

A Person-Centric Design Framework for At-Home
Motor Learning in Serious Games

by

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ABSTRACT

In motor learning, real-time multi-modal feedback is a critical element in guided training. Serious games have been introduced as a platform for at-home motor training due to their highly interactive and multi-modal nature. This dissertation explores the design of a multimodal environment for at-home training in which an autonomous system observes and guides the user in the place of a live trainer, providing real-time assessment, feedback and difficulty adaptation as the subject masters a motor skill. After an in-depth review of the latest solutions in this field, this dissertation proposes a person-centric approach to the design of this environment, in contrast to the standard techniques implemented in related work, to address many of the limitations of these approaches. The unique advantages and restrictions of this approach are presented in the form of a case study in which a system entitled the "Autonomous Training Assistant" consisting of both hardware and software for guided at-home motor learning is designed and adapted for a specific individual and trainer.

In this work, the design of an autonomous motor learning environment is approached from three areas: motor assessment, multimodal feedback, and serious game design. For motor assessment, a 3-dimensional assessment framework is proposed which comprises of 2 spatial (posture, progression) and 1 temporal (pacing) domains of real-time motor assessment. For multimodal feedback, a rod-shaped device called the "Intelligent Stick" is combined with an audio-visual interface to provide feedback to the subject in three domains (audio, visual, haptic). Feedback domains are mapped to modalities and feedback is provided whenever the user's performance deviates from the ideal performance level by an adaptive threshold. Approaches for multi-modal integration

and feedback fading are discussed. Finally, a novel approach for stealth adaptation in serious game design is presented. This approach allows serious games to incorporate motor tasks in a more natural way, facilitating self-assessment by the subject. An evaluation of three different stealth adaptation approaches are presented and evaluated using the flow-state ratio metric. The dissertation concludes with directions for future work in the integration of stealth adaptation techniques across the field of exergames.

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CHAPTER 1

INTRODUCTION

1.1 Dissertation Overview

Motor learning has become a widely popular topic in research due to the rise in technology to support motor skill acquisition over the last decade. Motor learning is defined here as the process by which an individual acquires and masters a motor skill, including both simple motor tasks (such as elbow flexion/extension) and more complex skills (such as pitching a baseball). In traditional learning environments, this learning is facilitated by a trainer, an expert in the execution of one or more motor skills who can demonstrate these skills to a learner, assess his or her performance, and provide feedback. This process can then be referred to as “supervised motor learning” since the learner is being guided through the process by a supervising agent. This type of motor learning is critical in rehabilitation and athletic training as well as other fields in which motor learning is put into practice.

Rehabilitation alone covers a wide variety of motor learning scenarios. Rehabilitation programs with physical therapy components span the country and include a variety of motor tasks and assessments. Physical therapists use motor learning as a method by which to revive motor function over time in the areas affected by conditions such as stroke. A primary limiting resource in these programs is trainer availability; one therapist often works with multiple individuals, and can only interact with each for a very limited amount of time each week. Yet the frequency of exercise required to maintain steady progress in rehabilitation often exceeds the time available to work with a trainer

for many individuals, resulting in the need for at-home self-training, a form of “unsupervised motor learning” in which the trainer is not physically present.

Traditionally, at-home programs involve the assignment of a series of exercises for the individual to complete at home, without real-time trainer feedback. This poses several issues for the learner:

1. Due to the lack of guiding feedback from an expert, the individual is unable to or experiences difficulty with assessing his or her own performance (“self assessment”) and is thus unable to perform the adjustments necessary to improve his or her performance. This slows the progression of mastery of a motor task.
2. Often an individual exhibits compensatory motion habits, particularly in the early stages of rehabilitation, in which the wrong limbs or joints are used to complete a motion. For example, an individual with impairment in the left arm may inadvertently use the right arm to complete a motor task, which limits his or her ability to improve motor ability in the impaired arm. A physical trainer can catch these errors while observing an individual’s motion in supervised learning, but it can be far more difficult for an individual to detect and correct his or her own compensatory behavior in unsupervised learning environments.
3. Due to the frequency and repetitive nature of many motor tasks, they can often become tedious for the learner if performed in a non-interactive manner with little to no feedback from the environment.

As a result of the above, many individuals often reduce compliance to at-home motor learning programs over time. Consequently, many technological solutions have

been developed in research to facilitate a more interactive experience in at-home motor learning. A summary of this field of work is presented in Chapter 2.

Perhaps one of the most significant limitations of research in this field is the tendency to focus on the collective group of motor learners rather than the individual. As a result, the strategies developed for motor assessment, feedback, and environmental design in these systems can have limited applicability to certain motor tasks and learners. In contrast, this dissertation proposes a person-centric approach to design in which a specific individual lies at the center of the research and is integral to its development. The process of creating an autonomous solution for guidance in at-home motor learning is explored using a case study, introduced in Chapter 4, in which an individual motor learner and trainer participate directly in the requirements, design and evaluation of a novel framework for at-home motor learning using serious games as a platform. While serious games have previously been developed to facilitate motor learning (and are summarized in Chapter 2), this dissertation proposes a “stealth adaptation” approach, as covered in Chapter 7, to improve upon the limitations of these approaches. The person-centered framework proposed in this work addresses three primary challenges in the field:

1. Motor Assessment, or the ability of an autonomous system to capture and analyze an individual’s motor performance in real-time, is the first challenge addressed in the case study. In Chapter 3, several popular models for motor learning are compared and discussed. The highly-debated topic of “mirror neurons” is presented and its implications for motor learning systems are addressed. In Chapter 5, a novel framework for motor assessment is derived from interactions

between the trainer and trainee in the case study, and is compared with several widely-known assessment methods in the field of upper-extremity stroke rehabilitation. The primary benefit of this framework is its applicability across various motor tasks and individuals, as is detailed in this chapter.

2. Motor Feedback, or the provision of concurrent or terminal feedback by a system on the correct and erroneous aspects of an individual's performance in a motor task to guide the learner, is addressed in Chapter 6. A multimodal approach is proposed here as it more accurately reflects the multimodal nature of motor feedback given by a trainer. Discussions on the integration of haptic, audio and visual modalities as well as the fading of feedback over time are presented in this chapter.
3. Serious Game design for motor learning is the final challenge addressed in this work. Specifically, this dissertation focuses on the integration of strategies for motor assessment and motor feedback into the core design of gameplay such that these processes do not interfere or interrupt with "flow state", a cognitive state of engagement detailed in Chapter 7 which is critical to learning in these games. Strategies for integration into game design as well as the adaptation of game difficulty in real-time to maintain player flow are presented in this chapter along with their evaluation in this case study.

Several other discussions related to the design of an autonomous motor learning system are also presented in this dissertation. The effect of motor learning models on system design is illustrated in an example using different accounts of the Mirror Neuron System in Chapter 3. Various considerations for multimodal integration, fading and fine

postural correction are provided in Chapter 6. Furthermore, an overview of Person-Centric research and its application in motor learning is given in Chapter 4. The work concludes in Chapter 8 with directions for future development of this research.

1.2 Previously Published Work

The contents of Chapter 4 include previously published work, *A Toolkit for Motion Authoring and Motor Skill Learning in Serious Games* by Tadayon et al. (2014). The contents of Chapter 5 partially include previously published work, *Interactive Motor Learning with the Autonomous Training Assistant: A Case Study* by Tadayon et al. (2015). Chapter 6 includes two previously published articles, *Autonomous Training Assistant: A System and Framework for Guided At-Home Motor Learning* by Tadayon et al. (2016) and *A survey of multimodal systems and techniques for motor learning. Journal of information processing systems* by Tadayon et al. (2017).

CHAPTER 2

SYSTEMS OVERVIEW

2.1 Virtual Reality/Augmented Reality

In the last 17 years, researchers have produced a plethora of interactive systems and environments intended to improve and augment rehabilitative motor tasks. Both hardware and software solutions have been designed to interact with users both with and without the presence of physical trainers and physicians. Among these systems, perhaps the most prevalent in research are virtual reality (VR) systems. These systems facilitate many of the interactions afforded by virtual learning environments including problem-oriented motor task progression, social interaction including cooperation and competition, and other features (Huang et al. 2010). A review of these systems by Holden (2005) indicates that tasks and skills learned in these virtual worlds can transfer directly to the real world, particularly in motor tasks that are considered more complex. These findings imply that in some cases, virtual environments can provide a more interactive alternative for motor training than non-virtual or real-world alternatives. Similarly, Dalgarno & Lee (2010) find that virtual environments can help in providing meaningful context to motor tasks, improving the sense of immersion and placement in a task, improve motivation and enhance spatial interaction. Saposnik & Levin's survey (2011) reinforces these assertions as it indicates that health outcomes are often shown to improve in clinical trials involving the use of these virtual systems.

The usage of Virtual Reality systems for clinical applications in motor learning dates to as early as 2001 in conjunction with pre-existing clinical programs (Jack et al. 2001). Shortly afterward, other successful evaluations of VR systems emerged including that of Merians et al. (2002) on post-stroke hand function. Cameirão et al. (2009) further reinforced these findings by indicating successful functional improvement in subjects under Barthel and FIR metrics in their system, the Rehabilitation Gaming System wherein a first-person avatar directly reflects a user's motion to produce a point-of-reference for motor correction in a virtual environment. As these virtual environments attempt to both replicate and augment a real-world feedback environment between a subject and trainer, often they use the rich multi-modal format of feedback present in such an environment (Mihelj et al. 2012).

Unfortunately, many limitations in VR technologies have prevented them from being implemented beyond a research environment. For example, a SWOT analysis by Rizzo & Kim (2005) indicated that VR environments and technology are very costly and often unaffordable for users. Additionally, the length of trials for these environments is limited (Laver et al. 2012). Other issues with the technology include its complexity, concerns for safety (especially with unsupervised home use), and regularly-needed maintenance (Lange et al. 2009a).

In addition to Virtual Reality, Augmented Reality (AR), where the real-world is “augmented” with a virtual layer using specialized display devices to provide improved interaction, information and learning, has seen some limited use in rehabilitation (Kirner & Kirner, 2011; Aung & Al-Jumaily, 2012). Further exploration in this technology is required before its comparative usefulness can be conclusively determined. Robotic

systems have also seen use as a hardware-centric solution, but the mechanical requirements of these systems suggest that further optimization is required before they can be adopted in real-world situations at a large scale (Perry et al. 2012, Kazemi et al. 2013).

2.2 Commercial Game Hardware

More recent solutions have attempted to address the issues of complexity and cost-efficiency. Pervasive gaming research has yielded a series of newer, more practical hardware for capturing and analyzing motion in both supervised and unsupervised scenarios (Magerkurth et al. 2005). Of particular note is the fact that much of these systems are already commercially available, dramatically reducing the manufacturing, production and distribution requirements that affect scalability in the previous systems. This has made off-the-shelf hardware a very useful and highly-adopted solution for rehabilitation systems in recent work. As an example, the Nintendo Wii remote has been used quite often in recent research for home based rehabilitation, including an implementation by Deutsch et al. (2008) to assist in rehabilitation of Cerebral Palsy and Brosnan (2009) for stroke.

These systems have been evaluated for cost-efficiency, usability, feasibility, and adoption rate among other requirements, and the results have been promising for researchers (Lange et al., 2009b; Joo et al., 2010). Saposnik et al. (2010) and Mouawad et al. (2011) found in their reviews that the Wii remote's tactile motor, infrared sensor, accelerometer/gyroscope, built-in audio output and configurable input keys altogether made it an effective and low-cost device for rehabilitative motion tracking and input.

Similarly, the Microsoft Kinect has been widely popular in recent research as a non-invasive external monitoring solution (Lange et al. 2011; Labelle, 2011; Chang et al. 2011; Chang et al. 2012). When compared, each device has a drawback that is addressed by the other; the Wii remote cannot record motion beyond a single limb since it only records its own rotation and movement, while the limbs that are occluded from the Kinect camera during motion tracking cannot be tracked and are usually estimated in space with a high rate of error (Tanaka et al. 2012).

Finally, due to the effectiveness of the above game-based hardware as motion tracking mechanisms, recent literature has pushed serious games into the limelight as software which can be combined with these devices to create an interactive rehabilitation experience in both the clinical and home settings. Serious games have been a natural fit in rehabilitative exercise because they maintain engagement over many repetitions of a motor task, provide a sense of challenge and encouragement for users, and consequently, help to maintain the motivation necessary to complete rehabilitation programs (Mihelj et al. 2012, Rodriguez-de Pablo et al. 2012). Ma & Bechkoum (2008) noted functional improvements over six-week periods in their serious game evaluation.

Perhaps an even more significant advantage of serious games in motor learning is that, when properly designed, they can encode performance tracking directly within game tasks. For example, Johnson et al.'s TheraDrive (2004) uses in-game telemetry to translate driving task performance to motor skill performance and functional improvement, as evaluated by Ruparel et al. (2009). Among the most prominent users of the person-centric approach to evaluation in serious games is Alankus et al., who in one case (2011) have revealed long-term improvement in a stroke subject through repeated

exposure to game-based therapy, and have also managed to reduce compensatory motion in subjects in their design (2012). Jacobs et al. (2013) have also shown that Dynamic Difficulty Adaptation (DDA) can improve the interactivity of these systems.

2.3 Serious Games for Motor Learning

In the serious game design, many advancements have been made within the last decade to specialize these games for motor learning. Initial efforts emphasized the aspects of serious games which make them useful for motor learning applications. It is well known that serious games incorporate an interactive input-output cycle which make them a natural platform for the introduction of learning objectives (Garris et al. 2002). Furthermore, they give meaningful context to repetitive motor tasks through the incorporation of “meaningful play” (Salen & Zimmerman, 2005) where correct actions have positive and significant consequences (Burke et al. 2009a). Finally, when designed well, serious games can maintain long-term interest and engagement from players (Johnson & Wiles, 2003).

As researchers began to introduce these games into the world of rehabilitation, several requirements for successful adaptation have emerged. Several studies were performed to gauge these requirements from the stroke population, which consisted primarily of the elderly (Wiemeyer & Kliem, 2012; Ogomori et al. 2011; Flores et al. 2008). Among these is customization. Because of the widely varying interests, physical conditions, and personal traits of individuals playing rehabilitation games, the design of the interface and gameplay elements should be heavily customizable and adaptable (Alankus et al. 2010; Rego et al. 2010). The design of such games should be person-

centered, including the difficulty, motion requirements, genre, pace of gameplay, and feedback design (González Sánchez et al. 2009).

Furthermore, the difficulty of these games should constantly and autonomously adapt to the abilities and physical strength of the player (Burke et al. 2009b; Gouaïch et al. 2012). By doing this, serious games can maintain a constant state of flow, wherein the player is constantly challenged without being overwhelmed or underwhelmed by the game's difficulty (Chen, 2007). Meta-cognitive strategies including self-assessment, modeling and thinking aloud are all shown to occur when the game design focuses on challenge and problem solving (Kim et al. 2009), assigning explicit and clear rewards to successful exercise completion while seamlessly correcting erroneous motion (Paras, 2005). Games should also be aware of and respond to a user's emotional state during gameplay (Hudlicka, 2009).

Another critical feature in rehabilitative games is the ability to perform on-the-fly assessment of performance (Shi et al. 2013). This real-time motor performance assessment has typically been done directly using analysis on the motion data captured by sensors, accelerometers and joint tracking cameras during gameplay (Serradilla et al. 2014) and has been used as a basis for the automatic adaptation of game difficulty (Perry et al. 2013). In addition, indirect assessment of performance has been indicated as a possibility by comparing in-game performance data to external motor performance data in standard outcome assessments. For example, Khademi et al. (2014) have shown a high correlation between an individual's game score in a commercial motion-based game and that individual's performance score in assessments such as the Fugl-Meyer Assessment.

While many of these challenges have been addressed in recent research, one critical problem remains in the design of serious games for rehabilitation. This problem is the relationship between game outcomes and motor learning outcomes (Barrett et al. 2016), and is a primary focus of this dissertation. How can one ensure that an individual's progression within gameplay directly corresponds to his or her progress in motor task performance? It has been established that one of the key challenges in games designed to teach is that game outcomes should be properly interleaved with learning outcomes (Watson, 2007), although this criterion has yet to be applied toward motor learning in rehabilitative research. Work by Chandrasekharan et al. (2010) hinted at this feat by applying common coding theory principles in game design, and Habgood & Ainsworth (2011) implicated the value of this integration in the application of instructional material in games for children.

However, despite significant advancements in rehabilitative game design in the last several years, there have been no studies implementing such an integration for motion exercises. As a general guiding point in serious game design for learning, Hall et al. (2014) developed a framework for the mapping of learning objectives to gameplay based on the following transitional characteristics: Goals, Choice, Action, Rules, Feedback. These five elements are contained in both a motor task and a game task; a robust strategy is necessary to map the two tasks together under these attributes in a manner that is context-independent (Arnab et al. 2015).

In addition to exploring how serious games can meet the requirements necessary for engagement during motor learning, recent work has also deeply explored how these games can support the cognitive processes behind this learning. The effectiveness of

serious games as learning platforms has been conveyed in research from the perspectives of psychology, pedagogy, and assessment (Connolly, 2013). At the psychological level, a variety of models ranging from behaviorism to experiential learning theory and cognitive theory have been applied to serious games to describe how they facilitate learning (Boyle, 2013). One such model views the cognitive process as an "executive control system", wherein the learning process is an interaction of four processes: attentional control, information processing, goal setting and cognitive flexibility (Boyle et al. 2013) and serious games designed to facilitate and augment these processes can support and improve learning outcomes over a range of domains. Another perspective uses time analysis via time-on-task assessment (amount of time spent by the user on a task) and time perspective (relative focus of the user on past, present or future) and shows how these metrics can relate to an individual's learning compatibility with a serious game (Usart & Romero, 2013).

It is shown by Blasko et al. (2014) that characteristics of the individual can affect enjoyment and engagement with a serious game, including the learner's sense of self-efficacy and motivation for engaging with the game, experience with games, demographic representation in the game, learning styles and working memory, among others. From a pedagogical standpoint, Orr and McGuinness present several classic models for learning used in serious games including Behaviorism, where learning occurs in a feedback cycle within the game environment, Cognitive Constructivism in which learning is the process of building on one's understanding of the subject matter through game progression, Socio-Constructivism in which this process is facilitated by a third-party agent, and more (Orr & McGuinness, 2014). Finally, on the topic of assessment, a

literature survey by Hainey et al. (2013) reveals that, depending on the domain of learning, serious games have utilized a variety of strategies for formative or summative assessment, or a combination of the two, within gameplay. Some strategies used include embedded assessment methods like game state monitoring, the use of quests as encapsulated learning units, and external assessment methods like quizzes. Moseley (2014) makes a case for embedded assessment that is implicit within gameplay; that is, the feedback on performance should be contextual within the game objectives.

2.4 Player Interest Considerations

Various factors may affect a player's enjoyment of a digital game. Blasko et al present an excellent and comprehensive overview of the literature in this subject in their article entitled "Individual Differences in the Enjoyment and Effectiveness of Serious Games" (Blasko et al. 2014). They break down the common disparities of serious game effectiveness into four categories of individual differences: motivational factors and self-efficacy, experiential factors and video game self-efficacy, demographic factors such as gender and age, and cognitive factors. Their findings in literature on each of these classes of distinction are summarized below:

2.4.1 *Motivational Factors*

The focus on self-efficacy as a factor stems from work by Bandura (1997) indicating its effect on effort, response to challenge, perseverance and commitment. An individual's perception of his or her ability to grow more experienced with training has a profound impact on training and is referred to as learning self-efficacy (Dweck, 1986).

This concept applies directly to the motor learning domain, where it has consistently been shown that an individual's belief in his or her own growth potential with respect to motor ability has a positive effect on motivation and outcomes (Schunk, 1995).

Interestingly, there have also been studies showing a link between perceived self-efficacy in the game domain and self-efficacy in other learning tasks as well, stressing the importance of design in games to maximize this attribute in players (Locke & Latham, 1990; White, 2008). To elicit this self-efficacy, games rely on both extrinsic and intrinsic motivation to varying degrees. Extrinsic motivation is considered a short-term motivator, but emphasis on this form of motivation is considered dangerous as it can destroy the intrinsic motivation that achieves permanent positive change in motor learning and rehabilitation (McCallum, 2012). Games that emphasize intrinsic motivation, on the other hand, through elements such as challenge and fantasy, have been highly effective in promoting the kind of self-efficacy which lasts outside of gameplay (Malone & Lepper, 1987).

2.4.2 Experiential Factors

The topic of video game experience and its effect on serious game effectiveness has recently been explored by Matthew White (2012a), who indicated an influential effect on background experience and confidence with videogames, or video game self-efficacy, on an individual's likeliness to appeal to and regularly use a video game as a learning agent. Video game experience produces an extraordinary amount of transferable skill that affects an individual's proficiency in another game due to the similarity at a high level of mechanics in design and structure between most games (Adams & Dormans,

2012). For example, an experienced game player can very quickly recognize a game's mechanics simply by knowing the genre of the game and instantly begin progressing through the game, while individuals without this background knowledge and familiarity must learn the game's mechanics from scratch, adding a large amount of training time (White, 2012b).

Often in the commercial games industry, developers rely on this prior knowledge in the production of new games such that newly published games lack an in-depth tutorial for new learners, which makes it highly likely for an inexperienced player to give up quickly (White, 2009; Orvis et al. 2005). It is therefore highly recommended that the design of new games accounts for the lack of experience in newer players by creating an intuitive design with the appropriate guidance to support this audience (Blasko et al. 2014). Such a design challenge is extremely important in the rehabilitative space, where the primary audience are older adults with little to no background experience in games (Wiemeyer & Kliem, 2011). Tutorials designed for this sort of guidance should emphasize the fundamentals that comprise gameplay, discussing not only the controls of the game but, perhaps more importantly, the main objectives and goals (White, 2012b).

One of the trickiest challenges in using a game approach is that, in addition to having various levels of game experience, players can have varying individual tastes and preferences for games as well. For commercial games, this does not introduce an issue since an individual can simply select the games with the highest appeal to his or her individual tastes for purchase and enjoyment. However, in serious games, often a narrative, genre, design and mechanics for an implementation are determined beforehand, resulting in the game being brought to the learner rather than the learner choosing the

game. Inevitably, these individual preferences have a significant effect on one's ability to enjoy, learn from, and benefit from a serious game (Ferdig, 2013). Some attempts at solving this challenge include the collection of common patterns of interest in a targeted audience, like older adults (Blocker et al. 2014), to maximize the effective audience for a gaming solution.

2.4.3 *Demographic Factors*

In demographics factors for game effectiveness, perhaps the most popularly explored attribute is gender. There is a plethora of work suggesting a divide between the effectiveness of game approaches between male and female audiences due to factors such as gender-role stereotypes and gender representation affecting causing greater exposure to games and perceived video game self-efficacy in males over females (Terlecki & Newcombe, 2005; Terlecki et al. 2011; Dean, 2009). This has been fueled largely by the appeal in commercial games to male audiences, manifesting in attributes such as the dominant presence of male player-controlled characters over female player-controlled characters in these games (Dickerman et al. 2008).

Furthermore, age may play a role in enjoyment of certain games over others (Blocker et al. 2014). There is a wealth of promising recent studies indicating that serious games can improve cognitive performance (Lustig et al. 2009) and, more applicably to this work, motor performance (Wiemeyer & Kliem, 2011) in older adults. Guidelines for the design of these games emphasize the importance of simple and intuitive interfaces, low complexity of game mechanics, explicit and direct feedback, task-focus, adaptive challenge, and sensitivity to higher response time and reduced sensory acuity (Ijsselsteijn

et al. 2007; Marin et al. 2011). Games which utilize real-time adaptation following flow theory (Csikszentmihalyi, 1990; Chen, 2007) to maintain a level of challenge that keeps the user within the zone of proximal development (Vygotsky, 1980) achieve the greatest success with these populations as they adapt to differences in individual ability and skill.

2.4.4 Cognitive Factors

Another influential factor in game effectiveness are individual distinctions in working memory, which also relate to above categories such as age and game experience. Working memory capabilities can affect the prevalence of symptoms such as hyperactivity or inattention during learning, while working memory training can help reduce these symptoms (Klingberg et al. 2005). While there have been studies such as (Colzato et al. 2013) indicating a correlation between video game experience and greater working memory capacity, not enough evidence has been drawn to indicate a causality relationship between these attributes.

2.4.5 Design for Adaptation

One of the goals of design in exergames for motor learning is to minimize the effects of individual disparity on game performance and motivation. Self-efficacy is targeted through the provision of direct feedback on motor performance, and the reflection of positive performance in gameplay through Evidence-Centered Design (Kim et al. 2016). Real-time assessment of the player during gameplay ensures that the system can adapt the level of challenge in gameplay through the adjustment of tolerance thresholds in each motor domain based on performance. This corresponds directly to

adjustments in the game's difficulty. Furthermore, gender-neutral avatar representations in game implementations will help to reduce perceived general bias during gameplay. Since the game implementations are focused on motor feedback, it is not difficult to meet many of the guidelines for the design of games for elderly audiences posed in (Ijsselsteijn et al. 2007; Marin et al. 2011) such as task-focused play, simple controls, explicit and direct feedback, and appropriate challenge level (attained through adaptation).

One of the primary goals of this work is to provide a platform by which many different game genres and types can be assigned to a single motor task. Therefore, the design of games is restricted mainly by the type of motor task, and among the range of game contexts that are deemed a natural fit for a motor task, the context with which a particular individual is the most familiar and comfortable can be chosen to design a game implementation for that individual. For this reason, while there are examples given for certain game scenarios applied to specific motor task, the final design should not restrict itself to any specific game.

2.5 Affective Game Design

Research on affective design in serious games has covered many different approaches to detection, response, and regulation over the past two decades, with a broad range of applications. Here some of the most popular general approaches to achieving affective interaction in these games are described.

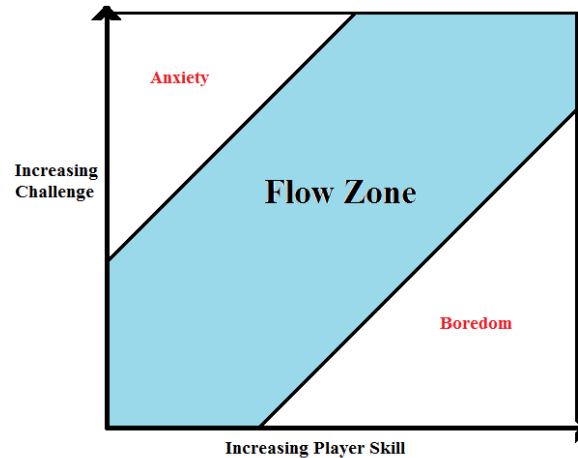


Figure 2.5.1: Flow Zone Diagram, Mapping Player Skill to Challenge.

The initial task of these systems is to accurately detect a player’s emotional state in real-time. To achieve this, a system must be able to capture and interpret visual or physiological data in real-time. To this end, there are several approaches given in recent literature. Sykes and Brown (2003) focus on the input controller to the game by capturing the amount of physical pressure exerted on it by the player. Sourina and Liu (2013) capture EEG data which is then analyzed and classified into various affective states. Jennett et al. (2008) opt for terminal metrics such as questionnaire response and completion time for game tasks. Each of these methods require a context and learning domain in which they can be considered optimal.

After emotional data is captured, the system must then classify into various emotional states. There are various forms of telemetry in recent work aimed at achieving this task. Potentially the most powerful and well-validated metric among these is “flow-state”. This metric uses the concept of “flow” originally used by Mihaly Csikszentmihalyi (1990). Jenova Chen (2007) claims that “flow” is an equilibrium of engagement wherein a player feels that the game experience presents a sufficient level of

challenge to maintain active engagement, and is neither too challenging (which would yield frustration) or too simple (which would yield boredom). An illustration of this concept is shown in Figure 2.5.1, wherein a “flow zone” is established in the mapping between challenge and player skill. The ideal game experience utilizes smart progression of game challenge as a player’s skill increases to maintain the zone of proximal development throughout gameplay.

“Flow state” has been observed through several methods in serious gaming research. For example, Nacke and Lindley (2008) correlate player response in objective domains including physiological data (EEG and ECG) with subjective information including questionnaire responses and compare the results across various configurations in first-person shooter games to determine the highest flow state response. Patterns in heart rate and electrodermal response have also been used to classify flow (Drachen et al. 2010). A primary issue with physiological data analysis is that it often requires a complex and intrusive configuration and involves heavy setup time, making it difficult to adopt in real-world scenarios. To address this, external monitoring techniques involving computer vision have been explored and are gaining popularity. Among these is the use of facial tracking and real-time emotional classification from video image data by Tan et al. (2012).

The final phase of affective gaming is to infuse the affective data into gameplay to provide a richer experience to the player. This can be done in a reactive manner by responding to detected emotional states, or a proactive manner by attempting to evoke or influence certain emotional states through game environments. Interventions for assistance, adaptive difficulty, or game objective manipulation have all been used to

achieve this task (Gilleade et al. 2005). Johnson and Wiles (2003) associated certain configurations of a game's user interface (UI) with flow response in subjects. Yannakakis et al. (2010) demonstrated that the game's camera view may also have a significant effect on flow state throughout a game experience.

Difficulty adaptation has been the most common approach to evoking and maintaining flow state in players. One approach to Dynamic Difficulty Adaptation (DDA) by Liu et al. (2009) used a player's anxiety to form an estimate of flow state, and attempted to maintain a desired level representing optimal experience. Chanel et al. (2008) modulated difficulty parameters such as fall speed in the Tetris game using quantitative and qualitative flow state metrics as real-time and terminal input.

A recent topic of exploration within the affective gaming field is the measurement of flow through a computational model with game-based parameters. As an example, Sharek and Weibe (2014) have recently attempted to achieve such a model by utilizing the ratio of active to intermittent gameplay phases and observing how often players click on the clock within their game interface. Computational usage of player emotional outputs to determine flow is a largely unexplored field and is addressed specifically within this work. A recent study by Craig et al. (2008) has taken the basic emotional states and mapped them to flow state, but few systems have been developed to utilize this information in real-time, particularly in the motor learning context.

CHAPTER 3

MOTOR LEARNING OVERVIEW

3.1 Cognitive Models

To understand what constitutes an effective system design for motor learning, it is useful to observe discussions of the motor learning process in literature. Two theories have been heavily discussed within this field of work: Motor Program Theory and Dynamic Pattern Theory (Muratori et al. 2013). Motor Program Theory, as referenced in Figure 3.1.1, uses “plans”, or command sequences generated and transmitted through the efferent and afferent neurological pathways as coding blocks for an action, are stored as modules in memory and then retrieved and synthesized during execution of a more complex goal (Keele et al. 1968). Schmidt et al. (1975, 2003) developed a more refined definition, the “Generalized Motor Program Theory”, wherein plans can consist of larger chunks or classes of more simple actions to help organize the planning process. The primary distinction of this theory is the decoupling of plans from muscles, which facilitates the use of multiple strategies to achieve a single motion goal (for example, retrieving an object on a surface by reaching directly for the object or pulling the surface toward the user). This distinction then helps to explain compensatory motion in subject during rehabilitation.

An overview of the second major theory, Dynamic Program Theory (Thelen et al. 1991), is given in Figure 3.1.2. This theory instead claims that motor actions are processed using an input-output method (Scholz et al. 1990) in the neuromuscular network such that the inputs include properties of the task (rules and objectives),

environment (weather, lighting etc.), and actor (physical properties, characteristics, mannerisms and traits, etc.) (Newell et al. 1986). Based on this approach, variations in these three categories can produce a multitude of actions and strategies to achieve the same motor goal or task (Heriza et al. 1991).

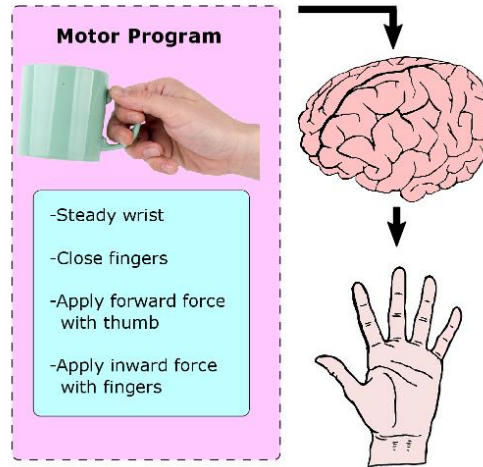


Figure 3.1.1: Motor Program Theory Overview. Sample motor program concept for grasping an object with a handle.

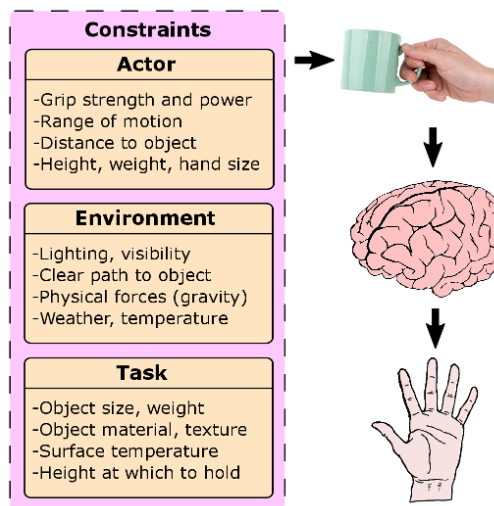


Figure 3.1.2: Dynamic Pattern Theory Overview. Sample pattern parameters for object grasping action.

This model suggests that successful motor skill acquisition for an individual depends greatly upon the strengths and characteristics inherent in that individual, which lends itself to person-centric approaches. While Dynamic Pattern Theory is not, by any means, an unanimously agreed-upon model for motor learning in rehabilitation, it is nevertheless a useful concept in explaining the significance and necessity of person-centric systems for at-home motor learning.

In almost any model for motor learning, several primary components are necessary for motor skill performance to improve: action observation, knowledge of performance, knowledge of results, and self-assessment (Wulf et al. 2010; Carr & Shepherd, 1989). In the broadest sense, these components can be described in the following way: for learning to occur, some form of initial blueprint or template for correct behavior is necessary. This template is provided by the trainer who, upon introduction of a new motion exercise, first begins by demonstrating the action required. The observation of this demonstration by an individual for the purpose of mentally capturing its characteristics is referred to as action observation. Once an action blueprint is attained, the individual will then attempt to perform this motion (and the processes behind successful attempts of this motion are explained by the models above). Upon performing the action, the individual must then be given some kind of feedback by the environment which indicates whether the goal of the action was attained (knowledge of results) and where the individual's action deviated from the ideal blueprint (knowledge of performance).

The individual then uses this information to determine what changes are necessary to improve performance on the next attempt (self-assessment). This cycle,

depicted on the right of Figure 3.1.3, has been used as an engine to drive motor skill acquisition in practice (Franceschini et al. 2010; Franceschini et al. 2012; Ertelt et al. 2007; Celnik et al. 2006; Celnik et al. 2008; Cross et al. 2008; Buccino, 2014).

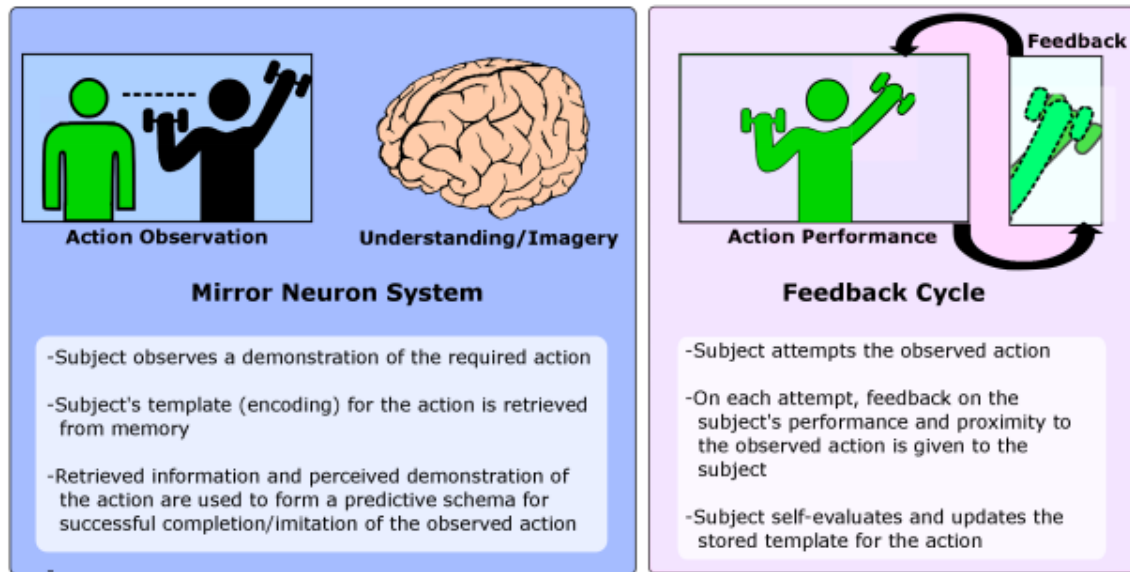


Figure 3.1.3: Mirror Neuron System (Left) and Feedback Cycle (Right). Process of action observation, attempt, feedback and self-evaluation are depicted.

As an example, a professional basketball trainer may show a trainee how to shoot a ball into a basketball hoop by first demonstrating the shot, describing his form and grip on the ball in the process. Details including "bend knees", "hold the back of the ball", and "arc upwards" together comprise a blueprint for a successful basketball shot for the trainee as the shot is demonstrated. The trainee then attempts the shot and misses, after which the trainer adjusts the trainee's grip and provides feedback on her posture. "Knowledge of results" in this example is provided by the basketball hoop - a shot either successfully goes through the hoop or misses. "Knowledge of performance" is the

trainer's feedback on form and posture, detailing why the miss occurred and what changes can be made to improve the accuracy of the next attempt.

3.2 Mirror Neuron System Overview

From a neurological standpoint, one of the most popular mechanisms recently used to explain the effect of guided training on motor learning is the Mirror Neuron system (Buccino et al. 2006), depicted on the left side of Figure 3.1.3. This is a system of neurons which activate when an individual attempts to "mirror", or replicate, an observed motion as if observing one's self in a mirror (via motor imagery). It has been hypothesized that the Mirror Neuron System aids in the acquisition and development of social skills (Oberman et al. 2006) as well as certain aspects of language comprehension (Zarr et al. 2013). This system has been put into substantial practice in rehabilitation in recent years through the design of training programs which elicit cycles of observation and mirroring from subjects (Garrison et al. 2010; Franceschini et al. 2010; Iacoboni & Mazziotta, 2007), and has shown promising results for both upper extremity (Ezendam et al. 2009) and lower extremity rehabilitation (Sütbeyaz et al. 2007). Virtual environments and serious games have much to benefit from the study of this system, as it is modulated by an individual's motivation (Cheng et al. 2006) and can be activated even when the physical limb is abstracted or non-present in a virtual context (Modroño et al. 2013).

Several models for motor learning stress the importance of prediction in the process. That is, before completing a motor action, the actor predicts the environmental feedback which will result from that action. Once the action is completed, the actual feedback received by the actor is compared to the prediction and the resulting prediction

error is used to adjust behavior for the next attempt or action. Several processes are said to contribute to prediction in motor learning: the decomposition of a complex motor task into simpler subtasks when mapping the visual space to the motor space (Ghahramani, 1997), the estimation of a sensorimotor context by the central nervous system using probability distribution among a variety of contextual models (Blakemore et al. 1998), a hierarchical structure for predictive modules under various layers of complexity in motor function (Haruno et al. 2003), and the role of these predictive structures in combination with motor task variation in the generalization of learned motion patterns (Braun et al. 2009). These factors and the ability to focus on task-relevant details in the environment have been used, for example, to model the learning process for a tennis player (Wolpert & Flanagan, 2010).

Other models for prediction rely on Bayesian hierarchical estimation as a driving force for the calculation of prediction error. In these approaches, a task is decomposed into layers of prediction such that higher layers predict the behavior of lower layers as priors, which in turn return the results of these predictions as posteriors. The selection of an action then becomes a problem of error minimization. Kilner and Friston et al. propose that the mirror neuron system utilizes a Bayesian predictive coding framework to infer the most likely intention behind an observed action during action observation (Kilner et al. 2007). They support this claim by indicating the link between behavioral prediction of motor action and encoding of intention in the mirror neuron system during action observation (Friston et al. 2011). While the mirror neuron system may rely on other neural pathways to form a full understanding of abstract attributes of an action (Kilner, 2011), the prediction applied to motor learning in this proposal is nevertheless attributed

to the action observation network (AON) for the sake of simplicity, since the feedback mechanisms used in this approach rely only on the act of predictive coding and error minimization having taken place. This hierarchical Bayesian prediction scheme of the brain helps depict it as a unified system of perception, cognition and action (Clark, 2013). An important element in this predictive learning mechanism is the influence of feedback from others. Through a shared experience, in this case motor exercise, an individual can use what is referred to as “active inference”, the concept of turning predictions into action, to influence and be influenced by a partner (Friston & Frith, 2015). Hence, prediction plays a direct part in communicative learning between a trainer and trainee during motor exercise.

3.3 Mirroring Mechanisms and Design Considerations

To illustrate the significance of cognitive models of motor learning and their impact on the design of motor learning systems, two differing perspectives on the function and role of the Mirror Neuron system are presented in this section. Arguments for each account of mirror neurons, along with their implications in the design of a motor learning system’s feedback mechanisms, are presented for consideration. The two accounts presented are that of Cecilia Heyes (2010) and Karl Friston et al. (2011), as follows:

3.3.1 Associative Account

From Heyes’ perspective (Heyes, 2010; Cook et al. 2014), mirror neurons are not an evolutionary feature that is fully configured from birth and immune to change. Heyes argues instead that mirror neurons are fully produced through the process of associative

learning (Heyes, 2010). In other words, mirror neurons are simply motor neurons that develop the “mirroring” feature through sensorimotor experiences throughout life in which one perceives correlations between observed actions and executed actions that are similar in form. An important aspect of this is the sensitivity of timing – the observed action (stimulus) and the executed action (response) should occur very closely to one another temporally, so that the idea that the former predicts the latter can be encoded as a form of association (Heyes, 2005; Heyes, 2011). Some examples that Heyes (2005) cites for the forming of this association in children and young adults include viewing one’s own actions directly or through a mirror, imitation of the subject by another individual, or synchronized training in subjects such as dance, sports or martial arts. These experiences throughout childhood and development serve as the basis for Heyes’ wealth of the stimulus argument, which claims that there is an abundance of the type of stimulus necessary for the process of associative learning to develop mirroring in motor neurons throughout human development as they associate with the information of visual neurons (Ray & Heyes, 2011).

Perhaps one of the most critical implications of Heyes’ associative account is that, since mirroring is learned through associative learning, it can also be altered or can vary from person to person (Catmur et al. 2007). There is a variety of work in support of this claim. For example, professional pianists are shown to have stronger activations of mirror neuron areas than non-pianists as measured through fMRI during the observation of piano playing (Haslinger et al. 2005). Another example indicated that the activation of mirroring mechanisms in monkeys while observing the use of tools, which was developed as a result of repeated exposure to the usage of these tools by human hands,

also occurred when the monkeys executed actions with their hands and mouths, suggesting that a metaphor was developed for the tools as extensions of the hand (Ferrari et al. 2005). Similar findings have been reported in human subjects as well (Mordoño et al. 2013).

Furthermore, associative learning means that the mirroring process can also be reversed when the subject performs a different action than the one observed and forms an association/correlation with the new “incompatible” action (Catmur et al. 2007). Evidence for this was shown when subjects moved their hands while watching movements of the feet and were shown to develop counter mirroring neurons which indicated the intent to move hands when observing foot movement (Catmur et al. 2008). This shaping of response draws strong parallels to classical (Pavlov & Gantt, 1928) and operant conditioning (Skinner, 1990), which are both phenomena that are well-supported by the associative learning model. A final claim supported by Heyes in the associative view, perhaps in clear contrast to the view of Friston, is that mirror neurons do not consistently encode high-level, generalized intentions or “goals” (Cook et al. 2014) such as grasping a food item in order to consume it (Fogassi et al. 2005). The evidence provided for this claim is that there are observed attributes like directional dependency/selectiveness in mirror neurons (Gallese et al. 1996) that would be inconsistent with the attributes of a mirror neuron system that encodes generalized goal information.

There are several critical implications on the design of a motor learning system if Heyes’ associative account of the mirror neuron system is supported. Since mirroring capabilities are learned, they can vary from individual to individual as stated above.

Therefore, the system should be aware, or attempt to be aware, of an individual's background or previous experience with respect to a motor task. It should attempt to actively discern, whether by measurement of response times to demonstration stimuli of a motion, or by baseline error rates derived when the individual first performs the motor task with the system, how much experience that individual has with each fundamental movement. Using this data, the system can approximate the mirror response of an individual to various types of motions depending on their composition and the fundamental movements involved. Having approximated this, the system can focus on the motor tasks in which this mirroring behavior is presumed to be weak to train the individual's mirroring mechanism for those motions. This type of person-centered adaptation supports the idea that individuals have a variety of background experiences and therefore will have potentially unique levels of "mirror" response to different tasks as they are demonstrated.

A second implication for design is that Heyes' account stresses the importance of immediate or short timing between observation and imitation to form strong correlation between the two representations. In the implementation of a motor task within gameplay, this implies that either a short delay or full synchronization between the actions of the virtual trainer and the actions of the motor learner should occur. This would form a stronger association than completely demonstrating the exercise, for example, prior to any user involvement in a "now your turn" fashion. This structure of synchronized training implies the need for a strong parallel delivery mechanism of this information.

One potential concern is the interweaving of sessions with a real trainer and at-home sessions with a virtual trainer. If there are differences in the way information and

feedback are presented in real training vs. training with the virtual interface, it may be possible for one training to affect the other in terms of mirroring ability. For example, if the motion trajectory that the trainer uses is not represented with enough precision in the system, and it reproduces, say, a square motion in an area where the trainer used an arc motion, then training in one environment could produce counter-mirroring mechanisms that undo the associations made in the other environment (Catmur et al. 2008).

Fortunately, as (Ferrari et al. 2005) and (Mordoño et al. 2013) demonstrate, the mirroring mechanisms are flexible enough to allow for “metaphors” or alternate representations of effector limbs. Since the mirroring occurs typically as a form of face-to-face interaction in associative learning, a third-person perspective may be more beneficial than a first-person perspective, although the effects of this would have to be explored further.

Not only should the representation of the virtual trainer match the individual’s real trainer to simulate a familiar environment, but the representation of the individual, mirrored as an avatar in the visual interface, should precisely or near-precisely match the motions of that individual to maximize the correlation between what is observed and what is felt in proprioception. It may be possible that the occlusion issues and tracking limitations of external monitoring systems like the Kinect make it a problematic choice for this type of implementation. Furthermore, this may rule out the idea of indirect character control in gameplay.

3.3.2 *Predictive Coding Account*

Friston views mirror neurons as prediction mechanisms for the underlying intent of observed action, and utilize error-minimization strategies in a hierarchical manner similar to what would be observed in hierarchical Bayesian inference (Kilner et al. 2007). In the predictive coding account, a hierarchy comprising the mirror neuron system consists of multiple levels which mutually communicate with one another to minimize error. The cycle works as follows (Kilner et al. 2007): a given level predicts the representation of a task at the lower level and transmits that information downstream as a prior. The lower level compares the prediction with its own representation of the action and submits feedback upstream in the form of an error. Once the higher level receives this error as a posterior, it updates its prediction and transmits the new prediction downstream to reset the cycle. This continues until the prediction error is minimized. Friston's view is that this hierarchical Bayesian error minimization strategy is the driving force behind the mirror neuron's proposed ability to understand the intentions of an action at multiple levels, including long-term goals, short-term goals, kinematic attributes and muscular activity (Hamilton & Grafton, 2007). It relies heavily on Wolpert's forward model or generative model of motor control wherein the consequences of an action or movement are predicted during execution (Wolpert et al. 1995; Wolpert & Miall, 1996) and claims that this model applies at every level of the hierarchy (a generative model is used to predict lower-level representation of a task).

Put simply, when observing an individual performing a motor task, and assuming there is information on goals or intentions related to that task from past experiences, one can form a prediction of how that individual will move to achieve the intended goal.

Once the prediction for these movements are in place one can also form predictions on how the movements will work in space at a physical level (kinematic information). When the individual makes their next move, one can compare what happened with one's prediction for what would happen at each level, form errors for those levels, and use those errors to adjust the predictions of the observed individual at each level. In this way, one can obtain error-minimized predictions of intent at multiple levels of granularity during observation. Hence, slightly varying versions of Wolpert's forward model are in play both when executing actions (predicting sensory feedback in the process, receiving the feedback, and updating our internal model) and observing actions.

As such, the predictive power of mirror neurons under the predictive coding extends to both our own actions and the observed actions of others, preserving the "mirror" property. Friston goes on to contribute another element to this prediction minimization scheme: active inference (Friston & Frith, 2015; Friston et al. 2011). Active inference is the follow-up of the body to the error-minimized predictions generated by predictive coding. The idea here is that actions are bound to the predictions generated for them, and in the process of acting one is attempting to prove those predictions correct by minimizing the error between the body's configuration during and after the action, or in other words, minimizing error on proprioceptive predictions.

An immediate observation when relating Friston's representation to the design of a motor learning system is that the process of assessing a user's performance can also benefit from the use of Bayesian inference and error minimization. Based on this view, the system or virtual trainer could generate a predictive model of the user using the same hierarchical predictive coding proposed by Friston, so that the player and system can co-

predict one another's intentions and act on those predictions with mutual active inference, minimizing the error for both entities when they arrive at a unified or near-unified model for predicting one another's behavior (Friston & Frith, 2015). The use of real-time Bayesian networks has been a popular approach in game-based assessment (Shute et al. 2017) and would make a nice fit in this model. This would change the way the system performs assessment at a fundamental level: rather than forming an assessment of a user on a per-attempt basis, the system would now need to form a prediction about the user's next action on multiple levels. Long-term intent could relate to a user's targeted performance goal in each domain, short-term intent could relate to the corrections being made by the user for this attempt to improve on the previous attempt, and kinematics would involve a predicted trajectory of motion for the user based on logged information of the user's performance in previous attempt. Error minimization using the hierarchical Bayesian inference scheme would help eliminate some inaccuracies in these predictions (example: the user's overall goal is to improve total repetitions by 5, but the predicted speed of motion indicates that this goal is unrealistic).

Another critical design consideration is the way in which feedback is given by the system. To support predictive coding as a mechanism for learning, the system should attempt to minimize entropy in the environment when the user is correctly performing a task, but should augment feedback on errors in each modality so that it activates the mechanisms in the coding scheme that update predictions when errors are clearly sensed in the environment. This would apply to feedback in the all domains. The more information a user has on the difference between the correct form of a motion and the erroneous motion, the more information the Bayesian network has to update its

predictions accurately, and since action inference is simply the body acting on these predictions, accuracy is everything.

As a final note, on a game implementation level, it may be useful to represent the user in a first-person (ego-centric) view rather than a third-person view (Cameirão et al. 2010). The reasoning for this is the important role that proprioceptive feedback plays in predictive coding. Should the in-game view be oriented in such a way that individuals can see themselves in-game in the same orientation that they see themselves in the real-world, then the burden on the process of translating visual input to proprioceptive meaning for the sake of updating and comparing prediction with actual results could be dramatically reduced, allowing the mirror neuron system to operate more effectively. There is some evidence for this in literature indicating a stronger activation of the MNS when the orientation of the observed effector is similar to the observer's orientation (August et al. 2006; Maeda et al. 2002; Strafella & Paus, 2000). As in the design for Heyes' approach, a highly accurate depiction of the user's motion should be displayed in the virtual domain to ensure that visually perceived error corresponds directly with actual error. Ultimately, the system should provide and maintain clear metrics for error and proficiency in each motor domain.

CHAPTER 4

CASE STUDY: AUTONOMOUS TRAINING

4.1 Challenges and Objectives

As highlighted in the literature review above, several challenges remain in the motor learning research field for the design of an automated serious gaming system to support unsupervised motor learning:

1. How can a trainer's assessment of performance be embedded into the design of a serious gaming environment for unsupervised motor learning?
2. Recent research (Sigrist et al. 2012) has revealed the optimal assignment of modalities to the various categories of feedback in motor learning; how can these modality assignments be implemented in such a way that they scale effectively with motor task complexity? Furthermore, how would these modalities manifest in a game, and what changes are necessary in the design of game mechanics to accommodate multiple modalities?
3. After having addressed 1 and 2 above, how can the assessment of one's motor performance within an automated system drive gameplay in such a way that game objectives align with motor learning goals?

4.2 Autonomous Training Assistant Overview

To address these challenges, the first task was to develop a system which met the requisites of an effective platform for at-home rehabilitation outlined above (low-cost, customizable, multi-modal, interactive, requiring little to no setup and accessible to an

individual with low strength in the upper extremity). To this end, a system has been designed, entitled the "Autonomous Training System" (ATA), which would serve as a testbed for the serious game research proposed for this dissertation.

4.2.1 System Design

The ATA includes the following components in its design:

1. Interactive virtual training software in which uses trainer designed exercises to guide a user. The software can provide feedback in the audio and visual modalities.
2. Authoring software usable by a trainer. The software uses the Kinect camera to allow a trainer to record a motion in real-time. This motion is then stored as a time-series of 3-dimensional positional and rotational points, which can be represented digitally within gameplay.
3. Custom-built rod-shaped training equipment entitled the "Intelligent Stick", which can capture motion in real-time using a 3-axis accelerometer and gyroscope and can transmit vibrotactile feedback cues to the user.
4. A Microsoft Kinect camera capable of recording and transmitting postural data in real-time, usable by both the trainer and trainee to facilitate exercise.

An overview of the system is shown in Figure 4.2.1.

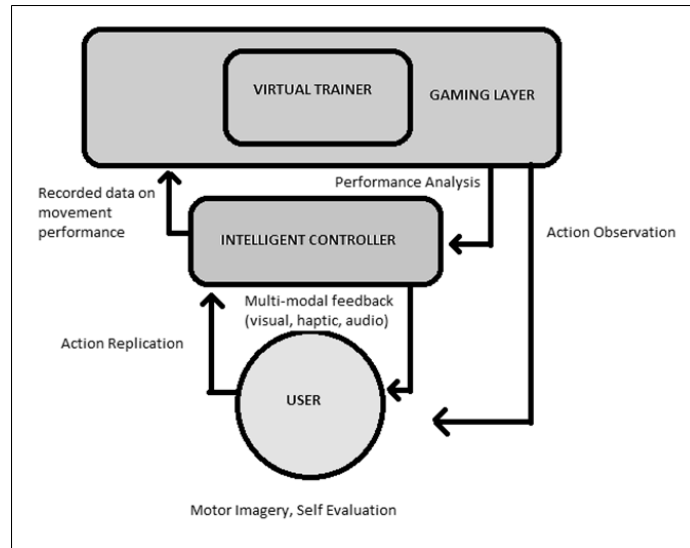


Figure 4.2.1: Interaction Diagram. Image based on Tadayon et al. (2014).

4.2.2 *Intelligent Stick*

The Intelligent Stick, as conveyed in Figures 4.2.2 and 4.2.3, acts as both the user’s motor input into the system and the system’s haptic output to the user (Hartveld & Hegarty, 1996). It is designed as a 3D-printed prototype with a plastic resin capable of conducting a haptic signal while maintaining a high degree of impact-resistance, protecting the device in case of drops or impact with surfaces. Within the device is an array of vibrotactile motors, an accelerometer and gyroscope which provide rotational and positional data, and a Bluetooth transmitter which acts as an interface between the device and the gaming or training software. Previous work has justified the usage of a rod-shape for this device (Tadayon et al. 2014). It can be summarized as follows:

- The shape allows for unimanual and bimanual tasks.
- The cylindrical surface is easier to grip than a rigid or flat surface.
- The form supports a large variety of motor tasks in the upper extremity.

- It can be adjusted in multiple dimensions including diameter, weight and length, making it more accessible.
- Its slender form aids against occlusion issues with the Kinect.
- Since the device is not worn, it is less intrusive and more user-friendly in rehabilitative scenarios since it is mobile and incurs no setup time.

The accelerometer and gyroscope capture data in the following forms:

1. The position (x, y, z) of the device's center in 3-dimensional space, and
2. The 3-dimensional angular tilt (yaw, pitch, roll) of the device.

It registers a datapoint [x,y,z] for position and a datapoint [y,p,r] for orientation at a sampling rate of approximately 100 Hz. These datapoints are transmitted to the software via Bluetooth wireless output as raw data for processing while the user swings the device during exercise. It is also capable of emitting vibrotactile signals and cues. This vibration originates from the motor inside the stick and can be felt evenly throughout its surface area. Vibration length is specified via the signal sent to the stick by the software.

4.2.3 Authoring Software

To allow trainers and physical therapists, the true experts behind an individual's exercise and rehabilitation program, to maintain authority over the exercises and tasks assigned to an individual over the course of at-home training, Motion Authoring software was developed as a part of the Autonomous Training Assistant system. The purpose of

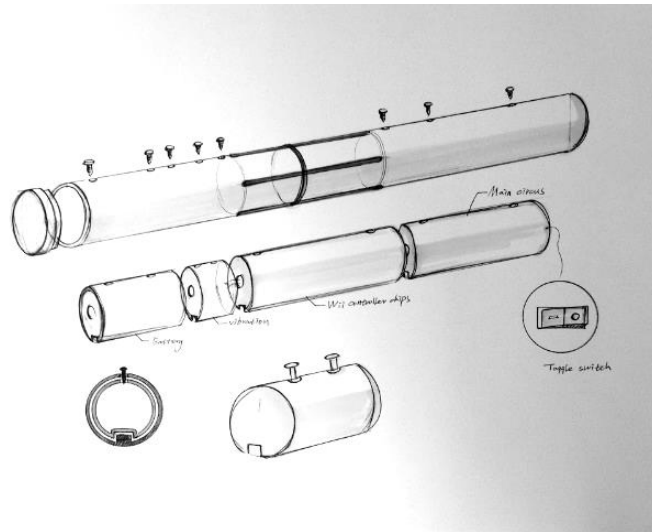


Figure 4.2.2: Intelligent Stick Design Sketch. Image based on Tadayon et al. (2015).



Figure 4.2.3: Intelligent Stick Prototype. Image based on Tadayon et al. (2014).

this software is to allow trainers and therapists to input motion tasks into the system in such a way that it can automatically handle a variety of motion tasks with a user-friendly interface.

For this to occur, it was first necessary to formalize the definition of a "motion task" as an object with quantifiable properties which is representable in 3-dimensional virtual space. If one were to consider the entire range of motion exercises, this is a near infeasible task. Thus, the scope of motion tasks is limited to upper extremity exercises with single degree-of-freedom motion. While this is a heavy restriction on the possible exercises defined in the system, it is applied as a suitable proof-of-concept indicating that a blueprint "class" can be defined in an automated system to capture a range of tasks, allowing for some variety of trainers to utilize the system. Furthermore, this simplification allows for a very clear set of feedback metrics to be applied to a motion task, thus reducing the overall complexity of the interface for trainers. Under these restrictions, the following properties define a motion task:

- Name - the name assigned by the trainer to the motion task.
- Description - a simple text description of the motion task for human reference.
- Primary Limb - The upper-extremity limb which controls the motion (hand, wrist, elbow, shoulder, etc.)
- Type - Unimanual for motions involving one arm or bimanual for motions involving both arms
- Axis of Rotation - The primary plane in 3D space along which the motion takes place (x, y, or z)
- Starting Position - A value (in degrees) for the initial position of the Primary Limb for the motion

- Degree of Motion - The amount of motion (in degrees) set as the current goal. Specific to each individual and assigned by the trainer based on current motor ability of the Primary Limb.
- Speed - The expected average pace or speed of motion, in degrees/sec., set as the current goal. Specific to each individual and assigned by the trainer based on current motor ability of the Primary Limb.
- Body Posture - The expected posture of the individual while performing the motor task. Must be selected among the preset values: seated/standing, arms out/down/forward, shoulders out/down, palms up/down, elbows out/in.
- Time Limit - For each session of the exercise, a time limit, in seconds, to complete as many repetitions as possible for the motion task. Set as a current goal and specific to each individual based on motor ability of the Primary Limb.

The first two properties are strictly designed for use by the system to explain a motion task to an individual, while the remaining properties are used to parameterize the motion itself. Using a combination of properties 3-10, a system can essentially take a 3D virtual trainer model (at the minimum, a polygonal figure with movable joints) and configure it to demonstrate the approximate motion assigned by the trainer. If a user's motion in 3-D space can be represented using a series of X/Y/Z acceleration values, then properties 5-10 can be used by the system to assess the user's motion in real-time and, given a well-defined representation of feedback, provide information in real-time to the user on his or her performance of the motion task.

Feedback in the system is treated as an action which occurs during an event when certain conditions are met (an event-driven or Event-Condition-Action (ECA) Architecture). A "feedback cue" or "rule" in the system is therefore given the following properties:

- Event: Parameter of Feedback (Progression, Pacing, Posture)
- Condition: Threshold of Feedback
- Action: Feedback Modality and description of feedback

Under this formalization, a training protocol is simply a set of rules or feedback cues for a specific individual and trainer.

4.2.4 Virtual Training Software

The third component of the Autonomous Training Assistant is the virtual assistant software, which is an interface designed for basic at-home training. This software provides the main logic for the interaction of the system with the user, and is designed using the Unity platform. A basic prototype interface of the software is shown in Figure 4.2.4 along with the data stream from the Kinect camera. While this basic interface can be used for training, a gaming layer can be built atop this software to provide a more interactive experience. The serious game elements of this interface are discussed in Chapter 7.

Since the Intelligent Stick's onboard motion sensing capabilities are, by themselves, insufficient for detecting and recording full-body postural information such as posture, the Kinect camera serves as an external postural tracking interface in conjunction with the stick's fine-grain motion tracking.

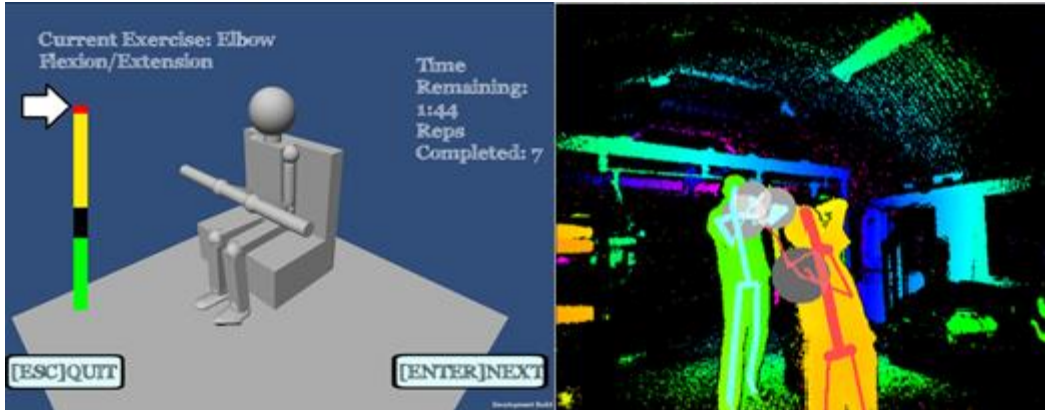


Figure 4.2.4: ATA Prototype Interface (Left) and Kinect Camera Data (Right). Image based on Tadayon et al. (2015).

The Kinect’s postural tracking is depicted on the right of Figure 4.2.4.

Information from this device is fused with real-time motion data from the Intelligent Stick to form a comprehensive motion profile of the user in each frame.

4.3 Evaluation 1: Usability Study

An initial evaluation of the system focused on its usability and intuitiveness for users. Details of this study are provided in (Tadayon et al. 2014); an overview of the study is presented here. The evaluation focused on the most basic elements of usability of the system, including how well the haptic signal was transmitted through the stick device, how well this information could be interpreted, and how easy the authoring interface was to understand. As such, non-impaired individuals participated in this study. This study was approved by the Institutional Review Board (IRB) at Arizona State University as STUDY00001211.

4.3.1 Procedure

Nine individuals (5 male, 4 female) participated in this study. Each individual was first given a verbal introduction of the Intelligent Stick device. After an introduction, each individual was then asked to complete three basic motor exercises including shoulder abduction/adduction, wrist rotation, and elbow flexion/extension. Each exercise began with a 10-15 second video clip indicating how the exercise could be performed with the stick. Participants were then instructed to complete five repetitions of the exercise using the Intelligent Stick, which provided feedback at the endpoints of each exercise with haptic vibrations. Following the exercise period for each task, each participant was asked to answer a survey consisting of the following questions:

1. On a scale from 1-5, how accurately do you think you were able to perform this motion task?
2. On a scale from 1-5, how easily do you think the vibrations on the intelligent stick conveyed the degree of motion required in the task?
3. On a scale from 1-5, how comfortably were you able to hold the Intelligent Stick controller during this exercise?
4. On a scale from 1-5, how easy was the Intelligent Stick controller to move around during the exercise?
5. On a scale from 1-5, how strongly did you feel the vibrations from the Intelligent Stick device?
6. Please provide any additional comments and feedback on the Intelligent Stick hardware for this exercise.

Upon completion of all motor exercises, each participant was then asked to author a motion of their own choosing into the system. After completing this task, each participant was presented with a survey on the motion authoring system consisting of the following questions:

Table 4.3.1: Motion Task Results. Based on results in Tadayon et al. (2014).

SURVEY RESULTS (SCALE 1-5)						
	Motion 1		Motion 2		Motion 3	
	Avg.	StDev.	Avg.	StDev.	Avg.	StDev.
Q1	4.78	0.44	4.89	0.33	4.78	0.67
Q2	4.67	0.71	4.89	0.33	3.44	1.74
Q3	4.44	0.53	4.78	0.44	4.89	0.30
Q4	4.78	0.44	4.89	0.33	4.89	0.33
Q5	4.89	0.33	4.78	0.44	3.56	1.59

Table 4.3.2: Motion Authoring Results. Based on results in Tadayon et al. (2014).

SURVEY RESULTS (SCALE 1-5)		
	Avg.	StDev.
Q1	4.56	0.53
Q2	4.44	1.01
Q3	3.89	1.05
Q4	4.56	0.73

1. On a scale from 1-5, how easy was the motion authoring software to use and navigate?
2. On a scale from 1-5, how accurately do you think your motion was captured based on its visual representation in the motion authoring interface?
3. On a scale from 1-5, how understandable was the information presented on the screen, including the visual representation of your motion?
4. On a scale from 1-5, how easily were you able to create and save your motion on the Intelligent Stick?
5. Please provide any additional comments and feedback on the motion authoring software for this exercise.

4.3.2 Results and Discussion

Results of the surveys are shown in Tables 4.3.1 and 4.3.2. Feedback was generally positive both for the usability of the stick during motion tasks and for the ease of use of the authoring interface. Question 3 results indicate that the stick was easier to hold when the subject's arm rested on a surface. Responses given to Question 6 indicated that the form of the stick's initial prototype were too bulky, and it was subsequently reduced in size to form the prototype shown in Figure 4.2.3. As predicted, motions with larger trajectories involving inner extremities like the shoulder produced more favorable usability results than motions of the wrist which were much smaller in size, as it was easier to distinguish the endpoint vibrations on larger, slower motions. A calculation error caused by a facing dependency of the accelerometer resulted in lower scores for Motion 3, and was later corrected in a subsequent iteration of the software. For the authoring

interface, there was some degree of confusion on the representation of motion on-screen, especially in areas where motion was slow and tightly packed, as these areas were difficult to visually depict in the 2-dimensional screen space.

4.4 Case Study Overview

Due to the high variability in individual subjects in motor ability, motor impairment, task mastery, interests, physical build, age, gender, and many other factors, it is argued in this dissertation that motor learning is a person-centric process. Despite this variability, the field of motor learning research often treats the learner as a static entity, and this is reflected in both the design process and the evaluation process. For most approaches, individual characteristics of learners are not considered or accounted for in design, resulting in heavily limited applicability toward users. This fundamental disconnect between the user and technology in the research process can be addressed through a person-centric approach, in which a single subject lies at the center of the design and evaluation process. Therefore, to address the challenges given in 4.1, a case study was utilized in the iterative design and evaluation of the Autonomous Training Assistant system.

This case study involves two primary participants: an individual with Cerebral Palsy who had developed hemiparesis - motor impairment on one side of the body, and his trainer, a martial arts expert who uses self-defense training as a context for motor learning and rehabilitation. The individual's condition has resulted in full motor control in one arm and impaired control in the other arm, which provides an effective platform for the usage of mirroring. Furthermore, since the subject and trainer use stick equipment

already in their martial arts training program, making the Intelligent Stick a perfect fit for this scenario.

4.5 Single Subject vs. Group Assessment

The contributions in this work, including the design, development and evaluation of the ATA system for motor learning, utilize a case study design with a single subject. Given the use of a case study in this dissertation, it is critical to highlight the benefits of this style of study over the conventional large-N study, and to justify its usage in this work. In this section, the single subject and small N designs are compared against the large-N approach for evaluation, and the advantages and disadvantages of each are discussed.

Randomized Clinical Trials (RCT) with large populations and randomization are often touted as a gold standard with respect to statistical confidence and evidence of impact (Sackett et al. 1996). However, these methods have several severe limitations that make them problematic in use for the evaluation of person-centric approaches. The format of these experiments requires extreme levels of environmental scope that place heavy restrictions on both their scope and, more importantly, their generalizability (Kelley & Kaptchuk, 2010; Stel et al. 2007). They are difficult and costly to produce, and due to the highly individually-variant nature of motor conditions in rehabilitation, the design of a control group can often be infeasible (Dijkers, 2009). The alternative to these trials are Small-N designs, where a single individual or small group, typically less than 10 individuals, are used to determine the effect of a particular experimental intervention. In these studies, individuals serve as their own “control” for the sake of study, through the

implementation of various conditions in temporal phases. These include a “baseline” period wherein some attribute of an individual (such as motor performance) is measured, an “intervention” period in which the experimental variable is applied, and a “follow-up” condition in which the effects of this intervention on the baseline values of the variable are studied (Barnett et al. 2012; Graham et al. 2012).

This format of evaluation is used with the ATA system to show the effects of an at-home training environment on a single subject over a period of several months. This case study, however, was not intended to measure outcomes but rather to demonstrate the feasibility of an automated, remotely maintained system for guided at-home training. When attempting to indicate changes in motor behavior, there are concerns with the validity of these approaches due to the lack of statistical significance in using a single subject or few subjects; these concerns, however, can be addressed with careful experimental design.

Barnett et al (2012) and Graham et al. (2012) critically study the usage of small-N studies and provide several arguments for their usefulness over RCTs. One such claim is that since these studies focus on repeated, frequent measures of the effects on an individual over time, they are highly beneficial in cases where the goal is to study not just whether a significant change has occurred, but also how that change has developed over time (Gorman & Allison, 1996; Saville & Buskist, 2003). For motor function and learning, this type of approach is beneficial because the nature of changing motor behavior may vary drastically from individual to individual. Furthermore, this type of evaluation affords the experimenter the opportunity to evolve the intervention over time, something that would be unreasonable in a large-sample study (Brossart et al. 2008). In

motor training, as an individual's proficiency increases, the difficulty and intensity of game tasks need to evolve with the user, and feedback frequency may be faded over time. Furthermore, the complexity of motions may increase over the duration of training. These evolutionary elements would be impractical to implement in large-N studies, as these studies do not appreciate customization and variation at the level of the individual. Perhaps for this reason, a significant quantity of the empirically-validated practices and interventions in place today in the rehabilitation space originated from small-N studies (Brossart et al. 2006).

Having established the reasoning for the employment of single-user and small-sample designs, there are still serious issues in statistical significance which they must address (Kazdin, 2011). The primary issue is that in a study design where a baseline is measured for an individual, a treatment is administered, and a follow-up measurement is made (typically referred to as the AB design), since the data corresponds to a single individual, one can indicate correlation in outcomes with the intervention but not causation, as a variety of factors may have contributed to the change. One attempt to address this problem is the ABAB design in which the subject is returned to baseline state and another baseline measurement is made, after which a second iteration of the intervention followed by a second follow-up occur (this loop can be repeated several times). This approach provides far more evidence in favor of causality of the intervention toward the outcome, but in many cases, this type of design is infeasible. In motor skill training, for example, the effects of learning over time of a motor skill cannot be "undone", so a second baseline measurement of the same individual cannot match the values found in the first baseline measurement if any change has occurred.

Another solution is the multiple-baseline design which measures baseline values for multiple individuals to show that the intervention can be replicated across these individuals. The key component in achieving this is being able to show that each baseline in the design is stable before introducing the intervention. In other words, for motor learning, an individual's baseline performance would have to be measured over a duration of time indicating stability or accounting for the change caused by the individual's interaction with a trainer or the mechanism previously in place for at-home rehabilitation, if any. Once this has been established, the change in motor condition caused by interventions such as the Autonomous Training Assistant can be extracted from the motion data recorded over the intervention phase to explain the results in the follow-up phase. Across multiple individuals, it must be shown that this change is consistent, reliable, and can occur across varying phase lengths (Barnett et al. 2012).

To analyze and form meaning from the data in single-case or small-subject designs, various statistical methods can be used (Brossart et al. 2006; Parker & Brossart, 2006). One of the biggest problems, however, is the strong effect of auto-correlation on the reliability of statistical analysis for small sample approaches (Jones et al. 1978; Matyas & Greenwood, 1990). Barnett et al. (2012) recommend the application of an autoregressive integrated moving average (ARIMA) model which attempts to model, capture and correct for the autocorrelation in the time-series data to improve the quality of analysis in follow-up (Box et al. 2015). In addition, a framework is necessary to evaluate and prove the validity of individually-cased experimental designs. As an example, Horner et al. (2005) provide five criteria to determine whether a single-subject design has successfully provided evidence of causality. To paraphrase:

1. The intervention and its format and parameters are well-defined.
2. The scope and contexts in which the intervention applies are well-defined.
3. The formally-defined procedures are precisely, consistently and regularly followed in practice.
4. The attribution of the result/outcome to the intervention is well-documented and indicated and influential factors are heavily controlled against in all phases.
5. The findings are consistently and sufficiently replicated and shown to be consistent across a variety of scenarios, individuals and phases.

The intent in this work is to show how individual motor function can be measured, responded to, and adapted to produce systems and game interfaces that guide and motivate the process. Hence, the use of an individual subject enables the evaluation of this framework, although it must be shown that the motor guidance strategies used are effective and facilitative of the motor learning process. As a final note, although the discussion is framed here in the context of rehabilitation, motor learning is intentionally used in the general context in this work, as the principles applied toward guidance are applicable across motor learning subdomains. As John Krakauer states in his work on neurorehabilitation (2006): “Motor learning does not need to be rigidly defined in order to be effectively studied. Instead it is better thought of as a fuzzy category (Shadmehr & Wise, 2005) that includes skill acquisition, motor adaptation, such as prism adaptation, and decision making, that is, the ability to select the correct movement in the proper context.” This allows the potential application of the framework toward non-impaired subjects in future studies, although no claim will be made that the results of such a study transfer to scenarios of rehabilitation or motor skill reacquisition or vice versa.

CHAPTER 5

MOTOR ASSESSMENT

5.1 Overview of Assessment Mechanisms

A primary motivation for this work is the decentralized and non-standardized nature of assessment in the field of motor learning research. Rather than a unified standard, there exists a wide variety of metrics and tools for assessment within rehabilitation programs and physical therapy/training programs worldwide, including the popular Wolf Motor Function Test (Wolf et al. 2001), the Fugl-Meyer Assessment (Fugl-Meyer et al. 1975), and the Barthel Index (Mahoney, 1965), among others (Lamola, 2015). Unifying efforts to merge these metrics have been made in more recent work (Smith & Taylor, 2004); yet it is ultimately up to individual physical trainers and programs to determine which assessment is the most appropriate for each individual (Barnes & Good, 2013). This has unfortunately yielded a fragmenting effect on motor learning systems research, as many of the systems developed rely on a specific metric and consequently bear the limitations of that metric (Harley et al. 2011).

To avoid this issue, several of the newer systems used in motor learning research offload the task of motor assessment to the physical trainer, using a "collaborative authoring" approach instead of relying on a specific assessment tool (Mehm et al. 2011). By allowing the trainer to regulate functional performance assessment of the individual over each assessment period, these systems can instead focus on the real-time micro-assessment. However, the nature of this micro-assessment remains an open problem in rehabilitation research, as there are multiple domains of performance to be assessed

(Loureiro et al. 2011). In order to provide guided training consistent with that of a real trainer, it is critical that a system base its training protocol on real training (Lehrer et al. 2011). Despite these findings, however, there is currently no known framework for the formalization of training into a format which can be interpreted by a variety of motor learning systems and games (Stucki et al. 2007). Hence, one of the main objectives of this work is to explore the development of a unifying framework for representing motion in a manner that is generalizable enough to incorporate the many training programs and protocols currently being implemented in practice.

5.2 Evaluation 2: Assessment Model

The first procedure of the person-centered design strategy was to address Challenge 1 in 4.1 using interactions between a real subject and trainer. This was achieved using the subject and trainer in the case study introduced above. This initial study focuses on simple stick training exercises as templates for the formation of a formal assessment protocol, and is featured in (Tadayon et al. 2015). This study was approved by the Institutional Review Board (IRB) at Arizona State University as STUDY00001742. The following procedure was implemented:

5.2.1 Procedure

The study was split into three main sessions: traditional training with the trainer's stick equipment, modified training using the Intelligent Stick with no haptic output, and modified training using the Intelligent Stick with haptic output. Since the virtual training software lacks training data in the initial stage, it was omitted from this study. The goal

was to gradually introduce this device into the individual's training and observe the response of the trainee and trainer to the device.

Each session included observation on the interactions between the trainer and trainee on four exercise tasks: elbow flexion/extension, wrist flexion/extension, bimanual steering, and wrist ulnar deviation. These exercises involve a single degree-of-freedom in the arm and were chosen by the subject's trainer as an initial training set for use in the evaluation since they meet the format of the framework given above. Each exercise began with a 1-minute trainer-held visual demonstration and was followed by 5 minutes of guided exercise between the subject and the trainer on that motor task. During these sessions, responses given by the subject to the trainer's feedback and the Intelligent Stick device were observed and recorded. For the third session of the study, the Intelligent Stick was equipped with vibrotactile responses programmed for the assigned exercises, and these vibrations were used in place of trainer feedback to guide the subject in the progression domain by indicating when a motion range goal was met. Data on the subject's observed response and performance variation in this phase were compared to the phases in which the trainer provided feedback in this domain to determine the suitability of the device as a guidance mechanism for progression. In addition, feedback on the device's usability was collected from the subject and trainer at the end of the evaluation.

Table 5.2.1: Motion Task Outputs. Based on results from Tadayon et al. (2015).

NAM E	DESCR .	LIMB	TYP E	AXIS	STR	END	SP D	POST	TIM E
ELB OW FLE X/EX T.	Stick at rest on knees, curl elbows	Elbow	Bi	X	0	60	20	Seated, elbows tucked	5m
WRI ST FLE X/EX T.	Stick at rest on knees, curl wrists	Wrist	Bi	X	0	30	30	Seated, elbows tucked	5m
STEE R	Stick out in front, standing, tilt	Should	Bi	Y	0	45	22.5	Standing, arms straight	5m
WRI ST ULN DV.	Stick upward in one hand, tild	Wrist	Uni	Z	0	25	25	Seated, elbows tucked	5m

Table 5.2.2: Training Protocol. Based on results from Tadayon et al. (2015).

PARAMETER	MODALITY	THRESHOLD	DESCRIPTION
PROGRESSION	Audio	Subject reaches a critical point in the motion	“Halfway there.”; “Almost there.”; “Good, back to starting position.”
	Haptic	Subject stops before reaching target	Trainer uses hand to nudge the stick up to the targeted range.
	Visual	n/a	Trainer positions palm at targeted range, asks subject to contact his palm
PACING	Audio	Subject moving consistently above or below expected speed	“Slow down.”; “Speed it up.”; “Keep a consistent pace.”
POSTURE	Audio	Subject’s elbows deviate from body	“Tuck in your elbows.”

5.2.2 *Results and Discussion*

The study began by capturing the four required motions using numeric values defined by the trainer under the definition of motion tasks within this model (speed shown in degrees/sec and time shown in minutes). These motions are shown in Table 5.2.1. Several categories of feedback from the trainer to the trainee were observed for the three sessions during each exercise, all of which serve as quantifiable parameters within the ATA framework as shown in Table 5.2.2. Since the trainer maintained protocol across all exercise sessions, the format of feedback remained consistent under the framework and representation developed above. One limitation of the trainer's protocol that could potentially be eliminated by an automated system was that for most feedback, particularly audio feedback, a sequential ordering was used as it was difficult for the trainer to convey multiple domains of information in parallel.

When the Intelligent Stick device was introduced into training, the trainer found the progression domain to be the best fit for haptic feedback given by the device, and selected specific values for range of motion for each exercise which were then encoded by a pair of endpoints in space at which the stick would deliver a short vibrotactile response. When the user moved the stick to complete a motion, the vibrations would signal that the user had completed a motion in one direction and must reverse to the other direction to hit the other endpoint and complete a repetition. Motion range values were selected and assigned by the physical trainer based on the subject's known functional ability and current experience in each of the motions used: 45 degrees in steering, 25 degrees in wrist ulnar deviation, 60 degrees in elbow flexion/extension, and 30 degrees in wrist flexion/extension. At 0 degrees and the endpoint values above, a half-second

vibration could be felt by the subject as a metaphor for the trainer's guiding hand. This representation of information was communicated beforehand to the subject, who used the vibrations to complete a series of repetitions in each of the motor tasks in the third session.

The subject and trainer reacted positively to the inclusion of the device and its haptic feedback across every exercise task. Usability factors including the weight of the stick and the strength of its vibrotactile response were all regarded positively based on feedback reported by the two individuals. Unfortunately, one major limitation of the device's usage was a lack of accessibility, as the subject's weak grip in the paretic arm made it difficult to hold and operate the device throughout the study. This issue was quickly remedied using the same solution that the subject and trainer already employed within their stick training exercises: a strap mechanism was added to the stick which would wrap around the device and the user's arm and secure the two together using a Velcro attachment. The strap was easy to operate by the subject using the nonimpaired arm without assistance from the physical trainer.

Since all of the assigned motions were fully represented by the Intelligent Stick device using the assessment framework developed above, this evaluation served as initial validation of the framework. Through this framework, the training protocol is formalized such that any new exercise which meets the limitations of dimensionality imposed by the table representation above can be captured and represented to a computerized system so that both the subject's performance and the trainer's goals can be measured and updated in real-time.

5.3 Evaluation 3: Unsupervised (At-Home) Assessment

Since the ultimate purpose of this work is to develop a system for at-home motor learning without the presence of a trainer, the next step was to evaluate the Autonomous Training Assistant's ability to assess the case study subject's motor performance in a home environment. The goal was to determine whether the system captures data which is considered useful to the trainer for setting and updating motion goals. This evaluation was approved by the Institutional Review Board (IRB) at Arizona State University as a part of STUDY00002090.

5.3.1 Procedure

For this study, the ATA system, including the Intelligent Stick device, Kinect camera, and virtual training software, were deployed within the home of the subject for a period of six months spanning from February to August of 2015. At the beginning of the study, the subject's trainer utilized the authoring software to design three basic stick exercises for the individual to complete at home: elbow flexion/extension, wrist flexion/extension, and steering. For each exercise, a time limit of 2 minutes was assigned per session. The subject was asked by the trainer to complete one session for all three exercises, at least twice a week each week for the duration of the study.

No individuals other than the subject were present during the at-home exercise sessions - the ATA system automated the sessions and all interactions with the system after deployment were done remotely by the research team and trainer. Monthly reports were sent to the trainer throughout the duration of the study, which were used to assign new motion ranges and new paces to each of the exercises. These reports contained

information on the subject's performance in the format requested by the trainer: for each exercise session, the amount of repetitions completed by the individual over the 2-minute period and the individual's average pacing in degrees/sec. were reported. As such, only periodic assessment of the individual's performance was accounted for during this period. Real-time assessment of the individual's performance during exercise was a capability of the system, but as there was no clear method yet for providing feedback based on this assessment, such analysis was not utilized for this study.

5.3.2 *Results and Discussion*

Data captured during this session include: motion data in form of vector fields representing the subject's motion pattern on an exercise, quantitative data representing average speed per exercise in degrees/sec., number of repetitions completed in 120 sec., average range in degrees per motion, motion accuracy in terms of percentage-proximity to desired range-of-motion in the primary axis of rotation, number of errors made in posture (where a postural error is defined as a 5-degrees-or-higher deviation from the expected body configuration per exercise), total session time per week and per month. Some samples of the data captured for this study are shown in Figure 5.3.1.

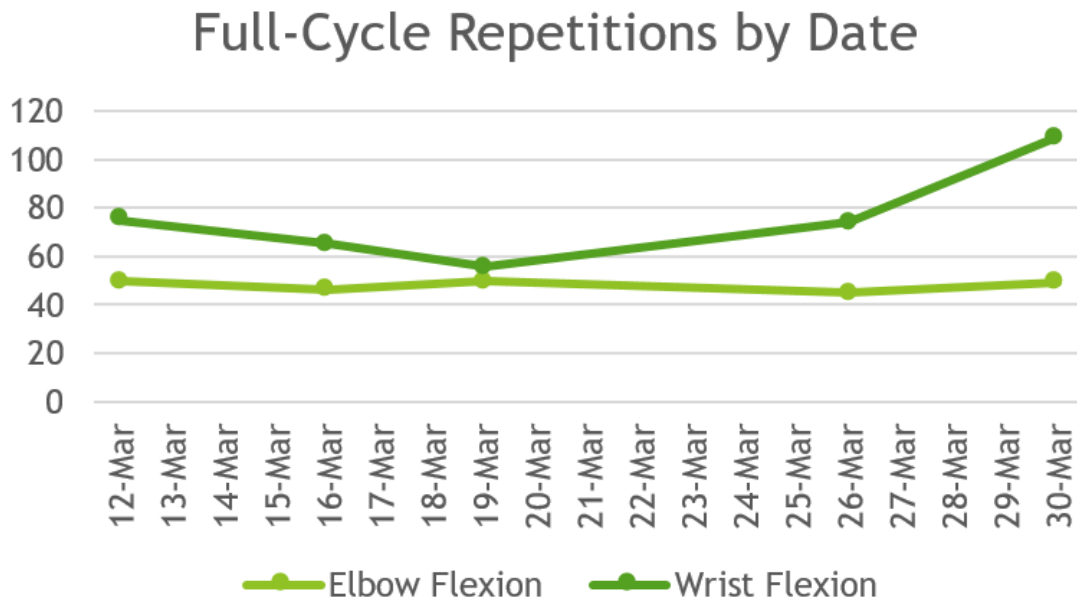


Figure 5.3.1: Full-Cycle Repetition Data for March 2015.

It is important to note that no conclusions on the system's impact on the subject's motor performance can be made from analyzing the data captured in this study, as a variety of outside factors can significantly influence this data. For example, the subject was under medication to ease spasticity and ataxia, two physical symptoms of Cerebral Palsy, over the course of this study. These two conditions may have had an influence on the subject's performance, although no conclusion can be drawn from the data provided in the study. Instead, this study successfully validates the claim that the ATA environment and the proposed framework for motor exercises provide a solution to Challenge 1 (i.e. successfully demonstrate a working at-home projection of a trainer's protocol in a remotely managed and unsupervised environment, and demonstrate that the trainer can draw assessments from the data provided and set new goals during training).

CHAPTER 6

MOTOR FEEDBACK

6.1 Overview of Feedback Mechanisms

Of the sensory channels, three are most commonly used in rehabilitative systems: visual, audio, and haptic. The combination of these channels to deliver feedback during exercise is no new feat; multimodality has been in use in physiotherapy practice for decades (Hartveld & Hegarty, 1996), and has recently been shown by Bongers et al. (2010) and Beurgens et al. (2012) to adapt to a variety of individual cases. Despite this, multi-modal feedback is not necessarily a generalizable approach. It has recently been shown by Sigrist et al. (2015), for example, that multi-modality is only truly beneficial to the learning experience when applied towards complex tasks. Studies have determined that the feedback given by such a system needs to be accurate, rewarding, and measurable (Parker et al. 2013; Parker et al. 2014). Furthermore, as made evident by Parker et al. (2011) in motor learning, the feedback must be frequent, explicit, and provide the knowledge of performance and knowledge of results necessary for self-assessment to occur.

How, then, should each modality be assigned in a system's feedback to maximize learning by an individual? Although the details of this assignment may vary by the characteristics of the individual, there are patterns in recent research which provide the basis for modality assignment in a multi-modal interface. To derive these patterns, Sigrist et al. performed a comprehensive review (2012) on modality assignments in motor

learning scenarios. This study provides a series of guidelines on the role of each sensory channel in the feedback process which optimize motor learning.

For the audio component, it is shown that error sonification is a best practice, since its effectiveness remains constant as the complexity of a task increases (Godbout & Boyd, 2010). Audio cues, in other words, are effective at preventing erroneous behavior within various aspects of a motion, both in the spatial and temporal domains. Furthermore, the rhythmic components of audio feedback allow it to effectively synchronize with repetitive motor tasks (Van Wijck et al. 2012). Its usage in conjunction with haptic and visual feedback has been well-noted in practice (Sigrist et al. 2015).

In contrast, for haptic feedback, error amplification is not shown to be an effective, scalable practice, as its effectiveness withers as the motion itself becomes more complex (Sigrist et al. 2012). Instead, the suggested best practice is haptic guidance, where the haptic channel becomes a representation of the correct trajectory of motion in the spatial domain (Alamri et al. 2007). This type of feedback has been shown not to decay in effectiveness under growing motion complexity (Milot et al. 2010). An example of haptic guidance is the "haptic tunnel", where haptic feedback represents the area in 3D space where a motion can be considered accurate (Mihelj et al. 2007).

The visual aspect of feedback is the main focus of most rehabilitative interfaces as it is the channel under which the richest set of feedback can be portrayed in motor learning (Rhoads et al. 2014). The most successful usages of this channel involve feedback pertaining to observational data of a motion, as this supports action observation in the motor learning process (Sigrist et al. 2012). Approaches have been developed in research to project an image of the user (Moya et al. 2011), the trainer (Ruttkey & Van

Welbergen, 2008), and both simultaneously (Bharadwaj et al. 2015). The dual avatar approach, where both the user and the trainer are represented on screen as dual points-of-reference for observation and self-assessment, is of interest in this work, as it can elicit action observation during the learning process, and improves the consistency between at-home and clinical exercise (Jung et al. 2013). A key aspect of this channel is that the complexity of visual feedback should be controlled and simplified such that it does not scale directly in complexity with the exercise (Eaves et al. 2011).

6.2 Multimodal Mapping Model

In this dissertation, it is proposed that the exploration of Challenges 2 and 3, as outlined in Section 4.1, will together address the lack of long-term success and low adoption rate of current serious gaming solutions for at-home rehabilitation. The goal of this work is to implement and compare, in practice, mechanisms in serious game design related to multi-modal feedback and performance mapping which have been supported in literature but not yet applied for unsupervised motor learning. Upon application of these principles to the Autonomous Training Assistant, findings and their implications for future design in the field are provided.

At the core of Challenge 2 lies a critical aspect of motor tasks in rehabilitation that has yet to be accurately addressed in research: that they are dynamic in complexity, and that an environment designed to promote learning of these motor tasks must be robust under increasingly complex tasks and motion patterns (Sigrist et al. 2012). As mentioned above, a major component of such an environment is multimodality, as multimodal feedback has been shown to adapt well to the complexity of a motion, both in

the spatial and temporal domains (Sigrist et al. 2015). As such, it is evident that an environment intended to support motor learning in the long term should make use of multiple modalities for feedback delivery.

A main goal in Challenge 2 is to explore the application of modalities to rehabilitative motor learning tasks at varying levels of complexity (defined as motion pattern dimensionality in space and speed variance in time). Specifically, it is crucial to address not only the assignment of modalities to the 3 main categories of feedback described in Chapter 5 (posture, progression, pacing) but also address how real-time assessment can be performed within these categories and how these modalities can be implemented in practice, using the Autonomous Training Assistant system as an application area and testing platform. A review of the field of multi-modal feedback in motor learning by Sigrist et al. (2012) provides a series of optimal modality alignments and best-practice implementations supported by evidence from multiple studies in each category. In the Autonomous Training Assistant, an initial attempt to validate or disprove these claims involves implementing the assignments within the next prototype of the system, which will be expanded to include a mechanism for feedback using the Event-Condition-Action architecture described in Chapter 4:

Sound interactions can be assigned to the "pacing" category, or the temporal aspect of a motion task. The best practice in this field is error sonification, or the use of audio signals to notify the individual of an error in his or her pacing during an exercise to correct motion which is too fast or too slow; error sonification is known to remain constant in its effectiveness as the temporal complexity of a task increases (Godbout &

Boyd, 2010). To implement error sonification, one's first task is implement a definition for error in pacing which holds independently of the motor task's complexity.

To this end, the practice of "tolerance thresholding" (Cohen & Sternad, 2008) wherein an individual's performance can deviate from an optimal value up to a certain tolerance threshold (defined within the parameter of the performance), is implemented in the system. For example, in the pacing category, an optimum pace and a tolerance threshold (in degrees/sec.) can be assigned to an exercise, such that the individual's pace can be slower or faster than the optimal value by at most the threshold value to be considered a "correct" motion. Once a user's motion pace leaves this "area of tolerance", as shown in Figure 6.2.1, it is considered an error and the appropriate feedback is provided. In this case, an audio cue will be delivered to the user as feedback whenever his or her pace during a motion deviates from the expected pace for that individual (set by the trainer) by at least the tolerance threshold (also set by the trainer). Various aspects of an audio signal can be used to indicate whether the user's pace is too slow or too fast: frequency, pitch and tonality are all examples of parameters which can represent the change required in an individual's pace to improve performance.

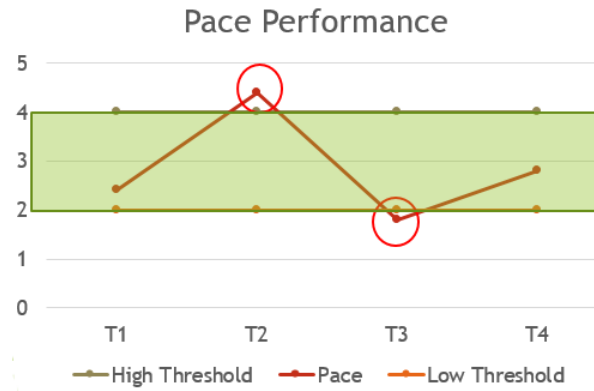


Figure 6.2.1: Thresholded Pacing Feedback Example. Line represents rate of motion at four different time values (T1-T4). Circled areas represent deviations from the range of tolerance for pacing, shown in green.

Under the same guidelines, haptic feedback will be assigned to the "progression" category, one of the two spatial aspects of an individual motion. For motor learning within this modality, the best practice approach is known as haptic guidance (HG). Unlike for audio, this approach does not seek to augment an individual's errors but rather guides the user through the correct trajectory of a motion. This is an important distinction because in contrast to haptic error augmentation, haptic guidance does not decrease in effectiveness as motion complexity increases (Milot et al. 2010). At this point, since motions will increase in complexity beyond single degree-of-motion tasks, a 2-point model for progression will no longer be effective, as a single start point and end point are insufficient to describe a motion that involves rotation in more than a single dimension.

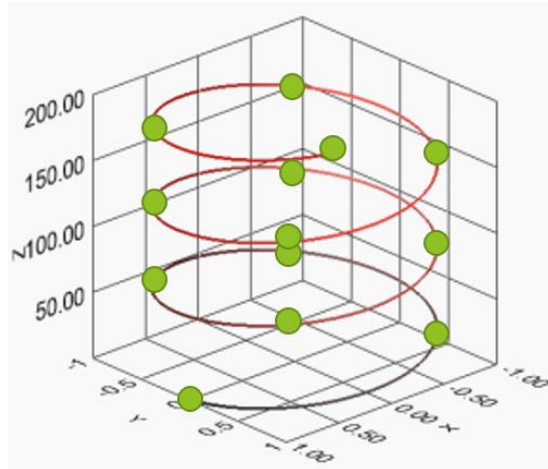


Figure 6.2.2: Critical Points Example. Curve represents trajectory of a 3-dimensional motion, with critical points along the trajectory highlighted in green.

As such, the representation of progression must be expanded beyond the endpoint representation. Here, the definition of the "end points" is expanded to include points which may occur along the trajectory of the motion, or "critical points". This set of points represents the lowest resolution at which a 3-dimensional motion trajectory can be accurately represented, and is depicted in Figure 6.2.2. Under this implementation, a haptic signal is given to the user at each critical point along the trajectory of the motion, similar to bread crumbs navigating an individual through a forest. The combination of critical point representation with haptic guidance is called "point-to-point haptic guidance". One immediate challenge with this approach is knowing how many critical points to use, and where to distribute them along a trajectory. In this research, the process is done manually in interaction with trainers, as their expertise guides the feedback of the training environment. Future work, beyond the scope of this dissertation, can examine how these points can be generated automatically via machine analysis of a complex motion trajectory.

Finally, postural information can be transmitted best through the visual channel. Here, there are two distinct representations of a motion to which an individual must have access as reference points for learning: the trainer's motion and one's own motion. Each of these is a "visual point-of-reference" and the act of using both to evaluate and improve one's own performance of a motion is referred to as "mirroring", as described in Related Work. In a wide variety of home rehabilitation interfaces, both motions are represented with "avatars" in some combination with one another. As an example, in an initial implementation of the Autonomous Training Assistant for the at-home study detailed above, a single avatar is used for both representations - it represents the trainer as it demonstrates a correct motion at the beginning of a session, and represents the user as it projects his or her motion on the screen during exercise.

In other implementations, these two points of reference are shown on screen simultaneously as a dual point-of-reference for a user. This allows the subject to self-evaluate easily in comparison with the trainer (Eaves et al. 2011), but requires a simplified representation to reduce cognitive load on the user (Bharadwaj et al. 2015). To simplify this representation, a "layered dual point-of-reference" technique is proposed as pictured in Figure 6.2.3, wherein the trainer's avatar is layered directly on the player's avatar as a semi-transparent "ghost" avatar. The player's task then becomes simple: to align his or her avatar's posture with that of the trainer's ghost projection so that the two merge into one. Superimposing one avatar on the other also makes it very clear where and how the player deviates from the trainer during a motion, providing rich Knowledge of Performance in addition to Knowledge of Results.

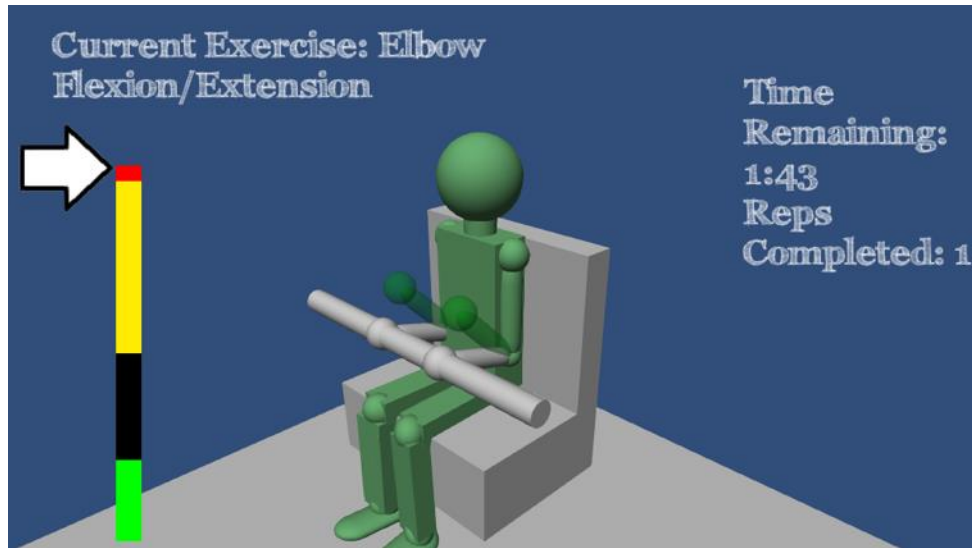


Figure 6.2.3: Superimposed Dual Avatar Example. Sample screenshot from the Autonomous Training assistant interface in which a green “ghost avatar” representing the trainer is superimposed on a gray avatar representing the subject.

6.3 Haptic Guidance Considerations

In this section, several alternative approaches for haptic guidance are considered. Although these approaches were not implemented in the current system, they are nevertheless worthy of consideration as alternative approaches for future work.

Under the current guidance mechanism, as the user moves the Intelligent Stick in 3D space, single-dimensional vibrotactile cues represent successful progression through the critical points in a targeted motion trajectory. However, should the critical points representing the motion be sufficiently sparse, there may be instances in which a user loses information on the motion’s trajectory and moves the stick in the wrong direction in space, causing a large trajectory error. For example, note the curve in Figure 6.3.1.

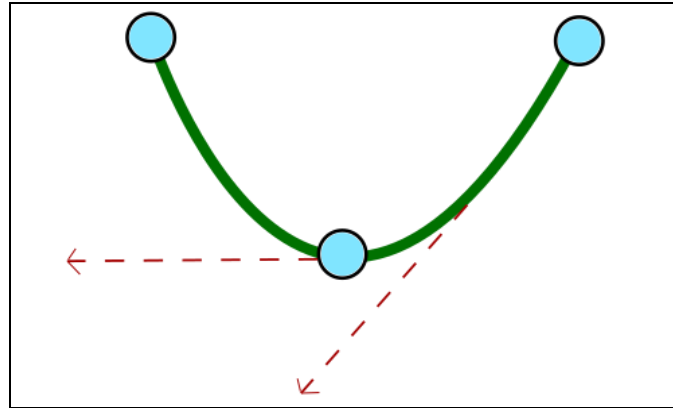


Figure 6.3.1: Example Error Trajectories in Sparse Tactile Guidance.

In this example, an arc motion is represented in 3 critical points. A novice learner who is less familiar with the structure of this motion may stray from the intended path from point-to-point, particularly under the paths indicated in red. This is because under the current strategy, critical points only convey the basic structure of a motion path, and the vibrotactile stimuli representing this information convey only the successful arrival at a critical point (a single-bit, unidimensional feedback stimulus). To resolve this issue, finer haptic guidance may be beneficial in future work.

Some of the key features of the haptic modality that can be utilized to provide fine-grain motion 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). The following example strategies exploit these attributes of the modality to provide more descriptive haptic guidance to users:

6.3.1: *Continuous Trajectory Representation*

Perhaps the simplest strategy for addressing the issue of point-to-point guidance is to instead convey the trajectory of a motion through a tactile trajectory. Under this approach, a static vibrotactile response, similar to that of the critical point strategy, is given as the user moves along the motion trajectory. In this case, however, the entire trajectory is represented as a tactile stimulus. In Figure 1 above, as long as the user is moving the stick along any point in the green line representing the arc of the motion, that individual will continue to receive a haptic response. Rather than a discrete, finite cue, this strategy utilizes a continuous vibration that halts when the user leaves the trajectory so that the user is immediately made aware of the point at which he or she deviated from the path, and can reverse the path of motion until the vibration returns.

This technique is advantageous in that it is a form of guidance, rather than error augmentation, similar to the original critical point technique. Haptic guidance has been shown to achieve better learning results when compared with haptic error augmentation as task complexity increases (Sigrist et al. 2013). Likely this is because guidance leaves error correction to the user, allowing one to develop self-assessment strategies for performance improvement (Scheidt et al. 2000). However, the technique can suffer from some of the same issues as the critical point strategy in extreme cases; users who stray too far from the path, especially novice users, may lose the original motion trajectory entirely. Furthermore, this strategy provides feedback at constant frequency – resulting in potential reliance on this feedback if it is used too often (Van Vliet & Wulf, 2006).

As an individual's proficiency in a motor skill increases, less feedback on the motion trajectory is necessary. Hence, a strategy for feedback fading is required. In this

case, if the tactile curve is discretized as a series of points, it is simply an extreme case of point-to-point navigation. To fade the amount of provided feedback, one can remove every other point from the trajectory of the curve, so that the frequency of tactile feedback is halved. This can be done continuously until arriving at the minimum number of tactile points needed to represent the motion trajectory, which is directly equivalent to the original critical point strategy described above.

6.3.2: *Tactile Tethering*

As another approach, one can use error-corrective feedback that takes advantage of the dimensions of distance and directionality via a 3-dimensional tactile array (McDaniel et al. 2008; Regenbrecht et al. 2005) and rhythmic distance representation (McDaniel et al. 2009). This approach utilizes a directional tactile force at the grip points of the stick which provides a constant force of feedback to the user intending to “pull” the stick toward the optimal trajectory, making it an ideal approach for fine error correction in progression. In other words, the vibrotactile signal is intended to “tether” the individual to the motion’s optimum trajectory, so it is referred to as a tactile tether. This method stresses the importance of conveying polarity (in this case, an attraction force) with the haptic modality (Bark et al. 2011; Spelmezan et al. 2009a; Spelmezan et al. 2009b). It requires a tactile configuration that can convey an intended direction, which requires, instead of a single stimulus point, a tactile surface, as depicted in Figure 6.3.2.

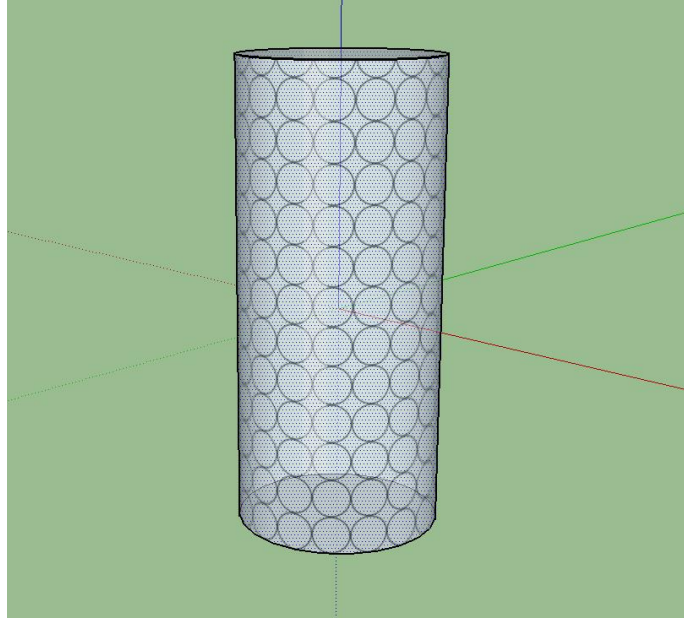


Figure 6.3.2: 3D Cylindrical Tactile Surface. Generated in SketchUp software.

If tactile actuators are arranged along the inner surface area of the grip portion of the Intelligent Stick, then it may be possible to convey a 3D directional vector of intended motion by activating the motor representing that direction from the central origin of the surface. This would allow the user to experience a tactile cue along the inner surface of the hand, which conveys directionality in a similar means to (McDaniel et al. 2010), with the primary difference being that the directional vector conveyed by the tactile stimulus is intercepted by the hand rather than radiating outward from the hand as is the case with wearables. Furthermore, rather than emitting a single signal, the tether can alternatively emit a regular pulse of tactile signals whose rhythm correspond to the distance of the stick from the intended path (McDaniel et al. 2009).

This technique manages to avoid the problem presented in the original point-to-point scheme by guaranteeing that at any time during the motion, a signal will be

available to guide the user back to the target trajectory. Furthermore, it improves the expressive capability of the haptic modality by adding new dimensions of information to the haptic signal. However, because the signals conveyed by this approach are more complex, they may require additional training to use. Furthermore, the use of this system limits the flexibility of use of the Intelligent Stick, as a specific area on the stick would need to be designated for the use of the tactile surface (the modular design of the stick alleviates this problem to an extent, but there will still be an additional setup involved when, for example, switching from unimanual to bimanual motion tasks).

Adaptation of this approach to increasing user proficiency can use a fading approach in which dimensionality of the feedback is reduced. As a user becomes more proficient at a motor task, smaller errors in trajectory occur, meaning that the tether's expression of distance is no longer necessary. Thus, this element is removed from the tactile signal and it will instead produce a continuous tactile stimulus conveying the direction needed to correct motion. Once a user has nearly mastered a skill, this continuous signal becomes a single, short vibration at the moment of error conveying the direction required to correct the error, which will reflect the fact that the user will quickly and accurately be able to perform the motion and only very minor errors will occur. Although the inner surface of the hand leaves very little room for the emittance of saltation patterns (Geldard et al. 1972), these could also be worth exploring as short-duration cues that provide directionality.

6.3.3 Volumetric Error Augmentation

The final approach is another form of error correction, but with a different strategy for conveying error. In this approach, the ideal motion trajectory and the area of tolerance around it are conveyed as a “virtual tunnel” in 3D space surrounded by a tactile force field (Rauter et al. 2010; Mihelj et al. 2007). Under this strategy, the user receives no feedback when moving within the boundaries of the tolerance area about the motion’s trajectory. However, when the user leaves this tunnel, as depicted on the left of Figure 6.3.3, a constant vibrotactile response is delivered along the entire tactile surface of Figure 6.3.2, indicating to the user that he or she has left the bounds of correct motion. In this case, unlike in the tethering approach, no directionality or distance is conveyed by the tactile response; instead, the user simply needs to reverse direction until the vibrotactile error response stops, signifying that the user is back within the tolerance region for the motion trajectory. Furthermore, unlike in the tethering approach, the tactile tunnel does not intend to produce optimal motion but rather “correct” motion; that is, the user is not guided toward the optimal motion trajectory depicted on the right of Figure 6.3.3 but rather the volume of correct motion depicted on the left of the figure, making this a coarse error augmentation strategy.

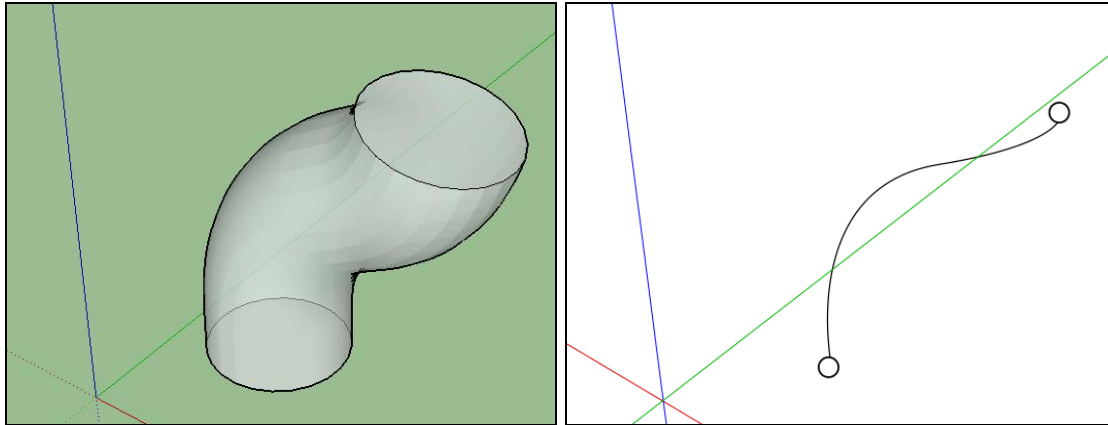


Figure 6.3.3: Area of Tolerance for Motion (Left) and True Motion (Right). Both images were generated in SketchUp software.

This approach provides perhaps the most detailed tactile representation of the shape and tolerance area about a motion trajectory. As the individual's proficiency increases, the tolerance area shrinks, resulting in a smaller tunnel that can be directly felt by the learner during subsequent exercise sessions. It does, however, introduce some of the same issues as those imposed by the haptic tether approach, as well as the "training effect" introduced by the first approach. The user may, for instance, attempt to "feel" the trajectory by touching the walls of the virtual tunnel, and can degrade in performance when this information is no longer available (outside of at-home training with the system).

As a user's proficiency improves and fewer errors are made, it may no longer be necessary for this mechanism to convey a constant vibrotactile response, but rather a single pulse to signify that an error has been made. This type of feedback assumes that the user's error is minimal and that corrective action can be quickly made by the user, thus sparing the need for a detailed or constant response.

6.4 Fine Postural Correction

When the user has reached a level of proficiency for which fine-grain posture correction is necessary, the addition of haptic guidance for joint angle correction and reduction of compensatory motion may drastically improve the quality of postural feedback offered by the system. However, the addition of these haptic signals to the Intelligent Stick would require the introduction of a haptic language to convey a variety of information from the device. Vibrotactile signals would need to be developed to convey information such as “wrong limb being used” or “flex elbow 15 degrees” which can be uniquely perceived and differentiated from the vibrotactile information on progressive guidance of the motion trajectory already being conveyed. This fusion of information may certainly be possible, but it will impose a heavy learning curve on novice users, as is expected in any haptic system that symbolically conveys a variety of commands (Förster et al. 2009). Also, design of a haptic language with this level of expressive capability will be exceedingly difficult. For these reasons, a separate source of haptic signals can be used which is exclusively responsible for conveying fine-grain information about posture.

Fortunately, a haptic framework is readily available for this task. The MOVEMENT framework by McDaniel et al. (McDaniel et al. 2010; McDaniel et al. 2011) introduces a set of guidelines for the elicitation of fundamental movements of targeted limbs or joints. In fine postural control, correction of a pose angle can be considered as a fundamental movement in the sense that the motion is limited to either a single instance or a brief sequence of flexion/extension, abduction/adduction, or pronation/supination occurring in a single degree of freedom along the sagittal, frontal or

horizontal plane. Hence, the motions involved in fine postural correction match the type of motions described in the MOVeMENT framework. A wearable sleeve or wristband similar to the haptic sleeve utilized in (McDaniel et al. 2012) requires minimal setup and can use the arm's surface to convey errors in pose angle as adjustments of fundamental movement. For detection of pose angle errors, the system currently relies on joint estimation from the Kinect's motion capture camera. While this is a relatively accurate measure in most cases of controlled movement even for finer pose angle estimation (Obdržálek et al. 2012), there are some limited upper extremity configurations which causes errors in the system's tracking mechanism (Plantard et al. 2015); therefore, it may be beneficial to include Inertial Measurement Units (IMUs) as a complementary measurement tool for pose angle tracking.

For this strategy, fine postural correction refers to any postural correction involving the elbow, forearm and wrist. Cues for fine pose angle correction can use the successfully-validated vibrotactile expressions (conveyed through saltation patterns) demonstrated in (McDaniel et al. 2012) to facilitate error correction: push/pull metaphor for elbow flexion and extension movements, and follow-me metaphor for forearm pronation and supination movements as well as wrist movements. This approach is advantageous in that it fits the guidelines conveyed in the MOVeMENT framework: saltation patterns are used to help guide the motion, patterns are mapped in the same plane as the required movements, haptic metaphors are exploited to convey directionality, and the vibrations are delivered locally at the area of error (McDaniel et al. 2010). However, there are two major challenges remaining for the use of this approach:

1. How can compensatory motion be corrected using the above approach?
2. How can the above approach be integrated with the multimodal feedback mechanism already being used by the Autonomous Training Assistant in such a way that the feedback given by the sleeve does not interfere with haptic information on progression or information being presented in any other modality?

The following solutions are proposed to address these challenges:

To address the first challenge, a simple and intuitive “reminder cue” mechanism is proposed, inspired by the approach taken in (Luster et al. 2013). The solution assumes that the haptic sleeve is worn on the paretic arm, and works as follows: when low intensity of the paretic arm is detected during exercise, the ATA system can occasionally send a reminder cue to the sleeve in the form of a single, short, burst activation of all of the actuators on the sleeve. This pattern will be distinct from the saltation patterns that represent fine postural correction, and will serve to remind the individual to use the paretic arm for the remainder of the exercise session. It can be delivered between attempts once a sufficient number of attempts at the motion task have been performed without usage of the paretic arm (the exact threshold value can be either determined through experimentation or individually prescribed by a trainer or therapist for each user). This is a simple but powerful mechanism for motivating individuals not to exhibit compensatory motion while exercising with the system, which can especially occur in the presence of serious games (Alankus & Kelleher, 2012).

To address Challenge 2 requires sequential scheduling of delivery such that the timing at which vibrotactile information for fine posture control is distinct from that of progression guidance. One solution is to deliver vibrotactile cues to the haptic wrist

between attempts while cues from the Intelligent Stick relating to progression guidance are delivered within attempts. This separation will allow users to alternate their attention between the motion from the stick to the position of their body; it also relates well to the required timing for each domain: postural errors should be corrected before making an attempt at a motion while postural errors that occur during the motion should be corrected within that timeframe. A less desirable alternative would be to dedicate the haptic modality entirely to fine postural correction (allowing usage of the Intelligent Stick's haptic feedback for postural information) and to use real-time visual motion display to correct and guide motion progression in the visual domain. This will be far more difficult to implement since the visual domain is already mapped to both coarse postural control and to the presentation of a serious game.

6.5 Information Transfer Overview

Due to the usage of multimodal feedback in this work, a discussion of how feedback in various modalities may be evaluated in motor learning systems is necessary. For this discussion, “perceptual bandwidth” is defined as the largest quantity or rate of information that one can perceive in a modality and time period. To simplify this discussion, the rate of transfer is used specifically in the scenarios below to compare between modalities.

6.5.1 *Perceptual Bandwidth Variations*

While there is no universally agreed upon estimate for the rate of transfer of vision, and while the actual rate varies depending upon the phase in the user's cognitive

process, one example estimate placed at the optic nerve is $\sim 3 \times 10^6$ bits/sec (Anderson et al. 2005). Rate of transfer in the haptic domain can vary wildly depending on the type of object, properties of the haptic signal, and the surface area on the body at which it is measured, but as an example, it can be estimated on the fingertips at around 100 bits/sec (Miller et al. 2003). For audio information, the rate of transfer at the human ear has been estimated at roughly 10,000 bits/sec (Sanders et al. 1993).

One major issue with static numeric estimates like the above is that they treat stimulus-response as an isolated event. These estimates become less useful in haptics, for example, when observing that humans interact with the world using more than just their fingertips. Consider, for example, that there are haptic patterns and signals which one can feel along the skin's surface to experience a wide variety of information. A haptic display can output complex images or text as patterns which can be felt and perceived by the hand or body to substitute for visual information (Ruspini et al. 1997). In addition to pressure, humans can also experience haptic sensations including vibrations, pain, and temperature. As such, one should take this complexity of expression in each modality into context when comparing the expressive power between them. As an example, one might typically associate properties like color, depth, texture, shape, distance, and size to the visual domain, yet with the proper design, many of these properties of objects and the environment can also be represented in the audio and haptic modalities (Belardinelli et al. 2009; Lederman & Klatzky, 2009).

6.5.2 Information Transfer

A useful metric for the evaluation of the relative effectiveness of a particular modality mapping in a multimodal environment is Information Transfer (IT), which measures the proportion of information carried by a set of stimuli that was recalled in their corresponding responses. Tan et al. (2010) have provided an estimated measure of IT under the following equation:

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

For the above equation, S_i and R_j represent a stimulus and its paired response, while K represents the total number of these pairings within the current evaluation mechanism. Using the joint probability of each pairing $P(S_i, R_j)$ to weigh the value of these pairings, this equation determines the average amount of IT for the entire set in bits. $P(S_i | R_j)$ is the conditional probability of a stimulus S_i given a response R_j . The above is certainly not the only method by which IT has been estimated and evaluated within literature; similar efforts have used metrics including survey results, percent-correct totals and error rates, but found less success than the above measure in finding an accurate value for the efficiency of transfer (Tan et al. 2010; Slater, 2004).

A typical IT evaluation will present a subject with K unique stimuli and expect K unique possible responses for these stimuli such that each stimulus can correspond to an exact response in the response set. The user's responses to randomly selected stimuli are then collected and form a stimulus/response confusion matrix for the user. From this

matrix, a maximum likelihood estimate for IT can be derived using the following equation:

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

Such that n is the total number of trials, n_{ij} is the number of times the stimulus-response (S_i, R_j) is elicited from the user, and n_i, n_j are the total values $n_i = \sum_{j=1}^K n_{ij}$ and $n_j = \sum_{i=1}^K n_{ij}$. Note that since bits are typically used as the unit of measure in this process, the maximum value represented by the number of bits used represents the maximum amount of information that can be transferred. 2 bits can represent a maximum of four unique symbols or items, while 4 bits can represent 16, and so on. In general, one can express this concept as $IT_{max} = \log_2 K$. The two IT values IT_{est} and IT_{max} can be compared to evaluate the effectiveness of the current mapping of modalities in a multimodal design. If we include time as a dimension, and are instead measuring the effectiveness of a series of stimuli over a timeframe, IT in this case can be represented as the rate IT_{rate} in bits/sec. Finally, one can determine K' , or the number of alternatives, using the reverse of the IT_{max} equation with IT_{est} as: $K' = 2^{IT_{est}}$.

6.5.3 Design Implications

One major drawback to the use of the IT measurement process above when analyzing the multimodal framework in the ATA is that the metric is limited in use to Absolute Identification (AI) tasks where there must be a precise, predetermined response

to a particular stimulus. As an example, Alluisi et al. (1957) presented subjects with Arabic numerals and measured the user's identification of these numerals through verbal or typed response, and Tan et al. presented tactile stimuli across the fingers of subjects with varying frequency and amplitude and asked subjects to identify pre-built patterns out of a set (Tan et al. 1999). In the Autonomous Training Assistant, this experimental setup may be possible for the assessment of audio stimuli related to pacing, where a set of audio signals can be varied in frequency and tone (for example, five frequencies and five tones generate 25 alternatives) and used to denote a variety of targeted pace values (25 different speeds, using the above stimuli), but in the visual domain, for instance, where the stimulus is a complex avatar representation of an intended pose and the individual's actual pose, the number of alternatives is incredibly high. An absolute identification experiment in this domain would require the constraint of the space to a limited number of represented poses (for example, "seated, arms straight", "standing, shoulders extended" among others) and the visual presentation of these poses as static images of the virtual trainer, along with the verbal response from a subject on the targeted pose, but this design would carry little meaning since it severely limits the space in which motion tasks can be represented. Instead, the design of information in each modality is based on the fact that motor learning is an imperfect process; it is concerned, as the use of tolerance ranges suggest, with how closely an individual's motion can match a targeted motion in the spatial (postural, progression) and temporal (pacing) domains. The stimuli presented in the visual, haptic and audio modalities are meant to convey this complex spatio-temporal information.

In the haptic domain, a stimulus is a vibrotactile cue in 3-dimensional space that is meant to convey a critical point along the trajectory of a motor task in space-time. To measure how well the subject interprets this trajectory using this stimulus, one can approximate information transfer using the distance at a certain point in time between the location of the Intelligent Stick in space and the intended location as represented by the critical point (using Dynamic Time Warping (DTW)). If the dimensionality of direction and distance are added, a haptic stimulus would also convey an intended direction and distance for the stick to travel. A set of these vibrotactile patterns can be generated (to convey, for example, 14 different directions and 6 different distances) and follow an absolute identification format by having subjects identify these patterns either verbally or through demonstration of the effect, to determine the influence of this added dimensionality on the expressive capability of the signal.

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 (84 in the above case)”? The DTW distance measure will answer this question in terms of motor performance: “How closely does an individual’s motion match an intended motion when using this design scheme to guide the subject?” While both of these metrics are subject to the proficiency of an individual with a motor skill, 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.

In the audio modality, a targeted temporal value should be expressed. Since this is of lower dimension than 3-dimensional spatial information, the number of required perceptually distinct patterns are far smaller in number. In fact, one only needs to convey to a user the direction of speed adjustment in the same manner a trainer would (“slow down” or “speed up”), and only when an error occurs because of individual deviation from a tolerance range about the targeted speed. In the current scheme, only a single bit of information is being transferred (2 variants, “too slow” or “too fast”) and they are represented by a low pitch or high pitch audio cue, respectively. Information Transfer assessment on this modality should examine not only the responses of individuals to these signals in real-time (play a random signal, observe whether the subject speeds or slows in pace), but the amount of time it takes for the subject to reach a targeted speed range using these signals. It may be possible that the current scheme is not expressive enough, and subjects will continuously make errors as they overcorrect and oscillate between fast and slow speeds, never quite falling into the intended speed range. This deviation between the stimulus and the intended response can be captured by the above time measure. Should this be the case, the modality can be extended in dimensionality, increasing the number of distinct stimuli. One can represent the stimulus as a continuous pulse instead of a single pulse, which varies in frequency according to the distance of the individual from the intended tolerance range. In this case, if 4 different frequencies were used to indicate relative distance, and 2 frequencies to indicate direction, the result is a 3-bit signal with a maximum of 8 different distinct patterns to convey, and with it one can measure the correction time for a targeted pace in addition to the IT_{est} and IT_{max} values above.

In the visual domain, the dual point-of-reference mirroring approach presents postural error to an individual as the difference between the virtual representation of that individual's posture and the virtual representation of the intended posture. As previously discussed, this design approach offers an incredibly large amount of perceptually distinct stimuli depending on the motion and the individual. A measure of information transfer in this domain would have to determine how well an individual is able to perceive the degree of error being shown by the differences in avatar posture. For example, if a motion requires 90-degree outward rotation of the shoulders and the individual's current rotation is 45, then it would be interesting to determine how well the individual was able to distinguish, based on the dual display, that a 45-degree error in posture has occurred. Once again, this is where a distance measure can be useful. The subject can be initially asked to make a 45-degree outward rotation, and then presented with the dual avatar display indicating a 90-degree targeted rotation, and then asked to either adjust his or her posture to match the trainer avatar's posture, or to verbally convey the angular difference being shown on screen.

Once the individual has made this adjustment, the Kinect pose angle measurement (or the measurement of the haptic sleeve IMU) can determine the distance between the individual's adjusted pose and the intended pose as a measure of error. If a verbal response is measured, one can determine how well the individual understood the quantity that is being expressed by the two avatars. This can be done with a variety of different poses and targeted pose angles to measure the expressive capability of this approach across the upper extremity domain. Should it be determined that the postural difference being shown on screen is not being conveyed accurately, measures such as zooming in to

the specific area where the postural adjustment is needed (objects at a closer distance can be perceived more clearly) can be taken to improve the transfer of visual information.

6.6 Perceptual Bandwidth Augmentation

As implicated above, perceptual bandwidth is related to the number of perceptually distinct stimuli that can be discerned from a modality. In motor learning, the system attempts to guide an individual's motion in the spatial and temporal domains. This results in feedback in multiple possible dimensions:

- **Error or Success Identification:** Whether an error has occurred. Alternatively, whether an individual has successfully completed an objective. (1 bit)
- **Directional Identification:** In what direction the user should move to correct the error or to get to the next goal or task. (temporal domain: 1 bit, spatial domain: 1 bit for fundamental movement, varies by precision for complex movements)
- **Distance Identification:** How far away the user currently is from an intended location. (varies by precision)

In each modality, the ATA currently makes use of one or more of these dimensions of feedback. As the number of these dimensions that are expressed in a single modality are increased, the perceptual bandwidth in that modality is increased since, with the appropriate design, one can increase the number of distinct patterns conveyed to facilitate the new dimensions of information. The current strategies in place as well as ideas for increasing dimensionality in each of these modalities are discussed below.

6.6.1 *Haptic Information*

In the haptic space, a point-to-point guidance has been utilized. Currently the critical point method only indicates if an individual has hit the next point in a sequence for a motion (success identification). The haptic vibrations do not encode the relative location of the next point to the current point in real-time. Since this information is missing, there can often be cases where communication efficiency is low, particularly in undertrained users or users who are experiencing a motion task for the first time. This issue is highlighted in the first question above, and the corresponding solution strategies indicate that by adding the dimensions of directional identification and distance identification, this issue can be addressed through more informative haptic signals that guide the user from point to point. With the increased dimensionality, the amount of uniquely varying (perceptually distinct) stimuli experienced by an individual would be increased. An interesting note is that as user proficiency increases, the dimensions of directional and distance identification become less necessary, so fading feedback can involve dimensional reduction of the signals over time.

6.6.2 *Audio Information*

In the audio channel, the goal of the ATA system is to provide feedback on errors in pacing. An audio stimulus must indicate that an error has occurred (in which the user's current rate of motion has deviated from the expected/targeted rate of motion by an amount equal to or greater than the tolerance threshold value set for the current exercise and user), and how the error can be corrected (whether the user's current rate of motion is too slow or too fast). The audio domain provides access to the properties of pitch, tone or,

in the case of a repeated series of audio cues, frequency to represent not only error identification and directional identification but distance identification as well, should it be necessary. In the case of error correction, it is potentially unnecessary to indicate the degree of error, or the distance between the user's current rate of motion and ideal rate of motion; if the error stimulus is delivered repeatedly until the error is corrected, and knowing only the direction of adjustment needed, the user can simply adjust his or her speed accordingly until he or she re-enters the tolerance range and the error cue stops.

However, should this information be necessary, one could encode it in the audio channel by assigning one of the properties of sound stimuli to distance, as indicated with frequency. A good example of the dimensional power of this channel is given by Wolf et al.'s use of error sonification for rowing tasks (Wolf et al. 2011). The current representation assumes that the audio feedback is a simple cueing signal; using human speech instead as an audio signal, the amount of perceptually distinct stimuli can be increased dramatically without the need for additional training from the user, providing a large increase in perceptual bandwidth. However, the use of human language incurs a delay in processing time, as it takes longer to communicate that an individual's pace, for example, is too fast by using a phrase or sentence rather than a single short audio cue, significantly reducing the maximum frequency at which the ATA system can deliver this information (O'Shaughnessy, 1987). The speech approach, therefore, does not scale well with increasing motion complexity, where for more advanced motions there can be rapid motions with high variation in the spatial and temporal domains.

6.6.3 *Visual Information*

While, as discussed above, the dimensionality and expressive potential of the visual channel is extremely high, there are still some limitations to the modality that apply directly to the ATA system. One is the inability of the eye to discern objects of similar shape or texture that are sufficiently close to one another from a certain distance and surpass the maximum resolution of the eye (Campbell & Green, 1965). In the example of layered dual point-of-reference (DPOR), avatars which are superimposed on one another may be indiscernible in cases where the user's pose angle varies only minimally from the desired level. At high levels of proficiency, this small variation may represent an error that should be corrected by the user due to a heavily reduced tolerance range. This imposes a potential limitation on information transfer due to a lack of perceptual distinctiveness between the visual representation of a correct posture and that of a slight error in posture, termed fine postural correction.

Since dimensionality in the visual domain is already quite high, and an extraordinary amount of information is already encoded in a visual display with the level of complexity of the ATA, it is difficult to increase this dimensionality to increase perceptual bandwidth in this modality. Instead, this issue can be resolved through careful consideration of the interface design. For example, the colors of the avatars and background can be chosen so that they contrast one another, making it easier to distinguish more subtle deviations between the two objects. As another example, when an error in pose occurs, the in-game camera can zoom in to the problem area, making it easier to discern the error due to the increased resolution at a closer distance. Finally, an alternative modality can be employed for fine postural correction.

6.6.4 *Multimodality*

Since the various spatial and temporal elements of feedback have been assigned across three modalities, this essentially creates three different sources of distinct information. During motor exercise, a user's performance depends on all three domains (posture, progression, performance). Hence, these modalities are combined to provide information on all three of these elements in real-time. This use of multimodality drastically increases the variety of information that can be given to a user at any point in time, but will it be possible for a user to process this complex information in real time? There are several considerations to be made here. The first is on the limitation of the human working memory, famously quantified by Miller as the magic number 7 ± 2 (Miller, 1956). Fortunately, Miller (1956) also provides the key to overcoming this limitation using "chunking". Humans utilize this approach in the processing of language by learning letters, then their combination into words, then the combination of words into phrases, and the combination of these phrases in various structures into sentences. In a similar manner, multidimensional information on motor performance can be recognized through the construction of patterns over the course of training. An individual using the ATA system may first associate an audio cue with the error identification dimension; after hearing several cues of high and low pitch, the individual can then identify the directional information encoded in the cues. Similar strategies can be used to train in the haptic and visual domain to synthesize the elements of information being presented.

The other concern with presenting this information is cognitive load (Sweller, 1988). The amount of cognitive load imposed on a user during the presentation of multimodal information depends on the method by which the modalities are integrated

and presented in real-time (Oviatt et al. 2004). In the current approach of the ATA system, where information is presented concurrently within each attempt, it is very possible that the presentation of information in multiple domains of motor learning in parallel may cause an individual to selectively focus on a single channel of information or to become overwhelmed by interfering signals across three modalities, especially since it involves timed tasks (Guadagnoli & Lee, 2004; Chen et al. 2012). It is proposed that, since postural and progression information both correspond to the spatial domain, they can be delivered in parallel under Wickens' multiple resource theory (2002) claiming that information distributed across modalities relating to a task synergistically can improve function, and Baddeley's theory (1992) that the working memory is extended in the provision of these multimodal inputs. Meanwhile, temporal information on pace can be delivered either terminally or between attempts, rather than within attempts, to prevent interference with information in the other domains. The implementation of this new design strategy can consider limitations on both cognitive load and working memory in the motor learner.

6.7 Feedback Frequency and Fading

The training effect that causes one to rely too heavily on feedback for motor learning, especially when feedback is provided too frequently for simple motor tasks, has been identified and validated in literature as the guidance hypothesis (Salmoni, 1984; Schmidt, 1991; Schmidt & Wulf, 1997; Schmidt et al. 1989). One of the most supported reasons for this phenomenon is that frequent feedback causes the learner to focus his or her attention to the external feedback stimuli being presented, and to consequently lose

focus on intrinsic or internal feedback mechanisms like proprioception (Van der Linden et al. 1993; Winstein et al. 1996). The specificity of learning hypothesis (Proteau, 1992) explains that during learning for simple motor tasks, when a host of information is available, the learner selects the sources that are the most optimized for learning the task at hand. Part of this optimality includes the frequency at which the guiding information is available, meaning that if extrinsic feedback by an external guiding force is regularly and frequently made available, the learner selectively relies on that feedback source by allowing it to replace some of the information obtained through proprioception and processing of intrinsic information on performance (Proteau, 2005; Proteau & Isabelle, 2002; Robin et al. 2005). As a result, when the external (augmented) feedback is removed, the learner is unable to retain performance of the motor task (Schmidt & Wulf, 1997).

However, there is a popular misconception that the guidance hypothesis applies universally to all types of motor learning; this is not necessarily the case (Guadagnoli & Kohl, 2001; Guadagnoli & Lee, 2004; Winstein, 1991; Wulf & Shea, 2002). In fact, it has been shown that for complex motor tasks, frequent concurrent feedback instead has a positive effect on skill acquisition and retention, even after the feedback is removed (Marschall et al 2007). There are several explanations offered for why this is the case. One posits that, in the process of learning the basic structure and properties of a complex motor task, learners may benefit from frequent feedback as it may reduce cognitive overload caused by internalization of the initial learning process (Wulf & Shea, 2002). Another explanation is that by shifting the focus of the learner to extrinsic information as stated above, this feedback promotes stronger automation of the internal learning process (Wulf, 2007). Finally, it is stated that reducing the frequency of this feedback as a

learner’s proficiency improves is beneficial since these automated internal mechanisms “take over” when the learner is experienced enough to begin fine-tuning performance on a learned task (Crowell & Davis, 2011). It is clear, then, that to determine how feedback should be delivered over the course of motor learning, several distinctions need to be made between the type of motor task, the proficiency of the learner, and the type and frequency of feedback. To simplify this discussion, specific modalities will not be addressed here, although the distinction between optimal feedback in these modalities may be addressed in future work.

6.7.1 Motor Task Complexity

As stated above, complex tasks require a different feedback mechanism for optimal learning than simple motor tasks. How, then, does one determine the complexity of a motor task? The attributes of a motor task relating to complexity can be derived from work by Gabriele Wulf and Charles Shea (2002) and are summarized in Table 6.7.1.

Table 6.7.1: Distinctions in Task Complexity. Data is based on Wulf & Shea (2002) and on the information presented in Tadayon et al. (2017).

	Simple Task	Complex Task
Time to Learn Motion Structure	Single Session	Multiple Sessions
Degrees of Freedom or Dimensionality	Single Degree of Freedom (Motion along 2D Plane)	Multiple Degrees of Freedom
Transfer/Ecological Validity	Artificial/Little real-world transfer	Transferable, Ecologically Valid

Note that these criteria do not consider the attributes of the learner. An individual who is a baseball pitcher, for example, can recognize the foundational elements of a pitching motion much more easily than an individual who has no experience with that class of motions. Furthermore, a motion may be more transferable for one individual than another depending on the context and the individual. These criteria can therefore be eliminated in describing the complexity of motions for the sake of the ATA framework, and instead focus on the third criteria: degrees of freedom. This is a highly desirable characteristic for describing the complexity of a motion from a system's standpoint because it is quantifiable and automatically measurable. Hence, motor task complexity for tasks used in the ATA is classified by the degrees of freedom involved in the motion, or its dimensionality. For example, a motion involving a single limb which rotates the arm or arms about on a 2-dimensional plane in space can be considered a "simple motion" while any motion which breaches this property can be considered a "complex motion". This allows a clear distinction between the two such that when a motion is entered into the system, its complexity can automatically be determined from the trajectory of the recorded motion.

6.7.2 Phases of Learner Proficiency

The phases of learning by which one masters a motor task, from the moment the task is first introduced to the moment the learner has fully acquired the skill, are also worthy of distinction as their characteristics help clarify the differences in feedback effectiveness between simple and complex motor tasks. Using the classification scheme

originally posed by (Fitts & Posner, 1967) and (Schmidt & Wrisberg, 2008) and adopted by Sigrist et al. in (2013), three phases of motor learning can be identified:

- *Phase 1:* After initial exposure to the motor task, the learner attempts to encode a motor program for the task. High levels of error occur in task execution as the learner attempts to adjust to the dynamics of the task
- *Phase 2:* Having developed a mental structure for execution of the task, the learner begins to refine his or her motion, focusing more on correcting errors and matching the targeted trajectory, speed and postural requirements of the task.
- *Phase 3:* Learner attempts at the task become highly consistent between repetitions, error is minimized, and the learner has either mastered or nearly mastered execution of the motor task.

Based on this classification, a critical link with the guidance and specificity of learning hypotheses become clear. It is apparent that, based on the characteristics of motor task complexity given above, simple motor tasks yield a relatively short or nonexistent Phase 1 in comparison to complex motor tasks because, since the dynamics of the task are simple, the learner can encode a motor program for the task immediately or with very little practice. During Phase 1, an individual is likely to benefit from frequent feedback due to its effect on automation of the internalized learning process and reduction of cognitive overload as previously explained. Once this initial proficiency is gained, the feedback can then be faded as it becomes less necessary in the second and third phases where the guidance hypothesis and specificity of learning hypothesis apply (since the focus is on error correction and motion refinement). Since Phase 1 learning does not apply in simple motion tasks, this characterization is consistent with the findings

in literature that frequent feedback has a negative effect on these tasks, yet a positive effect at the introductory stage of complex motor tasks (Wulf & Shea, 2002).

The ATA system can utilize this classification scheme in future work to subdivide its feedback strategy into phases. When it receives a motor task that is characterized as a simple task under the above guidelines, the system can skip to Phase 2 of its 3-phase mechanism. For complex motor tasks, the system can begin in the initial feedback phase. Using this scheme, frequency of feedback can be faded by the ATA as the system detects that a learner has moved to a higher level of proficiency. The first step in achieving this practice is to quantify proficiency in the system so that the thresholds between these phases can be clearly identified. Fortunately, there are psychometric tools in Game-Based Assessment (GBA), specifically for Stealth Assessment, that make it possible to quantify the user's proficiency in the eyes of the ATA system.

An individual's proficiency with a motor task can be calculated as a function of the individual's error rate or "hit rate" relative to tolerance thresholds in the progression, pacing and postural domain, the specific parameters of which will be determined through multiple regression analysis and the formation and fitting of a model within a control group. Comparison with observational data and findings by physiotherapists or expert trainers for a group of individuals will help map these values of proficiency to the phases of learning exhibited by an individual during the acquisition of a motor task. Once the threshold proficiency values are determined for the transitions between phases, the ATA system will then know when to fade feedback. As an additional note, it may be desirable to use the length of tolerance thresholds rather than the player's proficiency level for learning phase adjustment, since the game will adapt to keep the proficiency level at a

constant, targeted value. To discuss how to fade feedback, definitions for frequency and timing are required.

6.7.3 *Feedback Timing and Frequency*

The metrics related to granularity of motor learning are defined as follows:

Learning Units: A repetition is a single attempt at the completion of a motor task, while a session refers to a series of repetitions bounded by either time (a set duration) or a total number (a set number of repetitions).

To distinguish between different characteristics of feedback, one can refer to some commonly used classification factors by Schmidt and Lee in (2005):

Timing: Concurrent feedback is delivered in during a repetition or between repetitions in a single session while terminal feedback is delivered at the end of a session.

Source: Extrinsic or augmented feedback is provided by an external source while intrinsic or internal feedback is inferred from the effects of the motion itself and the environment.

6.7.4 *Feedback Delivery Strategy*

Based on all the evidence above, the following strategy is proposed for the adaptation of feedback frequency and type: Once a new motion is entered into the system, the system can first determine whether it is a simple motion or complex motion, as noted above. If the motion is classified as a simple motion, then the system skips the first phase of learning and begins the learner at Phase 2. If the motion is complex, the system begins at Phase 1.

Phase 1: In this phase, feedback is provided as concurrent, augmented feedback using the strategy given in the proposal. This means that while a user is completing a motion attempt during gameplay, not only is that user receiving intrinsic feedback on performance from game outcomes, but also from the vibrotactile interface, the audio cueing system, and the on-screen postural representation. This feedback is not necessarily delivered in unison from all three sources (strategies for integration are discussed below), but will be provided on each attempt to facilitate the formation of a motor program for the task (Schmidt & Lee, 2005). Once the individual has reached the threshold level for Phase 2 proficiency as discussed above, or the individual's trainer or therapist (in the case of rehabilitation) has determined that the individual can move to the next phase, the system will shift to Phase 2 feedback in the next session.

Phase 2: In this phase, feedback on posture and progression can be combined into the haptic channel; this is because the learner is at a level of proficiency where the basic structure of a motion and its postural requirements are clear, and only fine-grain haptic guidance is delivered on an as-needed basis, consistent with the haptic guidance strategy described by Sigrist et al. (2013). This need is determined by the system because of performance error; if the learner deviates from the tolerance threshold for either joint angle (posture) or motion trajectory (progression), a haptic signal can help guide the user back within the threshold, either through an external wearable for posture, or through the Intelligent Stick for progression. Feedback for pacing will no longer be delivered through an explicit audio cue but will be inferred by the learner because of his or her overall performance on the task. This can be delivered as visual, terminal feedback after the completion of a session by displaying the learner's total repetitions vs. the targeted

repetition amount for a timed session or total time to completion vs. the targeted time total for a session bound by a set number of repetitions.

If the learner notices that his or her repetition count, for example, is 3 lower than the goal set for the session, he or she can infer an error in pace, and speed up or slow down as necessary until the targeted value is reached. This can be embedded into gameplay with a scoring system, if the individual's score corresponds to the number of successfully completed repetitions. Notice that errors in performance are still made apparent in real-time during the game; an error in pacing during an attempt will result in consequences within the context of the game. However, this type of feedback can be viewed as the environment reacting to the individual's motion, which allows the individual to self-improve over the course of the game session. In summary: postural and progression feedback are no longer delivered continuously, but on an as-needed basis, while pacing feedback is delivered terminally. Once the individual has reached the threshold level for Phase 3 proficiency as discussed above, or the individual's trainer or therapist (in the case of rehabilitation) has determined that the individual can move to the next phase, the system will shift to Phase 3 feedback in the next session.

Phase 3: In this phase, all forms of feedback are delivered visually within the context of gameplay. The use of design principles for serious games helps to ensure that the outcomes of a game correspond directly with a user's performance in the motor domain. For example, the elements of each turn on a racetrack are based directly on variables corresponding to the tolerance thresholds in each domain of motor performance (posture corresponds to driver orientation during the turn, while the sharpness of a turn and track width represent progression parameters and the driver's speed of entry and exit

represent pacing parameters). If an individual makes an error in one of these domains, the car will move off the track in the game or it will take longer to successfully complete a turn, thereby indicating implicitly to the learner that the motor task was not executed with precision. Should the user's performance ever drop below the entry threshold for Phase 3, the system can return to Phase 2 feedback until the user has regained the required proficiency. Extrinsic feedback on all domains can be delivered in this phase as terminal feedback at the end of a gameplay session in qualitative form (for example, "slightly reduce your speed" or "tuck in your shoulders more during each turn") and can be abstracted within the game context (in the racing example below, it can be delivered as a series of "driving tips" to improve performance on the next track).

6.8 Tolerance Threshold Adaptation

A primary advantage of the use of tolerance thresholds is that they explicitly quantify the difficulty set for a motor task in each of the three domains of performance (postural, progression, pacing). This simplifies the process of difficulty adjustment both from a system standpoint and from a gameplay standpoint under the appropriate design. The primary purpose of adaptation is to maintain a zone of proximal development for the learner (Vygotsky, 1980), or keep them within the state of flow (Csikszentmihalyi, 1990; Chen, 2007). To maintain this state in a learner, the system needs a way to quantify difficulty in the game as well as proficiency of the learner. Since difficulty is quantified using tolerance ranges as above, the remaining task is to measure proficiency. As stated above, proficiency in the user can be treated as a function of that individual's success rate with respect to the currently set threshold values. This "hit rate" metric for adaptation is

utilized by across a variety of approaches toward rehabilitative game adaptation (Andrade et al. 2016; Pirovano et al. 2012; Ma et al. 2007) and can be summarized as follows:

To maintain challenge and engagement, the game parameters controlling difficulty should be constantly and dynamically adjusted to ensure that the rate of success or “hit rate” of a player reaches (and stays at) a pre-specified targeted value. This can be expressed as the following function:

$$P_t = \frac{S_t}{R_t} \quad P_a = \frac{S_a}{R_t}$$

where $P_t = [0 \dots 1]$ and $P_a = [0 \dots 1]$ are the targeted hit rate and actual hit rate, respectively, $S_t = [0 \dots R_t]$ is the targeted number of “successful” repetitions performed in a window of R_t repetitions, and $S_a = [0 \dots R_t]$ is the actual number of successful repetitions in that window. The definition of R_s can be defined more accurately with respect to the ATA by representing a sample log file entry based on a single attempt at a wrist exercise:

Progression: “MotionError” represents the maximum (or weighted average) distance of deviation of the player’s Intelligent Stick from the targeted trajectory of the motion during the repetition, calculated using Dynamic Time Warping between the two trajectories over the attempt. “MotionT” represents the maximum allowed value for this error (the tolerance threshold for motion deviation). “ArcError” represents the difference between the degree of motion (expressed as arc distance over the motion trajectory) of the user and the ideal degree of motion. “ArcT” represents the maximum allowed value for this error (the tolerance threshold for arc distance).

Pacing: “PaceError” represents the deviation between the player’s average speed and the targeted speed for the motion over an attempt. “PaceT” represents the maximum allowed value for this error (the tolerance threshold for pacing).

Posture: “PostError” represents the deviation between the player’s joint angle for an active joint involved in the postural requirements for the current motion as detected by the Kinect and the targeted value for that joint. If multiple joints are involved in postural requirements for a motion (for example, “shoulders tucked in, facing forward and trunk aligned with seat”) then this becomes an array of values. “PostT” represents the maximum allowed value for this error (the tolerance threshold or thresholds for posture).

Based on these values, the success rate on an attempt in each category can be defined as follows:

$$S_a(\textit{progression}) = \sum_{x=1}^{R_t} \begin{cases} 1 & \textit{if } MotionError(x) > MotionT \textit{ or } ArcError(x) > ArcT \\ 0 & \textit{otherwise} \end{cases}$$

$$S_a(\textit{pacing}) = \sum_{x=1}^{R_t} \begin{cases} 1 & \textit{if } PaceError(x) > PaceT \\ 0 & \textit{otherwise} \end{cases}$$

$$S_a(\textit{posture}) = \sum_{x=1}^{R_t} \begin{cases} 1 & \textit{if } PostError(x) > PostT \\ 0 & \textit{otherwise} \end{cases}$$

This separation allows the system to separately adapt the parameters of difficulty in the game for individual domains of performance. If an individual is performing very well in progression but suffering in performance in pacing, then the system can increase difficulty of game parameters related to progression while decreasing difficulty for pacing (or equivalently, reduce tolerance thresholds in progression and increase the

threshold for pacing). Furthermore, it allows us to define separate targeted rates $P_t(\textit{progression})$, $P_t(\textit{pacing})$, and $P_t(\textit{posture})$ for each domain. The window parameter R_t represents the number of attempts that are monitored before the system calculates the player's success ratio and makes a difficulty adjustment. It controls the rate of adaptation for the system, which can be static or dynamically adjusted. It may be desirable to adjust this value dynamically in relation to a player's phase of proficiency as determined by the mechanism discussed above (an evaluation can be designed to determine optimum rates of adjustment for the window parameter).

The set of target hit-rate parameters for an individual can be expressed as follows:

$$P_t = \{P_t(\textit{progression}), P_t(\textit{pacing}), P_t(\textit{posture})\}$$

These values are not necessarily the same for all players; higher targeted rates reduce the average difficulty of the game and target it towards casual audiences or players with less experience in games, while lower rates make gameplay much more difficult on average and are intended for expert audiences who enjoy high levels of challenge in gameplay or have much more experience with games (Missura & Gärtner, 2009). Therefore, the targeted hit rate values for a player should either be derived from that individual's background, or left in control of the player.

Now let's assume that for some player, a value for P_t and R_t have been determined. The player then initiates a game session on the ATA system and attempts a motion for R_t repetitions within the game. Once the player's hit ratio has been calculated for each domain in the form of the three S_a values listed above, the system then compares the resulting hit ratios P_a to the targeted ratio P_t and performs adjustment:

$$T = \{MotionT, ArcT, PaceT, PostT\}$$

$$T = \begin{cases} T - D, & P_a > P_t \\ T + D, & P_a < P_t \\ T, & P_a = P_t \end{cases}$$

In the above adaptation function, D is the magnitude of adjustment, and is defined separately for each feedback domain. It can be adjusted according to the magnitude of difference between the targeted rate and the actual hit rate:

$$\begin{aligned} D(\textit{progression}) &= |P_a(\textit{progression}) - P_t(\textit{progression})| * [\max(MotionT, ArcT) \\ &\quad - \min(MotionT, ArcT)] \end{aligned}$$

$$D(\textit{pacing}) = |P_a(\textit{pacing}) - P_t(\textit{pacing})| * [\max(PaceT) - \min(PaceT)]$$

$$D(\textit{posture}) = |P_a(\textit{posture}) - P_t(\textit{posture})| * [\max(PostT) - \min(PostT)]$$

This adjustment is then repeated after every R_t attempts of the motion task. The adjustment function requires as its parameters the maximum and minimum tolerance thresholds allotted for the individual and motor task. These two parameters should be defined by the individual's trainer and reflect the baseline and ultimate goal for performance of that individual for the motor task. In cases of severe impairment, for example, both of these values can be relatively high. If the individual already has some proficiency with the task, then both bounds would be set relatively low to reflect this level of expertise.

Here is a concrete example to summarize this technique, using the car racing example: Player X has been assigned a wrist pronation/supination task by his trainer, who notes in clinical training that the individual has high spatial and temporal awareness of

the motion task but has trouble keeping the shoulders tucked in during task execution. The trainer sets a relatively high goal for proficiency in progression and pacing, and a lower goal for posture to reflect the individual's rate of progress in that domain. Minimum error thresholds are set at 20 for progression and pacing, and 50 for posture, while maximum thresholds are set to 100 and 300, respectively. Since the individual has little experience with games, the targeted hit rate for all three domains is set to 0.6 (that means that for each set of motion attempts by the individual, the game will adjust difficulty until the target achieves 60% of those attempts without error).

Each value is initiated as follows:

$$MotionT = \max(MotionT) = 100 \quad ArcT = \max(ArcT) = 100$$

$$PaceT = \max(PaceT) = 100 \quad PostureT = \max(PostT) = 300$$

$$P_t(\textit{progression}) = P_t(\textit{pacing}) = P_t(\textit{posture}) = 0.6$$

$$R_t = 5$$

The individual then begins exercising with the ATA system. After the individual completes 5 repetitions of the exercise, the log entries for these 5 motion attempts display the following error values:

$$MotionError = \{70, 68, 68, 63, 71\},$$

$$ArcError = \{32, 12, 6, 85, 92\},$$

$$PaceError = \{76, 64, 45, 31, 32\},$$

$$PostError = \{212, 295, 315, 115, 110\}$$

Using the equations above, the target has achieved 100% success rate in progression and pacing, and an 80% success rate in posture. Since both of these success rates are above the targeted hit rate for the system, the difficulty must be increased to maintain challenge for the player. Using the above equations results in D values of 32 for progression and pacing and 50 for posture. This adjusts the tolerance thresholds for progression and pacing down to 68 and the tolerance threshold for posture down to 250 for the next 5 attempts. When reflected in gameplay for the racing game, this translates to a reduction in the width of the racing track by 32 and a reduction in the range of acceptable entry speeds going into the turn by 32, as well as a reduction in the allowable deviation from the targeted shoulder position by 50 for the next 5 turns on the racing track. This reduction in tolerance ranges is considered evidence, for the sake of the system's assessment, as an increase in proficiency by the player. This mechanism for adjustment requires extensive evaluation to determine how sensitive a player might be to adjustments in each feedback domain, and whether a weighted adjustment scheme with a weighting parameter that considers these sensitivities should be utilized in the adjustment function.

6.9 Multimodal Fusion Techniques

Multimodal fusion is a necessary discussion when implementing a system capable of providing feedback across 3 modalities. Since human interaction is multimodal in nature (Bunt et al. 1998; Quek et al. 2002), and since this type of interaction can be directly observed in guided training between a subject and trainer (Tadayon et al. 2015), a system designed to provide guidance should be able to weave feedback cues together in a

way that enhances the subject’s learning. HCI research has been interested in the topic of multimodal fusion for several decades in various application domains (Johnston et al. 1997; Wu et al. 1999; Chai et al. 2004; Mendonça et al. 2009; Song et al. 2012). A 2x2 classification model by Nigay and Coutaz (1993) highlights the common strategies used in this field to achieve fusion, and is presented in Table 6.9.1:

Table 6.9.1: Multimodal Classification according to Nigay and Coutaz (1993). Based on information presented in Tadayon et al. (2017).

		<i>Use of Modalities</i>	
		Sequential	Parallel
<i>Fusion Style</i>	Integrated	Alternate	Synergistic
	Non-Integrated	Exclusive	Concurrent

6.9.1 Style 1: Alternate

In this approach, cues in multiple modalities refer to the same information or feedback, but are delivered separately in sequence rather than in parallel. For the Autonomous Training Assistant, this can be achieved by choosing a particular domain of feedback (postural, progression, pacing) and providing feedback in the haptic, visual and audio modalities within the chosen domain, but at varying granularity levels. The “pacing” domain can be used as an example here. Assuming there are several different temporal frequencies (within an attempt, between two attempts, between sessions), one can map the three modalities of the system such that each modality is assigned to one of these ranges, and the three are then layered in sequence based on their frequency assignment. One can use rhythmic guidance to move the subject within a single attempt (Schaefer, 2014), and haptic rhythm to transition the user between attempts

(Holland et al. 2014) and provide an end-of-session visual report on the user's pacing via a scoring system (Sigrist et al. 2013).

Advantages: An important finding to consider related to this strategy is that there is a potential for individual bias toward modalities in subjects (Helbig & Ernst, 2008), which means that when multiple modalities are redundantly assigned to a particular piece of information, the system can guarantee that at some granularity, the user receives that information within a modality that matches his or her preference. A secondary advantage is that, due to the sequential ordering of feedback, collisions in which multiple modalities of feedback are delivered in parallel and each distracts from the other are completely avoided in this method (Vitense et al. 2003).

Disadvantages: One of the most blatant disadvantages of a sequential ordering focused on a single domain of feedback is that it leaves no opportunity for the system to provide feedback in other domains, essentially slowing the rate at which a user can master a motion task. If the only domain in which a user's motion is guided is progression, for example, separate sessions would be required to assist the user in pacing and posture, slowing the rate of mastery by a factor of 3. Another disadvantage is that cognitive overload effects may be observed if the user must constantly switch attention from one modality of feedback to another (Oviatt et al. 2004), but this limitation can be eliminated if the sequencing of feedback modalities is carefully designed.

6.9.2 *Style 2: Exclusive*

This approach to fusion, like the alternate approach above, favors the sequential delivery of information over the parallel. However, the difference is that in the exclusive

approach, each modality of feedback is assigned to a different domain of information, resulting in feedback on all necessary domains within a single session. In the Autonomous Training Assistant, this would be the equivalent of assigning each modality to a feedback type (as is currently proposed) but varying the frequencies (within attempt, between attempt, end of session) at which feedback is delivered between the modalities. As an example, the ATA system could provide feedback on progression using haptic guidance with the Intelligent Stick during an attempt as currently proposed, and could deliver audio feedback on pacing but only as a single audio cue at the end of each attempt, conveying whether the attempt was too fast, too slow or on target. Postural feedback could be delivered as a report at the conclusion of an exercise session, using a dual point-of-reference approach (Schönauer et al. 2012) which visually clarifies the deviation of current posture from expected posture. Alternatively, error-augmentation can be utilized in this approach, wherein feedback is only given when a sufficiently large error occurs, and only in a single domain and modality. For example, if the individual strays a significant distance from the tolerance range for the motion trajectory, a haptic tether can guide the user back toward the correct path in the same manner that a trainer would push or pull the user's arm back toward the intended path of the motion during an attempt.

Advantages: The greatest advantage of exclusive feedback is that it closely reflects the human strategy for guidance in real training scenarios. In these scenarios, trainers often utilize their observation to provide feedback as an intervention, using either their voice, a physical push/pull, or a visual demonstration to correct error and guide the user when a sufficiently large error occurs in a session. It is also known that when domains of feedback are independently mapped, the subject is able to organize the

information more efficiently in memory (Sigrist et al. 2013), which facilitates simultaneous processing in multiple categories.

Disadvantages: As apparent above in the alternate strategy, intermodal lag occurs in this sequencing method (Xiao et al. 2003) which can cause disadvantages in the rate of learning as the complexity of the motor task scales up for a subject. Furthermore, if temporal ranges are used, then the domain of feedback assigned to the most frequent temporal range or granularity level receives the most attention by a system and causes a disparity in the rate of learning for a motor task that may affect a user's mastery of that task over time.

6.9.3 *Style 3: Synergistic*

While sequential delivery of information certainly has its advantages, there are many advantages to providing feedback in parallel as well. The first method of parallel delivery is the synergistic method, in which multiple modalities of feedback are assigned to the same domain and delivered in parallel. For example, if the ATA system focuses on progression feedback, it could represent critical points with a simultaneous vibrotactile and audio cue while visually representing the motion of the Intelligent Stick within the game context. This way, multiple interfaces of feedback are focused on providing the same information in a redundant parallel manner in order to reinforce one another.

Advantages: Redundancy is particularly beneficial when a user's attention is focused on a single attribute of a motion task, since it can improve the subject's accuracy (Sun et al. 2011). Under this strategy, cognitive phenomena including sensory enhancement and inter-sensory facilitation can be experienced since the modalities are

being perceived in a synchronized manner to enhance the rate and precision of information processing (Carson & Kelso, 2004).

Disadvantages: Perhaps the only disadvantage of synergistic feedback, when achieved, is that it may slow down the rate of mastery of a motor task since information can only be delivered in a single domain in a session.

6.9.4 *Style 4: Concurrent*

In the concurrent approach to multimodal feedback, multiple modalities of information are fused in parallel, but each modality, as in the exclusive approach, is mapped to its own separate domain of feedback, resulting in information in multiple domains to be given to the subject at the same time. This is the style currently being used by the ATA system. As a user swings the Intelligent Stick, haptic guidance provides information on progression through vibrotactile cues at critical points. Meanwhile, the system is simultaneously monitoring an individual's pace during a motion. Whenever an error in motion occurs (a deviation of the user's pace from the tolerance range about the target value), an audio cue is delivered to inform the user of the error, and its tone represents the directionality of the error (too slow or too fast). Finally, information on posture is available through the dual point-of-reference mirroring scheme used on the visual interface. All information is being presented in parallel, but each modality is assigned a different task.

Advantages: This approach aligns closely with the multimodal integration discussed in Sigrist et al. (2013). It takes advantage of the phenomenon labelled "multiple resource theory" (Wickens, 2002) which implies that individuals can efficiently

compartmentalize information processing across modalities, with some degree of interference (Burke et al. 2006). This approach presents quite possibly the most efficient delivery of information, as both the domains of feedback and modalities of feedback are delivered in parallel, reducing the time needed to train on a motor task. Even under individual selectivity and bias toward feedback modalities or domains, this mode of feedback assures that information in other domains is not missed or delayed during training.

Disadvantages: Perhaps the greatest concern with adoption of the concurrent approach is the high likelihood of cognitive overload for most individual (Guadagnoli et al. 2004). Considering that most motor tasks are timed, and involve progression and repetition goals that place pressure on the user to meet expectations during an exercise session, cognitive overload is particularly of concern when concurrent feedback is applied in motor learning (Chen et al. 2012). Selectivity of attention is often likely and perhaps necessary under this approach.

6.9.5 Discussion

Based on the examples above, it seems that a mixed approach between concurrent and exclusive feedback delivery may be the best option. The key advantage of the motor learning scenario that makes this possible is that the postural and progression domain both represent spatial information about an individual's motion, making it possible to integrate them in parallel. Haptic guidance can move a user through a motion trajectory while the visual display can depict both the posture of the user and the movement of the stick through gameplay. Since pacing information is in the temporal domain, the audio

cues that inform the user about pacing errors can be reduced in granularity. Rather than being presented in parallel during an attempt with postural and progression information, pacing information can be represented with a single audio cue after a series of attempts that indicates how slow or fast the user is moving relative to the targeted rate, or terminally at the end of the session to indicate overall pacing performance.

This configuration allows information in similar domains (spatial) to be configured for parallel presentation, while information in unique domains (temporal) is layered between them, eliminating any distracting effects caused by a fully parallel approach. The reduced granularity of temporal feedback also provides the flexibility of using different modalities for this feedback. Since temporal feedback is no longer concurrent with spatial feedback during task execution, it can be delivered via the visual display instead of using an audio cue (in the car example, a score display indicating the player's timing and the targeted timing). Future evaluation on the ATA will need to determine what effect the various presentation styles above may have on an individual's performance and skill acquisition in the context of gameplay.

6.10 Mode Prioritization

For the sake of consideration, the idea of prioritizing the modality of feedback corresponding to the domain in which the user has made the highest degree of error is discussed here. This approach is advantageous in that it reduces the extraneous load (Paas et al. 2003; Sweller et al. 1998) presented by the motor learning environment and supports the type of selective learning entailed by the specificity of learning hypothesis (Proteau, 1992). In reference to the “exclusive” presentation style given above, this type

of sequentially selective feedback mechanism reflects the same method of feedback given in human interaction with trainers, where a trainer will focus on one error at a time during exercise and give feedback in the domain of the error. This allows the individual to focus attention to the error (Wulf & Prinz, 2001; Cirstea & Levin, 2007) and correct the error more efficiently than if multiple errors were being reported simultaneously.

As an example to illustrate this concept, one can imagine an individual completing a motion task in the presence of three different trainers, each of whom provides feedback on a different aspect of the motion. One trainer uses a guiding hand to push the individual's arm back on the right path when it strays, while another trainer verbally instructs the individual to speed up or slow down when the pace of the motion is off, and a final trainer demonstrates the correct posture visually in front of the individual. If all this is occurring in parallel for a complex motor task, either the individual may become overwhelmed or may not retain the information provided by the feedback of the three trainers after the session due to limitations of the working memory in processing information from multiple domains (Maehara & Saito, 2007). The consolidation of feedback to the domain of greatest error avoids this issue and more naturally relates to training experience with a human trainer.

There are some challenges, however, in the adoption of an approach which limits feedback to a single domain at a given time. One primary limitation is the scenario in which a single domain of error "dominates" the other domains, and feedback is constantly provided in that domain only, leading to a lack of guidance in the other domains. This relates well to the challenge of resource starvation for scheduling algorithms in Operating Systems research (Tanenbaum, 2009). If an individual has made

errors in all three domains, for example, but the error in pacing is regularly higher than errors in the other domains by a slight amount (whether due to a lack of correction by the individual after feedback or due to a tendency to underperform in that domain), then this domain will always receive priority for feedback, even though the errors made in the other domains are almost as severe. Ultimately, once the performance in pacing is corrected, feedback will finally shift toward the other domains, but this may severely slow the rate at which an individual learns a motor skill and may not be taking full advantage of human parallel processing capabilities.

Another challenge lies in the transfer of this feedback approach to game design. Ideally, performance in all the domains of motor performance is inherent in game performance under Evidence Centered Design (ECD) (Mislevy et al. 2003). However, if feedback is focused on a particular domain, then errors made in the other domains can be misattributed to the domain in which feedback is being provided. If an individual is receiving only feedback in pacing in the car race example below, then if that individual's car deviates from the race track during a turn as a result of progression error, then that individual may misattribute this consequence in the game to pacing error since only this type of error is being reported explicitly by the system. To prevent this, domain-selective feedback would have to be integrated into gameplay, which complicates design since game progression is intended to provide evidence of an integrated measure of motor performance.

Overall, the idea of domain-selective feedback is certainly worthy of consideration as a method of guided training that more accurately resembles trainer-trainee interactions in the real world, and as a way in which cognitive load issues caused

by parallel and potentially cross-interfering feedback mechanisms can be rectified. This method of feedback provision can be integrated into the current feedback loop of the system under the appropriate assessment model for performance. As an example in which this mechanism can apply well, if the ATA system detects that an individual is exhibiting compensatory motion (using limbs other than the targeted limb for a motion), it can activate the selective feedback mode described above in which it intervenes and focuses all feedback on the individual's posture. This reflects the fact that errors in other domains are of much lower priority than a blatant error in posture which can have both immediate and long-term consequences on skill acquisition and retention.

6.11 Multimodal Conflict Resolution

In addition to the implementation of multimodal fusion strategies as discussed in 6.9, future work should implement and validate strategies for the detection and correction of multimodal “conflicts” in cases where concurrent feedback is used. A “conflict” occurs when two or more modalities of feedback are given at the same time to convey different information, and the simultaneous information cannot be processed by the user at the same time, thus forcing the user to prioritize one modality of feedback or, in more severe cases, ignore the feedback completely. For example, an audio tone intended to correct the user's pacing and a haptic vibration intended to guide the user's progression may occur at the same time in a concurrent approach. In this case, rather than prioritize one of the two parallel feedback cues as discussed in 6.10, it may be more beneficial to modify the feedback such that the cues combine in a more synergistic manner to the user.

In this manner, the conflict would be considered “resolved” if the feedback occurs in such a manner that the user can process both cues at the same time.

One initial strategy to achieve this conflict resolution might be the creation of a series of “compound cues” within the training process. The user would be trained in such a system to recognize not only single modality cues, but also multimodal cues which represent multiple domains of information. For example, if the user in the example above was trained to recognize the vibration and tone combination cue above in the training process, then no conflict would be presented in this case. This approach, however, has several flaws. One is that it imposes a large amount of excess training on the user, which may significantly hinder progress and compliance. The second is that, depending on the number of feedback domains involved, the combinations required may quickly become impractical in number. For example, given that audio, visual and haptic feedback can all be combined to form patterns, and given only 4 unique feedback cues in each modality, the number of combinations required for training is 108, which is far more than most humans can distinguish in a reasonably-paced real-time training scenario.

A more effective approach may require the implementation of machine learning to the feedback process. A smarter system for concurrent feedback would implement a more flexible mapping in which each domain of feedback (posture, progression, and pacing) can be represented in any of the three modalities (audio, visual, and haptic) available. That is, haptic feedback can be used to convey information about posture, progression, or pacing, as can the other two modalities. Such a system would then begin with a baseline mapping for feedback, and then modify this mapping over time based on the response it receives from the user. This system would, for example, begin by using

the approach in the example above, observe that the user responded negatively to the combination of haptic feedback on progression and audio feedback on posture, and then switch its feedback configuration so that in the next instance, information on both domains is provided in the haptic modality (although sufficient evaluation would be needed to determine how these two different domains can best be represented in parallel in a haptic response).

To implement a learning approach, the system would need to analyze a user's response to feedback cues in real-time. Several metrics for evaluating the user's response can be explored in future work. One example is the use of information transfer (IT) as discussed in 6.5. Since the ATA system is provided with real-time performance data on the user in terms of deviation from the targeted value or range in three domains, it can evaluate the effectiveness of a modality pairing based on the immediate change in this performance in the affected domains after feedback is given as an approximation of IT, and use this to adjust its pairing until it determines that performance improvements were successfully made in both domains of feedback, rather than in one or neither as in the case of a "conflict". This strategy provides a more person-centric approach to multimodal integration.

6.12 Evaluation 4: Multimodal Feedback

To determine how an individual's learning may be impacted by the modality assignments in the ATA framework, the system's multimodal feedback functionality was evaluated as a part of the ongoing case study. Due to constraints including subject fatigue and time, it was not possible to evaluate all combinations of modalities with feedback

categories. Instead, the best practices highlighted in the Sigrist et al. (2012) review were evaluated in comparison to the individual's preferred mapping of modality. An estimate of Information Transfer (IT) in each modality serves as a form of evaluation for the effectiveness of the mapping in that modality. The evaluation was approved by the Institutional Review Board (IRB) at Arizona State University as a part of STUDY00002090. This section is based on work presented in Tadayon et al. (2016).

6.12.1 Procedure

The subject used the ATA interface to perform a series of three exercises assigned by the subject's physical trainer: umbrella, witik and twirl. For each exercise, three conditions were evaluated: one in which the mapping inspired by Sigrist et al. (2012) was used (Posture: Dual Avatar; Pacing: Error Sonification; Progression: Haptic Guidance), one in which the user chose the mapping of modalities (Posture: No Feedback; Progression: Haptic Guidance; Pacing: No Feedback), and a control condition in which the user attempted the exercises with no feedback from the system. Error Sonification was delivered as an audio tone with a high pitch when the subject's speed was higher than the maximum threshold set by the trainer, and a low pitch when the subject's speed was slower than the minimum threshold set by the trainer.

Visual feedback was given as a superimposed trainer avatar as shown in Figure 6.2.3. The trainer avatar automatically completed the motion in a repeated loop using data from the trainer, while the subject's avatar mirrored the subject's postural motion as captured with the Kinect camera. Haptic guidance was delivered as a half-second vibrational cue on the Intelligent Stick whenever the subject moved the stick through one

of the critical points in the motion's trajectory. After a 1-minute calibration period for each exercise session, the user then repeatedly performed the motor task over a period of 2 minutes. 9 total sessions were completed (3 for each exercise), with 4-minute breaks between each session to prevent fatigue and learning effects from interfering with subsequent sessions. For each exercise, the trainer assigned parameters for optimum rate of motion, trajectory, and postural position, as well as tolerance thresholds in each category. Information Transfer (IT) was then approximated as the subject's average deviation from the optimum values in each category, or "performance error" in each domain.

6.12.2 Results and Discussion

The values for performance error for each exercise and condition are shown in Table 6.12.1. The subject yielded the lowest average error values for all three exercises in the preference condition, wherein the subject chose to focus entirely on haptic feedback on progression, with the slight exception of pacing score on the twirl exercise, in which the Sigrist condition outdid the preference condition. Interestingly, the subject performed generally better in the pacing and postural categories in the preference condition despite receiving no feedback for these categories in this condition. It is postulated that this is due to a potential overload effect incurred by the subject when all three modalities of feedback were given in the Sigrist condition, as all three modalities of feedback were given in parallel using the "Concurrent" approach of Section 6.9.4. It is also possible that there were carryover effects between conditions despite the break intervals used to control them, although typically these effects are more influential over longer periods. It

was observed that during this condition, the subject seemed to focus almost exclusively on haptic feedback, establishing a case for individual preference.

Table 6.12.1: Average Performance Error for Case Study Subject. Evaluated on three experimental conditions: Sigrist et al. (2012) condition, Individual Preference condition, and control condition. Assessment categories are posture (top table), progression (middle table), and pacing (bottom table). Values for posture are in degrees, while progression are in accelerometer units and pacing are in accelerometer units/sec. This data is a more detailed look at the research introduced in Tadayon et al. (2016).

Posture	Sigrist	Preference	Control
Umbrella	12.26	6.76	27.01
Twirl	9.50	4.40	12.45
Witik	8.23	4.62	12.71

Progression	Sigrist	Preference	Control
Umbrella	7.51	3.08	15.00
Twirl	6.55	0.99	9.47
Witik	4.18	3.12	11.14

Pacing	Sigrist	Preference	Control
Umbrella	2.40	1.34	3.17
Twirl	1.32	1.45	3.46
Witik	1.74	1.44	2.57

This also explains the subject’s choice of mapping in the preference condition. As expected, both conditions yielded higher performance results than the control condition, indicating that the system’s feedback was beneficial to the subject. This is illustrated more clearly in Figure 6.12.1, which illustrates how the subject’s performance error in progression changes over the course of a 2-minute session of the umbrella motor task. It can be seen here that the subject’s error in progression increases over time when no feedback is present in the control condition, and decreases with the presence of feedback

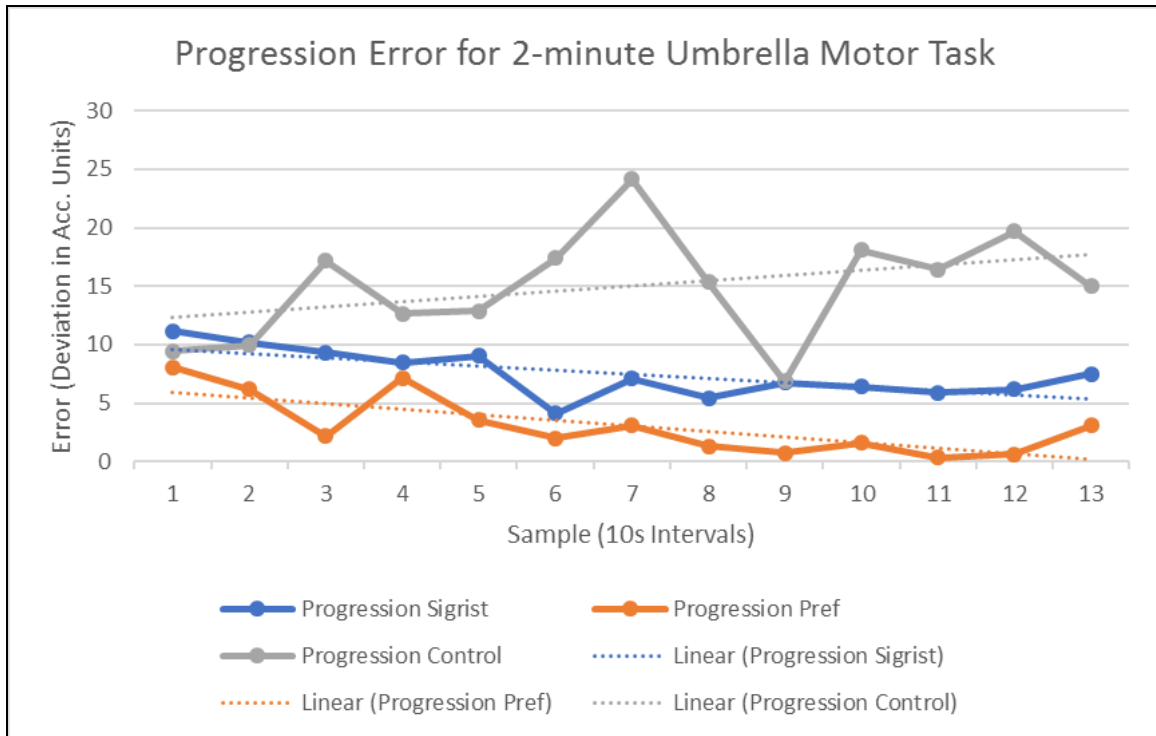


Figure 6.12.1: Progression Error for 2-minute Umbrella Motor Task. Error is given as accelerometer unit average deviation from the intended trajectory over a 10-second time interval sample. Trend lines are provided to indicate the difference in error trend between the control condition (where error is increasing over the session) and the two experimental conditions (where error is decreasing). This data is a more detailed look at the research introduced in Tadayon et al. (2016).

in the two experimental conditions, with improved overall performance in the preference condition over the Sigrist condition.

One conclusion that can be drawn from this information is that the individual’s preference may have an impact on the optimal assignment of modalities for each subject, and that a dynamic approach which takes into account user bias may be more useful than a static “best practice” approach. The generalizability of this claim is subject to further evaluation with a variety of subjects; nevertheless, the findings in this study present an interesting precedent for future work, discussed in Chapter 8.

CHAPTER 7

STEALTH ASSESSMENT AND ADAPTATION

7.1 Stealth Assessment Introduction

While there has been a plethora of work applying educational data mining as a means for assessment and design in games across learning domains, the motor learning domain presents an interesting application area worthy of exploration in the field of data analysis. Many of the principles applied for educational content analysis and adaptation can also be applied for motor learning, although this domain presents some key challenges that psychometric tools and game design would need to assess. These challenges need to be addressed in a game utilizing the framework of the Autonomous Training Assistant:

1. Frequent, real-time feedback requires fast, real-time psychometric methods to quantify performance.
2. Each individual has a unique, personalized standard or goal by which his or her performance is assessed in the ATA.
3. The standards of performance for an individual change as the game/system adapts to that individual and as that individual progresses (in line with Flow Theory (Csikszentmihalyi, 1990; Chen, 2007)).

7.1.1 Evidence Centered Design (ECD) Overview

Fortunately, the stealth assessment approach posed by Shute (Shute, 2015) provides a means by which a system can not only achieve this assessment, but do so in a manner that is interwoven in gameplay and invisible to the player. This approach is highly advantageous for the online assessment (van et al. 2014) mentioned in the challenges above because it can help reduce the detrimental effects on performance caused when an individual is aware that he or she is being assessed (Eysenck & Manuel, 1992). The procedures involved in applying stealth assessment to games using the Autonomous Training Assistant can be broken down by using the Evidence Centered Design (ECD) (Eysenck et al. 2003) framework employed by Shute (Shute & Wang, 2017) as follows:

Competency Model: The first task is to determine what constitutes “competency” from a motor performance perspective. This is where challenge 2 applies; since every individual has a differing motor ability, it may be impractical in many cases to assess “competency” of an individual by an absolute standard. Instead, competency is determined by observing an individual’s performance relative to a dynamic performance goal intended specifically for that individual, which is updated as the individual improves to maintain a zone of proximal development (Vygotsky, 1980), in line with the flow theory constantly attributed to successfully adaptive games (Csikszentmihalyi, 1990; Chen, 2007).

As an example for guidelines on general skills required to indicate competency in the motor domain, one can refer to the requirements of the Wolf Motor Function Test (Wolf et al. 2005), a highly-validated method for assessment of motor function in the

upper extremity of individuals with stroke. Test in the Functional Ability (FA) subtest of WMFT is scored on 0-5 scale on the following basis (Wolf et al. 2005): Postural correctness (typically, alignment of the head, shoulders, and trunk during a motion), speed of motion (measured against “normal” speed, although person-centric metrics are utilized as noted above to maintain flow), and fluidity and precision of motion (measured against “normal” motion trajectory).

While the quantification of these measures by scoring index relies on the accuracy of observation of the viewer, one advantage of stealth assessment is that by involving the system’s recordings in the assessment process, any observational bias that can be caused by this method is eliminated. The use of WMFT is beneficial as an example, but in general, the purpose of the ATA’s assessment framework is to avoid the limitations inherent in specific motor performance measures (due to the use of absolute standards of performance, vulnerability to human observation bias, and other factors); regardless, almost every measure available for motor performance includes measures of the spatial and temporal aspects of a motion as well as the spatial orientation of the individual involving a motion. For simplification, this system of assessment refers to these as progression, pacing and posture, respectively.

Task Model: To continue this example, one can select a motor task and a game in which that motor task can be embedded. It has already been shown in (Tadayon et al. 2015) how the ATA framework quantifies performance in a task-independent manner; for explanation, the example of “wrist pronation/supination” is used as a motor task. Upon selection of the task, the next task is to select a game which can provide, by design, clear indicators of performance in that task. This can be a very difficult undertaking, especially

if the underlying motor task is complex and involves several interwoven parts, and when considering that task demonstration and postural feedback must be incorporated in design to match the ATA framework. A few guidelines that help with this are that a motor task is short and repetitive, and that an exercise session includes repeated performance of a motor task and is constrained by either time or number of repetitions.

To match these properties for any motor task, the chosen game must include repetitive, short-duration mechanics which can be constrained by time or repetitions of a game action. Some examples of these include “burst games” (Amresh et al. 2014), although there are further constraints placed by a specific motor task on the types of game scenarios which can match that task for the purposes of stealth assessment.

7.1.2 Example of ECD

For this example, a racing game is used as an implementation. Using Hierarchical Task Analysis (Cox, 2007) an exercise session for wrist pronation/supination can be divided into sub-goals, and map them to their corresponding game goals in a racing game. Figure 7.1.1 shows this task mapping. Since a racing track can be simplified as a series of turns, the goal of completing a race can be subdivided accordingly into the goal of completing these turns. When modularized in this fashion, each turn represents a game task equivalent to a single repetition of the motor task. Note that if adjusting the spatial and temporal goals of the motor task on a per-repetition basis, one can do the same adjustment within the game by using a dynamic racing course structure (in other words, the “minimap” interface element is eliminated and the racing course is generated for an individual in real-time, where the difficulty of the next generated turn is based on

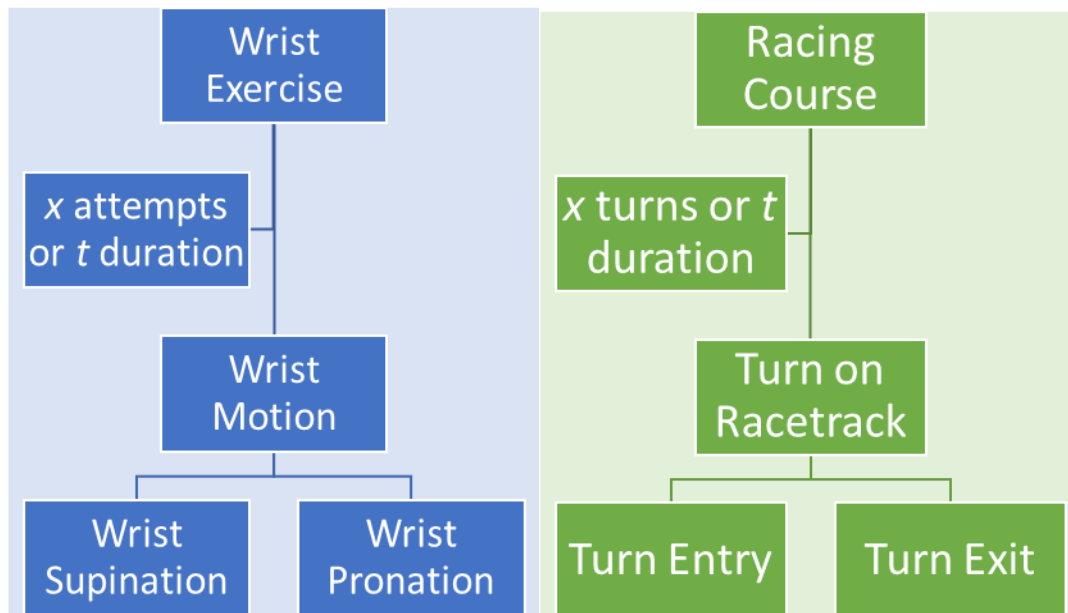


Figure 7.1.1: Mapping of Wrist Exercise to Racing Game.

one’s performance in the previous turn as determined by stealth assessment. Using these design constraints enables dynamic adaptation in this instance.)

Under this mapping, the gameplay behaviors which can serve as evidence of an individual’s performance of a motor task are identified as follows:

Progression relates to the precision of an individual’s motion with respect to the goal trajectory of a motor task. In the ATA framework, this motion is represented as a series of critical points and a tolerance range about those points wherein an individual can deviate without having made an “error”. More formally defined:

Let an individual's attempt of a motion be represented as an array of spatio-temporal point-triplets U , where each element

$$u_t = \{x_{1t}, y_{1t}, z_{1t}, x_{2t}, y_{2t}, z_{2t}, x_{3t}, y_{3t}, z_{3t}, t\} \in U$$

represents a set of three points representing the locations of the center and two ends of the Intelligent Stick at a time t . Let V represent a template for the targeted motion using the same format.

Finally, let $DTWDistance\{U, V\}$ represent the distance between the two trajectories obtained with Dynamic Time Warping as shown in (Su et al. 2014) to correct for temporal variation:

$$d = DTWDistance\{U, V\}$$

More realistically, two values of d are obtained for an attempt, d_1 and d_2 , based on the forward and backward segments of a motion (pronation and supination in this case), respectively. One can set d as the average or maximum of these values to represent an individual's error across an entire motion attempt.

Now let's assume that a tolerance range r is in place. This represents the maximum value of d that the system recognizes as a "correct" motion for the sake of competency. Furthermore, let's assume that the arc length L of the motion trajectory can be obtained as a sum of distance measure between adjacent points along the trajectory:

$$L = \sum_{i=0}^{N-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2 + (z_{i+1} - z_i)^2}$$

Then, based on the mapping above, since a single motion is represented as a turn in the racing game, then the arc length L of the motion, or the expected degree of motion in the progression domain, can represent the degree or sharpness of a turn. This relationship is based on the fact that when the subject needs to make a sharper turn while driving, the degree to which the individual turns the steering wheel is increased. A 60-degree pronation movement in the wrist, for example, will require the vehicle to turn 60 degrees to successfully stay on the track.

Furthermore, the tolerance range of error r can be related to the width of the racing track such that an error will result in the vehicle moving off the track, slowing its progression toward the end of the race course (likely in some cases, the system may need to auto-correct the position of the vehicle's position for novice players to prevent their vehicle from moving too far off the track. A wall can be implemented to this end as well.)

Pacing relates to the speed of an individual's motion, and its comparison to the targeted speed value for a motion attempt. Using the same representation for a motion as above (an array of sampled triplets of points in 3D space), one can estimate the instantaneous speed st of an individual's motion at a time t as the distance between the adjacent points at t and $t+1$:

$$s_t = \sqrt{(x_t + x_{t+1})^2 + (y_t + y_{t+1})^2 + (z_t + z_{t+1})^2}$$

and the estimated speed for the entire motion as the average of the instantaneous speeds:

$$S = \frac{\sum_{t=0}^T s_t}{T}$$

Based on the mapping used for the racing game, if a turn represents a motion attempt, then the speed values S_1 and S_2 corresponding to the two segments of the motion (pronation, supination) represent the angular velocities of the player's vehicle at the entry and exit of a turn, respectively. Note that this only adjusts the speed of a player's vehicle; under this design method, the vehicle's speed during straight segments of a course is automatically handled by the system, allowing a player to focus entirely on completing each turn successfully, as intended. The tolerance range r for speed is the maximum amount at which the player's speed can deviate from the targeted value. It can be represented in gameplay by the following logic: if the player's speed leaves the tolerance range during a turn, then the vehicle will move too slowly or too quickly through the turn and will veer off track.

Posture is perhaps the most difficult attribute of performance to embed within the design of the chosen game. Under the requirements of the ATA framework, a player must receive a layered dual point-of-reference representation of his or her avatar during gameplay to provide feedback on posture. This requires explicit visual feedback of a player's avatar during gameplay. To achieve this, one can observe that the limbs commonly involved in correct posture during an upper extremity motion are the

head/neck, shoulders and trunk (Wolf et al. 2005). Assume, then, that the driver's seat is presented as shown in the top left corner of Figure 2:

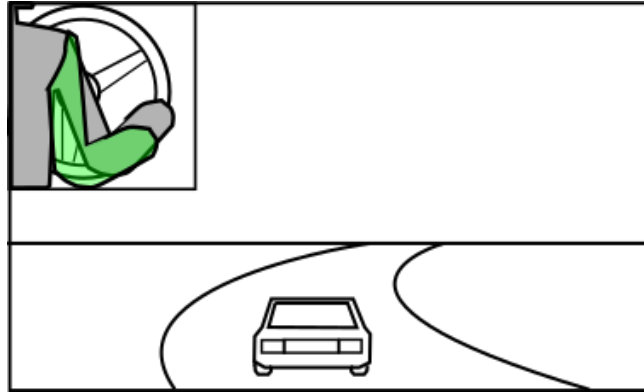


Figure 7.1.2: Dual Point-of-Reference UI Example Sketch.

In this example, since the wrist pronation/supination motion is concerned with one's shoulder positioning as a postural requirement, this information can be displayed visually using a green avatar representation of the trainer/expert's correct positioning superimposed on the player's avatar (displayed using Kinect joint tracking data) to indicate the difference in posture.

Posture in the ATA framework is quantified as a series of joint angles for the joint(s) involved in proper posture during a motion. A player's posture is represented as an array of pairs J , where each element:

$$j_t = \{\theta_t, t\} \in J$$

represents the player's joint angle at time t . Assuming that the targeted joint angle for the motion is θ , the error in an individual's joint angle at any time t can be calculated as $E = |\theta_t - \theta|$, and the postural error over the course of a motion then becomes the average of these values. A tolerance range r for postural error thus represents the maximum value of E allowed for an individual's posture to be considered correct.

Postural performance can be represented within gameplay as an event-driven mechanic; when an individual's posture leaves the range of tolerance, an error event occurs and the vehicle's course of motion can be affected in some negative way (for example, the vehicle can wobble in place). Careful interface design considerations are necessary to ensure that the link between this indicator and postural performance is obvious to the player.

Evidence Model: Now that the specific measures of motor performance have been determined in the Competency Model (CM), and have been linked to in-game mechanics and tasks in the Task Model (TM), the final step is to form statistical relationships between the two in the Evidence Model (EM). It is here where a psychometric tool is necessary to perform automated, real-time assessment of a player's performance based on in-game events. The following example represents the format of a single log entry for a player based on the above scheme:

PName	MotionName	TimeStart	TimeEnd	RepNum	MotionError	ArcError	PaceError	PostError	MotionT
JDoe	WristPS	00:15:36	00:17:12	3	123.11	215.1	-32.5	984.74	250.00

ArcT	PaceT	PostT	Date	TotalReps	TotalTime
300	250	450	10/01/2016 11:59AM	15	n/a

Figure 7.1.3: Player Log Entry for ATA using ECD.

Immediate inferences about the player’s performance can be made from the evidence presented in this log entry. For example, the player’s postural error value, represented by PostError, (see above for calculation) surpasses the tolerance range of 450 set for the current motion as shown under PostT, potentially indicating that the player’s posture has significantly deviated from the ideal posture for the exercise and requires correctional feedback.

7.2 Assessment/Adaptation Methods

Rather than making a claim based on a single log entry for the player, a smarter assessment system could examine the change in the player’s behavior over time, or the patterns of errors the player makes over the course of a game session, in order to make well-informed judgments on the individual’s performance and progress. For example, the postural error above could be related to fatigue, which may have developed over the course of the game session or may be related to external physical exertion by the individual prior to entering the game. The following are some psychometric tools and techniques worthy of exploration in this work to form real-time assessments on a player’s motor performance.

7.2.1 Cluster Analysis

One method of determining patterns in performance in players is cluster analysis. This technique uses a set of features (such as those in log data) to classify players with similar gameplay behavior or performance, or to classify the behavior of a single player based on performance. One major difficulty in the usage of clustering algorithms is the selection of a technique which results in the highest quality of segmentation. Due to the plethora of clustering techniques available, it is often advised to incorporate a multitude of techniques and to select the one that provides the clearest and most valid clustering. This also includes the selection of the best parameters for clustering, such as number of centroids or selection of the best dissimilarity metric.

Fortunately, there are a few guidelines which can help with this process. Cornforth and Adam provide an example for the inclusion of clustering algorithms as analysis methods in serious games using Minecraft Data (Cornforth & Adam, 2015). They utilize the very common dissimilarity metric of Euclidean Distance (Lloyd, 1982). Feature selection in their work is a matter of finding, from among multiple features in log data with redundant, similar, or inter-dependent information, a set of unique features that can, in combination, be descriptive enough to facilitate strong classification of player. While it is likely given the properties of the features present in ATA log data (exercise duration, progression error, pacing error, postural error) that they are unique enough to be selected as a feature set for clustering, there are still possibilities of correlation among some of the features. A postural error, for example, can yield a progression error (if a player is incorrectly holding the intelligent stick, the resulting motion pattern will also yield a high rate of error) and so it is possible that either the two features should not be

selected together for clustering, or some pre-processing would be required to remove the effect of progression error that may be attributed to postural error. Further discussion and guidelines on the selection of features for clustering can be found in (Mitra et al. 2002).

Once the appropriate features are selected, the clustering method must be chosen. Cornforth and Adam utilize Expectation Maximization (EM) (Witten & Frank, 2005), an extension of k-Means Clustering (Lloyd, 1982) which can estimate not only the means of clusters but also the variance of clusters. Since this is an iterative method, it may be undesirable if the classification is being performed in-situ. Another possibility is the usage of fuzzy clustering as performed in (Kerr & Chung, 2012), particularly when considering that unique classification/membership of a player to a certain category may be impractical given the implications of a single set of features.

There are several specific uses of clustering within the Autonomous Training Assistant framework. In the example above, combinations of the features “time spent” (end time – start time, “postural error”, “pacing error” and “progression error” can be used in clustering to determine if there is a descriptive pattern for exhaustion or fatigue. Under this clustering scheme, high levels of performance among all features (low duration, low errors in all dimensions), can indicate that the individual is performing well enough at the current difficulty that tolerance ranges should be reduced, and the corresponding gameplay elements made more difficult, to maintain flow in an adaptive game design. As an initial method for evaluation, k-Means clustering seems to be a good first attempt at clustering as it has been proven in other instances of game analysis as a method of highly descriptive representation and cluster separation (Drachen et al. 2014). Ideally the system would be able to perform this analysis live so that it can intervene

when a particular player state is detected; faster, more efficient methods for k-Means Clustering like FBK-Means (Sewisy et al. 2014) may be useful to this end, assuming the data can be balanced.

7.2.2 *Bayesian Networks*

While clustering can help determine some patterns in player behavior over the course of exercise sessions, for ease of adaptation, the system need only examine how the player's performance in each dimension of motor assessment can combine to form a single assessment of that player for the state of maintaining flow. In other words, the ATA system can maintain a quantified belief about the player's mastery of a motion that initially involves no knowledge (with some assumed default value assigned a priori), and updates itself as new evidence about the player's performance is made available in the form of real-time log entries. For this purpose, Bayesian Networks (Pearl, 1988) and Dynamic Bayesian Networks Reye, 2004), a form of Bayesian Network tailored for real-time analysis, have been touted in GBA, especially in stealth assessment, because of their ability to adapt quickly and frequently to constantly-updating real-time information on performance.

Shute et al., for example, applied a Bayesian Network approach to statistically relate evidence accumulated from gameplay to belief values in their Competency Model (CM) (Shute et al.2017). Conditional probability models utilized by Shute and other researchers in the education domain (Almond et al. 2001) typically make use of Samejima's Graded Response Theory (Samejima, 1969) containing parameters of Item Response Theory relevant to educational scoring. Whether or not this model fits the

properties of motion data, considering attributes such as the rate of skill improvements with motor function relative to performance in educational content, and the potential existence of spatio-temporal correlation or cross-influence between the motor performance features, is a worthwhile future effort, as there is little to no work covering statistical models for motor learning data. Haith et al, for example, apply Maximum Likelihood Estimation (MLE) in order to model decisions on hand positioning based on prior data (Haith et al. 2013), and their model could form a basis for statistical formalization of the evidence presented by motor data from the Intelligent Stick and Kinect camera.

Perhaps the most intriguing approach to Bayesian adaptation, and the most relevant to this work, is the approach by Pirovano et al. in their at-home rehabilitation game (Pirovano et al. 2012). In their approach, two alternative types of Bayesian real-time adaptation are discussed. The first utilizes a simple approximation of performance as a “hit ratio”, relating the number of successful attempts at an exercise (in the racing example, this would be the number of turns successfully completed so far) to the total number of attempts. The authors also assign a targeted ratio at the beginning of the exercise session based on information provided by an individual’s clinician or previous performances. Difficulty is then updated on a per-repetition basis based on the two ratios: if the target’s current hit ratio is less than the targeted ratio, then the parameters controlling difficulty in the game (in the example, turn sharpness, degree and track width) are modified to make the next repetition easier to perform, while the opposite occurs if the individual’s hit ratio is above the targeted value. This is, in its simplest form, the Bayes equivalent of maintaining a zone of proximal development, and can be applied in

the ATA framework by utilizing tolerance ranges in each performance category as parameters of adjustment. In this work, one can modify specific parameters based on performance in those domains (for example, if an individual is making high pacing errors but has nearly no error in posture or progression, then the tolerance range in pacing is widened while tolerance in the other two categories is narrowed).

In addition to the simple approach above, Pirovano et al. also use a Quest Bayesian adaptive method originally proposed by Watson and Pelli (1983) which is also of interest since it is designed to deal with haptic, visual and audio feedback during a task. While this method is typically intended to return a binary threshold value, the authors modify the technique to produce an evolving ratio of performance/difficulty similar to their first approach. The performance function used in their Quest algorithm utilizes the Weibull distribution, determined by King-Smith et al. (1994) as an efficient unbiased probability distribution over the Quest threshold.

Figure 7.2.1 shows an example of a Bayes net structure for assessment of competency in the ATA framework, developed in Netica. Notice that a link is included between postural performance and progression performance to model the potential dependence relationship between the two. The conditional probability functions linking the variables can be defaulted using Normal, Gaussian and Weibull distributions and then approximated through pilot testing of the game design within a sample set of players.

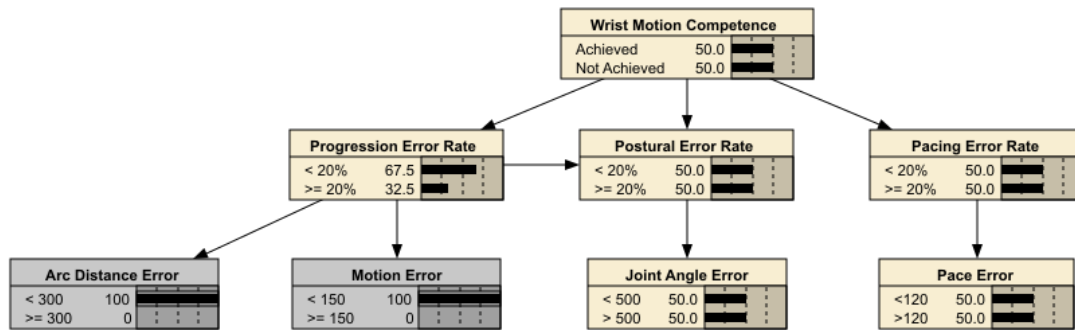


Figure 7.2.1: Example Bayes Net Structure for Wrist Motion Competency. Generated in Netica. Boxes represent assessment items stored in the network as error.

The net will then use Bayesian inference to update posterior probability values based on evidence fed into the evidence nodes through real-time log data on a per-repetition basis. Once the belief state for competency of the motion has surpassed a threshold value, the system reduces the tolerance ranges and the corresponding elements of the next turn in the race track are modified in real-time (narrower and sharper, for example) before the player’s car arrives at that turn for the next repetition of the motion.

7.2.3 Multiple Regression Analysis

One final psychometric method worthy of analysis is the Multiple Regression Analysis (MRA) used by Cameirão et al. (2010) for adaptation of their Virtual Reality game system for stroke rehabilitation. Performance in their approach is modeled as a function of four parameters of motion in each arm:

$$Performance = f(speed, interval, range, size)$$

These parameters correspond to the difficulty of a game in which the user must catch a series of flying spheres in 3D space. In this case, the authors used a quadratic regression model (Cohen et al. 2002) to reflect nonlinear correlation between performance and the difficulty variables. Modeled in the Autonomous Training Assistant based on the racing example design above, this would be given as follows:

$$Performance = f(trackwidth, turnsharpness, jointangle, turnrate)$$

To determine the effects of these game parameters on performance, as well as any interaction among these parameters, a four-factor Analysis of Variance (ANOVA) can be performed using the log data of a control set. The quadratic model with four variables as shown above including interactions, first and second-order terms, can be represented as:

$$P = m_0 + m_1 * trackwidth + m_2 * turnsharpness + m_3 * jointangle + m_4 * turnrate + m_{12} * trackwidth * turnsharpness + m_{13} * trackwidth * jointangle + m_{14} * trackwidth * turnrate + m_{23} * turnsharpness * jointangle + m_{24} * turnsharpness * turnrate + m_{34} * jointangle * turnrate + m_{11} * trackwidth^2 + m_{22} * turnsharpness^2 + m_{33} * jointangle^2 + m_{44} * turnrate^2$$

Upon completing the ANOVA, one can extract the parameters in this model that have the most significant impact on an individual's motor performance at each turn and use them to form the final relationship function to form a quantifiable relationship between game parameters and the expected performance of an individual, yielding a mechanism for automated adaptation in the framework.

7.3 Case Study: Island Fruit Game

This section explores the use of the Stealth Assessment and Stealth Adaptation strategies discussed in 7.2 in practice using the case study approach. As a metric for evaluation of the various approaches toward stealth adaptation, the “flow” metric discussed in Section 2.5 is used.

To begin, a prototype gaming layer was applied over the traditional ATA interface. This interface is depicted in Figure 7.3.1 for the racing game example previously discussed. In this scenario, the width of the racetrack represents the progression requirement of a motor task, while the sharpness of a turn and the smoothness of the user’s steering represent the pacing and postural requirements of the motor task, respectively. These parameters are adapted in real-time; if a user is performing above the expected level of performance at the motor task, subsequent turns on the racetrack become sharper, narrower, and require more precise steering. Similarly, low performance results in a wider track and easier turns. Since motor performance is directly measured in gameplay and reflected within game outcomes (poor performance results in the car going off the track, for example), the user is able to self-evaluate to improve performance in the same manner that humans naturally interact with our environment in the real world, facilitating an improved motor learning experience inspired by the Stealth Assessment technique proposed in (Shute et al. 2017).

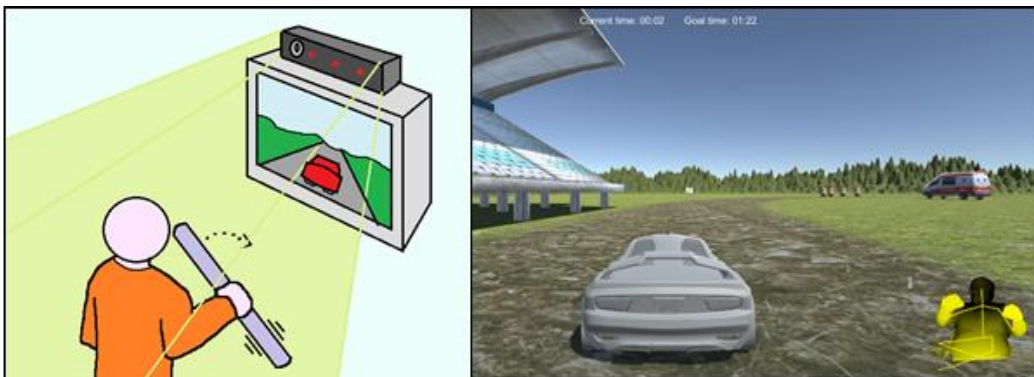


Figure 7.3.1: ATA System Overview (Left) and Sample Game Interface (Right).

The next step is to incorporate real-time flow-state assessment in this system. This is necessary because motor performance alone is insufficient information for a system to determine how well an individual is learning during the experience. A real trainer, for example, would observe and react to an individual's emotional response as well, including boredom and frustration. These can be measured within game design through flow state recognition. Here, flow state is measured externally through facial emotion recognition.

To receive facial data, the video feed from the Kinect camera is used. In addition to joint tracking, the Kinect serves as a real-time video recording mechanism, allowing a system to extract facial features. These facial features are then processed and the user's emotional state is classified using the Visage tracking SDK (<http://visagetechnologies.com/products-and-services/visagesdk/>). This allows the ATA system to classify the user's facial emotional state using the six basic emotions (happiness, sadness, anger, disgust, fear, surprise), which are then mapped to flow state.

Using this mechanism, one can determine at any point in real-time whether a player is in flow-state. The system can then use this emotional data in conjunction with motor performance data to perform its difficulty adjustment.

7.3.1 Flow Detection

To receive facial data, the video feed from the Kinect camera is used as non-intrusive input data. This data is then analyzed using Visage facial tracking in a similar method to Baron (2017). The Visage framework detects human facial features in real-time from the Kinect feed and forms a belief value in each of the six basic human emotions (happiness, sadness, anger, fear, surprise, and disgust) using the Facial Action Coding System (FACS) as described in (Ekman & Friesen, 1977). It represents its belief state as a value between 0 and 1 for each of these emotions which indicates how strongly it believes that the user is currently expressing that emotion. This is illustrated in Figure 7.3.2. These six values from FACS can then be mapped to affective state as shown by Craig et al. (2008), effectively creating a flow-state recognition engine.

Three possible flow-states can occur: boredom, flow and anxiety. Boredom can be mapped to the state in which all six belief values are substantially low (corresponding to the neutral expression in FACS). Anxiety can be linked to high levels of anger and low levels of happiness, while flow can be linked to high levels of surprise with low levels of sadness. Any other configuration of Visage's data can then be linked to a fourth "other" state to which a game will not react as it is deemed irrelevant in flow-state assessment.

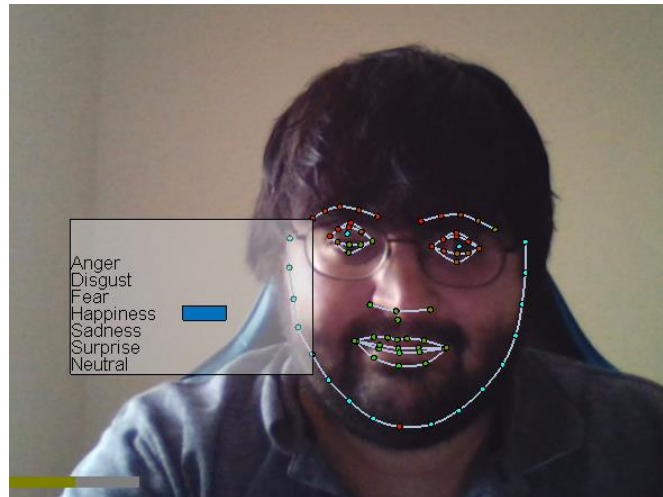


Figure 7.3.2: Visage Emotion Recognition Example. Values are displayed in real-time for 6 basic emotions and the neutral expression. Here, the software has detected with high confidence that the subject is experiencing happiness.

As these calculations are done in real-time, the system can also track a player's flow-state over the course of a game experience, thus allowing for adaptation and interaction. There are several limitations to this approach. The first is that it is subject to the Kinect camera's quality and the ability of the software to extract face data for a large variety of faces. This inevitably results in cases where the tracker is thrown off by a user's facial positioning or by external features like glasses. The other is the recognition accuracy of each result based on the facial data presented. The system may detect fear, for example, when the user was simply reacting to a cold temperature.

7.3.2 *Stealth Adaptation*

Using the above approach, the system can extract real-time information about motor performance and emotional feedback from the player. This amount of real-time information allows the system to make informed decisions about how to tailor the game

experience to the user in real-time in a similar manner to the dynamic training techniques employed by physical trainers in real-time. This information can help determine how well the system's approach to adaptation maintains the engagement of a player. Accordingly, several adaptation approaches were implemented in the system. These techniques include hit-rate stabilization, Bayesian Network analysis, and k-means clustering classification. The techniques are described below:

Hit-rate stabilization: This approach focuses on the player's overall rate of success, or "hit rate", with respect to the motion objective. For a motion task, like elbow flexion, a component of the game is assigned to provide evidence of that task. For example, a player may be required to complete an elbow flexion motion to complete a turn on a virtual race track. Using this mapping, the sharpness of the turn would correspond to the degree of motion required. In this case, a player successfully completes a turn by applying the correct degree of elbow rotation. A game can learn this value over time by measuring a player's hit-rate on each successive game objective, where a hit is a successful completion of the objective. The game can then respond in real-time by adjusting the difficulty parameters so that the player's hit-rate is reduced, thus increasing the level of challenge to maintain flow-state over time.

Bayesian Network analysis: In this approach, the game maintains prior beliefs about a player's mastery at various elements of a motor task, including posture, progression and pacing. These proficiencies are mapped to various game elements designed to measure and provide evidence of player skill level, such as the "turn sharpness" example above.



Figure 7.3.3: Island Fruit Game Prototype. Score is shown on the top left, while the high score for the current user is at top-center. Fruit pieces appear at the center of the screen, and the sword object (pictured at the center of the image) is used to slice the pieces in the trajectory of the motion task currently assigned to the subject.

Based on a player's performance in each category, the belief states are updated to maintain an up-to-date model of the player within the game's back-end. Difficulty is then fine-tuned for each individual parameter of gameplay as the player's mastery improves in each category.

Clustering classification: In this approach, a player is classified within various groups of performance, called clusters, based on patterns of performance over time using one or more indicator metrics. Often, log data representing the player's performance in various elements of a task serve as reliable indicators for this clustering. For example, in motor tasks, log data can provide information like task completion time, degree of motion, proximity to the ideal motion trajectory, stability of motion, postural correctness, and more. A player's cluster indicates his or her level of proficiency with respect to the

motion task, once this is known, the appropriate difficulty parameters can be set to meet the challenge demands of the player.

To determine the relative effectiveness of these techniques, flow-state ratio is used as a metric. Over a given period of time, a user's flow-state ratio represents the portion of this time period during which the system determined that the user was in flow-state. A perfect design, for example, would yield a flow-state ratio of 1, implying that the user experienced flow throughout the entire game session. These techniques are compared against one another to determine which yields the highest flow-ratio.

7.4 Evaluation 5: Flow-State Analysis

To compare the effectiveness of the above three learning approaches at maintaining flow-state, an at-home evaluation of the ATA system was conducted in the home of the subject in the case study from (Tadayon et al. 2015). The motor learning goal of the subject for this study was a horizontal stick motion exercise assigned by the subject's trainer. For this exercise, the subject was required to move the Intelligent Stick device along a diagonal plane with both arms, swinging in an arc motion from the lower right of the body to the upper left. The ideal motion trajectory requires the stick to contact three critical point in 3D space along the trajectory within a maximum and minimum tolerance radius of 10cm and 5cm, respectively, and at a minimum/maximum expected rate of approx. 6cm/sec and 9cm/sec, respectively. The subject was required to maintain a steady lower body positioning during the motion, within a maximum/minimum tolerance range of 10 degrees and 5 degrees, respectively. These requirements were assigned by the subject's trainer as baseline and end requirements for the motion. This evaluation was

approved by the Institutional Review Board (IRB) at Arizona State University as the final phase of STUDY00002090.

7.4.1 *Design*

To provide evidence of competency in the above requirements, the Evidence-Centered Design (ECD) and stealth assessment techniques discussed in (Shute et al. 2017) were used to design a serious game interface. These techniques were chosen for this work as they allow for person-centeredness directly within the design of gameplay. In this case, the implementation relies on a combination of the individual and the task. As discussed in Section 2.4, player interest considerations form a key component of the most effective game choice for motor learning. The subject's interest in gameplay was determined through a survey administered in the multimodal mapping study of 6.12, as highlighted in Appendix A. In this survey, the subject indicated an interest in a "ninja sword game with cool sound effects" where one could "control [the] sword with the stick, with some of the harder moves from real training". Furthermore, the trainer indicated that "vibrations should happen when the sword contacts a target in the game," which matches the individual preference environment determined in 6.12. Given the subject's younger age, it was determined that violence should be minimized in the sword motion interactions, resulting in the choice of fruit as targets, rather than virtual human opponents.

Finally, since the subject's training had reached a point where the motions themselves were highly complex, the game's design should allow for complex motion input in 3-dimensional space and reward the accuracy of this input. Based on the above,

the racing game prototype introduced in 7.1 would be ineffective here since a racetrack limits the degrees of freedom in motion to 2 (acceleration/deceleration in one dimension, left/right turns in the other). Instead, the above feedback indicates that a game involving real-time sword motion would be the best fit for this individual. To achieve this, an Island Fruit game similar to the Fruit Ninja game developed by Halfbrick Studios (<https://fruitninja.com/>) was developed. In this game, the subject controls a virtual sword using the Intelligent Stick device, and is required to slice fruit which is tossed in the air in a precisely-tuned interval. The Island Fruit game was designed to match the individual's training in the case study as follows:

Competency Model: The user's competency at a motor task is evaluated in three categories: posture, progression and pacing. Posture represents the ability of the user to maintain ideal body posture during the task. Pacing represents the speed of motion and its proximity to the ideal value, and progression represents how closely a user's motion trajectory matches the intended trajectory of a motion in space-time. These elements are standard across all motor learning scenarios within the Autonomous Training Assistant. Individual distinctions occur, however, in the details of these metrics, including the targeted values for this individual and the tolerance ranges designed by the trainer for the individual, which may vary over time. In this case, these parameters were given by the trainer as indicated above: 10-5cm deviation in progression, 10-5 degree deviation in posture, which relates specifically to torso positioning in this case, and 6-9cm/sec deviation in pacing.

Task Model: The specific task for this study, as selected by the subject's trainer, requires that the subject contact three critical points in a 45-degree upward arc swing

motion while maintaining steady lower extremity posture. This can naturally be matched to the task of slicing fruit in the air, where each fruit piece represents a critical point, their rate of motion represents the rate of motion required to complete the task, and the steady motion of the sword in virtual space requires that the postural requirement is met throughout the motion.

Evidence Model: Evidence of the first two categories (progression, pacing) can be determined by the contact of the in-game representation of the Intelligent Stick with the fruit objects. The center of each fruit object represents the critical point for the motion, while their radius represents the tolerance range about which a motion may be considered “correct” by the trainer. This allows for coarse-grain analysis (hit or miss the fruit) and fine-grain analysis (proximity of contact point to the center of the fruit). The postural requirement is integrated into the gameplay as follows: should the individual deviate from the required posture, there is a “balance loss” event in which the virtual sword wobbles, creating an undesirable trajectory which will miss the fruit in the air. The individual must maintain posture to prevent this event from occurring.

Feedback Environment: Once the game elements have been mapped to feedback domains, what remains is to determine how modalities of feedback are assigned within gameplay. There are two key considerations at play in this decision. The first is that, since stealth assessment yields a game design in which successes and errors in all domains of assessment are directly embedded in gameplay, as in the above implementation, most of the information relating to an individual’s performance on the motor task can be inferred directly from what is being depicted in real-time within the game’s interface (in the visual and audio domains). For example, if the user’s sword

doesn't reach one of the fruit objects before it falls to the ground, it can be inferred without any interruption in the game experience that the user was moving too slowly, resulting in a pacing error.

This key advantage of stealth assessment design significantly reduces the challenge of implementing multimodal feedback. The consequence of this design is that many multimodal feedback cues that were previously utilizing the “concurrent” style of feedback (discussed in 6.9.4), as is the case in the Sigrist environment in 6.12, can be modified into “synergistic” combinations in which multiple modalities represent the same information. Essentially, this allows the designer to map feedback in a manner that matches user expectation for the game scenario being developed. For a fruit slicing game, this means that visual, audio and haptic modalities should be focused on augmenting and representing the game's mechanics. When the user's sword slices a fruit object within the game, it means that the user's posture, progression, and pacing are all correct at that moment in time. Hence, a synergistic multimodal feedback cue can be given to reinforce this information to the user: as the sword slices the fruit, a slicing sound is emitted by the game, the fruit is visually sliced in the game's interface, and a half-second vibrotactile signal is emitted from the Intelligent Stick to indicate that a critical point has been successfully hit. When the user misses the object, it is represented visually by the sword object passing or not reaching the object on-screen, and in the other two modalities by the lack of feedback (no slicing sound, no haptic vibration for missing the fruit). The user can then infer the nature of the error from the relative position of the sword and fruit object. As mentioned in 6.9.4, this synergistic approach reduces the cognitive load that would

otherwise be imposed upon the user in a concurrent feedback design, allowing for a large quantity of information to be transmitted to the user in parallel during gameplay.

The second consideration in the design of the feedback environment is the individual's preference. It was determined manually through evaluation in 6.12 that the subject indicates a preference for haptic information on progression; this information should, however, be automatically determined by a more adaptive system in future work, as discussed in 8.1. Thus, the synergistic feedback environment above can be established as a baseline from the mechanics in the game scenario, and it can then be modified based on individual preference and selective choice. In this case, the subject's preference for feedback already matches the type of feedback that is provided in gameplay (haptic feedback when the user reaches a critical point successfully during a motion), so the baseline feedback mechanics of the game do not require modification. If the subject were averse to haptic feedback, and it interfered or distracted the subject as it might in other cases, then this feedback would be omitted from the game environment instead, which is possible due to the redundant nature of synergistic multimodal feedback. This second consideration allows for person-centeredness to dictate the final design of the feedback environment.

A screenshot of the Island Fruit game is shown in Figure 7.3.3. The Kinect joint tracker and 3-axis accelerometer/gyroscope on the Intelligent Stick form the basis of the real-time motion estimation in Unity, and together control the position and orientation of the sword within the game. Fruit objects are distributed in burst-intervals, with a 5-second pause between each deployment, such as each deployment of 3 fruits assesses a single

iteration of the motion task by the subject. This design was approved by the trainer prior to the evaluation.

Flow-state ratio was measured using the Visage face tracking interface for Unity. At each frame, the tracker uses the camera feed from the Kinect to estimate the subject's emotional state in the six basic emotions (anger, disgust, fear, happiness, sadness, surprise). The tracker returns a belief value from 0-1 in each of these categories at each frame of gameplay, representing how likely it believes the user is expressing that emotion. For example, a belief vector of (0.12, 0.03, 0.01, 0.65, 0.00, 0.25) represents that in the current frame, the subject is highly likely to be expressing happiness and surprise, and far less likely to be expressing other emotions). Note that the emotions expressed need not be disjoint, so the probability values need not add to exactly 1.

Here, a user's flow-state is estimated with Visage emotion-vectors using the threshold constant Ft . The following rules were used to determine the subject's state:

- If all values in the vector fall below Ft , the user is in the "boredom" state.
- Otherwise, if the "anger" value lies above Ft and the "happiness" value lies below Ft , the subject is experiencing "anxiety".
- Otherwise, if the "surprise" value lies above Ft and the "sadness" value lies below Ft , the subject is experiencing flow.
- If none of the above apply, the subject is in a state unknown to the system, labelled as "other".

A threshold value of $Ft = 0.25$ was used in this study as it was deemed the most accurate estimate based on pre-evaluations performed within the research team, but the optimal value of this threshold remains a topic for future research. Adaptable parameters

of the game's difficulty included the size of fruit, their speed of motion, and the minimum lower body motion required to "lose balance" within gameplay.

After a brief 1-minute tutorial discussing the game's controls, the subject played the game in four separate 5-minute sessions, with ten-minute breaks between sessions to help eliminate learning effects across conditions. Note that while learning effects cannot completely be controlled for in this design, the nature of dynamic difficulty adaptation is that it scales with player skill, such that minor variations in the player's entry skill level for any of the conditions should have minimized interference on the interpretation of their results. These sessions included a control condition in which no stealth adaptation was used, and three adaptation conditions: Bayes-Net, Cluster, and Hit-Rate. Described below:

Bayes-Net: The subject's competency in posture, progression and pacing were independently assessed and adapted for within gameplay using a Bayesian network. Progression was estimated as the proximity of the sword to the center of the fruit at the point of contact, pacing was estimated as the rate of motion of the sword relative to the fruit at the point of contact, and posture was estimated as the average angle of the user's torso relative to its ideal value over the duration of a single swing. In all cases, a non-contact with fruit was treated as an error. The belief network forms an estimate of competency in each category which is updated with new information between each swing. Parameters are adjusted between swings based on their respective categories (i.e. if progression mastery is poor relative to pacing and posture, then only the fruit size parameter is changed).

Cluster: The three competency evaluations above are treated as dimensions in a clustering space. Each set of performance values in posture, progression, and pacing for a single swing form a point in 3d space. Three clusters of performance representing low performance, average performance and high performance are formed after at least three swings are completed by the player, using k -means for assignment with $k=3$. Then once the user completes another swing, all difficulty parameters are adjusted based on the user's cluster of performance. Three pre-defined "levels of difficulty" were set, with parameter vectors of (10, 6, 10), (7.5, 7.5, 7.5) and (5, 9, 5) in the format of (fruit size, fruit speed, balance threshold). If the user's swing enters a "high performance" cluster, the difficulty is increased, and it is lowered if the user enters a "low performance cluster".

Hit-Rate: This method does not evaluate performance at the level of individual categories (posture, progression, pacing). Instead, it simply checks the amount of fruit sliced by a user on each swing. In this instance, three pieces of fruit are deployed on each interval (representing the three critical points) and the targeted hit-rate assigned by the trainer was 2 fruit pieces per swing. If the user hits all three fruit pieces in a single swing, difficulty parameters are increased by a constant value until either the user reaches the targeted value of 2 hits or the maximum difficulty value is reached for all parameters. In this case, the subject is considered to have mastered the exercise. If the subject only hits 1 or less fruit on a single swing, difficulty parameters are lowered until the minimum values are reached or the user hits the expected 2 fruit objects on a swing.

7.4.2 Procedure

In the above three conditions, the subject's emotional state was estimated by the Visage tracker in real-time. For each swing, an estimate of the user's flow-state is made based on the rules given above. Should the user be in the "anxiety" state, the difficulty of all parameters is lowered by a constant amount in addition to the adjustments made using the base learning technique. Similarly, the difficulty is increased if the game detects "boredom".

In each timed session, the subject was asked to complete as many swings as comfortably possible. Scoring was implemented as follows: on a spawn interval, a single fruit slice was worth 200 points, 2 slices were worth 600 points, and three slices was worth 1200 points. This incentivized the subject to try to hit as many fruit objects as possible in a swing, matching the intentions of the motor task. Emotional information was sampled each frame by the Visage framework, and the samples were averaged over multi-frame intervals to form a single 6-dimensional emotion vector for every 10 seconds of gameplay. This resulted in 30 vectors for each session. Flow-state ratio corresponds to the ratio of these vectors that are considered "flow vectors" based on the above rules.

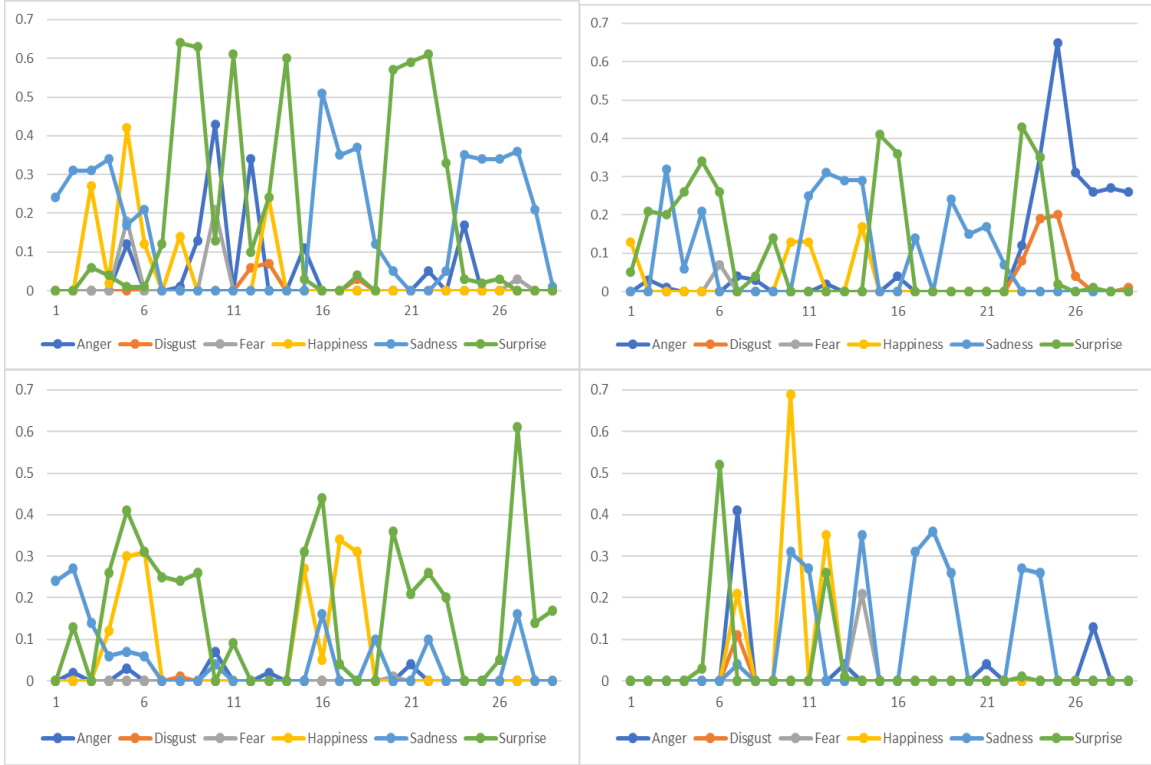


Figure 7.4.1: Affective Response Values for Case Study Subject. Responses shown are for Hit-Rate Stabilization (top-left), Clustering (top-right), Bayesian Network (bottom-left), and No Adaptation (bottom-right).

7.4.3 Results and Discussion

Figure 7.4.1 conveys the emotional data of the subject for each learning approach. The Bayesian-Network approach yielded the highest flow-state ratio of 0.300, followed by Hit-Rate Stabilization at 0.233, and Clustering at 0.200. The three approaches did not vary significantly from one another, and all three adaptation approaches beat the control approach (no adaptation), which yielded a flow-state ratio of 0.067 over the 5-minute session. One external interfering factor was the subject’s head movement during swings, and the occasional occlusion of the subject’s face by the Intelligent Stick device, resulting in random fluctuation in the emotional tracking data. However, these incidents affected

only a negligent number of data frames, which were discarded in the calculation of averages for 10-second intervals.

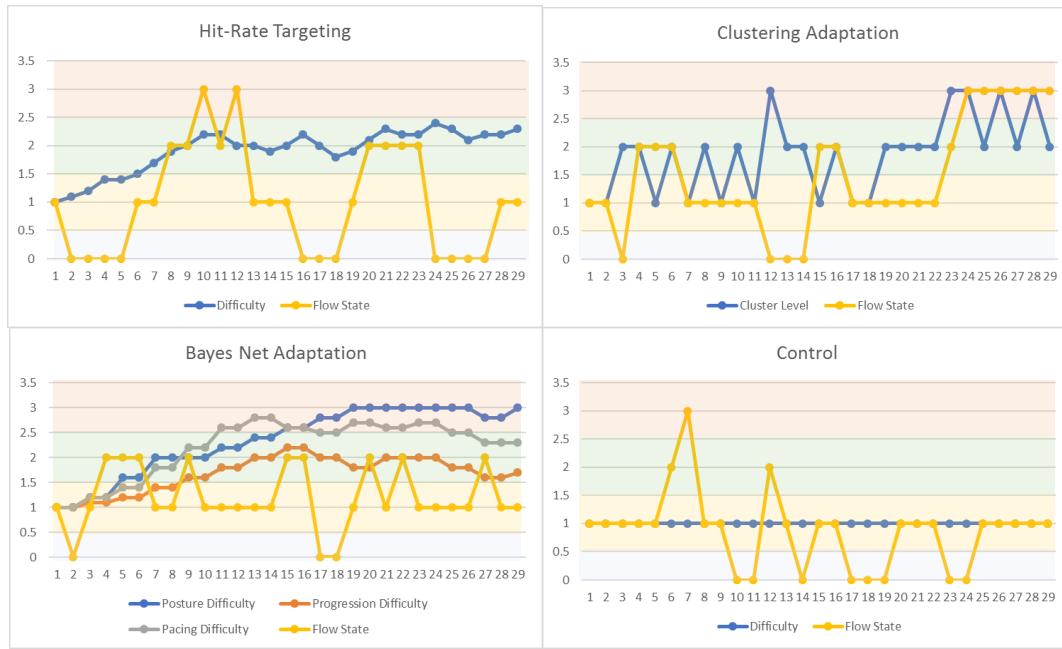


Figure 7.4.2: Flow State Progression Values for Case Study Subject. Responses shown are for Hit-Rate Stabilization (first), Clustering (second), Bayesian Network (third), and No Adaptation (fourth). Flow state value of 0 represents unknown state, 1 represents boredom state, 2 represents flow, and 3 represents anxiety. Difficulty parameters were normalized to a scale of 1-3, with 1 being the lowest difficulty and 3 being the highest in each parameter.

The difficulty parameters over each session are compared with the subject’s flow state output in Figure 7.4.2. Flow state outputs are represented on a scale from 0-3, with 0 being unknown state, 1 being boredom state, 2 being flow state, and 3 being anxiety state. In each case, the difficulty outputs are scaled to the range 1-3, with 1 representing the lowest difficulty (or highest tolerance range about the targeted value) and 3 representing the highest difficulty (or smallest tolerance range). These tolerance range values were provided by the trainer based on the subject’s current level of mastery of the chosen

exercise, and are given above. Difficulty in posture from 1-3 represents a tolerance range of 10 to 5 degrees, respectively, for deviation of the torso from the goal position before an error is detected. Difficulty in progression from 1-3 represents a tolerance range of 10cm to 5cm, respectively, for deviation of the stick's outer edge from its intended critical point at the closest point of passing, Difficulty in pacing from 1-3 represents a tolerance range of 9cm/s to 6cm/s, respectively, for deviation from the intended rate of motion for the exercise. In the case of hit-rate targeting and clustering, all three parameters had the same difficulty value at any point during the session since these strategies observed overall performance rather than independently assessing each parameter. Hence, a single difficulty value is represented in Figure 7.4.2 for these strategies. Hit-rate targeting performed finer adjustments to difficulty than clustering, which used only three difficulty values, one corresponding to each of 3 mastery clusters. For Bayes Net adaptation, since each domain was assessed and adapted to separately, three difficulty outputs are shown in Figure 7.4.2. Finally, difficulty was kept at a constant rate in the control condition, where no adaptation occurred.

It is evident from the figure that the rapid difficulty fluctuations in the clustering condition resulted in anxiety from the subject, particularly toward the end of the session. This condition presented the greatest rate of change in difficulty (one full unit over a 10 second interval) which made adjustment difficult at various points in the session, giving it a slightly lower flow-state ratio than the hit-rate targeting condition. For hit-rate targeting, the transition between difficulty was far smoother, with a change of no more than 0.2 in the 1-3 scale between two 10-second intervals. This is made evident by the observation that the frequency of flow state fluctuation was slower in this condition than in the

clustering condition, and as a result a slightly higher flow-state ratio was yielded by the system for the session. In contrast to the clustering and hit-rate targeting approaches, the Bayes Net approach utilized a far more precise method of difficulty tuning, but did so over a slower period. Each parameter (posture, pacing and progression) was adjusted independently of the others, but only one adjustment was made in each 20-second interval, resulting in a more gradual adaptation process. Much of this is due to the infeasibility of rapidly and repeatedly performing multiple mastery computations and updates in a Bayes Net, although the process could be multi-threaded to improve efficiency (and was not in this case). Due to this separation, it is made evident by the data that the user's best performance was in the posture domain, with a higher rate of error in pacing and the highest rate of error in progression. The lack of anxiety and relatively high flow-state ratio in this condition may potentially be attributed to the independence of these parameters in this strategy and the gradual rate of adjustment, although learning effects may have played a role as well since it was the third condition in the ordering (hit-rate, cluster, bayes, control). The dominance of boredom state in the control condition can clearly be attributed to the lack of adjustment as seen in this figure.

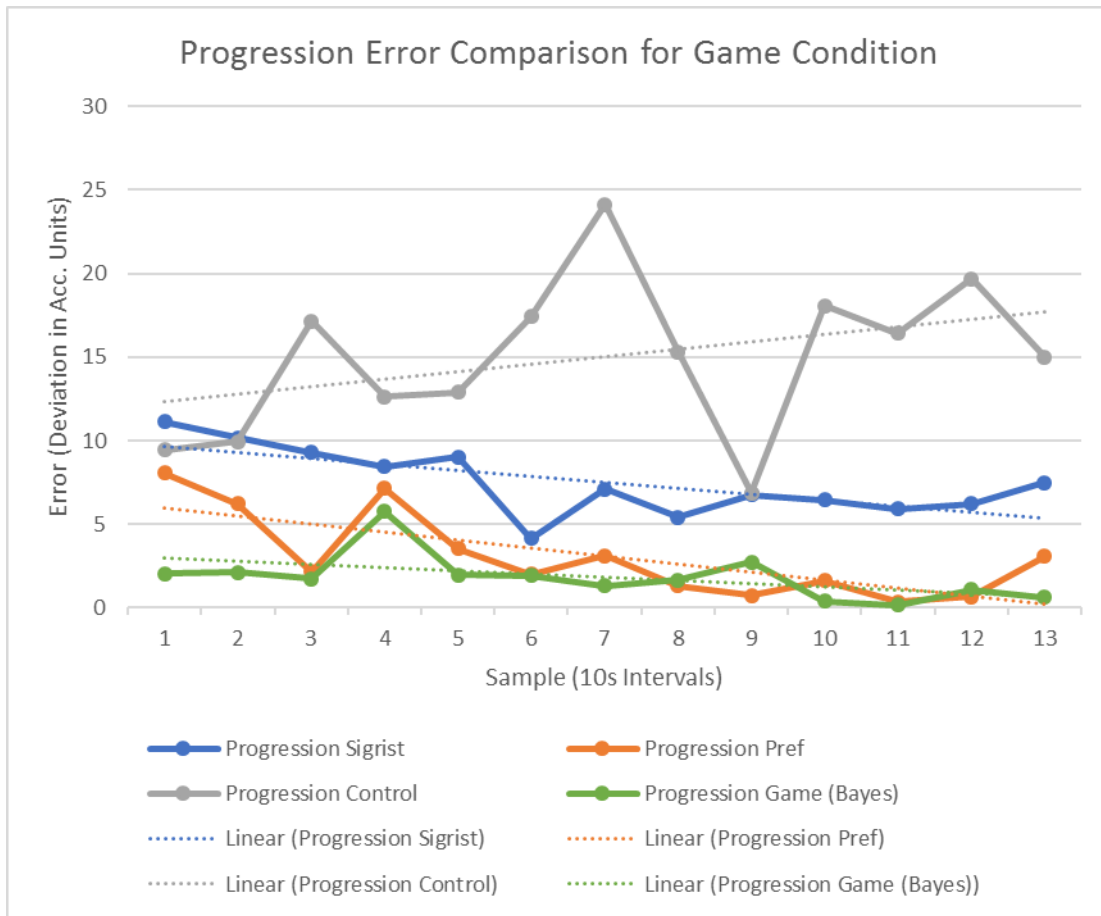


Figure 7.4.3: Progression Error Comparison for Game Condition. This is a copy of Figure 6.12.1 with an added “game condition” (in green) in which the user completes an arc swing motion using a stealth assessment game interface with synergistic feedback and Bayes Net difficulty adaptation over 2-minutes.

To illustrate the effect of the synergistic feedback environment employed in the game design in this study, one can refer to the multimodal mapping study in 6.12. In that evaluation, no gaming layer was present, and feedback given was concurrent over the course of a 2-minute session. For comparison, a copy of the data presented in Figure 6.12.1 is utilized in Figure 7.4.3, with performance data from the first 2 minutes of the “Bayes Net” session added as an example case for the game environment of feedback. It is difficult to compare the two environments directly as the subject was performing

different motor tasks (umbrella swing vs. arc motion) with different levels of task experience between the two tasks; however, the pattern of error presented by an adaptive approach can clearly be seen here. Note the increase in error that occurs from difficulty change at the 40s and 90s marks for the subject in the figure. This is indicative of an expected response by the user; while the error fluctuates due to difficulty adaptation, it follows a similar trend to the individual preference condition in that the error gradually reduces over the course of the session. Furthermore, perhaps due to the synergistic nature of feedback, the user tends to correct short-term error fairly quickly in the game condition (although, as stated above, the task and the user's experience level are different in this condition). This is illustrated best at the 40s mark, where the user adjusts for the increased difficulty within a 10s interval compared to the 20s error adjustment for the individual preference condition without a game layer.

One important consideration is the attribution of increased motivation in the subject to the addition of a gaming layer in this case study. From the beginning phase of the Case Study in Section 4.3 to the study performed above, post-surveys were administered to the subject to gain feedback on the effectiveness of the ATA system from the subject's point of view. These surveys, featured in Appendix A, indicate that the subject's reported interest in at-home training with the ATA system increased with the addition of an at-home guidance component in the first phase (from an interest level of 3 to 5, on a Likert scale from 1-10) and further with the addition of a game component in this phase (from an interest level of 5 to 9, on Likert scale from 1-10). While these findings alone do not conclusively relate any performance outcomes of this system to the

usage of a serious game design, they relate well to the role of meaningful play in improving long-term compliance and motivation (Salen & Zimmerman, 2005).

While the evaluation in this work was preliminary, the results indicated by flow-state measurement indicate a potential advantage in the combination of performance data and affective data for dynamic adaptation of gameplay in motor learning. To determine the relative advantages of these approaches more conclusively, an in-depth study including multiple threshold values for flow-state determination over a longer period is necessary. Furthermore, it may be beneficial to determine the interaction between performance adaptation and affective adaptation, as this was not covered in the current study, where both forms of adaptation were applied in each of the three experimental conditions. A long-term evaluation comparing the two adaptation methods would help determine which has a stronger effect on flow-state. Furthermore, a broader evaluation encompassing multiple subjects and game designs would determine the generalizability of these approaches across varying subject profiles and motor ability levels. These evaluations and the development and refinement of alternative adaptation techniques for motor learning can form the basis of future work.

CHAPTER 8

REMAINING CHALLENGES AND FUTURE WORK

This dissertation introduces a novel approach to the integration of person-centered motor assessment and feedback with novel techniques in serious gaming design and adaptation for the development of an automated system for guided motor learning. Through the case study approach, it has been shown that a focus on the individual attributes of the learner yield a system design that more accurately affects the individually unique nature of motor learning scenarios, whether in rehabilitation, athletic training, or other application areas. In this work, the scope of assessment was restricted intentionally to the unique attributes of a single motor learner and trainer in a case study to experimentally determine how these individuals' attributes, strengths, preferences, and motor tasks can inspire a more effective design for an automated trainer. From this case study, a three-category framework for motor assessment was derived which could accurately formalize the training protocol of the subject. Furthermore, it was determined through evaluation in Chapter 6 that individual characteristics of the learner may play a role in the optimal assignment of feedback in a multimodal system environment. Finally, the design principles in Chapter 7 were utilized to design a game which naturally fit the training protocol of the subject and trainer and allowed for complex motion tasks while seamlessly integrating assessment and feedback into gameplay.

Based on these findings, there are many topics left to be explored to optimize the system's design. Strategies for feedback fading, multimodal integration styles, fine postural correction, and other elements of system interface design in future work are

discussed throughout Chapter 6. Here, some additional topics for consideration in future work are presented.

8.1 Feedback Adaptation

As discussed in the case study evaluation in 6.12, individual preference may play a significant role in the optimal assignment of feedback modalities to domains of motor feedback. Therefore, an automated system designed for person-centric motor learning should be able to detect and respond to individual biases in responsiveness to certain modalities during multimodal integration. If the system should detect, for example, that the subject responds significantly better to feedback provided in the haptic domain than in other domains, as discovered in this case study, it may opt to use a mode-selective approach as discussed in Section 6.10 which utilizes the favored modality to give feedback exclusively in the domain with which the subject displays the highest rate of error. However, whether or not this type of assignment is feasible without impeding the subject's ability to improve in the other domains of performance is uncertain. An evaluation of this topic should carefully examine whether or not a significant change in error over time occurs in the non-prioritized assessment domains when mode-selectivity is active on a subject.

To fully automate this adaptation, the ATA would need to implement a machine learning approach for individualized real-time feedback adaptation as introduced in 6.11. Several findings in related work can help form the baseline for this approach. For example, Novatchov & Baca (2012) propose the use of Artificial Neural Networks (ANN) and Support Vector Machines (SVM) to analyze and extract features from sensor

data in real-time for classification of performance and feedback adaptation. However, this type of adaptation does not take into account a player's affective response. A more thorough solution may combine affective response with performance data to perform its classification of a feedback cue. Such a system would then be intelligent enough to identify cases in which, for example, a feedback signal may need to be changed despite producing high performance improvement due to a consistent anxiety response in the player to the signal, as such a signal may yield reduced compliance in the long-term. Future work can evaluate not only which classifiers are the most effective in determining player responsiveness to multimodal feedback, but also how often these classifiers should update the feedback mechanism of the learning environment. A balance may need to be considered between a sophisticated, but computationally expensive method that yields slower, more accurate updates in the feedback mechanism, or a faster but less accurate classifier that is more practical in real-time training scenarios.

8.2 Improved Player State Detection

While affective state detection was approached in this work in Chapter 7, a great deal of work remains in this domain. The primary advantage of the approach used in this work is that, since the Kinect camera is a non-intrusive external recording mechanism, no setup or wearables are required to receive and interpret affective data in real-time, improving usability for the learner. This is particularly important in rehabilitative scenarios where motor function may be limited enough to prevent a user from being able to incorporate wearables into the learning environment. However, this carries the large limitation of ignoring physiological data from the user, which can be used to detect more

complex player states like fatigue and distress that can be of use to the system.

Continuation of this work would involve the implementation of a strategy similar to those in Section 2.5 for the detection and intervention by the system on undesirable player states during exercise, such as fatigue, distraction, or compensatory motion. These would form the features of a more comprehensive approach to affective interaction in a motor learning system, and a non-intrusive method for detection similar to the Kinect face-tracking interface is worthy of exploration.

8.3 Generalization of Stealth Adaptation

In Chapter 7, a stealth adaptation approach was adopted to design a serious game implementation of the case study subject's motor learning protocol. It is claimed that, using the design strategy highlighted in Section 7.1, this approach can be utilized in a wide variety of motor learning scenarios and individuals. However, to date there has not yet been a comprehensive study linking game elements in exergames to the real-world motions and motor tasks to which they are a most natural fit. For individuals with more limited motor function in the upper extremity, the design used in the case study above may be untenable. A mapping framework which can assign gameplay elements across the spectrum of physical ability, motor tasks, individual interests, and training protocols would serve as a guideline by which both researchers and game developers can create personalized and optimal solutions for motor learning for a wide variety of individuals. Such a study would serve as a strong direction for future work in the field of stealth adaptation in games for motor learning.

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APPENDIX A
CASE STUDY SURVEYS AND RESPONSES

Survey 1: At-Home Deployment Evaluation

Please answer the following questions on a scale between 1 to 10 (1 being “very poor” and 10 being “excellent”).

Q: How would you rate the weight of the Intelligent Stick?

R: 8

Q: How well do the vibration patterns represent the movements?

R: 7

Q: How well do you notice yourself improving while using the tool?

R: 5

Q: How close is the avatar training compared to your exercise with your trainer?

R: 7

Q: How well are you able to understand the avatar?

R: 10

Q: How is the pacing of the avatar?

R: 7

Answer the following question using the space provided below.

Q: Please comment on any games you would like to play using the stick.

R: “Ninja sword game with cool sound effects, control sword with the stick, with some of the harder moves from real training”.

Survey 2: Multimodal Mapping Evaluation

Please answer the following with a number from 1 to 3, with 1 being “stick vibrations”, 2 being “audio cues”, and 3 being “on-screen avatars”:

Q: Which type of feedback did you like the most?

R: 1

Q: Which type of feedback were you able to understand the best?

R: 1

Q: Which type of feedback was the hardest to use?

R: 2

Please answer from 1 to 10, with 1 being “Very Poor” and 10 being “Excellent”:

Q: How well did you notice yourself improving in this session?

R (Sigrist Condition): 6

R (Preference Condition): 9

R (Control Condition): 3

Q: How helpful was the feedback provided in this session?

R (Sigrist Condition): 4

R (Preference Condition): 10

R (Control Condition): 0

Answer the following question using the space provided below.

Q: Please comment on any games you would like to play using the stick.

R: “Sword game with cool sword effects, control sword with the stick, with some of the harder moves from real training”. *Trainer:* “Vibrations should happen when the sword contacts a target in the game.”

Survey 3: Flow-State Evaluation

Please answer on a scale from 1 to 10, 1 being “Very Poor” and 10 being “Excellent”:

Q: How interesting is this game to play?

R: 10

Q: How easy was it to understand the rules of the game?

R: 10

Q: How easy was it to move the sword object in the game?

R: 7

Please answer from 1 to 10, with 1 being “Very Poor” and 10 being “Excellent”:

Q: How would you rate the level of challenge in this session?

R (Hit Rate Targeting): 6

R (Bayes Net): 6

R (Clustering): 9

R (Control): 2

Q: How often would you say you were overwhelmed/frustrated during this session? (1 =

Not at all, 10 = The entire time)

R (Hit Rate Targeting): 2

R (Bayes Net): 1

R (Clustering): 5

R (Control): 0

Q: How often would you say you were bored during this session? (1 = Not at all, 10 =

The entire time)

R (Hit Rate Targeting): 2

R (Bayes Net): 2

R (Clustering): 3

R (Control): 9

Q: How well do you think you did during this session?

R (Hit Rate Targeting): 9

R (Bayes Net): 7

R (Clustering): 5

R (Control): 10

Please answer on a scale from 1 to 10, 1 being “Very Unlikely” and 10 being “Very Likely”:

Q: How likely are you to continue playing this game in the next 3 months?

R: 9

APPENDIX B

PERMISSION STATEMENTS FROM CO-AUTHORS

Permission for including co-authored material in this dissertation was obtained from co-authors, Prof. Sethuraman Panchanathan, Dr. Troy McDaniel, Dr. Morris Goldberg, Bijan Fakhri, Miles Laff, Pamela Robles-Franco, Mengjiao Geng, Jonathan Zia, and Shayok Chakraborty.