconsistent stride pattern. Therefore, there appears to be an optimal level of variability that lies between the extremes of complete regularity and complete disorder and can be estimated using nonlinear measures.

Since many falls occur during ambulation, gait assessment is a valuable tool to predict and hopefully prevent future falls. Traditionally, spatial-temporal gait variability measures such as stride time or stride length variability, were estimated across several gait cycles recorded with gold-standard measurement systems such as motion caption or pressure sensing walkways (Verghese et al., 2009; Callisaya et al., 2010; König et al., 2014). Indeed, linear gait variability measures have successfully revealed greater sensitivity to age-related differences in lower-limb control, as well as predicting future falls among older adults compared to standard clinical assessments of balance and gait (timed up and go test, walking speed) (Hausdorff et al., 2001). However, when linear gait variability measures fail to predict falls, nonlinear measures may be able to augment gait assessment.

A challenge of nonlinear gait analysis is the requirement of numerous (>200) consecutive strides, thereby limiting data collection to the confines of the laboratory setting and treadmill walking while using gold-standard measurement systems such as motion capture and pressure-sensing footswitch systems (Malatesta et al., 2003; Raffalt and Yentes, 2020; Kiriella et al., 2020). However, the measurement tools used in these studies are often not feasible due to high equipment costs, portability, and the requirement of trained personnel for operation. Furthermore, treadmill walking may misrepresent the variability of the walker. Therefore, the development of a cost-effective and user-friendly tool that can be used outside of the laboratory setting to monitor gait complexity is highly desirable.

With the help of wearable sensors, such as smartwatches and physical activity monitors, with embedded inertial measurement unit systems, researchers and clinicians are able to capture physiological and movement data remotely and for extended periods of time, to assess functional health status and uncover fall risk among older adults (Patel et al., 2020; Nouredanesh et al. 2021). Gait assessment using wearable sensors affixed to the low back or lower limbs has demonstrated promising results for estimating linear variability measures in a free-living environment, augmenting traditional fall-risk assessments (Weiss et al., 2013; Del Din et al., 2019). Furthermore, gait complexity estimated in the free-living environment with wearable sensors has successfully distinguished between older adult fallers versus non-fallers with greater complexity found among non-fallers, reflecting greater adaptability (Ihlen et al., 2016). Adaptability can be defined as alterations from the typical stepping pattern to account for expected and unexpected imposed constraints (Balasubramanian et al., 2014). Overall, these results demonstrate the utility of a wearable sensor to identify gait complexity during daily-life walking and may be used to assess fall risk among older adults. However, to date, wearable sensors utilized for remote-based monitoring of gait are not user-friendly, as the sensor typically requires specific anatomical placement and secure attachment to the user. Furthermore, the wearable sensor must be given to or purchased by the user, which is not always feasible. Therefore, with advancements in and the ubiquity of smartphones, researchers are able to utilize the already built-in sensors, such as accelerometers, as a tool to monitor walking behaviour.

Previous research has demonstrated that smartphone-based accelerometers, while securely affixed to the body or placed in a pocket, are able to estimate spatial-temporal gait measures accurately and reliably compared to gold-standard measurement systems during overground walking in a controlled environment (Silsupadol et al., 2017; Manor et al., 2018; Shema-Shiratzky et al., 2022). These findings offer the potential of using smartphones to monitor gait complexity outside the confines of the laboratory setting and in the 'wild'. Currently, no study has used a smartphone to investigate gait complexity, while simply placed in the user's pant pocket, within the free-living environment. However, prior to the implementation of a smartphone accelerometer system to estimate gait complexity in the free-living environment, the system must be compared to known quantities to ensure validity. This dissertation aimed to develop a valid and reliable tool to be used in the free-living environment to estimate gait complexity among young and older adult populations. In doing so, new insights will be gained into the true dynamics of walking behaviour which can be used as a marker for the adaptability of the individual.

1.1. Dissertation Objectives

The global objective of this dissertation was the development and progression of a low-cost, practical, and user-friendly tool to monitor gait patterns in an unconstrained free-living environment among healthy young and older adults. To accomplish the global objective, three studies were designed with the following objectives:

Study 1) Validate the smartphone accelerometer during treadmill walking (highly controlled environment).

Study 2) Validate the smartphone accelerometer during overground walking in vacant corridors (semi-controlled environment).

Study 3) Implement the smartphone accelerometer to investigate age-related differences in gait patterns in a natural, free-living environment (uncontrolled environment).

1.2. Research Questions

1) What is the agreement and reliability of a smartphone accelerometer system compared to gold-standard motion capture and footswitch systems for estimating linear and nonlinear gait variability during treadmill walking? (Study 1)
2) What is the agreement and reliability of a smartphone accelerometer system compared to a gold-standard footswitch system for estimating linear and nonlinear gait variability during overground walking? (Study 2)

3) What are the differences in linear and nonlinear gait variability between young and older adults estimated with the smartphone system during free-living walking in an unconstrained environment? (Study 3)

1.3. Expectations and Hypotheses

I expected that: (1) the smartphone accelerometer system would demonstrate acceptable agreement and similar test re-test reliability to that of gold-standard motion capture and footswitch systems when estimating linear and nonlinear gait variability measures during treadmill walking (Study 1); (2) the smartphone accelerometer system would demonstrate acceptable agreement and similar test re-test reliability to that of a gold-standard footswitch system when estimating linear and nonlinear gait variability measures during overground walking (Study 2). I hypothesized that: (3) linear gait variability measures would differ between young and older adult groups during free-living walking in an unconstrained environment (Study 3); nonlinear gait variability measures would differ between young and older adult groups during free-living walking in an unconstrained environment (Study 3).

1.4. References

Balasubramanian, C. K., Clark, D. J., & Fox, E. J. (2014). Walking adaptability after a stroke and its assessment in clinical settings. *Stroke research and treatment*, *2014*, 591013. https://doi.org/10.1155/2014/591013

Boyd, R., & Stevens, J. A. (2009). Falls and fear of falling: burden, beliefs and behaviours. *Age and ageing*, *38*(4), 423–428. https://doi.org/10.1093/ageing/afp053

Bruijn, S. M., Meijer, O. G., Beek, P. J., & van Dieën, J. H. (2013). Assessing the stability of human locomotion: a review of current measures. *Journal of the Royal Society, Interface*, *10*(83), 20120999. https://doi.org/10.1098/rsif.2012.0999

Callisaya, M. L., Blizzard, L., Schmidt, M. D., McGinley, J. L., & Srikanth, V. K. (2010). Ageing and gait variability--a population-based study of older people. *Age and ageing*, *39*(2), 191–197. https://doi.org/10.1093/ageing/afp250

Del Din, S., Galna, B., Godfrey, A., Bekkers, E. M. J., Pelosin, E., Nieuwhof, F., Mirelman, A., Hausdorff, J. M., & Rochester, L. (2019). Analysis of Free-Living Gait in Older Adults With and Without Parkinson's Disease and With and Without a History of Falls: Identifying Generic and Disease-Specific Characteristics. *The journals of gerontology. Series A, Biological sciences and medical sciences*, *74*(4), 500–506. https://doi.org/10.1093/gerona/glx254

Hausdorff, J. M., Rios, D. A., & Edelberg, H. K. (2001). Gait variability and fall risk in community-living older adults: a 1-year prospective study. *Archives of physical medicine and rehabilitation*, *82*(8), 1050–1056. https://doi.org/10.1053/apmr.2001.24893

Ihlen, E. A. F., Weiss, A., Bourke, A., Helbostad, J. L., & Hausdorff, J. M. (2016). The complexity of daily life walking in older adult community-dwelling fallers and non-fallers. *Journal of biomechanics*, *49*(9), 1420–1428. https://doi.org/10.1016/j.jbiomech.2016.02.055

Lappan, N., Zecevic, A., Ming, Y., Hunter, S., & Johnson, A. (2021). Descriptive Epidemiology of Fall-Related Injuries Among Older Adults in Ontario, Canada. *Innovation in Aging*, *5*(Suppl 1), 784–785. https://doi.org/10.1093/geroni/igab046.2897

Kiriella, J. B., Di Bacco, V. E., Hollands, K. L., & Gage, W. H. (2020). Evaluation of the Effects of Prescribing Gait Complexity Using Several Fluctuating Timing Imperatives. *Journal of motor behavior*, *52*(5), 570–577. https://doi.org/10.1080/00222895.2019.1654971

König, N., Singh, N. B., von Beckerath, J., Janke, L., & Taylor, W. R. (2014). Is gait variability reliable? An assessment of spatio-temporal parameters of gait variability during continuous overground walking. *Gait & posture*, *39*(1), 615–617. https://doi.org/10.1016/j.gaitpost.2013.06.014

Mahlknecht, P., Kiechl, S., Bloem, B. R., Willeit, J., Scherfler, C., Gasperi, A., Rungger, G., Poewe, W., & Seppi, K. (2013). Prevalence and burden of gait disorders in elderly men and women aged 60-97 years: a population-based study. *PloS one*, *8*(7), e69627. https://doi.org/10.1371/journal.pone.0069627

Malatesta, D., Simar, D., Dauvilliers, Y., Candau, R., Borrani, F., Prefaut, C., & Caillaud, C. (2003). Energy cost of walking and gait instability in healthy 65- and 80-yr-olds. *Journal of applied physiology (Bethesda, Md. : 1985)*, *95*(6), 2248–2256. https://doi.org/10.1152/japplphysiol.01106.2002

Manor, B., Yu, W., Zhu, H., Harrison, R., Lo, O. Y., Lipsitz, L., Travison, T., Pascual-Leone, A., & Zhou, J. (2018). Smartphone App-Based Assessment of Gait During Normal and Dual-Task Walking: Demonstration of Validity and Reliability. *JMIR mHealth and uHealth*, *6*(1), e36. https://doi.org/10.2196/mhealth.8815

Nouredanesh, M., Godfrey, A., Howcroft, J., Lemaire, E. D., & Tung, J. (2021). Fall risk assessment in the wild: A critical examination of wearable sensor use in free-living conditions. *Gait & posture*, *85*, 178–190. https://doi.org/10.1016/j.gaitpost.2020.04.010

Patel, M., Pavic, A., & Goodwin, V. A. (2020). Wearable inertial sensors to measure gait and posture characteristic differences in older adult fallers and non-fallers: A scoping review. *Gait & posture*, *76*, 110–121. https://doi.org/10.1016/j.gaitpost.2019.10.039

Raffalt, P. C., & Yentes, J. M. (2020). On the application of entropic half-life and statistical persistence decay for quantification of time dependency in human gait. *Journal of biomechanics*, *108*, 109893. https://doi.org/10.1016/j.jbiomech.2020.109893

Rubenstein L. Z. (2006). Falls in older people: epidemiology, risk factors and strategies for prevention. *Age and ageing*, *35 Suppl 2*, ii37–ii41. https://doi.org/10.1093/ageing/afl084

Salari, N., Darvishi, N., Ahmadipanah, M., Shohaimi, S., & Mohammadi, M. (2022). Global prevalence of falls in the older adults: a comprehensive systematic review and meta-analysis. *Journal of orthopaedic surgery and research*, *17*(1), 334.

Shema-Shiratzky, S., Beer, Y., Mor, A., & Elbaz, A. (2022). Smartphone-based inertial sensors technology - Validation of a new application to measure spatiotemporal gait metrics. *Gait & posture*, *93*, 102–106. https://doi.org/10.1016/j.gaitpost.2022.01.024

Silsupadol, P., Teja, K., Lugade, V. (2017). Reliability and validity of a smartphone-based assessment of gait parameters across walking speed and smartphone locations: Body, bag, belt, hand, and pocket. Gait & Posture, 58 (2017) 516–522.

Sylliaas, H., Idland, G., Sandvik, L., Forsen, L., & Bergland, A. (2009). Does mortality of the aged increase with the number of falls? Results from a nine-year follow-up study. *European journal of epidemiology*, *24*(7), 351–355. https://doi.org/10.1007/s10654-009-9348-5 van Emmerik, R. E. A., Ducharme, S. W., Amado, A. C., & Hamill, J. (2016). Comparing dynamical systems concepts and techniques for biomechanical analysis. *Journal of sport and health science*, *5*(1), 3–13. https://doi.org/10.1016/j.jshs.2016.01.013

Verghese, J., Holtzer, R., Lipton, R. B., & Wang, C. (2009). Quantitative gait markers and incident fall risk in older adults. *The journals of gerontology. Series A, Biological sciences and medical sciences*, *64*(8), 896–901. https://doi.org/10.1093/gerona/glp033

Weiss, A., Brozgol, M., Dorfman, M., Herman, T., Shema, S., Giladi, N., & Hausdorff, J. M. (2013). Does the evaluation of gait quality during daily life provide insight into fall risk? A novel approach using 3-day accelerometer recordings. *Neurorehabilitation and neural repair*, *27*(8), 742–752. https://doi.org/10.1177/1545968313491004

CHAPTER 2

REVIEW OF THE LITERATURE

2.0. Human Gait, Variability, and Analysis

Human gait, under steady-state conditions, is highly periodic from one stride to the next. However, the stride-to-stride pattern does not exactly repeat itself, leading to oscillations in the gait cycle that can provide information about the quality of the gait control system and health status of the walker. Traditionally, the stride-to-stride fluctuations, that is, the oscillations that occur between consecutive ipsilateral heel contacts during steady-state gait were considered random noise produced by the neuromuscular system and were simply ignored and averaged out. As previously mentioned, the magnitude of variability was considered ‘error’ and reflected functional status of the behaviour. The idea of variability as error stemmed from motor learning research which posited that expert execution of a repeated motor task is performed reliably with little error. However, human performance researchers have noted that although the output performance of a repeated motor task yields minimal error, the production of the motor task displays a larger amount of error. This finding was first reported by Bernstein (1967) while investigating the performance of the hammer swing among expert blacksmiths. Bernstein found that the output variability of hammer tip end position was smaller than the movement pattern variability (trajectories of arm joint angles) of the swinging arm; famously stating “repetition without repetition.” Bernstein’s findings suggest that a skilled and repetitive motor task is performed with a multitude of movement strategies, prompting the idea of motor redundancy. Motor redundancy can be described as possessing more available movement patterns than necessary, enabling a variety of solutions to accomplish the same motor task. However, an assumption of linear measures of variability is that repetitions of the same motor task are independent and unrelated as they only estimate the magnitude of variability around a central point. Therefore, to investigate the temporal organization of a repeated performance, that is, the ordering of sequential repeated behaviour, nonlinear measures, rooted in Dynamical Systems Theory, were applied to time series data.

A time series is a sequential list of recorded numbers or observations measuring some quantity over time with the assumption that values are dependent upon adjacent values. The assumption of dependence is important as it provides information about how the behaviour changes with repeated measurement. Therefore, not only is the recording or measurement of values in a time series important, but the order of values. For this reason, linear statistical measures cannot describe all aspects of a time series. For example, consider the two lists of numbers: List A (2, 4, 6, 8, 10); List B (4, 6, 10, 2, 8). The mean and standard deviation for both lists are 6.0 and 3.16, respectively. However, by simply looking at the two lists, it is clear that they are different. Therefore, nonlinear measures which describe how the time series changes over time must be employed.

Dynamical Systems Theory and Complexity

Dynamical Systems Theory (DST), also known as Dynamics Theory, asserts that dynamical systems, are systems that evolve or change over time, or more specifically, the components comprising the system are changing over time. A subset of dynamical systems are systems that demonstrate nonlinear behaviours in relation to the goal of the system. To understand what a nonlinear system is, it is often easier to first describe a linear system. A linear system's output is directly proportionate to the system's input and therefore can be described by a straight line (i.e., $f(x) = ax + b$). Furthermore, a linear system follows the superposition principle which states that the sum of components making up the system equals the output. A nonlinear system is one that produces disproportionally larger or smaller output, relative to the input of the system (i.e., $y = aX^2$) and does not follow the superposition principle. Embedded within nonlinear dynamical systems are chaotic systems, which are systems producing complex patterns to support the stability of the system. First introduced by meteorologist, Edward Lorenz in the 1960s while predicting weather patterns, he discovered that a very small rounding error in the input parameters of the weather prediction model led to a large output change in the model's prediction. This finding lead to the notion of sensitive dependence on initial conditions, coining the term "the butterfly effect" as Lorenz asked does the flap of a butterfly's wings in Brazil cause a tornado in Texas? Since then, several authors have suggested that chaotic behaviour occurs naturally and represents the capability of making flexible adaptations to stressors placed on the human body during everyday life (Pool, 1989; Lipsitz and Goldberger, 1992; Goldberger, 1996).

In line with chaotic systems, Stergiou and colleagues developed the Optimal Movement Variability (OMV) model to interpret the production of biological fluctuations under healthy and unhealthy states (Stergiou et al., 2006). The OMV model is a continuum in which the level of predictability ranges from complete randomness or no predictability (stochastic) in the system's pattern to complete regularity (deterministic). A deterministic system is a predictable system with only one unique future state for the current state of the system while a stochastic system has many, potentially infinite, number of future states (McCamley and Harrison, 2016). In the middle of the continuum is suggested to be a system that produces behaviour that is erratic and yet constrained, demonstrating optimal flexibility and adaptability to expected and unexpected stressors.

Complexity is closely tied to chaos in that they both contain complex patterns that are suggestive of adaptability. There is no universal definition of "complexity" so it will be operationally defined. As discussed above, complex fluctuations emerge from a complex system. Therefore, the term system must first be defined. A system can be defined as a network of elements or interconnected components that interact to produce an output. For example, the gait control system is comprised of multiple interacting components that include sensory (i.e., neuronal receptors), mechanical (i.e., bones, joints), and cognitive (i.e., executive function) elements that interact to produce the stepping pattern. In order for a system to be complex, the system must contain the following features: deterministic origins, a network of entangled components (Delignières and Marmelat, 2012), and multiscale behaviour (Costa et al., 2005). A deterministic origin refers to the ability of future states of the system to be predicted, given the current state. However, human movement is considered to have some degree of both determinism and randomness (Riley and Turvey, 2002). For example, human gait has been modeled as a set of components making up the typical stride pattern, with embedded elements of randomness, governed by probabilistic rules, such that future strides are based on an equal probability of occurrence, but depend on past strides (Hausdorff et al., 1995; Ashkenazy et al., 2002).

The second feature of a complex system is that the system is comprised of multiple entangled and interconnected components, with widespread dependence on one another. Therefore, the system cannot be deconstructed into its separate components as opposed to a complicated system. A complicated system is composed of a large number of components and the interaction between components is not important, thereby dividing or separating out the separate components can provide knowledge of the whole. For example, a car engine can be broken down into its many parts and when combined describes the system's output. The interaction amongst the multiple components comprising a complex system is suggested to provide stability to the system by allowing the system to select and transition away from imposed constraints when needed due to motor redundancy, as described above.

The third feature of a complex system is multiscale behaviour, which is the system's behaviour operating across multiple spatial and temporal scales. For example, during steady-state gait, the ISI demonstrates a self-similar pattern such that the variability of ISI at shorter walking bouts (timescale = seconds) is correlated with the variability of ISI at longer walking bouts (timescale = minutes); also known as scale-invariance. Conceptually, it is likely that behavioural changes, due to aging and disease, result from physiological changes that are not isolated to one scale, but begin at smaller scales (micro) and cascade to larger behavioural scales (macro) (Figure 2.1).

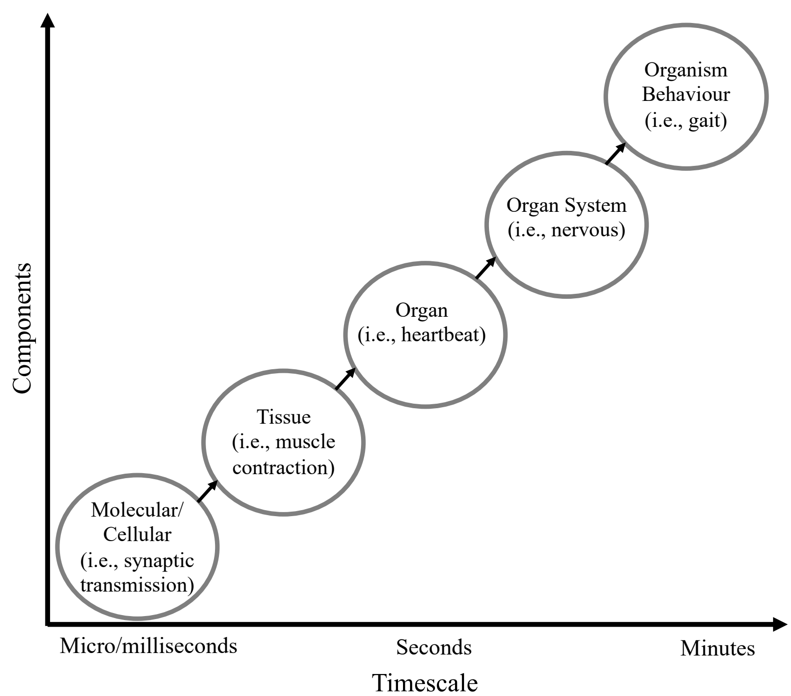

Figure 2.1. Theoretical conceptualization of multiple timescales and the components acting at the different timescales. As the number of components increase, so does the time in which they function. Figure created by author.

Measuring Complexity

Complexity of biological systems in humans was first investigated with heart rate variability. Previous research has investigated the fluctuations in the time intervals of the beat-to-beat QRS complex among healthy and diseased populations (Peng et al., 1993/1995; Mäkikallio et al., 1999; Goldberger et al., 2002). Interestingly, the findings supported the notion of an optimal amount of variability, located on a predictability continuum between complete order and complete disorder. The heart rate variability among diseased patients was found to be either very regularly or irregularly paced. These findings suggest that the seemingly erratic, yet periodic heart rate variability of healthy controls provide a greater adaptive capacity to rapidly accommodate expected and unexpected stressors of everyday life, dissipating the blood flow optimally. This was also shown in electroencephalography of cortical activity (Smits et al., 2016), respiration rate (Peng et al., 2002), postural control (Busa et al., 2016), and gait (Hausdorff et al., 1997b). The level or amount of complexity contained within physiological systems is commonly estimated with fractal (Hausdorff et al., 1997b; Kiriella et al., 2020) and entropy measurements (Costa et al., 2003).

Fractals

A fractal, derived from the Greek word "fractus" meaning fractured, can be thought of as an object that when magnified, reveals characteristics that resemble the whole object. This is known as self-similarity and scale-free, meaning it does not matter what scale you look at the object, the object will always look similar. There are many examples of naturally occurring fractal objects such as trees, coastlines (Figure 2.2), and networks of blood vessels in the human body. Fractals exhibit the phenomena of $1/f$ noise, also known as pink noise, which means that the power spectrum density is inversely related to the frequency. Therefore, lower frequencies have the majority of signal power, and then the power decays in a power-law fashion. The fractal structure is suggested to provide the system with flexibility, acting as a dissipative system, distributing disturbances or stresses placed on the system, across multiple spatial-temporal scales. For example, the fractal coastline will dissipate waves and the fractal cardiovascular system will dissipate blood flow. In terms of gait adaptability, fractal analysis can quantify the presence and strength of long- and short-range correlations in the stepping pattern, putatively exposing if there is a breakdown in the components that act at particular scales.

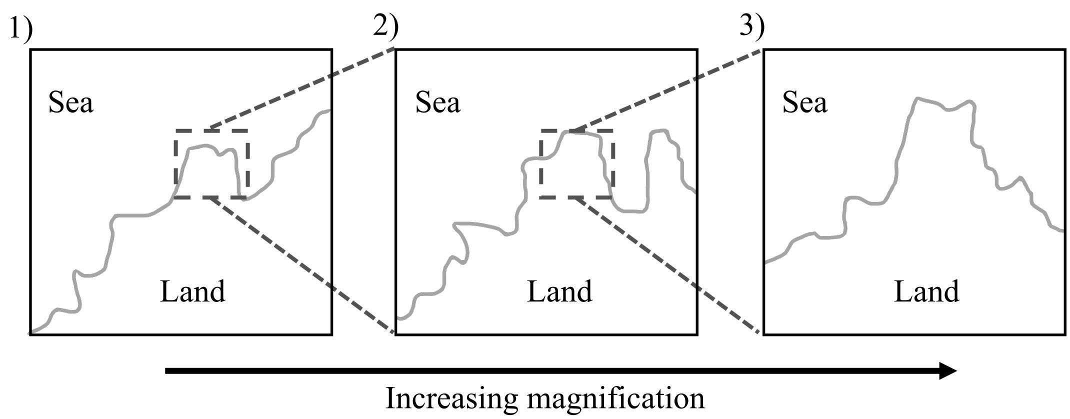

Figure 2.2. Coastline fractal example. When the coastline is magnified, the smaller features look similar to the bigger features, all represented by a jagged and irregular line, which is, a self-similar and scale-free fractal. Although the irregularities in the coastline are not identical, they are statistically (i.e., variance) self-similar. Figure adapted from McGarth (2016).

Fractal analysis during steady-state gait is often calculated with the detrended fluctuation analysis (DFA). The DFA provides a fractal scaling index (FSI) as a measure of the degree to which a stride interval at a given time scale is correlated with past and future stride intervals over different scales. An FSI value = 1.0 represents a truly scale-invariant time series, also known as pink noise, as described above. An FSI value = 0.5 represents a completely random (i.e., stochastic and uncorrelated) time series. An FSI value ≥ 0.5 and ≤ 1.0 indicates persistent long-range correlations such that a large stride will likely be followed by another large stride or vice versa. An FSI value < 0.5 indicates anti-persistent correlations such that a small stride will likely be followed by a large stride or vice versa. Healthy young adults demonstrate an ISI FSI ≈ 0.75-0.85 during steady-state overground walking which suggests a locomotor 'memory' such that stride intervals are related to past stride intervals hundreds of strides earlier. Not surprisingly, an FSI ≈ 0.75-0.85 is suggested to reflect a highly adaptable gait pattern, representing an optimal amount of variability, somewhere between randomness (FSI = 0.5) and overly structured (FSI > 1.0).

The DFA is calculated as follows: the time series is first integrated and then divided into non-overlapping boxes of equal length (n). A least-squares line of best fit is applied within each box. The integrated time series is then detrended by subtracting the line of best fit from within each box. Afterwards, the average root mean square (RMS) is calculated for each box length. This process is repeated with a range of box size lengths (n = 10-40). A logarithmic transformation is applied to the plot of RMS vs. box length (n) to create a log-log plot. Lastly, the slope of the line of best fit in the log-log plot is calculated to obtain the FSI (Terrier and Dériaz, 2012). Figure 2.3 provides a visualization of the DFA algorithm.

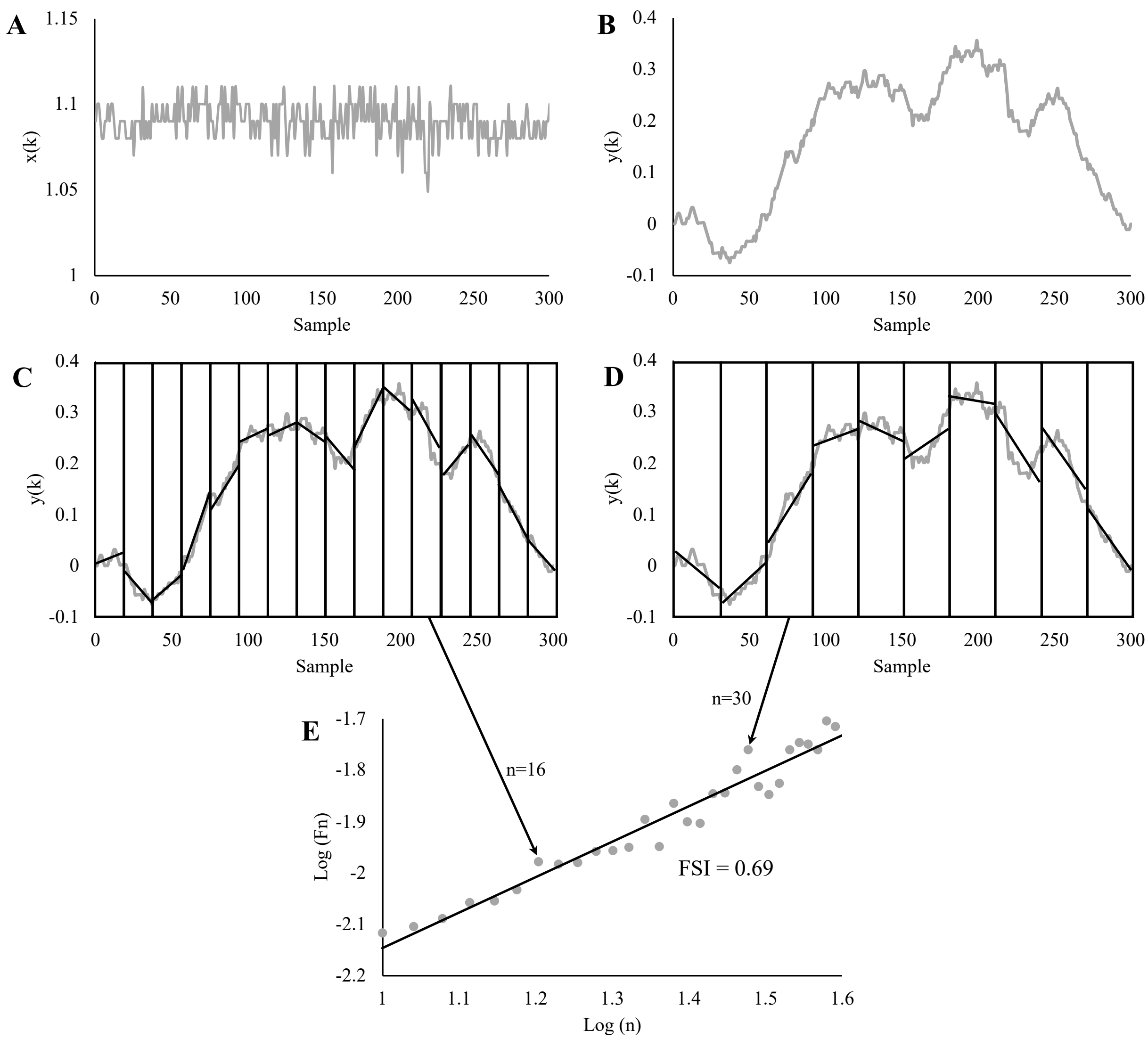

Figure 2.3. Visualization of the detrended fluctuation analysis applied to a treadmill walking inter-stride interval (ISI) series, x(k), 300 consecutive data points in length, outlined in plot A. Plot B is the integration of the ISI series, y(k). Plots C and D represent non-overlapping boxes (n) of size 16 and 30, respectively, with the line of best fit in each box. Plot E is the log transform of all box sizes (n) applied to the integrated time series (box size = 10 – 40) plotted against the log transform root mean square for each box size (Fn). Finally, the slope of the line of best fit of the log-log plot provides the fractal scaling index (FSI). Figure created by author and adapted from Rhea et al. (2014).

Entropy

In the realm of information theory, entropy can be defined as the loss of information in a time series. Entropy can quantify regularity or disorder of a time series, based on the probability of future states being predicted given the current and all possible states of the system. Entropy values typically range from zero to two, where a value of zero represents a completely periodic time series (i.e., a sine wave) and two represents a completely random time series (i.e., white noise) in which randomness implies a lack of predictability or correlation between data points. Therefore, lower entropy values represent little new information being generated by the system and therefore only tends to stay in a few configurations, while higher entropy values represent greater new information being generated and therefore the system has a greater number of configurations it can be in, making the prediction of future states difficult. For example, flipping a coin yields two possible results, heads, or tails with a one-in-two chance of being in either state prior to the flip. While the roll of a six-sided die has a one-in-six chance of landing on any particular number prior to rolling. Therefore, the die-system has a greater number of configurations or states it can be in (six possible states), compared to the coin-system which has a smaller number of possible states (two possible states). Thus, the coin-system can be considered to have a lower entropy value compared to the die-system since future states can be predicted with a higher probability than the die-system.

The first application of entropy to biological data was the approximate entropy (ApEn) calculation introduced in 1991 (Pincus, 1991) and was used to assess the regularity or repeatability of a time series. Researchers have interpreted ApEn as a possible measure of complexity since ApEn assesses the structure of a time series (Pincus, 1991; Rhea et al., 2011). The ApEn algorithm requires three input parameters: vector length m, similarity criterion r, and time series data length N. The m and r parameter values are typically set to $m = 2$ and $r = 0.2$ times the SD of the time series in gait studies (Yentes et al., 2013). The ApEn algorithm calculates the probability that short sequences of data points are repeated within a certain similarity criterion level throughout the time series.

The ApEn is calculated as follows (Yentes, 2016):

(1) The time series is divided into separate vectors of length m; if m = 2, then the time series is divided into pairs of elements for each vector.

(2) Given vector m(i), a comparison is made to determine which other vectors are similar to m(i). Vectors that are similar are counted as matches and selected if the elements in the paired vectors are ≤ the similarity criteria r. Self matches are also counted.

(3) Step (2) is repeated for each vector: m(i+1), m(i+2)…m(N-m+1).

(4) The conditional probability (C_i^m) of matches to total number of vectors is calculated for each vector.

(5) $\Phi_m$is calculated by summation of the natural logarithm of each C_i^m and dividing by the total number of vectors:

$$\Phi_m = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} lnC_i^m$$

(6) Steps (1) to (5) are repeated with m + 1:

$$\Phi_{m+1} = \frac{1}{N-m} \sum_{i=1}^{N-m} lnC_i^{m+1}$$

(7) ApEn is calculated by subtracting $\Phi_m - \Phi_{m+1}$:

$$ApEn\ (N, m, r) = \Phi_m - \Phi_{m+1}$$

The downside to ApEn is the self-similarity bias (counting self-matches), thereby representing greater system regularity than present. Additionally, ApEn appears to be very sensitive to data length and it is recommended that N ≥ 200 (Yentes et al., 2013). Therefore, sample entropy (SaEn) was introduced by Richman and Moorman (2000) to improve sensitivity to data length and to remove the self-similarity bias of the ApEn algorithm.

The SaEn algorithm requires the same input parameters as ApEn and is calculated as follows (Yentes, 2016):

(1) The time series is divided into separate vectors of length m; if m = 2, then the time series is divided into pairs of elements for each vector.

(2) Given vector m(i), a comparison is made to determine which other vectors are similar to m(i). Vectors that are similar are counted as matches and selected if the elements in the paired vectors are ≤ the similarity criteria r. Self matches are not counted.

(3) Step (2) is repeated for each vector: m(i+1), m(i+2)…m(N-m).

(4) The conditional probability (C_i^m) of matches to total number of vectors is calculated for each vector.

(5) B_i^m is calculated by summation of each C_i^m and dividing by N – m:

$$B_i^m = \frac{1}{N-m}\sum_{i=1}^{N-m} C_i^m$$

(6) A_i^m is calculated by repeating Steps (1) to (5) with m + 1:

$$A_i^m = \frac{1}{N-m}\sum_{i=1}^{N-m} C_i^{m+1}$$

(7) Calculate SaEn as follows:

$$A = \frac{(N-m-1)(N-m)}{2} A_i^m$$

$$B = \frac{(N-m-1)(N-m)}{2} B_i^m$$

$$SaEn = -ln\left(\frac{A}{B}\right)$$

Although both ApEn and SaEn measure the regularity of a system, there is no clear link between these measures and complexity. Generally, an increase in entropy is suggested to represent greater complexity. However, a randomly generated time series shows higher entropy values and at times, so do unhealthy physiological systems, compared to healthy physiological systems which are supposed to be highly complex. Therefore, an entropy algorithm should not result in such an extreme value that it appears well above a healthy system's state. One reason, as suggested by Costa et al. (2005), for such large entropy values given an unhealthy system is that both ApEn and SaEn only investigate point-to-point fluctuations and therefore only operate on a single scale. To account for this, Costa et al. (2002) developed the multiscale entropy (MSE) algorithm. The MSE algorithm applies a coarse-graining process to the original time series data, generating multiple time series with a particular scale, and then calculates the SaEn for each scale. The coarse-graining process calculates the average time series data values across nonoverlapping window sizes of increasing length for each scale as illustrated in Figure 2.4. Afterwards, a complexity index (CI) is determined by calculating the area under the curve of a SaEn (Y-axis) versus scale (X-axis) plot (Costa et al., 2002; Costa et al., 2003) to reflect the system's complexity (Costa et al., 2005; Busa and van Emmerik, 2016).

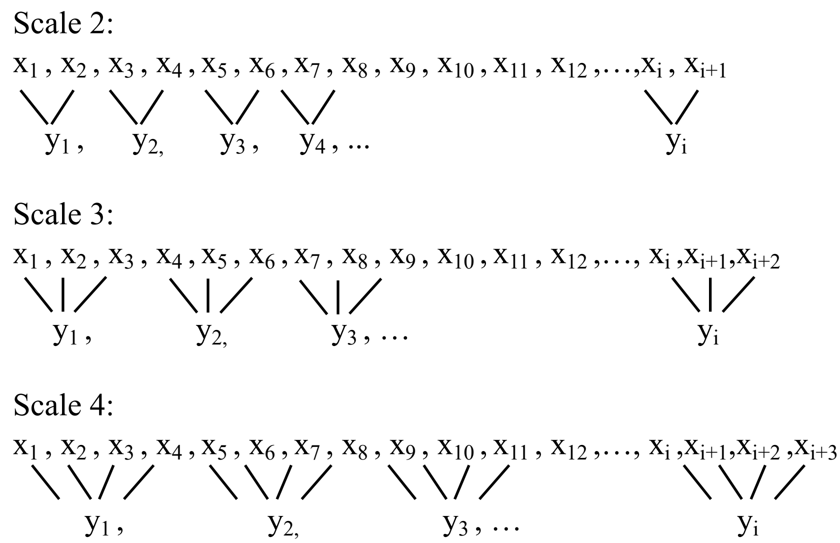

Figure 2.4. Visualization of the coarse-graining process. Scale one is the original time series, $x_1 \ldots x_i$. The y values represent the new time series, created from averaging the original time series. As the scale value increases, the number of time series values included in each window increases. The sample entropy is calculated for each newly generated time series of y values. Figure created by author and adapted from Costa et al. (2003).

MSE has been applied to heart rate data (Costa et al., 2002), center-of-pressure data (Busa and van Emmerik, 2016), and ISI data (Costa et al., 2003; Raffalt et al., 2018) for estimating physiological complexity and differentiating between healthy and unhealthy populations. The downside of entropy measurement (ApEn, SaEn, and MSE) is the need for a control group or control condition when interpreting complexity from these measures (Yentes and Raffalt, 2021). The control group or control condition is necessary when interpreting entropy results due to the directional sensitivity of entropy values based on the algorithm parameter selection. Without a control condition, one cannot interpret if the entropy value is high or low, or an artifact of parameter selection; one must look for consistent directional differences in entropy values between groups or conditions, based on parameter selection, and to potentially compare findings across different studies using these directional differences between conditions (Yentes and Raffalt, 2021). Furthermore, the coarse-graining process creates multiple time series of increasingly shorter lengths, therefore requiring a large amount of data to ensure a sufficient number of data points for the largest scale. Overall, higher entropy suggests the generation of new non-redundant information that may provide the system with new movement strategies, thereby increasing the flexibility of the system to adapt when necessary.

One criticism of entropy measurement is the type of measurement data used for the time series. A time series can consist of discrete or continuous measurement data. Discrete data are separate output values that describe the end result of a process or cycle, counted at particular times. For example, the ISI time series is constructed as the time difference between ipsilateral heel contact events, which are measured at a particular point in time. A continuous time series is one that evolves as a function of time. For example, the knee joint flexion-extension angle waveform between ipsilateral heel contact events. Even though digital recording of a human movement is sampled at discrete intervals, the time series can still be considered continuous given the measurement of interest. Although a subtle difference, some nonlinear measures, including entropy, can be applied to a continuous measurement to overcome data length concerns. For example, the acceleration curve of trunk movement throughout the stride is a continuous measurement. While sampling the trunk acceleration at 100Hz across 10 consecutive stride intervals with each stride interval approximately 1.2s in duration yields 1200 continuous data points. The measurement of continuous trunk acceleration has already exceeded the required minimum time series data length of 200 while only recording 10 strides and one could therefore apply ApEn to the time series. To acquire the same amount of data using a discrete measurement such as ISI, 1200 individual strides would have to be performed which would require 1440s (1200 x 1.2s) or 24 minutes of walking data. Therefore, continuous measurement reduces the amount of data required. However, careful consideration must be taken when selecting and interpreting the vector length m. One must ask if a vector length of 2 for a continuous measurement represents a vector length of 2 for a discrete measurement. Perhaps an m = 120 is more appropriate as it would consider all the points along the trunk acceleration waveform throughout the 1.2s stride.

Complexity and Aging

The loss of complexity (LOC) hypothesis by Lipsitz and Goldberger (1992) asserts that aging is associated with a loss of 1) functional/structural components and 2) coupling of components (interaction of components) that results in a decrease in behavioural complexity. For example, older adults have a reduction in motor neurons as well as muscle fibers (structural component), which coupled with a decrease in synchronicity of motor unit firing (interaction of components) results in a decreased complexity. Lipsitz and Goldberger (1992) found that the heart rate variability of young and older adults evaluated using linear measures (i.e., SD of inter-beat interval) was nearly identical, however, the ApEn was very different and reduced among older adults compared to younger adults. These findings provide evidence for the sensitivity of nonlinear compared to linear measures of variability and entropy analysis for distinguishing between different adult populations. However, as previously stated, ApEn does not consider multiple scales. A similar study was conducted using the MSE analysis and reported similar findings (Costa et al., 2002). The greater complexity of the young adults, compared to the older adults, reflects a pattern of variability that is not strictly regular and can be considered a bounded or “constrained type of randomness” producing irregular, yet structured fluctuations that enables flexible adaptation to unexpected stressors (Figure 2.5).

In terms of the ISI during steady-state gait, imagine an unexpected obstacle such as an uneven surface (i.e., depression) in the sidewalk. If the walker's ISI is too regular (rigid/inflexible), the walker may not be able to alter their stride time (either shorter or longer) as needed, resulting in a stumble that may be too great for the walker to remain stable and catch themselves, likely, leading to a fall (FSI >1.0, entropy approaching 0). However, if the walker demonstrates a more variable stride pattern, such that it is reflected as irregular yet somewhat periodic, the walker is able to select the appropriate stride time, since more stride time patterns are available to the walker, providing greater adaptive capacity, and decreased chance of falling, even if the unexpected obstacle (depression in the sidewalk) results in a stumble (FSI >0.5 and <1.0, entropy ≈ 1). Lastly, if the stride pattern is too irregular, the selected stride response is too inconsistent to generate any appropriate stride time (FSI ≈ 0.5, entropy approaching 2), potentially also leading to a fall. Therefore, this optimal amount of variability present in highly complex systems is suggested to stem from the availability of multiple movement strategies that the system can cycle through to support external environmental changes. Overall, the stepping pattern can be interpreted as the final output behaviour resulting from the interaction of multiple entangled components that make up the gait control system, operating on multiple spatial and temporal scales.

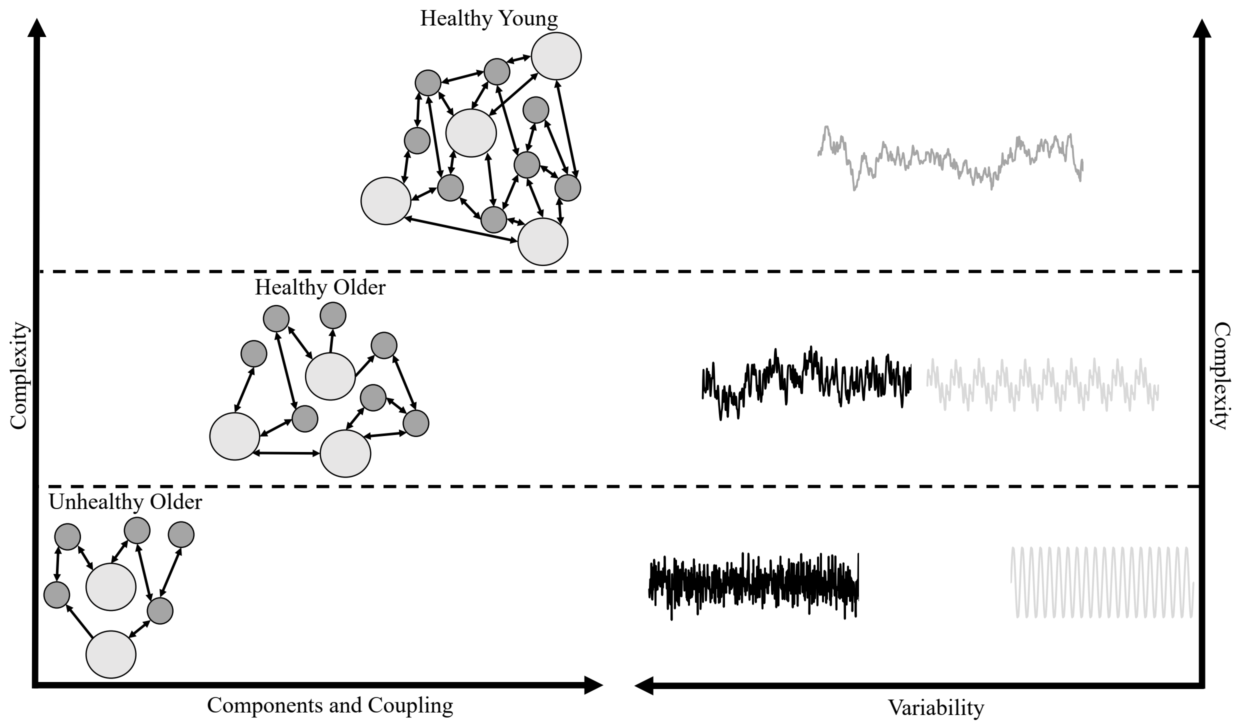

Figure 2.5. Theoretical conceptualization of complexity and aging and disease. The circles represent the components comprising the system, with the different sizes representing the scale of operation. For example, larger circles represent a greater spatial-temporal scale. The arrows represent the interaction amongst the components. A healthy young adult represents a highly complex system, with a great number of components and interactions across components. The healthy older adults represents a decrease in both the number and coupling of components, reflected as a decrease in complexity. An unhealthy older adult is represented by a greater reduction in components and coupling of components. On the right side of the figure, decreases in complexity are represented by either an increase or decrease in variability. Therefore, aging and disease is reflected by component and coupling deterioration, reducing regularity or increased disorder, and a breakdown of multiscale operation. Figure created by author, inspired by Stergiou et al. (2006) and Sleimen-Malkoun et al. (2014).

2.1. Falls, Aging, and Gait

Falls among older adults are a serious health issue, leading to a decreased quality of life, loss of independence, increased mortality, and high health care costs (Stevens et al., 2006; Dionyssiotis, 2012). A fall can be defined as an event causing a person to come to an unintentional rest on the ground or lower surface level, not as a result of a major internal event (i.e., stroke, loss of consciousness) or an external overwhelming hazard (Tinetti et al., 1988). Approximately 30% of community-dwelling adults over 65 years of age fall at least once a year (Tromp et al., 2001) and the percentage increases to 40 – 50% for those over 80 years of age (O'Loughlin et al., 1993; Blake et al., 1988). Five to 20% of falls result in a serious injury, fracture, hospitalization, death (Rubenstein, 2006), or admittance to a nursing home, accounting for the majority of fall-related health care costs. Furthermore, age is an independent risk factor to falling (Tinetti and Kumar, 2010) and since the number of older adults is growing, the healthcare system will be burdened with greater fall-related healthcare costs. For example, fall-related injuries among older adults cost the Canadian healthcare system an estimated $5.6 billion in 2018 (Parachute, 2021) and the number of older adults in Canada is projected to increase up to 25% of the total population by 2036 (Statistics Canada, 2015). Physicians and clinicians recommend a multifactorial approach to fall prevention among older adults with one component involving annual gait and balance assessments, as well as fall history reports (Moncada and Mire, 2017). Since the majority of falls among older adults occur during ambulation (Talbot et al., 2005; Sartini et al., 2010), gait assessment is paramount for clinicians and researchers to uncover fall risk and identify predictors. Moreover, monitoring walking performance outside the clinic can provide valuable information about rehabilitation progress and even objectively record fall events if monitoring throughout the day (Patel et al., 2012). The logging of fall incidence, via a wearable sensor, can capture falls that are largely unreported (Hoffman et al., 2018), augmenting fall-risk assessment. Furthermore, home-based assessments can reduce costly visits to the clinic (Patel et al., 2012).

Fall-Risk Assessment

Fall risk is determined using three domains of assessment: 1) self-reported questionnaires and clinician-guided interviews; 2) clinical assessments of balance and gait; and 3) biomechanical laboratory-based assessments of balance and gait. Moving across each domain involves an increase in resources such as time, space requirements, equipment, and trained personnel to administer the assessment. Therefore, fall risk is often determined using self-reported questionnaires and interviews to assess fall history, balance confidence, and fear-of-falling (FoF). For example, 26-30% of older adults who have already fallen will fall again within the same year (Tinetti, 1987; Curran-Groome et al., 2020). Balance confidence and FoF can be assessed using the Falls Efficacy Scale-International (FSE-I) and Activities-Specific Balance Confidence (ABC) Scale (with a higher score reflecting more confidence and less FoF), as well as simply asking if participants are afraid of falling (Yes; No; Somewhat) (Powell and Myers, 1995; Murphy et al., 2002). Evidence indicates a strong relationship between FoF and alterations in gait pattern, exhibited as a "cautious" or conservative gait that includes slower walking speed, increased stride width and time of double-support stance, and reduced stride length (Maki, 1997; Chamberlin et al., 2005). The conservative gait pattern is suggested to increase the susceptibility of falls among older adults (Nelson et al., 1999). Therefore, FoF and balance confidence are strong predictors of fall risk.

Clinical assessments of fall risk involve the performance of balance and gait tasks such as the Timed Up and Go Test (TUGT) where participants are asked to rise from an armchair, walk 3 meters, turn around, walk back and sit down on the chair (Shumway-Cook et al., 2000); the sit-to-stand test, where participants are asked to stand up from a chair five times as fast as possible without using their arms (Tiedemann et al., 2008); and walking speed measurement (Abellan van Kan, et al., 2009, Lusardi, 2012). Among clinical assessments of balance and gait, walking speed is considered to be a vital sign of functional status (Middleton et al., 2015) and may be the single best predictor of falling when walking speed is <1.0m/s (Kyrdalen et al., 2019; Montero-Odasso et al., 2005). Biomechanical laboratory-based assessments of balance and gait involve the use of specialized equipment for the quantification of whole-body or segment-specific kinematics or kinetics during static and dynamic movements. For example, center of pressure excursion during quiet upright standing on a force plate can assess balance control (Alexander and LaPier, 1998; Harringe et al., 2007). The spatial-temporal gait parameters such stride time, length, width, as well as the variability of these parameters, estimated across consecutive strides, recorded with a motion capture system, can assess gait control (Ferreira et al., 2022). Laboratory-based assessments of gait are suggested to be more robust compared to clinical assessments of gait for identifying fall risk and distinguishing between older adult fallers and non-fallers (Hausdorff et al., 2001).

Aging, Linear Gait Variability, and Fall Risk

Older adults typically exhibit increases in linear gait variability measures, compared to young adults (Kobsar et al., 2014b). Furthermore, advancing age among older adults (60 to 86 years of age) is found to be linearly related to greater gait variability in step length, width, and double support time (Callisaya et al., 2010). Although alterations in gait variability are associated with aging, it is unclear which measures are most indicative of fall risk. Callisaya et al. (2010) reported increases in step length and step time variability with aging was associated with an increased risk of falls. Hausdorff et al. (2001) reported, among older adults, stride time variability (SD of ISI series) was greater in fallers (106ms) compared to non-fallers (49ms) and may be a potential measure for evaluating fall risk. Furthermore, stride time variability was more robust at predicting future falls compared to other common fall-risk assessments such as mean gait speed and the TUGT. Verghese et al. (2009) reported increased stride length variability and swing time variability were the best predictors of falls as well as the only predictors of injurious falls among adults > 70 years of age. Among older adults, increased stride-to-stride variability in stride length, velocity, and double-support time, was found to increase the risk of future falls, even among those with no FoF (Maki, 1997). Hausdorff et al. (1997a) reported older adult fallers have an increased stride-to-stride variability of stride time, stance time and swing time, compared to young adults and older adult non-fallers during a six-minute overground walking test. An older adult was classified as a faller or non-faller based on self-reported fall history. Interestingly, walking speed was similar between fallers and non-fallers. Furthermore, recurrent fallers or those falling more than twice had an increase in stride-to-stride variability compared to one-time fallers.

Although the above studies report that increased gait variability was indicative of fall risk, other research suggests that too little variability may also increase fall risk. Brach et al. (2005) found that among older adults walking at > 1.0m/s, too little or too much step width variability, calculated as the coefficient of variation (COV), were more likely to fall than older adults with a moderate amount of variability. These findings suggest a nonlinear relationship between fall risk and magnitude of gait variability and closely matches the OMV model and LOC hypothesis, albeit with a linear gait variability measure.

Aging, Nonlinear Gait Variability, and Fall Risk

Older adults, even those in good health, undergo physiological changes simply due to aging. The components comprising the gait control system, that is, the sensory, cognitive, and mechanical elements all deteriorate over the lifespan. Since complexity measures reflect the final output behaviour from a network of interacting components, it is suggested that aging results in an up or down regulation of sensory and neuromuscular systems. Decreases in nerve conduction velocity, wasting of muscle mass, loss of motor neurons (Vandervoort, 2002), reduction in muscle fibers (Vandervoort, 2002), increased motor unit activation variability, discretized force generation, deterioration of brain regions (i.e., basal ganglia) (Raz et al., 2003), reduced mechanoreceptors and proprioception (i.e., muscle spindles and Golgi Tendon Organs), reduced lower-limb strength and velocity are some examples of physiological and behavioural changes due to aging. Therefore, the components generating the stepping pattern reduce in number (i.e., loss of motor neurons, muscle fibers), as well as their interaction or coupling with one another (i.e., motor unit), ultimately increasing neuromuscular noise. All of these changes may be associated with changes in spatial-temporal gait parameters, underscoring the value of gait assessment as a marker for functional status among the older adult population.

Aging and the concomitant increase in neuromuscular noise (Shaffer and Harrison, 2007, Hunter et al., 2016) is suggested to be a strong predictor of unstable gait; reflected as increased gait variability (Dingwell et al., 2017) and a loss of complexity (Buzzi et al., 2003). As gait complexity breaks downs, gait adaptability is suggested to decline, resulting in an increased risk of falling. Hausdorff et al. (1997b) reported the FSI was significantly lower in older adults compared with younger adults (FSI = 0.68 versus FSI = 0.87, respectively) during overground walking. Although the FSI values differed between the two age groups, linear variability measures of stride time intervals such as the coefficient of variation (COV), were unchanged with age. These findings suggest stride-to-stride fluctuations are more random in older adults, which may increase the risk of falling. Furthermore, the FSI measure appears to be sensitive to detect subtle age-related changes in gait function. Similar findings were reported by Herman et al. (2005) who found that older adult fallers demonstrated lower FSI values compared to older adult non-fallers, indicating a more random gait pattern, while stride time variability was not different between the two groups, further demonstrating the sensitivity of the nonlinear compared to linear measures, to detect changes in gait patterns.

In the context of the OMV continuum, as well as LOC hypothesis, highly periodic and consistent gait patterns are also considered less complex. Previous research has demonstrated that aging is also reflected as a decrease in entropy, trending towards zero or greater pattern regularity (Acharya et al., 2013). Therefore, a decrease in entropy suggests a locomotor control system that is overly constraining, rigid, and inflexible, reflecting a reduced adaptive capacity. Karmakar et al. (2007) investigated the ApEn ($N = 500$, $m=3$, $r = 0.4$) of minimum toe clearance during steady-state treadmill walking among young, older fall-risk and older non-fall risk adults and reported that older adults with a fall risk have significantly lower entropy, compared to young adults and older adults without a fall risk (ApEn: older fall-risk = 0.92, young = 1.02, older = 1.04). Fall risk was determined based on having one or more falls within the past 12 months. Interestingly, older adults without a fall risk demonstrated greater entropy compared to young adults. These findings may suggest that young adults are in the middle of the OMV continuum of complete regularity and randomness, since fall-risk adults tend to move towards a more rigid and inflexible pattern (expressed as a lower entropy value), while aging tends to increase entropy, closer towards randomness. The entropy of healthy young adults was found to be in between the older adults and the fall-risk older adults, demonstrating the utility of nonlinear measures for distinguishing gait patterns between different adult populations. The MSE has also been suggested as a tool for identifying fall risk among adults > 50 years of age. Riva et al. (2013) calculated the MSE on trunk acceleration and reported a positive relationship between fall history and MSE in the anterior-posterior direction, reporting greater gait complexity was associated with fall risk. These findings appear to be in contrast to those from Karmakar et al. (2007) who reported fallers exhibited lower entropy values relative to non-fallers. However, this may be due to methodological differences such as the age of participants recruited as well as the nonlinear methods themselves (ApEn versus MSE) and measurement type (continuous versus discrete). Furthermore, these results underscore the need for a control group or control condition for interpreting entropy measurement, which is not the case for the FSI.

Although limited, some research has mapped linear and nonlinear gait variability across the lifespan to track the maturation and deterioration of gait control. Evidence suggests gait variability remains relatively stable between 20 and 69 years of age, while gait instability increases with age (Terrier and Reynard, 2015). In that study, gait variability was assessed as the RMS ratio of medial-lateral trunk acceleration to total trunk acceleration in all three axes during treadmill walking, while gait instability was assessed using Lyapunov exponents along each trunk acceleration axis. The Lyapunov exponents result from a nonlinear calculation that can be used to diagnose if chaos is present within a dynamical system. A greater Lyapunov exponent was found along the medial-lateral direction beginning during the fourth decade of life and continued to increase over the next three decades, suggesting that gait instability begins to increase at an accelerated rate beginning between age 40-50. Bisi and Stagni (2016) investigated the MSE of trunk acceleration along all three axes across the lifespan and found that, along the anterior-posterior and vertical directions, complexity generally tended to decrease from children to young adults, and then trended towards an increase between young adults to older adults. Stride time variability was also found to be stable from young adults to those up to 84 years of age (Bisi and Stagni, 2016). These findings suggest the utility of nonlinear measures for detecting changes in gait complexity with aging.

It must be noted that gait complexity is, in fact, an indirect measure of fall-risk and age-related changes in gait adaptability, due to the fact that the entangled structural components making up the gait control system, cannot be, or have yet to be, isolated. This may be due to the spontaneous self-organized behaviours, also known as emergence, that occurs from a complex system since it operates in an open environment, with no central controller (McCamley and Harrison, 2016). The complexity of the stepping pattern is considered the totality of the network of coupled components and their multi-scale operation, producing nonlinear behaviour. Therefore, identifying which specific components have explicit contributions to the complex patterns that emerge is likely never to be uncovered in humans. Since age-related neuromuscular changes are well documented (Vandervoort, 2002; Aagaard et al., 2010; Hunter et al., 2016), complexity indirectly evaluates age-related neuromuscular changes as well as changes that may be subtle between older adult fallers and non-fallers.

Indeed, laboratory-based assessments can be considered the gold-standard for movement analysis. However, such assessments are often times not feasible due to high equipment costs and time, and the requirement of trained personnel, thereby restricting fall-risk assessment to the first two domains, as described earlier. With advancements in technology, quantification of gait parameters, similar to that of laboratory-based equipment are becoming possible, with the help of wearable sensors (Benson et al., 2018).

2.2. Wearable Sensors, Accelerometers, and Smartphones

With advancements in technology, wearable sensors have grown increasingly smaller and less expensive to the point of being seamlessly integrated into our everyday technology. Wearable sensors, such as smartwatches, smart rings, and smart garments, are non-invasive measurement systems that can gather physiological data such as heartrate, as well as movement data such as step counts to monitor health status outside the clinic and throughout the day (Patel et al., 2012; Deng et al., 2023). One of the most common wearable sensors is the accelerometer (Shull et al., 2014). The first commercially available accelerometer dates back to the 1920s, weighed approximately one pound, and was priced at over $7000 dollars in today's value (Walter, 1999). It wasn't until the 1950s when accelerometers were used to measure gait (Saunders et al., 1953). By leveraging micro-electromechanical system (MEMS) technology, accelerometers decreased in cost, size, and battery power consumption, providing portability and a more detailed study of human motion while recording along all three axes of motion (Shull et al., 2014; Sprager and Juric, 2015). Today, accelerometers are a standard component in smartphones, weighing <10 grams, and priced at $10-15.

Although there are different types of accelerometers such as piezoelectric, piezoresistive, and capacitive, acceleration measurement is described as a mass and spring system operating under Newton's second law of motion and Hooke's law. Hooke's law states that the force required to change the length of a spring by some distance scales linearly to that distance. Since the mass and spring stiffness quantities are known, the restoring force generated by the spring following a change in spring length (extension or compression) due to movement of the mass can be determined. This restoring force is then related to the acceleration of the mass:

$$\text{Newton's second law } F = ma\text{; Hooke's Law: } F = xk$$

$$F = ma = xk\text{, therefore,} \qquad a = xk/m$$

Where F = force, a = acceleration, m = mass, k = spring stiffness, x = spring length.

The most common accelerometer measures acceleration by measuring the change in capacitance as a mass, attached to springs, moves while surrounded by paired capacitors fixed to the housing. At rest, the voltage between the paired capacitors remains constant. As the mass undergoes movement relative to the housing, an imbalance between the capacitors creates an electrical output that is proportional to the magnitude of movement of the mass (Kavanagh and Menz, 2008) (Figure 2.6).

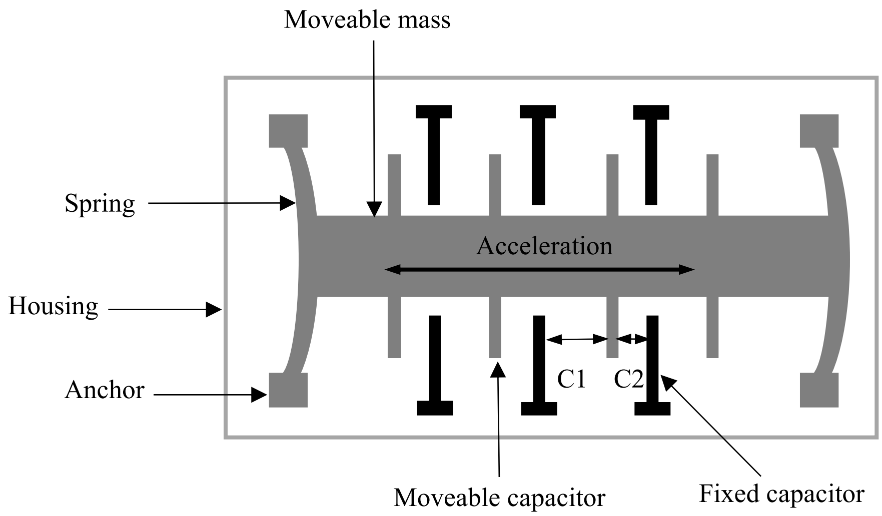

Figure 2.6. Diagram of a capacitive accelerometer. C represents capacitance. As the mass moves relative to the housing, the capacitance between the fixed and moveable capacitors changes, creating an imbalance between them (C1 and C2). The change in capacitance creates an electrical output signal that is related to the magnitude of acceleration. Figure created by author.

Conventional gait measurement involves the use of expensive laboratory equipment such as motion capture systems (i.e., Vicon), pressure-sensing walkways, force plates, and force-sensing resistor (FSR) footswitch systems that are considered the gold standard (GS) for gait analysis (Springer and Seligmann, 2016; Beauchet et al., 2008). However, such equipment, requires trained personnel for operation, and is typically restricted to the confines of the laboratory. Furthermore, the requirement of many continuous strides (>200) for nonlinear analysis of stride-to-stride fluctuations often restricts data collection to treadmill walking (Kiriella et al., 2020). Compared to overground walking, treadmill walking can misrepresent gait complexity as more or less healthy than it actually is (Hollman et al., 2016). For example, healthy young adults demonstrate decreased gait complexity during treadmill walking while Parkinson patients increase their gait complexity, similar to that of healthy young adults, likely due to the pace-keeping imposed by the treadmill belt. Therefore, efforts are being made to move data collection to overground walking while still capturing hundreds of continuous strides with the help of accelerometers. For example, Kobsar et al. (2014a) validated the use of a single accelerometer fixed to the low back among older adults for measuring linear and nonlinear gait variability measures compared to a gold-standard footswitch system during overground walking and reported the accelerometer performs similarly to that of typical research-grade equipment. Furthermore, Kobsar et al. (2014b) reported age-related effects while estimating stride time variability and stride time complexity (FSI) while using a single accelerometer fixed to the low back. These findings provide encouraging results for the use of a single accelerometer to estimate linear and nonlinear gait measures during overground walking and among different age groups. However, the majority of gait dynamics research is recorded in controlled environments such as a laboratory, vacant corridor, or indoor track center (Kobsar et al., 2014b; Yentes et al., 2018), thereby not reflecting a true representation of gait complexity compared to walking in the natural environment with constant obstacle negotiation challenges. Therefore, the development of a gait analysis tool that is low-cost, valid, and used in the natural free-living environment is highly desirable.

Wearables in the Free-Living Environment

Wearable accelerometer systems implemented for gait analysis in the free-living environment are typically affixed to the wearer's thigh (Godfrey et al., 2016), waist (Rispens et al., 2016), low back (Del Din et al., 2016), or chest (Brodie et al., 2015) and are used in combination with one another (Mancini et al., 2016; Tamburini et al., 2018), or as a single sensor (Weiss et al., 2013). Additionally, wearable sensors are suggested to provide valid and reliable estimates of spatial-temporal gait parameters when compared to gold-standard measurement systems (Kobsar et al., 2020). After recording acceleration during an activity, algorithms are applied to the acceleration curves to identify events of interest (e.g., heel contact), as well as the magnitude and duration of movement, typically using minimum or maximum amplitude detection thresholds, to classify the activity. For example, a specified number of repetitive peaks of a pre-defined magnitude within a specified duration in the vertical direction can differentiate walking from running or standing, where walking activity would have lower peak acceleration magnitudes compare to running, but greater peak magnitudes compared to standing. Therefore, accelerometers can be used for activity classification to capture walking bouts, and once walking bouts are identified, gait parameters can be estimated such as stride time, stride length, and walking speed (Del Din et al., 2016). For example, Brodie et al. (2015) identified walking bouts by three consecutive heel strike peaks in less than a three second period. Although wearable sensors can classify many types of activities, gait is the most commonly investigated as it is a strong predictor of future falls (Patel et al., 2020; Subramaniam et al., 2022).

Wearable sensors have moved beyond classifying activity or capturing the volume of activity, such as step count, enabling the quantification of spatial-temporal gait parameters and gait variability (Del Din et al., 2016/2019). Recent research has described the efficacy of gait analysis, via wearable sensors, in the natural environment; suggesting wearables can assess fall risk while monitoring for an extended period of time (>24 hours) (Nouredanesh et al., 2021). Furthermore, wearable sensors were found to identify future fallers when traditional clinical assessments could not (Patel et al. 2020). Weiss et al. (2013) monitored gait patterns over a 3-

day period among older adults using an accelerometer affixed to the low back. The accelerometer was able to identify walking bouts as participants went about their daily activities. Furthermore, step-to-step variability, reflected as frequency measurements (amplitude of dominant frequencies in the vertical axis), demonstrated the utility of a wearable sensor to detect fall risk among older adults, through long-term monitoring of gait in an unconstrained environment. Brodie et al. (2015) monitored gait patterns of older adults over an eight-week period using a pendant sensor equipped with an accelerometer and pressure sensor worn at sternum height and found older adult fallers, compared to non-fallers, took fewer steps per walking bout, and demonstrated greater step-time variability (SD of step time).

Differences in gait characteristics between in-lab and free-living walking have also been identified with the help of wearable sensors, supporting the necessity to record walking patterns in the natural environment (Del Din et al., 2016). For example, older adults exhibit greater step time variability during overground walking in the laboratory compared to free-living walking (Brodie et al., 2015). Hillel et al. (2019) compared in-lab dual task walking to free-living walking and reported free-living walking step regularity (reflecting gait asymmetry) was similar to that of dual-task walking in the laboratory setting among older adult fallers. The authors suggest these differences may be due to the reverse white coat syndrome where participants may act at their ‘best’, with greater effort, better mood, and less fatigue, compared to free-living gait recorded across seven days. Tamburini et al. (2018) reported significant differences in gait variability (SD and COV of stride time) between free-walking (city centre or university campus) and overground controlled-walking (straight vacant corridor or pathway) conditions among young adults. Gait variability was found to be greater during the free-walking condition. Therefore, wearable sensors may provide robust estimates of gait performance while recording in the free-living environment compared to the laboratory setting. Furthermore, wearable sensors may provide an authentic representation of gait as evidenced by differences between free-living and laboratory walking. However, it remains unclear which measures are most indicative of fall-risk and the age-related deterioration of the neuromuscular system. Just as gait complexity has demonstrated greater sensitivity to age-related changes and fall-risk assessment compared to linear variability measures in a controlled environment, it seems obvious that the same effect would take place in the free-living environment. However, literature estimating nonlinear gait variability and gait complexity in the free-living environment has been limited until recent (van Schooten et al., 2016; Ihlen et al., 2018; Schootemeijer et al. 2020).

In a follow-up study, Ihlen et al. (2016) reanalysed the acceleration data previously collected from Weiss et al. (2013) and applied multiscale entropy measures on walking bouts found throughout the day. Findings demonstrated greater entropy values (i.e., greater complexity) among older adult non-fallers compared to older fallers, reflecting greater gait adaptability. Furthermore, entropy measurement was better than the other conventional gait features for distinguishing fallers from non-fallers. Cavanaugh et al. (2010) recorded the number of steps per minute across a two-week period using the StepWatch activity monitor while attached to the ankle among inactive, moderately active, and highly active older adults. After recording, complexity (FSI, ApEn) and variability (COV) was assessed using the step count time series of 1-minute step counts for each day. The authors reported that complexity increased with increased physical activity, while COV was not different between the three levels of activity. Although that study calculated the FSI, the time series used was step counts per minute and not the fluctuations from one stride to the next. Shema-Shiratzky et al. (2020) compared gait complexity using sample entropy derived from a tri-axial accelerometer affixed to the low back while recording for seven days in the free-living environment and found greater sample entropy for healthy controls compared to those with multiple sclerosis. The findings thus far reveal the possibility of wearable sensors to estimate nonlinear gait measures in the free-living environment, with entropy measurement as the one of the most common nonlinear measures (Nouredanesh et al., 2021; Nohelova et al., 2021; Amirpourabasi et al., 2022). However, as discussed earlier, multiscale entropy must be used to measure complexity, as well as the inclusion of a control group to interpret the results.

The FSI value is generally established in the literature and shows consistent directional sensitivity such that older and pathological populations tend to show a decrease in FSI closer to randomness while healthy young adults show higher levels during overground walking. Surprisingly, it appears that only one study has estimated the FSI during daily life walking, conducted by Cavanaugh et al. (2010), although not applied to the ISI series. These gaps in the literature may be due to methodological limitations such as data length concerns, the selection of which nonlinear analysis should be performed (e.g., DFA, entropy, Lyapunov exponents), or perhaps nonlinear analysis is uncommon as the outcome measures are not easy to comprehend and interpret (e.g., does higher entropy mean better adaptability? is there such a thing as "too high"?). Additionally, how does a continuous measurement reflect the output of a system compared to a discrete measure. Does a continuous measurement reflect more subtle changes within a time series or are discrete measures more indicative of the interactions of the entangled components and the multi-scale behaviour of the system. What is more important, fluctuations throughout the movement pattern, or the end results of a movement pattern. These differences may in fact represent two fundamentally different, yet related aspects of a system's control. Currently, the majority of entropy measures estimated with wearable sensors in the free-living environment are conducted on the continuous measurement of the acceleration waveform instead of discrete ISI values to account for data length concerns, which wearables recording for extended periods of time would likely address. What is clear is that the estimation of gait complexity in the free-living environment is very novel and has been investigated only in the last decade. Furthermore, there is a lack of practicality due to the requirement of additional equipment and with ecological wearability as the vast majority of sensors require being securely affixed to a specific body location or placed in an external pocket (e.g., bag). Therefore, a smartphone accelerometer system may be a more user-friendly and viable alternative.

Smartphone Systems

With advancements in smartphone (SP) technology, researchers are beginning to access the built-in inertial sensors available such as tri-axial accelerometers to capture human movement (Konsolakis et al., 2018). Furthermore, with over 50% of the world's population owning a smartphone (O'Dea, 2021), requisite equipment for gait analysis appears to be already widely available. The utility of smartphone-based gait analysis systems is growing in the literature and offers the potential of monitoring gait outside the laboratory and for extended periods of time (Qin and Huang, 2015; Silsupadol et al., 2017; Lugade et al., 2021). The majority of studies have validated gait measures derived from smartphone-based accelerometers (SPAcc) against gold-standard measurement tools such as pressure sensing mats, inertial measurement unit systems, and motion capture systems (Nishiguchi et al., 2012; Yang et al., 2012; How et al., 2013; Rashid et al., 2021; Christensen et al., 2022). Findings have demonstrated that the SPAcc provides accurate and reliable spatial-temporal gait measures, such as stride time, step length, gait velocity, and cadence when placed in the front pocket or affixed to the lower back

(Silsupadol et al., 2017; Yang et al., 2012; Manor et al., 2018; Shahar and Agmon, 2021). However, the majority of these validation studies are conducted on healthy young adults, while walking short distances (< 25 meters) in a controlled environment (laboratory or vacant corridor) (Lemoyne et al., 2010; Yang et al., 2012). Furthermore, there is a lack of research reporting the validity of variability measures (linear or nonlinear) derived from SPAcc (Hammoud et al., 2015).

Currently, only one study has validated gait complexity derived from a SPAcc (Hammoud et al., 2015). In that study, the SPAcc was affixed to the right side of a belt worn around the hips and was compared against a pressure sensing insole sensor as participants walked back and forth along a vacant corridor. The findings suggested that the SPAcc performed similarly to that of the reference system for estimating gait FSI. However, the data collection methodology was not appropriate for capturing gait dynamics. The methodological issues included an absence of continuous steady-state walking and the sampling rate (38Hz) used to record walking data was too low. The analysis of a dynamical system requires a sufficient number of continuous data to uncover the system's pattern over time. Therefore, a protocol of participants walking back and forth along a corridor effectively breaks the temporal evolution of the stepping pattern, essentially creating short, separate trials with stride-to-stride fluctuations that are unrelated to one another. Furthermore, a low sampling rate may not provide enough resolution to accurately locate heel contact events. For example, Marmelat et al. (2019) recommends the sampling rate for kinematic (position) data should be set to around 120Hz to ensure adequate event detection accuracy when the DFA calculation is implemented on stride time data. Furthermore, no assessment of the test re-test reliability of the smartphone system was conducted, warranting further research.

Smartphone System Validation

In order for a new measurement system to replace an existing system, the new system must be compared to known and accepted quantities such as those derived from gold-standard systems. Furthermore, the new system should perform similarly across repeated measurements. The validation, that is, the assessment of a new system, compared to an existing system while recording simultaneously is called concurrent validation, and should evaluate the accuracy and precision of a measurement system. The vast majority of smartphone validation studies claim valid estimates of gait parameters derived from the smartphone system when compared to a gold-standard system. However, rarely do these studies use appropriate methods for concurrent validation.

Accuracy refers to the ability to measure a quantity close to its true value. However, the true value is likely unknown, so it is approximated by a reference or gold-standard system. Precision refers to the spread of repeated measurements. The Bland-Altman (BA) analysis measures the agreement (concordance) between two measurement systems instead of comparing the new system to a 'perfect' system, thereby providing the interchangeability between the gold-standard and new system. In other words, agreement assesses if measurement of the same variable by two different systems produce similar results. The BA analysis provides a plot of the mean of two different measurements ((system A + system B)/2) against the difference between the two measurements (system A – system B). Furthermore, the BA analysis provides an estimate of accuracy and precision (Montenij et al., 2016). The BA analysis provides a measure of accuracy by determining the average difference between the new and gold-standard systems, termed bias. The BA analysis provides a measure of precision with the 95% limits of agreement (LOA) and are generally calculated as follows: LOA = bias ± 1.96 x SD of the differences. The

LOA represent where 95% of the differences between the measurement systems are expected to be. Although the BA analysis involves the calculation of the LOA, acceptable boundaries for the LOA must be set *a priori* to determine agreement between the new and gold-standard systems (Giavarina, 2015). Therefore, *a priori* LOA are first defined and then the calculated LOA, based on the collected data, are compared (i.e., *a priori* LOA versus calculated LOA). Since the BA analysis does not provide a *p*-value as a decisive answer, the acceptable *a priori* LOA should be determined based on an expected difference between healthy and unhealthy populations for the measure of interest (Giavarina, 2015). The comparison between healthy and unhealthy populations provides some level of quantification of the acceptability criteria used for the new measurement system. The bias provided by the BA analysis can indicate whether the new system over or underestimates measurements relative to the gold-standard system. Therefore, the bias can be interpreted as systematic (predictable) error and can be corrected.

Although current smartphone validation studies often times report BA results such as bias and 95% LOA, the *a priori* acceptable boundaries are missing. Therefore, these studies claim agreement or validity without a criterion, making their claims meaningless. Only two studies to date has defined acceptable LOA to determine agreement between a smartphone and gold-standard measurement system (Rashid et al., 2021; Shema-Shiratzky et al., 2022). However, it is unclear where the acceptable boundary values, expressed as percentages relative of the mean (i.e., very good agreement = < 5%, good agreement = 5-10%), were derived from, or why there are varying levels of agreement as the new and gold-standard systems either agree or do not agree. Furthermore, the Pearson correlation coefficient is often used to determine the validity of smartphone systems. However, correlation measures the linear relationship between two different variables, while agreement measures the concordance (similarity) between two measurements for one variable (Ranganathan et al., 2017). Two measurements can be highly correlated but may not agree. For example, suppose two different raters, rater A and rater B, measure the same variable, but rater A consistently measures the variable two units lower than rater B. This result would produce a high correlation since both raters are consistent but does not provide a measure of bias. Therefore, caution must be taken when suggesting valid estimates of a new system using correlation.

Smartphones in the Free-Living Environment

To date, only a limited number of studies have implemented smartphones to estimate gait parameters in the free-living or home environments (Rye Hanton et al. 2017; Manor et al., 2018; Lugade et al., 2021). Furthermore, very few studies have implemented the smartphone system in a natural, user-friendly method such as in the user's pant pocket (Manor et al., 2018; Rye Hanton et al. 2017). Lugade et al. (2021) monitored walking patterns remotely for three days using the personal smartphones of young adults, older adult non-fallers, and older adult fallers, and reported young adults demonstrated greater gait velocity, cadence, and shorter step times compared to both older adult groups, which were not different from each other across all gait measures. The smartphone was placed horizontally by their right hip in a pouch on a belt. Although not statistically significant, some participants reported that the smartphone placement hindered some movements of daily activity, was not easily accessible, and not aesthetically pleasing. Furthermore, gait variability was not assessed which may have uncovered differences between the non-faller and faller adult groups. Rye Hanton et al. (2017) measured gait speed in the free-living environment throughout a 24-hour period using a smartphone placed in the hip pocket among frail and healthy older adults and reported significant differences between the two groups. The results from the above studies suggest smartphone-based gait systems are a viable option to estimate gait performance among different adult population groups.

Among all smartphone-based gait systems implemented in the free-living environment, no study to date has quantified linear or nonlinear gait variability. Furthermore, it is unknown how stride time complexity is reflected in the unconstrained environment. Does free-living walking represent maximum fractal scaling by increasing functional variance such that even healthy older adults exhibit greater FSI values closer to pink noise (FSI ≈ 1.0) or would free-living walking decrease FSI values towards randomness (FSI ≈ 0.5) due to the increased variance that is associated with free-living walking, as demonstrated with linear variability measures when comparing controlled and free-living walking conditions (Weiss et al., 2011/2013; Brodie et al., 2015; Tamburini et al., 2018). Therefore, free-living walking may be required to provide a true representation of gait complexity for the population of interest, and further provide a marker for the health status of the walker. Finally, there is a lack practicality with the use of current wearable sensors, due to the requirement of additional equipment and with ecologically valid wearability as the vast majority of sensors require secure attachment to a specific body location (i.e., low back) or placed in an external pocket (i.e., bag or pouch). Therefore, the development of a valid smartphone accelerometer system while simply placed in the pant pocket may be a user-friendly and viable alternative to monitor gait complexity in the wild.

2.3. References

Aagaard, P., Suetta, C., Caserotti, P., Magnusson, S. P., & Kjaer, M. (2010). Role of the nervous system in sarcopenia and muscle atrophy with aging: strength training as a countermeasure. *Scandinavian journal of medicine & science in sports*, *20*(1), 49–64. https://doi.org/10.1111/j.1600-0838.2009.01084.x

Abellan van Kan, G., Rolland, Y., Andrieu, S., Bauer, J., Beauchet, O., Bonnefoy, M., Cesari, M., Donini, L. M., Gillette Guyonnet, S., Inzitari, M., Nourhashemi, F., Onder, G., Ritz, P., Salva, A., Visser, M., & Vellas, B. (2009). Gait speed at usual pace as a predictor of adverse outcomes in community-dwelling older people an International Academy on Nutrition and Aging (IANA) Task Force. *The journal of nutrition, health & aging*, *13*(10), 881–889. https://doi.org/10.1007/s12603-009-0246-z

Acharya, U. R., Sree, S. V., Lim, C. M., Ang, P. C., Sekine, M., & Tamura, T. (2013). Comparison of walking parameters obtained from the young, elderly and adults with support. *Computer methods in biomechanics and biomedical engineering*, *16*(11), 1202–1212. https://doi.org/10.1080/10255842.2012.656613

Alexander, K. M., & LaPier, T. L. (1998). Differences in static balance and weight distribution between normal subjects and subjects with chronic unilateral low back pain. *The Journal of orthopaedic and sports physical therapy*, *28*(6), 378–383. https://doi.org/10.2519/jospt.1998.28.6.378

Ashkenazy, Y., Hausdorff, J. A., Ivanov, P. C., & Stanley, H. E. (2002). A stochastic model of human gait dynamics. Physica A – Statistical Mechanics and Its Applications, 316, 662–670.

Amirpourabasi, A., Lamb, S. E., Chow, J. Y., & Williams, G. K. R. (2022). Nonlinear Dynamic Measures of Walking in Healthy Older Adults: A Systematic Scoping Review. *Sensors (Basel, Switzerland)*, *22*(12), 4408. https://doi.org/10.3390/s22124408

Beauchet, O., Herrmann, F. R., Grandjean, R., Dubost, V., Allali, G. (2008). Concurrent validity of SMTEC® footswitches system for the measurement of temporal gait parameters. Gait & Posture, 27(1), 156-159.

Benson, L. C., Clermont, C. A., Bošnjak, E., & Ferber, R. (2018). The use of wearable devices for walking and running gait analysis outside of the lab: A systematic review. *Gait & posture*, *63*, 124–138. https://doi.org/10.1016/j.gaitpost.2018.04.047

Bernstein NA. The co-ordination and regulation of movements. Oxford; New York: Pergamon Press, 1967.

Bisi, M. C., & Stagni, R. (2016). Complexity of human gait pattern at different ages assessed using multiscale entropy: From development to decline. *Gait & posture*, *47*, 37–42. https://doi.org/10.1016/j.gaitpost.2016.04.001

Blake, A. J., Morgan, K., Bendall, M. J., Dallosso, H., Ebrahim, S. B., Arie, T. H., Fentem, P. H., & Bassey, E. J. (1988). Falls by elderly people at home: prevalence and associated factors. *Age and ageing*, *17*(6), 365–372. https://doi.org/10.1093/ageing/17.6.365

Brach, J. S., Berlin, J. E., VanSwearingen, J. M., Newman, A. B., & Studenski, S. A. (2005). Too much or too little step width variability is associated with a fall history in older persons who walk at or near normal gait speed. *Journal of neuroengineering and rehabilitation*, *2*, 21. https://doi.org/10.1186/1743-0003-2-21

Brodie, M. A., Lord, S. R., Coppens, M. J., Annegarn, J., & Delbaere, K. (2015). Eight-Week Remote Monitoring Using a Freely Worn Device Reveals Unstable Gait Patterns in Older Fallers. *IEEE transactions on bio-medical engineering*, *62*(11), 2588–2594. https://doi.org/10.1109/TBME.2015.2433935

Busa, M. A., Jones, S. L., Hamill, J., & van Emmerik, R. E. (2016). Multiscale entropy identifies differences in complexity in postural control in women with multiple sclerosis. *Gait & posture*, *45*, 7–11. https://doi.org/10.1016/j.gaitpost.2015.12.007

Busa, M. A., & van Emmerik, R. E. A. (2016). Multiscale entropy: A tool for understanding the complexity of postural control. *Journal of sport and health science*, *5*(1), 44–51. https://doi.org/10.1016/j.jshs.2016.01.018

Buzzi, U. H., Stergiou, N., Kurz, M. J., Hageman, P. A., & Heidel, J. (2003). Nonlinear dynamics indicates aging affects variability during gait. Clinical Biomechanics (Bristol, Avon), 18, 435–443.

Callisaya, M. L., Blizzard, L., Schmidt, M. D., McGinley, J. L., & Srikanth, V. K. (2010). Ageing and gait variability--a population-based study of older people. *Age and ageing*, *39*(2), 191–197. https://doi.org/10.1093/ageing/afp250

Cavanaugh, J. T., Kochi, N., & Stergiou, N. (2010). Nonlinear analysis of ambulatory activity patterns in community-dwelling older adults. *The journals of gerontology. Series A, Biological sciences and medical sciences*, *65*(2), 197–203. https://doi.org/10.1093/gerona/glp144

Chamberlin, M. E., Fulwider, B. D., Sanders, S. L., & Medeiros, J. M. (2005). Does fear of falling influence spatial and temporal gait parameters in elderly persons beyond changes associated with normal aging?. *The journals of gerontology. Series A, Biological sciences and medical sciences*, *60*(9), 1163–1167. https://doi.org/10.1093/gerona/60.9.1163

Christensen, J. C., Stanley, E. C., Oro, E. G., Carlson, H. B., Naveh, Y. Y., Shalita, R., & Teitz, L. S. (2022). The validity and reliability of the OneStep smartphone application under various gait conditions in healthy adults with feasibility in clinical practice. *Journal of orthopaedic surgery and research*, *17*(1), 417. https://doi.org/10.1186/s13018-022-03300-4

Costa, M., Goldberger, A. L., & Peng, C. K. (2002). Multiscale entropy analysis of complex physiologic time series. *Physical review letters*, *89*(6), 068102. https://doi.org/10.1103/PhysRevLett.89.068102

Costa, M., Goldberger, A. L., & Peng, C. K. (2005). Multiscale entropy analysis of biological signals. *Physical review. E, Statistical, nonlinear, and soft matter physics*, *71*(2 Pt 1), 021906. https://doi.org/10.1103/PhysRevE.71.021906

Costa, M., Peng, C. K., Goldberger, A. L., & Hausdorff, J. M. (2003). Multiscale entropy analysis of human gait dynamics. *Physica A*, *330*(1-2), 53–60. https://doi.org/10.1016/j.physa.2003.08.022

Curran-Groome, W., Klein, G., Miller, S. B., Hui, A., Wilson, J. S., Kuoiloi, C., Masarapu, V., Alabd, A., Mascaro, T., Logan, G., & Lubeck, J. (2020). Risk Factors of Recurrent Falls Among Older Adults Admitted to the Trauma Surgery Department. *Geriatric orthopaedic surgery & rehabilitation*, *11*, 2151459320943165. https://doi.org/10.1177/2151459320943165

Delignières, D., & Marmelat, V. (2012). Fractal fluctuations and complexity: current debates and future challenges. *Critical reviews in biomedical engineering*, *40*(6), 485–500. https://doi.org/10.1615/critrevbiomedeng.2013006727

Del Din, S., Godfrey, A., Galna, B., Lord, S., & Rochester, L. (2016). Free-living gait characteristics in ageing and Parkinson's disease: impact of environment and ambulatory bout length. *Journal of neuroengineering and rehabilitation*, *13*(1), 46. https://doi.org/10.1186/s12984-016-0154-5

Del Din, S., Galna, B., Godfrey, A., Bekkers, E. M. J., Pelosin, E., Nieuwhof, F., Mirelman, A., Hausdorff, J. M., & Rochester, L. (2019). Analysis of Free-Living Gait in Older Adults With and Without Parkinson's Disease and With and Without a History of Falls: Identifying Generic and Disease-Specific Characteristics. *The journals of gerontology. Series A, Biological sciences and medical sciences*, *74*(4), 500–506. https://doi.org/10.1093/gerona/glx254

Deng, Z., Guo, L., Chen, X., & Wu, W. (2023). Smart Wearable Systems for Health Monitoring. *Sensors (Basel, Switzerland)*, *23*(5), 2479. https://doi.org/10.3390/s23052479

Dingwell, J. B., Salinas, M. M., & Cusumano, J. P. (2017). Increased gait variability may not imply impaired stride-to-stride control of walking in healthy older adults: Winner: 2013 Gait and Clinical Movement Analysis Society Best Paper Award. *Gait & posture*, *55*, 131–137. https://doi.org/10.1016/j.gaitpost.2017.03.018

Dionyssiotis Y. (2012). Analyzing the problem of falls among older people. *International journal of general medicine*, *5*, 805–813. https://doi.org/10.2147/IJGM.S32651

Ferreira, M. I. A. S. N., Barbieri, F. A., Moreno, V. C., Penedo, T., & Tavares, J. M. R. S. (2022). Machine learning models for Parkinson's disease detection and stage classification based on spatial-temporal gait parameters. *Gait & posture*, *98*, 49–55. https://doi.org/10.1016/j.gaitpost.2022.08.014

Giavarina D. (2015). Understanding Bland Altman analysis. *Biochemia medica*, *25*(2), 141–151. https://doi.org/10.11613/BM.2015.015

Godfrey, A., Morris, R., Hickey, A., & Del Din, S. (2016). Beyond the front end: Investigating a thigh worn accelerometer device for step count and bout detection in Parkinson's disease. *Medical engineering & physics*, *38*(12), 1524–1529. https://doi.org/10.1016/j.medengphy.2016.09.023

Goldberger A. L. (1996). Non-linear dynamics for clinicians: chaos theory, fractals, and complexity at the bedside. *Lancet (London, England)*, *347*(9011), 1312–1314. https://doi.org/10.1016/s0140-6736(96)90948-4

Goldberger, A. L., Amaral, L. A., Hausdorff, J. M., Ivanov, P. C.h, Peng, C. K., & Stanley, H. E. (2002). Fractal dynamics in physiology: alterations with disease and aging. *Proceedings of the National Academy of Sciences of the United States of America*, *99 Suppl 1*(Suppl 1), 2466–2472. https://doi.org/10.1073/pnas.012579499

Hammoud, A., Duchêne, J., Abou-ghaida, H., Mottet, S., Goujon, J., Hewson, D.J. (2015). Validation of a Smartphone Gait Analysis System, International Federation for Medical and Biological Engineering Proceedings 45,910–913.

Harringe, M. L., Halvorsen, K., Renström, P., & Werner, S. (2008). Postural control measured as the center of pressure excursion in young female gymnasts with low back pain or lower extremity injury. *Gait & posture*, *28*(1), 38–45. https://doi.org/10.1016/j.gaitpost.2007.09.011

Hausdorff, J. M., Edelberg, H. K., Mitchell, S. L., Goldberger, A. L., & Wei, J. Y. (1997a). Increased gait unsteadiness in community-dwelling elderly fallers. Archives of Physical Medicine and Rehabilitation, 78, 278–283.

Hausdorff, J. M., Mitchell, S. L., Firtion, R., Peng, C. K., Cudkowicz, M. E., Wei, J. Y., et al. (1997b). Altered fractal dynamics of gait: Reduced stride-interval correlations with aging and Huntington’s disease. Journal of Applied Physiology, 82, 262–269.

Hausdorff, J.M., Peng, C.K., Ladin, Z., Wei, J.Y., Goldberger, A.L. (1995). Is walking a random walk? Evidence for long-range correlations in stride interval of human gait. Journal of Applied Physiology, 78, 349–358.

Hausdorff, J. M., Rios, D. A., & Edelberg, H. K. (2001). Gait variability and fall risk in community-living older adults: a 1-year prospective study. *Archives of physical medicine and rehabilitation*, *82*(8), 1050–1056. https://doi.org/10.1053/apmr.2001.24893

Herman, T., Giladi, N., Gurevich, T., Hausdorff, J. M. (2005). Gait instability and fractal dynamics of older adults with a "cautious" gait: Why do certain older adults walk fearfully? Gait & Posture, 21(1), 178-185.

Hillel, I., Gazit, E., Nieuwboer, A., Avanzino, L., Rochester, L., Cereatti, A., Croce, U. D., Rikkert, M. O., Bloem, B. R., Pelosin, E., Del Din, S., Ginis, P., Giladi, N., Mirelman, A., & Hausdorff, J. M. (2019). Is every-day walking in older adults more analogous to dual-task walking or to usual walking? Elucidating the gaps between gait performance in the lab and during 24/7 monitoring. *European review of aging and physical activity : official journal of the European Group for Research into Elderly and Physical Activity*, *16*, 6.

Hoffman, G. J., Ha, J., Alexander, N. B., Langa, K. M., Tinetti, M., & Min, L. C. (2018). Underreporting of Fall Injuries of Older Adults: Implications for Wellness Visit Fall Risk Screening. *Journal of the American Geriatrics Society*, *66*(6), 1195–1200. https://doi.org/10.1111/jgs.15360

Hollman, J. H., Watkins, M. K., Imhoff, A. C., Braun, C. E., Akervik, K. A., & Ness, D. K. (2016). Complexity, fractal dynamics and determinism in treadmill ambulation: Implications for clinical biomechanists. *Clinical biomechanics (Bristol, Avon)*, *37*, 91–97. https://doi.org/10.1016/j.clinbiomech.2016.06.007

How, T., Chee, J., Wan, E, Mihailidis, A. (2013). MyWalk : A Mobile App for Gait Asymmetry Rehabilitation in the Community. PervasiveHealth 13: 73-76.

Hunter, S. K., Pereira, H. M., & Keenan, K. G. (2016). The aging neuromuscular system and motor performance. *Journal of applied physiology (Bethesda, Md. : 1985)*, *121*(4), 982–995. https://doi.org/10.1152/japplphysiol.00475.2016

Ihlen, E. A. F., van Schooten, K. S., Bruijn, S. M., van Dieën, J. H., Vereijken, B., Helbostad, J. L., & Pijnappels, M. (2018). Improved Prediction of Falls in Community-Dwelling Older Adults Through Phase-Dependent Entropy of Daily-Life Walking. *Frontiers in aging neuroscience*, *10*, 44. https://doi.org/10.3389/fnagi.2018.00044

Ihlen, E. A. F., Weiss, A., Bourke, A., Helbostad, J. L., & Hausdorff, J. M. (2016). The complexity of daily life walking in older adult community-dwelling fallers and non-fallers. *Journal of biomechanics*, *49*(9), 1420–1428. https://doi.org/10.1016/j.jbiomech.2016.02.055

Karmakar, C. K., Khandoker, A. H., Begg, R. K., Palaniswami, M., & Taylor, S. (2007). Understanding ageing effects by approximate entropy analysis of gait variability. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society.*

IEEE Engineering in Medicine and Biology Society. Annual International Conference, *2007*, 1965–1968. https://doi.org/10.1109/IEMBS.2007.4352703

Kavanagh, J. J., & Menz, H. B. (2008). Accelerometry: a technique for quantifying movement patterns during walking. *Gait & posture*, *28*(1), 1–15. https://doi.org/10.1016/j.gaitpost.2007.10.010

Kiriella, J. B., Di Bacco, V. E., Hollands, K. L., & Gage, W. H. (2020). Evaluation of the Effects of Prescribing Gait Complexity Using Several Fluctuating Timing Imperatives. *Journal of motor behavior*, *52*(5), 570–577. https://doi.org/10.1080/00222895.2019.1654971

Kobsar, D., Charlton, J. M., Tse, C. T. F., Esculier, J. F., Graffos, A., Krowchuk, N. M., Thatcher, D., & Hunt, M. A. (2020). Validity and reliability of wearable inertial sensors in healthy adult walking: a systematic review and meta-analysis. *Journal of neuroengineering and rehabilitation*, *17*(1), 62. https://doi.org/10.1186/s12984-020-00685-3

Kobsar, D., Olson, C., Paranjape, R., Hadjistavropoulos, T., & Barden, J. M. (2014a). Evaluation of age-related differences in the stride-to-stride fluctuations, regularity and symmetry of gait using a waist-mounted tri-axial accelerometer. *Gait & posture*, *39*(1), 553–557. https://doi.org/10.1016/j.gaitpost.2013.09.008

Kobsar, D., Olson, C., Paranjape, R., & Barden, J. M. (2014b). The validity of gait variability and fractal dynamics obtained from a single, body-fixed triaxial accelerometer. *Journal of applied biomechanics*, *30*(2), 343–347. https://doi.org/10.1123/jab.2013-0107

Konsolakis, K., Hermens, H., Villalonga, C., Vollenbroek-Hutten, M., & Banos, O. (2018). Human Behaviour Analysis through Smartphones. *UCAmI 2018*. https://doi.org/10.3390/proceedings2191243

Kyrdalen, I. L., Thingstad, P., Sandvik, L., & Ormstad, H. (2019). Associations between gait speed and well-known fall risk factors among community-dwelling older adults. *Physiotherapy research international : the journal for researchers and clinicians in physical therapy*, *24*(1), e1743. https://doi.org/10.1002/pri.1743

Lemoyne, R., Mastroianni, T., Cozza, M., Coroian, C., & Grundfest, W. (2010). Implementation of an iPhone as a wireless accelerometer for quantifying gait characteristics. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, *2010*, 3847–3851. https://doi.org/10.1109/IEMBS.2010.5627699

Lipsitz, L. A., & Goldberger, A. L. (1992). Loss of 'complexity' and aging. Potential applications of fractals and chaos theory to senescence. *JAMA*, *267*(13), 1806–1809.

Lugade, V., Kuntapun, J., Prupetkaew, P., Boripuntakul, S., Verner, E., & Silsupadol, P. (2021). Three-Day Remote Monitoring of Gait Among Young and Older Adults Using

Participants' Personal Smartphones. *Journal of aging and physical activity*, *29*(6), 1026–1033. https://doi.org/10.1123/japa.2020-0353

Lusardi, M. (2012). Is walking speed a vital sign? Absolutely! *Topics in Geriatric Rehabilitation 28*(2), 67-76. doi: 10.1097/TGR.0b013e31824385a4

Maki B. E. (1997). Gait changes in older adults: predictors of falls or indicators of fear. *Journal of the American Geriatrics Society*, *45*(3), 313–320. https://doi.org/10.1111/j.1532-5415.1997.tb00946.x

Mäkikallio, T. H., Koistinen, J., Jordaens, L., Tulppo, M. P., Wood, N., Golosarsky, B., Peng, C. K., Goldberger, A. L., & Huikuri, H. V. (1999). Heart rate dynamics before spontaneous onset of ventricular fibrillation in patients with healed myocardial infarcts. *The American journal of cardiology*, *83*(6), 880–884. https://doi.org/10.1016/s0002-9149(98)01068-6

Mancini, M., Schlueter, H., El-Gohary, M., Mattek, N., Duncan, C., Kaye, J., & Horak, F. B. (2016). Continuous Monitoring of Turning Mobility and Its Association to Falls and Cognitive Function: A Pilot Study. *The journals of gerontology. Series A, Biological sciences and medical sciences*, *71*(8), 1102–1108. https://doi.org/10.1093/gerona/glw019

Manor, B., Yu, W., Zhu, H., Harrison, R., Lo, O. Y., Lipsitz, L., Travison, T., Pascual-Leone, A., & Zhou, J. (2018). Smartphone App-Based Assessment of Gait During Normal and Dual-Task Walking: Demonstration of Validity and Reliability. *JMIR mHealth and uHealth*, *6*(1), e36. https://doi.org/10.2196/mhealth.8815

Marmelat, V., Duncan, A., & Meltz, S. (2019). Effect of sampling frequency on fractal fluctuations during treadmill walking. *PloS one*, *14*(11), e0218908. https://doi.org/10.1371/journal.pone.0218908

McCamley, J. and Harrison, S. J. (2016). Introduction. In N. Stergiou (Ed.). Nonlinear Analysis for Human Movement Variability (pp. 1-28). Boca Ranton, FL: Taylor and Francis Group.

McGarth, D. (2016). Fractals. In N. Stergiou (Ed.). Nonlinear Analysis for Human Movement Variability (pp. 261-300). Boca Ranton, FL: Taylor and Francis Group.

Middleton, A., Fritz, S. L., & Lusardi, M. (2015). Walking speed: the functional vital sign. *Journal of aging and physical activity*, *23*(2), 314–322. https://doi.org/10.1123/japa.2013-0236

Moncada, L. V. V., & Mire, L. G. (2017). Preventing Falls in Older Persons. *American family physician*, *96*(4), 240–247.

Montenij, L. J., Buhre, W. F., Jansen, J. R., Kruitwagen, C. L., & de Waal, E. E. (2016). Methodology of method comparison studies evaluating the validity of cardiac output monitors: a stepwise approach and checklist. *British journal of anaesthesia*, *116*(6), 750–758. https://doi.org/10.1093/bja/aew094

Montero-Odasso, M., Schapira, M., Soriano, E. R., Varela, M., Kaplan, R., Camera, L. A., & Mayorga, L. M. (2005). Gait velocity as a single predictor of adverse events in healthy seniors aged 75 years and older. *The journals of gerontology. Series A, Biological sciences and medical sciences*, *60*(10), 1304–1309. https://doi.org/10.1093/gerona/60.10.1304

Murphy, S. L., Williams, C. S., & Gill, T. M. (2002). Characteristics associated with fear of falling and activity restriction in community-living older persons. *Journal of the American Geriatrics Society*, *50*(3), 516–520. https://doi.org/10.1046/j.1532-5415.2002.50119.x

Nelson, A.J., Certo, L.J., Lembo, L.S., Lopez, D.A., Manfredonia, E.F., Vanichpong, S.K., & Zwick, D. (1999). The functional ambulation performance of elderly fallers and non-fallers walking at their preferred velocity. *NeuroRehabilitation, 13*, 141-146.

Nishiguchi S, Yamada M, Nagai K, Mori S, Kajiwara Y, Sonoda T, Yoshimura K, Yoshitomi H, Hiromu Ito H, Kazuya Okamoto K, Reliability and Validity of Gait Analysis by Android-based Smartphone. Telemed and e-Health 18 (2012) 292–296.

Nohelova, D., Bizovska, L., Vuillerme, N., & Svoboda, Z. (2021). Gait Variability and Complexity during Single and Dual-Task Walking on Different Surfaces in Outdoor Environment. *Sensors (Basel, Switzerland)*, *21*(14), 4792. https://doi.org/10.3390/s21144792

Nouredanesh, M., Godfrey, A., Howcroft, J., Lemaire, E. D., & Tung, J. (2021). Fall risk assessment in the wild: A critical examination of wearable sensor use in free-living conditions. *Gait & posture*, *85*, 178–190. https://doi.org/10.1016/j.gaitpost.2020.04.010

O'Dea, S. (2021). Number of smartphone users worldwide from 2016 to 2021. Statista. https://www.statista.com/statistics/330695/number-of-smartphone-usersworldwide/

O'Loughlin, J. L., Robitaille, Y., Boivin, J. F., & Suissa, S. (1993). Incidence of and risk factors for falls and injurious falls among the community-dwelling elderly. *American journal of epidemiology*, *137*(3), 342–354. https://doi.org/10.1093/oxfordjournals.aje.a116681

Parachute. (2021). Potential lost, potential for change: The Cost of Injury in Canada 2021. parachute.ca/costofinjury

Patel, S., Park, H., Bonato, P. *et al.* A review of wearable sensors and systems with application in rehabilitation. *J NeuroEngineering Rehabil* **9**, 21 (2012). https://doi.org/10.1186/1743-0003-9-21

Patel, M., Pavic, A., & Goodwin, V. A. (2020). Wearable inertial sensors to measure gait and posture characteristic differences in older adult fallers and non-fallers: A scoping review. *Gait & posture*, *76*, 110–121. https://doi.org/10.1016/j.gaitpost.2019.10.039

Peng, C. K., Havlin, S., Stanley, H. E., & Goldberger, A. L. (1995). Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series. *Chaos (Woodbury, N.Y.)*, *5*(1), 82–87. https://doi.org/10.1063/1.166141

Peng C-K, Mietus, J., Hausdorff, J. M., Havlin, S., Stanley, H. E., & Goldberger, A. L. (1993). Long-range anticorrelations and non-Gaussian behavior of the heartbeat. *Physical review letters*, *70*(9), 1343–1346. https://doi.org/10.1103/PhysRevLett.70.1343

Peng, C. K., Mietus, J. E., Liu, Y., Lee, C., Hausdorff, J. M., Stanley, H. E., et al. (2002). Quantifying fractal dynamics of human respiration: Age and gender effects. Annals of Biomedical Engineering, 30, 683–692.

Pincus, S.M., Gladstone. I.M., Ehrenkranz, R.A. (1991). A regularity statistic for medical data-analysis. Journal of Clinical Monitoring and Computing 1991;7:335–45.

Pool, R., 1989. Is it healthy to be chaotic? Science 243, 604–607.

Powell, L. E., & Myers, A. M. (1995). The Activities-specific Balance Confidence (ABC) Scale. *The journals of gerontology. Series A, Biological sciences and medical sciences*, *50A*(1), M28–M34. https://doi.org/10.1093/gerona/50a.1.m28

Qin, D., Huang, M. (2015). A smart phone based gait monitor system. EAI Endorsed Transactions on Pervasive Health and Technology. 2 10.4108/eai.28-9-2015.2261519.

Raffalt, P. C., Alkjær, T., Brynjólfsson, B., Jørgensen, L., Bartholdy, C., & Henriksen, M. (2018). Day-to-Day Reliability of Nonlinear Methods to Assess Walking Dynamics. *Journal of biomechanical engineering*, *140*(12), 10.1115/1.4041044. https://doi.org/10.1115/1.4041044

Ranganathan, P., Pramesh, C. S., & Aggarwal, R. (2017). Common pitfalls in statistical analysis: Measures of agreement. *Perspectives in clinical research*, *8*(4), 187–191.

Rashid, U., Barbado, D., Olsen, S., Alder, G., Elvira, J. L. L., Lord, S., Niazi, I. K., & Taylor, D. (2021). Validity and Reliability of a Smartphone App for Gait and Balance Assessment. *Sensors (Basel, Switzerland)*, *22*(1), 124. https://doi.org/10.3390/s22010124

Raz, N., Rodrigue, K. M., Kennedy, K. M., Head, D., Gunning-Dixon, F., & Acker, J. D. (2003). Differential aging of the human striatum: longitudinal evidence. *AJNR. American journal of neuroradiology*, *24*(9), 1849–1856.

Rhea, C. K., Kiefer, A. W., D'Andrea, S. E., Warren, W. H., & Aaron, R. K. (2014). Entrainment to a real time fractal visual stimulus modulates fractal gait dynamics. *Human movement science*, *36*, 20–34. https://doi.org/10.1016/j.humov.2014.04.006

Rhea, C. K., Silver, T. A., Hong, S. L., Ryu, J. H., Studenka, B. E., Hughes, C. M., & Haddad, J. M. (2011). Noise and complexity in human postural control: interpreting the different estimations of entropy. *PloS one*, *6*(3), e17696. https://doi.org/10.1371/journal.pone.0017696

Richman, J.S., Moorman, J.R. (2000). Physiological time-series analysis using approximate entropy and sample entropy. American Journal of Physiology Heart and Circulatory Physiology, 278: H2039–H2049, 2000.

Riley, M. A., & Turvey, M. T. (2002). Variability and Determinism in Motor Behavior. *Journal of motor behavior*, *34*(2), 99–125. https://doi.org/10.1080/00222890209601934

Rispens, S. M., Van Dieën, J. H., Van Schooten, K. S., Cofré Lizama, L. E., Daffertshofer, A., Beek, P. J., & Pijnappels, M. (2016). Fall-related gait characteristics on the treadmill and in daily life. *Journal of neuroengineering and rehabilitation*, *13*, 12. https://doi.org/10.1186/s12984-016-0118-9

Riva, F., Toebes, M. J., Pijnappels, M., Stagni, R., & van Dieën, J. H. (2013). Estimating fall risk with inertial sensors using gait stability measures that do not require step detection. *Gait & posture*, *38*(2), 170–174. https://doi.org/10.1016/j.gaitpost.2013.05.002

Rubenstein L. Z. (2006). Falls in older people: epidemiology, risk factors and strategies for prevention. *Age and ageing*, *35 Suppl 2*, ii37–ii41. https://doi.org/10.1093/ageing/afl084

Rye Hanton, C., Kwon, Y. J., Aung, T., Whittington, J., High, R. R., Goulding, E. H., Schenk, A. K., & Bonasera, S. J. (2017). Mobile Phone-Based Measures of Activity, Step Count, and Gait Speed: Results From a Study of Older Ambulatory Adults in a Naturalistic Setting. *JMIR mHealth and uHealth*, *5*(10), e104. https://doi.org/10.2196/mhealth.5090

Sartini, M., Cristina, M. L., Spagnolo, A. M., Cremonesi, P., Costaguta, C., Monacelli, F., Garau, J., & Odetti, P. (2010). The epidemiology of domestic injurious falls in a community dwelling elderly population: an outgrowing economic burden. *European journal of public health*, *20*(5), 604–606. https://doi.org/10.1093/eurpub/ckp165

Saunders, J. B., Inman, V. T., & Eberhart, H. D. (1953). The major determinants in normal and pathological gait. *The Journal of bone and joint surgery. American volume*, *35-A*(3), 543–558.

Schootemeijer, S., Weijer, R. H. A., Hoozemans, M. J. M., van Schooten, K. S., Delbaere, K., & Pijnappels, M. (2020). Association between Daily-Life Gait Quality Characteristics and Physiological Fall Risk in Older People. *Sensors (Basel, Switzerland)*, *20*(19), 5580. https://doi.org/10.3390/s20195580

Shaffer, S. W., & Harrison, A. L. (2007). Aging of the somatosensory system: a translational perspective. *Physical therapy*, *87*(2), 193–207. https://doi.org/10.2522/ptj.20060083

Shahar, R. T., & Agmon, M. (2021). Gait Analysis Using Accelerometry Data from a Single Smartphone: Agreement and Consistency between a Smartphone Application and Gold-Standard Gait Analysis System. *Sensors (Basel, Switzerland)*, *21*(22), 7497. https://doi.org/10.3390/s21227497

Shema-Shiratzky, S., Hillel, I., Mirelman, A., Regev, K., Hsieh, K. L., Karni, A., Devos, H., Sosnoff, J. J., & Hausdorff, J. M. (2020). A wearable sensor identifies alterations in community ambulation in multiple sclerosis: contributors to real-world gait quality and physical activity. *Journal of neurology*, *267*(7), 1912–1921. https://doi.org/10.1007/s00415-020-09759-7

Shema-Shiratzky, S., Beer, Y., Mor, A., & Elbaz, A. (2022). Smartphone-based inertial sensors technology - Validation of a new application to measure spatiotemporal gait metrics. *Gait & posture*, *93*, 102–106. https://doi.org/10.1016/j.gaitpost.2022.01.024

Shull, P. B., Jirattigalachote, W., Hunt, M. A., Cutkosky, M. R., & Delp, S. L. (2014). Quantified self and human movement: a review on the clinical impact of wearable sensing and feedback for gait analysis and intervention. *Gait & posture*, *40*(1), 11–19. https://doi.org/10.1016/j.gaitpost.2014.03.189

Shumway-Cook, A., Brauer, S., & Woollacott, M. (2000). Predicting the probability for falls in community-dwelling older adults using the Timed Up & Go Test. *Physical therapy*, *80*(9), 896–903.

Silsupadol, P., Teja, K., Lugade, V. (2017). Reliability and validity of a smartphone-based assessment of gait parameters across walking speed and smartphone locations: Body, bag, belt, hand, and pocket. Gait & Posture, 58 (2017) 516–522.

Sleimen-Malkoun, R., Temprado, J. J., & Hong, S. L. (2014). Aging induced loss of complexity and dedifferentiation: consequences for coordination dynamics within and between brain, muscular and behavioral levels. *Frontiers in aging neuroscience*, *6*, 140. https://doi.org/10.3389/fnagi.2014.00140

Smits, F. M., Porcaro, C., Cottone, C., Cancelli, A., Rossini, P. M., & Tecchio, F. (2016). Electroencephalographic Fractal Dimension in Healthy Ageing and Alzheimer's Disease. *PloS one*, *11*(2), e0149587. https://doi.org/10.1371/journal.pone.0149587

Sprager, S., & Juric, M. B. (2015). Inertial Sensor-Based Gait Recognition: A Review. *Sensors (Basel, Switzerland)*, *15*(9), 22089–22127. https://doi.org/10.3390/s150922089

Springer, S., Seligmann, G.Y. (2016). Validity of the Kinect for gait assessment: a focused review. Sensors, 16(2), 194.

Statistics Canada. (2015). Population projections for Canada, Provinces and Territories 2009 to 2036. Catalogue no. 91-520-X.

Stevens, J. A., Corso, P. S., Finkelstein, E. A., & Miller, T. R. (2006). The costs of fatal and non-fatal falls among older adults. *Injury prevention : journal of the International Society for Child and Adolescent Injury Prevention*, *12*(5), 290–295. https://doi.org/10.1136/ip.2005.011015

Stergiou, N., Harbourne, R., & Cavanaugh, J. (2006). Optimal movement variability: a new theoretical perspective for neurologic physical therapy. *Journal of neurologic physical therapy: JNPT*, *30*(3), 120–129. https://doi.org/10.1097/01.npt.0000281949.48193.d9

Subramaniam, S., Faisal, A. I., & Deen, M. J. (2022). Wearable Sensor Systems for Fall Risk Assessment: A Review. *Frontiers in digital health*, *4*, 921506. https://doi.org/10.3389/fdgth.2022.921506

Talbot, L. A., Musiol, R. J., Witham, E. K., & Metter, E. J. (2005). Falls in young, middle-aged and older community dwelling adults: perceived cause, environmental factors and injury. *BMC public health*, *5*, 86. https://doi.org/10.1186/1471-2458-5-86

Tamburini, P., Storm, F., Buckley, C., Bisi, M. C., Stagni, R., & Mazzà, C. (2018). Moving from laboratory to real life conditions: Influence on the assessment of variability and stability of gait. *Gait & posture*, *59*, 248–252. https://doi.org/10.1016/j.gaitpost.2017.10.024

Terrier, P., & Dériaz, O. (2012). Persistent and anti-persistent pattern in stride-to-stride variability of treadmill walking: influence of rhythmic auditory cueing. *Human movement science*, *31*(6), 1585–1597. https://doi.org/10.1016/j.humov.2012.05.004

Terrier, P., & Reynard, F. (2015). Effect of age on the variability and stability of gait: a cross-sectional treadmill study in healthy individuals between 20 and 69 years of age. *Gait & posture*, *41*(1), 170–174. https://doi.org/10.1016/j.gaitpost.2014.09.024

Tiedemann, A., Shimada, H., Sherrington, C., Murray, S., & Lord, S. (2008). The comparative ability of eight functional mobility tests for predicting falls in community-dwelling older people. *Age and ageing*, *37*(4), 430–435. https://doi.org/10.1093/ageing/afn100

Tinetti M. E. (1987). Factors associated with serious injury during falls by ambulatory nursing home residents. *Journal of the American Geriatrics Society*, *35*(7), 644–648. https://doi.org/10.1111/j.1532-5415.1987.tb04341.x

Tinetti, M. E., & Kumar, C. (2010). The patient who falls: "It's always a trade off". *JAMA*, *303*(3), 258–266. https://doi.org/10.1001/jama.2009.2024

Tromp, A. M., Pluijm, S. M., Smit, J. H., Deeg, D. J., Bouter, L. M., & Lips, P. (2001). Fall-risk screening test: a prospective study on predictors for falls in community-dwelling elderly. *Journal of clinical epidemiology*, *54*(8), 837–844. https://doi.org/10.1016/s0895-4356(01)00349-3

Vandervoort A. A. (2002). Aging of the human neuromuscular system. *Muscle & nerve*, *25*(1), 17–25. https://doi.org/10.1002/mus.1215

van Schooten, K. S., Pijnappels, M., Rispens, S. M., Elders, P. J., Lips, P., Daffertshofer, A., Beek, P. J., & van Dieën, J. H. (2016). Daily-Life Gait Quality as Predictor of Falls in Older People: A 1-Year Prospective Cohort Study. *PloS one*, *11*(7), e0158623. https://doi.org/10.1371/journal.pone.0158623

Verghese, J., Holtzer, R., Lipton, R. B., & Wang, C. (2009). Quantitative gait markers and incident fall risk in older adults. *The journals of gerontology. Series A, Biological sciences and medical sciences*, *64*(8), 896–901. https://doi.org/10.1093/gerona/glp033

Walter PL. The history of the accelerometer: 1920s-1996 - prologue and epilogue 2006. *Sound and Vibration.* 2007 Jan;:84–92.

Weiss, A., Brozgol, M., Dorfman, M., Herman, T., Shema, S., Giladi, N., & Hausdorff, J. M. (2013). Does the evaluation of gait quality during daily life provide insight into fall risk? A novel approach using 3-day accelerometer recordings. *Neurorehabilitation and neural repair*, *27*(8), 742–752. https://doi.org/10.1177/1545968313491004

Weiss, A., Sharifi, S., Plotnik, M., van Vugt, J. P., Giladi, N., & Hausdorff, J. M. (2011). Toward automated, at-home assessment of mobility among patients with Parkinson disease, using a body-worn accelerometer. *Neurorehabilitation and neural repair*, *25*(9), 810–818. https://doi.org/10.1177/1545968311424869

Yang, M., Zheng, H., Wang, H., McClean, S., Harris, N. (2012). Assessing the utility of smart mobile phones in gait pattern analysis. *Health Technology,* 2;81–88.

Yentes J.M. (2016). Fractals. In N. Stergiou (Ed.). Nonlinear Analysis for Human Movement Variability (pp. 173-260). Boca Ranton, FL: Taylor and Francis Group.

Yentes, J. M., Hunt, N., Schmid, K. K., Kaipust, J. P., McGrath, D., & Stergiou, N. (2013). The appropriate use of approximate entropy and sample entropy with short data sets. *Annals of biomedical engineering*, *41*(2), 349–365. https://doi.org/10.1007/s10439-012-0668-3

Yentes, J. M., & Raffalt, P. C. (2021). Entropy Analysis in Gait Research: Methodological Considerations and Recommendations. *Annals of biomedical engineering*, *49*(3), 979–990. https://doi.org/10.1007/s10439-020-02616-8

CHAPTER 3

STUDY 1

EVALUATION OF A SMARTPHONE ACCELEROMETER SYSTEM FOR MEASURING NONLINEAR DYNAMICS DURING TREADMILL WALKING: CONCURRENT VALIDITY AND TEST-RETEST RELIABILITY

3.0. Abstract

The stride-to-stride fluctuations during human gait reveal complex patterns that may reflect the health status of the gait control system. The accelerometers embedded within smartphones may be a promising tool to capture gait patterns outside the laboratory and for extended periods of time. The current study evaluated the agreement and reliability of gait measures derived from a smartphone accelerometer system (SPAcc), compared to motion capture (MoCap) and footswitch gold standard (GS) systems during treadmill walking. Seventeen healthy young adults visited the laboratory on three separate days and completed three 8-minute treadmill walking trials, during each visit, at their preferred walking speed. The inter-stride interval (ISI) series was calculated as the time difference between consecutive right heel contacts, located within the signals of the SPAcc, MoCap, and footswitch systems. The ISI series was used to estimate common linear gait measures and nonlinear measures, including fractal scaling index, approximate entropy, and sample entropy. Bland Altman plots with 95% limits of agreement (LOA) and intraclass correlation coefficients (ICC) assessed agreement and reliability, respectively. The SPAcc was found to be within the acceptable LOA when compared to either GS system. The ICC values revealed moderate-to-excellent reliability for the SPAcc, with

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greater reliability found for linear compared to nonlinear measures, and were similar to both GS systems, except for FSI. These findings suggest the SPAcc is a valid and reliable method for estimating linear and nonlinear gait measures during treadmill walking.

3.1. Introduction

Innate stride-to-stride fluctuations during human gait reveal a complex structure that has been interpreted as a marker for the health status of the gait control system (Hausdorff et al., 1997). To investigate gait complexity, nonlinear measures are applied to time series data (e.g., stride time) recorded across hundreds of strides (Marmelat et al., 2014; Kiriella et al., 2020) to quantify the temporal structure of variability. Evidence suggests an optimal level of variability that lies on a continuum between complete regularity and complete randomness (Stergiou et al., 2006); allowing the walker to make flexible adaptations, when necessary, in response to environmental constraints, for the maintenance of balance and forward progression (Decker et al., 2010). Gait variability is traditionally evaluated using linear measures such the standard deviation (SD) of the measure of interest (e.g., SD of stride time); and greater variability is generally interpreted to indicate a less stable gait pattern and increased fall risk (Hausdorff et al., 2001). However, such measures may not be sensitive enough to differentiate between groups, such as young and older adults (Hausdorff et al., 1997). Nonlinear gait analysis may be more useful for clinical gait assessment (Hausdorff et al., 1997).

Gait complexity has been estimated using detrended fluctuation analysis (DFA), which provides the fractal scaling index (FSI) as a measure of the degree to which a stride interval is correlated with previous and later stride intervals over different time scales. Healthy young adults demonstrate an FSI of ~0.75-0.85; older adults and groups with illness or injury demonstrate a shift in FSI towards 0.5, representing a less adaptable gait pattern and increased fall risk (Hausdorff et al., 1995; Hausdorff et al., 1996; Hausdorff et al., 1997; Rhea and Kiefer, 2014). Other common nonlinear measures include approximate entropy (ApEn) and sample entropy (SaEn), both of which quantify the regularity of a time series (Yentes et al., 2013). Entropy measurement is a promising method for evaluating gait patterns between populations (e.g., young and older adults); with higher values suggesting greater adaptability (Arif et al., 2004).

A challenge in quantifying gait complexity is the requirement of hundreds (>200) of continuous strides. Therefore, gait complexity is typically captured within a controlled laboratory setting, while walking on a motorized treadmill, and recording with a gold standard (GS) system, such as a motion capture system (Vieira et al., 2017; Rhea et al., 2014). However, these GS systems are expensive, limited to the confines of the laboratory, and require trained personnel for operation. With the ubiquity of and advancements in smartphones (SP), researchers can access the built-in inertial sensors, such as tri-axial accelerometers, to capture human movement (Konsolakis et al., 2018). The utility of SP-based gait analysis systems offers the potential to monitor gait outside the laboratory and for extended periods of time (Qin and Huang, 2015; Lugade et al., 2021). The SP is typically affixed to the lower limb, low back, or placed in a pocket during a walking trial. Afterwards, a peak detection algorithm is applied to the acceleration curve to identify gait cycle events (e.g., heel contact) (Zou et al., 2020). From these events, spatial-temporal gait measurements such as step time (How et al., 2013) and stride time intervals (Manor et al., 2018) can be calculated. However, gait events derived from SP accelerometer (SPAcc) systems, must be compared to known quantities to ensure validity and reliability. The Vicon motion capture and force-sensing resistor (FSR) footswitch systems are considered GS systems for gait analysis (Springer and Seligmann, 2016; Beauchet et al., 2008). Although previous studies have validated SPAcc systems for measuring spatial-temporal gait measures during overground walking (Silsupadol et al., 2017; Yang et al., 2012), only one study has assessed gait complexity derived from a SPAcc compared to a GS system (Hammoud et al., 2015). These studies often use Pearson correlation coefficients, or Bland-Altman (BA) plots to measure the agreement between systems. However, Pearson correlation coefficients only provide a measure of the linear relationship between two measurements and so alone do not address validity. While BA analysis is appropriate for comparisons between methods, *a priori* defined acceptable limits of agreement (LOA) must be used, based on expected differences between healthy and unhealthy populations, to accept agreement (Giavarina, 2015). To date, only two studies have defined *a prior* acceptable LOA to determine agreement between a smartphone and gold-standard measurement system (Rashid et al., 2021; Shema-Shiratzky et al., 2022). Therefore, the aim of this study is to first define the *a priori* acceptable LOAs and evaluate the agreement and reliability of linear and nonlinear gait measures estimated with a SPAcc during treadmill walking. The expected findings for the present study were: 1) the smartphone accelerometer system would demonstrate acceptable agreement with gold-standard motion capture and footswitch systems when estimating linear and nonlinear gait variability measures during treadmill walking; 2) the smartphone accelerometer system would demonstrate similar test re-test reliability to that of gold-standard motion capture and footswitch systems across three separate sessions.

3.2. Methods

Participants

Seventeen healthy adults (*8F/9M;* mean±SD; age: 24.7±3.7 years, height: 1.73±0.1m, weight: 73.1±14.2kg; belt speed: 1.26±0.2m/s) volunteered to participate. Each participant provided written informed consent prior to participation. The university research ethics board granted approval for the study (certificate #2019-091). All participants completed a screening questionnaire to assess study eligibility. Inclusion criteria included: healthy young adults between 18 and 35 years of age, ability to perform repeated 10-minute walking bouts, and no neurological or musculoskeletal conditions or injuries within the past six months that might affect gait performance.

Equipment and set-up

All participants were asked to wear comfortable walking shoes, full length pants with front pockets, and a t-shirt. A wireless force sensitive resistor (FSR) footswitch sensor (12.7mm round) (Delsys, MA, USA), affixed directly to the bottom of the right foot inside the shoe, approximately 25mm from the posterior edge of the calcaneus bone with tape, was considered the GS FSR system and was used to record the time of heel contact. FSR data were sampled at 296Hz. A seven-camera motion capture system (Vicon, CO, USA), considered the GS motion capture system (MoCap), was used to record movement of a single reflective marker affixed to the right heel of the shoe, using double-sided adhesive tape. Motion capture data were sampled at 100Hz. A Google Smartphone (Pixel 2, ROC), with a custom-built application to access the embedded tri-axial accelerometer, was placed pointing downwards in the front right pants pocket at the start of each walking trial and was used as the SPAcc while sampling at 100Hz. A motorized treadmill (Bodyguard Fitness, QC, Canada) was used for walking trials. All participants wore a safety harness during treadmill walking trials to mitigate fall-related injuries in case of loss of balance.

Protocol

All participants visited the laboratory three times with each visit separated by at least 24 hours and were asked to wear the same attire for each visit. The preferred walking speed (PWS) was determined for each participant using the protocol from Dingwell et al. (2006). Briefly, the average between the upper and lower limits of what each participant considered comfortable was used as their PWS. All participants performed a five-minute treadmill familiarization walking period, at their PWS, prior to data collection trials (Alton et al., 1998; Zeni and Higginson, 2010). Participants performed a right foot stomp movement prior to the start of each walking trial, to create a known event within the signals of each system (Figure 3.1), which was used for temporal alignment of the three independent data collection systems during offline processing. Participants completed three 8-minute treadmill walking trials at their previously determined PWS. Although previous research has suggested that a single five-minute or ~256-stride trial is sufficient to quantify FSI (Delignieres et al., 2006), the average of three six-minute or 300-stride trials provides a more reliable estimate of FSI (Pierrynowski et al., 2005). Walking trials were separated by as much rest as needed to mitigate fatigue effects, determined by the participant's self-report. During visits two and three, participants repeated the collection protocol while walking with the same PWS as used during the first visit. Each participant completed nine trials in total.

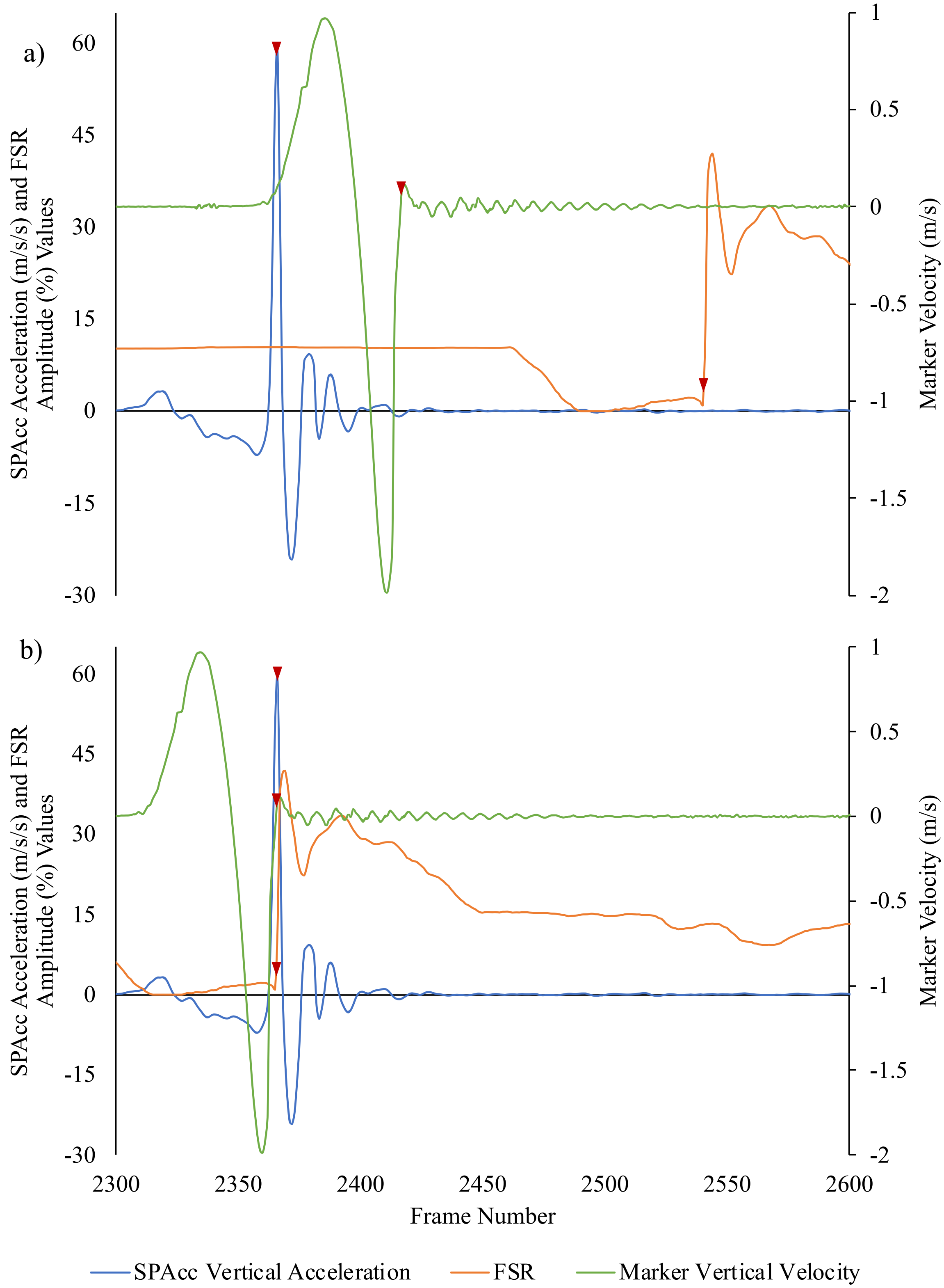

Figure 3.1. (a) Foot stomp event locations within the raw signals, used for signal alignment. The red markers represent the locations of foot stomp. Signal alignment for each trial and data stream was performed based on the foot stomp events located in the signals of each system. Participants

were asked to stand on the treadmill motionless before and after the foot stomp. The stomp of the MopCap system was determined by differentiating the marker displacement data along the vertical axis and locating the first positive vertical velocity value immediately following a negative value, where positive represents upward motion and negative represents downward motion of the right foot. The foot stomp of the FSR signal was determined by first locating the largest slope value in the first 5% of the signal, and then indexing backwards from this location until the first instant of an increase in signal amplitude is found, following a local minimum value. The foot stomp of the SPAcc signal was determined as the peak amplitude in the first 5% of the signal. The location of each foot stomp was checked visually prior to signal alignment. (b) The frame difference between the foot stomp events was calculated and used to align the signals to one another.

Data Processing

All data were processed using Matlab (R2021b, Mathworks Inc, MA, USA). From the SP, only the vertical axis acceleration data were used to determine SPAcc. Although the SPAcc was set to 100Hz, the actual sampling rate was found to be ~101.5Hz. SPAcc and FSR data were sample interpolated to 100Hz, using the Matlab "interp1" function, to match the MoCap sampling rate. Afterwards, the gravity bias was removed from the SP accelerometery data, and the data were multiplied by -1 to correct for the upside-down orientation of the SP. Two data streams were created for each system. One data stream was kept in raw form for nonlinear measures calculations. To construct the second data stream, the raw data were filtered using a fourth order low-pass Butterworth filter with cutoff frequencies selected based on a residual analysis approach (Fazlali et al., 2020). The residual analysis examined the difference between the raw and filtered data over a range of cutoff frequencies and quantified the signal content that remains when the filtered data is subtracted from the raw data (Winter, 1990). The second data stream was used in the calculation of linear measures. The MoCap, FSR, and SPAcc data were filtered with 6Hz, 13.8Hz, and 18.6Hz cutoff frequencies, respectively. Each trial was truncated to a length of 325 strides; the first 25 strides were discarded from every walking trial to ensure steady-state gait was achieved (Lindemann et al., 2008), saving 300 consecutive strides for further analysis.

FSR Processing

A custom algorithm was created in Matlab to determine the location of right heel contact events within the FSR signal. Right heel contact was determined as the point at which the FSR signal exceeded a threshold value for each stride. The threshold value was iteratively determined by calculating the maximum FSI value derived from threshold values between 0.1% and 15% (in steps of 0.1%) of the peak FSR signal. The iterations stopped at 15% as larger percentages were found to be greater than two frames away from the local minimums in the FSR signal and already exceeded 50% of the peak signal amplitude, indicating that heel contact already occurred. The advantage of this method, compared to selecting an arbitrary threshold, is that heel contact detection is tailored to not only each participant, but also to each trial. The time difference between each heel contact event was calculated and used as the ISI series (300 data points, representing 300 consecutive strides) for all dependent measures.

MoCap Processing

The location of right heel contact events, within the MoCap signal, were denoted by the change in anterior-posterior heel marker velocity signal as the instant the signal changed polarity from positive to negative (from the foot swinging forward to the instant the foot begins to move backward) (Zeni, et al., 2008) (Figure 3.2). The inter-stride-interval (ISI) series was calculated as the time difference between each right heel contact event and was used for dependent measures calculation.

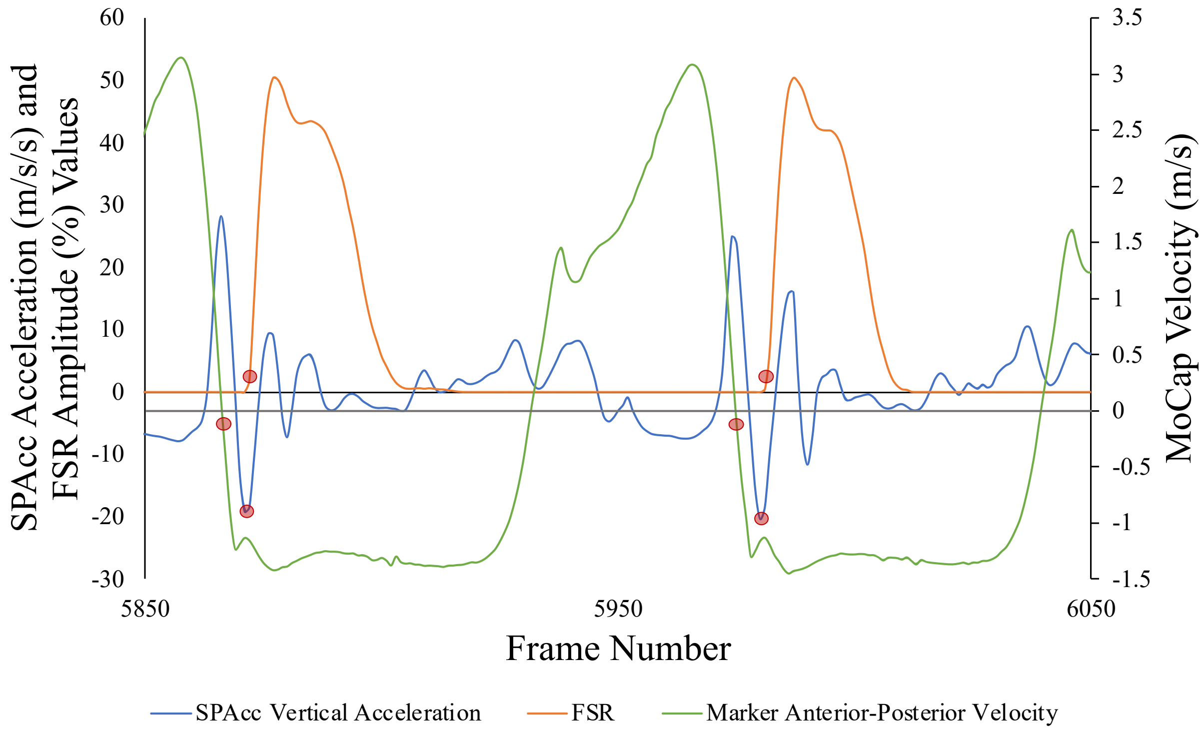

Figure 3.2. Representative plot of right heel contact locations in the signals recorded from the motion capture (MoCap), force-sensing resistor (FSR), and smartphone accelerometer (SPAcc) systems. The red circles represent heel contact event locations.

SPAcc Processing

The local minimum following the first local maximum in the vertical acceleration profile was considered right heel contact event (Manor et al., 2018) (Figure 3.2). The first local maximum was detected based on a threshold algorithm using the following rules: the signal must exceed a value of $10m/s^2$, and each peak is separated by greater than 0.8s. These values were selected based on pilot data and previous literature (Zou et al., 2020). These rules followed the assumptions, and were confirmed visually with pilot data, such that the vertical motion of the swinging lower-limb prior to heel contact should be greater than the acceleration due to gravity during walking and that the lower limit of a healthy adult's stride time is greater than 0.8s. Once the local maximums were located, the first minimum, relative to each local maximum was detected by searching forward along the signal starting at the local maximum. Right heel contact was confirmed by aligning the signals recorded from the SPAcc, FSR, and MoCap systems and identifying heel contact locations relative to those captured by the FSR and MoCap systems (Figure 3.2). Although the heel contact locations in the MoCap signal slightly preceded the heel contact locations within the signals from the other two systems, this slight bias does not affect the calculation of the ISI series since it is the relative time difference between events, not the temporal location of the events themselves within the time series. All heel contact events located in the SPAcc were visually checked to ensure accuracy. The ISI series was calculated as the time difference between each right heel contact event and was used for dependent measures calculation.

Dependent Measures

The following linear measures were calculated: i) average ISI (xISI; ms, representing average stride time and ii) SD of stride time, representing stride-time variability (STv; ms), and iii) stride time coefficient of variation (COV; %). The following nonlinear measures were calculated: i) FSI using DFA, ii) ApEn and iii) SaEn.

Calculation of DFA: The ISI series was first integrated and then divided into non-overlapping boxes of equal length (n). A least-squares line of best fit was applied within each box. The integrated ISI series was then detrended by subtracting the line of best from within each box. The root mean square (RMS) was calculated for each box and the average RMS was calculated across all boxes. This process was repeated with a range of box size lengths (n=10-40). A logarithmic transformation was applied to the plot of RMS vs. box length (n) to create a log-log plot. Lastly, the slope of the line of best fit in the log-log plot was calculated to obtain the FSI value (Terrier and Dériaz, 2012).

Calculation of ApEn and SaEn: The ApEn algorithm applied a sliding window to the ISI series to determine the probability that short sequences of data points of length m are repeated within a certain similarity criterion level r, throughout a sequence of data points. The SaEn algorithm was similar to ApEn, except it removed the self-matching bias. The m and r values were set to 2 and 0.2 times the ISI series SD, respectively (Yentes et al., 2013). The ApEn and SaEn algorithms have been described in detail elsewhere (see Chapter Two of this dissertation).

Statistical Analyses

Statistical analyses were performed using JMP v. 9.0 software (The SAS Institute, NC, USA). BA plots with 95% LOA were constructed using the mean of all walking trials for each participant, for each system to assess the agreement between systems. Normality of the differences between each paired measurement was assessed visually through histograms and quantitatively using Shapiro-Wilk tests (Giavarina, 2015). The *a priori* defined acceptable LOAs were based on published research, as follows: FSI=0.065 (Herman et al., 2005), COV=0.225% (Kobsar et al., 2014a), xISI=50msec (Hausdorff et al., 1997), and STv=11msec (Hausdorff et al., 1997); those values were selected as the LOA required in those studies to differentiate between young and older adults, and between older fallers and non-fallers. Since entropy values cannot be compared across studies unless consistent directional differences due to differing algorithm criteria (data length, m, and r) and participants (control and experimental groups) are identified (see Chapter Two of this dissertation), the acceptable LOA for ApEn and SaEn were selected as the mean difference values between original and surrogate-generated data sets, derived from the MoCap signals (Costa et al., 2003) and calculated as follows: 1) a surrogate ISI series was created for each original ISI series by randomly shuffling each original ISI series, using the Matlab "randperm" function, in order to remove the deterministic structure while maintaining the same mean and variance as the original ISI series. 2) The ApEn and SaEn values of each surrogate ISI series were calculated. 3) The surrogate ApEn and SaEn values were compared to the ApEn and SaEn values of the original ISI series using paired t-tests to confirm significant differences between the original and surrogate data. 4) The mean difference between the MoCap's original and surrogate data entropy values (e.g., mean of original ApEn – mean of surrogate ApEn) were calculated and selected as the acceptable LOA for the SPAcc and FSR. The randomly shuffled surrogate data is expected to tend toward the random side of the variability spectrum and was created as a control condition. Following this analysis, the acceptable LOA were selected as ApEn=0.042 and SaEn=0.097.

Intraclass correlation coefficients (ICC) model 2 form k ICC(2,k), where k=3, were used to assess the test-retest reliability of each system using the measures from each walking trial (Weir, 2005). Test re-test reliability is defined as an instrument's ability to measure consistently (produce a similar score) across repeated measurements. The measurement of a quantity results in a true score and error. Error can be divided into random (unpredictable) and systematic (directional) error. With repeated measurement over time, the random error should approximate zero as scores will vary in both positive and negative directions. With systematic error, the scores trend in a particular direction. The ICC provides a measure of reliability as a ratio of true score variance over the sum of true score variance and error variance. Therefore, the smaller the error variance, the larger the ICC. The true score variance is the variability between repeated measurements (i.e., measurements taken on different days). Although there are different forms of ICCs, ICC model 2 form k includes both systematic and random error terms and the k term represents the number of trials averaged for each visit (Weir, 2005). ICC values of <0.5, 0.5-0.75, 0.75-0.90, and >0.90 were interpreted as poor, moderate, good, and excellent, respectively (Koo and Li, 2016).

3.3. Results

Surrogate Analysis

The paired t-tests revealed significant differences between original and surrogate-generated data sets derived from the MoCap signals for ApEn: $t(16) = 5.73$, p-value < 0.001 and SaEn: $t(16) = 5.48$, p-value < 0.001. Construction of the surrogate datasets effectively degrades the information in the original dataset (healthy adult group) such that entropy tends towards randomness. These findings confirm that the surrogate datasets may act as a control condition that is significantly different from that of the healthy adult group's original data. This is an important step to account for the lack of a defined adult control group in the current study and to quantify a threshold to be used for *a priori* defined acceptable LOA.

Validity

The 95% LOA calculated for the SPAcc compared to either GS system were found to be within the *a priori* defined acceptable LOA for all dependent measures (Figure 3.3). With the exception of stride time COV, the LOA were narrower when the GS systems were compared to one another (Table 3.1). The 95% LOA calculated between the MoCap and FSR systems were found to be within the *a priori* defined acceptable LOA for all dependent measures (Figure 3.3). Compared to the MoCap system, the SPAcc revealed a slight negative bias for STv, stride time COV, and SaEn representing an overestimation of the SPAcc; a slight positive bias was found for xISI, FSI, and ApEn (Table 3.1). Compared to the FSR system, the SPAcc revealed a slight negative bias for all measures except for FSI, demonstrating the SPAcc, in general overestimates measures compared to the FSR system (Table 3.1). All descriptive statistics are outlined in Table 3.1.

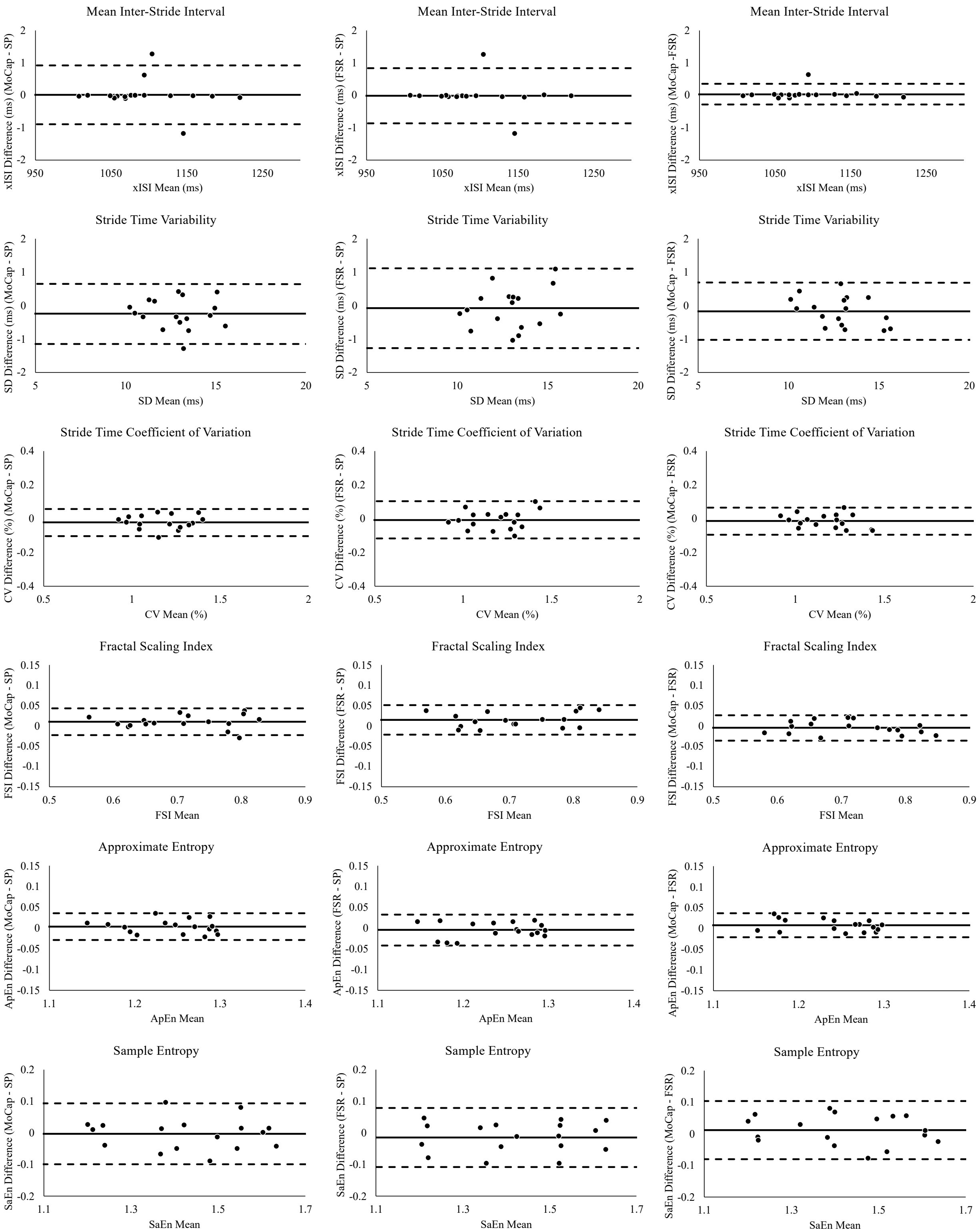

Figure 3.3. Bland Altman plots with 95% limits of agreement (LOA) for each dependent measure between each measurement system. The dashed black lines represent the 95% LOA, the solid black line represents the bias, the black circles represent the average of all trials from each participant (n = 17).

Table 3.1. Mean (±SD) of linear and nonlinear measures derived from the signals of each system, along with bias, 95% limits of agreement (LOA), and pre-defined acceptable LOA.

Measure	System			Bias (95% Limits of Agreement)			Acceptable ±LOA
	SPAcc	MoCap	FSR	MoCap versus SPAcc	FSR versus SPAcc	MoCap versus FSR	
Mean Inter-Stride Interval (ms)	1099.4 (56.9)	1101.4 (56.8)	1101.4 (56.8)	0.02 (-0.90, 0.93)	-0.02 (-0.86, 0.83)	0.03 (-0.29, 0.35)	50
Stride Time Variability (ms)	13.0 (1.6)	12.7 (1.6)	12.9 (1.8)	-0.25 (-1.15, 0.66)	-0.08 (-1.27, 1.12)	-0.17 (-1.03, 0.69)	11
Coefficient of Variation of Stride Time (%)	1.18 (0.15)	1.16 (0.15)	1.17 (0.17)	-0.02 (-0.10, 0.06)	-0.01 (-0.12, 0.10)	-0.02 (-0.10, 0.07)	0.225
Fractal Scaling Index	0.71 (0.08)	0.72 (0.08)	0.72 (0.09)	0.009 (-0.023, 0.043)	0.015 (-0.022, 0.051)	-0.005 (-0.036, 0.026)	0.065
Approximate Entropy	1.24 (0.05)	1.25 (0.05)	1.24 (0.05)	0.004 (-0.029, 0.036)	-0.005 (-0.041, 0.033)	0.008 (-0.021, 0.037)	0.042
Sample Entropy	1.43 (0.15)	1.41 (0.15)	1.40 (0.15)	-0.003 (-0.099, 0.094)	-0.015 (-0.110, 0.079)	0.012 (-0.080, 0.104)	0.097

Note: SPAcc = smartphone accelerometer system, MoCap = motion capture system, FSR = footswitch system. Negative bias [MoCap - SPAcc; FSR - SPAcc; MoCap - FSR] represents overestimation.

Reliability

Linear and nonlinear measures derived from the SPAcc system demonstrated moderate to excellent reliability while both GS systems demonstrated good to excellent reliability (Table 3.2). The ICC values for both GS systems were similar to one another across all measures. The linear measures revealed better reliability compared to the nonlinear measures for the SPAcc and were similar to both GS systems, except for FSI, which was lower for the SPAcc (0.73) compared to MoCap (0.81) and FSR (0.82) systems. Entropy measures derived from all systems demonstrated better reliability compared to FSI.

Table 3.2. Test-retest reliability results.

		SPAcc	MoCap	FSR
Measure	**Type**	**ICC(2,k)**	**ICC(2,k)**	**ICC(2,k)**
Mean Inter-Stride Interval	Linear	0.95 E	0.95 E	0.95 E
Stride Time Variability	Linear	0.80 G	0.83 G	0.82 G
Coefficient of Variation of Stride Time	Linear	0.83 G	0.88 G	0.85 G
Fractal Scaling Index	Nonlinear	0.73 M	0.81 G	0.82 G
Approximate Entropy	Nonlinear	0.90 E	0.87 G	0.87 G
Sample Entropy	Nonlinear	0.86 G	0.89 G	0.88 G

Note: M – moderate, G – good, E – excellent; k = 3.

3.4. Discussion

The current study assessed the agreement and reliability of SP-accelerometery derived linear and nonlinear gait measures, compared to GS measurement systems during treadmill walking. The results demonstrated acceptable limits of agreement for all dependent measures, suggesting that the SPAcc system is a valid method and performs similarly to that of GS motion capture and FSR systems. The SPAcc also demonstrated moderate to excellent reliability, across the three laboratory visits. With the exception of FSI, the ICC values were similar across all systems investigated. To date, no study has validated gait measures derived from a SPAcc during treadmill walking and the current study demonstrates encouraging results for the utility of a SPAcc to measure gait variability during treadmill walking among young adults.

The mean values for xISI across all systems were similar to previous treadmill walking research (Terrier and Dériaz, 2011) as well as overground walking while using a smartphone (Proessl et al., 2018). Mean STv and stride time COV derived from the SPAcc were found to be lower compared to previous accelerometer-derived research during treadmill (Terrier and Dériaz, 2011) and overground walking (Kobsar et al., 2014a; Ryan et al., 2020). The mean FSI values in the current study were similar to those reported by Terrier and Dériaz (2011) while using a triaxial accelerometer affixed to the low back during treadmill walking. The 95% LOA for FSI in the current were found to be narrower than the LOA reported by Kobsar et al. (2014b) who compared an accelerometer to an FSR system during overground walking. However, methodological differences, such as signal filtering, overground walking, population recruited, and number of strides included, may have contributed to the differences in values between the accelerometer and the SPAcc as used in the current study. The slight positive bias found for FSI compared to the other GS systems (0.009 to 0.015) represents a slight underestimation of the SPAcc. These findings suggest a slight systematic adjustment may be required when estimating the FSI using the SPAcc during treadmill walking. The mean SaEn (1.40-1.43) was found to be greater than mean ApEn (1.24-1.25) for all systems, which is as expected since SaEn does not count self matches and will therefore yield values closer to the random side of the variability continuum (closer to 2). In general, better agreement was found between the SPAcc and MoCap systems, compared to the SPAcc and FSR system across all measures, while the two GS systems demonstrated the best agreement to one another. This is not surprising since the sensors for both the MoCap and FSR systems are located close to the heel compared to the SPAcc which is placed in the front pants pocket, closer to the center of mass of the walker. Therefore, any subtle differences in heel contact event locations used to generate the ISI series may be due to sensor location compared to differences between the systems.

Across all systems, reliability was slightly better for linear measures (mean ICC=0.87) compared to nonlinear measures (mean ICC=0.85). The lowest ICC values were found for FSI for all systems investigated. This is not surprising due to the sensitivity of nonlinear measures and the between-day design of the current study. Previous research on between-day reliability also suggests that linear measures exhibit high reliability (Stolze et al., 1998) while nonlinear measures reveal low reliability (Ryan et al., 2020). This is evident in previous research by Raffalt et al. (2018), reporting ICC values of ~0.38 and ~0.6, for SaEn and FSI, respectively. Pierrynowski et al. (2005) also investigated the between-day reliability of FSI and reported an ICC of 0.82, calculated using three six-minute treadmill walking trials while recording the displacement of a right heel marker using a camera-based MoCap system to identify heel contact events. The current study used the same number of strides and trials, as recommended by Pierrynowski et al. (2005), to calculate FSI and found similar ICC values for both GS systems (MoCap=0.81, FSR=0.82), while the SPAcc revealed an ICC of 0.73. Perhaps the placement of the SP in the pants pocket, compared to the placement of the FSR and the MoCap marker being at the foot, may have contributed to differences in the calculation of FSI. Additionally, to better simulate real-world useability of the SP, the placement of the SP in the pocket was not fixed, allowing the device to move somewhat independently, possibly also affecting the reliability of the SPAcc FSI. Previous research has reported that pocket tightness does not affect the estimation of linear spatial-temporal gait measures using a SP (Manor et al., 2018), however, no studies have examined the potential impact on non-linear measures. Therefore, perhaps the pants pocket, not allowing for the SPAcc to be securely fixed to the walker, compared to the FSR sensor or MoCap marker, resulted in subtle differences in heel contact event locations, and coupled with the sensitivity of the FSI measure may explain the difference in FSI reliability between the SPAcc and the GS systems.

Interestingly, the entropy measures appeared to be more reliable than FSI, suggesting entropy is not as sensitive to between-day differences or that sensor location is not a factor contributing to differences in between-day reliability, as suggested for FSI. Additionally, perhaps the entropy algorithm itself is not as sensitive to subtle between-day differences. However, only one combination of algorithm input parameters (data length=300, m=2, and r=0.2 x ISI series SD) was used for entropy calculation. Future research should investigate the selection of different input parameters used to calculate entropy and the effect on between-day reliability. Furthermore, it should be noted that although the FSI and entropy measures are nonlinear, the DFA does estimate complexity, by quantifying changes in the stepping pattern across different time scales (i.e., seconds and minutes) while the ApEn and SaEn measures do not. Therefore, the between-day reliability may be explained by the differences in the nonlinear measures themselves. Using another entropy measure to quantify complexity, such as multiscale entropy, may reflect between-day reliability similar to FSI. However, multiscale entropy was not calculated as it requires a greater number of strides than were recorded in the current study and may not be practical for clinical populations.

3.5. Conclusion

This is the first study that has assessed linear and nonlinear measures derived from a SPAcc during treadmill walking and provides promising results for the utility of monitoring gait outside the traditional confines of the laboratory. Furthermore, this is the first study to use *a priori* defined LOA based on previously established and expected population differences to assess agreement. Future research should validate the SPAcc during overground walking to remove the influence treadmill walking may have on gait patterns to uncover a true representation of gait variability.

3.6. References

Alton, F., Baldey, L., Caplan, S., & Morrissey, M. C. (1998). A kinematic comparison of overground and treadmill walking. *Clinical biomechanics (Bristol, Avon)*, *13*(6), 434–440. https://doi.org/10.1016/s0268-0033(98)00012-6

Arif, M., Ohtaki, Y., Nagatomi, R., Inooka, H. (2004). Estimation of the effect of cadence on gait stability in young and elderly people using approximate entropy technique. *Measurement Science Review*, 4(2), 29-40.

Beauchet, O., Herrmann, F. R., Grandjean, R., Dubost, V., & Allali, G. (2008). Concurrent validity of SMTEC footswitches system for the measurement of temporal gait parameters. *Gait & posture*, *27*(1), 156–159. https://doi.org/10.1016/j.gaitpost.2006.12.017

Costa, M., Peng, C. K., Goldberger, A. L., & Hausdorff, J. M. (2003). Multiscale entropy analysis of human gait dynamics. *Physica A*, *330*(1-2), 53–60. https://doi.org/10.1016/j.physa.2003.08.022

Decker, L.M., Cignetti, F., Stergiou, N. (2010). Complexity and Human Gait. *Revista Andaluza de Medicina del Deporte*, 2010;3(1):2-12.

Delignieres, D., Ramdani, S., Lemoine, L., Torre, K., Fortes, M., Ninot, G. (2006). Fractal analyses for 'short' time series: A re-assessment of classical methods. *Journal of Mathematical Psychology, 50*(6), 525–544.

Dingwell, J. B., & Marin, L. C. (2006). Kinematic variability and local dynamic stability of upper body motions when walking at different speeds. *Journal of biomechanics*, *39*(3), 444–452. https://doi.org/10.1016/j.jbiomech.2004.12.014

Fazlali, H., Sadeghi, H., Sadeghi, S., Ojaghi, M., & Allard, P. (2020). Comparison of four methods for determining the cut-off frequency of accelerometer signals in able-bodied individuals and ACL ruptured subjects. *Gait & posture*, *80*, 217–222. https://doi.org/10.1016/j.gaitpost.2020.06.009

Hammoud, A., Duchêne, J., Abou-ghaida, H., Mottet, S., Goujon, J., Hewson, D.J. (2015). Validation of a Smartphone Gait Analysis System, International Federation for Medical and Biological Engineering Proceedings 45,910–913.

Hausdorff, J. M., Mitchell, S. L., Firtion, R., Peng, C. K., Cudkowicz, M. E., Wei, J. Y., & Goldberger, A. L. (1997). Altered fractal dynamics of gait: reduced stride-interval correlations with aging and Huntington's disease. *Journal of applied physiology (Bethesda, Md. : 1985)*, *82*(1), 262–269. https://doi.org/10.1152/jappl.1997.82.1.262

Hausdorff, J. M., Peng, C. K., Ladin, Z., Wei, J. Y., & Goldberger, A. L. (1995). Is walking a random walk? Evidence for long-range correlations in stride interval of human gait. *Journal of applied physiology (Bethesda, Md. : 1985)*, *78*(1), 349–358. https://doi.org/10.1152/jappl.1995.78.1.349

Hausdorff, J. M., Purdon, P. L., Peng, C. K., Ladin, Z., Wei, J. Y., & Goldberger, A. L. (1996). Fractal dynamics of human gait: stability of long-range correlations in stride interval fluctuations. *Journal of applied physiology (Bethesda, Md. : 1985)*, *80*(5), 1448–1457. https://doi.org/10.1152/jappl.1996.80.5.1448

Hausdorff, J. M., Rios, D. A., & Edelberg, H. K. (2001). Gait variability and fall risk in community-living older adults: a 1-year prospective study. *Archives of physical medicine and rehabilitation*, *82*(8), 1050–1056. https://doi.org/10.1053/apmr.2001.24893

Herman, T., Giladi, N., Gurevich, T., & Hausdorff, J. M. (2005). Gait instability and fractal dynamics of older adults with a "cautious" gait: why do certain older adults walk fearfully?. *Gait & posture*, *21*(2), 178–185. https://doi.org/10.1016/j.gaitpost.2004.01.014

How, T., Chee, J., Wan, E, Mihailidis, A. (2013). MyWalk : A Mobile App for Gait Asymmetry Rehabilitation in the Community. PervasiveHealth 13: 73-76.

Kiriella, J. B., Di Bacco, V. E., Hollands, K. L., & Gage, W. H. (2020). Evaluation of the Effects of Prescribing Gait Complexity Using Several Fluctuating Timing Imperatives. *Journal of motor behavior*, *52*(5), 570–577. https://doi.org/10.1080/00222895.2019.1654971

Kobsar, D., Olson, C., Paranjape, R., Hadjistavropoulos, T., & Barden, J. M. (2014a). Evaluation of age-related differences in the stride-to-stride fluctuations, regularity and symmetry of gait using a waist-mounted tri-axial accelerometer. *Gait & posture*, *39*(1), 553–557. https://doi.org/10.1016/j.gaitpost.2013.09.008

Kobsar, D., Olson, C., Paranjape, R., & Barden, J. M. (2014b). The validity of gait variability and fractal dynamics obtained from a single, body-fixed triaxial accelerometer. *Journal of applied biomechanics*, *30*(2), 343–347. https://doi.org/10.1123/jab.2013-0107

Koo, T. K., & Li, M. Y. (2016). A Guideline of Selecting and Reporting Intraclass Correlation Coefficients for Reliability Research. *Journal of chiropractic medicine*, *15*(2), 155–163. https://doi.org/10.1016/j.jcm.2016.02.012

Konsolakis, K., Hermens, H., Villalonga, C., Vollenbroek-Hutten, M., & Banos, O. (2018). Human Behaviour Analysis through Smartphones. *UCAmI 2018*. https://doi.org/10.3390/proceedings2191243

Lindemann, U., Najafi, B., Zijlstra, W., Hauer, K., Muche, R., Becker, C., & Aminian, K. (2008). Distance to achieve steady state walking speed in frail elderly persons. *Gait & posture*, *27*(1), 91–96. https://doi.org/10.1016/j.gaitpost.2007.02.005

Lugade, V., Kuntapun, J., Prupetkaew, P., Boripuntakul, S., Verner, E., & Silsupadol, P. (2021). Three-Day Remote Monitoring of Gait Among Young and Older Adults Using

Participants' Personal Smartphones. *Journal of aging and physical activity*, *29*(6), 1026–1033. https://doi.org/10.1123/japa.2020-0353

Manor, B., Yu, W., Zhu, H., Harrison, R., Lo, O. Y., Lipsitz, L., Travison, T., Pascual-Leone, A., & Zhou, J. (2018). Smartphone App-Based Assessment of Gait During Normal and Dual-Task Walking: Demonstration of Validity and Reliability. *JMIR mHealth and uHealth*, *6*(1), e36. https://doi.org/10.2196/mhealth.8815

Marmelat, V., Torre, K., Beek, P. J., & Daffertshofer, A. (2014). Persistent fluctuations in stride intervals under fractal auditory stimulation. *PloS one*, *9*(3), e91949. https://doi.org/10.1371/journal.pone.0091949

Pierrynowski, M. R., Gross, A., Miles, M., Galea, V., McLaughlin, L., & McPhee, C. (2005). Reliability of the long-range power-law correlations obtained from the bilateral stride intervals in asymptomatic volunteers whilst treadmill walking. *Gait & posture*, *22*(1), 46–50. https://doi.org/10.1016/j.gaitpost.2004.06.007

Proessl, F., Swanson, C. W., Rudroff, T., Fling, B. W., & Tracy, B. L. (2018). Good agreement between smart device and inertial sensor-based gait parameters during a 6-min walk. *Gait & posture*, *64*, 63–67. https://doi.org/10.1016/j.gaitpost.2018.05.030

Qin, D., Huang, M. (2015). Smartphone Based Gait Monitor System. EAI Endorsed Transactions on Pervasive Health and Technology. 2 10.4108/eai.28-9-2015.2261519.

Rhea, C.K., Kiefer, A.W. (2014). Patterned variability in gait behavior: how can it be measured and what does it mean? In: Li L, Holmes M, editors. Gait biometrics: basic patterns, role of neurological disorders and effects of physical activity. Hauppauge, NY: Nova Science Pub, Inc.; 2014. p. 17–43.

Rhea, C. K., Kiefer, A. W., D'Andrea, S. E., Warren, W. H., & Aaron, R. K. (2014). Entrainment to a real time fractal visual stimulus modulates fractal gait dynamics. *Human movement science*, *36*, 20–34. https://doi.org/10.1016/j.humov.2014.04.006

Ryan, N. S., Bruno, P. A., & Barden, J. M. (2021). Test-Retest Reliability and the Effects of Walking Speed on Stride Time Variability During Continuous, Overground Walking in Healthy Young Adults. *Journal of applied biomechanics*, *37*(2), 102–108. https://doi.org/10.1123/jab.2020-0138

Silsupadol, P., Teja, K., & Lugade, V. (2017). Reliability and validity of a smartphone-based assessment of gait parameters across walking speed and smartphone locations: Body, bag, belt, hand, and pocket. *Gait & posture*, *58*, 516–522. https://doi.org/10.1016/j.gaitpost.2017.09.030

Springer, S., & Yogev Seligmann, G. (2016). Validity of the Kinect for Gait Assessment: A Focused Review. *Sensors (Basel, Switzerland)*, *16*(2), 194. https://doi.org/10.3390/s16020194

Stergiou, N., Harbourne, R., & Cavanaugh, J. (2006). Optimal movement variability: a new theoretical perspective for neurologic physical therapy. *Journal of neurologic physical therapy : JNPT*, *30*(3), 120–129. https://doi.org/10.1097/01.npt.0000281949.48193.d9

Stolze, H., Kuhtz-Buschbeck, J. P., Mondwurf, C., Jöhnk, K., & Friege, L. (1998). Retest reliability of spatiotemporal gait parameters in children and adults. *Gait & posture*, *7*(2), 125–130. https://doi.org/10.1016/s0966-6362(97)00043-x

Terrier, P., & Dériaz, O. (2012). Persistent and anti-persistent pattern in stride-to-stride variability of treadmill walking: influence of rhythmic auditory cueing. *Human movement science*, *31*(6), 1585–1597. https://doi.org/10.1016/j.humov.2012.05.004

Vieira, M. F., Rodrigues, F. B., de Sá E Souza, G. S., Magnani, R. M., Lehnen, G. C., Campos, N. G., & Andrade, A. O. (2017). Gait stability, variability and complexity on inclined surfaces. *Journal of biomechanics*, *54*, 73–79. https://doi.org/10.1016/j.jbiomech.2017.01.045

Weir J. P. (2005). Quantifying test-retest reliability using the intraclass correlation coefficient and the SEM. *Journal of strength and conditioning research*, *19*(1), 231–240. https://doi.org/10.1519/15184.1

Winter, D.A. Biomechanics and motor control of human movement. John Wiley and Sons, Inc., New York; 1990.

Yang, M., Zheng, H., Wang, H., McClean, S., Harris, N. (2012). Assessing the utility of smart mobile phones in gait pattern analysis. Health and Technology. 2. 10.1007/s12553-012-0021-8.

Yentes, J. M., Hunt, N., Schmid, K. K., Kaipust, J. P., McGrath, D., & Stergiou, N. (2013). The appropriate use of approximate entropy and sample entropy with short data sets. *Annals of biomedical engineering*, *41*(2), 349–365. https://doi.org/10.1007/s10439-012-0668-3

Zeni, J. A., Jr, & Higginson, J. S. (2010). Gait parameters and stride-to-stride variability during familiarization to walking on a split-belt treadmill. *Clinical biomechanics (Bristol, Avon)*, *25*(4), 383–386. https://doi.org/10.1016/j.clinbiomech.2009.11.002

Zeni, J. A., Jr, Richards, J. G., & Higginson, J. S. (2008). Two simple methods for determining gait events during treadmill and overground walking using kinematic data. *Gait & posture*, *27*(4), 710–714. https://doi.org/10.1016/j.gaitpost.2007.07.007

Zou, Q., Wang, Y., Zhao, Y., Wang, Q., Shen, C., Li, Q. (2020). Deep learning-based gait recognition using smartphones in the wild. *IEEE Transactions on Information Forensics and Security*, vol. 15, pp. 3197-3212, 2020, doi: 10.1109/TIFS.2020.2985628.

CHAPTER 4

STUDY 2

VALIDATION OF LINEAR AND NONLINEAR GAIT VARIABILITY MEASURES DERIVED FROM A SMARTPHONE SYSTEM COMPARED TO A GOLD-STANDARD FOOTSWITCH SYSTEM DURING OVERGROUND WALKING

4.0. Abstract

Smartphones may be a viable tool to monitor gait variability in the free-living environment. However, measurements estimated using smartphone must first be compared to known quantities to ensure validity. The current study evaluated the agreement and test re-test reliability of a smartphone accelerometer system compared to a gold-standard footswitch system for estimating gait variability during overground walking. Seventeen healthy adults (24.6±3.7years) completed three 8-minute overground walking trials during each of three separate laboratory visits. A gold-standard (GS) footswitch system (FSR) was placed under the right heel of participants. A smartphone, with a custom application accessing the embedded accelerometer was placed in the front right pants pocket. Both systems recorded walking trials simultaneously. The inter-stride interval (ISI) was calculated for each trial as the time difference between consecutive right heel contact events within the FSR and vertical smartphone-accelerometry data. Linear and nonlinear measures were calculated using the 300-stride ISI series from each trial. Linear measures included: average ISI (ms), standard deviation of ISI (ms), stride time coefficient of variation (%). Nonlinear measures included: fractal scaling index (FSI), approximate entropy, sample entropy. Bland-Altman (BA) plots with 95% limits of agreement (LOA) were calculated and compared against *a priori* defined acceptable LOA to assess agreement between systems. Intraclass correlation coefficients (ICC) were calculated to assess reliability across the three visits. BA plots revealed acceptable LOA for all dependent measures. ICCs revealed good to

excellent reliability for both systems, except for FSI, which was moderate. On average, better reliability was found for linear (0.92-0.93), compared to nonlinear (0.81-0.82) measures for both systems. The smartphone system is a valid method and performs similarly to that of a GS research system during overground walking. These findings suggest the development and implementation of an inexpensive, easy-to-use, and ubiquitous telehealth instrument that may replace traditional laboratory equipment for use in the free-living environment.

4.1. Introduction

Variability is an innate characteristic of human movement and can be used to quantify the quality of the gait control system and adaptability of the walker (Hausdorff, 2007; Rhea and Kiefer, 2014; Hausdorff et al., 1997). Both linear and nonlinear variability measures are applied to spatial-temporal gait parameters to quantify the magnitude and structure of variability, respectively; providing insight into the walker's ability to remain stable and make necessary flexible adjustments to the stepping pattern for the maintenance of balance. For example, compared to young adults, older adults demonstrate increased magnitudes of stride time variability (Kobsar et al., 2014b) as well as increased disorder in the temporal structure of stride time, suggesting a more disorganized stepping pattern (Hausdorff et al., 1997; Hausdorff et al., 1995; Hausdorff et al., 1996). The increased disorder reduces the capacity of the walker to adapt to changing constraints during gait, when needed, thus increasing fall risk (Hausdorff, 2007). Although both linear and nonlinear measures reveal insights into the quality of the gait control system, nonlinear measures demonstrate greater sensitivity of variability differences between populations (Hausdorff et al., 1997). However, a large number of continuous strides (>200) is required for nonlinear analysis, often restricting data collection to treadmill walking in the confines of the laboratory. Treadmills provide the benefit of recording many continuous gait cycles at controlled walking speeds with minimal space requirements. However, treadmill walking has been demonstrated to alter gait patterns compared to overground walking, such as reducing long-range correlations in stride time (fractal scaling index = 0.72 versus fractal scaling index = 0.81, respectively) (Terrier and Dériaz, 2011), as well as increased stride time regularity (sample entropy = 1.893 versus sample entropy = 2.195) (Hollman et al., 2016). The effects of treadmill walking are suggested to constrain the stepping pattern by providing a form of cueing or pace keeping, imposed by the treadmill belt, and may misrepresent gait as more (Warlop et al., 2018) or less healthy than it truly is (Terrier and Dériaz, 2011; Hollman et al., 2016). Therefore, efforts should be made to measure gait patterns while walking overground, in a context with greater ecological validity, to provide a true representation of gait variability for the population of interest.

With advancements in smartphone (SP) technology, researchers are able to access the built-in inertial sensors available such as tri-axial accelerometers to capture human movement (Konsolakis et al., 2018). SP-based gait analysis systems offer the potential of monitoring gait outside the laboratory, without supervision, and for extended periods of time (Qin and Huang, 2015; Rye Hanton et al. 2017; Manor et al., 2018; Lugade et al., 2021). To date, the majority of studies have validated gait measures derived from SP-based accelerometers (SPAcc) against gold standard (GS) measurement tools such as pressure sensing mats and inertial measurement unit systems (Nishiguchi et al., 2012; Yang et al., 2012; How et al., 2013; Silsupadol et al., 2017; Shahar and Agmon, 2021). Findings have demonstrated that the SPAcc provides accurate and reliable spatial-temporal gait measures, such as stride time, step length, gait velocity, and cadence when placed in the front pocket or affixed to the lower back (Yang et al., 2012;

Silsupadol et al., 2017; Manor et al., 2018). Therefore, SPAcc systems may provide the means for monitoring gait patterns as a person walks freely overground (Nishiguchi et al., 2012; Yang et al., 2012; How et al., 2013; Silsupadol et al., 2017; Manor et al., 2018). However, the majority of these validation studies are conducted while walking short distances (<25 meters) and in a controlled environment (laboratory or vacant corridor) (Lemoyne et al., 2010; Yang et al., 2012; Silsupadol et al., 2017; Shema-Shiratzky et al., 2022). To date, only one study has validated a SPAcc-derived nonlinear gait measure (fractal scaling index), compared to an in-shoe pressure sensing system, during overground walking (Hammoud et al., 2015). Although the results indicated agreement between systems, methodological issues were present such as an insufficient number of data points and the absence of continuous steady-state gait. Additionally, no evaluation of the test-retest reliability was conducted, warranting further research. Therefore, prior to the implementation of a SPAcc system for quantifying gait variability in the free-living environment, an evaluation of the accuracy and reliability during overground walking must be conducted. The expected findings for the current study were: 1) the smartphone accelerometer system would demonstrate acceptable agreement with the gold-standard footswitch system when estimating linear and nonlinear gait variability measures during overground walking; 2) the smartphone accelerometer system would demonstrate similar test re-test reliability to that of the gold-standard footswitch system across three separate sessions.

4.2. Methods

Participants

Seventeen healthy young adults (*8F/9M;* mean±SD; age: 24.6±3.7years, height: 1.74±0.1m, weight: 73.7±14.2kg) volunteered to participate. Sample size was calculated using an α=0.05, β=0.8, and an expected intraclass correlation coefficient between 0.4-0.5 (Raffalt et al., 2018), resulting in 11-17 participants (Bujang and Baharum, 2017). Each participant provided written informed consent prior to participation. The university research ethics board granted approval for the study (certificate#:2019-091). All participants completed a screening questionnaire to assess study eligibility. Inclusion criteria included: healthy young adults between 18 and 35 years of age, ability to perform repeated 10-minute walking bouts, no neurological or musculoskeletal conditions or injuries within the past six months that might affect gait performance.

Equipment and set-up

All participants were asked to wear comfortable walking shoes, full-length pants with front pockets, and a t-shirt. A wireless force sensitive resistor (FSR) footswitch sensor (12.7mm round) (Delsys, MA, USA), affixed directly to the bottom of the right foot, approximately 25mm from the posterior edge of the calcaneus bone with tape, was considered the GS FSR system and was used to record the time of heel contact. FSR data were sample at 296Hz. A Google Smartphone (Pixel 2, ROC), with a custom-built application to access the embedded tri-axial accelerometer, was placed pointing downwards in the front right pants pocket at the start of each walking trial and was used as the SPAcc while sampling at 100Hz.

Protocol

All participants visited the laboratory three times, each separated by at least 24 hours and were asked to wear the same attire for each visit. Participants performed a right foot stomp movement prior to the start of each walking trial, to create a known event within the signals of both systems (Figure 4.1), which was used for temporal alignment of the two independent data collection systems during offline processing. Participants completed three 8-minute overground walking trials at their comfortable walking speed by completing continuous laps along vacant corridors around the laboratory. The distance of each was lap was approximately 88m. Although previous research has suggested that a single five-minute or ~256-stride trial is sufficient to quantify FSI (Delignieres et al., 2006), the average of three six-minute or 300-stride trials provides a more reliable estimate of FSI (Pierrynowski et al., 2005). Walking trials were separated by as much rest as needed to mitigate fatigue effects, determined by the participant's self-report. During visits two and three, participants repeated the data collection protocol while walking at their comfortable walking speed. Each participant completed nine trials in total.

Data Processing and Dependent Measures

All data were processed using Matlab (R2021b, Mathworks Inc, Natick, MA). From the SP, only the vertical axis acceleration data were used to determine SPAcc as the majority of acceleration took place along that axis due to the vertical orientation of device placement inside the pant pocket (as typically carried by users); visual inspection of signals from several different trials revealed no substantive change in waveform characteristics if the anterior-posterior and medial-lateral axis acceleration data were included. Although the SPAcc was set to 100Hz, the actual sampling rate was found to be ~101.5Hz. SPAcc and FSR data were sample interpolated to 100Hz, using the Matlab "interp1" function, to match the different collection frequencies used for both devices. Following interpolation, the gravity bias was removed from the SP accelerometery data, and the data were then multiplied by -1 to correct for the upside-down orientation of the SP. Two data streams were created for each system. One data stream was kept in raw form for the estimation of nonlinear gait measures. The second data stream was created by filtering the raw data using a fourth order low-pass Butterworth filter with cut-off frequencies selected based on a residual analysis approach (Fazlali et al., 2020). The second data stream was used in the estimation of linear measures. The FSR and SPAcc data were filtered with 13Hz and 19Hz cut-off frequencies, respectively. Each trial was truncated to a length of 325 strides; the first 25 strides were discarded from every walking trial to ensure steady-state gait was achieved (Lindemann et al., 2008), saving 300 consecutive strides for further analysis.

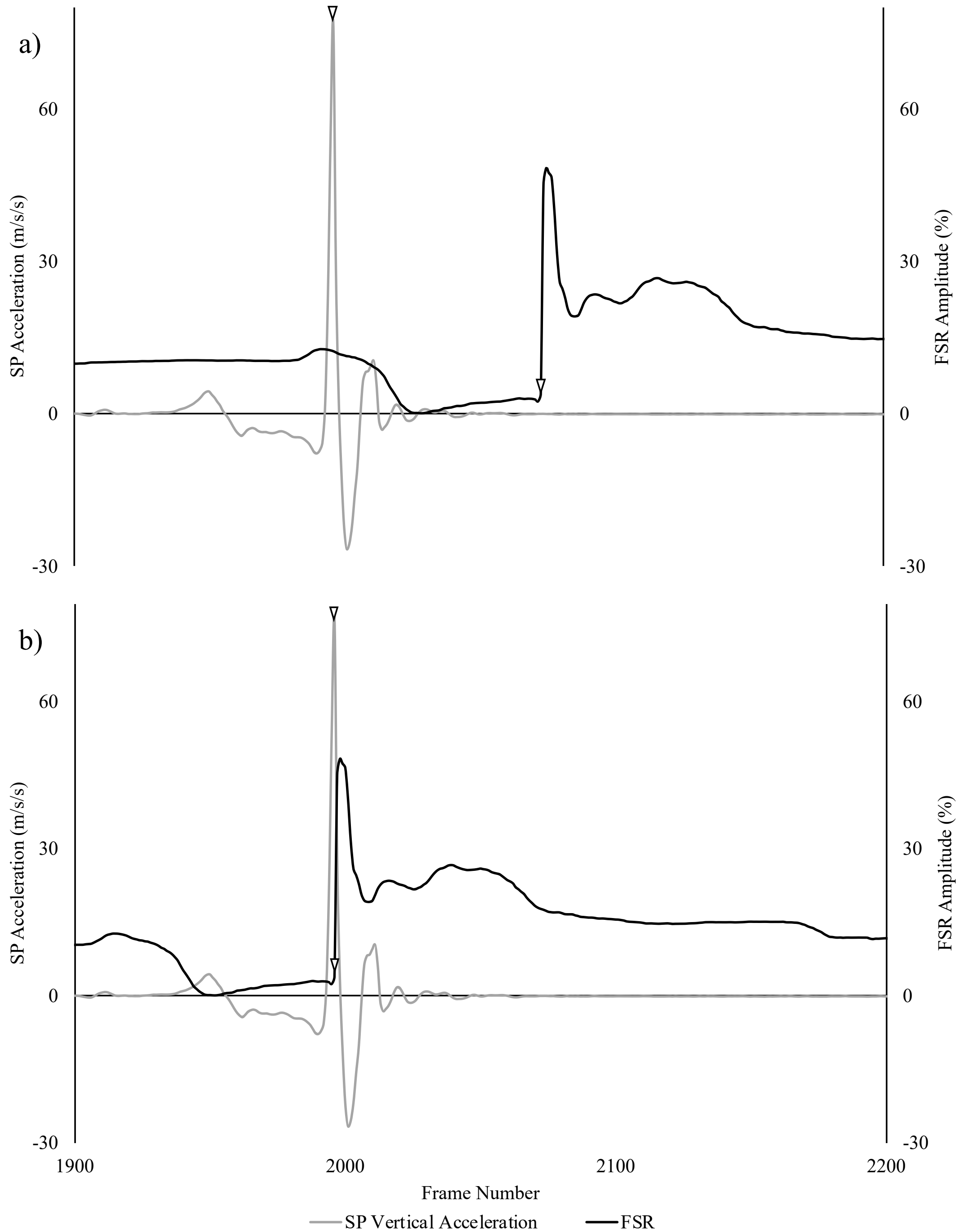

Figure 4.1. (a) Foot stomp event locations within the raw signals, used for signal alignment. The black markers represent the locations of foot stomp. Signal alignment for each trial and data stream was performed based on the foot stomp events located in the signals of each system. Participants were asked to stand motionless before and after the foot stomp. The foot stomp of the FSR signal was determined by first locating the largest slope value in the signal, and then indexing backwards from this location until the first instant of an increase in signal amplitude is found, following a local minimum value. The foot stomp of the SPAcc signal was determined as the peak amplitude value in the signal. The location of each foot stomp was checked visually

prior to signal alignment. (b) The frame difference between the foot stomp events was calculated and used to align the signals to one another.

FSR Processing

A custom algorithm was created in Matlab to determine the location of right heel contact events within the FSR signal. Right heel contact was determined as the point at which the FSR signal exceeded a threshold value for each stride and is described in detail elsewhere (see Chapter Three of this dissertation). The time difference between each heel contact event was calculated and used as the ISI time series (300 data points, representing 300 consecutive strides) for all dependent measures.

SPAcc Processing

The local minimum following the first local maximum in the vertical acceleration profile was considered right heel contact event (Manor et al., 2018) (Figure 4.2). The identification of right heel contact event locations is described in detail elsewhere (see Chapter Three of this dissertation). Right heel contact was confirmed by aligning the signals recorded from the SPAcc and FSR systems and identifying heel contact locations relative to those captured by the FSR system (Figure 4.2). All heel contact events located in the SPAcc were visually checked to ensure accuracy. The ISI series was calculated as the time difference between each right heel contact event and was used for dependent measures calculation.

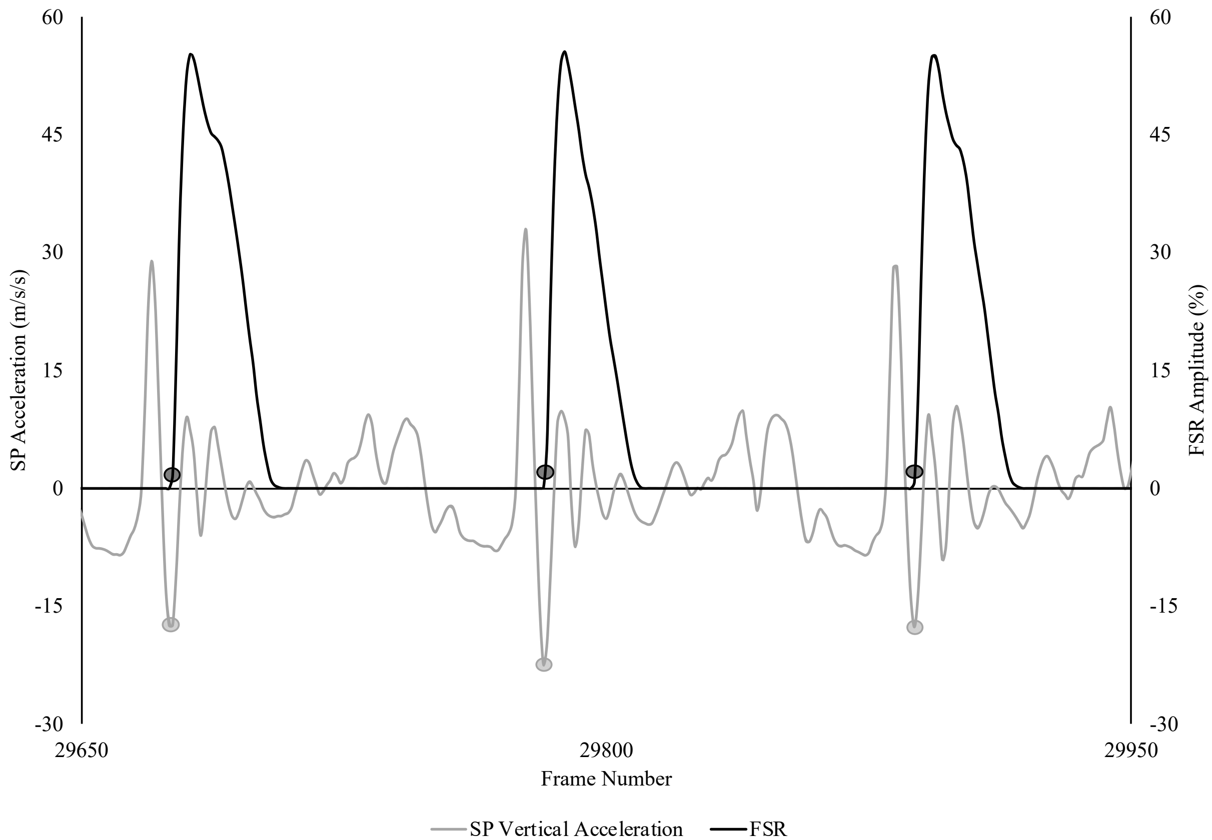

Figure 4.2. Representative plot of right heel contact locations in the signals recorded from the force-sensing resistor (FSR) and smartphone accelerometer (SPAcc) systems. The black and gray circles represent heel contact event locations within the FSR and SPAcc signals, respectively.

Dependent Measures

The following linear measures were calculated: i) average ISI (xISI; ms), representing average stride time and ii) SD of stride time, representing stride-time variability (STv; ms), and iii) stride time coefficient of variation (COV; %). The following nonlinear measures were calculated: i) FSI using DFA, ii) ApEn, and iii) SaEn.

Calculation of DFA: The ISI series was first integrated and then divided into non-overlapping boxes of equal length (n). A least-squares line of best fit was applied within each box. The integrated ISI series was then detrended by subtracting the line of best from within each box. The root mean square (RMS) was calculated for each box and the average RMS was calculated across all boxes. This process was repeated with a range of box size lengths (n=3-40). A logarithmic transformation was applied to the plot of RMS vs. box length (n) to create a log-log plot. Lastly, the slope of the line of best fit in the log-log plot was calculated to obtain the FSI value (Terrier and Dériaz, 2012).

Calculation of ApEn and SaEn: The ApEn algorithm applied a sliding window to the ISI series to determine the probability that short sequences of data points of length m are repeated within a certain similarity criterion level r, throughout a sequence of data points. The SaEn algorithm was similar to ApEn, except it removed the self-matching bias. The m and r values were set to 2 and 0.2 times the ISI series SD, respectively (Yentes et al., 2013). The ApEn and SaEn algorithms have been described in detail elsewhere (see Chapter Two of this dissertation).

Statistical Analyses

Statistical analyses were performed using JMP v. 9.0 software (The SAS Institute, NC, USA). BA plots with 95% LOA were constructed using the mean of all walking trials for each participant, for each system to assess the agreement between systems. Normality of the differences between each paired measurement was assessed visually through histograms and quantitatively using Shapiro-Wilk tests (Giavarina, 2015). The *a priori* defined acceptable LOAs were based on published research, as follows: FSI=0.065 (Herman et al., 2005), COV=0.225% (Kobsar et al., 2014a), xISI=50msec (Hausdorff et al., 1997), and STv=11msec (Hausdorff et al., 1997); those values were selected as the LOA required in those studies to differentiate between young and older adults, and between older fallers and non-fallers. As described in Chapters Two and Three of this dissertation, entropy values from previous studies can only be used if consistency in entropy values across a range of algorithm criteria (data length, m, and r) and between defined conditions (control and experimental) is assessed. Therefore, the acceptable LOA for ApEn and SaEn were selected as the mean difference values between original and surrogate-generated data sets, derived from the FSR signals (Costa et al., 2003) and calculated and compared with paired t-tests as described in Chapter Three of this dissertation. Following this analysis, the acceptable LOA were selected as ApEn=0.105 and SaEn=0.265. Intraclass correlation coefficients (ICC) model 2 form k ICC(2,k), where k=3, were used to assess the test-retest reliability of each system using the measures from each walking trial (Weir, 2005). ICC values of <0.5, 0.5-0.75, 0.75-0.90, and >0.90 were interpreted as poor, moderate, good, and excellent, respectively (Koo and Li, 2016).

4.3. Results

Surrogate Analysis

The paired t-tests revealed significant differences between original and surrogate-generated data sets derived from the FSR signals for ApEn: $t(16) = 15.4$, *p*-value < 0.001 and SaEn: $t(16) = 11.9$, *p*-value < 0.001. These results confirm that the surrogate datasets may act as a control condition that is significantly different from that of the healthy adult group's original data.

Validity

The 95% LOA calculated for the SPAcc compared to the FSR system were found to be within the *a priori* defined acceptable LOA for all dependent measures (Figure 4.3). A slight negative bias was found for mean ISI, stride time COV, ApEn, and SaEn representing an overestimation by the SPAcc; a slight positive bias was found for STv and FSI representing an underestimation of the SPAcc (Figure 4.3). All descriptive statistics are outlined in Table 4.1.

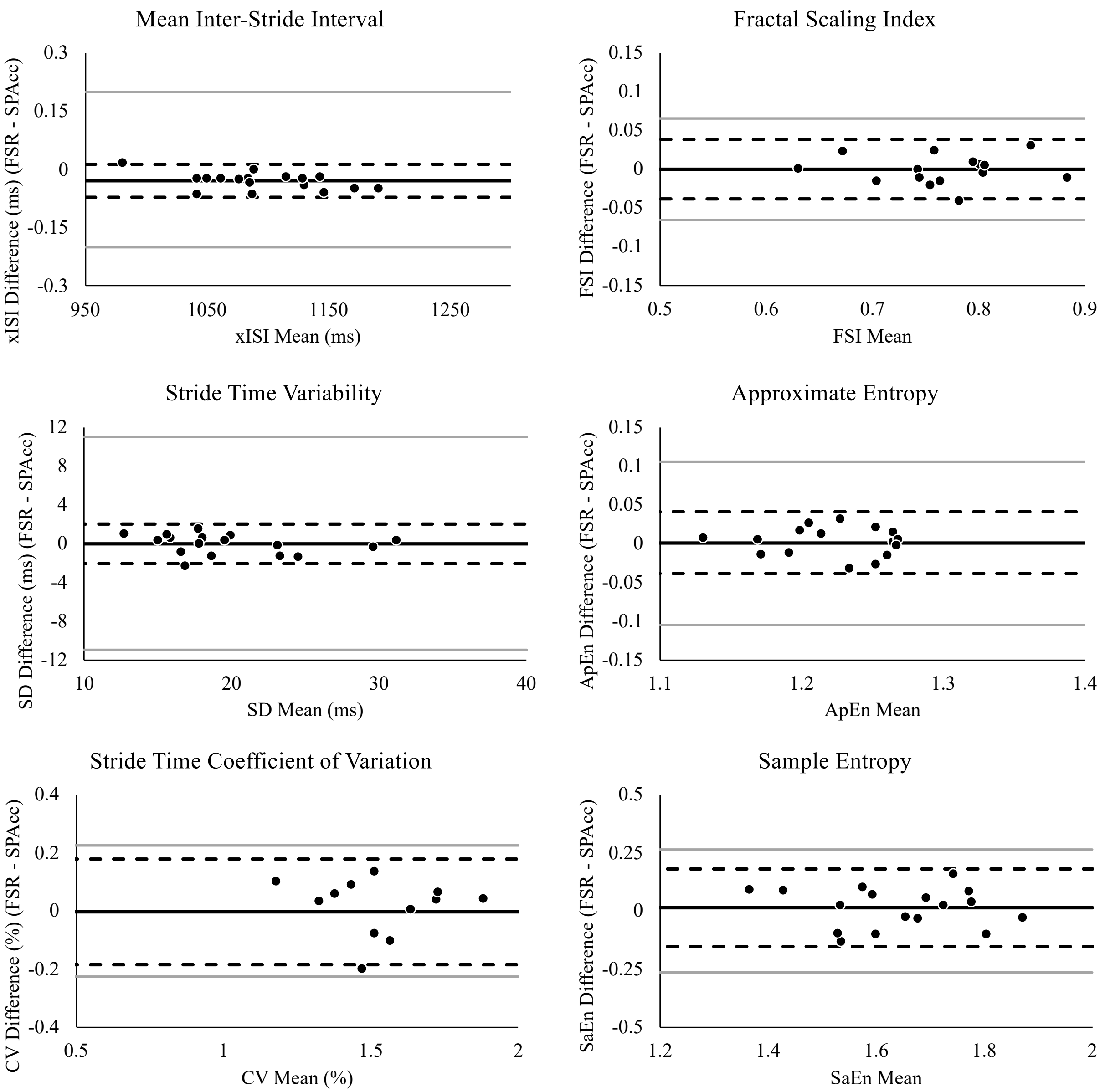

Figure 4.3. Bland Altman plots with 95% limits of agreement (LOA) for each dependent measure between each measurement system. The dashed black lines represent the 95% LOA, the solid black lines represent the bias, the gray lines represent the *a priori* defined acceptable LOA, the black circles represent the average of all trials from each participant (*n* = 17). Note, the acceptable LOA (gray lines) for mean inter-stride interval are for demonstrative purposes only since the true *a priori* defined acceptable LOA are much larger (±50ms).

Table 4.1. Mean (±SD) of linear and nonlinear measures derived from the signals of each system, along with bias, 95% limits of agreement (LOA), and pre-defined acceptable LOA.

Measure	System		Bias (95% Limits of Agreement)	Acceptable ±LOA
	SPAcc	FSR	FSR versus SPAcc	
Mean Inter-Stride Interval (ms)	1100.8 (53.2)	1100.9 (52.3)	-0.03 (-0.07, 0.01)	50
Stride Time Variability (ms)	19.5 (5.0)	19.5 (5.2)	0.001 (-2.04, 2.05)	11
Coefficient of Variation of Stride Time (%)	1.78 (0.49)	1.79 (0.52)	-0.003 (-0.18, 0.18)	0.225
Fractal Scaling Index	0.79 (0.08)	0.79 (0.08)	0.0001 (-0.038, 0.038)	0.065
Approximate Entropy	1.21 (0.06)	1.21 (0.06)	-0.001 (-0.038, 0.041)	0.105
Sample Entropy	1.62 (0.14)	1.61 (0.15)	-0.014 (-0.153, 0.181)	0.265

Note: SPAcc = smartphone accelerometer system, FSR = footswitch system. Negative bias [FSR - SPAcc] represents overestimation.

Reliability

The ICCs revealed good to excellent reliability for all dependent measures, except for FSI, for both systems (Table 4.2). On average, the linear measures revealed better reliability compared to the nonlinear measures (0.92-0.93 versus 0.81-0.82, respectively) for both systems. The ICCs for FSI were 0.67 and 0.70 for the SPAcc and FSR system, respectively. Entropy measures derived from both systems demonstrated better reliability compared to FSI (Table 4.2).

Table 4.2. Test re-test reliability results.

Measure	Type	SPAcc ICC(2,k)	FSR ICC(2,k)
Mean Inter-Stride Interval	Linear	0.94 E	0.94 E
Stride Time Variability	Linear	0.91 E	0.90 E
Coefficient of Variation of ISI	Linear	0.93 E	0.92 E
Fractal Scaling Index	Nonlinear	0.67 M	0.70 M
Approximate Entropy	Nonlinear	0.85 G	0.84 G
Sample Entropy	Nonlinear	0.90 E	0.93 E

Note: M - moderate, G - good, E - excellent, k = 3, ISI = inter-stride interval.

4.4. Discussion

The current study evaluated the agreement and test re-test reliability of SP-accelerometery derived linear and nonlinear gait measures during overground walking. The results demonstrated acceptable LOA across all dependent measures investigated, suggesting that the SPAcc system is a valid method and performs similarly to that of a GS FSR system commonly used in gait research. The SPAcc also demonstrated moderate to excellent reliability, across the three laboratory visits, with similar ICC values to that of the FSR system. To date, this is the first study that has validated nonlinear gait variability derived from a SPAcc during continuous overground walking and demonstrates promising results for the utility of a SPAcc to measure gait variability while simply placed in the user's pant pocket.

The mean xISI and STv values derived from the SPAcc were consistent with the values from previous overground walking research with the use of an accelerometer system (Kobsar et al., 2014a). The average stride time COV was found to be lower compared to previous research; 2.74% (Terrier and Dériaz, 2011) and 2.15% (Kobsar 2014b). The reliability of xISI in the current study was similar to previous work investigating between-day reliability of average stride time with the use of a smartphone (Manor et al., 2018), reporting excellent reliability across both home and laboratory visits. Interestingly, Manor et al (2018) also reported no effect of pocket tightness (tight, medium, loose) on deriving stride times from the smartphone, while placed in the user's front pant pocket. Although pocket tightness was not investigated in the current study, the reliability of xISI is in line with previous research and supports the idea of smartphones as an easy-to-use, low-cost, and practical gait analysis tool.

The FSI values derived from both systems are consistent with previous research (Terrier and Dériaz, 2011) and are within the expected range for the population investigated (FSI≅0.75-0.85) (Hausdorff et al., 1995; Rhea and Kiefer, 2014). To my knowledge, only one study has estimated a nonlinear gait measure derived from a SPAcc (Hammoud et al., 2015). That study compared the FSI derived from a SPAcc to an in-shoe pressure sensing system and reported

LOA of -0.08 to 0.012. The LOA reported by Hammoud et al (2015) are wider, but similar to the LOA for FSI reported in the current study (-0.038 to 0.038). Additionally, the BA plot reported in Hammoud et al (2015) revealed mean FSI values between 0.53-0.60 which are substantially lower than the FSI values in the current study. The differences in FSI values may be due to several methodological reasons: the sampling rate of 38Hz used by Hammoud et al (2015) was too low (Marmelat et al., 2019), an absence of continuous steady-state walking as participants repeatedly walked along a 25m corridor, stopping and turning around to walk back each time, and an insufficient number of data points collected (~74s of gait data). Analysis of a dynamical system requires a sufficient number of continuous data to uncover the evolution of the system's pattern over time. Thus, a protocol of participants walking back and forth along a corridor effectively breaks the temporal evolution of the stepping pattern, essentially creating short, separate trials with stride-to-stride fluctuations that are unrelated to one another. Although, the combining or "stitching" together of shorter gait trials to create a longer ISI series used for nonlinear analysis has been performed, previous research has shown this method to be unreliable for estimating the FSI (Marmelat et al., 2018). Without enough data points, the true dynamics of the system may be misrepresented (Yentes et al., 2013). Furthermore, a low sampling rate may not provide enough resolution to accurately locate heel contact event locations. The current study addresses the previously mentioned methodological issues by sampling at 100Hz, using 6-minute continuous steady-state walking trials, and as such, may explain the differences in FSI values.

The FSI values for both systems were found to be less reliable compared to all other measures investigated. This is not surprising as nonlinear measures are more sensitive, compared to linear measures, to subtle changes in input data, typically resulting in large changes in output behaviour. Therefore, any small between-day changes in the stepping pattern may influence the

FSI value. The current study attempted to mitigate reliability error in estimating gait FSI based on the recommendation by Pierrynowski et al (2005). However, the entropy measures, both of which are nonlinear, revealed excellent reliability in the current study. Differences in reliability between the FSI and entropy measures may be explained by the scale of each algorithm. The DFA calculation, used to compute the FSI of the ISI series, considers the stride pattern across multiple scales (seconds, and in the case of the present study, up to ~50 seconds), while the ApEn and SaEn measures calculation use a single scale (seconds). Therefore, the measures themselves may explain the differences in reliability, with multiscale measures putatively more sensitive to between-day changes in stride-to-stride fluctuations. Future research should investigate the reliability of both single- and multi-scale nonlinear measures to provide recommendations when estimating gait variability. A limitation of the current study is the absence of a defined control group for interpreting ApEn and SaEn values, as well as to confirm algorithm input parameter selection. Future research should validate the SPAcc while including an experimental group (i.e., older adults) as a way to define acceptable LOA, as well as extend the findings of the current study to other populations.

4.5. Conclusion

The current study is the first to demonstrate evidence of a smartphone accelerometer as a viable gait analysis tool to estimate linear and nonlinear measures among healthy young adults, during continuous overground walking in a controlled environment. Implications of the current study's findings are the development and implementation of an inexpensive, easy-to-use, and ubiquitous telehealth instrument that may replace traditional laboratory equipment for use in the free-living environment. Future research should utilize smartphones to explore gait variability in an unconstrained free-living environment and among different populations to obtain an authentic representation of gait variability and potentially monitor fall risk and rehabilitation (especially for those in rural areas).

4.6. References

Bujang, M.A., & Baharum, N. (2017). A simplified guide to determination of sample size requirements for estimating the value of intraclass correlation coefficient: a review. *Archives of Orofacial Science* 12, 1-11.

Costa, M., Peng, C. K., Goldberger, A. L., & Hausdorff, J. M. (2003). Multiscale entropy analysis of human gait dynamics. *Physica A*, *330*(1-2), 53–60. https://doi.org/10.1016/j.physa.2003.08.022

Fazlali, H., Sadeghi, H., Sadeghi, S., Ojaghi, M., & Allard, P. (2020). Comparison of four methods for determining the cut-off frequency of accelerometer signals in able-bodied individuals and ACL ruptured subjects. *Gait & posture*, *80*, 217–222. https://doi.org/10.1016/j.gaitpost.2020.06.009

Giavarina D. (2015). Understanding Bland Altman analysis. *Biochemia medica*, *25*(2), 141–151. https://doi.org/10.11613/BM.2015.015

Hammoud, A., Duchêne, J., Abou-ghaida, H., Mottet, S., Goujon, J., Hewson, D.J. (2015). Validation of a Smartphone Gait Analysis System, International Federation for Medical and Biological Engineering Proceedings 45,910–913.

Hausdorff J. M. (2007). Gait dynamics, fractals and falls: finding meaning in the stride-to-stride fluctuations of human walking. *Human movement science*, *26*(4), 555–589. https://doi.org/10.1016/j.humov.2007.05.003

Hausdorff, J. M., Mitchell, S. L., Firtion, R., Peng, C. K., Cudkowicz, M. E., Wei, J. Y., & Goldberger, A. L. (1997). Altered fractal dynamics of gait: reduced stride-interval correlations with aging and Huntington's disease. *Journal of applied physiology (Bethesda, Md. : 1985)*, *82*(1), 262–269. https://doi.org/10.1152/jappl.1997.82.1.262

Hausdorff, J. M., Peng, C. K., Ladin, Z., Wei, J. Y., & Goldberger, A. L. (1995). Is walking a random walk? Evidence for long-range correlations in stride interval of human gait. *Journal of applied physiology (Bethesda, Md. : 1985)*, *78*(1), 349–358. https://doi.org/10.1152/jappl.1995.78.1.349

Hausdorff, J. M., Purdon, P. L., Peng, C. K., Ladin, Z., Wei, J. Y., & Goldberger, A. L. (1996). Fractal dynamics of human gait: stability of long-range correlations in stride interval fluctuations. *Journal of applied physiology (Bethesda, Md. : 1985)*, *80*(5), 1448–1457. https://doi.org/10.1152/jappl.1996.80.5.1448

Herman, T., Giladi, N., Gurevich, T., & Hausdorff, J. M. (2005). Gait instability and fractal dynamics of older adults with a "cautious" gait: why do certain older adults walk fearfully?. *Gait & posture*, *21*(2), 178–185. https://doi.org/10.1016/j.gaitpost.2004.01.014

Hollman, J. H., Watkins, M. K., Imhoff, A. C., Braun, C. E., Akervik, K. A., & Ness, D. K. (2016). Complexity, fractal dynamics and determinism in treadmill ambulation: Implications for clinical biomechanists. *Clinical biomechanics (Bristol, Avon)*, *37*, 91–97. https://doi.org/10.1016/j.clinbiomech.2016.06.007

How T, Chee J, Wan E, Mihailidis A. (2013). MyWalk : A Mobile App for Gait Asymmetry Rehabilitation in the Community, 3–6.

Kobsar, D., Olson, C., Paranjape, R., & Barden, J. M. (2014a). The validity of gait variability and fractal dynamics obtained from a single, body-fixed triaxial accelerometer. *Journal of applied biomechanics*, *30*(2), 343–347. https://doi.org/10.1123/jab.2013-0107

Kobsar, D., Olson, C., Paranjape, R., Hadjistavropoulos, T., & Barden, J. M. (2014b). Evaluation of age-related differences in the stride-to-stride fluctuations, regularity and symmetry of gait using a waist-mounted tri-axial accelerometer. *Gait & posture*, *39*(1), 553–557. https://doi.org/10.1016/j.gaitpost.2013.09.008

Konsolakis, K., Hermens, H., Villalonga, C., Vollenbroek-Hutten, M., & Banos, O. (2018). Human Behaviour Analysis through Smartphones. *UCAmI 2018*. https://doi.org/10.3390/proceedings2191243

Koo, T. K., & Li, M. Y. (2016). A Guideline of Selecting and Reporting Intraclass Correlation Coefficients for Reliability Research. *Journal of chiropractic medicine*, *15*(2), 155–163. https://doi.org/10.1016/j.jcm.2016.02.012

Lemoyne, R., Mastroianni, T., Cozza, M., Coroian, C., & Grundfest, W. (2010). Implementation of an iPhone as a wireless accelerometer for quantifying gait characteristics. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, *2010*, 3847–3851. https://doi.org/10.1109/IEMBS.2010.5627699

Lindemann, U., Najafi, B., Zijlstra, W., Hauer, K., Muche, R., Becker, C., & Aminian, K. (2008). Distance to achieve steady state walking speed in frail elderly persons. *Gait & posture*, *27*(1), 91–96. https://doi.org/10.1016/j.gaitpost.2007.02.005

Lugade, V., Kuntapun, J., Prupetkaew, P., Boripuntakul, S., Verner, E., & Silsupadol, P. (2021). Three-Day Remote Monitoring of Gait Among Young and Older Adults Using Participants' Personal Smartphones. *Journal of aging and physical activity*, *29*(6), 1026–1033. https://doi.org/10.1123/japa.2020-0353

Manor, B., Yu, W., Zhu, H., Harrison, R., Lo, O. Y., Lipsitz, L., Travison, T., Pascual-Leone, A., & Zhou, J. (2018). Smartphone App-Based Assessment of Gait During Normal and Dual-Task Walking: Demonstration of Validity and Reliability. *JMIR mHealth and uHealth*, *6*(1), e36. https://doi.org/10.2196/mhealth.8815

Marmelat, V., Reynolds, N. R., & Hellman, A. (2018). Gait Dynamics in Parkinson's Disease: Short Gait Trials "Stitched" Together Provide Different Fractal Fluctuations Compared to Longer Trials. *Frontiers in physiology*, *9*, 861. https://doi.org/10.3389/fphys.2018.00861

Nishiguchi, S., Yamada, M., Nagai, K., Mori, S., Kajiwara, Y., Sonoda, T., Yoshimura, K., Yoshitomi, H., Ito, H., Okamoto, K., Ito, T., Muto, S., Ishihara, T., & Aoyama, T. (2012). Reliability and validity of gait analysis by android-based smartphone. *Telemedicine journal and e-health : the official journal of the American Telemedicine Association*, *18*(4), 292–296. https://doi.org/10.1089/tmj.2011.0132

Pierrynowski, M. R., Gross, A., Miles, M., Galea, V., McLaughlin, L., & McPhee, C. (2005). Reliability of the long-range power-law correlations obtained from the bilateral stride intervals in asymptomatic volunteers whilst treadmill walking. *Gait & posture*, *22*(1), 46–50. https://doi.org/10.1016/j.gaitpost.2004.06.007

Qin, D., Huang, M. (2015). Smartphone Based Gait Monitor System. EAI Endorsed Transactions on Pervasive Health and Technology. 2 10.4108/eai.28-9-2015.2261519.

Raffalt, P. C., Alkjær, T., Brynjólfsson, B., Jørgensen, L., Bartholdy, C., & Henriksen, M. (2018). Day-to-Day Reliability of Nonlinear Methods to Assess Walking Dynamics. *Journal of biomechanical engineering*, *140*(12), 10.1115/1.4041044. https://doi.org/10.1115/1.4041044

Rhea, C.K., Kiefer, A.W. (2014). Patterned variability in gait behavior: how can it be measured and what does it mean? In: Li L, Holmes M, editors. Gait biometrics: basic patterns, role of neurological disorders and effects of physical activity. Hauppauge, NY: Nova Science Pub, Inc.; 2014. p. 17–43.

Rye Hanton, C., Kwon, Y. J., Aung, T., Whittington, J., High, R. R., Goulding, E. H., Schenk, A. K., & Bonasera, S. J. (2017). Mobile Phone-Based Measures of Activity, Step Count, and Gait Speed: Results From a Study of Older Ambulatory Adults in a Naturalistic Setting. *JMIR mHealth and uHealth*, *5*(10), e104. https://doi.org/10.2196/mhealth.5090

Shahar, R. T., & Agmon, M. (2021). Gait Analysis Using Accelerometry Data from a Single Smartphone: Agreement and Consistency between a Smartphone Application and Gold-Standard Gait Analysis System. *Sensors (Basel, Switzerland)*, *21*(22), 7497. https://doi.org/10.3390/s21227497z

Silsupadol, P., Teja, K., & Lugade, V. (2017). Reliability and validity of a smartphone-based assessment of gait parameters across walking speed and smartphone locations: Body, bag, belt, hand, and pocket. *Gait & posture*, *58*, 516–522. https://doi.org/10.1016/j.gaitpost.2017.09.030

Terrier, P., & Dériaz, O. (2011). Kinematic variability, fractal dynamics and local dynamic stability of treadmill walking. *Journal of neuroengineering and rehabilitation*, *8*, 12. https://doi.org/10.1186/1743-0003-8-12

Warlop, T., Detrembleur, C., Stoquart, G., Lejeune, T., & Jeanjean, A. (2018). Gait Complexity and Regularity Are Differently Modulated by Treadmill Walking in Parkinson's Disease and Healthy Population. *Frontiers in physiology*, *9*, 68. https://doi.org/10.3389/fphys.2018.00068

Yang M, Zheng H, Wang H, Mcclean S, Harris N. (2012). Assessing the utility of smart mobile phones in gait pattern analysis. *Health Technology,* 2;81–88.

Yentes, J. M., Hunt, N., Schmid, K. K., Kaipust, J. P., McGrath, D., & Stergiou, N. (2013). The appropriate use of approximate entropy and sample entropy with short data sets. *Annals of biomedical engineering*, *41*(2), 349–365. https://doi.org/10.1007/s10439-012-0668-3

CHAPTER 5

STUDY 3

MONITORING GAIT COMPLEXITY IN THE WILD

5.0. Abstract

Human gait exhibits stride-to-stride fluctuations that may reflect age-related changes in gait adaptability; estimated with nonlinear measures that restrict data collection to controlled settings. This study investigated age-related differences in linear and nonlinear gait measures estimated from a smartphone accelerometer (SPAcc) system during free-living walking. Thirteen young adults (YA) (7F; 28.3±3.7 years old) and 11 older adults (OA) (7F; 68.7±2.8 years old) walked within a shopping mall with a SPAcc placed in their front right pants pocket. The inter-stride interval (ISI) was calculated as the time difference between ipsilateral heel contacts located within the SPAcc vertical axis signal. Linear measures included: mean ISI (s), stride time standard deviation (SD) (s) and coefficient of variation (COV) (%). Nonlinear measures included: fractal scaling index (FSI), approximate entropy (ApEn), sample entropy (SaEn) at scales 1-4, complexity index, statistical persistence decay (SPD) (strides), and entropic half-life (EnHL) (strides). One-way repeated measures analysis of variance was performed to compare the effect of age. A significant difference ($p<0.05$) between age groups (mean: YA, OA) was found for stride time SD (0.04s, 0.05s), stride time COV (3.47%, 4.16%), SaEn scale 1 (1.70, 1.86), SaEn scale 3 (2.12, 1.80), and SPD (31 strides, 23 strides). The greater SaEn at scale 1 found among OA suggests less stride time regularity. However, greater SaEn at scale 3 found among YA, suggests a greater number of stepping strategies available. The greater SPD found for YA suggests stride time dependence is preserved over a greater number of strides. FSI (0.93-0.95) was found to be greater than typical laboratory-based studies for both groups, suggesting a

shift in adaptive behaviour toward a more structured stepping strategy due to increased challenge during free-living walking. Overall, these findings suggest the SPAcc is a user-friendly and viable option for remote monitoring of gait dynamics.

5.1. Introduction

Reduced inter-stride complexity during gait is indicative of aged-related changes in neuromuscular function and increased risk of falling among older adults (Hausdorff et al., 1997). The human body can be considered a composite of interconnected and co-dependent elements (e.g., muscles and motor neurons) that interact with one another across different spatial and temporal scales to perform intended motor behaviours with flexibility (Peng et al., 2009). Flexibility refers to the capacity of the system to select different movement patterns according to the situation or task (Wagenaar et al., 2002). The breakdown in the elements, or in the connections between elements comprising the system is suggested to be the cause of the system's diminished ability to flexibly adapt to stressors placed on the system, as described by the Loss of Complexity hypothesis (Lipsitz and Goldberger, 1992) and Optimal Movement Variability model (Stergiou et al., 2006). Classic, linear measures which describe the magnitude of variation in a series of values independent of the ordering of the values, are the foundation of gait analysis and can provide insight into the stability of the walker where stability can be defined as one's ability to maintain upright equilibrium following exposures to external or self-generated perturbations (Bruijn et al., 2013; van Emmerik et al., 2016). Increases in gait variability have been interpreted as a decline in gait performance and are predictive of falls among older adults (Maki, 1997; Hausdorff et al., 2001; Marques et al., 2018). However, nonlinear approaches to gait analysis quantify the dependency of point-to-point fluctuations (i.e., structure of variability) across consecutive stride times which appear seemingly erratic, yet are structured, and are suggested to provide greater sensitivity for detecting diminished adaptive capacity between healthy and unhealthy states (Hausdorff et al., 1997). The breakdown in gait dynamics (i.e., stride-to-stride fluctuations) may not only manifest as overly disorganized patterns, but also as overly organized and structured patterns; both of which are suggestive of poorly adaptive systems and putatively increase fall risk.

In the seminal work of Hausdorff et al. (1995), stride time is described as a self-similar pattern that exhibits long-range correlations such that the current stride is related to past and future strides at remote locations within a time series, suggesting a locomotor 'memory' across hundreds of strides. The fractal scaling index (FSI), calculated using detrended fluctuation analysis (DFA), is a nonlinear measure that quantifies the presence of long-range correlations within the inter-stride interval (ISI) series. Among healthy young adults, ISI FSI values are generally between 0.75-0.85 (Hausdorff et al., 1995; Rhea and Kiefer, 2014), indicating statistical persistence during overground walking in a controlled environment (e.g., vacant walkway), while older adults and pathological gait patterns tend towards randomness (FSI=0.5). FSI values closer to 0.5 suggest a disorganized pattern and have been related to fall risk (Hausdorff, 2007). Furthermore, FSI values may provide greater sensitivity for detecting age- or disease-related changes in gait patterns and uncovering fall risk, compared to linear measures such as stride time coefficient of variation (COV) (Hausdorff et al., 1997).

Entropy analysis is another common nonlinear method applied to gait patterns to assess statistical regularity or the degree of uncertainty that future patterns within the time series will be repeated (Yentes and Raffalt, 2021). Gait patterns with higher entropy values are generally interpreted as suggesting greater adaptability, providing a rich array of novel stepping strategies available to the walker, if needed, to account for imposed constraints (i.e., obstacle negotiation) by modifying the typical stepping pattern. Approximate entropy (ApEn) and sample entropy (SaEn) are two of the first entropy-based measurements used in the literature to assess statistical regularity of gait patterns between different adult populations (Karmakar et al., 2007; Leverick et al., 2014). However, ApEn and SaEn only operate on a single scale and are therefore not considered complexity measures (e.g., FSI). Single scale stride time analysis can be defined as considering point-to-point fluctuations being controlled at only one particular window size (i.e., considering and comparing the groupings of two consecutive stride time intervals throughout the time series). Therefore, multiscale entropy (MSE) was developed to overcome the single-scale limitation of SaEn. MSE investigates point-to-point fluctuations of increasing length by calculating the SaEn on coarse-grained time series as described in Chapter two of this dissertation. MSE considers the relationship between increasing scales such that every increase in scale increases the particular window size being compared. MSE was developed because randomly generated time series (i.e., white noise), in which no relationship between data points exists, could produce higher entropy values at smaller scales which may incorrectly be interpreted as more complex than those generated from a pink noise time series (i.e., $1/f$ noise). However, across increasing scales, the SaEn of white noise decreases monotonically while pink noise is found to remain relatively flat, which can be interpreted as a complex system since it exhibits multiscale behaviour (Costa et al., 2002). The complexity index (CI) was developed as a quantitative measure of MSE by finding the area under the SaEn versus scale plot and has demonstrated differences between young and older adults with a greater CI value for young adults (Amirpourabasi et al., 2021). Overall, nonlinear measures segment the time series into windows of a particular size and investigate the pattern of variability within each window and compare these windows to one another across the time series. Complexity measures perform the same process of segmenting the time series into windows, but also compare the pattern of variability contained within windows of varying sizes, providing multiscale analysis of the time series.

Recently, attempts to quantify the stride number at which the stride time series decays away from statistical persistence, (i.e., towards randomness) and when statistical regularity (i.e., the degree of predictability of future stride times) is reduced by half has been introduced as novel metrics called “statistical persistence decay” (SPD) and “entropic half-life” (EnHL), respectively (Raffalt and Yentes, 2018/2020). The SPD and EnHL measures implement a reshaping procedure that generates multiple versions of the original time series with the relationship between adjacent data points becoming increasing less correlated with each successive reshaping (Zandiyeh and von Tscharner, 2013). The reshaping procedure increases the distance between adjacent data points of the original time series by rearranging the order of data points; gradually randomizing the original time series with each successive reshaping. The rearranging of data points occurs by incrementally separating the location of adjacent data points for each reshaped time series generated. The FSI and SaEn is calculated for each reshaped time series, and the point at which the FSI and SaEn values cross a critical threshold represents the stride at which the reshaped time series differs from the original time series. SPD and EnHL can be interpreted as a method to quantify at which stride the walker’s stride time is no longer related to adjacent stride times, thereby indicating when complexity and statistical regularity, respectively, break down. However, these measures have only been calculated using data from healthy young adults while walking in a controlled environment (e.g., treadmill), likely due to the requirement of hundreds of consecutive strides (Raffalt and Yentes, 2018/2020).

The embedded accelerometers within smartphones have revealed accurate and reliable results for estimating linear (i.e., stride time, stride length, gait speed, stride time variability) and nonlinear (i.e., FSI, SaEn) gait measures while walking in a controlled environment (Silsupadol et al., 2017; Di Bacco and Gage, 2023). In addition, smartphone systems have been implemented in the free-living environment to estimate linear gait measures such as stride time (Manor et al., 2018) and walking speed (Rye Hanton et al., 2017; Lugade et al., 2021), demonstrating promising results among healthy young, older, and clinical adult populations while simply placed in the user's pant pocket. However, researchers utilizing smartphone systems have yet to move beyond linear gait measures and examine the actual gait dynamics of the walker (i.e., gait complexity) in the free-living environment. By removing the confines of a controlled laboratory setting and permitting the individual to walk in the "wild", valuable insights into the authentic quantification of human gait patterns can be obtained. Therefore, the aim of the current study was to implement the previously validated smartphone accelerometer (SPAcc) system for estimating gait measures during unconstrained free-living walking among healthy young and older adults. I hypothesized that linear gait variability measures would differ between young and older adult groups during free-living walking in an unconstrained environment; nonlinear gait variability measures would differ between young and older adult groups during free-living walking in an unconstrained environment.

5.2. Methods

Participants

Thirteen healthy young adults (YA) (7F; mean±SD; age: 28.3±3.7 years of age, weight: 72.6±17.3kg, height: 1.74±0.1m) and 11 healthy older adults (OA) (7F; mean±SD; age: 68.7±2.8

years of age, weight: 76.9±8.7kg, height: 1.67±0.11m) volunteered to participate. Sample size was calculated *a priori* based on the FSI mean and variance values of YA and OA groups reported in Hausdorff et al. (1997), with 80% power and an alpha of 0.05, yielding n=11 for each group. Each participant provided written informed consent prior to participation. The university research ethics board granted approval for the study (certificate#2019-091). All participants completed a screening questionnaire, the Activities-specific Balance Confidence (ABC) Scale questionnaire, and fear of falling question (Yes; No; Somewhat) to assess study eligibility and physical activity level. Inclusion criteria included: No fear, or somewhat fearful of falling; an ABC score ≥ 67% (Lajoie and Gallagher, 2004); between 18 and 35 years of age, or ≥ 65 years of age; ability to perform repeated 10-minute walking bouts; self-reported fall history of < 2 falls in the past 12 months (Weiss et al., 2013); and no neurological or musculoskeletal conditions or injuries within the past six months that might affect gait performance. Participants were considered physically active if they performed 150 minutes or more of moderate-to-vigorous physical activity per week (Tremblay et al., 2011; Dale et al., 2016). Key participant characteristics are described in Table 5.1.

Table 5.1. Participant characteristics.

Participant	FoF	Fall history	ABC score (%)	Physically active	Type of physical activity
Older Adults					
1	No	0	99	No	N/A
2	No	0	95	Yes	Walking
3	No	0	99	Yes	Walking
4	No	0	92	Yes	Walking/hockey
5	No	0	98	Yes	Walking
6	No	0	93	Yes	Walking
7	Somewhat	0	74	Yes	Walking
8	No	1	78	Yes	Aerobics
9	No	1	92	Yes	Walking/cycling/aqua fitness
10	No	1	95	Yes	Walking/cycling
11	No	0	94	Yes	Walking
Young Adults					
1	No	0	99	Yes	Resistance traning/walking
2	No	0	99	Yes	Resistance traning
3	No	0	100	Yes	Resistance traning/soccer
4	No	0	100	Yes	Dance
5	No	0	99	Yes	Resistance traning/soccer
6	No	0	99	Yes	Resistance traning/soccer/volleyball
7	No	0	100	Yes	Walking
8	No	0	98	Yes	Resistance training/running/hockey
9	No	0	98	Yes	Walking
10	No	0	99	Yes	Resistance traning/soccer
11	No	0	96	Yes	Walking
12	No	0	99	No	N/A
13	No	0	100	Yes	Walking

Note: FoF = fear of falling, fall history = number of falls over the past 12 months, ABC = Activities-specific Balance Confidence Scale.

Protocol

Participants were asked to visit the local shopping mall and wear comfortable walking shoes and pants with front pockets. Participants were asked to complete four laps of the local shopping mall throughout a 2-hour period while the SPAcc was placed in their front right pant pocket. Participants were asked to walk at their comfortable walking speed. Each lap was ~12 minutes in duration. While completing the four laps throughout the 2-hour period, participants were instructed to do whatever they would normally do during a typical mall visit (i.e., browse and shop).

Data Processing

All data were processed using Matlab (R2021b, Mathworks Inc, MA, USA). From the smartphone, only the vertical axis acceleration data were used to determine SPAcc. SPAcc data were sample interpolated to 100Hz, using the Matlab "interp1" function, as the sampling rate was not constant. The gravity bias was then removed from the accelerometery data, and the data were multiplied by -1 to correct for the upside-down orientation of the smartphone. Two data streams were created for the accelerometery data. One data stream was kept in raw form for nonlinear measures calculations. To construct the second data stream, the raw data were filtered using a fourth order low-pass Butterworth filter with a 16Hz cutoff frequency, selected based on a residual analysis approach (Fazlali et al., 2020). The second data stream was used in the calculation of linear measures.

Right heel contact locations

The local minimum following the first local maximum in the vertical acceleration profile was considered right heel contact event (Di Bacco and Gage, 2023; Manor et al., 2018) (Figure 5.1). Due to the free-living walking protocol of the current study, the local maximums were not easily locatable using the rules as described in Chapter three of this dissertation to identify right heel contact events. Therefore, a protocol similar to previous research was used to approximate right heel contact events within the vertical acceleration profile using a Gaussian continuous wavelet transform (CWT) (McCamley et al., 2012). The CWT offers simultaneous time and frequency analysis by decomposing the signal to localized oscillations of a defined wavelet shape and scale and was used as a smoothing and differentiating function by locating features (i.e., local transients) over different scales (Addison, 2005). The CWT scale variable provides control over the width of the wavelet for the isolation of frequency features with a larger scale representing a stretched wavelet (i.e., slowly changing) and a smaller scale representing a compressed wavelet (i.e., rapidly changing); selected based on the location of transients and speed of oscillations within the original signal.

The following steps were used to locate right heel contact events:

1) Remove low frequency drift from lowpass filtered vertical acceleration using a high-pass filter with a 0.1Hz cutoff frequency (Silsupadol et al., 2017).
2) Integrate the filtered vertical acceleration signal using the built-in Matlab function "Cumtrapz", creating a vertical velocity signal, for signal smoothing.
3) Differentiate vertical velocity signal using a Gaussian CWT (acc CWT) with scale = 12. Scale 12 was selected visually due to the close approximation of the peaks in the acc CWT signal to that of the local minimums in the vertical acceleration signal (Figure 5.1).
4) Locate the local minimums within the acc CWT signal with the rules that each local minimum is separated by greater than 0.8s and below a threshold value set to 40% of the median of 10 minimum acc CWT values. The separation value of 0.80s was considered the lower limit of a healthy adult's stride time (Zou et al., 2020), while the threshold value was selected based on visual inspection of several trials.
5) Locate the local maximums relative to the local minimums within the acc CWT signal.
6) Locate the local minimums (right heel contact events) within the vertical acceleration signal relative to each local maximum found within the acc CWT signal (Figure 5.1).

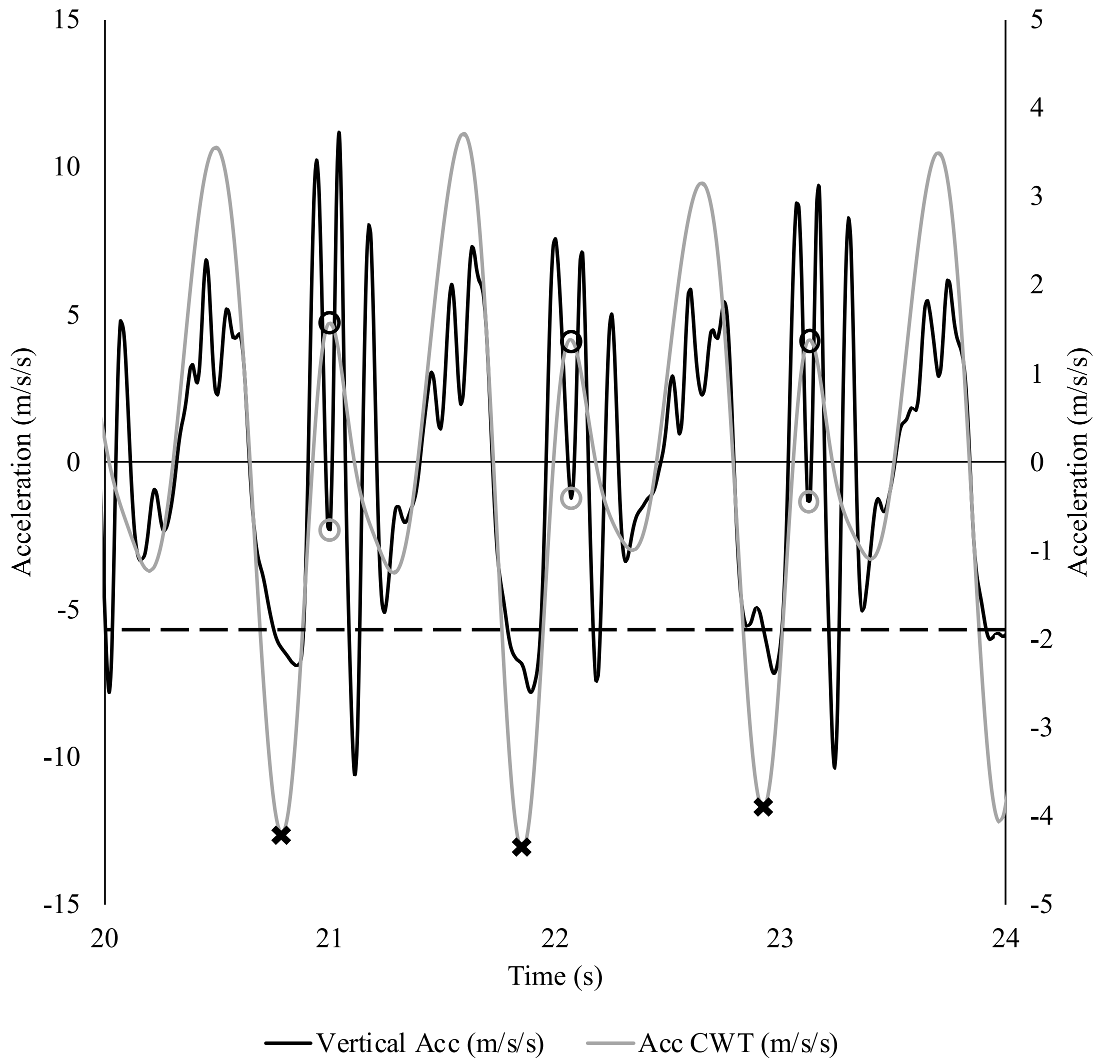

Figure 5.1. Method for determining the location of right heel contact events within the filtered smartphone accelerometer data. The vertical acceleration (Acc) (black line) is first integrated and then differentiated using a Gaussian continuous wavelet transform (CWT) (gray line). The local minimums are located (x) within the Acc CWT signal and those indexes are used to locate the local maximums (black circles) within the Acc CWT signal. The horizontal dashed line represents the threshold of local minimum crossings for the Acc CWT signal. Finally, the right heel contact events (gray circles) are located within the vertical Acc signal as the local minimum relative to each black circle.

The right heel contact event locations within the filtered vertical acceleration signal were then used to index the right heel contact locations within the raw vertical acceleration signal by creating a small three-frame offset from the filtered right heel contact locations and searching forward relative to those offsets within the raw vertical acceleration signal to locate the local minimums. The three-frame offset was selected to account for any signal shift that might have occurred due to filtering. This method was done as it became apparent that accelerometery data recorded from the smartphone during free-living walking was very noisy compared to the SPAcc data recorded during treadmill and overground walking in the controlled environment (Study 1 and Study 2 of this dissertation). The increased noisiness of the free-living walking environment was likely a function of accommodating surrounding obstacles (e.g., other people) and distractions (e.g., screens) imposed on the walker, thereby inducing an inconsistent gait pattern. All heel contact events located in the SPAcc were visually checked to ensure accuracy.

Walking bout segmentation

Once all right heel contact events were identified, walking bouts were located within the two-hour walking trial by the rule that walking bouts are separated by strides greater than 1.8s which was considered the upper limit of a healthy adult's typical stride time. Walking bouts greater than 24 consecutive right heel contact events, representing 24 strides, were used for further analysis. The first and last two strides were removed from each walking bout to ensure steady-state gait was achieved for further analysis. Therefore, walking bouts of 20 strides or greater were considered for analysis as that is the recommended minimum number of strides required to reliably estimate stride time variability (Lindermann et al., 2008) (Figure 5.2). The ISI was calculated for each walking bout as the time difference between consecutive right heel contact event locations and were used for dependent measures calculation.

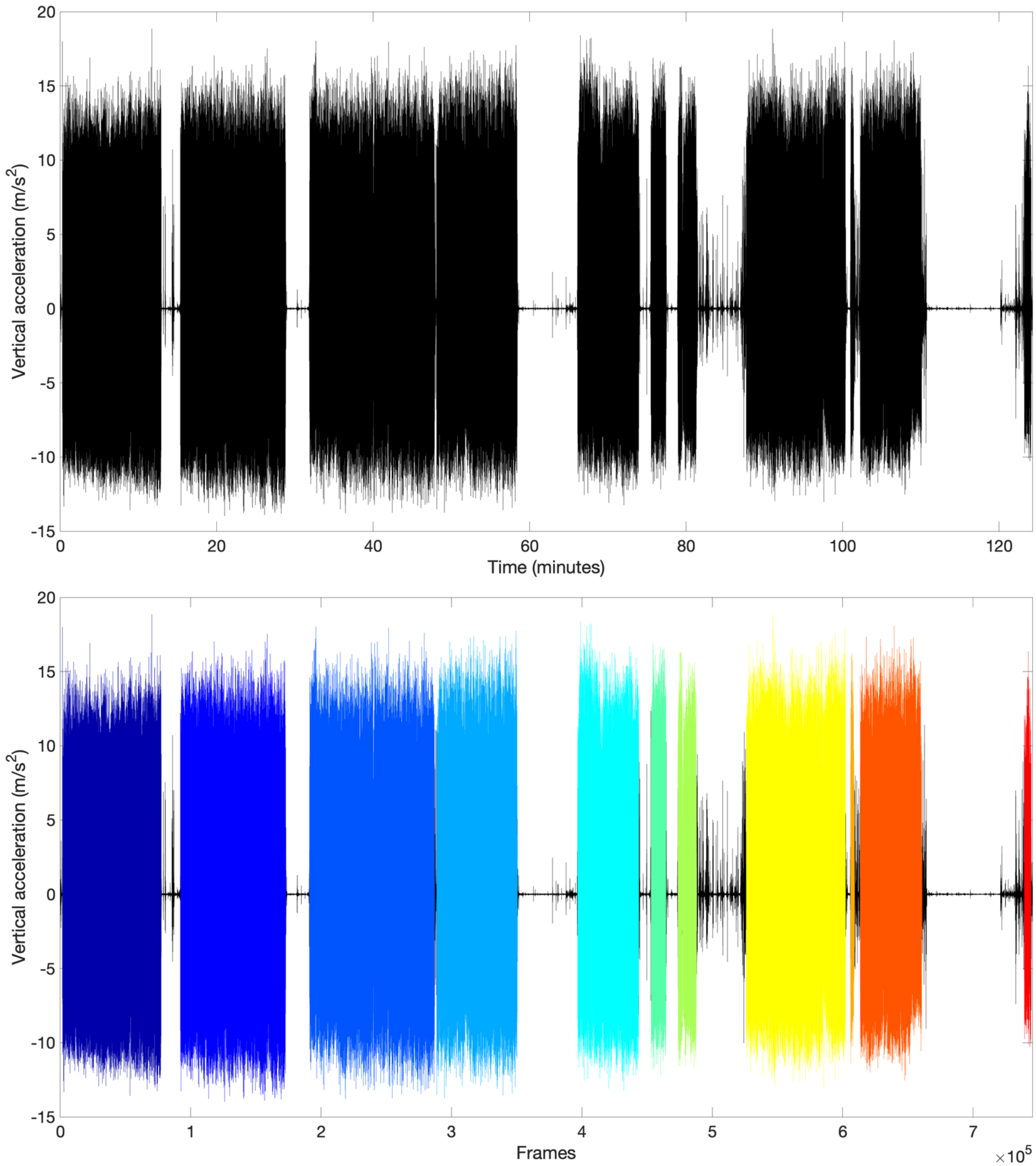

Figure 5.2. Representative plots of smartphone accelerometer data recorded from a young adult during free-living walking. Top figure represents filtered vertical acceleration of the smartphone while placed in the right front pant pocket. Bottom figure represents walking bout segmentation throughout the trial; each colour represents a different walking bout containing a minimum of 20 consecutive strides and used for further analysis.

Dependent Measures

The following measures were calculated on all walking bouts: mean ISI (xISI) (s), standard deviation (SD) of ISI (STv) (s), and stride time coefficient of variation (COV) (%). The following measures were calculated on walking bouts > 255 strides: FSI, ApEn, and SaEn. The MSE (SaEn at Scales 1 to 4) and CI (SaEn versus Scale area under the curve), SPD (strides) and EnHL (strides) were calculated on walking bouts of 800 strides. Eight hundred strides was used because that was the greatest number of strides completed within a single walking bout by all participants (see Table 5.2).

Calculation of DFA, ApEn, and SaEn measures is described in detail elsewhere (see Chapter Two of this dissertation). The input parameters, vector length m, and similarity criterion level r, used to calculate ApEn and SaEn were selected based on the qualitative analysis of plotting different combinations of m (2 and 3) and r (0.5, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40) parameters used for entropy calculation (Yentes et al., 2013; Yentes and Raffalt, 2021). After plotting the entropy measures for each combination of input parameters, entropy measure consistency and directional group difference consistency was qualitatively assessed such that entropy values should remain flat and the directional difference between groups should remain consistent, otherwise any differences found between groups may be due to parameter artifacts. This analysis is also performed so one may interpret and compare the results across studies based on the group directional differences and input parameters investigated. Group entropy differences should not ‘flip’ and entropy values should not continuously increase or decrease by altering the input parameters. Following this analysis, the m and r values were set to 2 and 0.15 times the ISI series SD, respectively, as these parameter values provided a consistent group directional difference which remained relatively flat leading up to the selection of these parameters. (Figure 5.3).

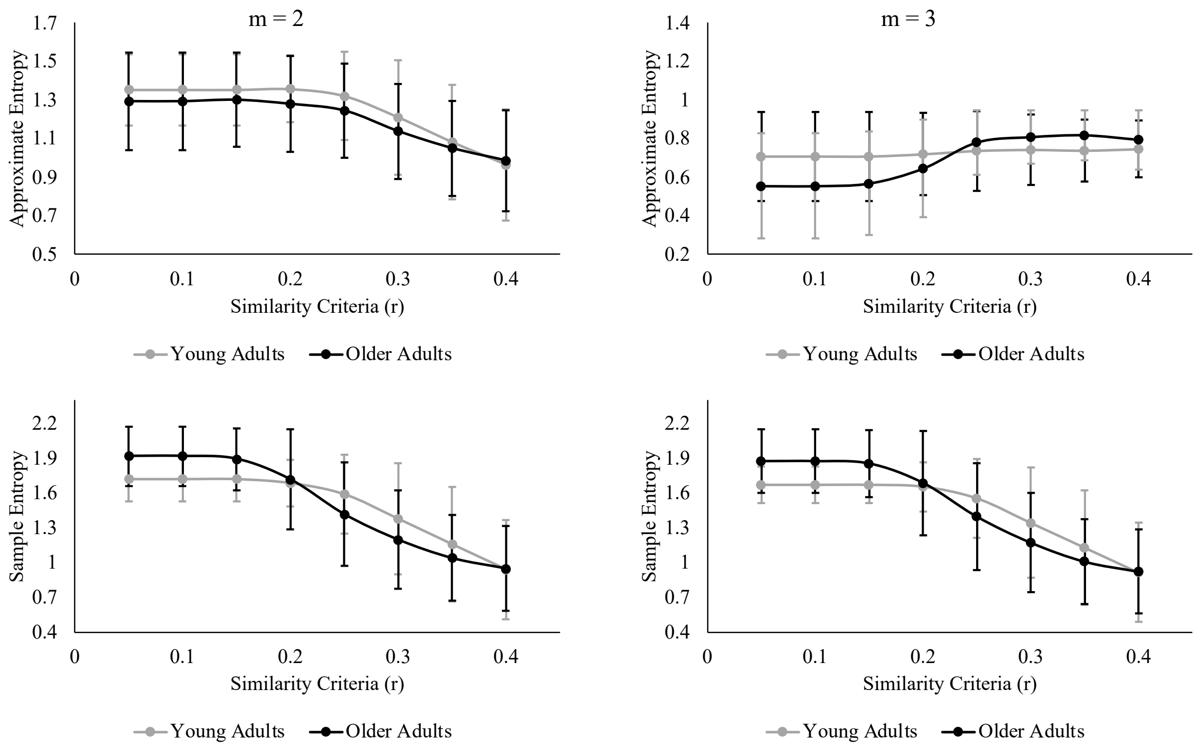

Figure 5.3. Determination of vector comparison length, m, and similarity criteria, r, for approximate and sample entropy calculations. The approximate and sample entropy values (y-axes) were calculated as the average across all trials for each age group and are plotted against the different r values (x-axes) that were tested. As demonstrated by the line plots, the entropy values are fairly flat and with parameter consistency between groups across r values with m = 2 between 0.05 and 0.15 for approximate entropy and sample entropy; both groups trended downward as r increased between 0.25 to 0.4. The young adult group was considered the control group. Following this analysis, m = 2 and r = 0.15 were selected for both sample and approximate entropy calculations. Note, for all entropy calculations, each r value tested was multiplied by the standard deviation of the inter-stride interval series of each walking bout greater than 255 consecutive strides. Error bars represent standard deviation.

Calculation of MSE: The coarse-graining process is applied to the time series of increasing scale number as described in Chapter two of this dissertation. The scale value specifies the number of data points averaged to obtain each element of the newly generated time series. Afterward, the

SaEn is calculated using the ISI series created at each scale and the SaEn (y-axis) is plotted against scale (x-axis).

Calculation of CI: The area under the SaEn versus scale curve (scales 1 to 4) was calculated using the built-in Matlab "trapz" function to determine the level of complexity for each group. CI was only calculated up to scale 4 to ensure 200 strides were contained in the largest scale (Yentes et al., 2013).

Calculation of SPD: SPD determines the stride count at which the FSI drops below a critical limit that represents uncorrelated noise. The lower the stride count, the fewer strides required for the stride-to-stride fluctuations to diverge from statistical persistence toward a value not different from uncorrelated noise. The original ISI series was first reshaped 100 times such that the distance between two subsequent ISI values was increased with each reshaping, gradually randomizing the original ISI series. For example, consider an original time series [1 2 3 4 5 6 7 8 9 10 11 12 13 14] and the reshaped time series [1 3 5 7 9 11 13 2 4 6 8 10 12 14]. The distance between adjacent data points has been increased by one space. Now consider a second reshaping [1 4 7 10 13 2 5 8 11 14 3 6 9 12] and third reshaping [1 5 9 13 2 6 10 14 3 7 11 4 8 12] of the original time series. The distance between adjacent data points is now separated by two spaces and three spaces, respectively. This process is repeated 100 times while incrementing the distance between data points by one location for each successive reshaping. Each iteration of the reshaping procedure created a new time series that was increasingly less correlated by rearranging the original order of the time series such that the relationship between consecutive data points became weaker, trending away from statistical persistence. Afterwards, the FSI is calculated for each reshaped time series, using the DFA and yielding 100 FSI values. One hundred randomized time series were then created by a random permutation of the data points in the original time series using the Matlab function "randperm". For each randomized time series, the FSI (FSI_{Random}) is calculated and the mean FSI_{Random} and corresponding SD of the 100 randomized time series are used to create a critical limit, as follows:

$$Critical\ limit = meanFSI_{Random} + (2\ x\ SDFSI_{Random})$$

Lastly, a plot of the FSI for each reshaped time series as a function of stride number was created and the stride number at which the FSI was less than the critical limit is the SPD (Figure 5.4).

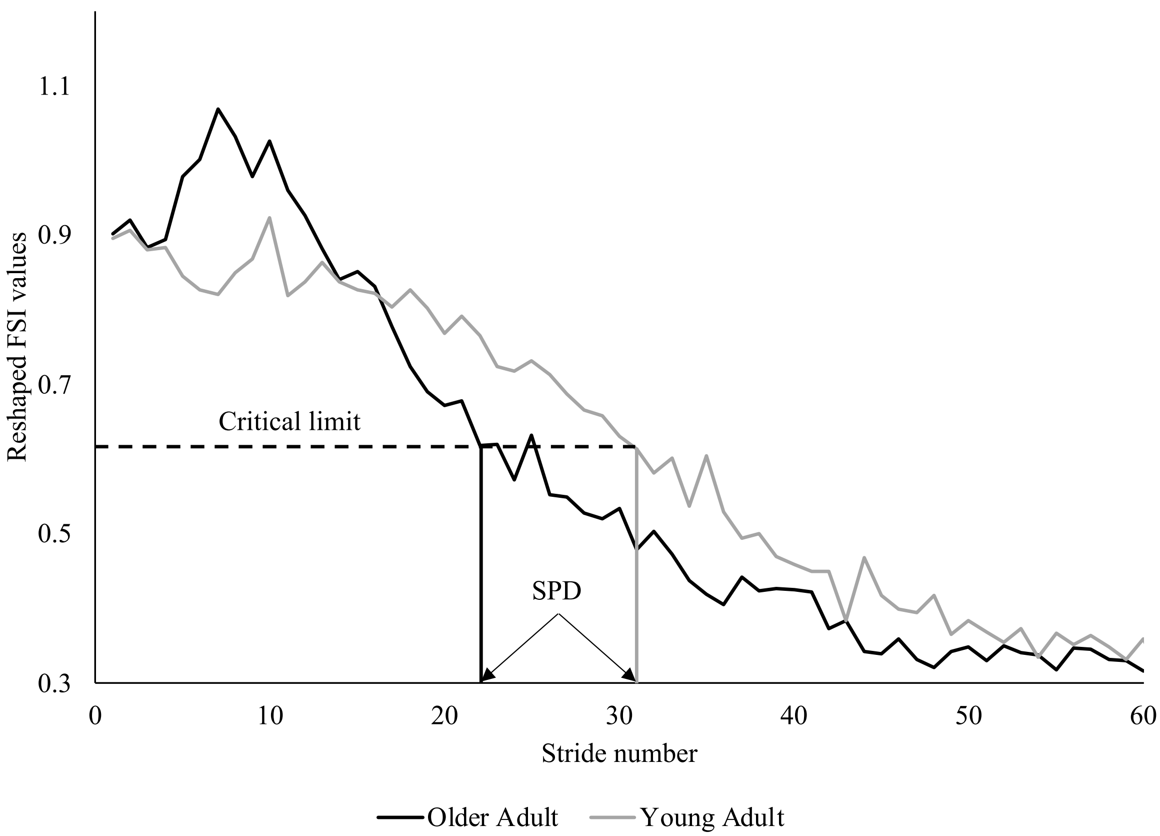

Figure 5.4. Representative plot of the statistical persistence decay (SPD) calculated from a single older adult and young adult walking bout, truncated to 800 strides. The black and gray vertical bars represent the stride number at which statistical persistence of the inter-stride interval fell below the critical limit, indicating uncorrelated noise for the older (stride 23) and young adults (stride 31), respectively.

Calculation of EnHL: EnHL estimates when the predictability in a time series is reduced by half, or in other words, how many strides can be taken before predictability in the time series is reduced by half . The reshaping method as performed for SPD is implemented and gradually randomizes the original time series 100 times and the SaEn is calculated for the original ($SaEn_{original}$) and each reshaped ($SaEn_{reshape}$) time series. Each reshaping increased the distance between two subsequent stride times. The SaEn for each reshaped time series is then normalized using the following equation:

$$\text{Normalized SaEn} = \frac{SaEn_{reshape} - SaEn_{original}}{SaEn_{random} - SaEn_{original}}$$

where $SaEn_{random}$ is the average of SaEn of 100 randomized time series generated using the Matlab "randperm" function. The SaEn for each reshaped time series is expected to fall between the lower and upper limits, represented by $SaEn_{original}$ and $SaEn_{random}$, respectively. The normalized SaEn values are then plotted against stride numbers 1-100 and the stride number at which the normalized SaEn exceeds a value of 0.5 is defined as EnHL and represents the stride number at which the predictability in the reshaped time series shifts to unpredictability (Zandiyeh and Von Tscharner, 2013) (Figure 5.5).

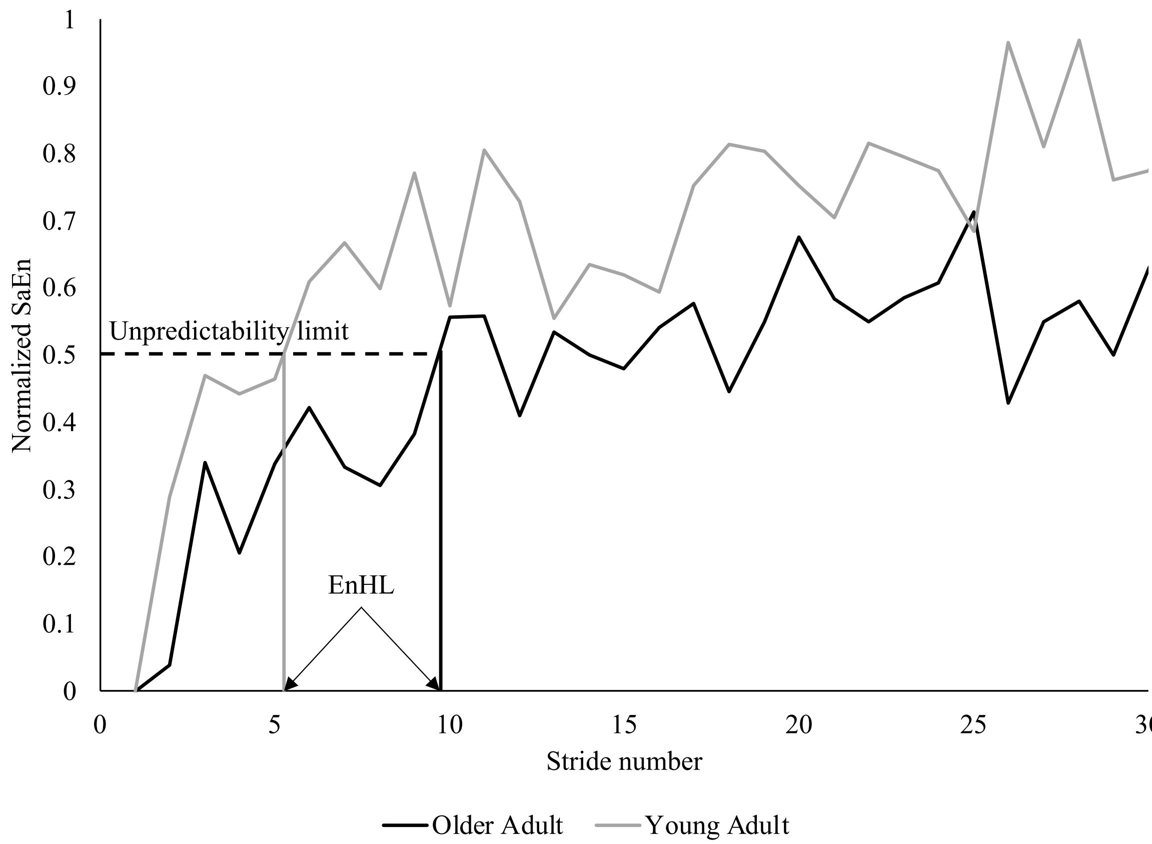

Figure 5.5. Representative plot of the entropic half-life (EnHL) calculated from a single older adult and young adult walking bout, truncated to 800 strides. The black and gray vertical bars represent the stride number at which sample entropy (SaEn) of the inter-stride interval exceeded the unpredictability limit, indicating entropy was halved for the older (~10) and young adults (~6), respectively.

Statistical Analysis

Statistical analyses were performed using JMP v. 9.0 software (The SAS Institute, NC, USA). A frequency table was created to describe the number of walking bouts and total number of strides identified, as well as the number of strides included for the longest and shortest walking bouts for each participant during the two-hour walking protocol (Table 5.2). Preliminary analysis revealed no significant sex-related differences for all dependent measures investigated ($p > 0.05$). Therefore, males and females were collapsed across groups. One-way repeated measures mixed effects analysis of variance (ANOVA) was used to test the effect of group

[YA/OA] for each dependent measure. Normality of data was assessed visually by plotting the distribution of each measure and numerically using the Shapiro-Wilk test. Non-normal data were log-transformed prior to statistical analyses. Results were statistically significant at $p < 0.05$.

5.3. Results

Frequency Table

Table 5.2. The number of walking bouts and total number of strides captured with the smartphone accelerometer system for each participant during the two-hour collection protocol. The number of strides within the longest and shortest walking bouts identified for each participant are also included. Note, a walking bout contains at least 20 consecutive strides after removing the first two and last two strides.

Participant	Walking bouts	Total strides	Longest bout (strides)	Shortest bout (strides)
Older Adults				
1	14	4091	823	21
2	20	4117	997	25
3	14	5286	1522	26
4	20	4439	1255	21
5	7	4515	1159	29
6	10	3933	963	23
7	5	1722	800	23
8	12	5774	2148	48
9	26	4593	816	22
10	12	5083	2218	25
11	10	3559	999	25
Young Adults				
1	12	4416	831	24
2	13	4520	1163	27
3	17	5455	1666	24
4	8	4879	1211	39
5	5	3927	1231	301
6	14	4045	948	24
7	9	5626	3322	34
8	11	4298	1831	21
9	8	3077	921	36
10	5	5204	3047	383
11	6	3527	928	21
12	9	5684	2186	21
13	10	3991	1017	24

Linear measures

The ANOVAs revealed a significant group difference for STv ($F(1,22) = 5.03$, $p < 0.04$) and stride time COV ($F(1,22) = 5.51$, $p < 0.03$). STv and stride time COV were significantly lower for YA compared to OA. No significant group difference was found for xISI ($F(1,22) = 0.02$, $p = 0.89$). All descriptive statistics are presented in Table 5.3.

Nonlinear measures

The ANOVAs revealed a significant group difference for SaEn ($F(1,22) = 6.5$, $p < 0.02$), Scale 1 ($F(1,22) = 4.66$, $p = 0.04$), Scale 3 ($F(1,22) = 7.38$, $p < 0.02$), and SPD ($F(1,22) = 5.04$, $p < 0.04$). SaEn and Scale 1 were significantly lower for YA compared to OA, while Scale 3 and SPD were significantly greater for YA compared to OA (Figure 5.6). No significant group differences were found for FSI ($F(1,22) = 0.58$, $p = 0.45$), ApEn ($F(1,22) = 0.08$, $p = 0.78$), scale 2 ($F(1,22) = 0.08$, $p = 0.78$), scale 4 ($F(1,22) = 1.02$, $p = 0.32$), CI ($F(1,22) = 1.37$, $p = 0.25$), and EnHL ($F(1,22) = 3.32$, $p = 0.08$). All descriptive statistics are presented in Table 5.3.

Table 5.3. Mean ± SD and ANOVA result of each gait measure calculated using the inter stride interval estimated from the smartphone accelerometer system for each group.

Measure	Older Adult	Younger Adult	Difference	*F*	*p*-value
xISI (s)	1.124 ± 0.083	1.128 ± 0.078	-0.004	0.02	0.89
STv (s)	0.047 ± 0.021	0.039 ± 0.019	0.008	5.03	<0.04*
Stride time COV (%)	4.16 ± 1.76	3.47 ± 1.58	0.69	5.51	<0.03*
FSI	0.93 ± 0.14	0.95 ± 0.10	-0.02	0.58	0.45
SaEn	1.89 ± 0.27	1.70 ± 0.15	0.19	6.5	<0.02*
ApEn	1.35 ± 0.18	1.37 ± 0.15	-0.01	0.08	0.78
SaEn Scale 1	1.86 ± 0.26	1.70 ± 0.15	0.16	4.66	0.04*
SaEn Scale 2	2.10 ± 0.37	2.14 ± 0.23	-0.04	0.08	0.78
SaEn Scale 3	1.80 ± 0.35	2.12 ± 0.48	-0.32	7.38	<0.02*
SaEn Scale 4	1.80 ± 0.16	1.90 ± 0.28	-0.10	1.02	0.32
CI Scale 4	5.77 ± 0.82	6.05 ± 0.73	-0.28	1.37	0.25
SPD (strides)	23 ± 11	31 ± 7	-8	5.04	<0.04*
EnHL (strides)	10 ± 11	6 ± 5	4	3.32	0.08

DF(1,22). xISI = mean inter-stride interval, STv = stride time variability, COV = coefficient of variation, FSI = fractal scaling index, SaEn = sample entropy, ApEn = approximate entropy, CI = complexity index, SPD = statistical persistence decay, EnHL = entropic half-life. Statistical significance $p < 0.05$ *.

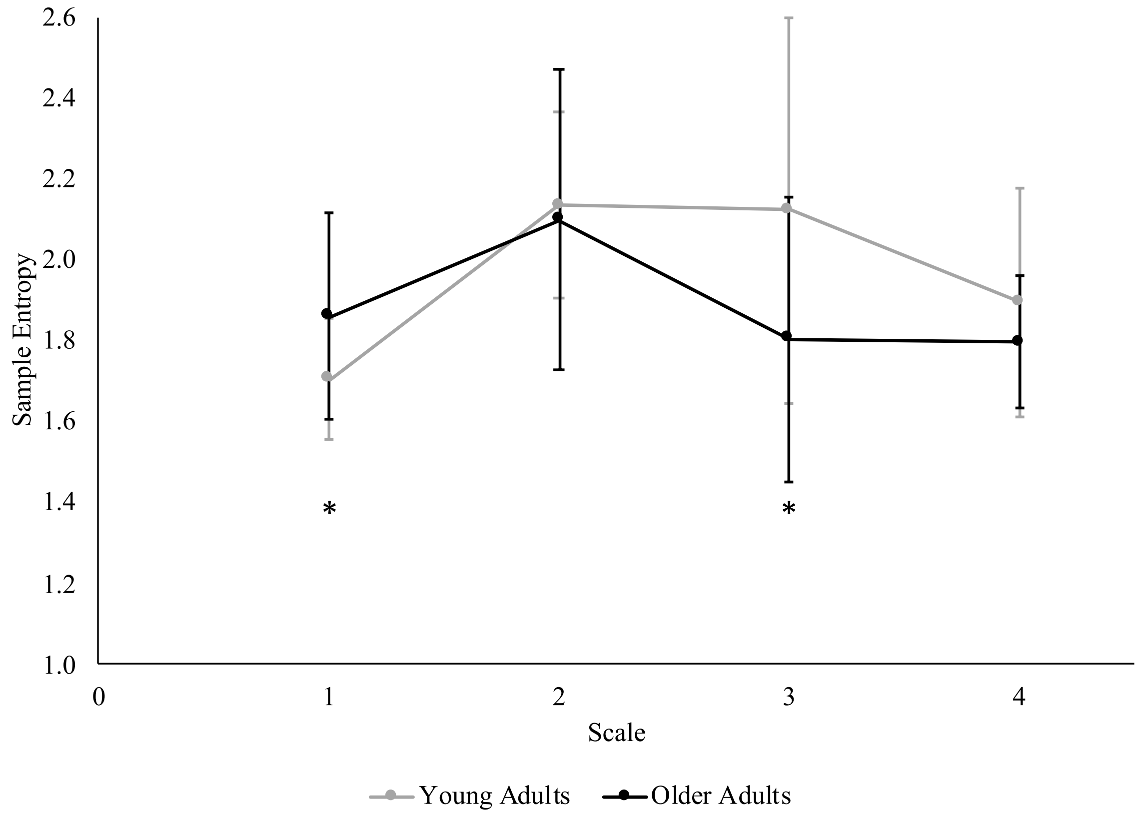

Figure 5.6. Sample entropy calculated for each scale, averaged for each group, with m = 2, r = 0.15 x standard deviation of inter-stride interval. Scale 1 = 800 strides, Scale 2 = 400 strides, Scale 3 = 266 strides, Scale 4 = 200 strides. Scales 2 to 4 were created following the coarse-graining process as described in Chapter two of this dissertation. * $p < 0.05$ between groups.

5.4. Discussion

The current study investigated the differences in linear and nonlinear gait measures between healthy young and older adults derived from a smartphone accelerometer system during overground walking in an unconstrained free-living environment. The results of the current study partially confirmed the hypotheses such that several linear and nonlinear measures differed between age groups. Overall, these findings suggest the smartphone accelerometer system may be a promising tool to estimate gait patterns in the free-living environment while simply placed in the user's pant pocket among healthy young and older adult populations. Furthermore, the current study was able to identify differences in a number of linear and nonlinear gait measures between healthy young and older adult populations. To my knowledge, this is the first study to demonstrate these findings and the implications of these findings are the implementation of an inexpensive, easy-to-use, and ubiquitous telehealth instrument to monitor walking remotely for extended periods of time without supervision.

Linear measures

The OA demonstrated greater stride time variability, compared to the YA which is similar to previous work during overground walking in a controlled environment (Kobsar et al., 2014) suggesting reduced stability. Additionally, both age groups demonstrated greater stride time variability compared to previous treadmill and overground walking research which may be associated with the free-living nature of the current study's walking protocol. For example, Tamburini et al. (2018) found that free-living walking increased stride time SD and stride time COV among healthy young adults compared to walking in a controlled (straight and predefined) overground environment, estimated with an accelerometer affixed to the low back. Brodie et al. (2016) reported step time variability was greater during 25 minutes of free-living walking compared to in-lab walking among older adults while recording with a wearable pendant sensor. Rispens et al. (2016) demonstrated stride time variability (SD) was greater during free-living walking compared to treadmill walking among older adults. Takayanagi et al. (2019) found gait speed was slower during free-living walking compared to in-lab walking. Furthermore, slower walking speed has been shown to increase stride time variability (SD and COV) (Beauchet et al., 2009). The current study's walking protocol likely resulted in frequent increases and decreases in walking speed to avoid obstacles and collisions such as other people surrounding the walker. Therefore, the increase in gait variability demonstrated in the current study may not necessarily be associated with a decrease in gait stability, but instead may reflect the free-living walking protocol (Tamburini et al., 2018), which underscores the need to interpret results within the context that data were collected.

Previous research has attempted to simulate real-world walking by manipulating the controlled walking environment and cognitive demands to investigate gait variability through dual-task and obstacle negotiation walking tasks to better reflect the free-living environment (Pieruccini-Faria and Montero-Odasso, 2019; Nohelova et al., 2021). Compared to single-task walking, dual-task walking has been found to increase stride time variability (COV) (Dubost et al., 2006; Lamoth et al., 2011) as well as increase stride-to-stride variability in gait velocity (Hollman et al., 2007) suggesting fewer attentional resources allocated toward controlling gait, as attentional resources were provided to the performance of the secondary cognitive task. Mirelman et al. (2017) demonstrated that during dual task (serial subtraction by 3s) or obstacle (10cm in height) negotiation walking, both young and older adults increased gait variability (e.g., stride length COV) compared to typical walking. Furthermore, a positive correlation was found between gait variability and pre-frontal cortex activation during the obstacle negotiation task among older adults only. Perhaps the free-living walking protocol used in the current study imposed greater task demands, requiring greater recruitment of attentional and cognitive resources (i.e., increased planning and decision making, integrating visual distractions), reflected as increased gait variability for both age groups and may further explain the greater variability found among the OA in the current study since ageing has been shown to increase the cognitive load of walking (Yogev-Seligmann et al., 2008). Although dual-task and obstacle negotiation walking were not specifically investigated in the current study, it can be well assumed that such tasks are innate during a free-living walking protocol. Baselining of gait measures may be required prior to collection, which can be done easily with the SPAcc, so that free-living walking can be compared to controlled walking values. Overall, these findings suggest free-living walking may better represent gait variability among YA and OA and may point to the need to update normative data for stride time variability. Furthermore, stride time variability may be an important distinguishing metric to detect differences between healthy age groups within the free-living environment.

Nonlinear measures

The mean FSI values of both age groups were found to be greater than previous overground walking research, especially for the OA (Hausdorff et al., 1997; Kobsar et al., 2014). Interestingly, the FSI values between age groups did not differ which was unexpected; partially rejecting one of the hypotheses. However, the majority (*n*=10/11) of participants in the OA group were considered to be physically active which may explain the lack of differences in statistical persistence found between age groups; similar to previous research during treadmill walking (Ducharme et al., 2019). Alternatively, the mean FSI value of the OA group may indicate an upregulation in adaptive behaviour of the stepping pattern due to the imposed constraints and task demands of the free-living walking environment (Ducharme and van Emmerik, 2018; Ducharme et al., 2018). Indeed, the free-living environment contains multiple obstacles (other people, tables, chairs, doors, etc.) for negotiation and distractions (screens, window shopping, conversations, noises, etc.) compared to controlled and unperturbed overground walking.

Therefore, the free-living environment may have shifted the structure of the stride-to-stride fluctuations to improve functionality or increase functional relevance of the stepping pattern, approaching optimal fractality (i.e., FSI=1.0 or 1/*f* noise). These findings are in line with the notion that FSI values are found to increase, demonstrating greater statistical persistence, during walking speeds other than preferred (Jordan et al., 2007) or asymmetric walking (Ducharme et al., 2018); effectively constraining the walker and inducing an adaptive behaviour by eliciting a highly structured stepping strategy as walking becomes more challenging (Jordan et al., 2007; Ducharme and van Emmerik, 2020). These findings are also in line with the OMV model such that FSI values between randomness (i.e., FSI=0.5) and high structuredness (FSI=1.0) suggest an FSI between these extremes may reflect optimal gait dynamics. Although walking in a controlled environment exhibits fractal dynamics between these extremes (FSI≈0.75-0.85) among healthy young adults (Jordan et al., 2007), perhaps in such a walking condition (i.e., treadmill walking), the walker is not challenged sufficiently to optimize the long-term correlations that demonstrate optimal fractal dynamics (FSI=1.0) or near optimal (FSI=0.93-0.95) as demonstrated in the current study during free-living walking.

Previous research has demonstrated that fractal scaling can be prescribed in a particular direction by timing heel contact events to an auditory (Kiriella et al, 2020) or visual (Rhea et al., 2014) timing imperative during treadmill walking. Therefore, it is conceivable that the free-living walking environment may have provided a stimulus to the stride time pattern for successful navigation of the walker's surroundings. The mean FSI value (0.95) of the YA group was found to be greater than previous research during overground walking in a controlled environment (0.83-0.87) (Kobsar et al., 2014; Hausdorff et al., 1997), suggesting perhaps the true value of the healthy locomotor system's statistical persistence. An assessment of baseline gait values during controlled overground walking should be conducted prior to free-living walking, as mentioned above, to elucidate the contribution of the free-living environment. To my knowledge, this is the first study to assess statistical persistence of stride time in the free-living environment and the current study's findings will need to be corroborated with further research.

The mean SaEn was found to be greater for OA compared to YA at scale 1 which is interpreted as reduced stride time regularity, tending toward the random side of the OMV spectrum since the YA are considered the control condition or healthy state. While only investigating single scale SaEn, Coates et al. (2020) found higher sample entropy during free-living walking among Parkinson's disease patients compared to healthy older adults suggesting a less regular stride pattern for unhealthy compared to healthy conditions. In the current study, the SaEn was found to increase at scale 2 for both age groups, which were not different from one another. However, the SaEn at scale 3 remained at the same level as scale 2 for the YA, while the OA revealed a significantly lower SaEn at scale 3 compared to the YA. These findings suggest the stride pattern for YA is maintained across three strides since coarse graining at scale 3 averages across three strides, while OA eventually dropped their entropy value at scale 3 suggesting less complexity and adaptability meaning fewer stride pattern strategies available for the OA to select from. These findings are similar to the notion that pink noise signals maintain their entropy values across multiple scales while highly irregular signals (e.g., white noise), which are considered less complex, decrease their entropy across multiple scales (Costa et al., 2002); referencing the importance of multiscale analysis and careful interpretation of equating greater entropy as greater complexity at smaller scales (i.e., scales 1 and 2 in the current study). The current study's findings are also in line with Ihlen et al. (2016) who found older adult non-fallers (healthy state) demonstrated greater MSE-based measures, compared to fallers (unhealthy state) during free-living walking recorded across three days with an accelerometer affixed to the low back. These findings may point to the relationship between greater gait complexity suggesting greater gait adaptability in the free-living environment.

Interestingly, previous research has suggested greater MSE is associated with fall risk among older adults. Riva et al. (2013) found that fall history was positively correlated with MSE of trunk accelerations among adults > 50 years of age during treadmill walking. Furthermore, single scale SaEn among older adults was found to be greater during treadmill walking compared to free-living walking (Rispens et al., 2016). Therefore, it is reasonable to suggest the difference in entropy, with greater entropy reported during treadmill walking, may be associated with in-lab versus free-living walking conditions. Free-living walking permits self-modulation of walking speed as well as a number of spatial-temporal gait parameters to adapt to the environment. These changes in spatial-temporal gait parameters are likely a consequence of a greater number of stepping strategies generated by the walker. Indeed, the current study has reported greater stride time variability for the YA group compared to previous treadmill and controlled overground walking research, indicating greater variations in the typical stride time across multiple strides. Therefore, the greater MSE reported in the current study for YA during free-living walking, compared to the greater MSE for the fall-risk group reported in Riva et al. (2013) during treadmill walking, may reflect greater complexity and ultimately greater adaptive capacity based on the environment as free-living walking is putatively more challenging and would therefore require greater complexity for successful steady-state walking compared to treadmill walking.

The CI was found to be the same between age groups which is similar to previous research reporting no difference in trunk or shank accelerations between older adult fallers and non-fallers during five minutes of overground walking along a 30m corridor (Bizovska et al., 2017), suggesting the CI is unable to discern between the two relatively high functioning groups since the faller group was considered low risk. These findings are in line with the lack of difference in statistical persistence, which is also a complexity indicator, found between age groups among healthy active adults in the current study. Although only up to scale 4 was investigated, future research should collect longer walking trials in the wild to assess greater scales with the help of the SPAcc. Overall, higher entropy suggests the generation of new non-redundant information that may provide the system with new movement strategies, thereby increasing the flexibility of the system to adapt when necessary. However, too much entropy within the time series and walking potentially becomes overwhelming or too irregular, compromising coordination and the ability to select a viable stride option, increasing fall risk (Riva et al., 2013). Future research should also investigate obstacle negotiation and gait complexity in a controlled environment as well as implement imaging equipment and other biofeedback instruments (i.e., heart rate monitor) to provide context of the free-living environment and ascertain walking intensity.

Although statistical persistence was found to not differ between age groups, the SPD was found to be different with YA maintaining statistical persistence across a greater number of strides compared to OA. The current study's SPD values ranged from 23 to 31 strides which is greater than previous treadmill walking research among young adults (~19 strides) calculated on a time series of similar length (785 strides) (Raffalt and Yentes, 2020). These findings suggest the OA exhibit a breakdown in stride time complexity in fewer strides compared to YA during free-living walking, suggesting a greater preservation of stride time dependence for the YA, and is in line with the age-related Loss of Complexity hypothesis (Lipsitz and Goldberger, 1992). Furthermore, free-living walking appears to maintain locomotor stride time dependency for a greater number of strides, for both age groups, compared to treadmill walking. These findings suggest free-living walking, for which participants are free to modulate walking speed, increases statistical persistence compared to treadmill walking, due to the greater number of stepping strategies permitted via an increase in the number of degrees of freedom available and may explain the greater SPD values. Additionally, the free-living walking protocol of the current study may have allowed mean FSI values (0.93-0.95) to shift closer toward the middle of the OMV continuum compared to the mean FSI value of 1.07 reported during treadmill walking in the aforementioned study (Raffalt and Yentes, 2020). For example, Ducharme and van Emmerik (2018) reported a stride time FSI of 0.7 during symmetric treadmill walking while asymmetric treadmill walking increased FSI to 0.9, suggesting an increase in adaptive response due to the perturbed walking condition. In addition, a quadratic relationship between stride time FSI and step length symmetry during asymmetric walking was found and demonstrated the best performance in step length symmetry was when FSI was located between 0.9 and 1.0, approaching optimal fractality, and may help explain the lower FSI but greater SPD found in the current study compared to Raffalt and Yentes (2020). Therefore, perhaps treadmill walking may have induced a stride time fractality that is highly structured, increasing statistical persistence that is beyond optimal, while free-living walking induced an FSI that is slightly less structured as a consequence of the environment and therefore delayed the decay of statistical persistence despite exhibiting a lower initial FSI value. These findings also point to the notion that there are limits to the structure of variability such that too little or too much may compromise gait performance and a sufficiently challenged walker may require greater adaptability expressed as a bounded limit of statistical persistence.

EnHL, similar to SPD, is designed to indicate the stride number at which statistical regularity of the ISI series is halved, or in other words, the stride number at which future stride times are unpredictable. A strong trend between age groups ($p = 0.08$) was found for EnHL with the predictability in stride time halved at 6 and 10 strides for young and older adults, respectively. These findings suggest the OA may maintain their stride time regularity over a greater number of strides, compared to YA, and may be in line with the greater SaEn at scale 1 found among OA compared to the YA. Perhaps the OA, beginning with a larger SaEn, permitted the longer (greater number of strides) preservation of stride time regularity as expressed by EnHL, compared to the YA group which exhibited lower SaEn prior to the EnHL calculation. Therefore, the greater SaEn at scale 1 among the OA may not reflect an overly irregular stride time pattern, but instead may reflect a greater number of useful stepping strategies that allowed statistical regularity to be maintained across a greater number of strides, prior to regularity breakdown (predictability in stride time is halved). In addition, the findings of the current study suggest predictability in stride time is halved between 6 and 10 strides and is much lower than the SPD of both age groups, perhaps due to the single-scale characteristic of the SaEn calculation compared to the multiscale characteristic of the FSI, using DFA. These findings suggest SPD may be more sensitive for detecting age related changes in gait patterns, and more specifically, the breakdown in the structure of stride-to-stride fluctuations, since statistical significance was not achieved for EnHL.

EnHL was found to be slightly lower compared to previous treadmill walking research among young adults (~12 strides) calculated on a time series of similar length (785 strides) (Raffalt and Yentes, 2020). Although SaEn was not reported in the aforementioned study, EnHL during free-living walking appears to occur in less strides, which may suggest free-living walking may be more challenging, providing greater task demands compared to treadmill walking. Future research should compare EnHL across different SaEn scales (i.e., EnHL applied to scales 2-4) to elucidate the difference found between the SPD and EnHL measures. It should be noted that SPD and EnHL are artificial measures in a sense that the reshaping procedure generates multiple time series data that are not from a biological system necessarily but are instead derivatives of that system, suggesting the need for careful interpretation of these measures. Future work should implement the SPAcc to monitor gait dynamics in the wild among different adult populations (i.e., fallers) and for extended periods of time (i.e., throughout a month) to help relate linear and nonlinear measures to different health states.

Indeed, while no participants in the current study fell during the free-living walking protocol, gait complexity and statistical regularity were predicted to breakdown many hundreds of strides earlier than the consecutive 800-stride time series used in the current study. Therefore, it is reasonable to suggest that although there is a substantial locomotor ‘memory’, even up to ~50 strides (Raffalt and Yentes, 2018), this ‘memory’ or long-term dependence may in fact become updated, shifting, for example, statistical persistence toward optimal fractality regularly and as needed based on past stride-to-stride fluctuations. With the help of wearable sensors, future research should strive for real-time estimates of gait complexity for every successive stride added to the time series as a type of sliding or expanding window throughout the walking bout. Doing so may provide real-time feedback, perhaps with only a delay of one stride, and may detect the breakdown in gait adaptability, alerting the walker into safety or prescribing a particular stride pattern related to optimal complexity (i.e., approaching FSI = 1.0) to predict and prevent falls.

5.5. Conclusion

This is the first study to demonstrate age-related differences in linear and nonlinear gait variability measures estimated with a SPAcc during free-living walking in an ecologically valid setting. The findings revealed age-related differences in a number of linear and nonlinear measures investigated. It was suggested that these age-related differences in gait patterns may not only reflect aging, but also the nature of free-living walking. Furthermore, the absence of age-related differences found in gait complexity (FSI and CI) may also be explained by free-living walking; perhaps providing a true representation of gait variability among the populations investigated. Further work needs to be done to uncover what aspects of free-living walking resulted in differences in the values found in the current study compared to previous in-laboratory based research. The implication of these findings is that the SPAcc is a user-friendly, accessible, and viable option for remote based monitoring of gait dynamics while simply placed in the user's pant pocket. Future research should implement the SPAcc to explore gait patterns among different adult populations and for extended periods of time as a telehealth tool to monitor gait adaptability, and potentially fall risk, remotely.

5.6. References

Addison P. S. (2005). Wavelet transforms and the ECG: a review. *Physiological measurement*, *26*(5), R155–R199. https://doi.org/10.1088/0967-3334/26/5/R01

Amirpourabasi, A., Chow, J. Y., Lamb, S. E, Kwek J. R. L, & Williams G. K. R. (2021) Effects of aging on gait complexity. *ISBS Proceedings Archive*: Vol. 39: Iss. 1, Article 25. Available at: https://commons.nmu.edu/isbs/vol39/iss1/25

Beauchet, O., Annweiler, C., Lecordroch, Y., Allali, G., Dubost, V., Herrmann, F. R., & Kressig, R. W. (2009). Walking speed-related changes in stride time variability: effects of decreased speed. *Journal of neuroengineering and rehabilitation*, *6*(1), 1-6.

Bizovska, L., Svoboda, Z., Vuillerme, N., & Janura, M. (2017). Multiscale and Shannon entropies during gait as fall risk predictors-A prospective study. *Gait & posture*, *52*, 5–10. https://doi.org/10.1016/j.gaitpost.2016.11.009

Brodie, M. A., Coppens, M. J., Lord, S. R., Lovell, N. H., Gschwind, Y. J., Redmond, S. J., Del Rosario, M. B., Wang, K., Sturnieks, D. L., Persiani, M., & Delbaere, K. (2016). Wearable pendant device monitoring using new wavelet-based methods shows daily life and laboratory gaits are different. *Medical & biological engineering & computing*, *54*(4), 663–674. https://doi.org/10.1007/s11517-015-1357-9

Bruijn, S. M., Meijer, O. G., Beek, P. J., & van Dieën, J. H. (2013). Assessing the stability of human locomotion: a review of current measures. *Journal of the Royal Society, Interface*, *10*(83), 20120999. https://doi.org/10.1098/rsif.2012.0999

Coates, L., Shi, J., Rochester, L., Del Din, S., & Pantall, A. (2020). Entropy of Real-World Gait in Parkinson's Disease Determined from Wearable Sensors as a Digital Marker of Altered Ambulatory Behavior. *Sensors (Basel, Switzerland)*, *20*(9), 2631. https://doi.org/10.3390/s20092631

Costa, M., Goldberger, A. L., & Peng, C. K. (2002). Multiscale entropy analysis of complex physiologic time series. *Physical review letters*, *89*(6), 068102. https://doi.org/10.1103/PhysRevLett.89.068102

Dale, L. P., LeBlanc, A. G., Orr, K., Berry, T., Deshpande, S., Latimer-Cheung, A. E., O'Reilly, N., Rhodes, R. E., Tremblay, M. S., & Faulkner, G. (2016). Canadian physical activity guidelines for adults: are Canadians aware?. *Applied physiology, nutrition, and metabolism = Physiologie appliquee, nutrition et metabolisme*, *41*(9), 1008–1011. https://doi.org/10.1139/apnm-2016-0115

Di Bacco, V. E., & Gage, W. H. (2023). Evaluation of a smartphone accelerometer system for measuring nonlinear dynamics during treadmill walking: Concurrent validity and test-retest reliability. *Journal of biomechanics*, *151*, 111527. https://doi.org/10.1016/j.jbiomech.2023.111527

Dubost, V., Kressig, R. W., Gonthier, R., Herrmann, F. R., Aminian, K., Najafi, B., & Beauchet, O. (2006). Relationships between dual-task related changes in stride velocity and stride time variability in healthy older adults. *Human movement science*, *25*(3), 372–382. https://doi.org/10.1016/j.humov.2006.03.004

Ducharme, S. W., & van Emmerik, R. E. (2018). Fractal dynamics, variability, and coordination in human locomotion. *Kinesiology Review*, *7*(1), 26-35.

Ducharme, S. W., Kent, J. A., & van Emmerik, R. E. A. (2019). Comparable Stride Time Fractal Dynamics and Gait Adaptability in Active Young and Older Adults Under Normal and Asymmetric Walking. *Frontiers in physiology*, *10*, 1318. https://doi.org/10.3389/fphys.2019.01318

Ducharme, S. W., Liddy, J. J., Haddad, J. M., Busa, M. A., Claxton, L. J., & van Emmerik, R. E. A. (2018). Association between stride time fractality and gait adaptability during unperturbed and asymmetric walking. *Human movement science*, *58*, 248–259. https://doi.org/10.1016/j.humov.2018.02.011

Ducharme, S.W., & van Emmerik, R. (2020). The interplay between physical activity and aging in locomotor fractal behavior. *Chaos, Soliton & Fractals: X.* 5. 100045.

Fazlali, H., Sadeghi, H., Sadeghi, S., Ojaghi, M., & Allard, P. (2020). Comparison of four methods for determining the cut-off frequency of accelerometer signals in able-bodied individuals and ACL ruptured subjects. *Gait & posture*, *80*, 217–222. https://doi.org/10.1016/j.gaitpost.2020.06.009

Hausdorff J. M. (2007). Gait dynamics, fractals and falls: finding meaning in the stride-to-stride fluctuations of human walking. *Human movement science*, *26*(4), 555–589. https://doi.org/10.1016/j.humov.2007.05.003

Hausdorff, J. M., Mitchell, S. L., Firtion, R., Peng, C. K., Cudkowicz, M. E., Wei, J. Y., & Goldberger, A. L. (1997). Altered fractal dynamics of gait: reduced stride-interval correlations with aging and Huntington's disease. *Journal of applied physiology (Bethesda, Md. : 1985)*, *82*(1), 262–269. https://doi.org/10.1152/jappl.1997.82.1.262

Hausdorff, J. M., Rios, D. A., & Edelberg, H. K. (2001). Gait variability and fall risk in community-living older adults: a 1-year prospective study. *Archives of physical medicine and rehabilitation*, *82*(8), 1050–1056. https://doi.org/10.1053/apmr.2001.24893

Hausdorff, J.M., Peng, C.K., Ladin, Z., Wei, J.Y., Goldberger, A.L. (1995). Is walking a random walk? Evidence for long-range correlations in stride interval of human gait. Journal of Applied Physiology, 78, 349–358.

Hollman, J. H., Kovash, F. M., Kubik, J. J., & Linbo, R. A. (2007). Age-related differences in spatiotemporal markers of gait stability during dual task walking. *Gait & posture*, *26*(1), 113–119. https://doi.org/10.1016/j.gaitpost.2006.08.005

Ihlen, E. A. F., Weiss, A., Bourke, A., Helbostad, J. L., & Hausdorff, J. M. (2016). The complexity of daily life walking in older adult community-dwelling fallers and non-fallers. *Journal of biomechanics*, *49*(9), 1420–1428. https://doi.org/10.1016/j.jbiomech.2016.02.055

Jordan, K., Challis, J. H., & Newell, K. M. (2007). Walking speed influences on gait cycle variability. *Gait & posture*, *26*(1), 128–134. https://doi.org/10.1016/j.gaitpost.2006.08.010

Karmakar, C. K., Khandoker, A. H., Begg, R. K., Palaniswami, M., & Taylor, S. (2007). Understanding ageing effects by approximate entropy analysis of gait variability. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, *2007*, 1965–1968. https://doi.org/10.1109/IEMBS.2007.4352703

Kiriella, J. B., Di Bacco, V. E., Hollands, K. L., & Gage, W. H. (2020). Evaluation of the Effects of Prescribing Gait Complexity Using Several Fluctuating Timing Imperatives. *Journal of motor behavior*, *52*(5), 570–577. https://doi.org/10.1080/00222895.2019.1654971

Kobsar, D., Olson, C., Paranjape, R., Hadjistavropoulos, T., & Barden, J. M. (2014). Evaluation of age-related differences in the stride-to-stride fluctuations, regularity and symmetry of gait using a waist-mounted tri-axial accelerometer. *Gait & posture*, *39*(1), 553–557. https://doi.org/10.1016/j.gaitpost.2013.09.008

Lajoie, Y., & Gallagher, S. P. (2004). Predicting falls within the elderly community: comparison of postural sway, reaction time, the Berg balance scale and the Activities-specific Balance Confidence (ABC) scale for comparing fallers and non-fallers. *Archives of gerontology and geriatrics*, *38*(1), 11–26. https://doi.org/10.1016/s0167-4943(03)00082-7

Lamoth, C. J., van Deudekom, F. J., van Campen, J. P., Appels, B. A., de Vries, O. J., & Pijnappels, M. (2011). Gait stability and variability measures show effects of impaired cognition and dual tasking in frail people. *Journal of neuroengineering and rehabilitation*, *8*, 2. https://doi.org/10.1186/1743-0003-8-2

Leverick, G., Szturm, T., & Wu, C. Q. (2014). Using entropy measures to characterize human locomotion. *Journal of biomechanical engineering*, *136*(12), 121002. https://doi.org/10.1115/1.4028410

Lindemann, U., Najafi, B., Zijlstra, W., Hauer, K., Muche, R., Becker, C., & Aminian, K. (2008). Distance to achieve steady state walking speed in frail elderly persons. *Gait & posture*, *27*(1), 91–96. https://doi.org/10.1016/j.gaitpost.2007.02.005

Lipsitz, L. A., & Goldberger, A. L. (1992). Loss of 'complexity' and aging. Potential applications of fractals and chaos theory to senescence. *JAMA*, *267*(13), 1806–1809.

Lugade, V., Kuntapun, J., Prupetkaew, P., Boripuntakul, S., Verner, E., & Silsupadol, P. (2021). Three-Day Remote Monitoring of Gait Among Young and Older Adults Using Participants' Personal Smartphones. *Journal of aging and physical activity*, *29*(6), 1026–1033. https://doi.org/10.1123/japa.2020-0353

Maki B. E. (1997). Gait changes in older adults: predictors of falls or indicators of fear. *Journal of the American Geriatrics Society*, *45*(3), 313–320. https://doi.org/10.1111/j.1532-5415.1997.tb00946.x

Manor, B., Yu, W., Zhu, H., Harrison, R., Lo, O. Y., Lipsitz, L., Travison, T., Pascual-Leone, A., & Zhou, J. (2018). Smartphone App-Based Assessment of Gait During Normal and Dual-Task Walking: Demonstration of Validity and Reliability. *JMIR mHealth and uHealth*, *6*(1), e36. https://doi.org/10.2196/mhealth.8815

Marques, N. R., Spinoso, D. H., Cardoso, B. C., Moreno, V. C., Kuroda, M. H., & Navega, M. T. (2018). Is it possible to predict falls in older adults using gait kinematics?. *Clinical biomechanics (Bristol, Avon)*, *59*, 15–18. https://doi.org/10.1016/j.clinbiomech.2018.08.006

McCamley, J., Donati, M., Grimpampi, E., & Mazzà, C. (2012). An enhanced estimate of initial contact and final contact instants of time using lower trunk inertial sensor data. *Gait & posture*, *36*(2), 316–318. https://doi.org/10.1016/j.gaitpost.2012.02.019

Mirelman, A., Maidan, I., Bernad-Elazari, H., Shustack, S., Giladi, N., & Hausdorff, J. M. (2017). Effects of aging on prefrontal brain activation during challenging walking conditions. *Brain and cognition*, *115*, 41–46. https://doi.org/10.1016/j.bandc.2017.04.002

Peng, C. K., Costa, M., & Goldberger, A. L. (2009). Adaptive data analysis of complex fluctuations in physiological time series. *Advances in adaptive data analysis*, *1*(1), 61–70. https://doi.org/10.1142/S1793536909000035

Pieruccini-Faria, F., & Montero-Odasso, M. (2019). Obstacle Negotiation, Gait Variability, and Risk of Falling: Results From the "Gait and Brain Study". *The journals of gerontology. Series A, Biological sciences and medical sciences*, *74*(9), 1422–1428. https://doi.org/10.1093/gerona/gly254

Raffalt, P. C., & Yentes, J. M. (2018). Introducing Statistical Persistence Decay: A Quantification of Stride-to-Stride Time Interval Dependency in Human Gait. *Annals of biomedical engineering*, *46*(1), 60–70. https://doi.org/10.1007/s10439-017-1934-1

Raffalt, P. C., & Yentes, J. M. (2020). On the application of entropic half-life and statistical persistence decay for quantification of time dependency in human gait. *Journal of biomechanics*, *108*, 109893. https://doi.org/10.1016/j.jbiomech.2020.109893

Rhea, C. K., Kiefer, A. W., Wittstein, M. W., Leonard, K. B., MacPherson, R. P., Wright, W. G., & Haran, F. J. (2014). Fractal gait patterns are retained after entrainment to a fractal stimulus. *PloS one*, *9*(9), e106755. https://doi.org/10.1371/journal.pone.0106755

Rhea, C.K., Kiefer, A.W. (2014). Patterned variability in gait behavior: how can it be measured and what does it mean? In: Li L, Holmes M, editors. Gait biometrics: basic patterns, role of neurological disorders and effects of physical activity. Hauppauge, NY: Nova Science Pub, Inc.; 2014. p. 17–43.

Rispens, S. M., Van Dieën, J. H., Van Schooten, K. S., Cofré Lizama, L. E., Daffertshofer, A., Beek, P. J., & Pijnappels, M. (2016). Fall-related gait characteristics on the treadmill and in daily life. *Journal of neuroengineering and rehabilitation*, *13*, 12. https://doi.org/10.1186/s12984-016-0118-9

Riva, F., Toebes, M. J., Pijnappels, M., Stagni, R., & van Dieën, J. H. (2013). Estimating fall risk with inertial sensors using gait stability measures that do not require step detection. *Gait & posture*, *38*(2), 170–174. https://doi.org/10.1016/j.gaitpost.2013.05.002

Rye Hanton, C., Kwon, Y. J., Aung, T., Whittington, J., High, R. R., Goulding, E. H., Schenk, A. K., & Bonasera, S. J. (2017). Mobile Phone-Based Measures of Activity, Step Count, and Gait Speed: Results From a Study of Older Ambulatory Adults in a Naturalistic Setting. *JMIR mHealth and uHealth*, *5*(10), e104. https://doi.org/10.2196/mhealth.5090

Silsupadol, P., Teja, K., & Lugade, V. (2017). Reliability and validity of a smartphone-based assessment of gait parameters across walking speed and smartphone locations: Body, bag, belt, hand, and pocket. *Gait & posture*, *58*, 516–522. https://doi.org/10.1016/j.gaitpost.2017.09.030

Stergiou, N., Harbourne, R., & Cavanaugh, J. (2006). Optimal movement variability: a new theoretical perspective for neurologic physical therapy. *Journal of neurologic physical therapy : JNPT*, *30*(3), 120–129. https://doi.org/10.1097/01.npt.0000281949.48193.d9

Takayanagi, N., Sudo, M., Yamashiro, Y., Lee, S., Kobayashi, Y., Niki, Y., & Shimada, H. (2019). Relationship between Daily and In-laboratory Gait Speed among Healthy Community-dwelling Older Adults. *Scientific reports*, *9*(1), 3496. https://doi.org/10.1038/s41598-019-39695-0

Tamburini, P., Storm, F., Buckley, C., Bisi, M. C., Stagni, R., & Mazzà, C. (2018). Moving from laboratory to real life conditions: Influence on the assessment of variability and stability of gait. *Gait & posture*, *59*, 248–252. https://doi.org/10.1016/j.gaitpost.2017.10.024

Tremblay, M. S., Warburton, D. E., Janssen, I., Paterson, D. H., Latimer, A. E., Rhodes, R. E., Kho, M. E., Hicks, A., Leblanc, A. G., Zehr, L., Murumets, K., & Duggan, M. (2011). New Canadian physical activity guidelines. *Applied physiology, nutrition, and metabolism = Physiologie appliquee, nutrition et metabolisme*, *36*(1), 36–58. https://doi.org/10.1139/H11-009

van Emmerik, R. E. A., Ducharme, S. W., Amado, A. C., & Hamill, J. (2016). Comparing dynamical systems concepts and techniques for biomechanical analysis. *Journal of sport and health science*, *5*(1), 3–13. https://doi.org/10.1016/j.jshs.2016.01.013

Wagenaar, R. C., Holt, K. G., Kubo, M., & Ho, C. L. (2002). Gait Risk Factors for Falls in Older Adults. *Generations: Journal of the American Society on Aging*, *26*(4), 28-32.

Weiss, A., Brozgol, M., Dorfman, M., Herman, T., Shema, S., Giladi, N., & Hausdorff, J. M. (2013). Does the evaluation of gait quality during daily life provide insight into fall risk? A novel approach using 3-day accelerometer recordings. *Neurorehabilitation and neural repair*, *27*(8), 742–752. https://doi.org/10.1177/1545968313491004

Yentes, J. M., & Raffalt, P. C. (2021). Entropy Analysis in Gait Research: Methodological Considerations and Recommendations. *Annals of biomedical engineering*, *49*(3), 979–990. https://doi.org/10.1007/s10439-020-02616-8

Yentes, J. M., Hunt, N., Schmid, K. K., Kaipust, J. P., McGrath, D., & Stergiou, N. (2013). The appropriate use of approximate entropy and sample entropy with short data sets. *Annals of biomedical engineering*, *41*(2), 349–365. https://doi.org/10.1007/s10439-012-0668-3

Yogev-Seligmann, G., Hausdorff, J. M., & Giladi, N. (2008). The role of executive function and attention in gait. *Movement disorders : official journal of the Movement Disorder Society*, *23*(3), 329–472. https://doi.org/10.1002/mds.21720

Zandiyeh, P., & Von Tscharner, V. (2013). Reshape scale method: a novel multi scale entropic analysis approach. *Physica A: Statistical Mechanics and Its Applications*, *392*(24), 6265-6272.

Zou, Q., Wang, Y., Zhao, Y., Wang, Q., Shen, C., Li, Q. (2020). Deep learning-based gait recognition using smartphones in the wild. *IEEE Transactions on Information Forensics and Security*, vol. 15, pp. 3197-3212, 2020, doi: 10.1109/TIFS.2020.2985628.

CHAPTER 6

GENERAL DISCUSSION

6.0. Dissertation Objectives Revisited

The global objective of this dissertation was the development and progression of a low-cost, practical, and user-friendly tool to monitor gait patterns in an unconstrained free-living environment among healthy young and older adults. To accomplish the global objective, three studies were designed with the following objectives: 1) validate the smartphone accelerometer during treadmill walking (highly controlled environment), 2) validate the smartphone accelerometer during overground walking in vacant corridors (semi-controlled environment), 3) implement the smartphone accelerometer to investigate age-related differences in gait patterns in a natural, free-living environment (uncontrolled environment). It was found that the smartphone accelerometer (SPAcc) system provided valid and reliable estimates of linear and nonlinear temporal gait variability measures similar to research-grade gold-standard (GS) equipment during treadmill (Study 1) and overground (Study 2) walking in controlled environments. Furthermore, the SPAcc was able to identify differences in a number of linear and nonlinear measures between healthy young and older adults while walking in an unconstrained free-living environment (Study 3). These findings suggest the smartphone system is viable option to remotely capture gait patterns while simply placed in the user's pant pocket among healthy young and older adult populations.

6.1. Discussion

From the small-scale structures (e.g., neurons) to the large-scale behaviours (e.g., steady-state walking), the healthy human body orchestrates a myriad of interconnected elements (e.g., motor units) to not only produce but optimize performance. The *hidden* structure of movement patterns, revealing a type of 'organized randomness', is suggested to provide a signature of health status. Gait patterns investigated through the lens of Dynamical Systems Theory has provided another framework for interpreting variations in the usual stride pattern across multiple gait cycles. These variations that evolve over time are theoretically related to adaptability with an optimal amount suggesting healthy states, while a breakdown towards the extremes of randomness or structuredness has been associated with aged and diseased states. For example, the statistical persistence of stride time has revealed a shift in gait dynamics (i.e., stride-to-stride fluctuations) towards randomness among older and diseased populations compared to healthy young adults (Hausdorff et al., 1997; Herman et al., 2005); putatively decreasing gait adaptability and increasing fall risk. Moreover, such measures have demonstrated greater sensitivity for distinguishing between healthy and unhealthy states compared to traditional variability measures (e.g., standard deviation), suggesting another dimension of information about movement patterns that was previously overlooked.

The concomitant increases in neuromuscular noise associated with aging and disease has been conceptualized by two prominent frameworks in the nonlinear analysis of human movement: the Loss of Complexity (LOC) hypothesis and the Optimal Movement Variability (OMV) model (Lipsitz and Goldberger, 1992; Stergiou et al., 2006). However, until recently with the help of wearable sensors, the investigation of the structure of gait dynamics has been restricted to controlled walking environments due to the requirement of hundreds of strides to sufficiently uncover the movement pattern. These controlled walking environments have previously misrepresented gait dynamics, increasing the difficultly of interpreting what is considered healthy for the population under investigation (Warlop et al., 2018; Hollman et al., 2020). The growing use of wearable sensors for gait analysis has provided encouraging results while recording in a free-living environment but is predominately limited to traditional measures of gait performance. Furthermore, current wearables are not user-friendly or widely accessible as they require secure attachment to specific body locations and must be given to or purchased by the user. With the ubiquity of smartphones and their embedded accelerometers, the potential for gait analysis is already in one's pocket. The accessibility of smartphones coupled with the information and sensitivity provided by nonlinear analyses of gait was the rationale for the work presented in this dissertation.

Validation

The two validation studies presented in this dissertation revealed that the SPAcc performs similarly to that of research-grade GS systems as the limits of agreement (LOA) were found to be within the *a priori* defined acceptability criteria for all measures of interest. Moving from treadmill walking to overground walking validation was important to confirm valid estimates of the measures of interest while progressing from controlled to uncontrolled walking environments. To date, only one study has validated a nonlinear gait measure from a SPAcc (Hammoud et al., 2015). However, as described in Chapters Two and Four of this dissertation, the data collection methodology was not appropriate for estimating gait dynamics. The current dissertation considered the flaws in the previous study and improved upon them. Furthermore, Study 1 and Study 2 provided robust methodology for the evaluation of agreement between the SPAcc and GS reference systems that was lacking in the literature for wearable sensor evaluation when estimating gait measures. Previous research has suggested agreement between systems in the absence of relevant and defined LOA acceptability criteria making the claim of agreement open to interpretation. As highlighted in Chapter Two of this dissertation, *a priori* LOA must be defined based on an expected difference in the measures of interest between the healthy and unhealthy populations under investigation (Giavarina, 2015). If the new system compared to the reference system is within the expected difference, then the new system can be used interchangeably with the reference system. In the body of literature presented in this dissertation, only two studies, to my knowledge, pre-defined acceptable LOA, although it is unclear why these particular values were selected (Rashid et al., 2021; Shema-Shiratzky et al., 2022). In Study 1 and Study 2 of this dissertation, I have provided specific and pre-defined acceptability criteria to determine the agreement between the SPAcc and GS reference systems. These criteria selected were based on previously published work reporting significant differences between the populations of interest for each dependent measure calculated. These populations were selected on the future use-case basis of the SPAcc (e.g., young versus older adults). In the absence of previously established criteria, the surrogate method was implemented to create a 'control' condition for approximate entropy and sample entropy (SaEn) acceptability criteria. Such methodology presented in this dissertation may help support future device validation research.

The test re-test reliability of the SPAcc proved similar to that of the GS systems across three testing sessions during both treadmill (Study 1) and overground (Study 2) walking. The intraclass correlation coefficients calculated in the first two studies from the SPAcc revealed good-to-excellent reliability for all dependent measures, except for the fractal scaling index (FSI), which was moderate. It was suggested that sensor location, while placed in the pant pocket, may have resulted in the discrepancies in reliability between the GS systems with sensor location at the foot for the FSI measure. It was also suggested that the multiscale property of the FSI resulted in the discrepancies in reliability, compared to all other measures investigated for both the SPAcc and the GS systems. To my knowledge, studies 1 and 2 presented in this dissertation are the first to evaluate the reliability of nonlinear measures derived from a SPAcc. Importantly, the SPAcc did not require secure attachment to the user, improving practicality, compared to the majority of current methods which affix the wearable sensor to the low back or hip with a belt which is not a viable option for long-term use (i.e., obstructing sitting, uncomfortable). For example, Lugade et al. (2021) found some participants reported hinderance of the belt pouch, containing the SPAcc, placed around the hip while sitting. Although comfortability of the SPAcc in the current dissertation was not assessed, the smartphone placed in the user's pant pocket is likely a natural carrying method.

Implementation and Interpretation

Study 3 of this dissertation revealed differences in linear gait variability measures between the young and older adults, which was expected; greater gait variability was found among the older adults. Increased gait variability, in general, suggests reduced walking stability (Hausdorff et al., 2001) where stability is defined as resistance to internal and external perturbations for the maintenance of balance and forward progression (Bruijn et al., 2013). In this sense, the maintenance of balance is referred to the walker's ability to remain within the current or typical stride pattern state across multiple gait cycles. However, the values for stride time variability were found to be greater than typical in laboratory-based studies for both age groups, which may also reflect the walking environment instead of walking stability *per se* (Tamburini et al., 2018). Therefore, the free-living walking values found in Study 3 may not necessarily be a warning sign of poor stability and underscore the importance of interpreting gait performance within the context of the environment.

Although speculative, the importance of walking condition on the estimate of gait measures among young adults may be gleaned through the progression of studies presented in this dissertation. The effect of fixed-pace treadmill walking has revealed differences in the majority of gait measures investigated, when compared to controlled overground walking, suggesting careful interpretation of results and the appropriate selection of walking condition. For example, stride time coefficient of variation increased from treadmill (1.18%) to overground (1.78%) walking among the young adult group. Furthermore, walking in a free-living environment revealed further differences compared to the aforementioned controlled walking conditions, highlighting perhaps a true representation of gait dynamics. For example, statistical persistence of stride time, estimated with the FSI, exhibited an increase among the young adult group across the three walking conditions (treadmill = 0.71, overground = 0.79, free-living = 0.95). Previous work has investigated statistical persistence between treadmill walking and overground walking with traditional research-grade laboratory equipment (Terrier and Dériaz, 2011; Warlop et al., 2018; Shi et al., 2019; Hollman et al., 2020), however, there appears to be a lack of literature comparing these walking conditions to free-living walking, which could be reliably done with the SPAcc.

Interestingly, the older adults in Study 3 exhibited an FSI similar to the young adults, which was unexpected, and was also greater than typical in laboratory-based studies. Previous research has suggested that as walking becomes more challenging, gait dynamics may shift to a more structured stepping strategy, increasing the adaptive behaviour to an optimal level (FSI approaching 1.0) (Ducharme and van Emmerik, 2018). It was suggested in Study 3 that the free-living walking environment, containing obstacles and other individuals walking, induced frequent changes in walking speed to avoid collisions that shifted the structure of variability towards greater statistical persistence, reflecting greater gait adaptability to accommodate the walking environment. Adaptability is referred to as the ability to select or transition to a different state, and in terms of gait, the ability to modify the typical stride pattern based on task demands. Jordan et al. (2007) reported a U-shaped relationship with stride time FSI and preferred walking speed and found walking speeds other than preferred increased statistical persistence. In addition, it was suggested that the physical activity level among the older adults in Study 3 may have preserved statistical persistence to a level similar to that of the young adults, similar to previous work (Ducharme et al., 2019). Overall, Study 3 provides a representation of stride time statistical persistence in the free-living environment among healthy young and older adults, and to my knowledge, is the first to have reported such measures, adding to the knowledge base of gait dynamics and the benefits of wearable sensors. However, the environmental aspects related to changes in statistical persistence need to be investigated further.

SaEn at scale 1 was found to be greater among older adults compared to young adults during free-living walking, indicating a more unpredictable and irregular stride time pattern tending towards the random side of the OMV model. The consequence of increased irregularity is diminished control, thereby increasing the challenge of performing desired movements such as selecting an appropriate stride time when desired. However, the young adults demonstrated greater SaEn at scale 3 compared to the older adults. Since the young adults were considered the reference condition, SaEn at scale 3 was interpreted as a greater repertoire of stride time strategies available to the young adults compared to the older adults. These findings point to the importance of multiscale entropy analysis and the requirement of a defined control group for interpretation of entropy-based measurement. Costa et al. (2003) demonstrated that during preferred walking speed among young adults, the stride time SaEn at smaller scales (1 to 4) was lower compared to surrogate data sets. However, at larger scales (5 and 6), the sample entropy of the original stride time series was greater compared to the surrogate data series, suggesting greater complexity. Considering the older adults in Study 3 of this dissertation as the surrogate data series, the older adults demonstrated a greater sample entropy at scale 1 which was maintained at scale 2 and eventually dropped at scale 3, while the young adults demonstrated a lower sample entropy at scale 1, which increased at scale 2 and was then maintained at scale 3. Therefore, the young adults gait pattern can be considered more complex as SaEn was found to be maintained at larger scales. Although only scales 1 to 4 were investigated in this dissertation, future work should implement the SPAcc to assess gait complexity across a greater number of scales.

The increases in neural noise with aging is a model, and gait complexity measures reflect the theoretical scaling across small to large scales both in time and space as well as the loss of physiological elements and connection between elements (see Chapter 2 Figures 2.1 and 2.5). Therefore, complexity measures provide an indirect approach to assess function within the context of this model and ultimately the capacity of the system to remain stable, yet adaptable. The claims of stability and adaptability in reference to any particular measure is likely not appropriate due to the connection between these two terms. Of course, a system that is rigid is likely not the most optimal state as it lacks the repertoire to adapt or transition to new or different states to account for imposed constraints. The terms linear and nonlinear clearly refer to different aspects when evaluating the variability of a repeated movement pattern. Interestingly, Study 3 revealed differences in linear (magnitude of) variability measures between age groups, while several nonlinear (structure of) variability measures revealed a lack of differences. Therefore, perhaps the magnitude of variability determines the typical bounds or width of limits occupied by the system, with wider limits among older adults, while both age groups perform similar transitions between states. Perhaps the older adults maintain a structure of stepping strategies similar to the young adults but take up a greater volume of space, explaining the similarities in gait complexity yet differences in linear gait variability between age groups. Importantly, these findings may have only been revealed due to free-living walking with the SPAcc, providing a true representation of gait variability, and by extension, stability and adaptability, as participants in both age groups successfully navigated the unconstrained free-living environment.

Fall risk, as described in Chapter Two of this dissertation, is evaluated across three domains: questionnaire and interviews, clinical assessments, and laboratory-based assessments. Laboratory-based assessments are suggested to be more robust compared to clinical assessments of gait for identifying fall risk and distinguishing between older adult fallers and non-fallers (Hausdorff et al., 2001). Although fall risk wasn't investigated in the current dissertation as only non-fallers were recruited, the SPAcc provides valid and reliable estimates of gait variability similar to laboratory-based equipment while in the pocket, and likely at a lower cost compared to clinical assessments that required trained personnel and visits to a clinic. Therefore, the SPAcc may be a practical and widely accessible option to evaluate fall-risk in the future and with greater sensitivity, similar to previous wearable systems presented in the literature (Weiss et al., 2013; Ihlen et al., 2016). Furthermore, it was suggested in Study 3 that the SPAcc could be used to quickly estimate gait parameters while walking in a controlled environment (e.g., unobstructed pathway) prior to free-living walking to establish a baseline level of gait variability. Baseline estimates of gait variability could be implemented using the SPAcc prior to gait training or rehabilitation efforts, as well as remotely monitor fall risk and training over the duration of an intervention by transmitting progress to the clinician. The use of gait complexity as a marker for gait rehabilitation progress, to my knowledge, has yet to be investigated likely due to the difficulty of interpreting such measures as well as the requirement of many consecutive strides. However, as further research is conducted in the field of Complexity Science, the value of the *hidden* structure of human movement will be elucidated.

Limitations and Future Directions

The series of studies presented in this dissertation are not without limitations. The two validation studies are limited to healthy young adults without a defined 'control' group for the interpretation of gait measures, especially for entropy-based measurement. Another limitation is that the free-living walking protocol was not inclusive of all walking environments such as sloped walking surfaces, uneven terrain, different lighting conditions, and stair climbing. The walking protocol used in Study 3 of this dissertation was designed to ensure multiple sufficiently long walking trials were collected. Future work should implement the SPAcc to monitor gait patterns throughout an extended duration of time (e.g., one month) to incorporate different free-living environments. Furthermore, the environmental context as well as walking intensity during free-living walking were not known during each walking bout identified, increasing the difficulty of interpreting the associated variability. Future work should utilize video recording equipment as well as other biofeedback tools, such as heart rate monitors, to provide information about the environment and intensity of walking. Study 3 was limited to only healthy young and older adults to ensure all participants could complete the walking protocol. The implications of Study 3 suggest the SPAcc may be able to capture gait dynamics remotely. Future work should implement the SPAcc to investigate gait dynamics among clinical populations such as older adult fallers to help uncover the link between gait complexity and fall risk during free-living walking.

6.2. Conclusion

Our understanding of gait complexity and the nonlinear analysis of human gait dynamics is largely limited to controlled walking environments while estimated with laboratory equipment. The importance of evaluating gait dynamics stems from the theoretical underpinnings of multiscale interactions among the myriad entangled elements comprising the healthy human body; indirectly evaluating gait adaptability. The body of evidence presented in this dissertation suggests the SPAcc may replace research-grade laboratory equipment when estimating gait dynamics in controlled settings. Furthermore, the SPAcc may be used to capture a true representation of gait variability and provide new insight into the dynamics of human gait as one navigates the free-living environment. However, further work needs be done to determine what aspects of the environment influence gait complexity. The implication of these findings is that the SPAcc is a user-friendly, accessible, and viable option for remote monitoring of gait dynamics while simply placed in the user's pant pocket. Future research should implement the SPAcc to explore gait patterns among different adult populations and for extended periods of time as a telehealth tool to monitor gait adaptability, and potentially fall risk, remotely.

6.3. References

Bruijn, S. M., Meijer, O. G., Beek, P. J., & van Dieën, J. H. (2013). Assessing the stability of human locomotion: a review of current measures. *Journal of the Royal Society, Interface*, *10*(83), 20120999. https://doi.org/10.1098/rsif.2012.0999

Costa, M., Peng, C. K., Goldberger, A. L., & Hausdorff, J. M. (2003). Multiscale entropy analysis of human gait dynamics. *Physica A*, *330*(1-2), 53–60. https://doi.org/10.1016/j.physa.2003.08.022

Ducharme, S. W., & van Emmerik, R. E. (2018). Fractal dynamics, variability, and coordination in human locomotion. *Kinesiology Review*, *7*(1), 26-35.

Ducharme, S. W., Kent, J. A., & van Emmerik, R. E. A. (2019). Comparable Stride Time Fractal Dynamics and Gait Adaptability in Active Young and Older Adults Under Normal and Asymmetric Walking. *Frontiers in physiology*, *10*, 1318. https://doi.org/10.3389/fphys.2019.01318

Giavarina D. (2015). Understanding Bland Altman analysis. *Biochemia medica*, *25*(2), 141–151. https://doi.org/10.11613/BM.2015.015

Hammoud, A., Duchêne, J., Abou-ghaida, H., Mottet, S., Goujon, J., Hewson, D.J. (2015). Validation of a Smartphone Gait Analysis System, International Federation for Medical and Biological Engineering Proceedings 45,910–913.

Hausdorff, J. M., Mitchell, S. L., Firtion, R., Peng, C. K., Cudkowicz, M. E., Wei, J. Y., et al. (1997b). Altered fractal dynamics of gait: Reduced stride-interval correlations with aging and Huntington's disease. Journal of Applied Physiology, 82, 262–269.

Hausdorff, J. M., Rios, D. A., & Edelberg, H. K. (2001). Gait variability and fall risk in community-living older adults: a 1-year prospective study. *Archives of physical medicine and rehabilitation*, *82*(8), 1050–1056. https://doi.org/10.1053/apmr.2001.24893

Herman, T., Giladi, N., Gurevich, T., Hausdorff, J. M. (2005). Gait instability and fractal dynamics of older adults with a "cautious" gait: Why do certain older adults walk fearfully? Gait & Posture, 21(1), 178-185.

Hollman, J. H., Von Arb, H. M., Budreck, A. M., Muehlemann, A., & Ness, D. K. (2020). Treadmill walking alters stride time dynamics in Parkinson's disease. *Gait & posture*, *77*, 195–200. https://doi.org/10.1016/j.gaitpost.2020.02.005

Ihlen, E. A. F., Weiss, A., Bourke, A., Helbostad, J. L., & Hausdorff, J. M. (2016). The complexity of daily life walking in older adult community-dwelling fallers and non-fallers. *Journal of biomechanics*, *49*(9), 1420–1428. https://doi.org/10.1016/j.jbiomech.2016.02.055

Jordan, K., Challis, J. H., & Newell, K. M. (2007). Walking speed influences on gait cycle variability. *Gait & posture*, *26*(1), 128–134. https://doi.org/10.1016/j.gaitpost.2006.08.010

Lipsitz, L. A., & Goldberger, A. L. (1992). Loss of 'complexity' and aging. Potential applications of fractals and chaos theory to senescence. *JAMA*, *267*(13), 1806–1809.

Lugade, V., Kuntapun, J., Prupetkaew, P., Boripuntakul, S., Verner, E., & Silsupadol, P. (2021). Three-Day Remote Monitoring of Gait Among Young and Older Adults Using Participants' Personal Smartphones. *Journal of aging and physical activity*, *29*(6), 1026–1033. https://doi.org/10.1123/japa.2020-0353

Rashid, U., Barbado, D., Olsen, S., Alder, G., Elvira, J. L. L., Lord, S., Niazi, I. K., & Taylor, D. (2021). Validity and Reliability of a Smartphone App for Gait and Balance Assessment. *Sensors (Basel, Switzerland)*, *22*(1), 124. https://doi.org/10.3390/s22010124

Shema-Shiratzky, S., Beer, Y., Mor, A., & Elbaz, A. (2022). Smartphone-based inertial sensors technology - Validation of a new application to measure spatiotemporal gait metrics. *Gait & posture*, *93*, 102–106. https://doi.org/10.1016/j.gaitpost.2022.01.024

Shi, L., Duan, F., Yang, Y., & Sun, Z. (2019). The Effect of Treadmill Walking on Gait and Upper Trunk through Linear and Nonlinear Analysis Methods. *Sensors (Basel, Switzerland)*, *19*(9), 2204. https://doi.org/10.3390/s19092204

Stergiou, N., Harbourne, R., & Cavanaugh, J. (2006). Optimal movement variability: a new theoretical perspective for neurologic physical therapy. *Journal of neurologic physical therapy: JNPT*, *30*(3), 120–129. https://doi.org/10.1097/01.npt.0000281949.48193.d9

Tamburini, P., Storm, F., Buckley, C., Bisi, M. C., Stagni, R., & Mazzà, C. (2018). Moving from laboratory to real life conditions: Influence on the assessment of variability and stability of gait. *Gait & posture*, *59*, 248–252. https://doi.org/10.1016/j.gaitpost.2017.10.024

Terrier, P., & Dériaz, O. (2011). Kinematic variability, fractal dynamics and local dynamic stability of treadmill walking. *Journal of neuroengineering and rehabilitation*, *8*, 12. https://doi.org/10.1186/1743-0003-8-12

Warlop, T., Detrembleur, C., Stoquart, G., Lejeune, T., & Jeanjean, A. (2018). Gait Complexity and Regularity Are Differently Modulated by Treadmill Walking in Parkinson's Disease and Healthy Population. *Frontiers in physiology*, *9*, 68. https://doi.org/10.3389/fphys.2018.00068

Weiss, A., Brozgol, M., Dorfman, M., Herman, T., Shema, S., Giladi, N., & Hausdorff, J. M. (2013). Does the evaluation of gait quality during daily life provide insight into fall risk? A novel approach using 3-day accelerometer recordings. *Neurorehabilitation and neural repair*, *27*(8), 742–752. https://doi.org/10.1177/1545968313491004

APPENDICES

Appendix A:

Questionnaire
(The information received will remain confidential)

Name: ___________________________________ Age: __________________________

DOB: ______________________ Sex: Male or Female

Height (cm or inches): ______________________ Weight (kg or lbs): _______________

Phone number: ________________________ E-mail:_________________________

Handedness: Right or Left Participant ID:___________________

Screening Questions

1) Are you afraid of falling? □ Yes □ No □ Somewhat

2) Are you generally in good health? □ Yes □ No

3) Do you have any diagnosed serious or chronic conditions? □ Yes □ No
   If yes, describe. (i.e., thyroid, metabolic disease?)
   ____

4) Do you have any diagnosed cardiovascular conditions?
   If yes, describe. (i.e., high blood pressure, heart attack, blood clots?) □ Yes □ No
   ____

5) Do you have any diagnosed neurological disorders?
   If yes, describe. (i.e., stroke, Parkinson's or Huntington's disease) □ Yes □ No
   ____

6) Do you have any diagnosed musculoskeletal condition?
   If yes, describe. (i.e., arthritis?) □ Yes □ No
   ____

7) Have you had any injury, pain or surgery in the previous 6 months on your ankle, knee, hip or low back? □ Yes □ No
   If yes, describe. (i.e., ACL tear, joint dislocation?)
   ____

7) Are you able to perform repeated bouts of 10-minute walking without an aid? □ Yes □ No
   If no, describe. (i.e., cane?)
   ____

8) Have you had any falls over the past 12 months? □ Yes □ No
   If yes, how many?
   ____

9) Do you perform at least 150 minutes of moderate- to vigorous-intensity aerobic physical activity per week, in bouts of 10 minutes of more?
If yes, describe. (i.e., brisk walking, swimming, cycling, etc.) □ Yes □ No
____

10) Do you participate in sports?
If yes, describe sport and level (i.e., soccer; recreational or competitive) □ Yes □ No
____

Eligible to participate □ Yes □ No

Principle investigator initials: _______

Appendix B:

Participant Code: ______________

ACTIVITIES-SPECIFIC BALANCE CONFIDENCE (ABC) SCALE

0____10____20____30____40____50____60____70____80____90____100

I do not feel at all confident	**I feel moderately confident**	**I feel completely confident**

Please use the scale to rate the <u>amount of confidence</u> you have in <u>avoiding a fall</u> when you have to:

Walk around house	__________
Walk up/down stairs	__________
Pick up object from floor	__________
Reach forward	__________
Reach forward on tiptoes	__________
Stand on chair to reach object	__________
Sweep the floor	__________
Walk outside to nearby car	__________
Get in/out of car	__________
Walk across parking lot	__________
Walk up/down ramp	__________
Walk in crowded mall	__________
Walk in crowd and bumped in to	__________
Ride escalator holding rail	__________
Ride escalator not holding rail	__________
Walk on icy sidewalk	__________