# Conscious Perception of Error Augmentation for Stroke Rehabilitation

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August 2022

A thesis submitted to McGill University in partial fulfillment of the requirements of the degree of Master of Science in Rehabilitation

To brave women in Iran who are fighting for freedom

Mahsa, Nika, Sarina, …

# Table of Contents

# List of Figures

# List of Tables

# Abstract

Previous work has demonstrated that the provision of feedback during arm movements enhances upper limb (UL) motor recovery after stroke. Error augmentation (EA) is an effective form of feedback that involves magnifying the errors in the patient's movements, with respect to the desired task. EA can improve the extent of motor learning through the use of virtual reality platforms. Additionally, implicit motor learning, where participants adapt their motor performance to movement errors without conscious awareness, seems to be more resilient and effective over time than explicit motor learning. This study aimed at 1. Assessing the feasibility of performing an EA task in people who have had a stroke and in healthy participants, 2. Measuring the limit of EA that can be used to provide implicit feedback, without the participants' conscious awareness, and 3. Estimating the extent of the error to which kinematic variables stay stable.

In this study, eight healthy and nine poststroke participants in chronic stroke stage were recruited to perform reaching movements to one of three directions. Participants were aged between 42 and 75 (yrs.) and performed the task with their dominant (healthy group) or affected arm (poststroke group). Participants' forearms were supported by an arm support device that allowed them to move their arm and forearm in the horizontal plane. A screen displayed the avatar of the participant's arm in real-time. During each trial, an error of 7.5° to 30° could be randomly added to the avatar's elbow angle by manipulating the visual feedback. At the end of each trial, participants were asked whether they were aware of the presence of EA. Finally, psychometric curves were used to measure 50% of the detection threshold in both groups under different directions in order to measure the implicitly applicable domain of EA. Kinematic variables were also calculated and compared between groups and in different EA conditions.

Results showed that all participants with different sociodemographic characteristics were able to complete 180 trials in less than 2 hours and could detect the presence of a 16.6° error in more than 50% of trials. Additionally, there were no between-group differences in either EA detection threshold or in any of the kinematic variables (speed, straightness, smoothness of the hand reaching movement, as well as elbow ROM). Furthermore, neither the kinematic variables nor the EA detection threshold was affected by movement direction. EA detection threshold for both groups was at 16.6° EA, and changes in the kinematic variables were observed as EA exceeded that threshold.

Based on our findings, EA can successfully be added to the reaching movement and can be detected by all participants at a specific threshold. In another word, using EA blew the detection threshold can prevent EA detection. It might provide a new idea for implicitly improving poststroke reaching performance using virtual reality platforms. These results are useful for researchers and practitioners using EA in clinical domains.

## Résumé

Des travaux antérieurs ont démontré qu'un retour d'information pendant les mouvements du bras améliore la récupération motrice des membres supérieurs (MS) après un accident vasculaire cérébral (AVC). L'augmentation de l'erreur (AE) est une forme efficace de feedback qui consiste à amplifier les erreurs dans les mouvements du patient, par rapport à une tâche souhaitée. L'AE peut améliorer l'étendue de l'apprentissage moteur grâce à l'utilisation de plateformes de réalité virtuelle. De plus, l'apprentissage moteur implicite, où les participants adaptent leur performance motrice aux erreurs de mouvement sans en avoir conscience, semble être plus résilient et efficace dans le temps que l'apprentissage moteur explicite. Cette étude visait à : 1. Évaluer la faisabilité de l'exécution d'une tâche d'AE chez des personnes ayant subi un AVC et chez des participants en bonne santé, 2. Mesurer la limite de l'AE qui peut être utilisée pour fournir un feedback implicite, sans que les participants en aient conscience, et 3. Estimer l'ampleur de l'erreur à laquelle les variables cinématiques restent stables.

Dans cette étude, huit participants en bonne santé et neuf participants au stade d'AVC chronique ont été recrutés pour effectuer des mouvements d'extension dans l'une des trois directions. Les participants étaient âgés de 42 à 75 ans et ont effectué la tâche avec leur bras dominant (groupe sain) ou affecté (groupe post-AVC). Les avant-bras des participants étaient soutenus par un dispositif de soutien mobile, qui leur permettait de déplacer leur bras et leur avant-bras dans le plan horizontal. Un écran affichait l'avatar du bras du participant en temps réel. Au cours de chaque essai, une erreur de 7,5° à 30° pouvait être ajoutée aléatoirement à l'angle du coude de l'avatar en manipulant le retour visuel. À la fin de chaque essai, il était demandé aux participants s'ils étaient conscients de la présence de l'AE. Enfin, des courbes psychométriques ont été utilisées pour mesurer 50% du seuil de détection dans les deux groupes sous différentes directions afin de

mesurer le domaine implicitement applicable de l'AE. Les variables cinématiques ont également été calculées et comparées entre les groupes et dans différentes conditions d'AE.

Les résultats ont montré que tous les participants, avec des caractéristiques sociodémographiques différentes, étaient capables de réaliser 180 essais en moins de 2 heures et pouvaient détecter la présence d'une erreur de 16,6° dans plus de 50% des essais. En outre, aucune différence entre les groupes n'a été constatée en ce qui concerne le seuil de détection de l'AE ou l'une des variables cinématiques (vitesse, rectitude, douceur du mouvement d'extension de la main, et ROM du coude). En outre, ni les variables cinématiques ni le seuil de détection de l'AE n'ont été affectés par la direction du mouvement. Le seuil de détection de l'AE pour les deux groupes était de 16,6° AE, et des changements dans les variables cinématiques ont été observés lorsque l'AE dépassait ce seuil.

D'après nos résultats, l'AE peut être ajoutée avec succès au mouvement d'atteinte et peut être détectée par tous les participants à un seuil spécifique. En d'autres termes, l'utilisation de l'AE en dessous du seuil de détection peut prévenir sa détection. Cela pourrait fournir une nouvel outil pour améliorer implicitement la performance d'atteinte post-AVC en utilisant des plateformes de réalité virtuelle. Ces résultats sont utiles pour les chercheurs et les praticiens qui utilisent l'AE dans des domaines cliniques.

## Acknowledgements

This work would not have been possible without the support and contributions of a number of individuals. First, I would like to express my deepest gratitude toward my supervisors, Dr. Philippe Archambault. Not only for his support, advice, and guidance regarding my master's project but also his commitment to supporting students in all aspects of their lives. Thanks a lot for truly making this an enriching learning experience. I would like to thank Dr. Mindy Levin for her valuable comments, guidances and providing me with some resources and lab facilities throughout the duration of this project. Also, l would like to acknowledge the committee members of my thesis, Dr. Joyce Fung, Dr.  Marie-Helene Milot, Dr. Nancy Mayo for their guidance and support throughout this process.

I would like to thank Christian Beaudoin for the invaluable expertise and for helping me to learn, develop, and understand the technological aspect of my project. Also, thank you Shaheen Ghayourmanesh for the development of EA program. I want to thank all the support staff, faculty members and directors, at the School of Physical and Occupational Therapy and many people at the JRH Research Centre for their patience and support.

I would not have been able to complete this effort without the support of my family and friends near and far. Special thanks to my parents for their kindness, patience, and endless support, and to my brother, Fazel for his unconditional psychological and emotional support throughout this part of my life. Most of all I thank my supportive husband and best friend, Saeed. Without his love and support, I would be lost.


## Contributions of Authors

The experiment was conducted and developed by Farnaz jahromi under the co-supervision of Dr. Philippe Archambault and Dr. Mindy Levin. The virtual environment used for the experiment was developed by Christian Beaudoin, and Dr. Philippe Archambault performed the statistical analysis of the data. This thesis was written by Farnaz Jahromi and subsequently reviewed by Mindy Levin and Philippe Archambault. The manuscript of this thesis was also reviewed by Caroline Rajda.

# Abbreviations

AROM: Active Range of Motion

CIMT: Constraint-induced Movement Therapy

EA: Error Augmentation

EMG: Electromyographic

ER: Error Reduction

KP: knowledge of Performance

KR: knowledge of Results

PNF: Proprioceptive Neuromuscular Facilitation

ROM: Range of Motion

UL: Upper Limb

VR: Virtual Reality

# CHAPTER 1: Introduction and Background

## 1.1 Stroke

Stroke, also called cerebrovascular accident, is a sudden loss of brain function caused by the interruption of blood flow and oxygen to the brain (ischemic stroke) or the rupture of blood vessels (hemorrhagic stroke). As a result, brain cells affected by stroke die (Public Health Agency of Canada, 2021). It is the leading cause of neurological disability in adults and the second leading cause of death worldwide (Feigin et al., 2019). According to the Public Health Agency of Canada, about 741,800 Canadians 20 years of age and older are living with a stroke. Of the number of stroke survivors, more than 400,000 Canadians are currently living with stroke-related disabilities, and this figure is expected to double in the next 20 years (Heart and Stroke Foundation, 2017). Despite many medical advances in management and prevention, only 10% of poststroke subjects completely recover. Almost 25% of them have a minor impairment, 40% have moderate to severe impairment, and 10% are left with severe disability, including hemiparesis, a condition characterized by motor weakness of one side of the body and requires long-term care (Heart and Stroke Foundation, 2017). It has been reported that the direct and indirect cost of stroke to the Canadian health care system is estimated to be approximately $3.6 billion per year (Heart and Stroke Foundation, 2017).

### 1.1.1 Upper Limb Impairments after stroke

Upper limb paresis is one of the most common impairments following a stroke, with loss of arm function occurring in up to 80% of stroke survivors (Lindsay et al., 2019). Upper limb motor complications can significantly impact mobility and health (Langhorne et al., 2009). Impairment of upper limb function contributes to functional disability in daily activities, including feeding, dressing, bathing, grooming, and writing, which can place a significant burden on stroke survivors and their caregivers, physically, socially and psychologically (Williams, 2001). Despite rehabilitation efforts, the upper limb does not recover as well as the lower limbs (Nakayama et al., 1994). In particular, individuals with stroke have difficulty with elbow extension movements. Elbow extension is a necessary component of many tasks of daily living (Oosterwijk et al., 2018). Lack of elbow extension is one of the main features of movement in people who have had a stroke, specifically in individuals with severe to moderate clinical impairments (Cirstea & Levin, 2000). Additionally, lack of elbow extension may considerably affect quality of life as it is an important predictor for motor recovery of UL in people who have had a stroke (Massie et al., 2011). Reaching is a fundamental element of many activities of daily living that requires elbow extension as well as shoulder flexion and wrist pronation or supination. The ability to reach and interact with the surrounding environment is an important component in a wide variety of everyday tasks. Therefore, even a minimal amount of recovery of the hemiparetic arm may lead to large changes in function.

### 1.1.2 Upper Limb Rehabilitation

Currently, a variety of techniques are employed for the rehabilitation of post-stroke individuals with upper limb movement impairments (Hatem et al., 2016; Pollock et al., 2014). There is some promise in these interventions for the reduction of motor impairment after stroke, but selection of the most appropriate intervention will differ between patients and depend on the severity of the impairment (Barreca et al., 2003). UL rehabilitation techniques include, mirror therapy and constraint-induced movement therapy (CIMT) which are specific interventions with promising early evidence for stroke recovery (Dohle et al., 2009; Yoon et al., 2014), conventional therapy, functional electrical stimulation, mental practice, robotics, and electromyographic (EMG) biofeedback. Most upper limb recovery approaches emphasize the need for repetitive, intensive and task-specific training (Perry, 2004). CIMT is one of the most investigated interventions to reduce functional problems in the affected UL. It involves intensive rehabilitation therapy of the affected UL while constraining the use of the unaffected side. Patients with minimal sensory and cognitive deficits and some degree of active range of wrist and arm motion may benefit from this type of therapy (Kwakkel et al., 2015). In mirror therapy, the patient moves his unaffected limb while watching the movement in the mirror. Mirror therapy uses visual feedback to enhance upper-limb function following stroke, improve activities of daily living and reduce pain (Gurbuz et al., 2016). The use of functional electrical stimulation to improve UL function after stroke has been supported by high-quality evidence from a recent systematic review and meta-analysis (Monte-Silva et al., 2019). Additionally, neurodevelopmental techniques and mental practice appear to be no more effective than other conventional therapy approaches (Gelber et al., 1995; Paci, 2003; Park et al., 2018). Evidence also suggests that EMG-biofeedback can result in modest improvements in arm function. According to the result of one systematic review, there was a significant improvement in UL function using a combination of EMG-biofeedback treatment and physiotherapy compared to physiotherapy alone (Langhorne et al., 2009).

### 1.1.3 Conventional Therapy

Conventional therapies for patients recovering from stroke designed to treat physical disabilities and sensory impairments include approaches such as Bobath or neurodevelopmental techniques, and proprioceptive neuromuscular facilitation (PNF). Conventional care for stroke management is delivered across a variety of healthcare settings and can be highly variable in duration, intensity, and type. In Bobath approach, the focus is on normalizing the muscle tone while facilitating normal movement patterns. In the PNF approach, muscles and nerves are manually stimulated to promote more functionally relevant movements. Therefore, in neurofacilitative approaches, therapist has an active role in applying movement and stimulating nerves and patient remains relatively passive in the treatment process (Pollock et al., 2014).

### 1.1.4 Robotic Training

Among different rehabilitation interventions, robotic training provides the opportunity to create individualized and enriched practice environments for upper limb improvement in chronic stroke survivors (Burgar et al., 2000; Krebs et al., 1999). Robotic-assisted arm devices can provide passive assistance (weight bearing), active assistance or resistance to movements during training for an isolated joint or multiple segments. Robotic therapy is also expected to provide stroke survivors with high-intensity, repetitive, and goal-directed trials that leads to normalized muscle tone, as well as improved strength and range of upper limb motion (Fasoli et al., 2003; Krebs et al., 2003; Posteraro et al., 2009). The importance of repetitive training is related to the exercising time that has been shown to be a critical factor for functional motor recovery (Mehrholz et al., 2012).

### 1.1.5 Benefits and Importance of Robotic Training in Stroke Rehabilitation

Effort has also gone into studying the benefits of training with robotic-assisted devices. It was shown that robotic-assisted training not only contributes to a decrease in upper limb disability by reducing motor impairment and improving arm muscle strength, but it is also a well-accepted treatment for people after stroke, as it can provide an opportunity for independent exercise and increase motivation due to the feedback provided by the device (Mehrholz et al., 2018; Prange et al., 2006).

The use of such technologies is rapidly increasing in stroke rehabilitation. Incorporation of such technologies as complementary therapies may increase motor learning and outcomes in stroke survivors and can lead to higher patient's satisfaction (Gilmore & Spaulding, 2007). However, based on current research, there is still no evidence for the added beneficial effects of high-intensity, technology-based upper-limb therapies over intensive usual care in stroke participants. A systematic review has indicated that when the duration and intensity of robotic-therapy are matched with usual care, no significant between-group differences were found in motor recovery, daily living activities (ADL), strength, and motor control (Norouzi-Gheidari et al., 2012). Other systematic reviews have shown that using robotic-assisted therapy with usual care is more effective than robotic therapy alone, in terms of ADL, motor control and muscle strength (Bertani et al., 2017). While the advantages of robotic training over usual care in terms of functional benefit are not clear, studies suggest that robotic-therapy may be an innovative approach to address the needs of repetitive, high accurate and task-oriented rehabilitation regimens (Duret et al., 2015; Levin et al., 2009).

### 1.1.6 Virtual reality for upper limb rehabilitation

Robotic devices used for therapy can be coupled with a virtual environment, which is commonly called a virtual reality environment. This combination may offer opportunities for new forms of motor skills retraining that could increase the potential for motor recovery after stroke (Laver et al., 2010; Mekbib et al., 2020).

One of the biggest advantages of virtual environments for UL rehabilitation is that they can enable patients to experience an environment that closely resembles the real world and perform activities that are similar to their real-world counterparts, which lets people who have had a stroke immediately begin to adapt their activities with necessary functional performances (Weiss et al., 2006). The use of virtual reality interventions for rehabilitation may enable simulated practice of functional tasks at a higher dosage than traditional therapies, as it can be more engaging for poststroke people to practice through 3D virtual environments and video games with motivating tasks than the traditional repetitive practice (Adamovich et al., 2009). Also, with the use of virtual reality, stroke individuals can also safely perform some activities that may be impractical or could not be performed in a clinical setting, such as shopping or cycling.

Several studies have demonstrated greater improvement of motor function in patients treated with virtual environment than conventional rehabilitation (Kiper et al., 2018; Lucca, 2009; Pollock et al., 2014). The findings from a Cochrane review on the efficacy of virtual reality on upper limb function and activity showed that interactive video gaming has a small positive effect on improving upper limb impairments in comparison with conventional rehabilitation therapy (Laver et al., 2017). Moreover, when virtual reality was used in addition to usual care there was a significant improvement in function of the arm (Kiper et al., 2018; Laver et al., 2017).

Despite all rehabilitation approaches including robotic therapy for UL recovery after stroke, the result has been disappointing in terms of functional improvement and impairments persist in 55% to 70% of the cases, despite intensive and prolonged rehabilitation (Chen & Winstein, 2009).

## 1.2 Motor learning

Motor learning has been defined as: “the acquisition of motor skills, the performance enhancement of learned or highly experienced motor skills, or the reacquisition of skills that are difficult to perform or cannot be performed because of injury, disease and the like (Magill, 2011).” There are two different motor learning mechanisms: explicit and implicit motor learning; meaning that learning can occur both intentionally and unintentionally.

Explicit motor learning can be defined as learning by verbal knowledge of movement or performance (Johnson et al., 2013). It is a more conscious form of learning that depends on working memory involvement. Indeed, the learner is aware of the rules about movement performance and the process of learning. To encourage explicit motor learning in rehabilitation, therapists may instruct patients to do bridging exercises while thinking about their performance, for example: “While lying on your back in bed, bend your knees up, press the feet into the mattress and lift your bottom off the bed”. Augmented feedback regarding the correct movement production is one way to transmit this knowledge and encourage learning.

In contrast to explicit learning, implicit motor learning refers to the acquisition of skills by exploration or under trial-and-error conditions, with little to no working memory involvement and with no or little conscious awareness (Kleynen et al., 2014). It is suggested that implicit motor learning takes place more automatically and in a less conscious manner than explicit motor learning (Kal, Prosée, et al., 2018).To learn implicitly basically means the learner is aware of the process of learning but is not informed of the facts and rules of the motor skill to be acquired. For example, in learning to ride a bicycle, the child is not necessarily aware of the rules and processes for cycling while trying to learn it but is able to learn and succeed by trial and error.

The ability to unconsciously adapt the nervous system to the environment is one of the most important aspects of recovery in terms of functioning for people who have had a stroke, so implicit learning might have a significant effect on everyday life for these individuals. Orrell and colleagues (2006) investigated implicit motor learning on a whole-body task after stroke. In this study, participants were instructed to practice a balance board task. In order to induce implicit motor learning, an errorless learning procedure was implemented, and task difficulty was gradually increased by reducing the balance board’s rotational resistance throughout practice. Practice resulted in a significant improvement in balance performance, which lasted a week later during a delayed retention test. A systematic review of 20 studies investigating implicit motor learning after stroke in different clinical settings indicated that implicit learning does not result in superior learning compared to explicit learning (Kal et al., 2016a). However, motor skills that are implicitly acquired may be better suited when performing a variety of cognitive tasks simultaneously (Kal et al., 2016a).

Current clinical practice shows therapists tend to rely on explicit motor learning or switch frequently between implicit and explicit learning approaches (Kal, van den Brink, et al., 2018; Kleynen et al., 2017). However, the type of learning that produces a change in performance is believed to be related to the complexity of the task (Halsband & Lange, 2006). It seems that the learning of complex tasks mostly occurs through the process of implicit learning. In addition, for people after stroke with cognitive deficits, it can be difficult to process large amounts of verbal explicit information; therefore, implicit motor learning could be useful by minimizing the involvement of cognitive resources, especially working memory. Studies also showed that performance of an implicitly learned task might aid multitask performance, so it can be more stable under dual-task conditions (use of two tasks performed simultaneously) and more durable in healthy population compared with its explicit counterparts (Kleynen et al., 2017; Orrell et al., 2006). In summary, while evidence about the relative benefits of explicit versus implicit learning is still lacking, implicit learning seems to be beneficial for poststroke individuals (Kal et al., 2016a; Kleynen et al., 2017; Lee et al., 1994).

### 1.2.1 Feedback

Feedback is a general term that refers to the sensory information people receive about their performance either during or following a motor task. Feedback is very important in the motor learning process. Some form of feedback is essential for learning to take place (Yamamoto & Ohashi, 2014).

When people perform a motor skill, they have access to two types of feedback: intrinsic and extrinsic. Intrinsic feedback refers to information that comes from producing movements and that is captured through the human senses. Information may come from outside of the body (exteroception), or within the body (proprioception: refers to the sense of position). Extrinsic feedback is provided by external sources (Gilmore & Spaulding, 2001). Examples include when a poststroke individual hears verbal feedback about his or her performance from a therapist, or when movement is tracked and is provided as feedback to the user in the form of a hand trajectory on a computer screen. Extrinsic feedback can provide information about the success or failure of a task (knowledge of results, KR) or about the quality of performance (knowledge of performance, KP). For example, when throwing a ball, feedback about task success or failure is KR, whereas information about the quality of the movement required to perform the task is KP.

### 1.2.2 Rehabilitation system based on visual feedback

Cirstea and colleagues (2006) analyzed the performance of a reaching task in physical and virtual environments, in both presence and absence of visual and haptic feedback. In this study, chronic stroke participants with mild-to-moderate and moderate-to-severe arm impairment were recruited. In addition to visual feedback in a virtual environment, a robot arm provided haptic feedback for the users by stopping the movement when they reached the virtual button. The results showed that accuracy and efficiency of the reaching movement were both increased when movement was presented with feedback than without feedback. The authors also reported that the performance was similar in both the physical and virtual environments. The effects of feedback on movement performance in stroke survivors indicated gradual improvements in UL performance compared to no-feedback treatment.

Indeed, adding extrinsic visual feedback to the environment may provide an encouraging condition for people with chronic neurological injuries to interact with the robotic devices (Boian et al., 2002; Popović et al., 2014). Therefore, robotic therapy can be paired with visual feedback delivered on a computer screen to enable task-specific training in order to improve upper extremity control in people who have had a stroke (Brewer et al., 2006). Linking visual feedback with robotic therapy represents an appropriate tool to enhance patient’s motor output during the training session.

## 1.3 Robotic training paradigms

Interactive virtual reality and robots offer methods to further facilitate motor learning. Besides increasing intensity and number of trials, robotic devices can deliver visual feedback or haptic forces to assist in training. Two main robotic training paradigms have been developed so far are error reduction (ER) and error augmentation (EA).

In error reduction, the robotic device will aid in minimizing movement errors relative to the prescribed behaviour. ER can improve motor learning by assisting participants to learn movements with little attention to the desired trajectory through improvement of proprioception awareness of the body (Patton & Mussa-Ivaldi, 2004). However, EA is an alternative and effective form of feedback that magnifies the errors in the stroke survivor’s movements from the desired task. EA can boost explicit motor learning by providing error feedback and consequently increasing a person’s awareness of movement errors or implicit motor learning by improving movement control in response to changes. In 2000, (Thoroughman & Shadmehr, 2000) revealed by EA that the motor system detects kinematic errors in one trial and proportionally corrects them in the subsequent trial in order to gradually improve performance of the new task.

### 1.3.1 Error Reduction Strategies

As mentioned previously, in an ER protocol, the practice conditions are set-up so that the likelihood of errors is reduced during learning. Indeed, the robot assists people who have had a stroke in performing a desired movement in order to simulate the desired “feel” of the movement. Assistance can be provided in a variety of ways, including, assisting with arm support (Kahn et al., 2006), limiting movement variability through viscoelastic forces (Patton et al., 2006), etc.
Robotic therapy devices can be paired with virtual reality simulations of activities of daily living, such as walking (Ekkelenkamp et al., 2007) or reaching (Kahn et al., 2006; Wang et al., 2011). In this method, the virtual reality platform can create different environments that allow practice of correction and control over a wide range of real-life scenarios. There is some evidence that suggests haptic stimulation might be as effective as conventional therapy in the initial stage of motor recovery (Liu et al., 2018). Krebs and colleagues (2006) demonstrated that training with robot assistance did not show any obvious advantage overactive reaching training in people who have had a stroke. Kahn and colleagues (2006) found in a pilot study that training with a haptic stimulator significantly increased range of arm movement, velocity of motion, and reaching movement ability.

### 1.3.2 Error Augmentation Strategies

The role of error in motor adaptation has been emphasized in many theoretical methods. In EA, the robot amplifies movement errors via haptic or visual feedback. It has been shown that presenting magnified visual feedback of the original error during training can improve the extent of motor learning (Patton et al., 2006). Some authors also reported that error leads to learning, so healthy individuals can learn more quickly if the error is larger (Yejun, Patton, et al., 2005). In addition, EA studies have shown that by drawing more attention to errors, participants are more likely to pay attention to them and make appropriate corrections. Indeed, EA makes errors more noticeable to the senses and hence may trigger adaptative responses.

Sharp and colleagues (2011) performed a reaching task in a robotic optical operation machine with healthy participants. The results showed that subjects who received EA were able to reach their desired target more quickly and accurately than their baseline performance in comparison with the control group. According to similar studies, it seems that error-enhancing training may be a potential way to promote motor recovery for brain-injured individuals (Patton et al., 2006).

### 1.3.3 EA Methods

There are various ways in which EA can be implemented. Robotic devices can visually or haptically amplify the error. Indeed, one of the commonly used haptic techniques to artificially increase performance error is to create a force-field that disturbs the limb motion during the movement (Patton et al., 2013).

Errors can also be visually augmented through manipulation of visual feedback. One method for visually augmenting the error is by adding an additional error to the visual feedback of the hand and arm movement and displaying the new hand path on the screen. Another method could be through prism glasses that deviate vision by some degrees and shift the visual scene to the right or left. It has been shown that in visual EA training, small reaching errors became more noticeable to the participants and encouraged them to make faster responses to correct their movement (Huang et al., 2010). Indeed, it has been proposed that amplified errors can increase the signal-to-noise ratio of the error, which may improve cognitive processing and self-evaluation (Yejun, Bajaj, et al., 2005). In a study conducted by (Patton et al., 2013), participants were asked to perform reaching movements under visuomotor rotation while holding the handle of a robotic system. The groups that had visual EA had better reaching performance than those who trained without augmented errors. Despite the effectiveness of visual feedback in the EA strategy alone, recent experiments demonstrate that providing physical and visual feedback in one trial can promote the adaptation process faster and can increase the subject's satisfaction with the task, leading to high engagement during the training (Shirzad & Loos, 2012). In this study, healthy subjects tended to be more satisfied during visual-haptic EA methods, in comparison with only the visual EA method.

### 1.3.4 EA Mechanisms

Early results suggest that EA can facilitate neurorehabilitation strategies in post-stroke individuals. Error signals may stimulate both sensory and motor function pathways with the aim of improving upper limb movements in both healthy and stroke subjects (Abdollahi et al., 2011). However, the neurological mechanism behind this phenomenon is still unclear.

One possible mechanism is the presence of a feedback/error-learning neural network, which could facilitate the learning process more quickly when the error is larger. Such an error-driven learning strategy might be related to neuromuscular adaptation during skill acquisition (Kawato, 1990). Another possibility is that increasing errors may heighten motivation and attention to reduce errors until participants experience only small or no errors. In addition, errors might speed up the process of updating motor commands by being exposed to motor errors and trying to reduce errors in the learning period (Shadmehr et al., 2010).

Recent work by Milot and colleagues (2018) revealed the activation of the error detection system and motor planning network during EA training. They used fMRI (Functional magnetic resonance imaging) to detect brain network activation in both EA and error reduction conditions in healthy subjects playing a computer-based pinball-like game. Results showed that the error detection system was strongly triggered during the whole training time period with EA more than with ER

### 1.3.5 Effectiveness of EA for stroke rehabilitation

Several clinical studies have endorsed EA for rehabilitation of upper limb movement and specifically on arm reaching abilities among individuals with poststroke hemiparesis (Patton et al., 2006; Yejun, Patton, et al., 2005)

In the study of (Abdollahi et al., 2014), robotic therapy with EA, compared with an equivalent amount of reaching practice without EA, resulted in improvements in arm function, as measured by the Fugl-Meyer Assessment and in the Wolf Function Motor Test. There was, however, no significant improvement in range of elbow motion in either group. Similarly, in a study conducted by (Patton et al., 2006), eighteen people who have had a stroke experienced training forces that either enhanced or reduced their errors in hand movement (haptic EA). Following this intervention, the EA group showed greater improvement in terms of Fugl-Meyer Assessment in comparison with the control group. Therefore, EA can be an effective method to enhance motor recovery. In 2013, Tropea and colleagues conducted a crossover experimental paradigm with eighteen post-stroke individuals in a six-week therapy program comparing ER and EA. They revealed that although ER led to a non-significant UL improvement in post-stroke participants, EA led to a very large effect size improvement in both the Modified Ashworth Scale and in the Motor Status Score (Tropea et al., 2013).

Brewer and colleagues (2005) used visual feedback distortion to encourage stroke survivors with motor deficits to push harder than their original capability (Brewer et al., 2005). Rossetti and colleagues showed a therapeutic benefit of using prisms to shift the visual field in stroke survivors with hemi-spatial neglect (Rossetti et al., 1998). Also, a recent systematic review concluded that error-amplification techniques benefit subjects more in motor learning than error-reduction methods. It has indicated that EA can not only promote motor learning processes greater and faster than the interventions involving ER paradigms, it also can be more effective than conventional repetitive practice in UL recovery (Liu et al., 2018). However, most of the considered studies have either short training periods or small sample sizes.

### 1.3.6 Error Amplification and skill level

It is worth considering that the effectiveness of EA is closely linked to the severity or nature of the motor deficit. In one comparison study, Milot and colleagues (2010) compared learning effects of ER and EA in a timing task. In their experiment, participants had to press a button with the use of wrist motion to activate a flipper in a computerized pinball-like game. Additionally, errors were reduced or increased through the use of a robotic device that alters the velocity of the wrist movement. The goal was to press the button to hit the target at a precise time to achieve an accurate trajectory. In the haptic guidance condition, when the participant hit the button late, the error was corrected by speeding up the motion, and by slowing down the motion when they hit the button early. However, in EA, early actions were sped-up and late actions were slowed down. The result of this study showed that EA-based training led to greater learning than ER on a timing-based tapping task for skilled participants, and haptic guidance was beneficial for unskilled participants (Milot et al., 2010). Thus, errors should be augmented according to the individual's initial skill level. Similarly, in 2017, (Marchal-Crespo et al., 2017) conducted an experiment in healthy subjects to investigate the effect of EA on complex tasks. Results showed that the training strategy that enhanced learning depended on the subjects' initial skill level. Although EA had a particular effect on more skilled individuals, motor training without error was suitable to increase motor learning in less-skilled participants. Even though these research experiments worked on healthy participants, it seems that for each person, there is a certain level of EA that can be optimal for learning and the added challenge of an EA paradigm is only beneficial for people with appropriate skill levels.

### 1.3.7 EA for elbow extension movements in stroke

As explained, visual feedback can facilitate movement retraining. Visual feedback activates the neural network that links motor and cognitive processes (Hanakawa., 2011), therefore it can encourage individuals to increase the active range of elbow motion (range of elbow motion that can be performed by people with stroke independently) during the designed task. Amplifying error with visual feedback makes the elbow seem as if it moves less than in reality, hence participants attempt to correct the error by moving and extending the elbow more than their usual extension. In other words, subjects are encouraged to work beyond the limit of the designed task and expand the range of elbow extension movement more than at the beginning of practice. The most recent experiments demonstrate that the combination of high intensity and repetitive practice with EA feedback to improve UL motor function, especially directed at elbow extension movement, is a successful strategy to improve upper limb rehabilitation in post-stroke individuals (Israely et al., 2018). Although repetitive, intensive training can have a significant effect on upper limb rehabilitation, measuring the limit of EA, that can be implicitly implemented to improve range of elbow motion, can provide important information for the design of effective robotic devices and rehabilitation programs based on individual needs.

## 1.4 Rationale

Among different rehabilitation techniques involving technology, EA is considered as a promising form of training for improving UL function after stroke. According to the study conducted by

Abdollahi and colleagues (2011), a real improvement in reaching performance occurred after a 6-week EA intervention. However, the key to a successful use of EA is to integrate it with a proper practice environment. When EA is combined with an appropriate robotic device, it might provide a good condition for people who have had a stroke to practice UL movements. Considering the role of VR in improving motor function, this can be done in a VR environment to improve UL function in people who have had a stroke.

In addition, implicit motor learning seems to be more resilient over time and more effective in dual-task conditions than explicit motor learning (Hodges & Williams, 2020; A. J. Orrell et al., 2006). For example, implicit learning in individuals with impaired movement and cognitive deficits was associated with a positive impact on their rehabilitation process, as it required less attention, as compared with explicit motor learning (Hochstenbach et al., 1998; Steenbergen et al., 2010).

EA can be implemented both explicitly and implicitly, although implicitly would be preferable, for reasons expressed before. In addition, EA seems to be promoting implicit motor learning based on subjects' skill levels (Lagarde et al., 2002). Scheidt and colleagues (Scheidt et al., 2001) demonstrated that there might be a practical limit to error augmentation. They have found that when force was used to disturb motions, participants gradually updated their movement based on the latest error they had experienced. Indeed, there may be a limit to which error could be amplified, with learning still occurring implicitly. Thus, one important question is how much can error augmentation be manipulated before it becomes explicit? Using EA in high-intensity training improves UL rehabilitation. However, the limit of EA can play an important role in a better functional outcome. Knowing the maximum level of EA that can implicitly be amplified is useful in designing robotic training devices which optimize individualized impairment-based training, through EA and implicit motor learning.

To determine if EA detection is happening implicitly, it is essential to know whether the error is affecting kinematic variables of motor performance. Motor reactions rely on conscious and unconscious learning processes (Kibele, 2006). Accordingly, the perception of error would have an impact on the quality of movement. Kinematic outcomes describe the spatiotemporal characteristics of the movement and measure its quality, such as straightness, smoothness, speed, and timing. Kinematic variables are often used to measure the quality of endpoint movement, however, in this study, we mainly focused on hand path straightness, smoothness, speed, and the extent of elbow movement (ROM). The reason for analyzing hand path motion was to see the effect of EA, applied to the elbow, on hand kinematic variables. Indeed, due to kinematic redundancy in arm movements, hand path may remain the same during reaching movements, even if elbow ROM increases due to the presence of EA. It is also known that participants, with or without stroke, tend to maintain similar hand paths despite the presence of perturbations during movement (Adamovich et al., 2001; Archambault et al., 1999). Therefore, hand path motion could provide a better understanding of the effects of EA on kinematic variables after stroke than elbow extension ROM.

## 1.5 Objectives and Hypotheses of the thesis

OBJECTIVE 1: As no previous study has examined awareness of elbow range error in an EA paradigm, the first objective of this study was to determine if healthy and poststroke individuals with different sociodemographic characteristics could safely perform EA tasks at four different EA levels and three directions, and are able to finish 180 trials in less than 2 hours. The purpose of a feasibility and pilot study is to assess the potential for a successful implementation of EA in healthy and poststroke individuals for measuring the practical limit of EA and to reduce threats to the validity of future studies.

HYPOTHESIS 1:

For specific objective I, it is hypothesized that this study is feasible in terms of recruitment, intervention, and outcome measurement.

- All participants are able to perform the task of reaching different EA levels and directions.
- Participants are able to detect the presence of 30° EA in more than 50% of trials.
- Both groups of participants are able to finish 180 trials in less than 2 hours.
- Participants do not experience minor or major side effects.

OBJECTIVE 2:

The second aim is to measure the practical limits of EA, that implicitly (without the participant's conscious perception) enhances elbow extension range of motion after stroke. Indeed, knowing the maximal level of error that can be added to a movement without conscious perception may then improve UL functional recovery during the exercise.

HYPOTHESIS 2:

There will be a threshold to the level of EA, beyond which participants will be aware of the presence of EA in 50% of trials.

OBJECTIVE 3:

The third objective is to estimate the extent of error to which kinematic variables including, smoothness, straightness, and speed of hand movement would remain unchanged during the reaching task.

HYPOTHESIS 3:

Elbow range of motion will increase with the level of EA, while smoothness, straightness and speed of hand movement will remain unchanged during the reaching task.

# CHAPTER 2: Manuscript

# Conscious Perception of Error Augmentation for Stroke Rehabilitation

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This manuscript will be submitted for review in *Experimental Brain Research*

## 2.1 Abstract

**Bckground and Rationale:** Impairment of upper limb (UL) function is one of the most common deficits following stroke. Visual error augmentation (EA) is an effective form of feedback that involves magnifying the error during movement. EA is considered a promising form of training to improve UL function after stroke. Furtheremore, implicit motor learning, where participants adapt to performance errors without conscious awareness, seems to be more resilient and effective over time than explicit motor learning. However, there might be a practical limit for motor learning with EA to occur implicitly. Indeed, there may be an upper limit to which error could be amplified, at which participants become consciously aware of its presence.

**Objectives:** 1. Assess the feasibility of performing reaching tasks under different EA conditions 2. Measure the practical limits of EA, that implicitly (without conscious perception) enhance elbow extension range of motion after stroke 3. Estimate the extent to which visual EA of hand movements is naturally adaptable (without changing smoothness, straightness, and speed) to improve elbow extension.

**Methods:** Nine poststroke participants with mild to moderate UL impairment, aged 42 to 75 (yrs.), and eight age-matched healthy individuals, were recruited to practice arm reaching movements in a simple virtual reality environment. All participants performed 120 reaches with four different EA levels in 7.5° increments (i.e., 7.5, 15, 22.5, and 30°), as well as 60 no EA trials in three different directions. Then, they were asked if they felt that EA was present or not (objective 2). Kinematic variables of the hand movement including, elbow range of motion, smoothness, straightness, and speed were computed based on the collected motion capture data (objective 3). These movement quality variables were compared using repeated-measures ANOVA with two within-subjects factors (3 directions, and 5 EA levels)

**Results:** This study was feasible in terms of EA implementation and outcomes. There were also no significant differences between the two groups in EA detection threshold and in the kinematic variables. Both groups were able to detect the presence of EA with errors above 16.6°+/- 5.2. As for the kinematic variables, significant changes were observed when elbow error was above the EA detection threshold.

**Conclusion:** It is concluded that there is a limit beyond which participants become consciously aware of the presence of EA. Knowing the 50% detection threshold will be useful in designing virtual reality tasks with EA, to optimize UL functional recovery through implicit motor learning.

**Keywords:** Error augmentation, Upper limb, Stroke, Arm reaching, Rehabilitation, Motor learning

## 2.2 Introduction

Impairment of upper limb (UL) function is one of the most common deficits following stroke, with approximately 40% of people experiencing UL paresis despite intensive and prolonged rehabilitation (Nakayama et al., 1994). Reaching is a fundamental element of many activities of daily living, and in stroke survivors, poor reaching performance is strongly correlated with UL impairments (Kamper et al., 2002). Various rehabilitation strategies can be used to improve UL function after stroke (Teasell & Kalra, 2004) and most UL recovery approaches emphasize the need for repetitive, intensive and task-specific training (Perry, 2004).

Skill acquisition and retention can be facilitated through the application of motor learning principles (Schmidt & Lee, 2011). Two major types of motor learning mechanisms are explicit and implicit learning. Explicit motor learning can be defined as learning by extrinsic feedback (external sources provide feedback during or after a performance) (Johnson et al., 2013). It is a conscious form of learning, relying on working memory processes. Indeed, through feedback about motor performance, the learner becomes aware of the movement rules and the process of learning. In contrast, implicit motor learning refers to the acquisition of skills by exploration or under trial-and-error conditions, with little to no working memory involvement or awareness (Kleynen et al., 2014). Implicit motor learning is suggested to take place more automatically and in a less conscious manner, as compared to explicit learning. To learn implicitly basically means that the learner is aware of the process of learning but is not informed of the facts and rules of the motor skill. Studies show that performance of an implicitly learned task might be more stable under dual-task conditions (use of two tasks performed simultaneously) and more durable in healthy populations compared with an explicitly learned task (Kleynen et al., 2017; Orrell et al., 2006).

Error augmentation (EA), is a promising form of feedback that involves physically magnifying the errors in the participant's movement during a task (Rozario et al., 2009) or magnifying the visual representation of movement, for example on a computer screen. Either method will first cause the movement to deviate from its intended course. Haptic and visual error augmentation increases movement control, with the participant gradually learning to neutralize the error-driven disturbance to the motion. In stroke rehabilitation, (Rozario et al., 2009) the current evidence suggests that augmenting visual error may enhance acquisition of skills and motor learning process (Yejun, Bajaj, et al., 2005). In the study of Abdollahi et al. (2014) involving 26 stroke participants, robotic therapy with EA, compared with an equivalent amount of reaching practice without EA, resulted in significant improvements in UL motor ability through functional tasks (Abdollahi et al., 2014). In a study conducted by Patton et al. (2006), eighteen post-stroke patients experienced training forces that either enhanced or reduced their errors in hand movement (haptic EA). Following this intervention, the EA group showed greater improvement in terms of Fugl-Meyer

Assessment compared to the control group (Patton et al., 2006). Hence, error augmentation training may be an effective method to enhance motor recovery.

Additionally, Scheidt and colleagues (Scheidt et al., 2001) demonstrated that there might be a practical limit to error augmentation. They have found that when force is used to disturb motion, healthy participants gradually updated their movement based on the latest error they had experienced. Indeed, there may be an approximate limit to which error could be amplified before changing from implicit to explicit motor learning. For implicit motor learning practice with EA, it is essential to know whether the error is affecting kinematic variables of motor performance. Motor reactions rely on conscious and unconscious learning processes (Kibele, 2006). Consequently, quality of the movement would be affected by error perception.

Therefore, the goal of the experiment was to measure the practical limits of EA which implicitly (without the participant's conscious perception) enhances elbow extension range of motion after stroke. We hypothesized that: 1) Performing elbow EA task in different conditions is feasible for healthy individuals and people who have had a stroke. 2) Additionally, there would be a threshold to the extent of EA that participants are able to detect the presence of EA. 3) And finally, we hypothesized elbow range of motion would increase with the level of EA, while movement smoothness, straightness and speed would remain unchanged during the reaching task.

## 2.3 Method

### 2.3.1 Population and Recruitment

The target populations included two subject groups: stroke survivors with moderate UL impairments and healthy adults of a similar age range without UL disabilities. Healthy participants were recruited from recruitment posters on social media, while poststroke participants were recruited from the CISSS Laval / Jewish Rehabilitation Hospital (JRH). All participants provided informed written consent in accordance with the Center for Interdisciplinary Research in Rehabilitation (CRIR) ethics committee and were aware that they always had the option of withdrawing from the study at any time. The study took place at the Jewish Rehabilitation Hospital, Laval, Canada.

### 2.3.2 Eligibility for participation

In order to join the study, stroke survivors had to meet the following inclusion criteria: 1) had ischemic or hemorrhagic stroke; 2) were in the chronic stroke stage (at least 6 months after stroke onset); 3) were aged between 18-75 years to reduce confounding effects of age-related changes on smoothness, straightness and speed of hand movement (Yan et al., 1998); 4) were medically stable and no longer receiving treatment; 5) had at least 30° active elbow movement; 6) had mild to moderate UL motor deficits (4-6/7 on Chedoke McMaster Hand or Arm Stroke Assessment) Gowland et al. (1993); 7) were able to understand and sign the consent form. They were excluded if they had: 1) additional neurological, orthopedic or rheumatoid impairments that could have an impact on task performance, such as severe sensory impairments (Nottingham Sensory Assessment, <25, (Lincoln et al., 1998), shoulder pain, muscle atrophy, or contracture; 2) visual impairment even with the use of contact lenses and glasses that could influence participant's ability to perform the task (MVPT-3, <55/145) (Brown et al., 2003); 3) elbow flexor muscle severe spasticity (Modified Ashworth Scale total arm >3/4) (Dunning, 2011); 4) proprioceptive deficits in the elbow (Fugl-Meyer UL Proprioception scale, <6/12); 5) aphasia or major cognitive impairment which could influence the ability to perform the experiment (Mini-Cog, 0-2) (Seitz et al., 2018).

The inclusion criteria for healthy individuals: 1) were aged between 18-75 years to reduce confounding effects of age-related changes; 2) were able to understand and sign the consent form.

Healthy participants were excluded if they had: 1) Upper limb disabilities; 2) major cognitive impairment, people who had difficulty understanding the experimental tasks (Mini-Cog, 0-2); 3) visual impairment that could influence participant's ability to perform the task.

### 2.3.3 Sample Size

Sample size calculation for this experiment was based on Julious study (Julious, 2005) which recommends a minimum sample size of 12 per group for feasibility studies. However, the recruitment process was affected by the outbreak of COVID-19, and we ended up having eight healthy participants and nine stroke survivors.

### 2.3.4 Data Collection

Clinical assessments and data collection were completed in a single 120-minute session for stroke participants (one-hour clinical assessments, one-hour data collection) and one 60-minute session for healthy individuals. Data collection took place at a research laboratory located at the Jewish Rehabilitation Hospital in Laval, from August 2021 to March 2022.

After the clinical assessments, all participants performed repetitive trials of a reaching task in a virtual reality environment. Different levels of error and conditions were randomly added to each trial, and participants were asked if they felt that EA was present or not after completing each task. This task is described in more detail in section 5.2.4.

### 2.3.5 Clinical Assessment

Clinical examinations were performed by researchers and used to verify the participant's eligibility for the study. Clinical assessments consisted of measuring range of elbow motion (ROM) by manual goniometer as well as clinical measurements, specifically: Chedoke-McMaster Stroke Assessment (Gowland et al., 1993), Motor-Free Visual Perception Test (MVPT) (Brown et al., 2003), Nottingham Sensory Assessment (Lincoln et al., 1998), Modified Ashworth Scale (Dunning, 2011), and Mini-Cog test (Seitz et al., 2018).

The Chedoke-McMaster stroke assessment evaluates the functional ability of the hemiparetic arm. This test consists of 7 tasks which are scored on a 7-point scale ( 1 to 7, most impairment through to no impairment, respectively) (Barreca et al., 2004). The MVPT was used to assess visual perception independent of motor ability. It consists of 65 items, each with 4 multiple response options. The visual procedural speed is also calculated by averaging the time spent on each question. This test has excellent test-test reliability (r = 0.92) (Brown et al., 2003). The Nottingham Sensory Assessment assesses tactile sensation, movement position, direction, and joint position. Items are scored on a 3-point scale for each join (from 0 = no proprioception and sensation to 2 = normal proprioception and sensation) (Lincoln et al., 1998). The Modified Ashworth Scale is used to measure muscle tone. This test is scored on a 6-point scale (from 0 = no increase in muscle tone to 4 = limb rigid in flexion and extension, including 1+ = slight increase in muscle tone). This test yielded reliable measurements in poststroke population (Gregson et al., 1999). Finally, the Mini-Cog test assesses cognitive and memory impairments, language comprehension, and visual-motor skills. The Mini-Cog has a sensitivity ranging from 76-99%, and specificity ranging from 89-93% with a 95% confidence interval (Borson et al., 2000). A score of 0-2 on this test indicates positive cognitive impairment and a score of 3-5 indicates negative cognitive impairment.

### 2.3.6 Experimental setup

Participants sat comfortably in an armless chair in front of a projection screen with their feet resting flat on the floor (Figure 1). Trunk flexion and rotation movements were restricted by wrapping a harness around the chair, the non-tested arm rested comfortably on the lap, and the tested forearm was connected to a mobile arm support device by a Velcro strap. This device supported the arm against gravity while allowing participants to perform planar reaching movements of the arm, using their elbow and shoulder (Figures 2 and 3).

**Figure 1. Illustration of physical set-up of the experiment**
An armless chair was placed in front of the projection screen. Participants sat comfortably with feet flat on the floor and hips and knees at 90°. Trunk movements were restricted by a harness, and the testing elbow was attached to an arm support device by a Velcro strap.

The height of the arm support device could be adjusted and was placed at the elbow level so that participants could move their arms in the horizontal plane. Participants also wore “anti-down” glasses, which prevented them from looking down to see their own arm. Anti-down glasses not only helped participants to concentrate on the screen while performing hand movements, but they also minimized the risk of bias by preventing a mismatch between the position of the real arm and the arm avatar displayed on the screen (Figure 4). Additionally, the room was darkened by turning off all lights in the physical environment to optimize viewing of the screen.

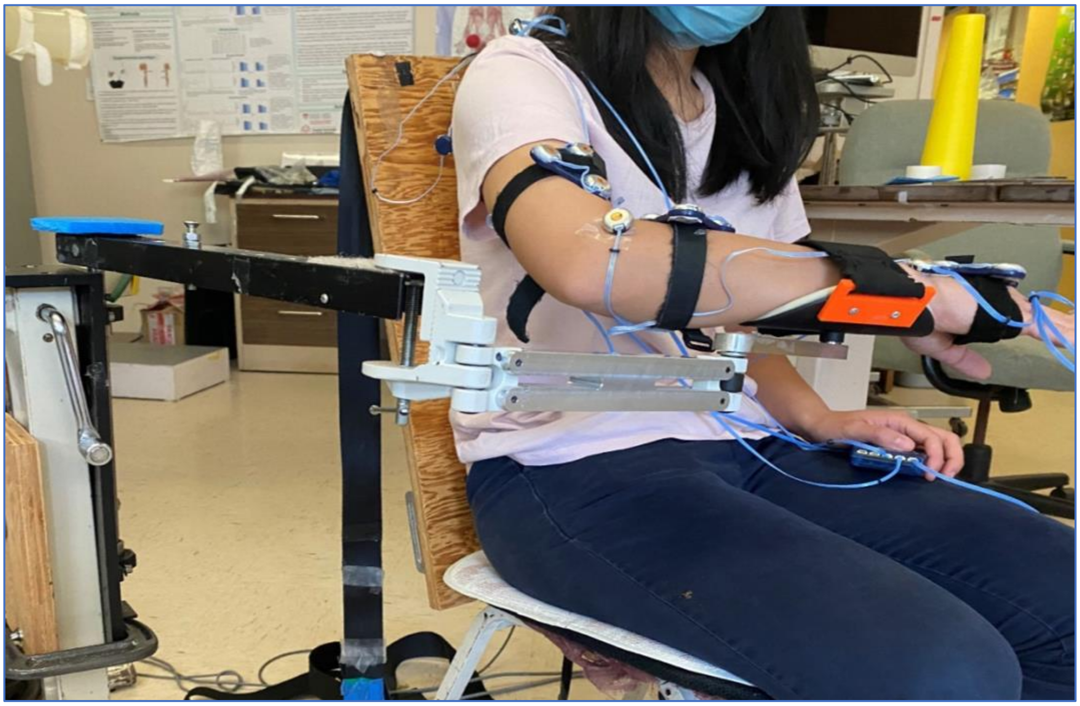

**Figure 2. Participant's arm on arm support device**

The arm support device was designed to restrain vertical arm movements while allowing horizontal movements.

**Figure 4. Anti-down glasses**

Anti-down glasses used to avoid mismatch between seeing the position of the arm in one place and feeling it in another place

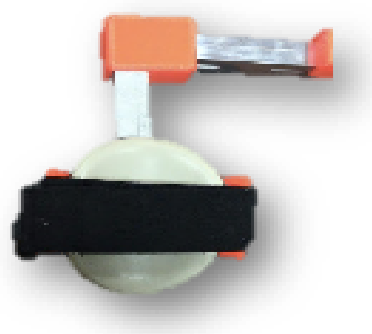

**Figure 3. Top-down view of Arm Support Device**

### 2.3.7 Motion Tracking

The three-dimensional arm position and orientation was recorded using an Optotrak Certus motion capture system (NDI, Canada). The Optotrak system tracked shoulder, elbow, and hand movements in different positions using two cameras; one camera was placed horizontally on the top of the projection screen and the other one was positioned vertically about 2-3 meters away from the chair (the vertical camera was positioned according to the participant's tested arm).

For motion recording with the Optotrak system, 15 infrared emitting markers (three rigid bodies and six individual markers) were placed on specific body landmarks, as follows. The rigid bodies were attached to the hand (three markers), forearm (three markers), arm (three markers), and six individual markers were placed on the anterior aspect of glenohumeral joints of the right and left arm, manubrium sternum, lateral side of elbow (lateral epicondyle), styloid process of the ulna, and the dorsal section of distal phalange of the middle finger. Data from the rigid bodies were used to calculate arm joint angles in order to provide a desired configuration of the avatar motion (Figure 5).

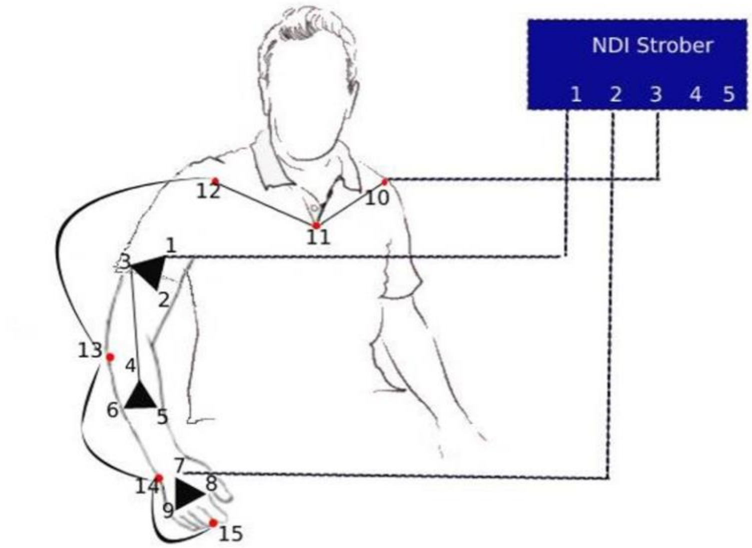


**Figure 5. Placement of the markers on the reaching arm**

Three rigid bodies (black triangles) were placed on the hand (three markers, 7,8,9), forearm (three markers, 4,5,6), upper arm (three markers, 1,2,3). Six individual markers (red dots) were placed on the anterior aspects of the glenohumeral joints (ipsilateral and contralateral; 10, 12), manubrium sternum (11), lateral side of elbow (13), styloid process of the ulna (14), and the dorsal section of distal phalange of the middle finger (15).

There were three calibration procedures for setting the position of the arm avatar in the virtual environment, the task workspace, and movement onset. Calibration for setting the position of the virtual reality environment was first performed by asking the participant to straighten the tested arm to 90 degrees of shoulder flexion. Consequently, limb lengths were measured and input into the system. In the second calibration operation, participants were asked to move their arm in large circles, while resting on the mobile armrest, to determine the task domain or workspace area. In the third calibration process, participants were instructed to set their starting position by moving their hand in front of their chest, about five centimetres away from the xiphoid process.

### 2.3.8 EA procedure

To display the hand position on the screen, the Optotrak camera was used to measure the position of the shoulder, elbow, and wrist. A custom-written computer algorithm read these data in real-time and calculated shoulder and elbow angles, which were then applied to the arm avatar appearing on the screen by forward kinematics. Forward kinematics uses specific equations to compute the end position of the hand, given the limb lengths and joint angles. The representation of the elbow on the screen could be manipulated by subtracting a fixed number of degrees from the measured elbow extension angle. As a result, the participant's arm avatar moved their elbow less than in reality. Thus, when EA was turned on, the participant needed to produce more elbow extension in order to obtain the same hand trajectory on the screen, as without EA.

### 2.3.9 Experimental Procedure

The arm of the participant was represented in real-time by an avatar in the virtual environment, while they engaged in a simple pick-and-place game (Figure 6).

**Figure 6. Display of the participant's arm avatar during reaching movements**

In this task, participants were asked to place the hand on the initial target, displayed on the screen (movement onset). At that time, a second target appeared, and the participant had to reach for it and stop the motion (movement offset). The reaching task designed here required a combination of shoulder and elbow motion. EA could increase the active range of motion (AROM) in the shoulder and the elbow by increasing the error into the actual motion. The increase in elbow ROM could be helpful in preparation for later functional reaching activities in rehabilitation.

At the start of the session, participants took part in a series of practice trials, during which they were asked to perform reaching movements without, and then with EA to each target, to develop a basic understanding of the task. Specifically, they were instructed to move their arm and reach the target on the screen and practice nine EA and nine non-EA trials in different directions. An EA level of 30° was used, and participants were asked to notice the difference between EA and non-EA. The habituation block was repeated if participants needed more practice.

Following the practice trials, participants performed a total of 180 trials (~40 minutes), where target location and EA level were randomized. This included 120 reaches with 4 different EA levels in 7.5° increments (i.e., 7.5, 15, 22.5, and 30°) and with 3 target directions: midline, contralateral and ipsilateral. The remaining trials (60/180 or 33%) were performed to the same targets and without EA. The order in the level of EA (from 0 to maximum) and in target location was randomly selected to avoid any anticipation of the EA condition by participants.

| EA conditions | | Ipsilateral | Midline | Contralateral |
|---|---|---|---|---|
| With EA | 7.5° | 10 | 10 | 10 |
| | 15° | 10 | 10 | 10 |
| | 22.5° | 10 | 10 | 10 |
| | 30° | 10 | 10 | 10 |
| Without EA | 0° | 20 | 20 | 20 |

**Table 1. Number of trials per condition**

To control for distance, targets were placed at 90% of the participant's calibrated reaching distance in each direction. The velocity of the movement was also controlled by asking participants to 'move at a comfortable speed'. To avoid fatigue, participants were able to rest between trials, as needed.

The EA levels used in our study (7.5° to 30°) were determined through pilot testing. Specifically, we constructed a profile based on the average reports of 5 healthy individuals. We set different EA values (more than 50 trials) and asked participants if they felt its effect or not. Then, we measured the maximal EA value for the experiment, based on the minimal EA level detected by all participants in more than 80% of trials. These measurements were used to determine four EA levels, from 7.5° to maximal value.

## 2.4 Data analysis

### 2.4.1 Outcome measures

In this thesis, we attempted to determine whether the reaching task under different EA conditions could be performed within two hours without causing any adverse effects on the participants and to detect the highest EA level in more than 50% of trials. The feasibility assessment considered the percentage of participants with different age, sex, stroke type, side of lesion, score in spasticity and hand dominance, who could successfully perform and complete the task and detect EA, with different EA values and directions.

| *Feasibility Indicators* | *Measurement* | *Criteria for success* |
|---|---|---|
| *Age* | Interview | No effect on outcomes |
| *Sex* | Interview | No effect on outcomes |
| *Stroke type* | Interview | No effect on outcomes |
| *Side of lesion* | Interview | No effect on outcomes |
| *Hand dominance* | Interview | No effect on outcomes |
| *Spasticity* | Modified Ashworth Scale | Scores > ¾, participants can complete the task |
| *Arm paresis* | Chedoke McMaster Stroke Assessment | Scores between 4 to 7, participants can complete the task |
| *EA levels* | Reaching the final target in at least 50% of trials in different EA levels | Participant is able to perform the task in different EA levels |
| *Target directions* | Reaching the final target in at least 50% of trials in different directions | Participant is able to perform the task in different directions |
| *EA detection* | Ask participants if EA was present or not | Participant is able to detect the presence of 30° EA in more than 50% of trials |
| *Length of the intervention* | Time to perform the assessment and 180 trails | Participants complete task in ≤ 2h |
| *Adverse effects during assessment* | Participant or assessor’s report | No major injuries or adverse events |
| *Adverse effects during intervention* | Participant or assessor’s report | No major injuries or adverse events |

**Table 2. Feasibility indicators**

The feasibility of the study was assessed using indicators for recruitment, procedure, and outcome.

The main outcome for the second objective was the participant's awareness of different values of EA. Accordingly, we asked participants, after each trial, to tell us if they had perceived that EA was present or not; then we calculated the percentage of successful EA detection for each trial condition (each direction and EA level). To quantify the perception of EA, we calculated the 50% detection threshold. This was performed by first plotting the probability of detection (Y axis) against EA level (X-axis). We expected that the EA detection rate would follow a sigmoid function. Therefore, for each participant and target direction, we used appropriate regression methods to fit a sigmoid function (Psychometric curve, Fig 7) to the measured error detection rate and then determined the EA angle at which 50% of errors were detected.

To analyze the arm movements, 2D hand position data in the X-Y plane were used to derive several kinematic variables. Position data were first filtered using a Butterworth, low-pass 2$^{nd}$ order filter (6 Hz cutoff). We then computed the hand speed with the use of hand marker, which was calculated as the center of 3 markers, 6, 7, and 8. Movement onset was defined as the time at which the speed of the hand marker exceeded and remained above 10% of its peak velocity for at least 20 milliseconds for participants with stroke or 5% of the peak velocity for at least 20 milliseconds for healthy participants. Movement offset was defined as the time at which the actual speed of the hand marker fell and remained below 10% of the peak velocity for at least 20 milliseconds for stroke participants or 5% of the peak velocity for at least 20 milliseconds for healthy participants. The following kinematic variables were then computed, using a custom MATLAB script: 1. Elbow range of motion (elbow ROM); 2. Average speed; 3. Movement straightness; and 4. Smoothness. Elbow ROM was calculated as the difference in elbow angles between movement onset and offset. Speed was the average speed between movement onset and offset. Straightness of hand trajectory was computed as the ratio of the length of the straight line over the actual length of the reaching path between onset and offset positions, and smoothness was the calculation of the number of velocity peaks during the reaching movement.

### 2.4.2 Statistical analysis

The primary outcome measure was the comparison of the 50% EA detection threshold across both groups and movement directions. To that end, we conducted a repeated measures analysis of variance (ANOVA) with one within-subjects factor (target direction: ipsilateral, midline or contralateral) and one between-subjects factor (group: stroke or healthy).

The performance and movement quality variables of the healthy and stroke groups in different conditions were also compared using repeated-measures ANOVA with two within-subjects factors (target direction: ipsilateral, midline or contralateral; and EA level: 0, 7.5°, 15°, 22.5° or 30°) and one between-subjects factor (group: stroke or healthy). Then, partwise differences corrected using Bonferroni method. To verify normality assumptions and identify potential outliers, distributions were examined, and homogeneity of variance assumptions was assessed with Levene's test. Aditionally, partial eta squared were used to estimate the effect sizes of different comparisons in the ANOVA models.

## 2.5 Results

### 2.5.1 Feasibility Indicators

Participant characteristics:

A total of 17 participants performed the reaching tasks (healthy group=8, poststroke group=9). Mean +/- SD age was 53.8 +/- 13.84 years. The groups were not significantly different in terms of age (t =-1.09, p=0.14), handedness ($\chi^2$ =0.007, p=0.92), or sex ($\chi^2$ =3.08, p=0.07). Participant characteristics are summarized in Tables 3 (poststroke) and 4 (healthy).

| | | |
|---|---|---|
| Age (yrs.) | Mean | 61.6 |
| | Median | 65 |
| | Range | 42-75 |
| Gender | Male | 8 |
| | Female | 1 |
| Handedness | Right | 8 |
| | Left | 1 |
| Stroke type | Ischemic | 7 |
| | Hemorrhagic | 2 |
| Side of lesion | Right | 6 |
| | Left | 3 |
| MAS scale (/4) | Mean | 1 |
| | Median | 1 |
| | Range | 0-1+ |
| Chedoke McMaster Stroke Assessment (/49) | Mean | 5.5 |
| | Median | 5 |
| | Range | 3-7 |
| Elbow ROM | Mean | 128° |
| | Median | 140° |
| | Range | 50°-150° |
| MiniCOG (/5) | Mean | 4 |
| | Median | 4 |
| | Range | 3-5 |

**Table 3. Demographic variables and clinical assessments**

Summarizes the demographic characteristics and clinical assessments of the 9 poststroke participants. Participants were between 42 to 75 years of age.

| | | |
|---|---|---|
| Age (yrs.) | Mean | 54.7 |
| | Median | 52 |
| | Range | 40 - 68 |
| Gender | Male | 4 |
| | Female | 4 |
| Handedness | Right | 7 |
| | Left | 1 |
| MiniCOG (/5) | Mean | 4.5 |
| | Median | 5 |
| | Range | 3 - 5 |

**Table 4. Demographic variables**

Summarizes the demographic characteristics of the 8 healthy participants who completed the task (180 trials). Participants were between 40 to 68 years of age.

Analysis showed that all healthy participants with different age, gender, and hand dominance were able to complete the 180 trials in different EA conditions (EA levels and directions) in less than two hours and detect the presence of errors at the EA level of 30° in more than 50% of trials. The poststroke individuals participating in our study were considered well-recovered with high scores in motor (mean Chedoke McMaster Stroke Assessment =5.5), muscle tone (mean MAS scale=1), and sensory assessments (sensation was intact for all participants except one). All poststroke participants were in the chronic stroke stage and among them, eight people of different ages, genders, stroke types, sides of lesion, elbow ROM, and functional abilities were able to complete the 180 trials in less than two hours and detect the presence of error during movements at an EA level of 30° in at least 50% of the trials. Due to a low cognitive score (Mini-Cog score of 3 out of 5), one participant in the poststroke group could not understand the difference between trials with and without EA and detect the error in trials. Consequently, this participant's data were excluded from further analyses.

## 2.5.2 Error Detection Threshold

The second objective of this study was to identify the practical limits of EA, that implicitly enhance elbow extension range of motion. It was considered that there would be a threshold to the level of EA, beyond which participants would be aware of the presence of EA in 50% of trials (2nd hypothesis). For the measure of mean error detection, psychometric curves were used to determine the 50% detection threshold in different conditions. Figure 7 displays the psychometric curves and the computed detection thresholds, obtained for one stroke and one healthy participant, for each of the three movement directions.

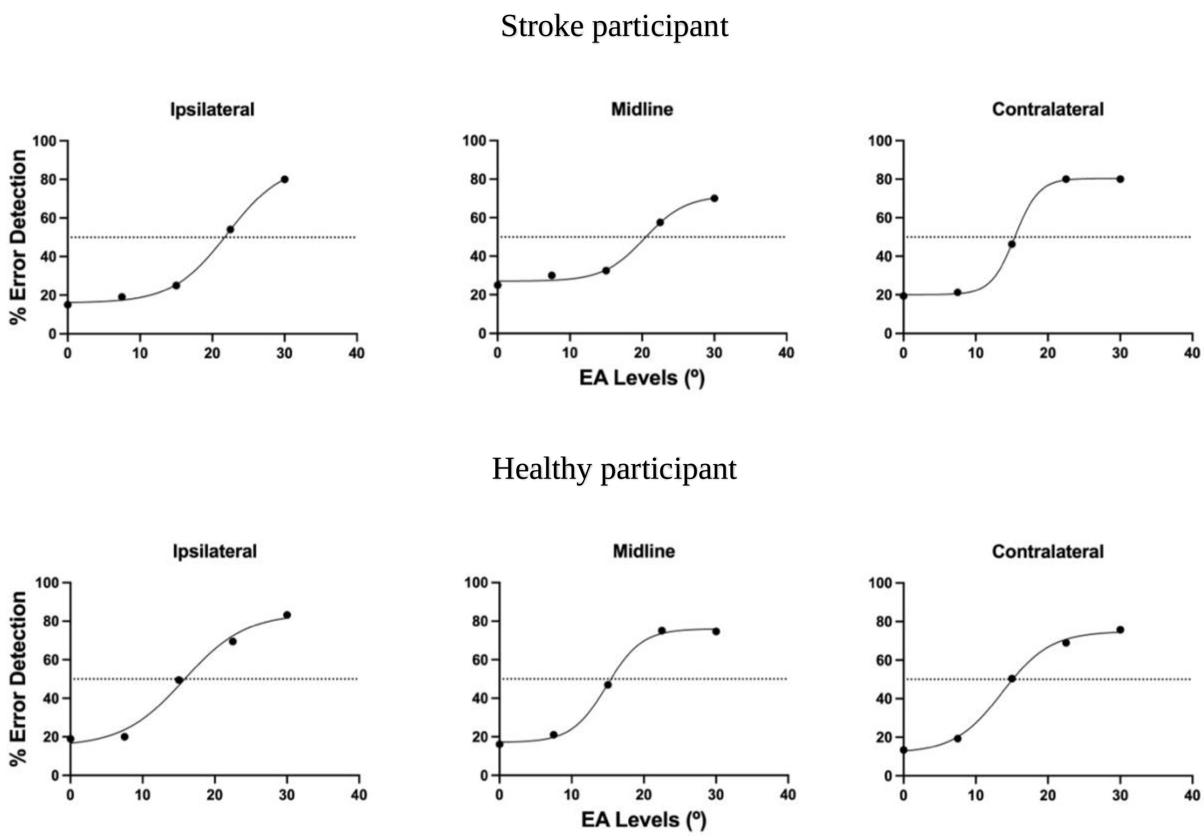


**Figure 7. Psychometric curves**

Psychometric curves were used to determine the 50% detection threshold in three conditions (ipsilateral, midline, contralateral), and two groups (stroke and healthy).

### 2.5.3 Mean Error Detection Rate

Figure 8 shows the results of mean EA detection rates for both groups of participants under all movement conditions (5 EA levels and 3 target directions). As can be seen, both groups s displayed a similar EA detection pattern for movements in all three directions, and EA detection rate increased with the level of EA.

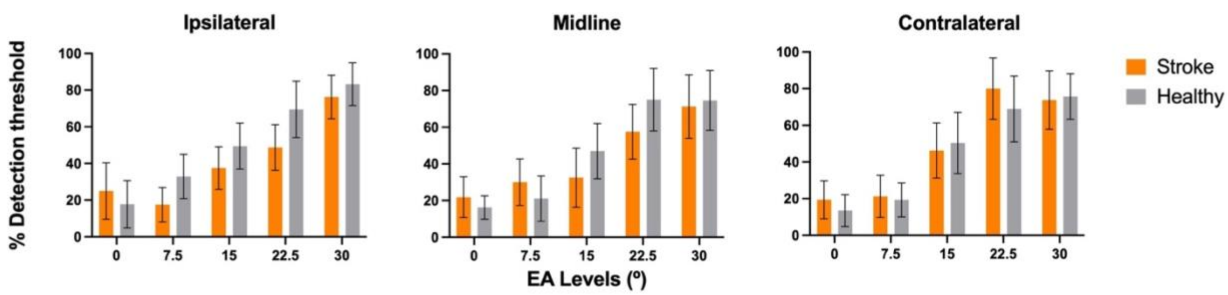


**Figure 8. Mean EA detection rate**

Graphs show mean detection rate by practice groups for each EA level and direction. Error bars are 95% confidence intervals of the mean.

The detection rates at EA levels of 22.5° and 30° were higher than the odds due to chance (i.e., 50%) for both groups, except for the stroke group at 22.5° in the ipsilateral direction where the rate was 48.8%. Conversely, the rate of EA detection at EA levels of 15° or less for both groups was less than 50%.

Figure 9 displays the mean 50% EA detection threshold for both healthy and stroke groups for all three target directions. Mean 50% detection threshold varied between 14.7° (SD=5.1) to 20.2° (SD=4.9) for both groups for targets in all directions.

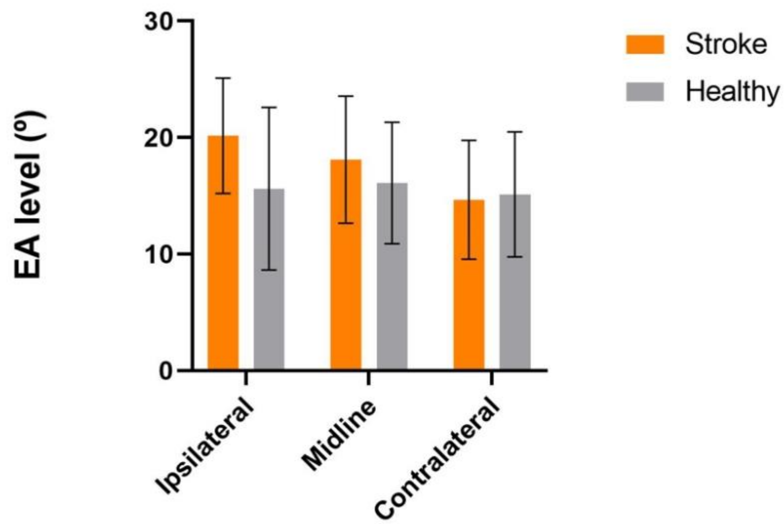


**Figure 9. 50% detection threshold**

50% detection threshold was calculated for both groups and three directions. Error bars are 95% confidence intervals of the mean.

Analysis was conducted to compare the 50% detection threshold between the three directions and two groups. Repeated ANOVA showed that there were no significant differences between healthy and poststroke groups in terms of the 50% detection threshold ($F=1.22$, $p=0.29$, $df=1$). There were also no statistically significant differences between the three directions ($F=1.22$, $p=0.48$, $df=2$). Finally, there was no group * direction interaction in EA detection ($F=0.4$, $p=0.67$, $df=2$). Considering that there were no meaningful differences in detecting the presence of error by each group and across all movement directions, we can say that the 50% error detection threshold was equivalent to the overall mean, e.g., at 16.6° of EA.

### 2.5.4 Reaching Performance

Figure 10 shows typical hand mean trajectories of a healthy and a poststroke participant in three different directions and three EA conditions. Average trajectories are shown by lines in different colors. The error ellipses around the mean trajectories of no-EA configuration are shown for clarity.

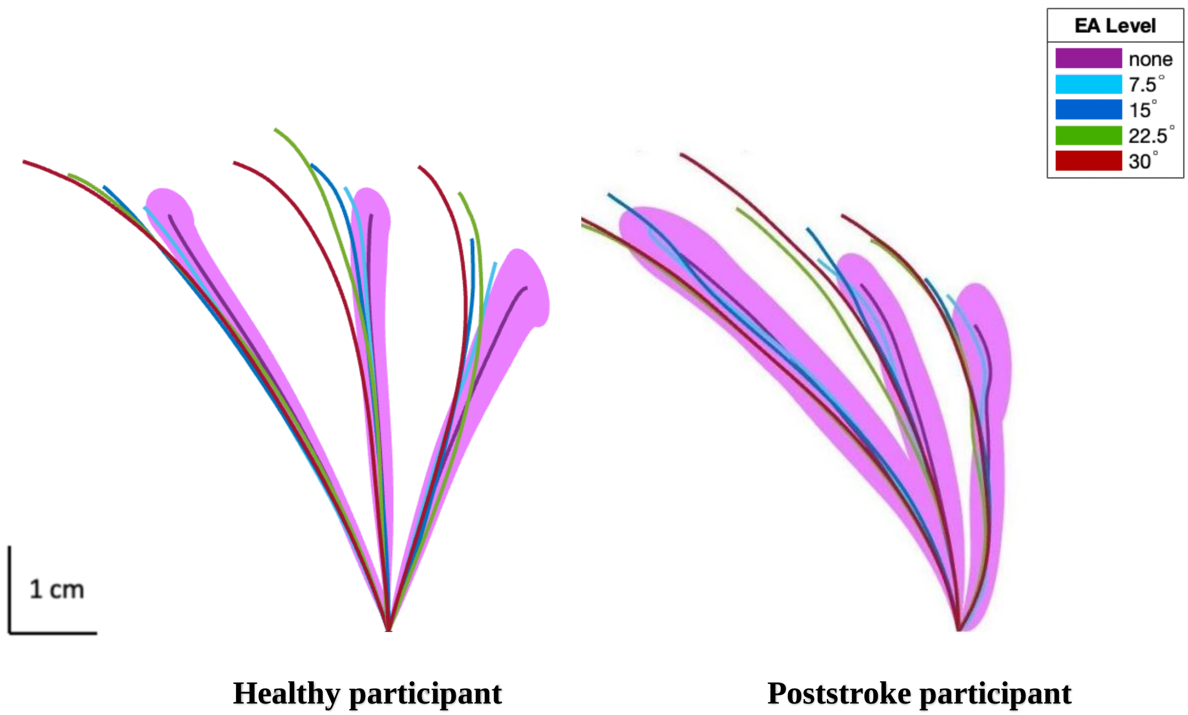


**Figure 10. Movement Trajectories**

Typical hand trajectories for one healthy and one poststroke participant, for each of the three directions and five EA conditions. Lines indicate the average trajectories. The ellipse indicates the error and, for clarity, is added to the 'no EA' condition only. Errors for other EA conditions were similar.

We analyzed changes in straightness, smoothness, speed, and elbow ROM of hand movement (Figure 11) to understand kinematic variable changes in the context of error augmentation. We expected that as error increased, kinematic variables would stay stable. Although there were no significant differences between groups in different EA conditions, there was a significant change in all kinematic variables above the EA detection threshold. To analyze these kinematic data, we performed a repeated analysis ANOVA with two within-subject factors (EA levels and target directions) and one between-subject factor (group).

| | **Group Effect** | | | **EA Level Effect** | | | | **Direction Effect** | | | **EA Level * Direction Effect** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | F | Sig. | $\eta^2$ | F | Sig. | $\eta^2$ | EA | F | Sig. | $\eta^2$ | F | Sig. | $\eta^2$ | EA |
| **Straightness** | 0 | 1.00 | 0 | 10.45 | <0.001 | 0.43 | 30° | 6.71 | 0.004 | 0.32 | 2.15 | 0.04 | 0.13 | 30° |
| **Smoothness** | 0.78 | 0.37 | 0.06 | 22.24 | <0.001 | 0.61 | 15° | 0.65 | 0.53 | 0.04 | 1.15 | 0.34 | 0.08 | ns |
| **Speed** | 3.05 | 0.10 | 0.18 | 4.27 | 0.004 | 0.23 | 30° | 34.32 | <0.001 | 0.71 | 1.85 | 0.07 | 0.12 | ns |
| **Elbow ROM** | 3.01 | 0.10 | 0.17 | 32.29 | <0.001 | 0.70 | 7.5° | 2.19 | 0.13 | 0.14 | 1.64 | 0.12 | 0.13 | ns |

**Table 5. Summary of Group, EA Level, Direction and interaction effects for kinematic outcomes**

The table shows the F value (F)m the significance (Sig.) and partial eta squared ($\eta^2$) for each main effect and for EA Level * Direction interaction. EA indicates the lowest level of EA at which the kinematic variable is different than at baseline (no EA), computed through pairwise comparisons.

Table 5 summarizes the ANOVA results for the kinematic data of interest, for group effect, EA Level effect, direction effect, and EA level * direction interaction. Data analysis revealed that there were no group differences in any of the movement variables. The EA level effect was always significant for all four variables. Pairwise comparisons were analyzed to examine differences between each EA level and baseline (no EA). Clearly, the changes in the kinematic variables appeared at detectable EA domains (EA > 15°), except for elbow ROM, where differences were significant starting at 7.5° of EA.

Target direction had a significant effect on straightness and speed, but not on the smoothness and elbow ROM. Smoothness did not vary with different movement directions, despite there being a strong association between movement straightness and direction. In addition, straightness was the only movement variable with a significant EA level * direction interaction, meaning that either reaching a target in different EA levels or directions affected the movement straightness. Particularly, straightness was only significantly different than the baseline in 30° of EA and ipsilateral direction. Pairwise comparisons indicated that there is a strong association between all described movement variables and EA levels greater than 30°.

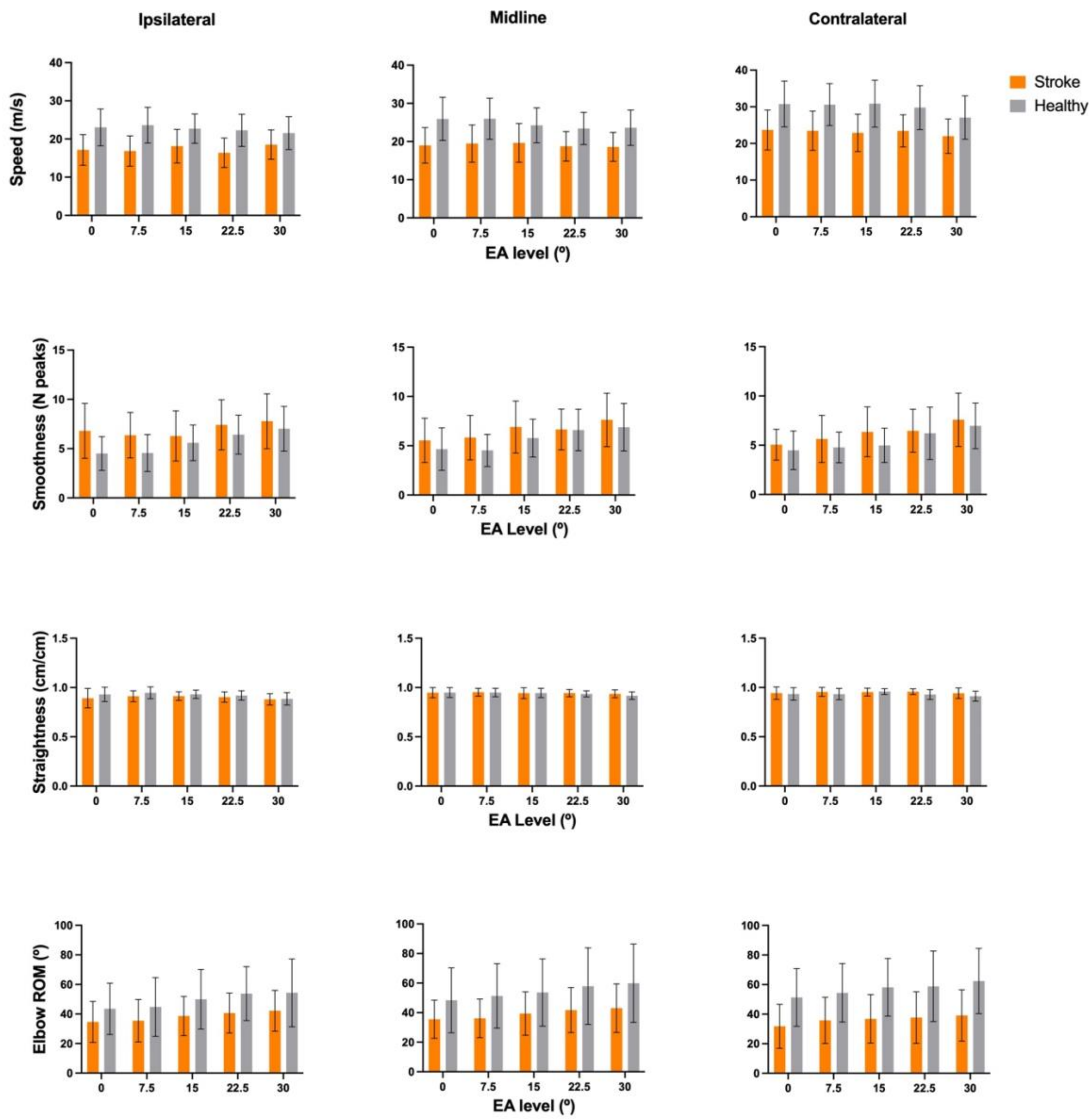


**Figure 11. Movement variables**

Movement variables were compared between 2 groups and 3 directions to analyze the effect of EA on performance. There were no significant differences between groups in different EA conditions, however, there was a change in movement variables as EA levels increased. Error bars are 95% confidence intervals of the mean.

## 2.6 Discussion

### 2.6.1 Feasibility of study

The objectives of this study were to assess the feasibility of an elbow EA task in stroke and healthy participants and to assess these participants' awareness of the presence of a movement error. Based on the evaluation of the feasibility criteria (table 2), it can be concluded that healthy individuals with different sociodemographic characteristics were able to complete the EA task under all defined conditions. Specifically, all eight healthy participants with different age, gender, handedness, and MiniCOG score were able to complete 180 trials in less than 2 hours and detected the presence of error at 30° of EA in more than 50% of trials.

Additionally, our sample included a total of nine poststroke participants. Among them one individual with minor UL motor deficits (MAS=1+, CMSA=3) and eight well-recovered (mean MAS=1, mean CMSA=6, mean elbow ROM=116.3°) poststroke participants. Only one of our stroke participants, with a low cognitive score (3/5 MiniCog) and restricted ROM (40° elbow extension), was unable to perform the task (e.g., unable to reliably differentiate between the error and the no error conditions during the practice of the EA task). Other eight poststroke participants with different age, gender, stroke type, and side of lesion were able to successfully complete all 180 trials, with no report of minor or major side effects such as elbow pain. The presence of error was detectable by these eight stroke participants in more than 50% of trials when EA level was at 30°, and in all three movement directions.

A 50% detection threshold was calculated for all 16 participants who completed the experiment and in all target conditions. Moreover, significant changes in the observed kinematic variables occurred in the detectable EA levels, and there was no difference in smoothness, straightness, and speed of hand movement below the EA detection threshold. Thus, it can be said that this study was feasible in terms of recruitment, EA implementation, and outcomes.

### 2.6.2 Practical Limit of Error Augmentation

In both groups, the rates of EA detection increased with the increase in EA level. In addition, neither group showed significant changes in EA detection threshold for different target directions. These results support the idea that there is a specific limit of error which is detectable for all movement directions. Specifically, the mean EA detection threshold was estimated at 15.6° +/- 5.5 for poststroke participants and 17.6° +/- 5.3 for healthy participants. As ANOVA did not reveal any significant group effects, then it can be said that the overall mean EA detection was 16.6° +/- 5.2 for both groups. This estimated detection threshold is only applicable to our small sample of well-recovered participants in the chronic stage of stroke. However, that sample included ischemic, hemorrhagic, right, and left-sided lesions.

According to the change in movement kinematic variables, it seems that the movement was modified without conscious perception. Considering the idea that poststroke rehabilitation practices can benefit from implicit motor learning paradigms, implementing error which takes place without participants' awareness at specific EA levels can be useful for improving UL rehabilitation for this group of patients.

### 2.6.3 Relationship between Error Detection and Implicit Motor Learning

The poststroke individuals participating in our study were considered well-recovered with close to normal scores in their motor and sensory assessments. However, they still had mild motor deficits, in comparison with their unaffected side or with healthy participants. Past research has indicated that the capacity for implicit motor learning could be affected for movements with the paretic arm in people with cerebellar lesion (Gómez-Beldarrain et al., 1998; Kal et al., 2016b). Additionally, the motor network of individuals with chronic subcortical stroke is also less engaged than that of healthy individuals (Wadden et al., 2015). In other words, there might be a difference between healthy individuals and those with even sub-cortical stroke lesions in their implicit motor learning capabilities. However, in our study, there were no significant differences between poststroke and healthy participants in EA detection threshold nor in the movement quality variables. This may contradict what has been previously proposed in the literature, as the capacity for implicit motor learning was similar in both of our groups. This discrepancy may be due to the fact that our sample was composed of mostly mild poststroke cases. In fact, the absence of implicit motor learning could depend on the stage of motor recovery (Pohl et al., 2001) and 8/9 of participants in our study were in the chronic stroke stage and close to completely recovered.

There is evidence that deficits in proprioception can affect motor learning (Aman et al., 2014). Thus, there might be a probability of failure in EA detection due to somatosensory deficits, causing proprioception disorders (Hazelton et al., 2022). However, assessment results in our study (Nottingham test) showed that our stroke participants had intact proprioception and sensation, except for one (elbow score = 1/2), This might provide another explanation for why there were no statistically significant differences between the two groups in terms of EA detection threshold.

In our study, we argued that the EA detection threshold represents the transition between implicit to explicit motor learning, as this represents the minimal level of error that participants begin to consciously perceive. This argument seems to be aligned with our findings, as a detection threshold could be calculated in all participants and for all movement directions, and the kinematic measures started to change when actual EA neared the detection threshold.

### 2.6.4 Relationship between Error Detection and Kinematic Measures

Reaching movement time was not affected by group (poststroke or healthy) or movement direction. In addition, there were no differences in straightness or smoothness of hand movement between groups or target directions. Our hypothesis was that with the increase in EA, elbow range of motion would increase, while smoothness, straightness, and speed of hand movement would remain unchanged. We found partial support for this hypothesis as we discovered that the elbow ROM did indeed increase with the increase in EA level and significant changes in kinematic variables occurred after reaching targets with EA greater than 15°.

### 2.6.5 Relationship between Kinematic Measures and Implicit Motor Learning

One of the most important findings in this experiment was the evidence of the relationship between kinematic variables and implicit motor learning through the changes in EA level. Our results indicate a significant increase in movement speed, straightness, and smoothness as EA level was above the detectable EA threshold. This means that significant changes took place when participants detected the presence of error. The reaching performance at these EA levels happened explicitly and with conscious perception. Interestingly, our results are compatible with results from previous studies on the effects of implicit and explicit motor learning on movement kinematics. According to these studies, the change from implicit to explicit conditions seems to affect movement quality performance (Wang et al., 2019).

### 2.6.6 Sample Size

To better understand the effect of small sample size in this study, we performed a new analysis to calculate the effect size of EA level, direction, group, and EA level* direction, using partial eta squared (Table 5). Based on Cohen's benchmarks (2013), effect sizes can be defined as small (η2

= 0.01), medium ($\eta 2$ = 0.06), and large ($\eta 2$ = 0.14) while using eta squared. A large effect size indicates a more meaningfull and practical result. When the effect size of an intervention is large, it is possible to detect this effect in a small sample size, while smaller effect size would require a larger sample size (Sullivan & Feinn, 2012). As a result of the large effect sizes in most of movement variables (Table 5), we decided to stop recruiting more participants before we reached our goal of 12 participants per group.

### 2.6.7 Study Limitations

Although the findings of this study were consistent across the two healthy and poststroke groups, some important limitations should be considered. First, we were only able to recruit a low number of participants with a total of nine poststroke and eight healthy individuals who completed the experiment. This can be considered sufficient for ensuring the feasibility objective (El-Kotob & Giangregorio, 2018). However, our sample only included one stroke participant with moderate motor impairments and one with some sensory limitations. Based on the impact of recovery levels on implicit motor learning, it is possible that EA detection threshold could differ for individuals with moderate arm impairment following stroke. Thus we cannot determine if the results of our EA analyses would also apply to individuals with moderate motor or sensory deficits. Second, participants in this study were specifically asked to focus on the presence of EA. The actual threshold could be higher when participants are unaware of the mechanism of EA, nor were made aware of the fact that EA might be present.

Finally, trial-to-trial changes of EA could have worked as a cue for EA presence and prevented participants from becoming accustomed to EA. Consiering the significant effect of repition on memory performance, the detection result might differ if we had a different EA implementation strategy, such as slowly increasing EA over many trials (Barber et al., 2008; Zhan et al., 2018).

## 2.7 Conclusion

In this study, we provided initial evidence on the feasibility of a reaching task with different EA levels in three directions. Both groups successfully performed the reaching task in different conditions and were able to detect the presence of EA affecting their elbow movements, over 14.7° to 20.1° (mean = 16.6°), in more than 50% of trials. It should be mentioned that there were no between-group differences in terms of EA detection. In addition, this study gave us a better understanding of the relationship between EA detection and implicit motor learning. It seems that augmenting elbow error by less than 16° was not detectable by all participants, meaning that the learning when using such levels of error may be happening implicitly and without conscious perception. Kinematic variables provide more support to this notion as they began to change when EA exceeded the detection threshold. Our results support the implementation of EA in poststroke rehabilitative tasks to improve arm abilities. Having a practical limit of EA can be useful in designing virtual reality tasks and environments with EA, to optimize upper limb functional recovery while maintaining conditions for implicit motor learning to occur.

# CHAPTER 3: Discussion and Conclusion

## 3.1 Thesis Findings and Discussion

The overall objectives of this study were to assess the feasibility of conducting EA detection experiment in different conditions and to investigate the error detection threshold during a reaching task in a poststroke population. Except for one poststroke participant with a low cognitive score (3/5 MiniCog) and restricted ROM (40° Elbow extension), all the other 16 healthy and poststroke participants with different age, gender, handedness, and cognitive score were able to complete the 180 trials in less than two hours and detected the presence of error in more than 50% of trials when the EA level was at 30°. To this should be added that poststroke participants had different stroke type, side of lesion, elbow ROM, MAS, and CMSA scores. The mean 50% detection threshold was between 14.7° to 20.2° (overall mean = 16.6°) for both the stroke and healthy groups and for all three movement directions (ipsilateral, midline, contralateral). Additionally, there were no between-group differences for either the EA detection rate or for any of the observed kinematic variables (smoothness, straightness, speed, elbow ROM of hand movement). We found, moreover, that there was no effect of movement direction on EA detection threshold, smoothness, and elbow ROM. Speed and straightness were the only measured kinematic variable affected by movement direction. For example, when reaching to the contralateral target, both groups performed faster than for the midline and ipsilateral directions.

Each of the four kinematic variables attempted to assess the quality of movement during the task performance at different EA levels. Interestingly, there was a significant change in all kinematic measures when elbow EA level neared its detectable range. This result provided the basis for a link between implicit learning and the EA detection threshold since participants were able to detect the error when there was a change in their reaching motion.

We believe that trials with error above the EA detection threshold were mostly performed explicitly and with conscious awareness, whereas trials, where EA was below the detection threshold, were performed without implicit knowledge of the error. This may explain why, at error levels of 22.5° and 30°, the movement was less precise and straight than for EA levels below the detection threshold.

Age, sex, or cognitive scores did not differ significantly between two groups, and that might explain the homogeneity of the results across groups. With regard to individual differences in arm movement kinematics, we might have obtained different results with a larger sample, that had included poststroke participants with more moderate functional impairments (Collins et al., 2018).

Altogether, this thesis has generated important results regarding the relationship between level of EA and implicit motor learning. Providing error augmented intervention may allow functional enhancements based on implicit or explicit motor learning in poststroke population. Our approach revealed that error distributions could be unique for each poststroke participant according to their motor learning capabilities. Customization of EA paradigm according to each patient's actual EA detection threshold could be useful in designing arm retraining protocols based on the level of impairments. This way, the detection threshold can be assessed through some practical trials and integrated into designed tasks to implicitly improve UL rehabilitation. Association between specific levels of EA and implicit learning establishes possibilities for new training environments using EA to enhance UL rehabilitation through implicit motor learning. However, further evidence would be required to verify the effectiveness of implicitly implementing EA in order to improve UL recovery. Such work is currently underway at the Jewish Rehabilitation Hospital (Laval, Canada). This experiment involves practicing the reaching task in a virtual environment with 30° of error and measuring the participants' performance after the experiment to develop a personalized training program using EA conditions (Rajda et al., 2022).

### 3.1.1 Directions for future studies

A better understanding of EA perception threshold may open various related research areas in the future. The results presented in this thesis suggest new questions including 1. To what extent does implicitly implemented EA contributes to motor recovery? 2. In terms of EA perception, would more severe poststroke patients display similar results as that observed in our study? 3. And finally, does the EA detection procedure itself has any lasting effects on the rehabilitation of arm movements?

As the number of participants in this study was limited, the next step would be to run a clinical trial (RCT) with a higher number of mild to moderate poststroke participants, to investigate the effectiveness of using EA below the detection threshold, for UL rehabilitation. Such a study EA can implicitly be implemented in a reaching task. Then, participants' functional recovery can be compared to the control group who practiced the same task in no EA condition. In this way, we can verify the effectiveness of practicing with EA in implicit conditions. Additionally, it would be important to consider the effects of the EA protocol on arm functional recovery after the intervention and at follow-up (three or six months). Answers to these questions would increase our understanding of the association between error augmentation and motor learning in stroke UL rehabilitation.

The information collected about the EA detection threshold in this study can be used to inform future research. For example, a new training environment can be created to improve UL rehabilitation through implicit or explicit motor learning, by modifying the EA level according to the patient's EA detection rate.

## 3.2 Conclusion

In this thesis, we presented brief results of an EA detection experiment. The first aim was the feasibility of implementing EA in various conditions into the reaching task. Secondly, we were looking to measure the EA detection threshold and the effect of different EA conditions on movement performance. Results indicated an association between EA detection threshold and implicit motor learning. This might provide new interventions to implicitly improve reaching performance in poststroke population through the use of virtual reality platforms that implement some form of EA. However, we must wait for the results of ongoing studies before we can validate such ideas.

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