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An Investigation of Kinetic Visual Biofeedback on Dynamic Stance Symmetry

Trisha J. Massenzo

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University

By

Trisha J. Massenzo

Director: Peter E. Pidcoe, PT, DPT, Ph.D

Associate Professor, Department of Physical Therapy

Virginia Commonwealth University

Richmond, VA

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Abstract

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The intent of the following research is to utilize task-specific, constraint-induced therapies and apply towards dynamic training for symmetrical balance. Modifications to an elliptical trainer were made to both measure weight distributions during dynamic stance as well as provide kinetic biofeedback through a man-machine interface. Following a review of the background, which includes research from several decades that are seminal to current studies, a design review is discussed to cover the design of the modified elliptical (Chapter 2).

An initial study was conducted in a healthy sample population in order to determine the best visual biofeedback representation by comparing different man-machine interfaces (Chapter 3). Index of gait symmetry measures indicated that one display interface optimized participant performance during activity with the modified elliptical trainer.

A second study was designed to determine the effects of manipulating the gain of the signal to encourage increased distribution towards the non-dominant weight bearing limb. The purpose of the second study was to better understand the threshold value of gain manipulation in a healthy sample set. Results analyzing percentage error as a measure of performance show that a range between 5-10% allows for a suitable threshold value to be applied for participants who have suffered a stroke.

A final study was conducted to apply results/knowledge from the previous two studies to a stroke cohort to determine short-term carryover following training with the modified elliptical trainer. Data taken from force measurements on the elliptical trainer suggest that there was carryover with decreased error from pre to post training. For one participant GaitRite® data show a significant difference from pre to post measurements in single limb support.

The results of the research suggest that visual biofeedback can improve symmetrical performance during dynamic patterns. For a better understanding of visual biofeedback delivery, one display representation proved to be beneficial compared to the others which resulted in improved performance. Results show that healthy human participants can minimize error with visual biofeedback and continue minimizing error until a threshold value of 10%. Finally, results have shown promise towards applying such a system for kinetic gait rehabilitation.

Chapter 1

Chapter 1: Introduction

Problem and study significance

Epidemiology

Stroke is one of the leading causes of death in the United States as well as the leading cause of prolonged disability (Go et al., 2012, Jackson et al., 2010, Go et al., 2014). Approximately 795,000 people in the United States experience a stroke each year (Go et al., 2012). On a global scale, in 2010 alone, 33 million people recorded having a stroke and of that population 16.9 million were noted for first occurrence (Mozaffarian et al., 2015). Total direct stroke-related medical costs between the years 2012 to 2030 have been projected to triple, amounting to $184.1 billion (Mozaffarian et al., 2015). In a study by Godwin et al., measurements from 2001 to 2005 were made to determine associated costs with outpatient rehabilitative services and medications. This group found that the average yearly cost for services and medications ranged based on the level of dependence upon inpatient discharge. For independent patients the total average cost was $15,624, where 66.7% of the cost went towards outpatient rehabilitation services. For modified dependence the total average cost was $21,691, 72.5% towards outpatient rehabilitation services. Finally, for dependent patients the total average cost was $18,574, 69.7% for outpatient rehabilitation services (Godwin et al., 2011). Of the U.S. stroke population, 65-85% is able to walk independently six months post stroke (Eng et al., 2007). Although this percentage is high, most individuals often experience complications with gait parameters such as balance, motor control, and speed. Walking independently is an important goal with rehabilitation, due to an early predictor linking dependence in walking to increased likelihood of entering nursing homes and increased probability of death (Eng et al., 2007). Although significant improvements in gait appear to occur within the first 6 months post-stroke, studies such as those by Edward Taub have shown that improvements can occur in the chronic phase as a result of constraint-induced training techniques (Taub, 2014). With constraint-induced training, many individuals can learn to independently walk either with or without assistive devices, therefore improving quality of life and life expectancy.

Posture

Postural control of the lower extremities is dependent on a combination of sensory processes in order to maintain balance during static and dynamic stances (Horak, 2006). Human sensory elements (e.g. somatosensory, visual and vestibular) interpret and react to complex environments by functioning together. Postural orientation, which is defined as a combination of body alignment and tone, and postural equilibrium, which is defined as an ability to stabilize the body's center of mass (COM), are two essential functional goals in maintaining postural control (Horak, 2006). Both can be influenced by sensorimotor functions reacting to features of the environment. For example, postural orientation can be altered by changing the compliance of a surface during static stance. With the uncertainty of somatosensory inputs, the visual and vestibular systems begin to override inputs for cognitive processing.

During static stance, postural control is maintained through stable positions of the body's COM. Although complete erect orientation is not possible, acceptable postural coordination of lower limb segments is achieved by small variations in postural sway during quiet standing

(Strang et al., 2011). Transitioning from static stance to walking, the goal of dynamic stance is to prevent falling while transitioning the COM out of the base of support for forward progression (Winter, 1995).

Healthy Gait

Normal, healthy gait can be defined as a rhythmic, symmetrical pattern of weight acceptance and unloading between each limb. Generally, each gait cycle can be divided into two phases: stance and swing. Approximately 60% of the cycle is spent in the stance phase and 40% of the cycle is spent in swing (Perry, 1992). Although healthy gait can be easily and quickly characterized by these two phases, gait is often divided into eight phases for a more detailed description. These phases include the following: initial contact, loading response, mid-stance, terminal stance, pre-swing, initial swing, mid-swing and terminal swing (Figure 1) (Perry, 1992).

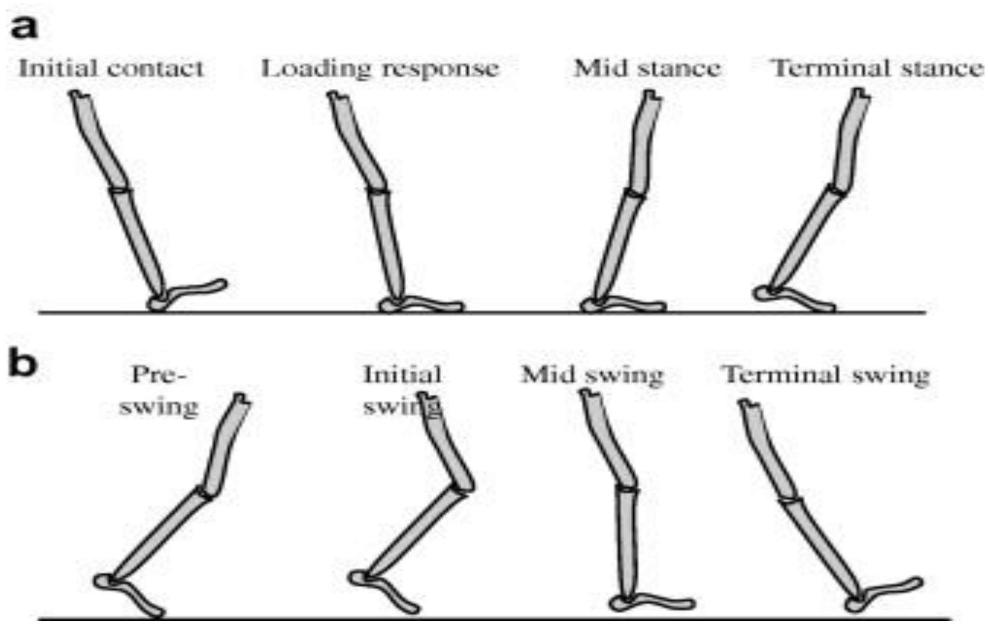

Figure 1. Eight phases of gait cycle. Four phases of gait in stance transitioning into weight acceptance and single limb support (a). Swing phases of gait allowing limb progression (b) (Liu et al., 2009).

These phases are often grouped as 3 separate tasks, namely weight acceptance, single limb support and limb advancement. Initial contact and loading response are grouped into weight acceptance, since in these phases weight begins loading with initial contact and the percent of loading increases as the limb prepares for 100% loading. Initial contact occurs when the foot initially contacts the ground. In this phase, the heel is flexed, ankle is dorsiflexed and the knee is extended. Following this phase is the loading response which accounts for shock absorption, due to knee flexion, and weight-bearing stability. During the loading response the heel is used as a rocker and limited by the ankle in plantar flexion to begin progression of weight acceptance. Following weight acceptance, single limb support occurs including both mid stance and terminal stance. Mid-stance then begins when the contralateral foot initiates toe-off and continues until the total body weight is aligned over the forefoot. In this first half of single support, the goal is for progression of the planted foot as well as limb and trunk stability. Single limb support is completed during terminal stance, which begins with heel rise and proceeds until the contralateral foot begins initial contact. The final task is limb advancement which is initiated in the final phase of stance, pre-swing, and continuing until terminal swing. During the final phase of stance, pre-swing occurs when the contralateral limb enters initial contact, while the ipsilateral limb increases ankle plantar flexion and decreases hip extension, and ends when the contralateral limb begins the loading response, as the ipsilateral limb finalizes toe-off. The first phase of swing begins with initial swing, as the foot is lifted from the ground (ankle is in dorsiflexion for toe-clearance) with progression controlled by hip flexion and knee flexion. Mid-swing occurs as the ankle continues dorsiflexion, knee extends in response to gravity and the hip flexes. The final phase of gait, terminal swing, continues ankle dorsiflexion, knee extension and hip flexion to prepare for initial contact with the ground (Perry, 1992).

In describing gait, the body can be divided into two units: the passenger and locomotor units (Perry, 1992). The passenger unit includes the head, neck, trunk and arms. This unit doesn't directly contribute to walking; instead it is viewed as a mass that sits on top of the locomotor unit. The passenger unit accounts for 70% of the body mass. The locomotor unit contributes to mobility and the following functions: propulsion, stance stability, shock absorption, and energy conservation. Orientation of the locomotor unit can be modified based on inputs from visual elements, vestibular functions and somatosensory cues. Visual inputs give way to navigation through a space and correct locomotor orientation for obstacle avoidance. The vestibular system accounts for both linear velocity and angular acceleration to provide feedback about spatial orientation. Lastly, somatosensory inputs sense the position of body segments relative to each other and with objects in which the body is in contact. To further describe the visual component of locomotor orientation, several studies have tested reduced vision during static and dynamic stance in addition to measuring the response to alterations in environmental optical flow patterns (Strang et al., 2011).

Postural sway during static stance increases drastically when vision is restricted often leading to decreased postural control of the locomotor unit (Strang et al., 2011). Strang et al. measured center of pressure (COP), the elliptical area (EA) containing the COP, and the path length (PL) the COP traversed during static stance in twenty-six healthy participants while altering visual and somatosensory inputs. Their results were consistent with previous research in finding that the amount and area of postural sway increased with restricted vision and more compliant surfaces. Strang et al. suggested that with the removal of visual and somatosensory inputs, the vestibular system compensates by increasing sway to receive feedback on spatial orientation. This compensatory activity ultimately leads to a decrease in postural control during static stance, often resulting in drastic variations during gait.

During dynamic stance, locomotion and navigation is accomplished by interpreting both optical flow stimuli and egocentric orientation (Warren et al., 2001, Pailhous et al., 1990, Konczak et al., 1994, Schmuckler et al., 1989, Warren et al., 1988, Rushton et al., 1998). Warren et al. studied the effects of both optical flow and egocentric orientation during path navigation. Results from this study displayed the importance of incorporating both features. During an initial egocentric view of an object, the participants were able to determine their own orientation within the space and navigate to the object, although the path of pursuit was curved. With the addition of optical flow patterns, the path of pursuit began to straighten towards the object leading to improved path navigation by decreasing time and length of pursuit (Warren et al., 2001).

Gait of Hemiplegic Stroke Patients

One of the most common limitations following stroke is gait dysfunction and an inability to ambulate efficiently, especially within an obstacle-driven environment. Imbalance often occurs due to a distortion in the patient’s body image. This can be the result of a brain lesion reducing the patient’s awareness of body position and weight (Perry, 1969). With this distortion the patient may no longer make adjustments in weight or brace to prevent a fall towards the involved side. Patients often experience an asymmetric limp and have slower and more abrupt gait patterns (Perry, 1969). Hemiplegic patients are dependent on non-reflexive primitive gait patterns that involve voluntary action and demonstrate weak and incomplete movements.

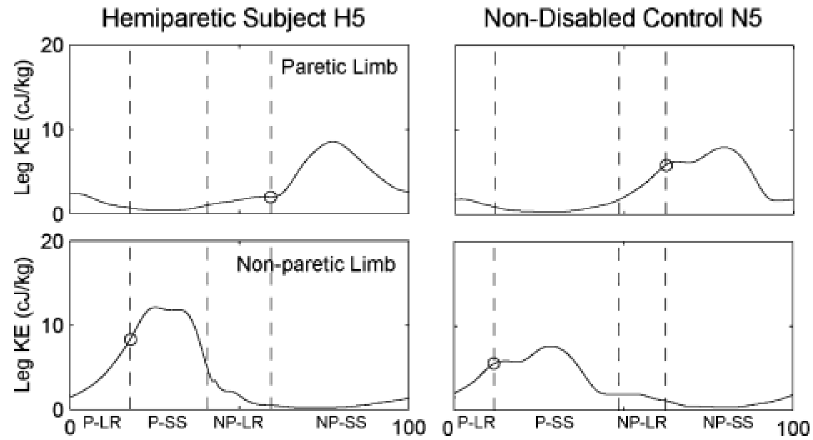

Figure 2. Comparison of kinetic energy during gait for hemiparetic vs. non-disabled control. Notice increased single stance in the non-paretic limb compared to the paretic, with an increase in kinetic energy for limb propulsion in the non-paretic limb. Circles indicate initiation of swing phases with toe-off. Kinetic energy during toe-off for the paretic limb is lower than both the non-paretic limb and the non-disabled control. This indicates a decrease in knee flexion corresponding to lack of propulsion in the paretic limb (Chen et al., 2005).

Incomplete movements are often evidenced by an inability to maintain flexion in the hip while extending the knee during initial contact in the stance phase, forward reaching is limited with the affected limb (Perry, 1969). Knee flexion is restricted corresponding to a lack of propulsion in the paretic limb during pre-swing (Figure 2) (Chen et al., 2005). This limitation in forward progression of the limb and the inability to shift weight onto the affected limb causes a decrease in the stance period of each gait cycle. One study in particular noted limitations in cadence and weight shifts in patients who were on average 43.4 months post stroke (vonSchroeder et al., 1995). Although cadence improved with rehabilitation, weight shifting onto the affected limb was still compromised (Figure 3). The vonSchroeder study found that cadence improved with rehabilitation but concluded that this improvement came as a result in compensating for gait abnormalities. As a consequence, stance phases on the affected limb remained the same, reflecting decreased stance on the affected limb compared to the unaffected. This result raised the issue that, although patients can alter their gait to improve cadence, asymmetries in weight bearing can still exist even if cadence has improved over time. Weight-bearing activities during rehabilitation are expected to provide a substantial influence to increase symmetrical performance during gait (Nugent, 1994).

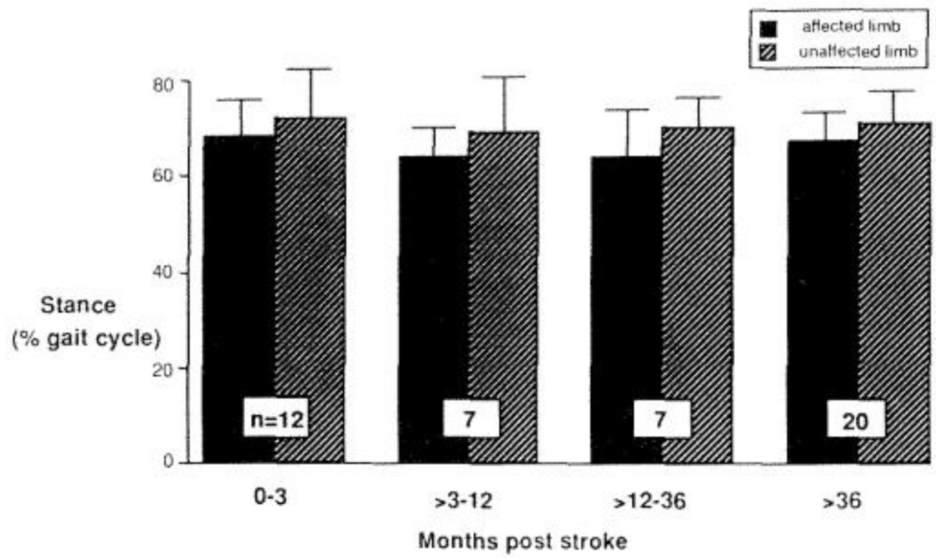

Figure 3. Stance Comparison of Affected vs. Unaffected Limb. Stance asymmetries were present in a study measuring stance characteristics between affected limb and unaffected limb in a sample set of 46 stroke participants. Participants tended to spend more time in stance and less in swing for the unaffected limb, even with rehabilitation experience (vonSchroeder et al., 1995).

Hemiparetic patients often develop a compensatory pattern in gait consistent with pelvic hiking and lateral displacement of the foot to compensate for reduced knee flexion during swing, thereby allowing limb clearance of the ground (Chen et al., 2005). This results in an increased mechanical energetic cost during walking (Figure 2) Percent weight loading on the unaffected limb can range from 57% to 70%, as opposed to a 50/50 distribution between both limbs, depending on the severity of the stroke and the length of physical therapy (Adegoke et al., 2012). Even with months of physical therapy, stance asymmetries during gait can still exist (Figure 3) (vonSchroeder et al., 1995). With the increase of disproportionate loading comes the increased risk of falling as well as difficulty with certain tasks such as walking through obstacles and ascending/descending stairs. Adegoke noted that with these more difficult tasks of obstacle avoidance and ambulating stairs, post-stroke patients tend to displace even more weight towards the unaffected limb therefore increasing the risk of fall (Adegoke et al., 2012). Along with asymmetrical weight distribution, sway tends to increase during static and dynamic stance which is related to greater postural unsteadiness (Nichols, 1997).

After a stroke, one primary goal with rehabilitation is the restoration of walking to an independent community ambulating level. A study conducted by Perry et al. looked at differences in community-dwelling individuals compared to those confined to the house and developed 6 levels of functional walking to establish a quantifiable assessment between independent and dependent walkers (Perry et al., 1995). In this study, the control of knee flexion and extension, as well as velocity, was a key indicator that differentiated between household and community ambulators. The ability to predict outcomes based on these variables allows clinicians to administer rehabilitation techniques specific to outcome goals to increase the probability of developing appropriate gait-like parameters thereby promoting independence in daily activities of life. Such rehabilitation techniques are focused on constraint-induced task-specific activities specifically related to real-world applications.

Theoretical framework

Constraint Induced Therapy

Following stroke, several neurological functions are impacted based on the infarcted area. Often internal recovery occurs in three phases within the first few weeks after incidence (Wieloch et al., 2006). The first phase is the activation of cell repair in both the affected area and diaschisis. Functional cell plasticity follows with axonal sprouting of existing pathways due to an increase in potentiation, and finally neurogenesis occurs, resulting in new pathways for connections (Wieloch et al., 2006). External events, through physical therapy, also promote cortical reorganization (Harvey, 2009). Previously, physical therapy was focused on teaching compensatory actions, therefore constricting patients to only involve the non-affected side to perform daily activities of life. Although these techniques are still applied on occasion, there is an increasing trend towards utilizing the model of constraint-induced movement therapy to promote cortical remapping (Harvey, 2009). Such techniques encourage patients to increase use of the affected side to perform specific tasks in and outside the clinic. Originally proposed by Donald O. Hebb in 1949, the activation of one cell and subsequent assistive stimulation of a secondary cell will promote axonal and dendritic sprouting to synaptically connect the two cells together, which is the basis of cortical remapping (Harvey, 2009). Promoting reorganization of neuronal connections can be achieved from constraining activities that force/encourage use of the impaired limb.

The principle of constraint-induced movement therapy was originally developed by Edward Taub at the University of Alabama at Birmingham, based on previous studies testing learned non-use in somatosensory deafferentated monkeys (Taub, 1993, Taub, 2014, Morris, 2006). Constraint-induced therapy not only involves the restriction of non-affected limb use, but also additional components in the model to encourage and monitor use of the affected limb in and outside the clinic (Taub, 2014). This rehabilitation protocol involves four basic components: (1) intensive training of affected limb; (2) implementing the shaping technique during therapy; (3) the transfer package; (4) discouraging compensation that leads to learned nonuse (Taub, 2014). The first component of therapy is achieved typically by restricting use of the non-affected limb during activity (most commonly by using a padded mit or sling for upper extremity training). In order to accomplish a specific task during therapy, patients are forced to use their affected limb. The second component is shaping, which adds incrementing levels of difficulty throughout training and provides feedback related to the quality of movement patterns. The transfer package (third component) is an approach to therapy outside the clinic by the use of such techniques as behavioral contracts and daily activity logs. This approach sets the patient accountable for using his or her paretic limb outside the limitations of the clinic. The final component encourages steady use of the paretic limb as opposed to compensating towards the unaffected side, which leads to learned non-use. Learned non-use is thought to occur over time when individuals begin compensating for deficits to perform daily activities of life. This results in forming habits of using the non-affected limb for daily tasks. The time frame of constraint-induced therapy occurs over several weeks to ensure that strength of the affected limb is comparable to the non-affected to allow coordinated movements during daily activities.

Although each component separately contributes to overall use of the affected limb during training, the protocol as an entirety results in longitudinal use once treatment duration is completed. Not only is constraint-induced therapy dependent on the treatment administered in the clinic, but also the patient's willingness to implement such methodologies outside the clinic as prescriptions for mobility.

Current Techniques for Gait Training

For gait rehabilitation, the first component of constraint-induced therapy is achieved by constraining the affected limb to progress forward and bear weight in normal patterns. Body-weight supported treadmill training (BWSTT) is one technique that promotes constrained task-oriented activity. During early-stage BWSTT, partial body weight is supported by a harness and two physical therapists assist the patient while walking on a treadmill (Figure 4) (Harvey, 2009, Werner et al., 2002). One therapist assists in the progression of the limb in correct alignment, while the other stands behind the patient shifting his or her pelvis to force them to bear weight equally on both sides. Although this technique is beneficial in promoting use of the paretic limb, activity is heavily dependent on therapist's fatigue, where therapists can last on average 15-20 minutes (Harvey, 2009, Jackson et al., 2010, Hidler et al., 2009). Due to fatigue, the therapist may guide the patient's limb in diverse range of motions throughout the treatment (Hidler et al., 2009). With ranging patterns throughout treatment, the patient is no longer consistent with motor control of the affected limb. Physical therapists are also susceptible to injury due to the physical demand and misalignment of body positioning in order to complete the task required during gait rehabilitation (Hidler et al., 2005). Another disadvantage of this technique is that it employs a subjective measure for gait parameters as opposed to an objective quantification of kinetic and kinematic patterns for accurate gait training.

Figure 4. Current dynamic gait rehabilitation technique for patients. Two physical therapists assist both progressions of the limb and weight shifts while the patient is walking on a treadmill (Werner et al., 2002).

Split-belt treadmills have also been implemented during gait rehabilitation to increase the speed of the paretic limb. In split-belt designs, the treadmill belt is “split” and the speed of each side can be independently controlled. During therapy, the physical therapist sets parameters to vary the speed of the belt on the side of the paretic limb. Often, the adjusted speed of the belt is slightly faster than the non-paretic side. This constrains the patient to progress the paretic limb faster, resulting in an increase of overall cadence and step length of the paretic limb (Reisman et al., 2013, Reisman et al., 2007). Although this tends to improve the cadence and step length of the patient, often this can lead to injury due to overuse and disproportionate loading in the joints (Kaplan et al., 2014). Another interesting note from split-belt training is that the results from increased step length do not correlate with increased stance time (Reisman et al., 2013). This might be due to the compensatory pattern that the patient chooses in order to match the adjusted belt speed.

In an effort to improve consistency and duration in treatment, robotic devices have been constructed to promote accurate alignment of the limb without the need of a therapist during limb progression (Hidler et al., 2009). The Lokomat® (Figure 5) is such a device that constrains the limb to a specific pattern. It controls both knee and hip kinematics and the amount of assistance it provides to the patient. Its components include a treadmill, robotic exoskeleton attachments for the legs, a body-weight support system and a control/biofeedback system to program speed and provide biofeedback to patients (Hidler, 2005). Although the Lokomat® solves the problem of consistency and duration, little evidence suggests that this device is a suitable alternative to conventional therapy. First, the Lokomat® restricts movement of the pelvis, thereby hampering weight shifting and loading between limbs. It also lacks variability in the gait profile that would allow modulation in parameters from the patient, therefore impeding carry-over from training to real-world applications. Often BWSTT produces a more favorable outcome in training compared to the Lokomat®, due to the amount of variability during therapist-assisted training (Harvey, 2009, Hornby et al., 2008).

Figure 5. Lokomat® system for gait rehabilitation. The Lokomat® provides assistance to the patient during gait rehabilitation by controlling hip and knee kinematics (Hidler et al., 2005).

Recent studies have incorporated other forms of training through biofeedback, specifically visual biofeedback, to encourage the participant to adjust postural orientation during therapy. Transitioning from kinematic training, both research and clinical practices have implemented biofeedback devices for kinetic training. These forms of balance training include balance plates, i.e. SMART Balance Master (NeuroCom International, Inc., Clackamas, OR, USA), and the Wii balance board (Nintendo, Kyoto, Kyoto Prefecture, Japan) which provide visual biofeedback to the user from vertical load measurements to adjust his or her weight on the measurement device (Barcala et al., 2013, Chen et al., 2002, Gil-Gómez et al., 2011, Goble et al., 2014). In a study by Chen et al., an experimental group using the SMART Balance Master for training was compared to a control group, in which both groups received the same therapeutic treatments outside of the scope of the study (Chen et al., 2002). The results of the study found that patients who used the SMART Balance Master in addition to conventional training performed significantly better in measurements of maximal stability, ankle strategy and center of gravity alignment. A study by Gil-Gomez et al. mirrors these results from the SMART Balance Master study. In this study, patients improved significantly in static balance when using the Wii balance board coupled with visual biofeedback compared to controls (Gil-Gómez et al., 2011). This study measured improvements through clinical-based tests, i.e. Berg Balance test, Brunel Balance assessment, timed stair test, to name a few. Participants also commented on increased motivation to perform this alternative treatment to conventional training. Although, static performance was improved through this training, when comparing these to dynamic measurements a need was proposed by the authors to produce such a device that would improve dynamic gait postural stability. Although this study from Gil-Gomez et al. suggests that the Wii balance board provides adequate training compared to conventional techniques, a study from Barcala et al. suggests there is no significant difference between the two therapeutic paradigms (Barcala et al., 2013). Barcala et al. evaluated such quantifiable measures as the Berg Balance scale, timed up and go and functional independence measures to determine the effect of the Wii balance board. In this study, there were no significant differences between the experimental group and the control. An interesting note to consider between the two studies is that the visual representation of postural stability differed between the studies. Although both studies used the Wii balance board platform, Gil-Gomez et al. developed a visual biofeedback system to couple to the device, whereas Barcala et al. used the factory settings. The difference in these findings suggests that user-centered biofeedback design is important and, as a result, interface design was initially investigated in the proposed research.

Impact of Visual Biofeedback during Walking

The rhythmic patterns of healthy gait primarily occur due to the combination of several senses delivering biofeedback to allow for adjustments. Of these senses, vision is a key component in maintaining appropriate postural static stance and path progression (Tcheang et al., 2011, Wan et al., 2012, Khan et al., 2010). In a study performed by Strang et al., postural sway was tested when vision was restricted (Strang et al., 2011). They found that as vision was reduced, postural control decreased leading to increased sway during stance. Lishman and Lee found that they could control postural sway when altering optical flow patterns of subjects (Nardini et al., 2012, Lishman et al., 1973). Subjects stood in the middle of a dynamic room while the researchers would control whether the room would sway towards or away from a central position. As the room swayed towards the subject, they would counteract the motion and step backwards. Both these experiments suggest that postural control during static stance can be influenced by vision.

Visual perception also contributes significantly in adjusting lower limb trajectories during ambulation. Studies implementing instrumented treadmills, such as the IVERT (Integrated Virtual Environment Rehabilitation Treadmill) system from Feasel et al., have proven that subjects can sense abnormalities in their gait based on visual biofeedback (Feasel et al., 2011). Taking this idea from perception to adjustments in gait, Dingwell et al. found that by visually displaying biofeedback from kinetic measurements subjects improved gait parameters in stance time, push-off forces and center of pressure (Dingwell et al., 1996, Dingwell et al., 1996). This study applied different visual biofeedback displays that incorporated differential, temporal and comparison elements to deliver information on the aforementioned gait parameters. Crowell et al. also implemented visual biofeedback, read from a subject-mounted accelerometer, to improve running mechanics; specifically, to reduce impact loading (Crowell et al., 2010). They found that with the additional element of visual biofeedback, subjects reduced their impact peaks and amplitude of peak acceleration. These studies not only suggest that participants can perceive their own gait asymmetries, but also make adjustments to gradually improve performance.

Implementation of visual displays to perform specific tasks serves to offload cognitive demand from the participant to optimally achieve the task. Employing visual representations of complex tasks/objects improve both the speed and accuracy of interpretation from the user. Often when applying a visual representation of non-visual information, patterns may develop that simplify interpretation of the non-visual information which allows the user to group objects for comparison rather than deciphering the individual objects themselves (Pomerantz et al., 1989, Hegarty et al., 2011). This action of pattern recognition significantly decreases the time of interpretation and increases accuracy through the implementation of visual representations. Kirsh and Maglio studied visual interactive systems and the effect on performance while a user interacted with the visual display (Kirsh et al., 1994, Kirsh, 1997). They subjectively measured performance of experienced Tetris players during the game and found that rotations of the objects were made more frequently than unexperienced players. Instead of making complicated internal calculations, these players manipulated the objects continuously until it matched the accurate placement. Kirsh later describes this method as complementary actions, actions that serve to decrease cognitive load (Hegarty et al., 2011, Kirsh, 1997). Applying these fundamentals from previous research to treatment of gait asymmetries, improved outcomes may result from off-loading internal cognitive processes to pre-calculated external visual representations, thereby giving promise to improved prescribed treatment plans for dynamic postural control. This may be especially important for patients who have suffered stroke, since they may have additional processing difficulty. Systems that implement these design fundamentals can play an influential role in gait rehabilitation.

In consideration of current rehabilitation techniques and their effectiveness, a low-cost system coupled to an elliptical trainer was developed that influences stability/balance during ambulation. This system was built based on two of the four principles of constraint-induced movement therapy developed by Edward Taub. It allows intensive training of the affected limb, while discouraging compensation since goals must be met by the affected limb independently. It also allows therapists to apply the shaping technique in constraint-induced movement therapy by modifying parameters within the visual biofeedback presented to the user.

Purpose of research

The purpose of this research was to determine the impact of training on a modified elliptical trainer that incorporated dynamic kinetic balance biofeedback via a visual interface in healthy and post-stroke individuals. Incorporating visual biofeedback has been viewed in previous research as a more intuitive approach when considering biomechanical variables. To understand both the cognitive demand and physical demand placed on the user during training, studies were conducted to test the effectiveness of the display and subsequent outcomes on dynamic postural stability. Biased weight-bearing approaches were tested that incorporate training while manipulating the gain of the left-right load signal to force the subject to increase the load on their non-dominant limb. When applied to a clinical population (e.g. stroke), this would involve getting the patient to increase loads on their paretic side. Thus taking them beyond symmetric gait training and forcing them to be **hyper-symmetric** (or load-biased on their weaker side). This approach is often used in both constrain-induced therapy and split-belt treadmill training on this population.

Specific Aims and Hypotheses

H1 – Visual biofeedback will influence and improve kinetic (weight-bearing) symmetric performance.

> SA1.1 – To build a novel training device that employs kinetic biofeedback through a visual display.
>
> SA1.2 – To determine if kinetic visual biofeedback has an influence on symmetric weight distribution in a healthy population.

H2 – One of the four display types will provide the best man-machine interface for improving symmetric and asymmetric weight bearing performance in a healthy population.

> SA2 – To determine which of four display types provides the best man-machine interface for improving symmetric and asymmetric weight-bearing performance in a healthy population.

H3 – There is a relationship between asymmetric weight-bearing and performance in a healthy population (age 20-30).

> SA3 – To determine the relationship between asymmetric weight-bearing and performance in a healthy younger population (age 20-30).

H4 – There is a relationship between asymmetric weight-bearing and performance in a healthy population (age 35-60).

SA4 – To determine the relationship between asymmetric weight-bearing and performance in a healthy older population (age 35-60).

H5 – Individuals with gait impairments secondary to stroke will be able to train hyper-symmetrically and will have a short term functional change in gait symmetry following visual biofeedback system training.

SA5.1 – To determine if participants with gait impairments secondary to stroke can perform successfully at the pre-defined value of gain manipulation.

SA5.2 – To determine if participants with gait impairments secondary to stroke will have a short-term functional change in gait symmetry post training with the visual biofeedback system.

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Chapter 2

Chapter 2: Design Review

Introduction

This chapter reviews the modifications that were made to an existing elliptical trainer in order to create a device that can provide kinetic biofeedback during dynamic stance. The design goals used during the development of the device were based on successes and failures of current systems and methods employed in the clinic and in research. This chapter will also describe the motivation for incorporating feedback from a single modality to assist in perceiving vertical load distribution during elliptical trainer use. Features of the system will be highlighted and described to provide an understanding of the intention behind the research.

Recent techniques for gait rehabilitation training include body weight supported treadmill training (BWSTT), split-belt treadmill training, and robotic training (i.e. the Lokomat®) (Harvey, 2009). Each system has attributes and shortcomings that helped lead to the development of the system used in this research. In both BWSTT and split-belt training, a physical therapist is required to help progress the paretic limb through each gait cycle. Although this training technique has been proven effective, the training duration is often limited by therapist fatigue (Jackson et al., 2010). Another disadvantage of these systems is limited control of lower extremity joint loading. Joint loads are dependent on initial contact and weight distribution. The patient may load his or her weight in an inappropriate fashion potentially leading to inaccurate training as well as increased susceptibility to injury (Patterson et al., 2008, Lu et al., 2007). To reduce inappropriate loading and dependence of the therapist during training, robotic devices like the Lokomat® were invented to control limb progression and weight transfer. This system has been successful, but is costly. As a result, these systems only exist in larger, more profitable facilities. A disadvantage of the Lokomat® is that the patient's independence during limb progression is limited. Specifically, system restraints control 100% of the movement patterns during rehabilitation (Harvey, 2009, Hidler et al., 2009). The patient is not challenged to accomplish the task at hand, therefore limiting his or her ability to independently ambulate during and post rehabilitation training in the transfer stage of rehabilitation. Increasing variability in training can be accomplished using split-belt treadmills. Although these systems again require therapist's supervision, they allow independent control of paretic limb cadence. Cadence is increased sequentially in pre-defined belt speed changes of the overall gait speed and on the paretic limb side only. Although this form of rehabilitation has been shown to increase overall cadence, the load transfer control associate with the Lokomat is missing. There is an obvious void in systems design to control both the kinematic and kinetic load transfers elements of gait in a way that is conducive to effective rehabilitation of patients with limited lower extremity control (e.g. patients who have suffered stroke).

With technological advancements in the past decade leading to improved cost-effective solutions, the incorporation of biofeedback in the clinic has drastically increased. Such systems as the SMART Balance Master and the Wii balance board have improved kinetic asymmetries in static stance. Studies such as Gil-Gómez et al. have shown that following training on the Wii balance board with visual biofeedback many of the subjects had favorable outcomes during clinical-based tests such as the Berg Balance test and Brunel Balance assessment (Gil-Gómez et al., 2011). Although these studies on static postural stability have shown drastic improvements in symmetry, static systems are often not transferable to dynamic stance such as walking.

To better understand the impact of visual biofeedback in dynamic systems, several systems have been developed for either single or split-belt treadmills. Participants were able to perceive their own asymmetries in gait in a study by Feasel et al. In this study an interactive virtual reality environment was coupled to a split-belt treadmill to integrate path navigation into a synthetic environment (Feasel et al., 2011). Although participants were able to sense their own gait asymmetries, there wasn't significant evidence to suggest that the system was suitable for short or long term adjustments. Dingwell and colleagues approached visual biofeedback in simplistic representations that captured and displayed the specific variable that the participant needed to adjust gait parameters to (Dingwell et al., 1996, Dingwell et al., 1996). Dingwell and colleagues employed three different displays representing separate variables, these displays having differential, temporal, and comparison elements. Results of this study showed improved stance time on the paretic limb, improved push-off forces and center of pressure. These studies suggest that participants not only perceive their asymmetries, but can adjust accordingly when specific variables are highlighted and enhanced during biofeedback delivery.

The device used in this research was designed and built to include kinematic control of lower extremity motion, kinetic feedback regarding weight distribution, and the ability to control gait symmetry via visual biofeedback. This novel gait training device was built with the intention to produce task-specific, constraint-induced training specifically for gait rehabilitation in a stroke population. Although this device can be used for multiple applications in gait rehabilitation, the system was developed to initially focus on a single population. It allows the user to independently control limb progression and weight distribution. Visual biofeedback was incorporated to allow the user to determine his or her performance in real-time and make adjustments in the symmetry of their loading patterns.

Design Goals

- Device needs to allow dynamic training for symmetrical balance.
- Device needs to promote independence in training while fully supporting at least up to 220lbs.
- Device needs to be cost-effective and produce favorable patient outcomes.
- Device needs to promote constraint-induced therapeutic techniques during training.
- Device needs to include visual biofeedback that maximizes/optimizes subject performance.

Device Design

Choosing the elliptical trainer

Although studies incorporating biofeedback in split-belt treadmills have shown some success in gait rehabilitation, there exists concern regarding the adequacy of control during joint loading. To improve control, an elliptical trainer was chosen as the foundation of the system. The gait cycle on an elliptical trainer has no swing phase. As a result, there is no heel strike or initial contact to initiate a stance phase. This decreases the chance of injury during training from impact loading (Lu et al., 2007). In addition, the kinematic pattern of ankle, knee, and hip motion is managed via distal control since the feet are always in contact with the elliptically moving pedals. This pattern has some cycle-to-cycle variation allowing the subject to respond to changes in their fatigue and required performance. Although treadmill training more closely simulates an overland gait pattern, suggesting that it is the best system for gait training, elliptical devices may be more useful in targeting specific gait variables (Damiano et al., 2011).

Another benefit to elliptical training is its ability to increase knee flexion. As noted by Chen et al. in their study measuring gait kinematics of stroke patients, knee flexion is greatly limited during walking which affects limb progression and as a consequence results in a pelvic-hiking action during swing (Chen et al., 2005). When measuring joint kinematics Lu et al. found that knee flexion was significantly greater during elliptical trainer use than overland walking, almost a 20^{0} increase respectively (Lu et al., 2007). Since knee flexion increases while training with an elliptical trainer, applying the trainer as the foundation of the system provided an added benefit during gait rehabilitation for stroke participants.

Visual biofeedback

Biofeedback can be delivered in multiple forms that include visual, audio and haptics either separately or in combination. Visual biofeedback has been heavily researched in the past few years and has been found to be the most appropriate modality for mobility training when conveying spatial information within an environment (Sigrist et al., 2013). Visual biofeedback allows a more intuitive approach to motor control. Performance can also be enhanced by incorporating either audio and/or haptic biofeedback, but these systems require additional user training to be successful. Once an individual is able to associate audio or haptic feedback with performance, many studies have shown that outcomes can be similar to those outcomes with using visual biofeedback (Batavia et al., 2001, Fernery et al., 2004, Sigrist et al., 2013). It is important to note though that when applying these modes of feedback success depends on the ability of the individual to accurately decipher the meaning of the information presented. Often the delivery of audio, haptic or multi-modal feedback becomes too difficult for the user to understand in already complex mobility tasks which contributes to increased cognitive load. As a result, visual biofeedback was selected for this research with careful consideration given to the design that minimizes cognitive load.

To decrease cognitive demand, biofeedback complexity is typically reduced. This however does not come without tradeoffs. Increasing the simplicity of the cognitive interpretation of an activity can result in the removal of essential elements. By reducing the complexity of the system there is an uncertainty if relevant aspects of the whole system have been captured for problem solving (Woods, 1995). Both elements of problem solving and the active association of components within the system can be lost when more complex situations are removed from motor performance biofeedback.

In order to provide an effective system associating performance through computerized aiding interpretation there is a need to produce a system that delivers enriched information to the user. This information should reduce unnecessary details while enhancing integral elements to allow efficient problem solving during activity. Therefore it is essential to balance contrasting elements of simplicity and complexity for effective interpretation of performance during biofeedback activity.

Although studies such as Huang et al. show that a multimodal approach applying visual-auditory biofeedback produced an improvement in postural and mobility performance, there is still concern that multimodal systems may be too complicated in certain mobility tasks without extensive training (Huang et al., 2006, Sigrist et al., 2013, Woods, 1995). In order to deliver enriched information about spatial elements while limiting the complex nature of the system, a single modality was chosen for this research to represent kinetic features during elliptical use. Visual biofeedback provides an intuitive method for understanding spatial representations and vertical load measurements (Sigrist et al., 2013). Positive impacts in lower limb rehabilitation have resulted from coupling visual biofeedback to postural balance training in elderly subjects, having either peripheral neuropathy or stroke, as well as younger subjects (Sihvonen et al., 2004, Wu, 1997, Shumway-Cook et al., 1988).

Hardware modifications and implementation of biofeedback

A novel gait trainer for symmetric kinetic training was constructed by modifying an elliptical trainer (NordicTrack®, Logan, UT) to measure vertical pedal loads and display biofeedback through a visual display. To measure vertical load independently, both pedals were equipped with material-matched strain gages (350 Ω) built into a Wheatstone bridge configuration (Figure 1) to create left and right side load cells.

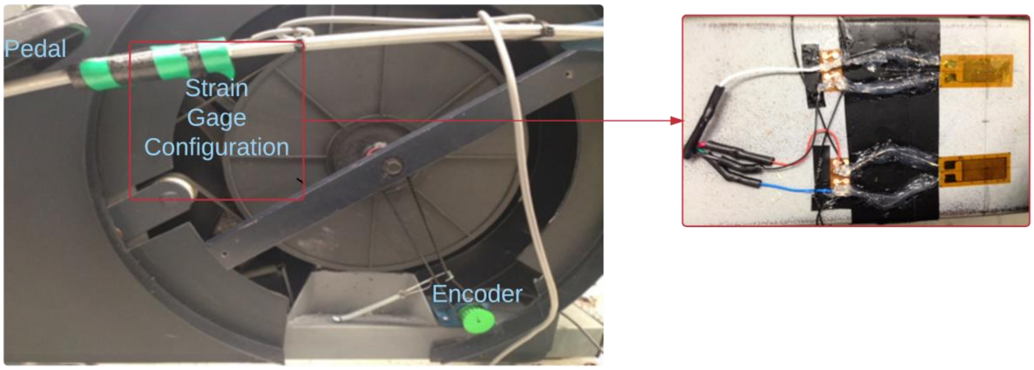

Figure 1. Attachments to the elliptical trainer. Strain gages were attached to the top and bottom of each ski of the elliptical to measure vertical load. The inset is a picture of one side of one ski. A 200 point quadrature encoder was attached to the elliptical to determine position of the flywheel.

The load cell signal was low-pass filtered (@10Hz 4th order Butterworth) to remove instrumentation noise and high frequency fluctuations in the load. Load cells were loaded and unloaded up to 140 pounds to determine hysteresis and linearity (Figure 2). Calibration equations were found for right and left load cells to convert voltage signals into real-world weight measurements (Table 1).

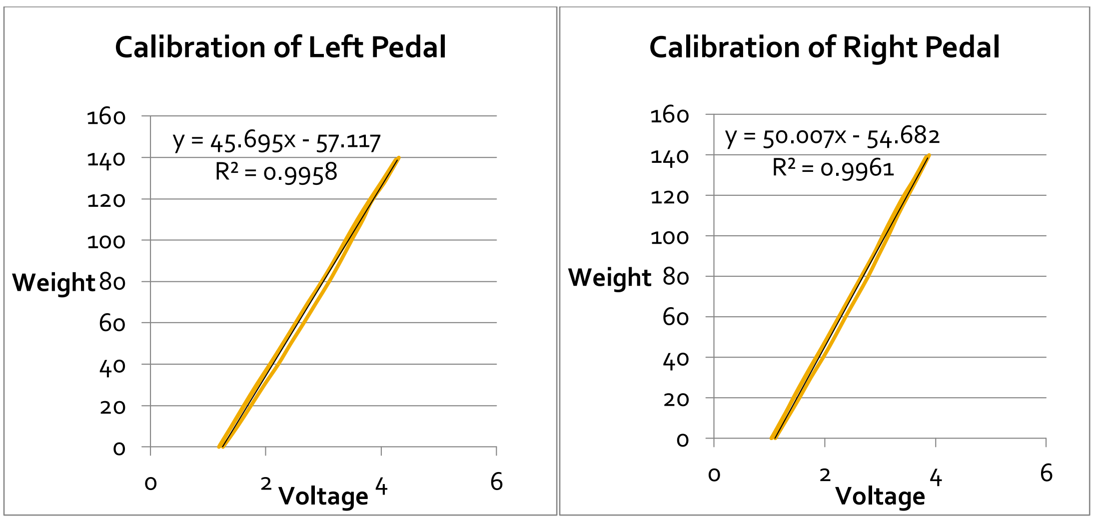

Figure 2. Calibration curves of the left and right pedal load cells. The left and right pedals were loaded then unloaded at a single point to determine the calibration equation for weight measurements.

Pedal	Hysteresis	Linearity
Right	3.37%	2.31% (+/-4.62 lbs.)
Left	3.50%	2.35% (+/- 4.7 lbs.)

Table 1. Hysteresis and linearity measurements. Hysteresis and linearity measurements to determine right and left load cell accuracy.

Each display was created through LabVIEW software (National Instruments™, Austin, TX) and presented averaged weight measurements for each revolution on the elliptical trainer.

The system sampled load cell data at a rate of 3000Hz using a 12bit A/D interface. Load cell data from each gait cycle was measured at 200 discrete points using a 200 point encoder with quadrature and index outputs (Figure 1).

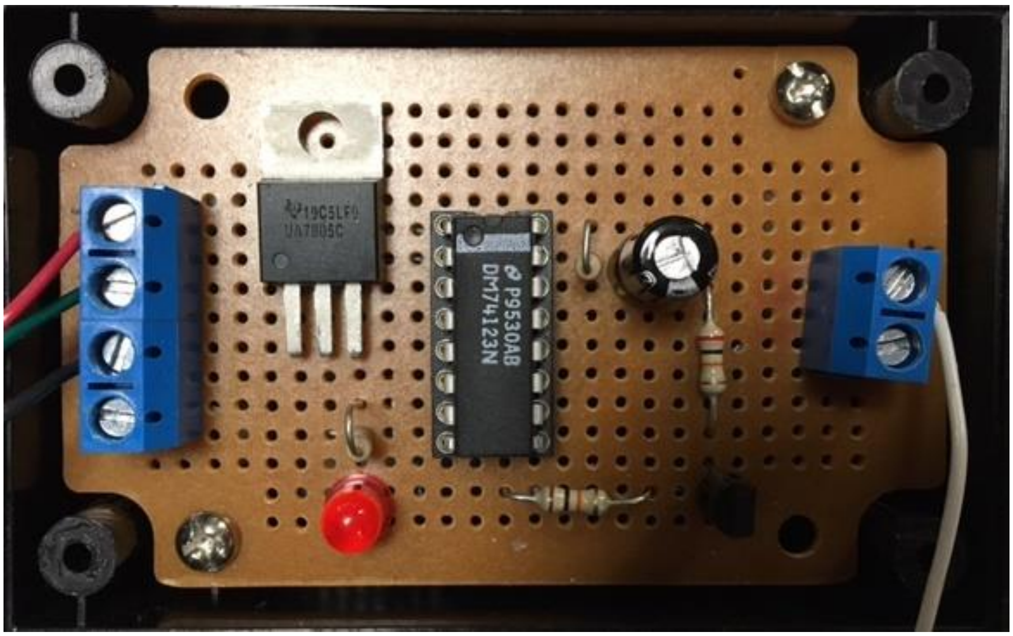

Figure 3. Conditioning circuit for encoder z-signal. This is a "one-shot" circuit design to widen the z-signal to facilitate identifying the beginning and end of each gait cycle.

The display was updated with each new data point as average gait cycle loads were computed from a circular buffer. Refresh rate of the monitor ran at 60Hz. Data was down-sampled to 300Hz for data analysis. Beginning and ending of a cycle were determined by the z-signal from the encoder. This signal was digitally widened by implementing a one-shot circuit configuration (tau = 0.002s) (Figure 3). Figure 4 show the general flow of the signal to produce the visual biofeedback presented to the user.

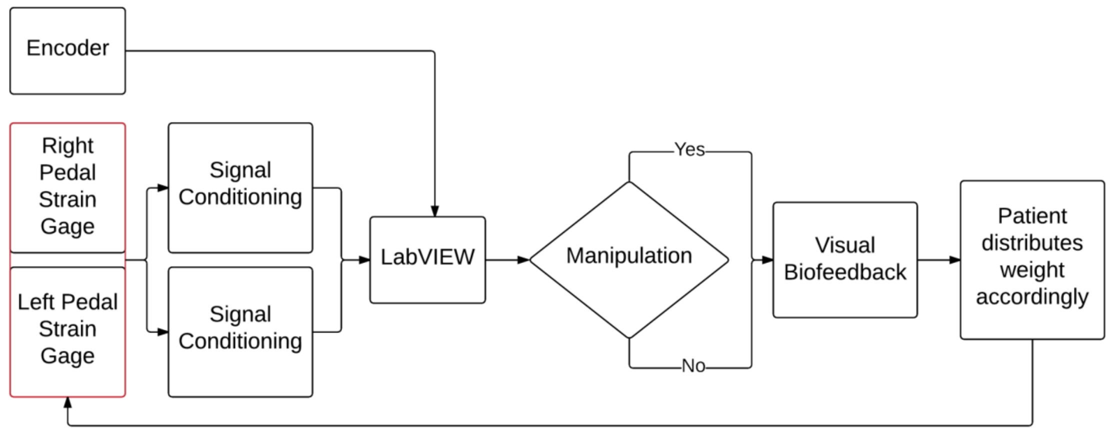

Figure 4. General flow diagram of the entire system. Vertical load was measured from the pedals of the elliptical. This signal was conditioned by a 10Hz low pass filter. A mounted quadrature encoder tracked flywheel positions to be used for averaging an array that used a circular buffer for load measurements based on flywheel position. The averaged array went through settings to control gain manipulation before being delivered as visual biofeedback to the user.

Design and mechanism of visual representation

Four independent visual displays were developed based on previous research that incorporated biofeedback into instrumented treadmill systems (Dingwell et al., 1996, Dingwell et al., 1996, Crowell et al., 2010). These were then tested on healthy participants to characterize performance. Each display provided a spatial representation of left and right loads. These were named *Tanks, Temporal, Differential,* and *Differential-Temporal.* Variable features of these displays include (1) the number display elements (number of objects capturing attention from the participant), (2) if they included a temporal history of past data samples, (3) if they presented pre-processed data, and (4) if they represented data from either both limbs or a single limb (Table 2). Figure 5 shows each of the visual displays as presented to the participant, along with a simplified depiction of each display.

Display	Display Elements	Temporal History	Pre-processing	Displayed Data
Tanks	4	No	No	Both limbs
Temporal	2	Yes	No	Single limb (non-dominant weight bearing limb)
Differential	1	No	Yes	Both limbs
Differential-Temporal	2	Yes	Yes	Both limbs

Table 2. Display type characteristics. Characteristics are as follows: display elements (number of objects to focus on), history (past data samples), pre-processing and the limb that data was delivered through the visual display (displaying either single limb or both limb data samples).

Results of a comparison study for these four displays are presented in Chapter 3. The results revealed that one display resulted in superior performance. This display was then used in all subsequent studies.

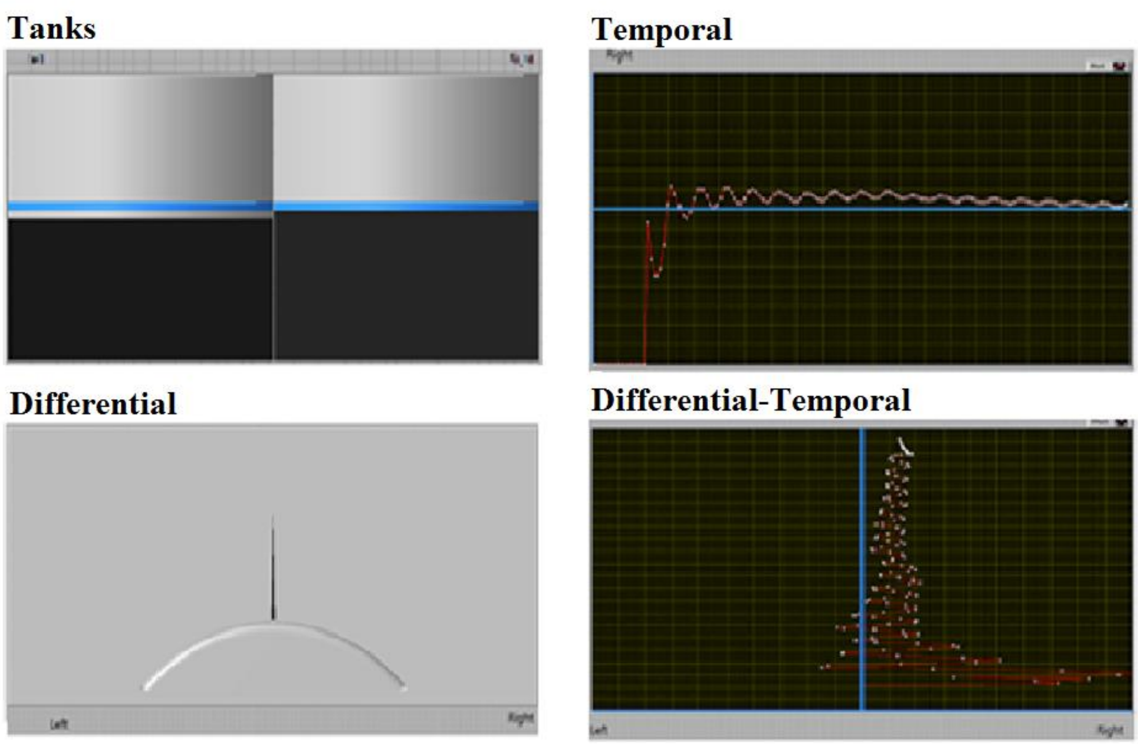

Figure 5. Visual displays of biofeedback. This shows the four displays constructed to display vertical load measurements as visual biofeedback.

To further promote constraint-induced therapeutic approaches to increase the use of a paretic limb, an additional modification was made to the biofeedback software. This allowed left and right loads to be scaled to encourage participants to present more weight to their non-dominant or paretic weight-bearing limb without their knowledge. This was accomplished by modifying the gain of the left and right load cell signals in the LabVIEW routine by a percent value. The method is similar to an approach by Ding et al., where changes the gain of the signal (from 0-25%) every two minutes were used to push the subject to distribute more weight to their non-dominant weight-bearing side. Ding et al. studied this approach with a force plate measuring weight distribution in static stance for chronic stroke participants (N=3) (Ding et al., 2012). In their study, they found that both weight distribution on the paretic limb and overall stance symmetry improved with the use of their system. The system used in the proposed research aimed to incorporate this methodology into a dynamic system that simulates a gait-like pattern.

Discussion

Constraint-induced training is a widely accepted approach in the rehabilitation of patients who have suffered stroke in both the acute and chronic phases following onset. The challenge in implementing this technique in gait training is that it is designed to bias training to the involved side, yet gait requires both legs. Current approaches to promote task-specific, constraint-induced activities include the use of split belt treadmills and robotics. Although these two approaches have seen some success, there are disadvantages which limit the transfer of this training into daily activities of living (ADL).

Although single and split belt treadmill training is effective in increasing the use of the paretic limb, there are several disadvantages in training. Training is heavily dependent on the physical therapist for weight shifts and limb progression (Jackson et al, 2010). This not only limits training duration due to therapist fatigue, but also lacks the quantitative assessment with each training session. Another disadvantage is limited control of lower extremity joint loading. This can lead to inappropriate joint loading and subsequent injury. The proposed system removes the need for assisted control of limb progression and weight shifts. It provides quantitative measurements of vertical load that can track training with each session.

The Lokomat® robotic is an attractive system for rehabilitation since it removes the need of multiple therapists to assist in gait training. The exoskeleton system controls limb progression, forcing the paretic limb to be involved during walking, and gathers objective measurements over the course of training. Although seemingly an impressive tool, the Lokomat® has failed to show significant improvements in gait (Harvey, 2009, Hornby et al., 2008, Cai et al., 2006). This could be attributed to the fact that it lacks the variability in training necessary for the patient to develop a motor plan to adjust for different variables when ambulating within a community (Cai et al., 2006). Another disadvantage is its financial burden to rehabilitation centers, making it difficult for medium to smaller facilities to obtain. One benefit of the system is that it does allow accurate limb alignment during gait, but this comes as a cost as well. The system hampers weight shifting from one limb to the other. This limits a patient’s ability to shift his or her weight accurately during walking. The proposed system is low cost compared to the Lokomat® (Table 3) and focuses on weight shifts from one limb to the other during gait training. It also allows some variability in training with manipulating the gain of the signal to force patients to develop specific motor plans to account for changes in the vertical load representations.

Supplier	Part No.	Quantity	Cost
Omega®	SGD-13/350-LY11	1 pack of 10	$67
Interface	SGA signal conditioner	2	$345 ($690 total)
NordicTrack	CXT910 (Elliptical Trainer)	1	~$600
Sparkfun	COM-10932 (Rotary Encoder)	1	$39.95
National Instruments™	NI USB-6009	1	$335
National Instruments™	Labview 8.5	1	$59
Video Products Inc.	VOPEX-xV-LC (VGA video splitter)	1	$30

Table 3. Parts and cost list of the system.

The proposed system is a low-cost alternative to current techniques in gait rehabilitation that promotes task-specific, constraint-induced training. The patient is able to independently train with only minimal supervision, making it an attractive system to both clinics and patients. It allows training to be variable through manipulating the gain of the signal, which should lead to improved outcomes in walking through an obstacle enriched environment.

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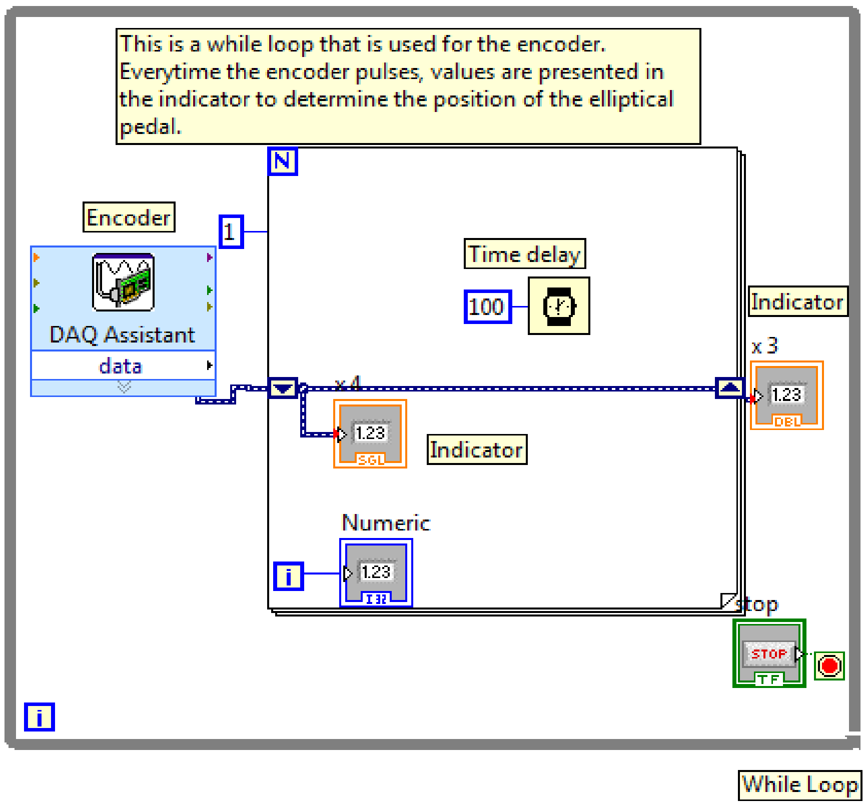
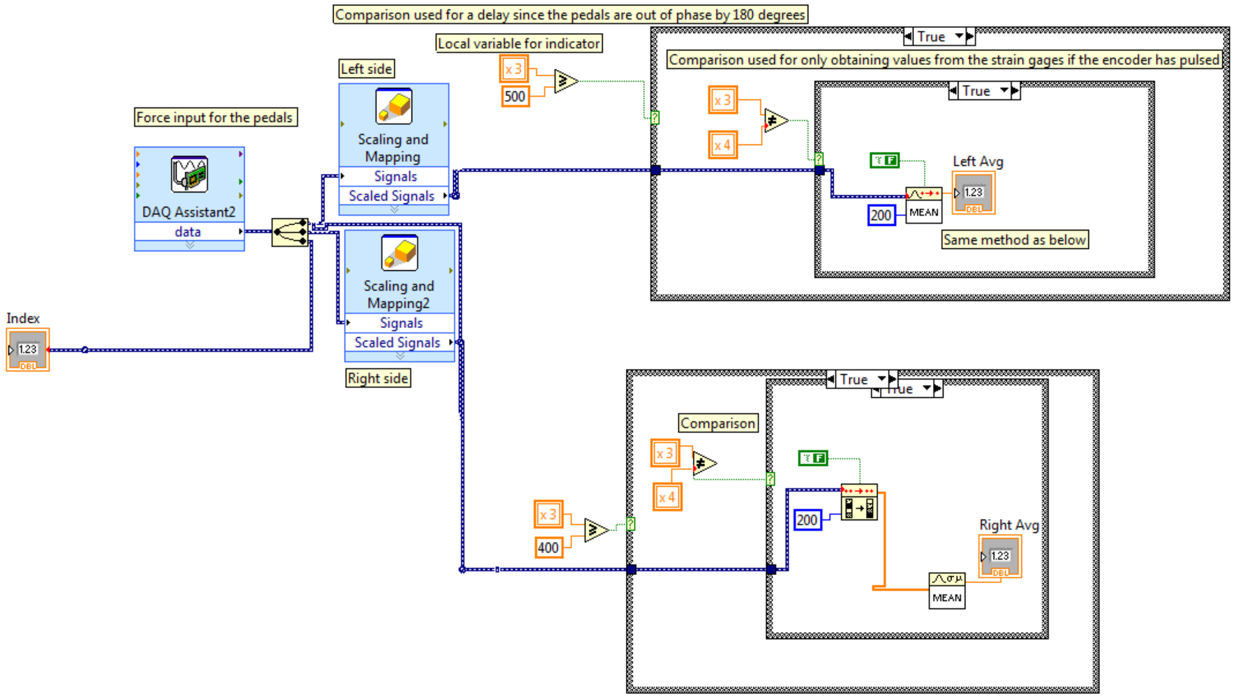
Appendix

Appendix A

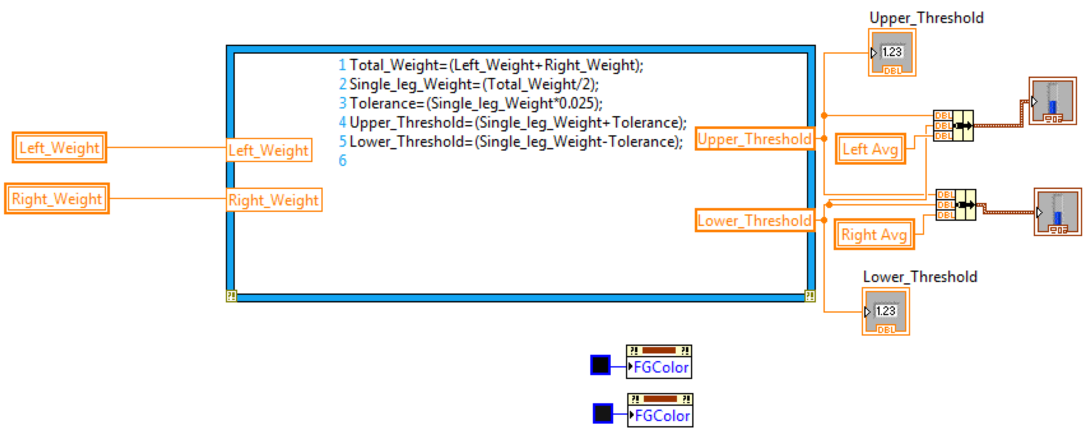
LabVIEW vi for acquiring vertical load and representing as visual biofeedback.



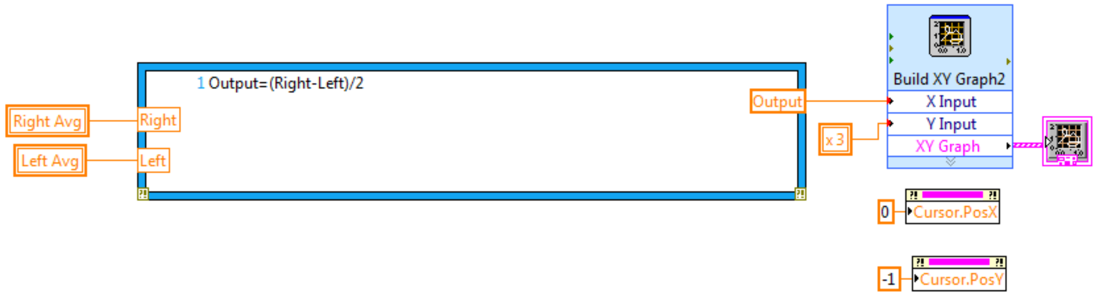
While loop in LabVIEW vi to read encoder pulses as an external clock. This loop uses a shift register to determine changing positions in the flywheel (encoder pulses).



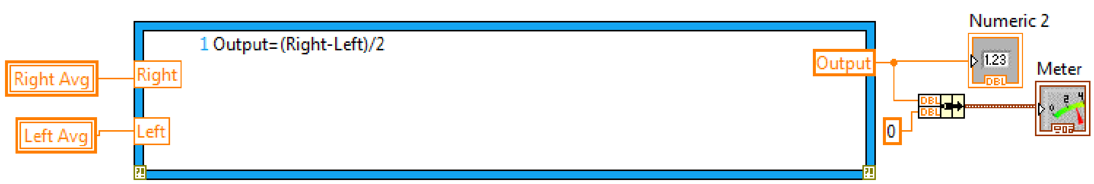
Component to LabVIEW vi that uses indicators from above (x3 and x4) to control when a weight measurement from either load cell enters the corresponding 200 point array. Weight measurements are acquired through the 12 bit DAQ card and scaled based on calibration curves.



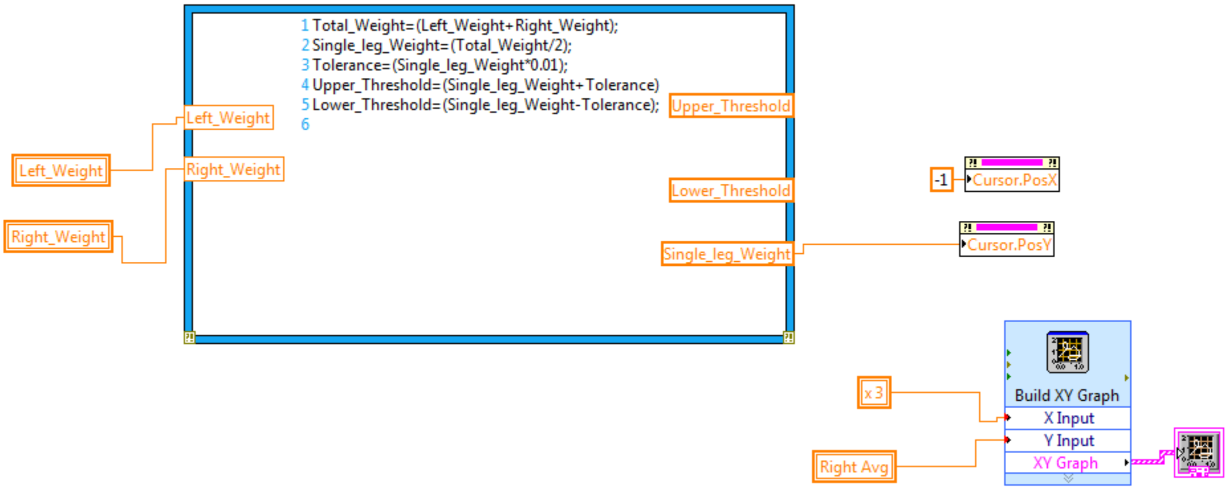
Mathscript code in LabVIEW vi that builds the Tanks display by inputting left and right weight measurements (averaged from 200 point array) to determine threshold values. Upper and lower thresholds for the display are found by calculating half of total body weight. These values are used as the blue target line on the Tanks display. Weight measurements are represented as the filler line in the corresponding tank.



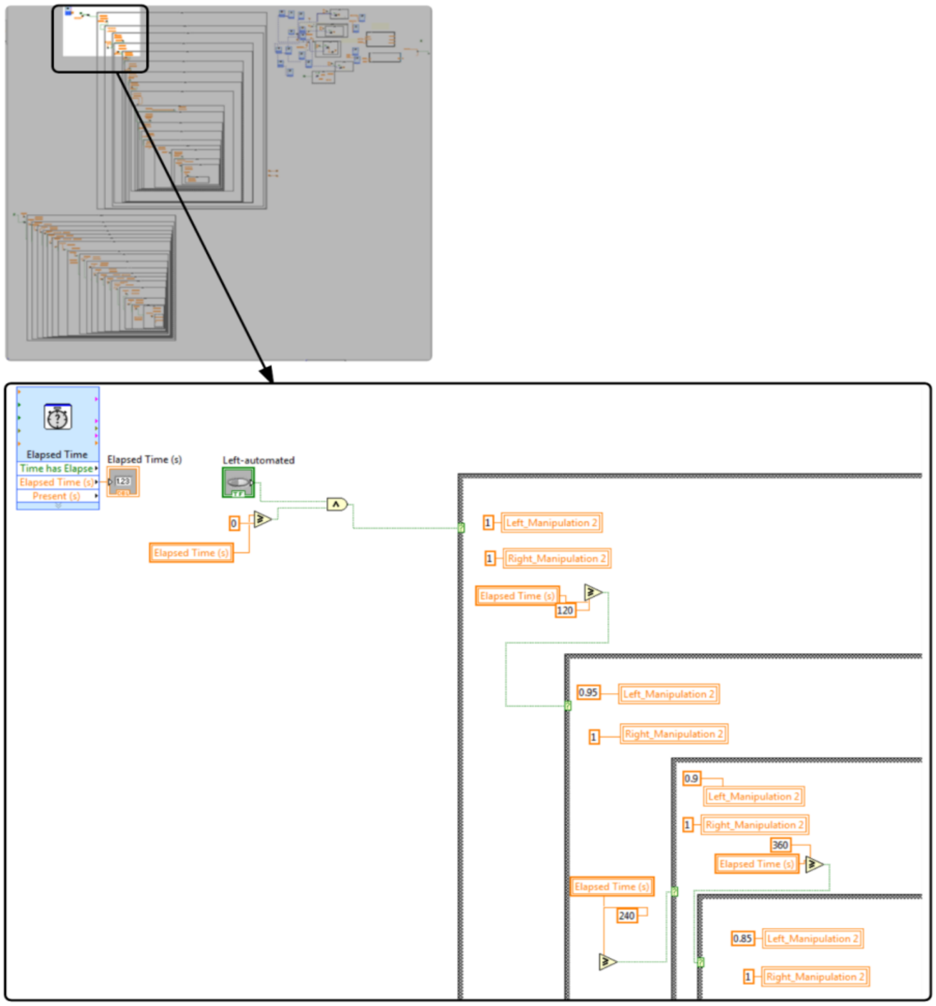
Mathscript code in LabVIEW vi that builds the Differential-Temporal display by inputting left and right weight measurements (averaged from 200 point array) to calculate the difference between right and left weight measurements. This calculation is presented as a single data point on the graph and changes with each encoder pulse.



Mathscript code in LabVIEW vi that builds the Differential display by inputting left and right weight measurements (averaged from 200 point array) to calculate the difference between right and left weight measurements. This calculation is presented as a single needle on a meter and changes with each encoder pulse.



Mathscript code in LabVIEW vi that builds the Temporal display by inputting left and right weight measurements (averaged from 200 point array) to determine the threshold value. Threshold for the display are found by calculating half of total body weight. These values are used as the blue target line on the Temporal display. Single-limb data are represented in the graph to compare with the target line.



Code to manipulate the gain of the vertical load signal. This is a portion of the LabVIEW vi that manipulates the gain of the load cell signal every 2 minute interval.

Chapter 3

Chapter 3: Does visual biofeedback have an effect on symmetric performance?

Abstract

Vision is a key component in maintaining postural control during both static and dynamic stance. Several research studies have observed differences in postural control when vision is either limited or visual objects are manipulated (Strang et al., 2011, Nardini et al., 2012, Lishman et al., 1973). These studies suggest that symmetry patterns in both static and dynamic stance can be manipulated through visual biofeedback. Recently, there has been an increasing trend of studying the effects of virtual based training for modifying mobility patterns (Tirosh et al., 2013, Hirokawa et al., 1989, Feasel et al., 2011, Dingwell et al., 1996, Dingwell et al., 1996). Due to increasing evidence supporting this technique in training, more visual systems are being developed and implemented as goal-based rehabilitation techniques. The goal of this study was to determine the effect of visual biofeedback on weight distribution during elliptical trainer use. An elliptical trainer was modified to measure vertical pedal load and to deliver visual biofeedback based on that load measurement. Four visual displays were constructed and tested to determine which man-machine interface optimized performance when attempting to produce symmetric left/right kinetics during exercise. These displays were constructed based on similar studies researching either gait kinematics or kinetics. An analysis of variance and student t-tests were performed to determine significant differences between the displays and baseline measurements. Correlation coefficients were also analyzed to determine if speed or day of performance influenced outcomes with each display type. Results of the study show that performance with all display representations was more favorable than in trials with no feedback. One display type (Differential-Temporal) outperformed other display types for the training duration. Based on correlation coefficients, speed and day of performance did not influence

outcomes. Future directions of the research will include the Differential-Temporal display for biofeedback delivery while modifying the load cell signals to encourage increased use of the non-dominant weight-bearing limb in healthy and stroke sample groups.

Introduction

The combination of inputs from multiple sensory systems provides the feedback required to maintain postural control in both static and dynamic situations. Receptors associated with processing visual, somatosensory, vestibular, and auditory stimuli provide information that allows us to maintain spatial awareness within a static or dynamic environment. Sensory integration provides movement cues that allow the orientation updates required for obstacle avoidance during path navigation (Tcheang et al., 2011, Wan et al., 2012, Khan et al., 2010).

Although human movement and control is achieved through the combined use of information from all senses, vision plays a significant role when attempting to efficiently ambulate and navigate through an environment rich with obstacles (Tcheang et al., 2011). As a result, vision is believed to be the best portal through which to introduce environmental cues (or biofeedback) to modify or control postural movements. The goal during this study was to determine the best man-machine interface for presenting visual biofeedback during elliptical trainer exercise where that information was designed to promote left/right weight bearing symmetry. The manipulation of spatial and temporal information via four different displays was used to determine if weight bearing performance could be influenced using visual feedback and if pre-processing the data stream (reducing cognitive load on the subject) had any impact.

Studies conducted to test the correlation between visual/proprioceptive feedback and postural control suggest vision/proprioception play a significant role in postural control (Strang et al., 2011, Jeka et al., 2000, Riley et al., 1997, Barcala et al., 2013). Specifically, Strang et al. found that postural sway increased during stance as vision was restricted and as the surface became more compliant, giving rise to decreased postural control during static stance (Strang et al., 2011). In a study by Lishman and Lee, balance responses were investigated when participants stood in the middle of a swaying room (Nardini et al., 2012, Lishman et al., 1973). In their research, they found that as the room swayed toward the participant, the participant would sway backwards to counteract the motion due to the perception that they were moving forward. This perception resulted since the image of the space appeared to enlarge or expand as it swayed towards the participants. As it expanded, the participants did not perceive movement of the room but instead egocentric movement forward. The reaction of participants to the swaying room suggests that by implementing different optical flow patterns, a person's postural control during static stance can be manipulated. Also it can be concluded that visual stimuli often overrides other sensory information for spatial orientation.

Transitioning from static stance to walking, current research in gait suggests that vision greatly influences movement patterns during walking to allow obstacle avoidance in enriched environments and that gait parameters can be altered due to changing characteristics of an environment and optical flow patterns (Pailhous et al., 1990, Warren et al., 2001, Konczak, 1994, Schmuckler et al., 1989). Two hypotheses have been proposed that dictate how a person steers to a goal based on visual stimuli. The first of these hypotheses is based on egocentric direction, which involves steering towards an object based on direction, with respect to the body's orientation in space with no influence of optic flow (Warren et al., 1988, Rushton et al., 1998, Tirosh et al., 2013). The second hypothesis involves optical flow for path navigation, which is used to reduce the error between the goal and the heading (Warren et al., 2001, Warren et al., 1988, Rushton et al., 1998). A study performed by Warren et al. found that in order to navigate towards a designated goal both the hypotheses of egocentric direction and optical flow applied (Warren et al., 2001). They found that optic flow increasingly dominated performance when it was introduced to an egocentric virtual representation. Where participants had curved paths with egocentric virtual representation, their paths began to straighten towards the object with addition of optical flow patterns (Warren et al., 2001). Therefore humans change path navigation based on both inputs from directional cues and optical flow, and the combination of both directional cues and optic flow improve path navigation significantly.

Delivery of biofeedback during overland and treadmill exercise has been studied extensively in the past few decades, with a general trend showing that gait parameters can be influenced with visual stimuli (Tirosh et al., 2013, Hirokawa et al., 1989, Feasel et al., 2011, Dingwell et al., 1996, Dingwell et al., 1996). In normal, healthy gait the limbs act as reciprocal pendulums switching between stance and swing phases for limb progression (Perry, 1992). This cyclic pattern allows for controlled progression along with appropriate weight acceptance and toe clearance. Studies such as Tirosh et al. have found that these controlled patterns can be influenced by visual stimuli. Specific to Tirosh et al., visual stimuli could alter toe clearance in healthy participants (Tirosh et al., 2013). In this study, they compared baseline activity (activity with no visual biofeedback) to biofeedback activity and found that the mean and median minimum toe clearance increased with the presence of the biofeedback. Participants became more aware of the target range for toe height than concern of striking the ground, leading to unconscious training of the overall goal.

By understanding how visual biofeedback systems can alter normal, pathological gait during treadmill training, similar techniques can be applied to rehabilitation training for lower limb injuries and neurological impairments. With the incorporation of visual stimuli, patients can easily decipher gait asymmetries while training and make adjustments accordingly. The IVERT (Integrated Virtual Environment Rehabilitation Treadmill) system, comprised of a virtual environment for path progression and a split-belt treadmill that adjusted speed based on ground reaction forces, has been tested on hemi-paretic patients and it was found that patients could easily perceive their own asymmetries based on the visual biofeedback alone (Feasel et al., 2011). Based on these results, it is evident that visual biofeedback can be used as an encouragement tool to allow immediate adjustments in gait. This idea was demonstrated in a comparison experiment between normal and trans-tibial amputee subjects (Dingwell et al., 1996). In this study, trans-tibial amputee subjects were on average 4.6 times more asymmetric than normal subjects. Although there was a significant difference between groups, there was an apparent decrease of asymmetries from pre to post training in amputee subjects. Asymmetries in stance time decreased by 26% from 7.53% to 5.18% in five minutes, and push-off forces and center of pressure improved from 2.47% to 1.38% and -1.58% to 0.56%, respectively.

Studies such as Dingwell et al. (1996) and Crowell et al. (2010) provided kinetic biofeedback through visual displays and found success from pre to post training (Dingwell et al., 1996, Crowell et al., 2010). Both studies incorporated features of either differential, temporal or comparison visual displays for kinetic feedback. Although comparisons were not made between each display, they were able to determine that visual biofeedback had an effect. Dingwell et al. found that trans-tibial amputees reduced asymmetries in gait (center of pressure, stance times, and push off forces) from baseline to post training by employing differential, temporal and comparison visual displays for biofeedback (Dingwell et al., 1996). In Crowell et al (2010) running mechanics were monitored with an accelerometer and subjects received visual biofeedback to reduce impact loading through a temporal display (Crowell et al., 2010). They found that with visual feedback most of the participants reduced the amplitude of peak acceleration, impact peaks, average loading rates and instantaneous loading rates when training and maintained this reduction ten minutes after the removal of the feedback. Although these studies did not look closely at differences between varying displays, they show that gait can be influenced by each type of display. These studies not only suggest that patients with asymmetrical gait can perceive asymmetries, but also can adjust and improve gait to produce symmetric performance with the incorporation of visual biofeedback. Our study aimed to determine the differences among various versions of visual displays adapted from these previous studies and to decipher which display produced the optimal man-machine interface. The purpose of applying visual displays was to supplement user internal memory for an external representation of the task at hand, thereby offloading memory storage onto perceptual processes (Hegarty, 2011, Card et al., 1999). Four different visual displays were designed that delivered kinetic biofeedback from weight distribution measurements between both left and right pedals. The study aimed to prove that visual displays could influence performance and that performance could be optimized with pre-processing the data.

To implement the findings from previous research, the study applied a visual biofeedback system to an elliptical trainer for symmetry training. An elliptical trainer was chosen as the base unit for two reasons. First, both pedals are isolated for single limb vertical force measurements. Second, ground/pedal reaction forces are much lower than treadmill use due to the removal of the impact phase with the ground (Lu et al., 2007).

Methods

Participants

This preliminary study was approved through Virginia Commonwealth University's institutional review board. Prior to entering the study all participants provided written informed consent. Fifteen subjects (7 male and 8 female, average age= 25.47 ± 4.88) were recruited based on a sample of convenience in the Richmond area. Healthy without injury to lower limbs within the past year with no cardiovascular complications was the inclusion criteria when recruiting for this study.

Device Design

A modified elliptical trainer (NordicTrack®, Logan, UT) was used to measure vertical loads as visual biofeedback (Chapter 2). Kinetic visual biofeedback was provided via computer monitor displaying representations of vertical load (Massenzo et al., 2015). The instrumentation associated with the modified elliptical trainer was explained in Chapter 2 of this document.

Four different feedback displays (Figure 1) were developed; these were labeled (1) tanks, (2) temporal, (3) differential and (4) differential-temporal and differed in the amount of data pre-processing performed prior to display. Display differences include display elements (number of objects that the participant had to focus on), history of past data samples, pre-processing the data, and whether data was projected for both limbs or for a single limb (Table 1).

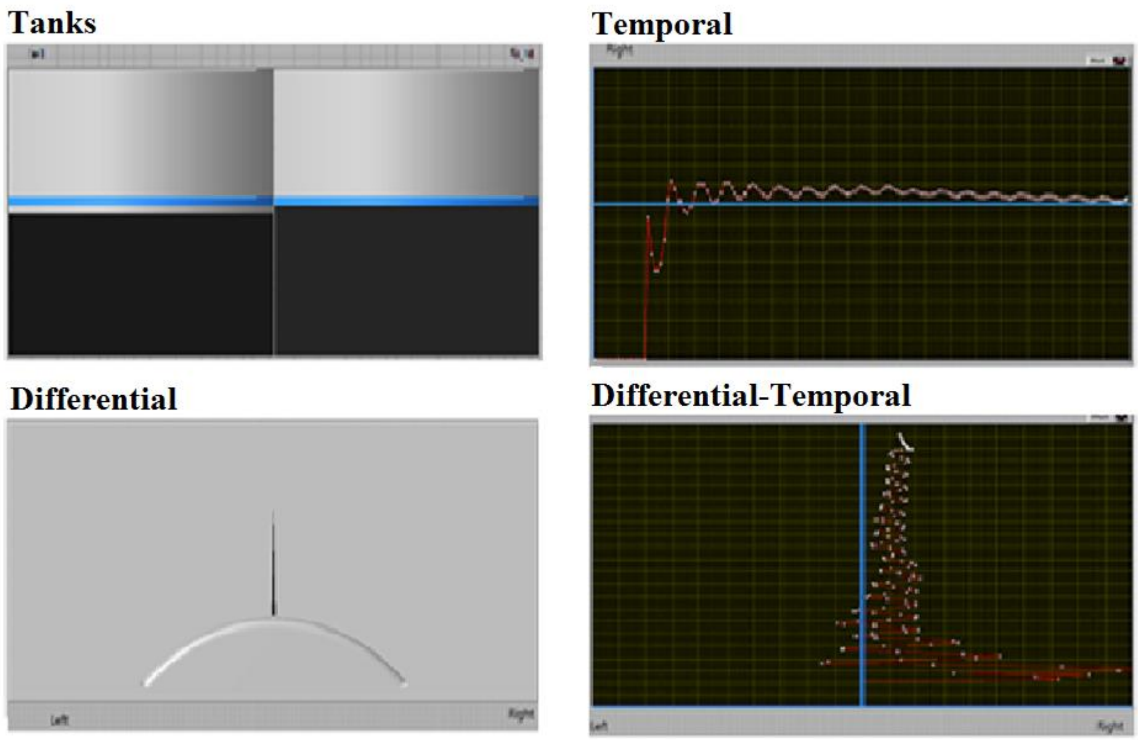


Figure 1. Visual displays of biofeedback. This shows the four displays constructed to display vertical load measurements as visual biofeedback.

(1) **Tanks** – The force data was presented as two moving vertical bars that changed their vertical dimension as a function of pedal load. The left bar denoted the left pedal forces and the right denoted the right pedal forces. Each bar had a horizontal target line for user reference. No temporal load history was provided. Since the display had a moving bar and static target line for both left and right sides, it was considered to have 4 display elements.

(2) **Temporal** – This display only utilizes a data stream from the subject's non-dominant limb. Temporal history was provided in the form of an x-y graph, where the y-axis represented averaged weight of each cycle and the x-axis represented number of pulses

from the encoder. Force data were represented as a white dot with a red line connecting each consecutive sample. The x-y graph had a solid blue line that remained static to represent the target line. Display elements were set at 2, since the display implemented both data points represented as dots and a static target line for a single limb.

(3) **Differential**- Force data was represented on a numberless gauge by a pointer. Presented data represented the difference between the right and left limb vertical load. Neither the temporal history nor a target line was provided. The user was instructed to maintain the pointer in the middle of the gauge. Since the display only employed a single pointer, the number of display elements was set at 1.

(4) **Differential-Temporal**- Force data was represented as a white dot with a red line connecting the consecutive data samples, displaying both the present data and the temporal history. The data was displayed through an x-y graph, with the y-axis representing encoder pulses and the x-axis representing values from the comparison equation. Presented data represented the difference between the right and left limb vertical load. A single target line was placed directly in the middle of the display. The amount of display elements was set at 2, since this display implemented single data points to represent the value from the comparison equation and a single static target line.

Display	Display Elements	Temporal History	Pre-processing	Displayed Data
Tanks	4	No	No	Both limbs
Temporal	2	Yes	No	Single limb (non-dominant weight bearing limb)
Differential	1	No	Yes	Both limbs
Differential-Temporal	2	Yes	Yes	Both limbs

Table 1. Display type characteristics. Characteristics are as follows: display elements (number of objects to focus on), history (past data samples), pre-processing and the limb that data was delivered through the visual display (displaying either single limb or both limb data samples).

At each encoder pulse, data accumulated from the previous encoder pulse were averaged and displayed. Each display incorporated the average values from the biofeedback but differed based on presentation.

Procedures

Each visual feedback display was tested separate from the other feedback displays in a random order with at least 24 hours in between sessions. During each session, participants warmed up on the elliptical trainer for five minutes with no visual display. They were then provided instructions on how to interpret the data presented on the display they were going to see that session. This was followed by a five minutes of activity with visual feedback and data collection.

Data Analysis

Vertical load was measured and later analyzed during use with each display. Data analysis was performed using both MATLAB (The MathWorks,Inc., Natick, MA) along with

Excel (Microsoft, Redmund, WA) and R (R Core Team, Vienna, Austria). Robinson's Index of Symmetry (IOS) was implemented for post-analysis data comparison for baseline and visual feedback measurements (Equation 1) (Herzog et al., 1989).

$$IOS = \frac{\frac{|Xright - Xleft|}{Xright + Xleft}}{2} \; x \; 100\% \qquad (1)$$

Perfect symmetry correlated to an IOS value of 0%, whereas anything above represented asymmetrical weight distribution. Weight-bearing dominance was found through baseline measurements as the limb that had the largest load values. An analysis of variance was performed with subsequent student t-tests, α=0.05, to determine significant differences of IOS values among the displays and the baseline measurement. The coefficient of variation (COV) of IOS values was also measured to determine amount of variation among the displays. Correlation coefficients were also measured to determine if speed and order of display biofeedback had an impact on performance as well.

Results

None of the participants had prior experience using the visual biofeedback system that was developed for the study, yet all participants appeared to easily adapt to the system, regardless of the display being presented. After recording baseline force measurements during the warm up period, all participants, except one, presented more weight on their left lower limb as compared to their right limb (Table 2). Participant 13 was identified as nearly symmetric compared to others, with a slight increase in load to the right limb. Overall, the sample group had an average Baseline Index of Symmetry (IOS) of 9.63.

Subject	Dominant weight-bearing side	Baseline IOS (%)
P1	Left	11.79
P2	Left	11.38
P3	Left	11.98
P4	Left	11.13
P5	Left	8.82
P6	Left	5.52
P7	Left	12.67
P8	Left	6.18
P9	Left	8.71
P10	Left	9.58
P11	Left	6.14
P12	Left	9.78
P13	Right	1.21
P14	Left	14.99

Table 2. Baseline Index of Symmetry (IOS) values. Baseline values for preferred leg for balance and Robinson's IOS for all participants. This table displays baseline values for all participants. All, except one, participants distributed more weight to the left limb compared to the right.

An analysis of variance was performed to find any differences in speed (average=0.83±0.14 cycles/sec) among the four displays. There were no significant differences in speed from one display to another (p-value>0.05). Correlation coefficients were also found to determine if speed correlated to performance among the displays (Figure 2). No correlation was found for speed ($R^2 < 0.20$). Correlation tests were performed to see if the order of display use correlated with performance (Figure 3). There was no correlation between performance and the day in which a visual display was applied ($R^2 < 0.1$).

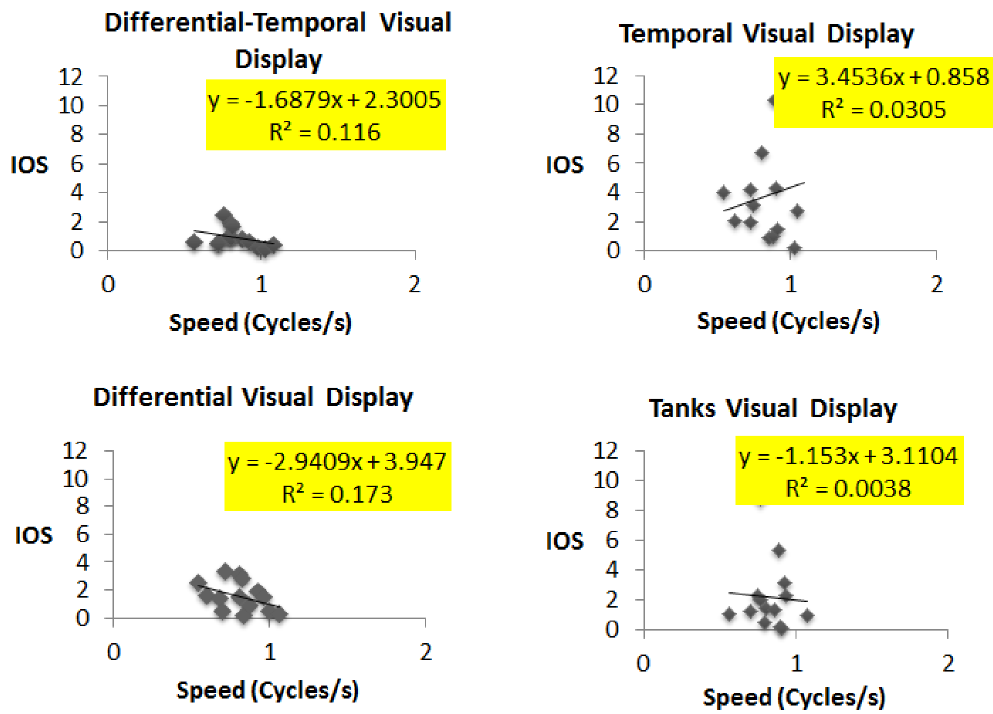


Figure 2. Correlation graphs for Speed. All correlation graphs show poor correlation between speed during activity and Index of Symmetry (IOS) values.

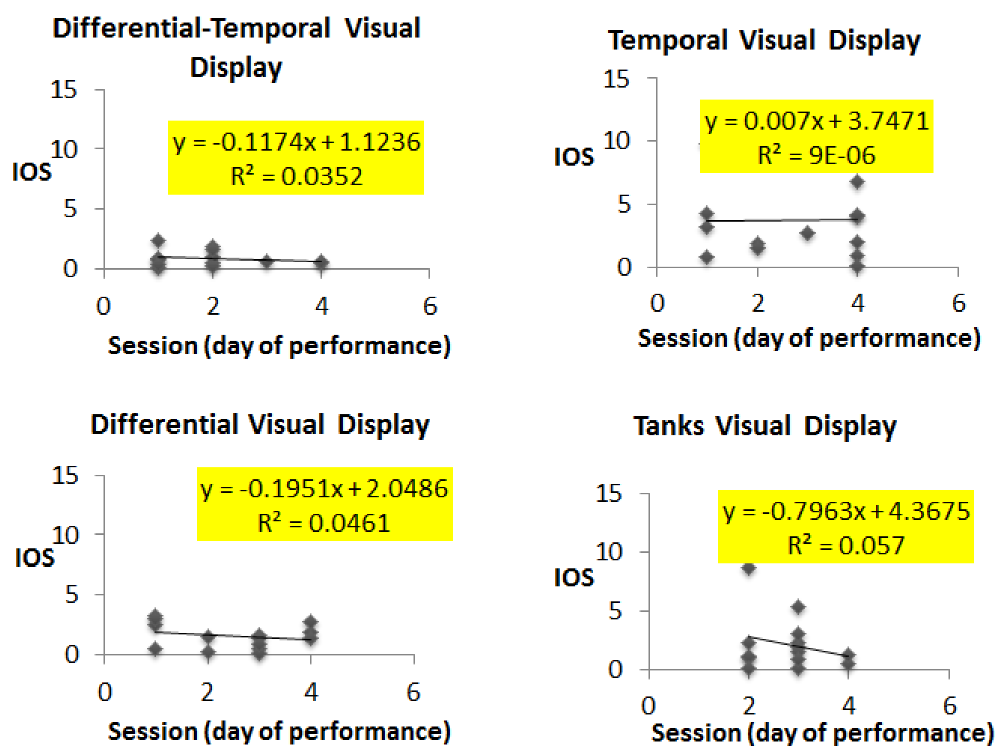


Figure 3. Correlation graphs for Day of Performance. All correlation graphs show poor correlation between day of performance and Index of Symmetry (IOS) values.

An analysis of variance indicated a significant difference in the dataset when analyzing for all groups (p-value<0.05). IOS values for Baseline measurements were significantly larger than measurements from all displays (Figure 4). The *Differential-Temporal* (0.90±0.67) had an IOS value significantly less than all other displays. Whereas, the *Temporal* (3.77±3.16) display had the largest IOS value, though only significant between the *Differential-Temporal* display. Although only a slight difference, the *Temporal* (8.78) display had a larger COV than all other displays (Figure 5).

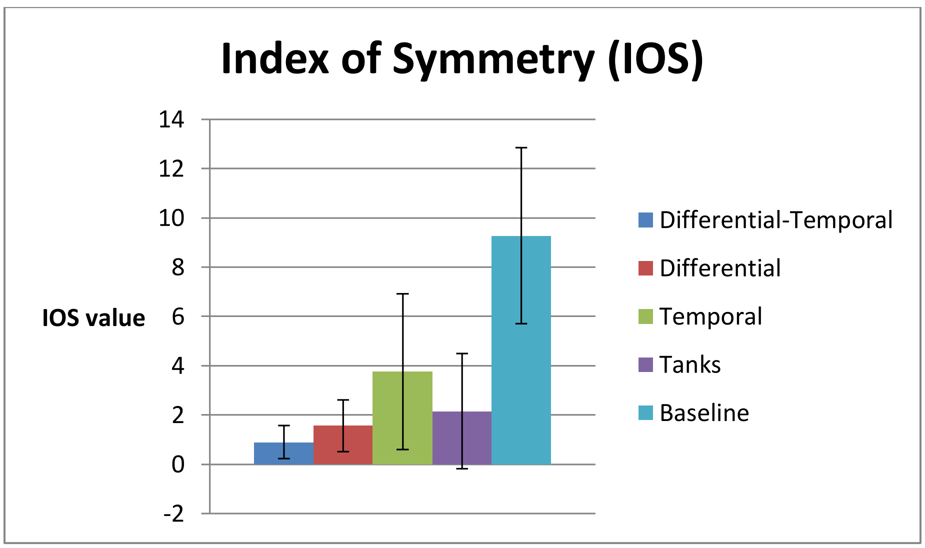


Figure 4. Baseline and display type Robinson's Index of Symmetry (IOS) values. Index of Symmetry (IOS) values averaged across the sample set for all displays and Baseline. Error bars indicate standard deviation of IOS values within the dataset. The sample set improved symmetry with the addition of visual biofeedback, and further improved symmetry with the incorporation of the Differential-Temporal display.

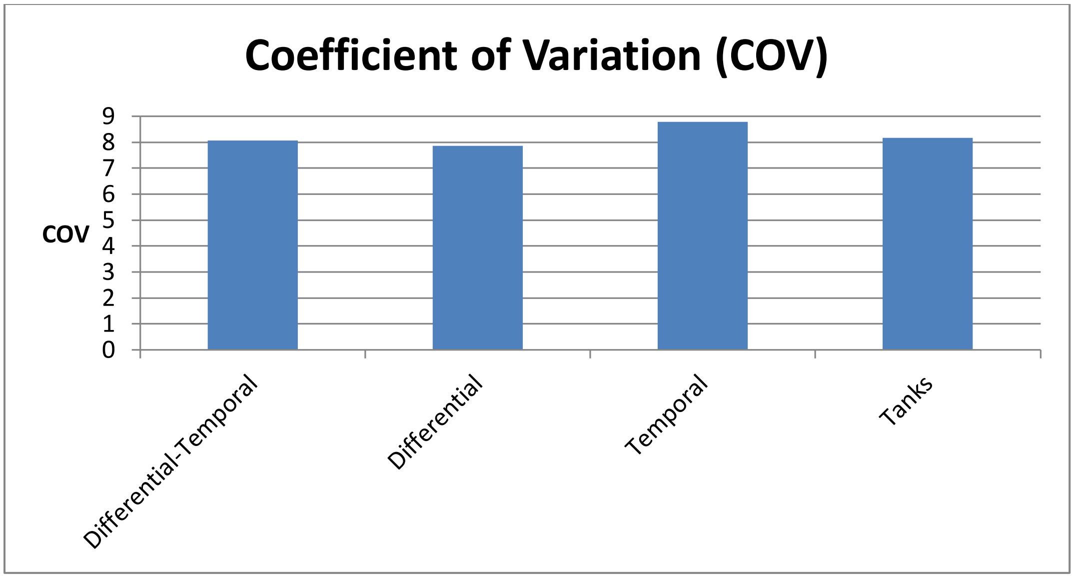


Figure 5. Coefficient of Variation among all displays. The Temporal display has a slightly larger COV as compared to the other displays but this is not significant.

Discussion

The goal of this study was to determine if visual biofeedback had an effect on performance and postural control during elliptical trainer use. A secondary goal was to determine which visual display was the optimal man-machine interface to promote symmetric performance. We also aimed to determine the differences among the displays, which were adapted from previous studies. All participants demonstrated an improvement from measurements in baseline to biofeedback activity, and we found that participants performed best with the Differential-Temporal visual display.

Most subjects appeared to present more weight on their left lower limb compared to their right, with an exception of one subject. This can be explained through studies testing asymmetries in lower limbs during static stance and walking (Sadeghi et al., 2000, Gentry et al., 1995, Grouios et al., 2009). Specifically, it was evident in these studies that humans predominantly used their left leg for balance/stability and right leg for fine motor mobilization. Taking this idea further, researchers such as Ingelmark and Chibber & Singh reported physical attributes that varied between legs. Ingelmark found that as humans developed to adulthood the leg contralateral to their dominant writing hand was much longer (Sadeghi et al., 2000, Peters, 1988). Chibber & Singh found that the left lower limb was significantly heavier than the right (Sadeghi et al., 2000, Peters, 1988, Chibbers et al., 1970). Since the training task of the current work incorporated a component of balance, it seemed plausible that participants would favor their predominant leg for balance.

We found that participants improved significantly from baseline measurements to visual feedback training (average p-value<= 6.632*10^-5 with 95% confidence). This suggests that visual biofeedback improves performance during symmetric kinetic training on an elliptical trainer. This idea is also supported in other works such as Tirosh et al. resulting in increased toe clearance due to visual biofeedback treadmill training. Similar to Tirosh's findings, we also observed that visual biofeedback during training influenced gait performance, with a drastic difference from baseline asymmetries to near symmetries with the visual displays.

We also found differences among the four displays, explicitly that the Differential-Temporal display had significantly smaller IOS values than the other displays, where the Temporal display had the largest values. The differences in IOS values may have resulted due to ranging complexities with each display causing an increase in the cognitive load of the user. The purpose of applying visual displays is to supplement user internal memory for an external representation of the task at hand, thereby offloading memory storage onto perceptual processes (Hegarty, 2011, Card et al., 1999). Often, complicated nonvisual data can be expressed through visual displays and easily interpreted due to pattern recognition (Hegarty, 2011, Pomerantz et al., 1989). If a misunderstanding occurs, often the visual display either includes or omits features that disrupt the attention or perceptual processes of the user. If the display includes too many features, causing a distraction, then the user may not focus on the key elements to accomplish the task; whereas, if the display omits crucial elements then the user is not given enough information to accomplish the task efficiently. Regarding our results, each display differs based on either the amount of information (e.g. goals or past data samples) or representation of the kinetic information (e.g. data points represented as either lines or shapes). The Differential-Temporal display may have had the lowest IOS score since it employed both a goal line and past data samples as well as displaying comparisons between both lower limbs through a series of connected line graphs. Although the design of the Temporal display aimed to simplify load representation for interpretation by showing information from a single limb, results show that it performed worse than all other display types. Instead of simplifying the load representation, the Temporal display may have increased cognitive load of the user since it only displayed data from a single limb. Redesigning the feedback system by implementing a multimodal approach may improve performance. Samman et al. noted that human performance could improve by utilizing additional modalities to recruit capacity from other senses (Samman et al., 2006). Another approach to improve user performance in the Temporal display could be to adjust scaling to zoom in on the displayed data. This approach may increase discriminability of the displayed data, thereby improving performance in highlighting the distance to the goal line (Garner, 1974). Alternatively, the Tanks display was initially viewed more challenging to the user to adequately interpret the differences between each limb, due to greater number of objects that required attention. Our initial thought was consistent with the results, where the Tanks had the second largest IOS value.

To determine if both speed and day of performance influenced IOS values, we also computed the correlation coefficients for both variables versus IOS values. The results showed that neither variable statistically correlated to the resulting IOS value. Therefore, neither speed nor day of performance influenced IOS outcomes.

Based on these results, we concluded that both the Differential and Differential-Temporal displays were more favorable for performance than the Temporal and Tanks displays. The Differential-Temporal average IOS value was significantly less than all other visual displays, therefore providing evidence that this display was best for human performance. Also, the results displayed that there was a significant difference between all displays and the baseline IOS values, confirming that visual biofeedback has an effect on weight-bearing symmetry during elliptical trainer use. Coefficient of Variation between all displays was also measured and reflected the greatest variation within the sample set in the Temporal display with the lowest value in the Differential. The Temporal display may have had the largest variation in the sample set due to the increased demand on the user to interpret bilateral results from a unilateral representation.

Conclusion

Comparing visual biofeedback training to baseline measurements, we saw a significant improvement in symmetry with the introduction of biofeedback. This suggests that visual biofeedback during kinetic symmetry training can influence gait patterns. We found that the

Differential and Differential-Temporal IOS scores were much less than the other two displays. We concluded that this came as a result due to the complexity of the display and pre-processing the data before it was displayed to the participants. These pre-processing techniques help to reduce the cognitive load required to interpret vertical load comparisons of both lower limbs that would be placed on the user during training.

Although the Differential display was consistently voted, through subjective measurements, the easiest display to interpret, the Differential-Temporal display performed significantly better than the Differential display. We deduced that this might be due to the clear differentiation between left, right and the goal for the Differential-Temporal display. The Differential-Temporal display has specific targets that the user can aim for, whereas the Differential has none. Also the representation of the data stream for the Differential-Temporal (connected line graphs) served as a better comparison between the left and right limbs for perceptual processes, as compared to the single needle dividing between the gauge in the Differential display. The best display for this particular training was the Differential-Temporal since it provided the same information as the other displays in an appropriate representation for effective interpretation by the user.

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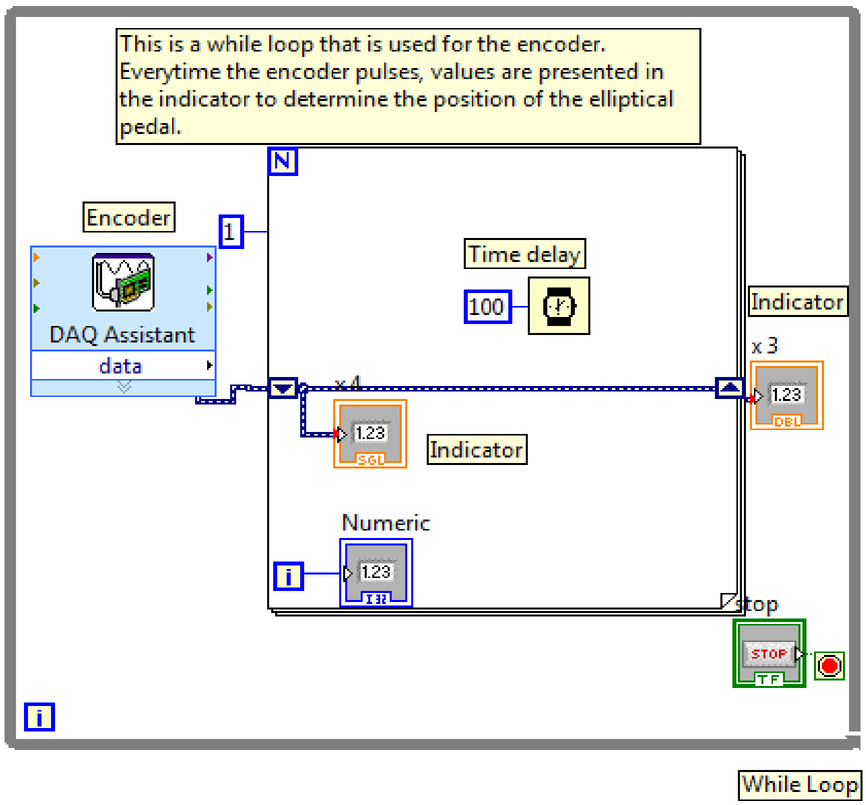
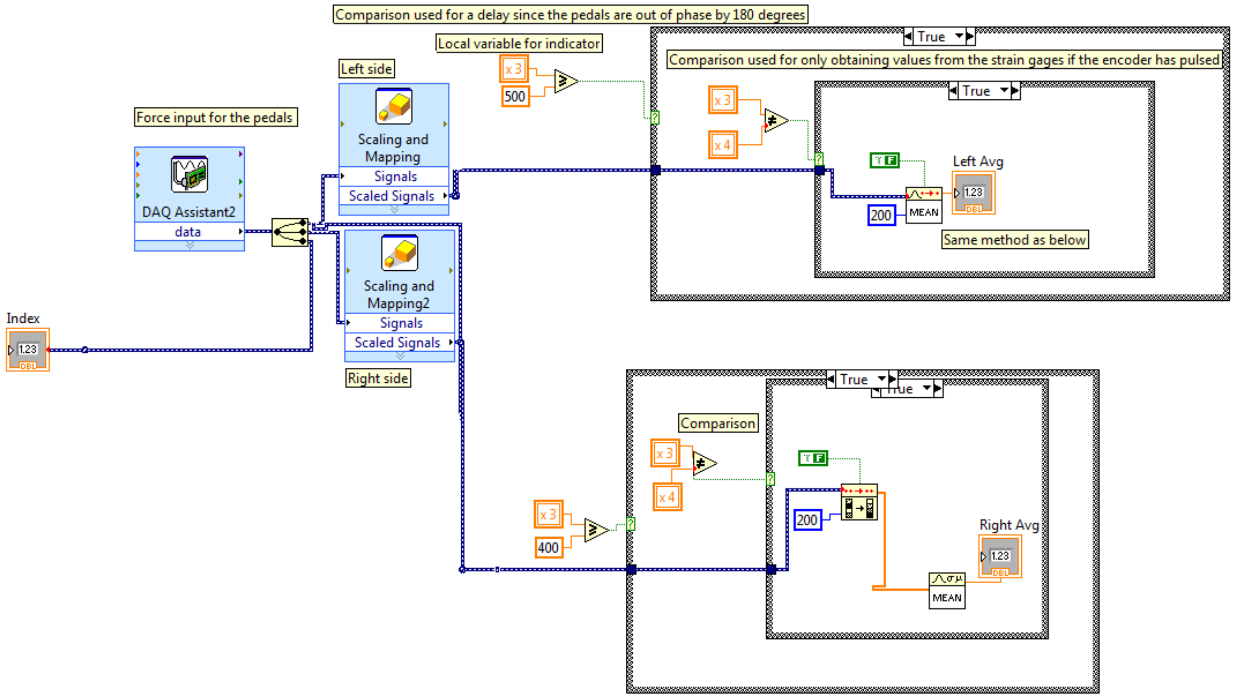
Appendix

Appendix A

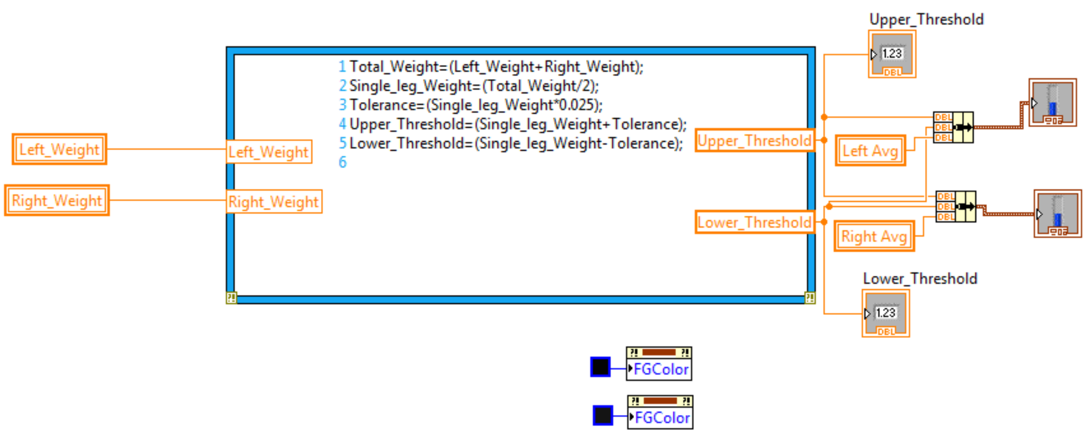
LabVIEW vi for acquiring vertical load and representing as visual biofeedback.



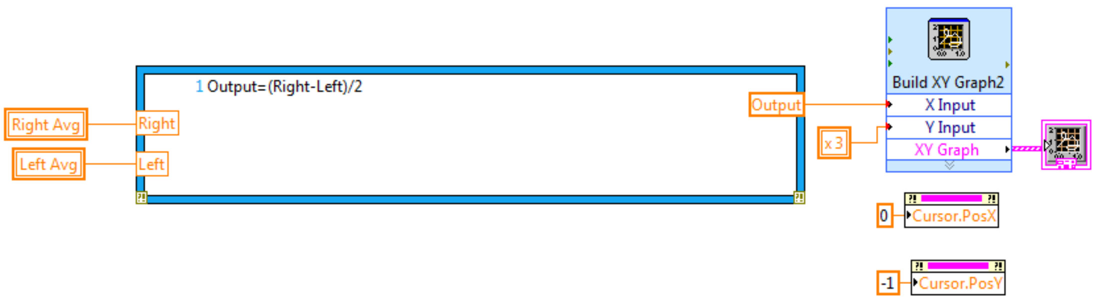
While loop in LabVIEW vi to read encoder pulses as an external clock. This loop uses a shift register to determine changing positions in the flywheel (encoder pulses).



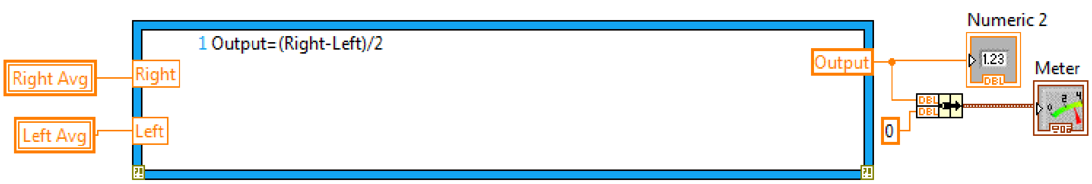
Component to LabVIEW vi that uses indicators from above (x3 and x4) to control when a weight measurement from either load cell enters the corresponding 200 point array. Weight measurements are acquired through the 12 bit DAQ card and scaled based on calibration curves.



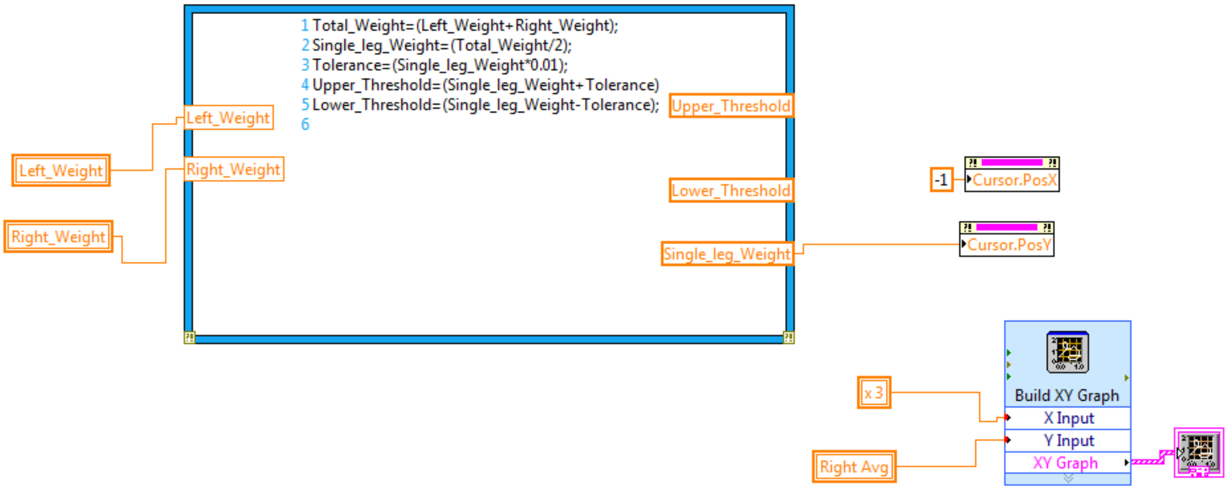
Mathscript code in LabVIEW vi that builds the Tanks display by inputting left and right weight measurements (averaged from 200 point array) to determine threshold values. Upper and lower thresholds for the display are found by calculating half of total body weight. These values are used as the blue target line on the Tanks display. Weight measurements are represented as the filler line in the corresponding tank.



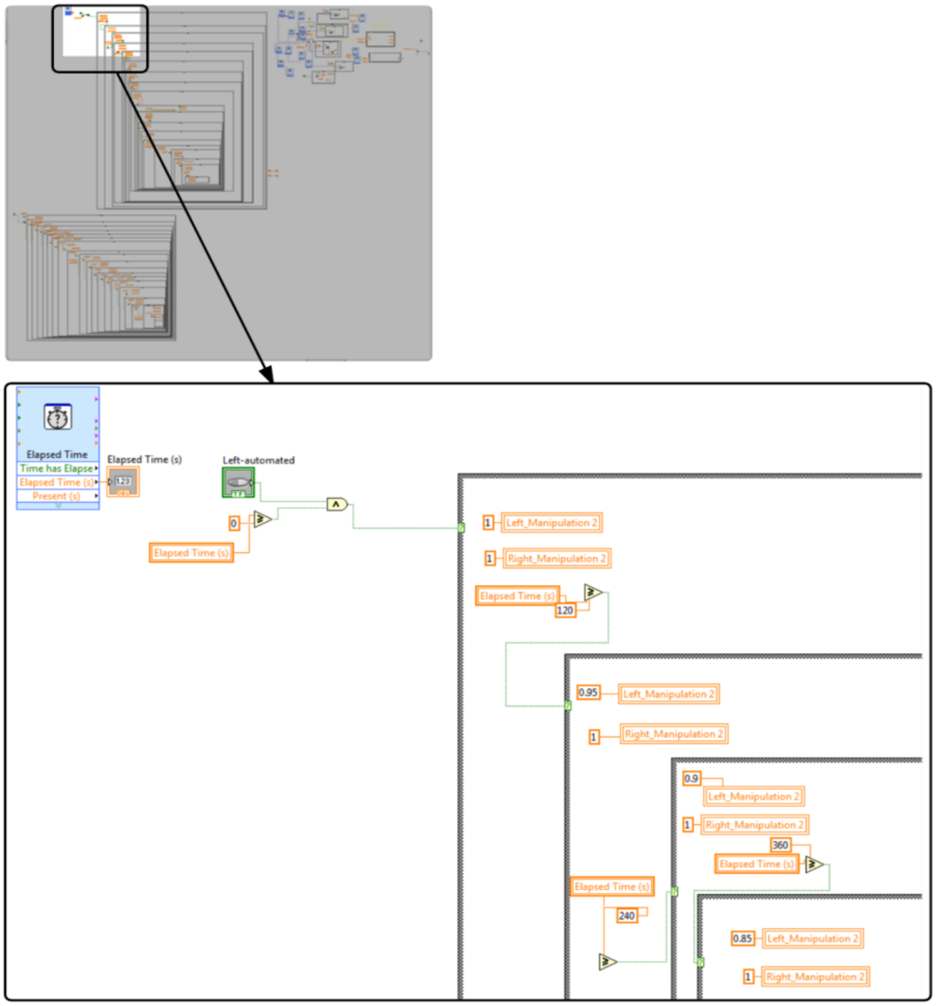
Mathscript code in LabVIEW vi that builds the Differential-Temporal display by inputting left and right weight measurements (averaged from 200 point array) to calculate the difference between right and left weight measurements. This calculation is presented as a single data point on the graph and changes with each encoder pulse.



Mathscript code in LabVIEW vi that builds the Differential display by inputting left and right weight measurements (averaged from 200 point array) to calculate the difference between right and left weight measurements. This calculation is presented as a single needle on a meter and changes with each encoder pulse.



Mathscript code in LabVIEW vi that builds the Temporal display by inputting left and right weight measurements (averaged from 200 point array) to determine the threshold value. Threshold for the display are found by calculating half of total body weight. These values are used as the blue target line on the Temporal display. Single-limb data are represented in the graph to compare with the target line.



Code to manipulate the gain of the vertical load signal. This is a portion of the LabVIEW vi that manipulates the gain of the load cell signal every 2 minute interval.

Appendix B

Matlab code to analyze the data.

```
%determining start and stop of each cycle from the index signal
fflag=0;
k=1;
cnt=1;
for i=1:length(Index)
    if Index(i)>4.1 & fflag==0
        P(k)=i;
        fflag=1;
        k=k+1;
    else
        cnt=cnt+1;
    end
    if cnt==200
        cnt=0;
        fflag=0;
    end
end
I=transpose(P);

Test(1:length(P)+1)=[0 P];
Test_2=[P 0];
Test_3=Test_2-Test;
Test_4=find(Test_3<100);

F=Test_2;
F(Test_4)=[];
clear I;
FF=transpose(F);
I=FF;

%to get Time from one cycle to the next-helping to determine speed
for jj=1:length(I)+100
      H(jj)=mean(Time(I(jj):I(jj+1)));
end

T=transpose(H);

%to get average Right load values from one cycle to the next
for jj=1:length(I)
      P(jj)=mean(Right(I(jj):I(jj+1)));
end

R=transpose(P);

%to get average Left load values from one cycle to the next
for jj=1:length(I)
      Y(jj)=mean(Left(I(jj):I(jj+1)));
end

L=transpose(Y);
```

```
%Once you open the array in matlab copy and paste into an excel file to
%store
%From excel look at the total average (removing the first and last
%minute)
% Use Rob IOS equation to determine any differences
```

Appendix C

R code to statistically evaluate the data.

```
data1<-read.csv(file.choose(), header=TRUE)
 hist(data1[,1],xlab="Diff",ylab="frequency")
 hist(data1[,2],xlab="Diff-Temp",ylab="frequency")
 hist(data1[,3],xlab="Temp",ylab="frequency")
 hist(data1[,4],xlab="Tanks",ylab="frequency")
 hist(data1[,5],xlab="Baseline",ylab="frequency")


//For non-parametric
wilcox.test(data1$D.T,data1$Tanks)
wilcox.test(data1$D.T,data1$Temp)
wilcox.test(data1$D.T,data1$Diff)
wilcox.test(data1$D.T,data1$Baseline)
wilcox.test(data1$Temp,data1$Diff)
wilcox.test(data1$Temp,data1$Baseline)
wilcox.test(data1$Tanks,data1$Diff)
wilcox.test(data1$Tanks,data1$Temp)
wilcox.test(data1$Tanks,data1$Baseline)
wilcox.test(data1$Diff,data1$Baseline)

//t tests
t.test(data1$D.T,data1$Temp)
t.test(data1$D.T,data1$Diff)
t.test(data1$D.T,data1$Baseline)
t.test(data1$Temp,data1$Diff)
t.test(data1$Temp,data1$Baseline)
t.test(data1$Tanks,data1$Diff)
t.test(data1$Tanks,data1$Temp)
t.test(data1$Tanks,data1$Baseline)
t.test(data1$Diff,data1$Baseline)

//anova
Stacked_Groups<-stack(data1)
Anova_Results<-aov(values~ind,data=Stacked_Groups)
summary(Anova_Results)
TukeyHSD(Anova_Results)

//chi square test
Stacked_Groups<-stack(data1)
chisq.test(Stacked_Groups$values)
```

Chapter 4

Chapter 4: Asymmetric ambulation: At what percent gain manipulation does individual performance begin to fail?

Abstract

Incorporating biofeedback into rehabilitation has been an increasing trend in physical therapy over the past decade with vast advancements in technology. Systems such as the Wii Balance Board and the SMART Balance Master have paved a way for visual biofeedback training focused on postural control in static stance. Although these systems are promising for static stance, there still exists a need to develop a system to promote adequate postural control in dynamic movements such as walking. Focusing on cadence, dynamic systems such as split-belt treadmills have been employed to increase speed of the affected limb. Although speed of the affected limb, as well as overall speed, is increased, vertical load is still a concern during training. The following work tests the consistency and performance of individuals running on an elliptical trainer that incorporates visual biofeedback. The system was developed based on a similar technique to split-belt treadmill training, although focusing on vertical load rather than speed, in which the gain of the signal was modulated to encourage more weight to be shifted to the non-dominant weight bearing side. The following study measured variables, such as variance, mean index of symmetry, percentage error, speed and weight offloaded, to determine performance at ranging percentages, from 0% to 25%, used to modify the signal of the load cells. The load cell signal from the non-dominant weight bearing limb was decreased to encourage weight distribution towards this side. Healthy participants were recruited and divided into two

separate groups based on age (younger=18 to 30 and older=35 to 60) to determine age-related differences when applying visual biofeedback. Each participant had a separate and independent routine that was randomly assigned. Following training, the NASA TLX was administered to determine workload during the activity. A non-parametric analysis of variance was conducted as well as Man Whitney tests to determine significant differences in percentage error values. Although qualitative differences existed between the younger and older groups, the results of the study showed that participants were able to increase the load on their non-dominant side in some cases up to 25%, but performance typically degraded after a 10% load bias. Since this training technique place a larger load on their non-dominant side, the method was define as hyper-symmetric training. Hyper-symmetric training was achieved by assigning less weighting to the non-dominant weight-bearing limb to encourage increased weight shifts. Based on significance testing with percentage error, a threshold value between 5-10% was found for a suitable ceiling for hyper-symmetric training.

Introduction

Constraint-induced training, developed by Edward Taub, is a popular technique in stroke rehabilitation which often leads to neural remapping in order to achieve certain tasks. This technique is composed of 4 principles to guide treatment that can be applied either in or outside the clinic. These principles include the following: (1) intensive training of the affected limb, (2) shaping technique, (3) implementing the transfer package for accountability outside the clinic, and (4) discouraging compensation towards the unaffected side (Taub, 1993, Taub, 2014, Morris, 2006). Although effective for upper extremity rehabilitation, this form of training can be difficult to apply for lower extremity training since bipedal mobility is dependent on both limbs. In order to force use of the paretic/affected limb or increase the lad on that side, certain training techniques have been applied such as body weight supported treadmill training (BWSTT) and robotics.

Both rehabilitation techniques have been widely implemented in clinics as training paradigms that aim to encourage use of the paretic/affected limb. BWSTT employs an overhead harness system to offload a certain percentage of body weight and often requires two physical therapists to assist in limb progression and weight shifting (Harvey, 2009, Werner et al., 2002). This training technique has shown much success both in the clinic and research by forcing the use of the paretic limb and through a key element of variability (Hidler et al., 2009). The variability of the path of limb progression and degree of weight shifting allows patients to develop multiple motor patterns that can transfer to a real world environment (Hornby et al., 2008). Although variability is an advantage to training, with ranging patterns and no way to objectively measure metrics there is a limitation of quantifying treatment over the course of rehabilitation. Another disadvantage of this training technique is the physical demand placed on the therapists (Harvey, 2009, Jackson et al., 2010, Hidler et al., 2009). Therapists are often susceptible to injury due to improper ergonomics while assisting in limb progression and weight shifting over the course of training. Overtime this activity can lead to injury due to overuse (Hidler et al., 2005).

To remove physical demand of the therapist, robotics such as the Lokomat® have been developed and substituted in the clinic (Hidler et al., 2009). The Lokomat® incorporates an exoskeleton with a treadmill system and overhead harness (Hidler, 2005). Instead of the therapist guiding limb progression, the exoskeleton guides the limb in a pattern that simulates overland walking. This allows training duration to be dependent on the patient as opposed to both patient and therapist endurance. Although this system removes the therapist's susceptibility to injury, it lacks the variability in training required for real world applications by constraining the limb to preset kinematics (Hornby et al., 2008, Cai et al., 2006). Another disadvantage is the limitation of weight shifting since the harness and exoskeleton limit significant shifting from one limb to another. The benefits to the Lokomat® system often do not outweigh the disadvantages in training as well as the cost to implement, on the order of $100,000 to $200,000 (Harvey, 2009, Hornby et al., 2008).

As patients become more independent in training, other systems can be implemented to train different characteristics of gait. One such characteristic is cadence of the paretic limb. Split-belt treadmill training controls speed of the paretic limb during training by providing controls for the separated belts. To increase both paretic limb and overall speed after training, therapists incrementally increase the speed of the belt of the paretic limb. Studies by Reisman et al. have shown that this significantly increases the cadence of the paretic limb and overall cadence (Reisman et al., 2013, Reisman et al., 2007). Although this is a positive outcome, training can lead to disproportionate loading on the paretic limb (Kaplan et al., 2014). As a side note, Reisman et al. noted that although there was an increase in step length this did not correlate to increased stance time (Reisman et al., 2013). This could be a result of the patient/participant adopting a compensated pattern to allow increased cadence without adequately shifting weight to the paretic side.

To offer independence in training while forcing use of the paretic limb, biofeedback systems have been implemented with balance training. Since visual systems tend to provide an intuitive approach to biofeedback interpretation, often vision is the most widely accepted approach to delivery of biofeedback. Systems such as the SMART Balance Master and the Wii Balance Board have been implemented in the clinic to train patients to shift weight towards their paretic limb (Barcala et al., 2013, Chen et al., 2002, Gil-Gómez et al., 2011, Goble et al., 2014). These systems couple vertical load measurement devices to software that displays weight measurements through visual biofeedback. From the biofeedback, patients adjust accordingly to produce symmetric distribution of weight. Studies such as those by Chen et al. and Gil-Gómez et al. have shown positive results when using these systems (Chen et al., 2002, Gil-Gómez et al., 2011). Not only did participants distribute their weight symmetrically in Chen et al., but improvements occurred in maximal stability, ankle strategy and center of gravity alignment (Chen et al., 2002). These studies give promise to visual biofeedback training related to improvements in postural control, but these systems were developed for quiet stance which is not commonly transferrable to dynamic stance. Several studies have looked at applying visual biofeedback to parameters in dynamic stance (Feasel et al., 2011, Dingwell et al., 1996, Dingwell et al., 1996, Crowell et al., 2010). For example, Dingwell et al. developed a system coupled to a treadmill that displayed variables in gait such as stance time, push-off forces and center of pressure. Researchers from this study found positive results when incorporating visual biofeedback for all 3 variables.

Although coupling visual biofeedback to systems for postural control has been utilized frequently, there still exists a question as to which representation offers the optimal interface for interpretation. To better understand if the design of the visual representation plays an effect on performance, a study by Massenzo et al. looked at four different visual representations that displayed vertical load measurements during elliptical trainer use (Massenzo et al., 2015). In this study, four display types were constructed, based on previous research, and used as visual biofeedback during elliptical trainer use. Participants used each display separately to distribute their weight across both pedals according to the information presented. Results of this study suggest that one display type performed the best over all others and all visual biofeedback displays resulted in better performance than no biofeedback. This study raises the concern of designing display representations in a manner that is intuitive to the user while presenting essential information to improve performance.

Another variable in biofeedback delivery to consider is the augmentation of the information/signal before it is displayed. A study by Ding et al. looked at adjusting the gain of the vertical load signal in a static system (Ding et al., 2012). Separate force plates were utilized to determine weight symmetry between left and right lower limbs. Researchers then modified the signal from the balance boards to encourage shifting onto the paretic limb by assigning less weighting to signals from the paretic limb. Results of this study showed that participants had an overall improvement in stance symmetry during quiet stance with an increase of weight bearing on the paretic limb. From the success of this study, poses the need to develop a system that adopts a similar technique applied to dynamic stance.

To expand on our previous study as well as implementing the findings gained from the Ding et al. study, the following experiment was designed to measure performance when manipulating the gain of vertical load signals from an elliptical trainer. Routines were developed to study at which manipulation percentage participants began to decrease performance to a point of failure. Failure was established by measuring percentage error and comparing to routines of no manipulation and no feedback. The purpose of the following study was to determine an appropriate threshold for hyper-symmetric biased training in a healthy sample set with younger and older adult participants.

Methods

Participants

This study was approved through Virginia Commonwealth University's institutional review board. Prior to entering the study all participants provided written informed consent. Inclusion criteria for the study were the following: no lower limb injuries within the past year, no cardiovascular disease and not diabetic. Two groups were recruited for the study. The first group (labeled as younger) consisted of individuals who met the inclusion criteria and ranged in age from 18 to 30 years old. The second group (labeled as older) also met the inclusion criteria, but ranged in age from 35 to 60 years old. Twenty-one participants (6 Male, 15 Female, average age= 23 ±2.02) met the inclusion criteria and were recruited for the younger group. Two participants were removed from the younger group since one noted lower back pain and could not complete the first session while the other was removed due to conflicts outside the control of the study. Fourteen participants (8 Male, 6 Female, average age=41±6.23) met the inclusion criteria and were recruited for the older group. One participant was removed from the study since they were unable to continue training over the three day period.

Device Design

A modified elliptical trainer (NordicTrack®, Logan, UT) was used to measure vertical left-right loads (Chapter 2). Dynamic kinetic visual biofeedback was provided via a computer monitor displaying differential-temporal representations of vertical load (Chapter 3) (Massenzo et al., 2015). Similar to the Ding et al. study, the gain of the vertical load signal was manipulated to encourage weight displacement towards the non-dominant weight-bearing limb (Ding et al., 2013). The manipulation of the gain ranged from 5 to 25% in 5% intervals and the gain manipulation sequences were randomized. Each routine had the following sequence: Baseline (no feedback), Zero_1 (feedback with zero gain manipulation), gain manipulation sequence, Zero_2 (feedback with zero gain manipulation), and Cooldown (no feedback) (Table 1).

<table>
<tr><th>Label</th><th>Sequence</th><th>Feedback?</th><th>Randomization?</th></tr>
<tr><td>Warm up</td><td>Warm up</td><td rowspan="2">No Feedback</td><td></td></tr>
<tr><td>Baseline</td><td>Baseline</td><td></td></tr>
<tr><td>Zero_1</td><td>Gain manipulation 0%</td><td rowspan="7">Feedback</td><td></td></tr>
<tr><td>Five</td><td rowspan="5">Gain manipulation (5%-25%)</td><td rowspan="5">Order Randomized</td></tr>
<tr><td>Ten</td></tr>
<tr><td>Fifteen</td></tr>
<tr><td>Twenty</td></tr>
<tr><td>Twenty-five</td></tr>
<tr><td>Zero_2</td><td>Gain manipulation 0%</td><td></td></tr>
<tr><td>Cooldown</td><td>Cooldown</td><td>No Feedback</td><td></td></tr>
</table>

Table 1. Modified elliptical trainer sequence. This categorizes the sequence of events for the modified elliptical. Participants started activity with the elliptical trainer using no feedback. After five minutes, participants transitioned into activity with visual biofeedback incorporating gain manipulation. Participants then transitioned into their Cooldown period with no visual biofeedback.

Procedures

Order of the gain manipulations was block randomized, allowing the order of manipulating the gain of the signal to be different for each participant. Data were collected from each subject in three sessions across three days with at least 24 hours in between each session in a two week period. Instruction on the activity was provided at the beginning of the first session as well as instruction on the NASA TLX survey. The NASA TLX survey was implemented in order to determine differences in workload in six categories: mental demand, physical demand, temporal demand, performance, effort and frustration. Since this survey has had wide acceptance and application in workload studies, many incorporating biofeedback delivery, it was implemented as a workload measurement tool after training (Hart, 2006). Prior to training, participants were asked to indicate which leg they kick with in order to determine which side was their non-dominant weight-bearing limb. Once this was determined, the program was set to train their non-dominant weight-bearing limb. For all sessions, gain of the load cells was modified to encourage weight shifts to the non-dominant limb.

During each session, participants warmed up on the elliptical trainer for a period of three minutes with no visual display followed by a Baseline measurement phase of 2 minutes. After measuring Baseline, visual biofeedback incorporated a randomized sequence of gain manipulations for two minutes in each condition (total of 14 minutes). Finally, visual biofeedback was removed for a Cooldown period lasting two minutes. An ABA experimental design was used for each session by measuring performance in no feedback and feedback conditions. Following warm up, participants ran on the elliptical for two minutes at 0% manipulation to determine how they performed with the display. For the following ten minutes, participants were required to adjust their weight distribution every two minutes with a shift in the percent manipulation. At the seventeen minute mark, the routine went back to 0% to determine how they performed with the display once the manipulation was removed. Finally, the display was turned off while the participant kept running on the elliptical for his or her cool down period of two minutes. During the manipulation phase, participants saw a shift depending on the magnitude of manipulation, but were not aware that the gain was manipulated the whole duration of the two minute period.

Data Analysis

Vertical load was measured and stored in an Excel file format, processed using MATLAB (The MathWorks, Inc., Natick, MA), and statistically analyzed using SPSS (IBM Corporation, Armonk, NY). Percentage error for each condition was computed and used to compare routines (baseline and percent manipulations) during each session (Equation 1). These metrics were also used to compare performance difference between the younger and older groups. Percent error is a measure to compare the value obtained from gain manipulation of the signal (e.g. 5-25%) to the unmodified weight measured on the pedal.

$$Percentage\ Error = \frac{|Approximate - Exact|}{|\mathrm{Exact}|} \times 100\% \qquad (1)$$

The following secondary variables were analyzed: weight offloaded and speed. Comparisons were made between groups as well as within from day 1 to day 3 to determine if there was a learning effect from one session to the next. Correlation coefficients were found for each group to determine if manipulation of gain as well as speed and weight offloaded was correlated to percentage error. A non-parametric ANOVA (Kruskal Wallis test) and corresponding Mann-Whitney u tests were performed to determine if there were significant differences between routines across the subjects. Threshold values for gain manipulation were determined by comparing percentage error of gain manipulations to inherent asymmetric error (Baseline percentage error). The gain manipulation value that had a percentage error below those found at Baseline was determined as the threshold value.

Results

Statistical analyses were conducted to determine if significant differences exist within and between groups. Kruskal Wallis tests indicated a significant difference in the dataset (p-value<0.05). Figures 1 and 2 represent stimulus-response error for Baseline (no feedback) and different levels of hyper-symmetric non-dominant biased training (via visual feedback) for normal subjects. Both groups demonstrate a baseline asymmetry with no visual feedback (labeled Baseline). Although both groups showed asymmetry, there was inherently greater asymmetry in the older group, where Baseline comparison showed statistical significance (Figure 1). Both groups also demonstrate improved symmetry when visual biofeedback was provided (labeled Zero_1). Along with statistical differences between Baseline, the younger group proved to be better at utilizing visual feedback to reduce asymmetric errors (Zero_1 comparisons showing a statistical significance). Comparing Baseline to Zero_1 for both groups showed statistically significant differences; therefore displaying that subjects were able to decrease error with the inclusion of visual feedback.

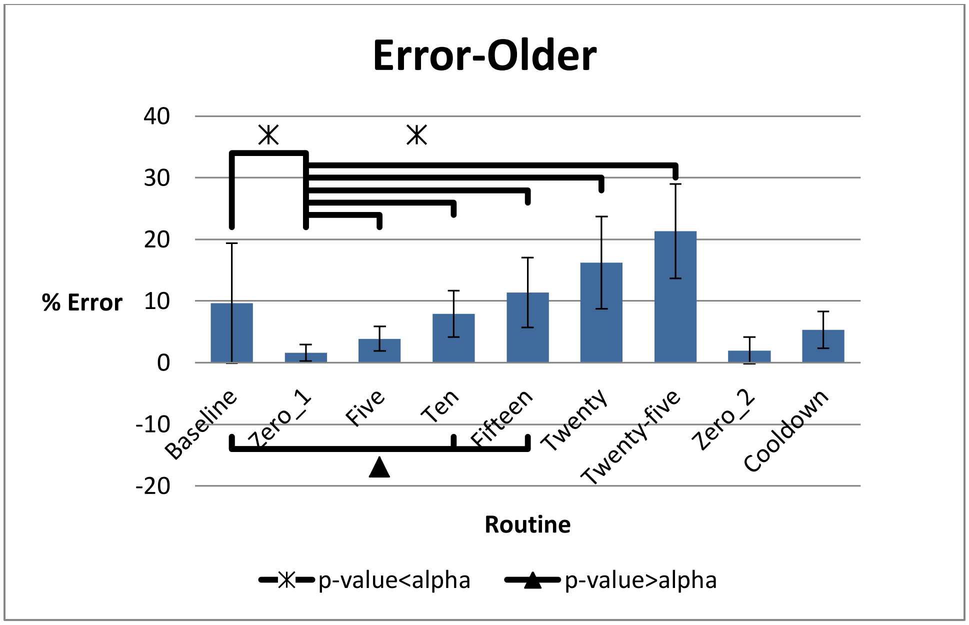


Figure 1. Mean percentage error for older healthy sample set. Stimulus-response percentage error for Baseline (no feedback), and different levels of hyper-symmetric non-dominant biased training (via visual feedback) for healthy older subjects. Error bars indicate standard deviation in the dataset.

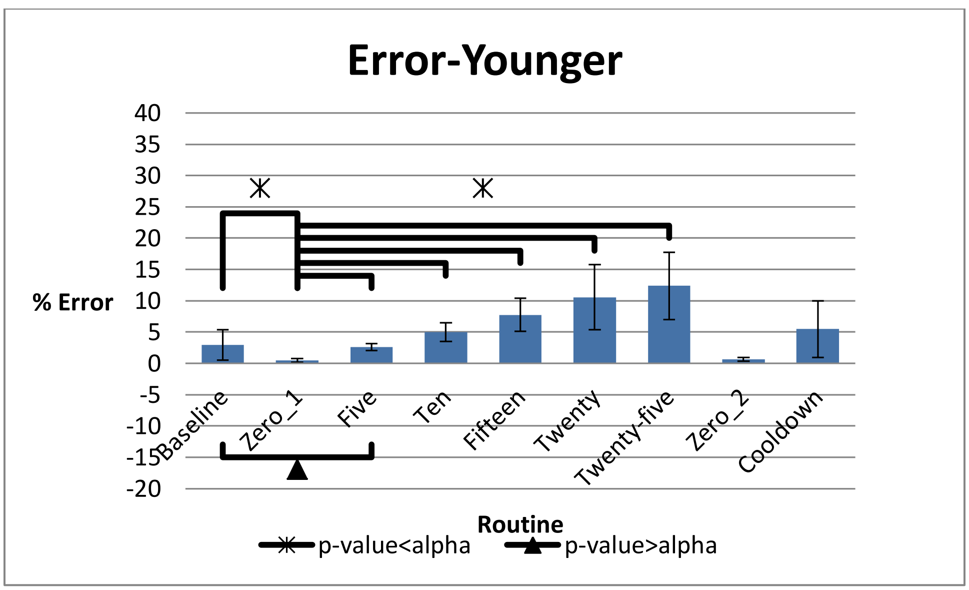


Figure 2. Mean percentage error for younger healthy sample set. Stimulus-response mean percentage error for Baseline (no feedback), and different levels of hyper-symmetric non-dominant biased training (via visual feedback) for healthy younger subjects. Error bars indicate standard deviation in the dataset.

When statistically comparing Zero_1 data (feedback with no gain manipulation) to all hyper-symmetric data, it was found that all hyper-symmetric trials were statistically different than Zero_1. Correlation coefficients demonstrate that increased error correlated with increasing hyper-symmetric stimulus (R^2=0.99 for Young and Older, Figures 3 and 4). This suggests that visual feedback had a limited impact on a subject's ability to minimize error when increasing biased training. Comparing Baseline values to hyper-symmetric biased values, errors exceeded and became statistically different than Baseline values at a level between 5 and 15% hyper-symmetry for the younger and older groups, respectively.

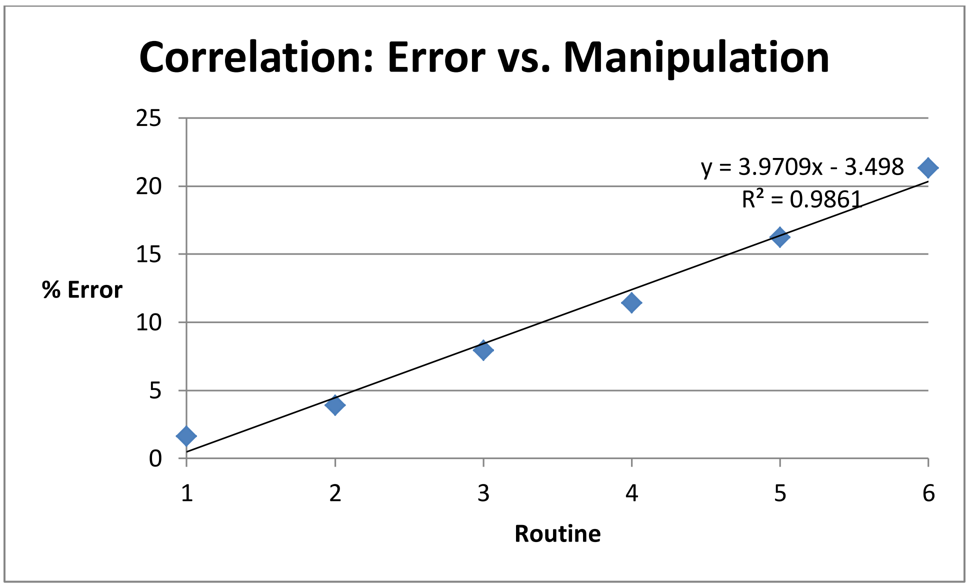


Figure 3. Correlation coefficient: percent manipulation vs. percentage error in older population. Trend line shows a linear trend with a strong correlation between percent manipulation and mean percentage error (R^2 = 0.9861).

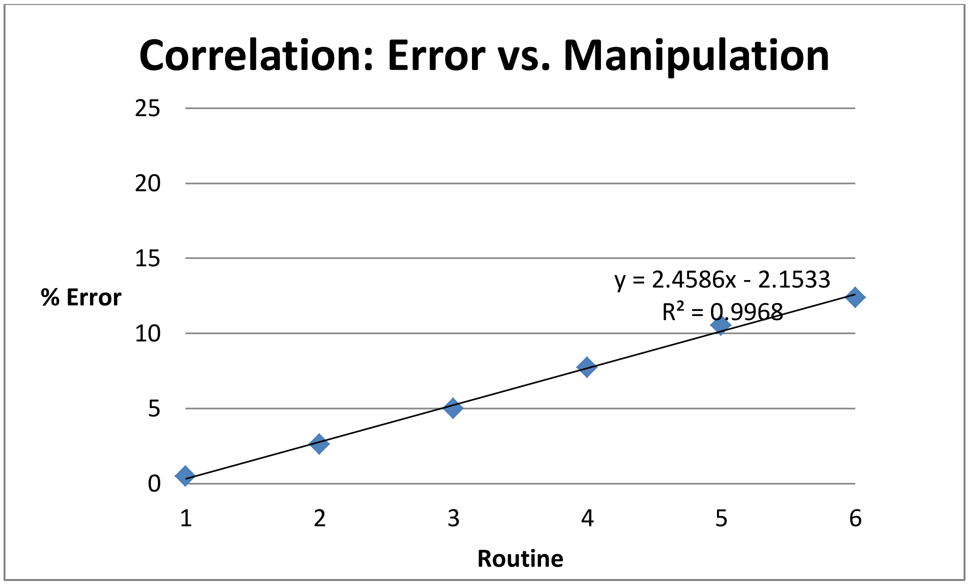


Figure 4. Correlation coefficient: percent manipulation vs. percentage error in younger population. Trend line shows a linear trend with a strong correlation between percent manipulation and mean percentage error ($R^2 = 0.9968$).

Kruskal Wallis tests indicated a significant difference in the dataset for each training session (p-value<0.05). Comparing stimulus-response error in younger and older groups over multiple days result in minimal significant differences among the 3 trials for both groups; therefore demonstrating no or limited learning effect for both groups (Figures 5 and 6). Significance testing showed differences in data at Baseline from Day 2 to Day 3 in the older group and at Zero_2 from Day 2 to Day 3 in the younger group. For all other routines, there were no significant differences among the three days.

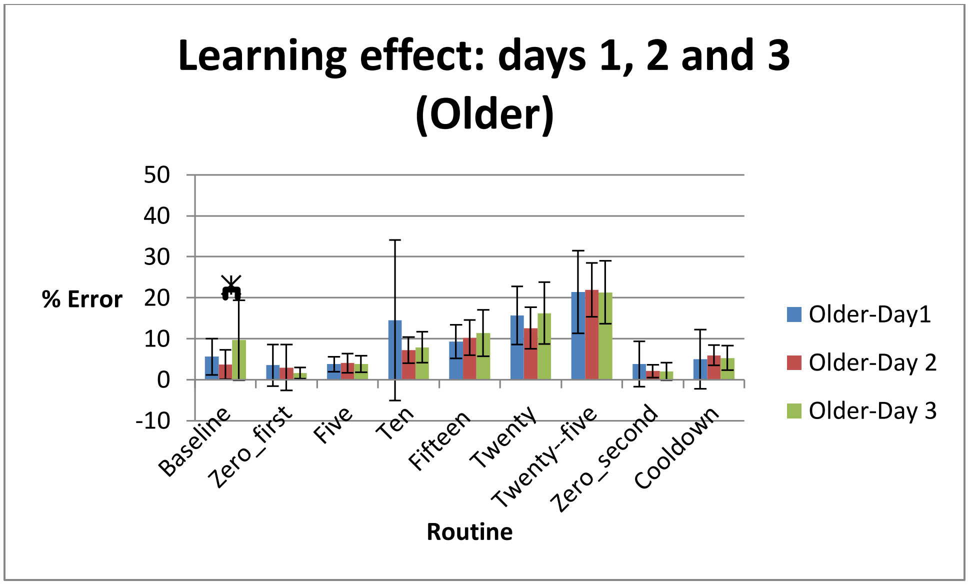


Figure 5. Learning effect (days 1, 2 and 3) for older sample set. Comparing percentage error over three sessions to determine if there was a learning effect from training in the older healthy group.

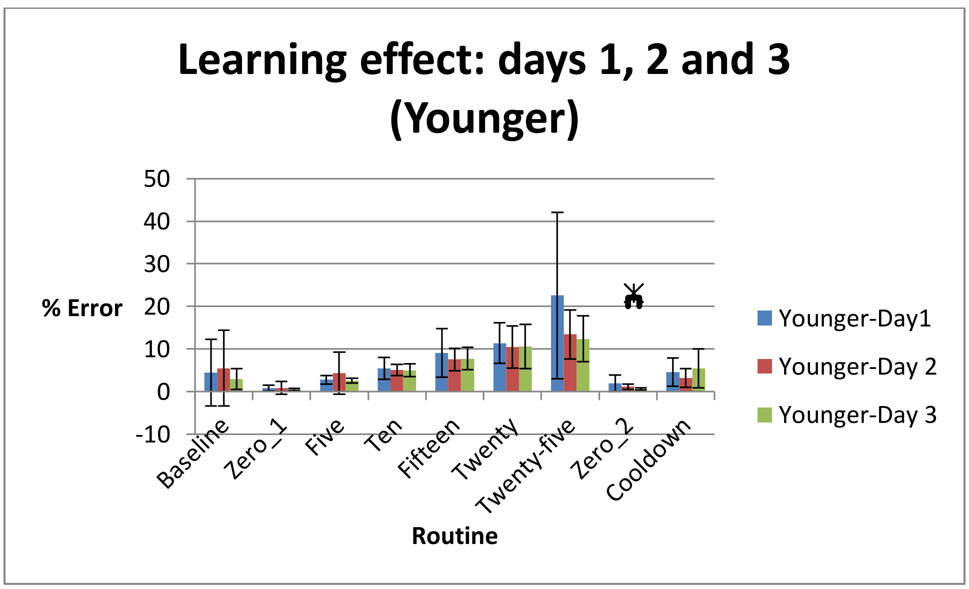


Figure 6. Learning effect (days 1, 2 and 3) for younger sample set Comparing percentage error over three sessions to determine if there was carryover in the younger healthy group.

Along with determining correlation between routines and error, correlation coefficients were found to determine if speed or offloading influenced error. Participants were consistent in self-selected speed for the duration of training. Correlating speed to error (R^2=0.21-Younger and

R^2=0.07-Older) suggests that speed has a poor correlation to error with or without visual feedback. Neither group showed a statistical difference in offloading from Baseline to feedback conditions with hyper-symmetric stimuli. Correlation coefficients suggest that offloading has a poor correlation to error (R^2=0.119-Younger and R^2=0.06-Older).

A NASA TLX survey was conducted post-data collection to determine perception of workload for the overall task. Figure 7 represents a subjective assessment of perceived workload in six different categories. This graph represents a global view of a single training session. Kruskal Wallis tests indicated no significant difference in the dataset for NASA TLX ratings (p-value>0.05).There is no statistical difference between groups (Younger vs. Older) for the perception of workload in any of the six categories.

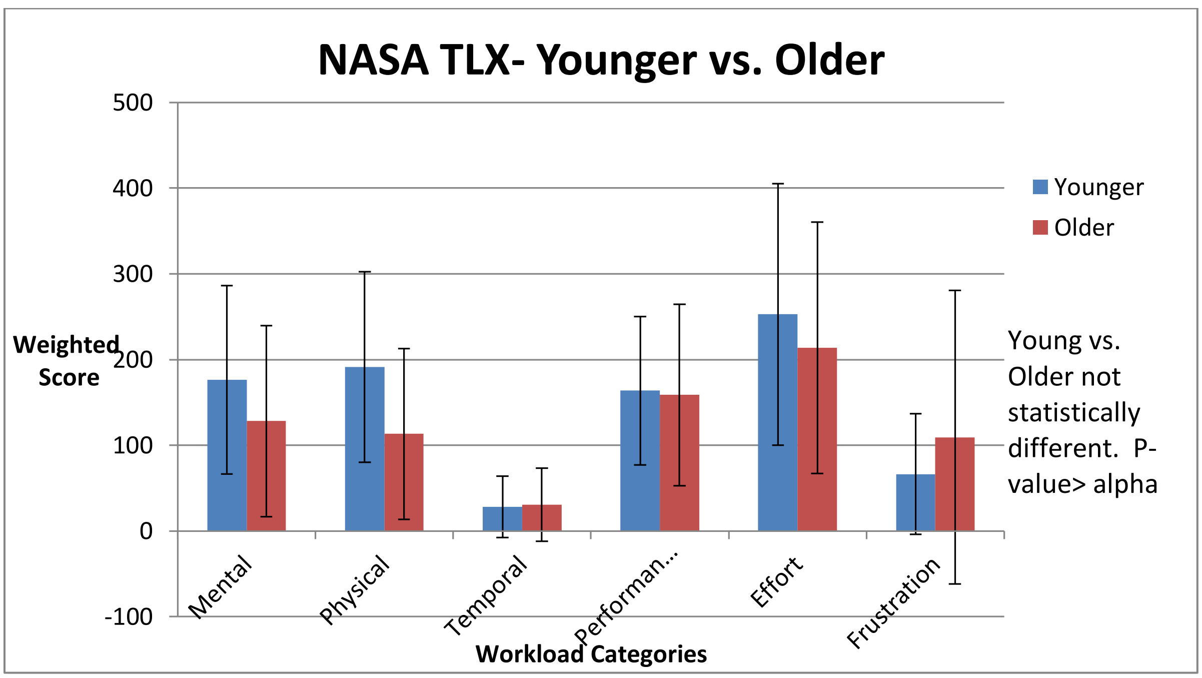


Figure 7. Perceived workload comparing younger versus older healthy age groups.

Discussion

This study was conducted to determine appropriate hyper-symmetric biased training threshold values in a healthy sample set with younger and older adult participants. Additionally, performance was determined based on percentage error while using visual biofeedback to manipulate the gain of the left/right load-bearing signal to encourage weight shifts to the non-dominant weight bearing side. Variables such as percentage error, speed and weight offloading were measured to assess the performance and efficacy of the system. The NASA TLX survey was implemented in order to determine differences in perceived workload in six categories: mental demand, physical demand, temporal demand, performance, effort and frustration. Since this survey has wide acceptance and application in workload studies, many incorporating biofeedback delivery, it was implemented as a workload measurement tool following elliptical training (Hart, 2006).

Asymmetric load percentages between 5% and 25%, were tested to determine a threshold value for both groups. Threshold values were determined by comparing percentage error values at gain manipulation to Baseline (inherent asymmetry). A ceiling value was found that showed minimized error compared to Baseline conditions. Similar to Ding et al. findings, participants who enrolled in this study were able to shift weight onto their non-dominant weight bearing limb during training. This suggests that participants are able to control weight shifts during use of both static and dynamic systems, even with manipulating the gain of the signal to encourage use of the non-dominant limb.

When determining how participants perform without feedback compared to feedback, there is a threshold value between 5 to 15% gain manipulation for the older population where error exceeds no feedback conditions. For the older population, below 15% gain manipulation asymmetry is still below natural Baseline asymmetry of that group. Therefore, this provides a suitable upper threshold for training. As it relates to stroke populations, a lower percentage is anticipated for training in order to limit risk of falling while ensuring that users are still learning during the task.

Although the two groups show similar trends in percentage error measured during use of the modified elliptical trainer, the younger adult group seemed to be inherently more symmetric than the older group throughout training. Existing stability research show consistent findings of neuro-muscular decline in aging populations, leading towards decreased balance (da Silva et al., 2013). Factors that influence stability due to aging include the following: a decrease in available fast twitch motor units, altered motor unit size and a decrease in alpha motor neurons within the spinal cord (Morrison et al., 2012, Orr, 2010). This decrease in alpha motor neurons reduces motor neuron excitability thereby slowing nerve discharge rates. As a consequence, aging populations exhibit slower reactions to an external stimulus and decreased magnitude of force generated. With these consequences balance both during quiet and dynamic stance is affected drastically,

Cognitive decline in aging is expected to be another differentiating factor in performance differences between groups. Other studies such as those by Bruijin et al. and Hogan show that age-related cognitive deficits can contribute to performance differences between young and older adults (Bruijin et al., 2012, Hogan, 2004). Hogan refers to the effect of general slowing with aging on memory, attention and reasoning which causes a delay in the speed of processing information not necessarily a change in the outcome produced (Hogan, 2004). Contributing this idea towards our outcomes, perhaps outcomes for both groups may have closely aligned if the older group was allotted more time for processing the information with each change in percentage. Perhaps the groups differed due to a higher cognitive load placed on the older adults attributed to a decline in executive function that affects both attention and planning processes (Greenwood, 2000). Not only do age-related deficits occur in the frontal cortex but also at the cerebellar level, which affects the integration of sensori-motor feedback for motor adaptability. Bruijin et al. concluded that gait adaptations differed between groups during split-belt treadmill activities with differing speeds on each belt due to age-related deficits within the cerebellum (Bruijin et al., 2012). Although this study had a greater gap between age groups compared to the present study, understanding the role of sensori-motor integration and age-related issues can lead to a better understanding in gait adaptations during particular tasks.

Although experience can contribute to improved performance in certain tasks, there exists some age-related cognitive decline in early adulthood that can contribute to decreased performance in cognitive testing and video gaming (Salthouse, 2009, Thompson et al., 2014). In determining age related differences in cognitive decline during video game applications, researchers from Simon Fraser University found that there is a steady decline after the age of 24 (Thompson et al., 2014). Results of this study show an age-related slowing in looking-doing latency, which is the delay between looking at a section of the display (StarCraft 2 video game) and performing an action. Although the constructed display for the present research provided a more simplistic interface than the StarCraft 2 video game, complexity of the overall task may stem from incorporating such a display to a highly complex motor task such as walking. Age-related factors involved in looking-doing latency may contribute to performance when attempting to achieve the goal when manipulating the gain of the signal. Although cognitive demands can be offloaded to the display interface, there still exists the slowing of decision-making due to increased age.

Other variables such speed and offloading were also evaluated to determine if additional factors influenced error. With minimal to no significance it can be concluded that these variables had no influence. For both groups, the ability to minimize error from one day to the next did not occur suggesting that there was no retention or learning effect from one session to the next. In relation to speed and offloading, participants were consistent with both variables for the duration of training. There were also no age-related differences to both selected pace and extent of offloading. Correlating speed to error (R^2=0.21, Younger and R^2=0.07, Older) suggests that error is not influenced by self-selected pace. There was no correlation for either group between offloading and error, therefore offloading did not affect performance with or without the visual display.

When viewing results of the NASA TLX survey, participants from both groups perceived workload similarly for each of the six categories. The largest contributor to workload was viewed as Effort (combination of Physical and Mental demands) for both groups, while Temporal (pace) was viewed to be the lowest contributor. Therefore, participants felt that they had to work both physically and mentally more in order to achieve the task. When comparing our results to another study by Caldwell et al., there appear to be differences in task load index rankings between our system and natural, unmodified gait on a standard treadmill; although no significance testing was performed since the raw data was unavailable (Caldwell et al., 2013). Due to directed visual biofeedback and knowledge of results, Mental, Performance and Frustration ratings increased with the modified elliptical. Since the protocol for the modified elliptical allowed participants to self-select their pace, Temporal workload decreased drastically from natural gait. There were no apparent differences in Physical and Effort demands from natural gait to modified gait with the elliptical. We concluded that this occurred since both activities require physical effort in order to accomplish the task, contributing to workload in both categories of Physical and Effort demand.

Conclusion

Natural asymmetry decreased with the introduction of visual biofeedback for both groups, although the older group was inherently more asymmetric than the younger sample group. This suggests that visual biofeedback can serve to minimize percentage error in weight distribution. Additionally, threshold values were found when comparing Baseline error values to values at hyper-symmetric biased training. For the older population, below 15% gain manipulation asymmetry is still below natural asymmetric values with no feedback.

Furthermore when deciding on threshold ranges, combining findings from our results and current literature lead towards a suitable protocol for additional studies with CVA participants. Adegoke et al. relate risk of falling in CVA populations to differentiated weight distributions between the paretic and non-paretic limbs. In this article, it was noted that patients could distribute weight between 7-20% more towards the non-paretic without falling (Adegoke et al., 2012). Correlating this result to our current study, an upper range between 7%-10% sets a suitable threshold for CVA populations when biasing training towards the paretic limb to limit the risk of fall. As a result, 5 to 10% was selected as the upper level of training on the paretic side to carry over to CVA studies.

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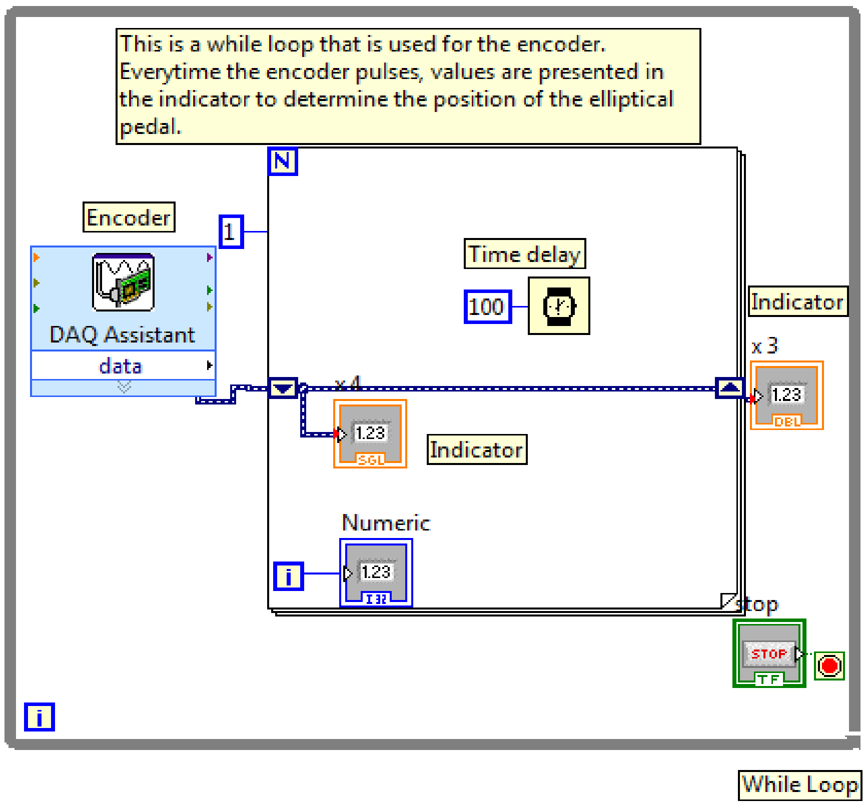
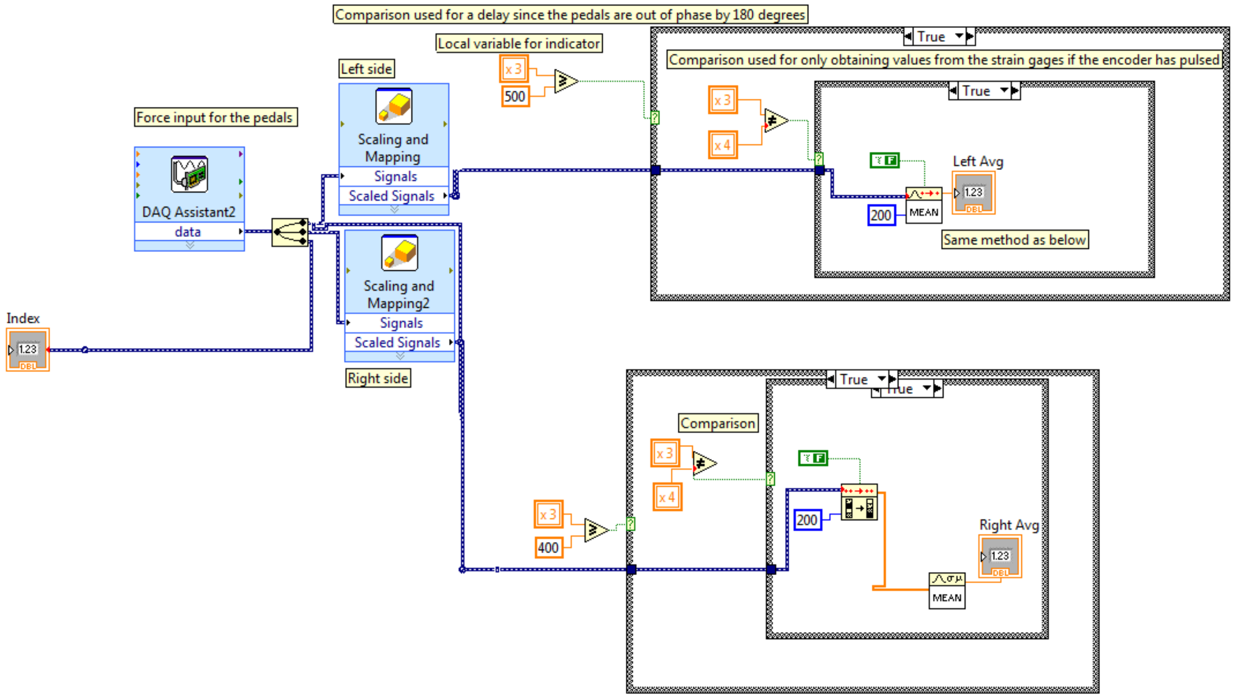
Appendix

Appendix A

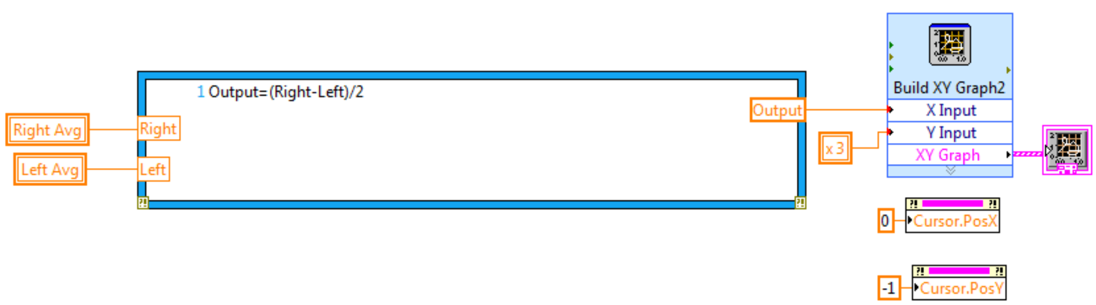
LabVIEW vi for acquiring vertical load and representing as visual biofeedback.



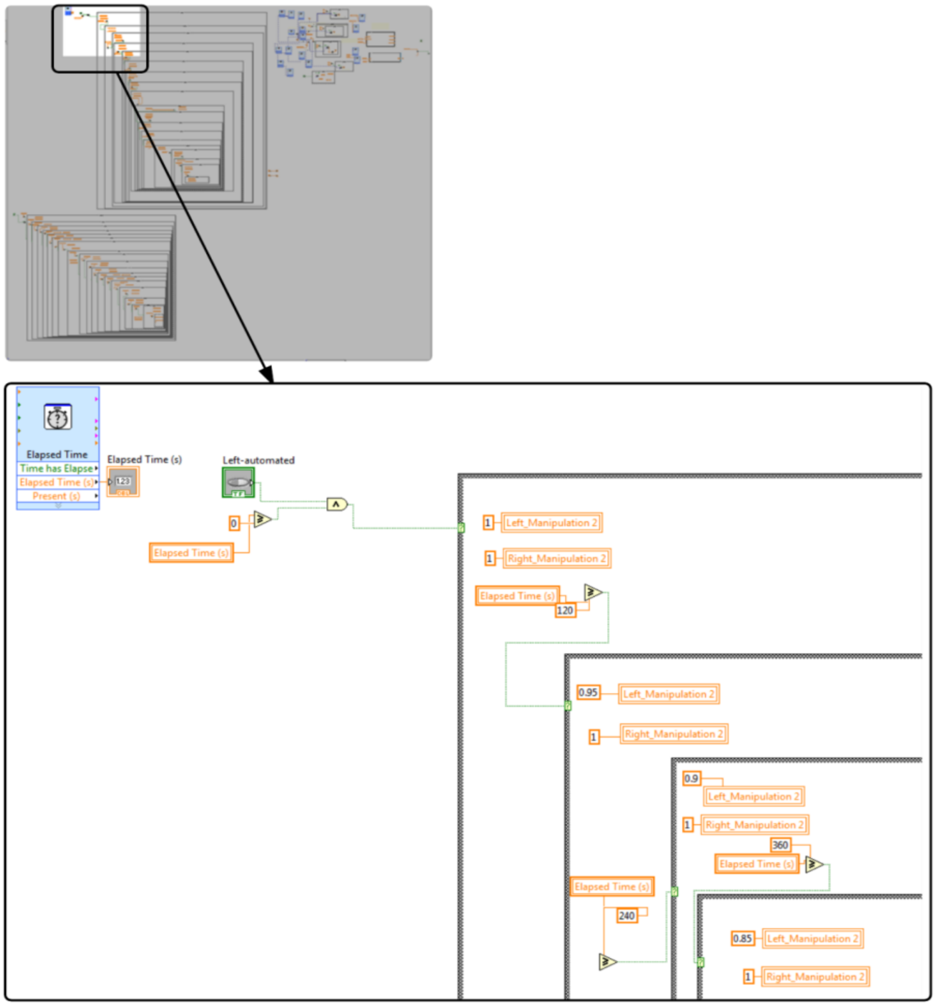
While loop in LabVIEW vi to read encoder pulses as an external clock. This loop uses a shift register to determine changing positions in the flywheel (encoder pulses).



Component to LabVIEW vi that uses indicators from above (x3 and x4) to control when a weight measurement from either load cell enters the corresponding 200 point array. Weight measurements are acquired through the 12 bit DAQ card and scaled based on calibration curves.



Mathscript code in LabVIEW vi that builds the Differential-Temporal display by inputting left and right weight measurements (averaged from 200 point array) to calculate the difference between right and left weight measurements. This calculation is presented as a single data point on the graph and changes with each encoder pulse.



Code to manipulate the gain of the vertical load signal. This is a portion of the LabVIEW vi that manipulates the gain of the load cell signal every 2 minute interval.

Appendix B

```
R=Right;
L=Left;
T=X_Value;




T_1=find(T>299 & T<300); %baseline
T_2=find(T>419 & T<420); %0 percent
T_3=find(T>539 & T<540); %2nd percentage
T_4=find(T>659 & T<660); %3rd percentage %T_4=find(T>479 & T<480);
T_5=find(T>779 & T<780); %4th percentage
T_6=find(T>899 & T<900); %5th percentage  %T_6=find(T>719 & T<720);
T_7=find(T>1019 & T<1020);  %6th percentage %T_7=find(T>839 & T<840);
T_7=find(T>838 & T<840);
T_8=find(T>1139 & T<1140); %2nd 0 percent
T_9=find(T>1259 & T<1260); %cooldown

R_baseline=[R(1:T_1)];
R_1=[R(T_1+1:T_2)];
R_2=[R(T_2+1:T_3)];
R_3=[R(T_3+1:T_4)];
R_4=[R(T_4+1:T_5)];
R_5=[R(T_5+1:T_6)];
R_6=[R(T_6+1:T_7)];
R_7=[R(T_7+1:T_8)];
R_cooldown=[R(T_8+1:T_9)];

L_baseline=[L(1:T_1)];
L_1=[L(T_1+1:T_2)];
L_2=[L(T_2+1:T_3)];
L_3=[L(T_3+1:T_4)];
L_4=[L(T_4+1:T_5)];
L_5=[L(T_5+1:T_6)];
L_6=[L(T_6+1:T_7)];
L_7=[L(T_7+1:T_8)];
L_cooldown=[L(T_8+1:T_9)];

TBW_baseline=R_baseline+L_baseline;
TBW_1=R_1+L_1;
TBW_2=R_2+L_2;
TBW_3=R_3+L_3;
TBW_4=R_4+L_4;
TBW_5=R_5+L_5;
TBW_6=R_6+L_6;
TBW_7=R_7+L_7;
TBW_cooldown=R_cooldown+L_cooldown;

%difference equation
Diff_baseline=(R_baseline-L_baseline)./2;
Diff_1=(R_1-L_1)./2;
```

```
Diff_2=(R_2-L_2)./2;
Diff_3=(R_3-L_3)./2;
Diff_4=(R_4-L_4)./2;
Diff_5=(R_5-L_5)./2;
Diff_6=(R_6-L_6)./2;
Diff_7=(R_7-L_7)./2;
Diff_cooldown=(R_cooldown-L_cooldown)./2;

ABS_Diff_baseline=abs((R_baseline-L_baseline)./2);
ABS_Diff_1=abs((R_1-L_1)./2);
ABS_Diff_2=abs((R_2-L_2)./2);
ABS_Diff_3=abs((R_3-L_3)./2);
ABS_Diff_4=abs((R_4-L_4)./2);
ABS_Diff_5=abs((R_5-L_5)./2);
ABS_Diff_6=abs((R_6-L_6)./2);
ABS_Diff_7=abs((R_7-L_7)./2);
ABS_Diff_cooldown=abs((R_cooldown-L_cooldown)./2);

Variance_1=var(Diff_1);


xdiff_baseline=1:length(Diff_baseline);
Goal_baseline(xdiff_baseline)=zeros;
%Bound_baseline(xdiff_baseline)=boundary(xdiff_baseline,Diff_baseline);
figure(1)
plot(Diff_baseline,xdiff_baseline,'r',Goal_baseline,xdiff_baseline,'b')
axis([-20,20,0,300])
title('Baseline-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')

xdiff_1=1:length(Diff_1);
Goal_1(xdiff_1)=zeros;
figure(2)
plot(Diff_1,xdiff_1,'r',Goal_1,xdiff_1,'b')
axis([-20,20,0,120])
title('Round 1 (0%)-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')


xdiff_2=1:length(Diff_2);
Goal_2(xdiff_2)=zeros;
figure(3)
plot(Diff_2,xdiff_2,'r',Goal_2,xdiff_2,'b')
axis([-20,20,0,120])
title('Round 2 (15%)-Difference Equation')
```

```
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')


xdiff_3=1:length(Diff_3);
Goal_3(xdiff_3)=zeros;
figure(4)
plot(Diff_3,xdiff_3,'r',Goal_3,xdiff_3,'b')
axis([-20,20,0,120])
title('Round 3 (25%)-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')


xdiff_4=1:length(Diff_4);
Goal_4(xdiff_4)=zeros;
figure(5)
plot(Diff_4,xdiff_4,'r',Goal_4,xdiff_4,'b')
axis([-20,20,0,120])
title('Round 4 (5%)-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')


xdiff_5=1:length(Diff_5);
Goal_5(xdiff_5)=zeros;
figure(6)
plot(Diff_5,xdiff_5,'r',Goal_5,xdiff_5,'b')
axis([-20,20,0,120])
title('Round 5 (10%)-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')

xdiff_6=1:length(Diff_6);
Goal_6(xdiff_6)=zeros;
figure(7)
plot(Diff_6,xdiff_6,'r',Goal_6,xdiff_6,'b')
axis([-20,20,0,120])
title('Round 6 (20%)-Difference Equation')
```

```
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')

xdiff_7=1:length(Diff_7);
Goal_7(xdiff_7)=zeros;
figure(8)
plot(Diff_7,xdiff_7,'r',Goal_7,xdiff_7,'b')
axis([-20,20,0,120])
title('Round 7 (0%)-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')



xdiff_cooldown=1:length(Diff_cooldown);
Goal_cooldown(xdiff_cooldown)=zeros;
%Bound_cooldown=boundary(Diff_cooldown);
figure(9)
plot(Diff_cooldown,xdiff_cooldown,'r',Goal_cooldown,xdiff_cooldown,'b')
axis([-20,20,0,120])
title('Cooldown-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 120],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 120],'LineStyle', '-',
'LineWidth',2,'Color','r')

%%
n_1=90;
n_2=90;
n_3=21;
n_4=90;
n_5=12;
n_6=27;
n_7=10;



T_interval_1=n_1:n_1+30;
T_interval_2=n_2:n_2+30;
T_interval_3=n_3:n_3+30;
T_interval_4=n_4:n_4+30;
T_interval_5=n_5:n_5+30;
T_interval_6=n_6:n_6+30;
T_interval_7=n_7:n_7+30;
```

```
%V_0_1=var(Diff_1(13:43));
%V_10=var(Diff_2(49:79));
%V_15=var(Diff_3(27:57));
%V_20=var(Diff_4(37:67));
%V_25=var(Diff_5(37:67));
%V_5=var(Diff_6(70:100));
%V_0_2=var(Diff_7(12:42));
%V_B=var(Diff_baseline(180:210));
%V_C=var(Diff_cooldown(30:60));

V_0_1_test=var(Diff_1(T_interval_1));
V_1_test=var(Diff_2(T_interval_2));  %first percentage
V_2_test=var(Diff_3(T_interval_3));  %second percentage
V_3_test=var(Diff_4(T_interval_4));  %third percentage
V_4_test=var(Diff_5(T_interval_5));  %fourth percentage
V_5_test=var(Diff_6(T_interval_6));  %Fifth percentage
V_0_2_test=var(Diff_7(T_interval_7));
V_B=var(Diff_baseline(180:210));
%V_B=var(Diff_baseline(1:31));
V_C=var(Diff_cooldown(30:60));

V_total=[V_B V_0_1_test V_1_test V_2_test V_3_test V_4_test V_5_test
V_0_2_test V_C];

M_0_1=mean(Diff_1(T_interval_1));
M_1=mean(Diff_2(T_interval_2));
M_2=mean(Diff_3(T_interval_3));
M_3=mean(Diff_4(T_interval_4));
M_4=mean(Diff_5(T_interval_5));
M_5=mean(Diff_6(T_interval_6));
M_0_2=mean(Diff_7(T_interval_7));
M_B=mean(Diff_baseline(180:210));
%M_B=mean(Diff_baseline(1:31));
M_C=mean(Diff_cooldown(30:60));

M_total=[M_B M_0_1 M_1 M_2 M_3 M_4 M_5 M_0_2 M_C];

ABS_M_0_1=mean(ABS_Diff_1(T_interval_1));
ABS_M_1=mean(ABS_Diff_2(T_interval_2));
ABS_M_2=mean(ABS_Diff_3(T_interval_3));
ABS_M_3=mean(ABS_Diff_4(T_interval_4));
ABS_M_4=mean(ABS_Diff_5(T_interval_5));
ABS_M_5=mean(ABS_Diff_6(T_interval_6));
ABS_M_0_2=mean(ABS_Diff_7(T_interval_7));
ABS_M_B=mean(ABS_Diff_baseline(180:210));
%ABS_M_B=mean(ABS_Diff_baseline(1:31));
ABS_M_C=mean(ABS_Diff_cooldown(30:60));


ABS_M_total=[ABS_M_B ABS_M_0_1 ABS_M_1 ABS_M_2 ABS_M_3 ABS_M_4 ABS_M_5
ABS_M_0_2 ABS_M_C];

V_T=transpose(V_total);
M_T=transpose(M_total);
ABS_M_T=transpose(ABS_M_total);
```

```
%M_0_1=mean(Diff_1(13:43));
%M_10=mean(Diff_2(49:79));
%M_15=mean(Diff_3(27:57));
%M_20=mean(Diff_4(37:67));
%M_25=mean(Diff_5(37:67));
%M_5=mean(Diff_6(70:100));
%M_0_2=mean(Diff_7(12:42));
%M_B=mean(Diff_baseline(180:210));
%M_C=mean(Diff_cooldown(30:60));
%%
%Getting AVG total body weight

AvgTBW_0_1=mean(TBW_1(T_interval_1));
AvgTBW_1=mean(TBW_2(T_interval_2));
AvgTBW_2=mean(TBW_3(T_interval_3));
AvgTBW_3=mean(TBW_4(T_interval_4));
AvgTBW_4=mean(TBW_5(T_interval_5));
AvgTBW_5=mean(TBW_6(T_interval_6));
AvgTBW_0_2=mean(TBW_7(T_interval_7));
AvgTBW_B=mean(TBW_baseline(180:210));
%AvgTBW_B=mean(TBW_baseline(1:31));
AvgTBW_C=mean(TBW_cooldown(30:60));

AvgTBW_total=[AvgTBW_B AvgTBW_0_1 AvgTBW_1 AvgTBW_2 AvgTBW_3 AvgTBW_4
AvgTBW_5 AvgTBW_0_2 AvgTBW_C];

AVGTBW_T=transpose(AvgTBW_total);

%%
%Getting speed
fflag=0;
k=1;
cnt=1;
for i=1:length(Index)
    if Index(i)>4.1 & fflag==0
        P(k)=i;
        fflag=1;
        k=k+1;
    else
        cnt=cnt+1;
    end
    if cnt==200
        cnt=0;
        fflag=0;
    end
end
I=transpose(P);

Test(1:length(P)+1)=[0 P];
Test_2=[P 0];
Test_3=Test_2-Test;
Test_4=find(Test_3<100);

F=Test_2;
```

```
F(Test_4)=[];
clear I;
FF=transpose(F);
I=FF;

%for jj=1:length(I)+100
 %     H(jj)=mean(Time(I(jj):I(jj+1)));
%end

%T=transpose(H);


T_1=90000; %baseline
T_2=126000; %0 percent
T_3=162000; %2nd percentage
T_4=198000; %3rd percentage %T_4=find(T>479 & T<480);
T_5=234000; %4th percentage
T_6=270000; %5th percentage  %T_6=find(T>719 & T<720);
T_7=306000;  %6th percentage %T_7=find(T>839 & T<840); T_7=find(T>838 &
T<840);
T_8=342000; %2nd 0 percent
T_9=378000; %cooldown


I_baseline=find(FF>T_1-1000 & FF<T_1);
I_1=find(FF>T_2-1000 & FF<T_2);
I_2=find(FF>T_3-1000 & FF<T_3);
I_3=find(FF>T_4-1000 & FF<T_4);
I_4=find(FF>T_5-1000 & FF<T_5);
I_5=find(FF>T_6-1000 & FF<T_6);
I_6=find(FF>T_7-1000 & FF<T_7);
I_7=find(FF>T_8-1000 & FF<T_8);
I_cooldown=find(FF>T_9-1000 & FF<T_9);

I_baseline=I_baseline(end);
I_1=I_1(end);
I_2=I_2(end);
I_3=I_3(end);
I_4=I_4(end);
I_5=I_5(end);
I_6=I_6(end);
I_7=I_7(end);
I_cooldown=I_cooldown(end);
%delete the smaller number in the breakup of I

%cycles-need to subtract each position to get number of cycles
Cycles_baseline=I_baseline;
Cycles_1=I_1-I_baseline;
Cycles_2=I_2-I_1;
Cycles_3=I_3-I_2;
Cycles_4=I_4-I_3;
Cycles_5=I_5-I_4;
Cycles_6=I_6-I_5;
Cycles_7=I_7-I_6;
Cycles_cooldown=I_cooldown-I_7;
```

```
%Cycles_9=I_9-I_8;

%Speed cycles/sec
Speed_second_baseline=Cycles_baseline/300;
Speed_second_1=Cycles_1/120;
Speed_second_2=Cycles_2/120;
Speed_second_3=Cycles_3/120;
Speed_second_4=Cycles_4/120;
Speed_second_5=Cycles_5/120;
Speed_second_6=Cycles_6/120;
Speed_second_7=Cycles_7/120;
Speed_second_cooldown=Cycles_cooldown/120;
%Speed_second_9=Cycles_9/120;

Total_speed=[Speed_second_baseline Speed_second_1 Speed_second_2
Speed_second_3 Speed_second_4 Speed_second_5 Speed_second_6 Speed_second_7
Speed_second_cooldown];

T_speed=transpose(Total_speed);
```

Chapter 5

Chapter 5: Hyper-symmetric training and short term functional change in gait symmetry for stroke participants: A case report

Abstract

Functional ambulation is a major goal in rehabilitation for stroke patients who have impaired gait. Often a person's ability to effectively ambulate can determine outcomes related to independence in daily activities of life for the future. There are several techniques that have been applied in the clinic for gait restoration, for example the use of static balance platforms, single and split-belt treadmills and robotics in rehabilitation. Although these systems or techniques are widely used, there are some disadvantages with applying them such as the physical demand on the therapist and the limitation of variability in training. In order to reduce the physical demand on the therapist without using robotics that hamper weight shifting, a novel modification was made to an existing elliptical trainer to incorporate kinetic visual biofeedback during gait training. The modified elliptical system mimics the approach used in split-belt treadmill training. That approach is designed to overload the paretic limb to provide a non-symmetric level of training. The modified elliptical system focuses on vertical load rather than speed. Overload bias is created by modulating the gain of the feedback signal to encourage more weight to be shifted to the paretic limb. Thirty participants were recruited, but only 4 enrolled into the study. Of the four, results of two participants were omitted secondary to their inability to consistently progress the pedals forward during. It was assumed that experimenter assistance to control the elliptical may have influenced subject performance. Based on previous studies, a Differential-

Temporal display was used for visual biofeedback and gain was manipulated up to 10% to encourage increased weight distribution towards the paretic limb. Following training, the NASA TLX was administered to determine workload during the activity. An ANOVA was used to determine significant differences in the percentage error values from the elliptical trainer data and for GaitRite® metrics that included step length, H-H base support and single and double limb support. Results of the study show that participants were able to reduce percentage error with visual biofeedback and maintain a reduction of error during Cooldown (post-training with no visual biofeedback). Analyses of overland gait show no difference in step length, H-H base support, and double limb support. However, single limb support values show a significant difference from pre to post measurements in one participant.

Introduction

Causes of stroke occur due to either a blockage or hemorrhage that impedes blood flow to the brain. This interruption can result in damage to surrounding tissue and influence the “chain of command” throughout the central and peripheral nervous system. Different motor and sensory processes can be altered depending on the location of infarction. Loss of motor control is often a primary concern following stroke. This reduction in control can negatively influence daily activities of life (ADLs). Approximately 795,000 stroke incidents occur each year in the United States. In 2010 alone, 33 million incidents occurred globally (Go et al., 2012, Mozaffarian et al., 2015). The leading cause of prolonged disability is thought to be a result of stroke (Go et al., 2012, Jackson et al., 2010, Go et al., 2014). A primary goal in stroke rehabilitation for physical therapists is to train individuals to a functional level that allows them to independently perform ADLs. Current stroke rehabilitation practices focus on constraint-induced (CI) movement therapy for both upper and lower extremities (Taub et al., 1993, Taub, 2014, Morris et al., 2006, Wolf et al., 2008).

CI movement therapy and repetitive task oriented techniques have had significant success in promoting use of the paretic limb during and after rehabilitation (Taub et al., 1993, Taub, 2014, Morris et al., 2006, Wolf et al., 2008). CI therapy incorporates four modes of training. These include: (1) intensive training of the affected limb, (2) shaping technique, (3) transfer package, and (4) discouraging compensation of the unaffected or lesser affected limb. Intensive training of the affected limb usually occurs in the clinic with forced use of the paretic limb to perform specific tasks. In this training the shaping technique can be applied by increasing the difficulty of the task over time, for example decreasing the amount of assistance during the course of treatment. The transfer package is a method that holds patients accountable for using their paretic limb outside the clinic, usually implemented through daily logs. The last component, discouraging compensation of the unaffected limb, is achieved by forcing use of the paretic limb, for example by implementing a padded mitt for upper extremity training. Variability in training can also be an influential technique to increase activity of sensorimotor systems in order to transfer from clinical applications to real world interactions (Hornby et al., 2008, Cai et al., 2006).

For gait rehabilitation, body weight supported treadmill training (BWSTT) is often utilized to force patients into a pattern that is similar to healthy gait (Harvey, 2009, Werner et al., 2002). During this training, patients are stabilized over a treadmill system with an overhead harness to offload a certain percentage of body weight. Over the course of rehabilitation, this percentage of offloading is decreased until the patient can accept substantial weight onto either limb. Another component of this training is assistance from two to three physical therapists contributing both to weight transfers and limb progression. Although many studies have shown that this is a successful training technique for patients, there are a few disadvantages. The number of personnel required per patient increases health care costs and the added physical demand placed on therapists' takes a toll (Harvey, 2009, Jackson et al., 2010, Hidler et al., 2009, Hidler et al., 2005). To decrease both the physical demand and health care costs, the Lokomat® system was developed (Hidler et al., 2009).

The Lokomat® employs a lower extremity exoskeleton to guide the limbs in correct kinematic alignment as well as applying both a treadmill and overhead harness system (Hidler et al., 2005). Although the Lokomat® was produced to decrease variability in kinematic alignment, this can have a negative impact when transferring from clinic training to a real world environment (Harvey, 2009, Hornby et al., 2008). As noted by Cai et al., a fixed position robotic exoskeleton limits the degrees of freedom during limb progression (Cai et al., 2006). This limitation of movement patterns trains the patient to remap cortical synapses to a discrete pattern, which is often one component of a naturally occurring activation pattern. Fixed trajectory rehabilitation is often counterproductive for transferring to a real world environment since it decreases the activity of sensorimotor systems (Hornby et al., 2008, Cai et al., 2006).

To allow patients to independently manipulate both kinematic and kinetic parameters, biofeedback systems have been implemented in the clinic both with static balance platforms and on treadmill systems. Systems such as the Wii balance board and SMART Balance Master have been developed to deliver biofeedback to patients with weight-bearing asymmetries (Chen et al., 2002, Gil-Gòmez et al., 2011, Barcala et al., 2013, Goble et al., 2014). Although there has been some success with these systems both in research and the clinic, often training does not transfer to weight bearing asymmetries in dynamic gait. Studies such as Dingwell et al. and Crowell et al. have produced such systems to deliver information on temporal, stance symmetry and kinematic variables (Dingwell et al., 1996, Dingwell et al., 1996, Crowell et al., 2010). These studies suggest that not only can patients interpret asymmetries in gait once training is complete, but they can adjust patterns to accomplish goals presented to them during training. Although these studies are promising, they do not account for weight bearing asymmetries. Previous studies by Massenzo et al. looked at displaying kinetic visual biofeedback to healthy populations and determining performance based on the displayed information (Massenzo et al., 2015). In this study, four different visual display types were constructed and tested to determine which produced the best performance for the cohort (Massenzo et al., 2015). One display resulted in the best performance compared to the others and a no feedback baseline measurement. This display incorporated both temporal aspects of displaying past samples to the participant in order to determine their error in accomplishing the task as well as a differential element that decreased the cognitive load in interpreting by implementing a difference algorithm to display both right and left pedal measurements as a single element.

To further explore the augmentation of visual biofeedback to users, a second study was conducted which manipulated the gain of the weight measurement signals to force users to distribute weight asymmetrically towards their non-dominant weight-bearing side. Ding et al. produced a similar algorithm applied to a Wii balance board and tested on a cohort of stroke patients with weight bearing asymmetries. In Ding et al. they found that weight bearing asymmetries diminished during and for a brief period after training (Ding et al., 2013). In this study, it was found that healthy participants were able to accomplish the task with up to a 5-10% asymmetry in left/right load.

This study applied the aforementioned system to stroke patients who have weight-bearing asymmetries to determine the system's effectiveness implementing a gain manipulated training technique. Effectiveness of the training device was depicted as the individual's ability to adjust distribution of weight on either pedal as well as measuring symmetry during overland gait post-training.

Methods

Participants

This study was approved through Virginia Commonwealth University's institutional review board. Prior to entering the study, all participants provided written informed consent. Inclusion criteria for recruiting were the following: chronic phase of cerebrovascular incident with the ability to walk independently with or without an assistive device. Thirty participants were recruited, but only 4 enrolled. Of those four, two were unable to perform the training so as a result, only two participants were used for post-data analysis (1 Female, age=75, 1 Male, age=19).

Device Design

A modified elliptical trainer (NordicTrack®, Logan, UT) was used to measure vertical loads as visual biofeedback (Chapter 2). Kinetic visual biofeedback was provided via computer monitor displaying differential-temporal representations of vertical load (Chapter 3) (Massenzo et al., 2015). Gain of the load cell signal was manipulated for hyper-symmetric training purposes. A gain manipulation value of 10% was implemented as a threshold for training (Chapter 4).

Procedures

Subjects were first instructed on the elliptical activity and asked to review and sign the informed consent documentation. Subjects were also instructed on the NASA TLX survey before training on the modified elliptical. The NASA TLX survey was implemented in order to determine differences in perceived workload in six categories: mental demand, physical demand, temporal demand, performance, effort and frustration. Since this survey has wide acceptance and application in workload studies, many incorporating biofeedback delivery, it was implemented as a workload measurement tool following elliptical training (Hart, 2006). Prior to training, the Mini-Mental State Examination was conducted to determine cognitive impairment. Participants then walked across the GaitRite® (GaitRite®, Franklin, NJ) system for three pre-training tests.

Table 1 displays sequence of training events from Baseline to Cooldown. Following pre-tests for overland gait, participants warmed up on the elliptical trainer for a period of three minutes with no visual display (Warmup) and continued for another 2 minutes during Baseline measurements (Baseline). Participants then ran on the elliptical for two minutes at 0% manipulation to determine how they performed with the display with zero manipulation. Both participants ramped up to 5% for percent manipulation for a period of two minutes. Due to physical fatigue, the one of the two participants only reached 5% instead of the threshold value (10%). This participant went from percent manipulation biased training straight to Cooldown for a period of two minutes. The other participant was able to reach 10% manipulation. Following 10% they reached a routine of 0% before Cooldown phase, where each condition lasted 2 minutes each. Finally, the display was turned off while the participant kept running on the elliptical for his or her Cooldown period of two minutes. During the manipulation phase, participants saw a shift depending on the magnitude of manipulation, but were not aware that the gain was manipulated the whole duration of the two minute period.

Following training, participants walked on the GaitRite® system for three post-training sets. At the end of the session participants completed the NASA TLX survey to determine perceived workload.

Data Analysis

Vertical load was measured continuously and stored in an Excel format. It was later analyzed using MATLAB (The MathWorks, Inc., Natick, MA) and statistically evaluated with SPSS (IBM Corporation, Armonk, NY). Percentage error was found to compare routines (baseline and percent manipulations) during the single session (Equation 1). Percentage error is a measure to compare the value obtained from gain manipulation of the signal (e.g. 5-10%) to the unmodified weight measured on the pedal.

$$Percentage\ Error = \frac{|Approximate - Exact|}{|\mathrm{Exact}|} \times 100\% \quad (1)$$

The following secondary variables were analyzed from a thirty second recording for each two minute increment during the routine: percent weight offloaded and speed. The variables were found to be non-normal, so a non-parametric analysis of variance (Kruskal Wallis test) and corresponding Mann-Whitney u tests were performed to determine if there were significant differences in the dataset All pre-post overland gait metrics (GaitRite® measured step length, % single stance, % double stance and H-H base support) were normally distributed, so an ANCOVA with velocity as a covariate and t-tests were conducted. Difference values between right versus left were compared for each GaitRite® metric from pre to post training.

Results

All participants enrolled in the study scored in between 24-30 in the Mini-Mental State Examination prior to training indicating no apparent cognitive deficits. Of the thirty participants recruited, only four were enrolled and two analyzed. Since Participants 2 and 3 required continual assistance during training for knee flexion and propulsion of the pedal, the data was not evaluated. Figures 1 and 2 represent stimulus-response error for Participants 1 and 4, respectively. Both participants demonstrate baseline (no feedback) asymmetry, while minimizing error with the introduction of visual biofeedback. Statistical testing resulted in significant differences from pre to post training on the elliptical trainer (Baseline to Cooldown) as well as differences from Baseline to routines with visual biofeedback. Differences in pre to post training on the elliptical trainer suggest that hyper-symmetric biased training may contribute to improved performance when reducing error.

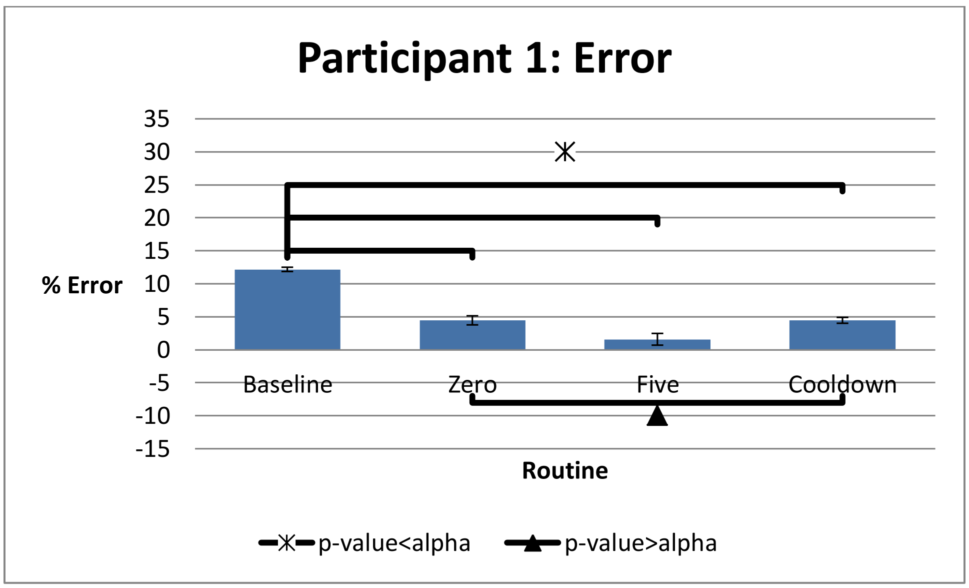


Figure 1. Stimulus-response percentage error for Participant 1. Stimulus-response percentage error for Baseline (no feedback), and different levels of hyper-symmetric non-dominant biased training (via visual feedback) for Participant 1.

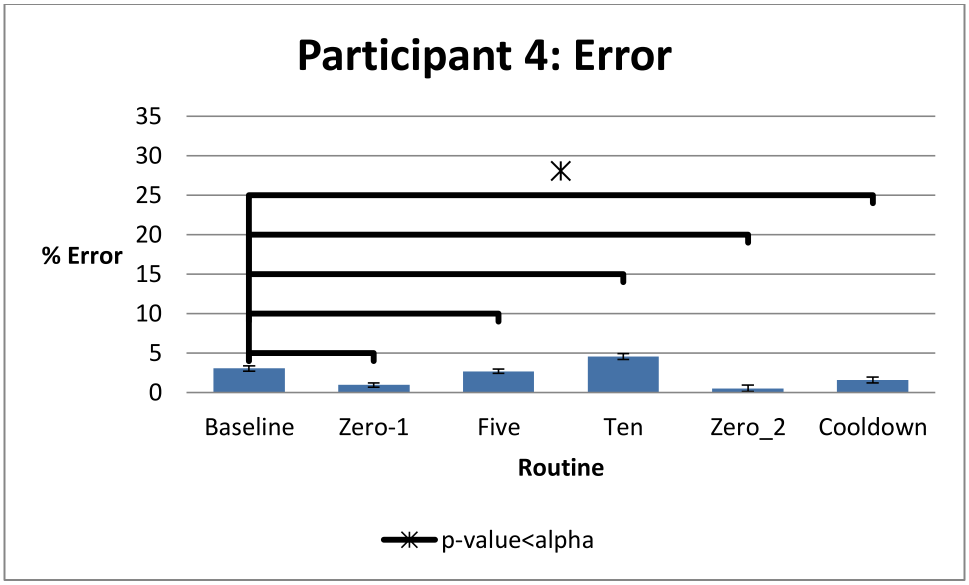


Figure 2. Stimulus-response percentage error for Participant 4. Stimulus-response percentage error for Baseline (no feedback), and different levels of hyper-symmetric non-dominant biased training (via visual feedback) for Participant 4.

Additionally, GaitRite® metrics were analyzed for Participants 1 and 4 to determine if there was carryover from training. Figures 3 and 4 represent step length and H-H base support over two tests for pre and post measurements, respectively. There were no significant differences between step length and H-H base support from pre to post training for either participant. Figures 5 and 6 represent single and double limb support, respectively. Although there were no significant differences between pre to post measurements for double support, there were differences in single support for one of the two participants. For Participant 1 there were significant differences in right and left single limb support prior to training. This difference was minimized post training, suggesting that Participant 1 may have some carryover from training to overland walking. Figure 7 represents the difference between right versus left comparing pre to post training for H-H base support. For Participant 4 there was a significant difference from pre to post, suggesting that H-H base support increased after activity with the modified elliptical trainer.

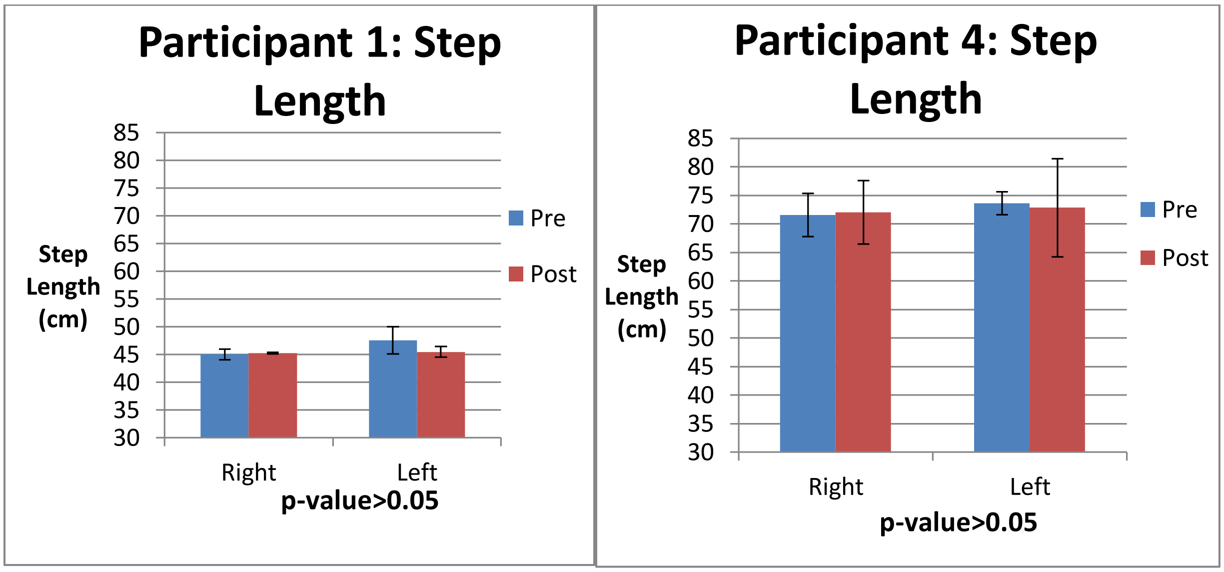


Figure 3. Step length for participants 1 and 4.

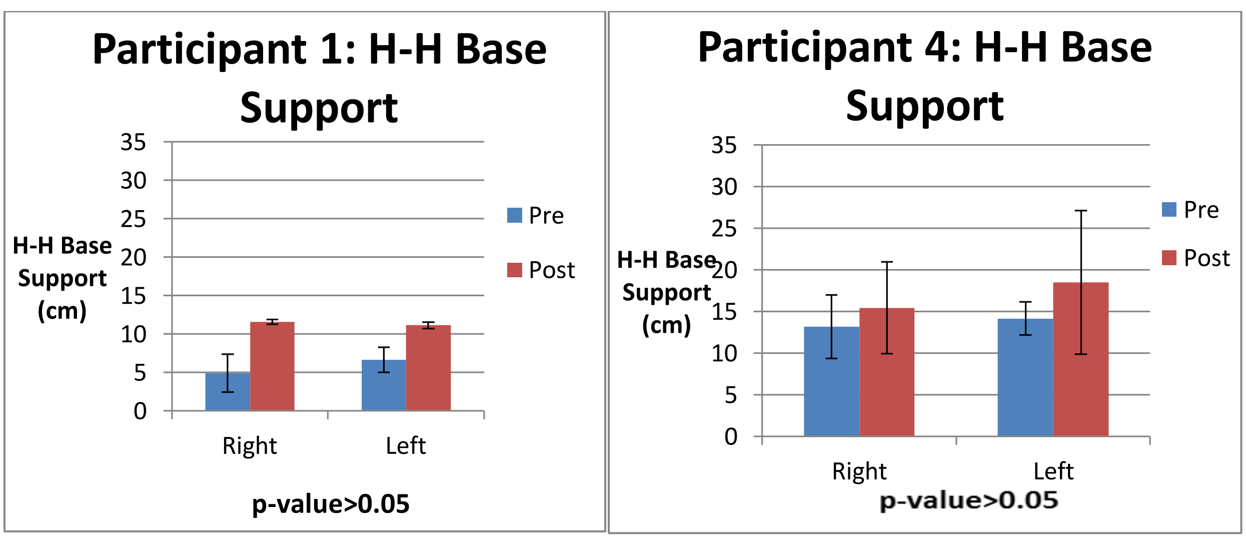


Figure 4. H-H base support for participants 1and 4.

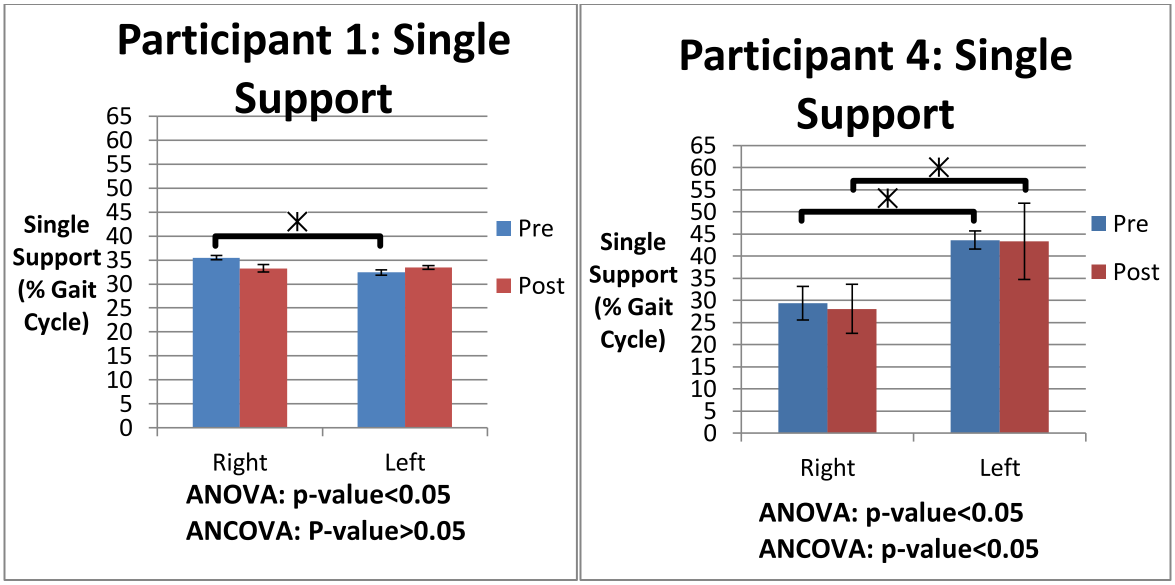


Figure 5. Single limb support for participants 1 and 4.

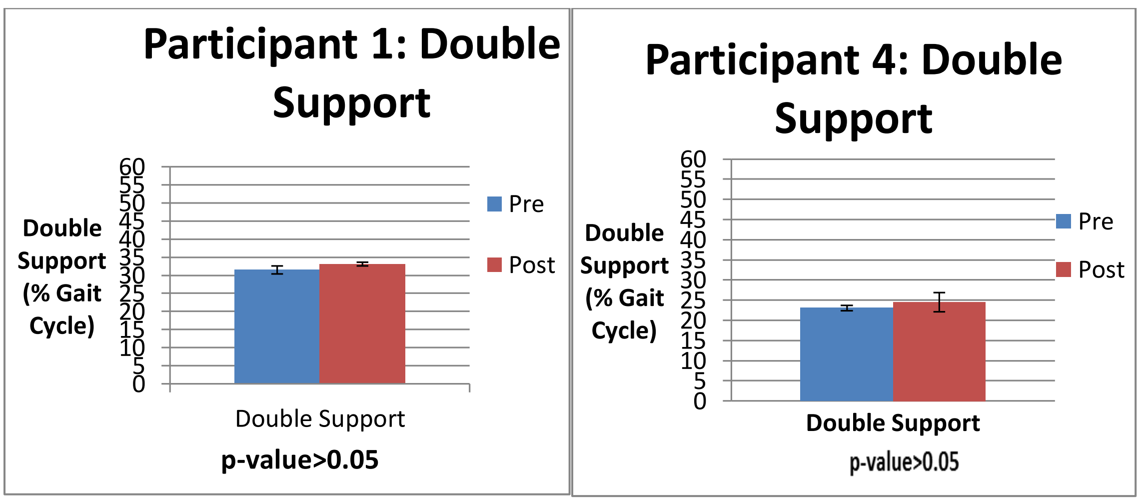


Figure 6. Double limb support for participants 1 and 4.

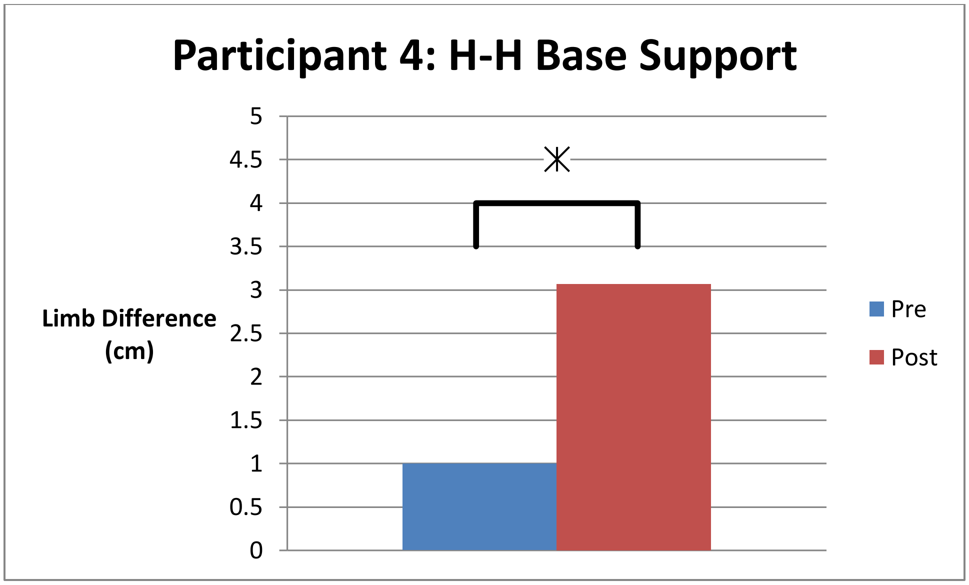


Figure 7. Limb Difference for H-H Base Support in Participant 4. This figure displays the right and left difference comparing pre vs. post training in H-H Base Support showing a significant difference in pre vs. post training.

Perceived workload was found by administering the NASA TLX survey after training (Figure 8). Subjective ratings were found for the entire training session rather than in between routines to ensure that participants were unaware of the gain manipulation for biased training. Participants found that the activity placed a higher demand in both Physical and Effort categories with Mental, Temporal and Frustration being the lowest. Participants 1 and 4 differed in perceived workload in the Performance category, where Participant 4 rated it higher than Participant 1.

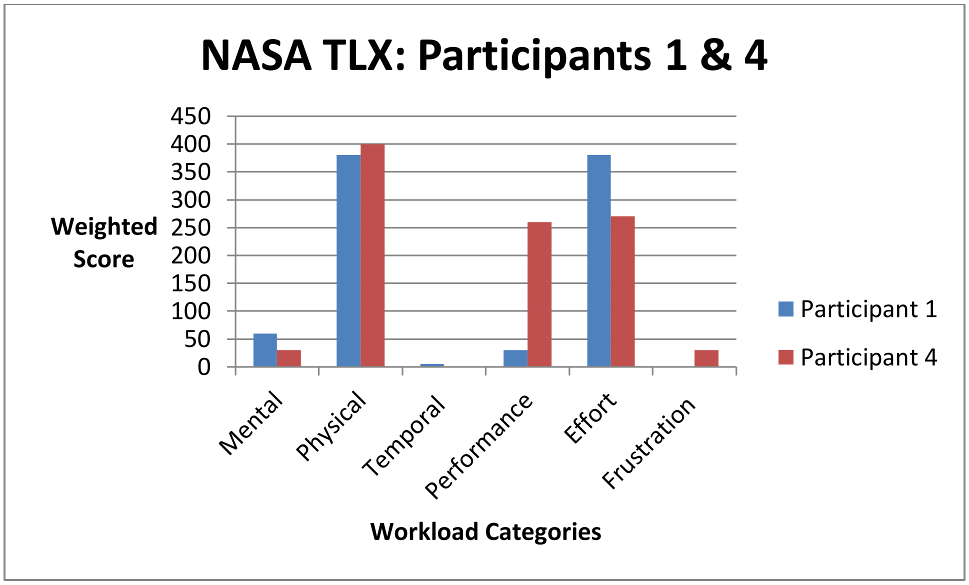


Figure 8. NASA TLX for perceived workload.

Discussion

The aim of this study was to determine if hyper-symmetric biased training resulted in carryover from training to overland walking in a stroke cohort. A secondary aim was to determine if participants could minimize error in weight placement with the use of visual biofeedback.

Mini Mental State Examination tests showed no apparent cognitive deficits in any of the participants enrolled in the study. Therefore, participants were capable of understanding the visual representation presented to them.

One of two participants reached only 5%, while the other participant reached the full 10%. This confirms that participants who have suffered a stroke have the capability of reaching hyper-symmetric routines in a range of 5-10%. However, physical endurance has the potential to dictate the extent of hyper-symmetric training and duration of training.

Furthermore, both participants were able to minimize error with the introduction of visual biofeedback without assistance from lab personnel to propel the pedals forward. Similar to studies such as Mirelman et al. and Lewek et al., participants were able to utilize visual biofeedback during gait to improve performance (Mirelman et al., 2009 , Lewek et al., 2012). Mirelman et al. found that the incorporation of visual biofeedback to a robotic training device resulted in greater improvements rather than training solely with the robotic device. This group reasoned that this occurred since participants were engaged with visual biofeedback training and resulted in purposeful training leading towards neuro-plastic events (Mirelman et al., 2009). Our results mirror Mirelman's study, suggesting that users can alter dynamic stance symmetry with visual biofeedback.

Participants were also able to adjust weight distribution according to gain manipulations. Ding et al. used a similar technique of gain manipulation to encourage weight distribution towards the paretic limb during static stance (Ding et al., 2013). Researchers from this study modified the standard Nintendo Wii Fit game system to control the gain ratio in the hopes of encouraging participants to lean more towards the paretic limb. The idea behind constructing this modification was to incorporate principles of constraint-induced movement therapy (CIMT) to lower limb balance rehabilitation. Much like our results, Ding et al. found that after intervention participants were able to adjust weight distributions while training, thereby increasing weight acceptance onto the paretic limb. Following the removal of visual biofeedback, participants were able to maintain decreased error compared to baseline measurements. Maintaining decreased error with the removal of visual biofeedback displays carryover from intervention in a single session while on an elliptical trainer.

Measurements in overland gait metrics were acquired by the use of the GaitRite® system before and after training intervention. These metrics were analyzed to determine if training influenced overland gait. Although there were no significant differences in step length, H-H base support and double limb support from pre to post, there were differences in single limb support for one out of two participants. Participant one's results suggest that training may have led to carryover in overland gait since asymmetries from single limb support were minimized. Alternatively, Participant four's results suggest that there was no carryover once they stepped off the elliptical trainer since asymmetry in single limb support was consistent pre to post training. This could be the result of single day training. Perhaps Participant four required several training sessions in order to see an effect in overland gait. Training duration could be another factor to differences in carryover as well. Participant one was only able to reach 5% gain manipulation, whereas Participant four reached 10%. This could have led to fatigue in the paretic limb post training, thereby leading to no differences in single limb support measurements for pre and post training.

Based on NASA TLX findings, both Physical Demand and Effort contribute more towards perceived workload compared to the other categories. Both participants ranked these two categories high whereas Mental, Temporal and Frustration were low. Due to the nature of controlling the pedals of the elliptical especially with increased use of the paretic limb it is expected that physical demand and perceived effort would play a large part in the overall workload of the activity.

Conclusion

This case study shows the effect of visual biofeedback and hyper-symmetric biased training on modifying dynamic stance symmetry during elliptical trainer use. With the introduction of visual biofeedback, participants were able to minimize percentage error and maintained improved weight distribution patterns once feedback was removed. When comparing pre to post overland gait metrics, there were no significant changes in gait except in single limb support for one out of two participants. These findings lead into future directions in research with determining long-term effects of training over the course of several sessions. It is expected that with training participants can minimize error during training and tend towards symmetric gait metrics.

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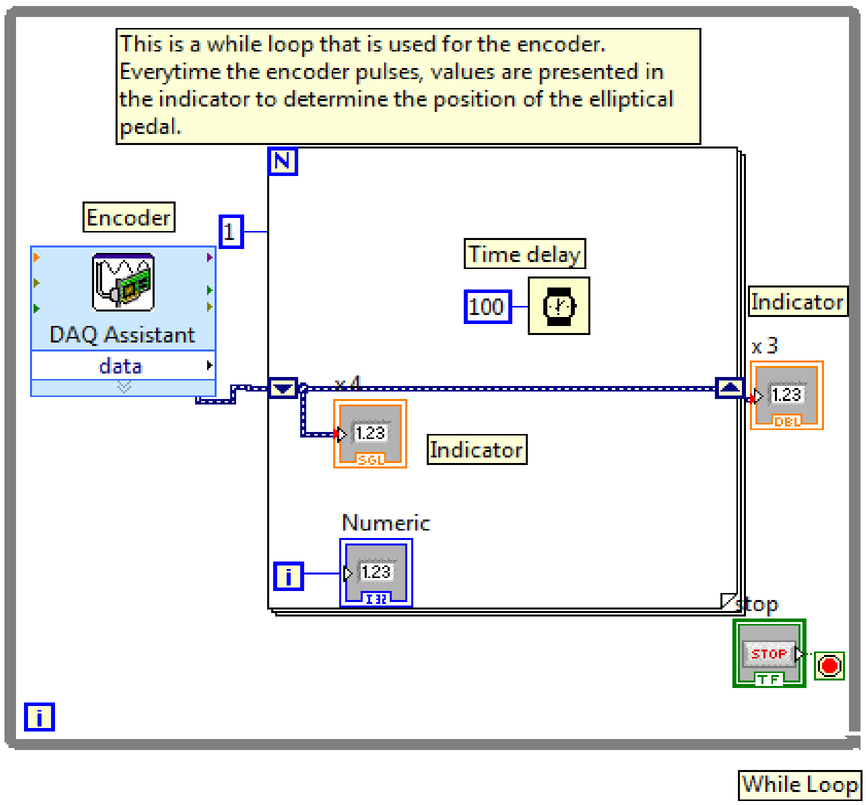
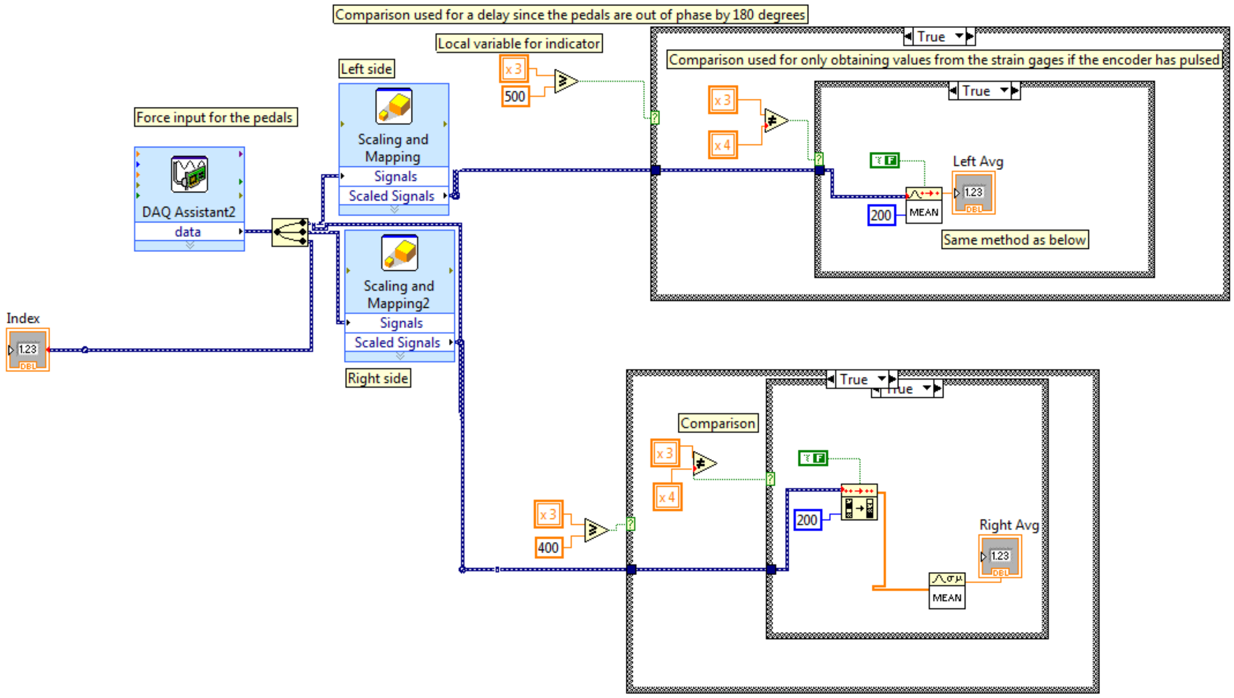
Appendix

Appendix A

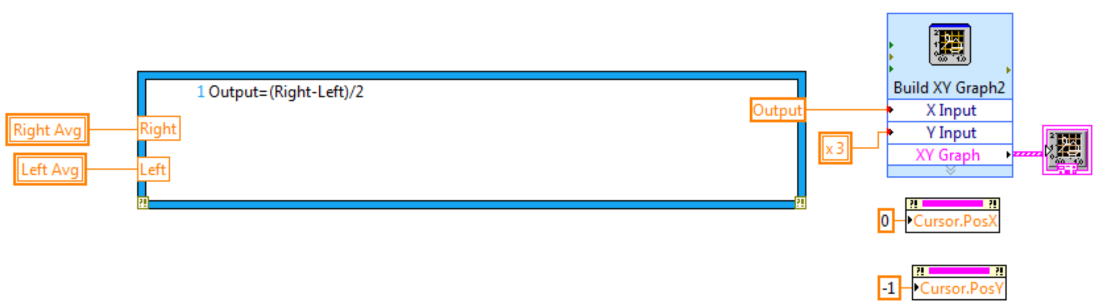
LabVIEW vi for acquiring vertical load and representing as visual biofeedback.



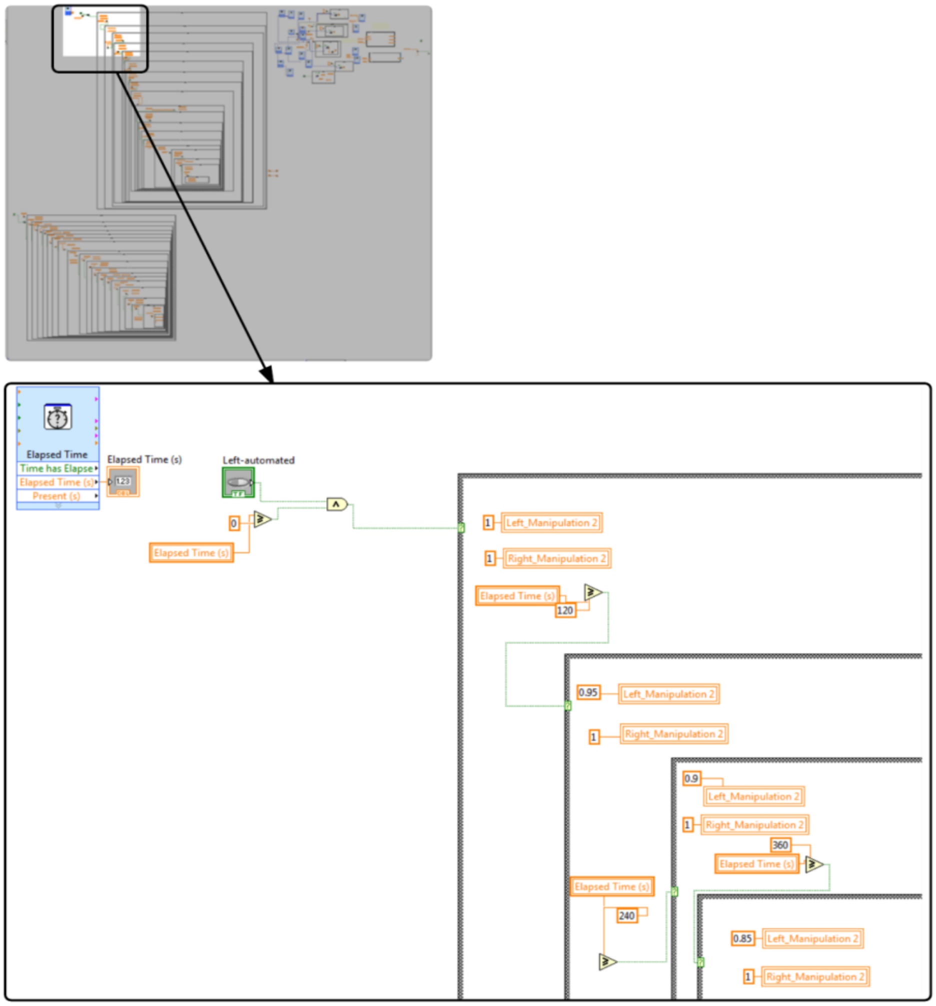
While loop in LabVIEW vi to read encoder pulses as an external clock. This loop uses a shift register to determine changing positions in the flywheel (encoder pulses).



Component to LabVIEW vi that uses indicators from above (x3 and x4) to control when a weight measurement from either load cell enters the corresponding 200 point array. Weight measurements are acquired through the 12 bit DAQ card and scaled based on calibration curves.



Mathscript code in LabVIEW vi that builds the Differential-Temporal display by inputting left and right weight measurements (averaged from 200 point array) to calculate the difference between right and left weight measurements. This calculation is presented as a single data point on the graph and changes with each encoder pulse.



Code to manipulate the gain of the vertical load signal. This is a portion of the LabVIEW vi that manipulates the gain of the load cell signal every 2 minute interval.

Appendix B

```
%determining error

R=Right;
L=Left;
T=X_Value;

%T_1=find(T>149 & T<150); %baseline
%T_2=find(T>319 & T<320); %0 percent
%T_3=find(T>339 & T<340); %2nd p


T_1=find(T>299 & T<300); %baseline
T_2=find(T>419 & T<420); %0 percent
T_3=find(T>539 & T<540); %2nd percentage
T_4=find(T>659 & T<660); %3rd percentage %T_4=find(T>479 & T<480);
T_5=find(T>779 & T<780); %4th percentage
T_6=find(T>899 & T<900); %5th percentage  %T_6=find(T>719 & T<720);
T_7=find(T>1019 & T<1020);  %6th percentage %T_7=find(T>839 & T<840);
T_7=find(T>838 & T<840);
T_8=find(T>1139 & T<1140); %2nd 0 percent
T_9=find(T>1259 & T<1260); %cooldown

R_baseline=[R(1:T_1)];
R_1=[R(T_1+1:T_2)];
R_2=[R(T_2+1:T_3)];
R_3=[R(T_3+1:T_4)];
R_4=[R(T_4+1:T_5)];
R_5=[R(T_5+1:T_6)];
R_6=[R(T_6+1:T_7)];
R_7=[R(T_7+1:T_8)];
R_cooldown=[R(T_8+1:T_9)];

L_baseline=[L(1:T_1)];
L_1=[L(T_1+1:T_2)];
L_2=[L(T_2+1:T_3)];
L_3=[L(T_3+1:T_4)];
L_4=[L(T_4+1:T_5)];
L_5=[L(T_5+1:T_6)];
L_6=[L(T_6+1:T_7)];
L_7=[L(T_7+1:T_8)];
L_cooldown=[L(T_8+1:T_9)];

TBW_baseline=R_baseline+L_baseline;
TBW_1=R_1+L_1;
TBW_2=R_2+L_2;
TBW_3=R_3+L_3;
TBW_4=R_4+L_4;
TBW_5=R_5+L_5;
TBW_6=R_6+L_6;
TBW_7=R_7+L_7;
TBW_cooldown=R_cooldown+L_cooldown;

Half_TBW_baseline=0.5*(TBW_baseline);
```

```
Half_TBW_1=0.5*(TBW_1);
Half_TBW_2=0.5*(TBW_2);
Half_TBW_3=0.5*(TBW_3);
Half_TBW_4=0.5*(TBW_4);
Half_TBW_5=0.5*(TBW_5);
Half_TBW_6=0.5*(TBW_6);
Half_TBW_7=0.5*(TBW_7);
Half_TBW_cooldown=0.5*(TBW_cooldown);


prompt='What is the % value?';
First_percent=input(prompt);
Second_percent=input(prompt);
Third_percent=input(prompt);
Fourth_percent=input(prompt);
Fifth_percent=input(prompt);


First=(First_percent)/100;
Second=(Second_percent)/100;
Third=(Third_percent)/100;
Fourth=(Fourth_percent)/100;
Fifth=(Fifth_percent)/100;




%%
%if worked the Right Side
%for baseline
for i=1:length(Half_TBW_baseline)
    Percent_E_baseline=((abs(Half_TBW_baseline-R_baseline))./R_baseline)*100;
end

%for Zero_1
for i=1:length(Half_TBW_1)
    Percent_E_1=((abs(Half_TBW_1-R_1))./R_1)*100;
end

%for First percent manipulation
for i=1:length(Half_TBW_2)
    Value_1=Half_TBW_2*First;
end


for i=1:length(Half_TBW_2)
    Adjusted_1=Value_1+Half_TBW_2;
end



for i=1:length(Half_TBW_2)
    Percent_E_2=((abs(Adjusted_1-R_2))./R_2)*100;
end
```

```
%for Second percent manipulation
for i=1:length(Half_TBW_3)
    Value_2=Half_TBW_3*Second;
end


for i=1:length(Half_TBW_3)
    Adjusted_2=Value_2+Half_TBW_3;
end



for i=1:length(Half_TBW_3)
    Percent_E_3=((abs(Adjusted_2-R_3))./R_3)*100;
end

%for Third percent manipulation
for i=1:length(Half_TBW_4)
    Value_3=Half_TBW_4*Third;
end


for i=1:length(Half_TBW_4)
    Adjusted_3=Value_3+Half_TBW_4;
end



for i=1:length(Half_TBW_4)
    Percent_E_4=((abs(Adjusted_3-R_4))./R_4)*100;
end



%for Fourth percent manipulation

for i=1:length(Half_TBW_5)
    Value_4=Half_TBW_5*Fourth;
end


for i=1:length(Half_TBW_5)
    Adjusted_4=Value_4+Half_TBW_5;
end



for i=1:length(Half_TBW_5)
    Percent_E_5=((abs(Adjusted_4-R_5))./R_5)*100;
end
```

```matlab
%for Fifth percent manipulation

for i=1:length(Half_TBW_6)
    Value_5=Half_TBW_6*Fifth;
end


for i=1:length(Half_TBW_6)
    Adjusted_5=Value_5+Half_TBW_6;
end




for i=1:length(Half_TBW_6)
    Percent_E_6=((abs(Adjusted_5-R_6))./R_6)*100;
end

%for Zero_2
for i=1:length(Half_TBW_7)
    Percent_E_7=((abs(Half_TBW_7-R_7))./R_7)*100;
end

%for Cooldown
for i=1:length(Half_TBW_cooldown)
    Percent_E_cooldown=((abs(Half_TBW_cooldown-R_cooldown))./R_cooldown)*100;
end

%%
prompt='What is the Time value?';
n_1=input(prompt);
n_2=input(prompt);
n_3=input(prompt);
n_4=input(prompt);
n_5=input(prompt);
n_6=input(prompt);
n_7=input(prompt);


%n_1=90;
%n_2=90;
%n_3=21;
%n_4=90;
%n_5=12;
%n_6=27;
%n_7=10;


T_interval_1=n_1:n_1+30;
T_interval_2=n_2:n_2+30;
T_interval_3=n_3:n_3+30;
T_interval_4=n_4:n_4+30;
T_interval_5=n_5:n_5+30;
T_interval_6=n_6:n_6+30;
T_interval_7=n_7:n_7+30;
```

```
E_0_1_test=mean(Percent_E_1(T_interval_1));
E_1_test=mean(Percent_E_2(T_interval_2));  %first percentage
E_2_test=mean(Percent_E_3(T_interval_3));  %second percentage
E_3_test=mean(Percent_E_4(T_interval_4));  %third percentage
E_4_test=mean(Percent_E_5(T_interval_5));  %fourth percentage
E_5_test=mean(Percent_E_6(T_interval_6));  %Fifth percentage
E_0_2_test=mean(Percent_E_7(T_interval_7));
E_B=mean(Percent_E_baseline(180:210));
%V_B=var(Diff_baseline(1:31));
E_C=mean(Percent_E_cooldown(30:60));

E_total=[E_B E_0_1_test E_1_test E_2_test E_3_test E_4_test E_5_test
E_0_2_test E_C];

Error_B=Percent_E_baseline(180:210);
Error_0_1=Percent_E_1(T_interval_1);
Error_5=Percent_E_2(T_interval_2);
Error_10=Percent_E_3(T_interval_3);
Error_0_2=Percent_E_4(T_interval_4);
Error_C=Percent_E_5(T_interval_5);



E_0_1stdev=std(Percent_E_1(T_interval_1));
E_1_stdev=std(Percent_E_2(T_interval_2));  %first percentage
E_2_stdev=std(Percent_E_3(T_interval_3));  %second percentage
E_3_stdev=std(Percent_E_4(T_interval_4));  %third percentage
E_4_stdev=std(Percent_E_5(T_interval_5));  %fourth percentage
E_5_stdev=std(Percent_E_6(T_interval_6));  %Fifth percentage
E_0_2_stdev=std(Percent_E_7(T_interval_7));
E_B_stdev=std(Percent_E_baseline(180:210));
%E_B_stdev=std(Percent_E_baseline(90:120));
%V_B=var(Diff_baseline(1:31));
E_C_stdev=std(Percent_E_cooldown(30:60));

E_total_stdev=[E_B_stdev E_0_1_stdev E_1_stdev E_2_stdev E_3_stdev E_4_stdev
E_5_stdev E_0_2_stdev E_C_stdev];

%%
%if worked the Left Side
%for baseline
for i=1:length(Half_TBW_baseline)
    Percent_E_baseline=((abs(Half_TBW_baseline-L_baseline))./L_baseline)*100;
end

%for Zero_1
for i=1:length(Half_TBW_1)
    Percent_E_1=((abs(Half_TBW_1-L_1))./L_1)*100;
end

%for i=1:length(Half_TBW_2)
%    Percent_E_2=((abs(Half_TBW_2-L_2))./L_2)*100;
%end
```

```
%for First percent manipulation
for i=1:length(Half_TBW_2)
    Value_1=Half_TBW_2*First;
end


for i=1:length(Half_TBW_2)
    Adjusted_1=Value_1+Half_TBW_2;
end




for i=1:length(Half_TBW_2)
    Percent_E_2=((abs(Adjusted_1-L_2))./L_2)*100;
end

%for Second percent manipulation
for i=1:length(Half_TBW_3)
    Value_2=Half_TBW_3*Second;
end


for i=1:length(Half_TBW_3)
    Adjusted_2=Value_2+Half_TBW_3;
end




for i=1:length(Half_TBW_3)
    Percent_E_3=((abs(Adjusted_2-L_3))./L_3)*100;
end

%for Third percent manipulation
for i=1:length(Half_TBW_4)
    Value_3=Half_TBW_4*Third;
end


for i=1:length(Half_TBW_4)
    Adjusted_3=Value_3+Half_TBW_4;
end




for i=1:length(Half_TBW_4)
    Percent_E_4=((abs(Adjusted_3-L_4))./L_4)*100;
end

%for Fourth percent manipulation

for i=1:length(Half_TBW_5)
    Value_4=Half_TBW_5*Fourth;
```

```
end


for i=1:length(Half_TBW_5)
    Adjusted_4=Value_4+Half_TBW_5;
end



for i=1:length(Half_TBW_5)
    Percent_E_5=((abs(Adjusted_4-L_5))./L_5)*100;
end

%for Fifth percent manipulation

for i=1:length(Half_TBW_6)
    Value_5=Half_TBW_6*Fifth;
end


for i=1:length(Half_TBW_6)
    Adjusted_5=Value_5+Half_TBW_6;
end




for i=1:length(Half_TBW_6)
    Percent_E_6=((abs(Adjusted_5-L_6))./L_6)*100;
end

%for Zero_2
for i=1:length(Half_TBW_7)
    Percent_E_7=((abs(Half_TBW_7-L_7))./L_7)*100;
end

%for Cooldown
for i=1:length(Half_TBW_cooldown)
    Percent_E_cooldown=((abs(Half_TBW_cooldown-L_cooldown))./L_cooldown)*100;
end











%Separating into arrays
R=Right;
L=Left;
```

```
T=X_Value;




T_1=find(T>299 & T<300); %baseline
T_2=find(T>419 & T<420); %0 percent
T_3=find(T>539 & T<540); %2nd percentage
T_4=find(T>659 & T<660); %3rd percentage %T_4=find(T>479 & T<480);
T_5=find(T>779 & T<780); %4th percentage
T_6=find(T>899 & T<900); %5th percentage  %T_6=find(T>719 & T<720);
T_7=find(T>1019 & T<1020);  %6th percentage %T_7=find(T>839 & T<840);
T_7=find(T>838 & T<840);
T_8=find(T>1139 & T<1140); %2nd 0 percent
T_9=find(T>1259 & T<1260); %cooldown

R_baseline=[R(1:T_1)];
R_1=[R(T_1+1:T_2)];
R_2=[R(T_2+1:T_3)];
R_3=[R(T_3+1:T_4)];
R_4=[R(T_4+1:T_5)];
R_5=[R(T_5+1:T_6)];
R_6=[R(T_6+1:T_7)];
R_7=[R(T_7+1:T_8)];
R_cooldown=[R(T_8+1:T_9)];

L_baseline=[L(1:T_1)];
L_1=[L(T_1+1:T_2)];
L_2=[L(T_2+1:T_3)];
L_3=[L(T_3+1:T_4)];
L_4=[L(T_4+1:T_5)];
L_5=[L(T_5+1:T_6)];
L_6=[L(T_6+1:T_7)];
L_7=[L(T_7+1:T_8)];
L_cooldown=[L(T_8+1:T_9)];

TBW_baseline=R_baseline+L_baseline;
TBW_1=R_1+L_1;
TBW_2=R_2+L_2;
TBW_3=R_3+L_3;
TBW_4=R_4+L_4;
TBW_5=R_5+L_5;
TBW_6=R_6+L_6;
TBW_7=R_7+L_7;
TBW_cooldown=R_cooldown+L_cooldown;

%difference equation
Diff_baseline=(R_baseline-L_baseline)./2;
Diff_1=(R_1-L_1)./2;
Diff_2=(R_2-L_2)./2;
Diff_3=(R_3-L_3)./2;
Diff_4=(R_4-L_4)./2;
Diff_5=(R_5-L_5)./2;
Diff_6=(R_6-L_6)./2;
Diff_7=(R_7-L_7)./2;
```

```
Diff_cooldown=(R_cooldown-L_cooldown)./2;

ABS_Diff_baseline=abs((R_baseline-L_baseline)./2);
ABS_Diff_1=abs((R_1-L_1)./2);
ABS_Diff_2=abs((R_2-L_2)./2);
ABS_Diff_3=abs((R_3-L_3)./2);
ABS_Diff_4=abs((R_4-L_4)./2);
ABS_Diff_5=abs((R_5-L_5)./2);
ABS_Diff_6=abs((R_6-L_6)./2);
ABS_Diff_7=abs((R_7-L_7)./2);
ABS_Diff_cooldown=abs((R_cooldown-L_cooldown)./2);

Variance_1=var(Diff_1);


xdiff_baseline=1:length(Diff_baseline);
Goal_baseline(xdiff_baseline)=zeros;
%Bound_baseline(xdiff_baseline)=boundary(xdiff_baseline,Diff_baseline);
figure(1)
plot(Diff_baseline,xdiff_baseline,'r',Goal_baseline,xdiff_baseline,'b')
axis([-20,20,0,300])
title('Baseline-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')

xdiff_1=1:length(Diff_1);
Goal_1(xdiff_1)=zeros;
figure(2)
plot(Diff_1,xdiff_1,'r',Goal_1,xdiff_1,'b')
axis([-20,20,0,120])
title('Round 1 (0%)-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')


xdiff_2=1:length(Diff_2);
Goal_2(xdiff_2)=zeros;
figure(3)
plot(Diff_2,xdiff_2,'r',Goal_2,xdiff_2,'b')
axis([-20,20,0,120])
title('Round 2 (15%)-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
```

```
xdiff_3=1:length(Diff_3);
Goal_3(xdiff_3)=zeros;
figure(4)
plot(Diff_3,xdiff_3,'r',Goal_3,xdiff_3,'b')
axis([-20,20,0,120])
title('Round 3 (25%)-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')


xdiff_4=1:length(Diff_4);
Goal_4(xdiff_4)=zeros;
figure(5)
plot(Diff_4,xdiff_4,'r',Goal_4,xdiff_4,'b')
axis([-20,20,0,120])
title('Round 4 (5%)-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')


xdiff_5=1:length(Diff_5);
Goal_5(xdiff_5)=zeros;
figure(6)
plot(Diff_5,xdiff_5,'r',Goal_5,xdiff_5,'b')
axis([-20,20,0,120])
title('Round 5 (10%)-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')

xdiff_6=1:length(Diff_6);
Goal_6(xdiff_6)=zeros;
figure(7)
plot(Diff_6,xdiff_6,'r',Goal_6,xdiff_6,'b')
axis([-20,20,0,120])
title('Round 6 (20%)-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
```

```
xdiff_7=1:length(Diff_7);
Goal_7(xdiff_7)=zeros;
figure(8)
plot(Diff_7,xdiff_7,'r',Goal_7,xdiff_7,'b')
axis([-20,20,0,120])
title('Round 7 (0%)-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 300],'LineStyle', '-',
'LineWidth',2,'Color','r')



xdiff_cooldown=1:length(Diff_cooldown);
Goal_cooldown(xdiff_cooldown)=zeros;
%Bound_cooldown=boundary(Diff_cooldown);
figure(9)
plot(Diff_cooldown,xdiff_cooldown,'r',Goal_cooldown,xdiff_cooldown,'b')
axis([-20,20,0,120])
title('Cooldown-Difference Equation')
xlabel('Difference ((R-L)/2))')
ylabel('Time(s)')
line('XData',[-Variance_1 -Variance_1],'YData',[0 120],'LineStyle', '-',
'LineWidth',2,'Color','r')
line('XData',[Variance_1 Variance_1],'YData',[0 120],'LineStyle', '-',
'LineWidth',2,'Color','r')

%%
prompt='What is the Time value?';
n_1=input(prompt);
n_2=input(prompt);
n_3=input(prompt);
n_4=input(prompt);
n_5=input(prompt);
n_6=input(prompt);
n_7=input(prompt);


T_interval_1=n_1:n_1+30;
T_interval_2=n_2:n_2+30;
T_interval_3=n_3:n_3+30;
T_interval_4=n_4:n_4+30;
T_interval_5=n_5:n_5+30;
T_interval_6=n_6:n_6+30;
T_interval_7=n_7:n_7+30;


%V_0_1=var(Diff_1(13:43));
%V_10=var(Diff_2(49:79));
%V_15=var(Diff_3(27:57));
%V_20=var(Diff_4(37:67));
%V_25=var(Diff_5(37:67));
```

```
%V_5=var(Diff_6(70:100));
%V_0_2=var(Diff_7(12:42));
%V_B=var(Diff_baseline(180:210));
%V_C=var(Diff_cooldown(30:60));

V_0_1_test=var(Diff_1(T_interval_1));
V_1_test=var(Diff_2(T_interval_2));  %first percentage
V_2_test=var(Diff_3(T_interval_3));  %second percentage
V_3_test=var(Diff_4(T_interval_4));  %third percentage
V_4_test=var(Diff_5(T_interval_5));  %fourth percentage
V_5_test=var(Diff_6(T_interval_6));  %Fifth percentage
V_0_2_test=var(Diff_7(T_interval_7));
V_B=var(Diff_baseline(180:210));
%V_B=var(Diff_baseline(1:31));
V_C=var(Diff_cooldown(30:60));

V_total=[V_B V_0_1_test V_1_test V_2_test V_3_test V_4_test V_5_test
V_0_2_test V_C];

M_0_1=mean(Diff_1(T_interval_1));
M_1=mean(Diff_2(T_interval_2));
M_2=mean(Diff_3(T_interval_3));
M_3=mean(Diff_4(T_interval_4));
M_4=mean(Diff_5(T_interval_5));
M_5=mean(Diff_6(T_interval_6));
M_0_2=mean(Diff_7(T_interval_7));
M_B=mean(Diff_baseline(180:210));
%M_B=mean(Diff_baseline(1:31));
M_C=mean(Diff_cooldown(30:60));

M_total=[M_B M_0_1 M_1 M_2 M_3 M_4 M_5 M_0_2 M_C];

ABS_M_0_1=mean(ABS_Diff_1(T_interval_1));
ABS_M_1=mean(ABS_Diff_2(T_interval_2));
ABS_M_2=mean(ABS_Diff_3(T_interval_3));
ABS_M_3=mean(ABS_Diff_4(T_interval_4));
ABS_M_4=mean(ABS_Diff_5(T_interval_5));
ABS_M_5=mean(ABS_Diff_6(T_interval_6));
ABS_M_0_2=mean(ABS_Diff_7(T_interval_7));
ABS_M_B=mean(ABS_Diff_baseline(180:210));
%ABS_M_B=mean(ABS_Diff_baseline(1:31));
ABS_M_C=mean(ABS_Diff_cooldown(30:60));


ABS_M_total=[ABS_M_B ABS_M_0_1 ABS_M_1 ABS_M_2 ABS_M_3 ABS_M_4 ABS_M_5
ABS_M_0_2 ABS_M_C];

V_T=transpose(V_total);
M_T=transpose(M_total);
ABS_M_T=transpose(ABS_M_total);

%M_0_1=mean(Diff_1(13:43));
%M_10=mean(Diff_2(49:79));
%M_15=mean(Diff_3(27:57));
%M_20=mean(Diff_4(37:67));
```

```
%M_25=mean(Diff_5(37:67));
%M_5=mean(Diff_6(70:100));
%M_0_2=mean(Diff_7(12:42));
%M_B=mean(Diff_baseline(180:210));
%M_C=mean(Diff_cooldown(30:60));
%%
%Getting AVG total body weight

AvgTBW_0_1=mean(TBW_1(T_interval_1));
AvgTBW_1=mean(TBW_2(T_interval_2));
AvgTBW_2=mean(TBW_3(T_interval_3));
AvgTBW_3=mean(TBW_4(T_interval_4));
AvgTBW_4=mean(TBW_5(T_interval_5));
AvgTBW_5=mean(TBW_6(T_interval_6));
AvgTBW_0_2=mean(TBW_7(T_interval_7));
AvgTBW_B=mean(TBW_baseline(180:210));
%AvgTBW_B=mean(TBW_baseline(1:31));
AvgTBW_C=mean(TBW_cooldown(30:60));

AvgTBW_total=[AvgTBW_B AvgTBW_0_1 AvgTBW_1 AvgTBW_2 AvgTBW_3 AvgTBW_4
AvgTBW_5 AvgTBW_0_2 AvgTBW_C];

AVGTBW_T=transpose(AvgTBW_total);

%%
%Getting speed
fflag=0;
k=1;
cnt=1;
for i=1:length(Index)
    if Index(i)>4.1 & fflag==0
        P(k)=i;
        fflag=1;
        k=k+1;
    else
        cnt=cnt+1;
    end
    if cnt==200
        cnt=0;
        fflag=0;
    end
end
I=transpose(P);

Test(1:length(P)+1)=[0 P];
Test_2=[P 0];
Test_3=Test_2-Test;
Test_4=find(Test_3<100);

F=Test_2;
F(Test_4)=[];
clear I;
FF=transpose(F);
I=FF;
```

```
%for jj=1:length(I)+100
 %     H(jj)=mean(Time(I(jj):I(jj+1)));
%end

%T=transpose(H);


T_1=90000; %baseline
T_2=126000; %0 percent
T_3=162000; %2nd percentage
T_4=198000; %3rd percentage %T_4=find(T>479 & T<480);
T_5=234000; %4th percentage
T_6=270000; %5th percentage  %T_6=find(T>719 & T<720);
T_7=306000;  %6th percentage %T_7=find(T>839 & T<840); T_7=find(T>838 &
T<840);
T_8=342000; %2nd 0 percent
T_9=378000; %cooldown



I_baseline=find(FF>T_1-1000 & FF<T_1);
I_1=find(FF>T_2-1000 & FF<T_2);
I_2=find(FF>T_3-1000 & FF<T_3);
I_3=find(FF>T_4-1000 & FF<T_4);
I_4=find(FF>T_5-1000 & FF<T_5);
I_5=find(FF>T_6-1000 & FF<T_6);
I_6=find(FF>T_7-1000 & FF<T_7);
I_7=find(FF>T_8-1000 & FF<T_8);
I_cooldown=find(FF>T_9-1000 & FF<T_9);

I_baseline=I_baseline(end);
I_1=I_1(end);
I_2=I_2(end);
I_3=I_3(end);
I_4=I_4(end);
I_5=I_5(end);
I_6=I_6(end);
I_7=I_7(end);
I_cooldown=I_cooldown(end);
%delete the smaller number in the breakup of I

%cycles-need to subtract each position to get number of cycles
Cycles_baseline=I_baseline;
Cycles_1=I_1-I_baseline;
Cycles_2=I_2-I_1;
Cycles_3=I_3-I_2;
Cycles_4=I_4-I_3;
Cycles_5=I_5-I_4;
Cycles_6=I_6-I_5;
Cycles_7=I_7-I_6;
Cycles_cooldown=I_cooldown-I_7;
%Cycles_9=I_9-I_8;

%Speed cycles/sec
Speed_second_baseline=Cycles_baseline/300;
Speed_second_1=Cycles_1/120;
```

```
Speed_second_2=Cycles_2/120;
Speed_second_3=Cycles_3/120;
Speed_second_4=Cycles_4/120;
Speed_second_5=Cycles_5/120;
Speed_second_6=Cycles_6/120;
Speed_second_7=Cycles_7/120;
Speed_second_cooldown=Cycles_cooldown/120;
%Speed_second_9=Cycles_9/120;

Total_speed=[Speed_second_baseline Speed_second_1 Speed_second_2
Speed_second_3 Speed_second_4 Speed_second_5 Speed_second_6 Speed_second_7
Speed_second_cooldown];

T_speed=transpose(Total_speed);
```

Chapter 6

Chapter 6: Conclusion of dissertation

The purpose of this dissertation research was to construct a low-cost system to encourage increased weight acceptance on the paretic limb while in dynamic stance. Although there exist devices aiming to improve gait symmetry, most focus on kinematics and velocity. Force platform devices coupled to visual biofeedback provide a promising technique, but training is often not transferrable to dynamic gait.. Kinetic visual biofeedback modifications were developed as an additional component to current training techniques.

This system is low-cost and provides real-time kinetic feedback during training (Chapters 2 and 3) that encourages biased training towards the non-dominant weight bearing limb (Chapters 4 and 5). Chapter 5 of the dissertation shows promise towards incorporating this technique to improve gait symmetry post training.

Future Research

Further research is needed to determine long-term effects of training with this system. A controlled trial with a large cohort of subjects who have suffered stroke is necessary to determine if such a device could improve current treatments in gait rehabilitation.

Further modifications can be made to the elliptical to improve ergonomics and assistance provided for patients who have had a stroke. One such modification would be an assist motor to help patients propel the pedals forward in a controlled fashion.

Vita

Trisha Jeanne Massenzo was born on September 8, 1988 in Johnson City, Tennessee and is an American citizen. She graduated from Morristown Hamblen East High School, Morristown, TN in 2006. In 2011, she received her Bachelor of Science from East Tennessee State University, Johnson City, Tennessee in Physics.