Customized Robotic Training Approaches Using the Statistics of Reaching Errors

BY

MORIA FISHER BITTMANN
B.S., UNIVERSITY OF MICHIGAN, 2006

THESIS

Submitted as partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Bioengineering
in the Graduate College of the
University of Illinois at Chicago, 2016

Chicago, Illinois

Defense Committee:

James L. Patton, Ph.D., Chair and Advisor
Felix C. Huang, Ph.D., Co-Advisor, Northwestern University
Ferdinando A. Mussa-Ivaldi, Ph.D., Northwestern University
John R. Hetling, Ph.D.
Thomas George Hornby, DPT, Ph.D., University of Illinois at Chicago
Daniel Corcos, Ph.D., Northwestern University

This thesis is dedicated to my husband, Russell, who has taught me that no dream is too big to become a reality. Thank you for being my biggest fan.

Acknowledgements

I would like to thank my thesis advisors Dr. James Patton and Dr. Felix Huang for their unwavering mentorship and guidance. It has truly been a privilege to learn from you throughout this process. I would also like to thank the members of my thesis committee – Dr. Sandro Mussa-Ivaldi, Dr. T. George Hornby, Dr. Daniel Corcos and Dr. John Hetling for their support and advice over the past several years. Each of you has contributed to my appreciation of science and desire to improve the field of rehabilitation.

I would also like to acknowledge members of the Robotics Lab at the Rehabilitation Institute of Chicago, both past and present who have inspired and supported me: Emily Mugler, Farnaz Abdollahi. Ismael Seanez, Meghan Morrow, Emily Lazarro, Molly Corrigan, Camilla Pierella, Ali Farshchian, Zachary Wright, Elias Thorp, Justin Horowitz, Amit Shah, Maura Casadio, Rajiv Ranganathan, Mei-Hua Lee, Alejandro Melendez, Davide Piovesan, Assaf Dvorkin, Devjani Saha, Zachary Danziger, Florian Gothuey, Jemina Fasola, Joseph Lancaster, Yazan Majid, and Eyad Hajissa.

I would also like to thank Dr. William Zev Rymer, Dr. Yasin Dhaher, Dr. Derek Kamper, Dr. Konrad Kording and Deborah Znajda Kitterman,at the Rehabilitation Institute of Chicago and Susan Lee, Jay Lin and Lukasz Zientara at University of Illinois at Chicago. I am also grateful for the hospitality from the Sensory Motor Performance Lab at ETH Zurich during my time there: Dr. Robert Reiner, Dr. Verena Klamroth-Marganska, Domen Novak, Georg Rauter, Peter Wolf, Urs Keller, and Maya Kamber.

Lastly, I would like to thank my friends and family for their unconditional support and enthusiasm. Thank you for volunteering to participate in my studies, reading papers, visiting me abroad, and keeping me company at coffee shops.

Contribution of Authors

Chapter 1 is a literature review that highlights the significance of the questions discussed in my dissertation. Chapter 2 is an unpublished co-authored manuscript for which I am the primary author. Chapter 3 is a published manuscript in the proceedings for IEEE Engineering in Medicine and Biology 2014 for which I was the primary author and major driver of the research. Chapter 4 is an unpublished co-authored manuscript for which I was the primary author and major driver of the research. My advisors, Dr. Huang and Dr. Patton assisted with the experimental design and writing. My supervisors at ETH Zurich, Dr. Riener and Dr. Klamroth-Marganska assisted with the experimental design. Chapter 5 is unpublished research that is part of a co-authored manuscript with my advisors, Dr. Huang and Dr. Patton. Chapter 6 is a discussion of the implications of the dissertation work.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
CPF	Challenge Point Framework
EA	Error Augmentation
EF	Error Field
VR	Visual Rotation

ABSTRACT

While upper extremity training with haptic and visual feedback has been shown to assist in restoring function for individuals with stroke and related brain injuries (Teasell, Foley, Bhogal, & Speechley, 2003), outcomes vary greatly amongst individuals. Recent studies have found that manipulating error signals during training can stimulate learning. In order to improve current methods, we believe that it is necessary to customize haptic and visual interactions to address individual motor impairments. We can customize training using the statistics of errors, intervening only on the most commonly occurring errors. In addition to rehabilitation, this technique can be applied to situations where error feedback is needed, such as learning new skills.

The primary goal of this thesis is to develop better training interventions to facilitate motor learning. Addressing the need for training tools for both skill learning and therapy, we explore strategies for improving upon current training paradigms. In the first study we show how force adaptation can cause participants to reach with the errors that are necessary for moving in a visually rotated scene. In the second study, we determine the best domain to represent error tendencies during learning. In the third study, we test how error statistics can enhance learning of a novel visual transformation. In the fourth study, we conduct a preliminary investigation using error statistics to customize training interventions for stroke survivors. Our results will contribute a basic understanding on how we can use error statistics to improve training environments and effect functional recovery.

I. INTRODUCTION

In everyday life we learn from experiencing mistakes. For example, in bowling if we miss a few pins we can adjust where we stand. While we have natural processes that allow us to improve based on our mistakes, the requirements could be burdensome for learning complex skills. This process can be further challenged when there is sustained brain injury following a stroke and individuals cannot correct their movement errors on their own. Scientists have devised interactive gaming environments to study this learning process. They have found that by manipulating how mistakes or errors are perceived, participants are able to learn new skills faster. The goal of this work is to explore error-based methods in which we might enhance motor learning. The following introduction details the state of the art for error-based learning and robotic training interventions for reaching impairments.

1. Error-based learning

Error-based learning is a basic principle used to acquire or refine motor skills, such as bowling. When we make mistakes, the motor system uses this information to improve performance. Scientists have suggested that ability to predict the outcomes of these movements relies on *internal models*, or neural representations of the environment (Mitsuo Kawato, 1990). When the movement does not match the desired goal, as in the case when we experience a new environment, error occurs. These errors are used to refine the internal model and adjust subsequent motor commands (Ghez, 1991; Miall & Wolpert, 1996; D. M. Wolpert, Ghahramani, & Jordan, 1995). This learning process has been extensively studied by introducing participants to novel environments such as a visual rotation, viscous curl field or inertial load. In these studies, participants initially demonstrate large movement errors but are able to recover their typical reaching patterns with practice (Lackner & Dizio, 1994; Sainburg, Ghez, & Kalakanis, 1999; Reza Shadmehr & F. A. Mussa-Ivaldi, 1994). There, however, is debate over which variables are used by the nervous system to learn such novel environments. Conditt et al. suggested that force adaptation is based on an internal representation of the states and not memorization of a temporal sequence of forces (Conditt, Gandolfo, & Mussa-Ivaldi, 1997). Hudson and Landy suggest that movement representations consist of state and time dependent coding, where each one uses different aspects of sensory feedback (Hudson & Landy, 2012). Regardless of the structure of the internal representations, by studying errors we can develop ways to support the learning process.

1.1. What is error?

The human motor system relies on multiple types of error information to adapt. Reaching error can be further distinguished into two categories: *within trial* error corrections made during the movement and *trial-to-trial* error corrections, which researchers speculate reflect a discrete process of updating the internal model (R. D. Seidler, Kwak, Fling, & Bernard, 2013). Computational methods have explained across trial error learning as a Bayesian updating process (Ernst & Banks, 2002; K. Kording & D. M. Wolpert, 2004; K. Wei & K. Kording, 2009; Daniel M Wolpert, Diedrichsen, & Flanagan, 2011). The central nervous system integrates error observations over time to achieve a neural representation which best approximates the motor plan. Even when the error signal is consistently noisy, such as when force perturbations changed from trial to trial, participants formed an approximation of the internal model based on the mean of the experienced forces (Scheidt, Dingwell, & Mussa-Ivaldi, 2001). Many of the aforementioned studies can explain how the central nervous system utilizes *across trial* errors; however, the process of using real-time errors within a trial might have additional benefit to learning.

1.2. Adaptation

While adaptation (learning) can only be inferred, there are several well-known methods for detecting clues of its existence. The aforementioned studies support the notion that an internal model is learned during repetitive practice; however, the best evidence of adaptation is when the distorted environment is removed. For example, consider the paradigm where participants experience forces initially perturbing them to the right. Over time, they recover straight-line reaching patterns. However, when the forces are suddenly removed, trajectories veer to the left. This phenomenon, called an *aftereffect,* is used to show evidence of the internal model acquired in response to the distorted condition (Held, 1962; Lackner & Dizio, 1994; Reza Shadmehr & F. A. Mussa-Ivaldi, 1994). Aftereffects are usually reflections of the initial perturbations. It has even been shown that such aftereffects can transfer to new regions in the workspace after training, highlighting the nervous system's ability to generalize its learning to other domains (Shadmehr & Mussa-Ivaldi, 1994). Under certain conditions, aftereffects can persist for hundreds of trials after the training considition is removed (J. L. Patton & F. A. Mussa-Ivaldi, 2004). Moreover, the structure of an aftereffect is based on the training conditions, so studies have also demonstrated the ability to design training conditions to obtain specific aftereffects (J. L. Patton & F. A. Mussa-Ivaldi, 2004; Yejun Wei &

Patton, 2004). Aftereffects, therefore, can be useful tools to either understand the amount of learning or to "trick" the nervous system into learning a new task.

1.3. Dynamic *vs.* kinematic adaptation

Exploration of the formation of internal models has led to the debate of whether kinematic and dynamic (haptic) adaptation utilizes the same processes. Krakauer et al. suggested that these processes are independent since adaptation to a kinematic distortion (a 30° visuomotor rotation) did not interfere with simultaneous adaptation to a dynamic perturbation (an inertial load) (J. W. Krakauer, Ghilardi, & Ghez, 1999). Further, Flanagan et al. showed that adaptation to a combined kinematic and dynamic perturbation resulted in participants having smaller errors when subsequently experiencing the kinematic perturbation (J. Randall Flanagan et al., 1999). On the other hand, when participants first adapted to a visual rotation and then a force field that were both position dependent, Tong and colleagues found that learning was impaired (Tong, Wolpert, & Flanagan, 2002). Thus, they concluded that these two adaptation mechanisms interfered with each other when the involved the same domain variables. These studies suggest that kinematic and dynamic adaptation some common neural resources, and hence reveal a new opportunity to *facilitate* learning — where adaptation in one environment can impact performance in another. Preliminary work has suggested that adaptation to a force field can facilitate performance in a visual rotation (Yejun Wei & Patton, 2004). However, this study lacked a control group and did not test the lasting effect of the training. Further investigation of how these mechanisms can be interchanged will be discussed in Chapter II.

1.4. Tools to facilitate learning

Interactive virtual displays and robots offer methods to further facilitate motor learning. One promising line of research involves improving training by amplifying feedback errors. This technique, called *error augmentation* (EA), is achieved via robot-generated forces or visual feedback gains that are proportional to the participant's error signal. Error augmentation studies using novel forces or visual transformations have demonstrated positive training effects for healthy participants (Mussa-Ivaldi & Patton, 2000; J. L. Patton & F. A. Mussa-Ivaldi, 2004) and stroke survivor subjects with reaching impairments (Abdollahi et al., 2014; Patton, Kovic, & Mussa-Ivaldi, 2006). In a study comparing error amplification to haptic guidance (forces reduced trajectory error), Milot found that EA training led to significantly greater learning than haptic guidance on a timing-based tapping task for skilled participants, but haptic guidance was beneficial for unskilled participants (Milot, Marchal-Crespo, Green, Cramer, & Reinkensmeyer, 2010). Thus, the added challenge of an EA paradigm was only beneficial for the participants appropriate skill level. In order for EA to be successful, researchers believe the amplification of feedback must still be believable (J. L. Patton, Y. J. Wei, P. Bajaj, & R. A. Scheidt, 2013; Y Wei, Patton, Bajaj, & Scheidt, 2005). They found that participants training with an offset error performed better than those training with EA gains of 2 and 3.1. Shirzad and Van der Loos found that training with low gains of visual and haptic EA together was the most beneficial to learning and had the highest subject satisfaction (Shirzad & Van der Loos, 2012). These studies suggest that for each person there exists a certain level of error amplification that is optimal for learning. This belief that the participant's skill level should dictate the difficulty of this task is consistent with a participant's "challenge point" (Guadagnoli & Lee, 2004). Our goal is thereby to create ideal practice conditions that consider participants' skill level and aptitude for learning.

1.5. Neural substrates involved in learning

While this thesis describes how error is observed and used externally, it is possible that our training interventions can be better informed by the underlying biological processes involved in error-based learning. Many studies have shown that the formation of internal models and the adaptive responses depends on the cerebellum (Blakemore, Frith, & Wolpert, 2001; Masao Ito, 2002; Tseng, Diedrichsen, Krakauer, Shadmehr, & Bastian, 2007; Daniel M Wolpert, Miall, & Kawato, 1998) and the motor cortex (Doyon et al., 1997). Studies with cerebellar disorders have revealed reduced performance in adaptation to both kinematic and dynamic adaptation tasks (Rabe et al., 2009), however, there are no definitive findings that suggest different neural substrates are utilized for kinematic and dynamic adaptation (Diedrichsen, Hashambhoy, Rane, & Shadmehr, 2005; John W Krakauer et al., 2004). Other aspects of learning, such as within trial error corrections, have been shown to depend on the posterior parietal cortex and basal ganglia (Desmurget et al., 1999; Frank, 2011; Makoto Ito & Doya, 2011). Further studies have shown that the anterior cingulate cortex (ACC) plays a crucial role in monitoring performance (Berns, Cohen, & Mintun, 1997; Ridderinkhof, Ullsperger, Crone, & Nieuwenhuis, 2004). Following a stroke, lesions in the motor cortex and basal ganglia can lead to impaired error processing (Dancause, Ptito, & Levin, 2002; Scheidt & Stoeckmann, 2007). Further, the lesion location can have a variety of implications on patients' specific motor impairments where survivors can exhibit large direction and timing errors, weakness, and spasticity—each at various levels of severity (Bushnell, Johnston, & Goldstein, 2001; Kalaska, Caminiti, & Georgopoulos, 1983; Lazarus, 1992; Mercier, Bertrand, & Bourbonnais, 2004). Beer et al. demonstrated that following a stroke, survivors have abnormal synergies in their affected arm that vary based on how the arm is positioned in the workspace (Beer, Dewald, Dawson, & Rymer, 2004). While it is difficult for us to directly accommodate the variety of affected brain areas, we are able to characterize differences in movement errors.

2. Application for stroke rehabilitation

2.1 Robotic therapy

Following a stroke, more than two-thirds of survivors have reduced arm function (Jorgensen, Nakayama, Raaschou, & Olsen, 1999) and only about half of patients with arm paresis recover useful function (Wade, Langton-Hewer, Wood, Skilbeck, & Ismail, 1983). To date, the most effective approaches to restoring arm and hand function have been task-specific, high-intensity treatments that involve active, repetitive movements (Barreca, Wolf, Fasoli, & Bohannon, 2003; Vliet, Carey, & Nilsson, 2012). Robotic devices have advantages for therapy since they can provide high-intensity repetitions and precise control of movement. Several modes of robotic therapy have emerged including passive, resistive, bi-manual, and active-assistance. Active-assistance has been the most commonly tested, and offers a similar approach to that of a therapist: if a patient cannot complete the task, the therapist will provide support (usually in the form of gravity assistance) to guide the arm (Reinkensmeyer, Emken, & Cramer, 2004). Several recent studies have had preliminary success with adaptive control algorithms that can assist the patient as needed or gradually reduce assistance (Casadio, Morasso, Sanguineti, &

Giannoni, 2009). While these algorithms provide support to counteract movement deficits often seen in the affected limb, they do not enforce attention on relearning coordination patterns needed for reaching movement. Error augmentation techniques, where visual or haptic feedback magnifies systematic errors, have been successful in several rehabilitation studies (Abdollahi et al., 2014; Cesqui et al., 2008; Patton, Kovic, et al., 2006; Patton, Stoykov, Kovic, & Mussa-Ivaldi, 2006; Reisman, Wityk, Silver, & Bastian, 2009). EA training even showed clinical improvements beyond repetitive practice or robotic assistance. Though the mechanisms behind EA are unknown, we believe one possible explanation is that EA elevates the error signal to a level that triggers a response from the nervous system. A critical aspect, therefore, would be to have the EA algorithm focus on each individual's specific error signal, customizing the intervention for the patient.

2.2 Current customization approaches

Despite the range of robotic therapy approaches, many current techniques are not flexible enough to address an individual's specific needs and deficits. The variation in abilities between stroke survivors presents a challenge to optimizing therapy. However, robotic devices are infinitely programmable and hence can provide rich set of opportunities to customize therapy. The implementation of Guadagnoli and Lee's Challenge Point Framework (CPF), where task difficulty is based on skill level, has been successful in rehabilitation interventions for Parkinson's and stroke (Onla-or & Winstein, 2008; Pollock, Boyd, Hunt, & Garland, 2014). Shirzad and Van der Loos have recently employed a CPF paradigm to optimize task engagement by determining subjects' desired difficulty (Shirzad & Van der Loos, 2015). However, in addition to adapting to desired difficulty, the optimal intervention also requires an understanding of the participant's impairment. Sundaram et al. proposed a computational framework to characterize different motor control strategies based on several kinematic variables (Sundaram, Chen, & Rikakis, 2011). Recent work from our group has shown that there are statistical tendencies during motor exploration that are unique to each stroke survivor (Felix C. Huang & James L. Patton, 2013). These statistical profiles can also be used to generate forces to perturb participants from their likely motor tendencies (Wright, Patton, Huang, & Lazzaro, 2015). Likewise, during reaching movements, there are statistical profiles of the error that can be modeled using simple probability density functions (M. E. Fisher, F. C. Huang, Z. Wright, & J. L. Patton, 2014). These error profiles not only can be used to identify participant-specific motor deficits but also to customize therapeutic interventions.

3. Description of the thesis

Accordingly, this thesis seeks to address how motor learning can be improved by manipulating the feedback of error to customize training. Having demonstrated the need for robotic training tools for both skill learning and therapy, I explore strategies for improving upon current training paradigms. These customized training techniques involve algorithms that use participants' own movement tendencies during goal-directed movements to 1) learn an ideal trajectory, 2) learn a visual transformation and 3) reduce errors caused by stroke. These studies, outlined in the following four chapters, have either been submitted or are in submission to academic journals. In the first study (Chapter II), I show how force field adaptation can present the necessary errors to teach participants to move in the presence of a visually rotated scene. This demonstrates the ability to use one set of error signals (caused by forces) to train another (caused by a visual distortion) — or "sensory crossover." In the second study (Chapter III), I seek to determine what is the best ordinate domain to define error during learning in order to model observed error tendencies. In the third study (Chapter IV), I test the benefit of customizing error augmentation based on error statistics to learn a novel visual transformation—error fields. In the fourth study (Chapter V), I conduct a preliminary investigation on the viability of such error fields for restoring reaching ability to stroke survivors. The results of these studies establish the benefits and limitations of using error statistics to create successful training interventions.

II. FORCES THAT SUPPLEMENT VISUOMOTOR LEARNING: A "SENSORY CROSSVER" EXPERIMENT

Moria F. Bittmann, James L. Patton

Previous studies on reaching movements have shown that people can adapt to either visuomotor (e.g., prism glasses) or mechanical distortions (e.g., force fields) through repetitive practice. Recent work has shown that adaptation to one type of distortion might have implications on learning the other type, suggesting that neural resources are common to both kinematic and kinetic adaptation. This study investigated whether training with a novel force field might benefit the learning of a visual distortion – specifically, when forces were designed to produce aftereffects that aligned with the ideal trajectory for a visual rotation. Participants training with these forces (Force Group) were tested on a visual rotation. We found surprisingly good performance after training with this novel field, comparable to a group that trained on the visual rotation directly. A third group tested the rate of learning with intermittent catch trials, where we zeroed the forces and switched to the visual rotation, and found a significantly faster learning rate than the group that trained directly on the visual rotation. Interestingly, these abilities continued to significantly improve one day later, whereas the direct training showed no such effect. All participants were able to generalize what they learned to unpracticed movement directions. We speculate that when forces are used in training, haptic sensors have a powerful influence on learning. Such methods can impact any situation where one might add robotic forces to the training process.

1. Introduction

In the fields of haptics, telerobotics, and rehabilitation, sensory-motor information is often challenged or distorted, creating demand for training methods to improve performance. Many studies have demonstrated our ability to adapt to visual distortions such as prisms, visual feedback rotations and stretches (Imamizu et al., 2000; J. W. Krakauer, Pine, Ghilardi, & Ghez, 2000) as well as haptic disturbances such as robot-applied force fields (Huang, Pugh, Patton, & Mussa-Ivaldi, 2010; Patton, Kovic, et al., 2006; Reza Shadmehr & Ferdinando A. Mussa-ivaldi, 1994). Following adaptation, if visual or haptic distortions are unexpectedly removed, evidence of learning is seen in the form of *aftereffects*, where trajectories are reflective of the distorted condition (Lackner & Dizio, 1994; Reza Shadmehr & F. A. Mussa-Ivaldi, 1994). One prospect of these phenomena is there may be ways to exploit them to enhance or otherwise alter learning.

While it is generally agreed that adaptation is due to the formation and updating of internal models in the CNS, there has been a long-standing debate whether the neural resources for adapting to visual and haptic distortions are the same. Several studies have tested possible interference effects caused by adapting to multiple novel environments simultaneously. Brashers-Krug, Shadmehr, & Bizzi (1996) showed evidence of retrograde interference where learning of one force field disrupted the retention of a previously learned force field (Brashers-Krug, Shadmehr, & Bizzi, 1996). Krakauer et al. (1999) suggested that tasks should only interfere if they compete for the same neural resources; hence, kinematic and dynamic movement errors were stored and processed separately in working memory. They found that participants learning a visual rotation were not affected by simultaneously learning an inertial load (J. W. Krakauer et al., 1999). Flanagan et al. (1999) showed that when participants adapt to a visuomotor rotation and viscous curl field separately, they had greater performance in a combined transformation, but only saw transfer effects subsequently on the visuomotor rotation condition (J. Randall Flanagan et al., 1999). They suggested that the lack of interference between conditions was due to the formation of two distinct internal models. Tong et al. (2002) later argued interference only occurs when both distortions are based on the same state, hence, interference was observed when both the force field and the visuomotor rotation depended on position (Tong et al., 2002). Sing and Smith (2010) found that participants that trained with a velocity-dependent force field and then a field of opposite direction had decreased performance (slower learning rate) with the second task (Sing & Smith, 2010). These results, though not in congruence, suggest that adaptation to kinetic and kinematic distortions occupy similar neural resources in working motor memory.

While many of these previous studies show how mechanisms of adaptation associated with visual and haptic distortions might interfere with one another, we propose that our knowledge about such shared neural resources can also be used constructively to facilitate training. Furthermore, we hypothesize that it is possible to capitalize on the phenomenon of aftereffects and create *positive interference* where aftereffects from force field adaptation cause subjects to perform better with a visual rotation. In a previous study, it was shown that aftereffects could be manipulated with specific training; Patton & Mussa-Ivaldi (2004) were able to "teach" subjects how to move in a curved trajectory by determining the magnitude of force needed to perturb subjects from a straight-line (J. L. Patton & F. A. Mussa-Ivaldi, 2004). Although training with forces to learn a visual distortion appears to be an indirect way of learning, we propose that by adding forces to the training procedure, we can capitalize on more sensory inputs (e.g., the cutaneous pressure sensors of the hand, combined with the proprioceptive force and stretch sensors in the muscles) and improve adaptation. Previous work from our lab has shown promising results when testing this idea of "sensory crossover," where adaptation to a specialized force field improved the learning of a visual rotation (Yejun Wei & Patton, 2004).

This paper presents a multi-day experiment that further tested how force field training could facilitate the learning of a visual rotation. Through iteration, forces were specially designed to result in aftereffects that aligned with the "desired" trajectory of the hand for a 30° visual rotation. Three groups of subjects were tested; one group of subjects trained directly on a visual rotation (Visual Rotation Group), one group trained with a customized force field (Force Group), and the third group of subjects trained with a customized force field with intermittent visual rotation trials (Mixed Group).

2. Methodology

2.1. Apparatus

The planar robotic manipulandum (Figure 1A) used for the experiment consisted of two brushed DC torque motors (PMI model JR24M4CH, Kolmorgen Motion Technologies, NY, USA) that control forces at a handle via a 4 bar linkage. Rotational digital encoders (model 25/045-NB17-TA-PPA-QAR1S, Teledyne-Gurley, Troy, NY, USA) reported absolute angular position, and a 6-axis force/torque sensor (Assurance Technologies, Inc., TI F/T Gamma 30/10, and Apex, NC, USA) reported the interface kinetics. A personal computer (PC) acquired the signals and controlled torques. Force and position data were collected and controlled at 100 Hz. A calibrated LCD projector was used to display the position of the robot handle and targets on a horizontal plane in front of the subject, which obscured the view of the actual limb and robot. A passive lightweight arm support under the elbow moved freely and supported the weight of the arm.

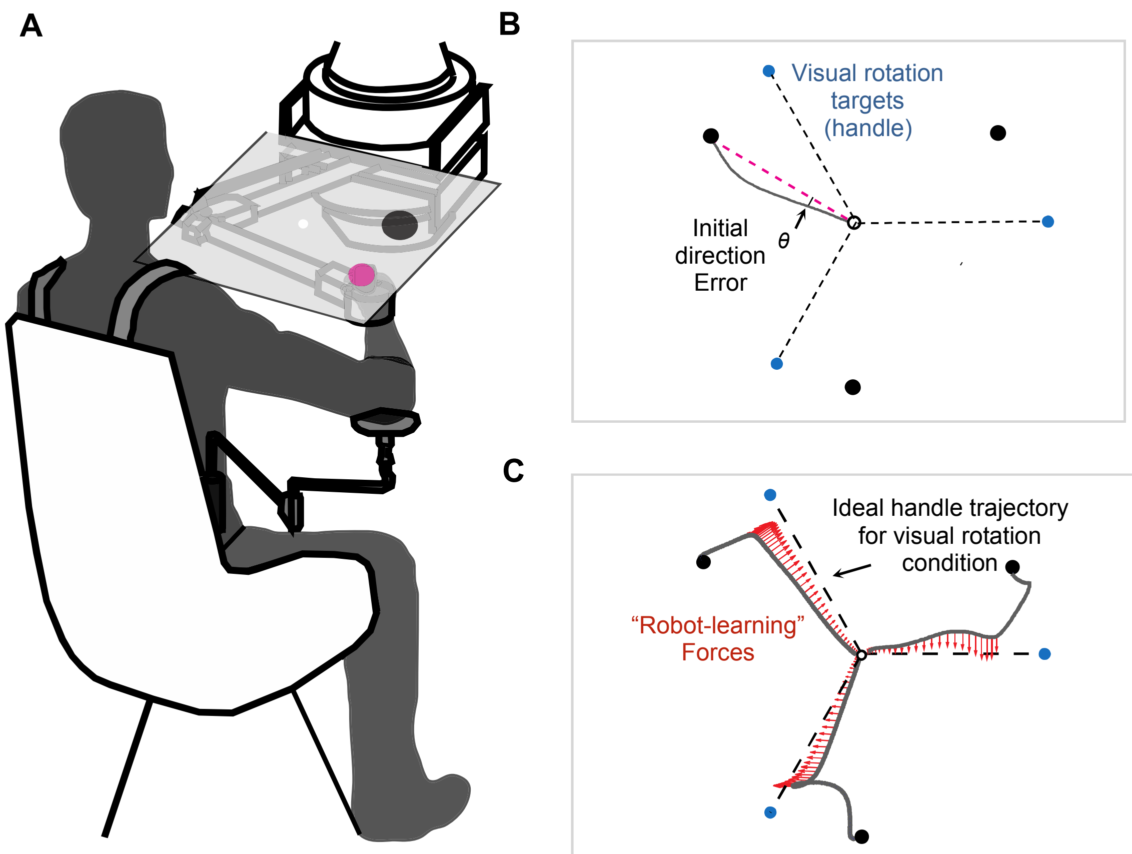


Figure 1: Experimental Setup. (A) Subject moves a robot handle with a horizontal feedback display. (B) Target locations shown on visual display. Center out reaching towards black targets, blue targets represent the desired handle position when visual feedback is rotated 30˚ in the counterclockwise direction. (C) Visualization of trajectory error calculation based on subject handle position (black line), where forces (red arrows) are adjusted during the Robot-Learning Phase such that participants reach along a desired trajectory (black dashed line).

2.2. Subjects

Thirty healthy right-handed participants (14 females) with a mean age of 25 (±3) and no history of neural or arm injury were recruited and tested at the Rehabilitation Institute of Chicago (RIC). All participants were consented using approved IRB and University guidelines for protection of human participants and confidentiality protection of personal health information.

2.3. Experimental Protocol

Participants moved the manipulandum handle on a horizontal plane at shoulder level from a central starting point to one of three possible targets in the plane 10 centimeters away. A new target was presented after the subjects moved the handle inside the starting point for 0.5 seconds; targets were presented in a random order so that the subjects could not predict the subsequent target. Participants were instructed to make center-out movements to the target and velocity feedback was given at the completion of each movement. The color of the target indicated if the movement was too fast (red), too slow (yellow), or just right (green, between 0.3 and 0.4 meters/second). Subjects were allowed to rest before initiating any movement after they had terminated at the target. For movements with visual rotation, the entire visual scene was rotated 30° about the starting point, so that the cursor only truthfully matched the actual position at the origin of each reach (Figure 1B). The experimental phases were:

1. **Baseline**: 30 movements without force or visual distortion (null field) for subjects to get familiar with the movements.
2. **Robot-learning**: 300 movements with the robot-learning algorithm applying forces one in every four movements. Forces iteratively "grew" until the desired trajectory was achieved following the previously developed algorithm (J. L. Patton & F. A. Mussa-Ivaldi, 2004), described in more detail in the following section.

3. **Intermittent Exposure to the Visual Rotation**: 240 movements, with a 30º visual feedback rotation intermittently introduced once every seven movements randomly. These movements assessed the initial errors in response to the visual distortion. The latter 120 movements were tested on a new target set ("generalization" targets).
4. **Training**:
   - Force Group: 240 movements with force field determined during adaptive-learning phase. Catch trials of null field were randomly distributed 1 in 7 trials.
   - Visual Rotation Group: 240 movements with a 30º visual rotation. Catch trials in a null field condition were randomly distributed 1 in 7 trials.
   - Mixed Group: 240 movements with force field determined during the adaptive-learning phase. Catch trials of a 30º visual rotation were randomly distributed 1 in 7 trials.
5. **Visual Rotation Test**: 30 movements to test how subjects responded to visual rotation in the training directions after training. For the Visual Rotation Group, this phase is just a redundant training phase. However, for the Force and Mixed Group, this phase tested the continuity of the learning of visual distortion when switched from force field training. The latter 15 movements were on the generalization target directions.
6. **Visual Rotation Test – Day 2**: 30 movements to test how subjects responded to visual rotation 24 hours after training. The latter 15 movements were on the unpracticed target directions to test for the subjects' ability to transfer (or generalize) their learning to unpracticed directions.
7. **Washout – Day 2**: 30 movements without force or visual distortion (null field).

These 7 phases totaled 900 movements for all subjects. Note that Phase 4 was the only phase that differed amongst the three subject groups.

2.4. Robot-learning – adaptive force field design

During the robot-learning phase of the experiment, training forces were custom designed to shift a subject's movement, $x(t)$, to align with the ultimate trajectory we sought (rotated 30º), $x_D(t)$. These training forces, initially set to 0 N, were applied intermittently (average of once every 4 movements, randomly presented) and adjusted based on the subject's responses. Specifically, for each trial iteration, i, a force $F_{D_i}(t)$ was applied to the robot handle in the first 200 milliseconds of the movement using the rule previously developed (J. L. Patton & F. A. Mussa-Ivaldi, 2004; Yejun Wei & Patton, 2004):

$$F_{D_i}(t) = F_{D_{i-1}}(t) + \mu(x(t) - x_D(t))_i \quad (1)$$

where the learning rate, μ, functioned in the range of 10-30 N/m. When the value of μ was large, forces became unstable and were impossible to learn, whereas a small μ requires a lengthy adaptive-learning phase. We heuristically determined μ to be 26 N/m. The force field determined at the end of the *robot-learning phase* were inverted and applied during training for the Force and Mixed Group (example in Figure 1C). Hence, as this phase progressed, subjects' reaches shifted closer to a trajectory 30º from their baseline reach (Figure 2, "robot-learning" phase), however characteristic hooks appeared towards the end of these actions.

2.6. Data Analysis

Our chosen measure of error was the *initial direction error*, commonly used in motor adaptation studies. It was defined as the angle between the cursor and start position to the straight-line path to the target measured 100 milliseconds after movement onset. We defined positive error to correspond to a counter-clockwise rotation from the actual trajectory to the desired trajectory.

To test our hypothesis that learning would be enhanced for subjects in the Mixed Group (experiencing "sensory crossover") as compared to the Visual Rotation Group, a best-fit exponential model determined the amount and rate of learning:

$$\boldsymbol{E_i = Ae^{-\frac{i}{B}} + C} \tag{2}$$

where E is the trajectory error for the trial i during training, A is the amount of learning, B is the time constant indicating the number of trials for the error to decrease 67% of the way to asymptote, and C is the asymptotic (steady-state) error value. The exponential regression was performed on the catch trials of the Mixed Group in the visual rotation condition and corresponding trials for the Visual Rotation Group.

To test how well force field learning transferred to the visual rotation, catch trials of the Mixed Group (null field) were compared to the corresponding trials for the Visual Group. Separate regressions were also performed to determine if results depended on movement direction.

Three statistical tests across groups evaluated rate of learning, amount of learning, and transfer to unpracticed targets (generalization). A repeated measures ANOVA tested group differences, and post-hoc pairwise comparisons evaluated pairwise differences corrected using the Bonferroni-Holm method. Significance was declared at the alpha level of 0.05.

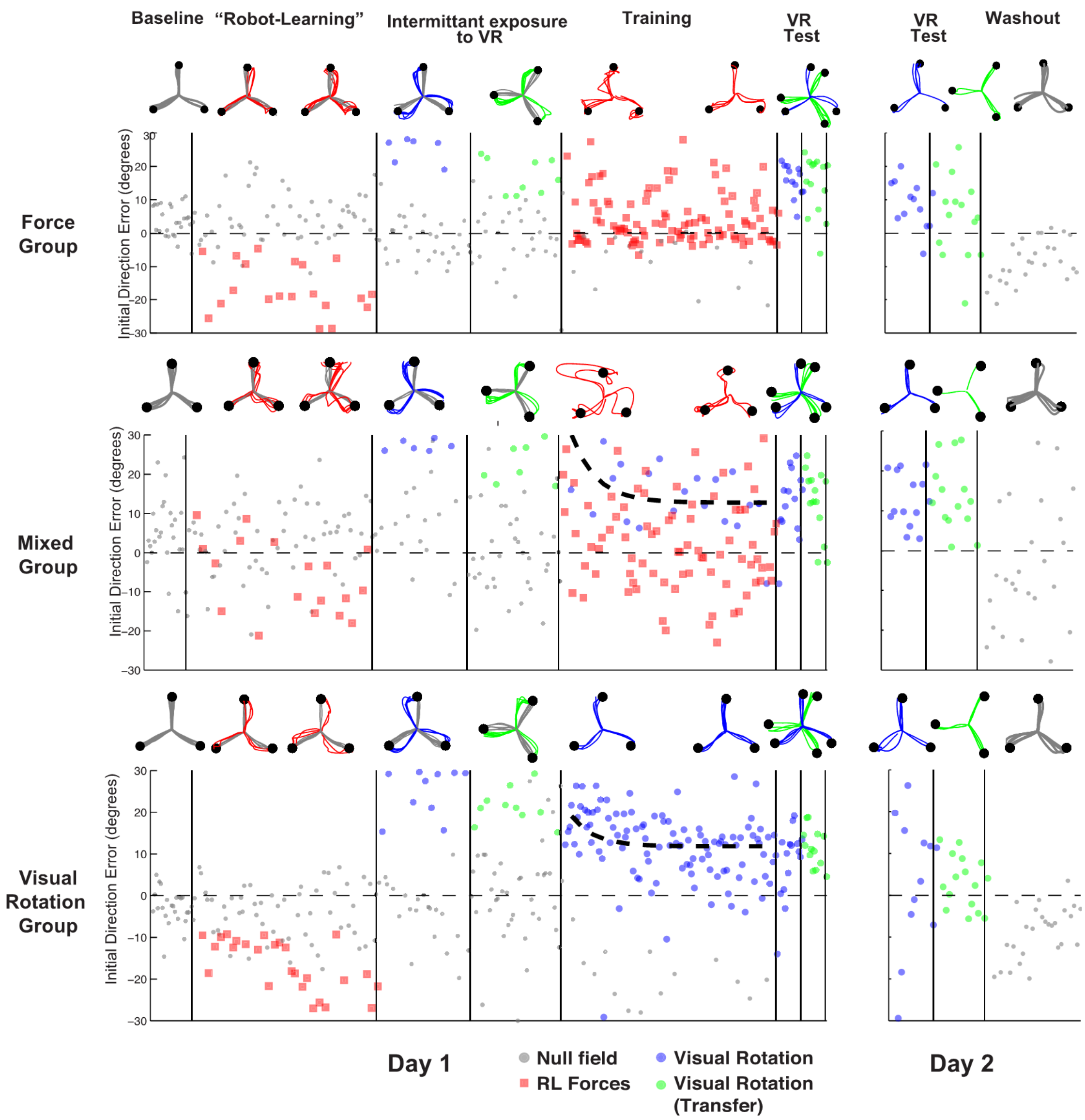


Figure 2: Handle trajectories and resulting initial direction errors across all trials for representative subjects from the Force Group (top), Mixed Group (middle), and Visual Rotation Group (bottom). All subjects experienced the same conditions except for during the training phase, where the Force Group trained with forces and null field probe trials, the Mixed Group trained with forces and visual rotation probe trials, and the Visual Rotation Group trained with visual rotation and null field probe trials. Exponential regressions were fit to probe trials (black dashed line) during training for the Mixed and Visual Rotation Groups to determine learning rate.

3. Results

All subjects showed evidence of constructive learning the visual rotation despite the type of training. Initial values of error did not significantly differ across groups. Most interestingly, however, was that force training led to both *faster* and *more* error reduction. Similar to what was previously found in Wei and Patton (2004), the Mixed Group had smaller time constants of error reduction during training-- 10±4 trials, compared to 18±8 trials ($p=0.0352$; Figure 3). Following training, the Force and Visual Rotation Groups had comparable change in error from intermittent exposure (Δ=-16.6±16.6and Δ=-18±1.9 degrees respectively, see Figure 4A), while the Mixed Group decreased error by -13.7±3.7 ($p=0.008$). Final error was significantly greater for the Mixed Group compared to the Visual Rotation Group ($p < 0.001$; Figure 4A).

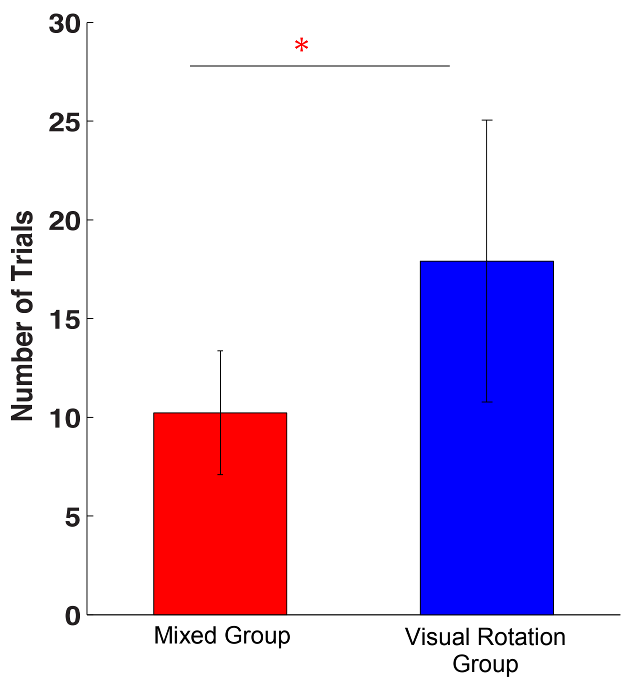


Figure 3: Force field learning appeared to be faster. Trajectory errors from the visual rotation catch trials of the Mixed Group during training were fit with an exponential regression to measure the rate of error decay for each subject. Corresponding trials were used from the Visual Rotation Group to compare the time course of learning a visual rotation. While variable, the numbers of trials were lower for the Mixed Group (10±4 trials) compared to the Visual Rotation Group (18±8 trials), ($p=0.0352$); Error bars show 95% confidence intervals for each group.

These effects were preserved and may have gotten better overnight (Figure 4A). The follow-up evaluation on Day 2 showed additional benefit to training, where the Force and Mixed Groups showed significant change from the previous day (Δ=4.9 ±4.0 and Δ=-7.4±2.9 degrees). The Visual Group did not change between days (Δ=0.5±1.2), and

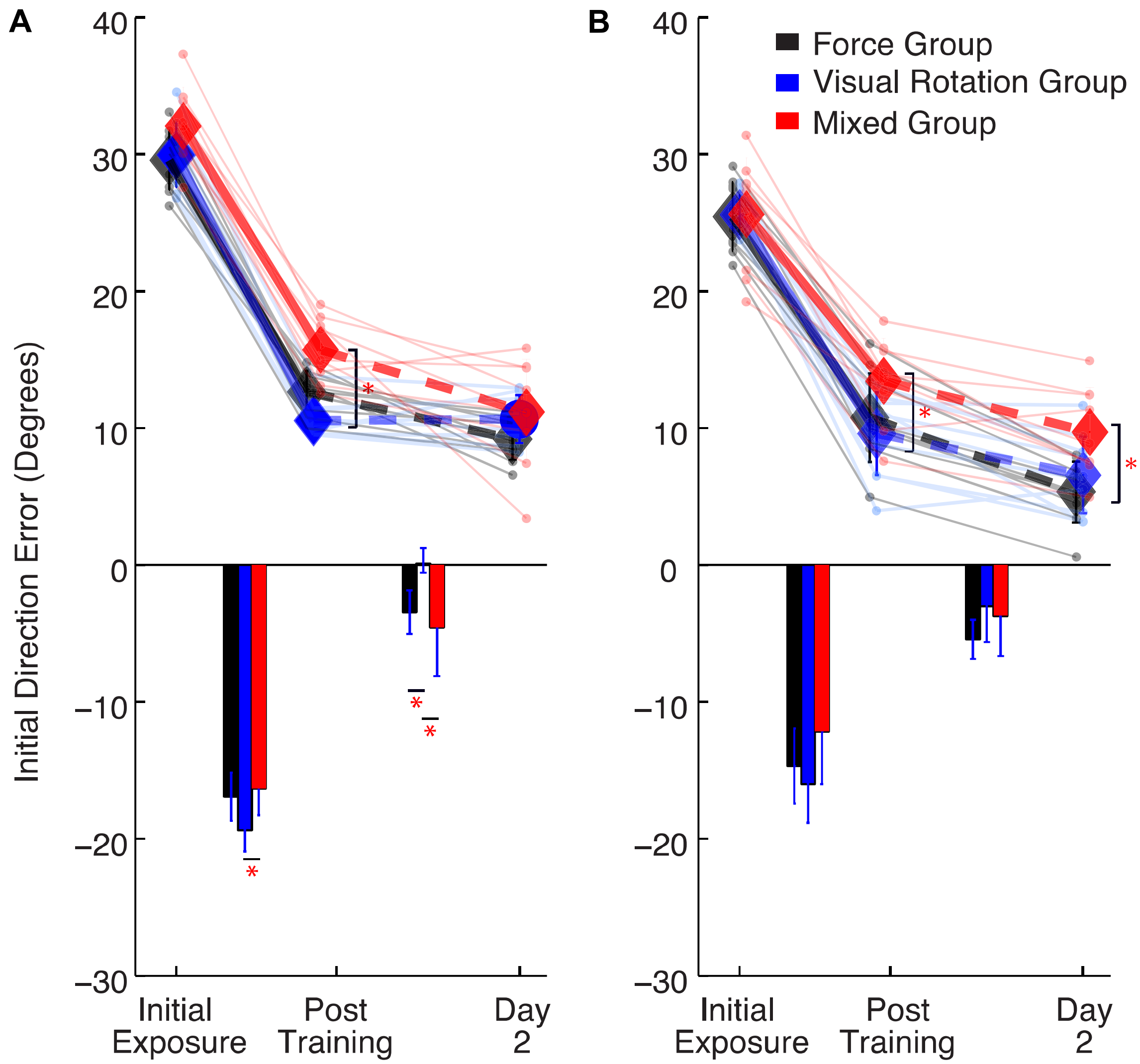
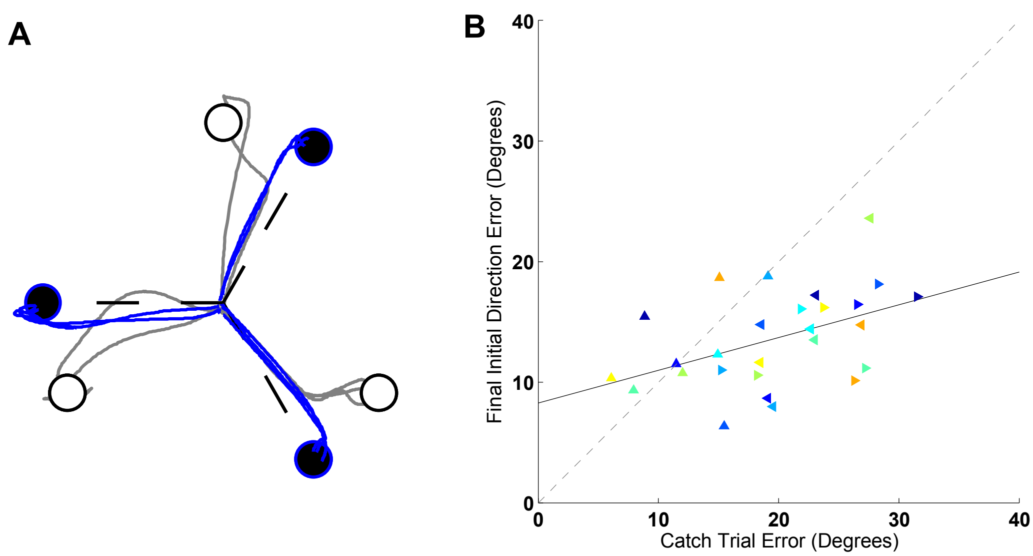


Figure 4: Change in initial direction error following training and 24 hours post training (day 2) for (A) practiced targets and (B) unpracticed (generalization) targets. Each participant's mean error and change between is shown with transparent circles and lines. The mean error and mean change are denoted with solid diamonds and bars respectively, where negative values indicate reduction in error. Error bars show the 95% confidence intervals across subjects. Following training, there the Visual Rotation Group had significantly lower error then the Visual Rotation Group (p<0.001) and change between from pre- to post-training was larger for the Visual Rotation Group than the Mixed Group. Between Day 1 and Day 2, the Mixed and Force Group shown additional improvement beyond the Visual Rotation Group (p=0.01 and p=0.001 respectively). Training had a similar effect on unpracticed targets. The Mixed Group had larger error than the Force Group immediately following training and on Day 2 (p=0.01).


A
B
Final Initial Direction Error (Degrees)
Catch Trial Error (Degrees)
0
10
20
30
40

force learning, when forces are unexpectedly turned off. Catch trials for the Force Group during learning revealed that error magnitudes were correlated with the final error in the visual rotation condition (Figure 5), where r=0.423 and p=0.015.

4. Discussion

This study demonstrated how training with forces might be used to facilitate learning of a purely kinematic transformation – a visual rotation. This was accomplished by specially designing training forces so that the resulting aftereffects aligned with the ideal trajectory for the visually rotated condition. These results reveal a new strategy for robotic training where alternative sensory modalities can contribute to learning, which we term sensory crossover. Trajectory errors during training decreased for all groups, however, when comparing catch trials during training we found that the Mixed Group reduced error more quickly than the control that practiced the visual rotation directly (Visual Rotation Group). While we expected the aftereffects of learning with forces to be beneficial for a visual rotation, it was surprising that it resulted in a larger error reduction over the same amount of trials for the Force Group. A second aspect of learning often associated with this paradigm, transfer (or generalization) to unpracticed motion directions, was found to be comparable across groups (i.e., no significant difference in the ability of subjects to transfer (or generalize) their learning to rotated targets). Finally, we were able to see that the amount of force field learning directly contributed to transfer for the visually rotated condition – after-effects correlated with errors in the visually rotated condition.

Similar to what was previously found in Wei & Patton (2004), force training led to improvements in performance beyond repetitive practice of the visual rotation for both subjects in the Force Group and the Mixed Group. We saw that when subjects in the Force and Mixed Group returned 24 hours after testing, they continued to improve, indicating that the full benefits of training might not be evident immediately after training. Previous studies have shown that retention of a force field persists and can even be successfully recalled up to five months later (Brashers-Krug et al., 1996). While error continued to decrease on the second day, the final error for all three groups still did not reach baseline levels, indicating that training was incomplete. Future iterations of this experiment might use catch trials to test if adaptation is complete (as indicated by the evidence in Figure 5), and adjust the length of training accordingly. This test would be performed either using null field catch trials as was done with the Force Group or catch trials using the visual rotation, as was done with the Mixed Group.

This adaptive training study further demonstrates the ability to *design aftereffects,* and shows how such aftereffects can persist when they are suddenly perceived as appropriate for a new task (operating in the presence of a visual distortion). Previous studies have shown that aftereffects can persist for around 385 trials if visual feedback is removed (J. L. Patton & F. A. Mussa-Ivaldi, 2004). Our results indicated that it is possible to retain an aftereffect if subjects found their performance to be successful – perhaps if they saw their large movement errors immediately after training they would quickly washout to their original straight-line reaching patterns. In this case de-adaptation (i.e., washout) from the learned force field may have been influenced by visual distortions. This persistence of the aftereffects is an important question in the areas of robotic teaching and robotic neurorehabilitation.

This study explored the idea of sensory crossover, where haptic forces were used to learn a kinetic transformation, as a technique to improve learning. Tong and colleagues (Tong et al., 2002) originally argued that adaptation to kinetic and kinematic visuomotor rotations interfere with the ability to learn since they occupy common neural resources in motor working memory. We tested their hypothesis with adaptation tasks that are complementary, demonstrating a constructive facilitation of learning. The Mixed Group in our study was able to switch from one context (force) to the other (visual rotation) without any observable loss of performance or sudden spikes in trajectory error. Similar to Tong et al., we tested subjects 24 hours later, i.e. when an aftereffect was no longer expected to be present but after motor memory consolidation is presumed to have been complete (Brashers-Krug et al., 1996; Shadmehr & Brashers-Krug, 1997; Shadmehr & Holcomb, 1997). While Tong et al. observed interference a day later, we were still able to see a positive effect a day after training, when the immediate benefits of aftereffects have long-since decayed away. This suggests that the learning process, not the motor learning consolidation process, was shared for both kinematic and kinetic adaptations.

Essentially, this constructive interference is an example of "priming," where subjects unknowingly perform better in a new environment. Our analysis of catch trails during force field training (Figure 5) provided further evidence that force field training primed the participant to perform better in a visual rotation condition. Catch trials during training that were more aligned with the ideal trajectory for the visually rotated condition were predictive of lower final errors in the visual rotation condition following training. Response priming, when exposure to one experience influences the responses under other conditions, has been shown to be quite useful in a number of applications of human performance and learning (Güldenpenning, Braun, Machlitt, & Schack, 2015; Schacter & Buckner, 1998) and retraining of human ability after brain injury (Stoykov & Madhavan, 2015). By "tricking" the nervous system into performing correctly, participants had comparable performance, retention, and ability to generalize to unpracticed directions.

Our results may also be due in part to a shifting of sensory modalities. Some researchers have shown that different movement features are learned at different rates (i.e., time constants) (Flament, Shaprio, Kempf, & Corcos, 1999; Smeets, van den Dobbelsteen, de Grave, van Beers, & Brenner, 2006; Smith, Ghazizadeh, & Shadmehr, 2006). For example, time-related features such as movement duration changed faster during learning than magnitude-related features such as peak velocity. The altered learning environment presented to the subjects in this study may cause them to shift their attention or notice errors more easily, resulting in the observed improvement in learning rate for the Mixed Group. The more quickly learned features become more critical to the task so that learning is accelerated. The seamless transition from one sensory training mode to another means that there appears to be another interesting tool to add to the arsenal of possible robotic training techniques.

Regardless of the underlying mechanisms, this work demonstrates certain prospects for motor training (and retraining). Further tests are needed, but one can imagine the utility of custom designed forces for providing a new way to teach transformations in areas such as sports performance, pilot training, surgical maneuvers, musical acts, and neurorehabilitation. However, it remains to be seen whether such work can also be effective in full body actions, in fine motor skills, in three-dimensional activities, or in the recovery from neuropathologies. In any case, such sensory crossover methods appear to be a viable method for either supplementing or completely replacing the training in some contexts.

5. Acknowledgements

We thank Yejun Wei for his early prototyping of the robotic techniques.

III. DISTRIBUTIONS IN THE ERROR SPACE: GOAL-DIRECTED MOVEMENTS DESCRIBED IN TIME AND STATE-SPACE REPRESENTATIONS

Moria E. Fisher, Felix C. Huang, Zachary A. Wright, and James L. Patton

Manipulation of error feedback has been of great interest to recent studies in motor control and rehabilitation. Typically, motor adaptation is shown as a change in performance with a single scalar metric for each trial, yet such an approach might overlook details about how error evolves through the movement. We believe that statistical distributions of movement error through the extent of the trajectory can reveal unique patterns of adaptation and possibly reveal clues to how the motor system processes information about error. This paper describes different possible ordinate domains, focusing on representations in time and state-space, used to quantify reaching errors. We hypothesized that the domain with the lowest amount of variability would lead to a predictive model of reaching error with the highest accuracy. Here we showed that errors represented in a time domain demonstrate the least variance and allow for the highest predictive model of reaching errors. These predictive models will give rise to more specialized methods of robotic feedback and improve previous techniques of error augmentation. This chapter was published in (M. E. Fisher et al., 2014).

1. Introduction

Error feedback is critical for supporting motor adaptation in rehabilitation, sports, piloting, and skilled manual tasks (Ishikawa & Sakaguchi, 2013; Shadmehr, Smith, & Krakauer, 2010). During goal-directed movements, predictions of sensory outcomes are compared with feedback errors in order to updated subsequent motor plans. Researchers have proposed that in order to compensate for a visual-motor rotation, an internal model is used to compare the desired goal with a motor plan. Error is calculated by comparing the goal trajectory and motor output, allowing for either online or trial-to-trial corrections (J. Randall Flanagan et al., 1999; Hinder, Riek, Tresilian, de Rugy, & Carson, 2010; J. L. Patton et al., 2013). This process involves many areas of the brain including the cerebellum, anterior cingulate cortex, and basal ganglia (R. D. Seidler et al., 2013). While error information in the human nervous system is clearly essential, little is known about their statistical properties or how they might be related to the learning process.

During motor adaptation, feedback errors are commonly classified into three categories: absolute error (the absolute deviation from a target), constant error (movement bias of the subject), and variable error (movement variability) (Lee, 2011). To measure performance change of a subject across trials, many studies use a scalar metric to represent the absolute error from each trajectory (e.g., maximum perpendicular error or initial offset angle). While such metrics effectively indicate changes in absolute error or any subject-specific constant error, they do not fully characterize variable errors. We believe that the variability in error, i.e. those occurring throughout the entire trajectory can reveal additional insight as to how the executed motor plan varies from trial to trial. Recent work by Wu et al. also suggests that movement variability is a key marker in the ability of the subject to learn, where there is greater learning as a result of a larger extent of exploration in the error space (Wu, Miyamoto, Gonzalez Castro, Olveczky, & Smith, 2014).

Many studies have demonstrated the occurrence of error- based learning, yet it is unclear what representation of error is most relevant to the motor system. Conditt et al. suggests that adaptation to a dynamic force environment involves an internal representation of the structure of the field (Conditt, Gandolfo, & Mussa-Ivaldi, 1997). Hudson and Landy suggest that movement representations consist of both position and vector coding, where each one uses different aspects of sensory feedback (Hudson & Landy, 2012). Generalization studies can also provide some insight as to how these errors our processed, where subjects experience a variation of a learned skill at new target locations, different speeds, or hand configurations. Goodbody and Wolpert found that generalization of learning a novel dynamically environment (such as a force field) was best when the force field was represented in state-space (Goodbody & Wolpert, 1998). What is not yet known is how to best describe error, particularly which domain, or metric representation, should be used to most reliably predict error tendencies.

Recent work by Huang and Patton showed how distribution analysis during free exploration can be used to identify patterns of deficit for stroke survivor subjects that might not be explained with analyzing velocity or hand- position alone (Felix C. Huang & James L. Patton, 2013). This approach provides a subject- specific picture of individual movement tendencies. One obvious speculation is whether individuals also produce unique profiles in the space of errors. Here, we performed a similar distribution analysis on *error* in targeted reaching movements. We focused on whether the error distributions were best characterized in either position or time domains. While there might be infinite possible coding mechanisms of error, we entertained versions of those most commonly used such as time or state-space (path length, distance along x- axis, distance to origin, and distance to target). As a first attempt at characterizing how the variability in error is represented across an entire trajectory, we compared the mean and standard deviations of perpendicular error across each ordinate domain. We hypothesized that errors represented in time would be the least variable and allow for the best predictive models of error distributions.

2. Methodology

2.1. Human subjects

Subject data was analyzed from a previous experiment in which 9 healthy subjects were intermittently exposed to a 30° visual feedback rotation while holding a planar manipulandum with a horizontal display (Figure 1A). Subjects were instructed to reach from the center position to 6 target directions (Figure 6A) and received feedback (colored targets) pertaining to their movement speed once they hit the target where yellow was too slow, red was too fast, and green was within the ideal velocity range. During the *intermittent exposure phase,* subjects experienced rotated visual feedback 1 in 7 trials, during the *learning phase* subjects

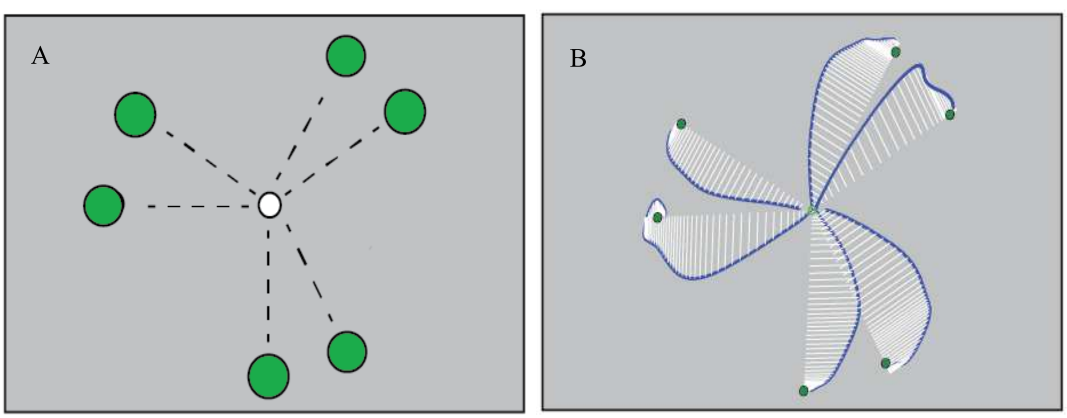


Figure 6: Experimental Setup. (A) Six target directions (green circles) and (B) Representative trajectories showing perpendicular error.

experienced rotated visual feedback continuously with catch trials (brief removal of the distortion) every 1 in 7 trials. All participants provided informed consent in accordance with the Northwestern University Institutional Review Board. Participants were aged 21-40 (mean age of 25 ± 3). Position of the robot cursor and handle were recorded at 500 Hz.

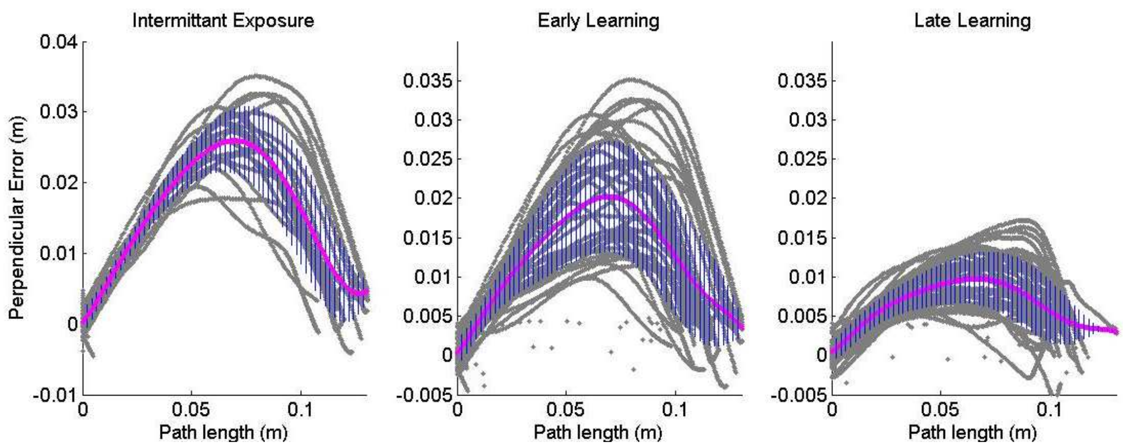


Figure 7: Change in variance of error during learning. Examples of trajectories of perpendicular error from a typical subject's center-out reaching movements during intermittent exposure (left), beginning of learning (center) and late in learning (right) were computed in terms of several ordinates, shown here with respect to path length. While the mean errors (magenta) exhibit evidence of learning across trials, the standard deviation (blue lines) successfully captures the trial-to-trial variation of error.

2.2. Ordinate domains

Ordinate domains were defined to be the dependent measure for the sequence of error calculations. Since we were unsure what type of space ordinate to use, we further divided space into two candidate representations: *Path length* was determined as the Euclidian distance between the current and previous sample (representative of the distance along the actual trajectory). To calculate *distance along x- axis*, trajectories were rotated to the horizontal axis (representative of the distance along the intended trajectory).

2.3. Mean and variability of movement error

For each trajectory, perpendicular error was measured as the distance from cursor position to the corresponding point along the ideal straight-line path (Figure 6B).

Perpendicular errors were then graphed with respect to time, path length, and distance along x-axis. The mean and standard deviation of perpendicular error were determined at each sample and fit with a 5th order polynomial to produce a smooth, continuous representation of error across the trajectory for each ordinate (Figure 7). Confidence intervals were calculated across subjects for all proposed ordinate domains using a significance level of 0.05 (Figure 8).

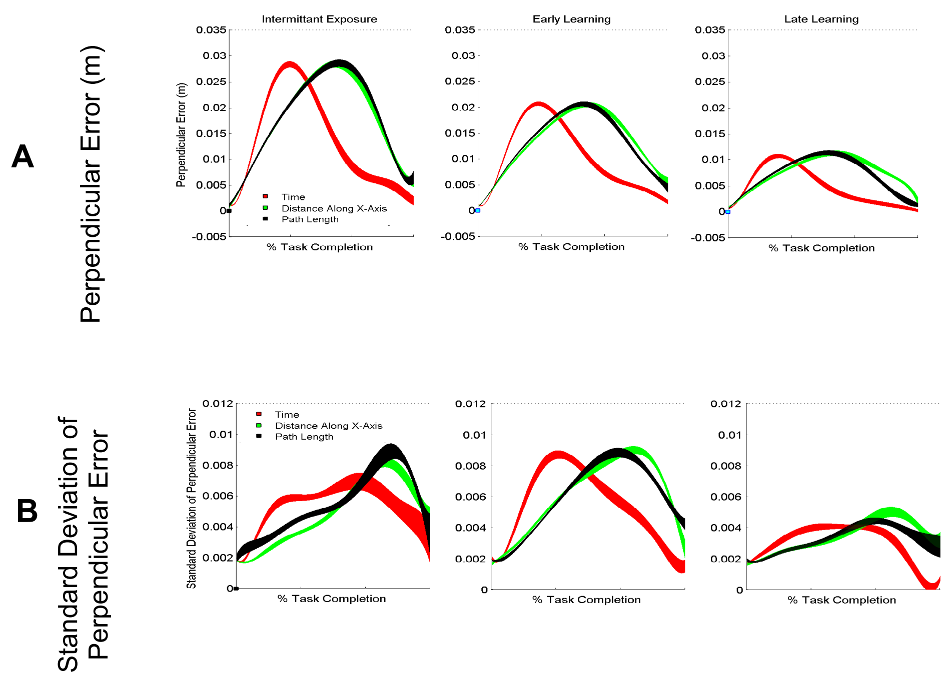


Figure 8: Error magnitude and variance change during learning. (A) Mean and (B) standard deviation of perpendicular error for each subject during intermittent exposure (left), early (center) and late learning (right) during center-out reaching movements. Mean error trajectories exhibit similar magnitudes in terms of time (plotted in milliseconds), path length, and distance (plotted as distance), but with differences peak location. In contrast, the variability of error in terms of time is markedly lower than the other ordinate descriptions during intermittent exposure and late learning. In addition, the peak of error variability in time occurs within a lower percentage of task completion compared to the ordinates associated with state space. Shaded region represents the 95% confidence interval for 9 subjects.

2.4. Predictive model of error

A Gaussian distribution was used to represent the magnitude and range of perpendicular error *(e)* at each sample, calculated with time (t) or path length (d), using Eq. 3 and Eq. 4 respectively, with continuous functions of mean (μ) and standard deviation of error (σ). The Gaussian function was scaled by a value, a, such that the integral of each Gaussian in time and space was equal to 1; likewise, the sum of the frequency of error occurring at each point in time and space was equal to 1.

$$\boldsymbol{p(t,\overrightarrow{err})} = \frac{\mathbf{1}}{\boldsymbol{f_\sigma(t)*\sqrt{2*\pi}}} \cdot \boldsymbol{e}^{\frac{-\left(\boldsymbol{err-f_\mu(t)}\right)^2}{\boldsymbol{2*(f_\sigma(t))^2}}} \tag{3}$$

$$\boldsymbol{p(d,\overrightarrow{err})} = \frac{\mathbf{1}}{\boldsymbol{f_\sigma(d)*\sqrt{2*\pi}}} \cdot \boldsymbol{e}^{\frac{-\left(\boldsymbol{err-f_\mu(d)}\right)^2}{\boldsymbol{2*(f_\sigma(d))^2}}} \tag{4}$$

Histograms showing the density of perpendicular error vs. time and perpendicular error vs. path length were calculated using a 50 x 50 grid. A model predicting the probability of error was constructed for each subject as a function of time and distance from origin spanning the same range as the raw data, shown in Figure 9.

2.5. Model goodness of fit

The coefficient of determination (R^2) was calculated to test how well the prediction of reaching errors (modeled using a Gaussian distribution for at each ordinate sample) explained the experimental data for a given reach. We performed two-way within-subject repeated measures ANOVA with factors being the ordinate domain and phase.

3. Results

Variability in Error

Changes in mean perpendicular error and standard deviation of perpendicular error were detected between intermittent exposure, early learning and late learning (Figure 7) for the three proposed ordinates—time, path length, and distance along x-axis.

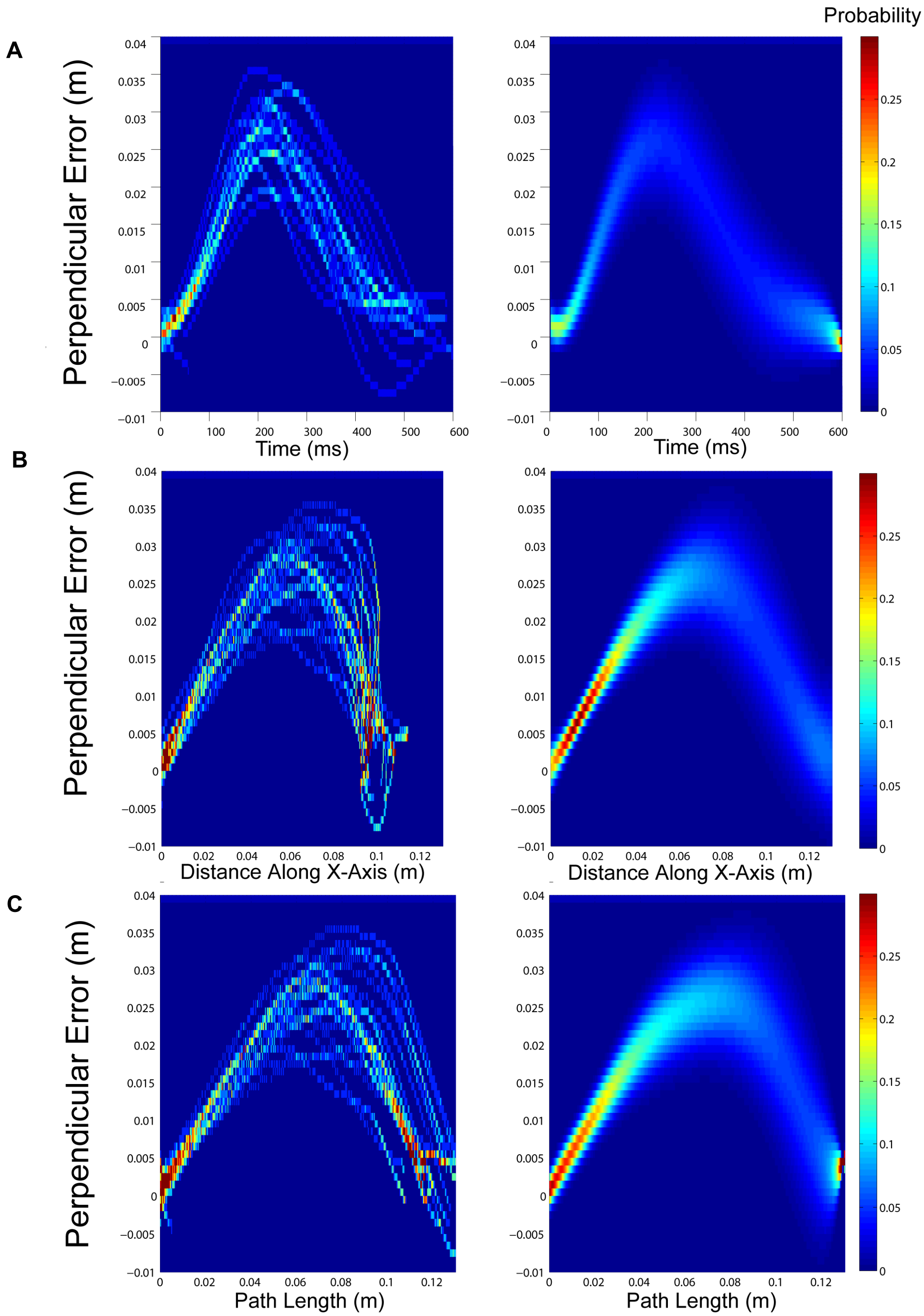


Figure 9: Comparison of histograms to model predictions. Histogram shows distribution of perpendicular errors during a reaching movement (left) and model predictions of error (right) during intermittent exposure to a visual rotation based on ordinates of A) time, B) distance along x-axis, and C) path length for a typical subject.

The distribution of mean perpendicular error across subjects (Figure 8A) showed significantly different locations of peak error, where peak occurred at 33±3% of task completion for time, and 59±3% and 57±4% for path length and distance along x-axis respectively. These trends were consistent across all experimental phases tested.

The peak location of standard deviation of perpendicular error across subjects (Figure 8B) was significantly different between time, path length, and distance along x-axis during intermittent exposure, early learning, and late learning. The overall variability was less for time as compared to path length (p=0.0105) and distance along x-axis (p=0.0018) during intermittent exposure. We found no significant difference in overall variability between ordinates during early learning and late learning.

Predictability of error

We calculated the coefficient of determination (R^2) between the probabilistic error model and the experimental data (Figure 9, Figure 10) for three proposed ordinate domains. Using a 2-factor within subject repeated measures ANOVA, we found significant differences between the three proposed ordain across phases (p=0.0458) and between ordinates (p=0.0042). Further post-hoc analysis using paired t-tests (with Bonferroni corrections for 9 possible comparisons) showed significantly different R^2 values between ordinates of time and distance along x-axis during intermittent exposure and early learning (p=0.0057, p=0.0468) and significantly different R^2 values between ordinates of path length and distance-along x-axis during intermittent exposure and early learning (p= 2.28 e-04, p=0.0291).

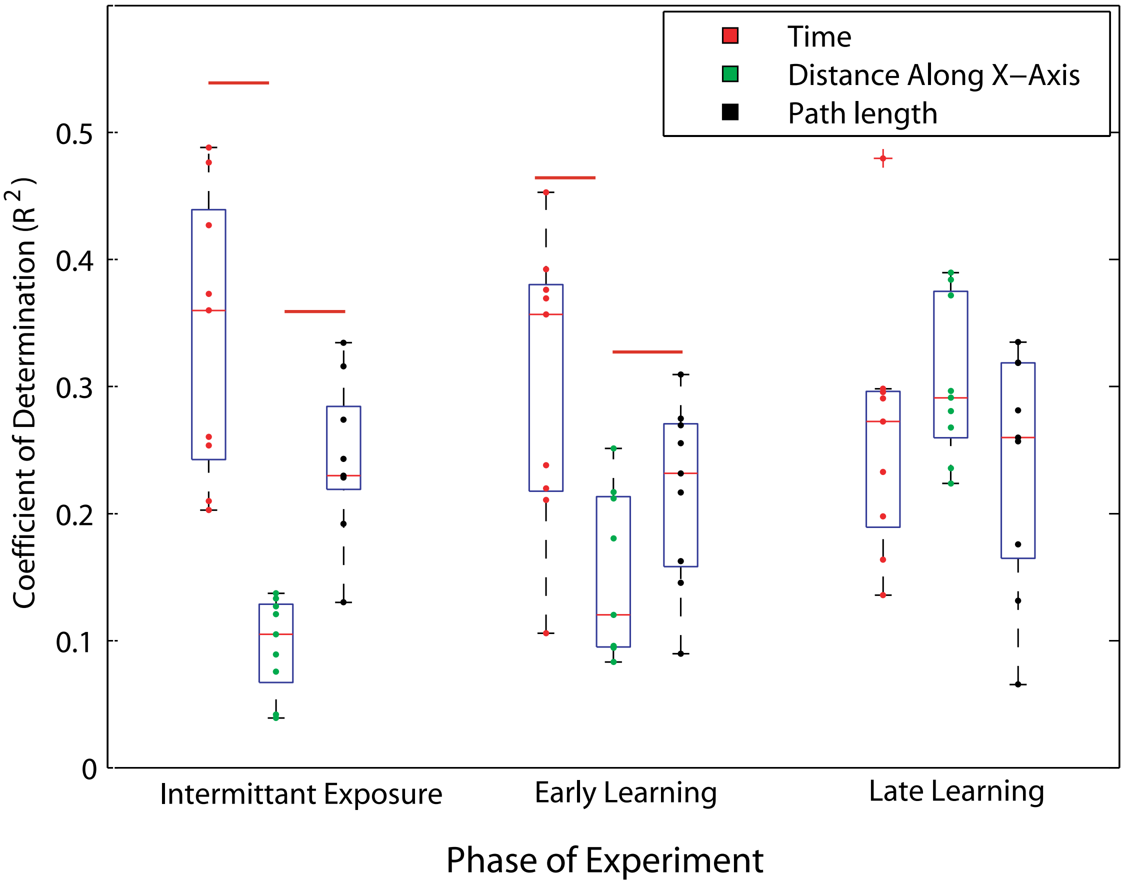


Figure 10: Coefficient of determination (R^2) values indicate the goodness of fit between the proposed error distribution model and experimental data for three possible ordinate domains during intermittent exposure (left), early learning (center) and late learning (right). Colored points denote individual subjects for each domain type, boxes denote subject means. Red bars indicate significant difference between pairs after post-hoc corrections.

4. Discussion

The purpose of this study was to test how variability in movement errors was reflected in different ordinate domains. We analyzed data from a previous experiment in which healthy subjects performed center-out reaching while experiencing a 30° rotated feedback condition. We examined how the distribution of perpendicular error varies based on the proposed ordinate domain, primarily focusing on time and state-space based ordinates.

We found that the average perpendicular errors across subjects exhibit the same magnitude regardless of ordinate domain, though there were differences in peak location. The similarity of the maximum values of perpendicular error across domains demonstrates how the use of trajectory norms is a justified tool for tracking learning in motor control studies. However, the difference in peak location further motivates the need to investigate in what other ways the ordinate domains may differ. It is possible that the differences in peak location might be attributed to direct relationships between variables, for example between position, time, and velocity. However, the trial-to-trial variation is not be constrained by such dynamic relationships, allowing for peak velocity to occur at any point in time.

During intermittent exposure, we found that the overall variability of error across subjects was lowest for the time domain than the two candidate ordinates based in state-space. This trend was also true, though not significant, during late learning. During intermittent exposure, where there is high error and low variability, time is the least noisy of the proposed ordinates. In phases of high variability, such as in early learning, it is difficult to discern differences in ordinates domain. Further, the variability of error during intermittent exposure and late learning appear to be scaled versions of each other, possibly suggesting that patterns of variability are unique to each phase of learning.

To demonstrate the effect of how variability in each ordinate domain contributes to the predictability of motor error distributions, we constructed a simple predictive model (Figure 9) using Gaussian distributions across each ordinate domain with the mean and standard deviation of perpendicular error (with continuous polynomials for each ordinate domain). This modeling approach was able to explain approximately 40% of experimental data for each phase. The time ordinate domain showed the highest result during intermittent exposure. Possible iterations of this predictive model would allow for multiple Gaussian distributions at each sampling point or use a different distribution that does not enforce normality. Since the first half of movement has the highest probability, there is also possibility that such a model would better describe the experimental data if we broke up the trajectory into the ballistic phase and subsequent corrective phases.

It remains uncertain whether multiple domains are used to update feedback in order to adapt to a visual-motor discrepancy. It is possible that the central nervous system could use multiple ordinate frames (including the ones we proposed) to update the motor plan or none of them. When observing the goodness of fit across phases, the ordinate of distance along the x-axis had an upward improvement from intermittent exposure to late learning (Figure 10). We believe that this ordinate is the most aligned to a state-representation and this improvement corresponds to previous evidence that a state space representation takes over once learning has plateaued (Conditt et al., 1997; Hudson & Landy, 2012).

Our findings that time offers the best ordinate domain for representing errors is in agreement with known constraints in sensory-motor control. Because sensory feedback is time- delayed, the motor system cannot react instantaneously to the state of the limb. Accordingly, our results suggest (Figure 8) that during the ballistic phase of goal-directed reaching movements errors align in time. If we only consider the feed- forward motor plan it is also possible that a spatial path is generated but is variable in time, Nashner and Berthoz showed that movement latencies associated with visual feedback is approximately 100 milliseconds, where peak error is shown to be with respect to the time domain (Nashner & Berthoz, 1978).

We conclude time to be the most substantive basis for a predictive model of performance error, since time-based errors demonstrated the least variance (Figure 8) and led to the best fit using our simple modeling approach (Figure 10). The ability to predict movement errors using the variability of subjects gives rise to better training techniques that are motivated by subjects' reaching errors, such as error augmentation.

5. Acknowledgments

This work was supported by the National Institute of Health (NIH) under grant R01NS053606.

IV. CUSTOMIZATION OF ERROR AUGMENTATION BENEFITS LEARNING A NOVEL VISUAL TRANSFORMATION

Moria F. Bittmann, Felix C. Huang, Verena Klamroth-Marganska, Robert Riener, James L. Patton

Recent motor control studies using interactive practice experiences that augment error have demonstrated promising results for enhancing the learning process. Despite this, the best method of error augmentation remains unclear. Here we evaluate how individual error tendencies can be customized for each participant, focusing the effort on the more probable errors and ignoring more random mistakes. We hypothesized that by using such customized forces – called *error fields*, participants would adapt to a novel visual transformation faster and have a larger change in error. We tested the ability of twenty-one subjects to adapt to a novel visual transformation while augmenting error either with a constant gain or with error fields training. We found indeed that error field participants adapted the fastest, and had the largest reduction in error. Furthermore, a predictable shift in error for this group suggested that the intervention directly addressed their individual error tendencies. These promising results support the need for customized interventions that consider the statistics of error tendencies to improve training experiences.

1. Introduction

The human motor system uses error feedback to correct for differences between intended and actual movements. Error feedback is also essential to certain mechanisms of motor learning (M. Kawato, 1990), in which existing motor plans are continually updated. It is believed that errors from previous movements are integrated statistically during the learning process (K. P. Kording & D. M. Wolpert, 2004; van Beers, 2009, 2012). Rehabilitation researchers have taken advantage of such movement errors by amplifying them to enhance the learning process, a technique known as *error augmentation (EA)*. Benefits from using error augmentation techniques have been seen with a variety of tasks, such as goal-directed reaching, walking, and stepping (Marchal-Crespo, Lopez-Oloriz, Jaeger, & Riener, 2014; Milot et al., 2010; James L. Patton & Ferdinando a Mussa-Ivaldi, 2004; Reisman et al., 2009; Y Wei et al., 2005). By making errors more noticeable with visual or haptic error augmentation interventions, there can be heightened motivation and attention, improving the rate and amount of motor learning (Alleva & Santucci, 2001).

The success of any particular training intervention has been suggested to rely on the skill level of the participants This concept, referred to as the *Challenge Point Framework,* suggests that the performance benefit can only be enhanced if the task is at the appropriate difficulty for the participant (Guadagnoli & Lee, 2004). Thus, each individual’s unique capabilities should help determine best practices. In rehabilitation applications, there is further need to adapt and customize in order to target individual motor deficits. Recent studies using robots for rehabilitation have shown success by increasing intensity incrementally (Choi, Gordon, Park, & Schweighofer, 2011) or allowing participants to choose therapy models (Klamroth-Marganska et al., 2014). Customized algorithms can tune interventions to variations in skill and ability. Rather than determining a universal gain for error augmentation, an optimal approach might be to customize error augmentation gains that focus on each individual’s regions of highest error and probability. Using straightforward statistical models, we previously demonstrated we could effectively characterize such error probabilities of participants' original movement errors during goal-directed reaching (M. Fisher, F. C. Huang, Z. A. Wright, & J. L. Patton, 2014).

The best practices for implementing error augmentation, however, are still unclear. Marchal-Crespo et al. found that the effects of haptic error augmentation were dependent on initial skill level, where positive training outcomes were only seen with skilled participants (Marchal-Crespo et al., 2014). Other studies testing different error augmentation gains suggest that not only is there an ideal scale magnification, but also that augmenting error outside of an appropriate range might be detrimental to learning (James L. Patton, Yejun John Wei, Preeti Bajaj, & Robert a Scheidt, 2013; Y Wei et al., 2005). Further studies that focused on using error throughout the learning process, have shown that excessively large or spurious errors diminish the adaptive response (Y. Wei & K. P. Kording, 2009). Recent work by our research group has made use of the statistical nature of movements by identifying individual deficits in range of motion, velocities, and accelerations during a free exploration task (Felix C. Huang & James L. Patton, 2013; Wright, Fisher, Huang, & Patton, 2014). Similarly, distributions are also observed in reaching errors, so error augmentation methods might focus on the more likely errors of the participant, ignoring errors that are spurious and not repeatable.

In this study, we evaluate a new form of error augmentation that is customized according to each individual's specific error tendencies. Statistical profiles from participants' movements inform the design of a haptic intervention. The algorithm first identifies regions of error tendencies. Then, training forces focus on amplifying these error prone regions while ignoring spurious errors. To test this error augmentation technique, participants learned to make straight-line reaches in a visually distorted space controlled by joint angles of the shoulder and elbow (similarly to that of (J. R. Flanagan & Rao, 1995)). We added an additional challenge by requiring participants to reach with a minimum angular jerk trajectory (Nakano et al., 1999). This required participants to improve both spatial and extent (timing) errors during reaching. We hypothesized that this new *error fields* treatment *(EF),* where forces are applied based on the statistical tendencies of error during goal directed reaching, would provide faster learning and greater final performance. Finally, we investigated how subjects' shifts in error distributions using this error field treatment could be predicted by the original distributions of error.

2. Methods

2.1. Human subject experiment

This experiment utilized a seven degree-of-freedom robotic arm exoskeleton device, the ARMin, located at the Sensory-Motor Systems Lab at ETH Zurich (Zurich, Switzerland) (Tobias Nef, Guidali, & Riener, 2009; T. Nef, Mihelj, & Riener, 2007). Twenty-one right-handed participants (10 female) performed the experiment, with 7 participants per group. All participants consented in accordance with the Ethics Board of the Canton Zurich. These methods were previously described in (M. Fisher, F. C. Huang, V. Klamroth-Marganska, R. Riener, & J. L. Patton, 2015).

2.2. Experimental protocol

Participants were asked to move the robotic exoskeleton with their right (dominant) arm along a straight-line path between two targets fifteen centimeters apart as shown on a vertical display (Figure 11A). Their elbow and shoulder joint controlled the X and Y cursor position on the screen. A proportional plus derivative (PD) controller was used to orient the robot in a planar reaching position such that only shoulder rotation (θ_2) and elbow flexion/extension (θ_4) were possible. Friction, gravity, and viscosity compensation were applied to counter the effects of moving an exoskeleton device.

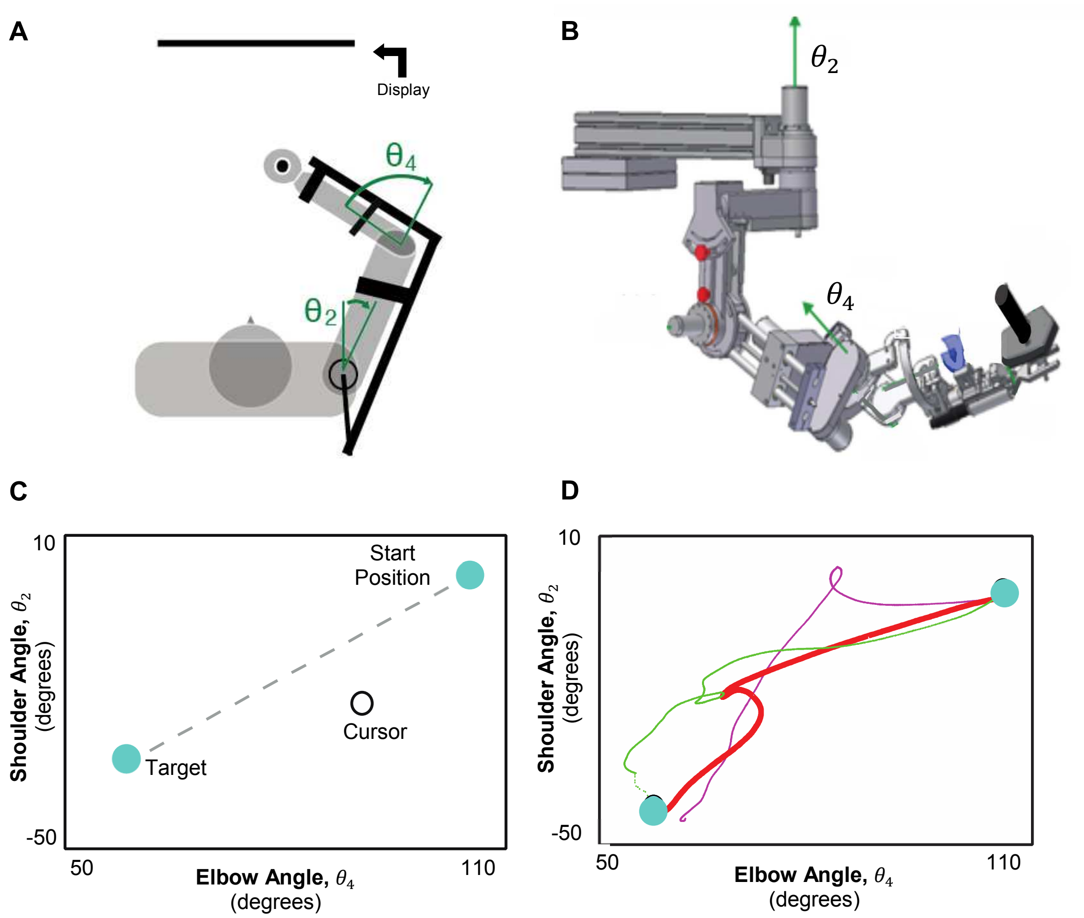


Figure 11: Experimental Setup. Participants performed a planar reaching task using the ARMin exoskeleton device. (A) Overhead view of the experimental setup with ARMin device locked in a planer position with vertical display, (B) Visual feedback of novel task condition where the cursor is controlled by joint angles, targets as they appeared on the visual display, (C) Schematic diagram of ARMin device, (D) Representative trajectories of participants initially exposed to novel joint-controlled task.

Participants were asked to reach in a straight line to the target. As soon as the target (blue sphere) appeared on the screen, participants could begin the reach. Participants were allowed to rest in the target before initiating the next reach. After completing a reach, the participant received feedback of movement time based on the color of the target. An ideal reach duration of 1.5 seconds would result in the target turning green upon completion of the trial. This time constraint was determined from pilot data where fast baseline reaching movements with feedback provided in a Cartesian space averaged around 1.5 seconds. The experimental task was to reach in a straight line in joint space coordinate system, where the position of the target was defined by angles of the shoulder and elbow (Figure 11B). Flanagan and Rao previously demonstrated that participants experienced errors initially, but could adapt to this nonlinear visual transformation after training (J. R. Flanagan & Rao, 1995). Conversely, in a Cartesian coordinate system, healthy participants would exhibit only negligible errors after they have become familiarized with the robotic device; thus, we chose this task to test how our training could improve learning for healthy subjects experiencing a novel task.

During the *Baseline Phase*, participants first became familiarized with the device by receiving real-time visual feedback of their endpoint position in a Cartesian reference frame on a vertical display (Unity 3D, Unity Technologies, San Francisco, CA). During the *Intermittent Exposure Phase*, participants were irregularly exposed to a joint-space coordinate system every one in seven trials. This was to test how participants first responded to the novel task without having the opportunity to adapt. During the first half of the *Intermittent Exposure Phase*, participants practiced with the same target set later used for training. The second half of the baseline phase involved a new set of targets that were later used to test generalization of training.

Table 1: Experimental Protocol

Phase #	Name	Condition	# of Trials	Catch Trials	Forces
1	Baseline	Cartesian	10	--	No
2	Initial Exposure	Cartesian	120	1:7 (Joint angle transformation)	No
3	Training	Joint Angle Transformation	70	--	Yes for Error Fields and EA Groups
4	Test	Joint Angle Transformation	23	--	No

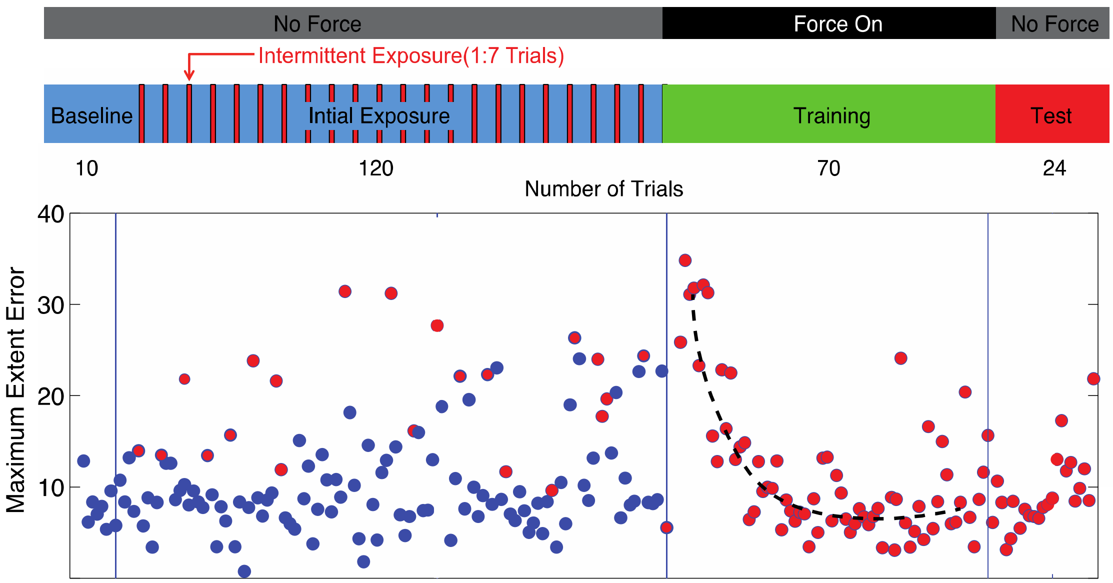


Figure 12: Experimental protocol (top), and representative errors across phases (bottom) for a subject from the EF Group where blue circles are for baseline reaching and red circles when reaching in joint-angle transformation. During training, the black dotted line represents the trials used to measure the time constant of error decay (Eq. 8).

Errors occurring during the intermittent exposure trials were characterized so that each participant had a unique profile of error's probability throughout the trajectory, otherwise known as their *error field*. All participants experienced a short pause prior to commencing training. Participants then trained for seventy trials (*Training Phase*) where the Error Field (EF) Group and Error Augmentation (EA) Group received forces and the Control Group received only visual feedback. Following training, participants were tested *(Test Phase)* on their ability to control the cursor with joint angles on the target set used during training and to unpracticed targets. The protocol is illustrated in Figure 12 and summarized in Table 1.

2.3. Subject customization

In order to customize a force field intervention, the distribution of movement error was calculated from reaches in which participants were intermittently exposed to a novel visual transformation requiring them to control the cursor with their joint-angles (Figure 11C). The nature of the task led to participants deviating both leftward and rightward from the straight-line path to the target (as shown in Figure 13).

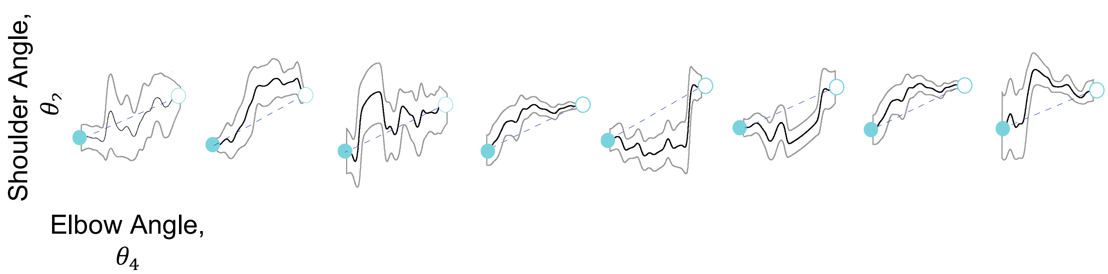


Figure 13: Errors differ across healthy subjects. Individuals have different error biases with reference to straight-line path (blue dashed line) to target. Dark lines indicate the mean trajectory and gray lines indicate 95% confidence intervals for participants in the Error Fields Group experiencing intermittent exposure to a joint-space configuration.

Error distributions were calculated for two measures of error: perpendicular (err_{perp}) and extent error (err_{ext}). At each time sample, a single Gaussian distribution was fit to the data, resulting in a time-based function that is continuous across the space of possible errors. The following steps denotes the characterization technique (illustrated in Figure 14):

1. Mean (μ) and standard deviation (σ) of joint-angle errors (err_{ext}, err_{perp}) were calculated across the trajectory from intermittent exposure trials in Phase 2.
2. Seventh order polynomials were used to fit the mean $f_{\mu}(t)$, and standard deviation $f_{\sigma}(t)$, across the first 1.5 seconds of the trajectory for both dimensions of error.

3. A single Gaussian distribution was created at every time sample to describe the probability, p, of different errors occurring. The continuous functions of mean and standard deviation were used to describe the single Gaussians at each location of time and error as shown in Eq. 5:

$$p(t, \overrightarrow{err}) = \frac{1}{f_{\sigma}(t) * \sqrt{2 * \pi}} \cdot e^{\frac{-\left(err - f_{\mu}(t)\right)^2}{2 * (f_{\sigma}(t))^2}} \tag{5}$$

2.4. Force Intervention

During training, the Error Fields (EF) and Error Augmentation (EA) Groups received perturbing forces that were based on their real-time perpendicular and extent errors. The amount of force was based on a scalar magnification of the error, represented by λ, such that the maximum torque applied would be 15 Newton-meters, well below the robot's safety limits. This factor was determined for each participant the EA and EF groups so that the 80% confidence interval of the theoretical forces would range from 5-15 Newton-meters. For the EA Group, the forces were generated based on the real time error:

$$\overrightarrow{F_{EA}} = \lambda \cdot \overrightarrow{err} \tag{6}$$

The forces applied for the EF Group were additionally based on the error probability (defined in Eq. 5):

$$\overrightarrow{F_{EF}}(t) = \lambda \cdot \overrightarrow{err} \cdot p(t, \overrightarrow{err}) \tag{7}$$

The forces occurred only during the first 1500 milliseconds of movement so that participants were able to reach the target and complete the movement. Forces applied to the EA group were also turned off after 1500 milliseconds.

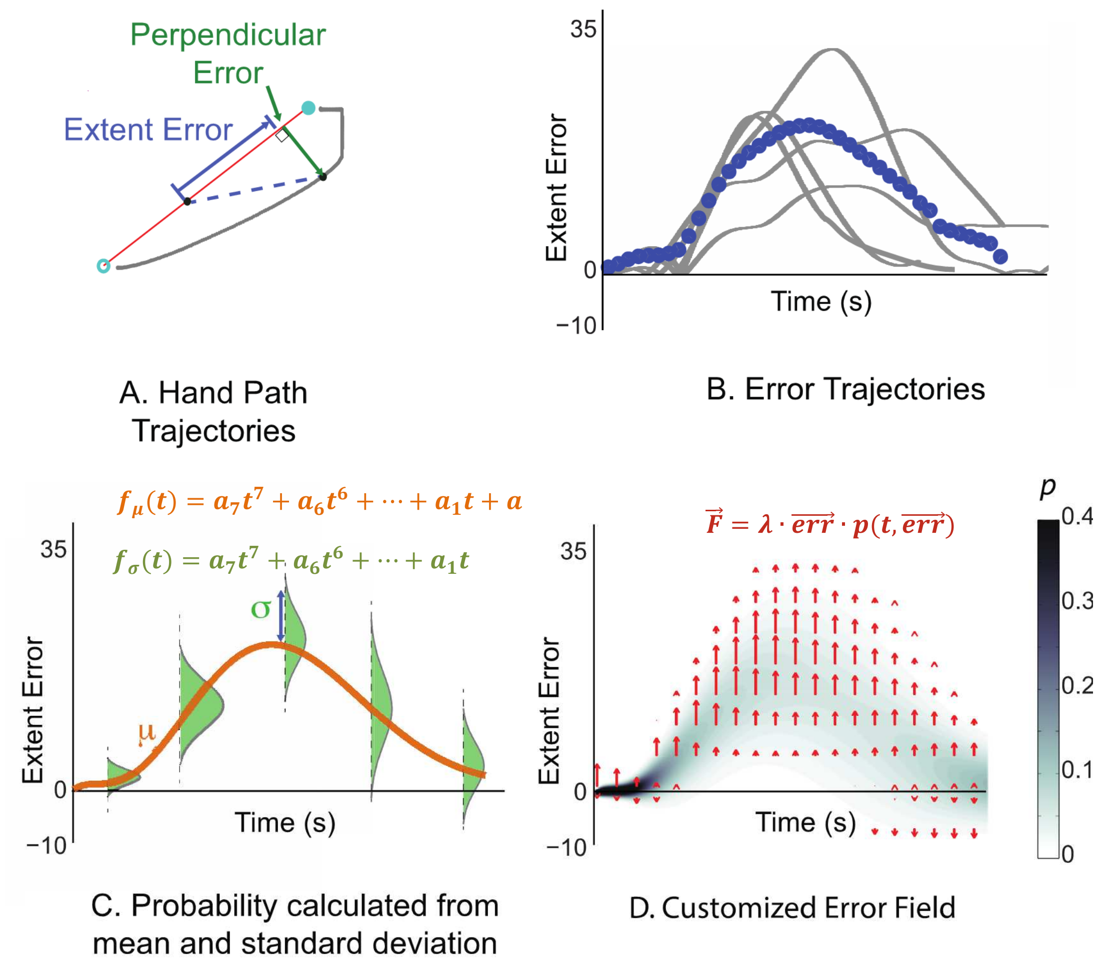


Figure 14: Process of customizing force training based on reaching errors. (A) Perpendicular and extent error are measured from intermittent exposure to joint angle control in Phase 1; (B) Mean (blue dots) and standard deviation (not pictured) are calculated across the trajectory; (C) Mean and standard deviation are fit with 7th order polynomials, allowing for Gaussian distributions to be created at each sample in time; (D) The probability of error dictates the amount of force (indicated by red arrows).

2.5. Error Analysis

We used two measures of error for assessing how participants learn. First, *perpendicular error* is the perpendicular deviation of the trajectory from the straight-line path, as shown in Figure 14A. If the ideal path between the origin and target is set as straight line along the horizontal axis, ($y_{path} = 0$), then the perpendicular error, err_{perp}, is the distance from the cursor to the ideal path. Secondly, we measured the extent error as the distance away from the ideal movement path measured by a minimum jerk model

(Flash & Hogan, 1985), also shown in Figure 14A, given an ideal reach time of 1.5 seconds. Individual and group error analyses were performed using each error measure separately. Errors from a representative participant throughout the experimental protocol are shown in Figure 12.

Change in Performance: To measure the effect of the interventation, or change in error, we took the average maximum extent and average maximum perpendicular error from initial exposure and final test trails (i.e. post-training). We subtracted the initial average error from the final average errors to determine the change.

Time Constant of Error Decay: The maximum extent and perpendicular errors occurring during the training phase (example in Figure 12) were fit as a function of trial number using a using nonlinear Nelder-Mead regression:

$$err_i = Ae^{i/B} + C \tag{8}$$

where err_i is the trajectory error for trial *i* within the training phase, *A* is the amount of learning (change in error due to training), *B* is the time constant indicating the number of trials for the error to decrease 67% of the way to the asymptote, and *C* is the asymptotic (steady-state) error value (previously described in (James L. Patton et al., 2013; Y Wei et al., 2005).

2.6. Prediction of final error distributions

To test the effect the intervention had on reducing errors, we wanted to evaluate how the final error magnitude and probability changed across the trajectory. Since the intervention is based on the initial distribution, we tested how the final error distribution changes with respect to the initial error distribution. We investigated three general cases of where the finals errors might occur, which would correspond to levels of force felt by the subject: 1) standard deviation = 0, mean error stays the same (participants would experience the maximum perturbations), 2) mean + 1 standard deviation, 67% of the data has shifted (participants would feel a small amount of force), and 3) mean + 2 standard deviations, 99% of the data has shifted (participants would feel zero forces). The exact amount of force felt at each of these levels varied by participant and the consistency of their initial error profiles.

If the intervention worked as planned, the location of final errors throughout the trajectory should be predicted by the initial error distribution. We determined the coefficient of determination for between the initial and final error for the three cases described above (*n*=0, 1, and 2):

$$R^2 = 1 - \frac{\sum_i (y_{initial} - f_{initial})^2}{\sum_i (y_{initial} - \bar{y})^2} \tag{9}$$

where $y_{initial} = \mu_{initial} - n \cdot \sigma_{initial}$, $f_{initial} = \mu_{final} + n \cdot \sigma_{final}$, and $\bar{y} = \frac{1}{1500} \sum_1^{1500} y_{initial}$.

Using the results of the model, we calculated the mean distance, *d*, between the locations of the initial and final error distributions using Eq. 10 below to verify the model prediction.

$$d(t) = \left| \mu_{initial}(t) - \sigma_{initial}(t)) - (\mu_{final}(t) + \sigma_{final}(t))) \right| \tag{10}$$

2.7. Statistics

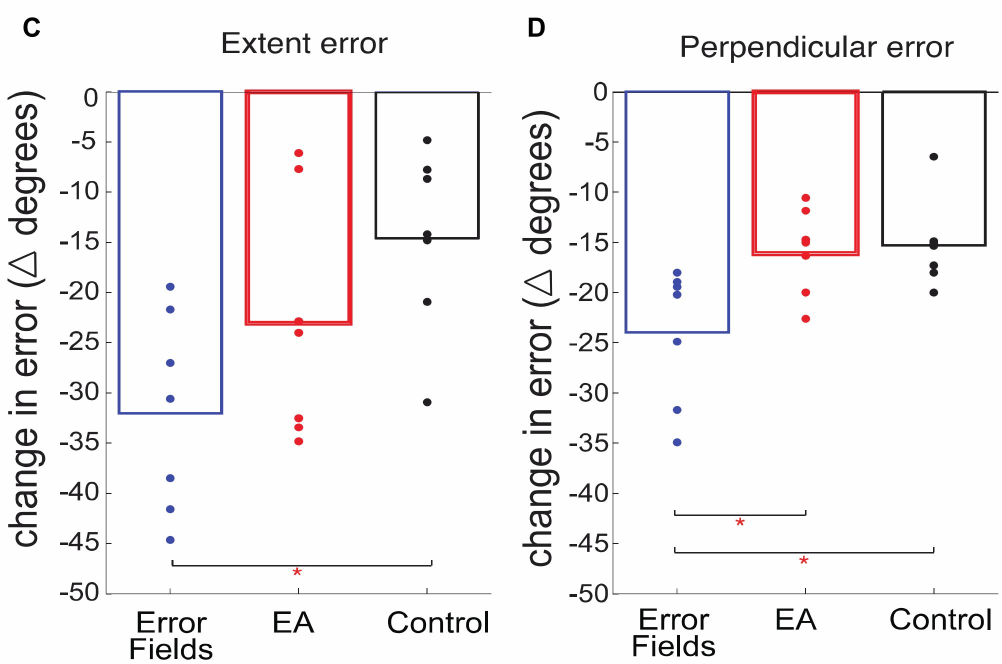
The significance for performance analysis was assessed first using repeated measured analysis of variance (ANOVA) and followed with paired t-tests to test the difference between groups. We used *Bonferroni-Holm* corrections for post hoc pair-wise comparisons.

3. Results

The EF Group received force field training that was augmented based on the probability of a particular error occurring. We compared the effect of the intervention to the EA Group, who received forces scaled to their errors, and a Control Group that trained with a null field (no force). Initial errors for all subjects were tested to determine initial skill levels and no difference was found between groups.

Differences in training forces: We compared the average forces received by each group during the start of training to ensure that the EF forces were initially scaled to match the magnitude of the EA forces. During the first five trials, peak force was similar for both the EA and EF Groups (8.7 ± 1.7 N and 8.2 ± 1.8 N respectively), but differed in location during the trajectory (570 ± 330 ms and 192 ± 90 ms respectively).

Change in Error: We measured the change in maximum perpendicular error and maximum extent error between the initial exposure to joint angle control and the final test (Figure 15C, Figure 15D). We found the decrease in error for the EF Group to be 32 ± 10 degrees for extent and 19 ± 18 degrees for perpendicular error. The change in error for the EA Group was 23 ± 12 degrees for extent and 16 ± 4 degrees for perpendicular while the change for the Control Group was 16 ± 10 degrees for extent and 15 ± 5 degrees for perpendicular error. These improvements in performance led to a significant change in both extent and perpendicular error between the EF and Control Group ($p=0.0098$ and $p=0.042$ respectively). The EF Group was significantly different than EA, with post-hoc corrections for only perpendicular error ($p=0.0392$).


C
Extent error
change in error (△ degrees)
0
-5
-10
-15
-20
-25
-30
-35
-40
-45
-50
*
Error Fields
EA
Control
D
Perpendicular error
change in error (△ degrees)
0
-5
-10
-15
-20
-25
-30
-35
-40
-45
-50
*
*
Error Fields
EA
Control

Time Constant of Error Decay: In terms of extent error, the amount of trials required for error to decay by 67% was 12±6 for the EF Group; lower than the 32±16 trials for the EA Group and 36±15 for the Control Group. This led to a significance of $p=0.0178$ across groups (0.0141 between EF and EA, and 0.0406 between EF and Control when corrected) as shown in Figure 15A. For perpendicular error, the amount of trials required for error to decay by 67% was 57 ±13 for the EF Group, 84±43 for the EA Group, and 106±43 for the Control Group, illustrated in Figure 15B. There was a significant difference between the EF Group and Control ($p=0.044$), but no other effect was seen between groups.

Generalization of Training to Unpracticed Targets: We measured the change in error reaching to unpracticed targets between intermittent exposure and post-training. All participants had lower reaching errors, but we found no statistical difference between groups.

Prediction of Final Errors: To determine the relationship between initial and final errors we measured the coefficient of determination (R^2) between the initial and final error distributions. We entertained theoretical models that were based on the standard deviation of the mean error across the entire trajectory. We found that the best fit (in terms of R^2 values) occurred when comparing one standard deviation below the mean initial error to one standard deviation above the mean final error. The EF Group had larger R^2 values for all three tested cases (where the final predicted errors are 0, 1, and 2 standard deviations of the mean) than the EA and Control Groups.

To test the model we measured the average distance between the initial error and prediction of final errors for the best performing case (mean plus 1 standard deviation).

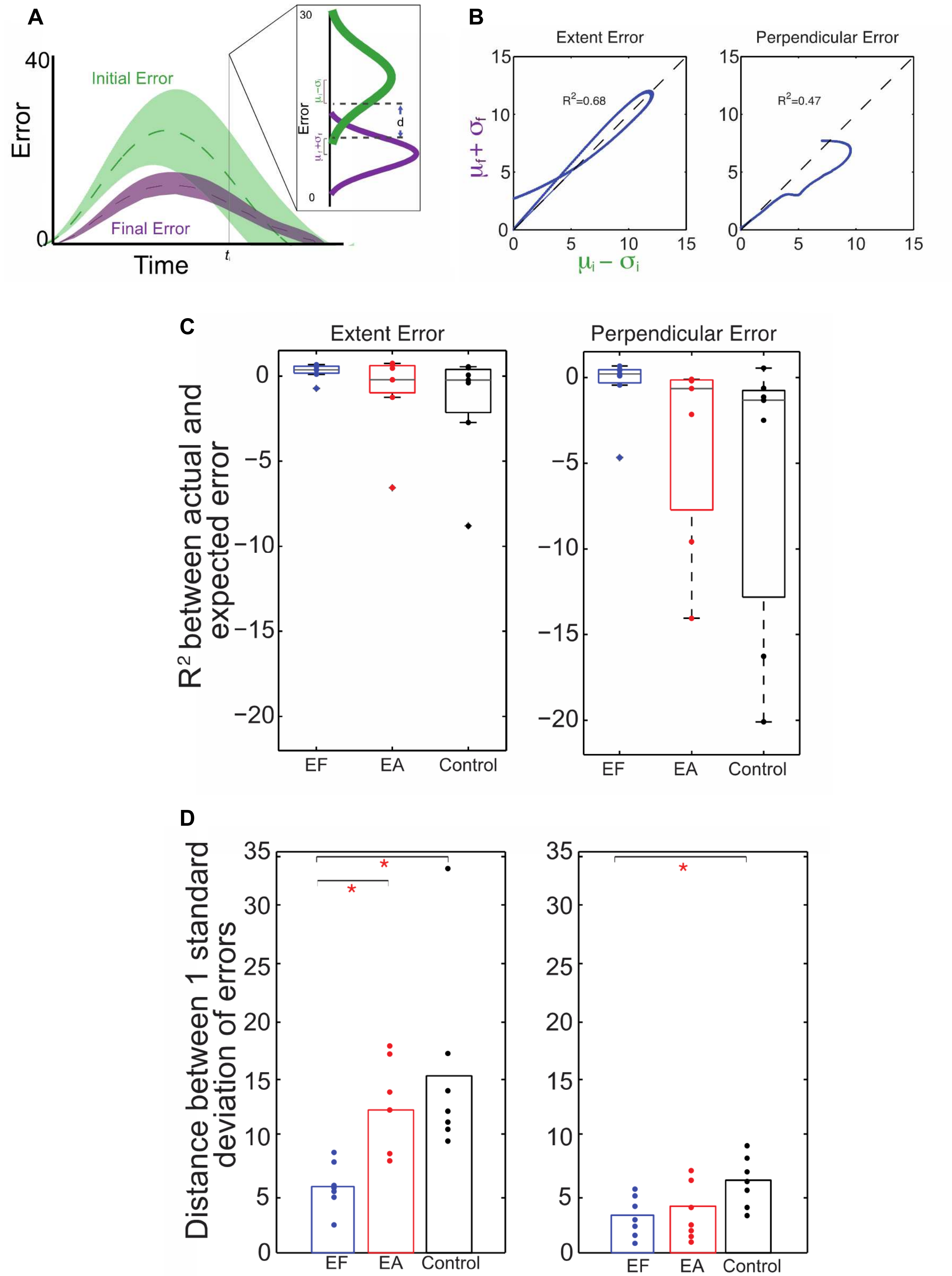


Figure 16: Results of model predictions for error change. A) Cartoon depiction of initial (green) and final (purple) distribution of error, where final errors were nonzero. B) Example subject showing the correlation between errors located 1 standard deviation from the mean with an ideal model line, and C) the model prediction Coefficient of Determination (R^2) values across groups; D) Distance between predicted and actual errors averaged across the trajectory and compared between groups.

We found the difference in extent error to be an average of 6 degrees less for the EF Group than the EA Group (p=0.009) and 10 degrees less for the EF Group than the Control Group (p=0.032), and no statistically significant difference between the EA and Control Group. For perpendicular error, we found the error for the EF Group to be 6 degrees less for the Control Group (p=0.0262), and no detectable significance between the EF and the EA Groups and between the EA and the Control Groups.

4. Discussion

In this study, we investigated a technique to customize error augmentation training based on distributions of error. Previous error augmentation (EA) studies have tested the optimal gain to amplify error during training (James L. Patton et al., 2013; Y Wei et al., 2005). Here we tested a method that varied gains across the trajectory according to the error probability. This *error field* approach involved scaling the amount of force applied by the robot based on the probabilities of reaching errors, such that unlikely errors led to weaker perturbing forces than frequently repeated errors. We found that participants receiving error field training had a greater improvement in performance. In addition, their errors decayed at a greater rate than the groups that received standard error augmentation or null field training.

Our primary result was a greater change in error for the EF Group for both perpendicular and extent error (Figure 15C & Figure 15D). Previously, studies from our group have shown the success of error augmentation over repetitive practice (Patton, Kovic, et al., 2006; James L. Patton et al., 2013; Y Wei et al., 2005). Here the EF Group demonstrated significant improvement over the EA Group for *extent error*, but no significant differences in perpendicular error. The fact that error reduced differently by direction might be explained by the so-called uncontrolled manifold (UCM) hypothesis, where some variables are stabilized at the cost of others (Latash, Scholz, & Schoner, 2002). In this task, extent errors are less devastating to task success than perpendicular errors. Extent errors are essentially timing errors that do little to change the task outcome, and hence might be given less priority in the learning process. However, we believe that the added benefit of our treatment focused attention onto extent errors, allowing participants in the EF Group to selectively decrease a distinct aspect of error that would not otherwise have been possible. In other words, the EF approach might be used to bias learning tendencies away from what is predicted by typical processes, such as the UCM.

The error field group learned the fastest (Figure 15A & Figure 15B), providing further support for the benefit of the error fields approach. According to our design, at the beginning of training, the errors that were most consistent with those observed during characterization received the largest forces. One possibility for this rapid decay in error is that participants responded to forces as if it there were a virtual wall in attempt to avoid force field interactions. Thus, participants received the greatest perturbing forces when they maintained their original systematic errors and thereby moved to regions of low probability faster in order to receive smaller augmenting forces. While participants in the EA Group also experienced low forces at regions of lower error, they still receive significant perturbing forces as they shifted from their original movement patterns (the EA approach does not “forgive” high errors with low probability). A secondary explanation is that the EF Forces provided more relevant sensory cues. By only exaggerating original movement patterns, participants were able to rapidly converge on a solution.

One possible explanation for the improved performance of the EF Group over the EA Group was that they received lower forces, however, the magnitude of forces were scaled such that they would be equal if participants maintained the same errors during training as they did during intermittent exposure. The subsequent changes in force level are thereby reflective of the divergent learning strategies between the EF and EA Groups. A secondary explanation could be that participants learned the optimal impendence needed to resist the forces, as previously shown by Burdet et al. (Burdet, Osu, Franklin, Milner, & Kawato, 2001). However, once participants in the EF Group began to shift away from their initial error profiles, they received lower forces--preventing the need for them to co-contract in order to reach.

While we established group differences in learning, we wanted to know whether the structure of error field training specifically influenced the participants' learning. We developed a model prediction based on the formula for the forces used in the intervention (a single Gaussian) to test if learning is observed throughout the trajectory or if our approach simply caused general learning effects (Figure 16A). When comparing the mean initial errors to the final errors, we found that the upper 33% of final error distributions were aligned with the lower 33% of the initial error across all participants (Figure 16B), suggesting that errors along the trajectory scale statistically following training. We saw this correlation of initial and final distributions was significant for the EF Group, but random for both the EA and Control group (Figure 16C). Using this model prediction, we could see that the structure of the intervention was evident in the final distributions for the EF Group, where the final distributions overlapped the initial distributions by the lowest amount (Figure 16D). Therefore, this technique was able to drive a predictable and specific change in behavior, giving us insight to the value of customization in training.

Although the error field treatment may have been the most beneficial for this experiment, it did not completely eliminate errors (Figure 16A). We believe that this is because the customization was based only on the initial characterization phase and does not capture new error patterns that emerge during training. To truly capture the "challenge point" required for optimal learning and correct new errors, we would need to increase task difficulty as the training progresses (Guadagnoli & Lee, 2004). Future implementation of this technique might thereby include repetitive re-characterization of error fields as the training progresses, which would ensure that smaller distributions of error that occur later in training will also be ushered closer to zero error. Such re-characterization techniques have been successful both with adaptive resistance training (Grimby, 1985) and adaptive assistance training (Klamroth-Marganska et al., 2014).

These results build upon previous studies on error augmentation techniques to enhance motor learning (Marchal-Crespo et al., 2014; Milot et al., 2010; James L. Patton & Ferdinando a Mussa-Ivaldi, 2004; Reisman et al., 2009; Y Wei et al., 2005). Our two most striking findings were (1) error fields improved on previous methods (Y Wei et al., 2005), and (2) error fields' subject-specific training conditions addressed each person's unique error profiles (Figure 13). This result was true in spite of widely differing initial errors in our subjects. It is also important to mention that error fields accommodated differences across the trajectory as well as movement direction. This indicates a detailed level of customization, more than simply adapting to each subject. It is possible that in some scenarios error probabilities are common across individuals, in which case, error fields might not have needed such customization. Furthermore, there may be some tasks where probability distributions are indistinguishable for certain directions, and error fields can be consolidated. These findings reveal the ability of an intervention to take advantage of movement statistics to facilitate training. Emphasizing useful information during motor learning is believed to be already a natural process used by the nervous system (D. J. Herzfeld & Shadmehr, 2014; Y. Wei & K. P. Kording, 2009). In such Bayesian learning models, relevant movement errors drive adaptation while spurious errors are discarded. We believe that our intervention promotes this process by emphasizing the most useful information (in this case, frequent reaching errors). Recent work by Herzfeld et al. (David J Herzfeld, Vaswani, Marko, & Shadmehr, 2014) further showed that prior experience of error governs the amount of learning. In our current paradigm, we are ensuring that only the task-relevant errors are amplified during training. In the case of the EF Group, change in error was observed only in regions where errors were familiar through previous experience. Furthermore, these changes align with recent findings from Takiyama et al. who showed that people learn most when they can expect the errors (Takiyama, Hirashima, & Nozaki, 2015). Through our modeling efforts (Fig. 5), we were able to show that enhancing likely movement errors resulted in the greatest learning payoff. Many studies of goal-directed movements focus on models of adaptation based on trial-to-trial error. We suggest that a more comprehensive approach would be to consider how probabilities of error throughout the trajectory change during learning.

This paper represents an important next step in advancing error augmentation methodology for motor skills training. The approach we used in this study can easily be adapted for customized therapy to accommodate wide differences in movement errors across patients, even when the neurophysiological sources of error are unknown. We believe that this strategy of focusing the intervention on error probabilities is applicable to any training situation where error can be measured and characterized. Beyond enhancing training, our findings support the idea that the nervous system relies on statistical error information for learning. Understanding the mechanisms of learning could then provide both the inspiration and the mathematical framework for better forms of intervention.

5. Acknowledgements

We would like to thank Zachary Wright, Ismael Seanez, Doman Novak, Georg Rauter, Urs Keller, Maya Kamber, and Peter Wolf. This work was supported by NINDR01NS053606 and NCCR Robotics.

V. CUSTOMIZED THERAPY USING DISTRIBUTIONS OF REACHING ERRORS

Moria Fisher Bittmann, Felix C. Huang, James L.Patton

While there have been recent success with robotic therapy approaches, differences in motor impairments across stroke survivors motivate the need for customized therapy. Our latest work with healthy participants used the likelihood of one's error to construct an individualized force field training environment we termed an *error field*. Likewise, we believe these error statistics could characterize individual motor impairments for stroke survivors. Here in a pilot study, we investigated this technique in rehabilitation therapy following stroke. We tracked three stroke survivors across multiple days using error field training, and found that individuals' errors reduced for all target directions across sessions. We also found evidence of improvement that reflected the effect of the training forces. These results provide encouraging preliminary evidence that error field training can be valuable for both characterizing deficits and custom-tailoring therapy.

1. Introduction

Following a stroke, more than two-thirds of survivors have reduced arm function (Jorgensen et al., 1999). There are large range of motor deficits that occur following a stroke, and the severity of such impairments can vary quite widely (Bushnell et al., 2001; Kalaska et al., 1983; Lazarus, 1992; Mercier et al., 2004). Stroke survivors can develop abnormal contraction coupling, or "synergies," that are based on the arm's orientation (Beer et al., 2004). Robotic therapy can offer many modes to training beyond conventional therapy such as high repetition, applying assistance-as-needed or gradually increasing intensity (Brewer, McDowell, & Worthen-Chaudhari, 2007; Jorgensen et al., 1999; Reinkensmeyer et al., 2004). Several studies have used adaptive control algorithms to account for individual differences where they adapt assistance for an individual on an as-needed basis, similar to a therapist (Vergaro et al., 2010; Wolbrecht, Chan, Reinkensmeyer, & Bobrow, 2008). However, there have been limitations to their success to generalize or lead to long-term functional improvements (G Kwakkel, Kollen, & Krebs, 2008; Mehrholz, Hädrich, Platz, Kugler, & Pohl, 2012). While these approaches ensure participants are able to complete the task, they do not address the individual impairments.

Recent studies have shown training benefits using error augmentation (EA), where error is magnified via haptic or visual feedback. Error augmentation techniques have led to improved clinical measures and reduced errors in tasks ranging from reaching, walking, and stepping (Abdollahi et al., 2014; Milot et al., 2010; Patton, Stoykov, et al., 2006; Reisman et al., 2009). Researchers believe that by drawing more attention to errors, participants are more likely to pay attention to and correct their mistakes. The optimal method for applying EA, however, remains unknown. Studies suggest that the appropriate gain might differ based on individual abilities (Milot et al., 2010; Shirzad & Van der Loos, 2012). In a recent study focusing on distributions of movements during motor exploration, Huang and Patton found that certain motor deficits were unique to each stroke survivor (Felix C. Huang & James L. Patton, 2013). Likewise, we believe there exists distributions of error during goal-directed movements that are unique to each participant.

Our previous work with healthy participants has shown that force field training based on participants' unique error statistics, or *error fields*, improved performance in a novel visual transformation (M. E. Fisher, F. C. Huang, V. Klamroth-Marganska, R. Riener, & J. L. Patton, 2015). Building upon traditional EA approaches, we used each participant's *error likelihood* to dictate the magnitude of augmented forces applied during training. This ensured that the intervention focused on errors made most frequently, and ignored spurious or random errors. We believe that such statistics of movement errors can also be used to customize the "motor relearning" of therapy for stroke survivors so that training can focus on the unique regions where frequent movement errors occur.

This study investigated how such error-defined customization of robotic therapy might reduce reaching error in the chronic stroke subject. We hypothesized that this *error fields* technique might not only characterize error tendencies of each subject, but also restore reaching ability across days of training. In this test case study, we evaluated three participants over five sessions of error field training, where training forces each day were updated on their baseline reaching movements. Prior to receiving training forces, participants trained with repetitive practice in a null field. We hypothesized that error field training could reduce reaching errors better than practice alone.

2. Methodology

2.1. Human subject experiment

Three stroke survivor subjects participated in this study at the Rehabilitation Institute of Chicago (Chicago, IL). The main inclusion criteria were 1) chronic stroke (8+ months post-stroke), 2) hemiparesis with moderate to severe arm impairment measured by the

Fugl-Meyer Assessment UE (FMA-UE score of 15-50, (Fugl-Meyer, Jaasko, Leyman, Olsson, & Steglind, 1975) , 3) primary cortex involvement. The exclusion criteria included 1) severe sensory deficits in the limb using the Two-Point Discrimination Test (Callahan, 1990), 2) severe spasticity (Modified Ashworth of 4 preventing movement (Ashworth, 1964)) and, 3) aphasia, cognitive impairment or visual deficits that would influence their ability to perform the experiment tasks. All participants provided informed consent in accordance with Northwestern University Institutional Review Board. Participant information is summarized in the table below, where clinical measures listed are from the affected arm.

Table 2: Summary of stroke survivor participants

Participant	Age (years)	Years past stroke	Lesion Type	Affected hand	AMFM		ARAT		BBT	
					Pre	Post	Pre	Post	Pre	Post
1	62	8	Hemorrhagic	R	22	23	17	17	6	8
2	60	10	Ischemic	R	21	22	16	16	7	8
3	60	2.5	Ischemic	L	19	19	20	20	10	8

2.2. Experimental conditions

Participants were asked to move a planar force feedback device, also called a manipulandum, as described in previous work (Scheidt, Reinkensmeyer, Conditt, & Mussa-Ivaldi, 2000), see Figure 1A. Real-time feedback of the handle position was provided to subjects using a large video display orientated upside-down and projected onto a mirror above the participant’s hand. The mirror height was positioned such that the visual feedback appeared to be co-incident with the hand. Participants were seated such that the shoulder of their affected arm was centered in the workspace, approximately 38 centimeters away from the robot. The wrist was secured in a brace connected to the robot handle so that only movement of the elbow and shoulder was possible. The brace was supported with a planar arm support. The robot control and instrumentation was mediated with a Simulink-based XPC Target computer, with a basic rate of 1 kHz. Data was collected at 200 Hz. The robot generated torques that compensated for some of inertial effects of the robot arm during all experiment phases.

Goal-directed reaching: Participants reached to ten target locations arranged in a pentagram pattern 18 cm apart (Figure 17A). After completing the reach, they received feedback of their movement time, where color indicated if the movement was too slow (yellow), too fast (red), or within the desired range (green). The ideal movement time was set at 750 milliseconds.

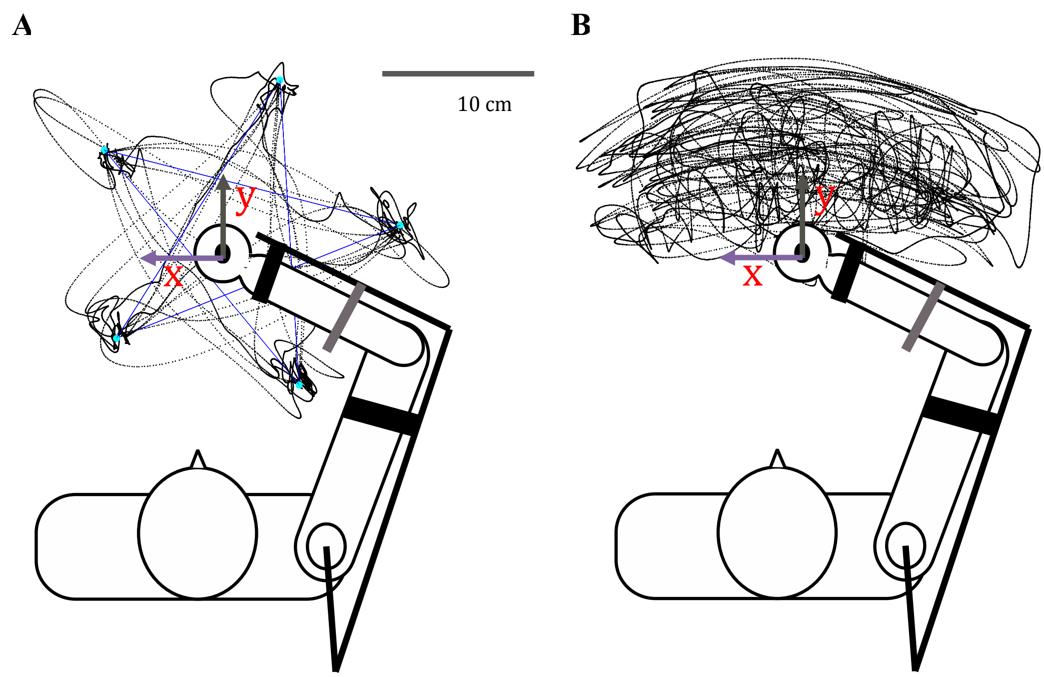


Figure 17: Overhead view of experimental conditions performed with planar manipulandum and arm support: (A) Participants performed goal-directed movements to 10 targets (each target represents two directions) and (B) freely explored the workspace during motor exploration trials.

Motor exploration: Participants were instructed to move the robot handle to various positions, speeds, and movement directions within the robot workspace (0.6 meters x 0.4

meters). They received continuous feedback of their cursor with real-time velocity represented as a "tail" trailing the cursor. A trial consisted of two cumulative minutes of movement with a speed greater than 0.04 meters/second. Following the trial, participants received a score that reflected the variety of movement patterns as previously described in (Felix C. Huang & James L. Patton, 2013; Wright et al., 2015).

2.3. Experimental protocol

At the beginning of each session, participants were asked to make goal-directed movements in a null field (6 trials in each direction) with interspersed epochs of motor exploration (1 in every 10 trials, 6 total per session). Training sessions were spaced every other day from each other, while initial assessments were spaced one week prior and one week post training. Participants trained in a null field (Session 2), prior to force field training (Session 3-7). Following characterization on Session 3-7, participants experienced Error Field training -- perturbing forces based on the most common errors exhibited during baseline. See Figure 18 for a full description of the protocol and Table 3 for the error field training schedule.

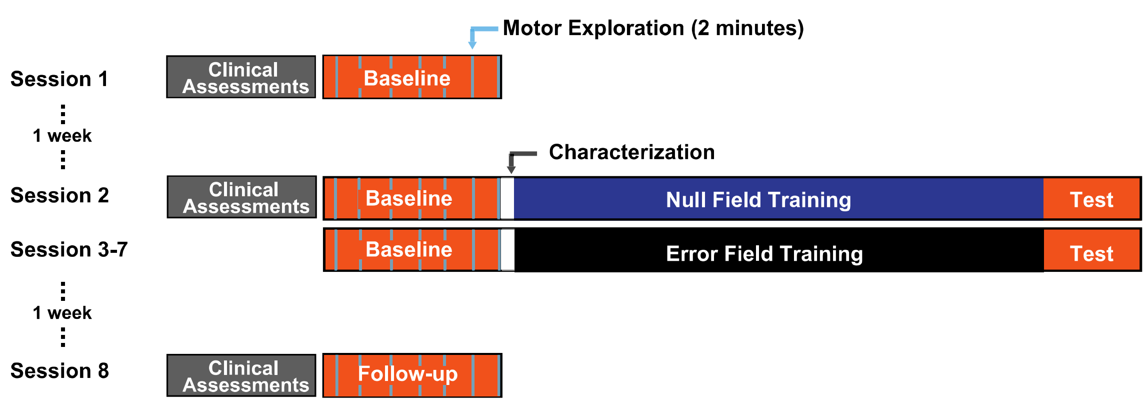


Figure 18: Experimental protocol across sessions

Before interacting with the robot on Session 1, 2, and 8, a physical therapist evaluated each participant. The evaluation including the following stroke assessments: Fugl-Meyer

Assessment (FMA), Action Research Arm Test (ARAT), Box and Blocks Test (BBT) and the Intrinsic Motivation Inventory (IMI) questionnaire.

Table 3: Force training session protocol (Session 3-7)

Phase	Name	Number of trials	Condition
1	Baseline	60, 6 motor exploration trials	Null field
Characterization			
2	Training	200	Error field (forces)
3	Test	60	Null field

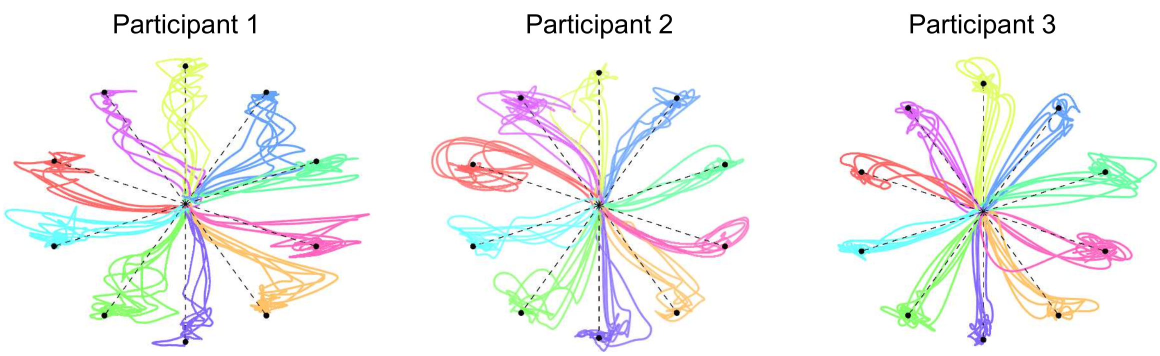


Figure 19: Initial error trajectories during characterization (session 1) for each participant. Characteristic movement errors vary with target direction and are not the same in participant. Note we have re-aligned the origins of all reaches for illustration purposes.

2.4. Force field customization

Baseline reaches at the beginning of each training day served as the basis for the design of the customized forces used for that session (see Figure 19). Distributions of error were calculated using the perpendicular distance from the straight-line path (*err*) with respect to the distance, *d*, along the path. In contrast to the previous study with healthy participants (M. E. Fisher et al., 2015), we chose path distance as the ordinate to parameterize error. Path distance was used instead of time because we discovered that stroke subjects initiated and timed their movements inconsistently. This path-dependent approach was nearly as accurate and avoided the potentially unwieldy forces associated with misaligned time-dependent forces.

The process for determining the *error field* is described below, for every target direction independently (see Figure 20 for example):

a) The mean and standard deviation of error across the trajectory were fit with seventh order polynomials, creating functions $f_\mu(d)$ and $f_\sigma(d)$ for the mean and standard deviation respectively.

b) The probability of the error occurring at each distance, *d*, along the trajectory was calculated in real-time by using a single Gaussian distribution:

$$\boldsymbol{p(d,\overrightarrow{err}) = \frac{1}{f_\sigma(d) * \sqrt{2*\pi}} \cdot e^{\frac{-\left(err - f_\mu(t)\right)^2}{2*(f_\sigma(d))^2}}} \tag{11}$$

c) A scaling factor, λ, was determined using the 80% confidence interval bounds of the error and finding the value such that the maximum force does not exceed 15 N.

d) Forces were applied based on the error probability and real-time measured error:

$$\boldsymbol{\overrightarrow{F_{EF}}(d) = \lambda \cdot \overrightarrow{err} \cdot p(d,\overrightarrow{err})}. \tag{12}$$

Forces did not begin until participants left the origin and ramped down to zero when participants were within 1 centimeter of the target.

2.5. Data analysis

Performance error

We used the initial characterization phase at the beginning of each session to measure the change in error either due to null field training or error field training. We also measured the movement time and peak velocity for each movement.

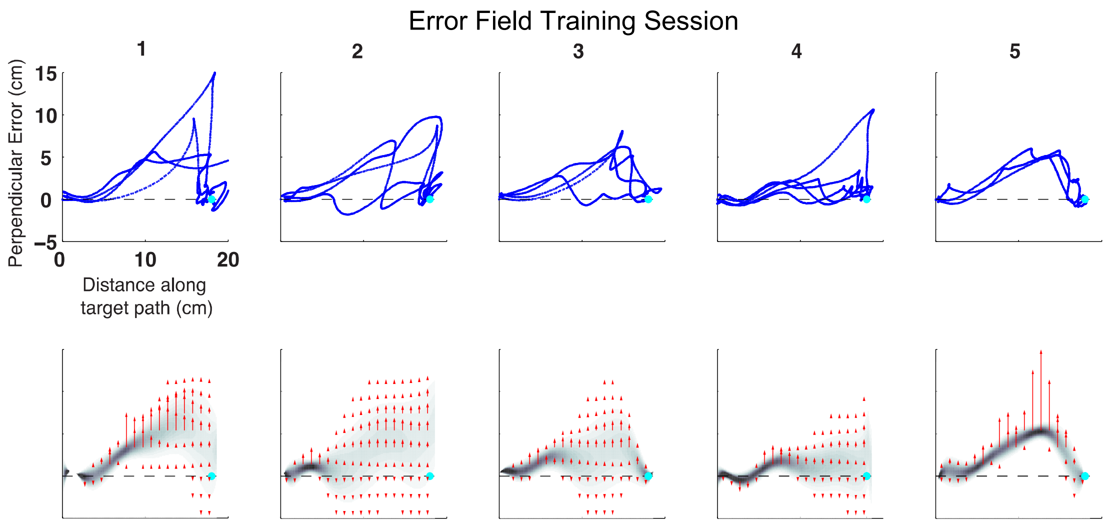


Figure 20: Customization of forces. Error field training is customized using each day's initial baseline errors (Phase 1). Top row shows the error trajectories across day for Participant 1, Target Direction 2. Bottom row shows the respective error distributions and resulting force field (red arrows) for the five error field training sessions.

Prediction of error change

We further explored the effect of the intervention on the change in error throughout the trajectory, previously described in Chapter IV. We entertained three possible models that would describe the location of the final distributions (in this case, we used the initial error of the following session to avoid any post-training fatigue effects) based on the initial mean, μ_i and standard deviation, σ_i, outlined in Table 4. These models are based design of the error field, where one standard deviation (σ) from the mean (μ) would equate to a low amount of force.

Table 4: Models for Error Change

Model #	Final Error Predication
1	$\mu_i - \sigma_i$
2	μ_i
3	$\mu_i - \mu(\sigma_i)$

We determined the coefficient of determination between the prediction, $f_{initial}$, and final error, $y_{initial}$, for the three model candidates to measure the change between session 2 and session 3 (change due to null field training) and session 3 to session 4 (change due to Error Field training).

$$R^2 = 1 - \frac{\sum_i (y_{initial} - f_{initial})^2}{\sum_i (y_{initial} - \bar{y})^2} \tag{13}$$

Using Model 1, we evaluated the success for all possible combinations across sessions to test the uniqueness of the model to predict errors beyond the following session.

Generalization to motor exploration

To test the transfer of training to participants' performance during the motor exploration condition, we calculated the change in velocity distribution across sessions (method is previously described in (Wright et al., 2015)). To gauge the expansion of reaching ability, we first calculated the 50th percentile contour of 2-D velocity and then found the coverage of data within the contour boundary. This value represents the estimated area of movement tendencies in the velocity domain.

Statistics

We performed a 2-way ANOVA for each participant using factors of target and session. Post-hoc t-tests were used to perform pairwise comparisons between sessions and corrected using the Bonferroni-Holm method. All analyses were considered significant at an alpha level of 0.05.

3. Results

The initial error magnitude depended on target direction

Our ANOVA results indicated that target direction and subject were significant factors on error across sessions ($p<0.001$). Further analysis of within subject target effects revealed that participants' reaching errors in the first (baseline) session varied across target directions (1-way ANOVA on target direction; $p<0.001$ for Participant 1, $p<0.001$

for Participant 2, p=0.016 for Participant 3) – see initial trajectory errors in Figure 19. Each participant appeared to be unique in the manner in which these initial errors varied across direction. At the end of training, targets were significantly different for Participant 1 (p < 0.001) and Participant 3 (p<0.001). These subject- and direction-specific errors reduced across training. In fact, errors no longer differed across movement direction by the end (session 8) for Participant 2 (ANOVA session – target interaction, p>0.05).

Performance improved across training

We found that all subjects significantly improved (decreased reaching error) between the initial baseline reaching on session 2 (start of training) to the final evaluation session on session 8 (see Figure 21). The error decreased an average of 2.8 cm for Participant 1 (40% error reduction, p=0.0152), 1.3 cm for Participant 2 (35% error reduction, p=0.0074), and 0.9 cm for Participant 3 (18% error reduction, p=0.0486).

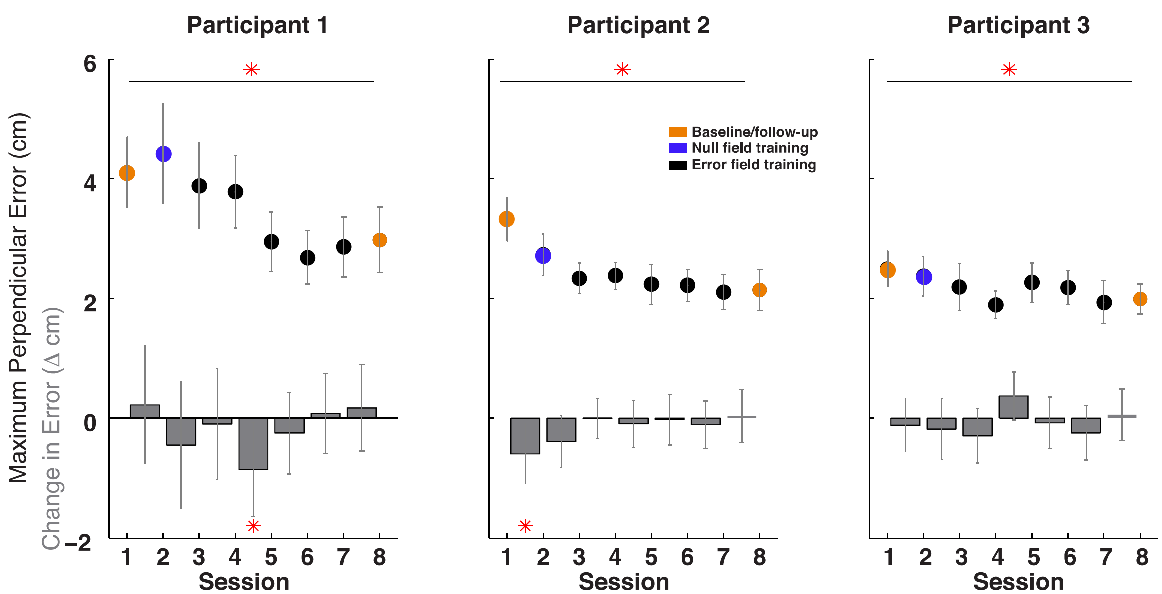


Figure 21: Error change across sessions. Mean initial error from the characterization phase of each training session, error bars represent the 95% confidence intervals for error change across all target directions. Gray bars represent the change in error between subsequent sessions. Significant overall change in session-to-session error is designated with a red asterisk.

While this preliminary study did not have a control group, we were able to compare sessions with to sessions without intervention. We compared the change in error due to one session of null field training (session 2 to 3) with that of one session of error field training (session 3 to 4) to see if one type of training had a greater effect. We found all subjects significant reduced error for both these training conditions ($p=0.001$, $p=0.027$, $p=0.043$ for session 2-3 and $p=0.001$, $p=0.037$, $p=0.025$ for session 3-4), but there were no detectable differences in error drop between these two conditions ($p>0.05$).

We also analyzed changes in movement time and peak velocity (Figure 22) in order to understand these error changes in the context of a well-understood motor control principle –the speed-accuracy trade-off (Fitts, 1954). We expected that as error decreased, participants would reduce movement time and increase peak velocity. Participant 1 showed no change in movement time, but had an average change in peak velocity of 0.1 m/s ($p< 0.001$). Participant 2 showed significant session-to-session interactions for movement time, but no overall change. There was a significant decrease in peak velocity of 0.2 m/s ($p<0.001$). For Participant 3, movement time changed from session 1 to session 8 by 150 ms ($p<0.001$), while peak velocity increased by 0.1 m/s ($p<0.001$).

Generalization to free exploration was positive

We used trials where participants freely explored the workspace (motor exploration) to test if error reduction had an effect on velocity distributions. Participants began at the same initial velocity coverage (1 ± 0.5 m/s). We detected no change in velocity coverage following training (measured at session 8) for Participant 1, but found a significant increase of 1 m/s for Participant 2 ($p=0.006$) and an increase of 3.7 m/s for Participant 3 ($p<0.001$).

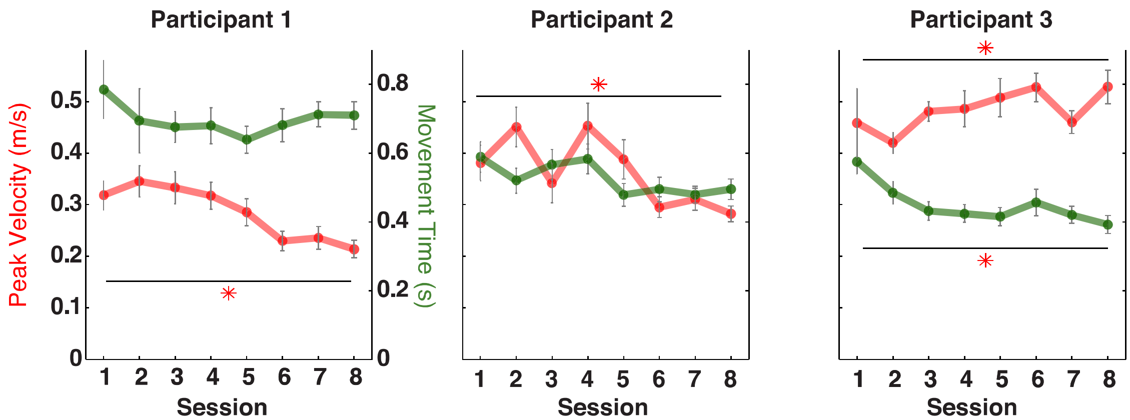


Figure 22: Change in movement time (green) and peak velocity (red) across sessions. Participant 1 and Participant 2 showed no overall change in movement time but decreased peak velocity (Δ=-0.1 m/s, p<0.001 and Δ=-0.2 m/s, p<0.001). Participant 3 decreased movement time by an average of 150 ms (p<0.001) and peak velocity increased by 0.1 m/s (p<0.001).

Prediction of error from initial distribution

Our modeling analysis revealed the best predictions of error change for the case that is based on the structure of training forces (Model 1). When we compared model predictions for all three models (Figure 23), we found only positive R^2 values for all three participants for the Model 1's prediction of change due to error field training (mean R^2=0.39±0.17, 0.64±0.21, 0.30±0.27). Model 2 showed limited success in predicting the change in error following error field training for Participants 1 and 2 for error field training (R^2=0.09±0.7, 0.11±0.9). See Table 5.

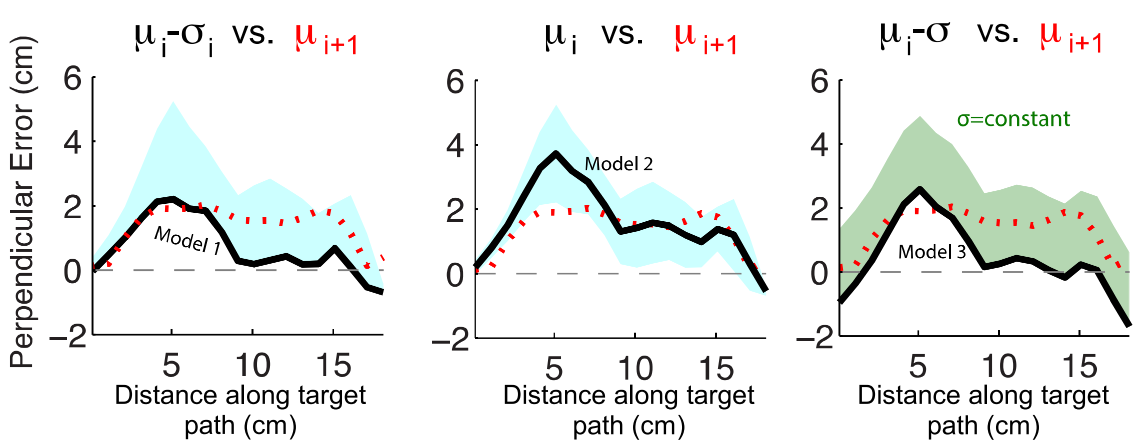


Figure 23: Depiction of model predictions (black line) where the initial distribution is used to predict the mean error from the following session (red dotted line). Model predictions were performed for error following one session of repetitive practice and error following one session of error field training.

Table 5: Model prediction values. The mean and standard deviation of model predictions values (R^2) shown are calculated across 10 target directions. For control comparison, we provide how well the model performed in predicting change due to null field training. Shaded boxes designate positive R^2 values.

R^2	Model 1		Model 2		Model 3	
	Error field Session 1	Null field training	Error field Session 1	Null field training	Error field Session 1	Null field training
Participant 1	0.39 ±0.17	-0.53 ±1.4	0.09 ±0.7	-2.0±1.9	-0.45 ±1.1	-5.5±12
Participant 2	0.64 ±0.21	-4.8±4.7	0.11 ±0.9	-3.4±5.4	-0.26 ±1.4	-14.3±15
Participant 3	0.30 ±0.27	-3.0±3.0	-3.0 ±6.6	-0.6±1.4	-2.9 ±3.5	-1.3±1.4

Model predictions across all possible sessions revealed no predicative power (average R^2 across target directions was negative). Model predictions were only observed (positive R^2) for measuring error in sessions immediately following training (Figure 24).

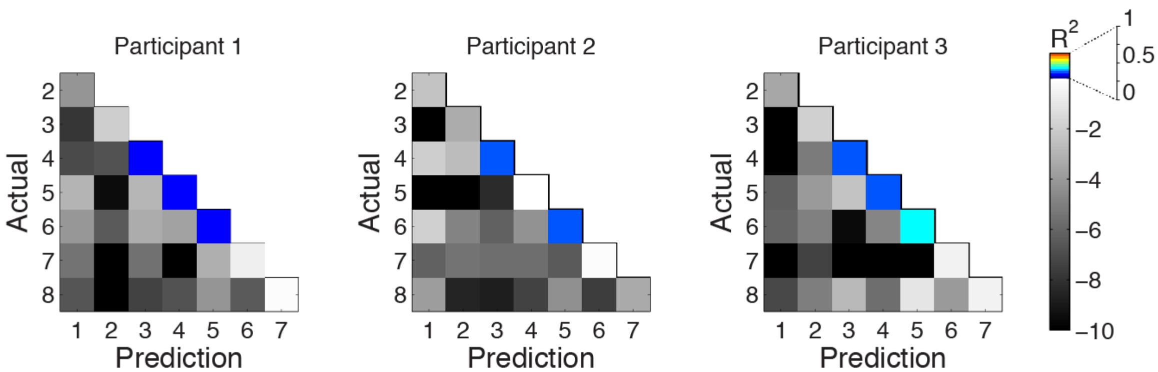


Figure 24: Average R^2 for model predictions (Model 1) across targets shown for all combinations of sessions. The model predicts the following session's error distribution based on the mean and standard deviation. Colored squares indicate positive R^2 values. Note that the prediction is only specific to the following session and that model predictions are no longer positive after session 6.

Clinical Measures

Given the short duration of our intervention, we did not anticipate changes from our short training invention. Accordingly, we found very limited evidence of improvement, see Table 2.

4. Discussion

This study examined whether error statistics during reaching can improve customization of force training for stroke survivor participants. We tested three stroke survivor participants across five training sessions where they received *error field* training—forces that augmented feedback based on error likelihood. We found that overall error significantly decreased for all participants from both error field and null field training. Our most important finding, however, was the evidence that error field training caused predictable changes in error, where the initial distribution was able to predict final errors. We saw that the errors following error field training were aligned with one standard deviation from initial error, where forces vanished during training.

We found that errors significantly differed based on target directions, which motivated the need to adapt training to 1) each participant and 2) each target direction. Previous research has suggested that such differences in movement errors are due to abnormal synergies following stroke and that velocity profiles can be location specific (Beer et al., 2004). Here we show possible manifestations of such synergies leading to large variations in locations of error. Not only were errors different in magnitude and variance with and between participants, but also they varied daily, suggesting the need for therapy interventions that change with the user.

Our results here showed that error fields could reduce perpendicular error beyond repetitive practice (Figure 21). Although the amount of reduction in error varied based on the magnitude of initial error (not surprisingly, participants with higher error had larger changes), participants averaged a 30% reduction in error. While null field training did decrease performance error for two participants, only error field training showed significant differences from the initial errors for all target directions. Even for participants beginning training with relatively low reaching errors (Participant 3), we were able to see a significant decrease in reaching errors.

We found that changes in error trajectories exhibited patterns that closely paralleled the structure of training forces (Figure 23). Given that the magnitude of training forces is governed by the participant's proximity to their errors, we found evidence that participants moved one standard deviation from the mean (resulting in relatively low forces). In our previous study of healthy subjects training with error fields, we also found that subjects similarly changed their error patterns to align with one standard deviation away from their initial mean, corresponding to the location where forces would reduce to zero (M. E. Fisher et al., 2015). Here we provide further evidence of learning that appears to "structured" due to the error field intervention, where the error distribution predicted the mean error observed at the start of the next session. We entertained the same model predictions for null field training and found no such effect (see Table 5).

Thus, while error did change due to null field training, it did not do so in a systematized manner. Exploration of model predictions for alternate sessions indicated that the predictive power is only unique to the following session's error profile (Figure 24). Further, as training progressed and errors are closer to zero, the model results were no longer positive across all targets. This ability to predict error changes could be a valuable tool in assessing the performance of a participant during training.

While we were able to show evidence that error field training promoted learning according to their intended design, such results did not necessarily translate into large performance gains when we compare one session of null field training to one session of error field training (Figure 21). Since we began error field training immediately after, it is unclear if improvements from null field training would be retained. Further we did not find differences in clinical measures (Table 2), suggesting that we might need to provide additional training sessions until we are confident the error field method has plateaued. In contrast, we believe the true benefit of error field training is to cause participants to move from their original pattern. We were successful in demonstrating how participants changed based on their variance, reaching errors with high probability and low variance only incrementally decreased by one standard deviation. This result is consistent with recent findings by others who have shown that high motor variability promotes learning (D. J. Herzfeld & Shadmehr, 2014; Wu et al., 2014).

This study revealed the need for therapy to adapt to the variation of errors seen in stroke survivor subjects. In our current approach, the error field is based on baseline trials characterized at the start of each session. While we believe this shows accountability to the needs of the stroke survivor, this also poses a limitation to our analysis abilities since the force field changes daily. To truly operate under the “challenge point framework” (Guadagnoli & Lee, 2004), where the greatest amount of learning is achieving by adjusting the task difficulty with the participant’s skill level, we would need to re-characterize during each training session.

In contrast to traditional clinical measures that evaluate task completion, here we showed a novel approach to leverage the high frequency error patterns employed by stroke survivors to customize therapy. This method ensured that training intervened on only the most relevant errors and adjusts to any day-to-day variation often seen in stroke survivors. Beyond the benefits of therapy for upper-extremity rehabilitation this approach could serve as a basis for a wide range of therapeutic approaches.

5. Acknowledgements

We would like to thank Emily Lazzaro for her help with recruitment and clinical evaluations, Zachary Wright for his technical assistance and advice on this project, and the Robotics Lab at RIC for insights and commentary.

VI. GENERAL DISCUSSION AND FUTURE DIRECTIONS

The body of work described in this dissertation describes how to improve training interventions using error statistics. This project also addresses practical applications of such interventions for skill learning, cross-modal training, and rehabilitation while providing insight to larger scientific questions surrounding motor control. The aforementioned studies increase our understanding of the complex neural process of error-based learning and adaptation.

1. **Contributions to motor learning**

1.1. Crossover ability of adaptation

Our work provides evidence of successful transfer of force field learning to visuomotor adaptation. Prior to this work, several studies have suggested that visuomotor and force field adaptation share neural resources (Bays, Flanagan, & Wolpert, 2005; J. Randall Flanagan et al., 1999; Tong et al., 2002). Such studies involve scenarios in which adaptation to forces and visuomotor perturbations are detrimental to each other, a concept referred to as *interference*. Here we expand upon the notion of "constructive" interference, first introduced by Wei and Patton, where one field type can help to learn another field (Yejun Wei & Patton, 2004). Our results showed that participants were capable of generalizing an aftereffect based on force field adaptation to improve performance in a visual rotation task (Chapter II). Even without having trained with the test condition, participants' performance resulted in lower error. This finding not only supports the hypothesis that adaptation mechanisms are shared but also presents an alternative framework: Instead of force adaptation interfering with visuomotor adaptation, it can be a viable substitute for training. Further, we saw that learning continued to improve on the day following training even after aftereffects would have degraded (Figure 4). We believe that the aftereffects caused by adaptation to customized forces, however, provided participants an implicit understanding of the trajectory needed for a visually rotated condition. This relates to a concept frequently referred to in psychology as “priming,” where a prior stimulus can influence the response to another condition (Schacter & Buckner, 1998). By priming participants with an understanding of the task demand (in this case the hand path for the visually rotated condition), they were able to use mechanisms one of type of adaptation to learn another. This resonates with previous studies that have shown how visual feedback showing the dynamics of an arm in an isometric condition can be used facilitate force field adaptation (Melendez-Calderon, Masia, Gassert, Sandini, & Burdet, 2011). Here we used the effects of force field adaptation (i.e., aftereffects) to train a visual rotation, demonstrating how adaptation mechanisms can be powerful training tools for learning new skills.

1.2. Characterization of individual learning strategies

In this work, we present evidence that neurologically intact participants can exhibit variations in movement distributions for some visuomotor tasks (Chapter II, Chapter IV). While many studies assume that healthy subjects exhibit similar error patterns during learning, only a few studies have acknowledged individual differences in learning based on information processing abilities (Ackerman, 1987) or level of skill (Guadagnoli & Lee, 2004). We found that such systematic differences in error also varied by target direction, further supporting the need for customized training interventions. Using simple statistical measures such as mean and standard deviation, we were able to characterize reaching errors by 40% (Chapter III). This work provides a clear, simple approach to tailor interventions to account for individual differences throughout learning.

1.3. Predicting how error changes across the trajectory

We developed a modeling approach that successfully revealed whether or not training forces had promoted the intended error changes. Recent studies have established other predictors of motor learning, such as motor variability, neural activity, and cognitive memory (Anguera, Reuter-Lorenz, Willingham, & Seidler, 2010; Rachael D Seidler, Mulavara, Bloomberg, & Peters, 2015; Wu et al., 2014). These approaches have demonstrated success in predicting the overall learning rate or the aptitude of an individual to learn. In order to improve upon robotic training interventions, however, it is also necessary to understand how participants change their reaching strategies *during* learning. In Chapter IV, we show evidence that the error field intervention caused subjects to shift error tendencies based on the structure of the force field (more specifically, by a standard deviation of the mean error). We found we could predict final across-trial errors for participants in the Error Field group. However, we were unable to predict final error distributions for participants training with error augmentation or repetitive practice, suggesting that the other training interventions caused random training effects. We also found we could predict changes in error distributions for stroke survivor subjects based on their performance in the previous session (Chapter V). Through this approach, we can measure the impact of our intervention and also predict how error distributions will change. Such predictions further allow us to measure the success of therapy and form a more detailed expectation of what participants are capable of learning.

1.4. Improving error augmentation interventions

This work presents a new approach to error augmentation (EA) techniques in which force feedback is magnified by both the real time error and the probability of the error. In its application, this technique amplified large, repeatable reaching errors and ignored random errors or errors close to zero. We found this to benefit training for healthy participants learning a novel visual transformation (Chapter IV) and reduce reaching errors exhibited by stroke survivor subjects (Chapter V). In contrast to recent work exploring the "optimal" EA gain (J. L. Patton et al., 2013), we show that changing the gain with respect to probability can improve training beyond traditional EA (Chapter IV, Figure 15). We believe that by allowing the amount of EA to vary we can operate with the challenge point framework (CPF), so that the task is appropriately challenging for each participant. Instead of determining a single number to augment error for each participant or subject group, feedback gains can be altered to address the most important errors.

2. Contributions to rehabilitation

2.1. Differences in error tendencies for stroke survivors

Our approach to customization revealed that error distributions were unique to each stroke survivor participant. Even though we only tested a small sample, we showed that stroke survivor subjects even with the same relative level of impairment (as tested through clinical assessments) have large differences in which target directions they demonstrated error, varying both by participant and target direction (Figure 19). In contrast, previous studies have described that deficits following stroke should be predictable based on the location of injury and time since stroke (Gert Kwakkel, Kollen, & Lindeman, 2004; Gert Kwakkel, Kollen, van der Grond, & Prevo, 2003). Our findings support a previous study by Beer et al., where they observed that the effects of abnormal muscle synergies following stroke varied throughout the workspace (Beer et al., 2004). Our results, therefore, establish the effect of abnormal coupling in terms of end-points errors, where a single participant can reach straight in one direction but deviate almost 15 cm when reaching to a different direction. Such differences also resonate with the unique distributions that Huang and Patton found between participants during self-directed motor exploration (Felix C. Huang & James L. Patton, 2013). Thus, there is need for therapy to quantify errors that are unique to each individual. Such characterization tools can provide better predictions of functional recovery and therapy outcomes.

2.2. Error-based customization

This work establishes a method to individualize therapy and also maintain a challenging environment. There is currently a large distinction between customization approaches in manual therapy and using robotics for stroke therapy. During manual therapy, clinicians are able to provide assistance when necessary and adapt tasks to the patient's appropriate skill level. Many robotic training studies exist that utilize assist-as-needed algorithms so that the stroke survivor receives robotic assistance to complete the task. However, there have been limited approaches that also increase the intensity of the training environment on an individual basis (Klamroth-Marganska et al., 2014; Shirzad & Van der Loos, 2015). In our application of error fields training (Chapter V), participants were perturbed away from their initial reaching patterns and had to adjust their reaching strategies to complete the task. Even with only a short duration of practice (five force training sessions that each averaged around 45 minutes) we were able to see reduction in error and positive transfer to motor exploration. By using error statistics, we determined which reaching patterns were repeatable and which were random, allowing us to focus training on regions where they exhibited systematic errors. While we chose to focus on perpendicular errors so that participants would eventually move straighter, our method is flexible and could be further customized to many definitions of error.

3. Limitations of this work and potential improvements

3.1. Optimal ordinate domains

In our efforts to effectively utilize error distributions for training interventions, we made several decisions as to what domain error should be defined. In Chapter III, we analyzed several possible ordinate domains and found that the variance of error changes based on the ordinate domain. For that particular data set, in which participants learned a visual rotation, we found that errors best aligned when defined with respect to time (Figure 10). This result served as the basis for implementing error field training in Chapter IV using time-dependent forces. In our intervention with stroke survivor subjects (Chapter V), we chose to use a position-dependent field to ensure that we could accurately quantify the states that led to high error. It remains unclear if time or position would serve as optimal ordinate for stroke therapy or how such analysis or ordinate domains extrapolates to other tasks.

3.2. Model predictions

To determine the effect of the error field (Chapters IV and V), we evaluated predictive models that were based on the structure of the intervention. Although we found success with the model that was the most synonymous with the design of the forces (mean – standard deviation), it is possible other models exist that could better explain how errors change following training. Further, recent motor control studies have shown how variability in error is important to learning (Wu et al., 2014). Our model analysis establishes that variability in error during the movement can be a predictor of change (Chapter IV and V), while our analysis of ordinate domains (Chapter III) showed that variability changes during learning. Further work needs to be done to understand the conditions where errors are more consistent and if variability can be used to measure if learning is stable.

3.3. Subject population and dosage

We found that performance gains from error field training with stroke survivor participants were modest (Chapter V). To better understand the impacts of training on rehabilitation, we need to collect additional subjects and compare them to participants experiencing only null field training. Furthermore, more clinically meaningful effect sizes might be obtained with higher dosage or duration. It remains uncertain what is the optimal number of training sessions. We saw that following error field training, error still remained for all participants (Figure 21) suggesting there were still opportunities to improve. Additionally, we saw improvements in peak velocity and movement time and transfer effects to motor exploration trials that had not yet plateaued.

3.4. Characterization algorithms

The characterization algorithm used for error field training considers that individuals have a central reaching strategy for each target direction. In designing the error field (Chapter III), we utilize a simple approach using the mean and standard deviation of error. This method of averaging assumes one reaching strategy for any given target -- either leftward or rightward of the straight-line path. For both the healthy (Chapter IV) and stroke survivor (Chapter V) studies, we found that participants maintained systematic errors in one direction. However, if participants had strategies that varied in direction, our approach using a single Gaussian distribution would not be able to adequately determine the error probability. To allow for more robust characterization opportunities, future iterations should use more advanced statistical averaging such as kernel density estimation or multivariate Gaussian distributions.

3.5. Intervention design

To best use error statistics to inform training, it is important that the characterization uses the most recent errors. Our modeling results from Chapter IV and Chapter V showed that during training participants moved to a lower region of error but did not continue o reduce errors to zero. Once participants moved away from their initial distributions of error during training, they minimized force exposure, which we believe caused training effects to plateau. To prevent this from occurring training could be divided up into smaller blocks so that errors could be resampled and update the error field. This would make certain that we focus on the most recent error patterns. Alternatively, to ensure what the error field was not simply shifting daily between two strategies, it could be beneficial to add a second term to the error field calculation based on the participant's average error patterns. This would ensure that even if there are day-to-day fluctuations, participants do not devolve into old patterns that have already been corrected.

4. Broad implications

This work detailed several scenarios where learning was enhanced with customized force training environments both in learning new visuomotor transformations and reducing reaching errors for stroke survivors. We showed that using statistics of errors, we were able to train participants to improve performance on a task without previous experience, a process we call sensory crossover. This surprising result provided the basis for cross modal training opportunities in which learning from the wrong environment can make us better learners at a task we have not practiced. This establishes possibilities for new training environments using combinations of sensory cues to enhance motor learning. We also demonstrated how the statistics of errors can be used to focus training on the most commonly occurring errors and discard errors that might be distracting to the learning process. In a world of emerging technology that gives us feedback on our performance, knowing how often we make errors can help us move smarter, faster, and more accurately. We can now offer more informative coaching and therapy that is truly customized to individual needs.

CITED LITERATURE

Abdollahi, F., Case Lazarro, E. D., Listenberger, M., Kenyon, R. V., Kovic, M., Bogey, R. A., . . . Patton, J. L. (2014). Error augmentation enhancing arm recovery in individuals with chronic stroke: a randomized crossover design. *Neurorehabil Neural Repair, 28*(2), 120-128.

Ackerman, P. L. (1987). Individual differences in skill learning: An integration of psychometric and information processing perspectives. *Psychological bulletin, 102*(1), 3.

Alleva, E., & Santucci, D. (2001). Psychosocial vs. "physical" stress situations in rodents and humans: role of neurotrophins. *Physiology & Behavior, 73*(3), 313-320.

Anguera, J. A., Reuter-Lorenz, P. A., Willingham, D. T., & Seidler, R. D. (2010). Contributions of spatial working memory to visuomotor learning. *Journal of cognitive neuroscience, 22*(9), 1917-1930.

Ashworth, B. (1964). Preliminary trial of carisoprodol in multiple sclerosis. *Practioner, 192*, 540-542.

Barreca, S., Wolf, S. L., Fasoli, S., & Bohannon, R. (2003). Treatment interventions for the paretic upper limb of stroke survivors: a critical review. *Neurorehabilitation and Neural Repair, 17*(4), 220-226.

Bays, P. M., Flanagan, J. R., & Wolpert, D. M. (2005). Interference between velocity-dependent and position-dependent force-fields indicates that tasks depending on different kinematic parameters compete for motor working memory. *Experimental Brain Research, 163*(3), 400-405.

Beer, R. F., Dewald, J. P., Dawson, M. L., & Rymer, W. (2004). Target-dependent differences between free and constrained arm movements in chronic hemiparesis. *Experimental Brain Research, 156*(4), 458-470.

Berns, G. S., Cohen, J. D., & Mintun, M. A. (1997). Brain regions responsive to novelty in the absence of awareness. *Science, 276*(5316), 1272-1275.

Blakemore, S.-J., Frith, C. D., & Wolpert, D. M. (2001). The cerebellum is involved in predicting the sensory consequences of action. *Neuroreport, 12*(9), 1879-1884.

Brashers-Krug, T., Shadmehr, R., & Bizzi, E. (1996). Consolidation in human motor memory. *Nature, 382*(6588), 252-255.

Brewer, B. R., McDowell, S. K., & Worthen-Chaudhari, L. C. (2007). Poststroke upper extremity rehabilitation: a review of robotic systems and clinical results. *Topics in Stroke Rehabilitation, 14*(6), 22-44.

Burdet, E., Osu, R., Franklin, D. W., Milner, T. E., & Kawato, M. (2001). The central nervous system stabilizes unstable dynamics by learning optimal impedance. *Nature, 414*(6862), 446-449.

Bushnell, C. D., Johnston, D. C., & Goldstein, L. B. (2001). Retrospective assessment of initial stroke severity comparison of the NIH Stroke Scale and the Canadian Neurological Scale. *Stroke, 32*(3), 656-660.

Callahan, A. (1990). Sensibility testing: clinical methods. In M. Hunter, L. Schneider, E. Mackin, & C. AD (Eds.), *Rehabilitation of the Hand* (Vol. 3rd ed., pp. 594–610). St. Louis: Mosby.

Casadio, M., Morasso, P., Sanguineti, V., & Giannoni, P. (2009). Minimally assistive robot training for proprioception enhancement. *Experimental brain research. Experimentelle Hirnforschung. Expérimentation cérébrale, 194*(2), 219-231.

Cesqui, B., Aliboni, S., Mazzoleni, S., Carrozza, M., Posteraro, F., & Micera, S. (2008). *On the use of divergent force fields in robot-mediated neurorehabilitation.* Paper presented at the Biomedical Robotics and Biomechatronics, 2008.

Choi, Y., Gordon, J., Park, H., & Schweighofer, N. (2011). Feasibility of the adaptive and automatic presentation of tasks (ADAPT) system for rehabilitation of upper extremity function post-stroke. *J Neuroeng Rehabil, 8*(1), 42-42.

Conditt, M. A., Gandolfo, F., & Mussa-Ivaldi, F. A. (1997). The Motor System Does Not Learn the Dynamics of the Arm by Rote Memorization of Past Experience. *Journal of Neurophysiology, 78*(1), 554-560.

Dancause, N., Ptito, A., & Levin, M. F. (2002). Error correction strategies for motor behavior after unilateral brain damage: short-term motor learning processes. *Neuropsychologia, 40*(8), 1313-1323.

Desmurget, M., Epstein, C. M., Turner, R. S., Prablanc, C., Alexander, G. E., & Grafton, S. T. (1999). Role of the posterior parietal cortex in updating reaching movements to a visual target. *Nature Neuroscience, 2*(6), 563-567.

Diedrichsen, J., Hashambhoy, Y., Rane, T., & Shadmehr, R. (2005). Neural correlates of reach errors. *The Journal of Neuroscience, 25*(43), 9919-9931.

Doyon, J., Gaudreau, D., Laforce Jr, R., Castonguay, M., Bedard, P., Bedard, F., & Bouchard, J. (1997). Role of the striatum, cerebellum, and frontal lobes in the learning of a visuomotor sequence. *Brain and cognition, 34*(2), 218-245.

Ernst, M. O., & Banks, M. S. (2002). Humans integrate visual and haptic information in a statistically optimal fashion. *Nature, 415*, 429-433.

Fisher, M., Huang, F. C., Klamroth-Marganska, V., Riener, R., & Patton, J. L. (2015). *Haptic error fields for robotic training*. Paper presented at the IEEE World Haptics Conference, Chicago, IL.

Fisher, M., Huang, F. C., Wright, Z. A., & Patton, J. L. (2014). *Distributions in Error Space: Goal-Directed Movements Described in Time and State-Space Representations.* Paper presented at the IEEE Engineering in Medicine and Biology, Chicago, IL.

Fisher, M. E., Huang, F. C., Klamroth-Marganska, V., Riener, R., & Patton, J. L. (2015). *Haptic error fields for robotic training.* Paper presented at the World Haptics Conference (WHC), 2015 IEEE.

Fisher, M. E., Huang, F. C., Wright, Z., & Patton, J. L. (2014). *Distributions in the error space: Goal-directed movements described in time and state-space representations.* Paper presented at the Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE.

Fitts, P. M. (1954). The information capacity of the human motor system in controlling the amplitude of movement. *Journal of Experimental Psychology, 47*(6), 381.

Flament, D., Shaprio, M. B., Kempf, T., & Corcos, D. M. (1999). Time course and temporal order of changes in movement kinematics during learning of fast and accurate elbow flexions. *Experimental Brain Research, 123*(3), 441-450.

Flanagan, J. R., Nakano, E., Imamizu, H., Osu, R., Yoshioka, T., & Kawato, M. (1999). Composition and Decomposition of Internal Models in Motor Learning under Altered Kinematic and Dynamic Environments. *The Journal of Neuroscience, 19*.

Flanagan, J. R., & Rao, A. K. (1995). Trajectory Adaptation to a Nonlinear Visuomotor Transformation: Evidence of Motion Planning in Visually Perceived Space *Journal of Neursophysiology, 74*(5), 2174-2178.

Flash, T., & Hogan, N. (1985). The Coordination of Arm Movements: Mathematical Model. *The Journal of Neuroscience, 5*(7), 1688-1703.

Frank, M. J. (2011). Computational models of motivated action selection in corticostriatal circuits. *Current opinion in neurobiology, 21*(3), 381-386.

Fugl-Meyer, A., Jaasko, L., Leyman, I., Olsson, S., & Steglind, S. (1975). The post-stroke hemiplegic patient. I. A method for evaluation of physical performance. *Scand J Rehabil Med, 7*, 13–31.

Ghez, C. (1991). The Control of Movement. In E. R. Kandel, J. Schwartz, & T. M. Jessell (Eds.), *Principles of Neural Science* (Vol. 3): Elsevier.

Goodbody, S. J., & Wolpert, D. M. (1998). Temporal and Amplitude Generalization in Motor Learning. *Journal of Neurophysiology, 79*(4), 1825-1838.

Grimby, G. (1985). Progressive resistance exercise for injury rehabilitation. Special emphasis on isokinetic training. . *Sports Med, 2*(5), 309-315.

Guadagnoli, M. A., & Lee, T. D. (2004). Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning. *Journal of Motor Behavior, 36*(2), 212-224.

Güldenpenning, I., Braun, J., Machlitt, D., & Schack, T. (2015). Masked priming of complex movements: perceptual and motor processes in unconscious action perception. *Psychological Research, 79*(5), 801-812.

Held, R. (1962). Adaptation to rearrangement and visual-spatial aftereffects. *Psychologische Beitrage, 6*, 439-450.

Herzfeld, D. J., & Shadmehr, R. (2014). Motor variability is not noise, but grist for the learning mill. *Nature Neuroscience, 17*(2), 149-150. doi:10.1038/nn.3633

Herzfeld, D. J., Vaswani, P. A., Marko, M. K., & Shadmehr, R. (2014). A memory of errors in sensorimotor learning. *Science, 12*(345), 1349-1353.

Hinder, M. R., Riek, S., Tresilian, J. R., de Rugy, A., & Carson, R. G. (2010). Real-time error detection but not error correction drives automatic visuomotor adaptation. *Experimental Brain Research, 201*(2), 191-207.

Huang, F. C., & Patton, J. L. (2013). Individual patterns of motor deficits evident in movement distribution analysis. *IEEE ... International Conference on Rehabilitation Robotics : [proceedings]*, 1-6.

Huang, F. C., & Patton, J. L. (2013). Individual patterns of motor deficits evident in movement distribution analysis. *IEEE ... International Conference on Rehabilitation Robotics : [proceedings], 2013*, 1-6.

Huang, F. C., Pugh, C. M., Patton, J. L., & Mussa-Ivaldi, F. a. (2010). Learning kinematic mappings in laparoscopic surgery. *Conference proceedings : ... Annual*

International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference, 2010, 2097-2102.

Hudson, T. E., & Landy, M. S. (2012). Motor learning reveals the existence of multiple codes for movement planning. *J Neurophysiol, 108*(10), 2708-2716.

Imamizu, H., Miyauchi, S., Tamada, T., Sasaki, Y., Takino, R., Pütz, B., . . . Kawato, M. (2000). Human cerebellar activity reflecting an acquired internal model of a new tool. *Nature, 403*(6766), 192-195.

Ishikawa, T., & Sakaguchi, Y. (2013). Both movement-end and task-end are critical for error feedback in visuomotor adaptation: a behavioral experiment. *PLoS One, 8*(2), e55801.

Ito, M. (2002). Historical review of the significance of the cerebellum and the role of Purkinje cells in motor learning. *Annals of the New York Academy of Sciences, 978*(1), 273-288.

Ito, M., & Doya, K. (2011). Multiple representations and algorithms for reinforcement learning in the cortico-basal ganglia circuit. *Current opinion in neurobiology, 21*(3), 368-373.

Jorgensen, H., Nakayama, H., Raaschou, H., & Olsen, T. (1999). Stroke. Neurologic and functional recovery the Copenhagen Stroke Study. *Phys Med Rehabil Clin N Am, 10*(4), 887-906.

Kalaska, J., Caminiti, R., & Georgopoulos, A. (1983). Cortical mechanisms related to the direction of two-dimensional arm movements: relations in parietal area 5 and comparison with motor cortex. *Experimental Brain Research, 51*(2), 247-260.

Kawato, M. (1990). Feedback-error-learning neural network for supervised learning. In R. Eckmiller (Ed.), *Advanced neural computers* (pp. 365-372). Amsterdam: North-Holland.

Kawato, M. (1990). Feedback-error-learning neural network for supervised motor learning. *Advanced neural computers, 6*(3), 365-372.

Klamroth-Marganska, V., Blanco, J., Campen, K., Curt, A., Dietz, V., Ettlin, T., . . . Riener, R. (2014). Three-dimensional, task-specific robot therapy of the arm after stroke: a multicentre, parallel-group randomised trial. *The Lancet Neurology, 13*(2), 159-166.

Kording, K., & Wolpert, D. M. (2004). Bayesian Integration in sensorimotor learning. *Nature, 427*, 244-247.

Kording, K. P., & Wolpert, D. M. (2004). Bayesian integration in sensorimotor learning. *Nature, 427*, 244-247.

Krakauer, J. W., Ghilardi, M.-F., Mentis, M., Barnes, A., Veytsman, M., Eidelberg, D., & Ghez, C. (2004). Differential cortical and subcortical activations in learning rotations and gains for reaching: a PET study. *Journal of Neurophysiology, 91*(2), 924-933.

Krakauer, J. W., Ghilardi, M. F., & Ghez, C. (1999). Independent learning of internal models for kinematic and dynamic control of reaching. *Nature Neuroscience, 2*(11), 1026-1031.

Krakauer, J. W., Pine, Z. M., Ghilardi, M. F., & Ghez, C. (2000). Learning of visuomotor transformations for vectorial planning of reaching trajectories. *J Neurosci, 20*(23), 8916-8924.

Kwakkel, G., Kollen, B., & Krebs, H. (2008). Effects of robot-assisted therapy on upper limb recovery after stroke: a systematic review. *Neurorehabilitation and Neural Repair, 22*, 111-121.

Kwakkel, G., Kollen, B., & Lindeman, E. (2004). Understanding the pattern of functional recovery after stroke: facts and theories. *Restorative neurology and neuroscience, 22*(3-5), 281-300.

Kwakkel, G., Kollen, B. J., van der Grond, J., & Prevo, A. J. (2003). Probability of regaining dexterity in the flaccid upper limb impact of severity of paresis and time since onset in acute stroke. *Stroke, 34*(9), 2181-2186.

Lackner, J. R., & Dizio, P. (1994). Rapid Adaptation to Coriolis Force Pertubations of Arm Trajectory. *Journal of Neurophysiology, 72*(1).

Latash, M. L., Scholz, J. P., & Schoner, G. (2002). Motor Control Strategies Revealed in the Structure of Motor Variability. *Excercise and Sport Science Reviews, 30*(1), 26-31.

Lazarus, J.-A. C. (1992). Associated movement in hemiplegia: the effects of force exerted, limb usage and inhibitory training. *Arch Phys Med Rehabil, 73*(11), 1044-1049.

Lee, T. D. (2011). *Motor Control in Everyday Actions*. Champaign, IL: Human Kinetics.

Marchal-Crespo, L., Lopez-Oloriz, J., Jaeger, L., & Riener, R. (2014). *Optimizing learning of a locomotor task: Amplifying errors as needed*. Paper presented at the IEEE Engineering in Medicine and Biology Society (EMBC), Chicago, IL.

Mehrholz, J., Hädrich, A., Platz, T., Kugler, J., & Pohl, M. (2012). Electromechanical and robot-assisted arm training for improving generic activities of daily living, arm function, and arm muscle strength after stroke (Review). *Stroke, 43*, e172-e173.

Melendez-Calderon, A., Masia, L., Gassert, R., Sandini, G., & Burdet, E. (2011). Force Field Adaptation Can Be Learned Using Vision in the Absence of Proprioceptive Error. *IEEe Transactions on Neural Systems and Rehabilitation Engineering, 19*(3), 298-306.

Mercier, C., Bertrand, A. M., & Bourbonnais, D. (2004). Differences in the magnitude and direction of forces during a submaximal matching task in hemiparetic subjects. *Experimental Brain Research, 157*(1), 32-42.

Miall, R. C., & Wolpert, D. M. (1996). Forward models for physiological motor control. *Neural networks, 9*(8), 1265-1279.

Milot, M.-H., Marchal-Crespo, L., Green, C. S., Cramer, S. C., & Reinkensmeyer, D. J. (2010). Comparison of error-amplification and haptic-guidance training techniques for learning of a timing-based motor task by healthy individuals. *Experimental brain research. 201*(2), 119-131.

Mussa-Ivaldi, F. A., & Patton, J. L. (2000). *Robots can teach people how to move their arm*. Paper presented at the IEEE International Conference on Robotics and Automation, San Fransciso.

Nakano, E., Imamizu, H., Uno, Y., Gomi, H., Yoshioka, T., & Kawato, M. (1999). Quantitative Examinations of Internal Representationsfor Arm Trajectory

Planning: Minimum Commanded Torque Change Model. *Journal of Neurophysiology, 81*, 2140-2155.

Nashner, L., & Berthoz, A. (1978). Visual contribution to rapid motor responses during postural control. *Brain research, 150*(2), 403-407.

Nef, T., Guidali, M., & Riener, R. (2009). ARMin III – arm therapy exoskeleton with an ergonomic shoulder actuation. *Applied Bionics and Biomechanics, 6*(2), 127-142.

Nef, T., Mihelj, M., & Riener, R. (2007). ARMin: a robot for patient-cooperative arm therapy. *Med Biol Eng Comput, 45*(9), 887-900.

Onla-or, S. P., & Winstein, C. J. (2008). Determining the optimal challenge point for motor skill learning in adults with moderately severe Parkinson's disease. *Neurorehabilitation and Neural Repair*.

Patton, J. L., Kovic, M., & Mussa-Ivaldi, F. A. (2006). Custom-designed haptic training for restoring reaching ability. *The Journal of Rehabilitation Research and Development, 43*(5), 643-643.

Patton, J. L., & Mussa-Ivaldi, F. a. (2004). Robot-assisted adaptive training: custom force fields for teaching movement patterns. *IEEE transactions on bio-medical engineering, 51*(4), 636-646.

Patton, J. L., & Mussa-Ivaldi, F. A. (2004). Robot-Assisted Adaptive Training: Custom Force Fields for Teaching Movement Patterns. *IEEE Transactions on Biomedical Engineering, 51*(4).

Patton, J. L., Stoykov, M. E., Kovic, M., & Mussa-Ivaldi, F. a. (2006). Evaluation of robotic training forces that either enhance or reduce error in chronic hemiparetic stroke survivors. *Experimental brain research., 168*(3), 368-383.

Patton, J. L., Wei, Y. J., Bajaj, P., & Scheidt, R. A. (2013). Visuomotor learning enhanced by augmenting instantaneous trajectory error feedback during reaching. *PLoS One, 8*(1), e46466.

Patton, J. L., Wei, Y. J., Bajaj, P., & Scheidt, R. a. (2013). Visuomotor Learning Enhanced by Augmenting Instantaneous Trajectory Error Feedback during Reaching. *PLoS One, 8*(1), e46466-e46466.

Pollock, C. L., Boyd, L. A., Hunt, M. A., & Garland, S. J. (2014). Use of the challenge point framework to guide motor learning of stepping reactions for improved balance control in people with stroke: a case series. *Physical therapy, 94*(4), 562-570.

Rabe, K., Livne, O., Gizewski, E. R., Aurich, V., Beck, A., Timmann, D., & Donchin, O. (2009). Adaptation to visuomotor rotation and force field perturbation is correlated to different brain areas in patients with cerebellar degeneration. *Journal of Neurophysiology, 101*(4), 1961-1971.

Reinkensmeyer, D. J., Emken, J. L., & Cramer, S. C. (2004). Robotics, motor learning, and neurologic recovery. *Annu Rev Biomed Eng, 6*, 497-525.

Reisman, D. S., Wityk, R., Silver, K., & Bastian, A. J. (2009). Split-belt treadmill adaptation transfers to overground walking in persons poststroke. *Neurorehabilitation and Neural Repair, 23*(7), 735-744.

Ridderinkhof, K. R., Ullsperger, M., Crone, E. A., & Nieuwenhuis, S. (2004). The role of the medial frontal cortex in cognitive control. *Science, 306*(5695), 443-447.

Sainburg, R. L., Ghez, C., & Kalakanis, D. (1999). Intersegmental dynamics are controlled by sequential anticipatory, error correction, and postural mechanisms. *Journal of Neurophysiology, 81*, 1045-1056.

Schacter, D. L., & Buckner, R. L. (1998). Priming and the Brain. *Neuron, 20*(2), 185-195.

Scheidt, R. A., Dingwell, J. B., & Mussa-Ivaldi, F. A. (2001). Learning to move amid uncertainty. *Journal of Neurophysiology, 86*, 971-985.

Scheidt, R. A., Reinkensmeyer, D. J., Conditt, M. A., & Mussa-Ivaldi, F. A. (2000). Persistence of Motor Adaptation During Constrained, Multi-Joint, Arm Movements. *Journal of Neurophysiology, 84*(2), 853-862.

Scheidt, R. A., & Stoeckmann, T. (2007). Reach adaptation and final position control amid environmental uncertainty after stroke. *J Neurophysiol, 97*(4), 2824-2836.

Seidler, R. D., Kwak, Y., Fling, B. W., & Bernard, J. A. (2013). Neurocognitive mechanisms of error-based motor learning. *Adv Exp Med Biol, 782*, 39-60.

Seidler, R. D., Mulavara, A. P., Bloomberg, J. J., & Peters, B. T. (2015). Individual predictors of sensorimotor adaptability. *Frontiers in systems neuroscience, 9*.

Shadmehr, R., & Brashers-Krug, T. (1997). Functional Stages in the Formation of Human Long-Term Motor Memory. *Journal of Neuroscience, 17*(1), 409-419.

Shadmehr, R., & Holcomb, H. (1997). Neural Correlates of Motor Memory Consolidation. *Science, 277*(5327), 821-825.

Shadmehr, R., & Mussa-ivaldi, F. A. (1994). Adaptive Representation of Dynamics during Learning of a Motor Task. *J Neurosci, 74*(May), 3208-3224.

Shadmehr, R., & Mussa-Ivaldi, F. A. (1994). Adaptive Representation of Dynamics during Learning of a Motor Task. *Journal of Neuroscience, 14*(5), 3208-3224.

Shadmehr, R., Smith, M. a., & Krakauer, J. W. (2010). Error correction, sensory prediction, and adaptation in motor control. *Annual review of neuroscience, 33*, 89-108.

Shirzad, N., & Van der Loos, H. (2012). *Error amplification to promote motor learning and motivation in therapy robotics.* Paper presented at the Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE.

Shirzad, N., & Van der Loos, H. M. (2015). Evaluating the User Experience of Exercising Reaching Motions With a Robot That Predicts Desired Movement Difficulty. *Journal of Motor Behavior*(ahead-of-print), 1-16.

Sing, G. C., & Smith, M. a. (2010). Reduction in learning rates associated with anterograde interference results from interactions between different timescales in motor adaptation. *PLoS Comput Biol, 6*(8).

Smeets, J. B. J., van den Dobbelsteen, J. J., de Grave, D. D. J., van Beers, R. J., & Brenner, E. (2006). Sensory integration does not lead to sensory calibration. *Proceedings of the National Acad*

Smith, M. a., Ghazizadeh, A., & Shadmehr, R. (2006). Interacting adaptive processes with different timescales underlie short-term motor learning. *PLoS biology, 4*(6), e179-e179.

Stoykov, M. E., & Madhavan, S. (2015). Motor Priming in Neurorehabilitation. *Journal of Neurologic Physical Therapy, 39*(1), 33-42.

Sundaram, H., Chen, Y., & Rikakis, T. (2011). *A computational framework for constructing interactive feedback for assisting motor learning.* Paper presented at the Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE.

Takiyama, K., Hirashima, M., & Nozaki, D. (2015). Prospective errors determine motor learning. *Nat Commun, 6*.

Teasell, R. W., Foley, N. C., Bhogal, S. K., & Speechley, M. R. (2003). An Evidence-Based Review of Stroke Rehabilitation. *Topics in Stroke Rehabilitation, 10*(1), 29-58.

Tong, C., Wolpert, D. M., & Flanagan, J. R. (2002). Kinematics and dynamics are not represented independently in motor working memory: evidence from an interference study. *J Neurosci, 22*(3), 1108-1113.

Tseng, Y.-w., Diedrichsen, J., Krakauer, J. W., Shadmehr, R., & Bastian, A. J. (2007). Sensory prediction errors drive cerebellum-dependent adaptation of reaching. *Journal of Neurophysiology, 98*(1), 54-62.

van Beers, R. J. (2009). Motor learning is optimally tuned to the properties of motor noise. *Neuron, 63*(3), 406-417.

van Beers, R. J. (2012). How does our motor system determine its learning rate? *PLoS One, 7*(11), e49373.

Vergaro, E., Casadio, M., Squeri, V., Giannoni, P., Morasso, P., & Sanguineti, V. (2010). Self-adaptive robot training of stroke survivors for continuous tracking movements. *J Neuroeng Rehabil, 7*, 13-13.

Vliet, P., Carey, L., & Nilsson, M. (2012). Targeting stroke treatment to the individual. *International Journal of Stroke, 7*(6), 480-481.

Wade, D., Langton-Hewer, R., Wood, V., Skilbeck, C., & Ismail, H. (1983). The hemiplegic arm after stroke: measurement and recovery. *Journal of Neurology, Neurosurgery & Psychiatry, 46*(6), 521-524.

Wei, K., & Kording, K. (2009). Relevance of error: what drives motor adaptation? *J Neurophysiol, 101*(2), 655-664.

Wei, Y., & Kording, K. P. (2009). Relevance of error: what drives motor adaptation? . *Journal of Neurophysiology, 101*(2), 655-654.

Wei, Y., & Patton, J. L. (2004). *Force Field Training to Facilitate Learning Visual Distortions: A "Sensory Crossover" Experiment*. Paper presented at the IEEE Haptics Symposium of the IEEE Virtual Reality Chicago.

Wei, Y., Patton, J. L., Bajaj, P., & Scheidt, R. (2005). A Real-Time Haptic/Graphic Demonstration of how Error Augmentation can Enhance Learning. *Proceedings of the 2005 IEEE International Conference on Robotics and Automation*, 4406-4411.

Wolbrecht, E. T., Chan, V., Reinkensmeyer, D. J., & Bobrow, J. E. (2008). Optimizing compliant, model-based robotic assistance to promote neurorehabilitation. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on, 16*(3), 286-297.

Wolpert, D. M., Diedrichsen, J., & Flanagan, J. R. (2011). Principles of sensorimotor learning. *Nature Reviews Neuroscience, 12*(12), 739-751.

Wolpert, D. M., Ghahramani, Z., & Jordan, M. I. (1995). An Internal Model for Sensorimotor Integration. *Science, 269*(5232), 1880-1882.

Wolpert, D. M., Miall, R. C., & Kawato, M. (1998). Internal models in the cerebellum. *Trends in cognitive sciences, 2*(9), 338-347.

Wright, Z. A., Fisher, M., Huang, F. C., & Patton, J. L. (2014, August 26-30). *Data sample size needed for prediction of movement distributions.* Paper presented at the IEEE Engineering in Medicine and Biology, Chicago, IL

Wright, Z. A., Patton, J. L., Huang, F. C., & Lazzaro, E. (2015). *Evaluation of force field training customized according to individual movement deficit patterns.* Paper presented at the Rehabilitation Robotics (ICORR), 2015 IEEE International Conference on.

Wu, H. G., Miyamoto, Y. R., Gonzalez Castro, L. N., Olveczky, B. P., & Smith, M. A. (2014). Temporal structure of motor variability is dynamically regulated and predicts motor learning ability. *Nat Neurosci, 17*(2), 312-321.

VITA

NAME: Moria Fisher Bittmann

EDUCATION: PhD, Bioengineering, University of Illinois at Chicago, Chicago, IL, USA, 2016

B.S., Mechanical Engineering, University of Michigan, Ann Arbor, Michigan, USA, 2006

RESEARCH EXPERIENCE:

Postdoctoral Researcher (January 2016 – Present)
UW Neuromuscular Biomechanics Lab, University of Wisconsin, Madison, WI
Advisor: Darryl Thelen, Ph.D.

Research Assistant (September 2010 – January 2016)
Robotics Lab, Rehabilitation Institute of Chicago, Chicago, IL
Advisors: James Patton, Ph.D., Felix C. Huang, Ph.D.

Visiting Researcher (May 2014 – August 2014)
Sensory-Motor Systems Laboratory, Swiss Federal Institute of Technology in Zurich, Switzerland
Advisor: Robert Reiner, Ph.D.

Research Assistant (August 2009 – August 2010)
Muscle Mechanics Lab, Musculoskeletal Tissue Emulation Laboratory Department of Plastic Surgery, School of Kinesiology, University of Michigan, Ann Arbor, MI
Advisors: Dennis Claflin, Ph.D., Mark Palmer, Ph.D., M.D.

Research Assistant (September 2007 – April 2008)
Developmental Neuromotor Control Laboratory School of Kinesiology, University of Michigan, Ann Arbor, MI
Advisor: Julia Looper, Ph.D.

TEACHING EXPERIENCE:

Guest Lecturer (March 31st, 2015), BioControls, Department of Bioengineering, University of Illinois at Chicago. "Frequency Response and Controller Design," Host: James L. Patton, PhD

Guest Lecturer (January 18th, 2015), Undergraduate Bioengineering Seminar, Department of Bioengineering, University of Illinois at Chicago. "Customized Error-Augmentation for Robotic Learning," Host: Daniela Valdez-Jasso, PhD

Guest Lecturer (February 20th, 2014), BioControls, Department of Bioengineering, University of Illinois at Chicago. "Root Locus and Controller Design," Host: James L. Patton, PhD

Guest Lecturer (April 2^{nd}, 2013), BioControls, Department of Bioengineering, University of Illinois at Chicago. "Bode Plots and Frequency Response," Host: James L. Patton,

Teaching Assistant (January 2013- May 2013), Interdisciplinary Product Development, Department of Bioengineering, University of Illinois at Chicago. Supervisor: Miri Kotche, Ph.D.

Teaching Assistant (August 2012-December 2012), Introduction to Bioengineering, Department of Bioengineering, University of Illinois at Chicago. Supervisor: Miri Kotche, Ph.D.

Teaching Assistant (August 2011-May 2011, August 2010-May 2010), Senior Design, Department of Bioengineering, University of Illinois at Chicago. Supervisor: Terri Layton, Ph.D.

OTHER TRAINING:

Fluent in MatLab, Simulink, XPC Target, C++, Adobe Illustrator, Microsoft Office, SolidWorks, AutoCAD, ADAMs View, MIMICS, Python, H3D, Mathematica
Proficient in LabView, JavaScript, Abaqus, ADINA,
Fluent in Hebrew

PUBLICATIONS:

Konrad K, Wei K, He K, Liang Y, Abdollahi F, **Bittmann M**. Learn faster when you are more variable. *Under Revision*. PLOS Computational Biology.

Fisher M, Huang F, Klamroth-Marganska V, Riener R, Patton J. Haptic Error Fields for Robotic Training. IEEE World Haptics. Chicago, IL. June 2015.

Melendez-Calderon A, **Fisher M**, Tan M, Burdet E, Patton J. Acquisition of motor skills in isometric conditions through synesthetic illusions of movement. IEEE World Haptics. Chicago, IL. June 2015.

Fisher M, Huang F, Wright Z, Patton J. Distributions in the Error Space: Goal-Directed Movements Described in Time and State-Space Representations. IEEE Engineering in Medicine and Biology Society (EMBS), Chicago, IL. August 2014.

Fisher M, Patton J. 2014. Customized Forces for Teaching Visuomotor Transformations. IEEE Engineering in Medicine and Biology Society (EMBS), Chicago, IL. August 2014.

Wright Z, **Fisher M,** Huang F, Patton J. Data sample size needed for prediction of movement distributions. IEEE Engineering in Medicine and Biology Society (EMBS), Chicago, IL. August 2014.

ABSTRACTS:

Fisher, M, Huang F, Klamroth-Marganska V, Riener R, Patton J. Customized Forces Using Distributions of Error Improve Learning a Visual-Motor Transformation. Society for Neuroscience, Chicago, IL, October 17-21, 2015.

Fisher M, Huang F, Wright Z, Patton J. Parameterization of Error in Time Versus Space for Goal-Directed Movements. Society for Neuroscience, Washington, DC. November 15-19, 2014

Fisher M, Patton J. 2013. Custom Designed Sensory Conflicts, Society for Neuroscience, San Diego, CA. November 9-12, 2013.

Fisher M, Patton J. 2012. Investigating motor adaptation using intermittent probe trials, Society for Neuroscience, New Orleans, LA. October 13-17, 2012.

Fisher M*, Abdollahi F*, Morehead JR, Bixby K. Effect of baseline variability in motor learning: Meta-analysis over multiple data sets. Translational and Computational Motor Control, New Orleans, USA, October 12, 2012

Fisher M, Bradley J, Schiffman C, Claflin D, Palmer M. 2011 "Early Force Responses of Active Skeletal Muscle Fibers During Stretch" ASME Applied Mechanics and Materials Conference, Chicago, IL.

AWARDS & HONORS:

Recipient; Swiss National Centre of Competence in Research (NCCR) Robotics Education Committee Grant, 2014.

Recipient; Graduate student presenter award, 2013 and 2014

Recipient; Graduate student council travel award, 2014 and 2015

University Honors, *University of Illinois at Chicago (Chicago, IL, USA), May 2012*

Dean's List, *University of Michigan College of Engineering (Ann Arbor, MI, USA), May 2010, 2009*

Mondialogo Engineering Award Honorable Mention for International Engineering Team Project Proposal

PROFESSIONAL MEMBERSHIPS:	IEEE student member EMBS student member Biomedical Engineering Society student member Society of Neuroscience student member Women in Science and Engineering member American Society of Mechanical Engineering member