AUGMENTED SENSORY FEEDBACK TO ACCELERATE MOTOR PERFORMANCE WITH COMPUTERIZED INTERFACES FOR REHABILITATION

by

Sean Patrick Sanford

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Sean Patrick Sanford, Candidate

ADVISORY COMMITTEE

____
Dr. Raviraj Nataraj, Chairperson Date

____
Dr. Noam Harel Date

____
Dr. George McConnell Date

____
Dr. Antonia Zaferiou Date

____
Dr. Damiano Zanotto Date

STEVENS INSTITUTE OF TECHNOLOGY
Castle Point on Hudson
Hoboken, NJ 07030
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ABSTRACT

Neurological traumas can impair motor function and compromise the ability to perform activities of daily living. Physical rehabilitation can aid in motor recovery, but these practices are frustrating due to their rigorous and repetitive nature. Emerging rehabilitation technologies utilize computerized interfaces, such as virtual reality to increase participant engagement and better train muscle-level control. These interfaces can readily provide enhanced augmented sensory feedback, especially at visual levels, to accelerate motor outcomes. Still, there remains a lack of understanding in optimizing the deployment of augmented sensory feedback for clinical motor rehabilitation. *In this research, I investigated how specific features of augmented visual feedback can improve motor performance during rehabilitation training*. The two primary features of interest were <u>complexity</u> and <u>intermittency</u>, which vary the amount and frequency of visual guidance provided, respectively. A key supplementary feature of augmented visual feedback is the level of body representation to leverage visual embodiment, which was also examined. I evaluated unique combinations of these features to improve functional performance of two different motor rehabilitation exercises, representing either a motion- or force-based task. For a two-legged squat exercise (motion-based), augmented visual feedback that was relatively complex with more body-discernible guidance cues produced the best performance during and after training. The dynamic embodiment may have facilitated the ability to effectively synthesize more feedback information during a synergistic, multisegment movement. Alternatively, training with simple feedback demonstrated a greater potential for motor learning of a task utilizing isometric muscle control (force-based). Complex feedback may have been interpreted as superfluous to this task, given the shifted emphasis to force control without dynamic embodiment. Thus, the additional cues may have hindered both learning and user experience, reflected in reduced performance and significant physical and cognitive stress changes. For training of either experimental task, intermittently providing visual feedback about real-time performance errors (i.e., concurrent bandwidth feedback) suggested a greater potential for motor learning. In conclusion, systematic variation of specific features in augmented feedback can significantly improve motor performance. Thus, optimizing computerized interfaces for motor rehabilitation requires a greater understanding of how sensory feedback affects the user for a given functional task.

Author: Sean P. Sanford

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1. INTRODUCTION

Neurological traumas, such as stroke or spinal cord injuries, reduce functional capabilities in the lower- and upper extremities and reduce the ability to complete activities of daily living (ADLs) [1], [2]. Physical rehabilitation is commonly prescribed during treatment regimens to restore normative functions. During physical rehabilitation, participants benefit from external feedback cues to help improve performance, such as verbal instructions from the therapist or a simple mirror to monitor spatial positioning [3]. Computerized interfaces are engaging to the participant and can provide more informative external feedback cues, including immersive virtual reality environments using head-mounted displays [4], [5]. Augmented sensory feedback, particularly visual feedback, can accelerate motor learning by guiding the participant towards a desired movement trajectory or muscle activation pattern [6]. The objective of visual feedback paradigms is to intelligently train the user for better movement performance and increase independence by improving functional capabilities. Unfortunately, there is a lack of integration between clinical rehabilitation and computerized interfaces, emphasizing improving motor performance (**Figure 1**). My research has identified features of augmented visual feedback for supplementary guidance during movement tasks [7], [8]. These features, identified as *1) complexity, 2) body representation,* and *3) intermittency,* have unique advantages and disadvantages in motor learning based upon task-specific characteristics, including the participant's experience. In this research, these features of visual feedback were evaluated in two distinct platforms to better understand the effects on improving motion and force control during muscle-driven exercises intended for rehabilitation. The two platforms were

Research

Problem: Lack of optimization in the deployment between computerized interfaces and clinical rehabilitation with emphasis on accelerating motor performance

Objective: Systematically leverage augmented visual feedback in virtual reality to identify features that accelerate positive motor performance

Outline

Introduction: Clinical motor rehabilitation, computerized interfaces, motor learning theories, and augmented sensory feedback

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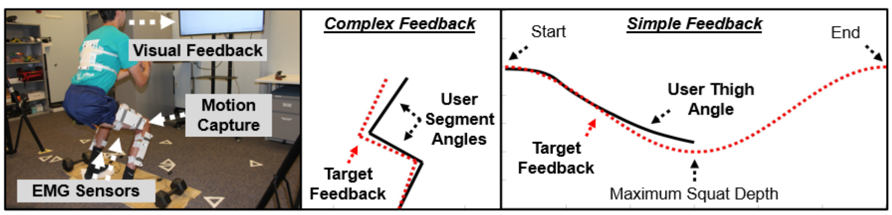
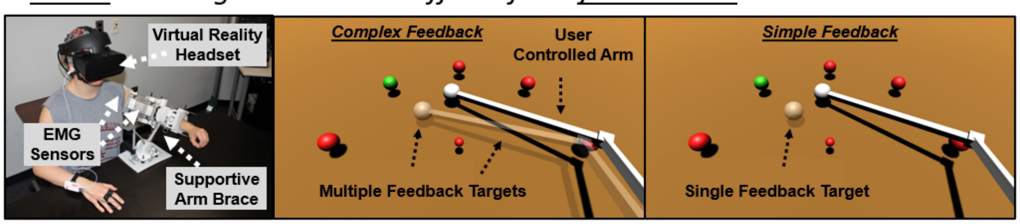
AIM 1: *Investigate the effects of specific features of augmented visual feedback on the performance of a motion-based rehabilitative task*



AIM 2: *Investigate the same effects for a force-based rehabilitative task*



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Conclusion and future directions

Appendix: Multimodal feedback and cognitive agency

Figure 1: The research is a systematic evaluation of augmented visual feedback features to target the lack of optimization in the deployment between clinical motor rehabilitation and computerized interfaces.

a dynamic lower-body motion-based task, the two-legged squat, and an isometric upper-extremity force-based task, where a machine learning classifier mapped muscle activity to movement within a virtual reality environment. The results of this research identified optimal features for accelerating motor learning during physical rehabilitation at a participant-specific level. In the Introduction, I will provide background information regarding the central pillars of my research, including clinical motor rehabilitation, computerized interfaces, motor learning theory, and augmented sensory feedback.

1.1. Clinical Rehabilitation of Motor Function

Neurological traumas, such as stroke and spinal cord injury (SCI), affect millions of people every year and are leading causes of death and disability [9]–[11]. 50% of SCI cases affect upper-extremity function [11], and up to 65% of stroke survivors have limited hand function 6-months following the injury [12]. People suffering from a stroke, or a traumatic brain injury, may require a more tailored sensory feedback paradigm than those having a spinal cord injury [13], [14]. For example, suppose damage to the brain lies in an area responsible for interpreting audio signals. It is crucial to consider the form of augmented sensory feedback as participants may have difficulty utilizing audio cues to improve motor performance. The functional capabilities of spinal cord injury participants are primarily dependent upon the injury site on the spinal column. For example, injuries to the lumbar section of the spine will mainly affect the lower extremities, while cervical level injuries will additionally affect autonomic and upper-extremity functions.

Physical rehabilitation aims to restore independent function through repetitive task training by promoting strength, flexibility, and neuroplasticity [11]. The primary objective of motor rehabilitation is to restore functional abilities for movement activities through rigorous practices that improve motor skills transferrable to ADLs (**Figure 2**). Functional movement actions include walking, sitting, standing, reaching, or grasping objects.

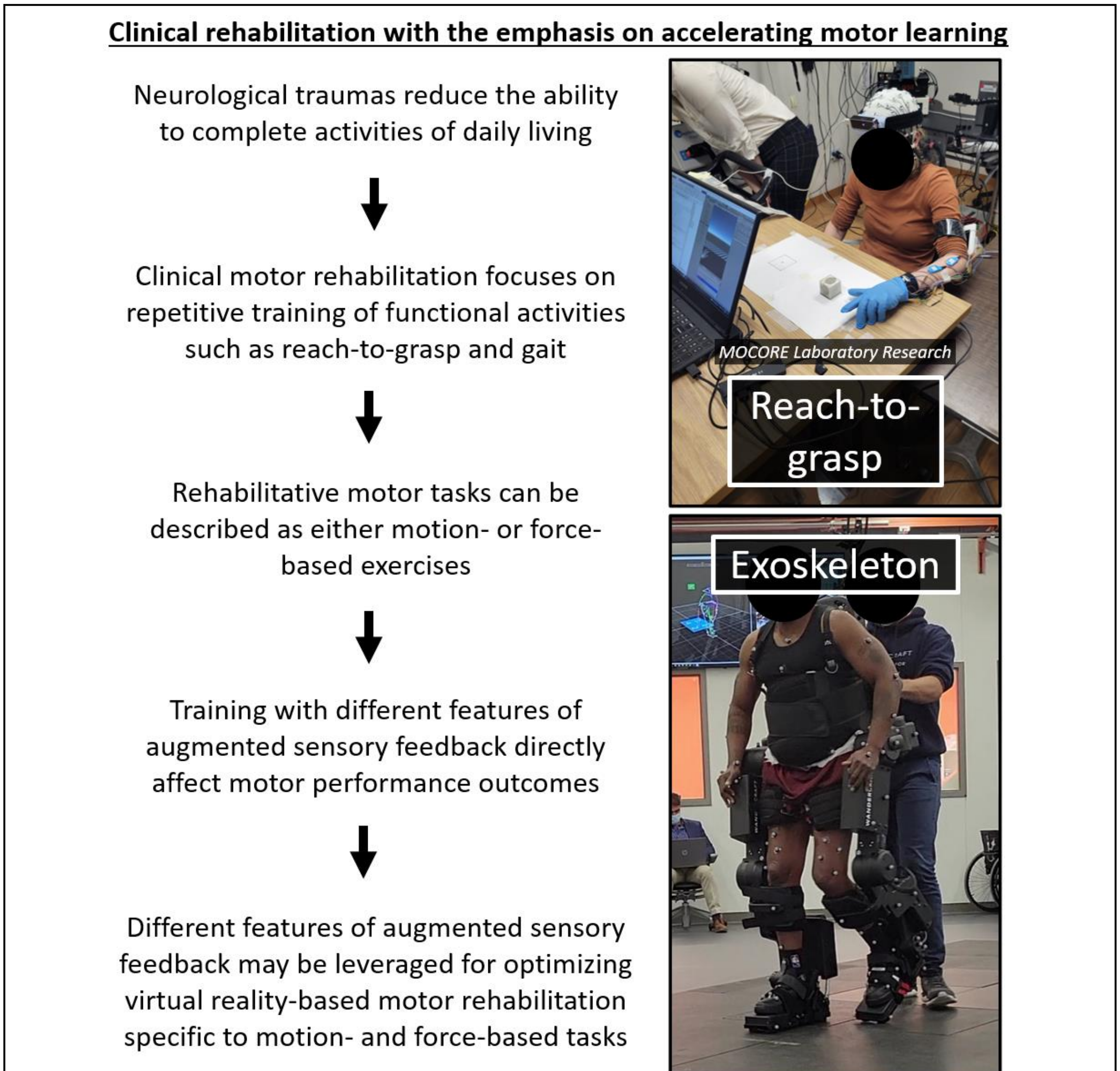

Figure 2: Clinical motor rehabilitation can be improved by leveraging specific features of augmented sensory feedback for motion- and force-based tasks.

Unfortunately, conventional rehabilitation processes are very time- and effort-intensive. A physical therapist will supervise and guide operational practices during conventional therapy regimens for persons with motor impairments [15], [16]. Physical rehabilitation for spinal cord injury typically includes joint exercises that facilitate greater strength and range of motion [16], [17]. Stroke rehabilitation typically centers on functional task practice [18], where there are adjustments to difficulty levels for each person. For eligible persons with hemiparesis, therapists may incorporate constraint-induced movement therapy to compel more engagement of the affected side [19]. Conventional rehabilitation can become frustrating to participants due to its tedious and repetitive nature [15]. Computerized interfaces can be integrated with conventional rehabilitation to design more efficient motion- and force-based protocols to achieve functional gains with fewer repetitions.

Conventional rehabilitation exercises are either motion-based or force-based, depending upon the action of the human body. Motion-based tasks, also known as dynamic exercises, are movements such as gait, sit-to-stand, or reaching. Tasks are commonly associated with ADLs and utilize concentric and eccentric muscle contractions to change joint angles of multiple body segments. Force-based tasks are isometric exercises that aim to promote greater muscle level control. Many ADLs employ both motion- and force-based tasks, such as reaching (motion) and grasping (force) for an object. Examples of isometric exercises in physical rehabilitation are leg extensions, wall sits, and side planks. Isometric exercises are usually done against an immovable object as they result in no change in muscle length, although tension and energy fluctuate to produce force. The capable force generated during an isometric exercise is wholly dependent on the length of the muscle [20]. During clinical motor rehabilitation, isometric exercises are uniquely beneficial as a bridge to dynamic functional tasks, as muscle weakness is a common clinical symptom of many neuromuscular traumas. Isometric exercises can increase strength and promote healthy blood flow while being intrinsically safe and suitable for clinical populations with motion limitations [20].

Understanding the body's nervous and musculoskeletal system is necessary to leverage augmented sensory feedback for optimizing clinical motor rehabilitation. The brain has several regions implicated in sensory feedback-based rehabilitation. Motor cortex regions are directly responsible for movements of body extremities. The sensory cortex adjacent to the motor cortex interprets sensory signals to the brain, such as touch and proprioception, to inform movement control. The cerebellum is responsible for balance, interpreting visual signals, and integrating sensory and motor cues in both feedback and feed-forward loops. Damage to the cerebellum would negatively impact motor coordination and the ability to comprehend augmented visual feedback. The musculoskeletal system generates forces through muscles attached to the body's skeletal system. Muscles are primarily responsible for movement and are soft tissue segments found across joints, bone to bone junctions. Muscles range in fiber pattern/structure and can consist of fast-twitch (type II) for rapid movements (e.g., eye muscles) to slow-twitch fibers (type I) for force generation and balance (e.g., soleus and back muscles). Other essential elements of the musculoskeletal system include ligaments attaching bone to bone, such as the anterior cruciate ligament (ACL), and tendons connecting muscle to bone, such as the Achilles. Following rupture of the ACL, commonly seen in athletics, rehabilitation with augmented visual feedback can reduce knee moment forces and help maintain a center of balance [21], [22]. Monitoring muscle activity, for example, the quadriceps muscle during

ACL rehabilitation [23], [24], is done through electromyography (EMG) sensors taped to the person's skin on the muscle mid-belly.

EMG sensors are a powerful tool of rehabilitation used to display muscle activity, especially during isometric force-based tasks. The real-time output from EMG sensors can also command myoelectric assistive devices, such as prosthetics or exoskeletons [25]–[27]. Clinical populations with severe injuries often require powered assistive devices to complete ADLs. Participants utilize residual muscle capabilities as a command interface to control robotic actuators, device joint angles, and applied forces. Unfortunately, inadequate training is one of the key contributing factors to the poor early adoption of myoelectric control [28]. Lack of motivation and faulty device functionality results in 20% of users reporting abandonment of their devices for more straightforward tools (e.g., hook hand) [29]. Augmented sensory feedback-based training has been proven effective for improving motor performance, and training powered assistive devices compared to no-feedback groups [30]. For example, the addition of augmented visual feedback increased locomotor adaptation for transtibial amputees utilizing a powered prosthesis [31]. Computerized interfaces, such as virtual reality environments, can display EMG activity and augmented sensory feedback to improve clinical motor rehabilitation [32].

1.2. Virtual Reality for Motor Rehabilitation

Following neurological trauma, motor training with computerized interfaces offers advantages, compared to conventional therapies, in terms of data monitoring and increases in cognitive engagement [33]. Virtual reality (VR) is used in clinical motor rehabilitation to motivate the participant [2], [34], [35] and, in some cases, can increase strength and endurance compared to conventional therapy [36]. Integrating VR environments into physical rehabilitation began decades ago [37]. However, the technology was nowhere near today's options, and equipment could cost thousands of dollars for a fully functional system. Today, VR is much more affordable and allows for creating enhanced augmented sensory feedback unobtainable in conventional therapy. Adding VR-based rehabilitation to conventional therapy regimens has improved functional outcomes in able-bodied and neurotraumatic populations [37]–[39]. The success of VR rehabilitation has been mainly attributed to increasing motivation and simulating task practices that have high physical and cognitive fidelity to ADLs [37]. *Virtual reality introduces immersive and customizable environments with gamifying elements* [40] *that increase cognitive engagement* [41] *and reduces neuropathic pain in people recovering from neurological trauma* [42]–[44] *(**Figure 3**)*. Although VR shows promise for neurorehabilitation, it remains unclear whether it is more effective than conventional therapy. Some studies have found that the effects on motor learning are equal when the training dosage is equal [45]. Although one treatment may not be more effective, participants tend to enjoy VR therapy more, motivating them to continue their rehabilitation regimen [41]. Still, there is a lack of systematic evaluation of the effects of various components of VR-based motor rehabilitation that integrates augmented sensory feedback to accelerate motor performance. Given the powerful flexibility and customizability of computerized interfaces, the effectiveness of VR rehabilitation lies in the more intelligent design of augmented sensory feedback.

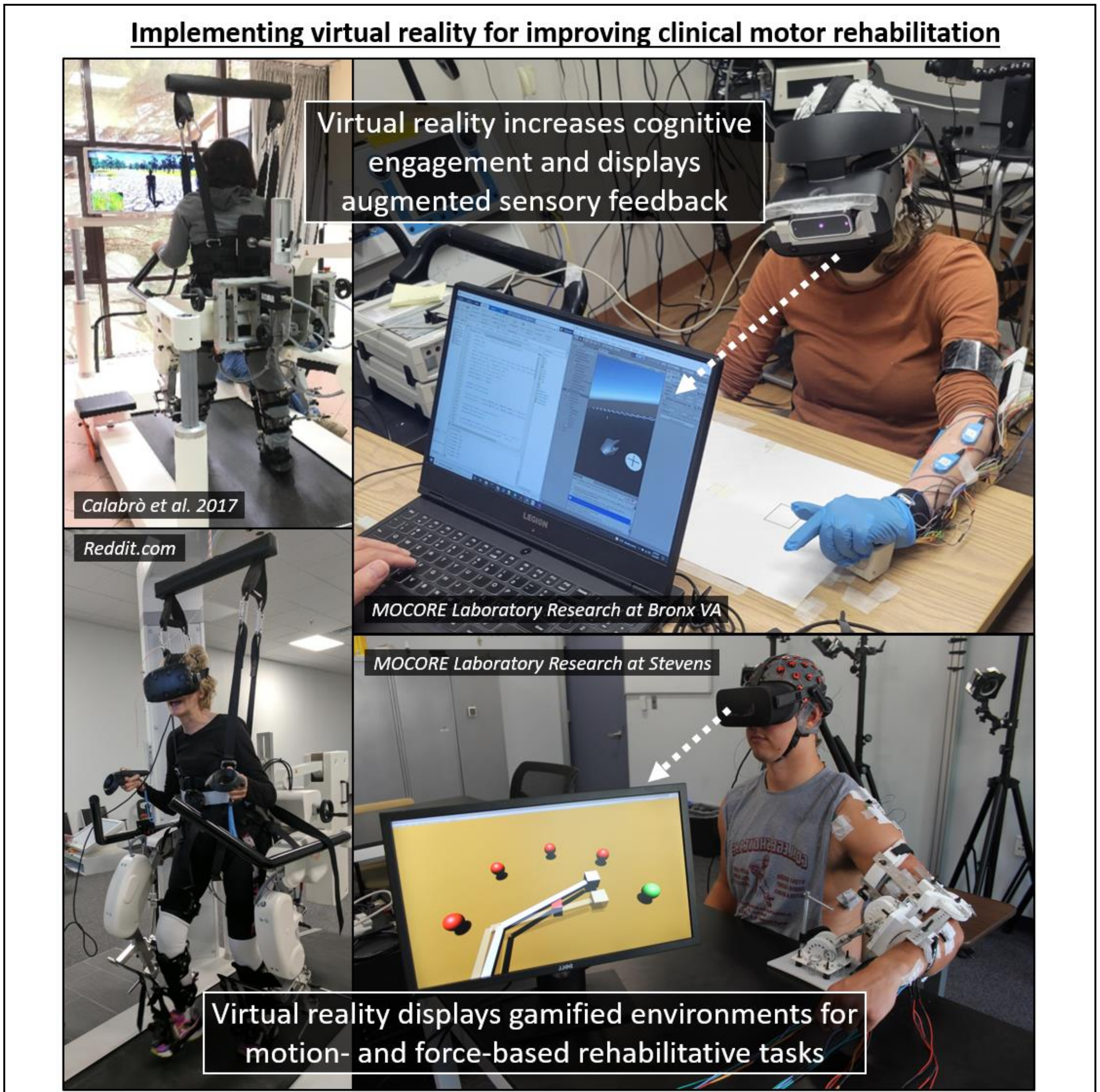

Figure 3: Virtual reality is used to increase cognitive engagement through gamified environments that display augmented sensory feedback for motor rehabilitative tasks.

When developing a VR-based rehabilitative task, the level of *immersion* and participant's perceived *sense of presence* might affect performance. Immersion is quantifiable and dependent upon the equipment used [46], and a participant's sense of presence is qualitative and defines the participant's perception of immersion in the VR environment [36]. Yao and Kim [36] describe it as, *"Immersion is a synchronicity of media, user, and contents where presence is only a human consciousness of being there."* Immersion ranges from low, moderate/medium, or high immersion, depending upon the technology used. Slater and Wilbur identified five categories to quantify immersion: inclusive, extensive, surround, vivid, and matching [47]. Each of the five categories influences but is not the sole determinant of the participant's perceptual experience. Miller et al. briefly described each category in an easy-to-read table format. They evaluated how immersion impacts the ability to assess and teach social skills in people with autism [46]. Highly immersive VR environments may increase strength and endurance [36], but more straightforward tools such as computer monitors may outperform head-mounted displays for simple tasks [16]. The participant's sense of presence versus technological complexity is often U-shaped, similar to the "uncanny valley" associated with the representation of human faces [49]. For example, a traditional computer interface with a monitor, speakers, keyboard, and mouse provides a greater sense of presence than a low-quality VR headset. Memory tasks do not directly improve by increasing the quality of 3D models in VR; however, increased sense of presence can improve memory task results [50]. Task-irrelevant immersive elements, such as extraneous objects, may detract from memory retention tasks if they distract from the desired stimulus [51]. These two principles imply including immersive elements into clinical motor rehabilitation has an unknown but ideal number that appears natural to the user but does not distract them from their assigned task. This number is likely different for individual users, making designing these VR environments difficult. *Fortunately, VR lends itself to enhanced forms of augmented* *sensory feedback and immersion for optimizing clinical motor rehabilitation at a participant-specific level.*

1.3. Augmented Sensory Feedback for Motor Training

Augmented sensory feedback provides visual, audio, or haptic cues to improve performance during functional tasks and accelerate motor learning [6]. Augmented feedback is a transformed display of the participants' performance, such as a bar graph representing grasp force or isometric muscle activity. Examples of VR-based augmented visual feedback are transparent target body positions that overlay a first-person perspective to guide spatial positioning [52]. The primary mechanism in any feedback modality is to provide information about participant performance either in real-time or immediately following task completion. Providing information about their performance allows them to make corrections or impose a self-competition element for improvement [41]. The optimal type of feedback to apply relies heavily on participant experience and the complexity of the task [53].

Compared to audio and haptic, augmented visual feedback is best for guiding spatial positioning [54], [55]. Audio and haptic feedback have advantages in unimodal situations, especially in simple tasks where visual feedback can be distracting. Audio feedback can cue the participant to start or stop an experiment and provide complex performance variables such as sonification error for standing or walking balance. Haptic feedback is a general term for anything related to touch sensation and can provide sonification of balance error through tactile actuators or vibration motors attached to the participant. Multimodal feedback, most commonly audio-visual or visuo-haptic, provides multiple sensory modalities as multiple sources of performance information and has been proven effective at accelerating motor learning in complex tasks.

Another term for sensory feedback is *biofeedback*, and it means providing biomechanics data back to the user to improve physical rehabilitation. Biofeedback has two primary types: biomechanical and physiological, each with three feedback categories [56]. Biomechanical data types include movement, postural control, and force utilizing motion capture and force plate systems. Physiological data types include neuromuscular, cardiovascular, and respiratory and use biological sensors to measure signals such as muscle activity or heart rate variability. Giggins et al. (2013) identified two strategies for providing feedback [56]: 1. Direct feedback, where the measured variable is explicit, such as heart rate variability directly from a watch, and 2. Transform feedback, where the measured variable maps to an audio, visual, or haptic feedback system. *The second strategy, transformed feedback of biomechanical data, is my focus and how to optimize the type of transform feedback to achieve the desired motor rehabilitation outcomes.*

1.3.1. Training versus Retention

Motor learning can be described as developing intrinsic mechanisms, such as muscle memory or proprioception, to repeat a movement independently. Physical rehabilitation has two distinct phases leveraged throughout any learning session, *training* and *retention*. The training phase is when augmented sensory feedback improves task performance by guiding the participant towards a desired movement trajectory or muscle activity pattern. The retention phase has no sensory feedback, forcing the participant to perform the task independently without movement support [3]. High performance during the training phase will induce the desired motor outcomes and benefits tasks of high complexity, such as full-body movements or controlling a myoelectric device. High performance during the retention phase indicates improvements in long-term learning and the development of independent movement strategies. Transfer tests can also evaluate retention. A transfer test is a different task presented during retention tests than during training to assess the transferability and generalizability of the benefits on non-practiced movements and muscle control [3]. It is important to note that high performance during training does not correlate to increased performance during retention; the opposite often occurs [57]. Optimizing VR rehabilitation paradigms depends on participant-specific needs to identify which phase of motor learning, training, or retention is most valuable. For example, a person learning to use an exoskeleton for the first time will benefit significantly from high performance during the training phase. As the person gains independence and moves towards at-home usage, value moves from the training phase to the retention phase of physical rehabilitation.

1.3.2. Theories of Motor Learning

Multiple motor learning theories and previous research have created a foundation for augmented sensory feedback-based motor rehabilitation. *The guidance hypothesis is a motor learning theory that indicates that higher reliance on feedback for assistance during training will negatively affect retention* [58]–[60]. When augmented sensory feedback is constantly provided during training or in a high frequency of trials, participants rely on the feedback for movement support. The ideal augmented sensory feedback would result in sustained performance in retention trials, indicating improved independence and muscle level control during training trials. The guidance hypothesis is traditionally evaluated over an extended period by altering the frequency of feedback as motor learning improves, including retention trials interspaced with training trials [58]–[60]. This theory is the basis for many other motor learning theories in that forcing participants to practice a movement on their own, and develop independent movement strategies, is beneficial for long-term learning.

The specificity of practice hypothesis suggests that *learning is specific to the source of afferent information that is more likely to ensure optimal accuracy* [61]. In other words, the task presented during training should closely resemble the desired motor or muscle control, and the feedback provided should be relevant to the task at hand. There are examples of presenting a different test during retention, known as transfer tests, to evaluate the transferability of functional outcomes. *High performance during training trials does not always coincide with high performance during retention; in fact, the opposite trend often occurs* [57]. Participants often believe that if they are performing well during training trials, they must be learning the best they can. It is crucial to ensure participants are constantly challenged during training to help accelerate the learning process. Additionally, having the participants perform a wide range of training exercises may be more advantageous than repeating the same task over numerous sessions. The review by Soderstrom and Bjork breaks down many examples of ways to structure rehabilitation paradigms to accelerate motor learning, including latent learning, distribution and variability of practice, and metacognition [57].

The participant's focus of attention during training can dramatically affect motor learning. Instructing participants to focus on an *extrinsic* part of the rehabilitative task will improve motor learning more than an *intrinsic* focus point [3]. An example is while learning to kick a soccer ball, should you focus on your leg and foot throughout the motion (intrinsic), or should you focus on the trajectory of the soccer ball (extrinsic)? An extrinsic focus typically outperforms an intrinsic one for improving motor learning. The participant's experience level will affect the optimal amount and frequency of augmented sensory feedback during training trials. *It is necessary to understand which stage of motor learning the participant is at or how much experience they have with the motor task*. Fitts and Posner introduced the three stages of motor learning in the 1960s: the Cognitive stage, the Associate stage, and the Autonomous stage [62]. During the first stage, the Cognitive stage, the participant would have little experience with the task, and errors to the target trajectory improve over a few short training sessions. Movements are slow, and considerable cognitive activity is required to control actions consciously. During the second stage, the associate stage, movements become more fluid, and less cognitive activity is required. During the final autonomous stage, movements become more consistent, and little to no cognitive activity is required. Improvements during the last two stages take much longer than the first stage.

Finally, there are distinct techniques for increasing cognitive engagement during motor rehabilitation [41]. Zimmerli et al. (2013) identified feedback elements for increasing engagement and motivation during robotic-assisted gait exercises. The first element is ensuring that participants can interact with their environment. Compared to walking on a treadmill without VR, participants integrated with a moving VR environment without external feedback cues were motivated to work harder. A second element is the introduction of real-time performance cues, which is the basis for augmented sensory feedback rehabilitation. By providing participants with an average gait velocity over time, researchers introduced an element of self-competition that significantly increased motivation and motor performance. Finally, they investigated the response to external competition as a virtual opponent. This final element was inconclusive as some participants enjoyed the external competition while others did not. Augmented sensory feedback that represented real-time participant performance significantly improved motivation and performance compared to the control group.

1.4. Features of Augmented Visual Feedback

Augmented visual feedback provides external cues during physical rehabilitation and is superior to audio and haptic feedback for guiding spatial positioning. *We have identified features of augmented visual feedback for guiding spatial positioning during motor tasks to optimize clinical rehabilitation.* In general, visual feedback helps produce consistent movement or muscle control for improving physical rehabilitation, such as improving isometric muscle control or helping restore natural gait [63]. Example gait improvements with visual feedback training include reducing joint moments [64], improving symmetry [65], increasing forward propulsion [66], and increasing stride length [67]. Improvements with visual feedback in assistive device training for various clinical populations range from wheelchairs [68] to prosthetics [31], [69]. There are many different modalities for providing visual feedback, including television screens [70], computer monitors [31], [66], signal lights [71], laser pointers [72, p. 2], and immersive virtual reality head-mounted displays [69], [73]. The optimal viewing modality can be influenced by the complexity of the task, as simple tasks often benefit more from simple feedback, and highly complex VR environments may be distracting or cognitively overloading. In VR, augmented visual feedback is the most exploitable sensory modality. VR introduced enhanced forms of augmented visual feedback, unable to be replicated in conventional therapy, such as complex avatars of one's position [52] or a target position represented as an instructor or virtual mirror [74]. Motion- and force-based motor tasks utilizing augmented visual feedback integrated with VR include guiding upper-arm position [75], [76], providing real-time muscle activity for controlling a prosthetic device [32], and training medical students on specific surgery practices [77]. Features of augmented visual feedback for guiding spatial positioning during motor tasks include 1) complexity (*simple* versus *complex*), 2) body representation (*abstract* versus *representative*), and 3) intermittency (*continuous* versus *bandwidth*) (**Figure 4**). These features are leveraged during VR-based rehabilitation to accelerate motor learning at a participant-specific level. One additional feature, *timing*, is defined in the following section and is a feature unique to augmented visual feedback already extensively researched in motor learning.

1.4.1. Timing (*concurrent* versus *terminal*)

Timing is a feature unique to augmented visual feedback that has already been extensively researched and directly means <u>when</u> to provide the feedback to the participant. *Concurrent* feedback is real-time information about performance, such as participant spatial position to match a desired movement trajectory, and helps the participant immediately reduce error to the target. *Terminal* feedback is provided after the exercise within a few seconds and includes information about the previous trial to help adjust for the next one [6]. Terminal

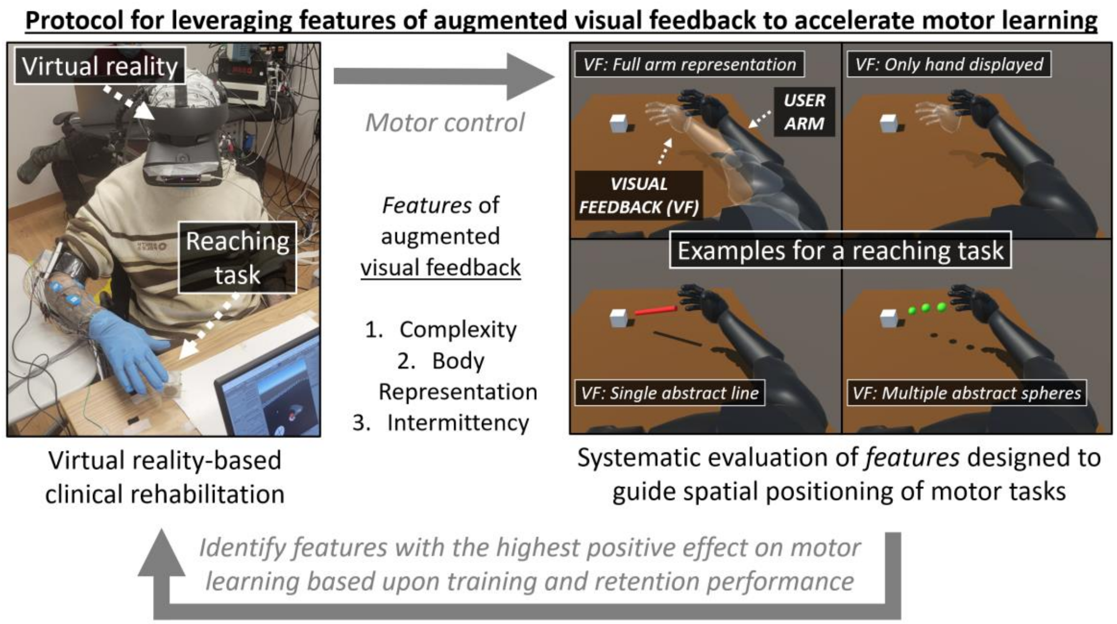

Figure 4: During training with augmented visual feedback to improve motor control, different features are evaluated for guiding spatial positioning to identify the optimal design to accelerate performance.

feedback has demonstrated comparatively better benefits in long-term retention [58], [59], but concurrent feedback generates more immediate performance improvements [78]. Concurrent feedback is most beneficial in the early stages of motor learning when the participant is inexperienced or naïve to the task, making significant adjustments and notable changes in performance [62]. Terminal feedback becomes beneficial in the latter stages of motor learning as the participant makes more minute changes and improves long-term learning [62]. Compared to terminal feedback, concurrent feedback can be ineffective for training simple tasks [53]. However, complex tasks such as multi-segmented movements benefit from concurrent feedback, especially in the early stages of motor learning [53], [62]. Concurrent feedback paradigms are most effective if they guide the learner toward an optimal movement while also reducing dependency on movement support [6]. Over-reliance on concurrent feedback degrades the development of intrinsic mechanisms [58], [60], which contribute to independent movement strategies. Terminal feedback aims to eliminate reliance on the feedback for movement support to reinforce the development of intrinsic mechanisms [55], [78], [79]. When developing clinical motor rehabilitation paradigms, the participant's experience and stage of motor learning will determine concurrent and terminal feedback. Some studies have found that combined concurrent and terminal feedback can be advantageous if still interspaced with retention trials [78]. *In my research, all augmented visual feedback was examined as concurrent feedback to investigate the real-time adaptation of motor performance and potential learning in short-term retention tests.*

1.4.2. Complexity (*simple* versus *complex*)

The first feature of augmented visual feedback we identified to leverage during motor rehabilitation is complexity and defines the <u>amount</u> of visual feedback provided. The complexity of visual feedback and the complexity of the motor task have similar definitions. Wulf and Shea (2002) defined simple tasks as capably learned in one session or are a single degree of freedom, while complex tasks have multiple degrees of freedom, require numerous training sessions to master, and are more ecologically valid [53]. Visual feedback complexity shifts from simple to complex as more targets are presented [6], [7]. *Simple* feedback provides a single DOF or variable about performance, and *complex* feedback provides two or more [7]. The optimal visual feedback complexity depends on the complexity of the task, i.e., overly complex feedback could be detrimental when training simple tasks.

Given their simplicity of function, simple visual feedback providing one performance variable is appropriate for one-dimensional or isometric tasks [6], [53]. Radhakrishnan et al. [80] found significant differences during a postural sway task for motion performance across different simple feedback types, utilizing visual and audio cues. Continuous feedback generated better endpoint precision but more significant movement intermittency than more discrete forms. Additionally, simple feedback can provide either spatial or temporal information. Different types (position versus temporal, mean versus variability) of simple feedback presented during training produce different performance and retention outcomes for the same motor task [81]. The spatial or temporal performance metric presented during training had the highest performance during retention tests. Complex feedback is advantageous for movements with high complexity when the information is relevant to the task but does not hinder performance by being overwhelming or providing too much information [73], [82]. For example, for training a complex dance movement, reduced feedback with only four variables about spatial position generated improved retention in performance compared to being trained with twelve [73]. This finding suggests complex feedback is beneficial if it only presents the most important features of motor performance and removes extraneous information.

Simple feedback is more appropriate for simple tasks as a singular focus target. The high focus on a distinct target may result in increased performance during training but may result in degraded development of intrinsic mechanisms [7]. On the other hand, complex feedback may cognitively overload or be ineffective during training if the participant finds the information irrelevant to the task. Complex feedback can be advantageous in real-time performance, providing more targets to guide multiple performance metrics. However, the body representation of the augmented visual feedback is crucial for allowing the participant to embody the feedback during training for improved results during retention tests.

1.4.3. Body Representation (*abstract* versus *representative*)

Another feature of visual feedback to be leveraged for motor rehabilitation is if the feedback displays body-discernible features. *Abstract* feedback displays training performance as line plots or bar graphs with no body-discernable features. In contrast, *representative* feedback—also known as natural—has apparent body-discernable features such as virtual avatars or mirrors of the participant's spatial position [6]–[8] (**Figure 5**). *There is a natural connection between simple-abstract and complex-representative feedback* [6].

Abstract feedback is considered best for simple tasks because of the simple nature of the feedback, typically a single line to trace or bar graph. For example, for EMG-driven prosthetic training, hand grasp force can be provided as a bar graph to train muscle level control [83]. Representative feedback is best for complex movement tasks [53], such as multi-joint movements that may appear disjointed when displayed as independent abstract lines [7]. In VR-based rehabilitation, complex-representative modes of augmented visual feedback help to train movement tasks [52] or simulate prosthetic devices in the virtual environment [84], [85]. During any whole-body movement, such as the gait or squat exercise, complex-representative visual feedback helps the participants embody the feedback display, leading to a greater development of multi-joint intrinsic mechanisms than abstract displays. After comparing combinations of augmented visual feedback features

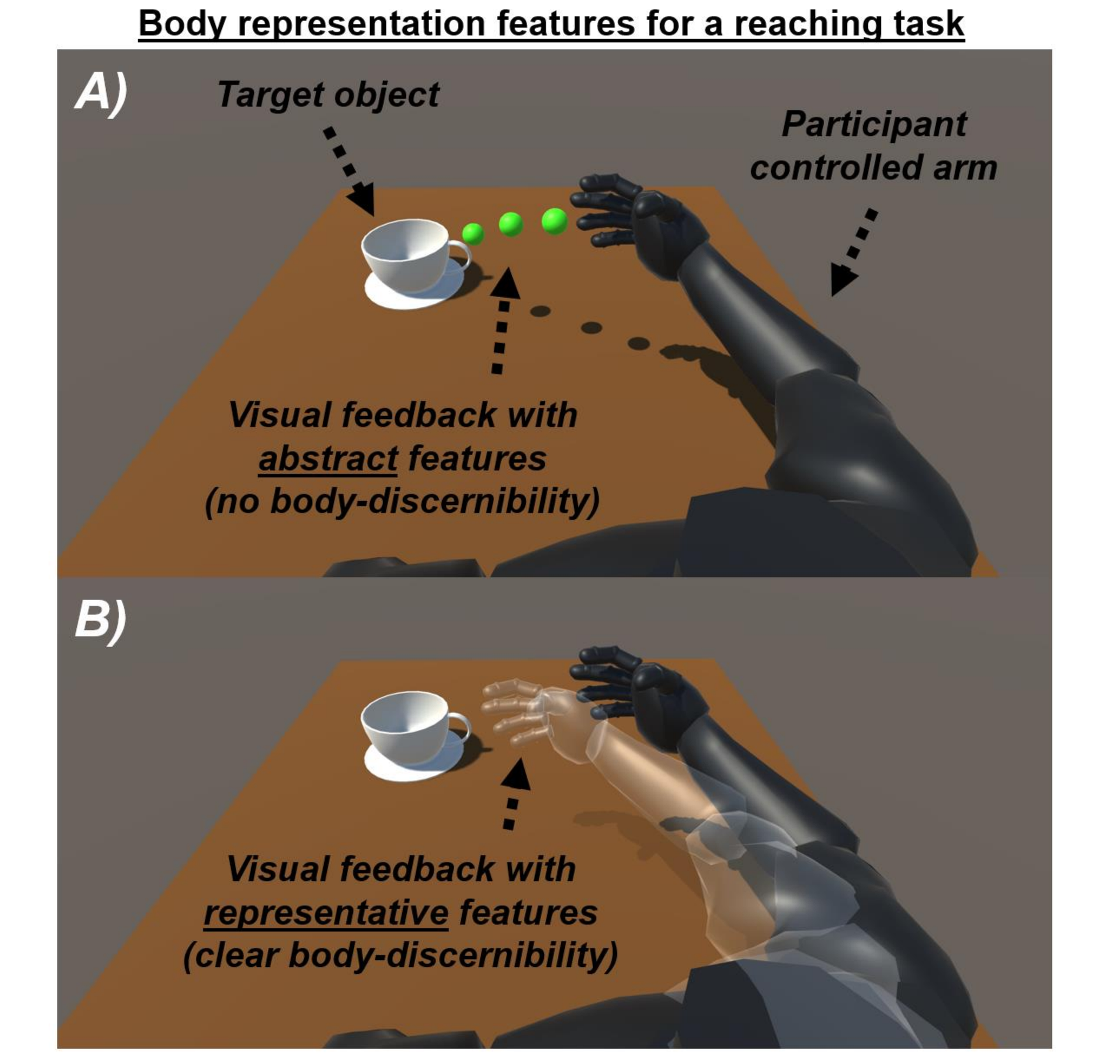

Figure 5: The augmented visual feedback feature of *body representation* is defined as either A) abstract or B) representative depending upon the body-discernibility of the target feedback. Abstract displays have no body-discernible elements while representative has clear body-discernibility. Different features provide different methods of guiding spatial positioning for motor tasks, i.e., reach-to-grasp.

(complexity and body representation) for the two-legged squat exercise in my thesis studies, complex-representative feedback demonstrated increased consistency in motion and muscle activity patterns [7].

Abstract feedback is appropriate during force-based motor exercises to maintain force control or muscle activity when representative feedback cannot relay the desired outcome measure. One disadvantage of complex-representative in augmented visual feedback is that it is only effective at guiding spatial positioning during movement exercises. Representative feedback would be ineffective for isometric or force-based tasks unless forces translate to virtual movements.

1.4.4. Intermittency (*continuous* versus *bandwidth*)

The final feature of augmented visual feedback during motor rehabilitation depends on the frequency of visual feedback provided during training. *Continuous* feedback involves constant, uninterrupted presentation of an individual's performed actions against desired targets throughout the movement task [86]–[88]. The classic approach to accelerate motor learning, presented earlier as the *guidance hypothesis*, is to effectively reduce the frequency of terminal feedback trials by interjecting additional retention trials [58], [89]. Theoretically, reducing the frequency of feedback trials promotes the development of independent movement strategies and improved intrinsic mechanisms [58], [59]. Reduced frequency of feedback methods to accelerate motor learning are faded [81], self-selected [90]–[93], and bandwidth [82], [94], [95]. Bandwidth feedback is the only reduced frequency paradigm developed for concurrent feedback.

Bandwidth feedback is the intermittent presentation of visual cues based on a performance criterion, such as movement error to a target trajectory. During bandwidth feedback, feedback is not displayed in times of low error but only when the error exceeds a performance threshold. These 'bands,' positive and negative error to a target trajectory, aim to stabilize performance at certain error levels (e.g., 5%, 10%, or 15% of maximum error) [96], [97]. The working principle with bandwidth feedback for long-term learning is to reduce reliance on the feedback as performance improves progressively. Typically, bandwidth feedback uses terminal feedback [82], [94], [95], [97]–[99]. Relatively fewer studies have investigated performance with concurrent bandwidth feedback. Examples include an isometric force task [87], a driving simulator [100], and the two-legged squat exercise [8]. For a single joint isometric force task, concurrent bandwidth feedback generated higher variability but higher regularity to a force target than continuous feedback [87]. They postulated that bandwidth feedback induced greater reliance on intrinsic mechanisms that produced lower approximate entropy. Concurrent bandwidth feedback showed more significant learning potential for the two-legged squat than continuous feedback [8]. Although the effects of concurrent bandwidth feedback on long-term motor learning have been under-researched, there is potential to improve short-term retention with implications for long-term regularity [87].

Continuous feedback is most advantageous in the early stages of motor learning until the participant begins to gain experience. Once they understand the motor task and desired outcomes, it is beneficial to transition to concurrent bandwidth feedback and terminal bandwidth to reduce reliance on the feedback for movement support gradually. Continuous feedback is best for increasing real-time performance, while bandwidth feedback shows potential for improving retention [8].

Other forms of augmented sensory feedback, including audio and haptic, effectively improve motor performance. Augmented haptic feedback as vibration can provide therapeutic benefits to neuro-deficit populations by recruiting additional muscle fibers [101] or positively affecting proprioception during motor rehabilitation [102]. Haptic feedback also enhances integration and immersion during VR-based rehabilitation [83], [103], [104]. Augmented multimodal feedback, combinations of visual and vibration, effectively improves motor performance and provides therapeutic benefits during complex motor rehabilitative tasks [6], [105].

1.5. Potential of Multimodal Feedback

Note from Author: "For a good part of my Ph.D. journey, I investigated vibration – or vibrotactile – feedback to create novel augmented multimodal (visual + haptic) feedback paradigms for improving task performance. Due to unforeseen circumstances, including and not limited to COVID, I decided to focus more of my time on visual feedback within virtual reality to ensure the quality of the work was high instead of trying to spread myself thin with a fully-fledged haptic feedback project. However, I did a lot of research and several pilot experiments (see Appendix) into the advantages of utilizing augmented haptic feedback, both in unimodal and multimodal paradigms." – Sean Sanford

Augmented haptic feedback is a broad term that encompasses any modality related to touch sensation [6]. Examples of haptic feedback include changes in applied forces, pressure, vibration, or temperature to relay information about the environment to the user. During physical rehabilitation, one example of haptic feedback is providing vibration repulsion or attraction to guide the participant towards the target movement trajectory [106]. Mapping haptic feedback magnitude, such as vibration magnitude, to position error provides additional levels of complexity and information about performance [107], [108].

In more complex scenarios such as utilizing an EMG-controlled assistive device, providing real-time haptic feedback mapped to hand force feedback results in greater user-device integration and improved task performance [83], [103]. This phenomenon can be described as sensory substitution and helps amputees or people with neurological trauma discern magnitude changes in device force control or proprioceptive movement error [109], [110].

A common form of augmented haptic feedback is applied forces or modulating the effort required by the participant (i.e., sensitivity). In a simple analogy, adding weight during strength training would add additional "forces" to affect motor rehabilitation. Another example of applied forces in motor learning is the effects of perturbations during gait, balance, or reaching studies. Two types are real perturbations, such as being pushed or pulled during gait or balance training, or visual perturbations applied in a VR environment to evaluate reaction time or internal movement models [111], [112]. Another example of applied forces includes modulating the sensitivity of a joystick commonly used in upper extremity motor rehabilitation or computerized interfaces for gaming [113].

A second augmented haptic feedback modality is vibration. Vibration is applied through an external device, such as a handle or standing platform, or vibration motors attached directly to the person's skin. Traditionally, vibration can produce unwarranted or adverse effects, such as the long-term usage of jackhammers by construction workers. Recently, researchers have been exploring vibration in more controlled environments to provide therapeutic benefits. Vibration feedback – also known as vibrotactile feedback – can be described as *explicit* or *implicit* depending upon its connection to task performance. Vibration is explicit if the cues are directly related to task performance or the participant focuses on utilizing the vibration to complete the task. Vibration cues range from velocity or position-dependent for upper extremity tasks by mapping error magnitude to vibration magnitude [114]. Another example of explicit haptic feedback includes mapping vibration magnitude to error magnitude during standing balance [115]. Multiple vibration motors can cue direction relative to a target trajectory [108]. One disadvantage of explicit augmented haptic feedback in conjunction with visual feedback is the possibility of cognitive overload, especially when tasks can be deemed simple enough to be mastered with visual feedback alone [108].

Implicit vibrotactile feedback is not directly coupled to task performance and can alter a participant's muscle activity or produce an illusory movement [101], [102]. These effects are unique to vibrotactile feedback because of the ability to affect afferent signal pathways and induce muscle stretch reflexes. The first implicit form of vibration includes whole-body vibration [116], [117]. It is common to the earlier jackhammer analogy as whole-body vibration can be detrimental if exposed for an extended duration. In recent years, researchers have been examining the therapeutic effects of vibration on muscle activity training. During isometric exercises, applying vibration universally increases EMG activity in both agonist and antagonist muscles [118]. For example, indirect vibration through an external device at the hands or feet may increase the EMG response during isometric exercises by recruiting additional muscle fibers [101], [119]. Factors such as vibration frequency, amplitude, and target force magnitude dramatically influence the subsequent effects on EMG activity compared to control groups without vibration [101]. Vibration also increases fatigue, believed to be due to the recruitment of additional motor units. Muscle fatigue is identified through frequency-domain analyses of the EMG activity by examining the mean or median frequencies [120].

The second form of implicit vibration alters user proprioception by applying direct vibration at the muscle-tendon junction. Direct muscle-tendon vibration may lead to an illusory movement effect in the direction of muscle stretch [102], such as a sensation of elbow extension during vibration on the proximal or distal bicep tendons. Unlike whole-body vibration, creating an illusory movement requires lower vibration frequencies to induce the desired effect and is more successful with Linear Resonant Actuators (LRAs). LRAs are vibration motors that act more like a ‘piston’ and require much more complex devices to control the various parameters (magnitude, amplitude, frequency). Eccentric Rotating Mass motors, often seen as small coin motors, are not as effective at inducing an illusory movement effect but can be utilized for other forms of augmented haptic feedback. Integrating VR with implicit vibration has been shown to amplify the observed illusory movement effect and shows potential for more effective therapy in people with severe sensory dysfunction [121].

Another unique form of augmented haptic feedback is electric stimulation, either to the muscle, nerve, spine, or brain levels [122]. Electrical stimulation can help to reduce neuropathic pain, reduce spasms, and reduce muscle atrophy in people suffering from neurological trauma. For example, functional electrical stimulation applied directly to the muscle mid-belly on the skin surface can be therapeutic following neurological trauma. Stimulating the muscles, whether involuntarily or voluntarily controlled, can increase blood flow and promote neuroplasticity during motor rehabilitation [123]. Stimulation applied in conjunction with motor rehabilitation tasks can assist participants in completing the movements when they may be unable to do them independently, such as ankle dorsiflexion for gait or hand function for reach to grasp. Combining one or more modes of augmented sensory feedback to create unique multimodal–also known as multi-sensory–feedback applications has shown promise in accelerating motor learning and improving motor performance [6].

Multimodal feedback increases the required attention during training, an advantage being high performance, but would be detrimental to developing long-term learning effects due to less reliance on intrinsic mechanisms. Multimodal feedback, such as audio-visual or visuo-haptic, can increase performance beyond unimodal sensory feedback [105]. The combinations of audio and visual (audio-visual) or haptic and visual (visuo-haptic) are more common than audio and haptic because of the required focus to use each sensory modality effectively. Augmented audio and haptic feedback can be considered less distractive and require less attention during movement tasks than visual feedback. A limitation of multimodal feedback is ensuring no cognitive overload that may prove detrimental to the participant.

Several experiments have investigated the positive benefits of integrating augmented haptic feedback with visual feedback and VR to improve motor rehabilitation. The most straightforward example of incorporating haptics into VR-based rehabilitation is the addition of applied pressures or vibration to improve motor performance or increase user-device integration. By providing vibration magnitude mapped to force magnitude on the nearby residual limb or another intuitive location, users can modulate low, medium, and high forces within a VR environment to significantly improve myoelectric device function [83]. Additionally, augmented vibrotactile and visual feedback guided upper-limb movements [108]. Compared to visual alone, vibration only benefitted simple, 1-degree-of-freedom (DOF) movements. The addition of augmented vibrotactile feedback did not benefit the training of complex (2+ DOFs) movements. During upper-arm robotic therapy, Scotto di Luzio et al. (2020) evaluated vibrotactile and visual feedback on improving posture [124]. Participants completed a robot-aided upper-extremity movement task to reach a target displayed in the virtual environment. Their results indicated that both feedback methods effectively improved head and neck angles compared to the control group and are valid solutions for real-time posture assessment.

In some cases, augmented haptic feedback did not help improve the performance of upper-extremity tasks or was detrimental when combined with visual feedback. The ineffectiveness is possibly due to the complexity of the task evaluated and the participant's experience. When tasks are considered simple or the participant is inexperienced, the proposed benefit of multimodal feedback could result in cognitive overload. Hasson and Manczurowsky (2015) determined that vibration did not improve an upper-extremity task's skill acquisition when presented independently or with visual feedback [114]. The task they evaluated was a simple, 1-DOF movement in which participants controlled the swing of a virtual myoelectric prosthetic arm. Their results concluded that augmented vibrotactile feedback could be detrimental as some participants may have had difficulty integrating the haptic information with the virtual component. I believe a more complex task with multiple

DOFs may demonstrate opposite results where augmented haptic feedback could be beneficial when combined with visual feedback.

Implicit types of vibrotactile feedback, as mentioned before, are not directly coupled to task performance. Physiological effects of vibration, including altering EMG signals or producing an illusory movement effect, can have therapeutic benefits in VR-based rehabilitation. A therapeutic effect of implicit haptic feedback, in any form, combined with visual feedback and VR, is the reported reduction in neuropathic pain and improved neuroplasticity, similar to 'mirror therapy.' Compared to traditional therapy, Saleh et al. (2017) reported greater cortical reorganization and greater improvement in clinical measures of post-stroke participants following a novel robotic-assisted upper-extremity VR task [125]. Bassolino et al. (2018) created a novel brain-computer interface for inducing embodiment and an illusory movement within a VR environment to observe user-controlled mirror therapy [126]. They utilized a unique form of haptic feedback by combining transcranial magnetic stimulation (TMS) with VR to create a TMS-evoked mirror therapy effect. Two studies, Pozeg et al. (2017) and Le Frank et al. (2020), utilized VR to enhance the illusory movement effect and therapeutic benefits induced by augmented vibrotactile feedback. Pozeg et al. (2017) determined that vibrotactile feedback reduced neuropathic pain in SCI participants and improved embodiment within the virtual environment [42]. Le Frank et al. (2020) found that VR enhanced the illusory movement effect of tendon vibration in healthy participants [127]. Combining augmented haptic feedback with visual feedback through VR can enhance the desired outcome measures such as improved motor performance, enhanced immersion or integration, more therapeutic benefits such as reducing neuropathic pain, or improving virtual embodiment.

2. SPECIFIC AIMS

I have identified a lack of optimization in the deployment between clinical rehabilitation and computerized interfaces, emphasizing improving motor performance. The overarching objective of my dissertation is to systematically leverage augmented visual feedback in VR to identify features that accelerate positive motor performance. Augmented visual feedback guides spatial positioning during motion- and force-based tasks to improve motor performance. Each augmented visual feedback has unique combinations of visual feedback features, including complexity, body representation, and intermittency. Changes in motor performance, including motion and muscle activity consistency, will be the primary outcome measure with additional supplementary results as measurable changes in neurophysiological signals. Finally, because of a natural connection in motor learning between features of complexity and body representation (i.e., simple-abstract and complex-representative), my focus is on evaluating the two features of complexity and intermittency for improving performance during motion- and force-based motor tasks.

<u>AIM 1</u>: *Investigate the effects of specific features (complexity and intermittency) in augmented visual guidance during training on the performance of a <u>motion-based</u> rehabilitation task.* I examined combinations of augmented visual feedback with features of complexity and intermittency for a motion-based task (two-legged squat) highly prevalent in clinical rehabilitation. During training, participants received concurrent visual feedback of their segmental (torso, thigh, shank) motions in the sagittal plane. I evaluated the effects of visual feedback features provided during training based on performance improvements found immediately after training (i.e., short-term retention). Greater feedback complexity required participants to process more visual information (i.e., feedback about additional segments). I investigated intermittency through augmented visual feedback provided continuously or periodically based on bandwidth thresholds (i.e., below a specified threshold).

AIM 2: *Investigate the effects of specific features (complexity and intermittency) in augmented visual guidance during training on the performance of a force-based rehabilitation task.* Our lab created a novel computerized (virtual reality) platform for rehabilitating upper-extremity muscle function to pursue this aim. The platform utilized a position-adjustable brace to provide gravity support and facilitate isometric training at varied muscle lengths for persons with severe motor impairment (e.g., spinal cord injury). Participants exerted muscular efforts within the brace to generate patterns of muscular activity classified as myoelectric commands for controlling virtual avatars (e.g., robot arm performing reach-to-touch tasks). The task was inherently force-based since the brace provided resistance to motion which served to amplify myoelectric signals. These muscle-based signals subsequently drove a virtual robot arm performing reach-to-touch tasks, from which to train muscle strength and coordination. Augmented visual feedback was in the form of a semi-transparent guide avatar that indicated the optimal (shortest) path lengths to reach targets. Variations in complexity and intermittency were applied during training.

We hypothesized that feedback complexity would improve post-training performance for both Aims if guidance includes body-level representations (i.e., complex-representative feedback). We also hypothesized that bandwidth feedback would improve post-training performance by reducing the reliance on the augmented feedback to promote intrinsic mechanisms for either motion- or force-based motor tasks.

3. PRIMARY METHODOLOGIES

Electromyography (EMG) records electrical activity in muscles during force-generating contractions. EMG can be collected in real-time during motor rehabilitation to determine the workload of individual muscles. Sensors placed on the muscle mid-belly, in alignment with the muscle fibers, measure the voltage difference from two different skin surface contact points. The frequency of action potentials traveling across multiple muscle motor units changes the time-varying amplitude of the raw EMG signal captured. Each motor unit consists of a single motor neuron and all muscle fibers it innervates. EMG recordings are highly susceptible to variance (noise) in signal strength due to cross-talk across the muscle structure, sensitivity to insecure electrode placement, and movement artifacts. Other major factors include muscle size and the amount of subcutaneous tissue under the skin surface. EMG signals are normalized across participants based upon recordings taken during maximum voluntary isometric contractions (MVICs). MVICs are individual trials with specific exercises for different muscles to extract a 100% EMG reading. Sensor locations and MVIC protocols are described in the ABCs of EMG [128].

The following are steps for filtering EMG data to determine individual bursts used for controlling a myoelectric device (**Figure 6**):

1. The raw signal is the difference in voltage across two electrodes.
2. Rectification takes the absolute value of the signal, making all values positive.
3. EMG must be sampled at least twice the highest frequency of interest to avoid signal aliasing, typically at least 1000 Hz. Applying a band-pass filter, around 10-500 Hz, removes baseline drift associated with movement artifact or user perspiration and

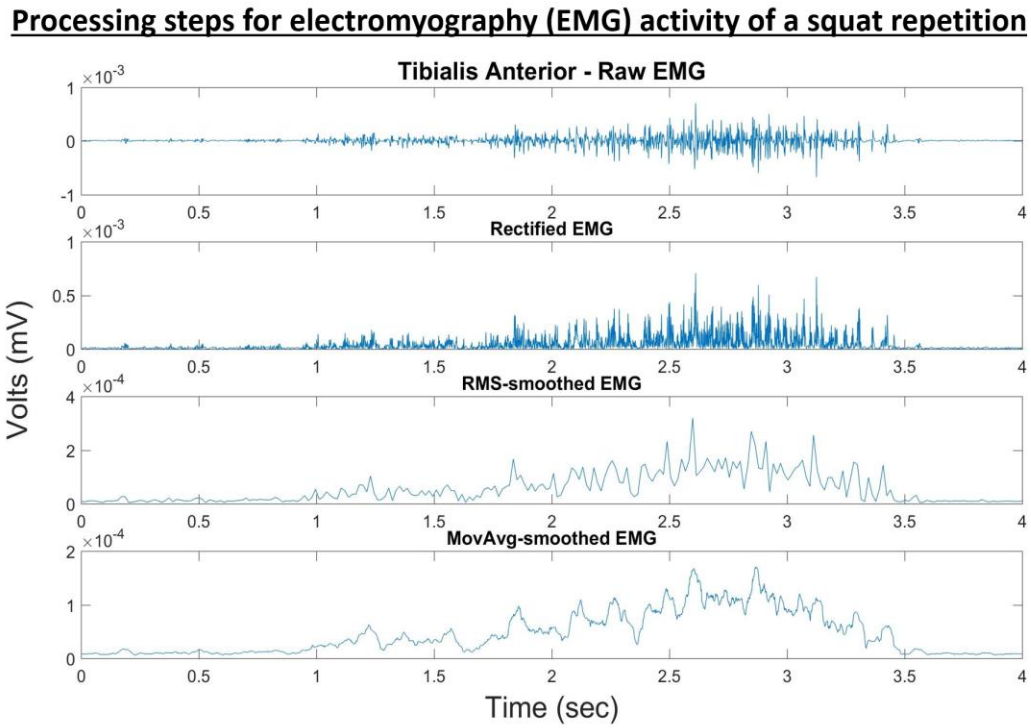

Figure 6: Sequential processing steps of tibialis anterior EMG activity during a single repetition of the two-legged squat exercise over a 4-second period. The raw EMG is the data collected directly from the EMG sensor. The rectified EMG is the absolute value of the raw EMG data. The root mean squared (RMS) and moving average (MovAvg) filters smooth the curve of data for easier analysis and integration to myoelectric devices.

preserves only the expected range of firing frequencies from the muscle. A notch filter at 60 Hz mitigates noise from power sources.

4. Some smoothing of the EMG signal occurs with the low-pass effects of the bandpass filter. Additional smoothing filters (root mean square, moving average) produce signals appropriate for simple on/off timings of bursts of muscle activity or create a robust (i.e., indicates clear intent and amplitude of effort) command signal for device operation.

Electroencephalography (EEG) measures brain activity through sensors attached to a scalp cap and placed on the participant's head, typically with electrode gel to reduce impedance. EEG offline measured cognitive loading, specifically the alpha- (α) and beta-

(β) band power in the primary motor and sensory cortexes. Changes in alpha and beta band power may indicate changes to potential motor learning [62] and the participant's ability to focus on external objects during VR rehabilitation [129]. A greater external focus of attention during rehabilitation helps to improve motor learning compared to an internal point of focus [3]. EEG data did not control elements of the VR environment. However, brain-computer interfaces show promising results for neurorehabilitation [4]. EEG can be utilized in brain-computer interfaces to introduce an element of user-control for increasing neuroplasticity [130].

Motion capture is the process of recording the movements of people and objects. Retroreflective markers are used in conjunction with infrared cameras that emit and receive light for tracking marker position. Markers are placed on anatomical landmarks to recreate marker-based skeletons preprogrammed into the motion capture software. Additionally, markers can be placed on foam boards to create *rigid bodies* for real-time streaming of body segments. Motion capture is used in real-world applications such as movies and video games. Motion capture helps train correct spatial positioning during motion-based tasks. Participant kinematic data can also be used for computational modeling to analyze internal body mechanics.

Machine learning is a computational intelligence technique that predicts *outputs*, such as future movement states, based on a pattern of *inputs*, such as EMG signals indicating real-time user intent [131]. During training with an assistive myoelectric device, users learn to produce machine-predictable muscle activation patterns and develop long-term retention for daily use [31]. Machine learning algorithms are evaluated by classification accuracy, accurately predicting desired outputs from new, untrained input data, and resulting performance during functional tasks [132]–[134]. Classical approaches for EMG-controlled devices use the following machine learning algorithms: support vector machine (SVM), linear discriminant analysis (LDA), or artificial neural network (ANN) [135], [136]. Support vector machines are supervised learning models that identify a unique solution using linear or non-linear functions. An optimal separation hyperplane is identified that aims to separate the classes by the maximum distance. LDAs can be used for real-time applications, although they are more effective for off-line analyzes due to their fast computational times. LDAs work by utilizing the entire data set and calculating the means between classes to reduce the dimensionality by a linear function. For real-time applications using EMG controllers, SVM has proven more effective compared to LDA [137]–[139], especially for dynamic tasks [140]. An artificial neural network is a multilayer intelligence system for predicting outputs from inputs based on a series of linear transformations (multiplications, additions) before applying a non-linear transfer function (e.g., step function). Weights and biases are parameter values for the multiplication and addition operations applied to individual input signals before summation at a network node. This architecture is analogous to multiple synaptic inputs to a particular neuron. During the training of any machine-learning algorithm, parameter values adapt to better match the algorithm outputs to actual outputs observed from an experiment. If properly trained, the algorithm should effectively predict outputs based on new inputs on which it was not previously trained.

Feature extractions are digital signal processing methods to identify and extract features for further analysis or a more accurate representation of the signal for machine learning processes [20]. Beyond filtering a signal, such as applying a notch filter to EMG data to remove noise from the power supply, feature extraction methods can help restructure data in a format more easily separated into distinct classes during classification. Feature extraction methods are either time-domain, frequency-domain, or time-frequency-domain. Time-domain features such as root mean square or moving average filters (**Figure 6**) are commonly used in real-time EMG applications to help smooth out the raw data for easier interpretation. Frequency-domain feature extractions are used for offline analyzes of EMG data. Examples include calculating the mean or median frequency changes of EMG signals to measure muscle fatigue. Comparatively, there are much fewer time-frequency-domain features than time-domain or frequency-domain. Although a major problem with the time-frequency domain is the high dimensionality of data sets, the results suggest possible improvement over time-domain features for complex EMG-control set-ups [20]. Reducing the dimensionality of the data set, such as through an LDA, also helps to convert complex data sets into fewer dimensions for easier computational requirements and allows for simpler classification models. Another example of reducing dimensionality is principal component analysis, which identifies trends in the data set [141]. The objective is to interpret the original data set, with high dimensions, as a new data set with fewer signals or dimensions that still represent most of the original data trends.

4. AIM 1: MOTION-BASED TASK

4.1. Introduction

The two-legged squat is a physical rehabilitation exercise clinically correlated to the sit-to-stand movement [142]. The squat exercise is commonly prescribed following neuromuscular or orthopedic trauma [143]–[145]. The motion-based task was a desirable platform for this research about augmented visual feedback because it is a multi-joint movement with a single modulation variable, squat depth. Squat technique, such as squat depth, highly influences muscle activations [146]–[148] and can be regulated through visual feedback [72], [149], [150]. Concurrent visual feedback can display squat depth [71], reduce hip and knee internal rotation [72], and increase movement symmetry during sit-to-stand [70].

This study evaluated the effects of various features of visual feedback, *complexity*, *body representation*, and *intermittency* for training motion and muscle activity consistency. Six unique concurrent visual feedback modes guided the thigh angle's real-time spatial positioning, and in some feedback modes, additionally the shank and torso segments. Four unique combinations of complexity and body representation were designed for continuous feedback (simple-abstract, simple-representative, complex-abstract, complex-representative). Only two bandwidth visual feedback modes were designed to evaluate the natural connections between simple-abstract and complex-representative. The objective was to identify differences in training and short-term retention performance, evaluated in retention trials performed immediately following training of each visual feedback mode.

4.2. Subject Recruitment

Eighteen neurotypical participants signed an informed consent approved by the local Institutional Review Board and were recruited from a University campus through printed flyers and word-of-mouth *(Twelve Males: 179 ± 5.0 cm in height, 163 ± 17.5 lbs in weight, 20.4 ± 0.9 years in age. Six Females: 166 ± 5.1 cm in height, 136 ± 16.7 lbs in weight, 19.7 ± 1.1 years in age)*. Varsity athletes were not recruited due to their experience with the squat exercise. All subjects were considered non-athletes or played a club sport and reported minimal to no weekly exercise with the squat maneuver. Individuals were excluded from this experiment if they reported the following: 1. Previous surgery to any lower extremity or of the spine/neck. 2. Chronic pain of any lower extremity or the back/neck within the last three months. 3. A musculoskeletal or neurological disease affecting normal gait function. 4. Sub-normal hearing or vision that is not correctable. 5. Any cardiovascular issues that make squat exercises difficult. 6. Inability to regularly squat to the maximum squat depth of 70 degrees.

4.3. Study Design

Each participant completed a single training session that incorporated two phases for the six augmented visual feedback modes, a *training* phase immediately followed by a short-term *retention* phase. During the training phase, ten trials of concurrent visual feedback guided thigh angle position at a unique target depth for the squat exercise. Concurrent visual feedback guided the motion of a 4-second squat cycle, which started and stopped at the erect standing position. The target movement trajectory for each body segment, shank, thigh, and torso, were symmetric sinusoids, representing angular positions, with the maximum squat depth at 2 seconds. Participants were instructed to minimize spatial positioning error to all visual targets presented during training trials. Immediately following the training phase, a retention phase began of ten retention trials without visual feedback support. Participants independently reproduced the movements to measure the training effects on short-term retention. The primary outcomes measures for the effects of visual feedback were the ability to increase accuracy (mean) and consistency (standard deviation) of motion and muscle activity performance across each phase.

4.4. Experimental Protocol

Upon entry, participants first self-selected the positions of both feet for subsequent squatting trials and tape outlined each foot position for consistent replacement of the feet. Next, participants were encouraged to stretch and warm up before EMG sensors and motion capture markers were attached. Before completing any squat trials, MVICs were collected for all muscle groups. A television was positioned five feet in front of the participant and placed approximately eye-level at an erect stance. Participants completed twenty trials for each augmented visual feedback mode consisting of a single squat repetition, a block of ten training trials with concurrent visual feedback followed by ten short-term retention trials (**Figure 7**). A 2-second countdown clock preceded the participants completing the 4-second squat movement for each training trial. Participants had a 6-second window to complete the squat at their discretion after a visual ‘start’ cue for each retention trial. There was a 4-second break after each training and retention trial. A 5-minute break separated each visual feedback mode to minimize fatigue and mitigate

Experimental protocol and trial blocking for the two-legged squat task

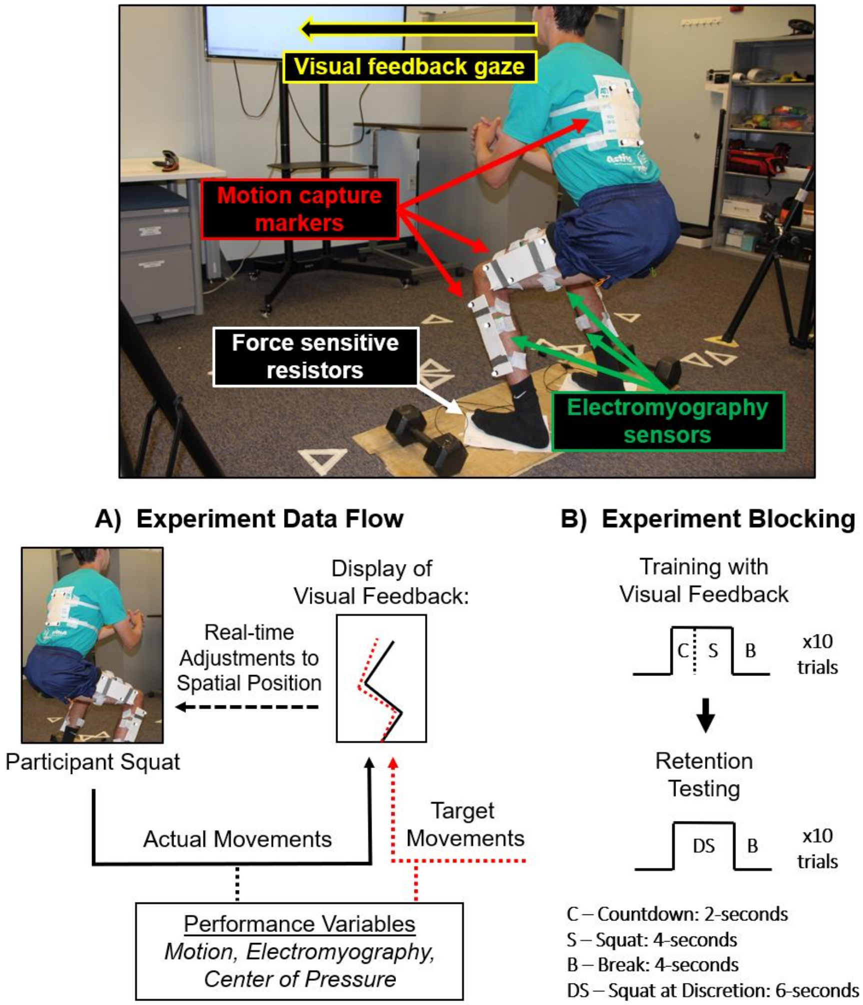

Figure 7: *Experimental set-up.* TOP) Retroreflective markers were used for motion capture analysis, electromyography sensors and force sensitive resistors measured muscle activity and center of pressure, respectively. BOTTOM-A) Participant and target movements were presented in real-time for adjusting spatial positioning. BOTTOM-B) For each visual feedback mode, participants completed ten training trials with visual feedback immediately followed by ten retention trials.

any overall learning effect across the session. The order of visual feedback modes was randomized for each participant.

4.5. Visual Feedback Modes

I developed six visual feedback modes with combinations of visual feedback complexity, body representation, and intermittency. The six visual feedback modes are: 1) Continuous-Complex-Representative, 2) Continuous-Complex-Abstract, 3) Continuous-Simple-Representative, 4) Continuous-Simple-Abstract, 5) Bandwidth-Complex-Representative, and 6) Bandwidth-Simple-Abstract. Continuous modes constantly displayed both the participants' position and the target position (**Figure 8**). The transparency or color of these visual cues never changed. Both the participant and target position visual cues gradually changed transparency during bandwidth modes based upon error to the target trajectory (**Figure 9**). The threshold for the feedback to begin appearing was set as +/- 5% of the maximum segment angle. Only two modes were presented with bandwidth feedback, complex-representative and simple-abstract, as these combinations are naturally coupled [6]. Simple and complex modes differed by the number of visual cues displayed. The cues represented body segment angles and were all independently controlled. Only the participant and target thigh angle positions were displayed during simple modes. The thigh position is most indicative of squat depth, and squat depth was the most influential parameter for altering muscle activity and internal joint and muscle forces. Complex modes presented three different participant-controlled variables and three target trajectories, the shank, thigh, and torso segments. Due to the squat being a closed-chain task, presenting real-time information on the shank and torso segments may benefit full-body movement control. Lastly, abstract modes of visual feedback presented sinusoidal targets with the participant trajectory traveling across the screen from left to right. The representative

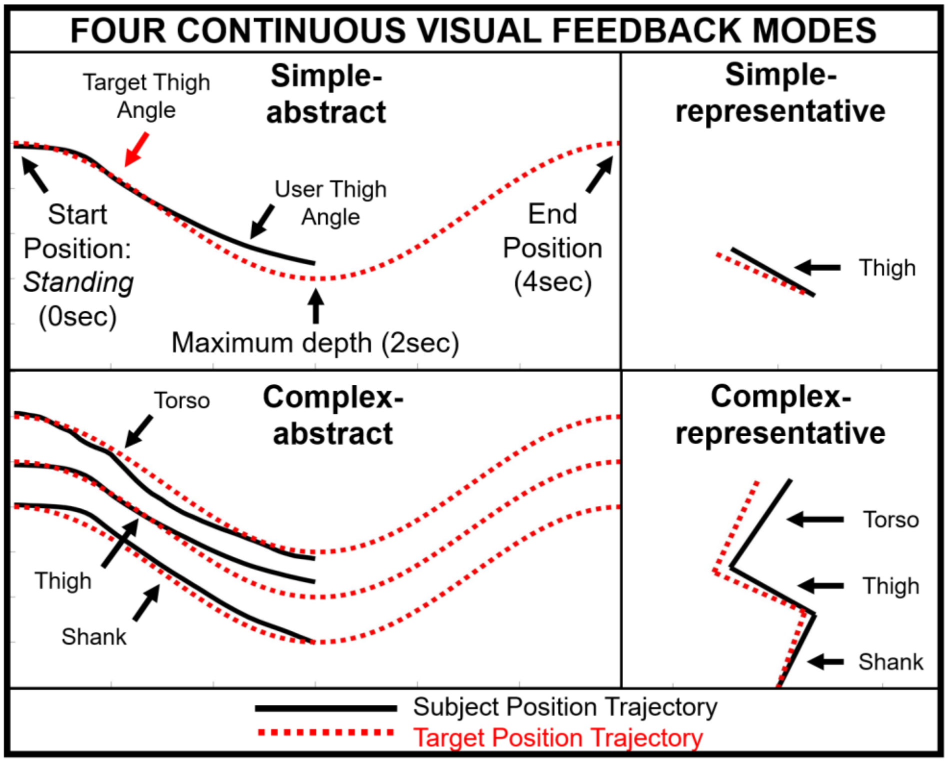

Figure 8: During each of the four continuous feedback modes, participant and target positioned were constantly displayed throughout the entire trial. Differences amongst feedback modes were based upon features of complexity and body representation.

modes displayed 2D line segments representing body segments connected at presumed joint locations in the sagittal plane. The participant followed the feedback as it squatted down and up to return to a standing position.

Due to each participant completing a single training session with all six visual feedback modes, the squat depths for each visual feedback mode were varied. The maximum squat depth represented as the maximum thigh angle were as follows: 1) 50° - Continuous-Simple-Representative, 2) 54° - Continuous-Simple-Abstract, 3) 58° - Continuous-Complex-Abstract, 4) 62° - Bandwidth-Simple-Abstract, 5) 66° - Bandwidth-Complex-Representative, and 6) 70° - Continuous-Complex-Representative. Varying the

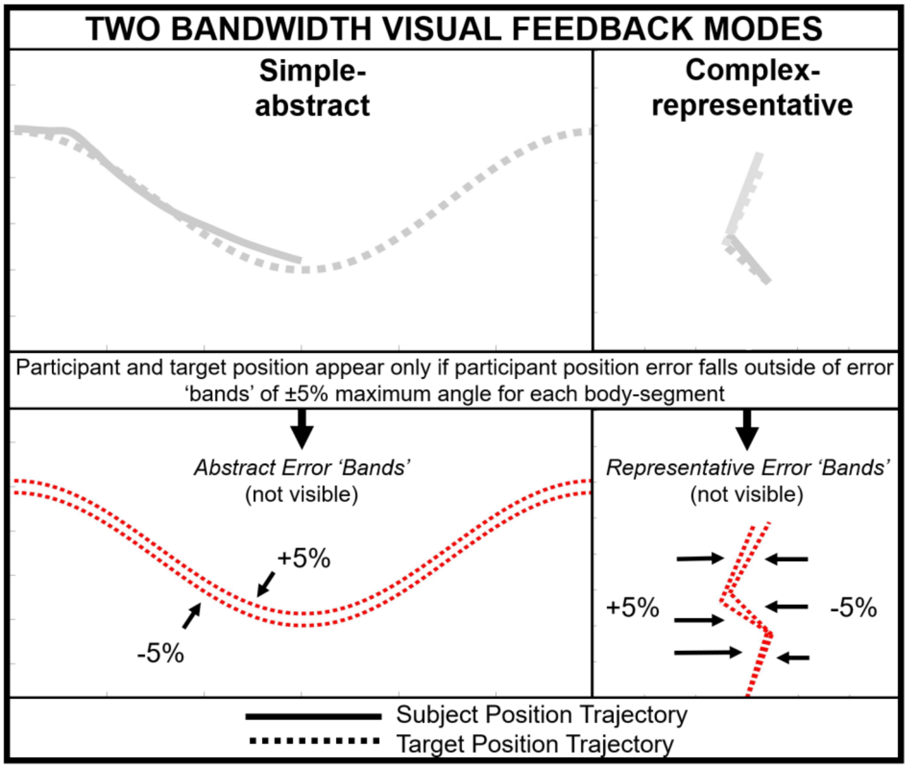

Figure 9: For the two bandwidth visual feedback modes, participant and target position gradually disappeared and reappeared based upon user error to the target trajectory. Bandwidth thresholds were set at +/- 5% for each individual body segment.

squat depth helped reduce the reliance on previous experience and forced the participant to adopt new movement strategies for each visual feedback mode. Before training trials for each visual feedback mode, the participant completed five practice trials where they attempted to squat to the new target depth. The practice trials' participant-specific average shank and torso values guided the participants during subsequent complex feedback training trials.

4.6. Measurement of Physiological Signals

During all experimental phases, wireless electromyography (EMG) sensors (*Trigno Wireless EMG System*, Delsys, Natick, MA, USA) were used to record muscle activity sampled at 1925.9 Hz. Sensors were placed bilaterally on seven muscle groups highly implicated with the squat exercise: tibialis anterior (ankle dorsi-flexor), gastrocnemius lateralis (ankle plantar-flexor, knee flexor), rectus femoris (hip flexor, knee extensor), vastus lateralis (knee extensor), biceps femoris (knee flexor), gluteus maximus (hip extensor/abductor), and erector spinae (trunk extensor). Each EMG sensor was placed on the mid-belly of the muscle aligned with the muscle fibers. MVICs were collected at the beginning of the experimental protocol before any squats were performed and were used to normalize EMG measurements across participants. The standing center of pressure was estimated using force-sensitive resistors from the same wireless EMG system. Four individual sensors were taped to the ground where each participant's feet were marked and coincided with specific foot pressure points (heel, big toe, 1st metatarsal, 5th metatarsal).

4.7. Motion Capture Analysis

Nine wide-angle infrared cameras (*Prime 17W* by Optitrack®, NaturalPoint Inc., Corvalis, OR, USA) captured the 3D motion of the participant's spatial position. Marker position data were streamed in real-time using motion capture software (*Motive* by Optitrack®) and processed at 30 frames per second in MATLAB® (Mathworks Inc., Natick, MA, USA) using a desktop computer (Dell Intel® Xeon® CPU E5-1660 v4 @ 3.20 GHz) for display on a big-screen television (25.8” H x 44.5” W, TCL Model:50FS3800). Spatial positioning of the shank, thigh, and torso segments streamed in real-time as marker clusters composed of foam boards and three non-collinear retroreflective markers. Two shank and thigh foam boards were taped on the outside of each leg. The shank boards were equally between the medial malleolus and the middle of the knee joint center of rotation. The thigh boards were equally between the lateral epicondyle of the knee and the greater trochanter at the hip. A single torso foam board was centered between the shoulder blades. Changes in the orientation of each marker cluster were to a global reference frame. The initial setpoint (zero angles) for orientation coincided with the standing position of each participant.

4.8. Data Analysis

All motion and EMG data were processed and analyzed using the *Statistics Toolbox* within MATLAB®. Motion and EMG performances were the mean (accuracy) and standard deviation (consistency) relative differences across all six visual feedback modes. Motion performance was the accuracy (minimizing error) and consistency (minimizing standard deviation in error) of the participants' performance relative to the target trajectory and depth. All motion data were normalized to a target depth of 60° to remove depth as a factor and allow direct comparisons across visual feedback modes. Participant error to the target trajectory was multiplied by 60 and then divided by the target depth for that feedback mode. EMG performance was the changes in mean EMG magnitude during individual squat bursts measured collectively across all fourteen muscles. Separate squats bursts were when EMG exceeded or fell below 10% of the MVIC. EMG data were rectified and filtered through a band-pass Butterworth filter (4-500 Hz, 3rd order).

The primary factor considered was the six visual feedback modes, and although three features of visual feedback were evaluated, all six modes were independently assessed. A one-sample Kolmogorov Smirnov test determined that performance data was not normally distributed, and therefore nonparametric statistical tests were required. A Kruskal Wallis one-way analysis of variance (ANOVA) made comparisons across all visual feedback modes, and a multiple comparison test, with Bonferroni correction, was used for individual comparisons. A Mann Whitney U test paired sample comparisons between each feedback mode's training and short-term retention blocks.

4.9. Results

In this study, I evaluated the effects of various features of visual feedback for improving motion and muscle activity accuracy (mean of error) and consistency (standard deviation of error). The primary features of interest were complexity and intermittency. Significant differences were observed between features of complexity and intermittency. Significant differences were also observed across individual visual feedback modes.

4.9.1. Motion Performance - Target Trajectory

The primary performance metric for each visual feedback mode was motion performance evaluated as participant error to the target trajectory (**Figure 10, Tables 1 and 2**). An ANOVA test indicated a significant difference across all visual feedback modes for both accuracy and consistency of the thigh angle to the target trajectory. Significant differences between visual feedback modes were observed during training. All visual feedback modes except bandwidth-simple-abstract exhibited significantly worse accuracy during retention than training.

Continuous-complex-abstract was the worst accuracy and consistency to the target trajectory of all visual feedback modes. Continuous-complex-abstract had significantly worse accuracy ($p<0.01$) and consistency ($p<0.05$) to the target trajectory during training trials compared to the other three continuous feedback modes. Continuous-complex-representative exhibited the largest performance difference in consistency to the target trajectory compared to continuous-complex-abstract ($p=0.0001$). Between matching continuous and bandwidth feedback for simple-abstract and complex-representative modes, continuous feedback resulted in significantly higher accuracy ($p<0.05$) and consistency ($p<0.05$) during training trials. Unique to the comparison between continuous and bandwidth modes was evaluating potential learning as an outcome measure, represented by the difference between retention and training performance. Both bandwidth feedback modes exhibited a positive potential learning trend for consistency to the target trajectory and were significantly better than continuous-simple-abstract ($p<0.01$).

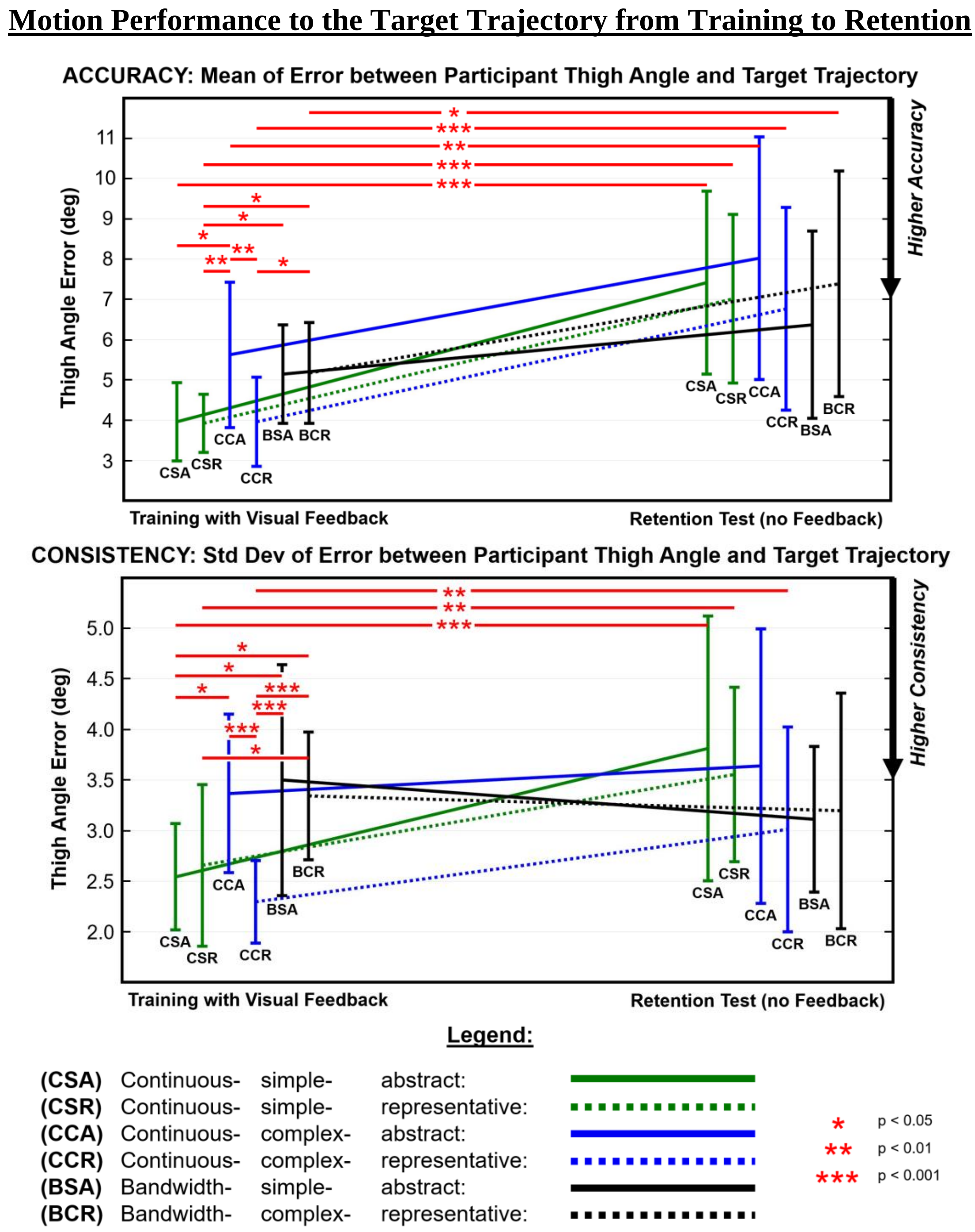

Figure 10: Motion performance was measured as the accuracy (mean error) and consistency (standard deviation of error) to the target trajectory.

Table 1: Motion performance results of participant thigh angle for **accuracy** to the **target trajectory**

Table 1A: Mean value of all four visual feedback (VF) modes for **accuracy** to the **target trajectory** (degrees, mean +/- 1 standard deviation)

	Visual Feedback Modes					
Block:	CSA	CSR	CCA	CCR	BSA	BCR
Training	4.0±1.0	3.9±0.8	5.6±1.9	4.0±1.1	5.1±1.3	5.2±1.3
Retention	7.4±2.3	7.0±2.2	8.0±3.1	6.8±2.6	6.4±2.4	7.4±2.9
Potential Learning	3.5±1.3	3.1±1.4	2.4±1.2	2.8±1.4	1.2±1.1	2.2±1.6

Table 1B: Post hoc comparisons, p-value, between visual feedback modes during **training**

	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	1.0	**0.0125**	1.0	0.0935	0.0550
CSR	x	x	**0.0037**	1.0	**0.0332**	**0.0186**
CCA	x	x	x	**0.0068**	1.0	1.0
CCR	x	x	x	x	0.0560	**0.0321**
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x

Table 1C: Post hoc comparisons, p-value, between visual feedback modes during **retention**

	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	1.0	1.0	1.0	1.0	1.0
CSR	x	x	1.0	1.0	1.0	1.0
CCA	x	x	x	1.0	0.5919	1.0
CCR	x	x	x	x	1.0	1.0
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x

Table 1D: Post hoc comparisons, p-value, between visual feedback modes for **potential learning**

	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	1.0	1.0	1.0	0.2460	1.0
CSR	x	x	1.0	1.0	0.4139	1.0
CCA	x	x	x	1.0	1.0	1.0
CCR	x	x	x	x	1.0	1.0
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x

Table 1E: Mann Whitney U test, p-value, for each visual feedback mode **between training and retention**

	CSA	CSR	CCA	CCR	BSA	BCR
	1.176E-05	**7.575E-06**	**0.0051**	**1.210E-04**	0.0791	**0.0155**

Note: Visual Feedback Modes – CSA (continuous-simple-abstract) – CSR (continuous-simple-representative) – CCA (continuous-complex-abstract) – CCR (continuous-complex-representative) – BSA (bandwidth-simple-abstract) – BCR (bandwidth-simple-representative)
Note 2: Significant P-values (p<0.05) bolded

Table 2: Motion performance results of participant thigh angle for **consistency** to the **target trajectory**						
Table 2A: Mean value of all four visual feedback (VF) modes for **consistency** to the **target trajectory** (degrees, mean +/- 1 standard deviation)						
	Visual Feedback Modes					
Block:	CSA	CSR	CCA	CCR	BSA	BCR
Training	2.5±0.5	2.7±0.8	3.4±0.8	2.3±0.4	3.5±1.2	3.3±0.7
Retention	3.8±1.3	3.6±0.9	3.6±1.4	3.0±1.0	3.1±0.7	3.2±1.2
Potential Learning	1.3±0.8	0.9±0.1	0.3±0.6	0.7±0.6	-0.4±0.4	-0.1±0.5
Table 2B: Post hoc comparisons, p-value, between visual feedback modes during **training**						
	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	1.0	**0.0440**	1.0	**0.0396**	**0.0211**
CSR	x	x	0.0808	1.0	0.0732	**0.0403**
CCA	x	x	x	**0.0008**	1.0	1.0
CCR	x	x	x	x	**0.0007**	**0.0003**
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x
Table 2C: Post hoc comparisons, p-value, between visual feedback modes during **retention**						
	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	1.0	1.0	0.3413	1.0	0.8621
CSR	x	x	1.0	0.3813	1.0	0.9494
CCA	x	x	x	0.6812	1.0	1.0
CCR	x	x	x	x	1.0	1.0
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x
Table 2D: Post hoc comparisons, p-value, between visual feedback modes for **potential learning**						
	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	1.0	0.4929	1.0	**0.0135**	**0.0236**
CSR	x	x	0.9608	1.0	**0.0357**	0.0599
CCA	x	x	x	1.0	1.0	1.0
CCR	x	x	x	x	0.3919	0.5843
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x
Table 2E: Mann Whitney U test, p-value, for each visual feedback mode **between training and retention**						
	CSA	CSR	CCA	CCR	BSA	BCR
	7.530E-04	**0.0018**	0.6464	**0.0038**	0.3506	0.1249

Note: Visual Feedback Modes – CSA (continuous-simple-abstract) – CSR (continuous-simple-representative) – CCA (continuous-complex-abstract) – CCR (continuous-complex-representative) – BSA (bandwidth-simple-abstract) – BCR (bandwidth-simple-representative)
Note 2: Significant P-values (p<0.05) bolded

4.9.2. Motion Performance - Target Depth

Significant differences were found between the participants' maximum and target depths (**Figure 11, Tables 3 and 4**). The participant's depth was the maximum depth over the entire trajectory evaluated for accuracy (mean of error) and consistency (standard deviation of error) to the target depth. A significant difference was observed in potential learning accuracy to the target depth. Significant differences were observed for individual feedback modes between training and retention.

Continuous-simple-abstract exhibited significantly better accuracy (p=3.29E-04) and consistency (p=0.02) during training than during retention. Continuous-simple-representative also showed significantly better accuracy (p=0.01) during training than retention. Additionally, for consistency to the target depth, the observable trends were that both continuous simple feedback modes decreased consistency. In contrast, both continuous complex and bandwidth feedback modes exhibited increased consistency from training to retention. Bandwidth-complex-representative was the only visual feedback mode with positive potential learning accuracy to the target depth, presented as higher performance during retention than during training, and was significantly greater than continuous-simple-abstract. Although no significant differences were found, both bandwidth visual feedback modes exhibited a positive potential learning effect for consistency to the target depth.

Motion Performance to the Target Depth from Training to Retention

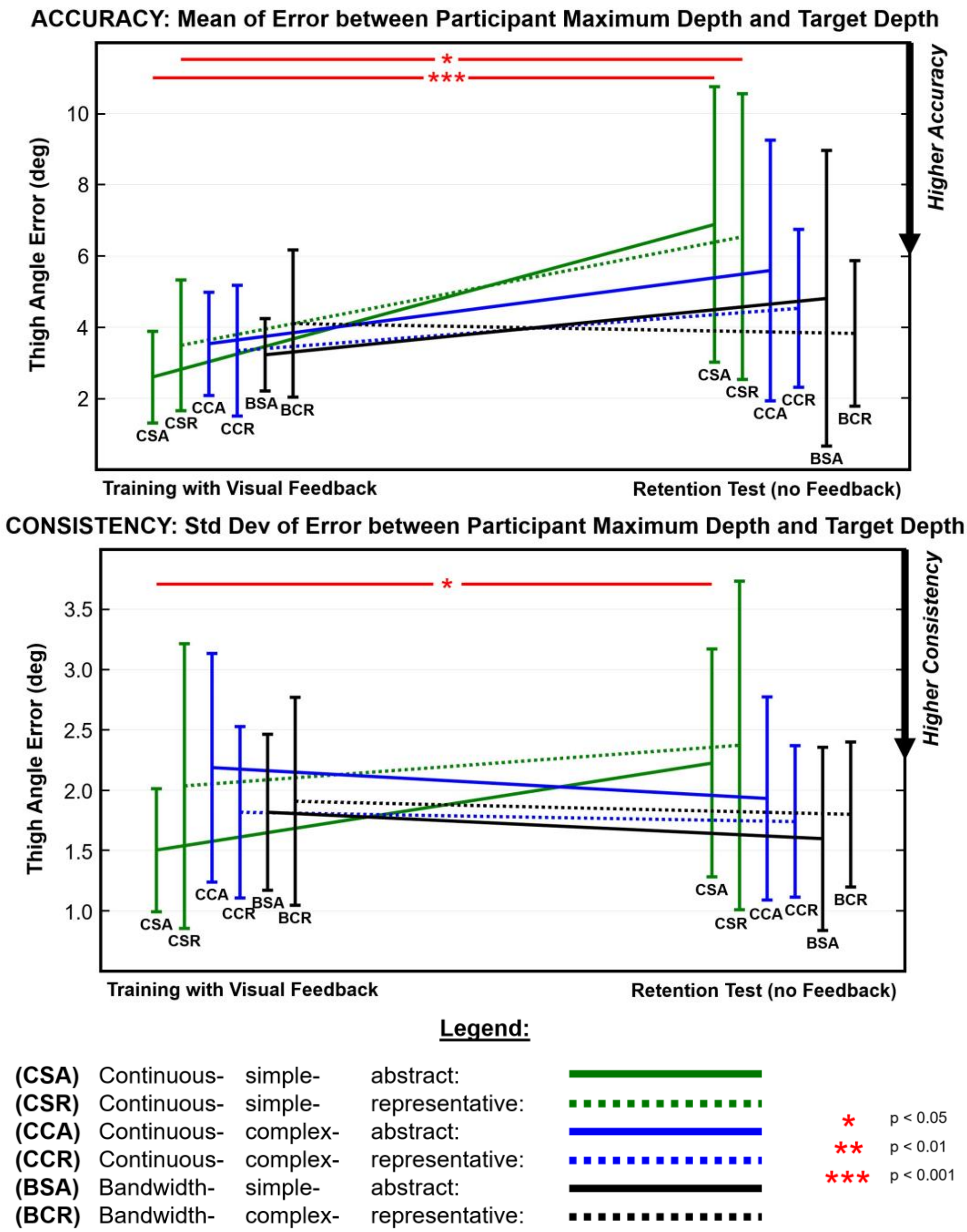

Figure 11: Motion performance was measured as the accuracy (mean of error) and consistency (standard deviation of error) of the participant maximum depth to the target depth.

Table 3: Motion performance results of participant thigh angle for **accuracy** to the **target depth**

Table 3A: Mean value of all four visual feedback (VF) modes for **accuracy** to the **target depth** (degrees, mean +/- 1 standard deviation)

	Visual Feedback Modes					
Block:	CSA	CSR	CCA	CCR	BSA	BCR
Training	2.6±1.3	3.5±1.9	3.5±1.5	3.3±1.9	3.2±1.0	4.1±2.1
Retention	6.9±4.0	6.5±4.1	5.6±3.8	4.5±2.3	4.8±4.3	3.8±2.1
Potential Learning	4.3±2.6	3.1±2.2	2.1±2.8	1.2±0.4	1.6±3.2	-0.3±0.03

Table 3B: Post hoc comparisons, p-value, between visual feedback modes during **training**

	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	1.0	0.8833	1.0	1.0	0.2424
CSR	x	x	1.0	1.0	1.0	1.0
CCA	x	x	x	1.0	1.0	1.0
CCR	x	x	x	x	1.0	1.0
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x

Table 3C: Post hoc comparisons, p-value, between visual feedback modes during **retention**

	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	1.0	1.0	1.0	0.4799	0.1803
CSR	x	x	1.0	1.0	1.0	0.4673
CCA	x	x	x	1.0	1.0	1.0
CCR	x	x	x	x	1.0	1.0
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x

Table 3D: Post hoc comparisons, p-value, between visual feedback modes for **potential learning**

	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	1.0	1.0	0.2607	0.2607	**0.0045**
CSR	x	x	1.0	1.0	1.0	0.0982
CCA	x	x	x	1.0	1.0	0.93381
CCR	x	x	x	x	1.0	1.0
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x

Table 3E: Mann Whitney U test, p-value, for each visual feedback mode **between training and retention**

	CSA	CSR	CCA	CCR	BSA	BCR
	3.294E-04	**0.0119**	0.2114	0.0738	0.8371	0.4765

Note: Visual Feedback Modes – CSA (continuous-simple-abstract) – CSR (continuous-simple-representative) – CCA (continuous-complex-abstract) – CCR (continuous-complex-representative) – BSA (bandwidth-simple-abstract) – BCR (bandwidth-simple-representative)
Note 2: Significant P-values (p<0.05) bolded

Table 4: Motion performance results of participant thigh angle for **consistency** to the **target depth**

Table 4A: Mean value of all four visual feedback (VF) modes for **consistency** to the **target depth** (degrees, mean +/- 1 standard deviation)

	Visual Feedback Modes					
Block:	CSA	CSR	CCA	CCR	BSA	BCR
Training	1.5±0.5	2.0±1.2	2.2±1.0	1.8±0.7	1.8±0.7	1.9±0.9
Retention	2.2±1.0	2.4±1.4	1.9±0.9	1.7±0.6	1.6±0.8	1.8±0.6
Potential Learning	0.7±0.4	0.3±0.2	-0.3±0.1	-0.1±0.1	-0.2±0.1	-0.1±0.3

Table 4B: Post hoc comparisons, p-value, between visual feedback modes during **training**

	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	1.0	0.2882	1.0	1.0	1.0
CSR	x	x	1.0	1.0	1.0	1.0
CCA	x	x	x	1.0	1.0	1.0
CCR	x	x	x	x	1.0	1.0
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x

Table 4C: Post hoc comparisons, p-value, between visual feedback modes during **retention**

	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	1.0	1.0	1.0	0.3919	1.0
CSR	x	x	1.0	1.0	0.6812	1.0
CCA	x	x	x	1.0	1.0	1.0
CCR	x	x	x	x	1.0	1.0
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x

Table 4D: Post hoc comparisons, p-value, between visual feedback modes for **potential learning**

	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	1.0	0.1803	0.6812	0.1776	0.3973
CSR	x	x	1.0	1.0	1.0	1.0
CCA	x	x	x	1.0	1.0	1.0
CCR	x	x	x	x	1.0	1.0
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x

Table 4E: Mann Whitney U test, p-value, for each visual feedback mode **between training and retention**

	CSA	CSR	CCA	CCR	BSA	BCR
	0.0200	0.5166	0.4198	0.7880	0.2750	0.7397

Note: Visual Feedback Modes – CSA (continuous-simple-abstract) – CSR (continuous-simple-representative) – CCA (continuous-complex-abstract) – CCR (continuous-complex-representative) – BSA (bandwidth-simple-abstract) – BCR (bandwidth-simple-representative)
Note 2: Significant P-values ($p<0.05$) bolded

4.9.3. Electromyography

Muscle activity performance outcomes were based on the consistency of mean EMG magnitude (**Figure 12, Table 5**). Significant differences were found between the two continuous and representative visual feedback modes during training trials. For an average EMG magnitude across all muscles, continuous-complex-representative exhibited significantly greater consistency (p=0.0215) in EMG activity than continuous-simple-representative. Additionally, two individual muscles, the rectus femoris (p=0.034) and tibialis anterior (p=0.035) exhibited significantly greater consistency during training with continuous-complex-representative than continuous-simple-representative.

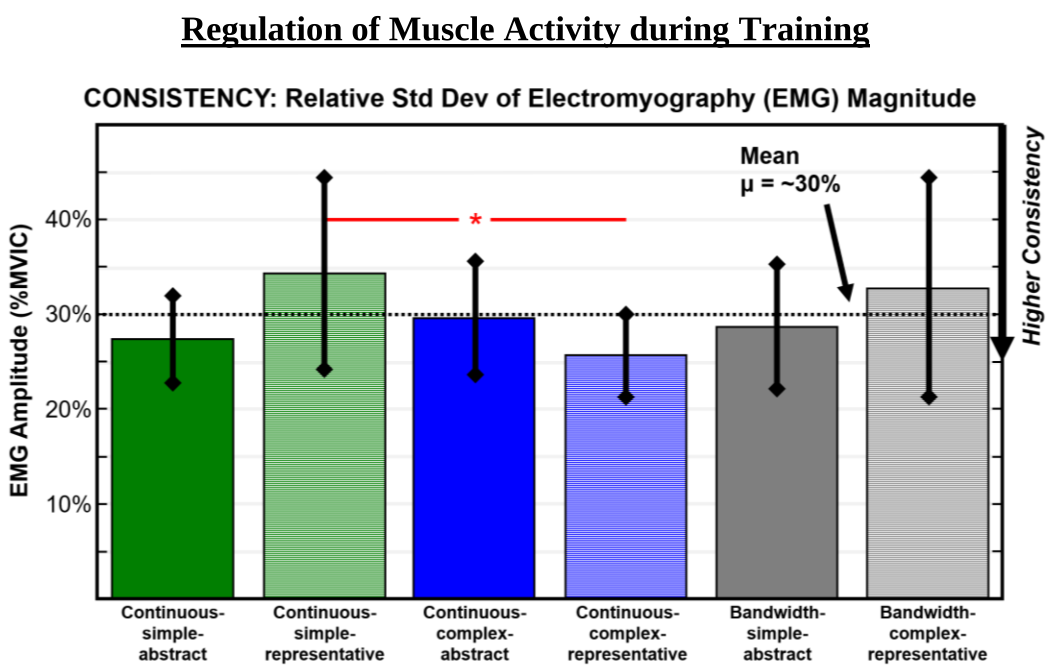

Figure 12: Electromyography performance was measured as the regulation of muscle activity during training trials. Muscle activity was measured as the mean magnitude of all EMG sensors normalized by the mean EMG magnitude.

Table 5: Electromyography (EMG) performance for **magnitude consistency of all muscles**						
Table 5A: Mean value comparisons across all four visual feedback (VF) modes (%MVIC, mean +/- 1 standard deviation)						
	Visual Feedback Modes					
Block:	CSA	CSR	CCA	CCR	BSA	BCR
Training	27.3±4.7	34.3±10.4	29.6±6.2	25.6±4.5	28.7±6.8	32.7±11.9
Retention	27.2±4.6	30.6±6.1	31.3±11.6	28.4±6.6	29.0±6.5	28.9±4.7
Table 5B: Post hoc comparisons, p-value, between visual feedback modes during **training**						
	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	0.4994	1.0	1.0	1.0	1.0
CSR	x	x	1.0	**0.0215**	1.0	1.0
CCA	x	x	x	0.4673	1.0	1.0
CCR	x	x	x	x	1.0	0.2093
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x
Table 5C: Post hoc comparisons, p-value, between visual feedback modes during **retention**						
	CSA	CSR	CCA	CCR	BSA	BCR
CSA	x	0.5843	1.0	1.0	1.0	1.0
CSR	x	x	1.0	1.0	1.0	1.0
CCA	x	x	x	1.0	1.0	1.0
CCR	x	x	x	x	1.0	1.0
BSA	x	x	x	x	x	1.0
BCR	x	x	x	x	x	x
Table 5D: Mann Whitney U test, p-value, for each visual feedback mode **between training and retention**						
	CSA	CSR	CCA	CCR	BSA	BCR
	0.8371	0.4964	0.9370	0.1032	0.9118	0.7397

Note: Visual Feedback Modes – CSA (continuous-simple-abstract) – CSR (continuous-simple-representative) – CCA (continuous-complex-abstract) – CCR (continuous-complex-representative) – BSA (bandwidth-simple-abstract) – BCR (bandwidth-simple-representative)
Note 2: Significant P-values (p<0.05) bolded

4.10. Discussion

This study evaluated the effects of specific features of augmented visual feedback for training motion and muscle performance for the two-legged squat exercise. By systematically comparing multiple visual feedback modes for the same motor task, this research aimed to identify the potential advantages and disadvantages of each feature of visual feedback. The objective was to determine the features that optimize motor rehabilitation, both in the training and short-term retention phases. Six unique visual feedback modes guided real-time spatial positioning of the two-legged squat, primarily focused on the participants' thigh body segment angular position. Three visual feedback modes, deemed to be complex feedback, also guided the shank and torso body segments naturally coupled to the thigh during the closed-chain movement. Significant differences across visual feedback modes were found for motion accuracy and consistency, measured as participant thigh angle error to the target trajectory and depth. Significant differences were also observed for specific modes for potential learning, calculated as the relative difference for an individual visual feedback mode between training and retention performance. Although three features of visual feedback were evaluated in this study, only complexity and intermittency were the primary features of interest, and research has been published in two scientific journals [7], [8]. Continuous feedback was more effective during training trials at increasing motion accuracy and consistency than bandwidth feedback. Continuous-complex-abstract exhibited the worst performance across all visual feedback modes, while continuous-complex-representative exhibited the highest relative performance. Although bandwidth feedback demonstrated low training performance, it indicated higher potential learning than continuous feedback.

The role of simple visual feedback in optimizing motion-based tasks is uncertain based on the results of this study. While the two-legged squat involves multiple segments, it is essentially a modulation of the single variable, squat depth. Thigh angle was the primary surrogate for squat depth, which is consistent with other squat studies [71], [151], [152]. My results indicated increases in motion consistency to the target depth for both continuous-complex modes and reductions for both continuous-simple modes. This observation suggests that complex feedback for matching a singular movement feature, such as squat depth, is overtly challenging during training. Yet concurrent complex feedback may still generate better development of intrinsic mechanisms relied upon during retention [89]. Both continuous-simple-abstract and continuous-simple-representative had similar motion performance to the target trajectory and maximum depth. Simple feedback is advantageous over complex feedback in accuracy and consistency to a target trajectory if displaying abstract feedback. This study demonstrates that visual feedback of additional DOF still benefits the primary performance variable if provided with body-discernible features.

For the naturally coupled visual feedback modes simple-abstract and complex-representative, the contrasting differences in potential learning support the findings of Soderstrom and Bjork [153] in that training results cannot infer retention results, and vice versa. Both continuous simple-abstract and complex-representative feedback modes presented similar performance during training, but only continuous-complex-representative was able to maintain performance during retention trials. Continuous-simple-abstract showed the lowest learning potential across all four motion performance metrics. Constant presentation of information without the additional context of other body segments may have precipitated over-reliance on a singular movement feature. Complex-representative modes may have mitigated over-reliance on continuous feedback by presenting additional body segment positions that allowed participants to interpret the feedback against their squat movements more holistically across their entire body.

Among the two continuous-complex visual feedback modes, continuous-complex-representative produced better accuracy and consistency than continuous-complex-abstract. This finding strongly suggests the importance of complex feedback and body representation during multi-segmented motion-based tasks. For some motor tasks, complex feedback can be overwhelming such that it degrades movement performance [82]. Complex feedback is appropriate if the additional feedback information is inherently important to a specific task, then performance is expected to improve [82]. Our study suggests that visual feedback more 'representative' of the body may further facilitate performance. Our streamlined continuous-complex-representative mode demonstrated notable advantages over continuous-complex-abstract, providing feedback cues as sinusoids. The visual gains of the sinusoids were normalized while representing additional body segments (torso, shank) moving synergistically with the thigh. These segments are functionally coupled due to the legs forming a closed chain [154] and the balance requirement of maintaining the body center of mass over the base of support [155]. These constraints require an inherent functional synergy across these segments. Despite this synergy, the additional feedback streams for the torso and shank segments only generate better performance in tracking the thigh segment if visual feedback represents their position as body segments rather than abstract sinusoids. Embodiment in rehabilitation is the first-person perspective of one's body during environmental interaction [156]. This study portrayed representative modes with body-discernible features as a stick figure of body position in the sagittal plane, resulting in a greater feeling of embodiment. The representative feedback modes still lacked embodiment features such as realistic body representation [74], [157], first-person perspective [52], [85], or direct mirroring [158], [159].

Our results indicate that continuous feedback is beneficial in increasing training performance, while bandwidth feedback proved to be more advantageous for retention. During movement training, providing a constant and uninterrupted stream of angular position information during continuous feedback resulted in clearly higher movement accuracy and consistency than intermittently removing position information. However, this may have degraded learning as participants were hyper-focused on the feedback for movement support. Bandwidth feedback was more beneficial for learning by reducing the reliance on augmented visual feedback during training. However, in this study, which we constrained in scope to observe short-term retention only, no significant differences were between visual feedback modes for retention. Bandwidth feedback modes showed higher performance improvement for the relative change from training to short-term retention, called "potential learning." These improvements in bandwidth feedback modes were significant compared to continuous-simple-abstract in potential learning for consistency to the target trajectory and accuracy to the target depth. Both bandwidth feedback modes showed a positive potential learning effect for consistency to both the target trajectory and target depth. This positive trend for movement consistency with bandwidth feedback could indicate that, despite relatively more challenges during *training*, bandwidth feedback can produce more significant relative improvements in short-term and presumably long-term *learning* of rehabilitative movements. Evidence suggests positive links in feedback-based learning between the generation of immediate and longer-term positive improvements [160], [161]. Higher potential learning with bandwidth feedback may further support the possibility of developing intrinsic mechanisms during training necessary for sustained long-term learning [82]. Our premise for potential learning is that performance during training provides the baseline to compare how much training benefit is retained. We posit that this effect may be continually leveraged with future training sessions in which the training performance error (baseline) itself may be subsequently reduced [78]. Our study demonstrated that complex and representative modes have superior training benefits for a motion-based task than abstract modes across both continuous and bandwidth feedback. This finding further suggests the potential benefit of representative features for multi-segmented movements. Immersive, visual-driven training platforms such as VR are well suited to leverage embodiment features for more effective feedback displays to increase movement retention.

Continuous-complex-representative also generated more consistent muscle activation patterns relative to continuous-simple-representative. The squat maneuver benefits the rehabilitation of the knee following rupture of the anterior cruciate ligament and patellar tendon [22], [63], [162]. During rehabilitation, it is advantageous to regulate the activation patterns of muscles surrounding the knee joint, such as the rectus femoris and tibialis anterior. The implications for continuous-complex-representative for regulating muscle activity also span movement rehabilitation with powered assistive devices. During ADLs, powered exoskeletons and prostheses often rely on myoelectric interfaces to discern user commands for desired movement execution [163]–[165], where more consistent muscle activation patterns are advantageous [132], [133].

No significant differences were observed in the changes in the center of pressure measured as the magnitude of the forward excursions or the consistency of excursion magnitude. Only forward excursions were evaluated since all visual feedback provided averages of the left and right sides projected onto the sagittal plane. It appears that varying visual feedback did not generate significant differences in the center of pressure. While beyond the scope of this study, this result would suggest any significant changes in internal mechanics would be due to changes in joint angles [166].

There were multiple limitations to our experimental approach, primarily the sample size and length of the study. The sample size of only eighteen participants resulted in the need for nonparametric statistical testing. There was also a lack of evaluation of long-term learning or classical retention effects. Motor adaptation should be confirmed over numerous weeks, including multiple training sessions and transfer tests more indicative of long-term learning. The scope of our investigation was restricted to a single training session per participant to assess both training and short-term retention performance. The two-legged squat movement can also be highly stereotypical for neurotypical participants, so pilot testing indicated it was necessary to change the squat depth for different visual feedback modes. Changing the squat depth would ensure the participants' reliance on the visual feedback for learning the new movement and would reduce the overall learning effect across the training session.

4.11. Conclusion

The objective of this study was to investigate how features of augmented visual feedback, complexity, body representation, and intermittency may affect motion and muscle activity during both training and short-term retention of the same motor task. The objective was to identify features that increased the accuracy and consistency of participant thigh angle to a target trajectory and the consistency of all EMG activity patterns. This study implies that complex-representative and bandwidth feedback may have notable advantages in regulating motor performance. Visual feedback that was complex and included body representative features outperformed other visual feedback modes that were otherwise simpler or more abstract. Continuous feedback outperformed bandwidth feedback during training to minimize error to a target trajectory, but the performance was unable to be maintained during retention trials. Bandwidth feedback demonstrated more significant promise for potential learning from relative improvement in independent performance immediately after training with visual feedback.

Providing continuous visual feedback in complex and body-representative features may be desirable in the training performance of a multi-segmented motion-based task. The implication that complex-representative feedback is optimal for motion-based tasks and can outperform simple and abstract feedback modes may be a valuable directive in VR-based rehabilitation. Additionally, introducing features of bandwidth feedback may be beneficial in supplementing retention effects for learning independent movement strategies. Bandwidth feedback may serve as a bridge between concurrent continuous feedback and terminal feedback by gradually increasing reliance on and developing intrinsic mechanisms. Additional evaluations of complex-representative and bandwidth feedback on long-term motor learning should be pursued. VR is becoming increasingly prevalent in physical therapy to enhance augmented visual feedback. VR may effectively train motion-based tasks and readily visualize custom body representations with complex-representative features. Incorporating VR to create person-specific 3-D body representations could increase real-time performance and the development of intrinsic mechanisms through additional embodiment features.

5. AIM 2: FORCE-BASED TASK

5.1. Introduction

After completing the motion-based squat task, my research utilized EMG as the primary platform for improving muscle level control. EMG – necessary for myoelectric control – is used for commanding assistive devices, such as prosthetics or exoskeletons, and monitors muscle activity during physical rehabilitation. VR effectively trains muscle activity patterns of myoelectric prostheses, both in real-world devices [32] and those simulated in an immersive VR environment [167]. In this study, the experimental platform is a VR-based force task. However, the unique property of the rehabilitation platform was that force inputs, i.e., participant isometric EMG activity patterns, were mapped to movement commands in the virtual space [40]. Acting in a haptic joystick design, participants donned a supportive arm brace, where pushing forward in the brace would induce the desired muscle contractions to command the virtual device forward. Due to the two-legged squat study findings, research focused on employing complex-representative and bandwidth feedback modes. Unique to this study, participants also completed a short pre-training phase (*baseline*, no feedback) before training and the post-training (*retention*) trials to further evaluate how each visual feedback mode affects performance and cognitive engagement.

Before the development of VR head-mounted displays, visual feedback was limited to external monitors or mirrors to guide spatial positioning. There is a desire to evaluate features of visual feedback within immersive VR environments because of the ability to create enhanced forms of visual cues unable to be recreated in conventional therapy. An example is representing the target trajectory as a transparent overlay to the user's body position, such as a "ghost-arm" during a reaching task to identify the desired path [52]. VR-based training can increase embodiment through avatars or 3D representations of body position [156].

In this study, we investigated how the complexity and intermittency of augmented visual guidance can facilitate improved functional performance of a muscle-based (myoelectric command) training task for upper-extremity rehabilitation. We utilize a novel computerized platform that incorporates myoelectric control of a virtual robot avatar to perform reach-to-touch tasks while the participant receives augmented visual guidance during training. The task employs a position-adjustable brace of the upper extremity to support users, such as those with spinal cord injury who are challenged to move their limbs against gravity [132], [168]. The brace also holds the arm isometrically to support resistance strength and coordination training at varied arm positions [169]. Thus, we are fundamentally investigating the effects of variations in augmented guidance for the performance of a force-based rehabilitation task [170], [171]. Another crucial and novel element of our investigation is the examination of concurrent feedback, as previous bandwidth investigations have utilized terminal feedback [58], [59].

Furthermore, we measure and evaluate user-centered response variables to potentially explain an underlying mechanism in how augmented guidance may induce the observed performance patterns. Specifically, we assess participant perceptions in agency [172] over the command interface. In addition, we measure the physiological stresses that are endured at cognitive (electroencephalography measures for loading [173]) and physical (electrodermal activity indicative of body arousal [174]) levels. These physiological stresses indicate well-being during training, which may help further identify participant tolerance of various visual feedback modes and may be an additional dimension of person-specific customization of VR-based training.

5.2. Subject Recruitment

Thirteen healthy participants signed an informed consent approved by the local Institutional Review Board. They were recruited from a university campus (*Seven Females: 21.2±2.0 years, 165.1±3.7 cm, 56.5±2.6 kg. Six Males: 22.3±2.1 years, 179.3±5.9 cm, 77.5±6.4 kg)*. All participants stated they were right-hand dominant. All participants were naïve to both the brace device and muscle-driven command interfaces. Individuals were excluded from participating if they reported any of the following: 1. Clinical diagnosis of cognitive or neuromuscular impairment. 2. Previous surgery to an upper extremity or the spine/neck. 3. Hearing or vision issues not correctable to normal levels. 4. Proneness to epileptic seizures due to visual stimuli.

5.3. Supportive Brace Apparatus

A novel computerized platform for isometric training of muscle function has been developed for motor rehabilitation of the upper extremity (**Figure 13**). The first principal component of this platform is a position-adjustable brace that isometrically supports the upper arm undergoing training. The brace was custom constructed using 3D printing and essential hardware components, and it allows the user to assume variable arm configurations. Support at varying configurations can enable physical therapists to develop training programs that promote muscle strength and coordination at different muscle lengths [175], [176], even for persons with severe motor dysfunction. In cases of severe motor disability, the brace provides gravity support to assume different configurations while a person can focus training effort on preserved muscles executing the computerized task. Fundamentally, the person will exert directional efforts against the brace's padded interior (contact-side). Isometric resistance from the brace amplifies the skin-surface EMG signals used to drive the motion of virtual avatars [177], [178].

The brace comprises an arm mount, an adjustable rod, and a secondary mount on the table directly in front of the participant. The arm mount component straps twice over the upper arm once over the forearm and allows adjusting and locking of the elbow angle. The arm mount has cut-outs for EMG sensors on the upper arm and forearm muscle mid-bellies. An adjustable rod attached to the forearm connects the arm mount to a second mount clamped to the table in front of the participant. The adjustable hinges on the mounts and rod allow the arm position to be adjusted at elbow and shoulder angles that are comfortable and within desired limits. In this study, we searched for arm positions deemed comfortable and neutral for each participant within the following angular ranges: shoulder ad/abduction (45-75°), shoulder internal rotation (0-45°), and elbow flexion (90-120°). We approximately defined *neutral* as an arm position where participants perceived they could produce high forces in the four orthogonal directions (forward, back, left, right) used to command the virtual avatar (robot arm).

While donning the brace, participants completed MVICs for normalizing EMG activity by producing maximum force in each of the four orthogonal directions. The average distribution across all participants for muscle activity in each orthogonal direction during MVIC trials is represented in **Figure 14**. Each direction drastically changed the distribution of muscle activity. This distribution promotes rehabilitation across multiple muscle sites and validates the platform as a suitable interface for commanding a myoelectric device through isometric contractions. Each direction presents notable changes in the pattern of EMG magnitude across muscle sites that machine learning algorithms would easily classify for determining direction intent. The data also represents a platform for deciding future brace utilization for clinical populations with more reduced muscle sets. Identifying the correlated muscle sets utilized in direction control will help determine the ideal inputs for optimizing myoelectric devices. A platform that provides feedback on correlated (and uncorrelated) arm muscle activity may also be used to improve unwanted co-contraction seen as part of the spasticity syndrome after spinal cord injury.

Experimental protocol and trial blocking for the VR force-based task

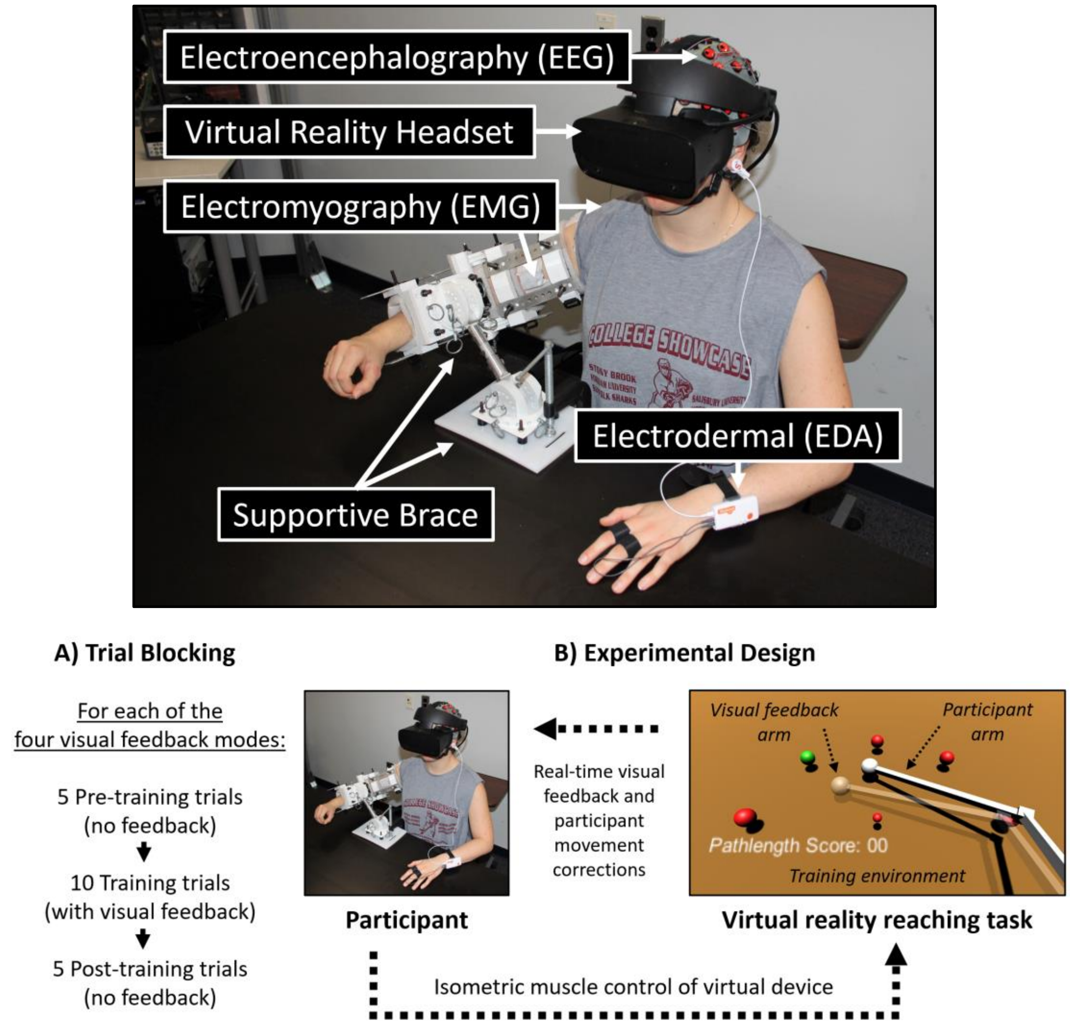

Figure 13. *Experimental set-up.* TOP) Participant arm placed in supportive brace fastened to the table to apply isometric muscular exertions. Worn EMG sensors record myoelectric patterns to command the VR robot arm avatar. EEG and EDA signals additionally recorded to measure participant cognitive loading and physical arousal, respectively. BOTTOM) For each visual feedback mode, participants completed pre-training and post-training trials (with no feedback) before and after training trials (with visual feedback). Isometric muscle control was used to command a virtual device through a variety of reaching tasks while receiving real-time visual feedback for making movement corrections to reduce error to the shortest path between targets.

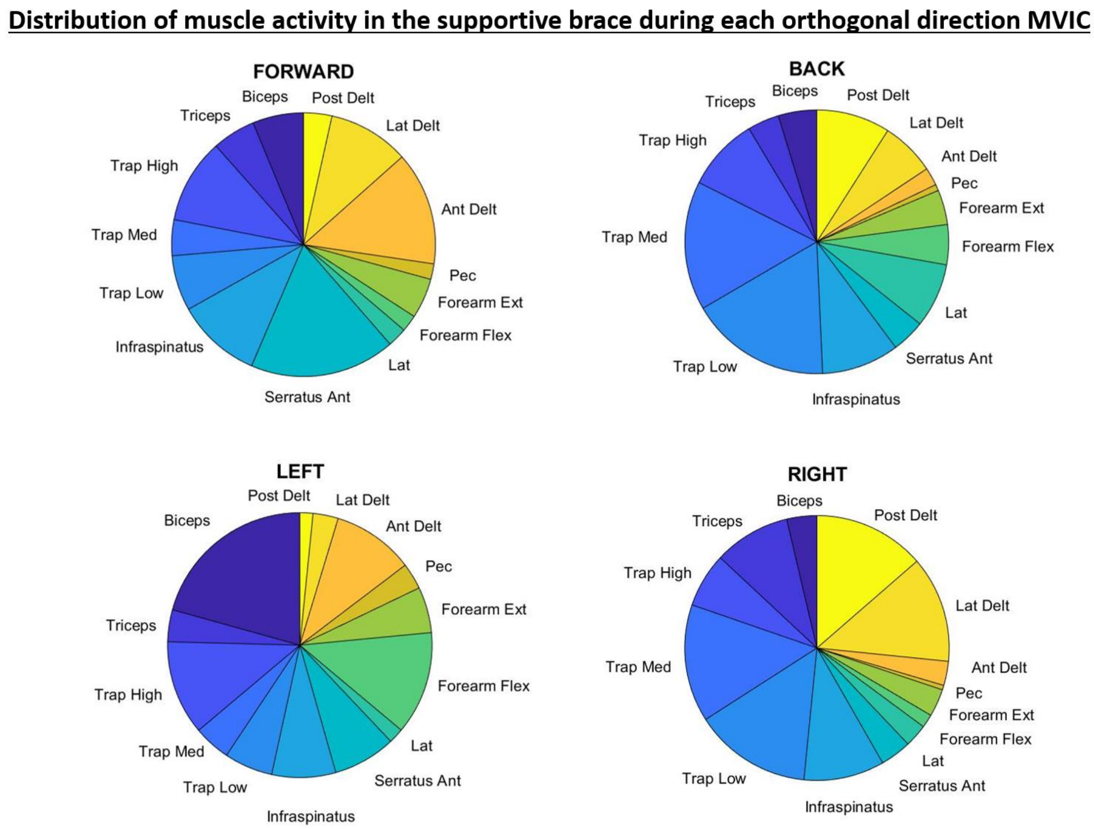

Figure 14. Four pie charts that indicate the average distribution across all participants of electromyography activity magnitude. The muscle activity represents the MVIC data collected for each orthogonal direction while donning the supportive brace.

5.4. Measurement of Physiological Signals

Fourteen wireless electromyography (EMG) sensors (*Trigno Wireless EMG System*, Delsys, Natick, MA, USA) were used to measure real-time muscle activity and serve as myoelectric inputs to control the virtual robot. EMG sensors were placed on the mid-belly of fourteen individual muscles of the arm and torso: brachioradialis, extensor digitorum, biceps brachii, triceps brachii, upper trapezius, middle trapezius, lower trapezius, infraspinatus, serratus anterior, latissimus dorsi, pectoralis major, anterior deltoid, lateral deltoid, and posterior deltoid. These muscles were identified as primary force-generating muscles in upper-extremity movements and targets for physical rehabilitation. All EMG data were sampled at 1728 Hz.

A 64-channel electroencephalography (EEG) scalp-recording cap (*g.USBamp*, g.tec neurotechnology USA, Inc.) measured brain activity during all experiment phases. Power spectrum analyses were performed offline to identify mean power in alpha (8-12 Hz) and beta (13-30 Hz) frequency bands as measures of cognitive loading. Only seven participants were available to have EEG measurements taken during all experiment phases. All EEG data were sampled at 256 Hz. Electrodermal (EDA) activity was measured as a proxy for emotional and physical arousal based on increases in skin conductivity (in microsiemen) of the left hand. Changes in galvanic skin response due to moisture were measured from electrode readings (*Shimmer3 GSR+ sensor*, Shimmer, USA) at the index and middle fingers. Only four participants were available to have EDA measurements taken during all experiment phases. All EDA data were sampled at 51 Hz. All EMG, EEG, and EDA data were synchronized offline.

5.5. Survey Measurement for Perception of Control

Immediately following each visual feedback block, participants completed a survey inquiring about their perception of control of the virtual avatar during training. Only ten of the eligible participants completed the survey. The survey included a statement and space to write a single number between 1 and 100, representing the extent to which they disagree (1) or agree (100) with the statement. The statement reflected sense of agency [179] and read as: *I was in full control of the virtual prosthetic arm during training*

5.6. Utilizing Support Vector Machines for EMG Classification

A support vector machine (SVM) [180] was used as the machine learning classifier for translating EMG activation patterns (14 muscle inputs) to direction outputs to be used as commands for the end-effector of the virtual robot arm. SVMs were trained uniquely for each participant. During pilot testing with our platform, we attempted using a single SVM to output eight directional commands (four orthogonal, four diagonal). However, the single SVM produced challenges in EMG control of multiple degrees of freedom, as is well-cited [181], and participants reported poor intuitive control. Thus, we alternatively created an ad hoc command architecture using two SVM structures in parallel. One SVM was trained to identify forward and backward command directions, and the other was separately trained to identify right and left command directions. Training trials with diagonal data were included in both classifiers. A manual threshold was specified in series with classifier output to denote 'no movement' of the end-effector when average EMG activity across all muscles was within 20% of the baseline (i.e., resting periods between target plateaus) EMG amplitude, presumably from sensor noise or hyperactivity at rest.

The main consequence of this command scheme was that participants primarily utilized sequences of diagonal movements (i.e., both SVM classifiers were producing command outputs concurrently) to move towards target locations. However, this approach was ultimately justified for our platform since participants reported seamless and natural control of the robot avatars. This perception may partly explain endpoint stiffness regulation as a function of arm posture [182], and diagonal translations may have better aligned with user endpoint forces. However, considerations of mapping arm posture to endpoint force synergies were beyond the scope of this study and held secondary to finding arm postures accommodating user comfort and stated preferences. More sophisticated approaches to the command interface may be enacted in future deployments, including those that better facilitate robust and concurrent control of multiple degrees of freedom. Still, the current scheme provided a sufficiently stable and consistent interface to discern performance effects due to variations in visual feedback features, as is the main objective of this study.

For classifier training, each participant would be placed in the brace to perform voluntary isometric contractions in specific directions as instructed by the experimenter. First, the participant would perform maximum voluntary isometric contractions (MVIC) in the four orthogonal directions: forward, back, left, and right. From these trials, we identified the average EMG across all muscles signifying 100% MVIC for normalizing target force levels during training trials. Second, data to train an SVM were collected in sixteen individual trials within the VR environment. In each trial, participants would exert effort at one of two force level targets, 20% or 40% MVIC, in one of eight movement directions, the four orthogonal directions, and their corresponding four diagonal directions in that same plane. If they reached and exceeded the force target, the virtual end-effector would slowly start moving in the intended direction to encourage them to maintain that force level. Participants maintained an isometric hold for no longer than 12 seconds at the desired force level for each trial. To standardize the classifier inputs during training, data were extracted from each trial and resampled from ~20000 down to 10000 sample points of EMG activity for each movement direction. Real-time input data to either SVM was provided as the root mean square filter with a window of 200 samples for the fourteen EMG sensors.

5.7. Virtual Reality Task Environment for Training and Testing

The 3-D VR task environment (**Figure 15**) was primarily comprised of a robot arm whose end-effector moves within the transverse plane (forward-back-right-left) based on SVM outputs commanded by the participant's myoelectric patterns. The remainder of the robot-arm linkage follows the end-effector according to inverse kinematics [183]. The end-effector moved towards target locations (marked by spheres) for both training and testing trials of functional performance. Participants were instructed to pursue targets as quickly as possible, and that performance was measured by the shortest pathlength taken between targets, i.e., end-effector pathlength. Participants performed reach-to-touch tasks with the robot arm either in training trials with augmented visual guidance or during testing trials with no added feedback. For training trials, there are five target spheres arranged equidistantly (at 0°, 45°, 90°, 135°, and 180°) from the starting position for conducting a point-to-point reaching task [184]. A color change of a random target sphere would cue the participant to command the end-effector to reach and contact that target before immediately returning to the starting position and pursuing the next target. The five targets were arranged randomly for testing trials, and participants could choose the order to contact all targets serially. Allowing participants to select the order of pursued targets strategically supports the development of motor control [185]. Participants were informed about their pathlength during training through a "Pathlength Score" display to facilitate learning with knowledge of results [186] and score gamification [187]. Pathlength score was explicitly computed as the ratio of the minimum pathlength (straight line distance) between targets over the actual pathlength traversed by the end-effector multiplied by 100. For the participant, score interpretations were intuitive, whereby the goal was to achieve a score as close to 100 as possible.

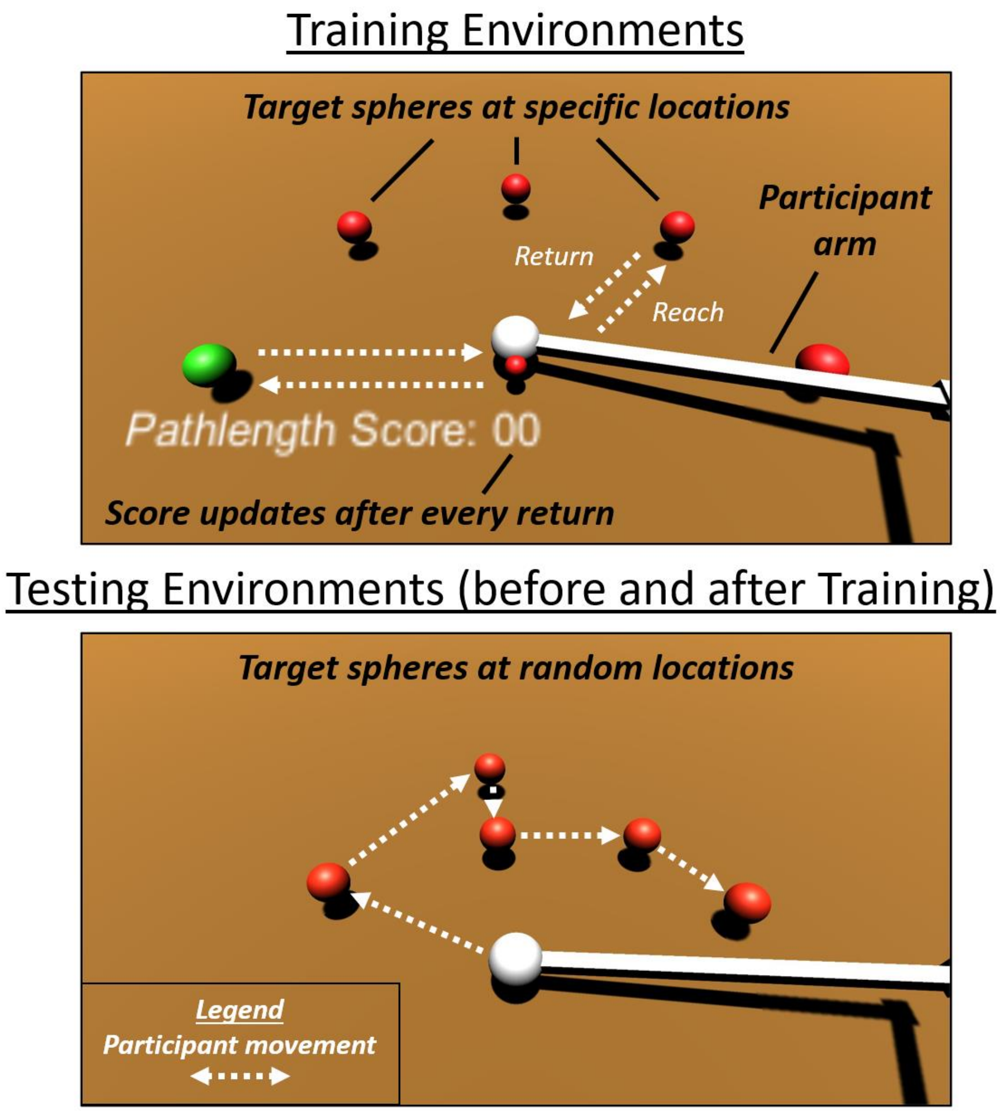

Figure 15. Three-dimensional virtual reality task environment shown for robot arm (white) under myoelectric control to make contact between its end-effector and target spheres. TOP) During point-to-point "training", the targets were positioned equidistantly from a central initial position as the participant received augmented visual guidance in moving to (reach) and from (return) the targets. BOTTOM) During "testing", augmented visual guidance was removed and targets were randomly positioned, and participants pursued targets in series and in the sequence order they choose.

5.8. Visual Feedback Modes Utilized for Augmented Training Guidance

Augmented training guidance in this study was presented as visual cues to suggest participant deviations from optimal (shortest) pathlengths between initial positions and targets. A second 'ghost' (semi-transparent) robot avatar was presented concurrently as a guide against the participant-controlled avatar during training. The end-effector position for the guide avatar was a projection of the participant-controlled avatar onto the optimal pathlength. Four modes of augmented visual feedback were created through concurrent variation of *complexity* (amount of visual information) and *intermittency* (frequency of visual information), with each feature tested at two levels (**Figure 16**).

Guidance complexity was specified as either *simple*, through the display of only the end-effector of the guide robot, versus *complex*, which also displayed the guide robot's arm linkage. The arm linkage of the guide robot similarly follows inverse kinematics of its end-effector and does not inherently provide additional feedback about error. However, my previous work [7] suggested that additional visual cues, even if redundant due to biomechanical coupling, may facilitate better motor learning if they signified greater body representation, e.g., serial sequence of body segments. In this previous study, the performance variable of interest was the thigh angle during the squat exercise. A serial body linkage improved motor performance by adding additional visual information about torso and shank segments. Thus, I seek to investigate if such feedback may positively contribute to motor learning despite the fundamental motor task difference of isometric, i.e., force-based, avatar control.

Guidance intermittency was specified as either *continuous*, whereby the guide avatar is always present, versus *bandwidth*, whereby augmented guidance was only provided if position error exceeded a particular threshold. This study specified the threshold as the mean error for a given participant during two practice training as part of initial accommodation. When this error is exceeded, a semi-transparent version of the guide arm appears and becomes opaquer in proportion to increasing error. The guide arm is fully opaque at twice the error magnitude of the threshold value. Pilot experimental sessions for this study and our previous work have indicated that modulating transparency of the guide arm in proportion to error magnitude ensured that intermittent transitions in feedback are not perceived as jarring to participants. The guide arm was presented at 20% transparency for continuous feedback modes. Pairing each unique level of one feature to another feature resulted in four visual feedback modes: 1) complex-continuous, 2) simple-continuous, 3) complex-bandwidth, and 4) simple-bandwidth.

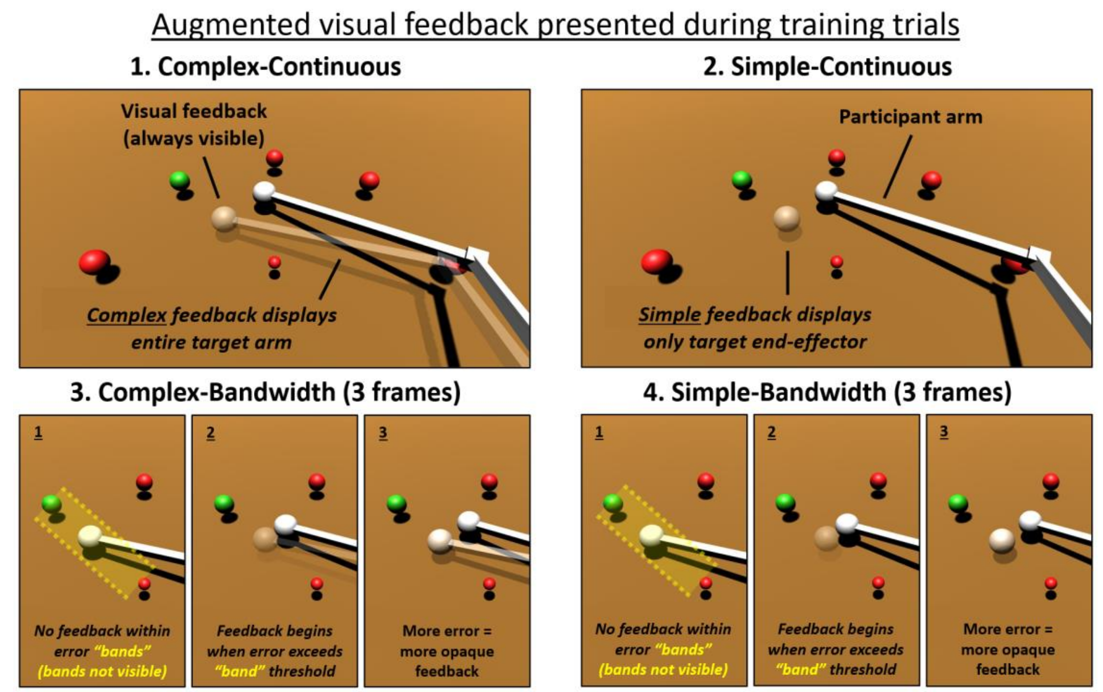

Figure 16. *Visual Feedback Modes for Augmented Guidance during Training.* All visual feedback modes project variations of a semi-transparent guide robot arm that follows the shortest (straight line) pathlengths between initial positions and active targets.

5.9. Experimental Protocol

Each participant completed a single session that evaluated the effects of all four visual feedback modes within four hours. The participant donned the upper-arm brace and had all skin-surface physiological (EMG, EEG, EDA) sensors placed upon arrival. Immediately after, several accommodation procedures occurred, including 1) brace adjustment for comfort and neutrality, 2) participant selection of an avatar end-effector speed (three speed choices presented), 3) a couple of minutes gaining experience commanding the virtual robot. Before testing each visual feedback mode, a couple of practice trials were conducted to determine baseline average performance errors (optimal pathlength deviations) to determine bandwidth thresholds. For each of the visual feedback modes, each participant underwent a three-block trial sequence: 1) Five testing trials (pre-training), 2) Ten training trials (training with augmented visual guidance), 3) Five testing trials (post-training). The order of visual feedback modes was randomized for each participant. Each trial was separated by 15 seconds, and a 15-minute break separated each three-block sequence for a visual feedback mode to mitigate fatigue effects. Participants were further queried intermittently throughout the session about how they felt and if they required an additional break.

5.10. Data and Statistical Analysis

All statistical analyses were performed using the *Statistics Toolbox* of MATLAB® (Mathworks Inc., Natick, MA, USA). All metrics for performance (completion time and pathlength score), perception (agency survey), and physiological engagement (alpha- and beta-band EEG activity for cognitive loading; EDA for physical arousal) were evaluated for each participant, visual feedback mode, and block of testing or training trials. Analysis of central interest in this study was the relative change in performance between post-training and pre-training trials for each visual feedback mode. We further evaluated the change in physiological measures from pre-training to either training or post-training. Finally, we observed participants' sense of agency for each visual feedback mode used for training. A two-factor Friedman (two-way ANOVA by ranks) test was performed for each of these metrics to identify significant differences across factors of complexity and intermittency. A paired t-test was the post hoc test for making multiple comparisons across visual feedback modes.

5.11. Results

5.11.1. Motion Performance - Pathlength Score and Completion Time

Results for both performance variables (pathlength score, completion time) are reported as the mean across participant-level averages within each block of trials. For each participant, the performance results during post-training blocks are divided (normalized) from those for pre-training to suggest the relative change in performance due to training with a particular visual feedback mode. When performing the multi-variate analysis (MANOVA) for both performance variables (pathlength, completion time), a significant difference ($p=1.8$ E-08) was observed across the independent variable of visual feedback modes. **Figure 17** presents the results for pathlength score alone. For the factors of complexity and intermittency, the two-way ANOVA indicated a significant difference for pathlength score based on complexity but not for intermittency (**Table 6**). No significant interactions were observed between these factors for either performance metric. The normalized pathlength score was significantly higher (p=0.0461) for simple feedback modes compared to complex modes. When examining individual feedback modes (**Table 7**), simple-continuous feedback generated better pathlength performance compared to both complex-continuous (p=0.0293) and complex-bandwidth (p=0.0449). Furthermore, an improvement in pathlength score during post-training compared to pre-training (i.e., normalized value greater than 1) was observed for all individual visual feedback modes. **Figure 18** presents the mean completion times during post-training when normalized by pre-training averages. Significant differences in completion time were not observed between pairs of individual visual feedback modes.

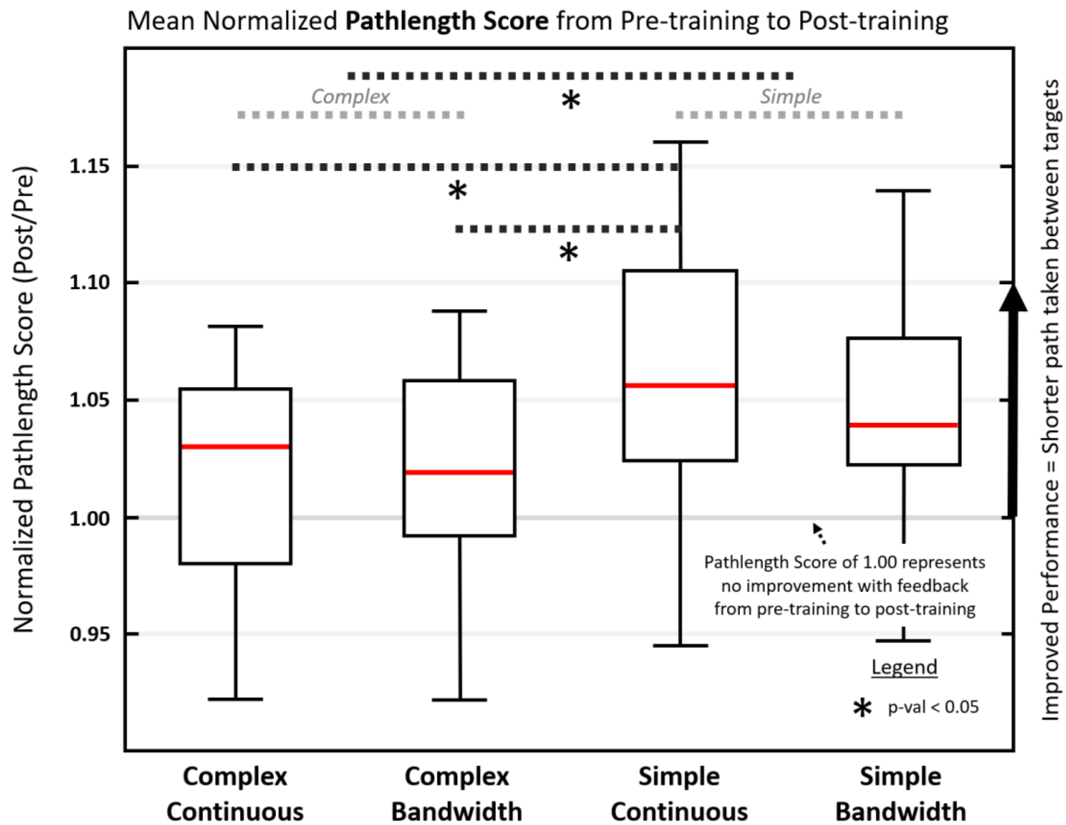

Figure 17. *Pathlength score* results indicate relative change in performance of pathlength minimization after training as score in post-training is divided (normalized) by pre-training for each participant.

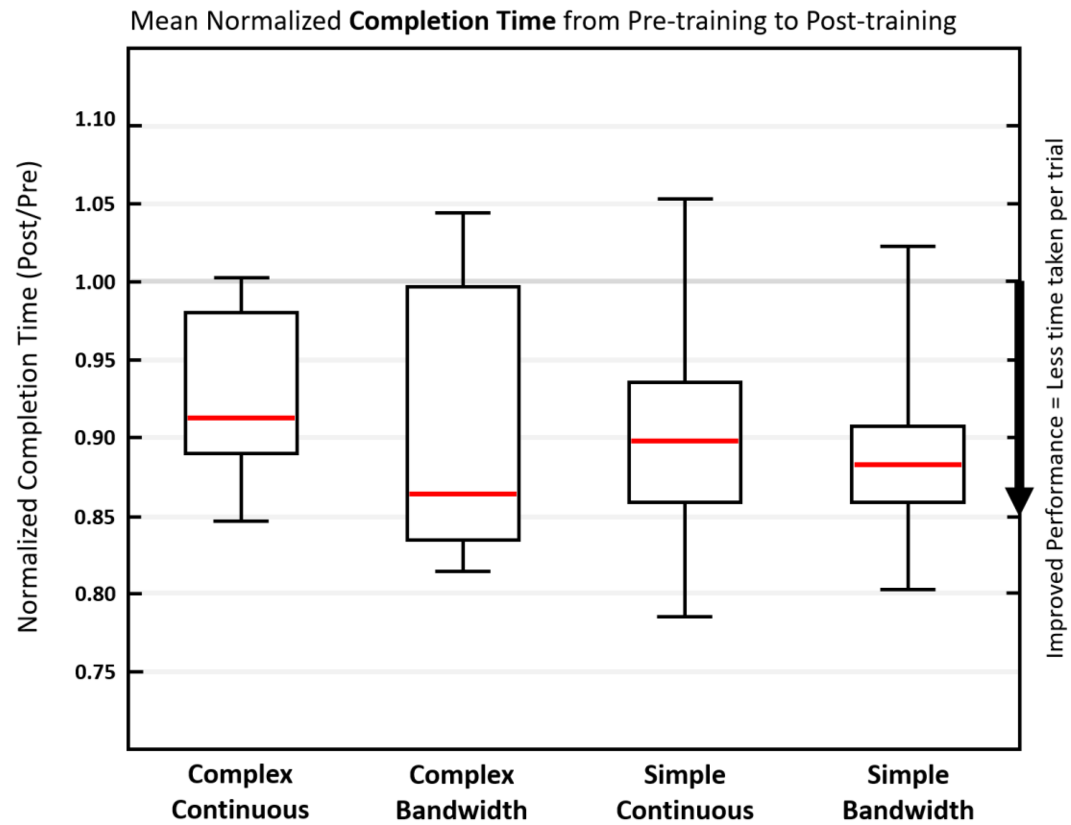

Figure 18. Results indicate relative change in trial *completion time* performance after training as mean time in post-training is divided (normalized) by time in pre-training for each participant.

Table 6: Performance results as the relative change from pre-training to post-training (Post/Pre ratio per participant)				
Table 6A: Mean performance across visual feedback modes				
	Visual Feedback Modes			
Metric:	CC	CB	SC	SB
Pathlength Score	1.01±0.05	1.02±0.05	1.06±0.06	1.05±0.05
Completion Time	0.92±0.05	0.91±0.09	0.90±0.07	0.89±0.06
Table 6B: Two-way ANOVA results based on factors of complexity and intermittency				
	Complexity		Intermittency	
Metric:	Chi-square	p-val	Chi-square	p-val
Pathlength Score	3.98	**0.046**	0.02	0.885
Completion Time	0.82	0.365	0.43	0.514

Note: Visual Feedback Modes – (CC) Complex-Continuous – (CB) Complex-Bandwidth – (SC) Simple-Continuous – (SB) Simple-Bandwidth
Note 2: Significant P-values (p<0.05) bolded

Table 7: Post hoc results comparing performance between pairs of visual feedback modes				
Table 7A: P-values for **pathlength score**				
	CC	CB	SC	SB
CC	x	0.726	**0.029**	0.171
CB	x	x	**0.045**	0.097
SC	x	x	x	0.480
Table 7B: P-values for **completion time**				
	CC	CB	SC	SB
CC	x	0.720	0.387	0.176
CB	x	x	0.473	0.299
SC	x	x	x	0.656
Note: Visual Feedback Modes – (CC) Complex-Continuous – (CB) Complex-Bandwidth – (SC) Simple-Continuous – (SB) Simple-Bandwidth *Note 2: Significant P-values (p<0.05) bolded*				

5.11.2. Electroencephalography

Figure 19 presents EEG data for alpha and beta powers measured across all channels, observed as relative changes from pre-training to training (Train/Pre ratio) *or* pre-training to post-training (Post/Pre ratio). Significant differences in EEG were observed based on intermittency (**Table 8**) and across individual feedback modes (**Table 9**). Significant differences were observed only for Post/Pre for the alpha band. Continuous feedback resulted in significantly higher (p=0.0116) EEG activity than bandwidth (intermittent) feedback. No significant interactions were observed between factors of complexity and intermittency. Additionally, complex-continuous (p=0.0318) and simple-continuous (p=0.0014) resulted in significantly higher EEG activity compared to simple-bandwidth. For the beta band, complex-bandwidth generated significantly higher (p=0.0384) EEG activity during training than simple-bandwidth. **Figure 20** presents a brain map of EEG alpha band activity averaged over all participants for simple-continuous and simple-bandwidth (Post/Pre). The simple modes are further examined since they result in better performance than complex modes. The higher alpha band activity preserved in post-training was generally distributed across the entire brain, including motor and sensory areas, suggesting a shift to continuous feedback produced a uniform effect on brain activity.

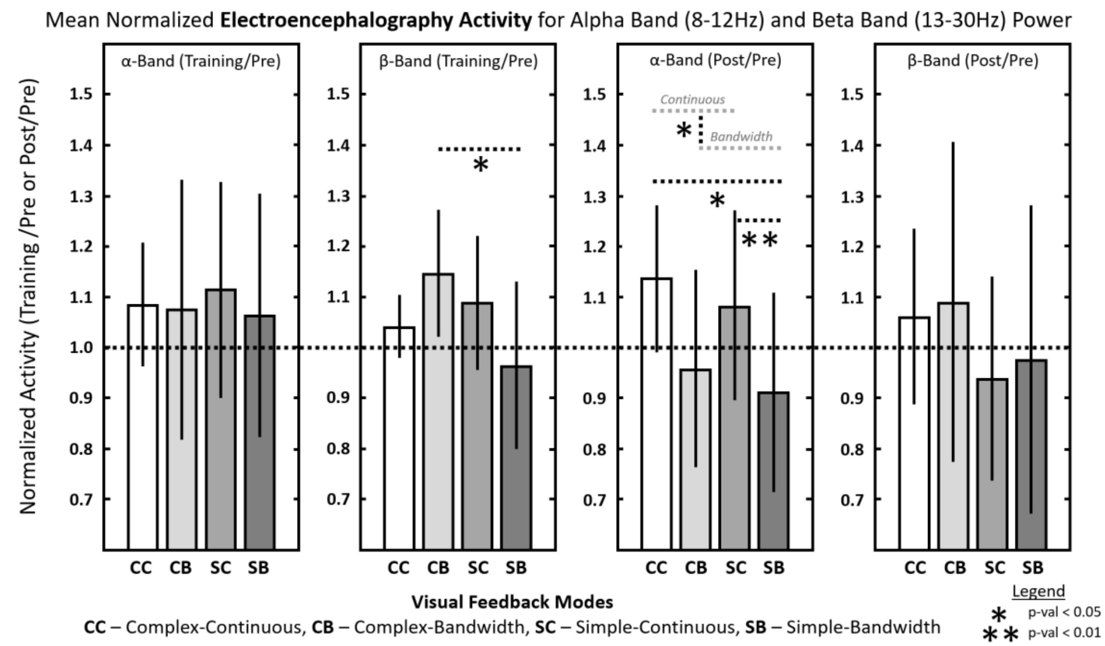

Figure 19. *Electroencephalography* results indicate change in alpha or beta band power during either training or post-training from pre-training.

Table 8: Electroencephalography **Alpha Band (8-12Hz)** and **Beta Band (13-30Hz)** power as the relative change from pre-training to training (Train/Pre) and pre-training to post-training (Post/Pre)				
Table 8A: Mean EEG results for across visual feedback modes				
	Visual Feedback Modes			
Metric:	CC	CB	SC	SB
Alpha Band – Train/Pre	1.08±0.12	1.07±0.26	1.11±0.21	1.06±0.24
Beta Band – Train/Pre	1.04±0.06	1.15±0.13	1.09±0.13	0.96±0.17
Alpha Band – Post/Pre	1.14±0.14	0.96±0.20	1.08±0.19	0.91±0.20
Beta Band – Post/Pre	1.06±0.17	1.09±0.32	0.94±0.20	0.98±0.30
Table 8B: Two-way ANOVA results based on factors of complexity and intermittency				
	Complexity		Intermittency	
Metric:	Chi-square	p-val	Chi-square	p-val
Alpha Band – Train/Pre	0.05	0.824	1.08	0.299
Beta Band – Train/Pre	0.93	0.334	0.09	0.766
Alpha Band – Post/Pre	0.45	0.504	6.38	**0.012**
Beta Band – Post/Pre	1.24	0.265	0.09	0.766

Note: Visual Feedback Modes – (CC) Complex-Continuous – (CB) Complex-Bandwidth – (SC) Simple-Continuous – (SB) Simple-Bandwidth
Note 2: Significant P-values ($p<0.05$) bolded

Table 9: Post hoc results comparing EEG band powers between pairs of visual feedback modes				
Table 9A: P-values for **Alpha Band – Training/Pre**				
	CC	CB	SC	SB
CC	x	0.904	0.734	0.827
CB	x	x	0.692	0.923
SC	x	x	x	0.584
Table 9B: P-values for **Beta Band – Training/Pre**				
	CC	CB	SC	SB
CC	x	0.072	0.322	0.212
CB	x	x	0.474	**0.038**
SC	x	x	x	0.092
Table 9C: P-values for **Alpha Band – Post/Pre**				
	CC	CB	SC	SB
CC	x	0.104	0.552	**0.032**
CB	x	x	0.248	0.600
SC	x	x	x	**0.001**
Table 9D: P-values for **Beta Band – Post/Pre**				
	CC	CB	SC	SB
CC	x	0.778	0.086	0.485
CB	x	x	0.065	0.444
SC	x	x	x	0.768
Note: Visual Feedback Modes – (CC) Complex-Continuous – (CB) Complex-Bandwidth – (SC) Simple-Continuous – (SB) Simple-Bandwidth *Note 2: Significant P-values (p<0.05) bolded*				

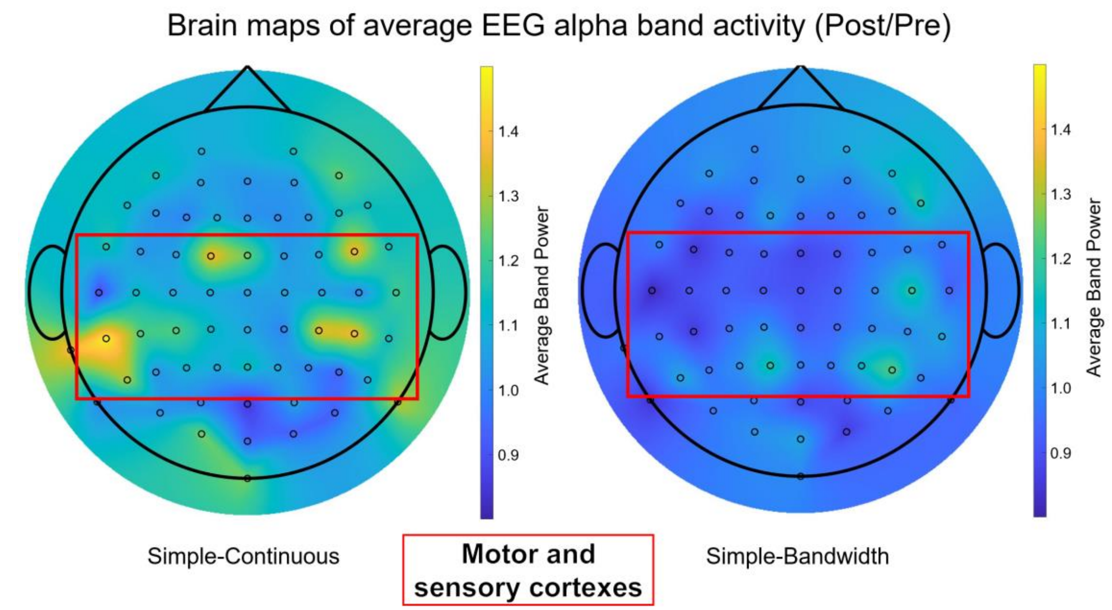

Figure 20. *Brain map of EEG activity averaged for all participants*. Electroencephalography (EEG) results to indicate changes in average alpha band activity during post-training from pre-training for simple-continuous (LEFT) and simple-bandwidth (RIGHT).

5.11.3. Electrodermal Activity

Figure 21 presents the relative changes in electrodermal activity for each visual feedback mode, from pre-training to training. Significant differences were observed for the factor of complexity (**Table 10**) and across individual feedback modes (**Table 11**). No significant interactions were observed between factors of complexity and intermittency. Simple feedback resulted in significantly higher (p=0.0239) skin conductance during training than complex feedback. Furthermore, complex-bandwidth feedback resulted in significantly lower conductance that either simple-continuous (p=0.0377) or simple-bandwidth (p=0.0218).

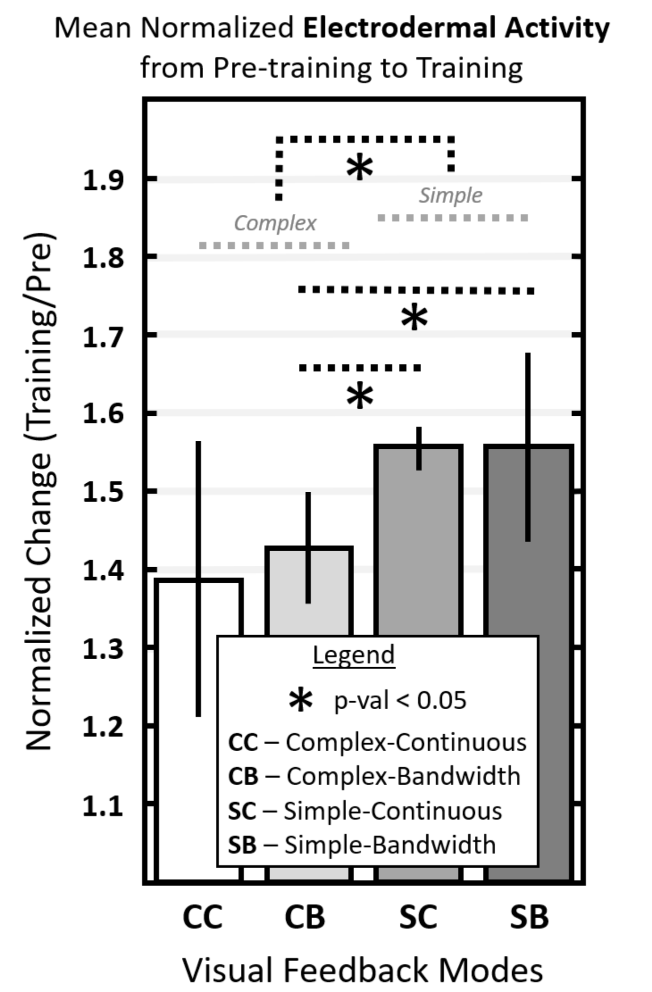

Figure 21. Relative change in *electrodermal activity results* during training compared to pre-training for each feedback mode.

Table 10: Electrodermal activity during training with each feedback mode. Results presented as the mean skin conductance during training divided by pre-training (Train/Pre)				
Table 10A: Mean EDA results (microsiemens)				
	Visual Feedback Modes			
Metric:	CC	CB	SC	SB
Training/Pre	1.39±0.18	1.43±0.07	1.56±0.03	1.56±0.12
Table 10B: Two-way ANOVA results based on factors of complexity and intermittency				
	Complexity		Intermittency	
Metric:	Chi-square	p-val	Chi-square	p-val
Training/Pre	5.10	**0.024**	0.17	0.681

Note: Visual Feedback Modes – (CC) Complex-Continuous – (CB) Complex-Bandwidth – (SC) Simple-Continuous – (SB) Simple-Bandwidth
Note 2: Significant P-values (p<0.05) bolded

Table 11: Post hoc results comparing EDA between pairs of visual feedback modes				
Table 11A: Post hoc comparisons, p-value, between visual feedback modes for **EDA activity – Training/Pre**				
	CC	CB	SC	SB
CC	x	0.733	0.197	0.304
CB	x	x	**0.038**	**0.022**
SC	x	x	x	0.973

Note: Visual Feedback Modes – (CC) Complex-Continuous – (CB) Complex-Bandwidth – (SC) Simple-Continuous – (SB) Simple-Bandwidth
Note 2: Significant P-values (p<0.05) bolded

5.11.4. Agency (Survey) Results

The mean survey score (80.65) for the perception of control (agency) was normalized for each participant by subtracting the mean across visual feedback modes to highlight better the model-level differences in survey scores (**Figure 22A**). The mean values for each feedback mode were: complex-continuous = 83.5/100, complex-bandwidth = 81.6/100, simple-continuous = 81.5/100, simple-bandwidth = 76/100. A significant difference (p=0.0249) was observed between complex-continuous and simple-bandwidth. No significant differences were observed based on factors of complexity or intermittency. **Figure 22B** plots agency against pathlength performance (relative change in score from pre-training to post-training).

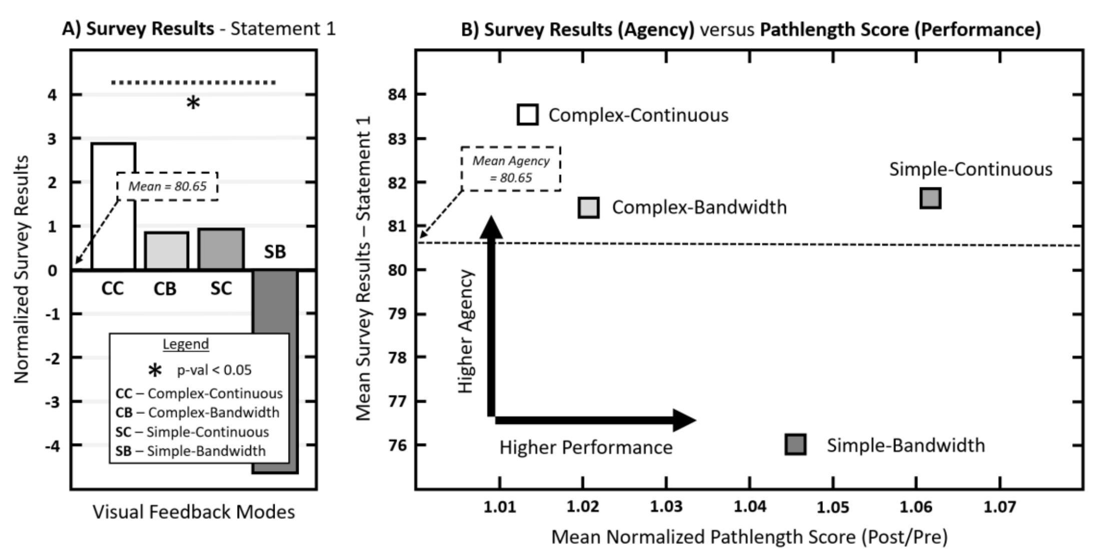

Figure 22. *Survey results.* A) Survey score results for agency for each visual feedback mode. B) Agency results versus relative change (pre to post) in pathlength score performance.

5.11.5. EEG and Agency versus Pathlength Score by Participant

EEG and agency results were additionally evaluated against Pathlength Score at a participant-specific level (**Figure 23**). For each participant, EEG alpha band power was plotted against Pathlength Score, both presented as post-training/pre-training, and a linear regression line was fitted for each visual feedback mode. The linear regression line for simple-continuous has a distinct negative slope, indicating higher cognitive loading resulted in lower performance. Additionally, agency results were plotted against Pathlength Score. Both simple feedback modes had a regression line that was notably negative, indicating that higher agency resulted in lower performance. For simple feedback, higher performance (Pathlength Score) is related to lower cognitive activity and lower agency. No significant differences were found for the slope of any regression lines.

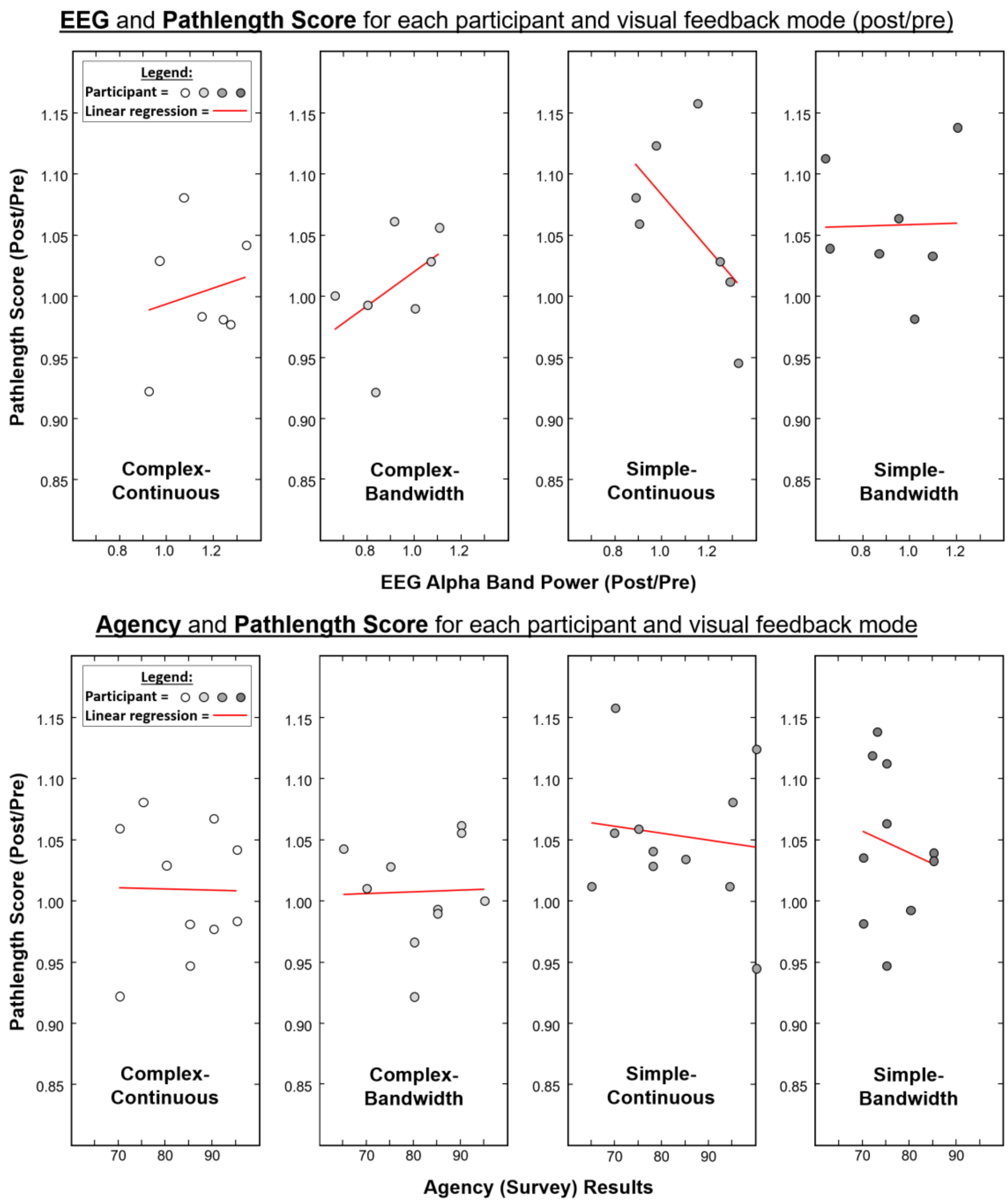

Figure 23. *EEG and Agency versus Pathlength Score by Participant*. TOP) EEG alpha band power and Pathlength Score both presented as post-training/pre-training. BOTTOM) Agency (survey) results and Pathlength Score (Post/Pre).

5.12. Discussion

This study primarily investigated changes in force-based motor performance with variations in features of augmented visual feedback, namely, complexity and intermittency. We leveraged a novel rehabilitative platform utilizing a computerized interface (i.e., immersive virtual reality) and a position-adjustable arm brace that provides gravity support during isometric strength training. My results demonstrated that variations in visual feedback features could generate significant differences in post-training performance. My results do not reflect true motor learning [188], which requires demonstration of long-term retention and skill acquisition; however, immediate (short-term) performance effects can be indicative of learning potential [189] and promise for neuromotor rehabilitation [190]. Immediate performance effects were characterized according to a relative change from pre-training to post-training for each participant and the feedback mode used for augmented guidance. For the point-to-point motor task in VR, simpler feedback (i.e., end-effector guide only) appeared to be more effective in improving performance. This more simple guide provided continuously produced the best pathlength performance overall.

I presented more complex feedback for this force-based task (i.e., participant held isometrically) with the inclusion of the links preceding the end-effector of the guide arm. In my previous work investigating visual feedback features for a motion-based task (i.e., participants' own motions drive computer display) [7], there was a single segment (thigh) whose observed motions were the primary trajectory target for performance. More complex feedback was presented as additional segment trajectories to match, namely the torso and shank. That study suggested that complex feedback representing the intrinsic coupling of all body segments facilitated better tracking of the thigh segment due to functional constraints for the squat. In the current study, the target segment to track is the end-effector, and motions of the links are constrained to the end-effector through inverse kinematics. While the presentation of these link positions is, in fact, extraneous to the primary target of the end-effector, its inclusion as additional real-time feedback tests whether presenting a kinematic synergy facilitates better motor learning. A major distinction with this study from my previous work with the squat task is that the participant is held isometrically and cannot dynamically embody [156] with the motion feedback being presented in real-time. Thus, complex feedback might only be effectively leveraged towards improved motor performance for rehabilitation paradigms utilizing motion-based inputs that allow the user to embody the avatar fully. It may be necessary and more challenging for a force-based task to effectively display kinetic synergies as complex feedback for rehabilitating motor coordination [191]. In this study, the additional information presented may have been perceived as distracting [51] or irrelevant to the primary objective [61]. Thus, my hypothesis regarding complexity was refuted for the presented motor task.

My hypothesis regarding intermittency is also refuted as continuous feedback outperformed bandwidth feedback. However, this result is consistent with my previous work investigating intermittency effects with the squat task [8]. In both studies, the guidance hypothesis [78] was not confirmed, suggesting these computerized rehabilitation protocols may not be able to facilitate the development of intrinsic mechanisms within a single session. Thus, follow-up sessions may be necessary to confirm the relevance of the guidance hypothesis to these specific motor paradigms, motion- and force-based tasks, with computerized feedback. Furthermore, the guidance hypothesis with intermittent feedback is often predicated on knowledge of results with terminal feedback [59]. Thus, a novel element of the current study is the inclusion of intermittency with concurrent feedback. However, given concurrent feedback's proven effectiveness in generating immediate performance [78], it is crucial to examine ways to leverage concurrent feedback in creating VR rehabilitation protocols that can further accelerate gains in motor function. As in my previous motion-based squat protocol, we did examine "potential learning" in terms of the relative retention in performance in post-training with no feedback after receiving augmented guidance during training. In the squat protocol, this potential learning was greater with bandwidth protocols. In the force-based task, due to only testing four visual feedback modes instead of six as in the motion-based task, additional trials were added to create a new pre-training (baseline) phase. Therefore, potential learning was evaluated as the relative difference between post-training (retention) and the new pre-training phase (baseline) completed before training. During the VR reaching task, training with concurrent bandwidth feedback induced significantly lower cognitive activity than continuous feedback, regardless of complexity. Amongst simple feedback, determined superior for performance, higher performance was related to lower cognitive stress (alpha band power), lower sense of agency (survey score), and higher physical stress. Lower alpha band activity is related to a greater focus on external objects during VR rehabilitation [129], which leads to greater performance and retention compared to an internal focus [3]. Lower alpha band activity [192] and lower cognitive activity identified via fMRI [193] indicates greater potential motor learning as participant experience increases and movements are completed more automatically and less consciously [62].

In this study, we observed two sets of user-centered metrics as potential explanatory variables for the performance with various modes of training feedback. First, we observed explicit agency from the survey responses, indicating that participants perceived complex-continuous augmented guidance provided greater control of the virtual arm than simple-bandwidth. Complex-continuous theoretically provided the most guidance, i.e., the guide robot arm are displayed fully (end-effector and arm links) and constantly during training. It is plausible that participants assumed the guide arm generated greater control or projected their intended actions on the guide arm versus the actual arm. My laboratory's previous findings measured agency implicitly for simple computerized reach [194] and grasp [195] tasks positively correlated with improved performance. This study suggests that a constrained myoelectric task may generate a perceptional inversion. Participants are not always aware of what is most beneficial to them for motor learning [3]. Participants may make selections based on comfort and neglect the possibility that challenging scenarios, which may be uncomfortable, will be more advantageous for motor learning.

Physiological measures such as EEG and EDA provide a more objective basis to discern fundamental user-centered responses. As inferred through cognitive loading, increased engagement can produce better performance in a VR environment [196]. When significant differences were discernible, this study confirmed, as expected, that simpler and intermittent feedback reduced EEG power. Since simpler feedback generally produced better performance, it may be inferred that complex feedback, as presented here, may have resulted in overloading that diminished performance [197]. Alternatively, simpler feedback generally produced greater physical arousal, as indicated by higher electrodermal activity [174]. For this study, the simpler feedback may have supported the user to be more physically engaged, without mental distraction, towards improved motor performance.

The major limitations of my study to demonstrate how variations in augmented visual guidance for training affect motor learning include constraints on the task, motor transference, and long-term retention. The task control space was limited to 2D due to challenges in attaining robust multi-dimensional control through the enacted pattern classifiers. More advanced machine learning methods for 3D myoelectric control [198], [199] may be enacted. However, the deployment of such approaches must be balanced against the feasibility considerations of time to train within single sessions [135] and classification accuracy [200]. Feasibility is crucial for clinical populations with reduced and compromised muscle sets to identify myoelectric commands [31], [135]. Ultimately, improved motor skill acquisition [153], [201] must be demonstrated by testing functional abilities in generalizable contexts that differ from training. Functional gains with isometric testing must be exhibited through improved abilities to perform dynamic tasks that better represent activities of daily living [40], [202]. Additional modifications could be pursued to facilitate better motor control, even within the training paradigm [112]. We did employ a measure of strategy to support motor control objectives by allowing users to self-select the order or target pursuits during testing blocks. However, more complex tasks (e.g., 3D control, additional tasks beyond point-to-point contact) are more versatile for synergistic control. Synergistic control involves manipulating the end-effector through forward dynamics [203], whereby the user enacts control upon a robot arm's elbow and shoulder joints.

5.13. Conclusion

In optimizing VR training for a force-based motor task, the complexity and intermittency of augmented visual guidance can significantly influence the resultant motor performance. When training upper-extremity function, additional visual feedback about the forearm and upper arm may be unnecessary when the primary objective is end-effector accuracy. For a virtual reaching task, training with simpler feedback (i.e., about end-effector only) resulted in significantly greater motor performance (e.g., minimal pathlengths, shorter completion times) and higher arousal (electrodermal activity). Furthermore, training with feedback presented more intermittently (i.e., bandwidth) resulted in improved muscle-level control in conjunction with lower cognitive (alpha band) activity. These post-training results with simple-bandwidth feedback indicated that participants were more positively allocating resources to physical engagement and performance. Future studies should investigate longitudinal comparisons of VR-based therapies that systematically leverage augmented visual guidance to conventional treatments and non-optimized VR protocols to determine if these performance advantages exist for similar therapeutic dosages. Furthermore, advanced feedback control systems to adapt VR rehabilitation systems for greater personalization for individual users may consider varying training features according to online measures of physiological variables (e.g., EEG, EDA).

6. PRIMARY CONCLUSIONS AND FUTURE DIRECTIONS

Following neurological trauma, clinical motor rehabilitation can be frustrating due to its rigorous and repetitive nature. Fortunately, computerized interfaces, primarily virtual reality, can provide additional motivation during physical rehabilitation and create enhanced forms of augmented visual feedback. Augmented visual feedback provides transformed displays of participant performance, relaying additional task information in real-time for immediate performance improvements. Unfortunately, the exact mechanisms behind leveraging VR and augmented visual feedback to improve motor learning is unknown. I identified a lack of optimization in the deployment of clinical rehabilitation and computerized interfaces, emphasizing improving motor performance. Therefore, my approach was to systematically leverage specific features of augmented visual feedback, mainly *complexity* and *intermittency*, for a motion- and force-based task. I examined how augmented visual feedback features affect training and retention of motor performance. I also identified potential avenues for expanding future research.

For a motion-based task, the two-legged squat, complex-representative modes increased motor performance more during training and retention compared to feedback deemed simpler and abstract. All motion-based tasks require some level of force-modulation, such as pushing off the ground during the squat exercise or reaching movements against gravity. Specifically, motion-based tasks involve changes in joint angles with multiple moving body segments. The motor outcomes for the squat exercise are influenced by one major performance variable, identified as changes in squat depth or thigh angle. My approach evaluated the differences behind guiding multiple body segments with complex feedback versus representing the movement as a single target driven by simple feedback. Simple feedback only provided information about the thigh segment angle, while complex feedback provided information about additional shank and torso body segments. We identified that the additional information from complex feedback was beneficial, but only if presented with clear body-discernible features. Training with complex-abstract feedback represented as disjointed lines was more challenging for the participant to stabilize performance. Complex-representative feedback presented as lines connected at presumed joint locations increased the motor performance and presumed embodiment with the visual feedback. Increased embodiment with the visual feedback during training led to an increase in the development of intrinsic mechanisms and independent movement strategies. Although simple and abstract feedback modes may have been advantageous during training, retention performance was negatively affected as participants could not effectively recreate the movement under independent control.

For the force-based task, controlled through isometric muscle activations, simple feedback showed the greatest potential to improve motor performance than complex modes. Force-based tasks primarily involve the modulation of a single force target or amplitude signal. Force-based tasks may more effectively train with simple feedback that removes erroneous feedback elements. The additional information provided during complex feedback was irrelevant to the primary objective, end effector accuracy, and any increase in embodiment was ineffective. For the force-based task, high performance with simple feedback was related to lower cognitive activity (cognitive stress), lower agency, and higher EDA (physical stress). Following training with simple or bandwidth feedback modes, a lower cognitive activity could indicate that participants' motor control transitioned to more automatic processes [62]. Movements controlled consciously in the early stages of motor learning produce higher cognitive activity. I postulate that this effect during post-training trials is a residual effect following training with augmented visual feedback. No significant differences observed during training could result from the gradual training effect over ten trials, and the average impact over the whole phase was insignificant. This finding is different than the result for the two-legged squat experiment, where additional target information during complex feedback was beneficial for performance. It may be necessary and more challenging for a force-based task to effectively display kinetic synergies as complex feedback for rehabilitating motor coordination.

There were limitations in directly comparing the results between the motion- and force-based tasks presented in this research. One of the limitations was that the additional information provided during the squat exercise was independently controlled, which was not the case for the force-based movement. During the force-based VR task, the additional forearm and upper arm target feedback were driven through inverse kinematics and may have been irrelevant to the primary objective. The participants were only able to control the end effector and end effector accuracy, the primary performance metric. Another significant difference between the two tasks was that the participants transformed display of performance never changed based on visual feedback modes for the VR reaching task. Unlike the squat exercise, where it was possible to train the motion without participant feedback performance, such as bandwidth feedback, it was necessary to constantly provide the participant position for the VR reaching task to complete the movement effectively. For example, it would be possible to display bandwidth or simple-representative feedback targets for the squat task while displaying the participant position as complex-representative. Hülsmann et al. developed a similar approach for the squat exercise by constantly displaying participants' positions in a 3D VR space while providing additional bandwidth-abstract feedback to highlight position errors [204]. The increased embodiment based upon specifically target feedback features, and not a combination with participant feedback, was not established and would be an interest in future studies. Another limitation was that the augmented visual feedback during the squat exercise was displayed as a third-person perspective. In contrast, the VR-based reaching task utilizing the head-mounted showed a first-person view.

<u>Concurrent bandwidth feedback showed potential for improving short-term retention in a motion-based task and decreasing cognitive activity in a force-based task.</u> I **firmly believe concurrent bandwidth augmented visual feedback in immersive VR environments should be leveraged for improving clinical motor rehabilitation**. Bandwidth feedback has been extensively researched in terminal feedback forms because conventional rehabilitation paradigms cannot create the concurrent bandwidth visual cues possible in VR environments. Whether the perspective is first- or third-person, VR-based training with continuous feedback from virtual avatars has shown to be effective for guiding spatial positioning [74], [204]. However, concurrent bandwidth VR-based feedback has not been extensively researched. A significant limitation of both studies was the lack of longitudinal results, which would indicate the long-term learning effects of

concurrent bandwidth feedback. Compared to continuous feedback for the two-legged squat, training with bandwidth feedback resulted in higher potential learning with higher relative performance levels during short-term retention tests. Training with bandwidth feedback removed the participant and target position during times of low error and forced the participants to develop independent movement strategies. Training with concurrent bandwidth also produced significantly lower cognitive activity (alpha band power) during the VR force-based task than continuous feedback during post-training trials. Increased alpha activity power is related to higher internal processing during VR-based cognitive studies [129] and indicates the participant is still consciously completing the action [62]. The decrease in alpha activity during post-training trials for the forced-based task may indicate that training with bandwidth feedback exhibited a higher focus on external processes for motor control. External processes are more effective for motor control as a focus on internal mechanisms can constrain the motor system by interfering with automatic control processes [3]. The decrease in alpha activity could also indicate that training resulted in greater muscle level control automatically and less activity of conscious force-based actions [62]. My research did not focus on cognitive activity as a primary interest measure and evaluated average changes in activity across all EEG sensors. Future studies should explore the effects of bandwidth feedback on individual brain regions, such as the motor and sensory cortexes. The changes in cognitive activity during force-based actions may benefit concurrent bandwidth feedback deployment for all motor tasks. This approach can expand cognition and motor performance knowledge because measuring EEG activity during motion-based tasks may be difficult.

My final takeaways are that there are significant and unique differences in motor performance outcomes with variations in augmented visual feedback. The effects of augmented feedback depend upon the type of task, motion- or force-based. Measures for well-being, such as physiological stresses or sense of agency, may also be influenced by variations in augmented feedback. In optimizing computerized interfaces for rehabilitation, features of augmented visual feedback should be selected based on:

1. The type of movement function to restore or rehabilitate
2. Whether the participant can embody the augmented feedback
3. The experience of the user and their well-being during training

Future directions should investigate augmented multimodal feedback for motion-based tasks. My results indicate that multimodal feedback would not be practical for force-based tasks as simple feedback is already more effective than more complex modes. However, motion-based exercises, especially multi-DOF movements with naïve participants, may benefit from multimodal feedback, especially in the early stages of motor learning. The provision of multiple visual feedback cues [204], or a combination of visual and haptic cues [83], [114], [124], may further accelerate performance for motor tasks. Over an extended period, feedback should be gradually reduced, changing from concurrent continuous to bandwidth, and finally, terminal in the latter stages of motor learning—however, caution not to relate changing the complexity of the feedback to gradually reducing frequency.

In summary, my results indicate:

- For a motion-based task, the two-legged squat, complex-representative modes increased motor performance more during training and retention compared to feedback deemed simpler and abstract. However, for the force-based task, controlled through isometric muscle activations, simple feedback showed the greatest potential to improve motor performance than complex modes. Concurrent bandwidth feedback showed potential for improving short-term retention in a motion-based task and decreasing cognitive activity in a force-based task.
- My final takeaways are that there are significant and unique differences in motor performance outcomes with variations in augmented visual feedback. Future directions should investigate augmented multimodal feedback for motion-based tasks.

7. SOURCES OF SUPPORT

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- The Charles V. Schaefer, Jr. School of Engineering & Science at Stevens Institute of Technology (https://www.stevens.edu/schaefer-school-engineering-science)
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8. APPENDIX

8.1. How it all started - Red tape augmented visual feedback

It is exciting to look back and see where my research started to where it ended up. At the beginning of the Ph.D. journey, augmented visual feedback was not my initial plan. The desire for visual feedback came about when figuring out how to get someone to squat the same way in two separate locations. The goal was to have the participant squat in the lab using motion capture equipment to analyze kinematics, and then subsequently squat the same way at a medical facility immediately before getting an MRI. The research objective was to use the MRI data for creating high quality computer simulations used to model participant kinematics and kinetics during the squat exercise. The first idea for visual feedback was created following my experience with an Introduction to Robotics course. During the course I learned how to analyze differences in color from an image. Therefore, I went down a rabbit hole of using colored tape to track thigh angle position (**Figure 24**). Different color tape was evaluated, with red being the winner and easiest to identify. Next, a camcorder was used to display the tape position and thigh angle. For real-time tracking, a rubber band or tape was put over a computer monitor position in front of the participant as the target to match at the desired squat depth. For off-line analysis, changes in angle of the colored tape were used to calculate changes in thigh angle position. At each frame, the outline and shape of the tape was identified separate from the background, and a line was generated through the middle to represent the thigh angle.

Red tape used to track thigh angle during my early research years

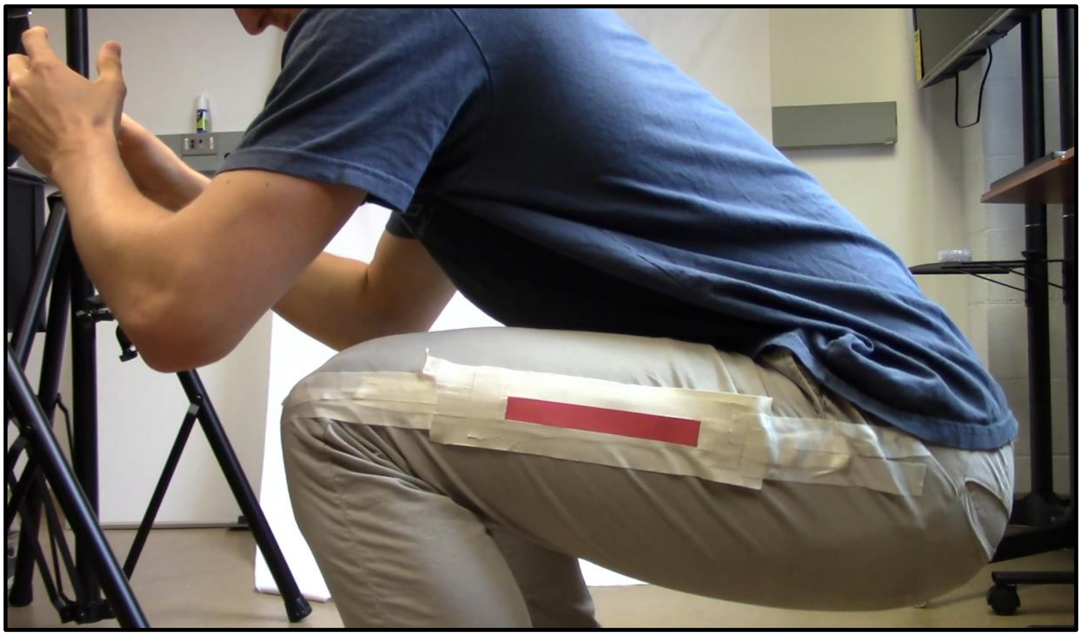


Figure 24. The first creation of augmented visual feedback utilized a camcorder and a piece of red tape on the thigh to represent thigh angle. For real-time feedback, a rubber band or additional piece of tape was placed over the monitor as a target to match for squat depth. The outline and shape of the tape was processed off-line using MATLAB color analysis to determine changes in thigh angle.

8.2. Supportive Brace Apparatus

The primary module of Aim 2, the force-based task, was a custom upper extremity supportive brace apparatus (**Figure 25**). As described in further detail in the Methods of Aim 2, the primary objective of the brace is to immobilize the forearm and upper arm to support the arm against gravity and provide restrictive forces for isometric training. The brace was constructed using computer aided design (Solidworks) and the original prototype included a chest plate. The chest plate was intended to use the participants body weight for helping to restrict their own forces, thus creating an all-in-one design. The participant would not need an external fixation device such as a table, and it would allow the participant to wear the brace while standing. The benefits for wearing the brace while standing are enhanced gamified environments that include gait or rotation movements during VR-based tasks.

Supportive brace apparatus for upper extremity isometric experiments

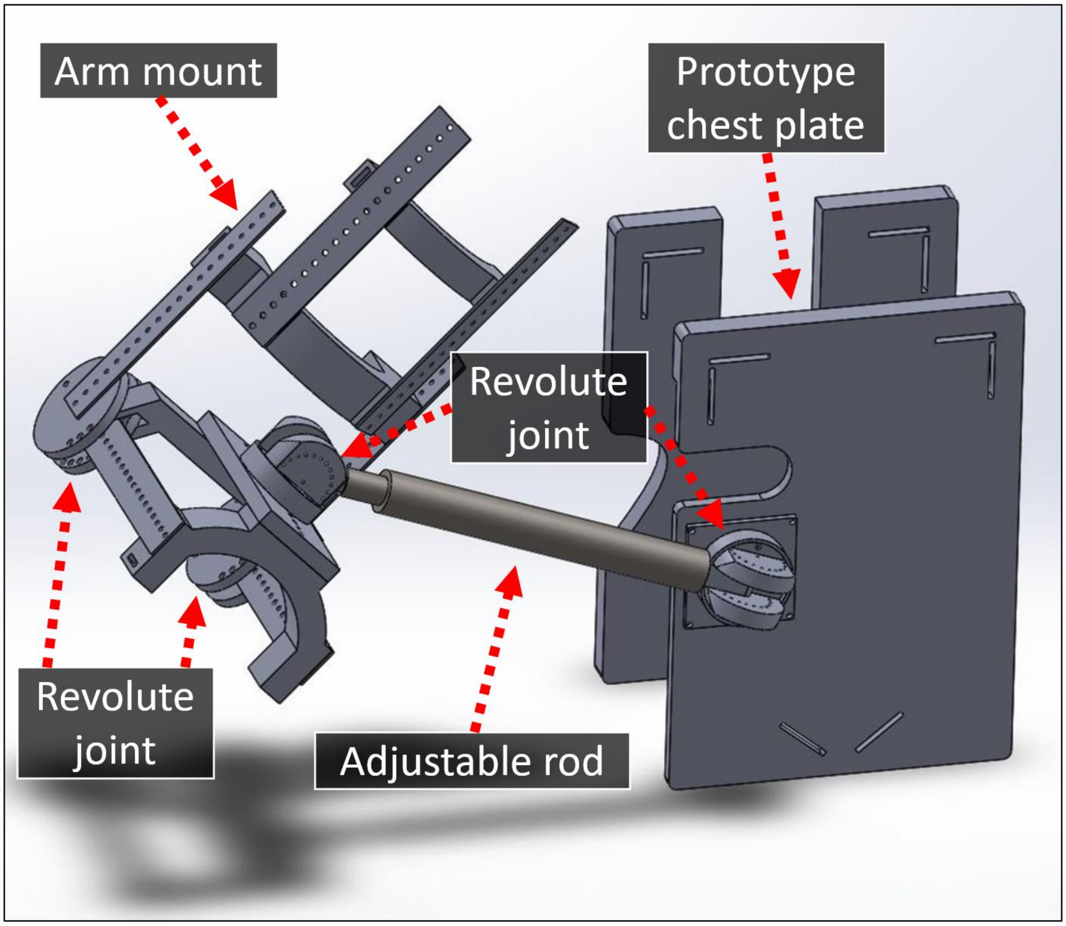


Figure 25. Computer aided design of the supportive brace with a prototype for the chest plate. The arm mount is the primary module for restricting flexion and extension of the elbow joint. The two revolute joints and adjustable rod attach the arm mount to the chest plate and restrict shoulder ab/adduction and in/external rotation.

8.3. Augmented Vibrotactile Feedback

Two pilot experiments were conducted on the effects of vibrotactile feedback with the supportive brace. One utilizing vibrotactile feedback in an *explicit* form, directly guiding task performance. The other utilizing vibrotactile feedback in *implicit* form, directly increasing EMG activation. The same VR environment and experimental protocol presented in Aim 2 were reevaluated with two unimodal vibrotactile and one multimodal feedback mode in the explicit experiment. The three sensory feedback modes were compared to a fourth control group, and the same performance metrics were evaluated pathlength score and completion time. Five neurotypical participants completed the explicit vibration experiment. In the implicit vibrotactile feedback experiment, direct vibration on the muscle-tendon junction was used to increase EMG activity during isometric contractions. We aimed to identify vibration patterns that could increase EMG activity in a controlled and systematic way. The objective was to increase the separability between muscle activation clusters within the machine learning classifier used for commanding the virtual device. We hypothesized that real-time vibration could increase muscle activation clusters' separability and lead to greater classification accuracy and improved control of the virtual device.

8.3.1. Explicit Vibrotactile Feedback

Explicit vibrotactile feedback can directly guide the participant towards a movement trajectory through an attraction or repulsion sensation. When position error to the target begins to increase during a movement task, the participants move toward the vibration during *attraction* types and away from the vibration during *repulsive* types. For simple motor tasks, such as standing balance, allowing the participant to choose their preferred method, attraction or repulsion, results in a higher score than choosing one that is undesired or feels unnatural to the task. This decision supports allowing the participants to make decisions within the experiment to increase agency and sense of control. When compared against each other, repulsive feedback has shown to be more effective than attractive and is often considered the standard for explicit guiding experiments [106].

In this study, the same experimental protocol presented in Aim 2 was used for evaluating unimodal and multimodal feedback paradigms of vibrotactile feedback (**Figure 26**). Twelve small coin motors were used to translate position error magnitude and direction changes. Three coin motors were attached vertically (or in a cluster) at the same height on the torso and equally placed on the participants' left, right, center, and back. For reference to height, the front motors were placed just below the sternum, and the back motors were placed at least 5 cm below the lower trapezius EMG sensor. Three coin motors were used instead of only one to distinguish changes in magnitude.

The three sensory feedback modes and one control group were described as follows: <u>Control</u> – no visual or vibrotactile feedback was provided during the training phase, <u>Simple-haptic</u> – the magnitude of position error to the shortest path between targets was the only information provided in real-time, and all vibration motors turned on and off together, Complex-haptic – the magnitude of position error was matched with a direction component as motors only turned on when acting as a repulsive sensation to guide participants towards the shortest path between targets, Multimodal feedback – simple-bandwidth visual feedback was combined with complex-haptic feedback. The vibrotactile feedback supported the simple-bandwidth information in the multimodal feedback mode and relayed the same information to reinforce performance improvement. To elicit changes in vibration magnitude for all haptic feedback modes, the bandwidth range from low-error threshold to high-error threshold was divided up into three equal quadrants between 0 and 100%. The group of coin motors turned on either one (0-33%), two (34-66%), or all three (67-100%), based upon the percentage of user position error.

Explicit vibrotactile feedback on the torso to guide motion during VR tasks

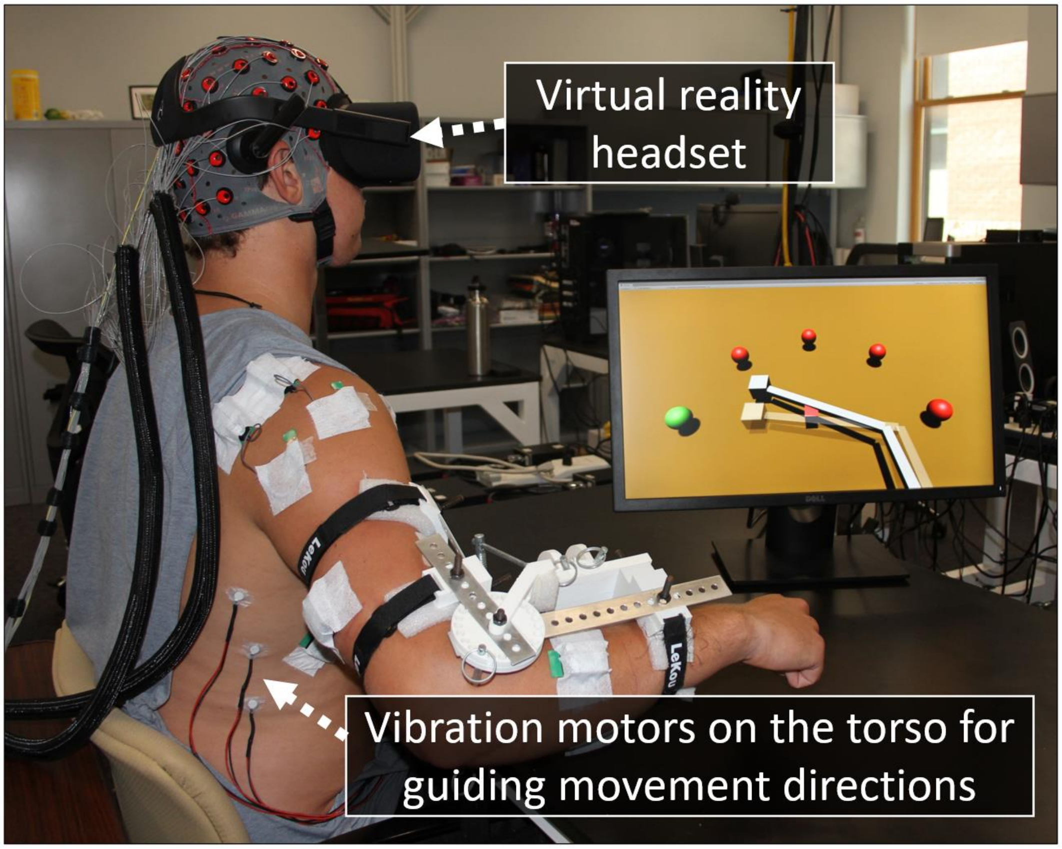


Figure 26. Explicit vibrotactile feedback involved coin motors attached to the torso for guiding direction during movement tasks. Vibration was provided in a repulsive direction, i.e., vibration on the right directed to move to the left (move away from the vibration).

8.3.2. Implicit Vibrotactile Feedback

Implicit vibrotactile feedback has unique properties compared to other forms of haptic feedback, such as applied forces and changes in pressure. During isometric exercises, EMG activity increases by applying indirect vibration through an external device, such as a vibrating handle or standing platform. Direct vibration, applied by placing motors directly on the muscle-tendon junction, can also increase EMG activity as well as create an illusory movement effect by altering afferent neurological signals and activating muscle stretch reflexes. The increase in EMG activity is a result of recruiting additional muscle fibers. This can be therapeutic or even rehabilitating when provided in shorter durations but can accelerate muscle fatigue during isometric strengthening exercises.

In this study, the objective was to systematically identify vibration patterns that could be utilized to increase the EMG activity of the upper-arm and torso muscles. Once vibration patterns were identified through pilot testing, real-time implicit vibrotactile feedback would be used in the same experimental protocol as Aim 2. The implicit feedback would be provided to increase the separability between the EMG activity clusters used to command the virtual device. The support vector machine responsible for mapping isometric activations to direction intent relies upon the unique EMG patterns for discerning different commands. We hypothesize that increasing the separability of EMG activity between the direction clusters will lead to improved real-time control of the virtual device and an increase in classification accuracy.

Vibration motors were placed on the muscle-tendon junction of four muscles to evaluate the effects of real-time vibration during isometric contractions (**Figure 27**).

Muscles evaluated were the biceps brachii, triceps brachii, pectoralis major, and back (primarily trapezius low and mid). For the biceps and triceps brachii, two coin motors were taped to the distal and proximal end of the muscles at the muscle-tendon junctions, above and below the restrictive brace straps. For the pectoralis major and back muscles, vibration motors were taped equidistantly around the EMG sensors at least 5 cm away. For each trial, the vibration motors followed the same pattern, first no vibration to indicate a control and baseline EMG activity, then the biceps brachii, triceps brachii, pectoralis major, and back. During a 15-second isometric hold at 20% or 40% MVIC, individual motors were turned on and off at 1.5-second intervals to determine the effects on EMG activity. Pilot experiments indicated higher quality motors, i.e., LRAs and not ERMs, are required for eliciting the desired effect.

Implicit vibrotactile feedback to increase EMG activity during isometric tasks

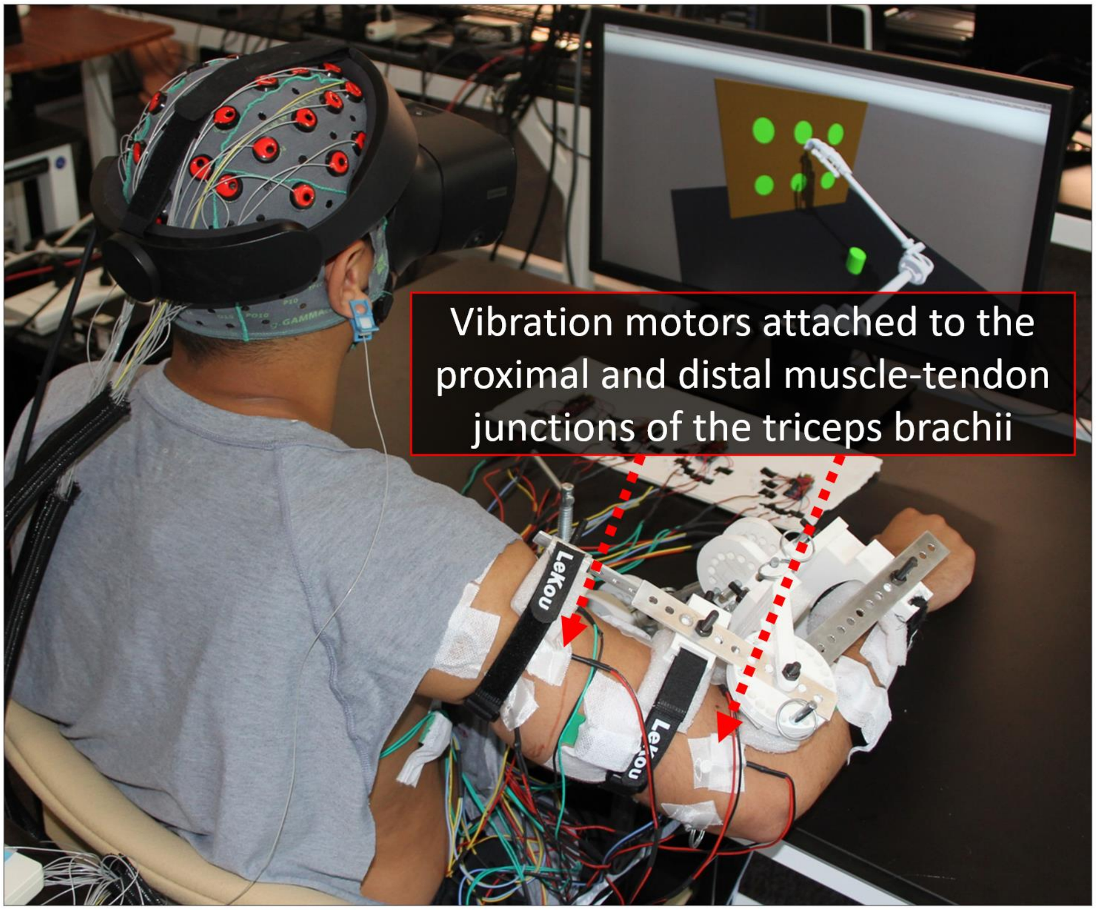


Figure 27. Implicit vibrotactile feedback to affect the afferent neurological pathways and muscle stretch reflexes to induce changes in neurophysiological signals or perceived proprioception during isometric exercises. Vibration to the triceps brachii can increase EMG activity and induce an illusory movement effect of arm flexion.

8.4. Sense of Agency

Throughout my research, I assisted extensively with additional projects that evaluated the effects of cognitive agency and how to leverage cognitive factors for improving physical rehabilitation. Sense of Agency (SoA) can be defined as the sense of control one has over their actions. This sense can be diminished in clinical populations, and this results in reduced motor function and ability to complete ADLs successfully. Along with SoA, other cognitive factors, including attention, memory, and cognitive engagement, play a role in physical rehabilitation at a participant-specific level. SoA is uniquely valuable in virtual reality-based physical rehabilitation when the participants' body position is occluded while wearing the head-mounted display. Two major research studies were conducted that evaluated the effects of SoA with altered control mechanisms.

8.4.1. Pinch and Reach VR

Participants completed a force-based grasping task and a motion-based VR reaching task with different control mechanisms (default, slot, fast, auto, and noise) to determine the optimal effects on performance and SoA [194], [195] (**Figure 28**). Intentional binding was used to measure the participants SoA. Immediately after completing a short force- or motion-based task, the participants would hear an audio beep at a random time internal between 0.1 and 1.0 seconds. The participants were instructed to estimate the delay interval. Literature states that average underestimation of the delay represents an increase in SoA with the control mechanism. Our results indicated that higher performance (lower error to the primary objective) was correlated to higher SoA. My lab published multiple papers [194], [195], [205] and a textbook chapter [206] with the results of these experiments.

Sense of Agency evaluated through force- and motion-based tasks

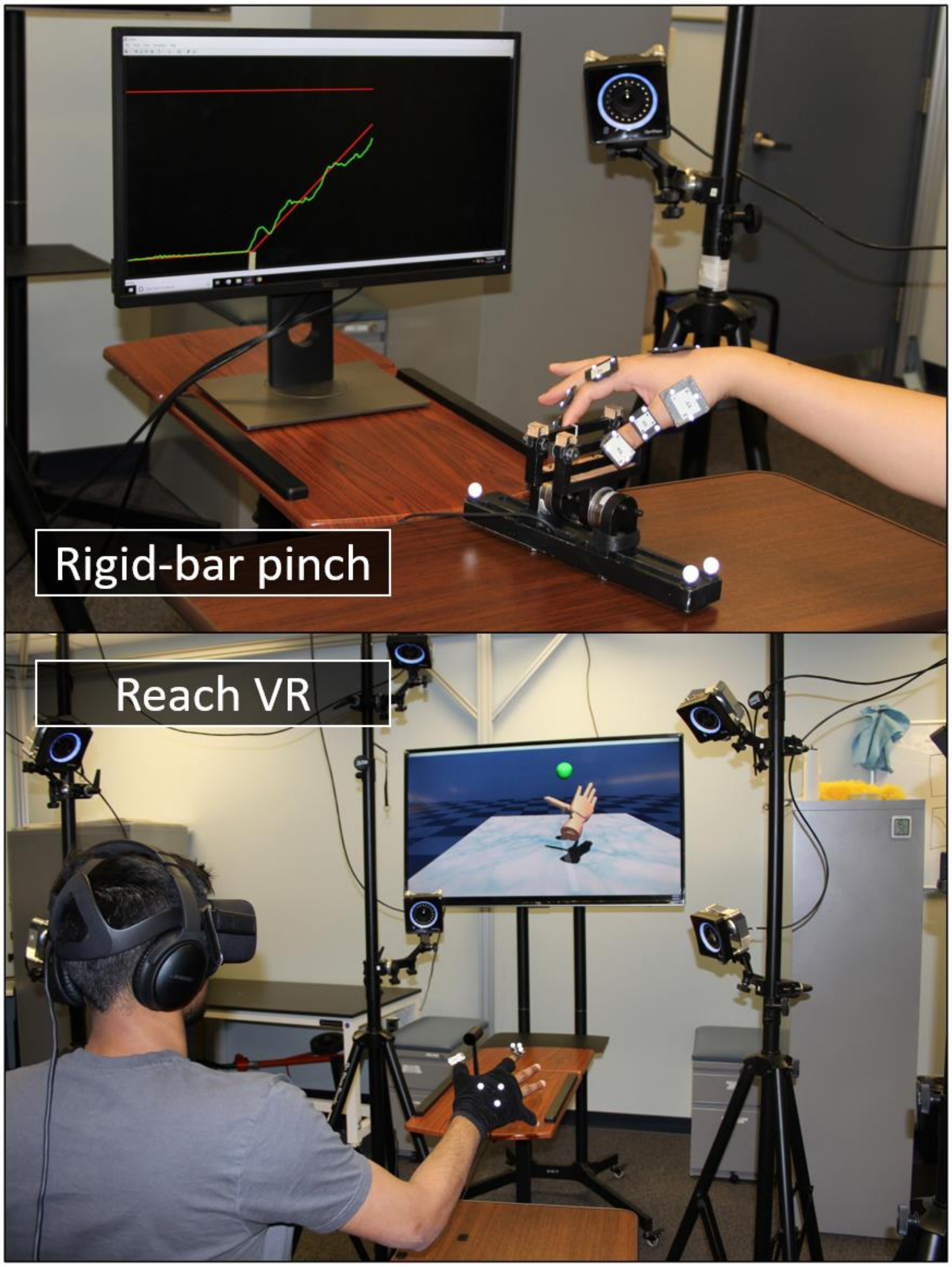


Figure 28. Sense of agency was initially evaluated over two experiments, TOP) a force-based experiment utilizing hand grasp of force measurements, and BOTTOM) a motion-based reaching experiment within a virtual reality environment.

8.4.2. Cognition Glove

In the second phase of the SoA research, a wearable smart glove was developed to artificially enhance the participants' SoA during reach-to-grasp tasks [207] (**Figure 29**). Pressure sensors were stitched to the glove under each finger and force inputs were used in a machine learning algorithm to indicate secure grasp. Sensory feedback from the glove was used to indicate to the participant they received secure grasp in both real-world and virtual scenarios. Sensory feedback attached to the glove as an audio beeper, a LED light, and a smaller vibration motor. In the real-world, the effects of immediate versus delayed sensory feedback were evaluated on able-bodied participants [207]. In able-bodied and clinical experiments, the effects of the sensory feedback from the glove were compared to enhanced visual and audio feedback provided in a VR environment. The objective was to identify features of sensory feedback that could be leveraged to enhance SoA and have the greatest positive impact on performance and retention results. Additionally, my lab was interested in evaluating the neurophysiological signals to determine cognitive adaptations to motor learning.

Training with a Cognition glove to enhance a participant’s Sense of Agency

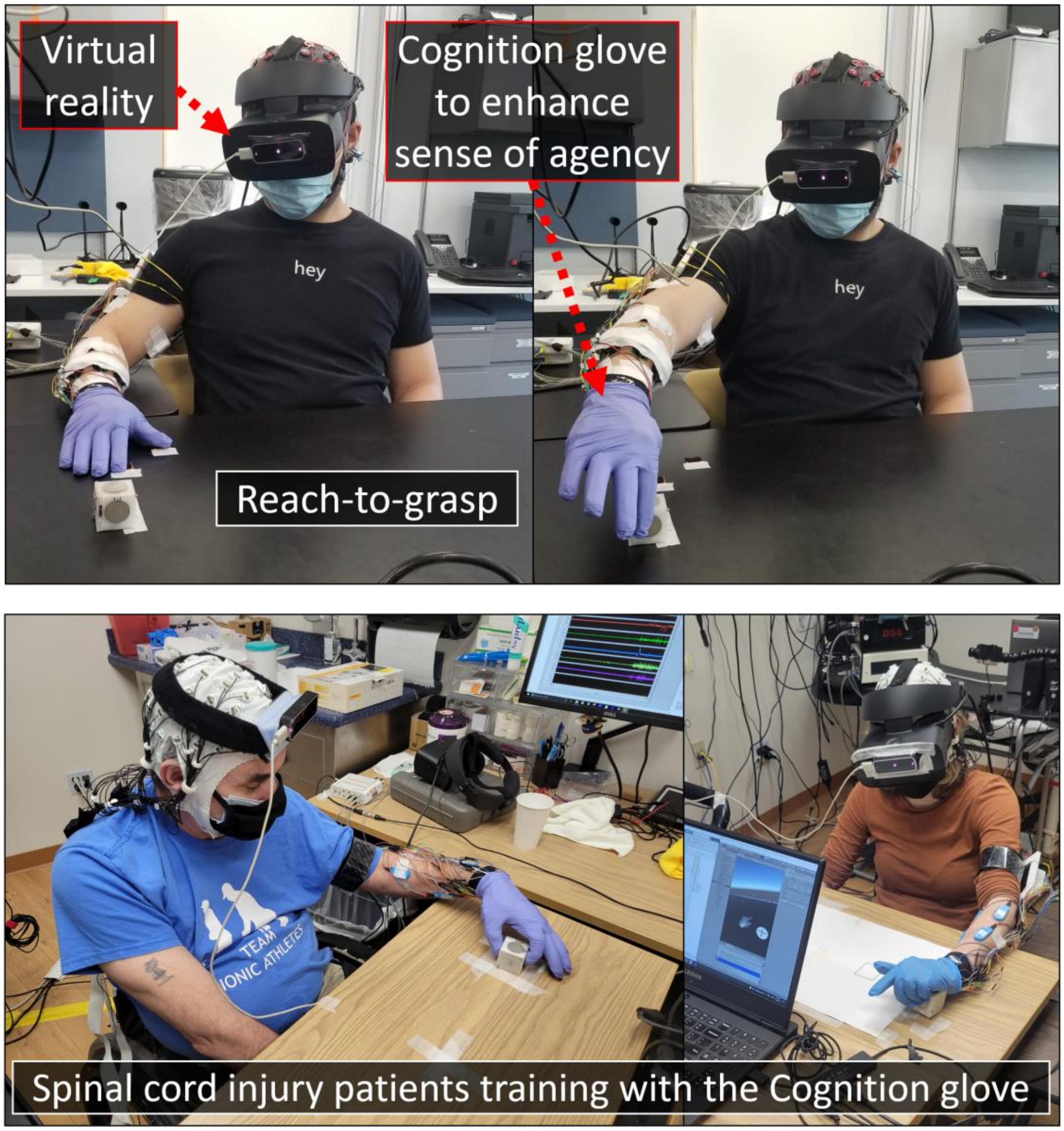


Figure 29. A custom wearable device, the Cognition glove, was developed by the MOCORE Laboratory to enhance the participant’s Sense of Agency during reach-to-grasp tasks. The glove could also integrate with virtual reality to provide enhanced forms of visual feedback. The device was tested on clinical populations including spinal cord and traumatic brain injuries.

8.5. Community Outreach

While working in the MOCORE Laboratory (and before COVID) my lab participated in various community outreach programs geared towards teaching students about engineering and our research. We created interactive workshops, i.e., fun games geared around our experiments, and presented experiments that guided them through the biomedical engineering field on a high level. During the summer of 2019, multiple local groups visited the MOCORE Lab. Each visit would begin with a presentation, explaining our research and background information on biomedical engineering and biomechanics. Next, students would complete various interactive workshops related to the experiments our lab has previously completed. During one visit, students took turns using the pinch apparatus, the VR reach paradigm, and a VR LEAP experiment designed by Samuel Wilder (**Figure 30**). Other lab visits focused primarily on the presentation to give the students a wide range of background information related to our research and the field of biomedical engineering (**Figure 31**). The student groups included PICO Solutions (K-6), Stevens CIESE PSEG Summer Camp (middle school), and the Stevens Art Harper Academy (high school). Finally, I also participated in clinical community outreach opportunities including the 2^{nd} Annual Spinal Cord Injury Research Community Fair located at Mount Sinai in Manhattan, NY (**Figure 32**).

Hoboken middle school students complete interactive workshops

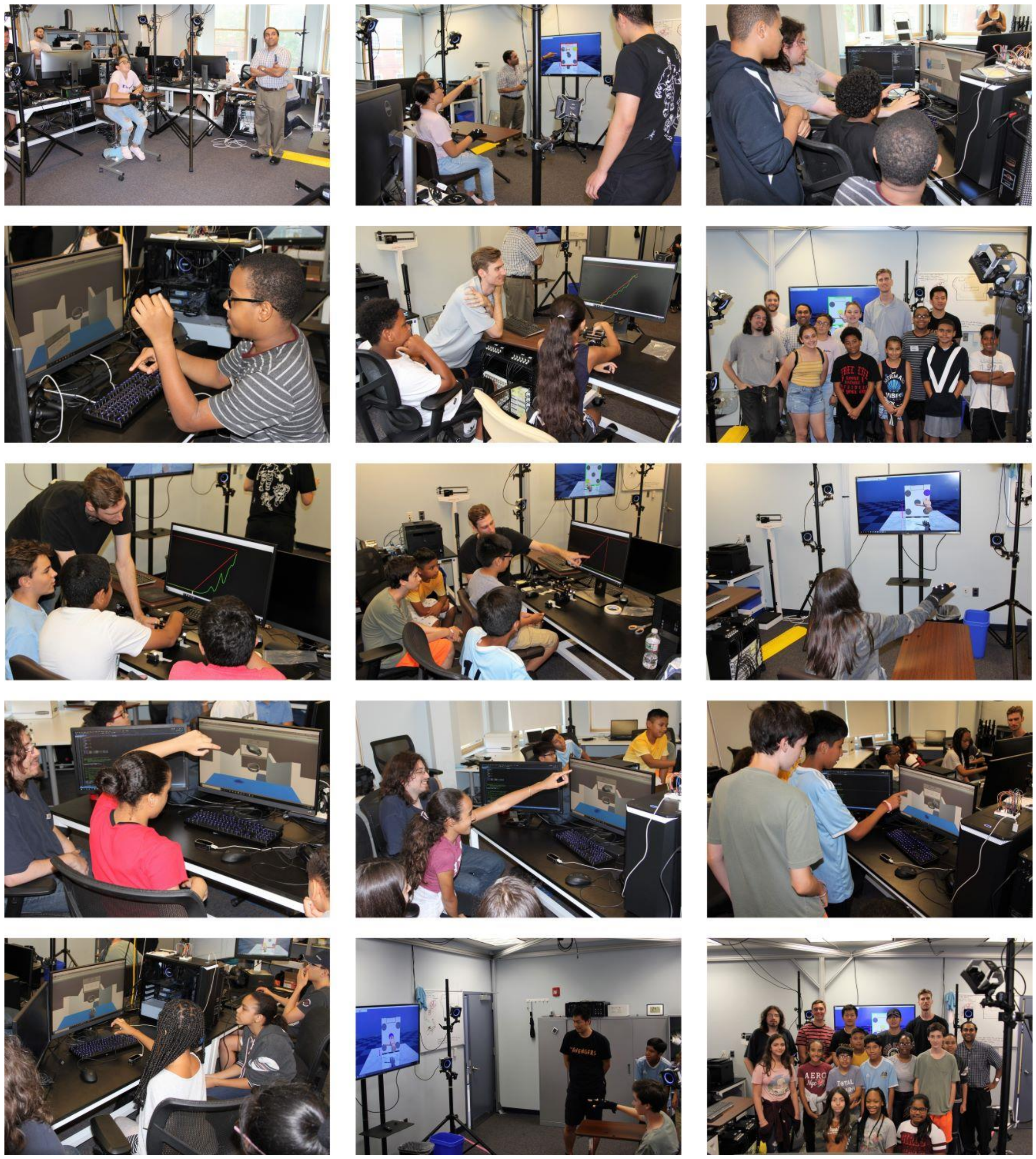


Figure 30. MOCORE graduate students Sean Sanford, Mingxiao Liu, and Samuel Wilder guided local Hoboken middle school students through interactive workshops geared around our research.

A lab presentation and virtual reality tasks for Hoboken summer students

Figure 31. Sean Sanford and Mingxiao Liu gave a presentation to a group of local summer students. Samuel Wilder developed and presented a virtual reality game around the LEAP gaming system

The MOCORE Lab volunteering at an SCI Community Fair

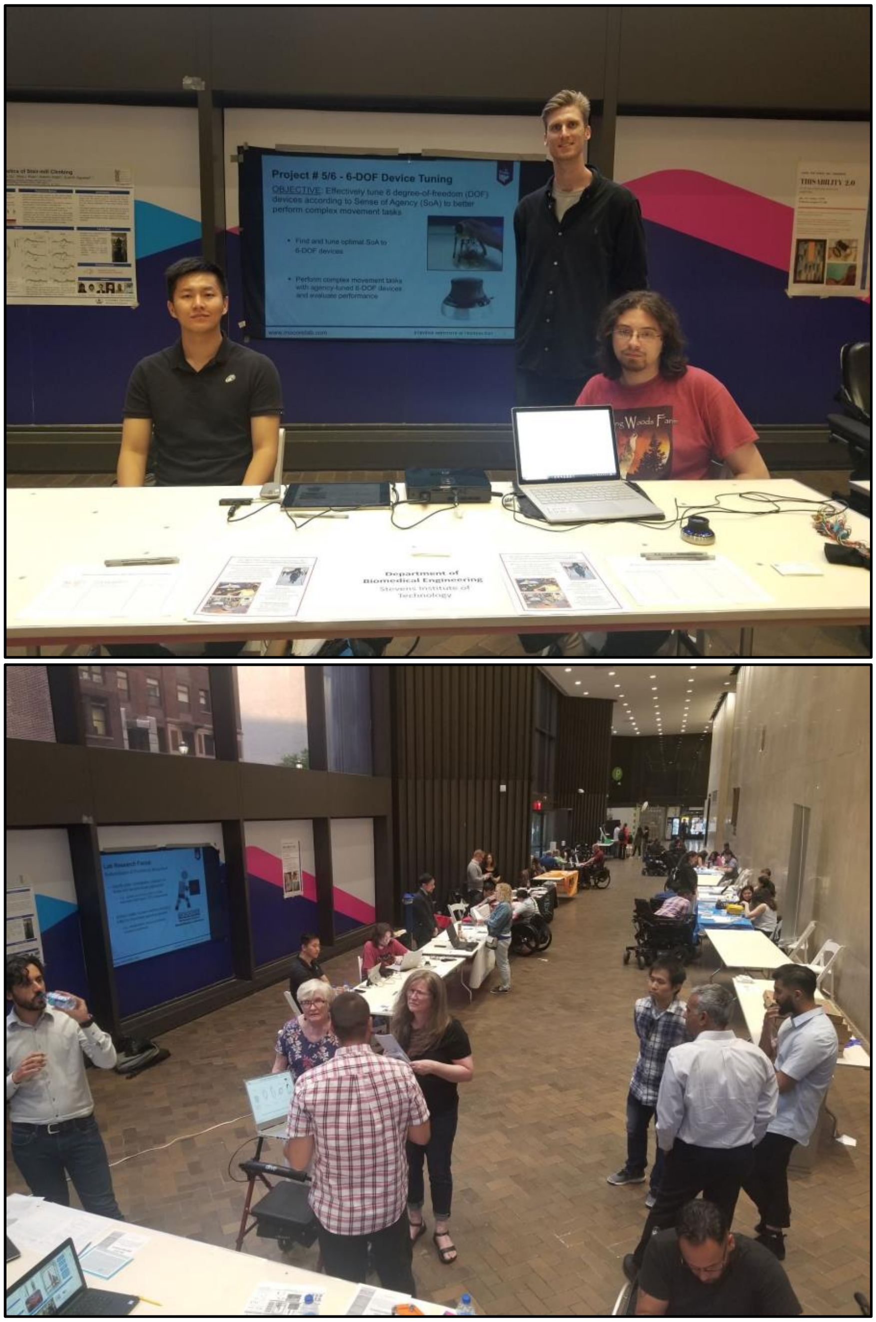


Figure 32. Members of the MOCORE Lab, Sean Sanford, Mingxiao Liu, and Samuel Wilder, participated in clinical community outreach opportunities including the 2nd Annual Spinal Cord Injury Research Community Fair located at Mount Sinai in Manhattan, NY.

8.6. MOCORE Virtual Reality Education Module

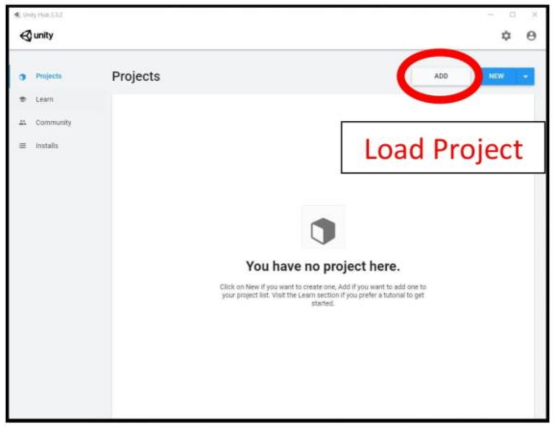
During COVID, I lead the development of a MOCORE VR education program that focused on providing high school students with the opportunities to develop VR programs with our assistance. These local NJ students developed simple keyboard-based VR games with our guidance of implementing areas of research (i.e., sensory feedback and SoA). Students would learn to develop VR games using the Unity engine. I would lead weekly meetings where students would present their progress on their games, and then look for us to provide feedback on making improvements and how to implement the game into a research study. Many of the students would go on to present their research at various high school conferences, with one student, the first to join the VR education module, Kwabena Boateng, winning 1st place in the 2022 Regeneron Westchester Science and Engineering Fair. Along with assisting the students to develop their own VR games, I created a VR education module that would teach naïve students the basics of using the Unity engine. I developed a basic tutorial that walks through how to create a user-controlled object in Unity that changes color upon collision with another object. This introduces the basics of user-controlled objects with event triggers for creating complex VR-based environments for motor and cognitive rehabilitation.

Section 1: Unity Basics

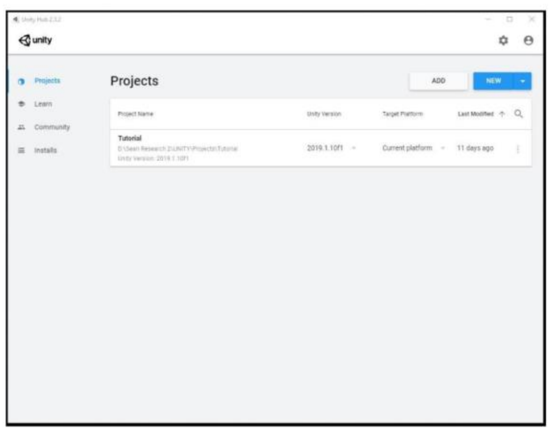
To begin, you will need to download Unity from their website. Next, step-by-step instructions will be provided for creating a basic environment in which a keyboard is used for moving an object. Upon collision with another object, both the User controlled object and the designated Target object change color. Additionally, information will be provided for understanding the Unity interface including the basics about materials, scripts, and scenes. A tutorial environment can be downloaded that has all of the following information included.

1. Download Unity
    a. Link: www.unity.com

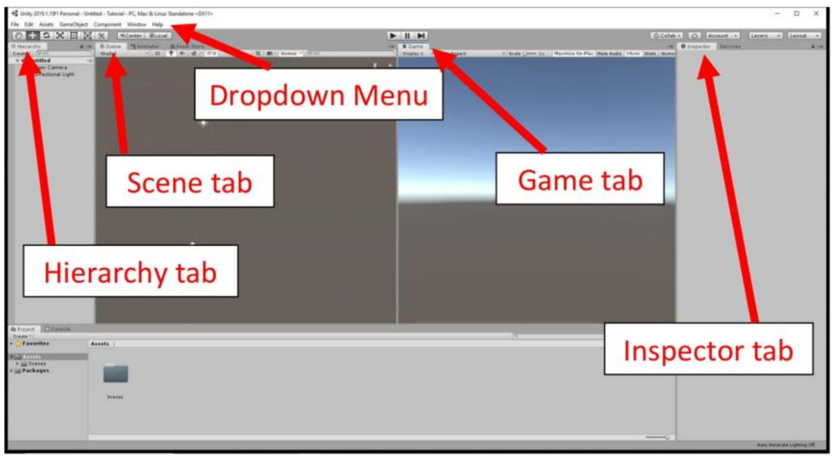
2. Unity Hub
   a. To load a project, select the Add button or press New to create a new project. This is where you will find the Tutorial project if downloaded from the MOCORE website.
   b. If creating a new project, press NEW and create a 3D Template.



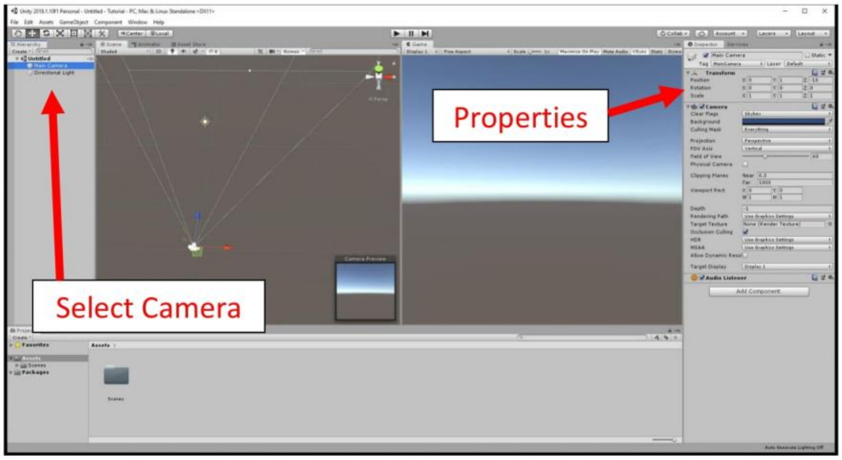
   c. Find the Unity Project file folder saved on your local computer. Press Add File on the load screen when the Project file folder is selected.



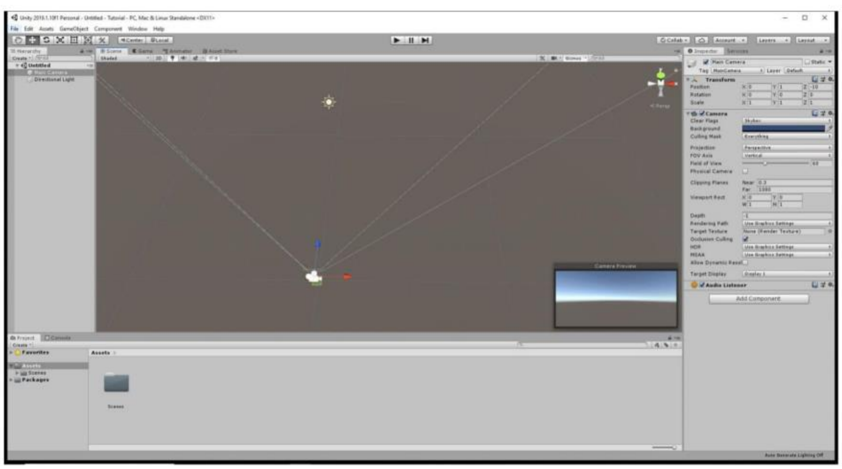
3. Main User Interface
    a. On the Main Screen you will see the basic dropdown menus at the Top, a Hierarchy tab on the left side where each object is identified, the Scene and Game windows split in the middle (which can also be overlaid if the Game window is dragged on top the Scene window, noted below), and the Inspector/Services tab on the right side for specifics about each object highlighted in the Hierarchy tab.



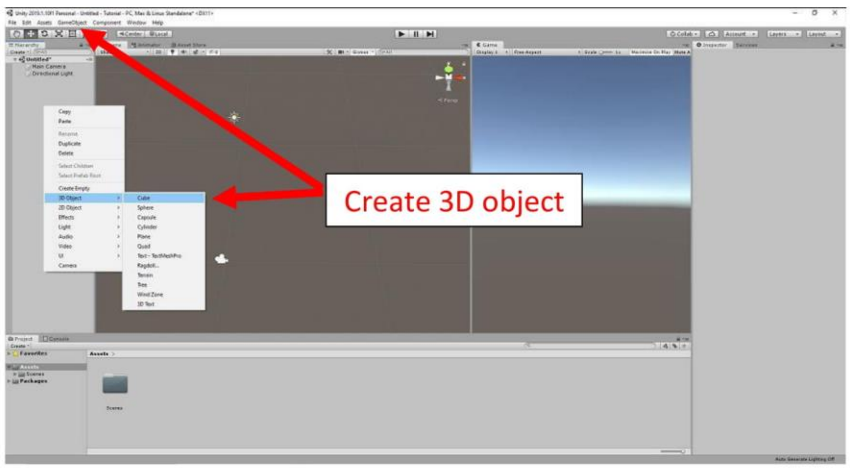
b. When the Main Camera is selected on the Hierarchy tab on the left side, object properties such as position, rotation, and scaling are listed under the Inspector tab.

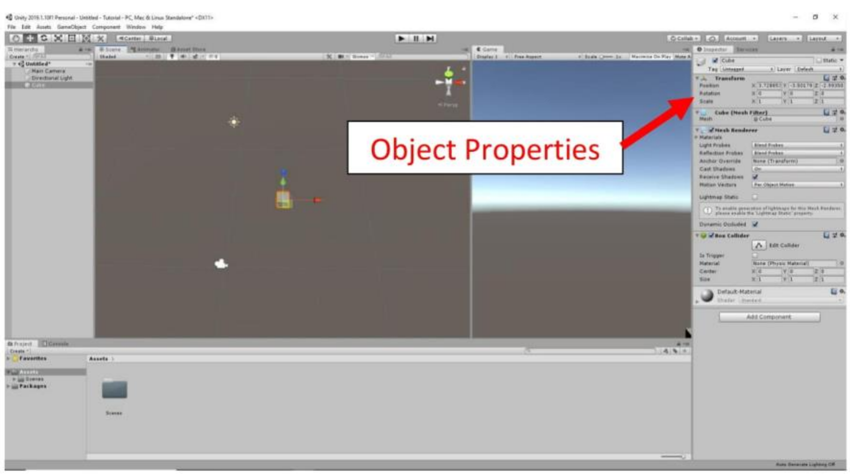


c. *Optional:* To save monitor space while working on the environment, the Game window can be overlaid on top of the Scene window by selecting the Icon (see below) and moving the window to the same position on the Scene window. You can then navigate between these two screens when working on the project. The Camera Preview previews what is seen in the Game window by the Main Camera.

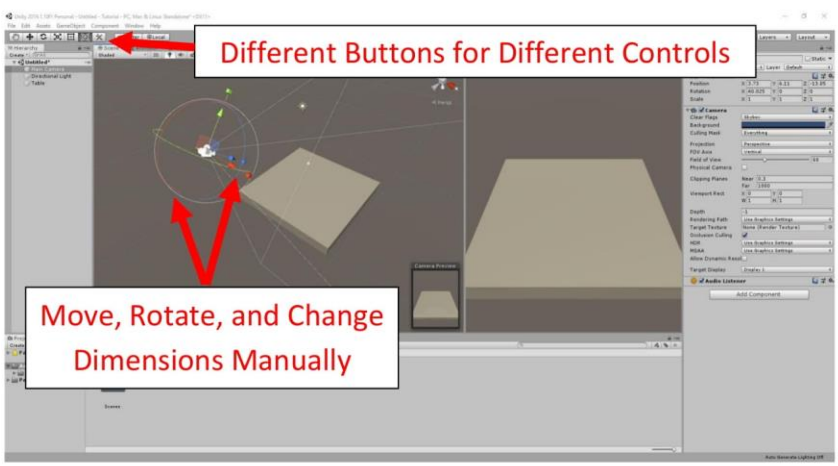


4. How-to: Create Objects
    a. Right click on the Hierarchy tab or mouse over the GameObject tab at the top of the screen in the Dropdown menu to create a new 3D object.
    b. For this tutorial we will be creating multiple objects including a table, and two spheres. One sphere will be controlled by the User and the second will be designated as a Target sphere.

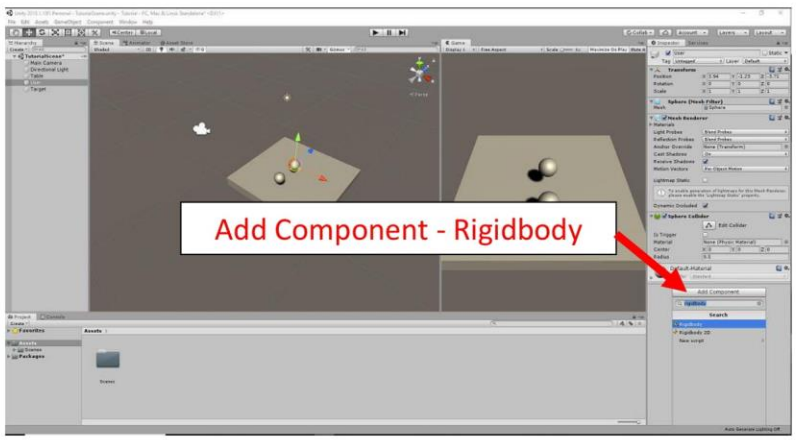


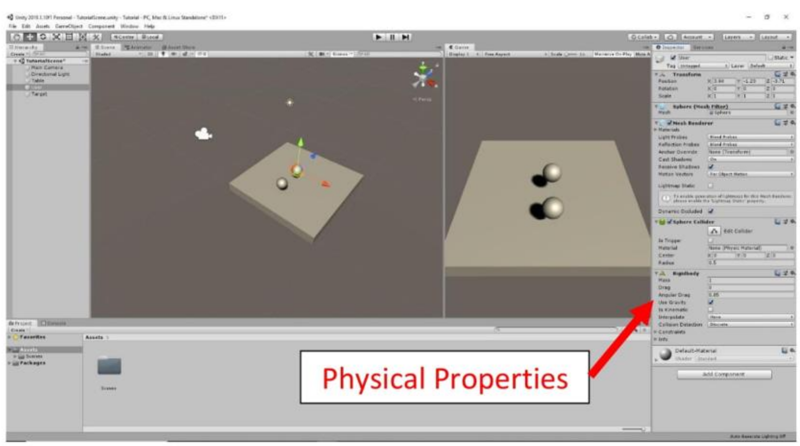


c. Additional Step: Moving Camera and Screen Orientation
   i. For better viewing and control of individual objects, move the orientation of the Scene screen by pressing the Middle Mouse or Right Mouse button to move and rotate the screen, respectively. The Scroll Wheel zooms Scene screen in and out.
   ii. To move individual objects, first select the object and use the Green, Blue, and Red arrows the change the objects Position.
      1. You can also manually adjust the position by changing the numbers with the Inspector tab.
   iii. To rotate the object use the Green, Blue, and Red circles.
   iv. To change the dimensions of the object use the Green, Blue, and Red cubes.
   v. In the top left corner there are different buttons for different object controls related to movement, rotation, or movement+rotation.
   vi. Move the Main Camera to a position the looks down upon the Table object at a comfortable height and rotation (~45 degrees).

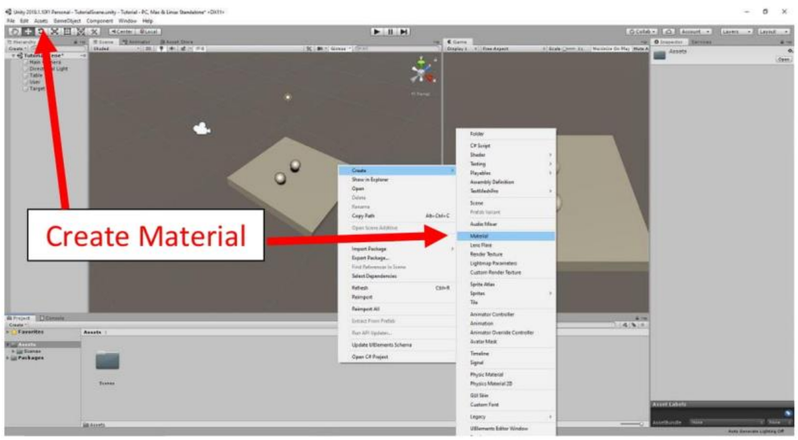


d. Next, create two spheres of equal size and label one 'User' and the other 'Target'. Move both spheres to directly above the Table Top.
e. Select the User ball, press Add Component at the bottom of the Inspector tab, and select RigidBody.
    i. By adding the Rigidbody Component the sphere now has a specified Mass and other physical properties.
    ii. Ensure that the Use Gravity box is checked on.
f. Repeat the last step for the Target ball.

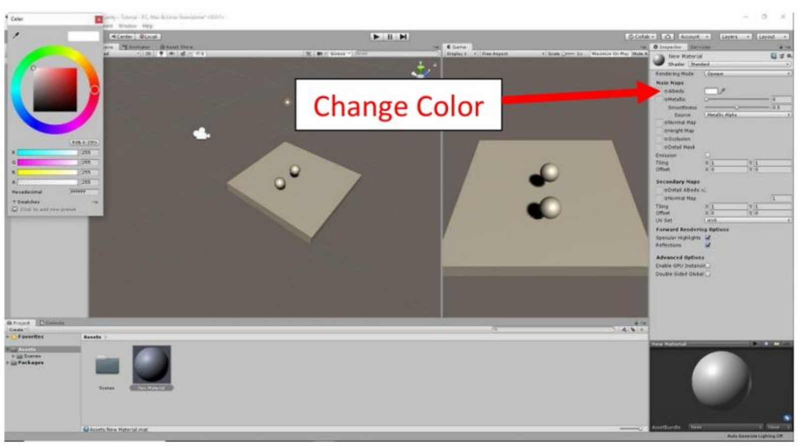




5. How-to: Create Materials
   a. Different material properties can be specified for each object such as color and transparency. For this tutorial, a basic introduction to different materials for different colors will be presented.
   b. This can also be found under the Assets tab at the Dropdown menu in the top left corner.



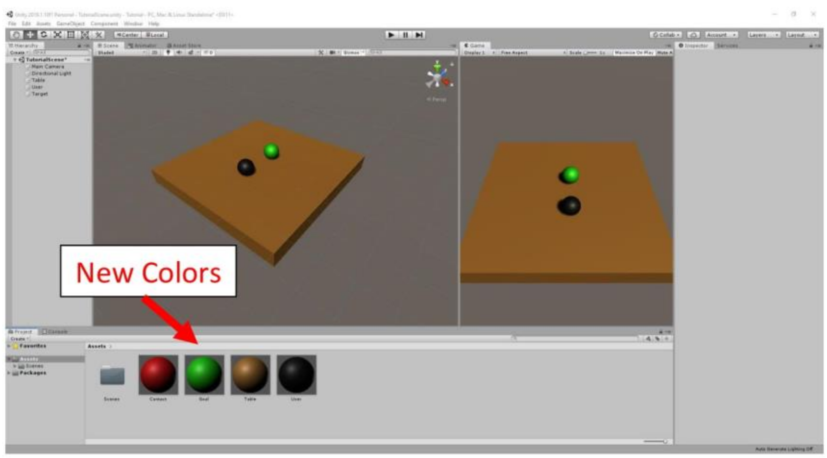
   c. After you create the material, select the white square next to the label Albedo under the Inspector tab to manually change the color.



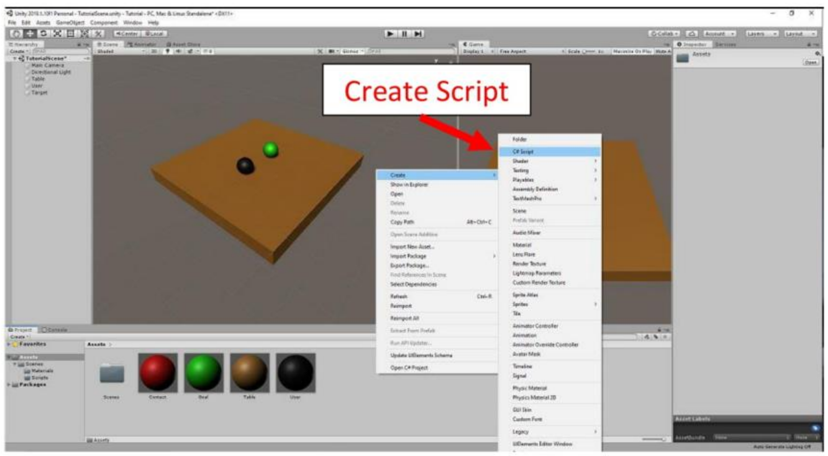
d. Create four colors. A brown one labeled Table, a black one labeled User, a green one labeled Goal, and a red one labeled Contact.

e. Drag and drop the material onto the object you want to apply the material too.

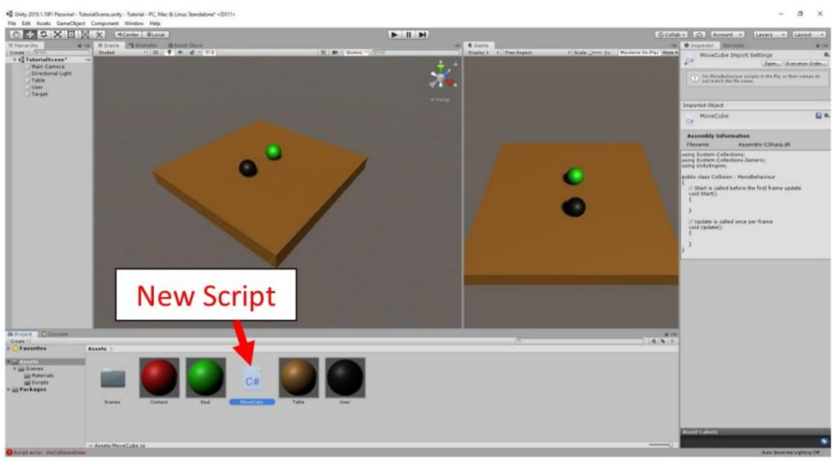
   i. Apply the Table color to the Table, the User object to the User sphere, and the Goal color to the Target object. The Contact object will be used at a later time.



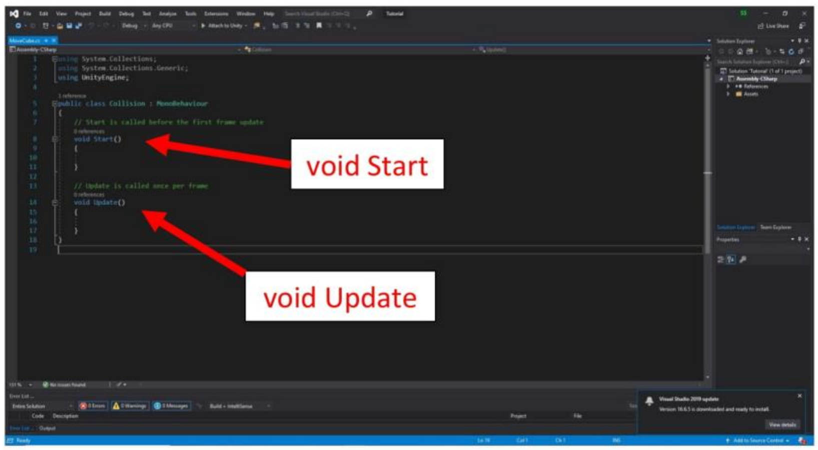
6. How-to: Create Scripts
    a. Now that the environment is created the final step is creating scripts that help run the task or for creating event triggers such as sound cues or color changes that correspond with your desired effect.
        i. We will create the following 2 scripts:
            1. One to move the User controlled sphere.
            2. One to change the material (and color) of both the User and Target spheres when they collide into each other.



b. Create a script and name it MoveCube. This Script will contain code written in C# within the Visual Studios program for controlling the User sphere with the computer keyboard.
    i. *Author note:* There are many ways to move an object. A google search for 'moving an object in Unity' will supply many examples. For example, you could apply a directional force that rolls the sphere across the table. In this tutorial we will present a simple code for changing the position in the X and Z directions based upon a set scaling factor.

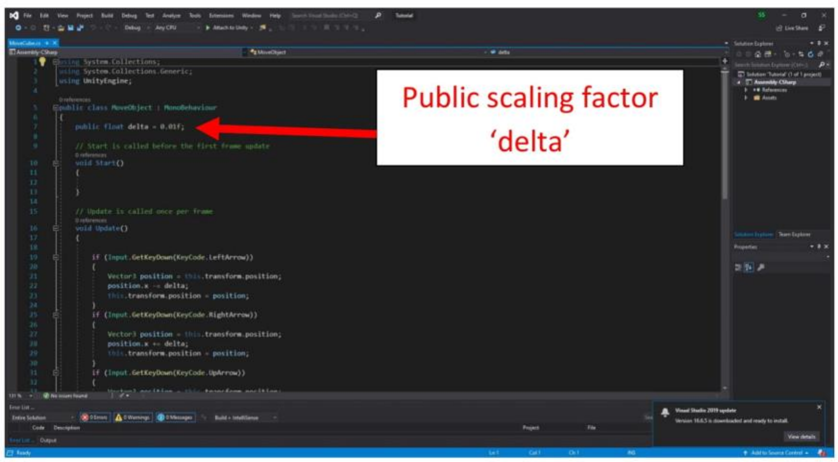


c. Double click on the new Script to load Visual Studio.
d. At the basic level, anything added following 'void Start' will be applied immediately upon playing the scene while 'void Update' will continuously run and be updated every frame of the scene (~50 Hz).

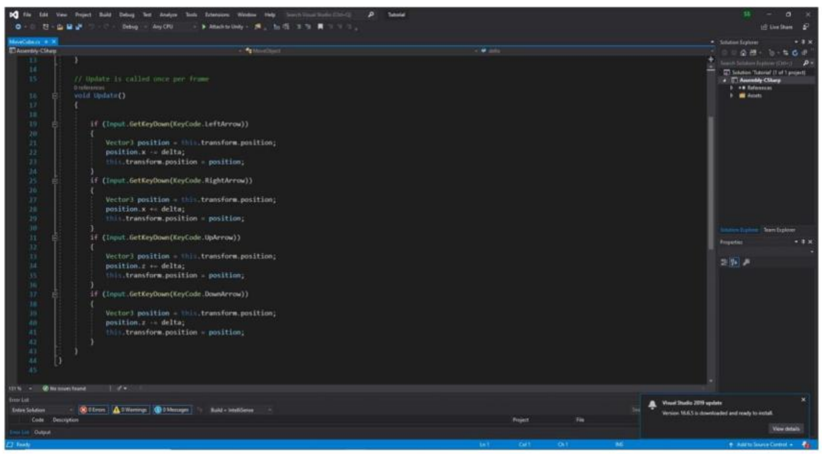


e. The following code has been created to change the position of the designated object based upon a scaling factor labeled as ‘delta’ according to arrow directions from a keyboard.

f. The variable labeled delta is identified as a ‘public’ variable. This means it is accessible from the User Main Screen within Unity and therefore can be changed. If the variable is set as ‘private’ it will be hidden from control within Unity and only accessible within Visual Studio.



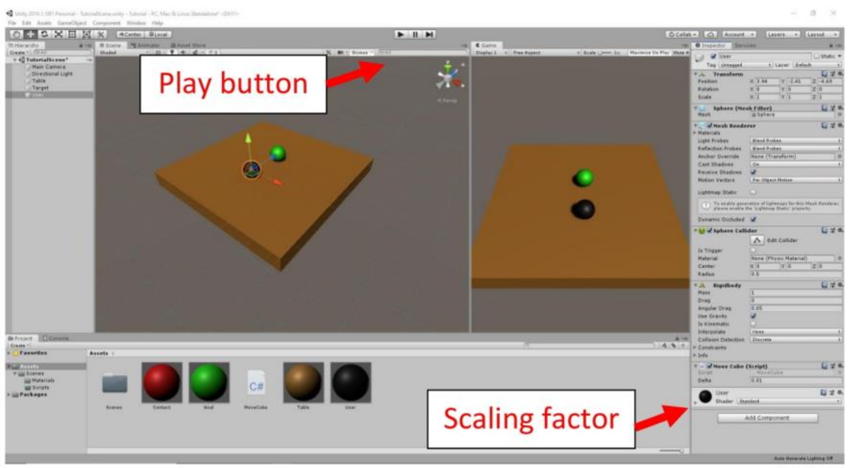
g. Upon each Update,
   i. IF a Left Arrow is detected the object moves in the -X direction
      1. By a factor of delta (specified within the Unity Program).
   ii. IF a Right Arrow is detected the object moves in the +X direction.
   iii. IF an Up Arrow is detected the object moves in the +Z direction.
   iv. IF a Down Arrow is detected the object moves in the -Z direction.



Author note: When creating this tutorial I accidentally swapped the User and Target sphere. Which sphere is which is completely up to you, but note here that the Target and User names are in different order from the previous steps.

Previously the upper sphere was renamed as User, in this case the black sphere which is positioned below, is labeled as 'User'. This will be corrected at a future date for consistency.

h. Apply the MoveCube script to the User sphere
i. There are multiple ways to apply a script to an object.
    i. You can press Add Component and find the correct Script you created.
    ii. You can drag and drop the script onto the component at the open area at bottom of the object information in the Inspector tab.
j. The 'delta' label can now be seen within the MoveCube script within the Inspector tab and can be changed between trials for modifying the scaling factor of the User sphere position change.



k. Now is a good time to test your Project if you have not already. Press the Play button at the top of the screen and wait for Unity to load. Once the program has loaded you should be able to control the position of the black User sphere by pressing the arrow keys on your keyboard. Each keypress is a movement command.
    i. *Note:* A 'delta' of 0.01 will be extremely low and movement will be tough to see at first. A recommended delta is between .1 and 1.

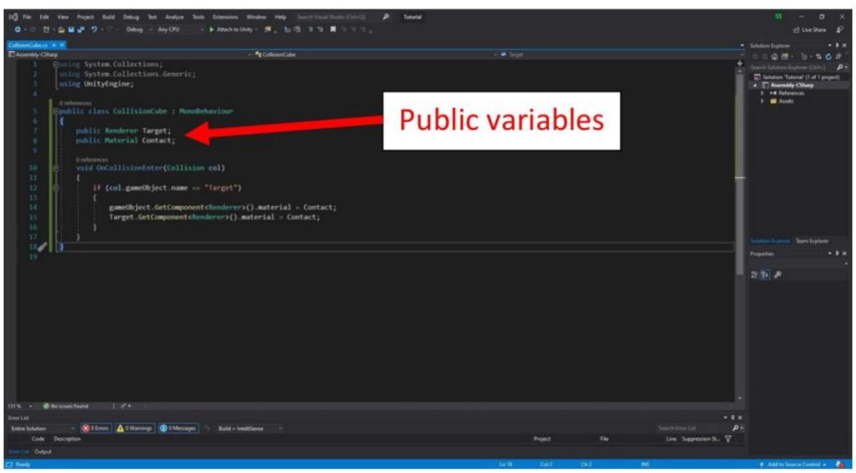
l. Next, create a second script and label it CollisionCube.
    i. This script will contain event triggers that will cause a color (material) change when the User sphere contacts the Target sphere.

m. The following image is an example script but as noted before there are multiple ways this can be done.

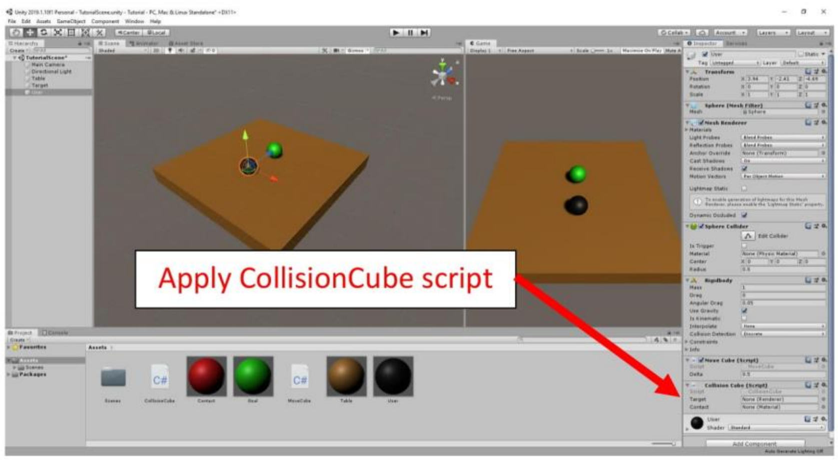
n. First, we created two public variables, on is a Renderer labeled Target and one is a Material labeled Contact.
    i. The Renderer label specifies which gameObject in the virtual environment is the 'Target' and will change color upon collision.
    ii. The Material label specifies which Material property will be used as the new material upon object collision.
        1. Because both objects are set as public they must both be set within the Unity environment. See below for further instructions.

o. The 'void Start' and 'void Update' were removed and a 'void OnCollisionEnter' was used.
    i. This is a code that exists within the program and must be called upon and used in a specific way. *Google 'Unity oncillisionenter' for further documentation.*

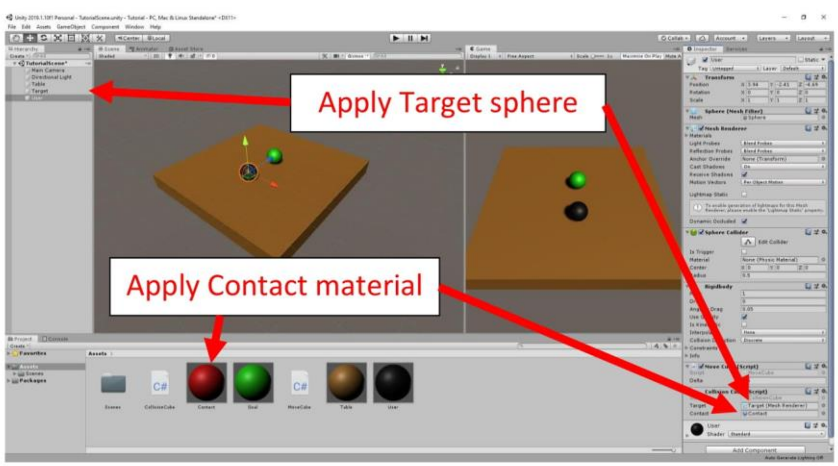
p. Finally, the code below states that IF the gameObject (which is the object this script is attached to) makes contact with an additional gameObject named "Target" that both the gameObject and Target will change materials to the specified material, in this case named 'Contact'.



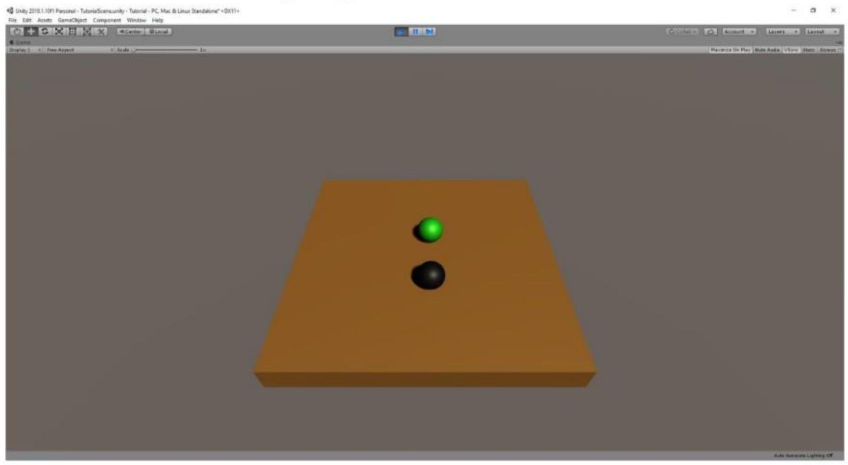
q. Apply the CollisionCube script to the User sphere.

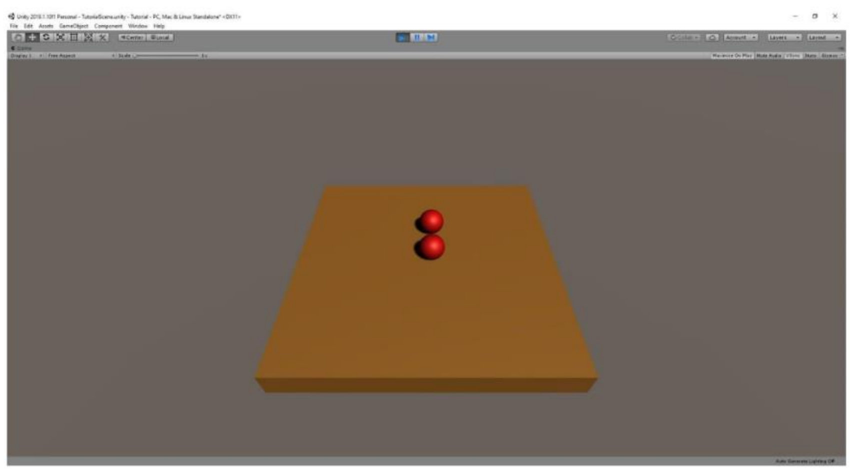


r. Click on the User sphere within the Hierarchy tab. Drag and drop the Target sphere from the Hierarchy tab to the Target option within the CollisionCube script within the User sphere. Additionally, drag and drop the Contact material to the Contact option within the same script.



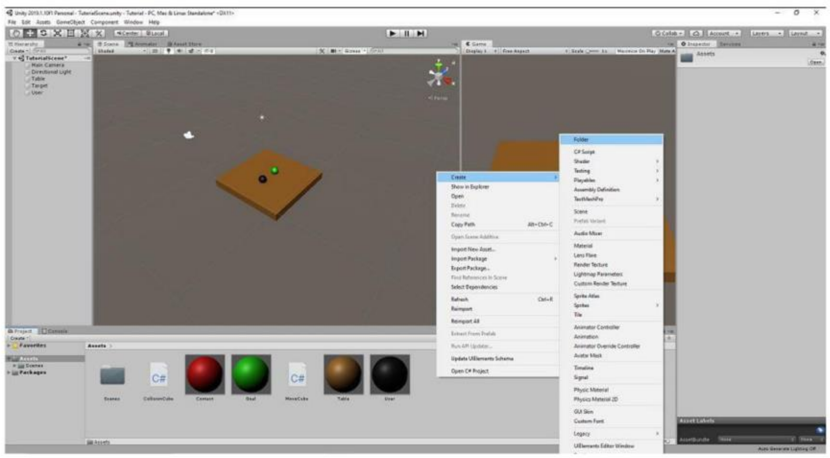
s. Press Play to test the environment.
   i. When the User sphere contacts the Target sphere both objects should immediately change to red.

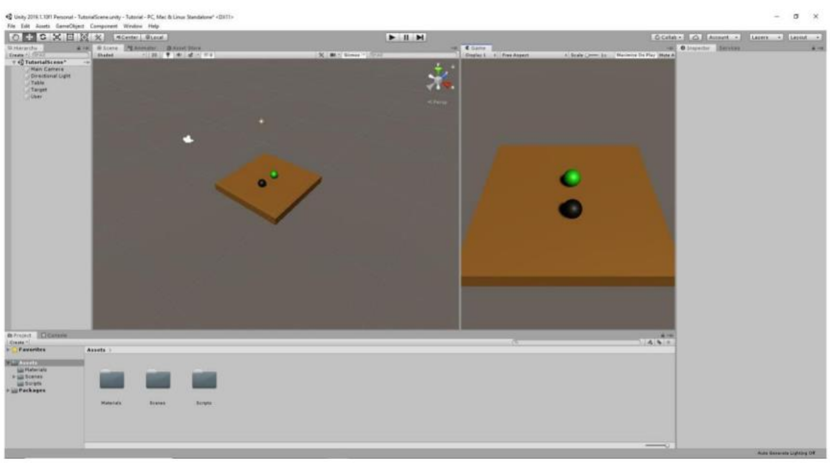




Congratulations! You have completed the MOCORE tutorial for creating a Unity project. Additional projects can be found in the following sections and downloaded from the MOCORE website. The basics will be removed, and the instructions will detail the specific differences with each project and the additional information not covered in this tutorial.

Optional: You can create folders to better organize your materials, scripts, and scenes.





9. REFERENCES

[1] Leemhuis, De Gennaro, and Pazzaglia, "Disconnected Body Representation: Neuroplasticity Following Spinal Cord Injury," *JCM*, vol. 8, no. 12, p. 2144, Dec. 2019, doi: 10.3390/jcm8122144.

[2] K. E. Laver, B. Lange, S. George, J. E. Deutsch, G. Saposnik, and M. Crotty, "Virtual reality for stroke rehabilitation," *Cochrane Database Syst Rev*, vol. 11, p. CD008349, Nov. 2017, doi: 10.1002/14651858.CD008349.pub4.

[3] G. Wulf, "Attentional focus and motor learning: a review of 15 years," *International Review of Sport and Exercise Psychology*, vol. 6, no. 1, pp. 77–104, Sep. 2013, doi: 10.1080/1750984X.2012.723728.

[4] D. Wen *et al.*, "Combining brain–computer interface and virtual reality for rehabilitation in neurological diseases: A narrative review," *Annals of Physical and Rehabilitation Medicine*, vol. 64, no. 1, p. 101404, Jan. 2021, doi: 10.1016/j.rehab.2020.03.015.

[5] J. Qian, D. J. McDonough, and Z. Gao, "The Effectiveness of Virtual Reality Exercise on Individual's Physiological, Psychological and Rehabilitative Outcomes: A Systematic Review," *IJERPH*, vol. 17, no. 11, p. 4133, Jun. 2020, doi: 10.3390/ijerph17114133.

[6] R. Sigrist, G. Rauter, R. Riener, and P. Wolf, "Augmented visual, auditory, haptic, and multimodal feedback in motor learning: A review," *Psychon Bull Rev*, vol. 20, no. 1, pp. 21–53, Feb. 2013, doi: 10.3758/s13423-012-0333-8.

[7] S. Sanford, M. Liu, T. Selvaggi, and R. Nataraj, "Effects of Visual Feedback Complexity on the Performance of a Movement Task for Rehabilitation," *Journal of Motor Behavior*, pp. 1–15, Jun. 2020, doi: 10.1080/00222895.2020.1770670.

[8] S. Sanford, M. Liu, and R. Nataraj, "Concurrent Continuous Versus Bandwidth Visual Feedback With Varying Body Representation for the 2-Legged Squat Exercise," *J Sport Rehabil*, pp. 1–10, Feb. 2021, doi: 10.1123/jsr.2020-0234.

[9] W. Johnson and D. Griswold, "Traumatic brain injury: a global challenge," *The Lancet Neurology*, vol. 16, no. 12, Nov. 2017, doi: 10.1016/S1474-4422(17)30370-8.

[10] "Stroke Facts | cdc.gov," May 25, 2021. https://www.cdc.gov/stroke/facts.htm

[11] M. Wyndaele and J.-J. Wyndaele, "Incidence, prevalence and epidemiology of spinal cord injury: what learns a worldwide literature survey?," *Spinal Cord*, vol. 44, no. 9, pp. 523–529, Sep. 2006, doi: 10.1038/sj.sc.3101893.

[12] B. H. Dobkin, "Rehabilitation after Stroke," *N Engl J Med*, vol. 352, no. 16, pp. 1677–1684, Apr. 2005, doi: 10.1056/NEJMcp043511.

[13] M.-H. Zhu *et al.*, "Visual feedback therapy for restoration of upper limb function of stroke patients," *International Journal of Nursing Sciences*, p. S2352013220300545, Apr. 2020, doi: 10.1016/j.ijnss.2020.04.004.

[14] R. Karamians, R. Proffitt, D. Kline, and L. V. Gauthier, "Effectiveness of Virtual Reality- and Gaming-Based Interventions for Upper Extremity Rehabilitation

Poststroke: A Meta-analysis," *Archives of Physical Medicine and Rehabilitation*, vol. 101, no. 5, pp. 885–896, May 2020, doi: 10.1016/j.apmr.2019.10.195.

[15] D. Y. Lim, D. M. Hwang, K. H. Cho, C. W. Moon, and S. Y. Ahn, "A Fully Immersive Virtual Reality Method for Upper Limb Rehabilitation in Spinal Cord Injury," *Ann Rehabil Med*, vol. 44, no. 4, pp. 311–319, Aug. 2020, doi: 10.5535/arm.19181.

[16] C. J. Winstein *et al.*, "Guidelines for Adult Stroke Rehabilitation and Recovery: A Guideline for Healthcare Professionals From the American Heart Association/American Stroke Association," *Stroke*, vol. 47, no. 6, Jun. 2016, doi: 10.1161/STR.0000000000000098.

[17] "Preservation of Upper Limb Function Following Spinal Cord Injury," *J Spinal Cord Med*, vol. 28, no. 5, pp. 434–470, 2005.

[18] M.-J. Driessen, J. Dekker, G. Lankhorst, and J. van der Zee, "Occupational therapy for patients with chronic diseases: CVA, rheumatoid arthritis and progressive diseases of the central nervous system," *Disability and Rehabilitation*, vol. 19, no. 5, pp. 198–204, Jan. 1997, doi: 10.3109/09638289709166527.

[19] G. Kwakkel, J. M. Veerbeek, E. E. van Wegen, and S. L. Wolf, "Constraint-induced movement therapy after stroke," *The Lancet Neurology*, vol. 14, no. 2, pp. 224–234, 2015.

[20] N. Nazmi, M. Abdul Rahman, S.-I. Yamamoto, S. Ahmad, H. Zamzuri, and S. Mazlan, "A Review of Classification Techniques of EMG Signals during Isotonic and Isometric Contractions," *Sensors*, vol. 16, no. 8, p. 1304, Aug. 2016, doi: 10.3390/s16081304.

[21] A. Z. Molka, P. Lisiński, and J. Huber, "Visual biofeedback exercises for improving body balance control after anterior cruciate ligament reconstruction," *J Phys Ther Sci*, vol. 27, no. 7, pp. 2357–2360, Jul. 2015, doi: 10.1589/jpts.27.2357.

[22] K. R. Ford, C. A. DiCesare, G. D. Myer, and T. E. Hewett, "Real-time biofeedback to target risk of anterior cruciate ligament injury: a technical report for injury prevention and rehabilitation," *J Sport Rehabil*, vol. Technical Notes 13, May 2015, doi: 10.1123/jsr.2013-0138.

[23] R. M. Palmieri-Smith, A. C. Thomas, and E. M. Wojtys, "Maximizing Quadriceps Strength After ACL Reconstruction," *Clinics in Sports Medicine*, vol. 27, no. 3, pp. 405–424, Jul. 2008, doi: 10.1016/j.csm.2008.02.001.

[24] T. Shaw, M. T. Williams, and L. S. Chipchase, "Do early quadriceps exercises affect the outcome of ACL reconstruction? A randomised controlled trial," *Australian Journal of Physiotherapy*, vol. 51, no. 1, pp. 9–17, Jan. 2005, doi: 10.1016/S0004-9514(05)70048-9.

[25] C. Fleischer, C. Reinicke, and G. Hommel, "Predicting the intended motion with EMG signals for an exoskeleton orthosis controller," in *Intelligent robots and systems, 2005. (IROS 2005). 2005 IEEE/RSJ international conference on*, Sep. 2005, pp. 2029–2034. doi: 10.1109/IROS.2005.1545504.

[26] T. Lenzi, S. M. M. De Rossi, N. Vitiello, and M. C. Carrozza, "Intention-Based EMG Control for Powered Exoskeletons," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 8, pp. 2180–2190, Aug. 2012, doi: 10.1109/TBME.2012.2198821.

[27] J. Fajardo, A. Lemus, and E. Rohmer, “Galileo bionic hand: sEMG activated approaches for a multifunction upper-limb prosthetic,” in *2015 IEEE Thirty Fifth Central American and Panama Convention (CONCAPAN XXXV)*, Tegucigalpa, Nov. 2015, pp. 1–6. doi: 10.1109/CONCAPAN.2015.7428468.

[28] A. Tabor, S. Bateman, E. Scheme, D. R. Flatla, and K. Gerling, “Designing Game-Based Myoelectric Prosthesis Training,” in *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, Denver Colorado USA, May 2017, pp. 1352–1363. doi: 10.1145/3025453.3025676.

[29] E. Biddiss and T. Chau, “Upper-Limb Prosthetics: Critical Factors in Device Abandonment,” *American Journal of Physical Medicine & Rehabilitation*, vol. 86, no. 12, pp. 977–987, Dec. 2007, doi: 10.1097/PHM.0b013e3181587f6c.

[30] B. Stephens-Fripp, G. Alici, and R. Mutlu, “A Review of Non-Invasive Sensory Feedback Methods for Transradial Prosthetic Hands,” *IEEE Access*, vol. 6, pp. 6878–6899, 2018, doi: 10.1109/ACCESS.2018.2791583.

[31] S. Huang, J. P. Wensman, and D. P. Ferris, “Locomotor Adaptation by Transtibial Amputees Walking With an Experimental Powered Prosthesis Under Continuous Myoelectric Control,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 5, pp. 573–581, May 2016, doi: 10.1109/TNSRE.2015.2441061.

[32] C. Antfolk, “Using EMG for Real-time Prediction of Joint Angles to Control a Prosthetic Hand Equipped with a Sensory Feedback System,” *J. Med. Biol. Eng.*, vol. 30, no. 6, p. 399, 2010, doi: 10.5405/jmbe.767.

[33] H. Bateni, “Changes in balance in older adults based on use of physical therapy vs the Wii Fit gaming system: a preliminary study,” *Physiotherapy*, vol. 98, no. 3, pp. 211–216, Sep. 2012, doi: 10.1016/j.physio.2011.02.004.

[34] M. Schultheis and A. Rizzo, “The application of virtual reality technology in rehabilitation,” *Rehabilitation Psychology*, vol. 46, pp. 296–311, Aug. 2001, doi: 10.1037/0090-5550.46.3.296.

[35] H. Sveistrup, “Motor rehabilitation using virtual reality,” *Journal of NeuroEngineering and Rehabilitation*, vol. 1, no. 1, p. 10, Dec. 2004, doi: 10.1186/1743-0003-1-10.

[36] S. Yao and G. Kim, “The Effects of Immersion in a Virtual Reality Game: Presence and Physical Activity,” in *HCI in Games*, vol. 11595, X. Fang, Ed. Cham: Springer International Publishing, 2019, pp. 234–242. doi: 10.1007/978-3-030-22602-2_18.

[37] M. C. Howard, “A meta-analysis and systematic literature review of virtual reality rehabilitation programs,” *Computers in Human Behavior*, vol. 70, pp. 317–327, May 2017, doi: 10.1016/j.chb.2017.01.013.

[38] A. V. L. de Araújo, J. F. de O. Neiva, C. B. de M. Monteiro, and F. H. Magalhães, “Efficacy of Virtual Reality Rehabilitation after Spinal Cord Injury: A Systematic Review,” *BioMed Research International*, vol. 2019, pp. 1–15, Nov. 2019, doi: 10.1155/2019/7106951.

[39] A. Webster, M. Poyade, S. Rooney, and L. Paul, “Upper limb rehabilitation interventions using virtual reality for people with multiple sclerosis: A systematic review,” *Multiple Sclerosis and Related Disorders*, vol. 47, p. 102610, Jan. 2021, doi: 10.1016/j.msard.2020.102610.

[40] N. Garcia-Hernandez, K. Garza-Martinez, V. Parra-Vega, A. Alvarez-Sanchez, and L. Conchas-Arteaga, "Development of an EMG-based exergaming system for isometric muscle training and its effectiveness to enhance motivation, performance and muscle strength," *International Journal of Human-Computer Studies*, vol. 124, pp. 44–55, Apr. 2019, doi: 10.1016/j.ijhcs.2018.11.010.

[41] L. Zimmerli, M. Jacky, L. Lünenburger, R. Riener, and M. Bolliger, "Increasing Patient Engagement During Virtual Reality-Based Motor Rehabilitation," *Archives of Physical Medicine and Rehabilitation*, vol. 94, no. 9, pp. 1737–1746, Sep. 2013, doi: 10.1016/j.apmr.2013.01.029.

[42] P. Pozeg *et al.*, "Virtual reality improves embodiment and neuropathic pain caused by spinal cord injury," *Neurology*, vol. 89, no. 18, pp. 1894–1903, Oct. 2017, doi: 10.1212/WNL.0000000000004585.

[43] D. Mouraux *et al.*, "3D augmented reality mirror visual feedback therapy applied to the treatment of persistent, unilateral upper extremity neuropathic pain: a preliminary study," *Journal of Manual & Manipulative Therapy*, vol. 25, no. 3, pp. 137–143, May 2017, doi: 10.1080/10669817.2016.1176726.

[44] B. Chi, B. Chau, E. Yeo, and P. Ta, "Virtual reality for spinal cord injury-associated neuropathic pain: Systematic review," *Annals of Physical and Rehabilitation Medicine*, vol. 62, no. 1, pp. 49–57, Jan. 2019, doi: 10.1016/j.rehab.2018.09.006.

[45] S. Prasad, R. Aikat, S. Labani, and N. Khanna, "Efficacy of Virtual Reality in Upper Limb Rehabilitation in Patients with Spinal Cord Injury: A Pilot Randomized Controlled Trial," *Asian Spine J*, vol. 12, no. 5, pp. 927–934, Oct. 2018, doi: 10.31616/asj.2018.12.5.927.

[46] H. L. Miller and N. L. Bugnariu, "Level of Immersion in Virtual Environments Impacts the Ability to Assess and Teach Social Skills in Autism Spectrum Disorder," *Cyberpsychology, Behavior, and Social Networking*, vol. 19, no. 4, pp. 246–256, Apr. 2016, doi: 10.1089/cyber.2014.0682.

[47] M. Slater and S. Wilbur, "A Framework for Immersive Virtual Environments (FIVE): Speculations on the Role of Presence in Virtual Environments," *Presence: Teleoperators & Virtual Environments*, vol. 6, no. 6, pp. 603–616, Dec. 1997, doi: 10.1162/pres.1997.6.6.603.

[48] K. A. Pollard *et al.*, "Level of immersion affects spatial learning in virtual environments: results of a three-condition within-subjects study with long intersession intervals," *Virtual Reality*, vol. 24, no. 4, pp. 783–796, Dec. 2020, doi: 10.1007/s10055-019-00411-y.

[49] K. A. Pollard *et al.*, "Level of immersion affects spatial learning in virtual environments: results of a three-condition within-subjects study with long intersession intervals," *Virtual Reality*, vol. 24, no. 4, pp. 783–796, Dec. 2020, doi: 10.1007/s10055-019-00411-y.

[50] L. B. Cadet and H. Chainay, "Memory of virtual experiences: Role of immersion, emotion and sense of presence," *International Journal of Human-Computer Studies*, vol. 144, p. 102506, Dec. 2020, doi: 10.1016/j.ijhcs.2020.102506.

[51] S. A. Smith, "Virtual reality in episodic memory research: A review," *Psychon Bull Rev*, vol. 26, no. 4, pp. 1213–1237, Aug. 2019, doi: 10.3758/s13423-019-01605-w.

[52] D. Blana, T. Kyriacou, J. M. Lambrecht, and E. K. Chadwick, “Feasibility of using combined EMG and kinematic signals for prosthesis control: A simulation study using a virtual reality environment,” *Journal of Electromyography and Kinesiology*, vol. 29, pp. 21–27, Aug. 2016, doi: 10.1016/j.jelekin.2015.06.010.

[53] G. Wulf and C. H. Shea, “Principles derived from the study of simple skills do not generalize to complex skill learning,” *Psychon Bull Rev*, vol. 9, no. 2, pp. 185–211, Jun. 2002.

[54] K. Nesbitt, “Designing multi-sensory displays for abstract data,” Jan. 2003, [Online]. Available: https://ses.library.usyd.edu.au/handle/2123/4135

[55] R. Sigrist, G. Rauter, R. Riener, and P. Wolf, “Terminal Feedback Outperforms Concurrent Visual, Auditory, and Haptic Feedback in Learning a Complex Rowing-Type Task,” *Journal of Motor Behavior*, vol. 45, no. 6, pp. 455–472, Nov. 2013, doi: 10.1080/00222895.2013.826169.

[56] O. M. Giggins, U. M. Persson, and B. Caulfield, “Biofeedback in rehabilitation,” *Journal of NeuroEngineering and Rehabilitation*, vol. 10, no. 60, 2013, doi: 10.1186/1743-0003-10-60.

[57] N. C. Soderstrom and R. A. Bjork, “Learning Versus Performance: An Integrative Review,” *Perspect Psychol Sci*, vol. 10, no. 2, pp. 176–199, Mar. 2015, doi: 10.1177/1745691615569000.

[58] A. W. Salmoni, R. A. Schmidt, and C. B. Walter, “Knowledge of results and motor learning: a review and critical reappraisal,” *Psychol Bull*, vol. 95, no. 3, pp. 355–386, May 1984.

[59] R. A. Schmidt, D. E. Young, S. Swinnen, and D. C. Shapiro, “Summary knowledge of results for skill acquisition: support for the guidance hypothesis,” *J Exp Psychol Learn Mem Cogn*, vol. 15, no. 2, pp. 352–359, Mar. 1989.

[60] R. A. Schmidt, “Frequent Augmented Feedback Can Degrade Learning: Evidence and Interpretations,” in *Tutorials in Motor Neuroscience*, J. Requin and G. E. Stelmach, Eds. Dordrecht: Springer Netherlands, 1991, pp. 59–75. doi: 10.1007/978-94-011-3626-6_6.

[61] L. Proteau, “Chapter 4 On The Specificity of Learning and the Role of Visual Information for Movement Control,” in *Advances in Psychology*, vol. 85, L. Proteau and D. Elliott, Eds. North-Holland, 1992, pp. 67–103. doi: 10.1016/S0166-4115(08)62011-7.

[62] P. M. Fitts and M. I. Posner, *Human performance*. Oxford, England: Brooks/Cole, 1967.

[63] A. Gokeler *et al.*, “Feedback Techniques to Target Functional Deficits Following Anterior Cruciate Ligament Reconstruction: Implications for Motor Control and Reduction of Second Injury Risk,” *Sports Med*, vol. 43, no. 11, pp. 1065–1074, Nov. 2013, doi: 10.1007/s40279-013-0095-0.

[64] R. E. Richards, J. C. van den Noort, M. van der Esch, M. J. Booij, and J. Harlaar, “Effect of real-time biofeedback on peak knee adduction moment in patients with medial knee osteoarthritis: Is direct feedback effective?,” *Clinical Biomechanics*, vol. 57, pp. 150–158, Aug. 2018, doi: 10.1016/j.clinbiomech.2017.07.004.

[65] I. Levin, M. D. Lewek, J. Feasel, and D. E. Thorpe, “Gait Training With Visual Feedback and Proprioceptive Input to Reduce Gait Asymmetry in Adults With Cerebral Palsy: A Case Series,” *Pediatric Physical Therapy*, vol. 29, no. 2, pp. 138–145, Apr. 2017, doi: 10.1097/PEP.0000000000000362.

[66] J. R. Franz, M. Maletis, and R. Kram, “Real-time feedback enhances forward propulsion during walking in old adults,” *Clinical Biomechanics*, vol. 29, no. 1, pp. 68–74, Jan. 2014, doi: 10.1016/j.clinbiomech.2013.10.018.

[67] M. Suteerawattananon, G. S. Morris, B. R. Etnyre, J. Jankovic, and E. J. Protas, “Effects of visual and auditory cues on gait in individuals with Parkinson’s disease,” *J. Neurol. Sci.*, vol. 219, no. 1–2, pp. 63–69, Apr. 2004, doi: 10.1016/j.jns.2003.12.007.

[68] J. Nunnerley, S. Gupta, D. Snell, and M. King, “Training wheelchair navigation in immersive virtual environments for patients with spinal cord injury - end-user input to design an effective system,” *Disabil Rehabil Assist Technol*, vol. 12, no. 4, pp. 417–423, May 2017, doi: 10.1080/17483107.2016.1176259.

[69] B. J. Darter and J. M. Wilken, “Gait Training With Virtual Reality–Based Real-Time Feedback: Improving Gait Performance Following Transfemoral Amputation,” *Phys Ther*, vol. 91, no. 9, pp. 1385–1394, Sep. 2011, doi: 10.2522/ptj.20100360.

[70] S. Abujaber, F. Pozzi, and J. Zeni, “Influence of weight bearing visual feedback on movement symmetry during sit to stand task,” *Clinical Biomechanics*, vol. 47, pp. 110–116, Aug. 2017, doi: 10.1016/j.clinbiomech.2017.06.005.

[71] J. A. Cotter, A. M. Chaudhari, S. T. Jamison, and S. T. Devor, “Knee Joint Kinetics in Relation to Commonly Prescribed Squat Loads and Depths,” *J Strength Cond Res*, vol. 27, no. 7, pp. 1765–1774, Jul. 2013, doi: 10.1519/JSC.0b013e3182773319.

[72] J.-Y. Yoon, M.-H. Kang, and J.-S. Oh, “Effects of Visual Biofeedback Using a Laser Beam on the EMG ratio of the Medial and Lateral Vasti Muscles and Kinematics of Hip and Knee Joints during a Squat Exercise,” *Journal of Physical Therapy Science*, vol. 23, no. 4, pp. 559–563, 2011, doi: 10.1589/jpts.23.559.

[73] D. L. Eaves, G. Breslin, and P. van Schaik, “The Short-Term Effects of Real-Time Virtual Reality Feedback on Motor Learning in Dance,” *Presence: Teleoperators and Virtual Environments*, vol. 20, no. 1, pp. 62–77, Feb. 2011, doi: 10.1162/pres_a_00035.

[74] Philo Tan Chua *et al.*, “Training for physical tasks in virtual environments: Tai Chi,” in *IEEE Virtual Reality, 2003. Proceedings.*, Los Angeles, CA, USA, 2003, pp. 87–94. doi: 10.1109/VR.2003.1191125.

[75] C. W. Antuvan, F. Bisio, E. Cambria, and L. Masia, “Discrete classification of upper limb motions using myoelectric interface,” in *2015 IEEE International Conference on Rehabilitation Robotics (ICORR)*, Singapore, Singapore, Aug. 2015, pp. 451–456. doi: 10.1109/ICORR.2015.7281241.

[76] S. Lee, Y. Kim, and B.-H. Lee, “Effect of Virtual Reality-based Bilateral Upper Extremity Training on Upper Extremity Function after Stroke: A Randomized Controlled Clinical Trial: Bilateral Upper Extremity Training in Post Stroke,” *Occup. Ther. Int.*, vol. 23, no. 4, pp. 357–368, Dec. 2016, doi: 10.1002/oti.1437.

[77] Y. Cai, C. Indhumathi, and W. Chen, "Multi-Modal VR for Medical Simulation," *International Journal of Virtual Reality (IJVR)*, vol. 08, no. 1, pp. 1–7, 2009.
[78] J. H. Park, C. H. Shea, and D. L. Wright, "Reduced-frequency concurrent and terminal feedback: a test of the guidance hypothesis," *J Mot Behav*, vol. 32, no. 3, pp. 287–296, Sep. 2000, doi: 10.1080/00222890009601379.
[79] C. M. Walsh, S. C. Ling, C. S. Wang, and H. Carnahan, "Concurrent versus terminal feedback: it may be better to wait," *Acad Med*, vol. 84, no. 10 Suppl, pp. S54-57, Oct. 2009, doi: 10.1097/ACM.0b013e3181b38daf.
[80] S. M. Radhakrishnan, V. Hatzitaki, A. Vogiannou, and D. Tzovaras, "The role of visual cues in the acquisition and transfer of a voluntary postural sway task," *Gait & Posture*, vol. 32, no. 4, pp. 650–655, Oct. 2010, doi: 10.1016/j.gaitpost.2010.09.010.
[81] D. E. Young and R. A. Schmidt, "Augmented Kinematic Feedback for Motor Learning," *Journal of Motor Behavior*, vol. 24, no. 3, pp. 261–273, Sep. 1992, doi: 10.1080/00222895.1992.9941621.
[82] J. Sadowski, A. Mastalerz, and T. Niznikowski, "Benefits of Bandwidth Feedback in Learning a Complex Gymnastic Skill," *Journal of Human Kinetics*, vol. 37, no. 1, pp. 183–193, Jun. 2013, doi: 10.2478/hukin-2013-0039.
[83] A. M. D. Nunzio *et al.*, "Tactile feedback is an effective instrument for the training of grasping with a prosthesis at low- and medium-force levels," *Exp Brain Res*, vol. 235, no. 8, pp. 2547–2559, Aug. 2017, doi: 10.1007/s00221-017-4991-7.
[84] U. Cote-Allard *et al.*, "A Transferable Adaptive Domain Adversarial Neural Network for Virtual Reality Augmented EMG-Based Gesture Recognition," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 546–555, 2021, doi: 10.1109/TNSRE.2021.3059741.
[85] J. M. Lambrecht, C. L. Pulliam, and R. F. Kirsch, "Virtual Reality Environment for Simulating Tasks With a Myoelectric Prosthesis: An Assessment and Training Tool:," *JPO Journal of Prosthetics and Orthotics*, vol. 23, no. 2, pp. 89–94, Apr. 2011, doi: 10.1097/JPO.0b013e318217a30c.
[86] S. M. Radhakrishnan, V. Hatzitaki, A. Vogiannou, and D. Tzovaras, "The role of visual cues in the acquisition and transfer of a voluntary postural sway task," *Gait & Posture*, vol. 32, no. 4, pp. 650–655, Oct. 2010, doi: 10.1016/j.gaitpost.2010.09.010.
[87] J. M. Schiffman, C. W. Luchies, L. Piscitelle, L. Hasselquist, and K. N. Gregorczyk, "Discrete bandwidth visual feedback increases structure of output as compared to continuous visual feedback in isometric force control tasks," *Clinical Biomechanics*, vol. 21, no. 10, pp. 1042–1050, Dec. 2006, doi: 10.1016/j.clinbiomech.2006.05.009.
[88] D. Maslovat, K. M. Brunke, R. Chua, and I. M. Franks, "Feedback effects on learning a novel bimanual coordination pattern: support for the guidance hypothesis," *J Mot Behav*, vol. 41, no. 1, pp. 45–54, Jan. 2009, doi: 10.1080/00222895.2009.10125923.
[89] R. A. Schmidt and G. Wulf, "Continuous Concurrent Feedback Degrades Skill Learning: Implications for Training and Simulation," *Hum Factors*, vol. 39, no. 4, pp. 509–525, Dec. 1997, doi: 10.1518/001872097778667979.
[90] M. Huet, C. Camachon, L. Fernandez, D. M. Jacobs, and G. Montagne, "Self-controlled concurrent feedback and the education of attention towards perceptual

invariants," *Human Movement Science*, vol. 28, no. 4, pp. 450–467, Aug. 2009, doi: 10.1016/j.humov.2008.12.004.

[91] C. A. Aiken, J. T. Fairbrother, and P. G. Post, "The Effects of Self-Controlled Video Feedback on the Learning of the Basketball Set Shot," *Front Psychol*, vol. 3, Sep. 2012, doi: 10.3389/fpsyg.2012.00338.

[92] J. Davis, "Effects of self-controlled feedback on the squat," Thesis, 2009. Accessed: Jul. 25, 2017. [Online]. Available: https://dspace.sunyconnect.suny.edu/handle/1951/48141

[93] P. G. Post, J. T. Fairbrother, and J. A. C. Barros, "Self-controlled amount of practice benefits learning of a motor skill," *Res Q Exerc Sport*, vol. 82, no. 3, pp. 474–481, Sep. 2011, doi: 10.1080/02701367.2011.10599780.

[94] J. E. Goodwin and H. J. Meeuwsen, "Using Bandwidth Knowledge of Results to Alter Relative Frequencies During Motor Skill Acquisition," *Research Quarterly for Exercise and Sport*, vol. 66, no. 2, pp. 99–104, Jun. 1995, doi: 10.1080/02701367.1995.10762217.

[95] D. E. Sherwood, "Effect of Bandwidth Knowledge of Results on Movement Consistency," *Percept Mot Skills*, vol. 66, no. 2, pp. 535–542, Apr. 1988, doi: 10.2466/pms.1988.66.2.535.

[96] A. Horta Miguel Junqueira, "Thin Bandwidth Knowledge of Results (KR) Improves Performance Consistency on Motor Skill Acquisition," *AJSS*, vol. 3, no. 6, p. 115, 2015, doi: 10.11648/j.ajss.20150306.13.

[97] H. Ugrinowitsch, A. A. C. Ugrinowitsch, R. N. Benda, and I. W. Tertuliano, "Effect of Bandwidth Knowledge of Results on the Learning of a Grip Force Control Task," *Percept Mot Skills*, vol. 111, no. 3, pp. 643–652, Dec. 2010, doi: 10.2466/23.25.PMS.111.6.643-652.

[98] M. P. Cruz, R. N. Benda, G. M. Lage, M. T. Cattuzzo, and H. Ugrinowitsch, "Bandwidth knowledge of results persists on motor skills acquisition," *Montricidade*, vol. 14, 2018.

[99] A. Badets and Y. Blandin, "Observational Learning: Effects of Bandwidth Knowledge of Results," *Journal of Motor Behavior*, vol. 37, no. 3, pp. 211–216, May 2005, doi: 10.3200/JMBR.37.3.211-216.

[100] S. de Groot, J. C. F. de Winter, J. M. L. García, M. Mulder, and P. A. Wieringa, "The Effect of Concurrent Bandwidth Feedback on Learning the Lane-Keeping Task in a Driving Simulator," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 53, no. 1, pp. 50–62, Feb. 2011, doi: 10.1177/0018720810393241.

[101] A. N. Pujari, R. D. Neilson, and M. Cardinale, "Effects of different vibration frequencies, amplitudes and contraction levels on lower limb muscles during graded isometric contractions superimposed on whole body vibration stimulation," *Journal of Rehabilitation and Assistive Technologies Engineering*, vol. 6, Jan. 2019, doi: 10.1177/2055668319827466.

[102] M. W. Taylor, J. L. Taylor, and T. Seizova-Cajic, "Muscle Vibration-Induced Illusions: Review of Contributing Factors, Taxonomy of Illusions and User's

Guide," *Multisens Res*, vol. 30, no. 1, pp. 25–63, 2017, doi: 10.1163/22134808-00002544.

[103] E. Raveh, S. Portnoy, and J. Friedman, "Adding vibrotactile feedback to a myoelectric-controlled hand improves performance when online visual feedback is disturbed," *Human Movement Science*, vol. 58, pp. 32–40, Apr. 2018, doi: 10.1016/j.humov.2018.01.008.

[104] T. Rose, C. S. Nam, and K. B. Chen, "Immersion of virtual reality for rehabilitation - Review," *Applied Ergonomics*, vol. 69, pp. 153–161, May 2018, doi: 10.1016/j.apergo.2018.01.009.

[105] R. Sigrist, G. Rauter, L. Marchal-Crespo, R. Riener, and P. Wolf, "Sonification and haptic feedback in addition to visual feedback enhances complex motor task learning," *Exp Brain Res*, vol. 233, no. 3, pp. 909–925, Mar. 2015, doi: 10.1007/s00221-014-4167-7.

[106] Beom-Chan Lee and K. H. Sienko, "Effects of attractive versus repulsive vibrotactile instructional cues during motion replication tasks," in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Boston, MA, Aug. 2011, pp. 3533–3536. doi: 10.1109/IEMBS.2011.6090587.

[107] Y. Li, W. R. Jeon, and C. S. Nam, "Navigation by vibration: Effects of vibrotactile feedback on a navigation task," *International Journal of Industrial Ergonomics*, vol. 46, pp. 76–84, Mar. 2015, doi: 10.1016/j.ergon.2014.12.008.

[108] K. Bark *et al.*, "Effects of Vibrotactile Feedback on Human Learning of Arm Motions," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 1, pp. 51–63, Jan. 2015, doi: 10.1109/TNSRE.2014.2327229.

[109] J. D. Brown *et al.*, "An exploration of grip force regulation with a low-impedance myoelectric prosthesis featuring referred haptic feedback," *J NeuroEngineering Rehabil*, vol. 12, no. 1, p. 104, Dec. 2015, doi: 10.1186/s12984-015-0098-1.

[110] A. R. Krueger, P. Giannoni, V. Shah, M. Casadio, and R. A. Scheidt, "Supplemental vibrotactile feedback control of stabilization and reaching actions of the arm using limb state and position error encodings," *J NeuroEngineering Rehabil*, vol. 14, no. 1, p. 36, Dec. 2017, doi: 10.1186/s12984-017-0248-8.

[111] E. Scalona, D. Hayes, Z. Del Prete, E. Palermo, and S. Rossi, "Perturbed Point-to-Point Reaching Tasks in a 3D Environment Using a Portable Haptic Device," *Electronics*, vol. 8, no. 1, p. 32, Jan. 2019, doi: 10.3390/electronics8010032.

[112] P. J. M. Bank, L. R. M. Dobbe, C. G. M. Meskers, J. H. de Groot, and E. de Vlugt, "Manipulation of visual information affects control strategy during a visuomotor tracking task," *Behavioural Brain Research*, vol. 329, pp. 205–214, Jun. 2017, doi: 10.1016/j.bbr.2017.04.056.

[113] S. Wilder, "Sense of Agency and Performance in Using 6-DOF Devices," Stevens Institute of Technology, 2020.

[114] C. J. Hasson and J. Manczurowsky, "Effects of kinematic vibrotactile feedback on learning to control a virtual prosthetic arm," *J NeuroEngineering Rehabil*, vol. 12, no. 1, p. 31, Dec. 2015, doi: 10.1186/s12984-015-0025-5.

[115] G. Ballardini, V. Florio, A. Canessa, G. Carlini, P. Morasso, and M. Casadio, "Vibrotactile Feedback for Improving Standing Balance," *Front. Bioeng. Biotechnol.*, vol. 8, p. 94, Feb. 2020, doi: 10.3389/fbioe.2020.00094.

[116] F. Yang, M. Underdahl, H. Yang, and C. Yang, "Effects of vibration intensity on lower limb joint moments during standing," *Journal of Biomechanics*, vol. 88, pp. 18–24, May 2019, doi: 10.1016/j.jbiomech.2019.03.012.

[117] F. D. Iorio, M. Cesarelli, P. Bifulco, A. Fratini, E. Roveda, and M. Ruffo, "The effect of whole body vibration on oxygen uptake and electromyographic signal of the rectus femoris muscle during static and dynamic squat," *Journal of Exercise Physiology Online*, vol. 15, no. 5, pp. 18–31, Oct. 2012.

[118] S. Rodríguez Jiménez, A. Benítez, M. A. García González, G. Moras Feliu, and N. A. Maffiuletti, "Effect of vibration frequency on agonist and antagonist arm muscle activity," *Eur J Appl Physiol*, vol. 115, no. 6, pp. 1305–1312, Jun. 2015, doi: 10.1007/s00421-015-3108-x.

[119] A. N. Pujari, R. D. Neilson, and M. Cardinale, "Fatiguing effects of indirect vibration stimulation in upper limb muscles: pre, post and during isometric contractions superimposed on upper limb vibration," *Royal Society Open Science*, vol. 6, no. 10, 2018, doi: 10.1098/rsos.190019.

[120] M. M. Alam, A. A. Khan, and M. Farooq, "Effects of vibration therapy on neuromuscular efficiency & features of the EMG signal based on endurance test," *Journal of Bodywork and Movement Therapies*, vol. 24, no. 4, pp. 325–335, Oct. 2020, doi: 10.1016/j.jbmt.2020.06.037.

[121] M. D. Rinderknecht, Yeongmi Kim, L. Santos-Carreras, H. Bleuler, and R. Gassert, "Combined tendon vibration and virtual reality for post-stroke hand rehabilitation," in *2013 World Haptics Conference (WHC)*, Daejeon, Apr. 2013, pp. 277–282. doi: 10.1109/WHC.2013.6548421.

[122] X. Navarro, T. B. Krueger, N. Lago, S. Micera, T. Stieglitz, and P. Dario, "A critical review of interfaces with the peripheral nervous system for the control of neuroprostheses and hybrid bionic systems," *J Peripher Nerv Syst*, vol. 10, no. 3, pp. 229–258, Sep. 2005, doi: 10.1111/j.1085-9489.2005.10303.x.

[123] E. F. Hodkin *et al.*, "Automated FES for Upper Limb Rehabilitation Following Stroke and Spinal Cord Injury," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 5, pp. 1067–1074, May 2018, doi: 10.1109/TNSRE.2018.2816238.

[124] F. Scotto di Luzio, C. Lauretti, F. Cordella, F. Draicchio, and L. Zollo, "Visual vs vibrotactile feedback for posture assessment during upper-limb robot-aided rehabilitation," *Applied Ergonomics*, vol. 82, p. 102950, Jan. 2020, doi: 10.1016/j.apergo.2019.102950.

[125] S. Saleh, G. Fluet, Q. Qiu, A. Merians, S. V. Adamovich, and E. Tunik, "Neural Patterns of Reorganization after Intensive Robot-Assisted Virtual Reality Therapy and Repetitive Task Practice in Patients with Chronic Stroke," *Front. Neurol.*, vol. 8, p. 452, Sep. 2017, doi: 10.3389/fneur.2017.00452.

[126] M. Bassolino *et al.*, "Non-invasive brain stimulation of motor cortex induces embodiment when integrated with virtual reality feedback," *Eur J Neurosci*, vol. 47, no. 7, pp. 790–799, Apr. 2018, doi: 10.1111/ejn.13871.

[127] S. Le Franc *et al.*, “Influence of virtual reality visual feedback on the illusion of movement induced by tendon vibration of wrist in healthy participants,” *PLoS ONE*, vol. 15, no. 11, p. e0242416, Nov. 2020, doi: 10.1371/journal.pone.0242416.
[128] P. Konrad, “The ABC of EMG: A Practical Introduction to Kinesiological Electromyography.,” Jan. 2005.
[129] E. Magosso, F. De Crescenzio, G. Ricci, S. Piastra, and M. Ursino, “EEG Alpha Power Is Modulated by Attentional Changes during Cognitive Tasks and Virtual Reality Immersion,” *Computational Intelligence and Neuroscience*, vol. 2019, pp. 1–18, Jun. 2019, doi: 10.1155/2019/7051079.
[130] R. Foong *et al.*, “Assessment of the Efficacy of EEG-Based MI-BCI With Visual Feedback and EEG Correlates of Mental Fatigue for Upper-Limb Stroke Rehabilitation,” *IEEE Trans. Biomed. Eng.*, vol. 67, no. 3, pp. 786–795, Mar. 2020, doi: 10.1109/TBME.2019.2921198.
[131] D. Michie, D. J. Spiegelhalter, and C. C. Taylor, “Machine Learning, Neural and Statistical Classification,” p. 298.
[132] A. B. Ajiboye and R. F. H. Weir, “A Heuristic Fuzzy Logic Approach to EMG Pattern Recognition for Multifunctional Prosthesis Control,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 13, no. 3, pp. 280–291, Sep. 2005, doi: 10.1109/TNSRE.2005.847357.
[133] M. V. Liarokapis, P. K. Artemiadis, P. T. Katsiaris, K. J. Kyriakopoulos, and E. S. Manolakos, “Learning human reach-to-grasp strategies: Towards EMG-based control of robotic arm-hand systems,” in *2012 IEEE International Conference on Robotics and Automation*, St Paul, MN, USA, May 2012, pp. 2287–2292. doi: 10.1109/ICRA.2012.6225047.
[134] B. Crawford, K. Miller, P. Shenoy, and R. Rao, “Real-time classification of electromyographic signals for robotic control,” *Proceedings of the National Conference on Artificial Intelligence*, vol. 2, pp. 523–528, 2005.
[135] K. A. Walsh, S. P. Sanford, B. D. Collins, N. Y. Harel, and R. Nataraj, “Performance potential of classical machine learning and deep learning classifiers for isometric upper-body myoelectric control of direction in virtual reality with reduced muscle inputs,” *Biomedical Signal Processing and Control*, vol. 66, p. 102487, Apr. 2021, doi: 10.1016/j.bspc.2021.102487.
[136] M. León, J. M. Gutiérrez, L. Leija, and R. Muñoz, “EMG pattern recognition using Support Vector Machines classifier for myoelectric control purposes,” in *2011 Pan American Health Care Exchanges*, Mar. 2011, pp. 175–178. doi: 10.1109/PAHCE.2011.5871873.
[137] D. C. Toledo-Pérez, J. Rodríguez-Reséndiz, R. A. Gómez-Loenzo, and J. C. Jauregui-Correa, “Support Vector Machine-Based EMG Signal Classification Techniques: A Review,” *Applied Sciences*, vol. 9, no. 20, Art. no. 20, Jan. 2019, doi: 10.3390/app9204402.
[138] A. Goen and D. Tiwari, “Classification of the Myoelectric Signals of Movement of Forearms for Prosthesis Control,” *Classification of the Myoelectric Signals of Movement of Forearms for Prosthesis Control*, vol. 5, Jan. 2016, doi: 10.18178/jomb.5.2.76-84.

[139] A. Dellacasa Bellingegni *et al.*, “NLR, MLP, SVM, and LDA: a comparative analysis on EMG data from people with trans-radial amputation,” *Journal of NeuroEngineering and Rehabilitation*, vol. 14, no. 1, p. 82, Aug. 2017, doi: 10.1186/s12984-017-0290-6.

[140] E. Scheme and K. Englehart, “On the robustness of EMG features for pattern recognition based myoelectric control: a multi-dataset comparison,” *Annu Int Conf IEEE Eng Med Biol Soc*, vol. 2014, pp. 650–653, 2014, doi: 10.1109/EMBC.2014.6943675.

[141] G. R. Naik, S. E. Selvan, M. Gobbo, A. Acharyya, and H. T. Nguyen, “Principal Component Analysis Applied to Surface Electromyography: A Comprehensive Review,” *IEEE Access*, vol. 4, pp. 4025–4037, 2016, doi: 10.1109/ACCESS.2016.2593013.

[142] B. M. Cahill, J. H. Carr, and R. Adams, “Inter-segmental co-ordination in sit-to-stand: an age cross-sectional study,” *Physiother Res Int*, vol. 4, no. 1, pp. 12–27, 1999.

[143] J. Neitzel and G. Davies, “The Benefits and Controversy of the Parallel Squat in Strength Training and Rehabilitation,” *Strength & Conditioning Journal*, vol. 22, p. 30, Jun. 2000, doi: 10.1519/00126548-200006000-00008.

[144] S. M. Gryzlo, R. M. Patek, M. Pink, and J. Perry, “Electromyographic Analysis of Knee Rehabilitation Exercises,” *J Orthop Sports Phys Ther*, vol. 20, no. 1, pp. 36–43, Jul. 1994, doi: 10.2519/jospt.1994.20.1.36.

[145] R. F. Escamilla, “Knee biomechanics of the dynamic squat exercise,” *Med Sci Sports Exerc*, vol. 33, no. 1, pp. 127–141, Jan. 2001.

[146] D. R. Clark, M. I. Lambert, and A. M. Hunter, “Muscle activation in the loaded free barbell squat: a brief review,” *J Strength Cond Res*, vol. 26, no. 4, pp. 1169–1178, Apr. 2012, doi: 10.1519/JSC.0b013e31822d533d.

[147] P. A. Swinton, R. Lloyd, J. W. L. Keogh, I. Agouris, and A. D. Stewart, “A biomechanical comparison of the traditional squat, powerlifting squat, and box squat,” *J Strength Cond Res*, vol. 26, no. 7, pp. 1805–1816, Jul. 2012, doi: 10.1519/JSC.0b013e3182577067.

[148] A. Paoli, G. Marcolin, and N. Petrone, “The effect of stance width on the electromyographical activity of eight superficial thigh muscles during back squat with different bar loads,” *J Strength Cond Res*, vol. 23, no. 1, pp. 246–250, Jan. 2009.

[149] S. Madhavan and R. K. Shields, “Movement Accuracy Changes Muscle-Activation Strategies in Female Subjects During a Novel Single-Leg Weight-Bearing Task,” *PM&R*, vol. 1, no. 4, pp. 319–328, Apr. 2009, doi: 10.1016/j.pmrj.2009.01.002.

[150] P.-N. Hwangbo, “The effects of squatting with visual feedback on the muscle activation of the vastus medialis oblique and the vastus lateralis in young adults with an increased quadriceps angle,” *J Phys Ther Sci*, vol. 27, no. 5, pp. 1507–1510, May 2015, doi: 10.1589/jpts.27.1507.

[151] K. Bloomquist, H. Langberg, S. Karlsen, S. Madsgaard, M. Boesen, and T. Raastad, “Effect of range of motion in heavy load squatting on muscle and tendon

adaptations," *Eur. J. Appl. Physiol.*, vol. 113, no. 8, pp. 2133–2142, Aug. 2013, doi: 10.1007/s00421-013-2642-7.

[152] G. D. Myer *et al.*, "The back squat: A proposed assessment of functional deficits and technical factors that limit performance," *Strength Cond J*, vol. 36, no. 6, pp. 4–27, Dec. 2014, doi: 10.1519/SSC.0000000000000103.

[153] N. C. Soderstrom and R. A. Bjork, "Learning Versus Performance: An Integrative Review," *Perspect Psychol Sci*, vol. 10, no. 2, pp. 176–199, Mar. 2015, doi: 10.1177/1745691615569000.

[154] M. L. Audu, R. R. Kirsch, and R. J. Triolo, "Three dimensional modeling of the lower extremity for the study of static standing postures in Functional Electrical Stimulation (FES)," in *Proceedings of the Second Joint 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society] [Engineering in Medicine and Biology*, Houston, TX, USA, 2002, pp. 2501–2502. doi: 10.1109/IEMBS.2002.1053395.

[155] D. Winter, "Human balance and posture control during standing and walking," *Gait & Posture*, vol. 3, no. 4, pp. 193–214, Dec. 1995, doi: 10.1016/0966-6362(96)82849-9.

[156] K. Kilteni, R. Groten, and M. Slater, "The Sense of Embodiment in Virtual Reality," *Presence: Teleoperators and Virtual Environments*, vol. 21, no. 4, pp. 373–387, Nov. 2012, doi: 10.1162/PRES_a_00124.

[157] R. S. Calabrò *et al.*, "The role of virtual reality in improving motor performance as revealed by EEG: a randomized clinical trial," *J NeuroEngineering Rehabil*, vol. 14, no. 1, p. 53, Dec. 2017, doi: 10.1186/s12984-017-0268-4.

[158] R. Willy and I. Davis, "The Effect of a Hip-Strengthening Program on Mechanics During Running and During a Single-Leg Squat," *J Orthop Sports Phys Ther*, vol. 41, no. 9, pp. 625–632, Sep. 2011, doi: 10.2519/jospt.2011.3470.

[159] L. P. Sewall, T. G. Reeve, and R. A. Day, "Effect of Concurrent Visual Feedback on Acquisition of a Weightlifting Skill," *Percept Mot Skills*, vol. 67, no. 3, pp. 715–718, Dec. 1988, doi: 10.2466/pms.1988.67.3.715.

[160] N. Schaffert and K. Mattes, "Testing immediate and retention effects of acoustic feedback on the boat motion in high-performance rowing," *jhse*, vol. 9, no. 2, pp. 616–628, 2014, doi: 10.14198/jhse.2014.92.02.

[161] E. Wierinck, V. Puttemans, and D. van Steenberghe, "Effect of tutorial input in addition to augmented feedback on manual dexterity training and its retention," *Eur J Dent Educ*, vol. 10, no. 1, pp. 24–31, Feb. 2006, doi: 10.1111/j.1600-0579.2006.00392.x.

[162] J. E. Earp, R. U. Newton, P. Cormie, and A. J. Blazevich, "Faster Movement Speed Results in Greater Tendon Strain during the Loaded Squat Exercise," *Front Physiol*, vol. 7, Aug. 2016, doi: 10.3389/fphys.2016.00366.

[163] Z. Tang, K. Zhang, S. Sun, Z. Gao, L. Zhang, and Z. Yang, "An Upper-Limb Power-Assist Exoskeleton Using Proportional Myoelectric Control," *Sensors*, vol. 14, no. 4, pp. 6677–6694, Apr. 2014, doi: 10.3390/s140406677.

[164] C. Fleischer and G. Hommel, “A Human–Exoskeleton Interface Utilizing Electromyography,” *IEEE Transactions on Robotics*, vol. 24, no. 4, pp. 872–882, Aug. 2008, doi: 10.1109/TRO.2008.926860.

[165] S. L. Carey, D. J. Lura, and M. J. Highsmith, “Differences in myoelectric and body-powered upper-limb prostheses: Systematic literature review,” *Journal of Rehabilitation Research and Development; Washington*, vol. 52, no. 3, pp. 247–262, 2015.

[166] T. S. Buchanan, D. G. Lloyd, K. Manal, and T. F. Besier, “Estimation of Muscle Forces and Joint Moments Using a Forward-Inverse Dynamics Model:,” *Medicine & Science in Sports & Exercise*, vol. 37, no. 11, pp. 1911–1916, Nov. 2005, doi: 10.1249/01.mss.0000176684.24008.6f.

[167] B. N. Perry *et al.*, “Virtual Integration Environment as an Advanced Prosthetic Limb Training Platform,” *Front. Neurol.*, vol. 9, p. 785, Oct. 2018, doi: 10.3389/fneur.2018.00785.

[168] J. L. Minkel, “Seating and mobility considerations for people with spinal cord injury,” *Physical therapy*, vol. 80, no. 7, pp. 701–709, 2000.

[169] D. J. Oranchuk, A. G. Storey, A. R. Nelson, and J. B. Cronin, “Isometric training and long-term adaptations: Effects of muscle length, intensity, and intent: A systematic review,” *Scandinavian journal of medicine & science in sports*, vol. 29, no. 4, pp. 484–503, 2019.

[170] N. Alavi, G. Herrnstadt, B. K. Randhawa, L. A. Boyd, and C. Menon, “Bimanual elbow exoskeleton: Force based protocol and rehabilitation quantification,” in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2015, pp. 4643–4646.

[171] M. Tiboni, A. Borboni, R. Faglia, and N. Pellegrini, “Robotics rehabilitation of the elbow based on surface electromyography signals,” *Advances in Mechanical Engineering*, vol. 10, no. 2, p. 1687814018754590, 2018.

[172] K. Aoyagi *et al.*, “Improvement of Sense of Agency During Upper-Limb Movement for Motor Rehabilitation Using Virtual Reality,” in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Berlin, Germany, Jul. 2019, pp. 118–121. doi: 10.1109/EMBC.2019.8856796.

[173] N. Kumar and J. Kumar, “Measurement of cognitive load in HCI systems using EEG power spectrum: an experimental study,” *Procedia Computer Science*, vol. 84, pp. 70–78, 2016.

[174] H. D. Critchley, “Electrodermal responses: what happens in the brain,” *The Neuroscientist*, vol. 8, no. 2, pp. 132–142, 2002.

[175] M. Noorkõiv, K. Nosaka, and A. J. Blazevich, “Effects of isometric quadriceps strength training at different muscle lengths on dynamic torque production,” *Journal of sports sciences*, vol. 33, no. 18, pp. 1952–1961, 2015.

[176] J. P. Folland, K. Hawker, B. Leach, T. Little, and D. A. Jones, “Strength training: Isometric training at a range of joint angles versus dynamic training,” *Journal of sports sciences*, vol. 23, no. 8, pp. 817–824, 2005.

[177] D. J. Berger and A. d'Avella, "Towards a myoelectrically controlled virtual reality interface for synergy-based stroke rehabilitation," in *Converging Clinical and Engineering Research on Neurorehabilitation II*, Springer, 2017, pp. 965–969.

[178] K. E. Gordon and D. P. Ferris, "Proportional myoelectric control of a virtual object to investigate human efferent control," *Experimental Brain Research*, vol. 159, no. 4, pp. 478–486, 2004.

[179] J. W. Moore and S. S. Obhi, "Intentional binding and the sense of agency: A review," *Consciousness and Cognition*, vol. 21, no. 1, pp. 546–561, Mar. 2012, doi: 10.1016/j.concog.2011.12.002.

[180] D. C. Toledo-Pérez, J. Rodríguez-Reséndiz, R. A. Gómez-Loenzo, and J. C. Jauregui-Correa, "Support vector machine-based EMG signal classification techniques: A review," *Applied Sciences*, vol. 9, no. 20, p. 4402, 2019.

[181] N. Parajuli *et al.*, "Real-time EMG based pattern recognition control for hand prostheses: A review on existing methods, challenges and future implementation," *Sensors*, vol. 19, no. 20, p. 4596, 2019.

[182] J. McIntyre, F. A. Mussa-Ivaldi, and E. Bizzi, "The control of stable postures in the multijoint arm," *Experimental brain research*, vol. 110, no. 2, pp. 248–264, 1996.

[183] S. Kucuk and Z. Bingul, *Robot kinematics: Forward and inverse kinematics*. INTECH Open Access Publisher, 2006.

[184] S. Yue, D. Henrich, W. L. Xu, and S. K. Tso, "Point-to-point trajectory planning of flexible redundant robot manipulators using genetic algorithms," *Robotica*, vol. 20, no. 3, pp. 269–280, 2002.

[185] M. F. Levin, P. L. Weiss, and E. A. Keshner, "Emergence of virtual reality as a tool for upper limb rehabilitation: incorporation of motor control and motor learning principles," *Phys Ther*, vol. 95, no. 3, Art. no. 3, Mar. 2015, doi: 10.2522/ptj.20130579.

[186] M. C. Cirstea and M. F. Levin, "Improvement of arm movement patterns and endpoint control depends on type of feedback during practice in stroke survivors," *Neurorehabil Neural Repair*, vol. 21, no. 5, pp. 398–411, Oct. 2007, doi: 10.1177/1545968306298414.

[187] F. Kern, C. Winter, D. Gall, I. Käthner, P. Pauli, and M. Latoschik, *Immersive Virtual Reality and Gamification Within Procedurally Generated Environments to Increase Motivation During Gait Rehabilitation*. 2019. doi: 10.1109/VR.2019.8797828.

[188] R. Ronsse *et al.*, "Motor Learning with Augmented Feedback: Modality-Dependent Behavioral and Neural Consequences," *Cerebral Cortex*, vol. 21, no. 6, Art. no. 6, Jun. 2011, doi: 10.1093/cercor/bhq209.

[189] M. A. Guadagnoli and T. D. Lee, "Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning," *Journal of motor behavior*, vol. 36, no. 2, pp. 212–224, 2004.

[190] A. Nieuwboer, L. Rochester, L. Müncks, and S. P. Swinnen, "Motor learning in Parkinson's disease: limitations and potential for rehabilitation," *Parkinsonism & related disorders*, vol. 15, pp. S53–S58, 2009.

[191] D. J. Berger and A. d'Avella, "Effective force control by muscle synergies," *Frontiers in computational neuroscience*, vol. 8, p. 46, 2014.
[192] A. W. Kiefer, J. Gualberto Cremades, and G. D. Myer, "Train the Brain: Novel Electroencephalography Data Indicate Links between Motor Learning and Brain Adaptations," *J Nov Physiother*, vol. 4, no. 2, p. 198, Apr. 2014, doi: 10.4172/2165-7025.1000198.
[193] J. Weaver, "Motor Learning Unfolds over Different Timescales in Distinct Neural Systems," *PLoS Biol*, vol. 13, no. 12, p. e1002313, Dec. 2015, doi: 10.1371/journal.pbio.1002313.
[194] R. Nataraj, S. Sanford, A. Shah, and M. Liu, "Agency and Performance of Reach-to-Grasp with Modified Control of a Virtual Hand: Implications for Rehabilitation," *Front. Hum. Neurosci.*, vol. 14, 2020, doi: 10.3389/fnhum.2020.00126.
[195] R. Nataraj and S. Sanford, "Control Modification of Grasp Force Covaries Agency and Performance on Rigid and Compliant Surfaces," *Frontiers in Bioengineering and Biotechnology*, vol. 8, p. 1544, 2021.
[196] K. H. Cho, M. K. Kim, H.-J. Lee, and W. H. Lee, "Virtual Reality Training with Cognitive Load Improves Walking Function in Chronic Stroke Patients," *Tohoku J Exp Med*, vol. 236, no. 4, Art. no. 4, Aug. 2015, doi: 10.1620/tjem.236.273.
[197] M. Bannert, "Managing cognitive load—recent trends in cognitive load theory," *Learning and Instruction*, vol. 12, no. 1, pp. 139–146, Feb. 2002, doi: 10.1016/S0959-4752(01)00021-4.
[198] M. V. Liarokapis, P. K. Artemiadis, K. J. Kyriakopoulos, and E. S. Manolakos, "A Learning Scheme for Reach to Grasp Movements: On EMG-Based Interfaces Using Task Specific Motion Decoding Models," *IEEE J. Biomed. Health Inform.*, vol. 17, no. 5, pp. 915–921, Sep. 2013, doi: 10.1109/JBHI.2013.2259594.
[199] N. Rabin, M. Kahlon, S. Malayev, and A. Ratnovsky, "Classification of human hand movements based on EMG signals using nonlinear dimensionality reduction and data fusion techniques," *Expert Systems with Applications*, vol. 149, p. 113281, Jul. 2020, doi: 10.1016/j.eswa.2020.113281.
[200] Y. Gu, D. Yang, Q. Huang, W. Yang, and H. Liu, "Robust EMG pattern recognition in the presence of confounding factors: features, classifiers and adaptive learning," *Expert Systems with Applications*, vol. 96, pp. 208–217, Apr. 2018, doi: 10.1016/j.eswa.2017.11.049.
[201] A. Utley, *Motor Control, Learning and Development: Instant Notes, 2nd Edition*. Routledge, 2018.
[202] H. Akima *et al.*, "Early phase adaptations of muscle use and strength to isokinetic training," *Med Sci Sports Exerc*, vol. 31, no. 4, pp. 588–594, Apr. 1999.
[203] D. P. Ferris and B. R. Schlink, "Robotic Devices to Enhance Human Movement Performance," *Kinesiology Review*, vol. 6, no. 1, pp. 70–77, Feb. 2017, doi: 10.1123/kr.2016-0040.
[204] F. Hülsmann, J. P. Göpfert, B. Hammer, S. Kopp, and M. Botsch, "Classification of motor errors to provide real-time feedback for sports coaching in virtual reality — A case study in squats and Tai Chi pushes," *Computers & Graphics*, vol. 76, pp. 47–59, Nov. 2018, doi: 10.1016/j.cag.2018.08.003.

[205] R. Nataraj, S. Sanford, M. Liu, and N. Y. Harel, "Hand dominance in the performance and perceptions of virtual reach control," *Acta Psychol (Amst)*, vol. 223, p. 103494, Mar. 2022, doi: 10.1016/j.actpsy.2022.103494.
[206] "Cognitive and Physiological Intent for the Adaptation of Motor Prostheses | Semantic Scholar", Accessed: Apr. 20, 2022. [Online]. Available: https://www.semanticscholar.org/paper/Cognitive-and-Physiological-Intent-for-the-of-Motor-Nataraj-Sanford/a3ed4be56fa992ac538c3d15972bb1eb2b0d544d
[207] M. Liu, S. Wilder, S. Sanford, S. Saleh, N. Y. Harel, and R. Nataraj, "Training with Agency-Inspired Feedback from an Instrumented Glove to Improve Functional Grasp Performance," *Sensors (Basel)*, vol. 21, no. 4, p. 1173, Feb. 2021, doi: 10.3390/s21041173.

10. VITA

Author: Sean Patrick Sanford

Degree: Doctor of Philosophy

Defense Date: May 2nd, 2022

Date of Birth: August 5th, 1992

Place of Birth: Jacksonville, North Carolina, USA

Education:

Ph.D. Department of Biomedical Engineering Stevens Institute of Technology, Hoboken, NJ	May, 2022
M.S. Department of Biomedical Engineering Stevens Institute of Technology, Hoboken, NJ	May, 2020
B.S. Department of Biomedical Engineering Rensselaer Polytechnic Institute, Troy, NY	May, 2016

Publications:

1. **S. Sanford**, B. Collins, M. Liu, S. Dewil, R Nataraj, "Visual feedback for virtual reality-based upper-extremity rehabilitation using isometric muscle control," *Frontiers in Virtual Reality,* (submission under review)
2. **S. Sanford**, M. Liu, R. Nataraj, "Concurrent Continuous Versus Bandwidth Visual Feedback with Varying Body Representation for the Two-Legged Squat Exercise," *Journal of Sport Rehabilitation,* February 2021, doi: 10.1123/jsr.2020-0234
3. K. Walsh, **S. Sanford**, B. Collins, N. Harel, R. Nataraj, "Performance Potential of Machine Learning Classification for Myoelectric Control with Reduced Muscle Inputs," *Biomedical Signal Processing and Control,* February 2021, doi: 10.1016/j.bspc.2021.102487
4. M. Liu, S. Wilder, **S. Sanford**, N. Harel, R. Nataraj, "Training with Agency-Inspired Feedback from an Instrumented Glove to Improve Functional Grasp Performance," *Sensors,* February 2021, doi: 10.3390/s21041173
5. R. Nataraj, **S. Sanford**, "Control Modification of Grasp Force Covaries Agency and Performance on Rigid and Compliant Surfaces," *Frontiers in Bioengineering and Biotechnology,* January 2021, doi: 10.3389/fbioe.2020.574006

6. **S. Sanford**, M. Liu, T. Selvaggi, R. Nataraj, "The Effects of Visual Feedback Complexity on Training the Two-Legged Squat Exercise," Conference Proceeding - *7th International Conference on Movement and Computing (MOCO)*. July 2020, doi: 10.1145/3401956.3404243
7. M. Liu, **S. Sanford**, S. Wilder, R. Nataraj, "Inducing Cognition of Secure Grasp and Agency to Accelerate Motor Rehabilitation from an Instrumented Glove," Conference Proceeding - *7th International Conference on Movement and Computing (MOCO)*. July 2020, doi: 10.1145/3401956.3404245
8. **S. Sanford**, M. Liu, T. Selvaggi, R. Nataraj, "Effects of Visual Feedback Complexity on the Performance of a Movement Task for Rehabilitaiton," *Journal of Motor Behavior*, June 2020, doi: 10.1080/00222895.2020.1770670
9. R. Nataraj, **S. Sanford**, M. Liu, K. Walsh, S. Wilder, A. Santo, D. Hollinger, "Cognitive and Physiological Intent for the Adaptation of Motor Prostheses," In book: Advances in Motor Neuroprostheses, pp. 123-153, April 2020, doi: 10.1007/978-3-030-38740-2_8
10. R. Nataraj, **S. Sanford**, A. Shah, M. Liu, "Agency and Performance of Reach-to-Grasp with Modified Control of a Virtual Hand: Implications for Rehabilitation," *Frontiers in Human Neuroscience*, vol. 14, no. 126, April 2020, doi: 10.3389/fnhum.2020.00126
11. V. S. Balaraj, P. C. Zeng, **S. P. Sanford**, S. A. McBride, A. Raghunandan, J. M. Lopez, A. H. Hirsa, "Surface shear viscosity as a macroscopic probe of amyloid fibril formation at a fluid interface," *Soft Matter*, vol. 13, no. 9, pp. 1780–1787, 2017, doi: 10.1039/C6SM01831A
12. S. A. McBride, **S. P. Sanford**, J. M. Lopez, A. H. Hirsa, "Shear-induced amyloid fibrillization: the role of inertia," *Soft Matter*, vol. 12, no. 14, pp. 3461–3467, 2016, doi: 10.1039/C5SM02916C
13. S. A. McBride, C. F. Tilger, **S. P. Sanford**, P. M. Tessier, A. H. Hirsa, "Comparison of Human and Bovine Insulin Amyloidogenesis under Uniform Shear," *J. Phys. Chem. B*, vol. 119, no. 33, pp. 10426–10433, Aug. 2015, doi: 10.1021/acs.jpcb.5b04488