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ADAPTABILITY OF STRIDE-TO-STRIDE CONTROL OF STEPPING MOVEMENTS IN HUMAN WALKING AND RUNNING

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ADAPTABILITY OF STRIDE-TO-STRIDE CONTROL OF STEPPING MOVEMENTS IN HUMAN WALKING AND RUNNING

by

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Dedication

This dissertation is dedicated to my parents Michael and Paulette Bohnsack and to my best friend, Lindsey John. May your spirit always live on.

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Adaptability of Stride-to-Stride Control of Stepping Movements in Human Walking and Running

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Walking and running are essential tasks people take for granted every day. However, these are highly complex tasks that require significant neural control. This is complicated by the inherent redundancy of the nervous system and by physiological noise. Humans may adopt different control strategies to achieve different goals (environmental or task specific). More specifically, walking/running on a treadmill only requires that one not walk off the treadmill. Of the many possible strategies that can achieve this goal, humans attempt to maintain a constant speed from each stride to the next (Dingwell, John et al. 2010). However, how humans alter the stride-to-stride regulation of their gait when the task goals change (e.g., by maintaining stride length and/or time, during running, or during a predicted walk to run transition speed) has not yet been demonstrated. In the first two of three experiments conducted, healthy adults either walked or ran on a motorized treadmill at a comfortable speed under the following conditions: constant speed, constant speed with the stride length goal (targets on the treadmill), constant speed with the stride time goal (metronome), or constant speed with both stride length and

stride time goals. In a third experiment, subjects walked and/or ran at a comfortable speed and also at their predicted theoretical walk to run transition speed. Goal functions derived from the task specifications yielded new variables that defined fluctuations either directly relevant to, or irrelevant to, achieving each goal. The magnitude of the variability, as well as the stride-to-stride temporal fluctuations in these variables, were calculated.

During walking, subjects exploited different redundancy relationships in different ways to prioritize certain task goals (maintain stride speed) over others (maintain stride length or stride time) in each different context. In general, subjects made rapid corrections of those stride-to-stride deviations that were most directly relevant to the different task goals adopted in each walking condition. Thus, the central nervous system readily adapts to achieve multiple goals simultaneously.

During running, subjects exhibited similar adaptations to walking, but over-corrected to prioritize maintaining stride speed even more strongly. This suggests that stepping control strategies adapt to the level of perceived risk. This purposeful adaptability of these stride-to-stride control strategies could be exploited to developing more effective rehabilitation interventions for patients with locomotor impairments.

During the predicted walk-to-run speeds, subjects were able to largely exploit the redundancy within task goal, and effectively operated at “uncomfortable” speeds. These results suggest that the stride speed control is robust even with additional novel tasks and uncomfortable, abnormal speeds of locomotion.

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Chapter 1

Introduction

Walking and running are essential tasks that most people take for granted every day. Both walking and running are specific types of locomotion that are imperative to our daily lives. On one hand, these tasks are considered to be relatively basic and simple to accomplish for both humans and animals alike. On the other hand, for the human nervous system, walking and running are highly complex tasks, which require significant neurological control (Zehr and Stein 1999, Warren, Kay et al. 2001, Bent, Inglis et al. 2004, Rossignol, Dubuc et al. 2006).

In order to produce efficient and adaptable locomotion, sensory inputs (Rossignol, Dubuc et al. 2006) must be integrated with neurological systems to generate the appropriate motor outputs. If the neural system is affected by pathologies or experiences any neural degeneration, this could significantly impede the ability to generate this precise coordination. Determining how the normal healthy nervous system coordinates these fundamental principles that influence control is central to understanding how humans regulate locomotion.

When the nervous system is unable to generate stable and consistent locomotion, as could be due to numerous different internal or external factors, falls can occur. Falls are the leading cause of non-fatal injuries for all ages (except those 16-24 years) (www.cdc.gov). One in three adults, ages 65+, falls annually (www.cdc.gov). With these

staggering statistics, the health care costs are rising exponentially. It is predicted in 2020, the health care costs for fall related injuries will be more than $55 billion dollars (www.cdc.gov). As researchers, it is important to find ways to help prevent falls and ways to better rehabilitate those people that have endured falls.

Falling is often linked to increased variability during walking (Maki, Holliday et al. 1994, Brach, Perera et al. 2010). The research is divided as to whether or not this variability leads to instability or is an indication of adaptability, suggesting that some variability can be beneficial while other variability can be detrimental to human locomotion. Instability is related to local instability, indicating how sensitive subjects are to very small (internally or externally generated) perturbations. Here, adaptability is referred to as the ability to counter act any perturbations or disturbances that occur during walking. Since falls are a common occurrence, we must first understand how humans are able to generate and regulate consistent stable locomotion. If we are able to understand the fundamental principles and the control paradigms used to generate locomotion, we may better understand what happens when these involved systems are damaged or decayed.

This dissertation focused on the control paradigms used to control stride-to-stride fluctuations in stepping movements (specifically, stride length, stride time, and stride speed) during both walking and running. These fluctuation dynamics require humans to adapt at *every* step (not just on average). While walking and running, humans experience many different physical and visual perturbations. There are uneven sidewalks, curbs, rugged terrain, gravel, and many other obstacles that cause people to alter or manipulate

their gait. When prognoses like aging or certain neurological pathologies disrupt these adaptation mechanisms, it becomes more difficult to account for any disturbances during locomotion and a fall or injury may occur. Although the neurophysiological mechanisms that implement these reactions are well known (Rossignol, Dubuc et al. 2006), the principles controlling *stride to stride* adaptation remain mostly unknown. The adaptability of these stride-to-stride control strategies could be exploited to develop more effective rehabilitation interventions for patients with locomotor impairments.

Objectives

The main objective of this dissertation was to determine how humans alter the stride-to-stride regulation of their gait when the task goals change. More specifically, in the experiments conducted here, our first two primary goals were to determine how stride-to-stride regulation changed when certain gait parameters were kept consistent, first during walking and then during running. Our third primary objective was to determine how humans alter their stride-to-stride control when forced to either walk or run at the same predicted theoretical walk-to-run transition speed, an "intermediate" speed where variability is known to increase.

DISSERTATION AIMS

From the previously mentioned objectives, three studies were designed. In the first experiment, the control of stride-to-stride fluctuations during walking were investigated. Subjects were given multiple simultaneous goals, including length markers,

a metronome and a constant treadmill belt speed. These additional goals were given to the subjects to maintain their stride lengths (L_n) and stride times (Tn). The second experiment used the same additional task goals while subjects were running on the treadmill. The third experiment required subjects to either walk or run at a comfortable walking or running speed and also at an "uncomfortable" intermediate speed to determine how either walking or running at a predicted walk-to-run transition speed would affect the control strategies used during walking or running.

Aim #1: Determine the extent to which humans adopt different stepping control strategies when presented with different task goals during walking.

When walking on a treadmill, subjects have been found to primarily control their stride speed (Dingwell, John et al. 2010). In this experiment, subjects were given different task goals to achieve while walking on a motorized treadmill at constant speed. Since the treadmill speed was kept constant, it was assumed that maintaining constant stride speed (S_n) would constitute one *implicit* task goal, as previously found (Dingwell, John et al. 2010). Subjects were then asked to also simultaneously maintain different combinations of different *explicit* task goals. Subjects walked under 4 conditions: (i) normal walking at constant speed, (ii) walking at constant speed and constant T_n, (iii) walking at constant speed and constant L_n, and (iv) walking at constant speed, T_n, and L_n combined. These task goals required subjects to voluntarily attempt to achieve them. The data obtained were used to test the following hypotheses:

HYPOTHESIS 1: When walking on the treadmill at constant speed, subjects will explicitly exploit the redundancy available between stride length (L_n) and stride time, (T_n) as they did previously (Dingwell, John et al. 2010).

HYPOTHESIS 2: When asked to also walk with either constant stride length (L_n) *or* stride time (T_n) individually, subjects will adopt "intermediate" control strategies.

HYPOTHESIS 3: When asked to also walk with *both* constant stride length (L_n) *and* constant stride time (T_n), subjects will adopt a single solution that equally achieves all task goals.

Hypothesis 2, in particular, was tested against the very plausible alternative that subjects would *not* try to exploit any remaining redundancies available in these tasks, but would instead choose to minimize their variations around the single solution that best satisfied both tasks. This experiment determined the extent to which healthy subjects can and chose to exploit task redundancies when made available. The results for this experiment are described in Chapter 3 of this dissertation.

Aim #2: Determine the extent to which humans adopt different stepping control strategies when presented with different task goals during *running*.

Running is a very different task than walking. Specifically, running involves a flight phase where both feet are in the air simultaneously, indicating that running has no period of double support. Thus, the relationship between stride length (L_n), stride time (T_n), and stride speed (i.e., $S_n = L_n/T_n$) may not be as explicitly fixed as it is in walking. Mechanically, running and walking are similar; however the control mechanisms utilized for both running and walking have not been compared directly (or indirectly). Additionally, the faster speeds involved in running impose unique challenges to the locomotor control system. Faster speeds would be expected to influence the subject to adopt longer stride lengths. With these longer L_n*'s*, the fixed length of the treadmill belt surface may encourage subjects to adopt different stride-to-stride control strategies than those used during walking. Therefore, we tested healthy subjects and repeated the same combinations of conditions tested in Experiment 1, only during running. The obtained data was used to test the following hypotheses:

HYPOTHESIS 4a: When running on the treadmill at constant speed, subjects will also explicitly exploit the redundancy available between L_n and T_n, as they do for walking (Dingwell, John et al. 2010).

HYPOTHESIS 4b: *Alternatively*, when running on the treadmill at constant speed, subjects will instead adopt a "*position* control" strategy

(Dingwell, John et al. 2010), and not the "*speed* control" strategy used in walking.

HYPOTHESIS 5: When asked to also run with either constant stride length (L_n) *or* stride time (T_n) individually, subjects will adopt either of the appropriate / relevant "intermediate" control strategies.

HYPOTHESIS 6: When asked to also run with *both* constant stride length (L_n) *and* constant stride time (T_n), subjects will adopt a single "concurrent" control strategy that equally achieves all task goals.

In particular, the outcome of testing Hypotheses 4a vs. 4b determined which control strategies were appropriately considered as "intermediate" in Hypothesis 5 and "concurrent" in Hypothesis 6. As in Aim #1, Hypothesis 5 was tested against the plausible alternative that subjects instead chose to minimize variations around the single solution that best satisfies both task goals. This experiment determined the extent to which healthy subjects adopted the same control strategies for running as they did for walking. The results for this experiment are described in Chapter 4 of this dissertation.

Aim #3: Determine the extent to which humans can *vary* their stepping control strategies during fast walking speeds and slow running speeds.

This experiment examined how control strategies would be affected when people were asked to walk or run at their predicted walk-to-run transition speed. By studying the

predicted walk-to-run transition, it is possible to gain a better understanding as to what happens as walkers or runners explore the speed limits for each type of locomotion. The walk-to-run transition is the distinct shift from walking to running that occurs at a characteristic speed as forward speed steadily increases. For this experiment, we asked subjects to either walk or run under each of the following 4 conditions: (i) normal walking at the subject's preferred walking speed (PWS), (ii) walking at the subject's calculated walk-to-run transition speed, (iii) running at the subject's preferred running speed, and (iv) running at the subject's calculated walk-to-run transition speed. For all trials, the treadmill speeds were determined based on each subject's leg length and Froude number (Vaughan and O'Malley 2005, Dingwell, John et al. 2010). The obtained data was used to test the following hypotheses:

HYPOTHESIS 7: When walking on the treadmill at PWS, subjects will explicitly exploit the redundancy available between L_n and T_n, as shown previously (Dingwell, John et al. 2010) and Aim #1.

HYPOTHESIS 8: When running on the treadmill at constant preferred speed, subjects will also explicitly exploit the redundancy available between L_n and T_n, as they do for walking (Dingwell, John et al. 2010) and Aim #2

HYPOTHESIS 9: When asked to either walk or run at their predicted W-R transition, subjects will be unable to maintain their desired

control strategies as used when walking/ running at a comfortable speed.

HYPOTHESIS 10: When asked to either walk or run at the predicted W-R transition speed, subjects will adopt different control strategies dependent on the form of locomotion.

The results from this experiment are described in Chapter 5 of this dissertation.

PRIMARY SIGNIFICANCE

This dissertation investigated control strategies used during walking, running, and for both walking and running at the predicted walk-to-run transition speed. These experiments sought to determine how introducing additional task goals altered subject's control of stride-to-stride fluctuations within three gait parameters, stride length, stride time and stride speed. The most significant findings of these experiments were that during treadmill walking and running subjects adopted similar control strategies of these stride-to-stride dynamics. Initially, we did not know if subjects would be able to maintain the same control strategy for running as they did for walking (Chapter 3 and (Dingwell, John et al. 2010)) since running has a flight phase (Novacheck 1998) and the mathematical coupling between L_n, T_n and S_n might be different while in the air. However, subjects controlled for the stride speed parameter, and used stride length and stride time to maintain a specific stride speed. Another main finding was that at the predicted walk-to-run transition speed, subjects were able to maintain a selected speed;

however, they manipulated L_n and T_n in distinctly different ways. These results have established that the stride speed control paradigm is robust even with additional task goals and determined that humans could voluntarily achieve simultaneous goals during treadmill locomotion.

CLINICAL IMPLICATIONS

These findings may play a role in clinical rehabilitation protocols as results indicate that healthy subjects maintain stride speed while exploiting the available redundancy (the multiple combinations of L_n and T_n that satisfy the same S_n) in both stride time and stride length. This is an important finding for gait retraining, either with manual manipulations or robotic assistive devices. Gait retraining should be structured around the idea that variability may innately be minimized with respect to stride speed and exploited in respect to stride length and stride time. Also, the data analyses used in these three experiments could also be utilized to study the control processes of additional locomotor task and potentially be extended to other continuous repetitive motions.

Chapter 2

Literature Review

Overview

People are faced with many challenges during locomotion everyday. Individuals are required to walk on multiple surfaces, avoid obstacles, and adapt to many different situations. These unpredictable environmental disturbances that we face daily can lead to potential injuries or falls, especially in elderly or impaired populations. Falling is the leading cause of non-fatal injury in all age groups except 15-24 year olds. One out of every three adults (age 65 +) falls each year (www.cdc.com). The health care costs associated with these walking related falls or injuries are rising quickly and are predicted to reach $54.9 billion by 2020 (www.cdc.com). The prevalence of these falls and related injuries is forcing hospitals and outpatient centers to be focused on rehabilitation and the recovery of injured patients. Locomotion is a large part of independence of these patients, and is a critical reason why researchers are focused on helping people prevent or avoid these falls in the first place, as well as learning how to teach people to regain their walking abilities.

While patient populations (elderly etc.), real world (i.e., ecologically valid) contexts, and perturbations are all important to study, there must first be a clear understanding of what healthy (biomechanically and neurologically intact) individuals do during normal, un-perturbed walking. As researchers, it is necessary to understand how people control stepping movements and what specific gait parameters people are

attempting to keep consistent during locomotion. It is necessary to determine how people manipulate their locomotor control paradigms to achieve steady locomotion during both walking and running.

General Locomotion Concepts

Locomotor Patterns: Mechanics & Dynamics

Locomotion is a highly researched topic. Experiments have looked at almost every aspect of walking; including but not limited to kinematics, kinetics, energy expenditure, metabolic costs and etc (Kirtley, Whittle et al. 1985, Novacheck 1998, Andriacchi and Alexander 2000). In clinical gait assessments, a clinician will often take physical measurements of walking speed, symmetry between limbs, range of motion, and muscle recruitment. More rigorous gait assessments will typically include motion capture, EMG analyses and kinetic data.

Walking is a cyclical process comprised of specific identifiable phases (Gage 1990). Each phase of the gait cycle is defined by the events that occur within the phase. The two main phases of the gait cycle are the stance and swing phases. The stance phase accounts for 60% of the gait cycle (Rosenrot, Wall et al. 1980, Vaughan 1996, Novacheck 1998). Walking is most often distinguished by a double support phase, where both feet are on the ground simultaneously and bearing weight (Chao, Laughman et al. 1983). Due to this double support phase, walking demonstrates substantially greater ground contact time (Segers, Aerts et al. 2006). Walking can also be modeled as an

inverted pendulum and as a passive dynamic system that uses potential and kinetic energy to move (Townsend 1981, Winter, Patla et al. 1990).

During running, the most noticeable difference from walking is the existence of a flight phase, in which no limbs are in contact with the ground (Mann 1980, Novacheck 1998). Running occurs at higher speeds and therefore stride lengths increase and stride times decrease (Cavanagh and Kram 1989, Novacheck 1998, Segers, Lenoir et al. 2007).

From a kinetic standpoint, running incurs much greater ground reaction forces when compared to walking (Cavanagh and Lafortune 1980). Running can be modeled as a mass-spring system, where energy is stored and returned (Blickhan 1989, McGeer 1990, Geyer, Seyfarth et al. 2005). The mass spring models exhibit fundamentally different dynamics than the inverted pendulum model for walking. By modeling running as a mass spring, the propulsive force during the stance phase is increased generating the flight phase. Again, the flight phase is one of the biggest distinctions between running and walking.

The most common measures used to characterize basic locomotor movements are stride length, stride time and stride speed (Mann 1980, Rosenrot, Wall et al. 1980, Öberg, Karsznia et al. 1993). While averages of these specified measures provide information about an activity for an extended period of time, it is important to also investigate what is occurring at each individual stride and how that influences the next stride (Dingwell, John et al. 2010, Decker, Cignetti et al. 2012, Terrier and Dériaz 2012). Thus, it is important to examine the relationships between consecutive movements.

Neural Control of Movement

Variability & Noise

The human nervous system is a complex integration of multiple networks. To add to the complexity of the system, noise is ubiquitous at every level, including sensory processing, planning, and motor system execution (Harris and Wolpert 1998, Faisal, Selen et al. 2008). Noise can be an advantage or disadvantage during human movement. On one hand, noise may aid a mechanism in exploring the task space and ultimately finding the best solution or the nervous system could moderate the effect of noise and improve task performance (Collins, Imhoff et al. 1996, Collins, Priplata et al. 2003, Eldar and Elowitz 2010, McDonnell and Ward 2011). On the other hand, noise can corrupt control (Takahashi, Nemet et al. 2003).

Noise within motor commands may result in variability (van Beers, Haggard et al. 2004). Van Beers et al suggests that in general, execution noise accounts for a large amount of movement variability. Regardless of the source of the variability, studies have shown that the CNS is robust and is able to perform skilled tasks in the presence of noise (Scholz and Schöner 1999, Cohen and Sternad 2009). Even with the previous findings, it remains unclear how the CNS accounts for the effects of this motor noise during redundant tasks.

Redundancy

When humans complete motor tasks, various strategies are used to yield the same outcome. This is because the human body is inherently redundant, meaning there are many more degrees of freedom than needed for any action (Wolpert, Ghahramani et al.

1995, Scholz and Schöner 1999, Scott 2004). This idea of an infinite number of possible task/goal solutions is also known as equifinity (Cusumano and Cesari 2006). Often tasks involve many variables that are controlled by the brain. However, the value of individual variables is not always held constant. For a redundant task, there is an infinite set of solutions that can satisfy the task goal. For example, take a task that might be reduced to something like X+Y=4. X and Y can be any value, as long as the sum remains constant. Hence, there are an infinite number of combinations of X and Y that equally satisfy X+Y=4. In a biomechanical context, X and Y might represent, for example, two joint angles of a given limb trying to maintain a constant endpoint position, similar to (Cusumano and Cesari 2006), or the forces applied by two fingers in a pressing task, similar to (Latash, Scholz et al. 2002).

Understanding how humans interpret redundancy has been a particularly difficult task. There have been many attempts to explain how the central nervous system optimizes this redundancy to produce regular, smooth motor outputs. However many of these strategies have mostly focused on finding the best solutions to resolve redundancy in a given task (Uno, Kawato et al. 1989, Alexander 1997, Harris and Wolpert 1998, Nishii and Taniai 2009): i.e., on finding the single, most "optimal" (in some sense), solutions that people might strive to achieve on average. However, these studies did not speculate about mechanisms to account for variability from trial to trial. Newer studies have combined mathematical and experimental approaches in hopes of determining the control mechanisms used to address this issue of how variability and redundancy are related in movement.

Experimental Approaches

Uncontrolled Manifold (UCM)

The Uncontrolled Manifold (UCM) was one of the original approaches attempting to describe the principles by which motor control is organized. More specifically, UCM was developed to approximate the stability of the movement by calculating the trial-to-trial variability. Although named the "uncontrolled" manifold, this approach maintains that control always exists, however the strength of the control may vary. An assumption that UCM makes is that if a variable is considered "stable," (i.e., less variable) this is an indication that the nervous system is controlling the variable during the task. These variability measures are based on trial to trial variability from previously recorded movement data.

For the UCM approach, a set of hypothesized control variables is created. From the previous example, the elemental variables are X and Y (i.e. joint angles in a kinematic task). Then for each independent variable a solution space is defined by all position solutions. For each individual variable (X and Y), two subspaces are created; one that contains all the configurations that do not affect the controlled variables (i.e., Uncontrolled), and an additional orthogonal subspace that contains the controlled variables (i.e., Controlled). The uncontrolled subspace of the manifold is where the redundancy of the task can be exploited. The solution manifold for a simple task like reaching can become more complex and multidimensional with the large number of kinematic variables that may need to be accounted for.

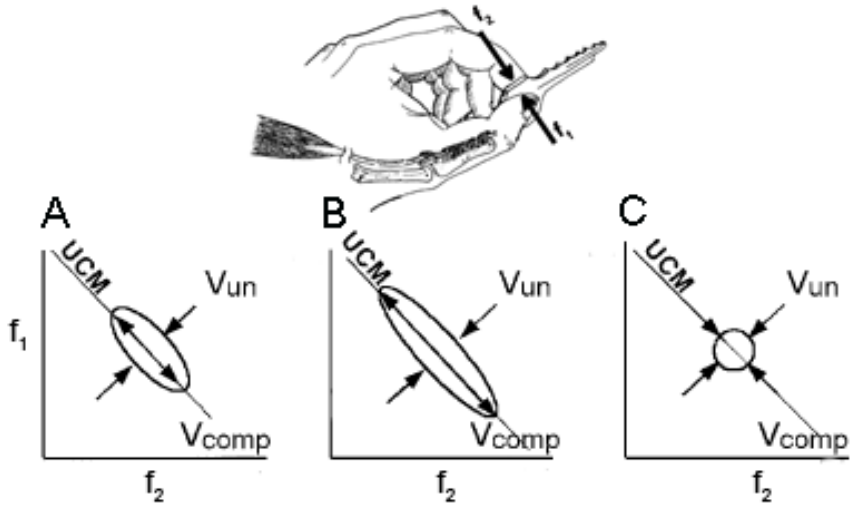

Figure 2.1. Example of UCM task. Different distributions of variance along the uncontrolled manifold. Variance along the manifold is called the compensated variance, V_{comp}. The variance perpendicular to the manifold, is the uncompensated variance, V_{un} The line along the manifold is where the task variables are constant. Motor control is identified by examining the ratio of the variances ($R_v = V_{comp}/V_{un}$).

For example, if you are required to use two fingers pressing on a key to yield constant force (figure 2.1), where f1=f2, the forces from the fingers are then projected onto a manifold where the distribution of these forces determines the level of control. There are many options of force combinations of f1 and f2 that yield the same total force. Part B in the figure above depicts a situation where the net force generated by the 2 fingers is strongly controlled, whereas part C indicates weak or no control. UCM quantifies the ratio between the variance along the manifold and the variance

orthogonal/perpendicular to the manifold to determine which variables are being controlled and how they are combined to complete a task (Latash, Scholz et al. 2002). The larger the variance that occurs along the uncontrolled manifold, where the inherent redundancy in the task is exploited, the more strongly "controlled" or "stabilized" the control variable is (Scholz, Schöner et al. 2000, Reisman, Scholz et al. 2002).

Tolerance Noise Covariation

Another approach, commonly used in reaching tasks, is the tolerance noise covariation method or TNC. TNC attempts to define the task goal independent of the experimental data, to gain insight as to how subjects organize the related task variables. The TNC manifold is defined in relation to a fixed external task goal. This approach assesses variability in terms of its cost to the outcome, rather than its covariance within the solution space (Müller and Sternad 2004, Cohen and Sternad 2009). Performance is evaluated based on the tolerance (the location), the covariation, and the noise (scattering) of the actual data. Each cost is defined in terms of the effect it has on the final goal: the tolerance cost measures the error at the goal that results from being a given average distance off of the solution manifold, the covariation cost measures the error at the goal that results from not aligning ones movements along the solution manifold, and the noise cost measures the error at the goal that results from the amplitude of the variability in the movement. The TNC method is used to examine how the variance structure changes over time throughout learning tasks.

Minimum Intervention Principle (MIP)

Another approach is the minimum intervention principle (MIP). MIP provides a theoretical basis for computational models to assess the redundancy issue. MIP relates the task related geometry to stochastic optimal control theory to hypothesize how human movements are regulated during redundant tasks (Todorov and Jordan 2002). MIP corrects only for deviations that interfere with the completion of the task goals (Cusumano and Cesari 2006). In other words, one assumes that it is not efficient to minimize errors that do not negatively affect the task goal. MIP accounts for exploration of a task space, rather than a joint space (UCM).

A well-respected computational mechanism used to implement MIP is stochastic optimal feedback control (OFC) (Todorov and Jordan 2002, Todorov 2004, Valero-Cuevas, Venkadesan et al. 2009). OFC is one of the primary methods of explaining motor variability in redundant tasks. OFC explains that the motor system allows variability within the task irrelevant variables and uses feedback to correct any errors in the task relevant variable that will interfere with achieving the stated task goals. Although this method provides insight into how people regulate variability during redundant tasks, it also does not account for the trial-to-trial dynamics.

Limitations of these Methods / Approaches

Although these previously mentioned approaches have provided much insight into how the human nervous system regulates variability during redundant tasks, most of these theories have significant limitations. UCM is limited by the tasks and how the

control variables are defined. In other words, UCM relies on the variance structure of the experimental data itself to infer control. However, this variance of the body variables may be completely independent of the task itself. This may lead to ambiguous interpretations of the data (Valero-Cuevas, Venkadesan et al. 2009, Cusumano 2013).

The TNC approach has been used in upper extremity tasks, however its learning focused approach does not lend well to tasks that are already highly "learned" like walking or running. Tasks need to be more "novel" for subjects "learning" to be measured and analyzed. TNC also relies solely on the distribution of the variability within the data to hypothesize what the subjects were "controlling."

The MIP approach is a more rigorous and computational approach. However, in its implementation, it has not yet been used to account for the trial-to-trial dynamics of redundant task experiments. All approaches analyze average measures of specified parameters to determine what parameters subjects manipulate during a given tasks. These average measures are unable to determine the trial-to-trial differences. The trial-to-trial dynamics are essential to understand the nervous system exploits redundancy from one movement to the next (Gates and Dingwell 2008, Dingwell, John et al. 2010).

Goal Equivalent manifold (GEM)

Another related approach, the Goal Equivalent manifold (GEM) is defined purely by the task, and provides a transformation of the body state variables to goal variables (Scholz and Schöner 1999, Cusumano and Cesari 2006). To determine what solutions are available for a specific task, a specific goal function must be defined. Any goal function

is defined as "the interaction between body variables (vector x(t)), goal variables of the task (vector y(t)), and the environment needed for perfect task execution" (Cusumano and Cesari 2006). The goal function is defined generally by (Cusumano and Cesari 2006) as:

$$f(x, y, t) = 0 \quad (1)$$

The goal function is defined so that it is not a true constraint, therefore the body does not always *have* to satisfy the goal. However when the goal function is specified and equifinality inherently exists within the task, all possible task solution strategies in the form of a manifold can be defined (Cusumano and Cesari 2006): i.e., all combinations of x and y such that $f(x,y,t) = 0$ *exactly*. Any combinations of x and y that lead to $f(x,y,t) \neq 0$ indicate errors in task performance.

For example, during the game of darts, the objective of the game is to hit the bull's-eye. This goal exists regardless of who throws the dart, how they throw the dart, and even if the dart is thrown at all (Dingwell, Smallwood et al. 2013). Unlike UCM, the GEM approach uses mathematical relationships between the body and the goal that are defined consistently for any and all subjects. The GEM makes no *a priori* assumptions as to which variables are controlled and which are not.

Separating "Variability" From "Control"

One fundamental difficulty is that measures of variability (e.g., standard deviation, coefficient of variation, etc.) only quantify the *average magnitude* of fluctuations across a large number of strides. They yield no "dynamic" information about

how each step directly influences subsequent steps (Dingwell and Cusumano 2000, Dingwell, John et al. 2010), and therefore are unable to quantify how errors change from one trial to the next. Many of these previously mentioned approaches attempt to answer how movements are controlled by the nervous system by determining the structure of the variance. One problem with this type of analyses is that the variance can be structured for a variety of reasons not always related to the specific task related control (Valero-Cuevas, Venkadesan et al. 2009).

One effective way to determine these trial-to-trial fluctuations is to apply Detrended Fluctuation Analysis or DFA. DFA is one way to determine the correlation between consecutive movements, i.e. trial to trial (Peng, Buldyrev et al. 1992, Hausdorff, Purdon et al. 1996, Todorov 2004, Cusumano and Cesari 2006, Delignières and Torre 2009). DFA can determine the statistical persistence or anti-persistence in any time series. DFA is used to compute a scaling exponent, alpha (α). An $\alpha < 0.5$ indicates that deviations in one direction are likely to be followed by deviations in the opposite direction (anti-persistence). An $\alpha > 0.5$ indicates that deviations are more likely to be followed by deviations in the same direction (persistence). Lower values of alpha indicate more tightly regulated variables (Peng, Buldyrev et al. 1992, Dingwell, John et al. 2010). When used in combination with the notion of a GEM, these DFA analyses can give greater insights into the degree of actual "control" being applied to different variables in redundant tasks than analyses of variance alone (Cusumano 2013).

An alternative method of determining the sequential relationships within a time series is to use a Lag 1 auto correlation (Dingwell, Smallwood et al. 2013). Similar to

DFA, Lag 1 auto correlations can determine the correlation between consecutive measures (Goldberger, Amaral et al. 2002). Lambda can be interpreted as a stability multiplier that measures the strength of responses to small external perturbations (Dingwell and Kang 2007, van Beers 2009). Lag 1 autocorrelation is used to determine a measure called lambda (λ) where $\lambda = 0$ indicates uncorrelated "white" noise, $\lambda < 0$ exhibits anti-persistence and for $\lambda > 0$ exhibits statistical persistence. As with DFA, lower values of λ indicate more tightly regulated variables (Peng, Buldyrev et al. 1992, Goldberger, Amaral et al. 2002, Dingwell and Kang 2007). In previous work from our lab (Dingwell, Smallwood et al. 2013) Lag 1 auto correction has been shown yield similar results to DFA, indicating that DFA and Lag 1 auto correlation are both effective ways of determining the correlations between consecutive measures (Cusumano 2013).

Dynamics and Control of Walking

Variability & Noise in Walking

For walking, increased gait variability has been prospectively linked to increased risk of falling (Maki 1997, Hausdorff, Rios et al. 2001, DeMott, Richardson et al. 2007). However, there remains considerable debate about which measures of gait variability are most relevant (Owings and Grabiner 2004, Moe-Nilssen and Helbostad 2005, Brach, Studenski et al. 2008), with some studies even finding non-intuitive and interesting results, such as decreases in speed (slower walking speeds) leading to instability, or too

little variability contributing to fall risk (Brach, Berlin et al. 2005, Beauchet, Allali et al. 2009).

Additionally, in some contexts additional variability can benefit task performance. For example, several recent studies have found that allowing variability in robotic locomotor gait re-training interventions leads to faster improvements in gait performance (Cai, Fong et al. 2006, Lewek, Cruz et al. 2009, Lee, Won et al. 2011). Some movement variability arises from the ubiquitous noise in the nervous system (Cordo, Inglis et al. 1996, Osborne, Lisberger et al. 2005, Stein, Gossen et al. 2005, Faisal, Selen et al. 2008). However, much of the movement variability we observe arises from redundancy or equifinality (Scott 2004, Todorov 2004, Cusumano and Cesari 2006). One reason these more variable robotic gait re-training interventions are more effective is likely that the device allows appropriate variability for relevant gait parameters, which permits patients to more fully explore that space of equally valid task solutions.

Functional / clinical implications

During walking, humans need to adapt at *every* step (not just on average) to respond to perturbations (Dingwell and Cusumano 2000, Dingwell and Marin 2006, Kang and Dingwell 2008). While the neurophysiological mechanisms that enact these responses are well known (Rossignol, Dubuc et al. 2006), the fundamental principles governing adaptation from one stride to the next remain mostly unknown. Detrended Fluctuation analyses (DFA) has been used repeatedly to quantify the temporal correlation structure of specific gait parameters, primarily stride time. DFA analyses indicate that

stride-to-stride variations in gait cycle timing exhibit statistical persistence (Peng, Buldyrev et al. 1992, Hausdorff, Peng et al. 1995, Terrier, Turner et al. 2005) and that these characteristics can be altered with aging or neurological degradation (Hausdorff, Mitchell et al. 1997) .

Variability has also been investigated during both treadmill and overground walking (Terrier, Turner et al. 2005, Terrier 2012, Terrier and Deriaz 2012, Terrier and Deriaz 2012). Prior research within our lab has shown that these stride to stride fluctuations can be directly interpreted in terms of the degree of control imposed on each specific gait variable (Fig. 1 and (Dingwell and Cusumano 2010, Dingwell, John et al. 2010)). Understanding how control is enacted from stride to stride therefore requires quantifying the specific temporal sequencing of those stride to stride fluctuations (Dingwell and Cusumano 2010, Dingwell, John et al. 2010).

Redundancy in Walking

From a neurological standpoint, walking is a highly complex task that requires significant amounts of control. The nervous system must integrate multiple systems simultaneously in order to generate functional locomotion (Rossignol, Dubuc et al. 2006). Due to this advanced multi-system integration, there are often multiple solutions to one problem. More specifically with locomotion, there are an infinite number of strategies people can choose to create stride lengths (L_n) and stride times (T_n). However, on average, humans choose a preferred combination of L_n and T_n thought to be based on minimizing energy expenditure (Srinivasan and Ruina 2006), and then attempt to make

corrections when errors occur. Often, when injury or paralysis happens, humans endure much greater energetic costs. Determining why healthy people chose specific strategies to control locomotion, can provide insights into how to re-train those that have lost the ability to generate consistent locomotion.

Since walking is a redundant task, many of the previously discussed approaches have been used to analyze walking. The UCM approach has been applied to determine the structure of variance in kinematic parameters (joint angles), joint moments, muscle activation patterns, etc. (Black, Smith et al. 2007, Scholz, Schöner et al. 2007, Auyang, Yen et al. 2009). However UCM is unable to determine the temporal structure of inter-trial fluctuations within kinematic parameters. Therefore this method does not allow us to quantify the control of goal relevant parameters (Cusumano 2013).

The TNC method has not been applied to walking as TNC is based on learning tasks. Since walking is a well-learned task, this type of analyses may not be appropriate. Also, TNC only creates a minimal space of variables to satisfy the given task.

However, the GEM method has been used successfully to address variability in human movement (Cusumano and Cesari 2006), and more recently the variability in stride to stride fluctuations during walking (Dingwell, John et al. 2010). The GEM approach is a more thorough approach because it allows us to analyze only body state variables that interact directly with goal level performance, and is designed for specific tasks with designated goal functions. Specifically for treadmill walking, the task goal is to maintain stride speed, and remain on the treadmill.

Dynamics and Control of Running

Running is a vastly studied topic due to the large number of humans that participate in the sport. Among these millions of people, 30-75% of runners get injured each year (Van Gent, Siem et al. 2007). Walking and running share some basic kinematic and kinetic characteristics. However, they are markedly different locomotive strategies as proven by the distinct transition between the two modalities. Similar to walking, running is very complex task that requires coordination of many different physiological systems. Due to this complexity, the central nervous system must regulate this coordination as well as variability within the motor outputs. Running is thought to share the same pattern-generating networks as walking (Cappellini, Ivanenko et al. 2006), which may indicate similarities in the control of variability. As in walking, some of the variability within gait parameters occurs because of equifinality: e.g., there are an infinite number of stride lengths (L_n) and strides times (T_n) that yield the same stride speed ~ ($Ln/Tn = Sn$) during running as there are in walking. However, within the literature, it is inconclusive where the equation may be violated with the existence of the flight phase during running. Few studies have investigated how the variability of stride parameters is controlled to achieve stable running gait.

Variability during running is important to understand since it has been suggested that people with injuries often have reduced variability (Hamill, van Emmerik et al. 1999, Bartlett and Kram 2008, Meardon, Hamill et al. 2011). It is unknown if these decreases in variability of certain kinematic variables exist prior to injuries or rather post injury.

Identifying this variability is extremely important in order to know which variability should be included and which variability should be minimized from the stride parameters that contribute to the task goal.

Similar to the fluctuations in stride intervals during walking, temporal fluctuations have been found to exhibit persistence during running as well (Jordan, Challis et al. 2006). These fluctuations in the temporal components of gait cycle are not random (Jordan and Newell 2008, Jordan, Challis et al. 2009). A comparison study between walking and running determined that DFA alpha values increased with walking speed, while this same values decreased with running speed (Jordan, Challis et al. 2009). Also, that slower running exhibited greater instability than fast walking at the same variety of speeds. However, these results only included stride times. These analyses did not include stride length, stride speed, or any coupling between these variables.

The variability found within running parameters is not simply noise within the nervous system but is thought to have a functional purpose (Jordan, Challis et al. 2009). Studies have speculated that this variability of movement might be necessary for the changes in coordination patterns and more specifically the ability to adapt to any perturbation (Bartlett and Kram 2008). However past studies were simply examining the variability itself, not the actual temporal fluctuations of the stride parameters (Cusumano 2013). Variability within the stride time parameter has been the focus of many studies. DFA has also been applied to stride time (~*Tn*) in both healthy and injured populations. A study by Meardon and Hamill showed that injured runners exhibit lower alpha values (Meardon, Hamill et al. 2011). Additional studies confirm that there is less variability in

kinematic parameters in injured populations (Hamill, van Emmerik et al. 1999, Bartlett and Kram 2008). Little to no evidence exists whether this is the cause or the effect of injury.

The walk-to-run transition has also been investigated in terms of variability and redundancy. Walking and running share symmetries in numerous kinematic and timing parameters, however, when reaching the W-R transition speed, increases in variability have often been proposed. Studies have shown that this variability exists in many different parameters, such as inter-limb coordination (kinematics of joint angles/limb trajectories) (Segers, Aerts et al. 2006), stride frequency (Li, van den Bogert et al. 1999), and the timing of the actual transition period (Segers, Aerts et al. 2006, Hreljac, Imamura et al. 2007, Van Caekenberghe, De Smet et al. 2010, Van Caekenberghe, Segers et al. 2010, Segers, De Smet et al. 2013).

Researchers have hypothesized that there are "critical fluctuations" near the gait transition. (Schöner and Kelso 1988, Diedrich and Warren 1995). These critical fluctuations are thought to be the result of phase shifts from stable attractors (Seay, Haddad et al. 2006). The general suggestion is that 'interesting dynamics' happen near transitions between stable solutions in systems. This could lead to very interesting control dynamics. However the studies investigating variability are inconclusive as to how this variability is regulated during running and at the W-R transition.

Implications for Current Dissertation

Determining the processes by which the nervous system accounts for motor noise and resolves redundancy can provide further knowledge on the underlying mechanisms that regulate movement. In this dissertation, we explored the effect of noise and redundancy in motor control during locomotion.

In the first study of this dissertation, we examined the effect of imposing additional tasks (goals) to subjects while treadmill walking. Subjects were asked to voluntarily control their stride length, stride time and stride speed using step length markers, a metronome and a treadmill. The intent of this experiment was to determine how humans alter the stride-to-stride regulation of their gait when the task goals change (i.e., by maintaining stride length and/or time). This study was intended to expand upon the current literature relating to this topic, more specifically the study by (Dingwell, John et al. 2010) where these "control" strategies were identified in normal treadmill walking.

One of the goals of this dissertation was to determine how robust these previously found control strategies are, and what effect imposing additional task goal(s) might have. The second study included a very similar analysis, however we extended the task to running rather than walking. The intent of this study was to determine if there were differences in how humans alter the stride-to-stride regulation of their gait during running.

Although common in the walking literature, there are few studies that apply task constraints or manipulations during running. In order to determine the robustness of the control paradigms used to coordinate and execute consistent running gait, it is important

to determine how specific individual parameters are controlled. One viable method to examine the variability within individual parameters is to constrain the specified variable. This method could allow us to learning more about what variability is "good" and what variability is irrelevant during running.

The third study of this dissertation directly compared walking to running. We were interested in determining how subjects control stride-to-stride fluctuations during the steady state at a predicted walk-to-run transition and more specifically at the fastest walking speed and the slowest running speeds. Many studies have determined that there is increased variability at the walk-to-run transition (Diedrich and Warren 1995, Li 2000, Seay, Haddad et al. 2006). However, it remains unknown if subjects change their control of specific gait parameters or if this variability comes from another source.

Chapter 3

Adaptability of Stride-to-Stride Control in Human Walking

Introduction

People are faced with many challenges during locomotion every day. Individuals are required to walk on multiple surfaces, avoid obstacles, and adapt to many different situations. These unpredictable environmental disturbances can lead to potential injuries and falls, especially in elderly or impaired populations (Maki 1997). Although external sources of variability are only one cause of variability, these situations can lead to increased variability of specific parameters during locomotion (Hausdorff, Rios et al. 2001). Increased variability of specific gait parameters may result in an increased chance of falling or injury (Maki 1997, DeMott, Richardson et al. 2007). On the contrary, the presence of variability may indicate that humans are utilizing the numerous combinations of gait parameters that allow them to walk more efficiently (Hausdorff, Purdon et al. 1996). More specific analyses of how humans both utilize or minimize variability of different gait parameters are needed.

To investigate measures of variability within certain gait parameters, it is necessary to first recognize how the central nervous system regulates and coordinates motor variability during walking. The higher order systems that control walking must incorporate the multiple sensory inputs to effective generate motor outputs fot efficient locomotion (Rossignol, Dubuc et al. 2006). Establishing the fundamental principles that guide this control is essential to understanding how humans regulate walking.

Most optimality principles, like minimizing energy cost (Kuo 2001, Srinivasan and Ruina 2006), predict an overall, *average* behavior (Collins 1995, Scott 2004). These methods are unable to explain the *variability* observed within movements (Körding and Wolpert 2004, Todorov 2004, Stein, Gossen et al. 2005, Faisal, Selen et al. 2008) including walking (Winter 1984, Hausdorff, Peng et al. 1995, Dingwell and Marin 2006, Kang and Dingwell 2008, Dingwell, John et al. 2010). Determining the nature of neuromotor variability is necessary to understanding how humans perform skilled movements (Körding and Wolpert 2004, Todorov 2004, Cusumano and Cesari 2006, Dingwell, John et al. 2010).

For walking, increased gait variability has been prospectively linked to increased risk of falling (Maki 1997, Hausdorff, Rios et al. 2001, DeMott, Richardson et al. 2007). However, there remains considerable debate about which measures of gait variability are most relevant, such as step width, trunk acceleration and stride time (Owings and Grabiner 2004, Moe-Nilssen and Helbostad 2005, Brach, Studenski et al. 2008). Additional studies have determined that too much or too little variability can lead to instability and/or falls (Brach, Berlin et al. 2005, Beauchet, Allali et al. 2009).

One fundamental difficulty is that measures of variability (e.g., standard deviation, coefficient of variation, etc.) only quantify the *average magnitude* of fluctuations across a large number of strides. They yield no "dynamic" information about how each step directly influences subsequent steps (Dingwell and Cusumano 2000, Dingwell, John et al. 2010). With these dynamic analyses, it is possible to investigate stride-to-stride fluctuations and how these fluctuations are regulated. Furthermore, in

some contexts additional variability could be beneficial. For example, several recent studies have found that allowing variability in robotic locomotor gait re-training interventions leads to faster and better improvements in gait performance (Cai, Fong et al. 2006, Lewek, Cruz et al. 2009, Lee, Won et al. 2011).

Some movement variability arises from the ubiquitous noise in the nervous system (Cordo, Inglis et al. 1996, Osborne, Lisberger et al. 2005, Stein, Gossen et al. 2005, Faisal, Selen et al. 2008). However, much of the movement variability we observe also arises from redundancy or equifinality (Scott 2004, Todorov 2004, Cusumano and Cesari 2006): i.e., there are often an infinite number of ways to achieve the exact same task goal. One possible reason these more variable robotic gait re-training interventions are more effective could be that the device allows appropriate variability for relevant gait parameters, which permits patients to more fully explore that space of equally valid task solutions.

During walking, humans need to adapt at each individual step (not just on average) to respond to a specific event or to maintain certain parameters (Dingwell and Cusumano 2000, Dingwell and Marin 2006, Kang and Dingwell 2008). The mechanisms by which these responses are implemented are known, (Rossignol, Dubuc et al. 2006), yet it is unknown how adaptation occurs from one stride to the next (Dingwell, John et al. 2010). Understanding how control is enacted from stride to stride therefore requires quantifying the specific temporal sequencing of those stride to stride fluctuations (Dingwell and Cusumano 2010, Dingwell, John et al. 2010, Cusumano 2013).

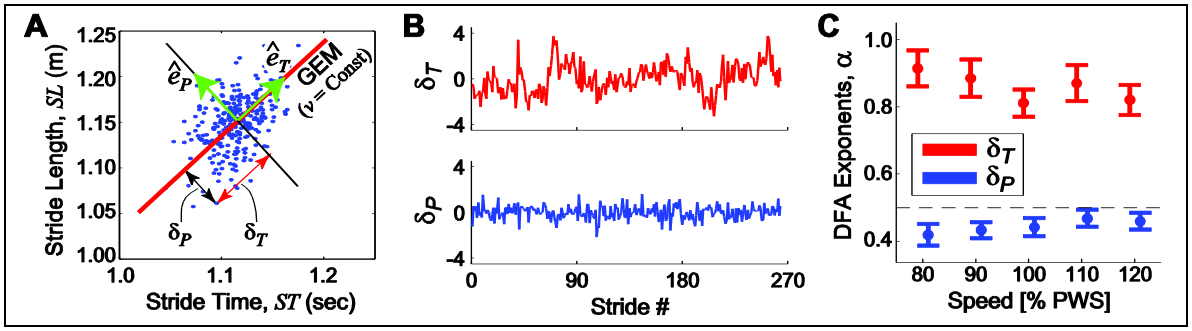

Fig. 3.1. A) Definition of "Goal Equivalent Manifold" (GEM) for walking at constant speed (L_n/T_n = Constant). B) Example time series of fluctuations tangent (δ_T) and perpendicular (δ_P) to the GEM in (A). C) DFA results confirming strong statistical persistence ($\alpha >> ½$), indicating very weak stride-to-stride control, for δ_T fluctuations and anti-persistence ($\alpha < ½$), indicating much stronger stride-to-stride control, for δ_T fluctuations ($p < 2\times10^{-12}$). Results from (Dingwell, John et al. 2010). Importantly, these distinctions were *only* apparent when analyzing δ_T and δ_P fluctuations. Analyses of L_n and T_n time series revealed *no* such differences.

Our lab recently demonstrated (Dingwell, John et al. 2010) that humans walking on a treadmill explicitly exploit the inherent redundancy between stride length (L_n) and stride time (Tn) to try to maintain ~constant stride *speed* ($Sn = L_n / Tn$) at each step (Fig. 3.1). Simple computational models showed that humans could have easily chosen a number of other alternative, but equally successful, strategies, but they did not (Dingwell, John et al. 2010). However, these initial results were obtained only for normal walking on a treadmill. The specific strategies people might use were not directly *manipulated* experimentally. However, the conceptual framework previously developed (Dingwell, John et al. 2010) provides an ideal tool to precisely predict the expected step-to-step fluctuation dynamics humans *should* exhibit when imposing any of a wide range of explicitly defined control strategies.

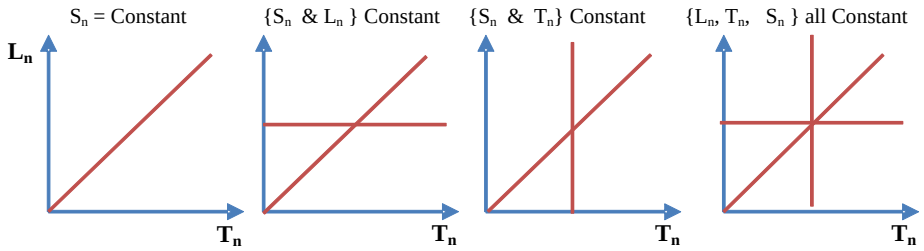

Fig. 3.1D: Schematic of 4 conditions to be tested in Aim #1 and their respective GEM's. Each GEM defines a specific redundancy between L_n and/or *Tn*. These experiments explicitly tested the ability of subjects to exploit these different redundancies.

Here, we directly manipulated the task conditions presented to subjects during treadmill walking. Stride length (L_n), stride time (*Tn*), and stride speed (*Sn*) conditions were given so as to explicitly vary the nature of the available redundancies (Fig 3.1.D). We hypothesized that subjects could complete the multiple simultaneously goals by utilizing a strategy that attempts to achieve an "intermediate" goal that partially satisfies each individual goal (e.g., Fig. 3.2, Left). Alternatively, subjects could determine the intersection of the two individual task goals and resort to minimizing variance around the single solution that equally satisfies *both* goals (e.g., Fig. 2.2, Right). Although, these are two plausible strategies for this task, there may be other additional strategies that satisfy the same overall goal. We directly tested these different alternatives for both walking and running in this dissertation.

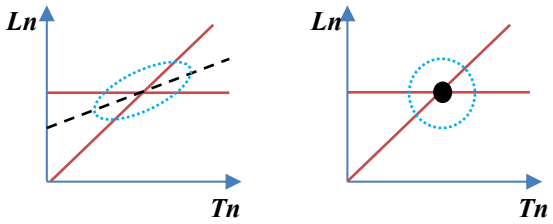

Fig. 3.2. Example schematics of possible strategies subjects might use when asked to achieve multiple simultaneous goals. Left: Subjects could adopt "intermediate" strategies that balance the competing demands of each individual task goal.Right: Alternatively, subjects could adopt the single, optimal solution that simultaneously achieves both (or all) task goals, but does not admit any redundancies.

Methods

Subjects

Fourteen (14) healthy adults between 18 and 35 years of age participated (Table 3.1). All subjects were pre-screened to ensure they had no lower leg injuries, surgeries, or cardiovascular, respiratory, neurological, musculoskeletal or visual conditions that could have affected their gait. This study was approved by the Institutional Review Board at the University of Texas and all participants provided written consent prior to participation.

Table 3.1 Subject Characteristics

Subject Characteristics (n=14)	
Age (yrs)	**24.14 ± 4.22**
Sex (female/male)	**9/5**
Height (m)	**1.70 ± 0.13**
Leg Length (m)	**0.93 ± 0.07**
Body Mass (kg)	**65.75 ± 11.75**

Experimental Protocol

Subjects walked on a Woodway Pro XL treadmill (Woodway USA, Waukesha, WI) with a motorized rubber belt. The treadmill belt dimensions were 2.23m long by 0.685m wide. All subjects wore a safety harness during the experimental session (Fig 3.3.). This harness did not interfere with their normal walking movements.

Subjects first acclimated to walking on the treadmill for at least 5 minutes at the beginning of the experiment and 2 minutes prior to each new condition. Walking speed was non-dimensionally scaled to each subject's leg length using the Froude method:

$$Walking\ speed = \sqrt{\mathrm{Fn} \times\ g \times l}, \tag{2}$$

where *Fn* is the Froude number, which was 0.16 for this study, *g* is gravity and *l* is leg length; measured from the greater trochanter to the floor (Vaughan and O'Malley 2005). For a subject with an "average" leg length (~0.93m), a Froude number of *Fn* = 0.16

yields a true walking speed of ~1.21 m/s. Subjects were asked to verify that this walking speed was comfortable.

Subjects were then asked to complete two 6-minute walking trials each under each of the following four experimental conditions: constant stride speed (SPD), constant stride speed and stride length (LEN), constant stride speed and stride time (TIM), and constant stride speed, length and time (ALL).

For all conditions, the treadmill speed was set to the selected Froude speed. For the SPD condition, the subjects were given no further instructions. For the LEN condition, subjects were asked to step on evenly spaced markers placed on the treadmill belt. One-inch wide strips of athletic tape were placed in the identical location (0.67m) for all experiments. For the TIM, subjects were asked to walk in time with a metronome. For the ALL condition, the subjects were asked to combine all three previously mentioned tasks while walking. For all trials, a waist high mirror was also placed in front of the treadmill to give subjects visual feedback of their foot placement that did not require them to bend their necks to look directly down at their feet (Smid and den Otter 2013).

Experimental conditions were presented in random order to each subject, with presentation order balanced across subjects. Trials were 6 minutes long and for marker placement accuracy were blocked by condition: i.e.,2 trials of each condition were collected before going onto the next condition. Subjects were given a minimum 2 minutes rest in between trials, and allowed as much rest as needed.

Data Collection and Processing

Whole-body kinematic data were recorded at 60 Hz using a 10-camera Vicon MX motion capture system (Oxford Metrics, Inc., Oxford, UK) for the entire duration of each trial. Each subject wore a standardized whole-body marker set of 57 markers, (Fig. 3) (Wilken, Rodriguez et al. 2012). Raw kinematic data were processed using Vicon Nexus software. Additional data analyses were performed using MatLab (MathWorks, Inc., Natick, MA).

Individual strides were determined by finding the local maxima of the distances between the pelvis and heel markers in the anterior-posterior direction (Zeni, Richards et al. 2008). These data were used to extract time series of the specified stride parameters: stride lengths (L_n), stride times (Tn), and stride speeds (Sn) for each walking trial. Stride length (L_n) was defined as the anterior-posterior distance between right heel strike to the next consecutive right heel strike. Stride time (T_n) was the amount of time it took to go from heel strike of one foot to the next heel strike by the same foot. Stride speed was calculated as $S_n = L_n/Tn$ for each stride in each trial. For consistency across analyses, all trials were truncated at 150 strides each.

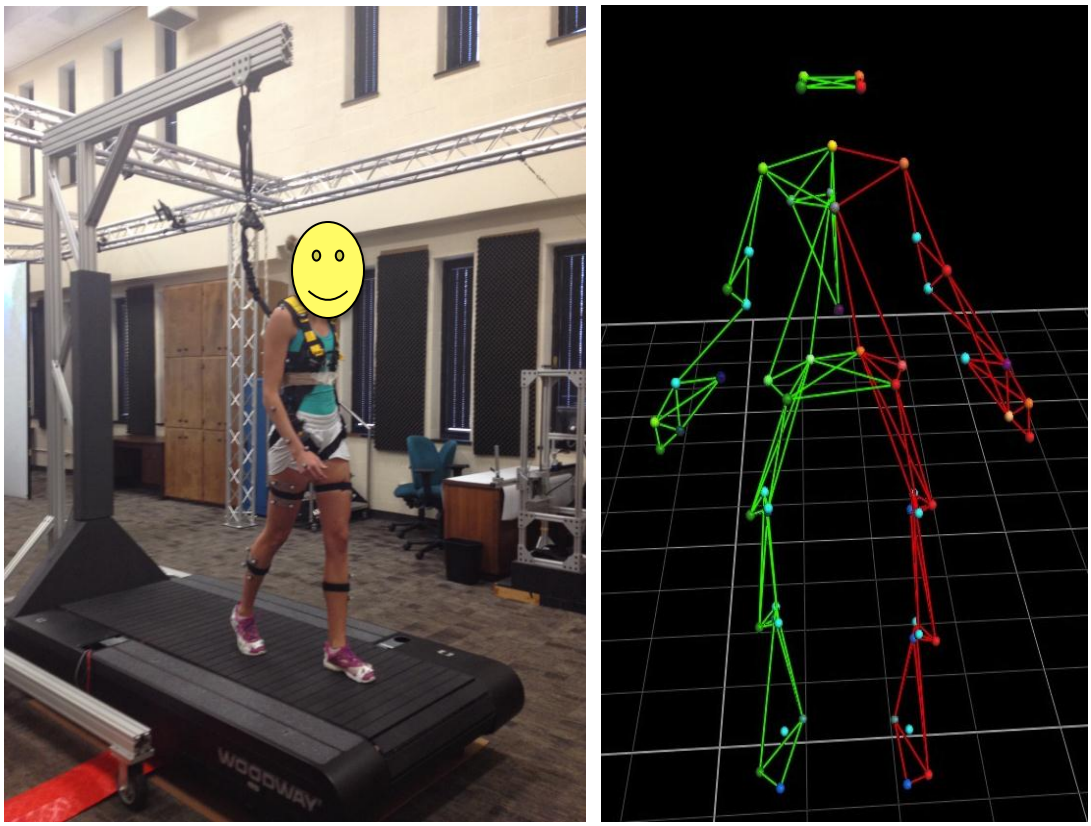

Figure 3.3. (Left) Subject walking on the Woodway treadmill in our laboratory. (Right) Computer generated image of the 57 marker set used in this study.

Dynamics of Primary Gait Parameters

Means and standard deviations were calculated across all strides for each L_n, T_n and S_n time series from each trial.

Detrended fluctuation analysis or DFA is one way to determine the correlation between consecutive movements (Peng, Buldyrev et al. 1992, Hausdorff, Purdon et al. 1996, Goldberger, Amaral et al. 2002). DFA can quantify the statistical persistence or anti-persistence for a given measure for consecutive movements, in this case specific gait parameters (L_n, T_n and S_n), independent of the magnitude of variability (Cusumano 2013).

DFA was used to compute a scaling exponent called alpha (α). An $\alpha < 0.5$ indicates that deviations in one direction are more likely to be followed by deviations in the opposite direction (anti-persistence). An $\alpha > 0.5$ indicates that deviations are more likely to be followed by deviations in the same direction (persistence). Smaller alpha values may be correlated with more tightly controlled processes, however there are other potential reasons for low alpha values to occur (Dingwell and Cusumano 2010, Dingwell, John et al. 2010).

An alternative viable method of determining the serial correlation structure in a time series is to compute the Lag-1 autocorrelation. Similar to DFA, Lag-1 autocorrelations quantify the correlation between consecutive data points (in this case, strides)(Dingwell and Cusumano 2010). However, for this study, we chose to use DFA as it captures fundamental dynamic information about a recorded time series, independent of variability magnitude (Cusumano 2013).

For each of the traditional gait variables (i.e., L_n, T_n, and S_n), the values of each dependent measure (i.e., mean, SD, and α) were computed for each trial. These data were then analyzed using 2-factor (Condition x Subject) repeated measures ANOVA, followed by Tukey post-hoc analyses. Statistical analyses were performed using SPSS and considered statistically significant if $p < 0.05$.

Root Mean Square Errors

For completeness, the variability was examined in two distinct analyses. In addition to the standard deviation analyses, the variance from each subject's mean

performance, % RMSE was also calculated. The %RMSE measured the variance from the task goal itself (L_n*, T_n*, S_n*).

To determine if subjects performed better relative to certain goals vs. others, we calculated the percent root mean square errors (%RMSE) with respect to stride length, stride time and stride speed. %RMSE quantifies the percentage error between the actual observed data points and the goals given (L_n*, T_n*, and S_n*). L_n* was defined as the goal stride length (the distance between step length markers on the treadmill). T_n* was the goal stride time (the time between beats of the metronome.) S_n* was the mean calculated stride speed. For each variable ("*x*"), %RMSE was calculated as:

$$\%RMSE = \left[\frac{\sqrt{(x_i - x^*)^2}}{n\_strides} / x^*\right] \times 100 \qquad (3)$$

"Perfect" execution would result in %RMSE = 0. Thus, a low %RMSE would verify that the goals for L_n and T_n we selected were reasonable and that these values were similar to the parameters humans normally exhibit while walking on a treadmill. Also, differences in %RMSE with respect to L_n, T_n, and/or S_n would indicate the relative degree to which each subject successfully achieved each sub-goal individually within each task (SPD, TIM, LEN, ALL). This allowed the different measures (L_n, T_n, S_n) with fundamentally different units (m, s, m/s, respectively) to be compared.

Speed GEM-Based Analyses

Utilizing the procedures developed in (Dingwell, John et al. 2010) these [T_n, L_n] data were then decomposed into new variables, tangent to (δ_T) and perpendicular to (δ_P) the Constant Speed GEM (Fig. 3.4). Although the constant speed requirement was different than the constant L_n or T_n requirements, we assumed the speed requirement was an "implicit" task goal whereas the length and time requirements were "explicit" task goals. The critical distinction here is that there were real physical consequences to consistently (over time) violating the speed requirement (i.e., subjects would eventually walk off the treadmill). However, there were no such corresponding physical consequences for errors made with respect to the imposed length and/or time requirements. These assumptions were validated by the RMSE analyses.

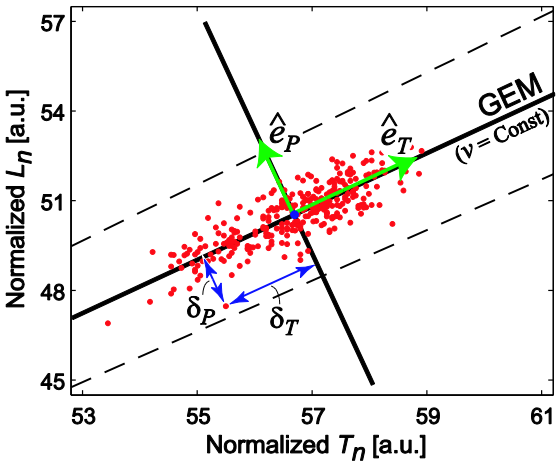

Figure 3.4. Schematic of the goal equivalent manifold (GEM) for the stride speed goal. δ_T identifies deviations tangent to the GEM. δ_P identifies deviations perpendicular to the GEM. *Ln* and *Tn* refer to normalized stride length and stride time respectively.

For the GEM-related variables (δ_T and δ_P), trial-to-trial differences were first analyzed in a 3-factor (Condition x Direction x Trial) repeated measures ANOVA. No significant differences were found between trials. Therefore, the data were pooled across trials and the values of each dependent measure were then subjected to a 3-factor (Condition x Direction x Subject) repeated measures ANOVA, followed by appropriate post-hoc analyses. The multiple trials obtained for each subject / condition were treated as independent observations in the original 3-factor ANOVA.

Directionality Analyses

Due to the multiple tasks imposed during walking, it is clear that the "speed GEM" is not *the* correct "GEM" for these other tasks (LEN, TIM, or ALL) precisely because those other tasks introduce other new goal functions. With these multiple task goals (GEM's), in theory, the structure of the data might be expected to "shift" specifically *away* from close-to-perfect alignment with the speed GEM towards something intermediate. An alternative option to the previously described data "shift," would be that everything collapses to control about a single fixed point and no directionality would exist.

To determine how these shifts occurred and how the statistical persistence changed at each orientation, the data were rotated in 1° increments through 180° coordinate transformation (Abe and Sternad 2013) with respect to the speed GEM. Unlike in (Abe and Sternad 2013), 0° was defined here for each trial as being aligned with the Speed GEM (Fig. 5). Transformations from 180°-360° were not performed as these simply mirror the analyses from 0°-180°. DFA □ values were then calculated for

all orientations for each trial. The maximum/minimum values of □ (αMax, αMin) and the respective orientations at which they occurred were then extracted (θMax, θMin). The αMin indicated the orientation at which the strongest statistical anti-persistence occurred, whereas the αMax indicated the orientation at which the strongest statistical persistence occurred. This analysis allowed us to determine how the persistence shifted with respect to the speed GEM. More specifically, this analysis determined how each additional task goal affected the distribution of the statistical persistence of the data in the [L, T] plane.

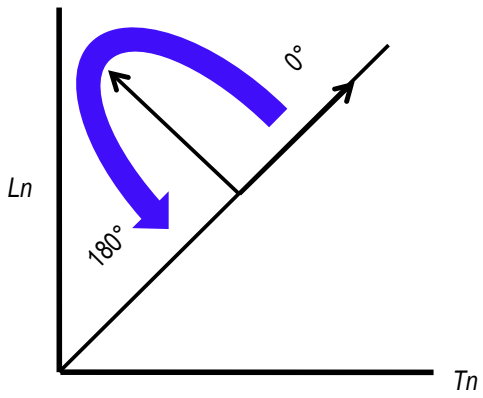

Figure 3.5: Schematic of the rotational analyses: 1° increments rotated from the speed GEM (0°) counterclockwise to 180°.

Statistical analyses were completed for the values αMax and αMin and orientation (θMax, θMin). Initially, trial-to-trial differences were run in a 3-factor (Condition x Direction x Trial) repeated measures ANOVA. No significant differences were found for Trial. Therefore, the values of each dependent measure (αMax, θMax, αMin, and θMin)

were subjected to a 3-factor (Condition x Direction x Subject) repeated measures ANOVA, followed by appropriate post-hoc analyses.

Results

There were slight fluctuations within the time series of L_n, T_n and S_n. However, qualitatively more drift was observed in L_n and T_n than in *Sn* (Fig. 3.6).

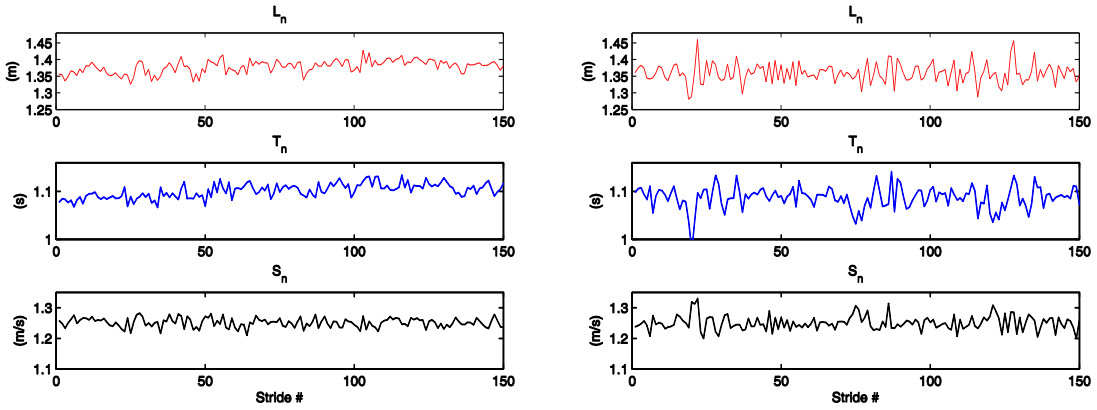

Figure 3.6. Raw time series data for stride length, stride time, and stride speed from one example subject during the SPD condition (left) and ALL condition (right).

Standard Stride Parameters

On average, when asked to focus on certain goals, subjects were able to do so. Subjects exhibited mean values of stride length, stride time, and stride speed for the LEN, TIM and ALL conditions that were within one standard deviation of the SPD condition (Fig. 3.7). For stride length, the SPD condition was significantly different from the LEN,

TIM and ALL conditions and the TIM condition was significantly different from LEN and ALL (L_n: p=0.00). For stride time, the SPD condition was significantly different from the TIM and ALL conditions, and TIM was also significantly different from the LEN and ALL conditions (T_n: p=0.00). However there were no significant differences across condition for stride speed (S_n: p=0.525). This confirmed that the subjects completed all tasks within their normal stepping parameters.

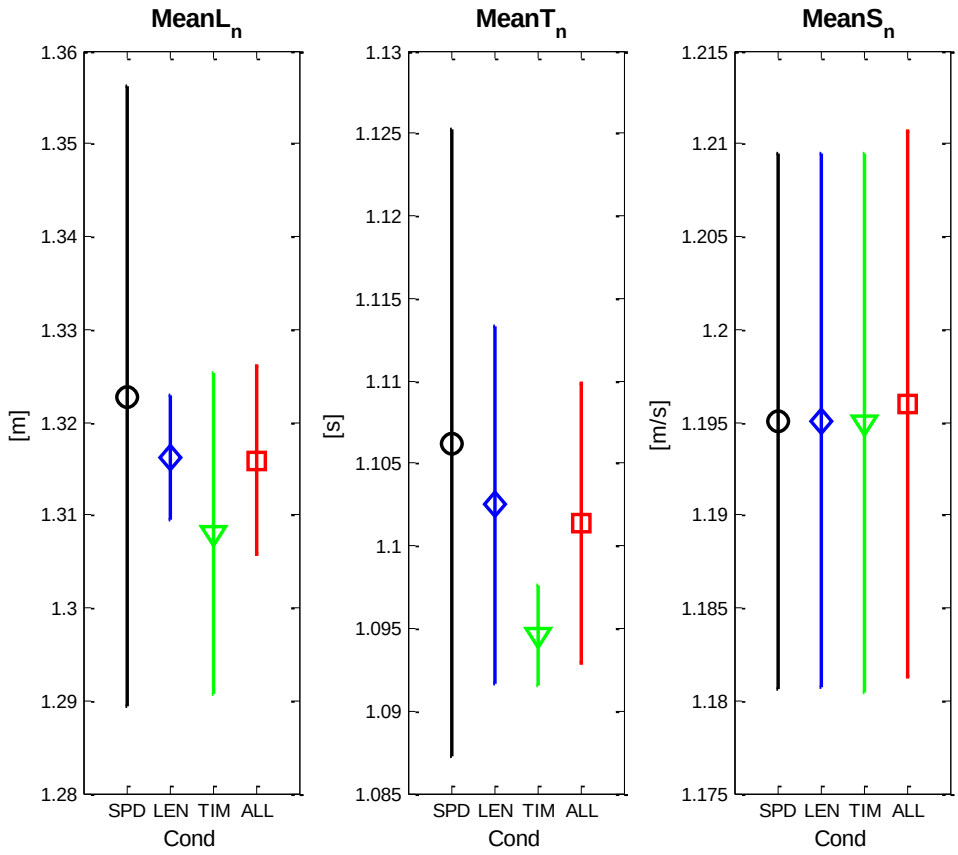

Figure 3.7. Mean values of L_n, T_n, and S_n for all 4 conditions: SPD (circles), LEN (diamonds), TIM (triangles), and ALL (squares). Error bars indicate ± SD.

Standard deviations of L_n, T_n, and S_n actually increased across conditions with multiple task goals (Fig. 8) indicating that the subjects became more variable when asked to achieve set values of these parameters. For L_n, the SPD condition was significantly smaller than the LEN, TIM and ALL conditions (p =0.00), as well as the ALL condition was significantly larger than the LEN and TIM conditions (p=0.00). For T_n, there were the SPD condition was significantly smaller than the LEN and ALL conditions (p=0.00). Additionally, TIM was significantly smaller than the LEN and ALL conditions, while ALL was significantly different than LEN as well (p=0.00). For S_n, SPD and TIM were significantly smaller than LEN and ALL, and ALL was also significantly larger than LEN (p=0.00).

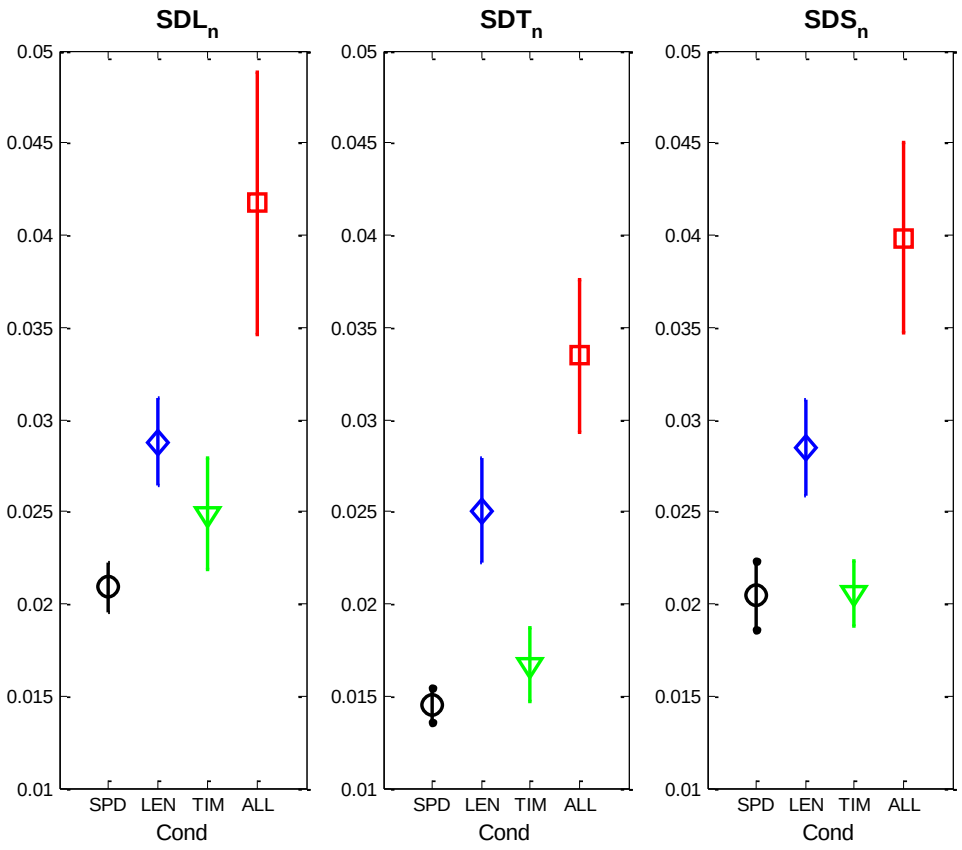

Figure 3.8. Standard Deviation values of L_n, T_n, and S_n for all 4 conditions: SPD (circles), LEN (diamonds), TIM (triangles), and ALL (squares). Error bars indicate 95% confidence intervals.

The DFA α's of L_n during the SPD condition were significantly different from the LEN, TIM and ALL conditions, and TIM was also significantly different than LEN and ALL. For T_n, SPD was significantly different than the remaining 3 conditions, LEN, TIM and ALL (p=0.00). However, there were no significant differences across conditions for *Sn* (p=0.241). These α values indicated that people quickly corrected the variables that they were asked to manipulate.

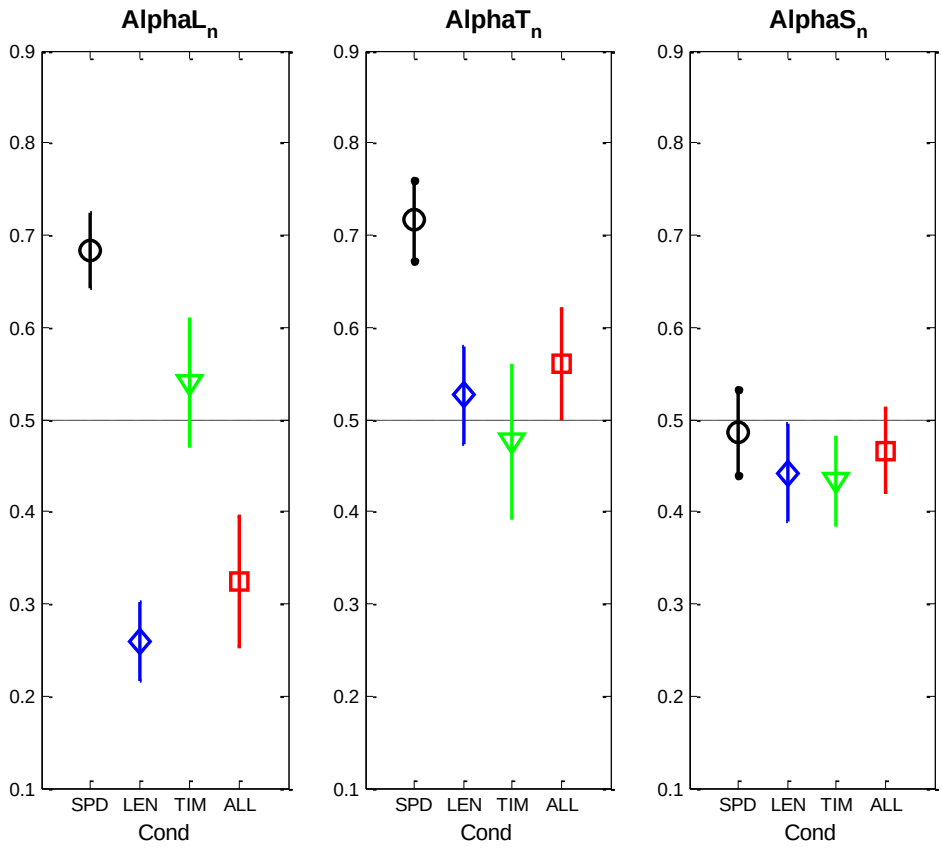

Figure 3.9. αvalues of L_n, T_n, and S_n for all 4 conditions: SPD (circles), LEN (diamonds), TIM (triangles), and ALL (squares). Error bars indicate 95% confidence intervals.

% RMSE

The root mean square error results indicated small percentage errors in all stride parameters, indicating that subjects generally achieved the given goals with reasonable success. For the L_n conditions, %RMSE significantly decreased from the SPD conditions to the LEN, TIM and ALL conditions, where subjects were asked to maintain the specified variables (see table below). For T_n, the same %RMSE decreased occurred for the same conditions with the exception of the ALL condition, where SPD and ALL were not significantly different.

Also, the %RMSE error across conditions (SPD, LEN, TIM, ALL) was consistently lower for stride speed (S_n).

	S_n	L_n	T_n
SPD	1.75 +/- 0.498	6.16 +/- 3.31	3.83 +/- 3.011
LEN	2.36 +/- 0.623	3.24 +/- 0.637	3.389 +/- 1.10
TIM	1.75 +/- 0.44	4.36 +/- 1.64	1.624 +/- 0.727
ALL	3.33 +/- 1.23	4.16 +/- 1.54	3.57 +/- 1.27

Table 3.2 %RMSE averages and standard deviations for L_n, T_n and S_n.

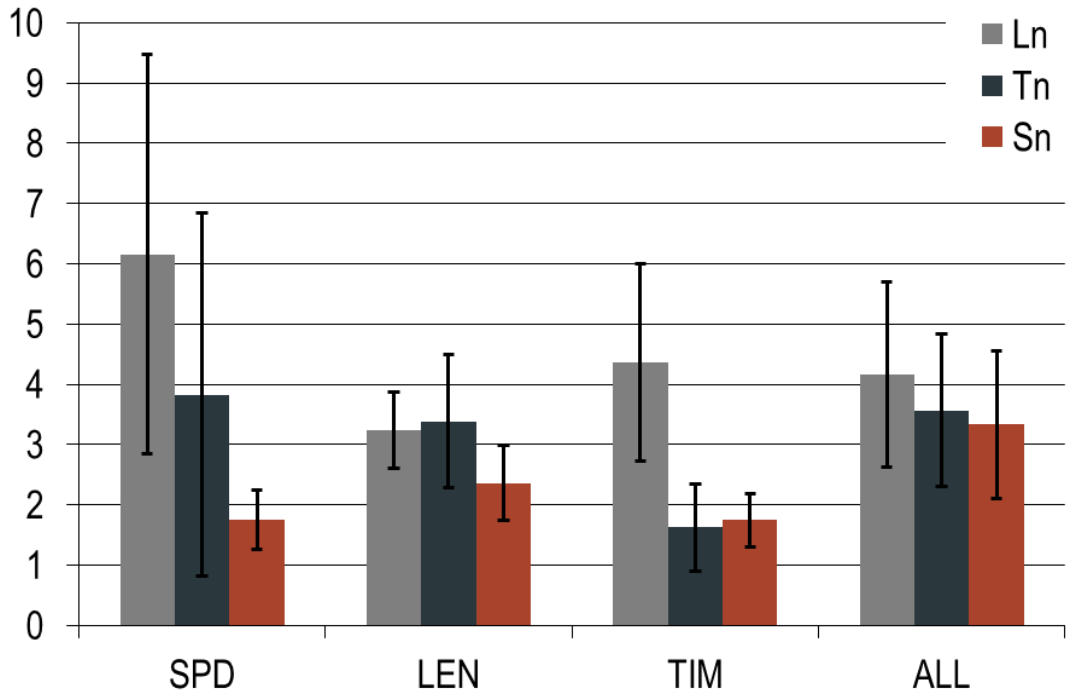

Figure 3.10. % RMSE errors across conditions for the stepping parameter, L_n, T_n, and S_n. Error bars indicate 95% confidence intervals.

Speed GEM Specific Parameters

When additional tasks were given in the LEN, TIM and ALL conditions, subjects' data clouds slightly shifted towards the imposed secondary goal. Qualitatively, subjects did not appear to select the "intersection" point of the two tasks (Fig. 11). Also, Fig. 11 depicts a representation of the given goal functions, as indicated by the colored lines. As a limitation of the treadmill belt length, these lines do not perfectly intersect. To divide the belt length into an even number of steps/revolution, we had to predetermine this distance and an appropriate stride time. Therefore, the stride length and stride time were not perfectly matched to the calculated preferred walking speeds of the subjects. However, to determine if this had any effect on the stride speed, we calculated the mean

stride speed for each subject and compared it to the set treadmill speed. Differences were less than one thousandth of a decimal place and therefore considered insignificant.

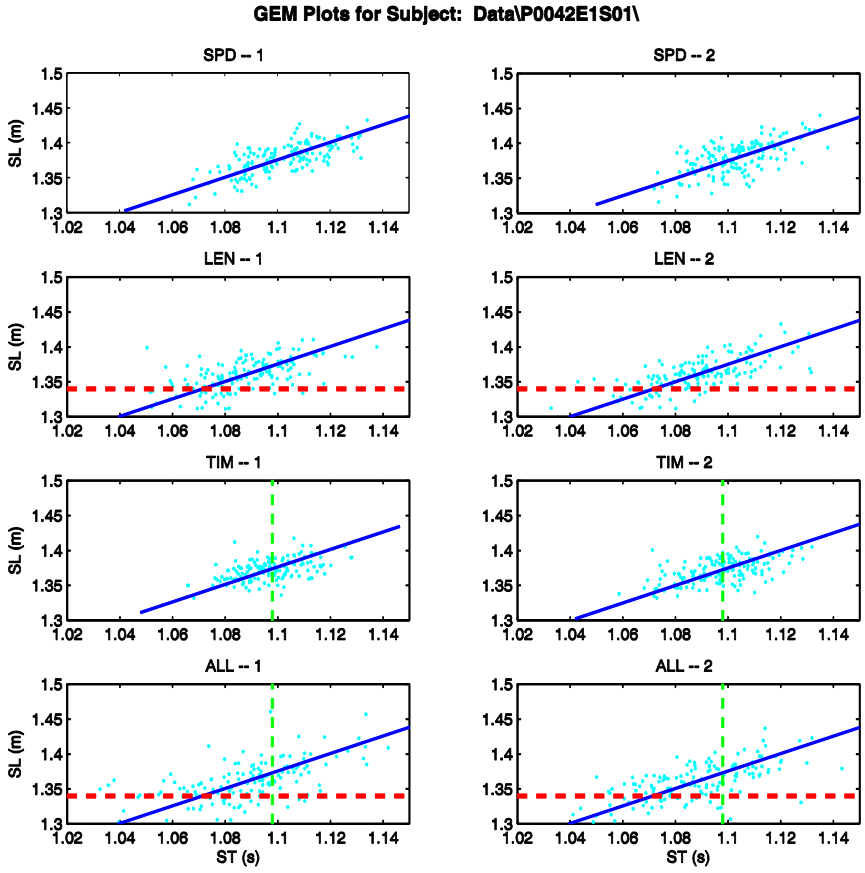

Figure 3.11. Example raw data with task goals indicated, SPD (Blue solid line), LEN (red dashed line), and TIM (green dashed line).

Subjects exhibited less variability in the perpendicular direction ($SD(\delta_P) < 1.0$) and greater variability in the tangent direction ($SD(\delta_T) > 1.0$) (Fig. 3.12A). The SPD condition was significantly smaller than the LEN, TIM and ALL for the tangent directions and significantly larger for the perpendicular direction, δ_T ($p = 0.0$) and δ_P ($p = 0.0$). However, the DFA α values (Fig. 3.12B) in the tangent direction (δ_T) for the LEN, TIM and ALL conditions were significantly smaller than the SPD condition ($p=0.00$). In the perpendicular direction (δ_P), there were no significant differences across conditions ($p=0.243$).

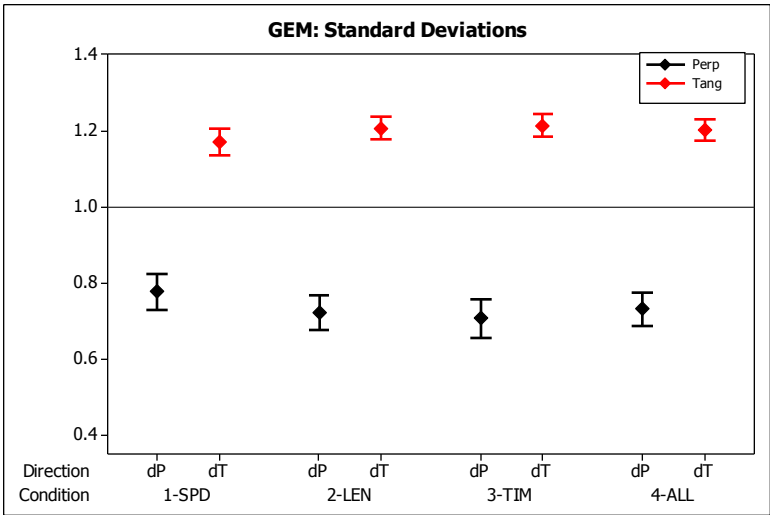

Figure 3.12. A) Standard deviations in the GEM directions: tangent (red) and perpendicular (black). These are normalized standard deviations measures, SD=1.

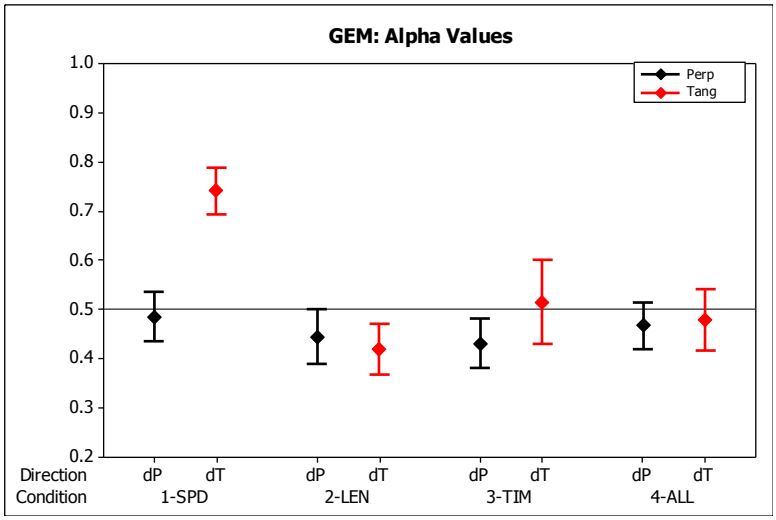

Figure 3.12. B) α values of the GEM directions for each of the experimental conditions. The threshold to determine persistence or anti-persistence is indicated by the horizontal line at 0.5.

Directionality Analyses

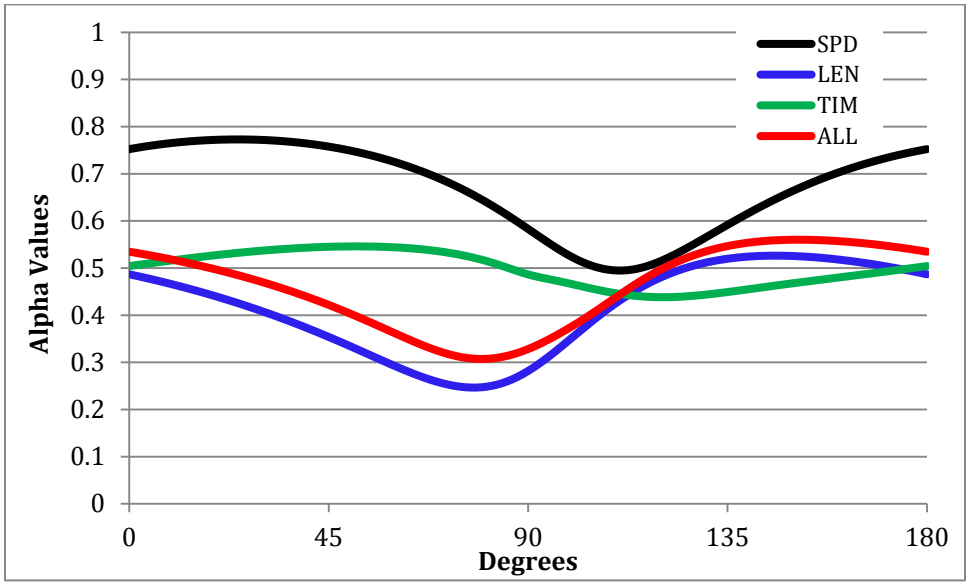

Figure 3.13. (A) The maximum and minimum values and coordinating angle measuresments for α for all orientations.

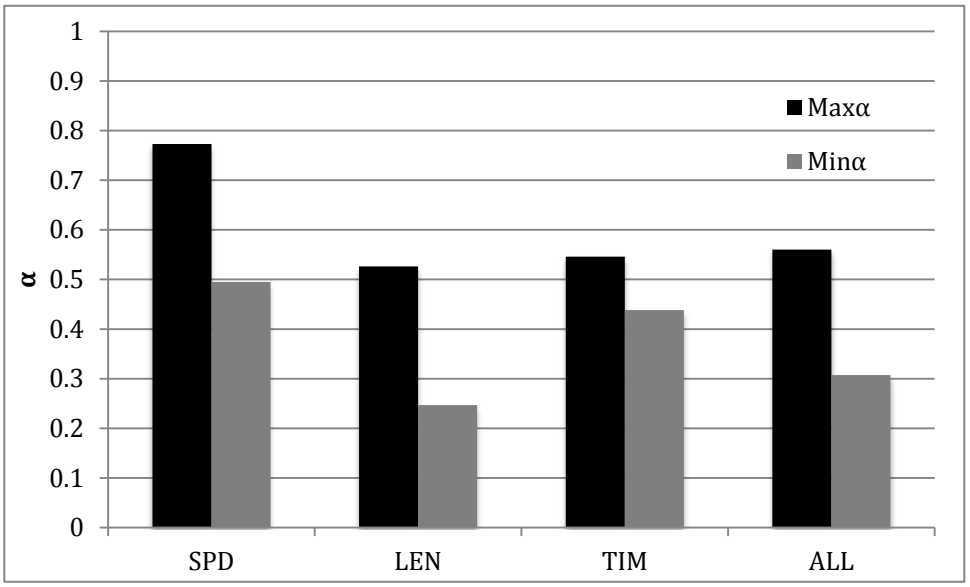

Figure 3.13. (B) The Maximum and minimum values of alpha calculated from the directionality analysis.

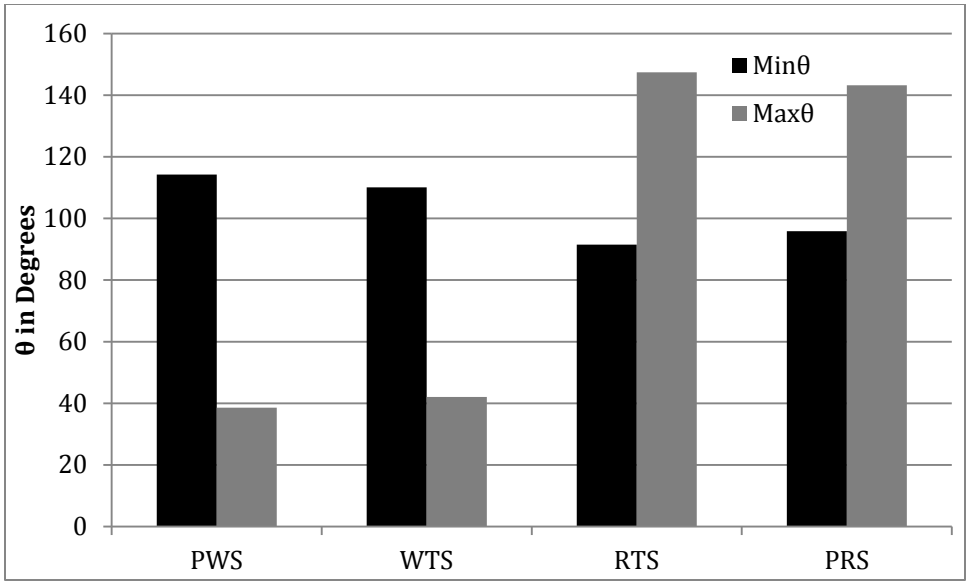

Figure 3.13. (C) The Maximum and minimum values of theta calculated from the directionality analysis.

The structural orientation of the statistical persistence (α) in the [T_n, L_n] plane changed as additional task goals were added. People shifted the orientation of maximal control away from the speed GEM and towards some intermediate "goal." During the LEN conditions, the minimum α value shifted towards the left (Fig. 13) or counterclockwise (Fig. 14), whereas during the TIM condition, the minimum α value shifted to the right, clockwise. The maximum α value for SPD was signifcantly larger (p=0.00) than for LEN, TIM and ALL. The maximum degree measurement, the LEN and ALL conditions were signifcantly different (p=0.00) from the SPD and TIM conditions.

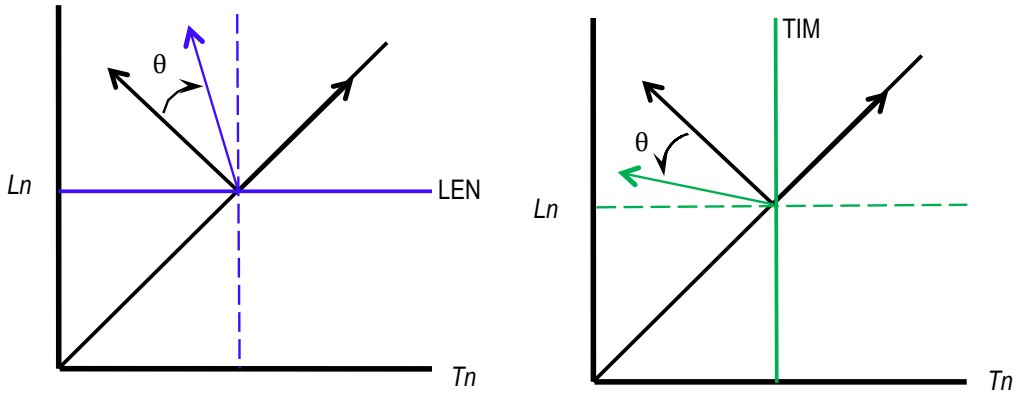

Figure 3.14. Indicates the shifting of the α values when multiple task goals were given.

Discussion

Movement variability is a key characteristic of perception–action systems. More specifically, the analysis of variability data can provide insight to determine the process by which this variability is generated and regulated. The completion of this experiment provided a specific strategy to determine which stepping variables are being tightly regulated and how the control of these parameters changes with additional tasks goals.

By utilizing a multi- faceted approach, it was possible to determine which variability was considered "task relevant", and "task irrelevant". With the ability to distinguish between these two types of variability, it is possible to tease out what variability should was essential to the task, and what variability should be reduced or removed. In a rehab setting, this is important so that clinicians to know what variability should be re-introduced to those that are learning how to walk again.

Results indicated that subjects reacted and accommodated multiple goals while adjusting their control strategies in systematically predictable ways. Furthermore, this

study determined that individuals had the ability to "prioritize" or show "favoritism" toward specific goals while walking. Collectively, subjects adapted and manipulated their selected gait parameters appropriately when they were asked to do so.

Subjects exhibited mean stride lengths, stride times, and stride speeds that all fell within their normal gait characteristics (Fig. 3.7). This was a critical finding, as the experimental design attempted to mitigate the subjects from having to adopt different or abnormal gait patterns. Subjects displayed increased variability in gait parameters when asked to control a specific variable. The GEM analyses indicated that the subjects were, in fact, trying to achieve the task goals, however they were not consistently "successful," leading to increased variability in the standard deviation measures. Due to the task requirements, subjects had to achieve these goals repeatedly across many consecutive strides, which may have contributed to their increased variability.

Although basic standard deviations indicated increased variability (Fig. 3.8), the GEM analyses showed subjects completed the given task goals. Subjects actively regulated the "goal" measures, as indicated by the α values (Fig. 3.9) for the dependent measures.

Subjects tightly regulated (i.e., over-corrected) L_n more than T_n during the LEN, TIM and ALL conditions (Fig. 3.9). However, in the presence of the metronome, L_n became less persistent as well, as predicted by the natural coupling of these parameters. One on hand, these different results for length markers and metronome conditions could be due to the nature of the task: LEN may be harder than TIM, regardless of the mode of feedback). On the other hand, it could be due to the mode of feedback itself, visual

stimulus vs auditory stimulus. These results are similar to Terrier's findings for treadmill walking, where subjects exhibited anti-persistence for stride length, time and speed (Terrier and Schutz 2003, Terrier, Turner et al. 2005, Terrier and Dériaz 2012). In addition to Terrier's findings, these analyses utilized a more detailed approach to determine that the real control is more subtle than adopting one intersection point of the task goals.

In the presence of a metronome, some studies have shown that subjects ignore or are not able to match the auditory cue (Decker, Cignetti et al. 2012, Terrier and Dériaz 2012). This is an important finding for gait retraining. For therapists interested in constraining a gait variable, it may be more effective to apply a visual goal rather than an auditory goal. Visual cues have also been found to be more effective during overground locomotion in a metronome/stepping stone study (Bank, Roerdink et al. 2011). Our results are consistent with the idea that subjects respond more strongly to visual cues.

Across all conditions, stride speed was tightly controlled. These results validated the original hypotheses of this study, that subjects exploit redundancy in the task and control for stride speed. This was not the only feasible option for treadmill walking; however, it is the strategy that people chose. Prior research has proven that there are other viable alternatives that subjects could choose; however, they do not (Dingwell, John et al. 2010).

For the GEM related variables, the standard deviation values depended on direction. The deviations in tangent direction were much larger than those in the perpendicular direction. The variance results possibly indicate that people actually *exploit*

this equifinality: i.e., subjects utilized a wide range of the infinite combinations of stride lengths and stride times that achieve the same speed. These results extend previous studies with the implementation of multiple simultaneous goals and more direct analyses (Terrier and Schutz 2003, Terrier, Turner et al. 2005, Dingwell and Cusumano 2010, Dingwell, John et al. 2010, Terrier and Dériaz 2012, Dingwell, Smallwood et al. 2013, Smallwood, Cusumano et al. In Revision).

Although the GEM analyses provided insight into the regulation of stepping parameters, the %RMSE analysis was able to provide an additional performance measure for the given task goals. These results indicated that when subjects were asked to achieve multiple simultaneous goals, prioritization occurred. These data indicated that subjects prioritized the speed goal and placed less importance on the additional goals (L_n and T_n). This prioritization may have occurred because of the associated risk with errors relating to the speed goal (i.e. a real physical penalty). Conversely, violating either of the other two goals (LEN and TIM) resulted in no real bodily penalty if an error were made.

Additionally, the directionality analyses extended the %RMSE analysis. The directionality analysis provided a more intricate examination of how subjects responded to multiple simultaneous task goals. Even though subjects prioritized the speed goal, the directionality analyses showed that subjects attempted to achieve any and all goals given. Subjects, in general, were able to achieve multiple goals at the same time.

In general, these results demonstrate humans have the ability to achieve and prioritize multiple simultaneous goals during continuous walking tasks. The analyses

method used to determine these walking results could also be used to investigate numerous different task goals and potentially be applied to other continuous tasks.

Chapter 4

Adaptability of Stride-to-Stride Control in Human Running

Introduction

Running is a vastly studied topic due to the large number of humans that participate in the sport. Among these millions of people, 30-75% of runners get injured each year (van Gent, Siem et al. 2007). Running studies typically consist of examining kinematics, kinetics, footwear, changes with speed and specific foot strike patterns. Numerous studies have also compared running to walking. Walking and running are the two most common forms of human locomotion. Running has both similarities and differences to walking. Walking and running share some basic kinematic and kinetic characteristics. However, they are markedly different locomotive strategies as demonstrated by the distinct transition between the two modalities.

There are many studies that indicate running is different from walking. Running endures greater ground reaction forces than walking (Cavanagh and Lafortune 1980, Novacheck 1998). Running has a flight phase, which is markedly different than the double support phase that occurs within the walking gait cycle (Novacheck 1998). From a kinematics standpoint, running has quicker, longer strides than walking (Nilsson, Thorstensson et al. 1985). From a modeling standpoint, running is modeled as a mass spring model, utilizing energy storage and return (Geyer, Seyfarth et al. 2005), whereas walking is modeled as an inverted pendulum (Kuo 2002, Kuo, Donelan et al. 2005).

Similar to walking, running is a very complex task that requires integration of many different physiological systems. Due to this complexity, the central nervous system must coordinate all involved systems to generate consistent motor outputs. Running is thought to share the same pattern-generating networks as walking (Cappellini, Ivanenko et al. 2006), which may indicate similarities in the control of walking and running.

As in walking, variability within gait parameters occurs because there are an infinite number of stride lengths (*Ln*) and strides times (*Tn*) that yield the same stride speed (*Ln/Tn =Sn*) during running. However, this mathematical equation may be violated with the existence of the flight phase during running. Few studies have investigated how the variability of stride parameters is controlled to achieve stable running gait.

Variability during running is important to understand since it has been suggested that people with injuries often have reduced variability (Hamill, van Emmerik et al. 1999, Bartlett and Kram 2008, Meardon, Hamill et al. 2011). It is unknown if these decreases in variability of certain kinematics exist prior to injuries or rather post injuries.

Similar to the stride-to-stride fluctuations during walking (Chapter 3), similar temporal fluctuations have been found during running as well. These fluctuations in the temporal components of gait cycle are not random (Jordan, Challis et al. 2006, Dingwell and Kang 2007, Dingwell and Cusumano 2010, Meardon, Hamill et al. 2011). Similar to our previous analysis of walking, DFA has been used to describe fundamental dynamic information about a time series. A comparison study between walking and running determined that, DFA α values increase with walking speed, while these same □ values decrease with running speed (Jordan and Newell 2008).

The faster speeds involved in running impose unique challenges to the locomotor control system. At faster speeds, the subject may implement longer *Ln*. With these longer *Ln's*, the fixed length of the treadmill belt surface may cause subjects to adopt very different control strategies than those used during walking.

Variability within the stride frequency parameter has been the focus of many studies. DFA has also been applied to stride time (*Tn*) in both healthy and injured populations. Meardon and Hamill showed that injured subjects during running exhibited lower α values (Meardon, Hamill et al. 2011), which they interpreted as "tighter control." They also tested healthy runners and found the same result, decreased α values at the end of a prolonged run (Meardon, Hamill et al. 2011). Additional studies confirm that there is less variability in kinematic parameters in injured populations (Novacheck 1998, Hamill, van Emmerik et al. 1999, Bartlett and Kram 2008). Overall, the literature is inconclusive as to whether this variability is the cause or the effect of the injury.

Although common in the walking literature, there are few studies that apply task constraints or manipulations during running. To determine the robustness of the control paradigms used to coordinate and execute consistent running gait, it is important to determine how specific individual parameters are controlled. One viable method to examine the variability within individual parameters is to constrain the specified variable. By constraining a particular gait parameter a situation with reduced variability can be simulated, (i.e subjects have less redundancy available to exploit). This approach could allow us to learn more about what variability is "good" (i.e., directly "relevant" for

control or adaptability) and what variability is "bad" (i.e., "irrelevant" for control) during running.

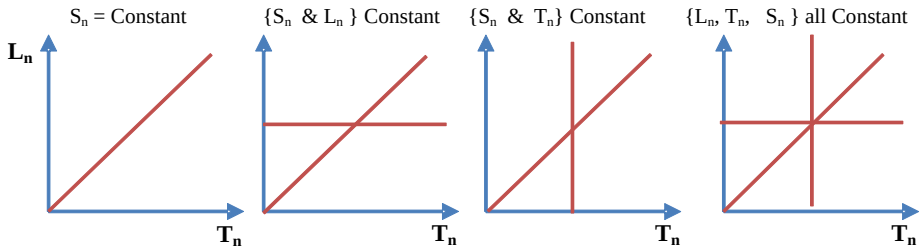

Fig. 4.1 Schematic of 4 conditions to be tested in Aim #2 and their respective GEM's. Each GEM defines a specific redundancy between *Ln* and/or *Tn*. These experiments explicitly tested the ability of subjects to exploit these different redundancies.

Here, the task conditions/goals presented to subjects were directly manipulated during treadmill running (Fig. 4.1). Stride length (L_n), stride time (T_n), and stride speed (*Sn*) goals were given to explicitly vary the nature of the available redundancies (Fig

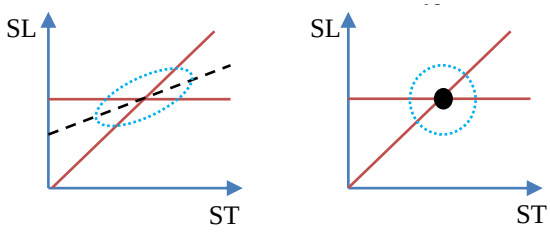

Fig. 4.2. Example schematics of possible outcomes when subjects are asked to achieve multiple simultaneous goals. Left: Subjects could adopt "intermediate" strategies that balance the competing demands of each individual task goal. Right: Subjects could adopt the single, optimal solution that simultaneously achieves both (or all) task goals, but does not admit any redundancies.

4.1). One initial hypothesis was that subjects could complete the multiple simultaneous goals by utilizing either an intermediate goal that partially satisfies both (e.g., Fig. 4.2, Left) or alternatively that subjects would instead determine the intersection of the two individual task goals and adopt a single "concurrent" control strategy that equally achieved all task goals simultaneously (e.g., Fig. 4.2, Right).

However, it was assumed that there might be multiple different strategies people *could* adopt (e.g., as in Fig. 4.2), and that any changes observed in how subjects regulated their stepping movements would be systematically related to the changes in imposed conditions. In other words, people would adjust their control strategies in reasonable and purposeful ways. If so, this would provide further evidence that our analyses are identifying actual stride-to-stride control strategies and that these strategies are malleable within subjects (i.e., the strategies themselves are "adaptable" to changing task conditions or goals.

Methods

The methods applied here in Chapter 4 largely replicate those used in Chapter 3. The primary difference, however, was that here, subjects were required to run rather than walk. All other experimental protocol details replicated those in Chapter 3 with three minor exceptions: subject recruitment requirements, the number of subjects tested, and the duration of each individual trial.

Subjects

Ten (10) healthy adults between 18 and 35 years of age participated (Table 4.1). They were pre-screened to ensure they had no lower leg injuries, surgeries, or cardiovascular, respiratory, neurological, musculoskeletal or visual conditions that could have affected their gait. This study was approved by the Institutional Review Board at the University of Texas and all participants provided written consent prior to participation. Subjects had to meet the requirement of being an active recreational runner, and were required to have run at least 10-15 miles, 3 times a week within the most recent month.

Table 4.1 Subject Characteristics

Subject Characteristics (n=10)	
Age (yrs)	**28.1 ± 3.87**
Sex (female/male)	**4/6**
Height (m)	**1.78 ± 0.10**
Leg Length (m)	**0.98 ± 0.044**
Body Mass (kg)	**70.9 ± 12.35**

Experimental Protocol

Subjects ran on a Woodway Pro XL treadmill (Woodway USA, Waukesha, WI) with a motorized rubber belt. The treadmill belt dimensions were 2.23m long by 0.685m wide. All subjects were required to wear a safety harness during the experimental session (Fig. 4.3).

Subjects acclimated to running on the treadmill for at least 5 minutes at the beginning of the experiment and 2 minutes prior to each new condition. Running speed was set for each subject using a preselected value of 3.22m/s to ensure that subjects were in fact "running" as opposed to an intermediate gait pattern between that of walking and running: i.e., "jogging". The selected treadmill speed matched the dimensions of the stride length and stride time goal, and created one intersection point of all three task goals. During the initial warm-up, subjects were asked to verify that the running speed was comfortable.

Subjects were asked to complete two 4-minute running trials each under each of the following four experimental conditions: constant speed (SPD), constant speed and stride length (LEN), constant speed and stride time (TIM), and constant speed, stride length and stride time (ALL).

For all conditions, the treadmill was set to the preselected speed. For the SPD condition, the subjects were given no further instructions. For the LEN condition, subjects were asked to step on evenly spaced markers placed on the treadmill belt. For the TIM, subjects were asked to run in time with a metronome. For the ALL condition, the

subjects were asked to combine all three previously mentioned tasks while running. A waist high mirror was also placed in front of the treadmill to give subjects visual feedback of their foot placement that did not require them to bend their necks to look directly down at their feet during all conditions.

Experimental conditions were presented in random order to each subject, with presentation order balanced across subjects. Trials were 4 minutes long and were blocked by condition: i.e., the 2 trials of each condition were collected consecutively for the step length marker placement accuracy on the treadmill. Subjects were given at least 2 minutes rest in between trials, and allowed as much rest as needed.

Data Collection and Processing

Whole-body kinematic data were recorded at 120 Hz using a 10-camera Vicon MX motion capture system (Oxford Metrics, Inc., Oxford, UK). Each subject wore a standardized whole-body marker set of 57 markers, (Fig. 4.3.) (Wilken, Rodriguez et al. 2012). Raw kinematic data were processed using Vicon Nexus software. Additional data analyses were performed using MatLab (MathWorks, Inc., Natick, MA).

Individual strides were determined by finding the local maxima of the distances between the pelvis and heel markers in the anterior-posterior direction (Zeni, Richards et al. 2008). These data were used to extract time series of the specified stride parameters: stride lengths (L_n), stride times (T_n), and stride speeds (S_n) for each running trial. These time series data were then subjected to several analyses to assess means, standard

deviations, etc. For consistency across analyses, all trials were truncated at 150 strides each.

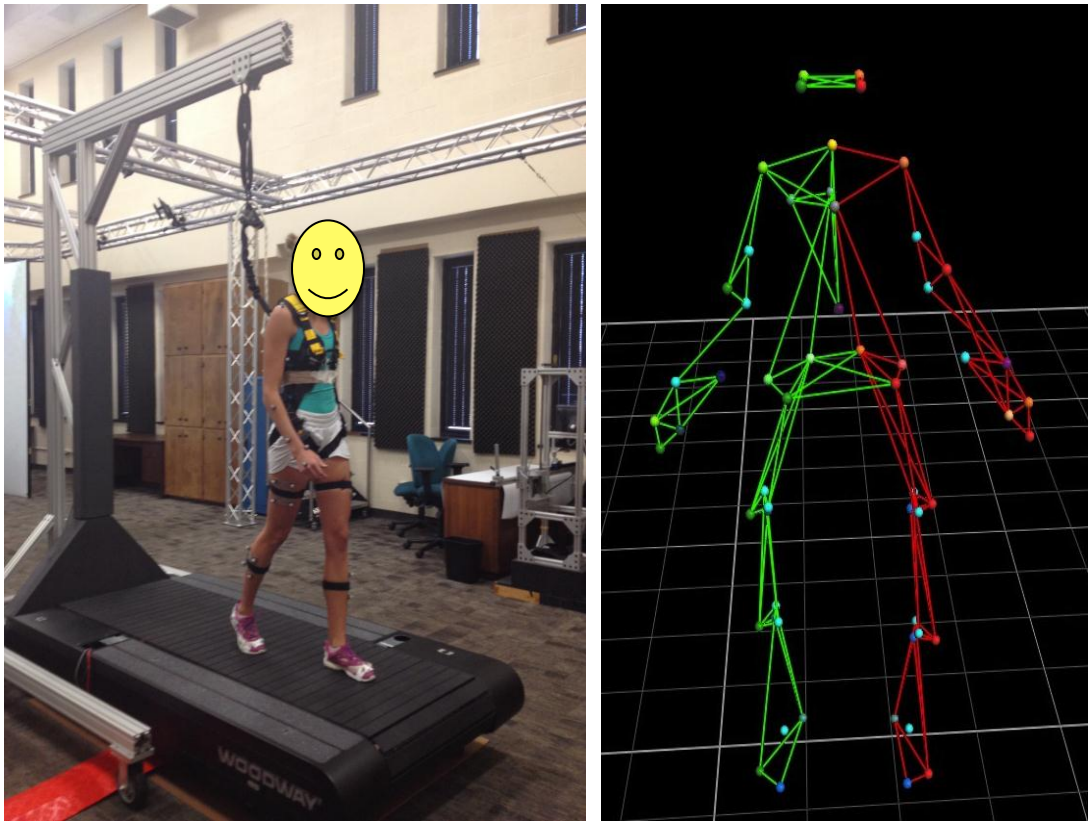

Figure 4.3. (Left) Subject running on the Woodway treadmill in our laboratory. (Right) Computer generated image of the 57 marker set used in this study.

Dynamics of Primary Gait Parameters

Stride length (L_n) was defined as the anterior-posterior distance between right heel strike to the next consecutive right heel strike. Stride time (T_n) was the amount of time it took to go from heel strike of one foot to then next heel strike by the same foot. Stride speed was calculated as $S_n = L_n/T_n$ for each stride in each trial. Means and standard deviations of L_n, T_n and S_n were calculated across all strides for L_n, T_n and S_n time series from each trial.

Detrended fluctuation analysis or DFA is one way to determine the correlation between consecutive movements (Peng, Buldyrev et al. 1992, Hausdorff, Purdon et al. 1996, Goldberger, Amaral et al. 2002). DFA can determine the statistical persistence or anti-persistence for a given measure for consecutive movements, in this case L_n, T_n and S_n. DFA was used to compute a scaling exponent, α. An $\alpha < 0.5$ indicates that deviations in one direction are more likely to be followed by deviations in the opposite direction (anti-persistence). An $\alpha > 0.5$ indicates that deviations are more likely to be followed by deviations in the same direction (persistence). Lower values of α, indicate more tightly regulated variables (Dingwell and Cusumano 2010, Dingwell, John et al. 2010).

An alternative viable method of determining the serial correlation structure in a time series is to compute the Lag-1 autocorrelation. Similar to DFA, Lag-1 autocorrelations quantify the correlation between consecutive data points (in this case, strides)(Dingwell and Cusumano 2010). However, for this study, we chose to use DFA as it captures fundamental dynamic information about a recorded time series, independent of variability magnitude (Cusumano 2013).

For each of these traditional gait variables (i.e., L_n, T_n, and S_n), the values of each dependent measure (i.e., mean, SD, and α were computed for each trial and were analyzed using 2-factor (Condition x Subject) repeated measures ANOVA, followed by Tukey post-hoc analyses. Statistical analyses were performed using SPSS and considered statistically significant if the measured p-values were $p < 0.5$.

Root Mean Square Errors

To determine if subjects performed better relative to certain goals vs. others, we calculated the percent root mean square errors (%RMSE) with respect to stride length, stride time and stride speed. %RMSE quantifies the percentage error between the actual observed data points and the goals given (L_n*, T_n*, and S_n*). L_n* is defined as the goal stride length (the distance between step length markers on the treadmill). T_n* is the goal stride time (the time between beats of the metronome.) S_n* is the mean calculated stride speed. For each variable ("*x*"), %RMSE was calculated as:

$$\%RMSE = \left[\frac{\sqrt{(x_i - x^*)^2}}{n\_strides} / x^*\right] \times 100 \qquad (4)$$

"Perfect" execution would result in %RMSE = 0. Thus, a low %RMSE would verify that the goals for L_n and T_n we selected were reasonable and that these values were similar to the parameters humans normally exhibit while walking on a treadmill. Also, differences in %RMSE with respect to L_n, T_n, and/or S_n would indicate the relative degree

to which each subject successfully achieved each sub-goal individually within each task (SPD, TIM, LEN, ALL).

Speed GEM-Based Analyses

Utilizing the procedures developed in (Dingwell, John et al. 2010) these [T_n, L_n] data were decomposed into new variables, tangent to (δ_T) and perpendicular to (δ_P) the Constant Speed GEM (Fig. 4.1.A). Although the constant speed requirement was different than the constant L_n or T_n requirements, we assumed the speed requirement was an "implicit" task goal whereas the length and time requirements were "explicit" task goals. There are real physical consequences to consistently (over time) violating the speed requirement (i.e., you could run off the treadmill), but there are no such corresponding physical consequences for errors made with respect to the length and time requirements. These assumptions were validated by the RMSE analyses previously mentioned and further investigated by the GEM analyses.

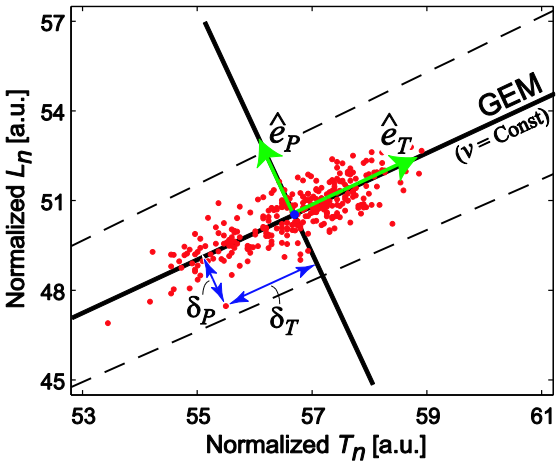

Figure 4.4. Schematic of the goal equivalent manifold (GEM) for the stride speed goal. δ_T identifies deviations tangent to the GEM. δ_P identifies deviations perpendicular to the GEM. *Ln* and *Tn* refer to normalized stride length and stride time respectively.

For the GEM-related variables (δ_T and δ_P), trial-to-trial differences were first analyzed in a 3-factor (Condition x Direction x Trial) repeated measures ANOVA. No significant differences were found for Trial. Therefore, the data were pooled across trials and the values of each dependent measure, (SD and α) were then subjected to a 3-factor (Condition x Direction x Subject) repeated measures ANOVA, followed by appropriate post-hoc analyses. The multiple trials obtained for each subject / condition were treated as independent observations in the original 3-factor ANOVA.

Directionality Analyses

Due to the multiple tasks imposed during walking, it is clear that the "speed GEM" is not *the* correct "GEM" for these other tasks (LEN, TIM, or ALL) precisely because those other tasks introduce other new goal functions. With these multiple task goals (GEM's), in theory, the structure of the data should "shift" specifically *away* from close-to-perfect alignment with the speed GEM towards something intermediate.

To determine how these shifts occurred and how the statistical persistence changed at each orientation, the data were rotated in one degree (1°) increments through 180° coordinate transformation (Abe and Sternad 2013) with respect to the speed GEM. In contrast to (Abe and Sternad 2013), 0° was defined for each trial as aligned with the Speed GEM (Fig. 5). Transformations from 180°- 360° were not performed as these simply mirror the analyses from 0°- 180° (Cohen and Sternad 2012). Once the α values were calculated at all orientations for each trial, the minimum and maximum values of α and their respective orientations were determined. The minimum value indicated the orientation at which the strongest statistical anti-persistence occurred, whereas the maximum value indicated the orientation at which the strongest statistical persistence occurred. This analysis allowed us to determine how the persistence shifted with respect to the speed GEM. More specifically, this analysis determined how each additional task goal affected the dissemination of data.

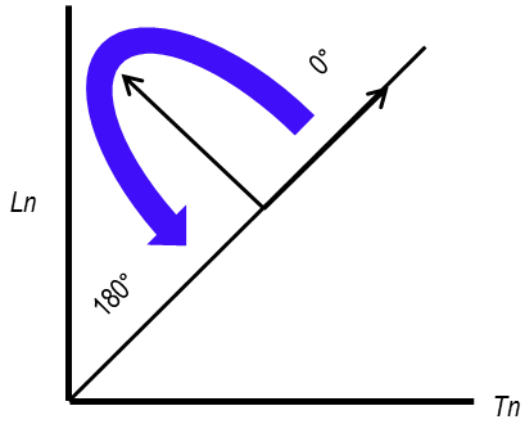

Figure 4.5. Schematic of the rotational analyses: 1° increments rotated from the speed GEM (0°) counterclockwise to 180°.

Results

During running, subjects exhibited small fluctuations in each of the stride parameters; L_n, T_n and S_n (Fig. 4.6). However, the raw data depicts more drift in L_n and T_n than in the S_n parameter.

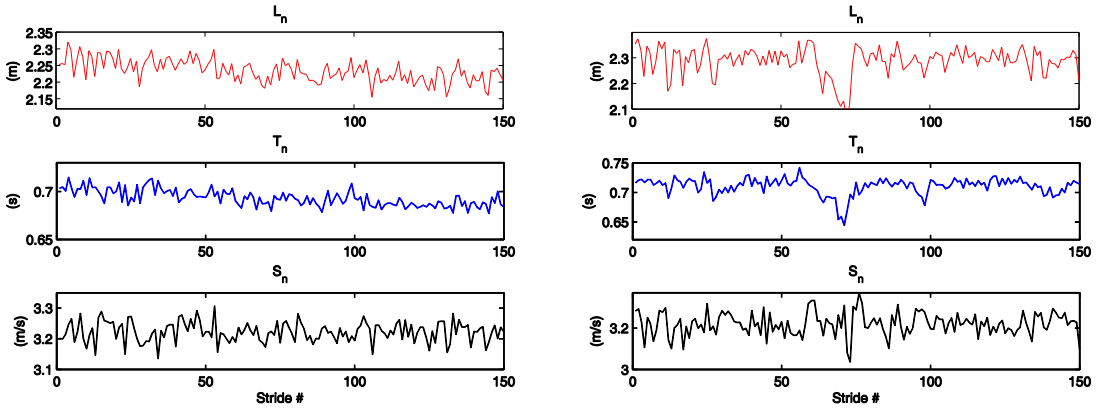

Figure 4.6. Raw time series data for stride length (red), stride time (blue), and stride speed (black) from one example subject for the SPD condition (left) and the ALL condition (right).

Standard Stride Parameters

The means of basic stride parameters (stride length, L_n, time, T_n, and speed, S_n) verified that, on average, people completed the task goals they were given. The means of each parameter were similar to the self-selected L_n and T_n during normal running. There were no significant differences within the means across any of the 4 conditions. ($p > 0.07$).

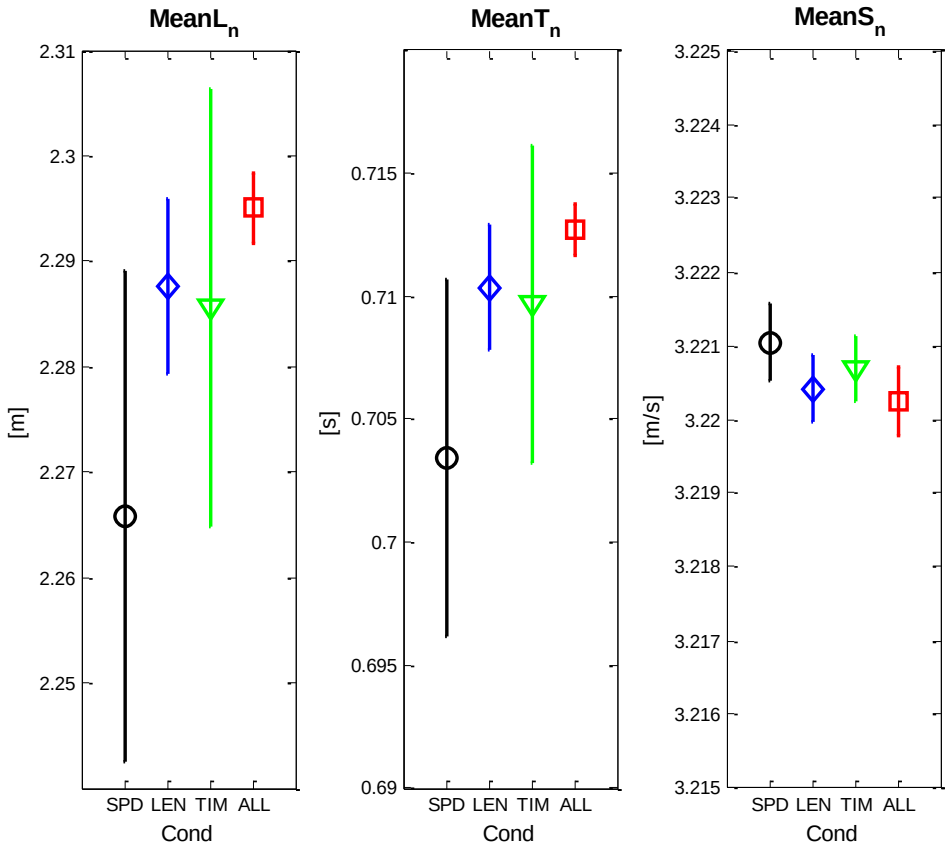

Figure 4.7. Mean values of L_n, T_n, and S_n for all 4 conditions: SPD (circles), LEN (diamonds), TIM (triangles), and ALL (squares). Please note the vertical scaling for each variable, as the between-subject standard deviations are minor.

When subjects were ask to "restrict" L_n, T_n, and S_n, subjects actually exhibited increased variability for the very measures they were instructed to maintain. Moreover, these changes in the structure of variance were proportional for all measures. There were differences across conditions in all three parameters, however these differences were very small (0.025 SD).

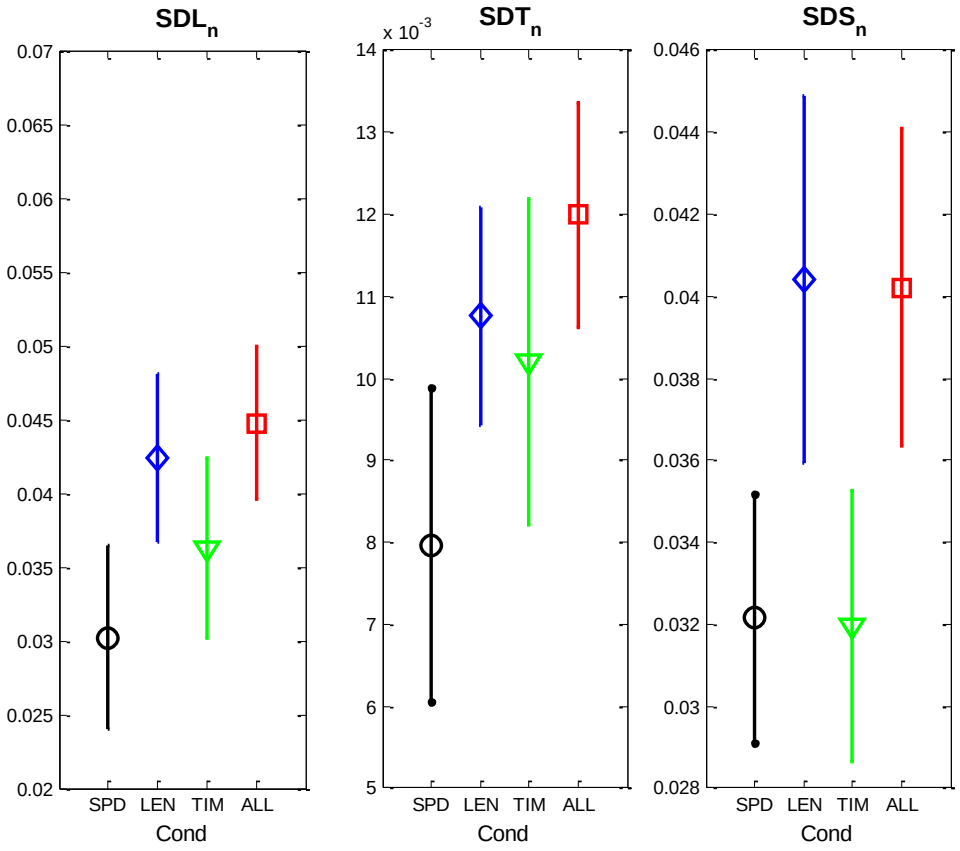

Figure 4.8. Standard Deviation values of L_n, T_n, and S_n for all 4 conditions: SPD (circles), LEN (diamonds), TIM (triangles), and ALL (squares).

Although the standard deviations results indicated that subjects were more variable across conditions, the DFA α measure provided a measure of the degree of control exerted over each variable, regardless of the magnitude of the variability (Cusumano 2013).

There were significant differences across all conditions for L_n (p = 0.002). For stride length, the LEN condition was significantly smaller than SPD (p=0.00), TIM (p=0.00) and ALL (p=0.045). Additionally for stride length, the SPD condition was significantly different from the ALL condition (p=0.002). There were significant differences across all conditions for T_n (p = 0.009), more specifically; the SPD condition was significantly different than LEN (p=0.00), TIM (p=0.011) and ALL conditions. (p=0.002) For stride speed, the LEN condition was significantly smaller than the SPD conditions (p=0.032).

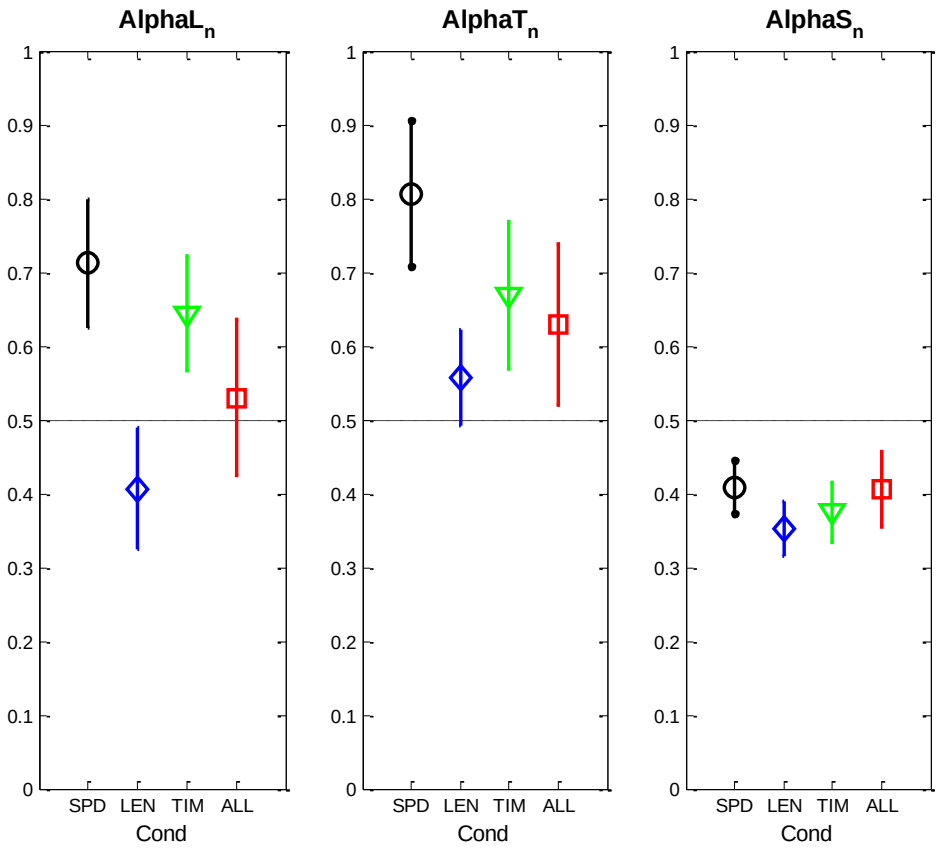

Figure 4.9. α values of L_n, T_n, and S_n for all 4 conditions: SPD (circles), LEN (diamonds), TIM (triangles), and ALL (squares).

%RMSE

The calculation of the percent root mean square error indicated a small percentage error in all stride parameters, indicating that subjects generally achieved the given goals with reasonable success. The smallest %RMSE occurred in the speed (S_n) parameter for all conditions. For the L_n parameter, the smallest %RMSE occurred in the conditions

where stride length was controlled. The SPD condition was significantly different from the LEN, TIM and ALL conditions. During the TIM and ALL condition, subjects' percent error was very similar for both T_n and S_n indicating that subjects may have weighted the speed and time goal approximately equally.

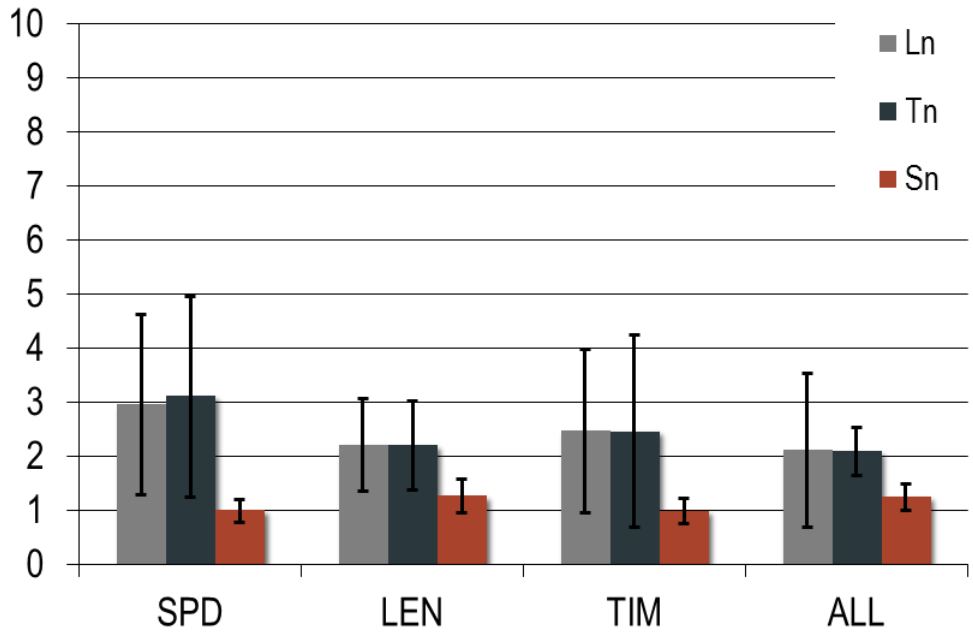

Figure 4.10 Percent root mean square error for all task goals for each stride parameters. Perfect task execution would have 0 % error.

	L_n	T_n	S_n
SPD	3.00 +/- 1.65	3.10 +/- 1.86	1.006 +/- 0.21
LEN	2.25 +/- 0.82	2.19 +/- 0.83	1.26 +/- 0.30
TIM	2.50 +/- 1.49	2.45 +/- 1.78	1.22 +/- 0.26
ALL	2.48 +/- 1.26	2.48 +/- 1.27	1.11 +/- 0.27

Table 4.2 %RMSE and standard deviations for L_n, T_n and S_n.

Speed GEM Specific Parameters

When additional tasks were given in the LEN, TIM and ALL conditions, subjects' data clouds slightly shifted towards the imposed secondary goal. Qualitatively, subjects did not appear to select the "intersection" point of the two tasks as originally hypothesized (Fig, 4.11). Subjects did not gravitate to one single "intersection" point, however they did change the location of the data centroid from the SPD or non-goal condition.

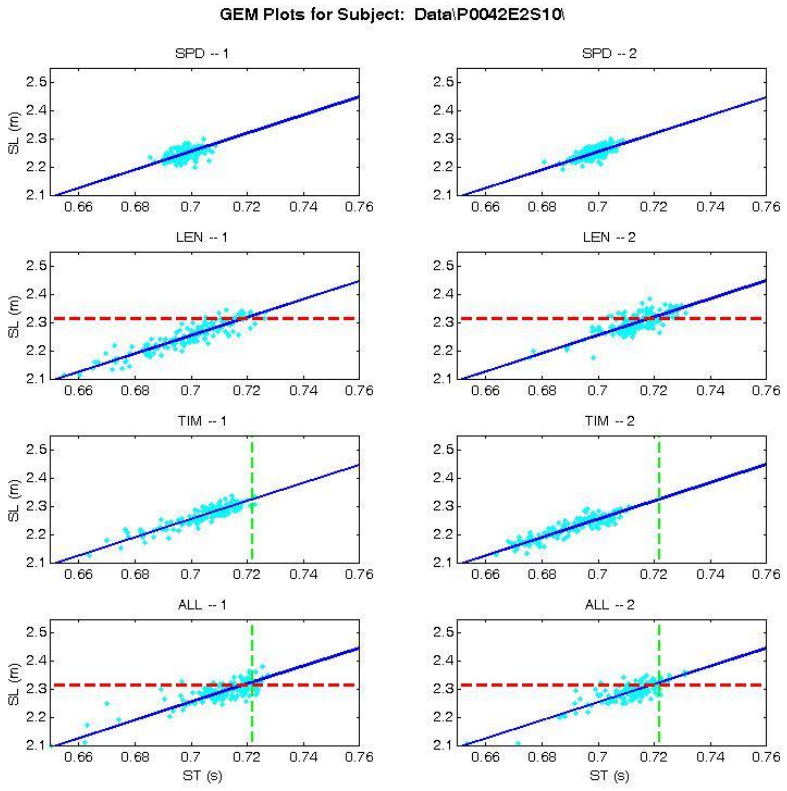

Figure 4.11. Example raw data with task goals indicated, SPD (Blue solid line), LEN (red dashed line), and TIM (green dashed line). The colored lines indicate the additional task goals, here they intersect, unlike the previous walking study.

Quantitatively, subjects exhibited less variability in the perpendicular direction ($SD(\delta_P) < 1.0$) and greater variability in the tangent direction ($SD(\delta_T) > 1.0$) (Fig. 12A). There were no differences in variability across conditions for δ_P ($p = 0.110$). In the perpendicular direction, subjects exhibited a trend for the variance to be slightly more aligned with the GEM from the SPD to LEN and TIM and ALL. However, this trend was not quite statistically significant δ_T ($p = 0.066$).

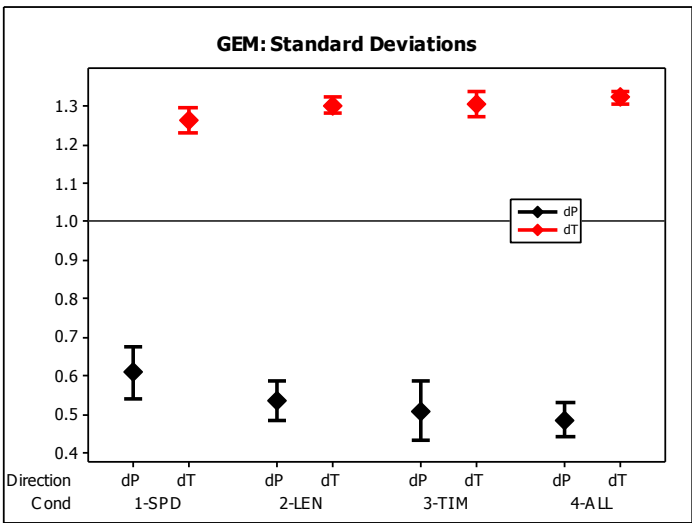

Figure 4.12. (A) describes the standard deviations along the tangent (red) and perpendicular (black) directions of the GEM. Standard deviations are normalized, SD =1.

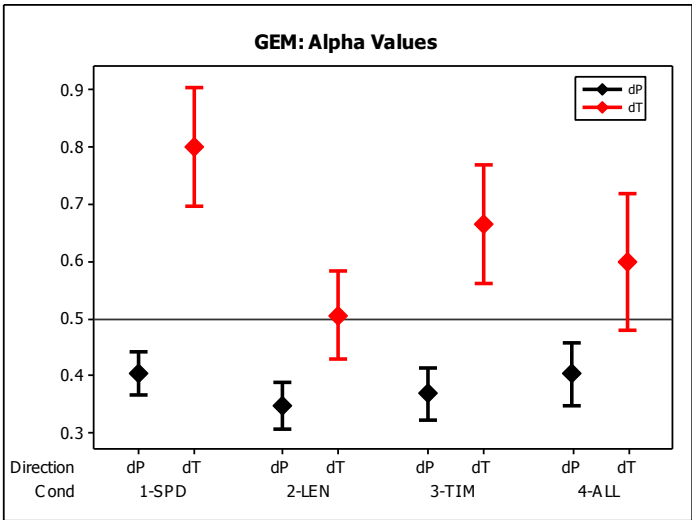

Figure 4.12. (B) illustrates the α value of the GEM directions for each of the experimental conditions. The threshold to determine persistence or anti-persistence is indicated by the horizontal line at α = 0.5.

The DFA α values (Fig. 4.12.B) in the tangent direction (δT) for the LEN, TIM and ALL conditions were significantly different than the SPD condition (p=0.002). In the perpendicular direction (δ_P), there were no significant differences across conditions (p=0.167).

Directionality Analyses

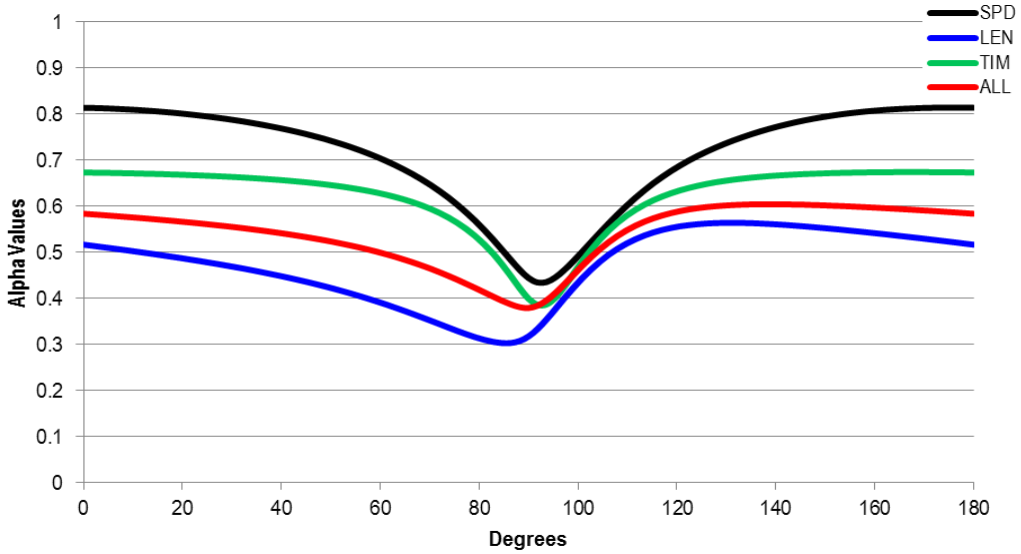

Figure 4.13. This figure shows the maximum and minimum value for the α measures for all 180 degrees.

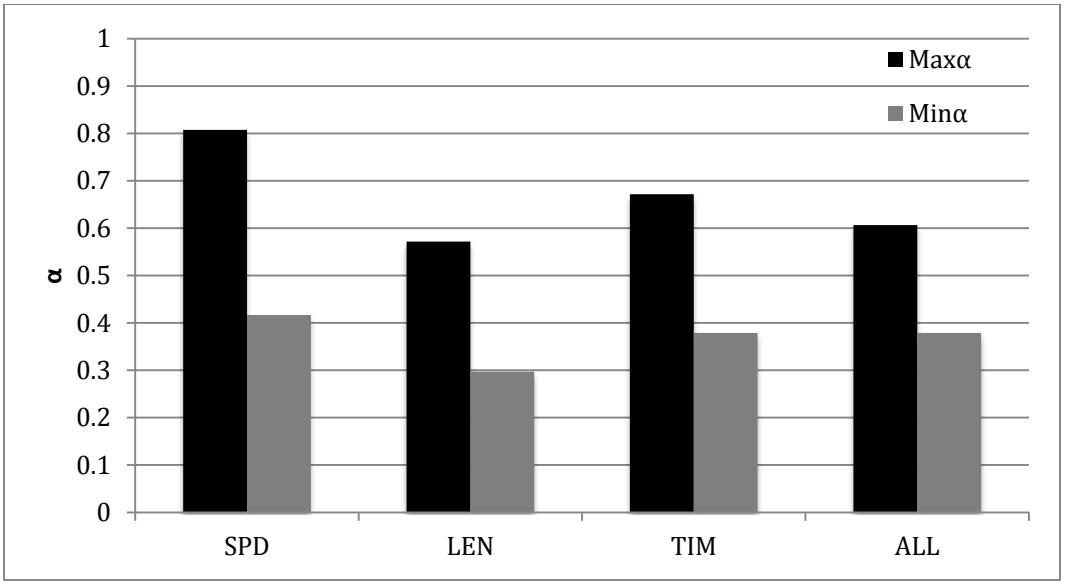

Figure 4.13. (B) The Maximum and minimum values of alpha calculated from the directionality analysis.

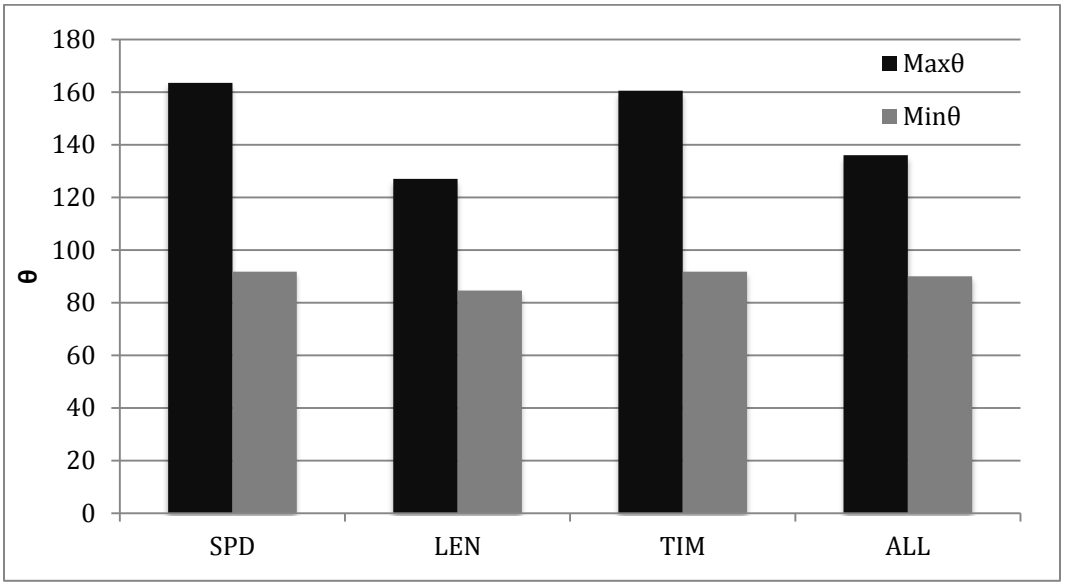

Figure 4.13. (C) The Maximum and minimum values of alpha calculated from the directionality analysis.

The structural orientation of the statistical persistence (α) in the [T_n, L_n] plane changed as additional task goals were added. People shifted the orientation of maximal control away from the speed GEM and towards some intermediate "goal." For the LEN condition, the minimum α value shifted towards the left (Fig 4.13) or counterclockwise (Fig 4.14) and was significantly different from the SPD, TIM, and ALL conditions.

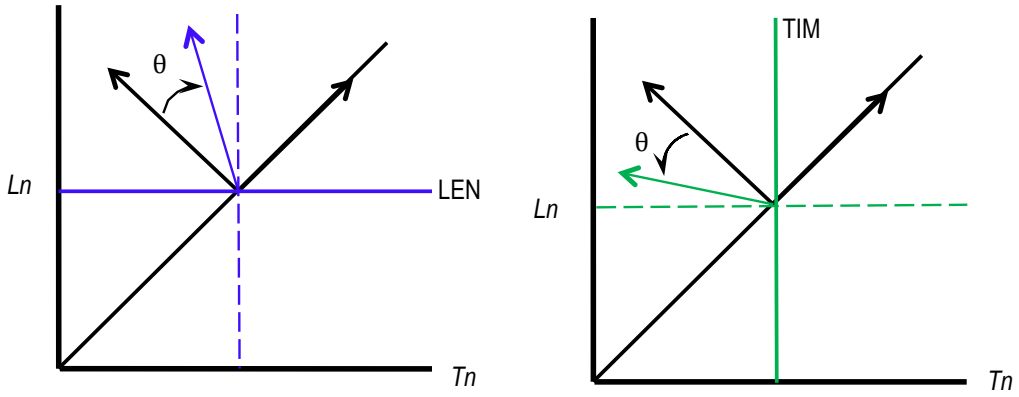

Figure 4.14. Indicates the shifting of the α values when multiple task goals are given.

Discussion

Determining how humans produce precise and repeatable goal-directed movements despite redundancy (Bernstein 1967, Scott 2004) and biological noise (Faisal, Selen et al. 2008) remains a dominant question in motor neuroscience research. The main objective of this study was to determine how people control stride-to-stride fluctuations during running. Variability within common gait parameters has been studied greatly, however investigating the fluctuations that occur from one stride to the next is essential to understanding how variability is controlled or regulated. This regulation is important because variability is often correlated with running injuries. Here, subjects were asked to maintain specific variables (*Ln, Tn*, and *Sn*) with the intention of learning how subjects respond to task goals that may reduce the available redundancy within a system. Here,

subjects reacted to and accommodated multiple goals while treadmill running. More specifically, subjects adapted and manipulated their selected gait parameters appropriately when they were asked to do so. Furthermore, this study determined that individuals have the ability to "prioritize" or show "favoritism" toward specific goals while running.

Subjects exhibited mean stride lengths, stride times, and stride speeds that were within in their normal running gait characteristics (Figs.4.7). This was a critical fact as the experimental design attempted to mitigate the subjects from having to adopt different or abnormal gait patterns. Even though the means of L_n, T_n and S_n were within a SD of the "control" condition (the SPD condition), subjects displayed increased variability in the standard deviation measures. Increased variability was exhibited across the conditions where subjects were asked to control a specific variable. Initially, this was an unexpected finding. To further examine subject's variability, the percent root mean square error (%RMSE) analysis was completed. The %RMSE measured the variance from the task goal itself (L_n*, T_n*, S_n*). The results indicated that subjects tried to minimize error in each parameter. However, subjects prioritized the speed goal and placed less importance on the additional goals (L_n and T_n). This "favoritism" may have occurred due to the associated risk of errors relative to the speed goal. If subjects continuously violated the speed goal over many strides, a real physical penalty existed: i.e., the subject could fall off either the front or the back of the moving treadmill belt. During running, this level of perceived risk may increase, and therefore drive the subjects to more tightly regulate the *Sn* parameter, which they did. The other two goals (LEN and TIM) had no real bodily

penalty if an error was made and subjects allowed more variability within these two parameters. Upon the recognition of prioritization or favoritism of the stride speed goal, we felt it was appropriate to use only the speed goal in our initial goal equivalent manifold analyses using the speed GEM.

The GEM analyses indicated that the subjects were, in fact, trying to achieve the task goals. However, they were not consistently "successful," leading to increased variability in the standard deviation measures. The subjects were more tightly regulating the "goal" measures, as indicated by the α values for the dependent measures. Again, each additional task goal the subject experienced was coupled with the stride speed goal from running on a motorized treadmill.

Subjects tightly regulated (i.e., over-corrected) L_n more than T_n during the LEN, TIM and ALL conditions (Fig. 4.9). However, in the presence of the metronome, L_n became less persistent as well. On one hand, these different results for length markers and metronome conditions could be due to the nature of the task: LEN may be harder than TIM, regardless of the mode of feedback. On the other hand, it could be due to the mode of feedback itself, visual stimulus vs auditory stimulus. These results are supported by the walking data from Chapter 3, as well as (Terrier 2012, Terrier and Deriaz 2012, Terrier and Deriaz 2012). Additional studies during walking (Decker, Cignetti et al. 2012, Terrier and Deriaz 2012) have shown that subjects may ignore the auditory stimulus while on the treadmill. This may be true for running tasks as well. This may indicate that subjects are better at maintaining or minimizing error relative to stride length, more so than stride time.

Upon comparison to the previous walking study in Chapter 3, walking and running exhibited various similarities from the applied analyses. For both types of locomotion, subjects exhibited increased variability in L_n, T_n, and S_n measures for the LEN, TIM and ALL conditions. The standard deviations of these measures increased across conditions, the lowest values occurred during SPD and the larger values in the ALL condition. Since this variability was found during the additional task goal conditions in both walking and running, this may have been a result of subjects having voluntarily maintained their stepping parameters. During both walking (Chapter 3) and running, subjects strongly controlled for stride speed during every condition. For the GEM variables, subjects also exhibited larger variability in the tangent direction in all conditions (>1.0); perpendicular deviations were smaller (<1.0) for running and walking.

On the other hand, the results show several differences when compared to our previous walking study (Chapter 3). As expected, with a faster speed during running, subjects exhibited longer stride lengths, shorter stride times and faster stride speeds. The %RMSE values for running were lower in all 3 parameters, L_n, T_n, and *Sn*. As this value measures how well the subjects performed on each goal, running subjects on average performed each of the task goals with slightly less error.

DFA α results indicated that during walking, subjects exhibited tighter control of L_n during the LEN condition, T_n during the time condition, and L_n and T_n during the ALL conditions. However, during running, the subjects exhibited much tighter control in the *Sn* parameter during all four conditions. These differences may be attributed to the level of perceived risk. With the treadmill belt moving faster during running, the penalty of

errors relative to the speed goal was more apparent to the subjects. In other words, the risk of falling off the front or back of the treadmill was greater as the belt speed was faster. Although research has shown that many kinematic parameters change in relation to speed, the tighter speed control during running was not originally hypothesized, as the goals do not change from walking to running, only the speed.

These results may also indicate that the size of the treadmill itself may affect the degree of control exerted by the subject. Several studies have tested these control measures and found slightly different results in different labs during walking (Dingwell, John et al. 2010, Decker, Cignetti et al. 2012, Terrier 2012, Terrier and Deriaz 2012, Terrier and Deriaz 2012). However, additional studies must be completed to verify the effect of treadmill size and design on these parameters.

Overall subjects controlled for the stride speed parameter, similar to Chapter 3 results. However, subjects manipulated L_n and T_n differently than during walking to achieve constant stride speed. This may be for many reasons, but we hypothesize that the level of perceived risk increases with the speed of locomotion. Future studies are needed to confirm this hypothesis. Additionally, research is still needed to validate these measures over ground or on a self-paced treadmill to remove the speed coupling with the additional task goals.

Chapter 5

Adaptability of Stride-to-Stride Control in Humans at a predicted Walk-to-run transition speed.

Introduction

Walking and running are the two primary forms of human locomotion. Walking is characteristically different than running. The main difference between walking and running is that walking has a double support phase during the gait cycle, whereas running has a flight phase (Novacheck 1998). Although there are many differences, this a key distinction between the two forms of locomotion. While these two forms of locomotion are markedly different, research suggests that both forms of locomotion may utilize a shared pattern generating network for locomotor control (Cappellini, Ivanenko et al. 2006). As walking speed increases, humans shift from a walking gait to a running gait at a very specific and very predictable gait transition speed (Diedrich and Warren 1995, De Smet, Segers et al. 2009). This speed is often referred to as the walk-to-run transition speed. The walk-to-run transition (W-R) normally occurs at 2.1m/s (Diedrich and Warren 1995). However, some studies have shown this speed may vary slightly, potentially due to differences in individual subject characteristics; height, build, muscle tone (Thorstensson and Roberthson 1987, Hreljac 1993).

A predominant question within the gait transition literature is why do humans switch gaits? It has been hypothesized that humans change gaits for a variety of reasons, such as metabolic efficiency, mechanical limits, and/or possibly mechanical stress

(undesirable loads/forces) (Diedrich and Warren 1995, Raynor, Yi et al. 2002). Studies have also looked at the walk-to-run transition compared to the run-to-walk to transition and found that these typically can occur at slightly different speeds (Turvey, Holt et al. 1999, Raynor, Yi et al. 2002). This is referred to as a hysteresis effect: i.e., people transition from walking to running at a consistently slightly faster speed when speed is gradually increased than they do from running to walking when speed is gradually decreased.

In addition to the hysteresis of the W-R transition, the W-R timing period has also been highly studied, (Segers, Aerts et al. 2006, Hreljac, Imamura et al. 2007, Van Caekenberghe, De Smet et al. 2010, Van Caekenberghe, Segers et al. 2010, Segers, De Smet et al. 2013). Treadmill inclination and speeds are also thought to contribute to gait changes as well as the timing of this phase shift (Hreljac, Imamura et al. 2007, Van Caekenberghe, Segers et al. 2010).

Walking and running share symmetries in numerous kinematic and timing parameters. However, when reaching the W-R transition speed, increases in variability have often been predicted (Seay, Haddad et al. 2006, Hreljac, Imamura et al. 2007). However, the studies investigating variability are inconclusive as to how this variability is regulated during running and at the W-R transition.

To further investigate the variability at the W-R transition, some studies have utilized a dynamical systems approach (Schöner, Haken et al. 1986, Li, van den Bogert et al. 1999) (Diedrich and Warren Jr 1995, Li 2000). The reported advantage of using this approach to study gait is that it provides a method of simplifying a complex

multidimensional system (Li, van den Bogert et al. 1999). These authors proposed that the walk-to-run transition is similar to a complex system that exhibits bifurcations between different stable attractor states. The preferred walking and running speeds act as the stable attractors, and the W-R transition is similar to a non-equilibrium phase transition (Diedrich and Warren Jr 1995, Aoi, Katayama et al. 2013). This non-equilibrium phase transition may be the cause of the increased variability often observed at the transition speed (Diedrich and Warren 1995). Due to the energy required to move a system away from a stable attractor (in this case, preferred walking speed (PWS) or preferred running speed (PRS)), experimental energy consumption measures can indicate when this gait transition occurs (Diedrich and Warren 1995). Although this approach provides potential insight into how and why a gait transition occurs, it does not explain how the transition affects the variability of actual gait parameters or the central nervous system.

Another approach that may provide a more generalized explanation of the motor plan and coordination of the musculoskeletal system variability is the approach used in (Dingwell, John et al. 2010). This approach indicates that some movement variability arises from the ubiquitous noise in the nervous system (Cordo, Inglis et al. 1996, Osborne, Lisberger et al. 2005, Stein, Gossen et al. 2005, Faisal, Selen et al. 2008). However, much of the movement variability we observe arises from redundancy or equifinality (Scott 2004, Todorov 2004, Cusumano and Cesari 2006): i.e., there are often an infinite number of ways to achieve the exact same task goal. During walking and running, humans need to adapt at *every* step (not just on average) to respond to

perturbations (Dingwell and Cusumano 2000, Dingwell and Marin 2006, Kang and Dingwell 2008, Meardon, Hamill et al. 2011). While the neurophysiological mechanisms that enact these responses are well known (Rossignol, Dubuc et al. 2006), the fundamental principles governing adaptation from one stride to the next remain mostly unknown, especially during the W-R transition.

Detrended Fluctuation Analysis (DFA) has been used repeatedly to quantify the temporal correlation structure of specific gait parameters. DFA indicates whether stride-to-stride variations in gait cycle timing or other relevant variables exhibit statistical persistence (Peng, Buldyrev et al. 1992, Hausdorff, Peng et al. 1995, Terrier, Turner et al. 2005). Prior research in our lab demonstrated that the results of these DFA analyses can be directly interpreted in terms of the degree of control imposed on each specific gait variable (Dingwell and Cusumano 2010, Dingwell, John et al. 2010). Understanding how control is enacted from stride to stride therefore requires quantifying the specific temporal sequencing of those stride to stride fluctuations (Dingwell and Cusumano 2010, Dingwell, John et al. 2010). The stride-to-stride fluctuations during walking and running have been investigated previously (Chapters 3 & 4). However, whether (and if so how) these fluctuation dynamics might change when nearing a predicted/theoretical W-R transition has not been explored. If the W-R transition represents a condition of increased system instability (Diedrich and Warren, 1995) then one would predict that this might incur substantial changes in stride-to-stride control as well.

The aim of this study was to determine how stride-to-stride fluctuations are controlled when subjects walk or run at their "calculated" W-R transition speed. Subjects

were asked to complete trials of PWS and PRS as well as walking and running at their predicted transition speed. Using previous analyses (Dingwell, John et al. 2010), we determined which of the main kinematic parameters (stride length, stride time, and stride speed) the central nervous system was most strongly actively regulating.

Our investigation of the W-R transition is relevant because W-R transition is a point where subjects exhibit some type of "bifurcation" and this bifurcation induces a certain level of "instability" into the system (i.e., it reflects a natural state of self-imposed instability). Our main objective was to determine how people regulate *steady-state* locomotion (i.e., where no "transition" occurs) in a context that imposes / induces this type of internally-generated instability. Another objective was to determine if people adopt the same stepping control strategies as they do during "preferred" steady state locomotion (walking or running) at their predicted W-R transition speed? In addition, to the previous question, does the instability imposed by having to walk or run at a naturally uncomfortable and/or unstable speed (i.e., the transition speed) require significant changes in how one regulates stepping movements in a stride-to-stride manner?

Methods

Experimental protocol

Ten (10) healthy adults between 18 and 35 years of age participated (Table 5.1). All subjects were pre-screened to ensure they had no lower leg injuries, surgeries, or cardiovascular, respiratory, neurological, musculoskeletal or visual conditions that could have affected their gait. This study was approved by the Institutional Review Board at the University of Texas and all participants provided written consent prior to participation. Subjects had to meet the requirement of being an active recreational runner, and were required to have run at least 10-15 miles, 3 times a week within the most recent month.

Table 5.1 Subject Characteristics

Subject Characteristics (n=14)	
Age (yrs)	**24.6 ± 2.04**
Sex (female/male)	**5/5**
Height (m)	**1.75 ± 0.11**
Leg Length (m)	**0.968 ± 0.04**
Body Mass (kg)	**68.91± 12.05**

Subjects walked or ran on a Woodway Pro XL treadmill (Woodway USA, Waukesha, WI) with a motorized rubber belt. The treadmill belt dimensions were 2.23m

long by 0.685m wide. All subjects were required to wear a safety harness during the experiment session (Fig 5.3.).

Subjects first acclimated to walking and running on the treadmill for at least 5 minutes at the beginning of the experiment and 2 minutes prior to each new condition. The speeds for each condition were determined using the Froude method, with specific Froude numbers chosen depending on what type of gait was required for each condition. All speeds were non-dimensionally scaled to each subject's leg length using the Froude method, $speed = \sqrt{\mathrm{Fn} \times\ g \times l}$, where *Fn* is the Froude number, g is gravity and l is leg length; measured from the greater trochanter to the floor (Vaughan and O'Malley 2005). For the calculated preferred walking condition (PWS), the Froude number was set to 0.16. For the predicted transition speed conditions (WTS, RTS) the Froude number was set to 0.5. For calculated preferred running condition (PRS), the Froude number was set to 0.84. For a subject with an "average" leg length (~0.93m), these Froude numbers (*Fn* = 0.16, 0.5 and 0.84) yielded true speeds of 1.2 m/s, 2.1 m/s, and 2.77 m/s respectively. Prior studies have verified these speeds to be appropriate (Diedrich and Warren 1995, McAndrew Young and Dingwell 2012, McAndrew Young and Dingwell 2012). Subjects were asked to verify that these speeds were comfortable.

Subjects were asked to complete two 4-minute walking trials of each of the following four experimental conditions: walking at the theoretically predicted preferred speed (PWS), walking at the theoretically predicted transition speed (WTS), running at the theoretically predicted transition speed (RTS), and running at the theoretically predicted preferred speed (PRS).

For all conditions, the treadmill was set to the appropriate calculated speed. For the PWS and the WTS condition, subjects were instructed to walk on the treadmill. For the RTS and PRS subjects were instructed to run on the treadmill. A waist high mirror was also placed in front of the treadmill to give subjects visual feedback of their foot placement that did not require them to bend their necks to look directly down at their feet during all conditions (Chapters 3& 4). No further instructions were given.

Experimental conditions were presented in random order to each subject, with presentation order balanced across subjects. Trials were 4 minutes long. Subjects were given 2 minutes rest in between trials, and allowed as much rest as needed.

Data Collection and Processing

Whole-body kinematic data were recorded at 120 Hz using a 10-camera Vicon MX motion capture system (Oxford Metrics, Inc., Oxford, UK) for the entire duration of each trial. Each subject wore a standardized whole-body marker set of 57 markers, (Fig. 3, (Wilken, Rodriguez et al. 2012). Raw kinematic data were processed using Vicon Nexus software. Additional data analyses were performed using MatLab (MathWorks, Inc., Natick, MA).

Individual strides were determined by finding the local maxima of the distances between the pelvis and heel markers in the anterior-posterior direction (Zeni, Richards et al. 2008). These data were used to extract time series of the specified stride parameters: stride lengths (L_n), stride times (T_n), and stride speeds (S_n) for each walking trial. For consistency across analyses, all trials were truncated at 150 strides each.

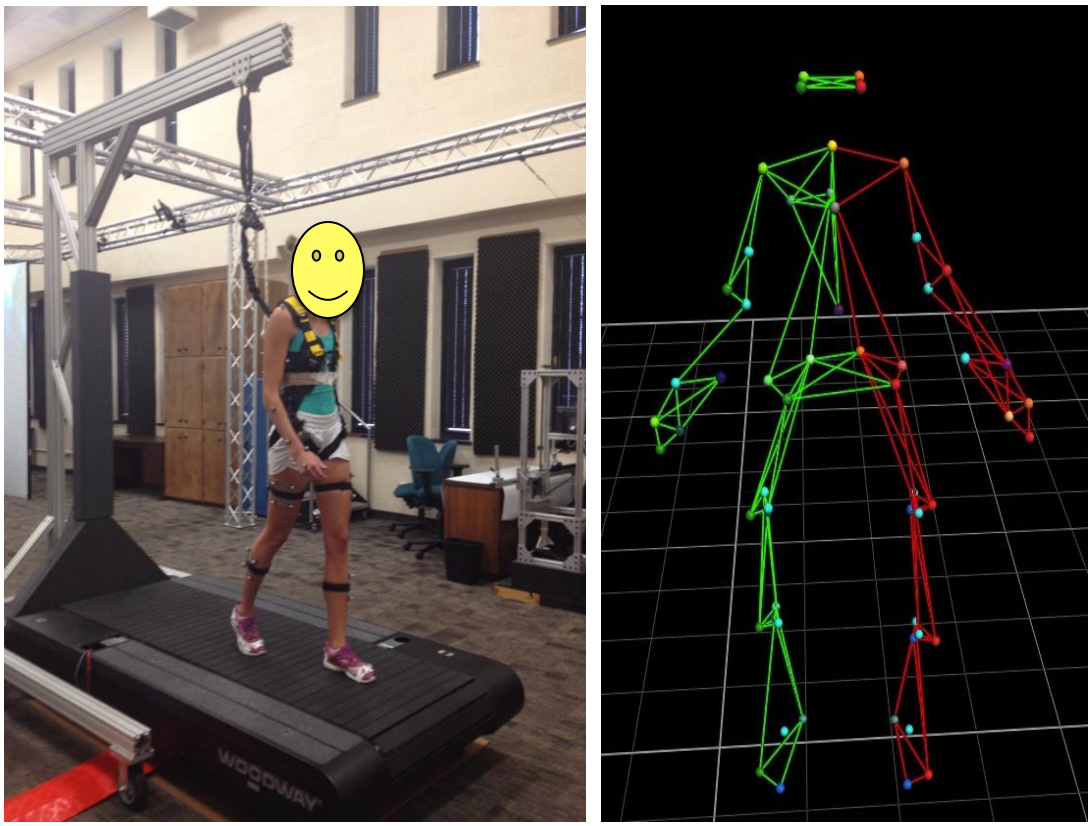

Figure 5.1. (Left) Subject walking on the Woodway treadmill in our laboratory. (Right) Computer generated image of the 57 marker set used in this study.

Dyanmics of primary gait parameters

Stride length (*Ln*) was defined as the anterior-posterior distance between right heel strike to the next consecutive right heel strike. Stride time (*Tn*) was the amount of time it took to go from heel strike of one foot to then next heel strike by the same foot. Stride speed was calculated as $S_n = L_n/T_n$ for each stride in each trial. Means, standard deviations, and DFA scaling components (α, see below) of L_n, T_n and S_n were calculated across all strides for L_n, T_n and S_n time series from each trial.

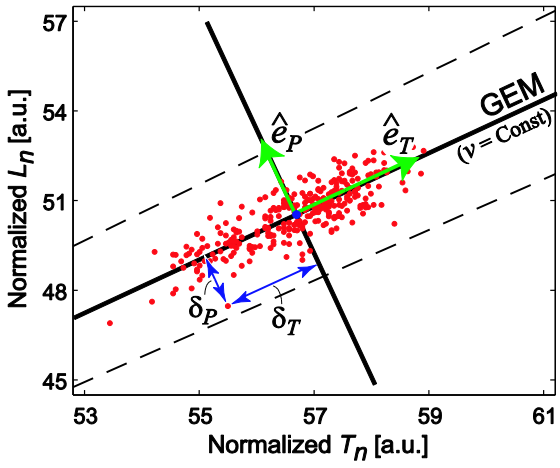

Figure 5.2. Schematic of the goal equivalent manifold (GEM) for the stride speed goal. δ_T identifies deviations tangent to the GEM. δ_P identifies deviations perpendicular to the GEM. L_n and T_n refer to normalized stride length and stride time respectively.

Detrended fluctuation analysis or DFA is one way to determine the correlation between consecutive movements (Peng, Buldyrev et al. 1992, Hausdorff, Purdon et al. 1996, Goldberger, Amaral et al. 2002). DFA can determine the statistical persistence or anti-persistence in a time series. DFA is used to compute a scaling exponent called alpha (α). An $\alpha < 0.5$ indicates that deviations in one direction are likely to be followed by deviations in the opposite direction (anti-persistence). An $\alpha > 0.5$ indicates that deviations are more likely to be followed by deviations in the same direction (persistence). Lower values of □ indicate more tightly regulated variables (Dingwell and Cusumano 2010, Dingwell, John et al. 2010).

For each of these traditional gait variables (i.e., L_n, T_n, and S_n), the values of each dependent measure (i.e., mean, SD, and scaling component α) (Dingwell and Marin 2006, Kang and Dingwell 2006) were computed for each trial and were analyzed using 2-factor (Condition x Subject) repeated measures ANOVA, followed by Tukey post-hoc analyses. Statistical analyses were performed using SPSS. Results were considered statistically significant if the resulting p-values were $p < 0.5$.

Speed GEM based Analyses

Utilizing the procedures developed by Dingwell, John et al. 2010, these [T_n, L_n] data were decomposed into new variables, tangent to (δ_T) and perpendicular to (δ_P) the Constant Speed GEM (Fig. 3.1.A). Prior work has demonstrated that, in the absence of any other goals, people choose to maintain constant *Sn* during both walking (Dingwell, John et al. 2010) & Ch. 3) and running (Ch. 4).

For the GEM-related variables (δ_T and δ_P), the values of each dependent measure were subjected to a 3-factor (Condition x Direction x Subject) repeated measures ANOVA, followed by appropriate post-hoc analyses. Trial-to-trial differences were run in a 3-factor (Condition x Direction x Trial) repeated measures ANOVA and no significant differences were found.

Results

Upon examination of the raw time series, L_n and T_n qualitatively exhibited more drift than S_n (Fig. 5.3) of for the WTS (left) and the RTS (right) conditions.

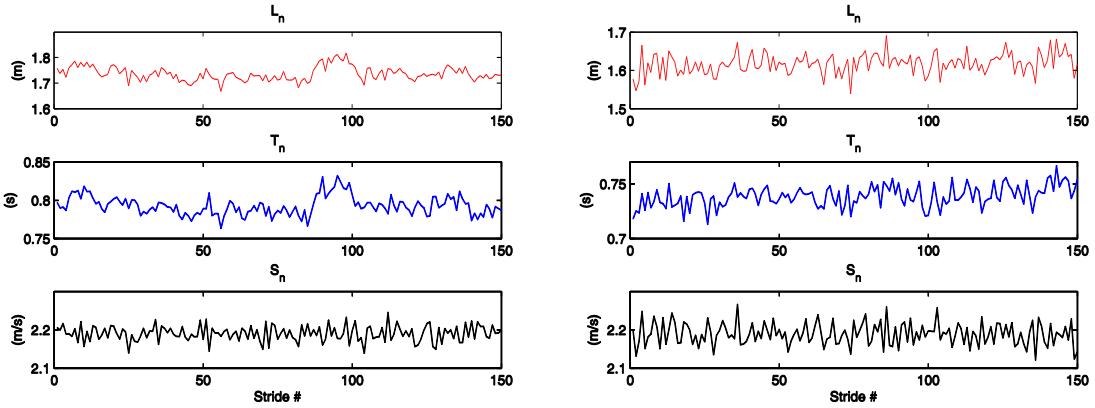

Figure 5.3. Raw time series data for stride length, stride time, and stride speed for the WTS (left) and RTS (right) conditions.

Standard Stride Parameters

As predicted, during the preferred walking speed condition, subjects exhibited the shortest stride lengths and longest stride times of any condition. At faster speeds, the stride length increased. The *Sn* mean verifies that subjects were walking/running at the same predicted transition speed. Within the walking conditions, from the PWS to the WTS conditions, L_n increased (~0.42) and T_n decreased (~0.27). Similarly, within the running conditions, the L_n increased (0.4) and T_n increased slightly (0.02).

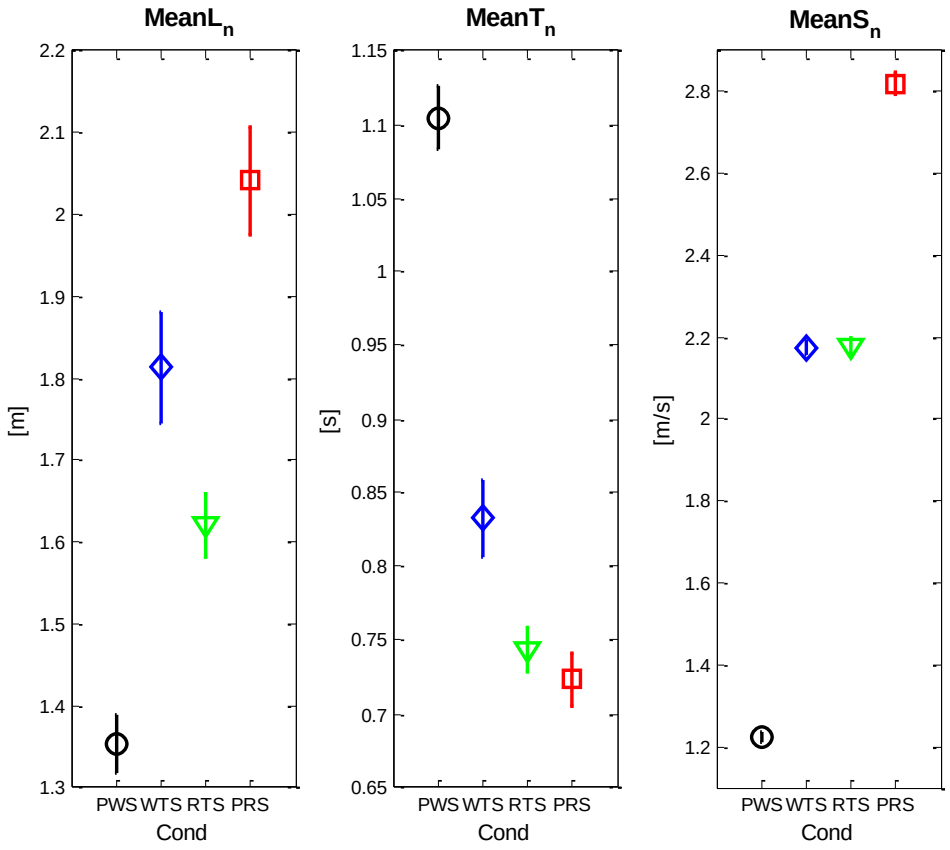

Figure 5.4. Mean stride length, stride time and stride speed values for all four conditions, preferred walking speed (black), walk at the transition speed (blue), running at the transition speed (green) and preferred running speed (red). Error bars indicate 95% confidence intervals.

For all gait parameters (L_n, T_n, and S_n), there were significant differences across all conditions (p=0.000). However, the main differences occurred at the predicted W-R transition (WTS and RTS). Here, subjects took longer, slower strides during WTS and faster, shorter strides during RTS. Subjects used very different magnitudes of the L_n and T_n parameters to effectively achieve the same S_n values. The mean values alone indicated

that subjects adopted different stride-to-stride control strategies for walking and running at the predicted W-R transition speed.

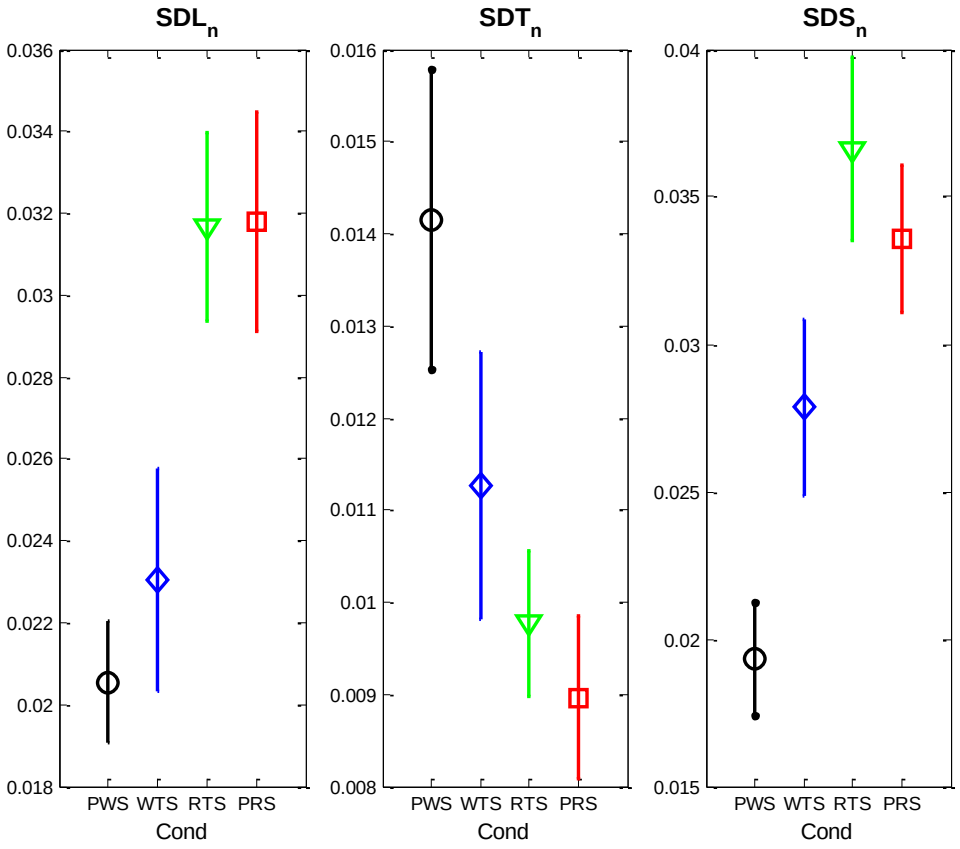

Figure 5.5. Standard deviations for stride length, stride time and stride speed values for all four conditions, preferred walking speed (black), walk at the transition speed (blue), running at the transition speed (green) and preferred running speed (red).

During the two walking conditions, subjects exhibited the lowest standard deviation values of L_n, and these were significantly different than both running conditions

(p= 0.017). At the faster running speeds, the variability within the T_n significantly decreased (p=0.00). The S_n variability was less for PWS than WTS yet was greater for RTS than PRS, and all conditions were significantly different from each other (p=0.00).

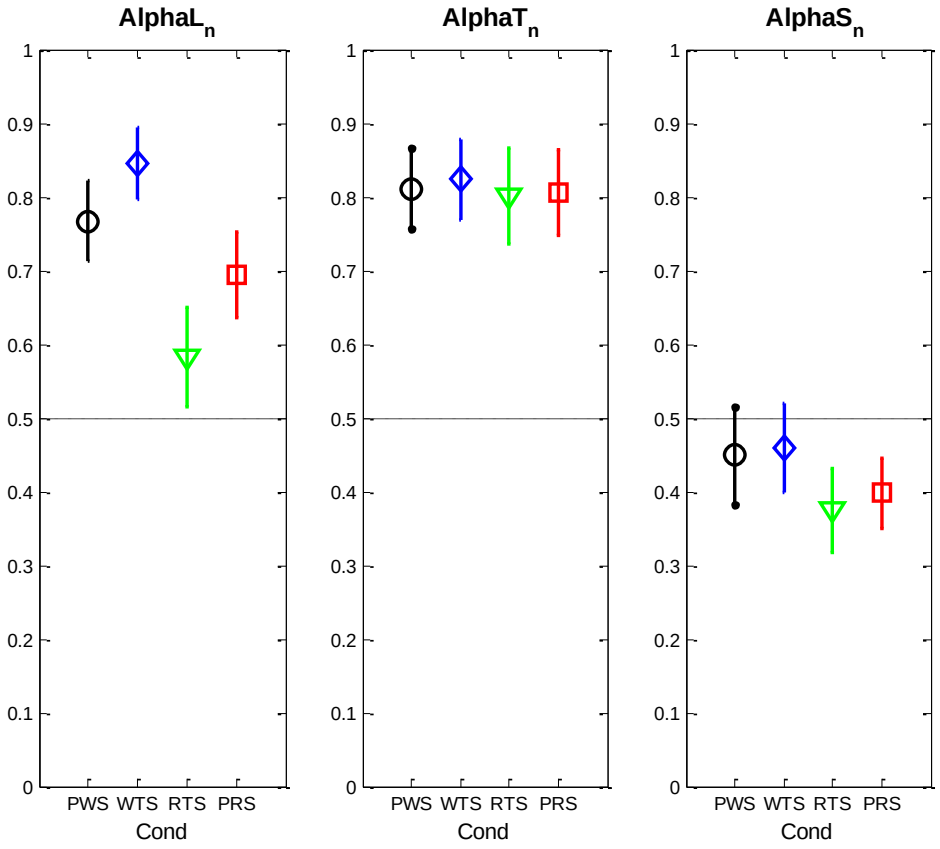

Figure 5.6. α values for stride length, stride time and stride speed values for all four conditions, preferred walking speed (black), walk at the transition speed (blue), running at the transition speed (green) and preferred running speed (red).

Speed GEM Specific Parameters

The α values for stride length varied across conditions (p = 0.00). However, all α values exhibited statistical persistence (α > 0.5). During the running conditions (RTS and PRS), subjects exhibited lower L_n α values than in both walking conditions (p=0.000). For stride time, there were no significant differences between conditions (p = 0.903) and again all α values exhibited statistical persistence. For stride speed, all conditions were tightly controlled (α < 0.5), with the only significant difference being between the WTS and RTS conditions (p = 0.037).

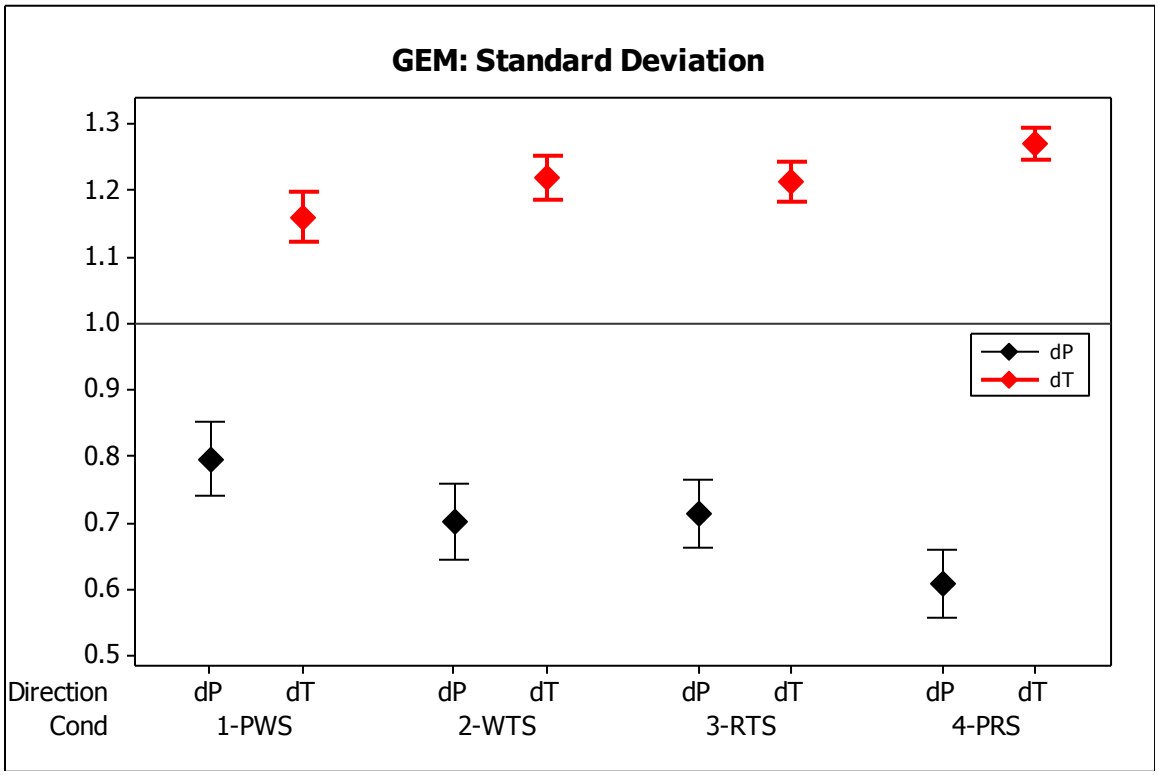

Figure 5.7.(A): Standard deviations along the tangent (red) and perpendicular (black) directions of the GEM.

Quantitatively, subjects exhibited less variability in the perpendicular direction ($SD(\delta_P) < 1.0$) and greater variability in the tangent direction ($SD(\delta_T) > 1.0$) across all conditions (p=0.00) (Fig. 5.7.A). In the tangent direction (δ_T), PWS was significant smaller from the PRS (p=0.00) and slightly smaller than WTS (0.053), however this difference was not statistically significant. In the perpendicular direction (δ_P), the PWS was significantly larger than the PRS (p=0.00) and slightly larger than WTS (p=0.06). The PRS was smaller than RTS (p=0.05). In both directions, while walking and running at the predicted W-R transitions subjects exhibited similar standard deviation values.

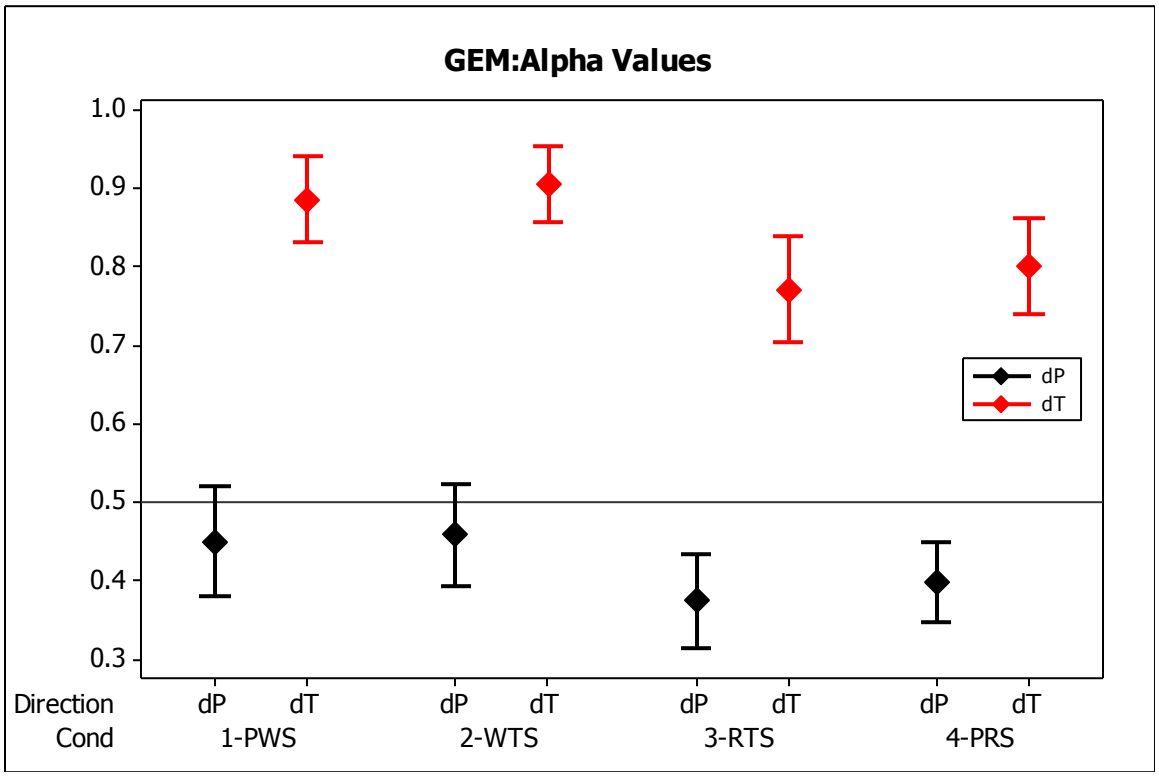

Figure 5.7. (B): α values of the GEM directions for each of the experimental conditions. The threshold to determine persistence or anti-persistence is indicated by the horizontal line at 0.5.

Subjects exhibited DFA α values (Fig. 5.7.B) in the tangent direction that were strongly statistically persistent ($\alpha > 0.5$). The PWS condition was significantly higher than RTS ($p=0.045$), while the WTS was significantly higher than the RTS ($p=0.011$). α values in the perpendicular direction (δ_P) were significantly higher for WTS than RTS ($p=0.026$). However, there were no other significant differences between conditions.

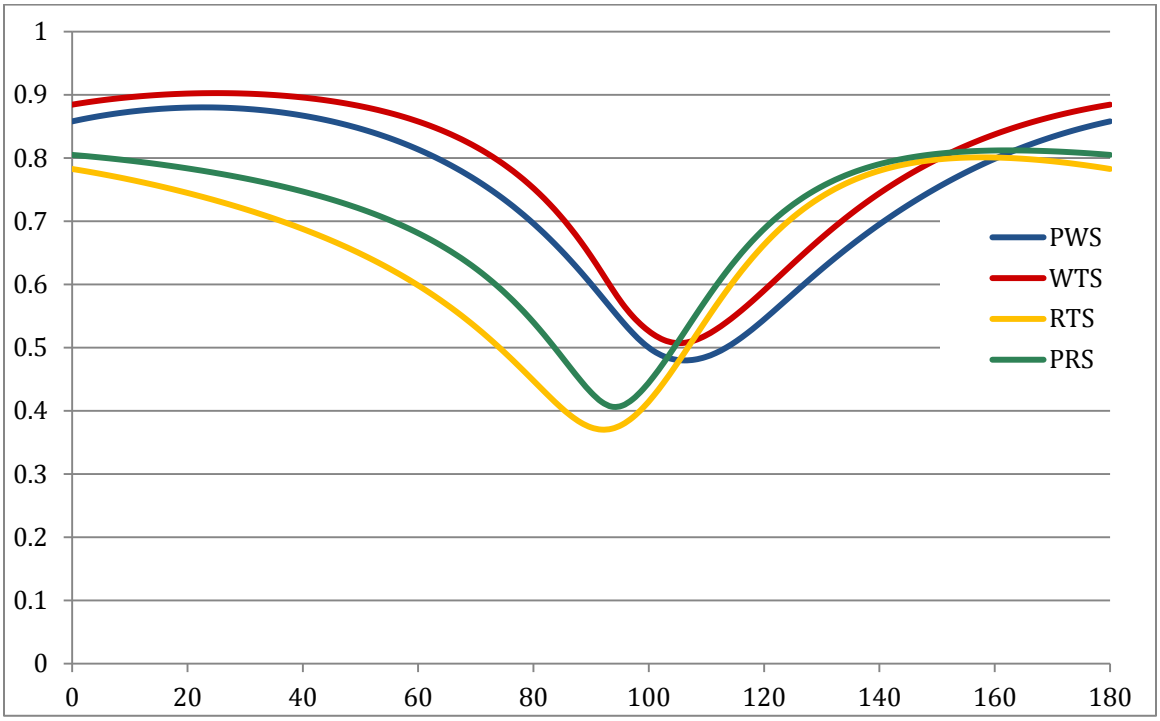

Figure 5.8. (A) Maximum and minimum value for the α measures for all 180 degrees.

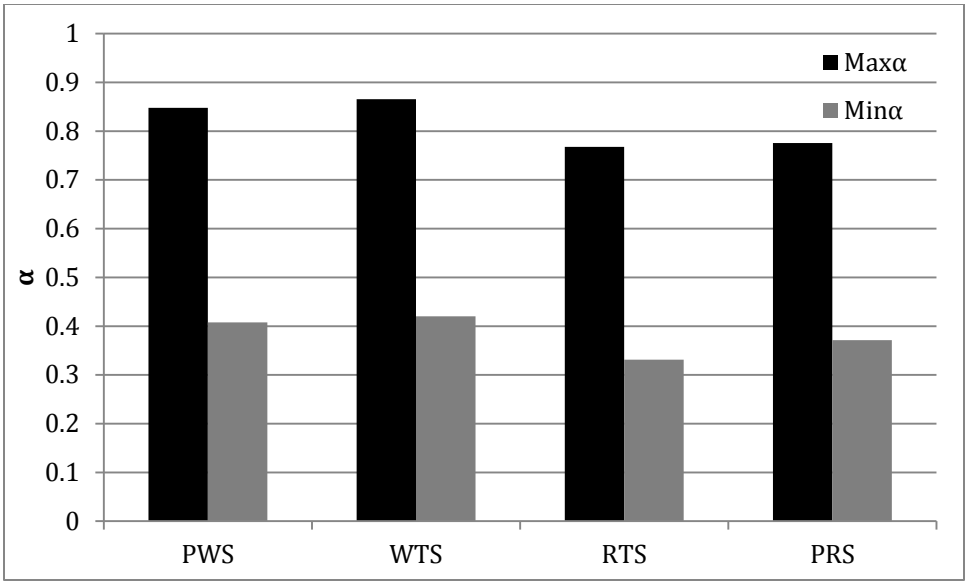

Figure 5.8. (B) The Maximum and minimum values of alpha calculated from the directionality analysis.

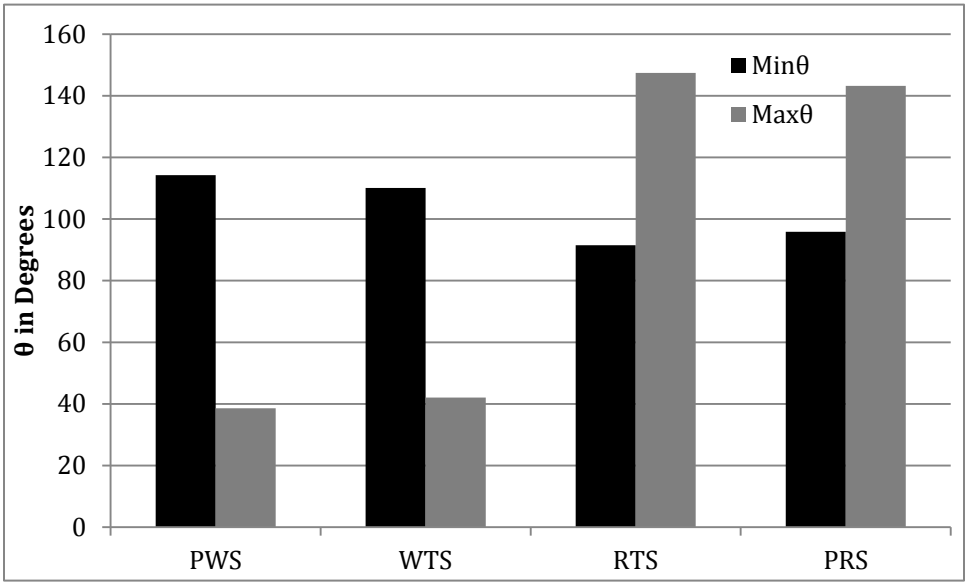

Figure 5.8. (C) The Maximum and minimum values of alpha calculated from the directionality analysis.

The structural orientation of the statistical persistence (α) in the [T_n, L_n] plane changed with the type of locomotion (i.e. walking or running). The minimum α value for the running conditions were smaller than both the walking conditions.

Discussion

Walking and running are thought of as two different tasks that usually occur at independent speeds. During this study, subjects were required to walk and run at their predicted W-R transition speed, as well as their calculated preferred walking and running speeds. Our rationale for investigating the predicted walk-to-run transition dynamics was based upon the assumption that these conditions would be more difficult or more "destabilizing" for subjects than their preferred walking and running conditions which were previously tested in Chapters 3 and 4 of this dissertation. Our results indicate that subjects were able to walk and run at the same predicted W-R transition speed. However, subjects used very different stride-to-stride control strategies, exhibiting very different stride lengths and stride times to achieve their predicted transition speed.

In the previous chapters of this dissertation, we tested "comfortable" walking (Chapter 3) and "comfortable" running speeds (Chapter 4). Here, we were interested in examining speeds at which walking and running felt "uncomfortable" and where greater active control was likely needed. Anecdotally, the majority of subjects commented that the predicted walk-to-run trials were uncomfortable and it was hard to maintain either walking or running without switching to the other form of locomotion.

Mean stride parameters (Fig.5.4) demonstrate that faster speeds required simultaneous changes in both stride length (L_n) and stride time (T_n). Subjects were able to

generate the same predicted transition speed by walking or by running. However, they manipulated different gait parameters to do so. Subjects exhibited longer mean L_n and T_n parameters during walking than running, reflecting that during walking at the transition speed, subjects remained in contact with the ground longer. When subjects changed from PWS to the WTS, stride lengths became longer and stride times decreased. Mathematically this makes sense: to achieve faster stride speeds, the ratio between L_n and T_n has to increase. Likewise, the opposite effect occurred from PRS to RTS, *Ln* decreased and T_n slightly decreased (~0.02s). The WTS and the RTS conditions provided variability measures for very fast walking and very slow running, where the variability has been shown to increase from a normal walking or running speed (Jordan and Newell 2008). The means of L_n, T_n, and S_n indicated that subjects were using different methods to accomplish the same goal, but additional measures were needed to determine variability.

The variability structure, as measured by the standard deviation, was unique to each individual stride parameter (Fig. 5.5). For stride length, subjects were more variable during both running conditions compared to the walking conditions. However for the stride time parameter, the variability decreased across conditions.

The DFA α values provided another more detailed approach to examine variability (Fig. 5.7B), independent of magnitude (Cusumano 2013). For the stride length parameter during the running conditions, the SD values indicated increased variability while the α measures indicated slightly lower α values, yet still statistically persistent values. This might suggest that subjects made more errors at faster running speeds, yet

these errors were also corrected more quickly than at the slower walking conditions. α values for stride time indicate "loose" control ($\alpha > 0.5$) of the T_n parameter across all conditions. As found in Chapters 3 and 4, stride speed was tightly controlled during all conditions ($\alpha < 0.5$).

For the GEM related variables, the standard deviation values depended on the direction. The deviations in tangent direction were much larger than those in the perpendicular direction. This suggests that people actually *exploited* this equifinality: i.e. subjects utilized a wide range of combinations of stride lengths and stride times that achieved the same speeds, similar to the results found by (Dingwell, John et al. 2010). The DFA α values indicate the subjects corrected all deviations in the perpendicular direction and slightly over corrected during the two running conditions.

Even though subjects walked and ran at the same predicted W-R speed, they did not appear to have significantly changed their overall control strategy, or to have adopted a completely new strategy. Subjects appeared to have largely maintained the speed control paradigm as previously discovered (Dingwell, John et al. 2010, Terrier and Deriaz 2012). Subjects exhibited differences in how they manipulated stride length and stride time, but there were no differences in the stride-to-stride control of the speed parameter for any conditions.

Additionally, within the GEM analyses, the standard deviation and α values were similar for the WTS and the RTS conditions. And yet, the α (L_n) analyses showed a large difference indicating that something was very different in the control between these two conditions, however that difference was not captured by the standard GEM analyses

alone (either in terms of variance or DFA). This may suggest that these subjects still satisfied the speed GEM control they started with, but for the RTS condition in particular, they achieved the speed GEM control in a very different manner.

For example, when examining the means (Fig. 5.4), subjects adopted very different mean *Tn* & *Ln* for WTS vs. RTS. Although they were walking/running at the same speed (i.e., the same speed GEM), they were, in fact, locomoting at very different mean operating points along that GEM. Perhaps the differences in α (L_n) may then suggest that these different locations along the GEM were (perhaps for biomechanical and/or other reasons) differentially sensitive to errors in L_n and T_n. This is only speculation at this point, as this is not a feature captured by our current GEM analyses.

The results from this study correspond with the results from chapter 3 and chapter 4, confirming that subjects use the same speed control strategy for walking and running. However, when either walking or running at the predicted W-R transition speed, subjects were able to utilize the GEM solution space and operate in very different locations along the GEM to achieve the same goal. These subjects were able to largely exploit the redundancy within task goal (more so than in (Dingwell, John et al. 2010), and effectively operate at "uncomfortable" speeds. Additionally, these results suggest that the stride speed control is robust even with additional novel tasks and uncomfortable, abnormal speeds of locomotion.

Chapter 6

Conclusions

In this dissertation, we investigated how humans regulate stride-to-stride fluctuations during locomotion. More specifically, we examined how humans alter the stride-to-stride regulation of their gait when the task goals change (e.g., by maintaining stride length and/or time, or by running rather than walking, and at a predicted walk-to-run transition speed).

For Aim #1, we determined the adaptability of stride-to-stride fluctuations during walking. In chapter 3, the results demonstrated that subjects exploited different redundancy relationships in different ways to prioritize a certain task goal, (maintain stride speed) over others (maintain stride length or stride time) in each different condition. Subjects also exhibited greater variability within stride parameters, even when asked to maintain specific variables.

We originally hypothesized that subjects would select either an intermediate goal solution, that was a combination of the two or three task goals, or that subjects would find an intersection point, where one solution satisfied all given task goals. However, we determined that subjects did not weight the given task goals equally, or find this intersection point. Subjects instead prioritized the speed goal over the LEN, TIM and ALL goals. Subjects were clearly doing something different than normal walking. However, it was not one of our originally hypothesized solutions. In general, subjects made more rapid corrections of the stride-to-stride deviations that were most directly

relevant to the different task goals adopted in each walking condition. Thus, the central nervous system readily adapts to achieve multiple goals simultaneously.

For Aim #2, we determined how adaptable people are at regulating stride-to-stride fluctuations during running. In Chapter 4, subjects exhibited similar adaptations as seen in the walking experiment, but over-corrected to prioritize maintaining stride speed even more than subjects did during the walking experiment. During running, subjects controlled stride parameters differently than they did during walking (Chapter 3). Subjects manipulated stride length and stride time in different ways, allowing more variability within the stride length and stride time parameters, to achieve a tightly regulated stride speed parameter. We believe subjects tightly regulated the stride speed as a result of increased level of perceived risk the subjects may have encountered. As the treadmill belt speed increased from walking to running, the penalty for violating the stride speed goal becomes increasingly apparent to the subject, and maybe cause the subject to focus or "favor" the stride speed goal even more. This purposeful adaptability of these stride-to-stride control strategies could be exploited to developing more effective rehabilitation protocols.

Although previous studies have shown that subjects exhibit statistical anti-persistence in the presence of a metronome during walking (Terrier 2012), our subjects only slighted decreased their amount of statistical persistence during the TIM conditions. Our results indicate that subjects were most affected by the LEN condition. The visual step length markers on the treadmill forced the subjects to maintain and control stride length more than any other condition. This finding may indicate that subjects are more

responsive to visual task goals than to auditory goals. This may be important for training purposes, and potentially for injury rehabilitation.

For Aim #3, we examined the adaptability of stride-to-stride fluctuations during fast walking and slow running speeds. In Chapter 5, we investigated how the previously determined control strategy, found in Chapters 3 and 4, changed as speed of locomotion became uncomfortable to the subjects. We initially hypothesized that subjects would be unable to maintain their "speed" control strategy as previously found in walking and running (Chapters 3 and 4). However, our results disproved our original hypothesis. Subjects were able to maintain their "speed" control strategy for both gaits and for all three speeds, i.e. calculated preferred walking speed, the predicted walk-to-run transition speed, and the calculated preferred running speed.

During their predicted theoretical W-R transition, subjects were able to utilize the entire GEM solution space and operate in very different locations along the GEM to achieve the same goal. These subjects were able to largely exploit the redundancy within task goal (more so than in Dingwell, John et al. 2010), and to effectively operate at "uncomfortable" speeds. Additionally, these results suggest that the stride speed control is robust even with additional novel tasks and uncomfortable, abnormal speeds of locomotion.

The results from all three of the experiments presented in this dissertation are consistent with the minimum intervention strategy (Todorov and Jordan 2002), indicating that subjects only strongly regulate the variables that are directly relevant to the specified goal (Dingwell, John et al. 2010). Here, we see that subjects perceive the given task goals

differently and on average interpret the constant stride speed goal as the most important goal. Even with novel task goals, subjects were able to determine the relevant variables for the given task and exploit the redundancy found in other related parameters. Our results are novel in the fact that we introduced length tasks, running tasks, and predicted transition speed tasks. Subjects were able to respond and achieve all task goals given.

These experiments have shown that relatively simple experimental tasks goals can yield greater understanding about control strategies used during treadmill walking and running. Prior studies have shown there are many other strategies that are able to satisfy the goal of stride speed, *Sn*, (Dingwell, John et al. 2010) as well as different fluctuation dynamics for *Sn* utilized during overground walking (Terrier, Turner et al. 2005). However, our results indicate that the speed control strategy for treadmill locomotion is robust even in the face of additional task goals and that the central nervous system readily adapts to achieve multiple goals simultaneously during locomotion.

Appendix 1: IRB Documents

IRB USE ONLY
Study Number: 2012-11-0076
Approval Date:
Expires:

Subject ID: _____

Informed Consent to Participate in Research
The University of Texas at Austin

Title: Determining how Humans Regulate Variability during Walking and Running – Experiment #1

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Introduction:

The purpose of this form is to provide you information that may affect your decision as to whether or not to participate in this research study. The person performing the research will answer any of your questions. Read the information below and ask any questions you might have before deciding whether or not to take part. If you decide to be involved in this study, this form will be used to record your consent.

Purpose of this Study:

You have been asked to participate in a research study about the variability of movements during walking. Human walking is naturally variable. For the elderly and/or other patients who have difficulty walking, this variability may indicate that they are more likely to fall. The purpose of this study is to determine how healthy humans regulate variations in their movements as they walk on a treadmill. We hope the results we obtain will help us better understand how the nervous system regulates movements during walking and will help us develop more effective interventions and treatments to help with people with walking impairments.

You have been chosen to participate in this study as part of a group of 20 healthy volunteers between the age of 18 and 35. You should have no history of physical or neurological problems that might affect their ability to walk on a treadmill.

What will you be asked to do?

You will be asked to complete the following procedures during a single visit:

- You will be asked to report to the Nonlinear Biodynamics Laboratory at the University of Texas at Austin, located in Bellmont Hall, Room 530. Wear comfortable shorts and shoes appropriate for extensive walking. Bring a sleeveless shirt, preferably a tank top. Gentlemen may be asked to perform shirtless.
- Before being admitted to the study, you will be screened for your suitability to participate by completing a brief Health History Questionnaire. You will also be asked about your typical weekly exercise habits.
- If you qualify to participate in the study, we will measure your height and weight, as well as the lengths of various individual body segments, including thigh, lower leg, and foot lengths, hip width, etc. These measurements do not hurt or feel uncomfortable.

- To become acclimated to the motorized treadmill, you will be asked to walk for at least 15-minutes at a range of speeds, including speeds slightly faster and slower than your comfortable walking speed. We will use these trials to determine your own personal "preferred" walking speed.
- Next, you will be asked to wear a number of small reflective markers attached to various points on your body to measure your movements. These markers will be attached with double-sided tape.
- You will then be asked to complete a series of 15-30 walking trials. Each trial will last 6 minutes. For each trial, the treadmill speed will be set to a moderate comfortable speed.
- During some trials, you will be asked to alter your normal stride to vary the length and/or timing of your steps in different ways. The magnitudes of these variations will be small enough that you can continue walking comfortably.
- You will be allowed at least 2 minutes, or as much time as you need, to rest between trials.
- You can stop the warm-up or any of the trials at any point and for any reason.
- Participation will involve a single experimental sessions, lasting approximately 2½ hours in duration.

What are the risks involved in this study?

The above procedures are not expected to be painful or uncomfortable in a healthy individual. If you do find any of the procedures to be prohibitively uncomfortable, you should immediately tell the investigator and they will be discontinued. None of the devices being used in this study are invasive.

- As during any moderate exercise, there is a risk of heart attack or stroke. This risk will be minimized by asking you to complete the Health History Questionnaire to ensure that you are physically active and that you do not have any illnesses or injuries, or are taking any medications that might indicate that you would be at undue risk of experiencing a heart attack or stroke.
- As during any moderate exercise, there is a risk that you could experience a muscular injury, such as a muscle strain. Also, it is possible that muscle soreness may develop 24 to 48 hours after testing. To help reduce these risks, a warm-up and stretching session will be mandatory prior to performing these tests, and you will be allowed as much time as you need to rest between trials to minimize the effects of fatigue.
- During the walking trials, there is a possible risk of injury from stepping up onto or down off of the treadmill that is elevated approximately 12 inches above the floor. There is also a risk that you could trip or fall while walking. To reduce these risks, you will be asked to wear a safety harness that will catch you in the event of a fall while not constricting your movements.
- Additionally, the treadmill that will be used is equipped with an emergency "STOP" button that the investigator conducting the experiment will control. In the event of any unwanted event, the investigator will press this button to stop the treadmill immediately.
- During the walking trials, there is a risk that you may become overexerted and/or tired. To reduce this risk, you will not be asked to perform any tasks that are beyond the scope of what you might do during your normal daily activities or during moderate exercise. Additionally, you will be allowed to rest as long as you need between trials, and you may stop at any time if you feel the need.
- Some slight discomfort may also be experienced during removal of the reflective markers, similar to removing a band-aid. If you experience skin irritation, this should subside on its own by the following day.
- There may also be additional risks that are unknown at this time. If you wish to discuss the information above or any other risks you may experience, you may ask questions now or contact the Principal Investigators listed on the front page of this form at any time.

What are the possible benefits of this study?

There are no direct benefits to you by participating in this study.

This study is part of a series of experiments we are conducting to investigate how humans control the variability in their movements during walking. We hope these studies will contribute to a better understanding of the neural and/or muscular control mechanisms humans use to regulate human locomotion.

Do you have to participate?

No, your participation is voluntary. You may decide not to participate at all or, if you start the study, you may withdraw at any time. Withdrawal or refusing to participate will not affect your relationship with The University of Texas at Austin (University) in anyway.

If you agree to participate, sign and return the form to the investigator. You will receive a copy of this form.

What are the alternatives to participating in this research?

Your participation in this study is entirely voluntary. You are free to refuse to be in the study, and your refusal will not influence current or future relationships with The University of Texas at Austin.

Will there be any compensation?

You will be compensated for your time in the amount of $25 for completing this experiment. If you anticipate that payments for *all* research and survey compensation received from UT Austin to collectively total $450.00 or more for the calendar year, you will also be asked to provide your social security number.

Disclosure of your social security number (SSN) is requested from you in order for The University of Texas at Austin to process compensation for research activities and to pay you if the total compensation from UT Austin amounts to $450 or more. No statute or other authority requires that you disclose your SSN for that purpose. Failure to provide your SSN, however, may result in no payment or compensation for participation beyond $449 for that fiscal year. Further disclosure of your SSN is governed by the Public Information Act (Chapter 552 of the Texas Government Code) and other applicable law.

What if you are injured because of the study?

By participating in this study, there is a small chance of being injured, as discussed above. If you are injured, the University has no program or plan to provide treatment for research-related injury or payment in the event of a medical problem. The University also has no program or plan for continuing medical care and/or hospitalization for research-related injuries or for financial compensation. In the event of a research-related injury, please contact the principal investigator. Eligible University of Texas at Austin students may be treated at the usual level of care with the usual cost for services at the Student Health Center, but no payment can be provided in the event of a medical problem.

What are my confidentiality or privacy protections when participating in this research study?

Each subject will be assigned a unique *Subject ID* code, which will *only* be identified with their name on the Subject Contact Information Form. The Health History Questionnaire will not contain any personally identifying information. If a potential subject is found to be ineligible to participate because they fail to meet inclusion criteria, all of their screening data and any other identifiable information will be destroyed. These two forms and this Informed Consent Form will be stored in a locked file cabinet inside a locked office. In all other cases, electronic data will only be identifiable by your unique *Subject ID* code. Only the director of the project (Dr. Dingwell) will have access to a master list that will link your identity to your code. The electronic data will be stored on DVD media and also kept in a locked file cabinet in Dr. Dingwell's office. These data will only contain fully de-identified, non-sensitive information and will be maintained indefinitely.

The records of this study will be stored securely and kept confidential. Authorized persons from The University of Texas at Austin and members of the University of Texas Institutional Review Board, have the legal right to review your research records and will protect the confidentiality of those records to the extent permitted by law. Throughout the study, the researchers will notify you of new information that may become available and that might affect your decision to remain in the study.

If in the unlikely event it becomes necessary for the Institutional Review Board to review your research records, then the University of Texas at Austin will protect the confidentiality of those records to the extent permitted by law. Your research records will not be released without your consent unless required by law or a court order. The data resulting from your participation may be made available to other researchers in the future for research purposes not detailed within this consent form. In these cases, the data will contain no identifying information that could associate you with it, or with your participation in any study. If the results of this research are published or presented at scientific meetings, your identity will not be disclosed.

Who should you contact if you have questions about the study?

Prior, during or after your participation, you can contact the researcher Dr. Jonathan Dingwell at 512-232-1782 or send an email to jdingwell@austin.utexas.edu. This study has been reviewed and approved by The University Institutional Review Board and the study number is *2012-11-0076*.

Who should you contact if you have questions concerning your rights as a research participant?

For questions about your rights or any dissatisfaction with any part of this study, you can contact, anonymously if you wish, the Institutional Review Board by phone at (512) 471-8871 or email at orsc@uts.cc.utexas.edu.

Participation:

If you agree to participate, sign and return the form to the investigator. You will receive a copy of this form.

Signatures:

You have been informed about this study's purpose, procedures, possible benefits and risks, and you have received a copy of this form. You have been given the opportunity to ask questions before you sign, and you have been told that you can ask other questions at any time. You voluntarily agree to participate in this study. By signing this form, you are not waiving any of your legal rights.

_____ I agree to be photographed and/or audio and/or video recorded.

_____ I do not want to be photographed and/or audio and/or video recorded.

_____

Printed Name of Participant

_____ _____

Signature of Participant Date

As a representative of this study, I have explained the purpose, procedures, benefits, and the risks involved in this research study.

_____

Printed Name of Person Obtaining Consent

_____ _____

Signature of Person Obtaining Consent Date

IRB USE ONLY
Study Number: 2012-11-0076
Approval Date:
Expires:

Subject ID: _____

Informed Consent to Participate in Research
The University of Texas at Austin

Title: Determining how Humans Regulate Variability during Walking and Running – Experiment #2

Investigator(s):

Jonathan B. Dingwell, Ph.D. – *Principal Investigator*
Department of Kinesiology & Health Education
University of Texas at Austin
Bellmont Hall, Rm. 536
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Austin, TX 78712-1415
Phone: (512) 232-1782
E-Mail: jdingwell@austin.utexas.edu

Nicole Bohnsack, M.S.
Department of Kinesiology & Health Education
University of Texas at Austin
Bellmont Hall, Rm. 530
2109 San Jacinto Blvd, Stop D3700
Austin, TX 78712-1415
Phone: (512) 471-4017
E-Mail: nicolebohnsack@austin.utexas.edu

Introduction:

The purpose of this form is to provide you information that may affect your decision as to whether or not to participate in this research study. The person performing the research will answer any of your questions. Read the information below and ask any questions you might have before deciding whether or not to take part. If you decide to be involved in this study, this form will be used to record your consent.

Purpose of this Study:

You have been asked to participate in a research study about the variability of movements during walking and running. Human walking and running is naturally variable. There is evidence to suggest that different aspects of this variability may be related to the risk of developing running-related injuries. The purpose of this study is to determine how healthy humans regulate variations in their movements as they walk or run on a treadmill. We hope the results we obtain will help us better understand how the human nervous system regulates movements during walking and running and will help us develop more effective interventions to help with people with running related injuries.

You have been chosen to participate in this study as part of a group of 20 healthy volunteers between the age of 18 and 35. You should have no history of physical or neurological problems that might affect your ability to run on a treadmill and you must be an active recreational runner.

What will you be asked to do?

You will be asked to complete the following procedures during a single visit:

- You will be asked to report to the Nonlinear Biodynamics Laboratory at the University of Texas at Austin, located in Bellmont Hall, Room 530. Wear comfortable shorts and shoes appropriate for moderate distance walking and running. Bring a sleeveless shirt, preferably a tank top. Gentlemen may be asked to perform shirtless.
- Before being admitted to the study, you will be screened for your suitability to participate by completing a brief Health History Questionnaire. You will also be asked about your typical weekly running experience.
- If you qualify to participate in the study, we will measure your height and weight, as well as the lengths of various individual body segments, including thigh, lower leg, and foot lengths, hip width, etc. These measurements do not hurt or feel uncomfortable.

- To become acclimated to the motorized treadmill, you will be asked to walk and run for at least 15-minutes at a range of speeds, including speeds slightly faster and slower than your comfortable walking and running speeds. We will use these trials to determine your own personal "preferred" walking and running speeds.
- Next, you will be asked to wear a number of small reflective markers attached to various points on your body to measure your movements. These markers will be attached with double-sided tape.
- You will then be asked to complete a series of 15-30 walking and running trials. Each trial will last 3-4 minutes. For each trial, the treadmill speed will be set to a moderate comfortable speed.
- During some trials, you may be asked to alter your normal stride to vary the length and/or timing of your steps in different ways. The magnitudes of these variations will be small enough that you can continue walking or running comfortably.
- You will be allowed at least 2 minutes, or as much time as you need, to rest between trials.
- You can stop the warm-up or any of the trials at any point and for any reason.
- Participation will involve a single experimental sessions, lasting approximately 2½ hours in duration.

What are the risks involved in this study?

The above procedures are not expected to be painful or uncomfortable in a healthy individual. If you do find any of the procedures to be prohibitively uncomfortable, you should immediately tell the investigator and they will be discontinued. None of the devices being used in this study are invasive.

- As during any moderate exercise, there is a risk of heart attack or stroke. This risk will be minimized by asking you to complete the Health History Questionnaire to ensure that you are physically active and that you do not have any illnesses or injuries, or are taking any medications that might indicate that you would be at undue risk of experiencing a heart attack or stroke.
- As during any moderate exercise, there is a risk that you could experience a muscular injury, such as a muscle strain. Also, it is possible that muscle soreness may develop 24 to 48 hours after testing. To help reduce these risks, a warm-up and stretching session will be mandatory prior to performing these tests, and you will be allowed as much time as you need to rest between trials to minimize the effects of fatigue.
- During the walking and running trials, there is a possible risk of injury from stepping up onto or down off of the treadmill that is elevated approximately 12 inches above the floor. There is also a risk that you could trip or fall while walking and running. To reduce these risks, you will be asked to wear a safety harness that will catch you in the event of a fall while not constricting your movements.
- Additionally, the treadmill that will be used is equipped with an emergency "STOP" button that the investigator conducting the experiment will control. In the event of any unwanted event, the investigator will press this button to stop the treadmill immediately.
- During the walking and running trials, there is a risk that you may become overexerted and/or tired. To reduce this risk, you will not be asked to perform any tasks that are beyond the scope of what you might do during your normal daily activities or during moderate exercise. Additionally, you will be allowed to rest as long as you need between trials, and you may stop at any time if you feel the need.
- Some slight discomfort may also be experienced during removal of the reflective markers, similar to removing a band-aid. If you experience skin irritation, this should subside on its own by the following day.
- There may also be additional risks that are unknown at this time. If you wish to discuss the information above or any other risks you may experience, you may ask questions now or contact the Principal Investigators listed on the front page of this form at any time.

What are the possible benefits of this study?

There are no direct benefits to you by participating in this study.

This study is part of a series of experiments we are conducting to investigate how humans control the variability in their movements during walking and running. We hope these studies will contribute to a better understanding of the neural and/or muscular control mechanisms humans use to regulate human locomotion.

Do you have to participate?

No, your participation is voluntary. You may decide not to participate at all or, if you start the study, you may withdraw at any time. Withdrawal or refusing to participate will not affect your relationship with The University of Texas at Austin (University) in anyway.

If you agree to participate, sign and return the form to the investigator. You will receive a copy of this form.

What are the alternatives to participating in this research?

Your participation in this study is entirely voluntary. You are free to refuse to be in the study, and your refusal will not influence current or future relationships with The University of Texas at Austin.

Will there be any compensation?

You will be compensated for your time in the amount of $25 for completing this experiment. If you anticipate that payments for *all* research and survey compensation received from UT Austin to collectively total $450.00 or more for the calendar year, you will also be asked to provide your social security number.

Disclosure of your social security number (SSN) is requested from you in order for The University of Texas at Austin to process compensation for research activities and to pay you if the total compensation from UT Austin amounts to $450 or more. No statute or other authority requires that you disclose your SSN for that purpose. Failure to provide your SSN, however, may result in no payment or compensation for participation beyond $449 for that fiscal year. Further disclosure of your SSN is governed by the Public Information Act (Chapter 552 of the Texas Government Code) and other applicable law.

What if you are injured because of the study?

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What are my confidentiality or privacy protections when participating in this research study?

Each subject will be assigned a unique *Subject ID* code, which will *only* be identified with their name on the Subject Contact Information Form. The Health History Questionnaire will not contain any personally identifying information. If a potential subject is found to be ineligible to participate because they fail to meet inclusion criteria, all of their screening data and any other identifiable information will be destroyed. These two forms and this Informed Consent Form will be stored in a locked file cabinet inside a locked office. In all other cases, electronic data will only be identifiable by your unique *Subject ID* code. Only the director of the project (Dr. Dingwell) will have access to a master list that will link your identity to your code. The electronic data will be stored on DVD media and also kept in a locked file cabinet in Dr. Dingwell's office. These data will only contain fully de-identified, non-sensitive information and will be maintained indefinitely.

The records of this study will be stored securely and kept confidential. Authorized persons from The University of Texas at Austin and members of the University of Texas Institutional Review Board, have the legal right to review your research records and will protect the confidentiality of those records to the extent permitted by law. Throughout the study, the researchers will notify you of new information that may become available and that might affect your decision to remain in the study.

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Who should you contact if you have questions about the study?

Prior, during or after your participation, you can contact the researcher Dr. Jonathan Dingwell at 512-232-1782 or send an email to jdingwell@austin.utexas.edu. This study has been reviewed and approved by The University Institutional Review Board and the study number is *2012-11-0076*.

Who should you contact if you have questions concerning your rights as a research participant?

For questions about your rights or any dissatisfaction with any part of this study, you can contact, anonymously if you wish, the Institutional Review Board by phone at (512) 471-8871 or email at orsc@uts.cc.utexas.edu.

Participation:

If you agree to participate, sign and return the form to the investigator. You will receive a copy of this form.

Signatures:

You have been informed about this study's purpose, procedures, possible benefits and risks, and you have received a copy of this form. You have been given the opportunity to ask questions before you sign, and you have been told that you can ask other questions at any time. You voluntarily agree to participate in this study. By signing this form, you are not waiving any of your legal rights.

_____ I agree to be photographed and/or audio and/or video recorded.
_____ I do not want to be photographed and/or audio and/or video recorded.

_____
Printed Name of Participant

_____ _____
Signature of Participant Date

As a representative of this study, I have explained the purpose, procedures, benefits, and the risks involved in this research study.

_____
Printed Name of Person Obtaining Consent

_____ _____
Signature of Person Obtaining Consent Date

IRB USE ONLY
Study Number: 2012-11-0076
Approval Date:
Expires:

Subject ID: _____

Informed Consent to Participate in Research
The University of Texas at Austin

Title: Determining how Humans Regulate Variability during Walking and Running – Experiment #3

Investigator(s):

Jonathan B. Dingwell, Ph.D. – *Principle Investigator*
Department of Kinesiology & Health Education
University of Texas at Austin
Bellmont Hall, Rm. 536
2109 San Jacinto Blvd, Stop D3700
Austin, TX 78712-1415
Phone: (512) 232-1782
E-Mail: jdingwell@austin.utexas.edu

Nicole Bohnsack, M.S.
Department of Kinesiology & Health Education
University of Texas at Austin
Bellmont Hall, Rm. 530
2109 San Jacinto Blvd, Stop D3700
Austin, TX 78712-1415
Phone: (512) 471-4017
E-Mail: nicolebohnsack@austin.utexas.edu

Introduction:

The purpose of this form is to provide you information that may affect your decision as to whether or not to participate in this research study. The person performing the research will answer any of your questions. Read the information below and ask any questions you might have before deciding whether or not to take part. If you decide to be involved in this study, this form will be used to record your consent.

Purpose of this Study:

You have been asked to participate in a research study about the variability of movements during walking. Human walking is naturally variable. For the elderly and/or other patients who have difficulty walking, this variability may indicate that they are more likely to fall. The purpose of this study is to determine how healthy humans regulate variations in their movements as they walk on a treadmill. We hope the results we obtain will help us better understand how the nervous system regulates movements during walking and will help us develop more effective interventions and treatments to help with people with walking impairments.

Subjects participating in this study will consist of approximately 20 healthy volunteers between the ages of 18 and 35. These will be subjects who have no history of physical or neurological problems that might affect their ability to walk on a treadmill.

What will you be asked to do?

You will be asked to complete the following procedures during a single visit:

- You will be asked to report to the Nonlinear Biodynamics Laboratory at the University of Texas at Austin, located in Bellmont Hall, Room 530. Wear comfortable shorts and shoes appropriate for extensive walking. Bring a sleeveless shirt, preferably a tank top. Gentlemen may be asked to perform shirtless.
- Before being admitted to the study, you will be screened for your suitability to participate by completing a brief Health History Questionnaire. You will also be asked about your typical weekly exercise habits.
- If you qualify to participate in the study, we will measure your height and weight, as well as the lengths of various individual body segments, including thigh, lower leg, and foot lengths, hip width, etc. These measurements do not hurt or feel uncomfortable.

- To become acclimated to the motorized treadmill, you will be asked to walk for at least 15-minutes at a range of speeds, including speeds slightly faster and slower than your comfortable walking speed. We will use these trials to determine your own personal "preferred" walking speed.
- Next, you will be asked to wear a number of small reflective markers attached to various points on your body to measure your movements. These markers will be attached with double-sided tape.
- You will then be asked to complete a series of 15-30 walking trials. Each trial will last 6 minutes. For each trial, the treadmill speed will be set to a moderate comfortable speed.
- During some trials, you will be asked to alter your normal stride to vary the length and/or timing of your steps in different ways. The magnitudes of these variations will be small enough that you can continue walking comfortably.
- You will be allowed at least 2 minutes, or as much time as you need, to rest between trials.
- You can stop the warm-up or any of the trials at any point and for any reason.
- Participation will involve a single experimental sessions, lasting approximately 2½ hours in duration.

What are the risks involved in this study?

The above procedures are not expected to be painful or uncomfortable in a healthy individual. If you do find any of the procedures to be prohibitively uncomfortable, you should immediately tell the investigator and they will be discontinued. None of the devices being used in this study are invasive.

- As during any moderate exercise, there is a risk of heart attack or stroke. This risk will be minimized by asking you to complete the Health History Questionnaire to ensure that you are physically active and that you do not have any illnesses or injuries, or are taking any medications that might indicate that you would be at undue risk of experiencing a heart attack or stroke.
- As during any moderate exercise, there is a risk that you could experience a muscular injury, such as a muscle strain. Also, it is possible that muscle soreness may develop 24 to 48 hours after testing. To help reduce these risks, a warm-up and stretching session will be mandatory prior to performing these tests, and you will be allowed as much time as you need to rest between trials to minimize the effects of fatigue.
- During the walking trials, there is a possible risk of injury from stepping up onto or down off of the treadmill that is elevated approximately 12 inches above the floor. There is also a risk that you could trip or fall while walking. To reduce these risks, you will be asked to wear a safety harness that will catch you in the event of a fall while not constricting your movements.
- Additionally, the treadmill that will be used is equipped with an emergency "STOP" button that the investigator conducting the experiment will control. In the event of any unwanted event, the investigator will press this button to stop the treadmill immediately.
- During the walking trials, there is a risk that you may become overexerted and/or tired. To reduce this risk, you will not be asked to perform any tasks that are beyond the scope of what you might do during your normal daily activities or during moderate exercise. Additionally, you will be allowed to rest as long as you need between trials, and you may stop at any time if you feel the need.
- Some slight discomfort may also be experienced during removal of the reflective markers, similar to removing a band-aid. If you experience skin irritation, this should subside on its own by the following day.
- There may also be additional risks that are unknown at this time. If you wish to discuss the information above or any other risks you may experience, you may ask questions now or contact the Principal Investigators listed on the front page of this form at any time.

What are the possible benefits of this study?

There are no direct benefits to you by participating in this study.

This study is part of a series of experiments we are conducting to investigate how humans control the variability in their movements during walking. We hope these studies will contribute to a better understanding of the neural and/or muscular control mechanisms humans use to regulate human locomotion.

Do you have to participate?

No, your participation is voluntary. You may decide not to participate at all or, if you start the study, you may withdraw at any time. Withdrawal or refusing to participate will not affect your relationship with The University of Texas at Austin (University) in anyway.

If you agree to participate, sign and return the form to the investigator. You will receive a copy of this form.

What are the alternatives to participating in this research?

Your participation in this study is entirely voluntary. You are free to refuse to be in the study, and your refusal will not influence current or future relationships with The University of Texas at Austin.

Will there be any compensation?

You will be compensated for your time in the amount of $25 for completing this experiment. If you anticipate that payments for *all* research and survey compensation received from UT Austin to collectively total $450.00 or more for the calendar year, you will also be asked to provide your social security number.

Disclosure of your social security number (SSN) is requested from you in order for The University of Texas at Austin to process compensation for research activities and to pay you if the total compensation from UT Austin amounts to $450 or more. No statute or other authority requires that you disclose your SSN for that purpose. Failure to provide your SSN, however, may result in no payment or compensation for participation beyond $449 for that fiscal year. Further disclosure of your SSN is governed by the Public Information Act (Chapter 552 of the Texas Government Code) and other applicable law.

What if you are injured because of the study?

By participating in this study, there is a small chance of being injured, as discussed above. If you are injured, the University has no program or plan to provide treatment for research-related injury or payment in the event of a medical problem. The University also has no program or plan for continuing medical care and/or hospitalization for research-related injuries or for financial compensation. In the event of a research-related injury, please contact the principal investigator. Eligible University of Texas at Austin students may be treated at the usual level of care with the usual cost for services at the Student Health Center, but no payment can be provided in the event of a medical problem.

What are my confidentiality or privacy protections when participating in this research study?

Each subject will be assigned a unique *Subject ID* code, which will *only* be identified with their name on the Subject Contact Information Form. The Health History Questionnaire will not contain any personally identifying information. If a potential subject is found to be ineligible to participate because they fail to meet inclusion criteria, all of their screening data and any other identifiable information will be destroyed. These two forms and this Informed Consent Form will be stored in a locked file cabinet inside a locked office. In all other cases, electronic data will only be identifiable by your unique *Subject ID* code. Only the director of the project (Dr. Dingwell) will have access to a master list that will link your identity to your code. The electronic data will be stored on DVD media and also kept in a locked file cabinet in Dr. Dingwell's office. These data will only contain fully de-identified, non-sensitive information and will be maintained indefinitely.

The records of this study will be stored securely and kept confidential. Authorized persons from The University of Texas at Austin and members of the University of Texas Institutional Review Board, have the legal right to review your research records and will protect the confidentiality of those records to the extent permitted by law. Throughout the study, the researchers will notify you of new information that may become available and that might affect your decision to remain in the study.

If in the unlikely event it becomes necessary for the Institutional Review Board to review your research records, then the University of Texas at Austin will protect the confidentiality of those records to the extent permitted by law. Your research records will not be released without your consent unless required by law or a court order. The data resulting from your participation may be made available to other researchers in the future for research purposes not detailed within this consent form. In these cases, the data will contain no identifying information that could associate you with it, or with your participation in any study. If the results of this research are published or presented at scientific meetings, your identity will not be disclosed.

Who should you contact if you have questions about the study?

Prior, during or after your participation, you can contact the researcher Dr. Jonathan Dingwell at 512-232-1782 or send an email to jdingwell@austin.utexas.edu. This study has been reviewed and approved by The University Institutional Review Board and the study number is *2012-11-0076*.

Who should you contact if you have questions concerning your rights as a research participant?

For questions about your rights or any dissatisfaction with any part of this study, you can contact, anonymously if you wish, the Institutional Review Board by phone at (512) 471-8871 or email at orsc@uts.cc.utexas.edu.

Participation:

If you agree to participate, sign and return the form to the investigator. You will receive a copy of this form.

Signatures:

You have been informed about this study's purpose, procedures, possible benefits and risks, and you have received a copy of this form. You have been given the opportunity to ask questions before you sign, and you have been told that you can ask other questions at any time. You voluntarily agree to participate in this study. By signing this form, you are not waiving any of your legal rights.

_____ I agree to be photographed and/or audio and/or video recorded.
_____ I do not want to be photographed and/or audio and/or video recorded.

_____
Printed Name of Participant

_____ _____
Signature of Participant Date

As a representative of this study, I have explained the purpose, procedures, benefits, and the risks involved in this research study.

_____
Printed Name of Person Obtaining Consent

_____ _____
Signature of Person Obtaining Consent Date

HEALTH HISTORY QUESTIONNAIRE

"Determining how Humans Regulate Variability during Walking and Running"

IRB # 2012-11-0076 ***Subject ID:*** _____

Date of Birth (mm/dd/yy): _____ Age: _____

MALE: _____ FEMALE: _____

Height: _____ ft./in. = _____ in.

Weight: _____ lbs.

1. Are you taking any medications on a regular basis? Y / N

2. Any over- the -counter meds? Y / N
   If yes, explain:

3. Do you have any disability or impairment that affects you when you walk? Y / N

4. Have you had any broken bones, surgery, or injury to lower extremities? Y / N
   If yes, explain:

5. Do you have arthritis? Does it cause pain or discomfort when you stand or walk? Y / N

6.	Have you had any significant medical problems within the last 10 years? If yes, explain:	Y / N
7.	Do you have a history of neurological diseases likely to affect your ability to stand or walk, including CVA (stroke), disc disease, peripheral neuropathy, or lower extremity weakness?	Y / N
8.	Do you have any history of back problems, such as low back pain? If yes, explain.	Y / N
9.	Do you have any problems with standing balance?	Y / N
10.	Do you have any drug and/or alcohol dependence?	Y / N
11.	Do you have any significant visual impairments? Examples: loss of binocular vision or the presence of double vision	Y / N
12.	Do you have any heart problems or coronary artery disease?	Y / N
13.	Do you have hypertension?	Y / N
14.	Do you have any lung or respiratory problems?	Y / N

15. Do you smoke? Y / N
Pattern?

16. Do you use alcohol? Y / N
Pattern?

17. Do you use caffeine (cola, coffee, etc.)? Y / N
Pattern?

18. Do you have any allergies that require medication? Y / N
If yes, explain.

19. Have you fallen during the past year? Y / N
If yes, explain how the fall occurred and what injuries (if any) resulted.

Please complete Physical Activity Information on the following pages…

HEALTH HISTORY QUESTIONNAIRE

"Determining how Humans Regulate Variability during Walking and Running"

IRB # 2012-11-0076 ***Subject ID: _____***

Please fill out the following three sections: **Work, Sport, and Leisure**

For each question, please circle the most appropriate answer.

Work Section:

Question	**Response**	**Points**
What is your main occupation?	low activity	1
	moderate activity	3
	high activity	5
At work I sit	never	1
	seldom	2
	sometimes	3
	often	4
	always	5
At work I stand	never	1
	seldom	2
	sometimes	3
	often	4
	always	5
At work I walk	never	1
	seldom	2
	sometimes	3
	often	4
	always	5

Work Section Continued:

Question	Response	Points
At work I lift heavy loads	never	1
	seldom	2
	sometimes	3
	often	4
	always	5
After working I am tired	very often	5
	often	4
	sometimes	3
	seldom	2
	never	1
At work I sweat	very often	5
	often	4
	sometimes	3
	seldom	2
	never	1
In comparison of others of my own age I think my work is physically	much heavier	5
	heavier	4
	as heavy	3
	lighter	2
	much lighter	1

Sport Section:

Question	Response	Points
Do you play sports?	Yes then continue to Sport Part I.	-
	No then continue on to "Leisure Section"	-

Sport Part I.

Question	Response	Points
In comparison with others of my own age I think my physical activity during leisure time is	much more	5
	More	4
	the same	3
	Less	2
	much less	1
During leisure time I sweat	very often	5
	Often	4
	sometimes	3
	Seldom	2
	Never	1
During leisure time I play sport	Never	1
	Seldom	2
	sometimes	3
	Often	4
	very often	5

Sport Part II.

Question	Response	Points
What sport do you play most frequently	low intensity	0.76
	medium intensity	1.26
	high intensity	1.76
How many hours do you play a week?	< 1 hour	0.5
	1-2 hours	1.5
	2-3 hours	2.5
	3-4 hours	3.5
	> 4 hours	4.5
How many months do you play in a year?	< 1 month	0.04
	1-3 months	0.17
	4-6 months	0.42
	7-9 months	0.67
	> 9 months	0.92

Running.

Question	Response
Do you run regularly?	Y / N
How many *times* per week do you typically run?	_____
How many *miles* long is your typical run?	_____
How many *miles* do you run per week?	

Leisure Section:

Question	Response	Points
During leisure time I watch television	never	1
	seldom	2
	sometimes	3
	often	4
	very often	5
During leisure time I walk	never	1
	seldom	2
	sometimes	3
	often	4
	very often	5
During leisure time I cycle	never	1
	seldom	2
	sometimes	3
	often	4
	very often	5
How many minutes do you walk and/or cycle per day to and from work school and shopping?	< 5 minutes	1
	5-15 minutes	2
	15-30 minutes	3
	30-45 minutes	4
	> 45 minutes	5

Final Total Score: _____
(To be completed by researcher)

For the Researcher *ONLY*: This is NOT to be filled out the study participant !

Exclusion Criteria by Question

1. 1- Are you taking any medications on a regular basis?
   (Exclusions include: Psychotropics, Antihistamines, Asthma Meds, Aldomet, Clonidine, Anti-Depressants, Anti-Anxiety Meds)

3. Do you have any disability or impairment that affects you when you walk?
   (If yes, excludes.)

5. Do you have arthritis? Does it cause pain or discomfort when you stand or walk?
   If yes to discomfort, excludes.

7. Do you have a history of neurological diseases likely to affect your ability to stand or walk, including CVA (stroke), disc disease, peripheral neuropathy, or lower extremity weakness?
   If yes, excludes.

9. Do you have any problems with standing balance?
   If yes, excludes.

10. Do you have any drug and/or alcohol dependence?
    If yes, excludes.

11. Do you have any significant visual impairments?
    Examples: loss of binocular vision or the presence of double vision
    If yes, excludes.

12. Do you have any heart problems or coronary artery disease?
    If yes, excludes.

13. Do you have hypertension?
    If yes, excludes.

14. Do you have any lung or respiratory problems?
    If yes, excludes.

Researcher Calculations:

Height:_____ ft./in. = _____ in. × 0.0254 = _____ m

Weight: _____ lbs. × 0.4567 = _____ kg.

BMI (kg/m^2): _____ (BMI > 35 excludes)

Appendix 2: Statistical Procedures and Results

Aim 1:

Tests of Between-Subjects Effects

Dependent Variable: MeanSL

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.306[a]	55	.006	112.751	.000
Intercept	190.412	1	190.412	3865066.708	.000
Cond	.003	3	.001	20.733	.000
Subj	.176	13	.014	275.495	.000
Cond * Subj	.124	39	.003	64.682	.000
Error	.003	55	4.926E-005		
Total	192.451	111			
Corrected Total	.308	110			

a. R Squared = .991 (Adjusted R Squared = .982)

Multiple Comparisons

Dependent Variable: MeanSL

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.006617527558860*	.001875879636290	.005	.001647659091630	.011587396026090
	3-TIM	.014754186473264*	.001875879636290	.000	.009784318006034	.019724054940494
	4-ALL	.006826815746738*	.001893169215019	.004	.001811141071863	.011842490421613
2-LEN	1-SPD	-.006617527558860*	.001875879636290	.005	-.011587396026090	-.001647659091630
	3-TIM	.008136658914504*	.001875879636290	.000	.003166790447274	.013106527381734
	4-ALL	.000209288187978	.001893169215019	1.000	-.004806386487097	.005224962862854
3-TIM	1-SPD	-.014754186473264*	.001875879636290	.000	-.019724054940494	-.009784318006034
	2-LEN	-.008136658914504*	.001875879636290	.000	-.013106527381734	-.003166790447274
	4-ALL	-.007927370726626*	.001893169215019	.001	-.012943045401501	-.002911696051751
4-ALL	1-SPD	-.006826815746738*	.001893169215019	.004	-.011842490421613	-.001811141071863
	2-LEN	-.000209288187978	.001893169215019	1.000	-.005224962862854	.004806386487097
	3-TIM	.007927370726626*	.001893169215019	.001	.002911696051751	.012943045401501

Based on observed means.
The error term is Mean Square(Error) = 4.93E-005.
*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: MeanST

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.109[a]	55	.002	54.425	.000
Intercept	133.454	1	133.454	3656916.337	.000
Cond	.002	3	.001	18.168	.000
Subj	.022	13	.002	46.276	.000
Cond * Subj	.085	39	.002	59.946	.000
Error	.002	55	3.649E-005		
Total	134.707	111			
Corrected Total	.111	110			

a. R Squared = .982 (Adjusted R Squared = .964)

Multiple Comparisons

Dependent Variable: MeanST

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.003751746031846	.001614520777069	.105	-.000525690401026	.008029182464517
	3-TIM	.011645873015973*	.001614520777069	.000	.007368436583301	.015923309448644
	4-ALL	.004872361846073*	.001629401467463	.021	.000555501202737	.009189222489409
2-LEN	1-SPD	-.003751746031846	.001614520777069	.105	-.008029182464517	.000525690401026
	3-TIM	.007894126984227*	.001614520777069	.000	.003616690551555	.012171563416899
	4-ALL	.001120615814328	.001629401467463	.901	-.003196244829208	.005437476457664
3-TIM	1-SPD	-.011645873015973*	.001614520777069	.000	-.015923309448644	-.007368436583301
	2-LEN	-.007894126984227*	.001614520777069	.000	-.012171563416899	-.003616690551555
	4-ALL	-.006773511169999*	.001629401467463	.001	-.011090371813335	-.002456650526663
4-ALL	1-SPD	-.004872361846073*	.001629401467463	.021	-.009189222489409	-.000555501202737
	2-LEN	-.001120615814328	.001629401467463	.901	-.005437476457664	.003196244829208
	3-TIM	.006773511169999*	.001629401467463	.001	.002456650526663	.011090371813335

Based on observed means.
The error term is Mean Square(Error) = 3.65E-005.
*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: MeanSS

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.163[a]	55	.003	4516.550	.000
Intercept	157.123	1	157.123	239853627.718	.000
Cond	1.481E-006	3	4.937E-007	.754	.525
Subj	.162	13	.012	19018.673	.000
Cond * Subj	3.850E-005	39	9.872E-007	1.507	.080
Error	3.603E-005	55	6.551E-007		
Total	158.744	111			
Corrected Total	.163	110			

a. R Squared = 1.000 (Adjusted R Squared = 1.000)

Multiple Comparisons

Dependent Variable: MeanSS

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	-.000013776511678	.000216313275781	1.000	-.000586866867322	.000559313844167
	3-TIM	.000086955947219	.000216313275781	.978	-.000486134408626	.000660046302863
	4-ALL	-.000945116416232*	.000218306988671	.000	-.001523488822297	-.000366744010166
2-LEN	1-SPD	.000013776511678	.000216313275781	1.000	-.000559313844167	.000586866867322
	3-TIM	.000100732458797	.000216313275781	.966	-.000472357897048	.000673822814441
	4-ALL	-.000931339904654*	.000218306988671	.000	-.001509712310719	-.000352967498588
3-TIM	1-SPD	-.000086955947219	.000216313275781	.978	-.000660046302863	.000486134408626
	2-LEN	-.000100732458797	.000216313275781	.966	-.000673822814441	.000472357897048
	4-ALL	-.001032072363351*	.000218306988671	.000	-.001610444769416	-.000453699957285
4-ALL	1-SPD	.000945116416232*	.000218306988671	.000	.000366744010166	.001523488822297
	2-LEN	.000931339904654*	.000218306988671	.000	.000352967498588	.001509712310719
	3-TIM	.001032072363351*	.000218306988671	.000	.000453699957285	.001610444769416

Based on observed means.
The error term is Mean Square(Error) = 6.55E-007.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: SDSL

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.017[a]	55	.000	10.089	.000
Intercept	.094	1	.094	2993.846	.000
Cond	.007	3	.002	74.229	.000
Subj	.004	13	.000	10.974	.000
Cond * Subj	.006	39	.000	5.106	.000
Error	.002	55	3.139E-005		
Total	.112	111			
Corrected Total	.019	110			

a. R Squared = .910 (Adjusted R Squared = .820)

Multiple Comparisons

Dependent Variable: SDSL

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	-.007895126134303*	.001497465354083	.000	-.011862441360692	-.003927810907914
	3-TIM	-.003976255639130*	.001497465354083	.049	-.007943570865519	-.000008940412742
	4-ALL	-.020832976704761*	.001511267169845	.000	-.024836857821425	-.016829095588097
2-LEN	1-SPD	.007895126134303*	.001497465354083	.000	.003927810907914	.011862441360692
	3-TIM	.003918870495272	.001497465354083	.054	-.000048444731316	.007886185721661
	4-ALL	-.012937850570558*	.001511267169845	.000	-.016941731687222	-.008933969453894
3-TIM	1-SPD	.003976255639130*	.001497465354083	.049	.000008940412742	.007943570865519
	2-LEN	-.003918870495272	.001497465354083	.054	-.007886185721661	.000048444731316
	4-ALL	-.016856721065730*	.001511267169845	.000	-.020860602182395	-.012852839949066
4-ALL	1-SPD	.020832976704761*	.001511267169845	.000	.016829095588097	.024836857821425
	2-LEN	.012937850570558*	.001511267169845	.000	.008933969453894	.016941731687222
	3-TIM	.016856721065730*	.001511267169845	.000	.012852839949066	.020860602182395

Based on observed means.

The error term is Mean Square(Error) = 3.14E-005.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: SDST

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.011[a]	55	.000	8.582	.000
Intercept	.056	1	.056	2511.530	.000
Cond	.007	3	.002	96.917	.000
Subj	.002	13	.000	5.954	.000
Cond * Subj	.003	39	7.108E-005	3.172	.000
Error	.001	55	2.241E-005		
Total	.067	111			
Corrected Total	.012	110			

a. R Squared = .896 (Adjusted R Squared = .791)

Multiple Comparisons

Dependent Variable: SDST
Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	-.010557332384270*	.001265264007663	.000	-.013909464137605	-.007205200630935
	3-TIM	-.002165098927129	.001265264007663	.328	-.005517230680464	.001187032826407
	4-ALL	-.018975540705289*	.001276925673608	.000	-.022358568335278	-.015592513075300
2-LEN	1-SPD	.010557332384270*	.001265264007663	.000	.007205200630935	.013909464137605
	3-TIM	.008392233457241*	.001265264007663	.000	.005040101703906	.011744365210577
	4-ALL	-.008418208321120*	.001276925673608	.000	-.011801235951109	-.005035180691131
3-TIM	1-SPD	.002165098927129	.001265264007663	.328	-.001187032826407	.005517230680464
	2-LEN	-.008392233457241*	.001265264007663	.000	-.011744365210577	-.005040101703906
	4-ALL	-.016810441778261*	.001276925673608	.000	-.020193469408250	-.013427414148272
4-ALL	1-SPD	.018975540705289*	.001276925673608	.000	.015592513075300	.022358568335278
	2-LEN	.008418208321120*	.001276925673608	.000	.005035180691131	.011801235951109
	3-TIM	.016810441778261*	.001276925673608	.000	.013427414148272	.020193469408250

Based on observed means.
The error term is Mean Square(Error) = 2.24E-005.
*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects
Dependent Variable: SDSS

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.013[a]	55	.000	10.378	.000
Intercept	.083	1	.083	3627.602	.000
Cond	.007	3	.002	104.685	.000
Subj	.003	13	.000	10.539	.000
Cond * Subj	.003	39	8.183E-005	3.560	.000
Error	.001	55	2.299E-005		
Total	.097	111			
Corrected Total	.014	110			

a. R Squared = .912 (Adjusted R Squared = .824)

Multiple Comparisons

Dependent Variable: SDSS

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	-.008033858779004*	.001281395541457	.000	-.011428728669468	-.004638988888540
	3-TIM	-.000110719002062	.001281395541457	1.000	-.003505588892526	.003284150888602
	4-ALL	-.019391710139642*	.001293205888276	.000	-.022817869814968	-.015965550464316
2-LEN	1-SPD	.008033858779004*	.001281395541457	.000	.004638988888540	.011428728669468
	3-TIM	.007923139777043*	.001281395541457	.000	.004528269886579	.011318009667507
	4-ALL	-.011357851360738*	.001293205888276	.000	-.014784011036064	-.007931691685411
3-TIM	1-SPD	.000110719002062	.001281395541457	1.000	-.003284150888602	.003505588892526
	2-LEN	-.007923139777043*	.001281395541457	.000	-.011318009667507	-.004528269886579
	4-ALL	-.019280991137680*	.001293205888276	.000	-.022707150813006	-.015854831462354
4-ALL	1-SPD	.019391710139642*	.001293205888276	.000	.015965550464316	.022817869814968
	2-LEN	.011357851360738*	.001293205888276	.000	.007931691685411	.014784011036064
	3-TIM	.019280991137680*	.001293205888276	.000	.015854831462354	.022707150813006

Based on observed means.

The error term is Mean Square(Error) = 2.30E-005.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: AlphaSL

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	4.891[a]	55	.089	5.917	.000
Intercept	22.636	1	22.636	1506.155	.000
Cond	3.128	3	1.043	69.372	.000
Subj	.477	13	.037	2.440	.011
Cond * Subj	1.236	39	.032	2.110	.005
Error	.827	55	.015		
Total	28.474	111			
Corrected Total	5.718	110			

a. R Squared = .855 (Adjusted R Squared = .711)

Multiple Comparisons

Dependent Variable: AlphaSL

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.423907127009192*	.032764495631752	.000	.337102392556647	.510711861461738
	3-TIM	.143215587553765*	.032764495631752	.000	.056410853101220	.230020322006311
	4-ALL	.358890155103515*	.033066478933766	.000	.271285360102652	.446494950104377
2-LEN	1-SPD	-.423907127009192*	.032764495631752	.000	-.510711861461738	-.337102392556647
	3-TIM	-.280691539455527*	.032764495631752	.000	-.367496273908072	-.193886805002981
	4-ALL	-.065016971905778	.033066478933766	.213	-.152621766906640	.022587823095285
3-TIM	1-SPD	-.143215587553765*	.032764495631752	.000	-.230020322006311	-.056410853101220
	2-LEN	.280691539455527*	.032764495631752	.000	.193886805002981	.367496273908072
	4-ALL	.215674567549849*	.033066478933766	.000	.128069772548986	.303279362550712
4-ALL	1-SPD	-.358890155103515*	.033066478933766	.000	-.446494950104377	-.271285360102652
	2-LEN	.065016971905778	.033066478933766	.213	-.022587823095285	.152621766906640
	3-TIM	-.215674567549849*	.033066478933766	.000	-.303279362550712	-.128069772548986

Based on observed means.

The error term is Mean Square(Error) = .015.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: AlphaST

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	2.783[a]	55	.051	2.652	.000
Intercept	35.844	1	35.844	1878.209	.000
Cond	.900	3	.300	15.717	.000
Subj	.594	13	.046	2.395	.012
Cond * Subj	1.292	39	.033	1.736	.030
Error	1.050	55	.019		
Total	39.850	111			
Corrected Total	3.833	110			

a. R Squared = .726 (Adjusted R Squared = .452)

Multiple Comparisons

Dependent Variable: AlphaST

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.189830920327200*	.036920824474422	.000	.092013772798236	.287646411267203
	3-TIM	.240216563798934*	.036920824474422	.000	.142400244564450	.338032883033417
	4-ALL	.155952477012117*	.037261115764517	.001	.057234605823184	.254670348201049
2-LEN	1-SPD	-.189830920327200*	.036920824474422	.000	-.287646411267203	-.092013772798236
	3-TIM	.050386471766314	.036920824474422	.527	-.047429847468370	.148202791000798
	4-ALL	-.033877615020703	.037261115764517	.800	-.132595486209635	.064840256168430
3-TIM	1-SPD	-.240216563798934*	.036920824474422	.000	-.338032883033417	-.142400244564450
	2-LEN	-.050386471766314	.036920824474422	.527	-.148202791000798	.047429847468370
	4-ALL	-.084264086786917	.037261115764517	.120	-.182981957975850	.014453784402215
4-ALL	1-SPD	-.155952477012117*	.037261115764517	.001	-.254670348201049	-.057234605823184
	2-LEN	.033877615020703	.037261115764517	.800	-.064840256168430	.132595486209635
	3-TIM	.084264086786917	.037261115764517	.120	-.014453784402215	.182981957975850

Based on observed means.

The error term is Mean Square(Error) = .019.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: AlphaSS

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.230[a]	55	.022	1.905	.009
Intercept	23.084	1	23.084	1965.446	.000
Cond	.051	3	.017	1.439	.241
Subj	.521	13	.040	3.413	.001
Cond * Subj	.665	39	.017	1.453	.100
Error	.646	55	.012		
Total	25.027	111			
Corrected Total	1.876	110			

a. R Squared = .656 (Adjusted R Squared = .311)

Multiple Comparisons

Dependent Variable: AlphaSS

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.043780724486332	.028964138015897	.438	-.032955518835718	.120516967808183
	3-TIM	.052853120618230	.028964138015897	.273	-.023883122703820	.129589363940080
	4-ALL	.019942167818219	.029231094239986	.903	-.057501336937151	.097385672573390
2-LEN	1-SPD	-.043780724486332	.028964138015897	.438	-.120516967808183	.032955518835718
	3-TIM	.009072396131997	.028964138015897	.989	-.067663847190053	.085808639453848
	4-ALL	-.023838556668213	.029231094239986	.847	-.101282061423383	.053604948087157
3-TIM	1-SPD	-.052853120618230	.028964138015897	.273	-.129589363940080	.023883122703820
	2-LEN	-.009072396131997	.028964138015897	.989	-.085808639453848	.067663847190053
	4-ALL	-.032910952800110	.029231094239986	.675	-.110354457555281	.044532551955260
4-ALL	1-SPD	-.019942167818219	.029231094239986	.903	-.097385672573390	.057501336937151
	2-LEN	.023838556668213	.029231094239986	.847	-.053604948087157	.101282061423383
	3-TIM	.032910952800110	.029231094239986	.675	-.044532551955260	.110354457555281

Based on observed means.
The error term is Mean Square(Error) = .012.

Tests of Between-Subjects Effects

Dependent Variable: SDDPn

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.452[a]	55	.026	3.862	.000
Intercept	65.000	1	65.000	9505.953	.000
Cond	.152	3	.051	7.387	.000
Subj	.521	13	.040	5.865	.000
Cond * Subj	.777	39	.020	2.915	.000
Error	.376	55	.007		
Total	67.335	111			
Corrected Total	1.828	110			

a. R Squared = .794 (Adjusted R Squared = .589)

Multiple Comparisons

Dependent Variable: SDDPn

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.070169739666266*	.022100191686800	.013	.011618517261332	.128720962071200
	3-TIM	.097131879120531*	.022100191686800	.000	.038580656715597	.155683101525465
	4-ALL	.081155587977457*	.022303884395387	.003	.022064711561743	.140246464393170
2-LEN	1-SPD	-.070169739666266*	.022100191686800	.013	-.128720962071200	-.011618517261332
	3-TIM	-.026962139454365	.022100191686800	.617	-.085513361859299	.031589082950770
	4-ALL	.010985848311290	.022303884395387	.960	-.048105028104623	.070076724727004
3-TIM	1-SPD	-.097131879120531*	.022100191686800	.000	-.155683101525465	-.038580656715597
	2-LEN	.026962139454365	.022100191686800	.617	-.031589082950770	.085513361859299
	4-ALL	-.015976291143174	.022303884395387	.890	-.075067167558888	.043114585272739
4-ALL	1-SPD	-.081155587977457*	.022303884395387	.003	-.140246464393170	-.022064711561743
	2-LEN	-.010985848311290	.022303884395387	.960	-.070076724727004	.048105028104623
	3-TIM	.015976291143174	.022303884395387	.890	-.043114585272739	.075067167558888

Based on observed means.

The error term is Mean Square(Error) = .007.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: SDDTn

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.650[a]	55	.012	3.873	.000
Intercept	152.468	1	152.468	49991.939	.000
Cond	.069	3	.023	7.490	.000
Subj	.235	13	.018	5.932	.000
Cond * Subj	.345	39	.009	2.901	.000
Error	.168	55	.003		
Total	154.665	111			
Corrected Total	.817	110			

a. R Squared = .795 (Adjusted R Squared = .590)

Multiple Comparisons

Dependent Variable: SDDTn

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	-.050626734039671*	.014759638851706	.006	-.089730236365262	-.011523231714081
	3-TIM	-.061603136584200*	.014759638851706	.001	-.100706638909790	-.022499634258609
	4-ALL	-.058744570428960*	.014895675265239	.001	-.098208481316469	-.019280659541451
2-LEN	1-SPD	.050626734039671*	.014759638851706	.006	.011523231714081	.089730236365262
	3-TIM	-.010976402544628	.014759638851706	.879	-.050079904870219	.028127099781162
	4-ALL	-.008117836389389	.014895675265239	.948	-.047581747276898	.031346074498320
3-TIM	1-SPD	.061603136584200*	.014759638851706	.001	.022499634258609	.100706638909790
	2-LEN	.010976402544628	.014759638851706	.879	-.028127099781162	.050079904870219
	4-ALL	.002858566155340	.014895675265239	.997	-.036605344732369	.042322477042848
4-ALL	1-SPD	.058744570428960*	.014895675265239	.001	.019280659541451	.098208481316469
	2-LEN	.008117836389389	.014895675265239	.948	-.031346074498320	.047581747276898
	3-TIM	-.002858566155340	.014895675265239	.997	-.042322477042848	.036605344732369

Based on observed means.

The error term is Mean Square(Error) = .003.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: AlphaDPn

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.215[a]	55	.022	1.913	.009
Intercept	23.081	1	23.081	1998.305	.000
Cond	.050	3	.017	1.435	.243
Subj	.519	13	.040	3.454	.001
Cond * Subj	.654	39	.017	1.452	.100
Error	.635	55	.012		
Total	24.997	111			
Corrected Total	1.850	110			

a. R Squared = .657 (Adjusted R Squared = .313)

Multiple Comparisons

Dependent Variable: AlphaDPn

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.043376170844072	.028722883548190	.438	-.032720904085451	.119473245773395
	3-TIM	.052697338077229	.028722883548190	.268	-.023399736852294	.128794413006552
	4-ALL	.020592813981699	.028987616181792	.893	-.056205631303683	.097391259266882
2-LEN	1-SPD	-.043376170844072	.028722883548190	.438	-.119473245773395	.032720904085451
	3-TIM	.009321167233257	.028722883548190	.988	-.066775907696266	.085418242162580
	4-ALL	-.022783356862473	.028987616181792	.861	-.099581802147656	.054015088422910
3-TIM	1-SPD	-.052697338077229	.028722883548190	.268	-.128794413006552	.023399736852294
	2-LEN	-.009321167233257	.028722883548190	.988	-.085418242162580	.066775907696266
	4-ALL	-.032104524095630	.028987616181792	.686	-.108902969380812	.044693921189753
4-ALL	1-SPD	-.020592813981699	.028987616181792	.893	-.097391259266882	.056205631303683
	2-LEN	.022783356862473	.028987616181792	.861	-.054015088422910	.099581802147656
	3-TIM	.032104524095630	.028987616181792	.686	-.044693921189753	.108902969380812

Based on observed means.

The error term is Mean Square(Error) = .012.

Tests of Between-Subjects Effects

Dependent Variable: AlphaDTn

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	3.963[a]	55	.072	3.880	.000
Intercept	33.659	1	33.659	1812.598	.000
Cond	2.024	3	.675	36.340	.000
Subj	.493	13	.038	2.040	.034
Cond * Subj	1.428	39	.037	1.972	.010
Error	1.021	55	.019		
Total	38.858	111			
Corrected Total	4.984	110			

a. R Squared = .795 (Adjusted R Squared = .590)

Multiple Comparisons

Dependent Variable: AlphaDTn

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound

1-SPD	2-LEN	.356219984429579*	.036419881340779	.000	.259730840689586	.452709128169572
	3-TIM	.243910230782060*	.036419881340779	.000	.147421087042067	.340399374522053
	4-ALL	.296863097009162*	.036755555545865	.000	.199484633605511	.394241560412813
2-LEN	1-SPD	-.356219984429579*	.036419881340779	.000	-.452709128169572	-.259730840689586
	3-TIM	-.112309753647619*	.036419881340779	.016	-.208798897387612	-.015820609907626
	4-ALL	-.059356887420517	.036755555545865	.379	-.156735350824168	.038021575983334
3-TIM	1-SPD	-.243910230782060*	.036419881340779	.000	-.340399374522053	-.147421087042067
	2-LEN	.112309753647619*	.036419881340779	.016	.015820609907626	.208798897387612
	4-ALL	.052952866227202	.036755555545865	.480	-.044425597176649	.150331329630853
4-ALL	1-SPD	-.296863097009162*	.036755555545865	.000	-.394241560412813	-.199484633605511
	2-LEN	.059356887420517	.036755555545865	.379	-.038021575983334	.156735350824168
	3-TIM	-.052952866227202	.036755555545865	.480	-.150331329630853	.044425597176649

Based on observed means.
The error term is Mean Square(Error) = .019.
*. The mean difference is significant at the 0.05 level.

Aim 2:

Tests of Between-Subjects Effects

Dependent Variable: MeanSL

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.105[a]	39	.003	13.829	.000
Intercept	379.263	1	379.263	1939228.358	.000
Cond	.009	3	.003	14.808	.000
Subj	.043	9	.005	24.170	.000
Cond * Subj	.045	27	.002	8.458	.000
Error	.007	36	.000		
Total	396.198	76			
Corrected Total	.113	75			

a. R Squared = .937 (Adjusted R Squared = .870)

Multiple Comparisons

Dependent Variable: MeanSL

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	-.021800466251791*	.004422378706791	.000	-.033710936712296	-.009889995791286
	3-TIM	-.019804495720524*	.004422378706791	.000	-.031714966181029	-.007894025260019
	4-ALL	-.029279451384075*	.004690640958814	.000	-.041912413028693	-.016646489739458
2-LEN	1-SPD	.021800466251791*	.004422378706791	.000	.009889995791286	.033710936712296
	3-TIM	.001995970531366	.004422378706791	.969	-.009914499929339	.013906440991871
	4-ALL	-.007478985132385	.004690640958814	.394	-.020111946777002	.005153976512433
3-TIM	1-SPD	.019804495720524*	.004422378706791	.000	.007894025260019	.031714966181029
	2-LEN	-.001995970531366	.004422378706791	.969	-.013906440991871	.009914499929339
	4-ALL	-.009474955663651	.004690640958814	.200	-.022107917308269	.003158005981167
4-ALL	1-SPD	.029279451384075*	.004690640958814	.000	.016646489739458	.041912413028693
	2-LEN	.007478985132385	.004690640958814	.394	-.005153976512433	.020111946777002
	3-TIM	.009474955663651	.004690640958814	.200	-.003158005981167	.022107917308269

Based on observed means.

The error term is Mean Square(Error) = .000.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: MeanST

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.010[a]	39	.000	13.903	.000
Intercept	36.567	1	36.567	1938432.138	.000
Cond	.001	3	.000	15.325	.000
Subj	.004	9	.000	24.417	.000
Cond * Subj	.004	27	.000	8.415	.000
Error	.001	36	1.886E-005		
Total	38.200	76			
Corrected Total	.011	75			

a. R Squared = .938 (Adjusted R Squared = .870)

Multiple Comparisons

Dependent Variable: MeanST

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	-.006897277777877*	.001373472029909	.000	-.010596349956978	-.003198205598777
	3-TIM	-.006227888888989*	.001373472029909	.000	-.009926961068089	-.002528816709888
	4-ALL	-.009266833333433*	.001456787079172	.000	-.013190291866344	-.005343374800523
2-LEN	1-SPD	.006897277777877*	.001373472029909	.000	.003198205598777	.010596349956978
	3-TIM	.000669388888989	.001373472029909	.961	-.003029683290312	.004368461068089
	4-ALL	-.002369555555656	.001456787079172	.377	-.006293014088566	.001553902977455
3-TIM	1-SPD	.006227888888989*	.001373472029909	.000	.002528816709888	.009926961068089
	2-LEN	-.000669388888989	.001373472029909	.961	-.004368461068089	.003029683290312
	4-ALL	-.003038944444545	.001456787079172	.177	-.006962402977455	.000884514088566
4-ALL	1-SPD	.009266833333433*	.001456787079172	.000	.005343374800523	.013190291866344
	2-LEN	.002369555555656	.001456787079172	.377	-.001553902977455	.006293014088566
	3-TIM	.003038944444545	.001456787079172	.177	-.000884514088566	.006962402977455

Based on observed means.

The error term is Mean Square(Error) = 1.886E-005.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: MeanSS

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	5.696E-005[a]	39	1.460E-006	1.691	.057
Intercept	754.349	1	754.349	873328778.966	.000
Cond	5.890E-006	3	1.963E-006	2.273	.097
Subj	8.645E-006	9	9.606E-007	1.112	.379
Cond * Subj	4.116E-005	27	1.524E-006	1.765	.056
Error	3.110E-005	36	8.638E-007		
Total	788.297	76			
Corrected Total	8.805E-005	75			

a. R Squared = .647 (Adjusted R Squared = .264)

Multiple Comparisons

Dependent Variable: MeanSS

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.000621696834463	.000293898497191	.168	-.000169838581439	.001413232250165
	3-TIM	.000359109409102	.000293898497191	.617	-.000432426006800	.001150644824804
	4-ALL	.000799116554180	.000311726430511	.067	-.000040433536008	.001638666644168
2-LEN	1-SPD	-.000621696834463	.000293898497191	.168	-.001413232250165	.000169838581439
	3-TIM	-.000262587425461	.000293898497191	.808	-.001054122841163	.000528947990441
	4-ALL	.000177419719817	.000311726430511	.941	-.000662130370371	.001016969809805
3-TIM	1-SPD	-.000359109409102	.000293898497191	.617	-.001150644824804	.000432426006800
	2-LEN	.000262587425461	.000293898497191	.808	-.000528947990441	.001054122841163
	4-ALL	.000440007145178	.000311726430511	.501	-.000399542945011	.001279557235166
4-ALL	1-SPD	-.000799116554180	.000311726430511	.067	-.001638666644168	.000040433536008
	2-LEN	-.000177419719817	.000311726430511	.941	-.001016969809805	.000662130370371
	3-TIM	-.000440007145178	.000311726430511	.501	-.001279557235166	.000399542945011

Based on observed means.

The error term is Mean Square(Error) = 8.638E-007.

Tests of Between-Subjects Effects

Dependent Variable: SDSL

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.014[a]	39	.000	11.162	.000
Intercept	.108	1	.108	3456.620	.000
Cond	.002	3	.001	26.170	.000
Subj	.006	9	.001	22.504	.000
Cond * Subj	.004	27	.000	4.944	.000
Error	.001	36	3.131E-005		
Total	.125	76			
Corrected Total	.015	75			

a. R Squared = .924 (Adjusted R Squared = .841)

Multiple Comparisons

Dependent Variable: SDSL

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	-.012141581527803*	.001769526450790	.000	-.016907318231477	-.007375844824130
	3-TIM	-.006056487804213*	.001769526450790	.008	-.010822224507887	-.001290751100540
	4-ALL	-.014519579892592*	.001876866229257	.000	-.019574407003368	-.009464752781816
2-LEN	1-SPD	.012141581527803*	.001769526450790	.000	.007375844824130	.016907318231477
	3-TIM	.006085093723690*	.001769526450790	.008	.001319357020016	.010850830427364
	4-ALL	-.002377998364889	.001876866229257	.589	-.007432825475665	.002676828746087
3-TIM	1-SPD	.006056487804213*	.001769526450790	.008	.001290751100540	.010822224507887
	2-LEN	-.006085093723690*	.001769526450790	.008	-.010850830427364	-.001319357020016
	4-ALL	-.008463092088479*	.001876866229257	.000	-.013517919199254	-.003408264977703
4-ALL	1-SPD	.014519579892592*	.001876866229257	.000	.009464752781816	.019574407003368
	2-LEN	.002377998364889	.001876866229257	.589	-.002676828746087	.007432825475665
	3-TIM	.008463092088479*	.001876866229257	.000	.003408264977703	.013517919199254

Based on observed means.

The error term is Mean Square(Error) = 3.131E-005.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: SDST

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.001[a]	39	2.799E-005	9.019	.000
Intercept	.008	1	.008	2462.041	.000
Cond	.000	3	5.169E-005	16.653	.000
Subj	.000	9	4.467E-005	14.392	.000
Cond * Subj	.000	27	1.779E-005	5.733	.000
Error	.000	36	3.104E-006		
Total	.009	76			
Corrected Total	.001	75			

a. R Squared = .907 (Adjusted R Squared = .807)

Multiple Comparisons

Dependent Variable: SDST

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	-.002786606148087*	.000557111311697	.000	-.004287033465619	-.001286178830555
	3-TIM	-.002234375005590*	.000557111311697	.002	-.003734802323122	-.000733947688057
	4-ALL	-.004021391674852*	.000590905779559	.000	-.005612835171209	-.002429948178495
2-LEN	1-SPD	.002786606148087*	.000557111311697	.000	.001286178830555	.004287033465619
	3-TIM	.000552231142597	.000557111311697	.755	-.000948196175135	.002052658460130
	4-ALL	-.001234785526865	.000590905779559	.176	-.002826229023222	.000356657969692
3-TIM	1-SPD	.002234375005590*	.000557111311697	.002	.000733947688057	.003734802323122
	2-LEN	-.000552231142597	.000557111311697	.755	-.002052658460130	.000948196175135
	4-ALL	-.001787016669362*	.000590905779559	.023	-.003378460165719	-.000195573173005
4-ALL	1-SPD	.004021391674852*	.000590905779559	.000	.002429948178495	.005612835171209
	2-LEN	.001234785526865	.000590905779559	.176	-.000356657969692	.002826229023222
	3-TIM	.001787016669362*	.000590905779559	.023	.000195573173005	.003378460165719

Based on observed means.

The error term is Mean Square(Error) = 3.104E-006.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: SDSS

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.006[a]	39	.000	8.966	.000
Intercept	.098	1	.098	6068.328	.000
Cond	.002	3	.001	31.722	.000
Subj	.004	9	.000	24.308	.000
Cond * Subj	.001	27	2.687E-005	1.670	.075
Error	.001	36	1.609E-005		
Total	.105	76			
Corrected Total	.006	75			

a. R Squared = .907 (Adjusted R Squared = .806)

Multiple Comparisons

Dependent Variable: SDSS

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	-.008269249234972*	.001268630122443	.000	-.011685958341005	-.004852540128939
	3-TIM	.000175792253296	.001268630122443	.999	-.003240916852937	.003592501359329
	4-ALL	-.008060414652354*	.001345585443590	.000	-.011684381919681	-.004436447385028
2-LEN	1-SPD	.008269249234972*	.001268630122443	.000	.004852540128939	.011685958341005
	3-TIM	.008445041488168*	.001268630122443	.000	.005028332382135	.011861750594201
	4-ALL	.000208834582718	.001345585443590	.999	-.003415132684808	.003832801850045
3-TIM	1-SPD	-.000175792253296	.001268630122443	.999	-.003592501359329	.003240916852937
	2-LEN	-.008445041488168*	.001268630122443	.000	-.011861750594201	-.005028332382135
	4-ALL	-.008236206905550*	.001345585443590	.000	-.011860174172877	-.004612239638224
4-ALL	1-SPD	.008060414652354*	.001345585443590	.000	.004436447385028	.011684381919681
	2-LEN	-.000208834582718	.001345585443590	.999	-.003832801850045	.003415132684808
	3-TIM	.008236206905550*	.001345585443590	.000	.004612239638224	.011860174172877

Based on observed means.

The error term is Mean Square(Error) = 1.609E-005.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: AlphaSL

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	3.145[a]	39	.081	4.444	.000
Intercept	24.122	1	24.122	1329.143	.000
Cond	1.053	3	.351	19.337	.000
Subj	.744	9	.083	4.557	.000
Cond * Subj	1.307	27	.048	2.668	.003
Error	.653	36	.018		
Total	28.945	76			
Corrected Total	3.798	75			

a. R Squared = .828 (Adjusted R Squared = .642)

Multiple Comparisons

Dependent Variable: AlphaSL

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.305643063904193*	.042601145914303	.000	.190908500528352	.420377627280034
	3-TIM	.068462191920921	.042601145914303	.388	-.046272371455120	.183196755296763
	4-ALL	.181862871437154*	.045185338743476	.002	.060168489737852	.303557253136457
2-LEN	1-SPD	-.305643063904193*	.042601145914303	.000	-.420377627280034	-.190908500528352
	3-TIM	-.237180871983371*	.042601145914303	.000	-.351915435359212	-.122446308607530
	4-ALL	-.123780192467139*	.045185338743476	.045	-.245474574166441	-.002085810767836
3-TIM	1-SPD	-.068462191920921	.042601145914303	.388	-.183196755296763	.046272371455120
	2-LEN	.237180871983371*	.042601145914303	.000	.122446308607530	.351915435359212
	4-ALL	.113400679516333	.045185338743476	.075	-.008293702183170	.235095061215635
4-ALL	1-SPD	-.181862871437154*	.045185338743476	.002	-.303557253136457	-.060168489737852
	2-LEN	.123780192467139*	.045185338743476	.045	.002085810767836	.245474574166441
	3-TIM	-.113400679516333	.045185338743476	.075	-.235095061215635	.008293702183170

Based on observed means.

The error term is Mean Square(Error) = .018.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: AlphaST

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	3.186[a]	39	.082	4.738	.000
Intercept	32.729	1	32.729	1898.098	.000
Cond	.633	3	.211	12.235	.000
Subj	1.263	9	.140	8.141	.000
Cond * Subj	1.225	27	.045	2.631	.004
Error	.621	36	.017		
Total	37.676	76			
Corrected Total	3.807	75			

a. R Squared = .837 (Adjusted R Squared = .660)

Multiple Comparisons

Dependent Variable: AlphaST

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.249358176950688*	.041524603354451	.000	.137522987239792	.361193366661582
	3-TIM	.138019135260971*	.041524603354451	.011	.026183945550076	.249854324971866
	4-ALL	.177355926293965*	.044043492927014	.002	.058736794764179	.295975057823752
2-LEN	1-SPD	-.249358176950688*	.041524603354451	.000	-.361193366661582	-.137522987239792
	3-TIM	-.111339041689817	.041524603354451	.051	-.223174231400712	.000496148021278
	4-ALL	-.072002250656822	.044043492927014	.373	-.190621382186609	.046616880873165
3-TIM	1-SPD	-.138019135260971*	.041524603354451	.011	-.249854324971866	-.026183945550076
	2-LEN	.111339041689817	.041524603354451	.051	-.000496148021278	.223174231400712
	4-ALL	.039336791033094	.044043492927014	.808	-.079282340496892	.157955922562881
4-ALL	1-SPD	-.177355926293965*	.044043492927014	.002	-.295975057823752	-.058736794764179
	2-LEN	.072002250656822	.044043492927014	.373	-.046616880873165	.190621382186609
	3-TIM	-.039336791033094	.044043492927014	.808	-.157955922562881	.079282340496892

Based on observed means.

The error term is Mean Square(Error) = .017.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: AlphaSS

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.483[a]	39	.012	3.230	.000
Intercept	10.791	1	10.791	2816.854	.000
Cond	.039	3	.013	3.432	.027
Subj	.244	9	.027	7.085	.000
Cond * Subj	.206	27	.008	1.987	.027
Error	.138	36	.004		
Total	11.859	76			
Corrected Total	.621	75			

a. R Squared = .778 (Adjusted R Squared = .537)

Multiple Comparisons

Dependent Variable: AlphaSS

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.056422006541977*	.019572409619129	.032	.003709061299260	.109134951784693
	3-TIM	.034333811440308	.019572409619129	.312	-.018379133802609	.087046756683025
	4-ALL	.003830381349650	.020759675348764	.998	-.052080140206710	.059740902905811
2-LEN	1-SPD	-.056422006541977*	.019572409619129	.032	-.109134951784693	-.003709061299260
	3-TIM	-.022088195101768	.019572409619129	.675	-.074801140344485	.030624750141148
	4-ALL	-.052591625192426	.020759675348764	.072	-.108502146748587	.003318896363934
3-TIM	1-SPD	-.034333811440308	.019572409619129	.312	-.087046756683025	.018379133802609
	2-LEN	.022088195101768	.019572409619129	.675	-.030624750141148	.074801140344485
	4-ALL	-.030503430090758	.020759675348764	.466	-.086413951646918	.025407091465602
4-ALL	1-SPD	-.003830381349650	.020759675348764	.998	-.059740902905811	.052080140206710
	2-LEN	.052591625192426	.020759675348764	.072	-.003318896363934	.108502146748587
	3-TIM	.030503430090758	.020759675348764	.466	-.025407091465602	.086413951646918

Based on observed means.

The error term is Mean Square(Error) = .004.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: SDDPn

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.650[a]	39	.042	8.030	.000
Intercept	22.123	1	22.123	4199.458	.000
Cond	.183	3	.061	11.599	.000
Subj	.706	9	.078	14.889	.000
Cond * Subj	.703	27	.026	4.945	.000
Error	.190	36	.005		
Total	24.928	76			
Corrected Total	1.839	75			

a. R Squared = .897 (Adjusted R Squared = .785)

Multiple Comparisons

Dependent Variable: SDDPn

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.087765305547016*	.022952207220810	.003	.025949797596044	.149580813497989
	3-TIM	.115364245655509*	.022952207220810	.000	.053548737704536	.177179753606482
	4-ALL	.137707064138478*	.024344492053544	.000	.072141816856543	.203272311420414
2-LEN	1-SPD	-.087765305547016*	.022952207220810	.003	-.149580813497989	-.025949797596044
	3-TIM	.027598940108593	.022952207220810	.629	-.034216567842580	.089414448059565
	4-ALL	.049941758591562	.024344492053544	.189	-.015623488690574	.115507005873498
3-TIM	1-SPD	-.115364245655509*	.022952207220810	.000	-.177179753606482	-.053548737704536
	2-LEN	-.027598940108593	.022952207220810	.629	-.089414448059565	.034216567842580
	4-ALL	.022342818483069	.024344492053544	.796	-.043222428799066	.087908065765005
4-ALL	1-SPD	-.137707064138478*	.024344492053544	.000	-.203272311420414	-.072141816856543
	2-LEN	-.049941758591562	.024344492053544	.189	-.115507005873498	.015623488690574
	3-TIM	-.022342818483069	.024344492053544	.796	-.087908065765005	.043222428799066

Based on observed means.

The error term is Mean Square(Error) = .005.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: SDDTn

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.364[a]	39	.009	9.540	.000
Intercept	121.292	1	121.292	123996.089	.000
Cond	.044	3	.015	15.128	.000
Subj	.164	9	.018	18.678	.000
Cond * Subj	.142	27	.005	5.375	.000
Error	.035	36	.001		
Total	127.072	76			
Corrected Total	.399	75			

a. R Squared = .912 (Adjusted R Squared = .816)

Multiple Comparisons

Dependent Variable: SDDTn

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	-.046582690757989*	.009890364022476	.000	-.073219687800763	-.019945693715214
	3-TIM	-.050281980756022*	.009890364022476	.000	-.076918977798797	-.023644983713248
	4-ALL	-.070249188743883*	.010490315203038	.000	-.098501990602971	-.041996386884795
2-LEN	1-SPD	.046582690757989*	.009890364022476	.000	.019945693715214	.073219687800763
	3-TIM	-.003699289998134	.009890364022476	.982	-.030336287040908	.022937707044841
	4-ALL	-.023666497985994	.010490315203038	.128	-.051919299845082	.004586303873293
3-TIM	1-SPD	.050281980756022*	.009890364022476	.000	.023644983713248	.076918977798797
	2-LEN	.003699289998134	.009890364022476	.982	-.022937707044841	.030336287040908
	4-ALL	-.019967207987961	.010490315203038	.245	-.048220009847048	.008285593871327
4-ALL	1-SPD	.070249188743883*	.010490315203038	.000	.041996386884795	.098501990602971
	2-LEN	.023666497985994	.010490315203038	.128	-.004586303873293	.051919299845082
	3-TIM	.019967207987961	.010490315203038	.245	-.008285593871327	.048220009847048

Based on observed means.

The error term is Mean Square(Error) = .001.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: AlphaDPn

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.481[a]	39	.012	3.199	.000
Intercept	10.767	1	10.767	2793.587	.000
Cond	.038	3	.013	3.325	.030
Subj	.245	9	.027	7.056	.000
Cond * Subj	.204	27	.008	1.962	.030
Error	.139	36	.004		
Total	11.836	76			
Corrected Total	.620	75			

a. R Squared = .776 (Adjusted R Squared = .533)

Multiple Comparisons

Dependent Variable: AlphaDPn

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.056210652820854*	.019631992930846	.034	.003337236184524	.109084069457184
	3-TIM	.033636638554907	.019631992930846	.332	-.019236778081623	.086510055191237
	4-ALL	.004762506823167	.020822872994405	.996	-.051318220349109	.060843233995243
2-LEN	1-SPD	-.056210652820854*	.019631992930846	.034	-.109084069457184	-.003337236184524
	3-TIM	-.022574014266047	.019631992930846	.662	-.075447430902377	.030299402370483
	4-ALL	-.051448145997787	.020822872994405	.082	-.107528873169863	.004632581174488
3-TIM	1-SPD	-.033636638554907	.019631992930846	.332	-.086510055191237	.019236778081623
	2-LEN	.022574014266047	.019631992930846	.662	-.030299402370483	.075447430902377
	4-ALL	-.028874131731841	.020822872994405	.516	-.084954858903916	.027206595440435
4-ALL	1-SPD	-.004762506823167	.020822872994405	.996	-.060843233995243	.051318220349109
	2-LEN	.051448145997787	.020822872994405	.082	-.004632581174488	.107528873169863
	3-TIM	.028874131731841	.020822872994405	.516	-.027206595440435	.084954858903916

Based on observed means.

The error term is Mean Square(Error) = .004.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: AlphaDTn

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	3.359[a]	39	.086	4.609	.000
Intercept	31.312	1	31.312	1675.875	.000
Cond	.978	3	.326	17.441	.000
Subj	1.085	9	.121	6.450	.000
Cond * Subj	1.235	27	.046	2.448	.006
Error	.673	36	.019		
Total	36.509	76			
Corrected Total	4.031	75			

a. R Squared = .833 (Adjusted R Squared = .652)

Multiple Comparisons

Dependent Variable: AlphaDTn

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-SPD	2-LEN	.308614061488594*	.043224750426993	.000	.192199989499844	.425028133477344
	3-TIM	.143032546025869*	.043224750426993	.011	.026618474037119	.259446618014619
	4-ALL	.215680851055372*	.045846771213028	.000	.092205081462196	.339156620648549
2-LEN	1-SPD	-.308614061488594*	.043224750426993	.000	-.425028133477344	-.192199989499844
	3-TIM	-.165581515462825*	.043224750426993	.003	-.281995587451575	-.049167443474075
	4-ALL	-.092933210433322	.045846771213028	.197	-.216408980026498	.030542559160054
3-TIM	1-SPD	-.143032546025869*	.043224750426993	.011	-.259446618014619	-.026618474037119
	2-LEN	.165581515462825*	.043224750426993	.003	.049167443474075	.281995587451575
	4-ALL	.072648305029604	.045846771213028	.400	-.050827464563772	.196124074622780
4-ALL	1-SPD	-.215680851055372*	.045846771213028	.000	-.339156620648549	-.092205081462196
	2-LEN	.092933210433322	.045846771213028	.197	-.030542559160054	.216408980026498
	3-TIM	-.072648305029604	.045846771213028	.400	-.196124074622780	.050827464563772

Based on observed means.

The error term is Mean Square(Error) = .019.

*. The mean difference is significant at the 0.05 level.

Aim 3:

Tests of Between-Subjects Effects

Dependent Variable: MeanSL

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	5.882[a]	39	.151	372.041	.000
Intercept	212.487	1	212.487	524192.541	.000
Cond	4.652	3	1.551	3825.588	.000
Subj	.768	9	.085	210.608	.000
Cond * Subj	.210	27	.008	19.213	.000
Error	.015	36	.000		
Total	227.373	76			
Corrected Total	5.896	75			

a. R Squared = .998 (Adjusted R Squared = .995)

Multiple Comparisons

Dependent Variable: MeanSL

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
	2-WTS	-.460138321*	.0065321917	.000	-.477730997	-.442545645
1-PWS	3-PRS	-.687975226*	.0065321917	.000	-.705567903	-.670382550
	4-RTS	-.268071937*	.0065321917	.000	-.285664613	-.250479261
	1-PWS	.460138321*	.0065321917	.000	.442545645	.477730997
2-WTS	3-PRS	-.227836905*	.0065321917	.000	-.245429582	-.210244229
	4-RTS	.192066384*	.0065321917	.000	.174473708	.209659060
	1-PWS	.687975226*	.0065321917	.000	.670382550	.705567903
3-PRS	2-WTS	.227836905*	.0065321917	.000	.210244229	.245429582
	4-RTS	.419903289*	.0065321917	.000	.402310613	.437495966
	1-PWS	.268071937*	.0065321917	.000	.250479261	.285664613
4-RTS	2-WTS	-.192066384*	.0065321917	.000	-.209659060	-.174473708
	3-PRS	-.419903289*	.0065321917	.000	-.437495966	-.402310613

Based on observed means.

The error term is Mean Square(Error) = .000.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: MeanST

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.904[a]	39	.049	574.622	.000
Intercept	52.845	1	52.845	622025.122	.000
Cond	1.707	3	.569	6697.719	.000
Subj	.104	9	.012	136.607	.000
Cond * Subj	.040	27	.001	17.442	.000
Error	.003	36	8.496E-005		
Total	56.961	76			
Corrected Total	1.907	75			

a. R Squared = .998 (Adjusted R Squared = .997)

Multiple Comparisons

Dependent Variable: MeanST

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-PWS	2-WTS	.2717027253*	.00299044093	.000	.2636487885	.2797566620
	3-PRS	.3810719126*	.00299044093	.000	.3730179759	.3891258494
	4-RTS	.3610918547*	.00299044093	.000	.3530379180	.3691457915
2-WTS	1-PWS	-.2717027253*	.00299044093	.000	-.2797566620	-.2636487885
	3-PRS	.1093691874*	.00299044093	.000	.1013152506	.1174231241
	4-RTS	.0893891295*	.00299044093	.000	.0813351927	.0974430662
3-PRS	1-PWS	-.3810719126*	.00299044093	.000	-.3891258494	-.3730179759
	2-WTS	-.1093691874*	.00299044093	.000	-.1174231241	-.1013152506
	4-RTS	-.0199800579*	.00299044093	.000	-.0280339946	-.0119261211
4-RTS	1-PWS	-.3610918547*	.00299044093	.000	-.3691457915	-.3530379180
	2-WTS	-.0893891295*	.00299044093	.000	-.0974430662	-.0813351927
	3-PRS	.0199800579*	.00299044093	.000	.0119261211	.0280339946

Based on observed means.

The error term is Mean Square(Error) = 8.50E-005.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: MeanSS

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	24.761[a]	39	.635	758967.023	.000
Intercept	320.641	1	320.641	383295536.839	.000
Cond	23.606	3	7.869	9406349.643	.000
Subj	.123	9	.014	16370.318	.000
Cond * Subj	.017	27	.001	766.270	.000
Error	3.012E-005	36	8.365E-007		
Total	359.843	76			
Corrected Total	24.761	75			

a. R Squared = 1.000 (Adjusted R Squared = 1.000)

Multiple Comparisons

Dependent Variable: MeanSS

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-PWS	2-WTS	-.951207905*	.0002967434	.000	-.952007103	-.950408708
	3-PRS	-1.594442505*	.0002967434	.000	-1.595241703	-1.593643308
	4-RTS	-.955496221*	.0002967434	.000	-.956295419	-.954697024
2-WTS	1-PWS	.951207905*	.0002967434	.000	.950408708	.952007103
	3-PRS	-.643234600*	.0002967434	.000	-.644033797	-.642435403
	4-RTS	-.004288316*	.0002967434	.000	-.005087513	-.003489118
3-PRS	1-PWS	1.594442505*	.0002967434	.000	1.593643308	1.595241703
	2-WTS	.643234600*	.0002967434	.000	.642435403	.644033797
	4-RTS	.638946284*	.0002967434	.000	.638147087	.639745482
4-RTS	1-PWS	.955496221*	.0002967434	.000	.954697024	.956295419
	2-WTS	.004288316*	.0002967434	.000	.003489118	.005087513
	3-PRS	-.638946284*	.0002967434	.000	-.639745482	-.638147087

Based on observed means.

The error term is Mean Square(Error) = 8.37E-007.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: SDSL

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.018[a]	39	.000	1.033	.462
Intercept	.067	1	.067	151.194	.000
Cond	.004	3	.001	3.356	.029
Subj	.003	9	.000	.807	.613
Cond * Subj	.010	27	.000	.832	.686
Error	.016	36	.000		
Total	.105	76			
Corrected Total	.034	75			

a. R Squared = .528 (Adjusted R Squared = .017)

Multiple Comparisons

Dependent Variable: SDSL

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-PWS	2-WTS	-.00174706732	.006847959605	.994	-.02019017814	.01669604351
	3-PRS	-.01963716858*	.006847959605	.033	-.03808027940	-.00119405776
	4-RTS	-.01080314774	.006847959605	.404	-.02924625856	.00763996309
2-WTS	1-PWS	.00174706732	.006847959605	.994	-.01669604351	.02019017814
	3-PRS	-.01789010126	.006847959605	.060	-.03633321209	.00055300956
	4-RTS	-.00905608042	.006847959605	.555	-.02749919124	.00938703040
3-PRS	1-PWS	.01963716858*	.006847959605	.033	.00119405776	.03808027940
	2-WTS	.01789010126	.006847959605	.060	-.00055300956	.03633321209
	4-RTS	.00883402084	.006847959605	.575	-.00960908998	.02727713166
4-RTS	1-PWS	.01080314774	.006847959605	.404	-.00763996309	.02924625856
	2-WTS	.00905608042	.006847959605	.555	-.00938703040	.02749919124
	3-PRS	-.00883402084	.006847959605	.575	-.02727713166	.00960908998

Based on observed means.

The error term is Mean Square(Error) = .000.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: SDST

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.001[a]	39	1.909E-005	6.427	.000
Intercept	.009	1	.009	2991.666	.000
Cond	.000	3	9.319E-005	31.369	.000
Subj	.000	9	2.780E-005	9.356	.000
Cond * Subj	.000	27	6.997E-006	2.355	.008
Error	.000	36	2.971E-006		
Total	.010	76			
Corrected Total	.001	75			

a. R Squared = .874 (Adjusted R Squared = .738)

Multiple Comparisons

Dependent Variable: SDST

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-PWS	2-WTS	.002891752184*	.0005592200755	.000	.001385645487	.004397858882
	3-PRS	.005189213979*	.0005592200755	.000	.003683107282	.006695320676
	4-RTS	.004388535369*	.0005592200755	.000	.002882428671	.005894642066
2-WTS	1-PWS	-.002891752184*	.0005592200755	.000	-.004397858882	-.001385645487
	3-PRS	.002297461795*	.0005592200755	.001	.000791355097	.003803568492
	4-RTS	.001496783184	.0005592200755	.052	-.000009323513	.003002889882
3-PRS	1-PWS	-.005189213979*	.0005592200755	.000	-.006695320676	-.003683107282
	2-WTS	-.002297461795*	.0005592200755	.001	-.003803568492	-.000791355097
	4-RTS	-.000800678611	.0005592200755	.488	-.002306785308	.000705428087
4-RTS	1-PWS	-.004388535369*	.0005592200755	.000	-.005894642066	-.002882428671
	2-WTS	-.001496783184	.0005592200755	.052	-.003002889882	.000009323513
	3-PRS	.000800678611	.0005592200755	.488	-.000705428087	.002306785308

Based on observed means.

The error term is Mean Square(Error) = 2.97E-006.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: SDSS

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.041[a]	39	.001	1.083	.406
Intercept	.078	1	.078	80.920	.000
Cond	.008	3	.003	2.703	.060
Subj	.008	9	.001	.908	.529
Cond * Subj	.024	27	.001	.942	.559
Error	.035	36	.001		
Total	.158	76			
Corrected Total	.075	75			

a. R Squared = .540 (Adjusted R Squared = .042)

Multiple Comparisons

Dependent Variable: SDSS

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-PWS	2-WTS	-.00858428142	.010067908814	.829	-.03569944692	.01853088408
	3-PRS	-.02809213405*	.010067908814	.040	-.05520729955	-.00097696855
	4-RTS	-.01739032295	.010067908814	.325	-.04450548845	.00972484255
2-WTS	1-PWS	.00858428142	.010067908814	.829	-.01853088408	.03569944692
	3-PRS	-.01950785263	.010067908814	.231	-.04662301813	.00760731287
	4-RTS	-.00880604153	.010067908814	.818	-.03592120703	.01830912397
3-PRS	1-PWS	.02809213405*	.010067908814	.040	.00097696855	.05520729955
	2-WTS	.01950785263	.010067908814	.231	-.00760731287	.04662301813
	4-RTS	.01070181111	.010067908814	.714	-.01641335439	.03781697660
4-RTS	1-PWS	.01739032295	.010067908814	.325	-.00972484255	.04450548845
	2-WTS	.00880604153	.010067908814	.818	-.01830912397	.03592120703
	3-PRS	-.01070181111	.010067908814	.714	-.03781697660	.01641335439

Based on observed means.

The error term is Mean Square(Error) = .001.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: AlphaSL

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.693[a]	39	.043	2.808	.001
Intercept	34.974	1	34.974	2263.123	.000
Cond	.696	3	.232	15.017	.000
Subj	.343	9	.038	2.469	.026
Cond * Subj	.658	27	.024	1.577	.100
Error	.556	36	.015		
Total	38.758	76			
Corrected Total	2.249	75			

a. R Squared = .753 (Adjusted R Squared = .485)

Multiple Comparisons

Dependent Variable: AlphaSL

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-PWS	2-WTS	-.0773201358	.04033268404	.239	-.1859452160	.0313049444
	3-PRS	.0853950184	.04033268404	.167	-.0232300618	.1940200987
	4-RTS	.1779874147*	.04033268404	.000	.0693623345	.2866124950
2-WTS	1-PWS	.0773201358	.04033268404	.239	-.0313049444	.1859452160
	3-PRS	.1627151542*	.04033268404	.001	.0540900740	.2713402344
	4-RTS	.2553075505*	.04033268404	.000	.1466824703	.3639326308
3-PRS	1-PWS	-.0853950184	.04033268404	.167	-.1940200987	.0232300618
	2-WTS	-.1627151542*	.04033268404	.001	-.2713402344	-.0540900740
	4-RTS	.0925923963	.04033268404	.118	-.0160326839	.2012174766
4-RTS	1-PWS	-.1779874147*	.04033268404	.000	-.2866124950	-.0693623345
	2-WTS	-.2553075505*	.04033268404	.000	-.3639326308	-.1466824703
	3-PRS	-.0925923963	.04033268404	.118	-.2012174766	.0160326839

Based on observed means.

The error term is Mean Square(Error) = .015.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: AlphaST

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.643[a]	39	.016	1.075	.415
Intercept	47.581	1	47.581	3099.020	.000
Cond	.008	3	.003	.181	.908
Subj	.252	9	.028	1.821	.098
Cond * Subj	.397	27	.015	.957	.541
Error	.553	36	.015		
Total	51.072	76			
Corrected Total	1.196	75			

a. R Squared = .538 (Adjusted R Squared = .037)

Multiple Comparisons

Dependent Variable: AlphaST

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-PWS	2-WTS	-.0125159468	.04020147733	.989	-.1207876576	.0957557639
	3-PRS	.0054065042	.04020147733	.999	-.1028652065	.1136782150
	4-RTS	.0101131411	.04020147733	.994	-.0981585697	.1183848518
2-WTS	1-PWS	.0125159468	.04020147733	.989	-.0957557639	.1207876576
	3-PRS	.0179224511	.04020147733	.970	-.0903492597	.1261941618
	4-RTS	.0226290879	.04020147733	.942	-.0856426229	.1309007987
3-PRS	1-PWS	-.0054065042	.04020147733	.999	-.1136782150	.1028652065
	2-WTS	-.0179224511	.04020147733	.970	-.1261941618	.0903492597
	4-RTS	.0047066368	.04020147733	.999	-.1035650739	.1129783476
4-RTS	1-PWS	-.0101131411	.04020147733	.994	-.1183848518	.0981585697
	2-WTS	-.0226290879	.04020147733	.942	-.1309007987	.0856426229
	3-PRS	-.0047066368	.04020147733	.999	-.1129783476	.1035650739

Based on observed means.

The error term is Mean Square(Error) = .015.

Tests of Between-Subjects Effects

Dependent Variable: AlphaSS

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.097[a]	39	.028	3.109	.000
Intercept	12.284	1	12.284	1357.192	.000
Cond	.091	3	.030	3.347	.030
Subj	.623	9	.069	7.650	.000
Cond * Subj	.367	27	.014	1.504	.125
Error	.326	36	.009		
Total	14.598	76			
Corrected Total	1.423	75			

a. R Squared = .771 (Adjusted R Squared = .523)

Multiple Comparisons

Dependent Variable: AlphaSS

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-PWS	2-WTS	-.0099032947	.03086650954	.988	-.0930338167	.0732272272
	3-PRS	.0639217737	.03086650954	.182	-.0192087482	.1470522956
	4-RTS	.0772563063	.03086650954	.076	-.0058742156	.1603868282
2-WTS	1-PWS	.0099032947	.03086650954	.988	-.0732272272	.0930338167
	3-PRS	.0738250684	.03086650954	.097	-.0093054535	.1569555903
	4-RTS	.0871596011*	.03086650954	.037	.0040290791	.1702901230
3-PRS	1-PWS	-.0639217737	.03086650954	.182	-.1470522956	.0192087482
	2-WTS	-.0738250684	.03086650954	.097	-.1569555903	.0093054535
	4-RTS	.0133345326	.03086650954	.973	-.0697959893	.0964650546
4-RTS	1-PWS	-.0772563063	.03086650954	.076	-.1603868282	.0058742156
	2-WTS	-.0871596011*	.03086650954	.037	-.1702901230	-.0040290791
	3-PRS	-.0133345326	.03086650954	.973	-.0964650546	.0697959893

Based on observed means.

The error term is Mean Square(Error) = .009.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: SDDPn

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.926[a]	39	.024	2.663	.002
Intercept	34.381	1	34.381	3853.907	.000
Cond	.185	3	.062	6.900	.001
Subj	.363	9	.040	4.516	.001
Cond * Subj	.341	27	.013	1.415	.164
Error	.321	36	.009		
Total	37.377	76			
Corrected Total	1.248	75			

a. R Squared = .743 (Adjusted R Squared = .464)

Multiple Comparisons

Dependent Variable: SDDPn

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-PWS	2-WTS	.0800722500	.03064427315	.060	-.0024597388	.1626042388
	3-PRS	.1506986189*	.03064427315	.000	.0681666301	.2332306078
	4-RTS	.0685472721	.03064427315	.133	-.0139847167	.1510792610
2-WTS	1-PWS	-.0800722500	.03064427315	.060	-.1626042388	.0024597388
	3-PRS	.0706263689	.03064427315	.116	-.0119056199	.1531583578
	4-RTS	-.0115249779	.03064427315	.982	-.0940569667	.0710070110
3-PRS	1-PWS	-.1506986189*	.03064427315	.000	-.2332306078	-.0681666301
	2-WTS	-.0706263689	.03064427315	.116	-.1531583578	.0119056199
	4-RTS	-.0821513468	.03064427315	.051	-.1646833357	.0003806420
4-RTS	1-PWS	-.0685472721	.03064427315	.133	-.1510792610	.0139847167
	2-WTS	.0115249779	.03064427315	.982	-.0710070110	.0940569667
	3-PRS	.0821513468	.03064427315	.051	-.0003806420	.1646833357

Based on observed means.

The error term is Mean Square(Error) = .009.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: SDDTn

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.313[a]	39	.008	2.373	.005
Intercept	109.515	1	109.515	32423.927	.000
Cond	.058	3	.019	5.691	.003
Subj	.119	9	.013	3.904	.002
Cond * Subj	.123	27	.005	1.352	.197
Error	.122	36	.003		
Total	114.623	76			
Corrected Total	.434	75			

a. R Squared = .720 (Adjusted R Squared = .417)

Multiple Comparisons

Dependent Variable: SDDTn

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-PWS	2-WTS	-.050374174	.0188556916	.053	-.101156834	.000408487
	3-PRS	-.084161289*	.0188556916	.000	-.134943950	-.033378629
	4-RTS	-.044026853	.0188556916	.109	-.094809513	.006755808
2-WTS	1-PWS	.050374174	.0188556916	.053	-.000408487	.101156834
	3-PRS	-.033787116	.0188556916	.294	-.084569777	.016995545
	4-RTS	.006347321	.0188556916	.987	-.044435340	.057129982
3-PRS	1-PWS	.084161289*	.0188556916	.000	.033378629	.134943950
	2-WTS	.033787116	.0188556916	.294	-.016995545	.084569777
	4-RTS	.040134437	.0188556916	.164	-.010648224	.090917098
4-RTS	1-PWS	.044026853	.0188556916	.109	-.006755808	.094809513
	2-WTS	-.006347321	.0188556916	.987	-.057129982	.044435340
	3-PRS	-.040134437	.0188556916	.164	-.090917098	.010648224

Based on observed means.

The error term is Mean Square(Error) = .003.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: AlphaDPn

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.103[a]	39	.028	3.093	.000
Intercept	12.311	1	12.311	1346.461	.000
Cond	.093	3	.031	3.378	.029
Subj	.624	9	.069	7.587	.000
Cond * Subj	.370	27	.014	1.499	.127
Error	.329	36	.009		
Total	14.635	76			
Corrected Total	1.432	75			

a. R Squared = .770 (Adjusted R Squared = .521)

Multiple Comparisons

Dependent Variable: AlphaDPn

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-PWS	2-WTS	-.0095563368	.03102301451	.990	-.0931083622	.0739956885
	3-PRS	.0642289705	.03102301451	.182	-.0193230548	.1477809959
	4-RTS	.0784014453	.03102301451	.073	-.0051505801	.1619534706
2-WTS	1-PWS	.0095563368	.03102301451	.990	-.0739956885	.0931083622
	3-PRS	.0737853074	.03102301451	.100	-.0097667180	.1573373327
	4-RTS	.0879577821*	.03102301451	.036	.0044057567	.1715098075
3-PRS	1-PWS	-.0642289705	.03102301451	.182	-.1477809959	.0193230548
	2-WTS	-.0737853074	.03102301451	.100	-.1573373327	.0097667180
	4-RTS	.0141724747	.03102301451	.968	-.0693795506	.0977245001
4-RTS	1-PWS	-.0784014453	.03102301451	.073	-.1619534706	.0051505801
	2-WTS	-.0879577821*	.03102301451	.036	-.1715098075	-.0044057567
	3-PRS	-.0141724747	.03102301451	.968	-.0977245001	.0693795506

Based on observed means.

The error term is Mean Square(Error) = .009.

*. The mean difference is significant at the 0.05 level.

Tests of Between-Subjects Effects

Dependent Variable: AlphaDTn

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.826[a]	39	.021	1.519	.104
Intercept	49.478	1	49.478	3550.331	.000
Cond	.217	3	.072	5.195	.004
Subj	.223	9	.025	1.778	.107
Cond * Subj	.409	27	.015	1.087	.402
Error	.502	36	.014		
Total	53.149	76			
Corrected Total	1.328	75			

a. R Squared = .622 (Adjusted R Squared = .213)

Multiple Comparisons

Dependent Variable: AlphaDTn

Tukey HSD

(I) Cond	(J) Cond	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1-PWS	2-WTS	-.0213086089	.03830105162	.944	-.1244620416	.0818448237
	3-PRS	.0708609800	.03830105162	.267	-.0322924526	.1740144126
	4-RTS	.1049718458*	.03830105162	.045	.0018184132	.2081252784
2-WTS	1-PWS	.0213086089	.03830105162	.944	-.0818448237	.1244620416
	3-PRS	.0921695889	.03830105162	.094	-.0109838437	.1953230216
	4-RTS	.1262804547*	.03830105162	.011	.0231270221	.2294338874
3-PRS	1-PWS	-.0708609800	.03830105162	.267	-.1740144126	.0322924526
	2-WTS	-.0921695889	.03830105162	.094	-.1953230216	.0109838437
	4-RTS	.0341108658	.03830105162	.810	-.0690425668	.1372642984
4-RTS	1-PWS	-.1049718458*	.03830105162	.045	-.2081252784	-.0018184132
	2-WTS	-.1262804547*	.03830105162	.011	-.2294338874	-.0231270221
	3-PRS	-.0341108658	.03830105162	.810	-.1372642984	.0690425668

Based on observed means.

The error term is Mean Square(Error) = .014.

*. The mean difference is significant at the 0.05 level.

Appendix 3: Matlab Code

Stepping Parameter Code:

```
%=========================================================================%
%  Stepping_parameters_from_CSV - Calculates and exports stepping
%  parameters from raw marker coordinates imported from VICON in CSV format
%
%  Last Modified   - Nicole Bohnsack       -  010/28/13
%
%  input files are in the format of P#### E# X## XXX T#
%  where-->P###=Project #, E#=Experiment #, X##=Subject/Patient/Control #,
%  XXX=Condition code, T#=Trial#
%
%  exports a .MAT file named S##_ExportFormat with sub folders titled for each
Condition
%  and Trial (ALL1 ALL2 SPD1 SPD2, etc) which each contain 6 columns of data:
%  Step/Stride(Length, Time, Speed, Width, Lateral Speed, Lateral Placement)
%
%  Batch processing of data requires all .CSV files to be located in
%  the same folder as this m_file
%
%=========================================================================%
clear all;                                          %  Clear Memory          %
close all;                                          %  Close All Windows     %
clc                                                 %  Clear Command Window  %
tic                                                 %  Start Stopwatch       %
%=========================================================================%
Conditions = ['SPD'; 'LEN'; 'TIM'; 'ALL']; %['NOP'; 'VIS';'MLP']%list all
conditions in this vector to automate process
Num_Cond = 4; %the number of conditions that were tested
Num_Trials = 2; %the number of trials per condition

ExperimentID='E1';
ProjectID='P0042';
Sample_Freq = 60; %collection frequency in hertz


Sub=[1,2,3,4,5,6,7,8,9,10,11,12,13,14];%(Enter the subject# in order. For
example, if you wanted to process subject #1, #4, and #10, this vector would be
(Subj=1,4,10))
Tred_Speed=[1.25,1.25,1.2,1.25,1.16,1.16,1.16,1.16,1.16,1.16,1.2,1.25,1.16,1.2]
;% in m/s (You will need to enter the appropriate treadmill speed into this
vector - order should match the order of subjects listed above)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%loop structure: OutputFormat, Subject#, Condition#, Trial#
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
for Output=1:2%Will output both L and R strides...need to make more efficient
%The options for output are the following: 1=Right Stride; 2=Left Sride;
3=Right_Left Step; 4=Left_Right Step; 5=Steps; 6-10 are repeats but using
treadmill speed for SL and SS calc
%figure_dummy=1;
for Subjs=13:13;
    %Subjs=1:length(Sub);
    Subj=Sub(Subjs);
    Tred_Spd=Tred_Speed(Subjs);
    %- clear old data before moving on to next subject:
    clear SPD1 SPD2    LEN1 LEN2
    clear TIM1 TIM2    ALL1 ALL2

    if Subj < 10
```

```
        SubjectID = ['S0', int2str(Subj)];

    elseif Subj >= 10
        SubjectID = ['S', int2str(Subj)];
    end

    SubjID=SubjectID;

     for Cond=1:Num_Cond
        ConditionID=Conditions(Cond,:);

        subfolder = strcat('Data\',ProjectID, ExperimentID, SubjID,'\');
        csv_ftemp = strcat(ProjectID, ExperimentID, SubjID, ConditionID, 'T')

        d = dir([subfolder,csv_ftemp,'*']);
        ntrials = length(d)


        for count=1:ntrials %Num_Trials
            Trial=count;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%
        %Assign marker names to data from .CSV files

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%

         %.CSV format
            subfolder = strcat('Data\',ProjectID, ExperimentID, SubjectID);
            csv_file=strcat(subfolder,'\',ProjectID, ExperimentID, SubjectID,
ConditionID, 'T', int2str(count), '.csv')
            [data, text]=xlsread(csv_file);
             [rows, cols]=size(data);

             %pull in markers of interest - columns are x,y,z coords
             %VICON coordinate system: direction of progression is in the -y
direction; +z is up, and left is +x...weird convention, but it works
             %coodinate system origin is at the center of the treadmill
             %missing data is filled in with NaNs

               RHEEcoordsDumb= data(5:rows, 15:17); %columns are x,y,z coords
               LHEEcoordsDumb= data(5:rows, 9:11);
               RTOEcoordsDumb= data(5:rows, 18:20);
               LTOEcoordsDumb= data(5:rows, 12:14);
               LPSIcoordsDumb= data(5:rows, 3:5);
               RPSIcoordsDumb= data(5:rows, 6:8);

%transform coords into regular V3D convention (x is direction of progression, y
is up, z is lateral)
%Adjusted the z-coordinates so that reference point is the left side of the
treadmill
%For UT treadmill: coincides with y as direction of progression and +z up
%this value shifts the coordinate axes to left side of treadmill
                     RHEEcoords(:,1)=RHEEcoordsDumb(:,2);
                     RHEEcoords(:,2)=RHEEcoordsDumb(:,3);
                     RHEEcoords(:,3)=(RHEEcoordsDumb(:,1))+343;

%this puts the coordinates into meters
                     RHEEcoords=RHEEcoords./1000;
                     LHEEcoords(:,1)=LHEEcoordsDumb(:,2);
                     LHEEcoords(:,2)=LHEEcoordsDumb(:,3);
                     LHEEcoords(:,3)=(LHEEcoordsDumb(:,1))+343;
```

```
                    LHEEcoords=LHEEcoords./1000;

                    RTOEcoords(:,1)=RTOEcoordsDumb(:,2).*-1;
                    RTOEcoords(:,2)=RTOEcoordsDumb(:,3);
                    RTOEcoords(:,3)=(RTOEcoordsDumb(:,1))+343;
                    RTOEcoords=RTOEcoords./1000;

                    LTOEcoords(:,1)=LTOEcoordsDumb(:,2);
                    LTOEcoords(:,2)=LTOEcoordsDumb(:,3);
                    LTOEcoords(:,3)=(LTOEcoordsDumb(:,1))+343;
                    LTOEcoords=LTOEcoords./1000;

                    LPSIcoords(:,1)=LPSIcoordsDumb(:,2);
                    LPSIcoords(:,2)=LPSIcoordsDumb(:,3);
                    LPSIcoords(:,3)=(LPSIcoordsDumb(:,1))+343;
                    LPSIcoords=LPSIcoords./1000;

                    RPSIcoords(:,1)=RPSIcoordsDumb(:,2);
                    RPSIcoords(:,2)=RPSIcoordsDumb(:,3);
                    RPSIcoords(:,3)=(RPSIcoordsDumb(:,1))+343;
                    RPSIcoords=RPSIcoords./1000;


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%   % upsample data to 120Hz via interpolation if the
collection freq=60Hz
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%

        if Sample_Freq==60

            freq_multiplier=100;                                    %Can upsample
to whatever you want 2:120Hz; 10:600Hz; 1000:6000Hz
            time2cut = 2;                                           % seconds /
time to cut off from the beginning & end of upsampled data
            Samp_Freq = Sample_Freq*freq_multiplier;                % Up-sampling
Frequency
            buffer = Sample_Freq*time2cut;                          % # samples in
orig data to cut off from beginning & end of data
            cut=buffer*freq_multiplier;                             % # samples in
upsampled data to cut off from beginning & end of data

%-------------------------------------------------------------------------------
--------
       %Samp_Freq=Sample_Freq;
      %buffer=120*(100/freq_multiplier); %SHOULD WE REMOVE THIS ALL TOGETHER?%
      %cut=(Samp_Freq*freq_multiplier)/2; % the # frames to cut from beginning
and end of the data
%-------------------------------------------------------------------------------
--------


            RHEEcoords60=RHEEcoords; clear RHEEcoords
            Front_Buffer_dumb=RHEEcoords60(1:buffer,:);
            Front_Buffer=flipud(Front_Buffer_dumb);
            End_Buffer_dumb=RHEEcoords60((length(RHEEcoords60)-
buffer):length(RHEEcoords60),:);
            End_Buffer=flipud(End_Buffer_dumb);
            RHEEcoords60=[Front_Buffer;RHEEcoords60;End_Buffer];

            LHEEcoords60=LHEEcoords; clear LHEEcoords Front_Buffer_dumb
Front_Buffer End_Buffer_dumb End_Buffer
            Front_Buffer_dumb=LHEEcoords60(1:buffer,:);
```

```
            Front_Buffer=flipud(Front_Buffer_dumb);
            End_Buffer_dumb=LHEEcoords60((length(LHEEcoords60)-
buffer):length(LHEEcoords60),:);
            End_Buffer=flipud(End_Buffer_dumb);
            LHEEcoords60=[Front_Buffer;LHEEcoords60;End_Buffer];

            RTOEcoords60=RTOEcoords; clear RTOEcoords Front_Buffer_dumb
Front_Buffer End_Buffer_dumb End_Buffer
            Front_Buffer_dumb=RTOEcoords60(1:buffer,:);
            Front_Buffer=flipud(Front_Buffer_dumb);
            End_Buffer_dumb=RTOEcoords60((length(RTOEcoords60)-
buffer):length(RTOEcoords60),:);
            End_Buffer=flipud(End_Buffer_dumb);
            RTOEcoords60=[Front_Buffer;RTOEcoords60;End_Buffer];

            LTOEcoords60=LTOEcoords; clear LTOEcoords Front_Buffer_dumb
Front_Buffer End_Buffer_dumb End_Buffer
            Front_Buffer_dumb=LTOEcoords60(1:buffer,:);
            Front_Buffer=flipud(Front_Buffer_dumb);
            End_Buffer_dumb=LTOEcoords60((length(LTOEcoords60)-
buffer):length(LTOEcoords60),:);
            End_Buffer=flipud(End_Buffer_dumb);
            LTOEcoords60=[Front_Buffer;LTOEcoords60;End_Buffer];

            RPSIcoords60=RPSIcoords; clear RPSIcoords Front_Buffer_dumb
Front_Buffer End_Buffer_dumb End_Buffer
            Front_Buffer_dumb=RPSIcoords60(1:buffer,:);
            Front_Buffer=flipud(Front_Buffer_dumb);
            End_Buffer_dumb=RPSIcoords60((length(RPSIcoords60)-
buffer):length(RPSIcoords60),:);
            End_Buffer=flipud(End_Buffer_dumb);
            RPSIcoords60=[Front_Buffer;RPSIcoords60;End_Buffer];

            LPSIcoords60=LPSIcoords; clear LPSIcoords Front_Buffer_dumb
Front_Buffer End_Buffer_dumb End_Buffer
            Front_Buffer_dumb=LPSIcoords60(1:buffer,:);
            Front_Buffer=flipud(Front_Buffer_dumb);
            End_Buffer_dumb=LPSIcoords60((length(LPSIcoords60)-
buffer):length(LPSIcoords60),:);
            End_Buffer=flipud(End_Buffer_dumb);
            LPSIcoords60=[Front_Buffer;LPSIcoords60;End_Buffer];

            %resample

%RHEEcoordsT(:,1)=resample(RHEEcoords60(:,1),freq_multiplier,1,100);

RHEEcoordsT(:,1)=interp1(1:length(RHEEcoords60(:,1)),RHEEcoords60(:,1),
1:1/freq_multiplier:length(RHEEcoords60(:,1)),'spline');
            RHEEcoords(:,1)=RHEEcoordsT(cut:length(RHEEcoordsT(:,1)-cut),1);

%RHEEcoordsT(:,2)=resample(RHEEcoords60(:,2),freq_multiplier,1,100);

RHEEcoordsT(:,2)=interp1(1:length(RHEEcoords60(:,2)),RHEEcoords60(:,2),
1:1/freq_multiplier:length(RHEEcoords60(:,2)),'spline');
            RHEEcoords(:,2)=RHEEcoordsT(cut:length(RHEEcoordsT(:,2)-cut),2);

%RHEEcoordsT(:,3)=resample(RHEEcoords60(:,3),freq_multiplier,1,100);

RHEEcoordsT(:,3)=interp1(1:length(RHEEcoords60(:,3)),RHEEcoords60(:,3),
1:1/freq_multiplier:length(RHEEcoords60(:,3)),'spline');
            RHEEcoords(:,3)=RHEEcoordsT(cut:length(RHEEcoordsT(:,3)-cut),3);
```

```
%LHEEcoordsT(:,1)=resample(LHEEcoords60(:,1),freq_multiplier,1,100);

LHEEcoordsT(:,1)=interp1(1:length(LHEEcoords60(:,1)),LHEEcoords60(:,1),
1:1/freq_multiplier:length(LHEEcoords60(:,1)),'spline');
            LHEEcoords(:,1)=LHEEcoordsT(cut:length(LHEEcoordsT(:,1)-cut),1);

%LHEEcoordsT(:,2)=resample(LHEEcoords60(:,2),freq_multiplier,1,100);

LHEEcoordsT(:,2)=interp1(1:length(LHEEcoords60(:,2)),LHEEcoords60(:,2),
1:1/freq_multiplier:length(LHEEcoords60(:,2)),'spline');
            LHEEcoords(:,2)=LHEEcoordsT(cut:length(LHEEcoordsT(:,2)-cut),2);

%LHEEcoordsT(:,3)=resample(LHEEcoords60(:,3),freq_multiplier,1,100);

LHEEcoordsT(:,3)=interp1(1:length(LHEEcoords60(:,3)),LHEEcoords60(:,3),
1:1/freq_multiplier:length(LHEEcoords60(:,3)),'spline');
            LHEEcoords(:,3)=LHEEcoordsT(cut:length(LHEEcoordsT(:,3)-cut),3);


%RTOEcoordsT(:,1)=resample(RTOEcoords60(:,1),freq_multiplier,1,100);

RTOEcoordsT(:,1)=interp1(1:length(RTOEcoords60(:,1)),RTOEcoords60(:,1),
1:1/freq_multiplier:length(RTOEcoords60(:,1)),'spline');
            RTOEcoords(:,1)=RTOEcoordsT(cut:length(RTOEcoordsT(:,1)-cut),1);

%RTOEcoordsT(:,2)=resample(RTOEcoords60(:,2),freq_multiplier,1,100);

RTOEcoordsT(:,2)=interp1(1:length(RTOEcoords60(:,2)),RTOEcoords60(:,2),
1:1/freq_multiplier:length(RTOEcoords60(:,2)),'spline');
            RTOEcoords(:,2)=RTOEcoordsT(cut:length(RTOEcoordsT(:,2)-cut),2);

%RTOEcoordsT(:,3)=resample(RTOEcoords60(:,3),freq_multiplier,1,100);

RTOEcoordsT(:,3)=interp1(1:length(RTOEcoords60(:,3)),RTOEcoords60(:,3),
1:1/freq_multiplier:length(RTOEcoords60(:,3)),'spline');
            RTOEcoords(:,3)=RTOEcoordsT(cut:length(RTOEcoordsT(:,3)-cut),3);


%LTOEcoordsT(:,1)=resample(LTOEcoords60(:,1),freq_multiplier,1,100);

LTOEcoordsT(:,1)=interp1(1:length(LTOEcoords60(:,1)),LTOEcoords60(:,1),
1:1/freq_multiplier:length(LTOEcoords60(:,1)),'spline');
            LTOEcoords(:,1)=LTOEcoordsT(cut:length(LTOEcoordsT(:,1)-cut),1);

%LTOEcoordsT(:,2)=resample(LTOEcoords60(:,2),freq_multiplier,1,100);

LTOEcoordsT(:,2)=interp1(1:length(LTOEcoords60(:,2)),LTOEcoords60(:,2),
1:1/freq_multiplier:length(LTOEcoords60(:,2)),'spline');
            LTOEcoords(:,2)=LTOEcoordsT(cut:length(LTOEcoordsT(:,2)-cut),2);

%LTOEcoordsT(:,3)=resample(LTOEcoords60(:,3),freq_multiplier,1,100);

LTOEcoordsT(:,3)=interp1(1:length(LTOEcoords60(:,3)),LTOEcoords60(:,3),
1:1/freq_multiplier:length(LTOEcoords60(:,3)),'spline');
            LTOEcoords(:,3)=LTOEcoordsT(cut:length(LTOEcoordsT(:,3)-cut),3);


%RPSIcoordsT(:,1)=resample(RPSIcoords60(:,1),freq_multiplier,1,100);

RPSIcoordsT(:,1)=interp1(1:length(RPSIcoords60(:,1)),RPSIcoords60(:,1),
1:1/freq_multiplier:length(RPSIcoords60(:,1)),'spline');
            RPSIcoords(:,1)=RPSIcoordsT(cut:length(RPSIcoordsT(:,1)-cut),1);
```

```
%RPSIcoordsT(:,2)=resample(RPSIcoords60(:,2),freq_multiplier,1,100);

RPSIcoordsT(:,2)=interp1(1:length(RPSIcoords60(:,2)),RPSIcoords60(:,2),
1:1/freq_multiplier:length(RPSIcoords60(:,2)),'spline');
             RPSIcoords(:,2)=RPSIcoordsT(cut:length(RPSIcoordsT(:,2)-cut),2);

%RPSIcoordsT(:,3)=resample(RPSIcoords60(:,3),freq_multiplier,1,100);

RPSIcoordsT(:,3)=interp1(1:length(RPSIcoords60(:,3)),RPSIcoords60(:,3),
1:1/freq_multiplier:length(RPSIcoords60(:,3)),'spline');
             RPSIcoords(:,3)=RPSIcoordsT(cut:length(RPSIcoordsT(:,3)-cut),3);


%LPSIcoordsT(:,1)=resample(LPSIcoords60(:,1),freq_multiplier,1,100);

LPSIcoordsT(:,1)=interp1(1:length(LPSIcoords60(:,1)),LPSIcoords60(:,1),
1:1/freq_multiplier:length(LPSIcoords60(:,1)),'spline');
             LPSIcoords(:,1)=LPSIcoordsT(cut:length(LPSIcoordsT(:,1)-cut),1);

%LPSIcoordsT(:,2)=resample(LPSIcoords60(:,2),freq_multiplier,1,100);

LPSIcoordsT(:,2)=interp1(1:length(LPSIcoords60(:,2)),LPSIcoords60(:,2),
1:1/freq_multiplier:length(LPSIcoords60(:,2)),'spline');
             LPSIcoords(:,2)=LPSIcoordsT(cut:length(LPSIcoordsT(:,2)-cut),2);

%LPSIcoordsT(:,3)=resample(LPSIcoords60(:,3),freq_multiplier,1,100);

LPSIcoordsT(:,3)=interp1(1:length(LPSIcoords60(:,3)),LPSIcoords60(:,3),
1:1/freq_multiplier:length(LPSIcoords60(:,3)),'spline');
             LPSIcoords(:,3)=LPSIcoordsT(cut:length(LPSIcoordsT(:,3)-cut),3);

end


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
   %Calculate heel strike and toe off events

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

            time=length(RHEEcoords)/Samp_Freq; %calculate the length of the
trial in seconds
             %calculate sacrum marker
             SAC= (LPSIcoords+RPSIcoords)./2; %take average of the LPSI and
RPSI markers

             %Calculate heel strike locations-according to Zeni 2008 Gait and
Posture publication
             %heel strike occurs when the distance between the heel marker and
the sacrum marker in direction of progression are at a maximum:
             %HS=max (Loc_heel-Loc_sacrum)); +x is direction of progression
             clear R_RHEE_SAC_Dist L_LHEE_SAC_Dist

             R_RHEE_SAC_Dist=RHEEcoords(:,1)-SAC(:,1);
             L_LHEE_SAC_Dist=LHEEcoords(:,1)-SAC(:,1);
             R_RTOE_SAC_Dist=RTOEcoords(:,1)-SAC(:,1);
             L_LTOE_SAC_Dist=LTOEcoords(:,1)-SAC(:,1);

             %take derivative of each to look for slope change
             R_der=diff(R_RHEE_SAC_Dist);
             L_der=diff(L_LHEE_SAC_Dist);
```

```
            R_der_toe=diff(R_RTOE_SAC_Dist);
            L_der_toe=diff(L_LTOE_SAC_Dist);

            %find when slope goes from negative to positive for toe off
            R_HS_loc=zeros(1,500);
            L_HS_loc=zeros(1,500);
            R_TO_loc=zeros(1,500);
            L_TO_loc=zeros(1,500);

            clear dumb h
            dumb=1;
%
            %find when slope goes from positive to negative for heel strike
            clear dumb h
            dumb=1;
            for h=1:length(R_der)-1;
                if R_der(h+1)*R_der(h)<0 && R_der(h+1)<R_der(h)
                    R_HS_loc(dumb)=h+2;
                    dumb=dumb+1;
                end
            end

            clear dumb h
            dumb=1;
            for h=1:length(L_der)-1;
                if L_der(h+1)*L_der(h)<0 && L_der(h+1)<L_der(h)
                    L_HS_loc(dumb)=h+2;
                    dumb=dumb+1;
                end
            end

            R_HS_loc_temp=nonzeros(R_HS_loc);
            clear R_HS_loc
            L_HS_loc_temp=nonzeros(L_HS_loc);
            clear L_HS_loc
%             R_TO_loc=nonzeros(R_TO_loc);
%             L_TO_loc=nonzeros(L_TO_loc);
            prm =2;

            R_HS_loc(1)=R_HS_loc_temp(1);
            for peak_count=2:length(R_HS_loc_temp)-2
                time_peak=[R_HS_loc_temp(peak_count)-
(prm*freq_multiplier):R_HS_loc_temp(peak_count)+(prm*freq_multiplier)];
                R_RHEE_SAC_Dist_Max=R_RHEE_SAC_Dist(time_peak);

                [Dumb, R_loc]=max(R_RHEE_SAC_Dist_Max);
                R_HS_loc(peak_count)=R_loc+time_peak(1);

%                 figure(1)
%                 plot(R_RHEE_SAC_Dist_Max);
%                 hold on
                clear time_peak R_loc Dumb R_RHEE_SAC_Dist_Max
            end
            clear peak_count time_peak

            L_HS_loc(1)=L_HS_loc_temp(1);
            for peak_count=2:length(L_HS_loc_temp)-2
                time_peak=[L_HS_loc_temp(peak_count)-
(prm*freq_multiplier):L_HS_loc_temp(peak_count)+(prm*freq_multiplier)];
                L_LHEE_SAC_Dist_Max=L_LHEE_SAC_Dist(time_peak);

                [Dumb, L_loc]=max(L_LHEE_SAC_Dist_Max);
                L_HS_loc(peak_count)=L_loc+time_peak(1);
```

```
%                   figure(2)
%                   plot(L_LHEE_SAC_Dist_Max);
%                   hold on
                 clear time_peak L_loc Dumb L_LHEE_SAC_Dist_Max
             end
             clear peak_count time_peak




%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%
%check to make sure R_HS, R_TO alternate with L_HS, L_TO
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%
             if(R_HS_loc(1)>L_HS_loc(1)); %indicates a left foot first start -
determine if the patient started on their left or right foot
                R=1; L=0;
             else
                R=0; L=1;
             end
             problem=1;
             for check=150 %1:length(R_HS_loc)-2
                 if R==1
                     if R_HS_loc(check)<L_HS_loc(check)
                        Prob_R_HS(problem)=R_HS_loc(check);
                        fprintf('Detected Heel Strikes do not properly
alternate between L-R: see Prob_R_HS for location of anomoly');
                        problem=problem+1;
                     end
                 end

                 if R==0
                     if L_HS_loc(check)<R_HS_loc(check)
                        Prob_R_HS(problem)=R_HS_loc(check);
                        fprintf('Detected Heel Strikes do not properly
alternate between L-R: see Prob_R_HS for location of anomoly');
                        problem=problem+1
                     end
                 end
             end



%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%
%calculate stepping parameters - in steps and strides
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%

%for right to left steps
%check to make sure there are at least 152 strides
             if length(R_HS_loc)>=152;
                 for d=2:152
                     if(R_HS_loc(1)>L_HS_loc(1));
%indicates patient started on left foot, stepping with right
                         R=1; L=0;
                     else
                         R=0; L=1;
                     end
```

```
%=========================================================================
===========
                    if R==0 %Indicates subject started on Right foot, stepping
with left

%Determine right-to-left and left-to-right Step Time
                        R_L_ST(d-1)=(L_HS_loc(d-1)-R_HS_loc(d-1))/Samp_Freq;
%finds number of frames between HS events and then divides by capture rate (hz)
                        L_R_ST(d-1)=(R_HS_loc(d)-L_HS_loc(d-1))/Samp_Freq;

%Determine right-to-left and left-to-right Step Length
            R_L_SL_instant(d-1)=abs(LHEEcoords(L_HS_loc(d-1),1)-
RHEEcoords(L_HS_loc(d-1),1));
            L_R_SL_instant(d-1)=abs(RHEEcoords(R_HS_loc(d),1)-
LHEEcoords(R_HS_loc(d),1));

%Determine right-to-left and left-to-right Step Length using treadmill speed
            R_L_SL(d-1)=LHEEcoords(L_HS_loc(d-1),1)-RHEEcoords(R_HS_loc(d-
1),1)+(R_L_ST(d-1)*Tred_Spd);%*1000);
%uses treadmill speed to calc step length
            L_R_SL(d-1)=RHEEcoords(R_HS_loc(d),1)-LHEEcoords(L_HS_loc(d-
1),1)+(L_R_ST(d-1)*Tred_Spd);%*1000);
%uses treadmill speed to calc step length

 %Determine right-to-left and left-to-right Step Width
%take average location of left and right heel markers at heel
 %strike for each leg and report in global coord (left side of tred)
                        R_HS_Zcoord=RHEEcoords(R_HS_loc(d-1),3);
                        L_HS_Zcoord=LHEEcoords(L_HS_loc(d-1),3);
                        R_L_SWabs(d-1)=(R_HS_Zcoord-L_HS_Zcoord);
                        R_L_SW(d-1)=abs(R_L_SWabs(d-1));
                        R_L_LP(d-1)=L_HS_Zcoord+(R_L_SWabs(d-1)/2);
                        clear R_HS_Zcoord L_HS_Zcoord

                        R_HS_Zcoord=RHEEcoords(R_HS_loc(d),3);
                        L_HS_Zcoord=LHEEcoords(L_HS_loc(d-1),3);
                        L_R_SWabs(d-1)=(L_HS_Zcoord-R_HS_Zcoord);
                        L_R_SW(d-1)=abs(L_R_SWabs(d-1));
                        L_R_LP(d-1)=R_HS_Zcoord+(L_R_SWabs(d-1)/2);
                        clear R_HS_Zcoord L_HS_Zcoord

%determine step speed and lateral step speed
                        R_L_SS_instant(d-1)=R_L_SL_instant(d-1)./R_L_ST(d-1);
                        L_R_SS_instant(d-1)=L_R_SL_instant(d-1)./L_R_ST(d-1);

                        R_L_SS(d-1)=R_L_SL(d-1)./R_L_ST(d-1);
                        L_R_SS(d-1)=L_R_SL(d-1)./L_R_ST(d-1);

                        R_L_LS(d-1)=R_L_SW(d-1)./R_L_ST(d-1);
                        L_R_LS(d-1)=L_R_SW(d-1)./L_R_ST(d-1);



%=========================================================================
====================
                    else %Indicates subject started on Left foot, stepping
with Right

                        R_L_ST(d-1)=(L_HS_loc(d)-R_HS_loc(d-1))/Samp_Freq;
%finds number of frames between HS events and then divides by capture rate (hz)
                        L_R_ST(d-1)=(R_HS_loc(d-1)-L_HS_loc(d-1))/Samp_Freq;

%Determine right-to-left and left-to-right Step Length
```

```
                        R_L_SL_instant(d-1)=abs(LHEEcoords(L_HS_loc(d),1)-
RHEEcoords(L_HS_loc(d),1));
                        L_R_SL_instant(d-1)=abs(RHEEcoords(R_HS_loc(d-1),1)-
LHEEcoords(R_HS_loc(d-1),1));

%Determine right-to-left and left-to-right Step Length using treadmill speed
                        R_L_SL(d-1)=LHEEcoords(L_HS_loc(d),1)-
RHEEcoords(R_HS_loc(d-1),1)+(R_L_ST(d-1)*Tred_Spd);%*1000); %uses treadmill
speed to calc step length
                        L_R_SL(d-1)=RHEEcoords(R_HS_loc(d-1),1)-
LHEEcoords(L_HS_loc(d-1),1)+(L_R_ST(d-1)*Tred_Spd);%*1000); %uses treadmill
speed to calc step length
                       %Determine right-to-left and left-to-right Step Width
                       %take average location of left and right heel markers
at heel
                       %strike for each leg and report in global coord (left
side of tred)
                       R_HS_Zcoord=RHEEcoords(R_HS_loc(d-1),3);
                       L_HS_Zcoord=LHEEcoords(L_HS_loc(d),3);
                       R_L_SWabs(d-1)=(R_HS_Zcoord-L_HS_Zcoord);
                       R_L_SW(d-1)=abs(R_L_SWabs(d-1));
                       R_L_LP(d-1)=L_HS_Zcoord+(R_L_SWabs(d-1)/2);
                       clear R_HS_Zcoord L_HS_Zcoord

                       R_HS_Zcoord=RHEEcoords(R_HS_loc(d-1),3);
                       L_HS_Zcoord=LHEEcoords(L_HS_loc(d-1),3);
                       L_R_SWabs(d-1)=(L_HS_Zcoord-R_HS_Zcoord);
                       L_R_SW(d-1)=abs(L_R_SWabs(d-1));
                       L_R_LP(d-1)=R_HS_Zcoord+(L_R_SWabs(d-1)/2);
                       clear R_HS_Zcoord L_HS_Zcoord

                       %determine step speed and lateral step speed
                       R_L_SS_instant(d-1)=R_L_SL_instant(d-1)./R_L_ST(d-1);
                       L_R_SS_instant(d-1)=L_R_SL_instant(d-1)./L_R_ST(d-1);

                       R_L_SS(d-1)=R_L_SL(d-1)./R_L_ST(d-1);
                       L_R_SS(d-1)=L_R_SL(d-1)./L_R_ST(d-1);

                       R_L_LS(d-1)=R_L_SW(d-1)./R_L_ST(d-1);
                       L_R_LS(d-1)=L_R_SW(d-1)./L_R_ST(d-1);

                   end

               end
           else
               fprintf('not enough strides for this trial');
           end

%              figure(1)
%              plot(R_L_SL)
%              hold on
%              plot(L_R_SL,'g')

           clear d

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
           %Calculate generic steps
              Step_ST = zeros(1,150); Step_SL_instant = zeros(1,150); Step_SL
= zeros(1,150); Step_SS_instant = zeros(1,150);
              Step_SS = zeros(1,150); Step_SW = zeros(1,150);         Step_LS
= zeros(1,150); Step_LP = zeros(1,150);
```

```
            if R==0 %Indicates subject started on Right foot, stepping with
left
                count_ST=1; count_SL=1; count_SL_inst=1; count_SS_inst=1;
count_SS=1; count_SW=1; count_LS=1; count_LP=1;

              for iceman=1:75;

                Step_ST(1,count_ST)=R_L_ST(iceman); count_ST=count_ST+1;
                Step_ST(1,count_ST)=L_R_ST(iceman); count_ST=count_ST+1;

                Step_SL_instant(1,count_SL_inst) = R_L_SL_instant(iceman);
count_SL_inst=count_SL_inst+1;
                Step_SL_instant(1,count_SL_inst) =
L_R_SL_instant(iceman);count_SL_inst=count_SL_inst+1;

                Step_SL(1,count_SL) = R_L_SL(iceman); count_SL=count_SL+1;
                Step_SL(1,count_SL) = L_R_SL(iceman); count_SL=count_SL+1;

                Step_SS_instant(1,count_SS_inst) = R_L_SS_instant(iceman);
count_SS_inst=count_SS_inst+1;
                Step_SS_instant(1,count_SS_inst)= L_R_SS_instant(iceman);
count_SS_inst=count_SS_inst+1;

                Step_SS(1,count_SS) = R_L_SS(iceman); count_SS=count_SS+1;
                Step_SS(1,count_SS)= L_R_SS(iceman); count_SS=count_SS+1;

                Step_SW(1,count_SW) = R_L_SW(iceman); count_SW=count_SW+1;
                Step_SW(1,count_SW)= L_R_SW(iceman); count_SW=count_SW+1;

                Step_LS(1,count_LS) = R_L_LS(iceman); count_LS=count_LS+1;
                Step_LS(1,count_LS)= L_R_LS(iceman); count_LS=count_LS+1;

                Step_LP(1,count_LP) = R_L_LP(iceman); count_LP=count_LP+1;
                Step_LP(1,count_LP)= L_R_LP(iceman); count_LP=count_LP+1;
                end

            else %started on left foot
              count_ST=1; count_SL=1; count_SL_inst=1; count_SS_inst=1;
count_SS=1; count_SW=1; count_LS=1; count_LP=1;

              for iceman=1:75;

                Step_ST(1,count_ST)=L_R_ST(iceman); count_ST=count_ST+1;
                Step_ST(1,count_ST)=R_L_ST(iceman); count_ST=count_ST+1;

                Step_SL_instant(1,count_SL_inst) = L_R_SL_instant(iceman);
count_SL_inst=count_SL_inst+1;
                Step_SL_instant(1,count_SL_inst) = R_L_SL_instant(iceman);
count_SL_inst=count_SL_inst+1;

                Step_SL(1,count_SL) = L_R_SL(iceman); count_SL=count_SL+1;
                Step_SL(1,count_SL) = R_L_SL(iceman); count_SL=count_SL+1;

                Step_SS_instant(1,count_SS_inst) = L_R_SS_instant(iceman);
count_SS_inst=count_SS_inst+1;
                Step_SS_instant(1,count_SS_inst)= R_L_SS_instant(iceman);
count_SS_inst=count_SS_inst+1;

                Step_SS(1,count_SS) = L_R_SS(iceman); count_SS=count_SS+1;
                Step_SS(1,count_SS)= R_L_SS(iceman); count_SS=count_SS+1;

                Step_SW(1,count_SW) = L_R_SW(iceman); count_SW=count_SW+1;
                Step_SW(1,count_SW)= R_L_SW(iceman); count_SW=count_SW+1;
```

```
                Step_LS(1,count_LS) = L_R_LS(iceman); count_LS=count_LS+1;
                Step_LS(1,count_LS)= R_L_LS(iceman); count_LS=count_LS+1;

                Step_LP(1,count_LP) = L_R_LP(iceman); count_LP=count_LP+1;
                Step_LP(1,count_LP)= R_L_LP(iceman); count_LP=count_LP+1;
                end

             end


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%
             %calculate stride parameters
             for d=2:151
                     if(R_HS_loc(1)>L_HS_loc(1)); %indicates patient started on
left foot, stepping with right
                         R=1; L=0;
                     else
                         R=0; L=1;
                     end

%================================================================================
====================
                     if R==0  %Indicates subject started on Right foot,
stepping with left

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%
                        %Calculate Stride Time
                        R_StrideT(d-1)=R_L_ST(d-1)+L_R_ST(d-1);
                        L_StrideT(d-1)=L_R_ST(d-1)+R_L_ST(d);

                        %determine stride length
                        R_StrideL_instant(d-1)=R_L_SL_instant(d-
1)+L_R_SL_instant(d-1);
                        L_StrideL_instant(d-1)=L_R_SL_instant(d-
1)+R_L_SL_instant(d);

                        R_StrideL(d-1)=R_L_SL(d-1)+L_R_SL(d-1);
                        L_StrideL(d-1)=L_R_SL(d-1)+R_L_SL(d);

                        %Determine Right and Left Stride Width
                        R_StrideLP(d-1)=RHEEcoords(R_HS_loc(d),3);
%Lateral Position relative to edge of treadmill for heel marker
                        R_StrideW(d-1)=(RHEEcoords(R_HS_loc(d),3)-
RHEEcoords(R_HS_loc(d-1),3)); %NOTE: these calculations assume Z-coords have
been shifted to edge of treadmill.
                        L_StrideLP(d-1)=LHEEcoords(L_HS_loc(d),3);
                        L_StrideW(d-1)=(LHEEcoords(L_HS_loc(d),3)-
LHEEcoords(L_HS_loc(d-1),3));

                        %Determine stride speed and lateral speed
                         R_StrideS_instant(d-1)=R_StrideL_instant(d-
1)./R_StrideT(d-1);
                         L_StrideS_instant(d-1)=L_StrideL_instant(d-
1)./L_StrideT(d-1);

                         R_StrideS(d-1)=R_StrideL(d-1)./R_StrideT(d-1);
                         L_StrideS(d-1)=L_StrideL(d-1)./L_StrideT(d-1);

                         R_StrideLS(d-1)=R_StrideW(d-1)./R_StrideT(d-1);
                         L_StrideLS(d-1)=L_StrideW(d-1)./L_StrideT(d-1);
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%
                     else %indicates patient started on left foot, stepping
with right

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%
%Calculate Stride Time
                        R_StrideT(d-1)=R_L_ST(d-1)+L_R_ST(d);
                        L_StrideT(d-1)=L_R_ST(d-1)+R_L_ST(d-1);

%determine stride length
                        R_StrideL_instant(d-1)=R_L_SL_instant(d-
1)+L_R_SL_instant(d);
                        L_StrideL_instant(d-1)=L_R_SL_instant(d-
1)+R_L_SL_instant(d-1);

                        R_StrideL(d-1)=R_L_SL(d-1)+L_R_SL(d);
                        L_StrideL(d-1)=L_R_SL(d-1)+R_L_SL(d-1);

%Determine Right and Left Stride Width
                        R_StrideLP(d-1)=RHEEcoords(R_HS_loc(d),3);
%Lateral Position relative to edge of treadmill for heel marker
                        R_StrideW(d-1)=(RHEEcoords(R_HS_loc(d),3)-
RHEEcoords(R_HS_loc(d-1),3)); %NOTE: these calculations assume Z-coords have
been shifted to edge of treadmill.
                        L_StrideLP(d-1)=LHEEcoords(L_HS_loc(d),3);
                        L_StrideW(d-1)=(LHEEcoords(L_HS_loc(d),3)-
LHEEcoords(L_HS_loc(d-1),3));

 %Determine stride speed and lateral speed
                         R_StrideS_instant(d-1)=R_StrideL_instant(d-
1)./R_StrideT(d-1);
                         L_StrideS_instant(d-1)=L_StrideL_instant(d-
1)./L_StrideT(d-1);

                         R_StrideS(d-1)=R_StrideL(d-1)./R_StrideT(d-1);
                         L_StrideS(d-1)=L_StrideL(d-1)./L_StrideT(d-1);

                         R_StrideLS(d-1)=R_StrideW(d-1)./R_StrideT(d-1);
                         L_StrideLS(d-1)=L_StrideW(d-1)./L_StrideT(d-1);
                    end
             end


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%
    %Organize output data in single maatrix in proper format for GEM and other
analyses
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%
             %for stride output
             if Output==1;
             trial_str=num2str(count);
             temp_name=strcat(ConditionID,trial_str);
             temp_data=[(R_StrideL)',R_StrideT',(R_StrideS)', (R_StrideW)',
(R_StrideLS)', (R_StrideLP)']; % divide by 1000 to put in meters, not mm
             eval([temp_name '=' 'temp_data',';'])
             file_name=strcat(SubjectID,'_R_Stride')
             end
```

```
            if Output==2;
            trial_str=num2str(count);
            temp_name=strcat(ConditionID,trial_str);
            temp_data=[(L_StrideL)',L_StrideT',(L_StrideS)', (L_StrideW)',
(L_StrideLS)', (L_StrideLP)'];
            eval([temp_name '=' 'temp_data',';'])
            file_name=strcat(SubjectID,'_L_Stride')
            end

            %for step output
            if Output==3;
            trial_str=num2str(count);
            temp_name=strcat(ConditionID,trial_str);
            temp_data=[(R_L_SL)',R_L_ST',(R_L_SS)', (R_L_SW)', (R_L_LS)',
(R_L_LP)'];
            eval([temp_name '=' 'temp_data',';'])
            file_name=strcat(SubjectID,'_R_L_Step')
            end

            if Output==4
            trial_str=num2str(count);
            temp_name=strcat(ConditionID,trial_str);
            temp_data=[(L_R_SL)',L_R_ST',(L_R_SS)', (L_R_SW)', (L_R_LS)',
(L_R_LP)'];
            eval([temp_name '=' 'temp_data',';'])
            file_name=strcat(SubjectID,'_L_R_Step')
            end

            if Output==5
            trial_str=num2str(count);
            temp_name=strcat(ConditionID,trial_str);
            temp_data=[(Step_SL)',Step_ST',(Step_SS)', (Step_SW)', (Step_LS)',
(Step_LP)'];
            eval([temp_name '=' 'temp_data',';'])
            file_name=strcat(SubjectID,'_Steps')
            end

      %for sride output
            if Output==6;
            trial_str=num2str(count);
            temp_name=strcat(ConditionID,trial_str);
            temp_data=[(R_StrideL_instant)',R_StrideT',(R_StrideS_instant)',
(R_StrideW)', (R_StrideLS)', (R_StrideLP)']; % divide by 1000 to put in meters,
not mm
            eval([temp_name '=' 'temp_data',';'])
            file_name=strcat(SubjectID,'_R_Stride_inst')
            end

            if Output==7;
            trial_str=num2str(count);
            temp_name=strcat(ConditionID,trial_str);
            temp_data=[(L_StrideL_instant)',L_StrideT',(L_StrideS_instant)',
(L_StrideW)', (L_StrideLS)', (L_StrideLP)'];
            eval([temp_name '=' 'temp_data',';'])
            file_name=strcat(SubjectID,'_L_Stride_inst')
            end

        %for step output
            if Output==8;
            trial_str=num2str(count);
            temp_name=strcat(ConditionID,trial_str);
            temp_data=[(R_L_SL_instant)',R_L_ST',(R_L_SS_instant)', (R_L_SW)',
(R_L_LS)', (R_L_LP)'];
```

```
            eval([temp_name '=' 'temp_data',';'])
            file_name=strcat(SubjectID,'_R_L_Step_inst')
            end

            if Output==9
            trial_str=num2str(count);
            temp_name=strcat(ConditionID,trial_str);
            temp_data=[(L_R_SL_instant)',L_R_ST',(L_R_SS_instant)', (L_R_SW)',
(L_R_LS)', (L_R_LP)'];
            eval([temp_name '=' 'temp_data',';'])
            file_name=strcat(SubjectID,'_L_R_Step_inst')
            end

            if Output==10
            trial_str=num2str(count);
            temp_name=strcat(ConditionID,trial_str);
            temp_data=[(Step_SL_instant)',Step_ST',(Step_SS_instant)',
(Step_SW)', (Step_LS)', (Step_LP)'];
            eval([temp_name '=' 'temp_data',';'])
            file_name=strcat(SubjectID,'_Steps_inst')
            end


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%
%clear all variables before next trial interation
            clear LHEEcoords LHEEcoords60 LHEEcoordsDumb LHEEcoordsT
LPSIcoords LPSIcoords60 LPSIcoordsDumb LPSIcoordsT
            clear LTOEcoords LTOEcoords60 LTOEcoordsDumb LTOEcoordsT
            clear RHEEcoords RHEEcoords60 RHEEcoordsDumb RHEEcoordsT
RPSIcoords RPSIcoords60 RPSIcoordsDumb RPSIcoordsT
            clear RTOEcoords RTOEcoords60 RTOEcoordsDumb RTOEcoordsT
            clear L_HS_loc L_HS_loc_temp L_LHEE_SAC_Dist L_R_LS L_R_SL_instant
L_R_SS_instant L_R_ST L_R_SW
            clear R_HS_loc R_HS_loc_temp R_RHEE_SAC_Dist R_L_LS R_L_SL_instant
R_L_SS_instant R_L_ST R_L_SW
            clear L_StrideLS L_StrideL_instant L_StrideS_instant L_StrideT
L_StrideW L_TO_loc L_der
            clear R_StrideLS R_StrideL_instant R_StrideS_instant R_StrideT
R_StrideW R_TO_loc R_der
            clear SAC Test_X1 Test_X2 check cols d data dumb h problem q rows
s temp_data temp_name text time trial_str xL xR ySacL ySacR
            clear Samp_Freq Step_SL_Instant Step_ST Step_SS_instant Step_SW
Step_LS Step_LP Step_SL Step_SS R_L_SS R_L_SL L_R_SL L_R_SS
            clear R_StrideS R_StrideL L_StrideS L_StrideL
        end
    end
   filename=file_name;
   clear file_name
    save(filename,'SPD*', 'LEN*', 'TIM*', 'ALL*'); %add all the condition names
to this list

end
end
toc
```

GEM Analyses Code

```
%=========================================================================%
%  GEM_CAREN2.m    -  Runs GEM Analyses on Re-Structured Trish Data
%
%  First Written   -  Jon Dingwell    -  02/10/2012
%  Last Modified   -  nicole bohnsack    -  04/29/2013
%
%=========================================================================%


%-------------------------------------------------------------------------%
clear all;                                          %  Clear Memory          %
close all;                                          %  Close All Windows     %
clc                                                 %  Clear Command Window  %
tic                                                 %  Start Stopwatch       %

Starting_Directory = pwd
Conditions = ['SPD'; 'LEN'; 'TIM'; 'ALL']; %['NOP'; 'VIS';'MLP']%list all
conditions in this vector to automate process
Num_Cond = 4; %the number of conditions that were tested
% Num_Trials = 2; %the number of trials per condition
ExperimentID='E1';
ProjectID='P0042';
Sample_Freq = 60; %collection frequency in hertz
Sub=[1,2,3,4,5,6,7,8,9,10,11,12,13,14];%(Enter the subject# in order. For
example, if you wanted to process subject #1, #4, and #10, this vector would be
(Subj=1,4,10))
Tred_Speed=[1.25,1.25,1.2,1.25,1.16,1.16,1.16,1.16,1.16,1.16,1.2,1.25,1.16,1.2]
;% in m/s (You will need to enter the appropriate treadmill speed into this
vector - order should match the order of subjects listed above)
Leg_length=[0.97,1.06,1.03,1.03,0.9,0.9,0.88,0.85,0.87,0.89,0.92,0.96,0.88,0.9]
;

counter = 1;

% Loop for Subjects
for Subjs=1:14;
    %Subjs=1:length(Sub);
    Subj=Sub(Subjs);
    Tred_Spd=Tred_Speed(Subjs);


    %- clear old data before moving on to next subject:
    clear SPD1 SPD2    LEN1 LEN2
    clear TIM1 TIM2    ALL1 ALL2

    if Subj < 10
        SubjectID = ['S0', int2str(Subj)];

    elseif Subj >= 10
        SubjectID = ['S', int2str(Subj)];
    end

    SubjID=SubjectID;


  %load data file %%%%%%%%%%%%%%%%%%%%%%%%%
    subfolder = strcat(SubjectID);
%     foldern = ['Data\',subfolder,'\'];
    foldern = ['E1_6000hz\'];
    eval(['load ', foldern, subfolder, '_R_Stride.mat;']);
```

```
    %- Each *.mat file will contain 25 Matrices:
    %-           NOP#, APP#, APV#, MLP#, MLV#
    %-      where '#' indicates Trial Number (1-5)
    %- Each Matrix contains 5 columns of data:
    %-           [SL, ST, SS, SW, LS]
    %-      where:   SL = Step Lengths [m]
    %-               ST = Step Times [s]
    %-               SS = Step Speeds (i.e., SL./ST) [m/s]
    %-               SW = Step Widths [m]
    %-               LS = Lateral Step Speeds (i.e., SW./ST) [m/s]

    % Loop for Conditions:
 for Cond = 1:Num_Cond
        ConditionID=Conditions(Cond,:);
        %Added on 4/30% used to determine how many trials per condition%%%%%
%         subfolder = strcat('Data\',ProjectID, ExperimentID, SubjID,'\');
%         csv_ftemp = strcat(ProjectID, ExperimentID, SubjID, ConditionID,
'T');

%          d = dir([subfolder,csv_ftemp,'*']);
        d = who([ConditionID,'*']);
        ntrials = length(d);


        % Loop for Trials
        for count=1:ntrials %Num_Trials
            Trial=count;


            disp(['Subj ' int2str(Subj) '  /  Cond ' Conditions(Cond,:) '  /
Trial ' int2str(Trial)])

            %-- Clear variables to be calculated / replaced for each trial:
            clear SL  SS  ST  SW  LS
            clear SLn SSn STn SWn LSn
            clear STShift SLShift DeltaTn DeltaPn
            clear X Y Xn Yn

            %-- Define SL, ST, and SS data for THIS trial:
            eval(['SL = ' Conditions(Cond,:) int2str(Trial) '(:,1);']);
            eval(['ST = ' Conditions(Cond,:) int2str(Trial) '(:,2);']);
            eval(['SS = ' Conditions(Cond,:) int2str(Trial) '(:,3);']);
            eval(['SW = ' Conditions(Cond,:) int2str(Trial) '(:,4);']);
            eval(['LS = ' Conditions(Cond,:) int2str(Trial) '(:,5);']);




%=========================================================================
==
            %-- First, Normalize everything (SL & ST & SW) to unit variance:
            SLn = SL ./ std(SL);
            STn = ST ./ std(ST);
            SSn = SLn ./ STn;
            SWn = SW ./std(SW);
            LSn = SWn ./ STn;
            Tn = ST./mean(ST);
            Ln = SL./mean(SL);
```

```
%=========================================================================
==
            %-- Define GEM from slope defined by average speed:
            %--  (+/- 3 s.d.'s will plot lines on graphs a bit longer than the
data
            V = mean(SS);  %-- V = treadmill speed -- defines the slope of the
GEM!

            %=== X & Y here are just used for plotting the GEM as a line at
speed V
            X  = [(mean(ST)-4*std(ST)), mean(ST), (mean(ST)+4*std(ST))];
            Y = V.*X;
            Y_t = 1.098;
            X_l = 1.34;
            %===  NORMALIZED ("__n") DATA ARE USED FOR DOING GEM CALCULATIONS:
            Vn = mean(SSn);
            Xn  = [(mean(STn)-4*std(STn)), mean(STn), (mean(STn)+4*std(STn))];
            Yn = Vn.*Xn;

%-------------------------------------------------------------------------
-
            %-- Calculate Deviations Perpendicular & Tangent to the GEM:
            %-- Use "geometrical" method -- See my notes...
            STShift = STn - mean(STn);              %- Shifts ST data to
mean(ST) location...
            SLShift = SLn - (Vn.*mean(STn));        %- Shiftf SL data to same
set point...
            SWShift = SWn - (Vn.*mean(STn));          %- Shiftf SW data to same
set point...
            %%%% how do I make this for SW%%%%
            DeltaTn = (1./sqrt(1+(Vn.^2))) .* (STShift + (Vn.*SLShift));
            DeltaPn = (1./sqrt(1+(Vn.^2))) .* ((-Vn.*STShift) + SLShift);

            %-------------------------------------------------------------
-------------
%-- Calculate Means & SD's for 3 starting variables:
            MeanSL = mean(SL);                  SDSL = std(SL);
            MeanST = mean(ST);                  SDST = std(ST);
            MeanSS = mean(SS);                  SDSS = std(SS);
            MeanSW = mean(SW);                  SDSW = std(SW);
            MeanLS = mean(LS);                  SDLS = std(LS);

            MeanSLn = mean(SLn);                SDSLn = std(SLn);
            MeanSTn = mean(STn);                SDSTn = std(STn);
            MeanSSn = mean(SSn);                SDSSn = std(SSn);
            MeanSWn = mean(SWn);                SDSWn = std(SWn);
            MeanLSn = mean(LSn);                SDLSn = std(LSn);

            MeanDPn = mean(DeltaPn);            SDDPn = std(DeltaPn);
            MeanDTn = mean(DeltaTn);            SDDTn = std(DeltaTn);


%=========================================================================
=
          %Directionality analyses%
%=========================================================================
==
%     % Normalized varibales for sternad way (SMT) %
                L_prime=(SL-MeanSL)/SDSL;
                T_prime= (ST-MeanST)/SDST;
%     %Fitting line to data to determine slope for theta speed%%%
                pfline = polyfit(T_prime,L_prime,1);
                slope = atan(pfline(1,1));
```

```
%     %For Theta Prime Calculation
                Theta_p = (0:0.01*pi:pi);
                Theta_test = Theta_p + slope;
%     %For plotting purposes: see below
           counter2 = 1;
           for tt = 1:length(Theta_test)
           % for tt = 1:length(Theta_Prime)
                theta_temp = Theta_test(tt);
                d_theta(:,counter2) = T_prime.*cos(theta_temp)+
L_prime.*sin(theta_temp);
%                 hfig = figure;
%                 plot(d_theta(:,counter2),char(line_color(counter2))); hold
on;
                SMT(:,counter2) = d_theta(:,counter2);
                counter2 = counter2+1;
           end

%-------------------------------------------------------------------------
-
%-- Compute "Stability" (lambda) of each measure:
            N = length(ST);

            PSL = polyfit(SL(1:(N-1),1), SL(2:N,1), 1);
LambdaSL = PSL(1);
            PST = polyfit(ST(1:(N-1),1), ST(2:N,1), 1);
LambdaST = PST(1);
            PSS = polyfit(SS(1:(N-1),1), SS(2:N,1), 1);
LambdaSS = PSS(1);
            PSW = polyfit(SW(1:(N-1),1), SW(2:N,1), 1);
LambdaSW = PSW(1);
            PLS = polyfit(LS(1:(N-1),1), LS(2:N,1), 1);
LambdaLS = PLS(1);

            PDP = polyfit(DeltaPn(1:(N-1),1), DeltaPn(2:N,1), 1);
LambdaDP = PDP(1);
            PDT = polyfit(DeltaTn(1:(N-1),1), DeltaTn(2:N,1), 1);
LambdaDT = PDT(1);                      PSMT = polyfit(SMT(1:(N-1),1),
SMT(2:N,1), 1);              LambdaSMT = PSMT(1);

%-------------------------------------------------------------------------
-
%-- Compute scaling exponents (alpha) of each measure:
            [nSL  fSL  pSL]  = DFA(SL);          AlphaSL = pSL(1);
            [nST  fST  pST]  = DFA(ST);          AlphaST = pST(1);
            [nSS  fSS  pSS]  = DFA(SS);          AlphaSS = pSS(1);

            [nSL  fSL  pSL]  = DFA(SLn);         AlphaSLn = pSL(1);
            [nST  fST  pST]  = DFA(STn);         AlphaSTn = pST(1);
            [nSS  fSS  pSS]  = DFA(SSn);         AlphaSSn = pSS(1);
            [nDPn fDPn pDPn] = DFA(DeltaPn);     AlphaDPn = pDPn(1);
            [nDTn fDTn pDTn] = DFA(DeltaTn);     AlphaDTn = pDTn(1);
%=========================================================================
=====
            %calculating Directionality %
%=========================================================================
=====
            [rr cc ] = size(SMT);

            for ii = 1:cc
                [nSMT   fSMT   pSMT]   = DFA(SMT(:,ii));
                AlphaSMT(ii,1) = pSMT(1);
                clear nSMT fSMT pSMT
            end
```

```
            AlphaSMT_data(:,count,Cond)=AlphaSMT;
%==========================================================================
            %-- Put Final Dependent Measures into Big Fat Matrix:
%==========================================================================


            RowNum = counter;
            OutData(RowNum,  1:3)  = [Subj, Cond, Trial];

            OutData(RowNum,  4:13)  = [   MeanSL,    MeanST,    MeanSS,
MeanSW,    MeanLS,    MeanSLn,   MeanSTn,   MeanSSn,   MeanSWn,   MeanLSn];
            OutData(RowNum, 14:23) = [     SDSL,      SDST,      SDSS,
SDSW,      SDLS,     SDSLn,     SDSTn,     SDSSn,     SDSWn,     SDLSn];

            OutData(RowNum, 24:25) = [  MeanDPn,   MeanDTn];
            OutData(RowNum, 26:27) = [    SDDPn,     SDDTn];

            OutData(RowNum, 28:32) = [ LambdaSL,  LambdaST,  LambdaSS,
LambdaSW, LambdaLS];
            OutData(RowNum, 33:34) = [ LambdaDP,  LambdaDT];

            OutData(RowNum, 35:39) = [ AlphaSL,  AlphaST,  AlphaSS,  AlphaSLn,
AlphaSTn];
            OutData(RowNum, 40:42) = [ AlphaSSn,  AlphaDPn, AlphaDTn];
            OutData(RowNum, 43:43) = [ AlphaSMT];

            counter = counter +1;
%- Below is a single-line list of all of the colums in "OutData"
%- Save and use this text to cut-paste as column headings into Excel / Minitab!
%- [Subj, Cond, Trial, MeanSL, MeanST, MeanSS, MeanSW, MeanLS, MeanSLn,
MeanSTn, MeanSSn, MeanSWn, MeanLSn, SDSL, SDST, SDSS, SDSW, SDLS, SDSLn, SDSTn,
SDSSn, SDSWn, SDLSn, MeanDPn, MeanDTn, SDDPn, SDDTn, LambdaSL, LambdaST,
LambdaSS, LambdaSW, LambdaLS, LambdaDP, LambdaDT, AlphaSL,  AlphaST,  AlphaSS,
AlphaSLn, AlphaSTn, AlphaSSn,  AlphaDPn, AlphaDTn
%==========================================================================
================
%Saving Directionality Files
%==========================================================================
================
   %For SPD
            if Cond == 1 && count == 1

              OutDataSPD1(Subjs,  1:2)  = [Subj, Trial];
              OutDataSPD1(Subjs,  3:103)  = [AlphaSMT];

            end
            if Cond == 1 && count == 2
              OutDataSPD2(Subjs,  1:2)  = [Subj, Trial];
              OutDataSPD2(Subjs,  3:103)  = [AlphaSMT];

            end
    %For LEN
             if Cond == 2 && count == 1

              OutDataLEN1(Subjs,  1:2)  = [Subj, Trial];
              OutDataLEN1(Subjs,  3:103)  = [AlphaSMT];

            end
            if Cond == 2 && count == 2
              OutDataLEN2(Subjs,  1:2)  = [Subj, Trial];
              OutDataLEN2(Subjs,  3:103)  = [AlphaSMT];
```

```
            end
    %For TIM
              if Cond == 3 && count == 1

              OutDataTIM1(Subjs,  1:2)  = [Subj, Trial];
              OutDataTIM1(Subjs,  3:103)  = [AlphaSMT];

            end
            if Cond == 3 && count == 2
              OutDataTIM2(Subjs,  1:2)  = [Subj, Trial];
              OutDataTIM2(Subjs,  3:103)  = [AlphaSMT];

            end
    %For ALL
              if Cond == 4 && count == 1

              OutDataALL1(Subjs,  1:2)  = [Subj, Trial];
              OutDataALL1(Subjs,  3:103)  = [AlphaSMT];

            end
            if Cond == 4 && count == 2
              OutDataALL2(Subjs,  1:2)  = [Subj, Trial];
              OutDataALL2(Subjs,  3:103)  = [AlphaSMT];

            end

        end   %- for Trial = 1:Num_Trials



    end   %- for Cond = 1:Num_Cond
  counter2 = counter2 + 1;
 save([SubjID,'_alphaSMT','.mat'],'AlphaSMT_data');

end   %- for Subj = 1:Num_Subj

%- Return to original working directory (Should have never left??):
eval(['cd ' Starting_Directory])

%- Save final data file to disk for Statistical Analysis in Minitab:
save(['OutData_1_7GEM.dat'],'OutData','-ascii','-double','-tabs')
save(['OutData_1_7GEM.mat'],'OutData')

save OutDataSPD1.dat OutDataSPD1 -ascii -double -tabs
save OutDataSPD2.dat OutDataSPD2 -ascii -double -tabs
save OutDataLEN1.dat OutDataLEN1 -ascii -double -tabs
save OutDataLEN2.dat OutDataLEN2 -ascii -double -tabs
save OutDataTIM1.dat OutDataTIM1 -ascii -double -tabs
save OutDataTIM2.dat OutDataTIM2 -ascii -double -tabs
save OutDataALL1.dat OutDataALL1 -ascii -double -tabs
save OutDataALL2.dat OutDataALL2 -ascii -double -tabs

clear OutData*

disp('All Done!')
disp(['Time Elapsed = ' num2str(toc) ' sec.'])
%- End of Program ------------------------------------------------------
```

RMSE Code

```
%================================================================================%
%RMSE CALCULATIONS
%  Last Modified   -  nicole bohnsack    -  04/29/2013
%================================================================================%


clear all;                                              %  Clear Memory             %
close all;                                              %  Close All Windows        %
clc                                                     %  Clear Command Window     %
tic                                                     %  Start Stopwatch          %

Starting_Directory = pwd
Conditions = ['SPD'; 'LEN'; 'TIM'; 'ALL']; %['NOP'; 'VIS';'MLP']%list all
conditions in this vector to automate process
Num_Cond = 4; %the number of conditions that were tested
% Num_Trials = 2; %the number of trials per condition
ExperimentID='E2';
ProjectID='P0042';
Sample_Freq = 120; %collection frequency in hertz
Sub=[1,2,3,4,5,6,7,8,9,10];%(Enter the subject# in order. For example, if you
wanted to process subject #1, #4, and #10, this vector would be (Subj=1,4,10))
Tred_Speed=[3.22,3.22,3.22,3.22,3.22,3.22,3.22,3.22,3.22,3.22,];% in m/s (You
will need to enter the appropriate treadmill speed into this vector - order
should match the order of subjects listed above)
N_strides = 150;
counter = 1;

% Loop for Subjects
for Subjs=1:10;
    Subj=Sub(Subjs);
    Tred_Spd=Tred_Speed(Subjs);
%     LegL=Leg_length(Subjs);%for non-dimensionalized i_hat value
%     Tim_nd=LegL./9.81; % for non-dimensionalized t_hat value
%     Tim_val=sqrt(Tim_nd) % for non-dimensionalized t_hat value

    %- clear old data before moving on to next subject:
    clear SPD1 SPD2    LEN1 LEN2
    clear TIM1 TIM2    ALL1 ALL2

    if Subj < 10
        SubjectID = ['S0', int2str(Subj)];

    elseif Subj >= 10
        SubjectID = ['S', int2str(Subj)];
    end

    SubjID=SubjectID;


  %load data file %%%%%%%%%%%%%%%%%%%%%%%%%
    subfolder = strcat(SubjectID);
%     foldern = ['Data\',subfolder,'\'];
%     foldern = ['DissertationData\E1_6000hz\'];
    foldern = ['E2_6000hz\'];
    eval(['load ', foldern, subfolder, '_R_Stride.mat;']);


    %- Each *.mat file will contain 25 Matrices:
    %-           NOP#, APP#, APV#, MLP#, MLV#
    %-      where '#' indicates Trial Number (1-5)
    %- Each Matrix contains 5 columns of data:
    %-           [SL, ST, SS, SW, LS]
    %-      where:   SL = Step Lengths [m]
```

```
    %-              ST = Step Times [s]
    %-              SS = Step Speeds (i.e., SL./ST) [m/s]
    %-              SW = Step Widths [m]
    %-              LS = Lateral Step Speeds (i.e., SW./ST) [m/s]

    % Loop for Conditions:
    for Cond = 1:Num_Cond
        ConditionID=Conditions(Cond,:);
        %Added on 4/30% used to determine how many trials per condition%%%%%
        subfolder = strcat('Data\',ProjectID, ExperimentID, SubjID,'\');
        csv_ftemp = strcat(ProjectID, ExperimentID, SubjID, ConditionID, 'T')

         d = who([ConditionID,'*']);
        ntrials = length(d);

        % Loop for Trials
        for count=1:ntrials %Num_Trials
            Trial=count;



            disp(['Subj ' int2str(Subj) '  /  Cond ' Conditions(Cond,:) '  /
Trial ' int2str(Trial)])

%-- Clear variables to be calculated / replaced for each trial:
            clear SL  SS  ST  SW  LS
            clear SLn SSn STn SWn LSn
            clear STShift SLShift DeltaTn DeltaPn
            clear X Y Xn Yn

%-- Define SL, ST, and SS data for THIS trial:
            eval(['SL = ' Conditions(Cond,:) int2str(Trial) '(:,1);']);
            eval(['ST = ' Conditions(Cond,:) int2str(Trial) '(:,2);']);
            eval(['SS = ' Conditions(Cond,:) int2str(Trial) '(:,3);']);
            eval(['SW = ' Conditions(Cond,:) int2str(Trial) '(:,4);']);
            eval(['LS = ' Conditions(Cond,:) int2str(Trial) '(:,5);']);


%================================================================================
==
%-- First, Normalize everything (SL & ST & SW) to unit variance:
            SLn = SL ./ std(SL);
            STn = ST ./ std(ST);
            SSn = SLn ./ STn;
            SWn = SW ./std(SW);
            LSn = SWn ./ STn;
%================================================================================
==
%-- Define GEM from slope defined by average speed:
%--  (+/- 3 s.d.'s will plot lines on graphs a bit longer than the data
            V = mean(SS);  %-- V = treadmill speed -- defines the slope of the
GEM!


            %=== X & Y here are just used for plotting the GEM as a line at
speed V
            X  = [(mean(ST)-20*std(ST)), mean(ST), (mean(ST)+20*std(ST))];
            Y = V.*X;
            StrideTime = 0.7217;
            StrideLength = 2.314;
            y_temp = ones(2,1).*(2.314);
            x_temp = ones(2,1).*(0.7217);
            goalSL = 2.314;
```

```
            goalST = 0.7217;

%===  NORMALIZED ("__n") DATA ARE USED FOR DOING GEM CALCULATIONS:
            Vn = mean(SSn);
            Xn  = [(mean(STn)-4*std(STn)), mean(STn), (mean(STn)+4*std(STn))];
            Yn = Vn.*Xn;

%-------------------------------------------------------------------------------
-
            %-- Calculate Deviations Perpendicular & Tangent to the GEM:
            %-- Use "geometrical" method -- See my notes...
            STShift = STn - mean(STn);              %- Shifts ST data to
mean(ST) location...
            SLShift = SLn - (Vn.*mean(STn));        %- Shiftf SL data to same
set point...
            SWShift = SWn - (Vn.*mean(STn));          %- Shiftf SW data to same
set point...
            %%%% how do I make this for SW%%%%
            DeltaTn = (1./sqrt(1+(Vn.^2))) .* (STShift + (Vn.*SLShift));
            DeltaPn = (1./sqrt(1+(Vn.^2))) .* ((-Vn.*STShift) + SLShift);

%-------------------------------------------------------------------------------
-
%-- Calculate Means & SD's for 3 starting variables:
            MeanSL = mean(SL);                  SDSL = std(SL);
            MeanST = mean(ST);                  SDST = std(ST);
            MeanSS = mean(SS);                  SDSS = std(SS);
            MeanSW = mean(SW);                  SDSW = std(SW);
            MeanLS = mean(LS);                  SDLS = std(LS);

            MeanSLn = mean(SLn);                SDSLn = std(SLn);
            MeanSTn = mean(STn);                SDSTn = std(STn);
            MeanSSn = mean(SSn);                SDSSn = std(SSn);
            MeanSWn = mean(SWn);                SDSWn = std(SWn);
            MeanLSn = mean(LSn);                SDLSn = std(LSn);

            MeanDPn = mean(DeltaPn);            SDDPn = std(DeltaPn);
            MeanDTn = mean(DeltaTn);            SDDTn = std(DeltaTn);



%-------------------------------------------------------------------------------
-
%-- Compute "Stability" (lambda) of each measure:
            N = length(ST);

            PSL = polyfit(SL(1:(N-1),1), SL(2:N,1), 1);
LambdaSL = PSL(1);
            PST = polyfit(ST(1:(N-1),1), ST(2:N,1), 1);
LambdaST = PST(1);
            PSS = polyfit(SS(1:(N-1),1), SS(2:N,1), 1);
LambdaSS = PSS(1);
            PSW = polyfit(SW(1:(N-1),1), SW(2:N,1), 1);
LambdaSW = PSW(1);
            PLS = polyfit(LS(1:(N-1),1), LS(2:N,1), 1);
LambdaLS = PLS(1);

            PDP = polyfit(DeltaPn(1:(N-1),1), DeltaPn(2:N,1), 1);
LambdaDP = PDP(1);
            PDT = polyfit(DeltaTn(1:(N-1),1), DeltaTn(2:N,1), 1);
LambdaDT = PDT(1);
```

```
%-------------------------------------------------------------------------
-
%-- Compute scaling exponents (alpha) of each measure:
            [nSL  fSL  pSL]  = DFA(SL);          AlphaSL = pSL(1);
            [nST  fST  pST]  = DFA(ST);          AlphaST = pST(1);
            [nSS  fSS  pSS]  = DFA(SS);          AlphaSS = pSS(1);

            [nSL  fSL  pSL]  = DFA(SLn);         AlphaSLn = pSL(1);
            [nST  fST  pST]  = DFA(STn);         AlphaSTn = pST(1);
            [nSS  fSS  pSS]  = DFA(SSn);         AlphaSSn = pSS(1);
            [nDPn fDPn pDPn] = DFA(DeltaPn);     AlphaDPn = pDPn(1);
            [nDTn fDTn pDTn] = DFA(DeltaTn);     AlphaDTn = pDTn(1);
%=========================================================================
%RMSE Calculation%
%=========================================================================
% RMSE = sqrt(mean((y - yhat).^2));  % Root Mean Squared Error

%
   %stride speed%
            Tots1 =(((SS- V).^2)./N_strides);
            Bob1 = sum(Tots1);
            Abc1 = sqrt(Bob1);
            RMSESS = Abc1./V;
            RMSESSp = RMSESS .* 100;

   %Stide Length %
            Tots2 =(((SL-goalSL).^2)./N_strides);
            Bob2 = sum(Tots2);
            Abc2 = sqrt(Bob2);
            RMSESL = Abc2./goalSL;
            RMSESLp = RMSESL .* 100;
   %Stide Time %

            Tots3 =(((ST-goalST).^2)./N_strides);
            Bob3 = sum(Tots3);
            Abc3 = sqrt(Bob3);
            RMSEST = Abc3./goalST;
            RMSESTp = RMSEST .* 100;

%-------------------------------------------------------------------------
-
%-- Put Final Dependent Measures into Big Fat Matrix:
%             RowNum = 25.*(Subj-1) + 5.*(Cond-1) + Trial;
                  %from CAREN data  25: 5 con x 5 trials, 5: conditions%
%             RowNum = 8.*(Subj-1) + 4.*(Cond-1) + Trial;
                  %use this for nicole dissertation%
            RowNum = counter;
            OutData(RowNum,  1:3)  = [Subj, Cond, Trial];

            OutData(RowNum,  4:13)  = [   MeanSL,    MeanST,    MeanSS,
MeanSW,    MeanLS,    MeanSLn,   MeanSTn,   MeanSSn,   MeanSWn,   MeanLSn];
            OutData(RowNum, 14:23) = [     SDSL,      SDST,      SDSS,
SDSW,      SDLS,     SDSLn,     SDSTn,     SDSSn,    SDSWn,     SDLSn];

            OutData(RowNum, 24:25) = [  MeanDPn,   MeanDTn];
            OutData(RowNum, 26:27) = [    SDDPn,     SDDTn];

            OutData(RowNum, 28:32) = [ LambdaSL,  LambdaST,  LambdaSS,
LambdaSW, LambdaLS];
            OutData(RowNum, 33:34) = [ LambdaDP,  LambdaDT];

            OutData(RowNum, 35:39) = [ AlphaSL,  AlphaST,  AlphaSS,  AlphaSLn,
AlphaSTn];
```

```
            OutData(RowNum, 40:42) = [ AlphaSSn,  AlphaDPn, AlphaDTn];
            OutData(RowNum, 43:45) = [ RMSESSp,   RMSESLp,   RMSESTp];
            counter = counter +1;
            %- Below is a single-line list of all of the colums in "OutData"
            %- Save and use this text to cut-paste as column headings into
Excel / Minitab!
            %- [Subj, Cond, Trial, MeanSL, MeanST, MeanSS, MeanSW, MeanLS,
MeanSLn, MeanSTn, MeanSSn, MeanSWn, MeanLSn, SDSL, SDST, SDSS, SDSW, SDLS,
SDSLn, SDSTn, SDSSn, SDSWn, SDLSn, MeanDPn, MeanDTn, SDDPn, SDDTn, LambdaSL,
LambdaST, LambdaSS, LambdaSW, LambdaLS, LambdaDP, LambdaDT, AlphaSL,  AlphaST,
AlphaSS,  AlphaSLn, AlphaSTn, AlphaSSn,  AlphaDPn, AlphaDTn



    end   %- for Trial = 1:Num_Trials

    end   %- for Cond = 1:Num_Cond


    end   %- for Subj = 1:Num_Subj

%- Return to original working directory (Should have never left??):
eval(['cd ' Starting_Directory])

%- Save final data file to disk for Statistical Analysis in Minitab:
save OutData_E2_1_21.dat OutData -ascii -double -tabs


disp('All Done!')
disp(['Time Elapsed = ' num2str(toc) ' sec.'])
%- End of Program ------------------------------------------------------------
```

Experimental Subject Data

Chapter 3:
Experiment 1

E1 Subjects	Sex	Age	Height (m)	Leg Length (m)	Weight (kg)	Dom. Leg	Speed
1	F	27	1.72	0.97	54.5	R	1.2
2	M	22	1.87	1.06	75.297	R	1.25
3	F	26	1.9	1.03	90.8	R	1.25
4	M	21	1.87	1.03	82.33	R	1.25
5	F	22	1.65	0.9	57.7	R	1.16
6	F	30	1.62	0.9	54.4	R	1.16
7	M	20	1.765	0.88	79.545	R	1.16
8	F	22	1.66	0.85	64.5	R	1.16
9	F	28	1.62	0.87	59.1	R	1.16
10	F	23	1.62	0.89	55	R	1.16
11	F	34	1.64	0.92	66	R	1.2
12	M	21	1.7	0.96	63.5	R	1.25
13	F	22	1.64	0.88	55	R	1.16
14	F	20	1.65	0.91	62.8	L	1.2

Chapter 4:
Experiment 2

E2 Subjects	Sex	Age	Height (m)	Leg Length (m)	Weight (kg)	Dom. Leg	Speed
1	F	25	1.63	0.91	56.8	R	3.22
2	F	33	1.69	1	60	R	3.22
3	F	27	1.68	0.98	55	R	3.22
4	M	32	1.8	1.01	75	R	3.22
5	M	27	1.9	1.03	85	R	3.22
6	M	27	1.74	1.02	72	R	3.22
7	M	26	1.93	1.01	87.8	R	3.22
8	M	35	1.75	0.99	86.4	R	3.22
9	M	23	1.66	0.91	66.5	R	3.22
10	F	26	1.7	0.94	64.5	R	3.22

Chapter 5:
Experiment 3

E3 Subjects	Sex	Age	Height (m)	Leg Length (m)	Weight (kg)	Dom. Leg	PWS	RTS	PRS
1	F	27	1.68	0.99	55	R	2.8	4.9	6.3
2	F	30	1.62	0.92	56.5	R	2.7	4.8	6.2
3	M	24	1.8	0.99	69.9	R	2.8	4.9	6.4
4	M	26	1.93	1.01	87.2	R	2.8	5	6.5
5	F	25	1.63	0.91	58.7	R	2.7	4.7	6.1
6	M	26	1.93	1.03	88.6	R	2.8	5	6.5
7	M	21	1.87	1.03	80.9	R	2.8	5	6.5
8	F	23	1.675	0.95	60	R	2.7	4.8	6.3
9	F	22	1.65	0.92	61.8	R	2.7	4.8	6.2
10	M	22	1.76	0.93	70.5	R	2.7	4.8	6.2

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