Anticipatory and Invisible Interfaces to Address Impaired Proprioception in Neurological Disorders

by

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ABSTRACT

The burden of adaptation has been a major limiting factor in the adoption rates of new wearable assistive technologies. This burden has created a necessity for the exploration and combination of two key concepts in the development of upcoming wearables: anticipation and invisibility. The combination of these two topics has created the field of Anticipatory and Invisible Interfaces (AII)

In this dissertation, a novel framework is introduced for the development of anticipatory devices that augment the proprioceptive system in individuals with neurodegenerative disorders in a seamless way that scaffolds off of existing cognitive feedback models. The framework suggests three main categories of consideration in the development of devices which are anticipatory and invisible:

- Idiosyncratic Design: How do can a design encapsulate the unique characteristics of the individual in the design of assistive aids?
- Adaptation to Intrapersonal Variations: As individuals progress through the various stages of a disability/neurological disorder, how can the technology adapt thresholds for feedback over time to address these shifts in ability?
- Context Aware Invisibility: How can the mechanisms of interaction be modified in order to reduce cognitive load?

The concepts proposed in this framework can be generalized to a broad range of domains; however, there are two primary applications for this work: rehabilitation and assistive aids. In preliminary studies, the framework is applied in the areas of Parkinsonian freezing of gait anticipation and the anticipation of body non-compliance during rehabilitative exercise.

DEDICATION

This dissertation is dedicated to my loving family, without whom this degree would not have been possible. I'm eternally grateful for the sacrifices that you all have made in support of my academic journey.

TABLE OF CONTENTS

CHAPTER Page

LIST OF TABLES

LIST OF FIGURES

Figure Page

Chapter 1

INTRODUCTION

As the baby-boomer generation ages into the geriatric population, the adoption of assistive technology grows with it at an alarming rate. With each passing day, new wearable devices are deployed which explore applications in all aspects of life ranging from entertainment to health. Healthcare has specifically become a focal point in this progression due to growing demand. The last five years alone have given rise to a broad suite of exercise bands (Nike Fuel Band, Fitbit, JawBone, etc.), smart watches (Pebble, Apple Watch, Galaxy Gear), and mobile health apps. These technologies offer access to information that was previously unavailable and provide platforms for a plethora of new assistive devices and services through remote monitoring. However, one of the main barriers of entry for these devices is the burden of adaptation. Every time a new device is released, it brings with it a new interface and an entirely new set of interactions to which the user is forced to adapt in order to be able to adequately use the technology.

This burden has created a necessity for the exploration and combination of two key concepts in the development of upcoming wearables: anticipation and invisibility. Anticipation of user needs shifts the paradigm of interaction with these devices to allow the device to predict and respond to user behaviors through contextual information. Invisibility will allow users to utilize these devices in day-to-day activities without the device impeding their primary task or objective. The combination of these two topics has created the field of Anticipatory and Invisible Interfaces (AII).

1.1 Problem Statement

This dissertation explores the concept of AII for assistive devices through the lens of neurodegenerative disorders. The fundamental contribution of this research is to propose a framework and considerations that guide the development of devices to augment an individual's proprioceptive system in a way that seamlessly integrates into their own perception of self. This framework looks to shift the burden of adaptation from the user to the device. Systems designed under this framework anticipate an individual's needs based on current context and adopt a person-centric approach by adapting to the user based upon their personal characteristics. The interface for the device is abstracted from the user and considers internal and external context as an implicit input paradigm rather than the traditional approach of using explicit interaction. Thus, the interaction is able to take place without the attention of the user and the technology can cater to the human seamlessly. Ideally, this will open the doors to adoption for a new generation of person-centric assistive devices.

1.2 Previously Published Work

The contents of Chapter 5 include previously published work, *SmartGym: An Anticipatory System to Detect Body Compliance During Rehabilitative Exercise* by Tadayon *et al.* (2017). The contents of Chapter 6 include two previously published articles, *A shoe mounted system for parkinsonian gait detection and real-time feedback* by Tadayon *et al.* (2015a) and *Utilizing Neural Networks to Predict Freezing of Gait in Parkinson's Patients* by Zia *et al.* (2016). The contents of Chapter 6 also include work that is currently in review, *HaptiCadence: A System for Continuous and Discrete Vibrotactile Feedback to Promote Steady Gait in Parkinson's Patients.*

Chapter 2

DEFINITIONS

2.1 Anticipatory Interfaces

With the rise of mobile devices comes a greater ability to infer about a user's location, activity, and social setting than ever before. As these devices continue to advance with new sensors, a shift may occur from inference to prediction of context that will, in parallel, open the door for anticipation within computing applications. Robert Rosen defines an anticipatory system as one that "contains an internal, predictive model of itself and its environment, which allows it to change state at an instant in accord with the model's predictions pertaining to a later instant" (Rosen, 2012). Although the principle of anticipation has been known, most existing approaches on the interaction-cycle for assistive devices have been "laissez-faire". In simple terms, a device will wait for explicit interaction from the user before it processes and provides an output.

In discussing applications, it is important to first differentiate prediction from anticipation since the two are often incorrectly used interchangeably. Predictive applications are those that simply build predictions of the user's current or future context. Anticipation is set in the domain of action that is based on the predictions of future context in order to impact the future to the benefit of the user. Applications in the field of anticipatory computing rely on two key steps prior to the ability to anticipate. These are to sense the surrounding context and then create a predictive model of this context. Once the predictive model has been created, the system then uses this for anticipation of a user's future needs (Pejovic and Musolesi, 2015).

2.2 Invisible Interfaces

One of the crucial factors affecting the future expansion of anticipatory devices is their ease of use. Many current approaches to the development of devices have embedded the interface for the applications into the existing interface of the mobile phone or other technology in order to create a non-obtrusive feedback loop. Pantic et al. take this one step further and state that the key to anticipatory interfaces is "ease of use" and the ability to "unobtrusively sense certain behavioral cues of the users and to adapt automatically to his or her typical behavioral patterns and the context in which he or she acts" (Pantic *et al.*, 2007).

It is this ability to unobtrusively sense behavior cues and to use those as inputs for technology that is deemed an invisible interface in this work. Future endeavors seek to abstract the traditional methods of explicit human-computer interaction away from the user and instead use both internal and external context as the primary inputs for the technology. This promotes the principles of ubiquitous computing and transforms the technology into an extension of the person.

Although most applications in mobile computing still maintain the need for interaction with a physical interface, there has been a major effort towards the development of context-aware applications. These systems are generally split into two major subcategories: external context (physical) and internal context (logical). Context is any information that can be used to characterize the situation of an entity where an entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including location, time, activities, and the preferences of each entity (Hong *et al.*, 2009).These systems face many challenges including determining relevant information, dealing with uncertainty, and privacy (Baldauf *et al.*, 2007).

2.3 Body Compliance

Body compliance is a field of research pertaining to the study of the proprioceptive system and how an individual's body responds to what the brain is willing it to do. While this field is traditionally explored within the domain of prosthetics where the brain is willing a technology to respond (Rossi *et al.*, 2019; Clites *et al.*, 2018), research is also being done in the application of similar principles to the domain of neurodegenerative disorders where many of the neural pathways of motion often get interrupted in a similar fashion (Dursun Erbil *et al.*, 1996). In this context, the devices look to augment an individual's sense of self and provide an extension to a person's natural ability to determine potentially dangerous body positions. This could mean things such as being off balance, putting too much pressure on a single joint, or walking in a manner in which you may trip and fall. Because this is traditionally such an autonomous process, this area also comes with the additional necessity of minimizing cognitive load in the delivery of feedback.

Chapter 3

RELATED WORK

3.1 Anticipatory Interfaces

Since the concept of anticipation in mobile computing is quite novel, few applications exist that are truly anticipatory. The majority of the work in this area has utilized robotics. Within robotics, the principle of anticipation has been on the forefront in navigation (Gorbenko and Popov, 2012), perception (Hoffmann, 2007), and human movement characterization (Rett and Dias, 2007). Similarly, authors have explored applications in gaming through eye-tracking to predict a player's actions (Koesling *et al.*, 2011). These early systems have helped to show the applicability and usefulness of anticipation, but are restricted in context.

Within the mobile domain, recent literature focuses on the predictive applications of internal and external context. One example of an application that explores the usefulness of mobile phones in determining external context is SoundSense (Lu *et al.*, 2009). This project explored the use of the microphone to determine characteristics such as activity, location, and social events. The authors proposed a scalable framework for modeling sound events and were able to classify four different activities: walking, driving a car, riding an elevator, or riding a bus (the precision on riding a bus was much lower with respect to the others). Similarly, a project that explored internal context, called EmotionSense, was designed to infer a user's emotional state from microphone data (Rachuri *et al.*, 2010).

Furthermore, one of the other major research efforts on the classification of human behavior and extrapolation of context through mobile phones is Darwin Phones

(Miluzzo *et al.*, 2010). The authors developed an initial framework in the mobile domain that is able to automate the updating of models over time, pool models that have been created and evolved within other mobile devices, and combine classification results from multiple mobile phones. This methodology is a step above many approaches in literature that rely on the local sensing abilities of a single mobile device rather than crowd-sourcing the classification.

A host of other applications exist within the mobile domain which look at context prediction; many literature surveys cover these in detail. Instead, the focus of this work lies specifically in the next step beyond prediction: anticipation, a concept largely left unexplored within the realm of this research.

Pejovic & Musolesi have proposed the potential for applications of anticipatory computing within the emerging field of digital behavior change interventions in mobile environments (Pejovic and Musolesi, 2015). The authors have referenced UbiFit (Consolvo *et al.*, 2008) and BeWell (Lane *et al.*, 2011) as two applications that have taken very rudimentary steps towards the inclusion of anticipation in mobile applications as well as provided potential architectures for applications in this domain (Pejovic and Musolesi, 2015). UbiFit is a personal health application that was designed to monitor the weekly activity and provide subtle feedback when the user is lacking in this activity. The system predicts negative longterm health implications by monitoring daily activity levels. For feedback, the app displays a virtual garden which thrives if the user is meeting activity goals and remains barren if the user has remained inactive for too long. BeWell is a mobile application that monitors a user's health along three dimensions: sleep, physical activity and social interaction. This application used movement and ambient noise during sleep to predict sleep duration and quality. Much like UbiFit, this application provides intelligent feedback to the user to promote better health through an ambient display of an aquatic background which becomes more active as its user makes healthier decisions.

3.2 Invisible Interfaces

The literature in this domain is quite developed and uses context as an input in a variety of different ways. A unique approach that has been taken looks to combine the influences of internal and external user context to proactively determine recommendations (Liu, 2014). The system builds a context history and a profile for the user in each of these contexts in order to accurately be able to predict the user's needs simply based on past behavior.

Fenza et al. explore the usefulness of internal context in the healthcare domain by using a network of wearable sensors to determine the individual's current state of health and provide personalized services based on that. The authors use Fuzzy Logic to automatically characterize context and find healthcare services that approximately meet this context (Fenza *et al.*, 2011).

Muñoz et al. explore the development of a context aware messaging system in a hospital environment (Muñoz *et al.*, 2003). Users (doctors, nurses, physicians, etc.) are given mobile devices to write messages to each other that are only sent when a specified context is encountered. For instance, a nurse could leave a message for the next doctor entering a given room. The system automates the delivery based upon sensed context across many devices. However, this system doesn't fully embrace the concept of an invisible interface since the main method of interaction is still a physical one from the user rather than an automated interaction solely based on context.

3.3 Remaining Challenges

The existing bodies of work in the areas of anticipatory and invisible interfaces have already addressed many challenges related to the development of assistive aids, however there exist several shortcomings that have not yet been addressed due to the limited contexts in which these devices have been explored. Most work in this field has used standard study design approaches to solve problems with anticipatory/invisible interfaces. In doing so, they treat users as a relatively homogeneous entity where a single user is just a "part of the whole" and the focus is on solving the "function" (for example, raising awareness of an oncoming freezing-of-gait episode) rather than accounting for the individual's specific problem with that function. Therefore, these approaches have not sufficiently addressed the following challenges:

1. In the realm of disability, every individual is a unique case. How can a device account for these idiosyncrasies between various individuals in the design of anticipatory and invisible solutions?

2. As individuals progress through the various stages of a disability/neurological disorder, their proprioceptive capabilities, motor ability and reactive capacities change in time. How can an anticipatory/invisible device account for this change in its model of an individual and/or how is this reflected in its design?

3. How can the proprioceptive system be augmented in a seamless way without detracting from the subject's primary motor task?

Chapter 4

PROPOSED FRAMEWORK

In this dissertation, a framework is proposed to address the limitations of existing approaches in the field of anticipatory and invisible interfaces. There are three critical principles in the design of AII, within the context of assistive devices, that need to be considered: idiosyncratic design, adaptation to intrapersonal variation, and context aware invisibility. The proposed framework guides the development of functional devices through the lens of these principles as a holistic approach to the production of real-world assistive technologies. This research looks to address limitations in existing approaches and create a set of generalizable criteria for the design of systems that augment the proprioceptive system and provide additional feedback protocols to an individual's sense of body compliance in various contexts.

4.1 Idiosyncratic Design

One of the biggest limiting factors in most prior approaches is that the concept of interpersonal variation often gets lost in the mix of population grouping. Therefore, subjects are treated as groups and experiments are designed around observing shifts between and within these groups rather than within the individual. This methodology in study design has also translated into the approaches taken in systems design as well. Traditionally, Randomized Clinical Trials (RCT) with large populations and randomization on subject selection and group assignment have been argued as the standard for scientific study design (Sackett *et al.*, 1996). However, in contexts such as Freezing of Gait with Parkinson's Disease, where we don't have a concrete understanding of the underlying basis and only a rudimentary understanding of the

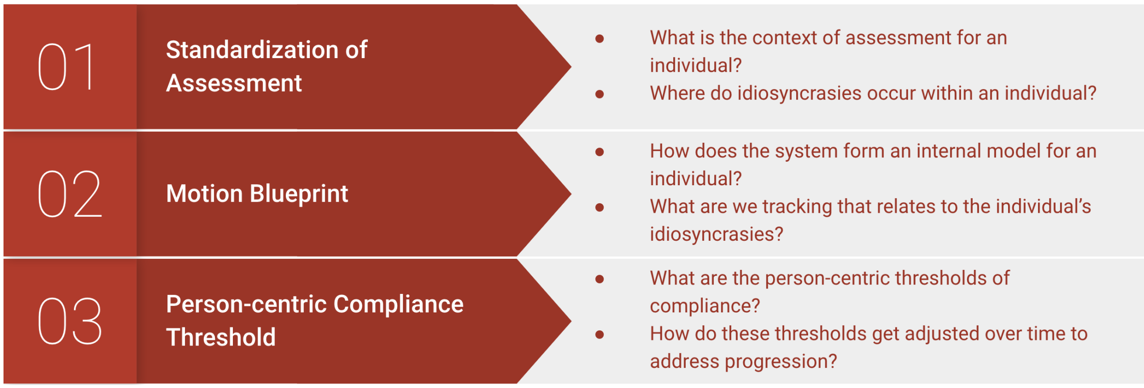

Figure 4.1: Considerations for Idiosyncratic Design

pathophysiology (Lewis and Barker, 2009; Diamond and Jankovic, 2006), it is critical to consider a multi-baseline approach as interpersonal variation can be substantial. In this style of approach, the subject's performance is compared against their own abilities and progression which necessitates that the system builds a baseline and a person-centric intervention method for which to compare pre and post measures (Barnett *et al.*, 2012; Graham *et al.*, 2012). This means that the subject serves as their own "control" within the study and progression/outcomes are measured against their baseline. Thus, in an idiosyncratic approach, it is important that the study and device design consider the following questions (Fig 4.1):

1. What is the context of assessment for an individual? Where do idiosyncrasies occur within an individual?

2. How does the system form an internal model for an individual? What are we tracking that relates to the individual's idiosyncrasies?

3. What are the person-centric thresholds of compliance?

4.1.1 *Standardization of Assessment*

In the design of assistive technologies with AII that take idiosyncrasies into account, we must consider the characteristics of the individual that distinguish the nature of their range of ability and ailment from others with similar conditions. The appropriate characteristics to consider are determined by their relevance to the task that the user is trying to perform through the use of the assistive device. As an example, unique features associated with an individual's angular range of joint motion would be important to consider within an application that is looking to augment rehabilitative exercise programs for individuals with limited motor control. This characterization of an individual becomes the building block for a standard of comparison to denote progress over time and is a critical step in the "sensing of the context" portion of the anticipation loop.

A standardized assessment is applied to all the individuals uniformly, and therefore the assessment itself is not necessarily person-centric. That is, the assessment or metric is not uniquely designed for each individual. However, in order for a machine to learn what distinguishes one individual from another, it must use some common context by which to compare and contrast them. In other words, the varying performances of individuals under a standardized assessment serve as the basis for their idiosyncrasies. If a user scores very highly on a range of motion assessment, that individual is considered to have a very healthy range of motion, so a system expects large and flexible motions to be the norm for that individual compared to another who scores very poorly. The underlying mechanisms of musculoskeletal function in these individuals are understood at a very basic level by this system through quantitative evaluation of their assessment outcomes.

Clinical practice in rehabilitation, for example, might use the Parkinson's disease

Activities of Daily Living Scale (PADLS) (Hobson *et al.*, 2001) to determine motor function or the Berg Balance Test (Bogle Thorbahn and Newton, 1996; Qutubuddin *et al.*, 2005) to determine fall risk within the Parkinsonian population. Other examples of clinical assessments to encapsulate idiosyncrasies are show in Table 4.1. Medical experts often rely on these baseline assessment metrics to diagnose and create individually-tailored programs for each patient. As such, an AII device can benefit from this approach in a similar manner by having a metric of comparison.

Context	Assessment	Description
Parkinsonian Disease Stage	Modified Hoehn and Yahr Staging (Hoehn, 1997)	Used to describe the motor symptom progression in 8 different stages
Clinical Spasticity in Cerebral Palsy	Ashworth Scale (Charalambous, 2014)	Muscle tone assessment by scoring the resistance encountered in a specific muscle group by passively moving a limb through its ROM on a 5-point scoring scale
Balance and Mobility	Timed Up and Go (TUG) (Salarian *et al.*, 2010)	TUG includes several complex subcomponents, namely: sit-to-stand, gait, 180 degree turn, and turn-to-sit; the only outcome is the total time to perform the task.

Table 4.1: Examples of Standardized Assessments in Clinical Practice

4.1.2 Motion Blueprint

Once a standardized method of measurement has been established, it is important to create a model to digitally encapsulate the individual. In the context of assistive devices for augmentation of the proprioceptive system, this model is deemed the "motion blueprint" as it gives the device a snapshot of the user's current body context. Over time, the motion blueprint becomes a temporal series of snapshots which allow the system to then make inferences on future context based on the current and past. This is a critical step in the "prediction of the future context" of the anticipation process.

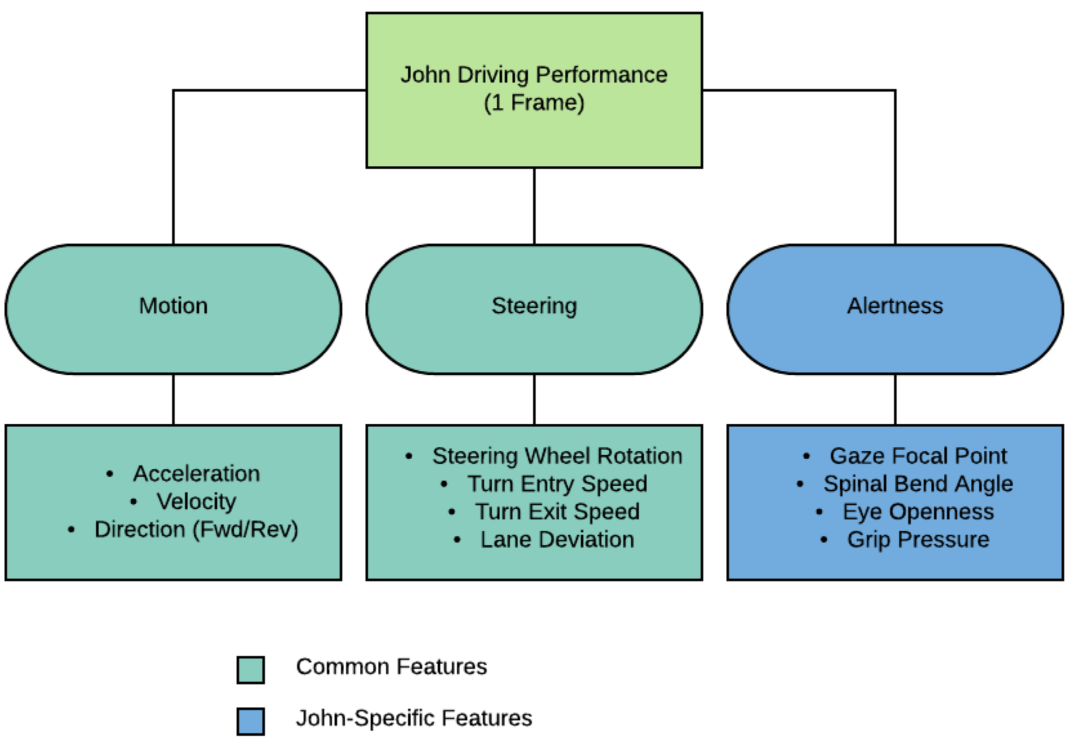

Figure 4.2: A Simple Example of a Motion Blueprint

This blueprint can be distinguished from the standardized assessment above in that it is a method used by an AII to determine the changes that occur in an individual over time, or in other words, intra-personal variation, as opposed to the standardized assessment which determines the difference between that individual and others under the same context, or inter-personal variation. In the previous case, a system would determine, for example, an individual's risk level for Parkinsonian Gait, using some kind of metric or assessment that involves their motion (ex: H & Y Stage, UPDRS). Now, the system needs to take a closer look into the individual and determine in what contexts he or she is walking, whether it be at home or in public spaces, and what other attributes of that individual characterize the type of sensing that can occur. Based on this information, we can then determine what type of features characterize the individual's motion in real-time. The set of these features comprises a blueprint for that individual's motion. In some cases, noncompliance characterizes itself in a similar manner between most or all individuals. For example in FoG, festinating gait is a commonly recognized precursor of the episode. This clues us in on the usage of ankle/heel/etc. data as good features to form blueprints for most individuals. However, perhaps one individual has a very pronounced knee movement in his or her normal gait which is notably affected when shuffling occurs. This unique attribute can be captures in a highly effective standardized assessment strategy as denoted above, and then incorporated into the feature set that forms that individual's blueprint, as it is an idiosyncrasy of that individual's motion.

For example, as shown in figure 4.2, a motion blueprint for a delivery driver could be rotational angle of the steering wheel, to see how sharply and safely the driver executes turns, the acceleration and speed of the car, and, in that individual's case since he is prone to late night driving, the back posture, since the driver tends to lean into the steering wheel when falling asleep. The standardized assessment could be a driving course or map, because it provides a standard context to determine how each driver behaves in the same environment.

4.1.3 Person-Centric Compliance Threshold

After the system understands the context by which individuals differ (standardized assessment) and characterizes the changes that can occur in an individual (motion blueprint), the system must then determine at what precise point those changes cause an individual to become noncompliant (compliance threshold). This progression of metrics moves the AII system from identifying to monitoring to anticipating the individual.

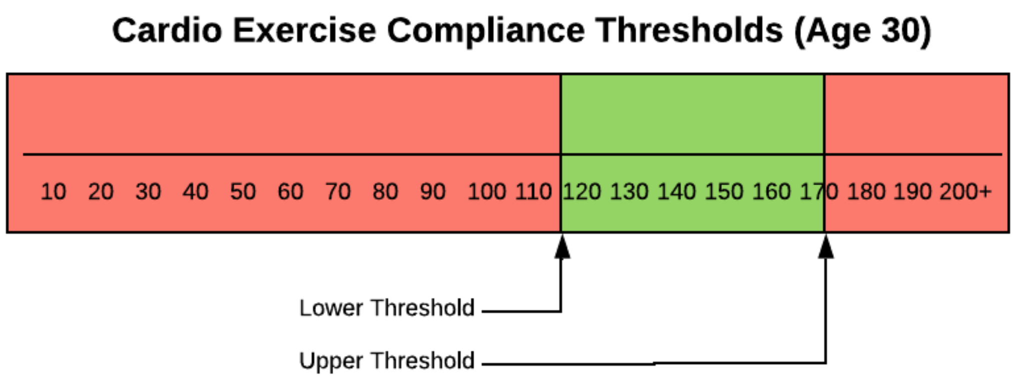

Figure 4.3: A Simple Example of a Compliance Threshold

The last step within the anticipatory loop is the "feedback and delivery" portion which looks to provide a signal to disrupt the future context of an individual if the system deems that it is a dangerous one. An important consideration in the delivery of feedback is the understanding of what performance thresholds exist within the limitations of the individual's spectrum of ability. These thresholds become person-centric determinations of compliant versus non-compliant states for the individual and determine when feedback should be delivered.

As an example, one of the main considerations in the prescription of standard exercise programs by trainers is an individuals fitness threshold as measured by their resting heart rate. People of varying levels of fitness, weight, BMI, etc. cause them to have different basal heart rates and thus different levels of tolerance for strenuous activity. Knowing that, a system can then determine their target heart rate and unsafe heart rate threshold as an upper bound as shown in figure 4.3. A AII treadmill device can anticipate that an individual will have a heart attack or other complication based on this information and intervene when the heartbeat for that specific individual (based on his or her blueprint and assessed fitness) surpasses the threshold of compliance.

4.2 Adaptation to Intrapersonal Variations

As individuals progress through the various stages of a disability/neurological disorder, their proprioceptive capabilities, motor ability and reactive capacities change in time. These changes can either be improvements through continued use of AT or could be a degradation due to the disorder. Thus, it is important that the thresholds for feedback discussed in the above section also adapt over time to address these shifts in ability. In considering the principle of adaptation, it is important to answer the following questions:

1. What specific parts of the system need to be adapted?
2. How do we know when the thresholds need to be changed?
3. To what degree and how often are the values adapted?

4.2.1 Characteristics of Adaptation

There are two main points of adaptation that can occur within the system in order to shift the burden of adaptation from the user to the device. Those two things are:

adaptation of threshold and adaptation of feedback.

Adaptation of Threshold As an individual fluctuates in their degree of body compliance over time, it is critical that the system adapts the thresholds for which they are considered compliant to match this change in ability. The system should maintain an optimal compliance target in order to maintain engagement and to eliminate frustrations associated with unrealistic or undemanding goals. Similarly, static thresholds can result in injury do to impaired ability as a result of fatigue or other internal factors associated with degraded motor performance. A user straining to hit an unrealistic threshold based on their current internal context given slower muscle response time and/or limited range of motion.

As an example, in the case of a bilateral jumping exercise for muscle rehabilitation, an individual may get tired after a number of repetitions and no longer be able to hit the target jump-height threshold. The system should, either through internal sensing or external intervention, relax the goal threshold over time or make recommendations on taking a break. In the external intervention approach, this could be a trainer pausing the system and instructing the individual to rest or adjusting the goals for the next set of repetitions manually.

Adaptation of Feedback As an individual gets more experience using an AII, the goal is that they adapt to the feedback quite well. However, if feedback is never adjusted over time, this can create a dependency on feedback which can cause relapses in motor performance with the absence of the device. Thus, the frequency of feedback could be faded over time to address this issue of dependency and promote the reconstruction of the body's natural systems for sensation of compliance and proprioception.

As an example, in the case of providing feedback for the correction of gait, a starting point might be providing feedback on every step that the user takes. As the user adapts to this feedback over time, feedback might fade to only providing signals on every other step or every third step. Once this level of adaptation is achieved, the system might switch to only providing feedback on incongruent steps after an anomaly is detected. This progression gradually softens the dependency curve. However, this approach may not always be feasible in instances where the individual's proprioceptive systems cannot be rebuilt and require longterm augmentation.

4.2.2 Triggers of Adaptation

As mentioned in section 4.2.1, baseline thresholds of compliance can either be determined in a "supervised" context where an expert can provide measures through observation or they can be determined in an "unsupervised" context where the system has a training period to gather baseline conditions from the user himself/herself. Once the system has a baseline, the upper and lower limits for compliance should be updated over time based on user performance. A continued pattern of errors could result in a relaxation of boundary values and a pattern of repetitive successful actions could result in a tapering of boundaries. Tadayon discusses an example of this model of adaptive feedback thresholds within the application of serious games for rehabilitation (Tadayon, 2017) and outlines two applicable approaches: cluster analysis and bayesian networks.

4.2.2.1 Cluster Analysis

This technique uses a set of features (such as those developed in the motion blueprint) to classify subjects with similar motor capabilities or performance, or to classify the behavior of a single subject based solely on their own performance. This allows the approach to be used as an adaptation technique for both inter and intrapersonal variations. The system determines over time what "categories of performance" an individual can fall into by creating up to K classifications and then collecting performance data for that individual over time to train itself. This approach requires time for the system to learn about the individual and can become stronger and more fine-tuned the more data the system gets over time.

For the intrapersonal scenario, each performance of a task (ex. a step taken or a repetition of a motion of exercise) is considered against the set of historical performance data points. Using a pre-defined set of rules, the system will categorize the new point within an existing cluster of data. A rudimentary approach could simply look to classify as compliant or non-compliant based on the various parameters of the data point. A more complex approach could further sub-classify non-compliant points based on suspected cause. For example, threshold relaxation should occur only temporarily for non-compliance due to fatigue versus cognitive load.

In the interperonsal scenario, this approach looks to classify an individual with others who have similar characteristics or progression/regression patterns over time. This is a common prediction technique in domains such as online shopping where user behavior can be easier compared to others in a similar cohort. As an example, if two users buy 3 products and have the similar reviews of those products, when User A purchases product 4 and rates it well, we know that we can recommend it to User B based on their history and patterns of behavior. The biggest challenge is that in domains that are less binary, such as motion performance, the selection of the clustering criteria becomes much more nuanced. Because of the idiosyncrasies associated with motion, the assumption that interpersonal variations can be generalized over time relies on there being an immense and well distributed dataset in order to find accurate segments. However, assuming a representative dataset, principles of domain adaptation and transfer learning could be effectively applied.

4.2.2.2 Bayesian Networks

In this approach, the system maintains a qualified belief about the user's current state of progress which is adapted in real time based on current performance trends. Bayesian Networks (Pearl, 1988) and more specifically Dynamic Bayesian Networks (Reye, 2004), a form of Bayesian Network tailored for real time analysis, can be excellent models for adaptation. As an example, Pirovano et al. utilize a simple approximation of performance as a "hit ratio", relating the number of successful attempts at a motion to the total number of attempts (Pirovano *et al.*, 2012). The authors take a naive approach in assigning a preliminary target ratio based on previous performance or expert opinion. Performance is then monitored on a "per-attempt" basis (in the example of Parkinsonian gait, this could be per step) based on a comparison of the targets current hit ratio and the target ratio. If the current hit ratio is below the target then criteria around compliance can be loosened while the opposite occurs if the hit ratio is above the target.

4.2.3 Windows of Adaptation

After first identifying what should be adapted (section 4.2.1) and when it should be adapted (section 4.2.2), the AII should then consider how threshold or feedback should be adapted. Regardless of if the threshold or feedback are being manipulated, considerations must be made as to if the shift should exist within the spatial and/or temporal domain. Within the spatial domain, the system considers how big of a step up or down should be taken. Within the temporal domain, a shift in frequency is taken into account. In the hit-ratio detection approach outlined in section 4.2.2.2, the system should default to making shifts in small increments to the frequency of feedback delivered. The windows for frequency are determined by iterations which are encompassed in the motion blueprint outlined in section 4.1.2. Once the system determines what comprises one full iteration, it can then create a window that is first very frequent (once per iteration) and can relax over time when it determines that the individual's performance has become relatively consistent. If, after frequency adjustment, the ratio still does not reach a desired positive outcome, bigger shifts should be considered. Adaptation of feedback should always be considered before adaptation of threshold as it has smaller longterm consequences (increased device reliance versus compliance performance degradation).

As an example, in the case on adaptation for Freezing of Gait, if the system continuously detects degraded performance over time it may eventually classify the individual as a higher risk category on the FoG scale. At the point, if the AII was providing feedback only on steps where non-compliance was predicted, the system might change the frequency of feedback towards a more consistent method of feedback on some compliant steps as well as all those predicted to be non-compliant. It this still doesn't achieve the desired hit-ratio, the system might again adapt frequency to provide feedback on every step. Given that providing feedback on every step is the upper limit on our ability to increase frequency, if positive change is still not detected, the system should then determine the degree to which target gait parameters (target cadence, target step length) should be loosened.

4.3 Context Aware Invisibility

There are two main considerations in creating a device that are contextually invisible:

1. The data collection/input mechanism of the device should blend into the user's existing day-to-day activities.

2. The feedback delivery of the device should scaffold off of existing cognitive models and not introduce additional cognitive load.

4.3.1 Invisible Interface

Traditional devices require that the individual explicitly interacts with some sort of visible interface or physical buttons. The concept of invisibility looks to abstract the interface away from the user and use the individual's movement, body characteristics and internal context as an implicit form of interaction. This means that the user is, in effect, constantly interacting with the device through his or her activities of daily living. As an example, in the scenario of body compliance during rehabilitative exercise, an individual simply using the exercise equipment becomes the input for the technology.

As technology becomes more ubiquitous, the ability to seamlessly embed devices into day-to-day environments becomes easier. In order for a device to be contextually invisible, the design must first consider what elements within the environment are static and thus applicable as hosts for which the technology may be embedded. In scenarios where the external environment is changing, the subject's clothing or body can be considered as the static anchors for the system. The context of environment becomes the determinant of a wearable or embeddable approach.

4.3.2 Invisible Feedback

The concept of context aware invisibility relies on the device's ability to fade feedback into a subconscious process and not detract from primary motor tasks such as walking or exercising. This means that feedback needs to be designed in a way that does not introduce a secondary cognitive task on the user, but instead, almost becomes an extension of their own proprioceptive system.

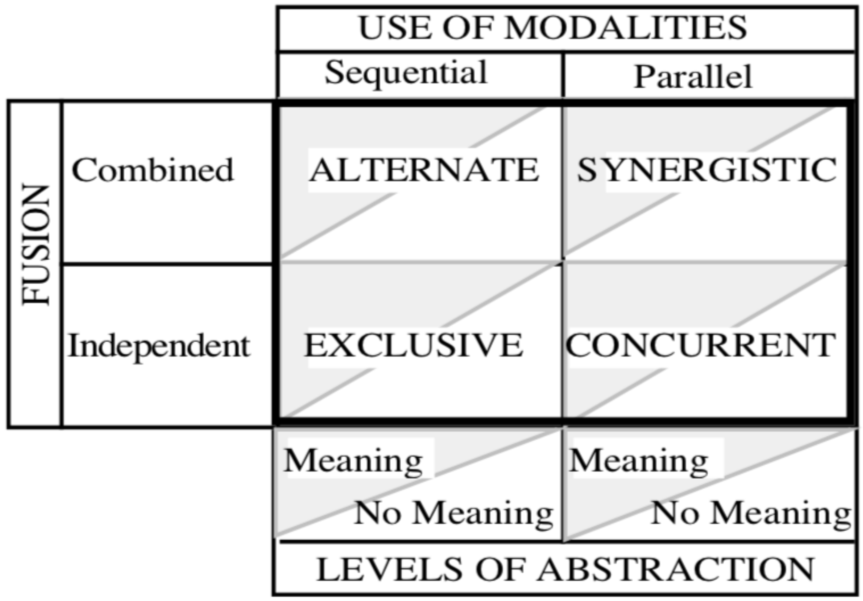

Figure 4.4: Nigay and Coutaz (1993) Classification Model for Multimodal Feedback Systems

Since human interaction is multimodal by nature (Bunt *et al.*, 1998), AII's must consider the integration of feedback modalities in trying to scaffold off of existing cognitive models. Much prior work in the realm of HCI has been interested in suggesting strategies for weaving different mediums of feedback across multiple application domains (Johnston *et al.*, 1997; Wu *et al.*, 1999; Chai *et al.*, 2004; Mendonça *et al.*, 2009; Song *et al.*, 2012). Nigay and Coutaz (1993) present a classification model of multimodal systems (figure 4.4) which support two salient properties: concurrency of processing and data fusion. The concurrency of processing dimension primarily covers the absence or presence of parallelism in the presentation of feedback cues across multiple modalities. An example would be providing auditory and visual cues at the same time. The dimension of fusion looks at the combination of different types of data. The union of the axis "Fusion" and "Use of modalities" result in four categories of systems: "Exclusive", "Alternate", "Concurrent", and "Synergistic".

Alternate In this approach, multimodal feedback, where the different modalities represent the same type of information, is delivered sequentially. This means that information related to a single task can be first provided through auditory, then through haptic and finally through visual in a progressive manner. Given the variation in degrees of freedom and perceptual bandwidth, the different modalities can vary with respect to the granularity of the feedback that they are providing. In the rehabilitative exercise example, a device could first play an auditory tone to inform the user that they are off balance and allow the user to attempt to correct their posture. If they do not respond well after a certain amount of time, it may switch to providing haptic guidance to inform the user of which direction they need to shift their body. If they are still not centered, the system can provide visual information to show exactly what part of their body is misaligned. Given that all modalities are focused on a specific type of information, the system loses the ability to provide feedback across the multiple dimensions necessary for body compliance.

Synergistic In this approach, cues across multiple modalities are presented together and are all uniformly assigned to the same type of information or task. This means that the system determines a single type of motor adjust to focus on at one time and uses any combination of feedback modalities to inform the user. As an example, in the Parkinsonian gait application, this could look like the combination of rhythmic auditory stimulation with haptic patterns to provide feedback on step cadence and gait rhythm. This approach works well in scenarios where there is a single point of focus for the user at any given time such as simple motions since the device is focusing all attention on an individual piece of information. However, for more complex and dynamic tasks, the device is determining a prioritization scheme and may have to forgo the delivery of other relevant critical information.

Exclusive The exclusive feedback category of systems refers to those which sequentially deliver multimodal feedback cues with each modality being associated to a different type of information or task. This is achieved by segmenting the different classifications of feedback and assigning each to its own modality and presenting those consecutively as an individual progresses through a movement. This allows the individual to focus on a single piece of feedback at a time and also categorize feedback modalities to create associations with intended behaviors. However, given that the feedback modalities are presented sequentially, this can have significant impact if there are two different pieces of information that need to be delivered to the user simultaneously. It, in essence, creates a race condition where certain feedback types need to be inherently prioritized over others. In considering body compliance during rehabilitative exercise, this could mean that we are prioritizing feedback related to safety and injury over cues related to progression.

Concurrent This approach differs from the exclusive approach in that it looks to provide feedback across multiple modalities in parallel cues. The feedback cues are not combined and maintain that each modality provides a disjoint type of information to the user. In the Parkinsonian gait application, this could be implemented by using auditory feedback to provide information relative to postural stoop while also using haptic feedback to provide step length and cadence information. This approach allows for all relevant information to be simultaneously presented and relies on the individual to be able to effectively compartmentalize the different cues being delivered. The user is also put under additional cognitive load as they are undergoing a constant exercise in prioritization of feedback response. This may mean that their personal preferences for getting feedback in one modality over another will result in their prioritization of response to that information.

Chapter 5

BODY COMPLIANCE DURING REHABILITATIVE EXERCISE

5.1 Introduction

Training and exercise programs, under the guidance of skilled therapists and trainers, have become important tools during the rehabilitation process for individuals who exhibit issues with proprioception. In the past, these programs have been impossible to adequately implement in an at home environment due to the need for a trainer to observe and provide realtime feedback on body compliance during the performance of the motions required for exercise. Non-compliance caused by impaired proprioception can result in serious injuries and counteract the intended benefits of the exercise programs which, if left uncorrected, can significantly slow motor learning as a consequence. New research is actively seeking new automated methods for the detection and intervention of non-compliance in unsupervised environments. Within the realm of non-compliance detection and prevention, there are two main challenges that together comprise the bulk of the scope of work:

- **Anticipation:** how does a system anticipate the occurrence of non-compliance?
- **Intervention:** how does a system intervene to correct the behavior of the individual to prevent prolonged non-compliance?

In this application, an anticipatory system is introduced to detect and intervene before non-compliance or compensation occurs (Tadayon *et al.*, 2017). The application of anticipation, rather than detection, in this space is especially important given the subsequent risk of injury to the individual that increases for any time spent in a non-compliant state. Although detection has been adequately explored in prior work, this level of forethought and prediction has been lacking. Once risk of injury is adequately detected, the system provides multimodal feedback through auditory, visual and haptic cues to correct the harmful behavior before it results in injury. The feedback protocols have been mapped to the same modality of feedback that the trainer would give which was dependent on the context or type of issue.

The initial application area of rehabilitative exercise for individuals with cerebral palsy is used to provide a context to demonstrate the effectiveness of the system in anticipating and correcting body position. Although cerebral palsy is not neurodegenerative in nature, because the symptoms have "varying severity and complexity" across the lifespan of an individual, it is still considered within the domain. In this application, the SmartGym, an intelligent Total Gym Pro that monitors an individual's performance and provides feedback through haptic, auditory and visual cues is proposed. Prior work shows the need for an effective tool for anticipation, rather than detection, of potentially dangerous body states, which is explored in the design of the SmartGym. An overview of the implementation of anticipation is given with details and justifications for design decisions in the feedback that the system provides. The prototype is evaluated for both usability and effectiveness in a case study involving an adult with cerebral palsy who has developed a hemiparetic lower extremity and her physical trainer. The system is deployed within the subject's regularly scheduled training and presents feedback to test the effectiveness of replicating the trainer's feedback.

The proposed approach has two main objectives:

1. Anticipate when a user is going to become non-compliant before injury occurs

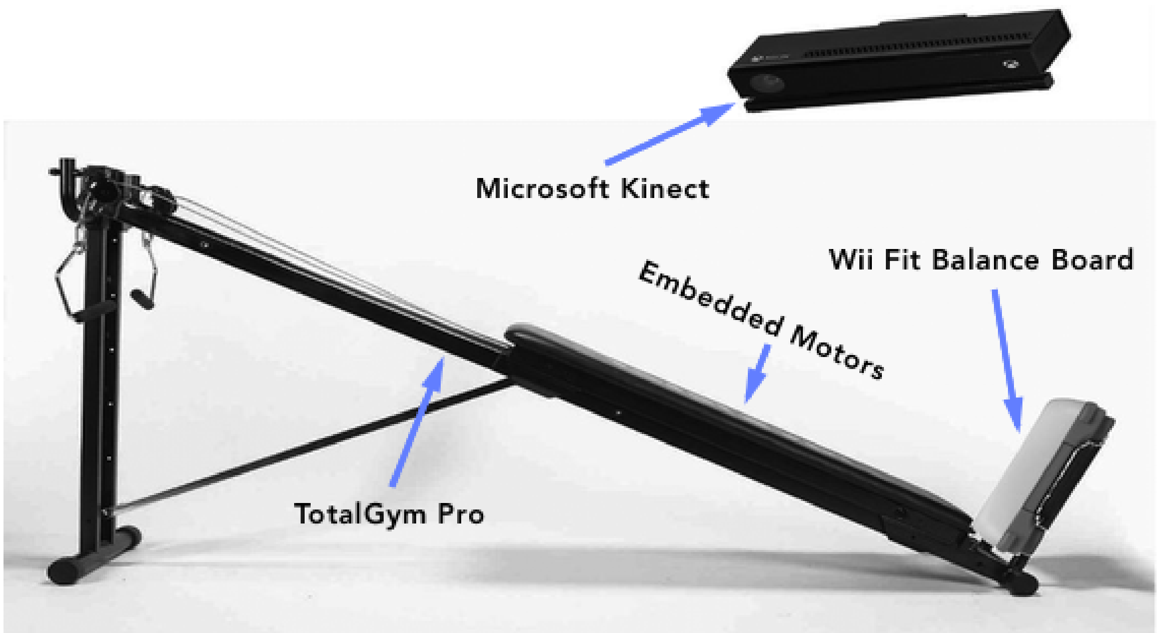

Figure 5.1: System Design for the SmartGym (Tadayon *et al.*, 2017).

2. Provide multimodal feedback to an individual so that they can correct their body in real-time

To achieve the goal of anticipation, the system breaks down the problem of non-compliance by looking at sensing events that occur before risk of injury. In determining the risk of an accidental fall from the Total Gym machine, the system considers center of balance and postural stability as both of these are key attributes that worsen gradually throughout the individual's exercise routine. These attributes worsen due to lack of attention to proper form and are often exaggerated due to fatigue. In calculating center of balance, the SmartGym measures pressure placed by each foot against the landing plate of the Total Gym Pro and warns the user when compensation occurring between the affected limb and unaffected limb is sensed. Compensation can lead to early fatigue and can also lead to the individual being imbalanced before the start of a movement leading to injury during landing. Secondly, the system considers postural stability by looking at body alignment and warning the user if he or she is leaning to one side while lying down on the machine. By sensing these two indicators, the system can anticipate that the user is going to enter a non-compliant state and provide feedback to correct this before injury.

In order to provide feedback to the individual, three modalities are used: auditory, visual, and haptic. The three feedback channels were chosen to map to the feedback that is given by the instructor during supervised exercise. The instructor begins by verbally informing the individual to correct posture or balance. He or she will then visually show the correct body positioning themselves so that the individual can mirror this. Finally, the trainer will physically touch the limb or area of the body that is out of position to shift it back into place. This methodology is emulated in the SmartGym since the system begins by making an auditory tone, then displaying a visual feed of the subject's body superimposed upon an image showing the correct body posture, and finally vibrating the Total Gym board to inform the user of the direction that he or she must shift in order to return to a compliant state.

The SmartGym has been built and integrated with the Total Gym Pro (a commercially available piece of exercise equipment). The system consists of a Wii Balance Board, a laptop with Bluetooth communication, a Microsoft Kinect, an array of pancake motors, an Arduino Uno and a webcam. The laptop serves as the central link between all the devices and uses information from each of the sensors to anticipate when the user is going to enter a non-compliant state.

The Balance Board is positioned on top of the landing platform of the exercise equipment and is used to detect pressure applied by the feet. Each of the user's feet has two pressure sensors under it to measure the difference between pressures put on the ball of the foot versus pressure put on the heel. This pressure is used to determine balance throughout the exercise motions. The system is able to detect

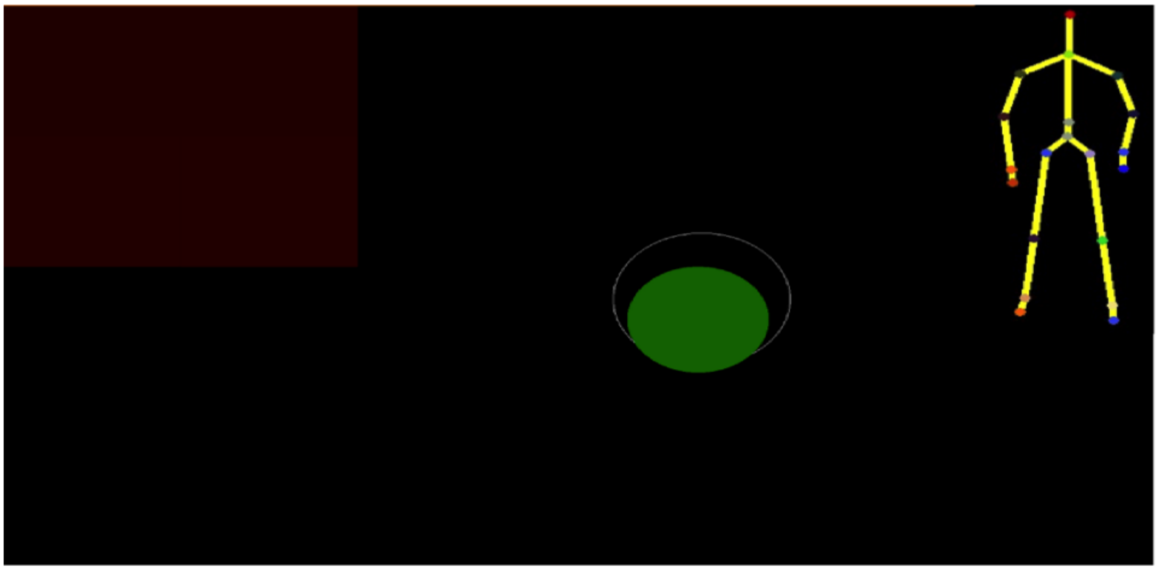

Figure 5.2: Interface Design for the SmartGym That Includes a Visualization for Pressure Between Feet on the Left, Center of Balance in the Middle, and Joint Tracking on the Right (Tadayon *et al.*, 2017).

if the user is compensating by using one foot more than the other or, similarly, if the user is compensating by prioritizing the ball or heel of one foot. This is done by comparing cumulative pressure on each of the four pressure sensors within the Wii Fit Balance Board. When pressure placed on one sensor is measured as greater between two repetitions of the exercise, the system flags the event as compensation. A webcam is also placed facing the individual's feet to give a heads-up display indicating where the user's feet are positioned on the Balance Board to avoid false positives because of incorrect alignment of the feet. This is an important factor given that impaired proprioception is a common side-effect within our target user population.

The Kinect is positioned above the exercise equipment and faces down toward the user to measure joint and skeletal position. Prior work has shown that the camera can achieve a high degree of accuracy in measuring joint angle positions within 50-100mm (Wang *et al.*, 2015; Mobini *et al.*, 2014). This measure gives insight into postural stability during movement and warns the user when his or her body exits

Figure 5.3: Location of the Pressure Sensor and Pancake Motor Pairs Along the Outside of the Total Gym Pro (Tadayon *et al.*, 2017).

the threshold for compliance. Measurements are collected for the shoulders, elbows, wrists, hands, hips, knees and feet. Before starting the exercise, the user is asked to hold a neutral state in which all joints are lined correctly for the upcoming motion. The system captures these positions and uses them to create a bounding box around each of the joints that determines the threshold for compliance. This threshold is set as a variable within the system and can be adjusted by the trainer to become smaller as the individual progresses within their exercise routines. As an example, the baseline threshold of compliance for knee position was set to check within 100mm of the normalized perfect posture. All information from these sensors is streamed to the laptop, which handles all of the processing and gives the auditory and visual feedback.

Two arrays of six pancake vibration motors were embedded onto the Total Gym Pro's padded board and placed horizontally spanning the outside edges of the board as shown in Fig. 5.3. Each of these motors has a pressure sensor connected to it which will detect if the user is beginning to lean or slide to one side of the board before or during the exercise. These motors and pressure sensors were connected to an Arduino Uno which served as the logic unit for this feedback mechanism. If the pressure sensors pass a certain threshold as determined by the user's upper-body weight, the haptic motors are activated and are used to guide the user back to a neutral state where he or she is balanced on the board. Twelve motors were used in order to fully span

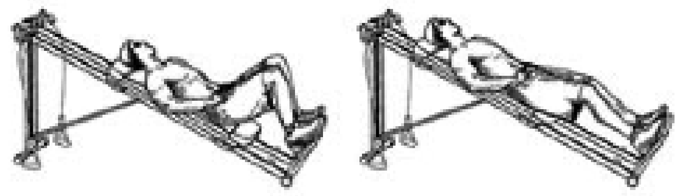

Figure 5.4: Squat Exercise (Tadayon *et al.*, 2017).

the area on the board that a user's body could encompass. This allows the device to detect shifts from the shoulders all the way down to the user's hips. The motors will continue to vibrate until the user shifts his or her body to rectify their postural stability. Given the information that is gathered through the Kinect and presented on the visual interface, this information can sometimes be redundant, but serves to offer the user multiple modalities of feedback that he or she can choose between. Occasionally, a user's vision might be pre-occupied with an alternate task and thus haptics can be a more effective method of providing knowledge of performance.

The system was designed for use by an individual with cerebral palsy during rehabilitative exercise. Specifically, an exercise is employed wherein the individual starts with his or her feet against the landing plate, as shown in Fig. 5.4, and presses off to slide up and then lands back on the plate. According to the trainer in this work, the key components of this exercise are to ensure that the individual has both knees and feet together throughout the entire exercise and to make sure that they are positioned on the center of the exercise equipment in order to avoid falling off or injuring themselves. The trainer's role is to monitor the individual throughout this exercise and to provide feedback whenever he or she is breaking these safety guidelines. The interface and feedback have been mapped to the same protocol that the trainer uses in instructing the individual to correct body positioning as shown in Table 5.1.

Behavior	Trainer Feedback	SmartGym Feedback
Uneven Feet	Tell the subject and demonstrate correct positioning with his own body	Show heat map with differentiating colors to show which foot is uneven. Camera on the user's feet to also augment lack of proprioception.
Imbalanced	Tell the subject to align their body	Circle shown which changes to green once proper balance is achieved
Sliding Off Platform	Tell the subject to move back to the center of the board. If that doesn't work, physically help the subject by pushing the non-compliant body part back onto the equipment.	Red points shown on body map to signify which joints are out of position. Tone played until body is compliant. Haptic signals also used to guide the user.

Table 5.1: Feedback Protocol

For the purposes of this system, only individuals with moderate, hemiparetic cerebral palsy are considered as these individuals can often gain better motor control through rehabilitative exercises. However, this design can also be used in many other domains where hemiparesis can occur such as in stroke since the same principles of body compliance and compensation play major roles.

5.2 Idiosyncratic Design

5.2.1 Standardization of assessment

In determining the standardization of assessment, the SmartGym considered the main goal of the exercise program being delivered. Due to the hemiparetic nature of the disorder, all of the motions where focused on the elimination of compensation from the unaffected limb and the re-development of muscular control on the affected side. Thus, compensation was selected as the criteria by which to asses the user over time. Because the trainer had method of measuring compensation outside of strict observation, the introduction of this assessment method required the acquisition of a baseline. The trainer was able to adequately look at the subject while performing the exercises and note when he presumed compensation was occurring, but had no way of quantifying it. Through the use of the SmartGym, the system was first used without any feedback provided as an assessment period and collected baseline measurements.

5.2.2 Motion Blueprint

Once compensation had been identified as the key metric of measurement, the system must then break down compensation into its atomic components to create a blueprint of the user's body compliance during exercise. Through feedback from the trainer, it was determined that balance and body position are the two critical components that lead to compensation with position being a leading indicator and balance being a lagging indicator. Thus, the system must create a mapping of the users body and consider measuring these critical components to provide snapshots of compensation throughout the exercise regimen.

Postural stability and balance were primarily collected through the use of the WiiFit balance board which was able to detect shifts in body weight between the two lower limbs during the preparation period as well as the landing period of the exercise. Pressure sensors embedded within the platform were also used to detect when the subject was leaning towards one side or another. The pressure sensors were synced to the individual's body weight and measured only when equilibrium was breached between the two sides of the platform. Similarly, a Microsoft Kinect camera was used to measure joint and skeletal position as these are the two critical underlying factors that lead to postural instability and, consequently, compensatory behavior. Combined, these data points served as the holistic blueprint for which thresholds of compliance would need to be determined by the trainer.

5.2.3 Person-centric Compliance Threshold

Once a blueprint was put in place, the trainer provided an initial set of guidelines on what was considered compliant based on his prior experience working with the subject. Without this initial input, the system would assume that a "compliant" state for the subject occurs when their body weight is completely equally distributed between the left and right feet. Similarly, the system would assume that the individual should be fully aligned with respect to their shoulders, hips and knees. However, based on experience, the trainer noted that the affected limb could currently only maintain a 20-30% threshold of body weight and thus these parameters were adapted to be person-centric. Throughout the exercise routine, they were continuously adapted based on observation of system feedback where the trainer would note that the subject was starting to be fatigued and thus the thresholds should be slightly relaxed. Similarly, feedback methodologies needed to be adapted to match the trainer's existing modalities.

As shown in table 5.1, an initial feedback protocol was developed to map to the trainer's existing approach based on this subject's learning methodlogy. In a preliminary user study, the system tracked the amount of time spent in a noncompliant state and found that the subject was much quicker to respond to haptic feedback rather than the other modalities. Survey results also showed that the subject preferred haptic feedback over visual since the haptic feedback mapped better to her internal perception of self. This demonstrates the importance of learning preference in the development of person-centered technologies and the need to develop adaptive feedback protocols which can support various learning biases. Because of the modularity in the feedback design of the SmartGym, the mappings can be easily adjusted to shift preferences to one modality over another. Although relatively little research has been done to examine the effects of learning styles and learning style preferences in the realm of motor learning in contrast to classroom learning (Alvine, 2015), the Learning Styles Hypothesis developed from Pashler et al. claims that learners will perform better when instructed using their preferred style of learning (Pashler *et al.*, 2008). Thus, a few approaches to adapting for visual, auditory and kinesthetic learners are discussed below. Although these protocols rely on a primary feedback modality, they still maintain principles of multimodality and redundant feedback. The primary feedback modality is denoted through the use of perceptual bandwidth in that the modality which conveys the most information relevant to the intended behavior is deemed as the primary.

Although the use of a primary modality for feedback can help map more closely to an individual's preferred style, very rarely is an individual a strictly unimodal learner. Rather, learning styles fall on a spectrum of preference where, although there may be one style with a greater preference than the others, the individual may still learn well in other modalities. The predominate standard for learning style evaluation in research is the VARK questionnaire. The VARK measures four perceptual preferences: visual (V), aural (A), read/write (R), and kinesthetic (K) to provide scores in each of these of these learning types (Fleming and Baume, 2006). Prior work has suggested that the threshold of neural activation is reached earlier by multimodal learning than by unimodal learning (Seitz and Dinse, 2007; Shams and Seitz, 2008). These stimuli are also typically perceived more precisely and quickly than strictly unimodal stimuli (Doyle and Snowden, 2001; Forster *et al.*, 2002; Fort *et al.*, 2002; Giard and Peronnet, 1999). This holds true even during active movements (Hecht *et al.*, 2007) such as the jumping squat motion discussed in the application. Therefore, although having a primary modality to support learning styles is important, maintaining some level of redundancy can have beneficial effects in motor learning contexts.

5.2.3.1 Visual Learners

Behavior	Trainer Feedback	SmartGym Feedback
Uneven Feet	Tell the subject and demonstrate correct positioning with his own body	Show heat map with differentiating colors to show which foot is uneven. Positive tone played once balance is achieved.
Imbalanced	Tell the subject to align their body	Circle shown which changes to green once proper balance is achieved. Positive tone played once balance is achieved.
Sliding Off Platform	Tell the subject to move back to the center of the board. If that doesn't work, physically help the subject by pushing the non-compliant body part back onto the equipment.	Red points shown on body map to signify which joints are out of position. Overlay a compliant outline over the subject's body. Haptic signals also used to guide the user.

Table 5.2: Visual Feedback Protocol for the Trainer and SmartGym

For informing the user of uneven foot placement, the system shows a heat map of the pressure plate that the user is standing on. The heat map is split into four quadrants that show colors spanning from light red for little pressure to dark red for high pressure. The user's goal is to get all four quadrants to the same color to achieve symmetry. When conformity is achieved, a tone is played to reinforce that the user is now ready to perform the exercise. In this scenario, visual feedback is used to inform the user of the non-compliance as well as provide feedback on knowledge

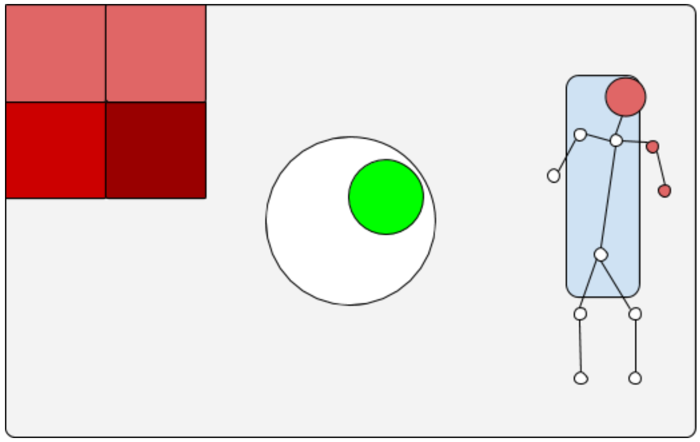

Figure 5.5: Interface Design for Prioritizing Visual Feedback.

of performance and knowledge of results as the heat map adapts while the user is adjusting his or her positioning. Auditory feedback is used strictly to reinforce the feedback on the user's knowledge of results.

Similarly, if the user's body is imbalanced, the system gives this feedback through the use of a ball that shifts around the interface with the user's weight distribution. If the user leans to the right, for example, the ball will shift to the right side of the screen. There is a target circle in the middle of the interface within which the user must attempt to center the ball. As shown in figure 5.5, when the ball fully enters the compliant zone, it changes color from red to green. An audio tone is played to reinforce and affirm this compliance.

If the user is sliding off of the platform, the system can show the user's skeletal outline as an overlay to the underlying platform to show how the body is aligned with the device. The user can visually see that his or her body is off-center and areas that need to be adjusted will be marked in red as shown in figure 5.5. As the user shifts the body, so does the avatar to give feedback on performance and progression towards compliance. A haptic pattern can also be given to the user's back on the side that he or she is leaning towards to "nudge" the user back towards the center of the board. In this scenario, the haptic feedback serves as as a secondary feedback mechanism that supports the visual feedback being given by the system. Once the user is centered on the board, the haptic feedback stops and the avatar will no longer have red zones for non-compliance.

One of the main challenges with this approach is that the interface can easily become too cluttered and the user has to shift his or her gaze from one point-of-interest to another in order to get a full understanding of what adjustments need to be made. This can become especially chaotic when having to also conduct a complex movement for the exercise. As the user is shifting up and down on the platform, it can become very difficult to maintain a line of sight on the feedback interface.

5.2.3.2 Auditory Learners

Behavior	Trainer Feedback	SmartGym Feedback
Uneven Feet	Tell the subject and demonstrate correct positioning with his own body	Play audio of trainer giving feedback on which foot is uneven and what needs to be done to correct. Visual check mark displayed on the interface when the user is compliant.
Imbalanced	Tell the subject to align their body	Play audio of trainer telling the subject to place equal pressure on the affected limb. Visual check mark on the interface when the user is compliant.
Sliding Off Platform	Tell the subject to move back to the center of the board. If that doesn't work, physically help the subject by pushing the non-compliant body part back onto the equipment.	System tells the user which way to shift his or her torso in order to align with the platform. Haptic signals also used to guide the user.

Table 5.3: Auditory Feedback Protocol for the Trainer and SmartGym

Auditory feedback protocols can be developed to map directly to the instructions that the trainer regularly gives. In most scenarios, even if the trainer is demonstrating visually, the trainer is also explaining verbally what the undesired behavior is and what the correct positioning should be. This feedback protocol would rely on the verbal instructions that the trainer gives at critical points and use haptic and visual cues as secondary feedback points strictly to reinforce the feedback on the user's knowledge of results. Audio of the trainer's instructions could be pre-recorded and played back to the subject when the system anticipates non-compliant behaviors.

As an example, to inform the user of uneven foot placement, the system could play an audio clip of the instructor explaining which foot is misaligned and what the subject needs to do to adjust his or her body. Progression clips could also be played as the user is making adjustments giving words of encouragement to reassure the subject that his or her postural corrections are acceptable. Once the user has reached compliance, an auditory confirmation can be played and a visual check mark can be displayed on the screen showing that the feedback has effectively been addressed. Similarly, when the user is imbalanced, the system can relay the trainer's voice telling the subject to shift his or her weight to one direction or the other and a visual check mark can confirm this for the subject as well after the necessary adjustment is made. Lastly, if the user is sliding off of the platform, the system can tell the subject to either shift his or her torso to the right or the left. Haptic patterns can also be used here to guide the user back into the center of the board. Once the user is realigned with the board, an auditory confirmation message can be played along with the discontinuation of the haptic signal.

One of the main challenges of auditory feedback is that these signals can often make it challenging to provide multiple instruction points at one time. The system must play the audio synchronously so that the user can process one message at a time. This greatly reduces the effectiveness of the protocol for on-the-fly modifications and rather requires the user to pause, adjust, and then continue motion. This approach also relies on there being a finite number of potential variations of non-compliance that can be pre-recorded.

5.2.3.3 *Kinesthetic Learners*

Behavior	Trainer Feedback	SmartGym Feedback
Uneven Feet	Tell the subject and demonstrate correct positioning with his own body	Haptic patterns on the user's shank to convey what direction ankles need to be rotated or knees need to be shifted. Camera on the user's feet to also augment lack of proprioception.
Imbalanced	Tell the subject to align their body	Haptic pattern at the subject's hips to convey weight distribution. Ball shown on the screen to reinforce weight shifts and center of balance.
Sliding Off Platform	Tell the subject to move back to the center of the board. If that doesn't work, physically help the subject by pushing the non-compliant body part back onto the equipment.	Haptic signals also used to guide the user to the center of the balance. If the user is leaning to one side, haptic array activates to pull the user back into the center.

Table 5.4: Kinesthetic Feedback Protocol for the Trainer and SmartGym

Kinesthetic feedback protocols rely on haptics as the primary mode of information transfer. Within the SmartGym application, the subject preferred haptic feedback over visual or auditory and reacted much faster to these signals. The current system relies on two rows of haptic motors aligned on the sides of the Total Gym Pro.

However, for this approach, more vibrotactile motors would need to be added to the system in order to effectively communicate these various behavior changes. Namely, this approach proposes the use of haptic bands, such as the Myo Armband (noa, 2020), to provide additional feedback sites at each of the user's shanks.

For informing the user of uneven feet, the system will use the haptic bands on the subject's legs to show patterns relating to fine motor adjustments of the lower limbs. The patterns can be directional or circumferential to inform the user of which body site is noncompliant (ankles or knees) and also what the corrective action should be. The intensity of the vibrations can give feedback on progression so that the user knows how far he or she is from being in a compliant state. A heads up display can be used to show where the user's feet are positioned as an optional redundant feedback mechanism. Similarly, a pattern can be played on the user's lower back, right behind the hips, with two actuators to give the user an idea of his or her center of balance. If the subject shifts weight to one side, vibrations on that side of the hip can intensify to push the user back to the other side. An affirmative auditory tone can be played when the user reaches compliancy. Likewise, if the user is sliding off of the platform, the system can use the protocol designed in the initial implementation to guide the user back into place. That is that if the user is leaning to one side, the array of motors on that side of the exercise equipment will activate and will stay active until the user is centered again.

Haptic feedback has the benefit that the user does not need to maintain visual attention throughout the motion of the exercise. Visual attention can be selective to augment the feedback gained from the vibration signals and can be used to reaffirm corrective actions. Although kinesthetic signals provided through the system have the advantage of asynchronicity in many respects, patterns displayed at a specific site still need to be synchronized. For example, patterns for knee shift and ankle rotation of the same foot cannot be displayed at the same time since they rely on the same output mechanisms.

Haptics for fine motor control

The principles of using haptic feedback for fine motor control have been well explored in the literature. Applications for these principles span from the field of medicine where devices with vibrotactile feedback for robot assisted surgery have been proposed (Schoonmaker and Cao, 2006) to whole body vibration therapy for rehabilitation of fine motor control (Cochrane *et al.*, 2009). Within the context of the SmartGym application, the utilization of haptic feedback has been proposed for fine motor control of the lower limbs as the subject responded more quickly to vibrotactile signals and also noted that this mode of feedback mapped more closely to her internal perception of body. Specifically, the goal of the haptic feedback is to affect the rotation of the ankle in the transverse plane and also provide feedback on knee positioning during the initiation and termination of motion. Although haptic feedback for lower limbs has not been explored nearly as much as feedback for the upper limbs, some work has been done to test the effectiveness of site-specific haptic feedback for the feet. Mildren et al. have investigated the use of vibrotactile feedback provided at the foot sole (heel or metatarsals) or foot dorsum in an ankle joint-matching task along the sagittal plane (Mildren and Bent, 2016). Some of the key features of the haptic modality that can be utilized to provide fine motor control guidance are its abilities to convey directionality (McDaniel *et al.*, 2008; Regenbrecht *et al.*, 2005), distance (McDaniel *et al.*, 2009) and spatial error (Lee *et al.*, 2011; Bark *et al.*, 2011; Kapur *et al.*, 2010).

As shown in figure 5.6, the trainer defines an acceptance threshold for foot positioning which can then be sensed through the use of the Microsoft Kinect. The

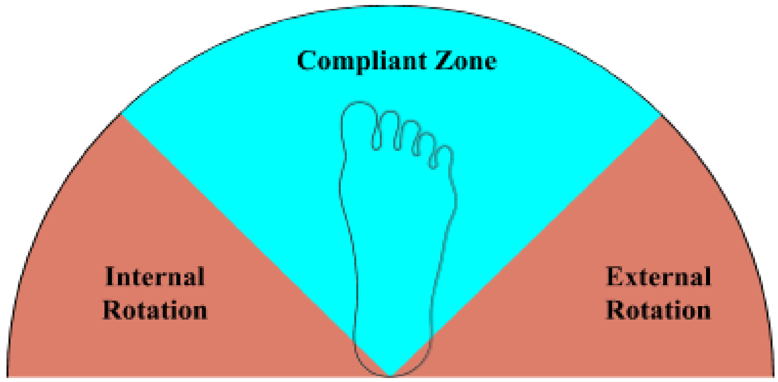

Figure 5.6: Ankle Rotation Acceptance Threshold

system needs to provide feedback on which limb is noncompliant and how to correct the issue. Currently, the individual's back is already occupied through the use of a vibrotactile display for gross motor functions that include overall body posture with respect to the exercise equipment. A rudimentary thought would be to implement patterns within the haptic display that could distinguish between gross motor issues and fine motor issues. However, there exist a few complications with this approach; primarily, maintaining mutual exclusivity between patterns involving upper body and lower body actions is a challenge. This is necessary because of overlapping patterns in the case of non-compliance in both the upper body and the lower limbs, wherein the feedback could become indiscernible. Similarly, providing haptic feedback on the back for an intended result in one of the lower limbs requires two cognitive steps: first the user must understand which limb the pattern is intending to affect, and afterwards he or she must perceive what the intended corrective action is. Site-specific haptic signals address these limitations.

Haptic Push/Pull Metaphor

One potential approach for site-specific signals would require the use of an additional set of motors that could be placed on each side (interior and exterior) of the the user's ankles and knees as shown in figure 5.7. The ankle is chosen because haptic sensitivity and spatial acuity is highest when the vibration is provided in distal body parts (Wilska, 1954). This approach would map to the same metaphors used in the design of feedback protocols for gross motor functions in this application and could thus potentially reduce the learning period for this new signal. The proposed vibrotactile feedback is built to push or pull the user's lower limbs back into a compliant state depending on ankle internal or external rotation and knee separation. With this approach, multiple patterns could be explored using the various degrees of freedom that vibration motors provide. As an example, if the user's right foot is externally rotated, the haptic motor on the inside of the ankle could activate and remain active until the user shifts his or her foot back in. Similarly, the feedback protocol could activate the motor on the outside of the ankle if the foot is internally rotated. The strength of the haptic signal could be modulated to various intensities depending on how far away the user was from a compliant state and could gradually diminish to an off state as the user shifts the affected foot in the right direction. Similarly, haptic signals could be produced on the inside and outside of the knee to affect knee abduction and adduction respectively.

This approach is beneficial in that it allows separate haptic motors for the knees and ankles so that the user does not have to first discern which body site needs to be adjusted. It allows for higher levels of granularity in feedback as the system can inform the subject of the exact body part that is out of compliance and can also provide information on the degree to which this body part needs to be adjusted in order to become compliant. Also, it maps to existing cognitive patterns that the user has developed for gross motor function as the same pattern design philosophy is used for those signals so the learning curve may be less steep. Where this approach is limited is that, when integrated with gross motor feedback, the user now has many different body sites (left back, right back, inside and outsides of both knees, insides and outsides

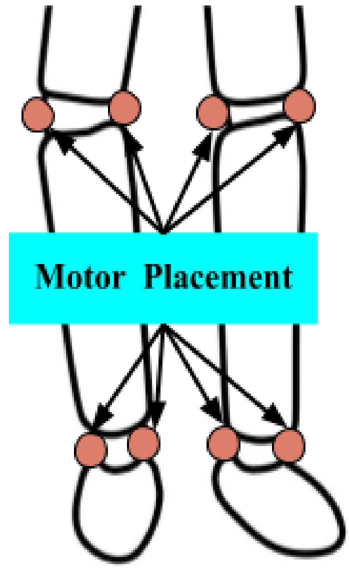

Figure 5.7: Haptic Motor Placement for Metaphor Approach

of both ankles) that he or she must pay attention to. There may be an issue with information overload if several of these body sites are out of compliance and the user must prioritize which feedback to attend to first. However, this could be addressed through software with a precedence structure where the most important corrections are given the highest intensity of vibrations. A secondary potential limitation is that the subject of the user study may lack the tactile sensitivity needed to easily perceive the patterns on the affected limb. In this case, this approach may not be suitable and a different body site may need to be used.

Follow the Signal (Saltation)

Another potential approach for fine motor feedback is through the use of a haptic illusion of apparent motion called saltation (Geldard and Sherrick, 1972). This approach would use a band of vibration motors placed around the shank (midpoint between the knee and ankle) that vibrate in a series of quick vibrotactile bursts which would be perceived as a train of evenly spaced phantom vibrations. Although the calf is not a common spot for haptic feedback, it maintains a similar vibratory threshold as that of

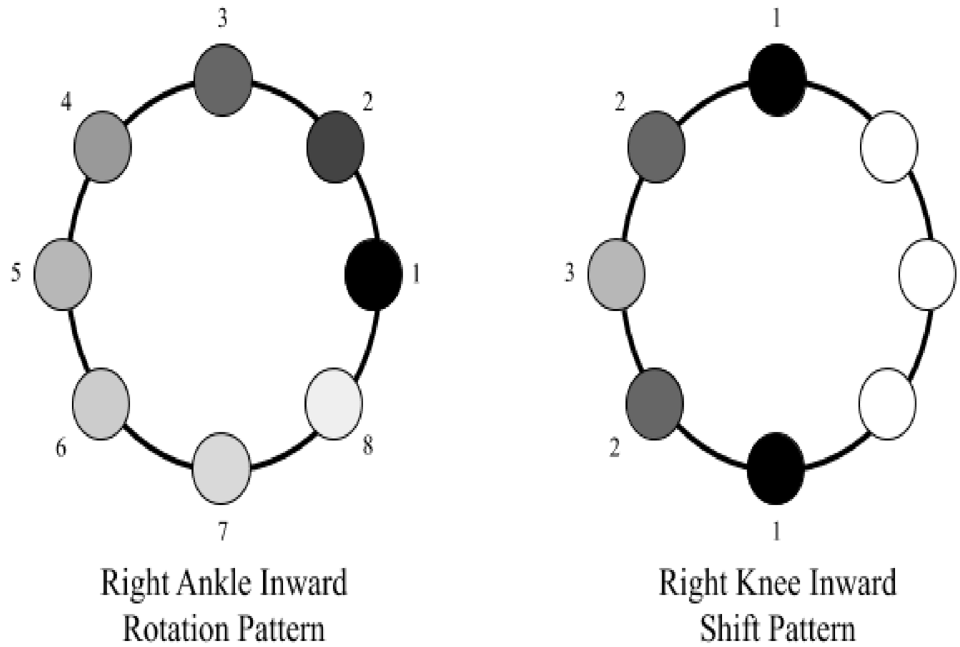

Figure 5.8: Haptic Patterns for Both Ankle Rotation and Knee Shifts Showing Patterns of Activation with Numbers and Shading Indicating the Order of Tactor Activation

the upper arm (Wilska, 1954) which has commonly been used in haptic applications. Jones & Ray explored the development of pattern recognition with tactile displays and found that participants were able to identify tactile patterns presented with a one-dimensional display and achieved an overall rate of 99% correct, with only two participants making one error each (Jones and Ray, 2008). Their approach explored the use of haptic patterns for navigational cues or instructions and used circumferential and directional patterns. This approach would build on this existing work and explore the application of these results to body compliance tasks. As an example, if the user's right foot is externally rotated, the haptic feedback would play a circumferential pattern starting from the outside of the band and rotate clockwise to indicate the need for inward rotation. A separate directional pattern could be derived for the traversal shifts of the knees inward. Figure 5.8 shows the tactile array and activation orders for the two desired behaviors.

One of the major benefits of this approach is that the denotation of type of non-compliance as well as corrective behavior are embedded in a pattern and thus the feedback does not need to be tied to a specific body site. If we find that the affected limb is not sensitive enough to vibrational feedback, as an example, it would be easy to shift the site of this feedback to the hips through the use of a haptic belt (McDaniel *et al.*, 2008). Similarly, because it encodes several pieces of information into a single array of motors, the user may not be overwhelmed given that the distribution of motors across body sites is now more limited. However, the negative effect of this encoding is that information must now either be sequentially presented to the user or separate encodings would need to be developed for more complex dual adjustments since the same motors are involved in multiple patterns. Providing information on two behaviors for the same appendage in parallel, such as right knee shift and right ankle rotation, would result in pattern overlap and render both patterns meaningless. This approach could be integrated with the haptic feedback for gross motor functions through separate encodings and arrays. The haptic display currently being used for the back could be augmented with more strips of motors to create a two dimensional array that could display similar patterns using saltation for gross adjustments.

5.3 Adaptation to Intrapersonal Variations

Cerebral palsy (CP) is a term that encompasses a group of conditions that have in common an impairment in brain function or structure that causes an enduring impairment in the development of motor control, often (but not invariably) with additional central nervous system impairments such as epilepsy, learning disabilities, and sensory difficulties (Rosenbaum *et al.*, 2007). Cerebral palsy affects people in different ways and can affect body movement, muscle control, muscle coordination, posture and balance. Although cerebral palsy is a permanent life-long condition, some of the symptoms of CP can improve over time through involvement in rigorous exercise programs under the guidance of trained professionals (Verschuren *et al.*, 2007). One of the major limitations of these programs is strict adherence to the exercise regimen in the home environment where the trainer is not present. Thus, it is important to develop anticipatory protocols that can learn about an individual's performance and adapt the characteristics of the exercise to create progressive functional goals to maintain maximal effectiveness and engagement.

Within the SmartGym application, an anticipatory system is proposed to predict subject injury by monitoring predictive characteristics of exercise performance. The system relies on the trainer to develop and adapt acceptance criteria for body compliance over time as the user progresses through an exercise program. In order for this system to be fully autonomous, two challenges need to be addressed: the development of methods for creating performance baselines specific to an individual and methods of creating performance adaptation within the evaluation criteria for a given algorithm.

5.3.1 Development of Baseline Criteria

A physiotherapist will typically design motor therapy exercises for a patient based on a number of factors, including the patient's age, gender, usual handedness, and the specific characteristics of his or her medical condition. The difficulty level of the exercises and even the body parts activated during the various tasks may be adapted to an individual patient's needs under the discretion of the therapist. For example, a jumping squat exercise might be adapted for a hemiparetic user to allow for landing mostly on the unaffected limb until the affected side builds the muscle mass to support weight. However, if a user who could support weight load on the affected limb was exhibiting the same behavior, the trainer might deem this as compensatory and instruct the subject to maintain compliance during the landing portion of the exercise by landing equally on both feet. To develop a standardized assessment of the nature of CP within the individual, therapists apply an industry standard test called the Gross Motor Function Measure (GMFM). The GMFM is a validated instrument designed to assess motor status specifically in CP and to quantify change over time or as a result of intervention (Russell *et al.*, 1989). It consists of 88 metrics within eight dimensions that span a broad range of common daily activities: (1) supine; (2) prone; (3) four point position; (4) sitting; (5) kneeling; (6) standing; (7) walking and (8) climbing. Scores are expressed as a percentage and are standardized to expected performance so that a normally developing child would score 100%. As this assessment is closely tied to activity, it is the role of the therapist to analyze an individual's performance of the tasks and scores to build an exercise program which will benefit most in the target areas. In doing this, the therapist also must determine which body parts are at risk for non-compliance in the conduction of these exercises based on the individual.

With this understanding, it would be very challenging and likely impractical to try to automate a system in which the device determines what parts of the body need to maintain compliance. Rather, it is important to maintain a human-in-the-loop solution even when considering automation where the input of the trainer serves as the initial building block. With the critical points as an input, the system can do an evaluation of baseline performance to get a quantitative assessment of a user's current ability. As an example, for the individuals with hemiplegia, the percent of strength asymmetry between the corresponding muscle group on the affected versus the unaffected extremity can be calculated and used as a baseline for developing protocols to detect compensation. If a subject has 20% of the muscle strength on the affected limb, then the system can develop an initial goal of supporting 25% of the weight supported by the unaffected limb. Similarly, range of motion should also be measured as a percentage of ability in the unaffected limb. This metric should be used in feedback protocols around limb and joint posture and positioning during the movement of the exercise. If a subject can only move the affected limb 10% of the rage than he or she can move the unaffected limb, then wider initial thresholds should be put in place that consider a user compliant. Additionally, data collected during the rehabilitation session can be used to further improve the patient experience. Such in-session data (e.g., the time taken to perform an exercise, the accuracy of the motion performed or the stimuli-response time) can be used to evaluate the initial configuration of the system. If motion performance is not being successfully completed then the compliance criteria should be configured to make accomplishment easier. Similarly, if the exercises are being completed trivially, acceptance criteria could be made incrementally more difficult.

5.3.2 Goal Adaptation

The concept of Flow Theory was first proposed by Csikszentmihalyi and suggests that in the development of an adaptive program, it is important to find a balance between the annoyance of an activity that is perceived as trivial and the frustration of one that is perceived as too difficult (Csikszentmihalyi, 2002). This theory has been extensively explored in the development of games (Charles *et al.*, 2005), virtual reality for stroke rehabilitation (Ma *et al.*, 2007), and even specifically in the area of exercise programs for Cerebral Palsy (Tadayon *et al.*, 2016, 2015b). Creating goals that adapt to user progress has also been shown to be incredibly effective in maintaining adherence to exercise programs (Petosa and Holtz, 2013). For body compliance, this means narrowing target thresholds, where the user is considered in a compliant state, as muscular control and proprioceptive abilities are enhanced while keeping in mind safety criteria set by the trainer in the initial evaluation.

Overall, algorithms for updates to compliance metrics should be made primary based on a user's performance but should also use an individual's affect and physiology as evaluations before and after updates are made.

Within the SmartGym application, there are two important variables to consider when adapting target benchmarks: frustration and fatigue. Measuring frustration is a critical metric in the advancement of goal criteria as it gives insight into the achievability of a new goal. If a compliance goal is too ambitious, a user may fail many times in trying to achieve that posture and become frustrated with the feedback provided by the system. This can have negative consequences for motor progression and can result in abandonment of the regimen. However, as shown through the principles of Flow Theory, maintaining an optimal level of challenge can increase engagement and have an astoundingly positive effect on performance. Prior work has demonstrated the ability to extrapolate engagement and frustration from facial tracking and expression recognition (Grafsgaard *et al.*, 2013) which could be used in the adaptation protocol. When the system senses that the user has missed the objective multiple times and has ruled out fatigue as a factor (discussed in the next paragraph), this could trigger a frustration check where the subject's engagement can be evaluated and if deemed too high, a simple rollback can be done on goal criteria.

Muscle fatigue is another critical factor in a user's ability to maintain compliance as thresholds are narrowed. Given that individuals with CP often have lower level of muscle mass and strength in their affected limbs, fatigue often occurs much quicker than in their healthy counterparts. Fatigue is a common complaint among people performing physical activities on the basis of training or rehabilitation and can cause limbs to become less responsive over time. Fatigue can have a negative effect on proprioception, kinesthesia, joint position sense, somatosensation, balance, and reflexive joint stability (Abd-Elfattah *et al.*, 2015). Local fatigue can be estimated through the use of surface EMG sensors (Luca, 1993) and could provide insight into the nature of the performance. If the system detects repeated non-compliance due to fatigue, feedback should be provided instructing the user to take a break by resting in a neutral position before continuing the exercise. Performance goals should not regress until the user re-attempts these metrics after a recovery period in order to accurately assess whether the fundamental cause of failure was muscle fatigue or an over ambitious goal.

5.3.3 Limitations

An automated system provides many benefits over traditional self-monitored approaches if adopted for at-home training. In many cases the system can make decisions based on measured, quantifiable data that trainers often don't have access to in order to enhance exercise programs for maximum effectiveness. The system can ensure that the subject is maintaining peak levels of motivation and develop more informed justifications for failures to complete motions accurately. However, this proposed approach is limited in that there exists a subject performance ceiling where the system can no longer make progressive adaptations. As an example, if a patient has been undergoing an exercise program for a long duration and has capitalized on the beneficial aspects of a given exercise, the system can't make a new exercise recommendation but would rather rely on the trainer to step in and make this update. Similarly, there exists limitations on the ability to programmatically understand which body parts should have compliance criteria put in place and what the safety limitations on those metrics are for a given individual.

5.4 Evaluation 1: Real-Time Feedback

The aim of evaluation of this system is to test the effectiveness of the proposed system in affecting non-compliant behaviors to avoid injury in the home environment. The subject was a 35 year old female participant undergoing a rehabilitative exercise program for hemiparetic cerebral palsy and her trainer. The participant had limited motor control on the left side of her body and is using a strength building program that incorporates a variety of exercises to rebuild muscle strength. For the purposes of this study, the focus is limited to a specific exercise (jumping squat) as an initial proof-of-concept for the system.

The participant was first given an overview of the study and then asked to complete an informed consent form. The participant then underwent a 10-minute familiarization phase during which the interface and feedback pattern were described. Each feedback was demonstrated twice and the expected behavior was described. The participant then completed two trials with each trial consisting of the following:

Five minute session in which the subject completed the jumping squat exercise without any feedback from the trainer and the system collected data without providing feedback. Five minute session wherein the trainer provided feedback and the system collected data but provided no feedback. Five minute session in which the system provided feedback and the trainer observed the session for safety purposes.

Breaks were given between sessions and trials to control for fatigue. The session times were determined by the trainer as this was a standard session time assigned to the subject during regular workouts. The system tracked two main values: the amount of time spent in a non-compliant state and the cumulative pressure applied by each foot. Time spent in non-compliance was determined by a multitude of factors including whether the joints and bones were correctly aligned throughout the motion, whether the upper-body was centered on the Total Gym Pro device and whether the center of balance was over both feet. These criteria were split into two categories: measurements for upper body included the positioning of the body from the waist up and measurements for lower body included positioning of the hips and legs. Threshold values were used for variability of position that were defined by the trainer to determine when a joint or bone would be considered non-compliant. Cumulative pressure was tracked as it is a measure of compensatory behavior which the system aimed to reduce. These metrics were not displayed to the subject but were collected for offline comparison.

After the two trials, the subject was given a questionnaire with eight Likert-scale questions and one open-response question:

- Q1: How comfortable was the gym equipment without any embedded sensors?
- Q2: How comfortable was the gym equipment with the embedded sensors?
- Q3: How well do the vibration patterns represent the intended movements?
- Q4: How well did the visualization of the ball represent your center of balance?
- Q5: How well did the color quadrant visualization represent your center of balance?
- Q6: How easy was the interface to understand?
- Q7: How well do you feel that interface helped in your ability to complete the exercise?
- Q8: How well do you feel you can complete the exercise independently using the feedback provided by the system?

- Q9: Please comment on any improvements/changes you would like to see in the system.

5.4.1 Results & Discussion

Overall, the subject seemed to report a positive response to the use of the SmartGym, but did show a faster response rate to the feedback given for upper body versus lower body compliance as shown in Table 5.5. For upper body compliance (waist and above), the subject spent on average 10 seconds less in a non-compliant state when using the system versus getting the feedback from the trainer. Some potential factors that could have affected this are that the system's feedback was much more immediate than the trainer's in instructing the subject that their body was misaligned. Secondly, the system's feedback was persistent until the behavior was fixed whereas the trainer would take pauses between commands. This made the trainer's feedback easier to ignore during the first instruction.

Feedback	**Upper Compliance**		**Lower Compliance**	
	Trial 1	**Trial 2**	**Trial 1**	**Trial 2**
None	123	157	93	120
Trainer	41	35	25	24
System	34	22	40	38

Table 5.5: Non-Compliance Times Measured in Seconds

However, for lower body compliance, it was observed that the subject on average reacted 13 seconds slower than when receiving instruction from the trainer. Part of the limitation here was that the Kinect would sometimes lose tracking and attempt to re-track the joints, potentially causing a slight delay in the feedback. More insight into this behavior was provided in the questionnaire when the subject mentioned that the lower body feedback that the system was giving didn't map well to the subject's internal image of body alignment and therefore seemed wrong. When given no feedback from the trainer or the system, the subject struggled to maintain a compliant form during the five-minute trials. The subject was non-compliant for 123 and 157 seconds in the trails for upper body and for 93 and 120 seconds in the trials for lower body. In all areas where feedback was provided (either from the system or from the trainer) the subject performed better during the second trial, suggesting that there might be a slight learning effect between trials. However, due to the implementation of feedback methods for the first trial before the second, this learning effect didn't change the trainer-versus-system comparison. Also, it is important to note that no feedback was given regarding the amount of time spent in non-compliant states between sessions.

Feedback	**Left Leg**		**Right Leg**	
	Trial 1	**Trial 2**	**Trial 1**	**Trial 2**
None	130	120	240	275
Trainer	180	174	300	311
System	243	296	297	320

Table 5.6: Cumulative Pressure (in lbs) Placed Against the Wii Balance Board.

Cumulative pressure also increased significantly for the affected leg relative to the unaffected one when using the feedback provided by the SmartGym as shown in Table 5.6. Some of the difference between the trainer and system feedback in this category can be attributed to the observation that the trainer often misses moments when compensation occurs that are not easily discernible to the eye. Throughout the two trials, there were only two explicit instances in which the trainer told the subject to make sure to land on both feet at the same time. During these trials, the system identified 12 instances in which compensation was occurring. Therefore in total, the system identified 10 instances of compensation missed by the trainer over the observed sessions.

In the post-experiment questionnaire, the system was evaluated for usability, intuitiveness and overall functionality. Trends were observed in the subject's responses that seemed to match what was shown in the data. Overall, the subject seemed to prefer the feedback that was given on upper body compliance to the feedback that was given on lower body compliance. She rated the vibration patterns as being very representative of the intended motions but added comments about the visualizations that the Kinect provided, noting that they often seemed incorrect. This was an interesting point of feedback as it provides evidence that the external tracking of the subject's body did not map well to the internal and impaired proprioception and thus created a conflict. Because of this, the subject felt less comfortable following the feedback of the system as it related to joint and bone positions. The ball visualization and heat map were rated highly representative of their intended movements which can be seen through the cumulative pressure outcomes. Results from the questionnaire are shown in Table 5.7.

Question	Score
Q1	3
Q2	3
Q3	5
Q4	4
Q5	2
Q6	5
Q7	4
Q8	5

Table 5.7: Questionnaire Responses Based on Likert-Scale: 1(Low) to 5(High)

5.5 Future Work: Feedback Fading

Prior work in the area of motor learning has shown that accuracy and consistency, in a delayed retention test, is greater in individuals who practice motor skills in feedback-faded environments as compared to those who practice with feedback provided during every trial (Schmidt *et al.*, 2018; Winstein and Schmidt, 1990; Wulf and Schmidt, 1989). As a result, clinicians who deal with physical therapy for neurological disorders have shifted focus to the incorporation of frequency manipulation of extrinsic feedback during intervention sessions (Palisano, 2012; Levac *et al.*, 2011; Zwicker and Harris, 2009). This principle also holds true in the specific case of intervention techniques for Cerebral Palsy. Spearing & Poppen explored the use of switches that were attached to the left shoe of a male university student with CP who dragged his foot while walking (Spearing and Poppen, 1974). He was provided with a negative stimulus in the form of a bicycle horn whenever his foot dragged in an effort to restore normal gait. Foot dragging was reduced to near zero even when the feedback from the bicycle horn was gradually faded. However, in a study conducted by Burtner et al. with children with CP, no statistically significant difference was found between feedback subgroups of children who received faded feedback versus those who did not, although the 100% feedback group consistently demonstrated less error in retention (Burtner *et al.*, 2014). This study was conducted over a 24 hour period where as the study involving the university student was conducted over four months suggesting that signal fading may need to occur over longer temporal spans to prove effective within this population.

5.5.1 Feedback Fading Design

The initial design of the SmartGym application provides signals in haptic, audio and visual modalities for various behaviors as mirrored in the protocol that is used by a trainer. In designing protocols for feedback fading of these signals, critical points for performance analysis must be developed through metrics for individual progression in motor learning. Prior work has proposed the separation of the motor learning process into three distinct stages (Anderson, 1982): cognitive, associative, and autonomous.

Cognitive Stage

The cognitive stage is the first stage of motor learning and varies in length by individual. In this stage, the learner has no mental model or cognitive scaffolding for which to build off of in the acquisition of a new motor ability. During this stage of the learning process, the primary goal of the subject is to develop an understanding of the skill and the motions involved. The learner is still familiarizing himself or herself with the objectives of the skill and begins to consider contextual factors that will affect the user's abilities to produce the movement. The individual relies heavily on somatosensory feedback and typically uses trial and error as the main learning mechanism. Due to the nature of this stage, all feedback should be maintained and provided consistently to reaffirm and negate positive and negative behaviors respectively. The consistency of this feedback through repetition builds mental models for the intricacies involved in producing the movement correctly. Similarly, within this stage it is important to maintain feedback redundancy and provide multimodal cues on performance that reinforce the learning process. Once the user has repeated the motion enough to develop a rudimentary understanding of the metrics for compliance, cognitive associations are built between stimulus-response couplings.

Associative Stage

In this stage of the motor learning process, the subject begins to develop a more refined movement through practice and has developed strong mental associations with feedback signals. Although responses to feedback are not yet automatic, the attention with respect to motions shifts to "how to do" from "what to do" in the cognitive stage. This is the stage in which proprioception plays a larger role as focus is put on the movement of the body in space and what is being felt from the joints and muscles to inform corrections and adjustments. In this stage, the system should begin gradually fading feedback signals to shift the dependency in performance evaluation from extrinsic feedback to intrinsic. The approach on signal reduction should begin by eliminating redundancy in skills that the user has become very competent in as a minimization technique which will force user attention to skills that he or she is still lacking in where consistent, multimodal feedback is still provided. As an example within the SmartGym application, the current approach to providing feedback on gross motor adjustments in the upper torso is through the primary modality of the haptic channel with vibrotactile actuators along the user's back and is reinforced through visual feedback of skeletal tracking where body parts that are non-compliant are marked in red. If the user consistently seems to be performing well in this area overall, a reduction technique could involve disabling visual feedback for this behavior and allowing the subject to rely more heavily on his or her own proprioceptive signals combined with haptic signals. As a secondary effect, reducing signal in the general spaces where users are progressing effectively allows users to heighten focus in specific feedback areas.

Autonomous Stage

In the final stage of motor learning, the skills become mostly automatic. Progression to this level allows the learner to perform the skill almost innately with very little cognitive involvement compared to the first stage of motor development. It is at this stage that the subject is considered an expert in the intended movement and now may use feedback signals only as reminders rather than directional cues. Once an individual achieves this level of proficiency, a more aggressive approach can be taken in scaling down the frequency of extrinsic stimuli. The system should consider in what areas of motor performance the user is continuously achieving trivial success and completely eliminate feedback protocols for those areas in a systematic manner. One specific area of feedback should be evaluated at a time to eliminate potential confounding effects between feedback areas. The system should then remove any stimulus provided for that behavior and evaluate if the user is still able to achieve the desired goal over a span of time. If the user maintains his or her success rate, then the system can move on to evaluate a different area of compliance. However, if the user does not retain performance attributes, then feedback should be reinstated for the behavior.

5.5.2 *Feedback Fading Evaluation*

Stimulus fading approaches for feedback protocols in the motor learning space can provide many benefits in that they promote stimulus-behavior independence and support the construction of neural pathways for successful motion. This approach works to shift an individual's performance reliance from extrinsic to intrinsic signals that better allow for adaptations to changing contexts by reinforcing the proprioceptive systems. However, one of the major limitations of feedback fading systems within the domain of cerebral palsy is that beneficial and learned behaviors can revert over time (Spearing and Poppen, 1974). Another potential limitation is that if feedback is faded too early, this can introduce a great deal of frustration in the user, and it would be difficult for the system to differentiate between frustration due to lack of feedback versus frustration due to difficulty of the task. Furthermore, if feedback is not faded early enough or rapidly enough and the user develops a dependency on the feedback early on, frustration and high error can develop when that feedback should be faded.

Chapter 6

PARKINSONIAN GAIT ANTICIPATION

6.1 Introduction

The affects of Parkinson's disease (PD) on an individual remains largely a mystery even under today's modern medical practices. According to the Parkinson's Disease Foundation, there are currently an estimated 7-10 million people worldwide who are living with PD (www.parkinson.org). Domestically in the United States, around 60,000 people are diagnosed with the disease annually and have a combined direct and indirect cost of $25 billion per year to the healthcare system.

Parkinson's disease is a neurodegenerative brain disorder with a progression period typically spanning around 20 years within an individual. While the disease itself is not fatal, the Center for Disease Control (CDC) has rated secondary complications that result from the disease as the 14th highest cause of death in the United States (www.parkinson.org). As a result, a nationwide push has been established to conduct fruitful research on this disease and its complications. Largely because of this initiative, there are now multiple medical treatment methods to mitigate the symptoms of the disease including medication as well as an invasive procedure known as deep brain stimulation (DBS).

The symptoms of PD can be categorized into three main groups: primary motor symptoms, secondary motor symptoms and non-motor symptoms. According to the National Institute of Neurological Disorders, the primary motor symptoms include bradykinesia, tremor, rigidity, and postural instability, which often cause secondary effects (secondary motor symptoms) in an individual. Of the secondary motor symptoms in PD, one of the most disconcerting is issues with the individual's gait. Specifically, reduced step length, increased cadence, increased stride time, and postural stoop. In parallel, during the later stages of the disease, these symptoms are also accompanied by an episodic phenomenon that is unexplained by bradykinesia or rigidity known as freezing of gait (FoG). Freezing of gait is defined as a "brief, episodic absence or marked reduction of forward progression of the feet despite the intention to walk". This description fully encapsulates the variable nature of the episodes including those in which the individual cannot initiate gait ("start hesitation") and cessation in forward progression during ambulation ("turn" and "destination" hesitation), as well as periods of shuffling where traditional aspects of the gait cycle degenerate and steps can often become centimeters in length. Freezing episodes that occur during forward progression can often be triggered by environmental factors such as high pressure or timed tasks. Examples include trying to walk down a narrow hallway or having to cross a street where you have a fixed amount of time to get from one side to the other. These factors can have a large impact on an individual's quality of life since independence is limited. Due to this secondary symptom not being well understood within the current pathophysiological models for Parkinson's, there does not exist an effective treatment option to address it medically. This phenomenon actually responds poorly and often paradoxically to treatment with traditional dopaminergic medications that are regularly used to treat other symptoms of PD. However, a linkage found that FoG, during walking, results when the sequence effect is superimposed on a reduced step length (Chee *et al.*, 2009).

Due to the implicit dangers that FoG provides, significant research has been done to explore methods of offsetting the episodes from resulting in a full freeze and preventing them from occurring as frequently. However, to date, the overwhelming majority of this prior body of work has looked to utilize the auditory and visual feedback channels in technologies that cue changes in gait characteristics (Nieuwboer, 2008; Bachlin *et al.*, 2010). The main limitation that this approach has introduced is that these devices often occupy the primary sensory channels used in travel as people rely on their sight and hearing to avoid obstacles and navigate their environment. This research proposes the development of a system to track step patterns and to provide haptic cueing to an individual to offset the progression of freezing of gait episodes (Tadayon *et al.*, 2015a). Specifically, this research seeks to accomplish two main goals. The first is to extend the existing model for normal human gait to be able to detect the abnormal cycles in Parkinsonian gait. This involves the development of new and adaptable algorithms that can accommodate for variations based on human-centric characteristics. Secondly, this research looks to develop a ubiquitous system that can monitor day-to-day activities and provide real-time cueing to the user to offset the FoG episode so that the individual can continue their normal gait cycles.

6.2 Implementation 1: Context Detection

Under the lens of context detection, an initial goal in the detection of FoG events is to create an accurate digital model to represent Parkinsonian gait characteristics. This is a challenging problem in that Parkinsonian cycles, immediately before and during a FoG event, are inherently unique from traditional gait models and thus require the identification of distinct features and events within this new model. One critical consideration is to stray away from the traditional detection of heel-strike and toe-off events that occur in normal gait because these characteristics are often degraded beyond recognition in patients with PD. Instead, this work implements analysis on the frequency domain as the main method of step detection and uses pressure shifts between the toe and heel as a validation method, rather than detection, in order to develop a model for start and stop events. This model can then be applied

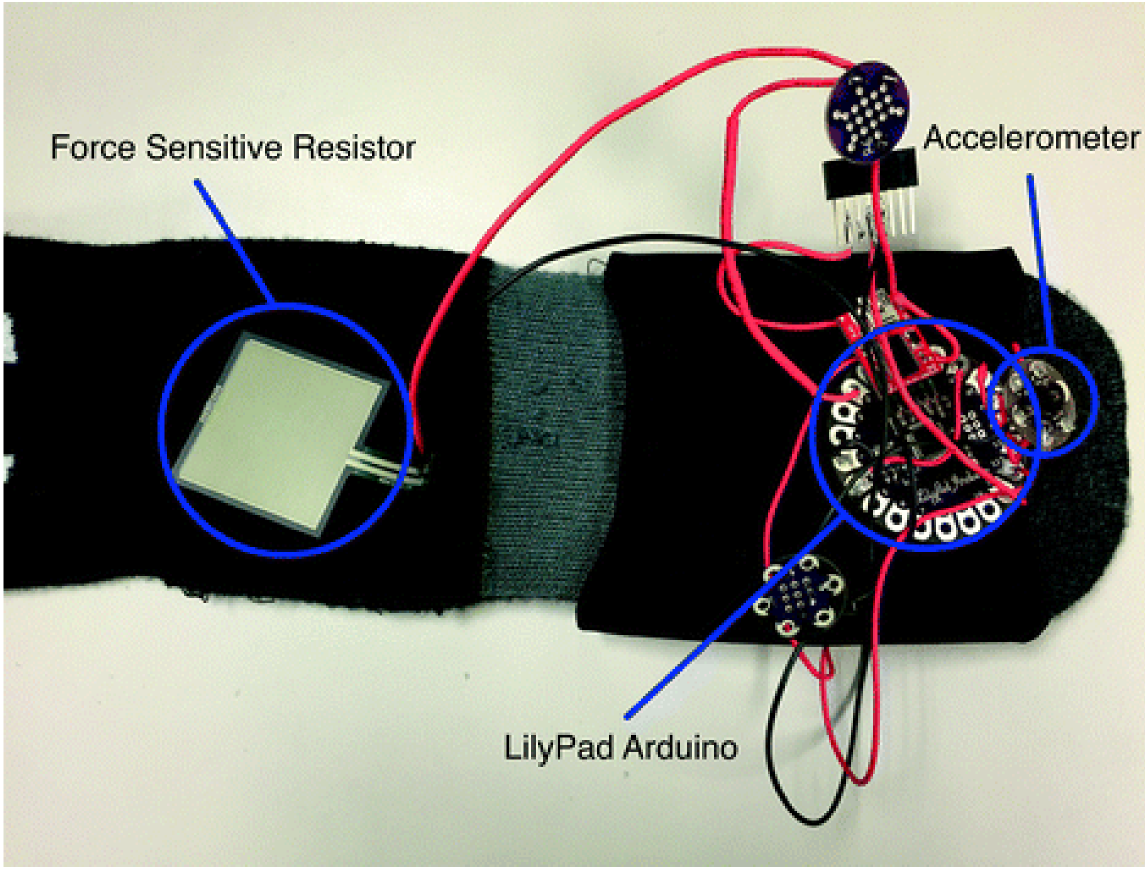

Figure 6.1: Sock With Embedded Sensors and Actuators (Tadayon *et al.*, 2015a).

to an assistive device that the user can wear everyday with minimal intrusion.

Some of the primary considerations in the development of a device that can be used in everyday environments are form factor and weight. A device that is expected to be worn daily needs to be relatively small and should be embedded into the clothing that a user already wears. Similarly, it should not be significantly heavy as a device that is worn on the feet would add weight to each of foot during gait and may introduce concerns around fatigue due to the extra weight. This work demonstrates the development of a device that can be worn on the user's sock and can be easily hidden using pockets over the sock. The batteries for the device will be worn over the shank to decrease the amount of weight carried by the foot since these are the heaviest pieces.

To implement the approach discussed above, a system was designed that consists of two small devices that can be worn over each of the user's socks. The devices consist only of a microprocessor, an accelerometer, an XBee module, and a pressure sensor. Processing is currently being done offline; however, in future iterations, these devices could integrate with the user's smartphone as a central location for online calculations.

As shown in Fig. 6.1, the device was built using the Lilypad board for easy embedding into the sock. The accelerometer is worn above the toe since this was the location that was found to have the least angular displacement during toe-off events and reduced the distortion of the signal during those events. The pressure sensor is worn under the heel and is used as a method of validating steps taken by the user. The pressure data relies on a threshold value that will be person-centric and easily adjustable depending on the weight of the individual using the system. The device streams data for both acceleration and pressure that is annotated with timestamps to a computer for storage. Once the walking data is collected, it is processed to first identify which events were steps and then to determine the length of each of those steps.

6.3 Implementation 2: Motion Modeling and Prediction

In the process of anticipating FoG episodes, it is important to consider the characteristics of gait that make that individual unique so as to be able to more accurately predict anomalies. In the first study described above, a naive approach was taken in the consideration of individuality. A running average stride length was calculated based on the acceleration of the foot during each step. Through offline processing, stride comparisons were made against the subject's historic data to determine if whether the new data point was an outlier. This approach was expanded upon by

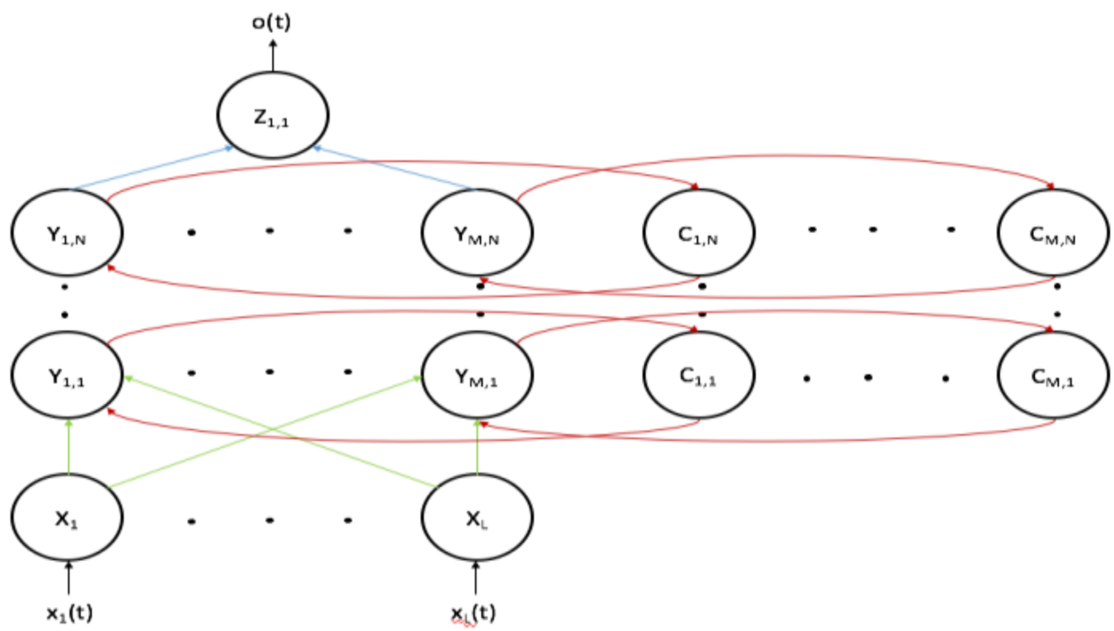

Figure 6.2: Layered Recurrent Network (LRN) Model (Zia *et al.*, 2016).

Zia et al. through the implementation of a neural network (Zia *et al.*, 2016). A class of neural networks known as layered recurrent networks (LRNs) was applied to an open-source FoG experimental dataset donated to the Machine Learning Repository of the University of California at Irvine. The independent variables in this experiment – the subject being tested, neural network architecture, and down sampling of the majority classes – were each varied and compared against the performance of the neural network in predicting impending FoG events. The effectiveness of neural networks in predicting the onset of Parkinsonian symptoms has not been extensively explored; however, previous publications have proposed other methods of predicting FoG. Such studies include analyzing skin conductance (Mazilu *et al.*, 2015), motion data (Mazilu *et al.*, 2013), and EEG data (Handojoseno *et al.*, 2015) using a variety of methods. Though previous studies have attained reasonable success in this area, neural networks provide the benefit of adaptability to each patient's unique symptom presentation while other methods require varying degrees of tailoring to account for human factors. The LRN model used is shown in Fig. 6.2.

6.4 Implementation 3: Context Invisibility & Cueing

Due to the debilitating nature of FoG combined with the fact that its prevalence often responds poorly to dopaminergic medication (Bloem *et al.*, 2004), years of research have been dedicated to exploring assistive systems that can counteract freezing episodes and return the individual to a normal gait cycle. These systems operate under the understanding that Parkinson's disease has an adverse effect on the basal ganglia, which are thought to play an important role in regulating motor programs involved in gait and in the fluidity and sequencing of movement (Hausdorff *et al.*, 1998). Due to this impairment, it is postulated that, for individuals with PD, the autonomic processes of balance and gait are shifted to the frontal cortex and require an individual's active attention through somatosensory cueing in order to operate undisturbed. Similarly, delayed gait initiation in freezers was found to be related to greater variability in deciding which limb to activate during stepping tasks (Okada *et al.*, 2011), which suggests that an inadequate ability to select a motor response interfered with output. Many of these systems look at providing auditory or visual feedback to drive users' attention back to their gait and ultimately create synchronicity between strides by guiding the user through the response selection process.

Visual Cueing Martin and Hurwitz first explored the value of visual cueing as a rehabilitory technique in 1962 where they suggested that placing visual cues perpendicular to the direction of travel spaced one step length apart was most effective in improving gait in patients with PD (Martin and Hurwitz, 1962). Since this initial discovery, much work has been done to explore the positive effects of visual cueing within the space. Espay et al. developed a system which was composed of a set of augmented reality goggles combined with headphones to “display a life-size virtual tiled-checkerboard superimposed on the real world” (Espay *et al.*, 2010). This was a multi-session intervention in which the participants use the device twice daily (30 minute sessions) over the course of two weeks. The approach was found to improve walking velocity and stride length, with an overall improvement in gait as measured by the Freezing of Gait Questionnaire. It is important to note that of the fifteen participants in this study, two of them did not follow the recommended procedures outside of the lab environment, because they felt the device was “clunky” or “embarrassing to use in public” highlighting the importance of discrete feedback and form factors that do not obstruct day-to-day living.

In another study, authors explored the attachment of lasers to the participants shoes (Ferraye *et al.*, 2016). In this approach, lasers are mounted to the front of each of the individuals shoes and the shifting of bodyweight to the heel as an individual is about to initiate a step activates a laser on the load bearing side. The laser lines are projected orthogonally in front of the patient’s stepping foot and are activated intermittently, in-parallel with the step frequency of the subject. Although the initial evaluation was posed as a case study, a larger study was conducted with the device later to show that the device was associated with a significant reduction in the number of FOG episodes (Barthel *et al.*, 2018). Similarly, other devices have looked at using a walker to project the target laser lines rather than the shoe with similar results (Van Gerpen *et al.*, 2012; Bunting-Perry *et al.*, 2013).

The major limitation of visual cueing in real-world environments is that users are expected to be staring at the floor as they walk making them oblivious to their surroundings. This can prove especially dangerous in contexts such as crossing a street or walking in a crowded area. Looking downward may also accentuate deterioration in an already stooped posture causing steps to become even shorter. A secondary limitation is the visibility of these projected lines as they often depend on having enough contrast with the surface that they are being projected onto as well as having lighting conditions that adequately support their visibility. The overarching goal of these systems is to help the individual identify an appropriate step magnitude and eliminate that process as a cognitive task.

Auditory Cueing The effects of Rhythmic Auditory Stimulation (RAS) within Parkinsonian gait is a topic that has been well explored in literature. Thaut *et al.* (1996) first defined RAS as "metronome-pulse patterns" which were embedded into an exercise program over the course of two weeks. Participants were asked to do activities including walking on a flat surface and stair stepping which were synced to the target rhythm. Three different rhythm cadences were tested: a baseline or comfortable pretest cadence, a quick cadence which was set to 5-10% above the baseline, and a fast cadence which was another 5-10% above the quick cadence. Between these three different conditions, it was found that the "quick" cadence had the best overall performance with a target threshold of 10% above baseline cadence. This study found that participants with RAS improved their gait velocity by 25%, stride length by 12%, and step cadence by 10% more than self-paced subjects.

One of the main limiters in RAS is that often the feedback can become asynchronous to the stepping pattern of the individual and actually cause disturbances in gait as the subject tries to adapt. To further advance research in the space, Miyake (2009) proposed the development of context-aware RAS feedback protocols which shifted the burden of adaptation from the user to the device and allowed the feedback to sync to the individual's steps. The device detects the stepping cadence of the individual through accelerometry and, through a phase-shift in the metronome, will automatically adjust to match their gait cycle. Moens et al. expanded the body of work around adaptive feedback protocols by extending beyond the concept of the metronome and looking at adaptive music as a delivery mechanism (Moens *et al.*, 2017). In doing so they found that fixed tempo metronomes resulted in the highest increase for cadence, velocity and stride length, fixed-tempo music increased velocity and stride length, and adaptive-tempo music increased stride length.

Similar to visual cueing, auditory cueing is limited in its application in real-world environments due to the congestion of a sensory channel used in navigation. We often use sounds to navigate our environment and avoid dangerous situations. As an example, we know to step away from a curb when we hear a car approaching from our rear. Also, despite its efficacy in literature, RAS suffers from a major drawback in that its effectiveness weakens through time. As such, longitudinal cuing is not recommended (Cubo *et al.*, 2004; Rubinstein *et al.*, 2002) as the efficiency of RAS decreases exponentially over longer durations. It is best suited for short interaction cycles during rehabilitative exercise programs.

6.4.1 Cueing Approach

Given that the visual and auditory channels are the primary channels used for day-to-day navigation, the aforementioned solutions have stark limitations in real-world environments. This has led to the exploration of haptics as a medium for feedback in this context. Given the degrees of freedom that the haptic medium provides in both spatial and temporal domains, it has a unique advantage in being able to encapsulate the benefits of visual and auditory channels without blocking the sensation needed for navigation. It is hypothesized that, through intelligently designed haptic patterns, the step amplitude feedback of visual cues and the rhythmic timing feedback of auditory cues can be delivered in a non-intrusive manner.

This section presents a novel approach to the development of vibrotactile patterns

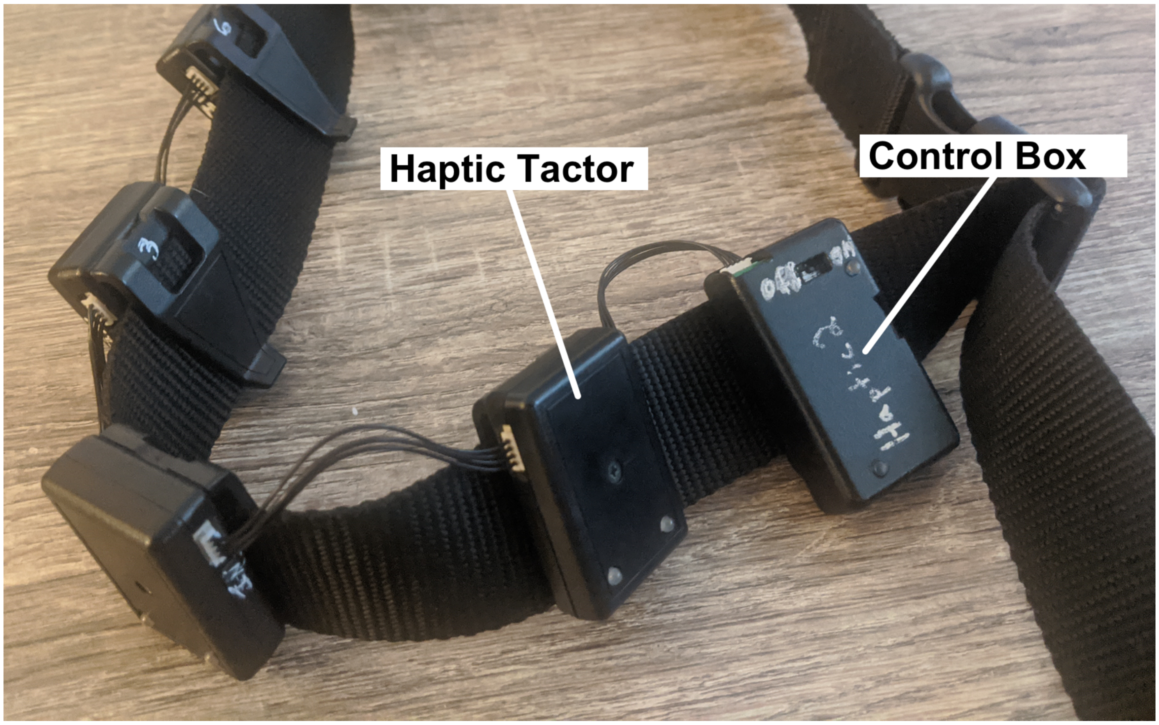

Figure 6.3: The Haptic Belt Which Contains Six Haptic Tactors and a Control Box for Communication.

that vary across spatial and temporal domains to create intuitive, directional cues for gait cycles. Under this approach, cueing is delivered through a haptic belt (McDaniel *et al.*, 2010), pictured in figure 6.3, that contains six vibrotactile motors equally spaced around an individual's abdomen. The long-term goal of this work is to create a discrete device that can be worn during day-to-day navigation tasks which will subdue stride variability and ultimately reduce the impact of freezing episodes. The approach is evaluated in a study with nine participants who have Parkinson's and experience FoG.

6.4.2 Hardware & Software Design

The system consists of a haptic belt with six modular tactors and a control box as shown in figure 6.3. Each of the tactors contains a pancake motor which vibrates with an intensity similar to a cell phone. These tactor modules can be controlled

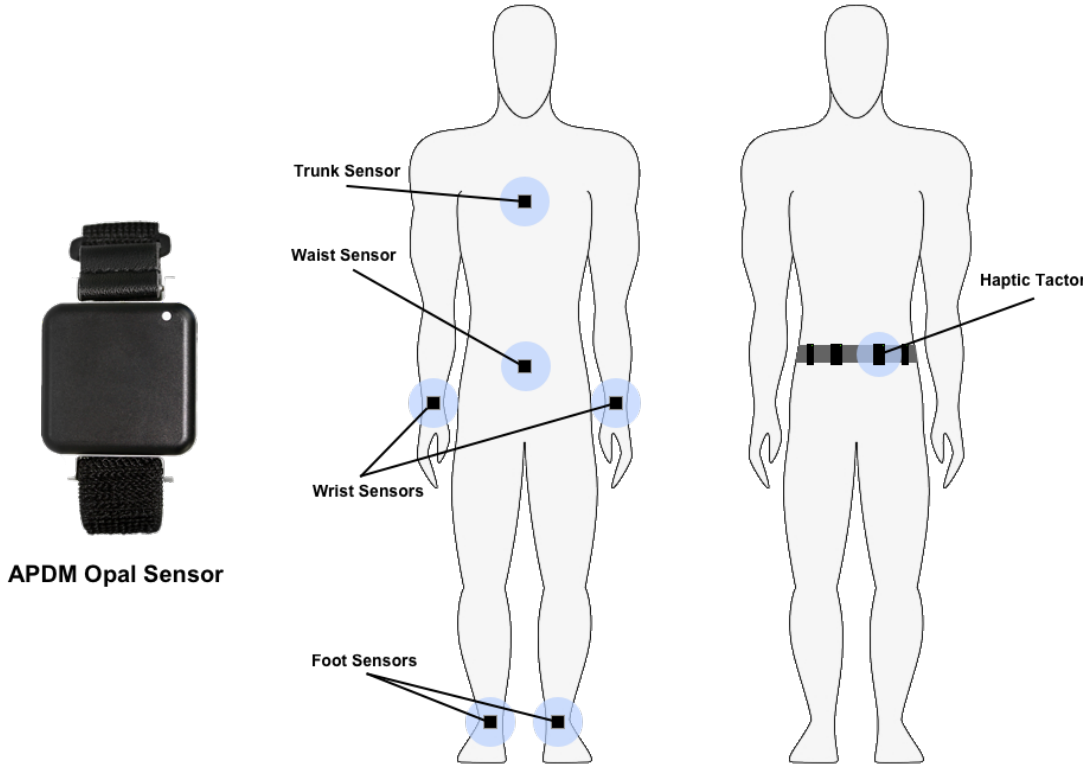

Figure 6.4: The Placement of the Opal Sensors and Haptic Tactors on the Haptic Belt.

independently which means that the timing and frequency of the independent modules can be varied to create simple or complex patterns that only activate specific modules. The control box houses a bluetooth chip which allows for remote control of the belt over serial communication. A simple interface was developed for controlling which pattern to deliver depending on the trial as shown in figure 6.4. The belt itself is made of a nylon material with an adjustable buckle that allows for tightening or loosening as necessary in order to achieve a snug fit and ensure that all of the tactors are in close contact with the subject's body. To measure gait characteristics, a total of six APDM Opal sensors (https://www.apdm.com/wearable-sensors/) were used. Placement of the sensors is shown in figure 6.4. The APDM Moveo Explorer (https://www.apdm.com/kinematics/) was used to analyze gait characteristics from the sensor data.

6.4.3 Haptic Cueing Design

When developing protocols for information delivery, two important neurological characteristics need to be evaluated: sensation and perception. With respect to sensation in the consideration of body site for haptic cueing, it is important to have an understanding of spatial acuity and sensitivity to vibration on various parts of the human body. One of the foundational pieces of literature in the space of sensitivity was published by Wilska where comparisons of vibrotactile sensitivity at various body sites increases as your move from the proximal structures (center of body) to the distal anatomical structures (extremities) (Wilska, 1954). Similarly, in a study conducted by Weinstein (Weinstein, 1968) and later verified by E. H. Weber (Weber, 1996), it was found that spatial acuity improves from proximal to distal body parts as well. Once we know a signal can be well-sensed, we must then consider the cognitive load of information perception as it relates to the feedback signal. Jones & Sarter suggest that the ability to localize a point of haptic stimulation is best when it's presented near anatomical points of reference (Jones and Sarter, 2008). Therefore, providing feedback at the point closest to the body part for intended behavior modification will theoretically result in the greatest level of perceptual ability. These principles were used in the design and development of the initial iterations of the Parkinsonian gait device. However, within the populations of individuals with Parkinson's disease, the location of haptic feedback remains a research question that requires further exploration.

This domain provides a unique set of challenges in that the feedback site can play an important role in the intuitiveness of the perceived signal. If the perception of the signal does not map to an almost innate response, the feedback protocol could

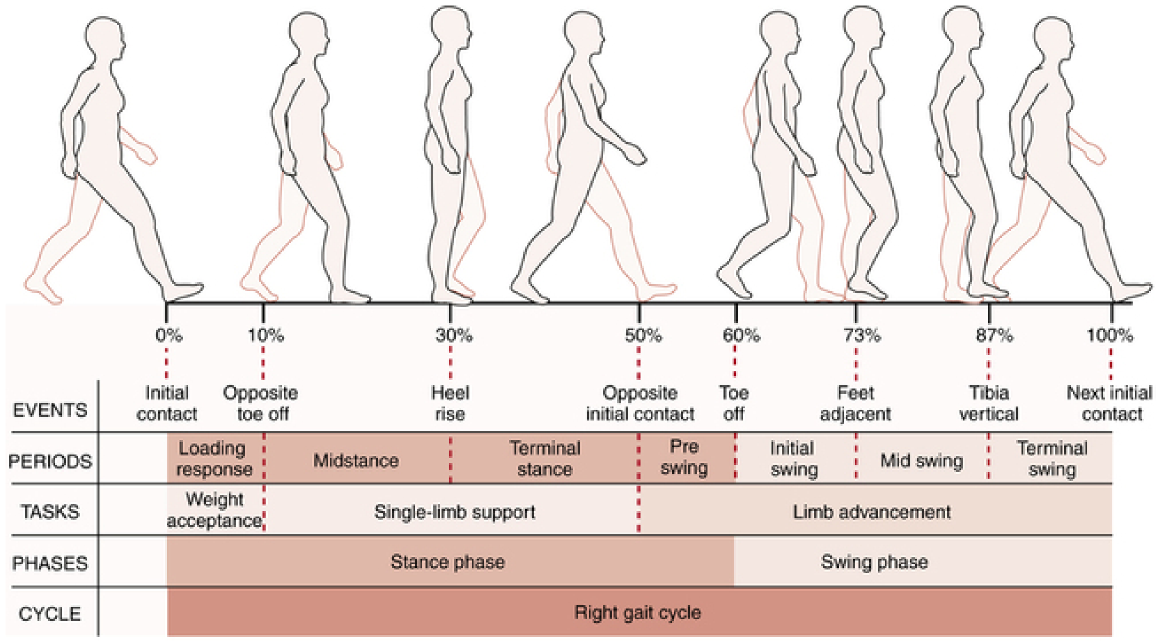

Figure 6.5: Ordering of the Various Events in the Gait Cycle (Donald, 2002)

introduce a secondary cognitive task and actually induce a freezing episode rather than prevent it (McIsaac *et al.*, 2015). For this reason, a study is conducted to evaluate the intuitiveness and effectiveness of haptic patterns designed for real-time gait modification. The goal of this study is to conduct a comparative analysis of cueing signals provided at the hip and at the shanks of individuals with PD. Similarly, the intuitiveness of the design strategies for various patterns that map to cadence and step amplitude thresholds will be evaluated. The two main strategies for feedback design are as follows:

Haptic Metronome In this design strategy, we look to map haptic signals to an almost literal translation as a form of sensory substitution for gait characteristics to limit cognitive load. Feedback for step cadence is provided through location-specific, timed pulses that correlated with the target step frequency for each foot. The beginning of a pulse provided on the right side of the body represents the timing for a toe off event for the right foot and similarly a pulse on the left side relates to the left foot step initiation. As a reference, figure 6.5 depicts the ordering of the various events in the gait cycle. The dimension of time is used to map step amplitude as the duration of the signal denotes the intended step length. As an example, when the system predicts an upcoming FoG episode, an alternating pulse pattern will play either at the user's hips or at their shanks. Subjects will be informed to modify their step frequency to match the pattern and increase the length of steps with the duration of the signal. If the tactor is vibrating, then the user should maintain mid-swing and continue forward movement until the signal stops at which point he or she should have a heel strike event for that foot. Based on prior research that evaluated the effectiveness of auditory and visual stimuli for improving gait characteristics, haptic signals should convey a normalized step length for each subject, as determined by leg length ($normalizedStepLength = 0.8 * legLength$) (Hof, 1996). Although it is not as important that each step hit this threshold, having this as the stimulus goal can be very favorable. Chee et al. demonstrated that when visual cues were set to this person-centric normalization, most participants benefited (Chee *et al.*, 2009). Similarly, research conducted by Willems et al. found that providing cues operating at a cadence 10% to 20% above an individuals baseline value results in a statistically significant increase in stride length for individuals who exhibit freezing with Parkinson's disease (Willems *et al.*, 2006).

This mapping strategy was developed as an extension of existing work that has looked at the application and relative success of auditory feedback in this space. Rhythmic auditory stimulation (RAS) has been shown to have beneficial effects within the domain (Bachlin *et al.*, 2010; Hausdorff *et al.*, 2007a; Arias and Cudeiro, 2010). Regular metronome ticking sounds were provided as a form of RAS with a rate of 110% of the natural cadence of the tested patient. This feedback served to enhance their gait speed and reduced gait variability (i.e., it improved gait stability (Hausdorff *et al.*, 2007a)) and was found to have a 76% reduction in freezing episodes (Arias and Cudeiro, 2010). However, auditory signals introduce limitations for navigation which can be alleviated through the use of haptics.

Vibrotactile Metaphors (follow the signal) In this approach, patterns are developed by scaffolding off of existing cognitive structures to derive meaning from the signals. Patterns are designed with a push/pull metaphor used to coax the user into taking steps that follow the signal. As an example, using an array of vibrotactile actuators that go around a user's hip, a simple pattern can be developed that starts from the back of the user and travels along the left side of the waist to the front to denote taking a step with the left foot as shown in figure 6.6. The initiation of the signal would map to the toe off event of the left foot and the user would follow the pattern with his or her foot moving forward until the signal reaches the front mid-section of the waist where the user would terminate the step. To address step length, the principles of conveying distance through the on/off modulation times of vibrotactile motors has been explored by McDaniel *et al.* (2009). Similarly, in this approach, distance is metaphorically associated with the speed of of the overall pattern. As an example, a quick signal that travels across the side of a user could denote short, terse steps where as one that moves slowly along the hip could denote long pronounced steps.

The benefits of haptic metaphors in signal perception have been well researched in prior work (Snibbe *et al.*, 2001; Panchanathan *et al.*, 2014; Mcdaniel, 2012). Although haptic metaphors can have a higher learning curve as the mapping is not as direct as literal translations, this approach is hypothesized to have a stronger recall in real world settings since stronger associations can be formed between stimulus-response couplings. Metaphors often rely on a haptic illusion of apparent motion called salta-

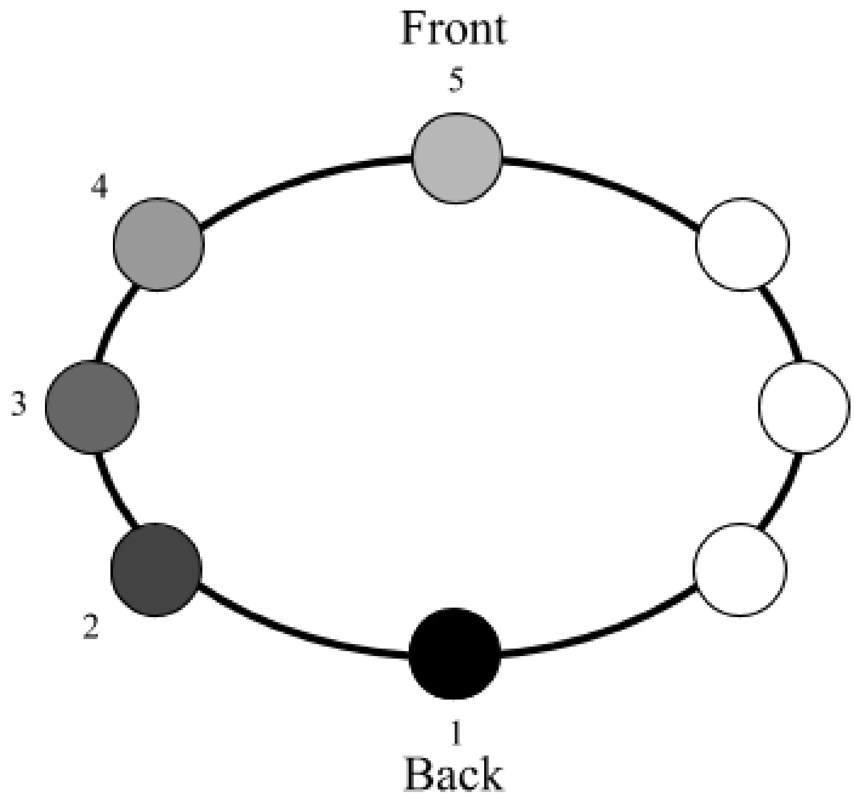

Figure 6.6: Haptic Pattern for a Step Taken with the Left Foot. Numbers Denote Order of Actuator Activation.

tion (Geldard and Sherrick, 1972) where groups of pulses in equal temporal succession provided at distinct body sites are reported to be perceived as a linearly sweeping movement of discrete pulses at the actual locations of feedback and also at illusory sites between them. Within this application, this allows for a seamless method of conveying directionality that maps to a physiotherapists approach of occasionally physically touching the subject on the leg that needs to produce longer steps.

6.4.4 Human Perceptual Bandwidth for Haptics

Human perceptual bandwidth is the limit on the amount of information which can be perceived at any given instance through an individual's sensory receptors. When considering the ability to process information through a given modality, it is important to look at the bandwidth in a temporal rather than discrete context to get a better understanding of the limitations imposed by these sensory bandwidths in real world applications. The maximum rate at which information may be reliably processed by a channel has been studied for the various modalities (touch, vision, and hearing) (Savica *et al.*, 2016). Vision was found to have the highest information transfer rate of 1,000,000 bits/sec followed by hearing which had a limit of 10,000 bits/sec and lastly the sense of touch which had a limit of 100 bits/sec (subject to both the type of stimulus and the surface dimensions of reception). These perceptual rates, however, are limited in their ability to fully encompass the ability to effectively understand information through a given sensory channel. These differences in maximum rate of perception make it difficult to translate perceptual stimuli from one domain to another and maintain the granularity of feedback. However, various strategies have been explored in translating stimuli through sensory substitution. These systems typically translate from higher perceptual bandwidths to lower and propose various mapping strategies that fit within the limitation of the substitution. As an example, mappings for various dimensions common in visual stimuli such as distance, direction, color, size and shape to haptic stimuli have been explored with various degrees of success (Lederman and Klatzky, 2009; Erp, 2005; Cappelletti *et al.*, 1998).These mappings often utilize the various dimensions of haptic sensation including pressure, vibration, temperature, pain and limb movement.

6.4.4.1 Information Transfer

Information transfer (IT) is a quantitative measure of the increase in information that results from knowledge and recognition of the received signal. Ideally, the output should have a high correlation with the input signal denoting that the user did perceive all of the information that was given. The formula (Tan *et al.*, 1999) for Information

Transfer (IT) is as follows:

$$IT = \sum_{j=1}^{k} \sum_{i=1}^{k} P(S_i, R_j)\, log_2\left(\frac{P(S_i|R_j)}{P(S_i)}\right)$$

where (S_i, R_j) represent a given stimulus-response pair and k is the number of alternatives from which the user perceives and responds. Thus IT is the average of the amount of information, measured in bits, weighted by the joint probability of stimulus-response pairs. $P(S_i, R_j)$ is the joint probability of stimulus S_i and response R_j, and $P(R_j)$ is the probability of R_j. The maximum likelihood estimate of IT, IT_{est} , can be computed by counting how often stimulus-response pairs, (S_i, R_j), occur within a k x k confusion matrix:

$$IT_{est} = \sum_{j=1}^{k} \sum_{i=1}^{k} \left(\frac{n_{ij}}{n}\right) log_2\left(\frac{n_{ij} n}{n_i n_j}\right)$$

where n is the total number of trials in the experiment, n_{ij} is the number of times the joint event (S_i, R_j) occurs, and $n_i = \sum_{j=1}^{k} n_{ij}$ and $n_j = \sum_{i=1}^{k} n_{ij}$ are the row and column sums. Because IT is measured in bits, we can express the maximization of the IT function, IT_{max}, with respect to the number of alternatives, k, since a single bit can express a maximum of two different pieces of information given an on/off state. Similarly, two bits could represent four and four bits could represent 16, etc.

$$IT_{max} = log_2(k)$$

It follows that if there are only two alternatives, then the maximum IT is one bit. A simple comparison between the IT_{est} and the IT_{max} can provide insight into whether or not the full bandwidth of perception is utilized effectively in the given feedback design. If IT_{est} is less than the IT_{max} then there exists a gap between the information being presented and the information being perceived. The number of alternatives should be reduced in this scenario to address this perceptual rift. The optimal number of alternatives can be derived by setting IT_{max} equal to IT_{est} and reduced to $k' = 2^{IT_{est}}$.

6.4.4.2 Parkinsonian Gait Information Transfer

A major challenge in considering IT within the domain of gait adaptation is that the measure was developed with Absolute Identification (AI) tasks in mind where a given stimulus should elicit a distinct response. However, within the application of the gait modification system for Parkinson's, it can be challenging to identify AI tasks with respect to haptic stimuli for gait adjustments given that there aren't always discrete values of interpretation. There are two main response categories that the device looks to provide feedback for: cadence and step amplitude. Thus, the goal of haptic feedback within this application is to convey distance and rhythm for steps, once a FoG event is predicted, as these are the two basic building blocks of cadence and step amplitude. Based on prior research that evaluated the effectiveness of auditory and visual stimuli for improving gait characteristics, haptic signals should convey a normalized step length for each subject, as determined by leg length ($normalizedStepLength = 0.8 * legLength$) (Hof, 1996). Although it is not as important that each step hit this threshold, having this as the stimulus goal can be very favorable. Chee et al. demonstrated that when visual cues were set to this person-centric normalization, most participants benefited (Chee *et al.*, 2009). Similarly, research conducted by Willems et al. found that providing cues operating at a cadence 10% to 20% below and individuals baseline value results in a statistically significant increase in stride length for individuals who exhibit freezing with Parkinson's disease (Willems *et al.*, 2006). Thus, the desired response to stimulus within this system is not necessarily concerned with perfection, as the range in acceptable cadence suggests, but rather that the subject makes progress and elicits some level of behavior change in the spatial and temporal domains.

In considering the dimensionalities of distance and rhythm, it is thus important to consider multiple design patterns for rhythm and distance given the target thresholds and follow an AI format by having subjects identify these patterns either verbally or through demonstration of the intended gait characteristics. This would give insight into the expressive capability of the signal and thus the effectiveness of the information transfer within the designed patterns. The main measure being performed in this case is "how many perceptually distinct patterns are being successfully recognized by the individuals compared to the number of intended response variations"? While this metric is subject to the proficiency of an individual with estimating gait characteristics and the sensitivity of that individual to the modality presented as well as the effect of pre-training, this method provides valuable information on the perceptual bandwidth in the haptic channel. Information transfer could be approximated as the error between the subject's response and the expected response after sending a corrective signal.

6.4.5 Increasing Bandwidth: Information Encoding

As discussed above, perceptual bandwidth is measured by the number of perceptually distinct stimuli that can be discerned through a modality. The maximization of bandwidth relies on high effectiveness in utilizing the sensory and perceptual capabilities of our skin. In order to achieve this goal for haptic interfaces, highly efficient feedback protocols need to be developed which encode meaning through the various degrees of freedom that haptic signals allow (location, frequency, time, etc). As an initial proof of concept, a prototype was developed which contained a single haptic motor on each of the user's ankles which was used to convey a static pattern that solely gave feedback with respect to cadence. The device played an alternating rhythmic feedback loop that was meant to inform the user of when to take a step with each foot. However, given a single actuator, it is difficult to encode directionality, distance and timing in a manner that is intuitive. Thus, a follow up study was conducted using a more complex system for signal delivery that allows for greater dimensionality in the patterns provided. Fundamentally, the system needs to provide feedback in to main areas:

1. **Cadence**: Haptic patterns need to give the user a step pattern to regulate his or her speed of walking. (1 bit)

2. **Step Amplitude**: Feedback also should inform the user of how far away he or she currently is from an intended step length. (1 bit)

Within this project, the approach is to develop a set of vibrotactile patterns through the use of a haptic belt. Although a great deal of prior work has been done to examine the effectiveness of providing tactile feedback at various body sites, there hasn't been much work in the area of feedback sites for Parkinson's. This domain provides a unique set of challenges in that the information transfer through the feedback site can play an important role in the intuitiveness of the perceived signal. If the perception of the signal does not map to an almost innate response, the feedback protocol could introduce a secondary cognitive task and actually induce a freezing episode rather than prevent it. Similarly, the patterns need to be encoded to map to existing cognitive structures in order to limit the use of working memory. Miller quantified the limitation of the human working memory to 7 +/- 2 as the magic number (Miller, 1956). Within the PD population, prior research has shown that there may exist even stricter limitation on working memory as a result of cognitive deficiencies that accompany the disease (Parrao-Diaz *et al.*, 2005). Miller also provides insights into overcoming this limitation (Miller, 1956) through the use of information "chunking". This theory suggests that the human brain has the ability to create scaffolding structures for information where building blocks of data are combined into larger informational units. An example of this approach is in the processing of language. We begin by learning letters as the basic building block, then their combination into words, then the combination of words into phrases, and the combination of these phrases in various structures into sentences. Through a similar approach, information on gait performance can be recognized through the construction of signals into patterns and patterns into behaviors. The learning curve for these patterns can be greatly reduced if there already exist cognitive structures that feedback signals can utilize.

Thus the approach looks to compare literal (low level) versus metaphorical (high level) mappings of feedback to test the effectiveness of these protocols in eliciting the desired gait behaviors. An example of a direct mapping could be that the haptic belt vibrates on the side of the body that the user needs to increase step length on and uses frequency as a sensory substitution method to denote distance. An example of a metaphorical approach to pattern development would be building a pattern that vibrates from the back of the user down the right sight of the hip to the front of the user to signify a step taken with the right leg. In each of these mappings, to increase the perceptual bandwidth to touch, the full dimensionality of vibrotactile signals are planned to be used.

6.5 Idiosyncratic Design

In determining a metric of assessment, it is first important to consider the idiosyncratic characteristics of the problem space. In doing so, the system must first determine a standard of assessment that may be used in the development of a blueprint and thresholds. Clinical measures such as the MDS-UPDRS (Goetz *et al.*, 2008) have complete sub-sections dedicated to measuring regression of walking characteristics and specifically, freezing of gait. However, these clinical assessment do not give enough specificity that a system would be able to adequately measure it. Thus, this application further broke down the problem of freezing into its component parts. Specifically, stride symmetry was the primary metric of assessment as this was indicative of how much freezing an individual was experiencing (Plotnik and Hausdorff, 2008).

Once a metric of assessment has been determined, the system must then determine how to accurately create a blueprint of motion based on this metric. In the application domain of freezing of gait, the biometric characteristics of gait are the most obvious in determining the building blocks of a motion blueprint. Wert *et al.* (2010) note gait speed, step width, stance time, and cadence as primary metrics. For individuals with Parkinson's, because a linkage found that FoG, during walking, results when the sequence effect is superimposed on a reduced step length (Chee *et al.*, 2009), it may be important to consider step length and step cadence as critical factors. Both of these elements are entirely unique to an individual and represent a model of their movement characteristics while walking. In section 6.2, the system design is outline of a wearable technology which uses a combination of accelerometers and pressure sensors to determine step lengths. Section 6.4 further discusses the measurement of cadence through the use of APDM sensors to augment the sock-worn device.

In the development of person-centric thresholds for step length, the system first underwent a training period to understand what an individual's "normal" step length looked like (section 6.3. In this training period, a normalized distribution was created (motion blueprint) to represent the individuals gait. Once in an evaluation state, the system would look for outliers using the standard $1.5 * IQR$ method, however, this could be adapted based on the individual. Furthermore, section 6.4 outlines the development of a person-centric threshold for cadence. Again, the system used a training period to understand baseline cadence for an individual and then set the target threshold to 110% of the baseline as this was shown to have the most positive result in reducing freezing episodes (Arias and Cudeiro, 2008; Hausdorff *et al.*, 2007b).

6.6 Adaptation to Intrapersonal Variations

Because Parkinson's is a disease which progresses over a very long duration (years and sometimes decades), intrapersonal variations have often been overlooked. An approach to threshold variation in the context of non-compliant steps was mentioned in section 6.5 in that the outlier detection formula can be adapted by individual. Since steps often naturally become shorter with age, this means that instead of looking for a traditional outlier, we may vary either the entirety of the step length distribution by shifting the entire dataset one phase left (shorter steps) or by re-developing a baseline once the system hits a consecutive number of false positives for non-compliant steps. In doing this, the system is adapting the entire blueprint to the individual over time. Because the current evaluations of the system were not longitudinal, these shifts did not need to occur within the contexts of the studies conducted.

In order to adapt the feedback over time, section 6.10 outlines a rudimentary approach. In this evaluation, a baseline feedback protocol was developed that provided feedback on every step that the user took regardless of if they were exhibiting reduced cadence or shortened steps. However, as one of the cases within the trials, feedback was randomly delivered on only 50% of the steps taken by the individual and was silent on other steps. This was to assess whether there was a learning or progression metric to be evaluated within this context. Although no learning effect was found, further research should be conducted in a longitudinal study as other feedback protocols have found minor improvements in no-feedback conditions after sustained use of devices over many weeks (Espay *et al.*, 2010).

6.7 Context Aware Invisibility

In developing an invisible interface, the application considers both directions of interaction. That is making an invisible input protocol for the user to provide information to the system as well as creating an invisible feedback protocol for information provided from device to subject. Within the Parkinsonian gait device, this has been explored in multiple different ways.

Invisibility of Input The implementation of the shoe worn device has abstracted the interface away from the subject and uses their movement during steps as an implicit input to the system. The use of an accelerometer combined with a pressure sensor allow the system to consistently be collecting information on gait without the need to disrupt the user. Thus, the biomechanics of the person's gait become the data entry and allow for the anticipatory loop to persist with a pseudo human-in-the-loop approach. Although the processing is currently being done offline, this autonomous data collection enabled the use of the device in real-world environments without interfering with the person in the wild.

Invisibility of Feedback Feedback provided to the user should, similarly, be invisible and not create significant additional cognitive load. Given that the primary goal of gait is navigation through an environment, an invisible system should not block the primary modalities used in this context: visual and auditory. People need to look at their surroundings as well as listen for potential hazards while navigating in unpredictable domains. As an example, we need to listen for oncoming traffic and look for other people while crossing a street. Because of these limitations, the PD device has provided feedback signals through the use of haptics. In order to minimize cognitive load, these signals have been designed in a way to map to cognitive models. For a longer explanation on this, please refer to section 6.4.3.

6.8 Evaluation 1: Context Detection

In the initial evaluation of the system, two primary components were assessed: the accuracy of detecting when steps were taken and the accuracy of the calculation of stride length. As a preliminary study, these components were evaluated for an individual with normal gait characteristics so that a baseline could be formed to determine the practicality of distance calculation using a single accelerometer.

Overall, ten separate trails were conducted where the subject walked 8 steps forward down a hallway, turned around, and then walked 8 steps back. Each of the steps was manually measured by marking off the heel-strike locations along a tape measure which spanned the entire hallway. Stride length was measured using the distance between heel-strike events on each foot. As shown in Fig. 6.7, the pressure values validated the starting and stopping points for each step. The acceleration curve follows what one would expect to see for normal gait and allows visual identification of the points where the heel-strike and toe-off events are occurring as well as adequately showing the mid-swing. The system was able to accurately detect every step event within the data, but was limited in accuracy with respect to the distance calculated. This was due to the posture of the foot during mid-swing that is not accounted for with a single-accelerometer approach. A solution is to modify the system to use an IMU in order to solve for this issue in accuracy by receiving angular acceleration from the foot and shank. Since this study, other research has been conducted to show

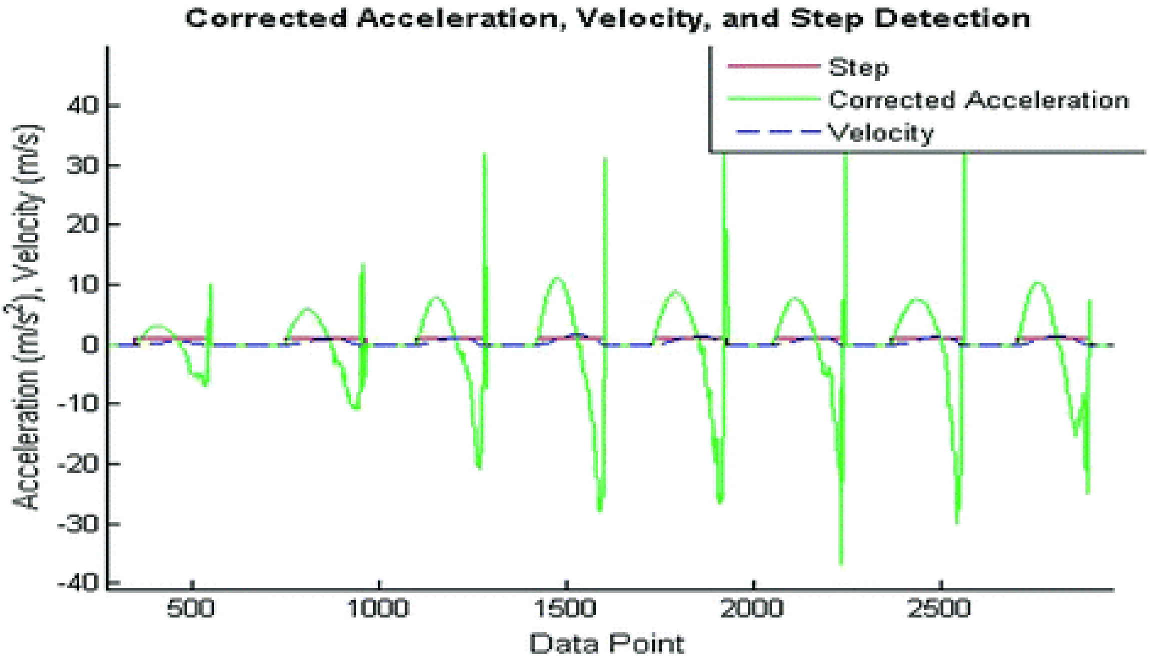

Figure 6.7: Graph Showing Corrected Acceleration, Velocity and Step Detection (Tadayon *et al.*, 2015a).

height-adaptive methods for more accurately calculating step length (Zhang *et al.*, 2018).

Although more extensive evaluation is required, preliminary results have shown that this system does show promise in being able to detect asynchronous steps. Future work may augment the single-accelerometer approach to include an IMU in order to more accurately determine angular acceleration of the foot and thus make the distance calculation much more accurate. This is because single-accelerometer approach has an inherent flaw in that offset error in the acceleration will cause the velocity calculation error to rise linearly with time. The effectiveness of site-specific haptic stimulation will be evaluated as well once step length can be more accurately determined since recent research has shown its effectiveness (Rabin *et al.*, 2013). The system with these modifications will be evaluated for effectiveness as a tool for the anticipation and prevention of Freezing of Gait episodes.

6.9 Evaluation 2: Motion Modeling and Prediction

In the dataset used for this study, motion data was captured from each subject using three accelerometers with different placement (shank, thigh, and torso) (Bachlin *et al.*, 2010). Any FoG events that occurred were then manually time-stamped into the dataset by an independent observer. In this study, three subjects were chosen at random and only the data from the three-axis shank accelerometer was used. For each subject, neural networks were trained using the first half of their dataset. In this training period, each time-stamp where FoG occurred was shifted 1,000 samples (approx. 5 seconds) toward t = 0 such that the networks were trained to recognize the precursor symptoms of each FoG event. Once these networks were trained, they were tested using the second half of the dataset to yield the results shown in the following section. For each subject, several different neural networks were tested. The parameters that were varied include:

1. N - number of hidden layers
2. M - number of hidden units per layer
3. f0 - number of samples included in back-propagation through time (BPTT) algorithm
4. D - down sampling factor

After these trials were performed, the precision and recall for each network configuration were calculated. The precision is the percentage of FoG warnings by the trained network that correctly predicted a FoG event while the recall is the percentage

				Subject 1		Subject 2		Subject 3	
f_0	D	N	M	P%	R%	P%	R%	P%	R%
100	1	1	3	-	-	100	11	-	-
100	1	1	5	-	-	100	4	-	-
100	3	1	3	-	-	89	30	57	27
100	3	1	5	-	-	96	16	62	25
1000	1	1	3	-	-	100	5	-	-
1000	3	1	3	42	47	100	2	-	-
1000	3	1	5	-	-	100	10	-	-

Figure 6.8: Precision and Recall Values in Trials (Zia *et al.*, 2016).

	Subject 1	Subject 2	Subject 3
Training	18	9	39
Testing	5	15	26

Figure 6.9: Number of FoG Events per Dataset (Zia *et al.*, 2016).

of FoG events that were predicted by the trained network. Only the configurations which yielded statistically-significant precision and recall values are shown in the Fig. 6.8. Fig. 6.9 indicates the number of FoG events present in each dataset used for training and testing.

These results suggest that LRNs may be a viable method of predicting FoG events. The data shows that FoG events were predicted up to 47% of the time for Subject 1, 30% for Subject 2, and 27% for Subject 3 while the corresponding network precision was 42%, 89%, and 57% respectively. As listed in figure 6.8, the most effective networks (highlighted) were those that were both small and utilized down sampled data. This may indicate that larger networks, which detect more nuanced patterns, require either more computation time or more extensive datasets to provide comparable predictive power. Based on the results, LRNs may be used in the future to assist

Parkinson's patients in their daily lives.

6.10 Evaluation 3: Invisibility of Cueing

The aim of the study is to evaluate the effectiveness of haptic patterns in allowing an individual to seamlessly understand and follow a target cadence. Based on prior work (Arias and Cudeiro, 2008; Hausdorff *et al.*, 2007b), the frequency of cue presentation was set to a target cadence of 110% of the ON-period baseline cadence for each subject during comfortable walking. Stimulation at this frequency is known to reduce the confounding variable of stride time (Arias and Cudeiro, 2008; Hausdorff *et al.*, 2007b) which is strongly associated with FOG events. Two patterns were tested which varied in complexity with a binary and simple representation as well as one with higher level analogous representation of movement. A third pattern was introduced which randomly skipped cueing on 50% of an individual's steps to test any residual effects on gait. The study also looked to evaluate whether a dual task affected an individual's ability to adequately sense, process and respond to the haptic stimuli to simulate cognitive tasks that often occur in day-to-day activities. This was done through the introduction of a serial subtraction task on certain trials while the individual's were receiving cueing from the belt. As metrics of evaluation, we primarily look at how this intervention effects cadence, gait speed, stride length.

6.10.0.1 Participants

A total of 9 subjects with Parkinson's disease who also have issues with freezing of gait participated in the study with 3 men and 6 women with ages ranging from 57 to 76. Prior to participation, the following set of screen questions were asked to evaluate selection criteria:

1. Do you ever experience freezing, or the feeling your feet are stuck to the floor,

Subject	NFOG-Q	2 Point Ab (cm)	2 Point Back (cm)
1	14/28	4.1	2.5
2	19/28	5.0	5.8
3	25/28	4.6	5.4
4	25/28	5.6	6.7
5	13/28	4.1	4.5
6	14/28	3.9	3.9
7	19/28	5.1	3.0
8	14/28	4.9	4.6

Table 6.1: Subject NFOG-Q Scores and Two Point Discrimination Results

when walking or getting up out of a chair?

2. Do you have any diagnosed neurological or orthopedic conditions (other than PD)? If so, what?
3. How far or for how long (in minutes) can you walk?
4. How far can you walk without resting?
5. If you take seated rests, how far can you walk?
6. Do you ever use a cane or walker? If so, in what situations?
7. Do you have any numbness or tingling in your hands or feet?
8. How is your vision? Do you wear glasses?
9. What medications do you take for Parkinson's disease and in what dosages?
10. Do you have any questions for me?

11. After hearing about the study, can you describe to me in your own words or show me what you understand you will be doing during the study and the potential risks?

The subjects MDS-UPDRS (Goetz *et al.*, 2008) score as well as their score on the New Freezing of Gait Questionnaire (NFOG-Q) (Nieuwboer *et al.*, 2009) was recorded prior to the study. NFOG-Q scores ranged from 9/28 to 25/28. This means that there was a wide distribution of heavy freezers to those with minimal freezing. A two point discrimination test was also administered on both the abdomen as well as the back of each participant to ensure that they could sense two points with at least 10cm between. This value was used because this was the closest that the tactor modules could sit next to one another on the belt depending on the size of the individual's waist. The two point discrimination on the abdomen ranged from 3.9cm to 5.6cm and on the back from 2.5cm to 6.7cm. This was measured given that the dynamic haptic cues required the ability to sense two points with 10cm between them. For additional information on this, please refer to table 6.1. The sessions were also scheduled around an hour after the subject had taken their last dose of medication to verify that they were in the ON state.

6.10.0.2 Procedure

The goal of the study was to assess an individual's ability to match a desired target cadence through haptic patterns. Although freezing can occur in many different contexts such as gait initiation, obstacle avoidance, turning, etc., this study was primarily looking at freezing that occurs in the middle of continuous walking. The participant was first asked to walk down and back a 20 meter hallway in order for the system to get a baseline, comfortable cadence. This cadence was input to the system and was used to calculate target thresholds for all other cueing conditions.

Two different primary cueing conditions were evaluated: haptic metronome and haptic metaphor. A third condition in which cue fading occurred with the haptic metaphor was also evaluated to test any short-term learning effects that may occur. In each of these conditions, a trial consisted of the subject walking 20 meters in a single direction with no turns or obstacles down a carpeted hallway. It is important to note that the hallway was wide enough to not illicit freezing episodes on its own.

In each of these cue conditions, the study consisted of six trials: 2 training trials, 2 single-task trials and 2 dual-task trials. The order of the trials was as follows:

1. Training Trial #1
2. Training Trial #2
3. Single Task Cueing Trial #1
4. Dual Task Cueing Trial #1
5. Dual Task Cueing Trial #2
6. Single Task Cueing Trial #2

The trials were organized in this way to offset any potential confounding variables around learning between trials. It is also important to note that in the last feedback condition (feedback fading), no training occurred as the subject had already learned the feedback pattern in the metaphor condition. Dual task trials consisted of the individual walking to the desired step pattern while also being given a secondary, disjoint cognitive task. In these trials, subjects were tasked with a serial three subtraction task where they were given a three digit number right before the start of the walking and asked to count backwards by 3's for the duration of the trial. This was to evaluate the intuitiveness of perceiving the feedback through the haptic belt.

Introducing a secondary cognitive task is known to be a trigger of freezing episodes (O'Shea *et al.*, 2002). Thus, the study considered if the introduction of additional cognitive load would offset an individual's ability to effectively follow the desired increase in cadence or if the patterns were innate enough that the user could split attention.

6.10.0.3 Results

Feedback	Average Change in Cadence	St Dev	Range
Metronome with Single Task	9.03%	7.53%	2.81 - 10.27%
Metronome with Dual Task	2.25%	4.67%	-4.13 - 9.49%
Metaphor with Single Task	1.40%	7.88%	-12.24 - 10.34%
Metaphor with Dual Task	-7.11%	10.25%	-25.76 - 1.38%
Fading with Single Task	-1.96%	4.81%	-9.59 - 4.59%
Fading with Dual Task	-2.06%	3.09%	-6.80 - 2.81%

Table 6.2: Average Change in Cadence by Various Feedback Protocols Across All Subjects

A summary of the participants NFOG-Q scores as well as their performance on the two point discrimination test can be seen in table 6.1. Overall, every subject showed an increase in cadence under the single task condition of the haptic metronome feedback protocol with an average increase of 9.03% over their baseline gait. One participant showed a 26.42% increase in cadence. Under the dual task scenario with this feedback, an average increase of only 2.25% was found. Under the haptic metaphor condition, subjects showed a very slight increase in cadence under the single task with an average of on 1.40% increase in steps per minute, but a decrease of 7.11% in the dual task scenario. This signifies that these higher level feedback patterns may be introducing too much additional cognitive load and require more of a subject's attention to accurately perceive. In the feedback fading condition, a decrease was detected across both conditions (single task and dual task) signifying that, at least in the short term, no learning effect occurs between steps through the use of this system. However, further research needs to be conducted to evaluate any potential learning effects after prolonged use. For this scenario, a longitudinal study is suggested where the subjects use the device for at least 30 minutes a day for a minimum of two weeks as outlined in Espay *et al.* (2010). A summary of the data can be found in table 6.2.

6.11 Parkinsonain Gait Future Work

6.11.1 Multimodal Feedback Design

The effectiveness of anticipatory applications relies heavily on the ability for the approaches to accurately measure and process contextual information that are predictors of future context. In determining predictive indicators for freezing of gait (FoG) episodes, it is important to first try to gain insight into fundamental causes of the phenomenon. One of the principle challenges in characterizing freezing of gait for individuals with Parkinson's disease is that it is still not fully understood why the disease has an episodic effect on gait at all (Giladi *et al.*, 2001). However, several models have been proposed in attempting to characterize the episodic nature of FoG (Nieuwboer and Giladi, 2013; Plotnik *et al.*, 2012; Lewis and Barker, 2009; Vandenbossche *et al.*, 2013; Jacobs *et al.*, 2009):

- **Threshold Model**: This model assumes that the episodes occur when the accumulation of various motor deficits reinforce each other to a point of motor breakdown.

- **Interference Model**: This model suggests that the episodes represent an inability to deal with multiple, concurrent cognitive, limbic and motor inputs which causes an interruption in the automatic process of gait as the individual is trying to address other stimuli.

- **Cognitive Model**: This model proposes that FoG is caused by a failure to process response conflicts which leads to indecision.

- **Decoupling Model**: This model views FoG as an issue in the disconnection between the preparatory system from the intended motor action as a result of which automatic movements are broken.

However, none of these models still fully encompass the complexity or variability of freezing episodes. Moreover, walking styles of PD patients differ greatly across subjects (including diverse motor anomalies) (Nieuwboer *et al.*, 2004). Thus, eventual patterns in the data that lead up to a FoG event will also likely be highly subject-specific and vary greatly by individual. Nevertheless, previous work suggests that there is a deterioration of the normal gait before FoG which can be expressed in various ways (Plotnik *et al.*, 2012; Nieuwboer *et al.*, 2004; Nutt *et al.*, 2011). Although the pathophysiology of this symptom remains enigmatic, early research has indicated that there may exist a dual requirement of a reduced step length and a successive step-to-step amplitude reduction that leads to FoG episodes (Chee *et al.*, 2009). Some potential metrics of exploration for the estimation of the properties of step length and step amplitude can be described as follows:

- **Postural Stoop** - The angle of the upper body plays an important role in gait as it defines the center of gravity for an individual's weight. As the angle shifts forward, taking longer steps becomes physically more difficult. Festination while walking is defined clinically as a tendency to move forward with increasingly rapid, but ever smaller steps, associated with the centre of gravity falling forward over the stepping feet. This is a common occurrence for individuals with Parkinson's and can be measured through an IMU being placed on the chest. An interesting challenge to explore would be to determine if there is a standardization that could be developed for stoop threshold to define a potentially dangerous angle. Furthermore, although early research has indicated that postural instability can potentially play an important role in the activation of FoG episodes (Nantel and Bronte-Stewart, 2014), more work needs to be done to determine the predictive capabilities of this measurement.

- **Cadence** - Walking cadence is a representation of walking speed and is typically measured in strides taken per minute. In Parkinson's, modulation of cadence remains intact and unaffected even for individuals who experience severe gait issues; however, cadence is used as a compensatory mechanism for a decrease in stride length to maintain walking pace (Morris *et al.*, 1994). Thus, this measure can be used as a secondary indicator for shortened step length and can also provide contextual information to help limit false positives within the prediction algorithm. As an example, a system may detect shortened stride lengths over a prolonged period of time and may flag this as a FoG episode. However, the individual may be just standing in a slow-moving line where large strides are infeasible. In this scenario, the system could denote a slow cadence as well which would indicate that the user is intentionally taking shorter steps. If the system noticed a fast cadence in combination with decreased stride length, this would be a much stronger indicator for a FoG episode and could greatly increase the precision of predictive algorithms.

- **Electromyographic Data** - Some early work has been done in analyzing differences of EMG patterns that occur in standard gait termination versus those that occur during freezing (Nieuwboer *et al.*, 2004). This study found that a consistent pattern of premature timing of tibialis anterior and gastrocnemius activity occurred before freezing, as distinct from standard gait stopping events, which was interpreted as a disturbance of central gait cycle timing. The study found that the timing of these events rather than the magnitude of the signals were the primary indicator which correlates directly with findings that the timing of stepping is fundamental to freezing. Although these signals occur in close proximity to the actual freezing event, this data in combination with kinematic data could further validate and help predict episodes. A limiting factor with the inclusion of this metric is the concept of mobility as there are no current mobile solutions that provide the level of granularity and precision while also allowing for real time signal decomposition required for utilizing these signals in an "in the wild" setting.

- **Environmental Context** - While FoG episodes are typically considered a motor impairment, some research has been done to show that there may be a perceptual bias that contributes to these events. Specifically, key differences have been shown in the perceptual processing capabilities of individuals with PD who experience freezing episodes compared to those who do not (Almeida and Lebold, 2010; Davidsdottir *et al.*, 2005). Generally speaking, freezing episodes are more likely to occur when an individual is undergoing a high-stress or timed task such as navigating through a narrow corridor or crossing a street. These observations fit within both the interference model and the decoupling model as the individual has to process multiple inputs and factor those into the planning/timing process for gait. Thus, adding some sort of sensing capability where the system could detect the environmental context of a user and enter a "heightened-awareness" state could greatly increase the recall capabilities of predictive algorithms.

6.11.2 Pre-Training & Domain Adaptation

In the realm of neurological disorders, no two individuals ever manifest the same exact symptoms. This is especially true in the case of Parkinson's disease where disease progression can vary drastically by individual and some individuals can exhibit conditions that don't affect others at all. Issues with mobility are a primary example of this as only about 70% of the PD population experiences falls on an annual basis as a result of a mobility issue (Wood *et al.*, 2002). Even for those that do exhibit mobility challenges, there are various degrees to which this may inhibit the individual as mobility issues can manifest as stooped posture, freezing of gait (FoG), festination, shuffling steps, falling, or any combination of these. One of the main challenges of neural networks for predicting FoG is the need for extensive labeled training data to develop robust models for classification. Prediction, as opposed to detection, is a three-class classification problem where the two classes of detection (FoG and Normal Gait) are considered as well as a third class pre-FoG. Within the PD application, a naive initial approach was taken to attempt to address the person-centered nature of FoG patterns in that, for each subject, the neural network was trained using the first half of their dataset and tested using the remaining. This approach greatly limits the size of the training set and can result in overfitting if the training data is not well representative of the intra-subject variation in gait patterns that can lead to freezing episodes. To address this limitation, domain adaptation techniques may be utilized so that the network can be trained on a larger, more representative dataset and fine-tuned to address variations by individual.

In domain adaptation, the primary goal is to develop a robust model from a broad source distribution such that it will perform well when tested on a different, but related, target distribution. In order to broaden the source distribution in the PD application, pre-training can be conducted on the entire labeled dataset of Parkinsonian gait rather than on a single individual's gait data as done by Mazilu et al in their work comparing feature learning approaches to unsupervised ones based on PCA (Mazilu *et al.*, 2013). This study ran on the UCI Daphnet Freezing of Gait Data Set (Bachlin *et al.*, 2010) and was able to achieve an F1-measure of 56% by varying the window of data to be considered as pre-FoG between one and six seconds. However, the authors did note that this window will probably vary between individuals even for different FoG episodes for the same patient further highlighting the need for fine tuning. One potential method for fine tuning is in the use of the Backpropagation Through Time (BPTT) algorithm that is used to update the weights of the recurrent neural network (RNN) (Werbos, 1990). Once the network is trained on the generalized gait data, we can implement a Truncated Backpropagation Through Time (TBPTT) technique to limit the depth of error propagation within our network so that we only propagate through the latter layers. This is motivated by the observation that earlier layers encapsulate more generic features of Parkinsonian FoG that would be useful in addressing overfitting concerns, but latter layers become progressively more specific to the details of the classes contained in the original dataset (Sutskever, 2013). Thus, conducting error correction for these end layers could result in more person-specific categorizations. More recently, Torvi *et al.* (2018) also studied the application of transfer learning on gait characteristics between two individuals with Parkinson's. In this study, they evaluated the performance of Long Short-Term Memory (LSTM) architectures to predict FoG at short time durations.

Chapter 7

REMAINING CHALLENGES & FUTURE WORK

This dissertation introduces a novel framework for the design and development of a new category of assistive devices with anticipatory and invisible interfaces. The fundamental contribution of this research is to propose a set of guidelines and considerations that guide the development of devices to augment an individual's proprioceptive system in a way that seamlessly integrates into their own perception of self. The framework looks to shift the burden of adaptation from the user to the device. Systems designed under these principles anticipate an individual's needs based on current context and adopt a person-centric approach by adapting to the user based upon their personal characteristics. In this work, the scope of assessment was restricted to explore application areas related to neurodegenerative disorders as these context provide a unique set of circumstances that mandate the benefits described above. In Chapter 5, a preliminary motion monitoring system that is embedded into exercise equipment is presented and evaluated through the lens of the framework. Opportunities for further evaluation within this context are also presented. In Chapter 6, a multi-study body of work is presented in the real of FoG anticipation for individuals with Parkinson's disease. Three different evaluations are presented to encompass the different steps of anticipation: sensation, prediction and feedback. Each of these evaluations validates modules of the proposed framework.

Based on the results presented, there are many topics left to be explored to optimize the design of these systems through this framework. Chapter 5 discusses the need to explore feedback fading approaches and Chapter 6 presents the opportunities to explore multi-modal feedback as well as domain adaptation techniques. Here, some additional topics for consideration in future work are presented.

7.1 Generalization of Motion Blueprint

In examining the applicability of domain adaptation and transfer learning to the realm of motor performance, it is critical to identify similarities between features that can be normalized across different application spaces. Although the topic of "motor performance" as a whole may be too generalized to identify meaningful feature overlap, future research should look into sub-dividing categories of motion with enough specificity for which templates of blueprints may be developed. As an example, in the development of predictive models for freezing, human gait involves significant subject-based variability and a machine learning model trained on a particular patient's data may not generalize well to other patients.

In section 6.11.2, a preliminary approach is discussed in adapting gait characteristics from one individual with FoG to another. However, it may be beneficial to consider other domains in which issues with gait are predicted as a generalized approach. In this scenario, instead of looking strictly at freezing, algorithms look at a more generalized category of compliant versus non-compliant walking patterns. Research would then need to be done to determine if some of the same predictors of non-compliance in other domains can extend to freezing. Examples would include step asymmetry issues with stroke patients (Allen *et al.*, 2011) and gait-based predictions of falls in the elderly (van Schooten *et al.*, 2015). Predictive characteristics could consider festination, step asymmetry, and cadence as examples of predicting factors.

7.2 Standardized Assessment for Proprioception

One of the primary challenges in the design of idiosyncratic systems under the proposed framework is the identification of a standardized assessment protocol. This problem is especially true as it relates to proprioceptive evaluation given that the field is quite diverse and no true clinical standards yet exist. Currently both "proprioception" and "kinaesthesis (kinaesthesia)" continue to be used as terms in the published literature noting that there isn't even a strict agreement on the fundamental biophysical structures. Future work should look at current assessment tools used in research to identify commonalities for a generalized approach. Similarly, looking at current clinical protocols for determining proprioceptive ability, including threshold to detection of passive motion, joint position reproduction, and active movement extent discrimination (Han *et al.*, 2016), as a means of generalizing an assessment protocol should be considered.

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APPENDIX A

PERMISSION STATEMENTS FROM CO-AUTHORS

Permission for including co-authored material in this dissertation was obtained from co-authors, Prof. Sethuraman Panchanathan, Prof. Narayanan Krishnamurthi, Prof. Troy McDaniel, Jonathan Zia, Lekha Anantuni, and Ramesh Tadayon.