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Evaluating Robotic Assistance and Developing a Wearable Hand Activity Monitor to Improve Upper Extremity Movement Recovery after Stroke

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Evaluating Robotic Assistance and Developing a Wearable Hand Activity Monitor to Improve Upper Extremity Movement Recovery after Stroke

DISSERTATION

submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in Biomedical Engineering

by

Justin Bradley Rowe

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2015
DEDICATION

Hi Mom
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ABSTRACT OF THE DISSERTATION

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In their daily lives, stroke survivors must often choose between attempting upper-extremity activities using their impaired limb, or compensating with their less impaired limb. Choosing their impaired limb can be difficult and discouraging, but might elicit beneficial neuroplasticity that further reduces motor impairments, a phenomenon referred to as “the virtuous cycle”. In contrast, compensation is often quicker, easier, and more effective, but can reinforce maladaptive changes that limit motor recovery, a phenomenon referred to as “learned non-use”. This dissertation evaluated the role of robotic assistance in, and designed a wearable sensing system for, promoting the virtuous cycle.

In the first half of the dissertation, we use the FINGER robot to test the hypothesis that robotic assistance during clinical movement training triggers the virtual cycle. FINGER consists of two singly-actuated mechanisms that assist individuated movement of the index and middle fingers. 30 chronic stroke participants trained in FINGER using a GuitarHero-like game for nine sessions. Half were guided by an adaptive impedance controller towards a success rate of 85%, while the other half were guided towards 50%. Increasing assistance to enable successful practice decreased effort, but primarily for less-impaired participants. Overall, however, high success practice was as effective (or more) as low success
practice and even more effective for highly impaired individuals. Participants who received high assistance training were more motivated and reported using their impaired hand more at home. These results support the hypothesis that high assistance clinical movement training motivates impaired hand use, leading to greater use of the hand in daily life, resulting in a self-training effect that reduces motor impairment.

The second half of the dissertation describes the development of the manumeter - a non-obtrusive wearable device for monitoring and incentivizing impaired hand use. Contrasted against wrist accelerometry (the most comparable technology), the manumeter uses a magnetic ring and a wristband with mangetometers to detect wrist and finger movement rather than gross arm movement. We describe 1) the inference of wrist and finger movement from differential magnetometer readings using a radial basis function network, 2) initial testing in which distance traveled estimates were within 94.7%±19.3 of their goniometricly measured values, 3) experiments with non-impaired participants in which the manumeter detected some functional activities better than wrist accelerometry, and 4) improvements to the hardware and data processing that allow both subject-independent tracking of the position of the finger relative to the wrist (RMS errors < 1cm) and highly reliable detection of whether the hand is open or closed. Its performance and non-obtrusive design make the manumeter well suited for measuring and reinforcing impaired hand use in daily life after stroke.

The contributions of this dissertation are experimental confirmation that high assistance movement training promotes the virtuous cycle, and development of a wearable sensor for monitoring hand movement in daily life. Training with robotic assistance and hand use feedback may ultimately help individuals with stroke recover to their full potential.
Chapter 1 Introduction

“A person needs new experiences. It jars something deep inside allowing them to grow. Without change, something sleeps inside us and seldom awakens. The sleeper must awaken!”
- Duke Leto Atreides (Frank Herbert, Dune 1965)

Every year roughly 795,000 Americans suffer either an original or a recurrent stroke, and although the mortality rate of stroke has been on the decline for the last decade, the incidence rate has remained largely unchanged [1]. While encouraging, the gradual decrease in stroke mortality has meant that the number of people left with stroke related motor impairments has been steadily increasing. One out of every six people worldwide can be expected to have a stroke in their lifetime [2], and stroke is recognized as the leading cause of serious disability in the united states [1]. There are currently an estimated 6.6 million individuals in the US that have suffered at least one stroke [1], and roughly one third of these individuals can be expected to suffer from serious, chronic motor impairments [3]. As the national average age increases this population is expected to grow at an increasing rate [4]. Over 80% of the individuals in this growing population who exhibit severe weakness six months after their stroke can be expected to develop chronic impairments in their contralesional arm or hand [5].

Fortunately, numerous studies have now demonstrated that rehabilitation therapy can help to reduce the effects of these chronic motor impairments [6]–[9]. However, despite the evidence that the functional outcomes of rehabilitation therapy are related to both its duration and its intensity, the amount of therapy that a patient receives is often limited by its cost [1][10]. This is particularly troubling given that it has been convincingly demonstrated that reducing the intensity and duration of rehabilitation can reduce a stroke survivor’s potential for recovery [11]–[13]. As such, there is a great need for new devices and methods that will allow us to increase the effectiveness of rehabilitation therapy while reducing its cost.
As we develop these new therapies it is important that we consider the mechanisms underlying post-stroke motor recovery and its potential complications. Although the process is not fully understood, the success of rehabilitation therapy is attributed to activity dependent plastic reorganization of the surviving neuronal resources in the central nervous system [14]. The central nervous system supports many different mechanisms not only for modifying the synaptic strength of existing neuronal connections, but even for rerouting neurons to completely new areas [15]. When guided by active use or an effective form of rehabilitation therapy, these plasticity mechanisms can allow meaningful improvements in motor function. However, when not properly guided these same plasticity mechanisms can also enable maladaptive changes that impair motor recovery [16]. One of the most notorious of these maladaptive processes is the learned nonuse phenomenon.

1.1 The development of learned nonuse
In a recent meta-study evaluating the effect of the dose of rehabilitation therapy on the outcome of that therapy it was found that trials requiring large doses of therapy were much more likely to produce clinically meaningful improvements in motor ability [17]. This result is consistent with numerous animal model studies which have consistently required a very high dose of practice for the animals to recover to their full potential [18], [19].

However, for patients suffering from severe motor impairments obtaining a sufficiently large dose of practice can seem prohibitively difficult. Choosing to use their impaired limbs after their injuries can be very frustrating, and the positive results of motor practice occur at a relatively slow timescale. From a learning standpoint, motor practice is simultaneously too frustrating and too boring. It is frustrating in the sense that even the smallest amount of exploration can require an exhausting amount of effort, and it is boring in the sense that it can often seem like there are no open avenues of new, actionable information to explore. To further complicate the scenario, stroke related motor impairments typically only affect one side of the body, so it is often faster and more energy efficient for stroke survivors to simply compensate for the poor motor control on their impaired side by using their less impaired side instead. Compensation
strategies like this one are not altogether undesirable in that they allow stroke survivors to be more active and to do the tasks that they need to do to live productive lives. However, over time compensation can reinforce a vicious cycle that prevents stroke survivors from recovering to their full potential.

This cycle has been well explained by [20], and is illustrated in Figure 1. After their initial injuries, it can be very difficult for stroke survivors’ to use their impaired limbs either in therapy or in their day to day lives. When they do attempt to use their impaired limbs, their attempts often result in failures with embarrassing or even painful consequences. This punishment de-incentivizes future exploration with their impaired limbs and encourages compensation using their less impaired limbs. Given that it is already much more efficient for them to use their impaired limbs, this can lead to asymmetry in their upper extremity use. If this asymmetry becomes too extreme it can cause the cortical representation of their unused impaired limbs to shrink – thereby making them even more difficult to use [20]–[22]. This further perpetuates the cycle and creates a maladaptive pattern that can be very difficult to escape without direct intervention [20].
Although learned nonuse was originally presented within the context of behavioral psychology as a product of operant conditioning [23], it could just as accurately be explained in terms of principals of motor learning. Studies investigating the process by which the human motor system adapts to unfamiliar dynamic environments have revealed that motor adaptation serves to minimize the error and effort of future movements [24], [25]. Computational models guided primarily by these rules have demonstrated that, below a certain ability threshold, the easiest most effective way for the CNS to minimize the error and effort of its movements is to simply compensate with the less impaired limb [21].

It is also important to note that learned nonuse describes a perceived sense of futility, not actual futility. Learned nonuse refers to the tendency of individuals with unilateral motor impairments to neglect their impaired limb in favor of compensating with their unimpaired limb. Although learned nonuse is not a true motor impairment in the sense that it is not defined by hard anatomical constraints, it has the same immobilizing effect as a true motor impairment and it can interfere with the correction of true motor impairments (and possibly even make them worse). Fortunately, learned nonuse is believed to be reversible [26], and because it is the result of conditioning and maladaptive motor learning and not anatomical limitations, there is good reason to believe that correcting learned nonuse might be easier than correcting other more anatomical forms of motor impairment. This makes learned nonuse an attractive target for neuro-rehabilitation. Not only would correcting learned nonuse restore untapped movement potential, but it would lay the groundwork for future improvement by enabling individuals with motor impairments to incorporate motor practice with their impaired limbs into their day to day lives – thus turning the vicious cycle of learned nonuse into a virtuous cycle of recovery.

1.2 Existing therapies for correcting learned nonuse
The effects of learned nonuse have now been established both experimentally and computationally [21], [27]–[29], and the need for direct intervention of the learned nonuse phenomena has inspired a very deliberate form of therapy called constraint induced therapy
(CIT) [30]. CIT drives participants to use their impaired arms in their day to day lives by 1) restraining their unimpaired arm with a movement impeding mitten and 2) providing intensive therapy to the impaired arm [31]. The movement impeding mitten addresses the bottom pathway to learned nonuse as shown in

Figure 1 by turning the tables and making it harder and for patients to use their unimpaired arm than it is for them to use their impaired limb. Similarly, the intensive therapy is meant to address the top pathway by increasing the cortical representation of the impaired arm – thereby making it easier to use outside of therapy. These interventions have proven to be effective at increasing both in-lab measurements of motor capacity and out of lab measurements of spontaneous impaired limb use [8], and are a “gold standard” of therapy for patients who can qualify to participate.

Despite its effectiveness, however, potential patients of CIT have reported being apprehensive about the demands that the therapy would place on them, and therapists have reported believing that CIT would be very difficult to implement and possibly too demanding for some patients [32]. In its unmodified form, CIT requires patients to restrain their unimpaired hand for 90% of their waking day for 14 days. Therapists are also required to provide them with six hours of intense physical therapy on every weekday during this 14 day period. Although the short overall duration of the therapy might offset some of the cost of providing 6 hours of therapy 5 days a week, widespread adoption of CIT would likely be very expensive. These requirements do not undermine the value of CIT, but the difficulty that CIT poses both to therapists and to patients suggest that there is still a need for other forms of therapy that address the problem of learned nonuse in a less taxing way.

1.3 New alternatives for correcting learned nonuse

1.3.1 Using robotic devices to enable successful impaired limb use

Rather than addressing learned nonuse by increasing the difficulty and failure rate associated with using the less impaired arm, a similar effect could be achieved by decreasing the difficulty
and failure rate associated with using the more impaired arm. This is often the implicit goal of robot assisted rehabilitation therapy. Rehabilitation robots take the daunting task of making goal oriented movements with the impaired arm and scale the challenge down to a level that is within the capabilities of a particular individual. This reduces the barrier to entry to rehabilitation therapy and allows participants to succeed at their attempted movements. Because the new task (as redefined by the robotic assistance) no longer seems prohibitively difficult, recipients report a greater willingness to complete the large number of repetitions necessary to drive recovery [33]. More pointedly, by using robotic devices it is possible to deliver a much higher dose of therapy than would be practical otherwise [34].

Although numerous studies have demonstrated that robot assisted therapy can improve motor function after stroke [35]–[39], and although therapy provided by robots has proven to be at least as effective as a comparable dose of non-robotic therapy [34], there is some concern that robot assisted therapy might interfere with the error-driven learning mechanisms of the central nervous system. Numerous studies in the field of motor learning have demonstrated that motor adaptation is guided by the minimization of task errors [24], [25]. Although ultimately undesirable, these errors are essential to the learning process. As such, there is some concern that rigid robotic devices that do not allow errors, or that break the natural relationship between motor outputs and their resulting errors, might mask this important training signal [40][41].

There is also concern that robotic devices might interfere with the effort minimization processes that drive learning in the central nervous system [42]. In addition to reducing task error, robotic assistance can also reduce the effort required to complete a given task. Depending on how this assistance is provided, it can create a situation in which the CNS can safely reduce its motor output without incurring much of an error penalty. Since the CNS is always seeking to minimize its motor output, this can allow the CNS to “slack”. Studies comparing therapies that required active participation to therapies in which the participants were passively moved by robotic device have demonstrated that active involvement is
important for motor recovery [43]. As such, the slacking could reduce the effectiveness of robot assisted physical therapy.

Although the role of error and effort minimization are well understood in the unimpaired motor system, it is less clear what role these learning mechanism play in the impaired motor system. In particular, for highly impaired subjects computational models suggest that these learning mechanisms might maladaptively contribute to learned nonuse [21]. For individuals with severe motor impairments, the easiest way to minimize error and effort is to compensate using the impaired limb. Such compensation reinforces learned nonuse, and can cause motor impairments to get worse instead of better [21]. Consequently, for individuals below a particular motor ability threshold it not be undesirable for robot assisted therapy to conflict with these learning mechanisms.

In order to use robotics for physical therapy without either encouraging maladaptive change or interfering with the natural learning mechanisms of the human motor system, it is important that we understand how the human motor system responds to robot assisted practice. The first half of this dissertation will examine the motivational value of robot assisted therapy in correcting learned nonuse and reducing motor impairment. It will also explore the question of whether the benefits of robot assisted therapy outweigh its potential disadvantages and evaluate whether enabling high success therapy might be more beneficial for highly impaired individuals than for individuals with moderate motor ability.

1.3.2 Using wearable sensors to provide augmented feedback of impaired limb use

Perhaps the largest disadvantage to using robotic devices to assist in neurorehabilitation is that most of the devices that have seen wide adoption can only be used in a laboratory or clinic. Because these devices are expensive, bulky, and often anchored to the ground, they cannot be easily integrated into the daily lives of the people that need them. While they do increase the dose of therapy that can be provided in the clinic, the maximum dose of therapy that they can
provide is severely limited by the fact that stroke survivors only spend a small fraction of their time in clinics. This is particularly true during the chronic stage of their injuries, but is also true during their acute phase.

In a rigorous multisite study performed across 5 hospitals in Melbourne Australia observing and recording the daily activity of stroke patient during their in-patient treatment, it was found that only 73% of the participants received daily therapy from a physical therapist (PT) and only 24% were treated by both a PT and an occupational therapist (OT). When subjects did get access to a physical therapist, the average session duration was only 24+/-12 minutes. Of that time, only 33% was spent working on the upper extremity and only 6% involved movement of the impaired arm [44]. Time spent with a therapist (PT, OT, or other) accounted for only 5.2% of the average patient’s day (full day counted from 8am-5pm).

Similar results have been found for outpatient therapy. In a study counting the number of movement repetitions completed during outpatient rehabilitation, it was found that the average therapy sessions consisted of ~39 active movements, ~34 passive movements, and ~12 purposeful (functional, goal directed) movements [45]. For reference, rodent studies in which the animals recover almost fully from stroke-like lesions in the brain commonly require at least 400 movements per day [19]. Similar studies in primates typically require upwards of 600 movements per day [18].

One possible take away from this is that patients should be spending more time – or more intensive time – in the clinic. This is by all means a desirable goal, and it is possible to substantially increase the duration and dose of therapy provided within a standard outpatient session [46], [47]. However, there is a ceiling on how long and how intensive a therapy session can be. In contrast, the ceiling on the amount of task-oriented practice that patients could accrue over the course of an entire day is very high, and focusing on this underutilized time could potentially be a very efficient and cost effective way of complimenting the dose of therapy provided in the clinic.
The value of targeting time spent outside the clinic is even clearer given learned nonuse develops outside the clinic. Every time that a stroke survivor is presented with a choice of either using their impaired limb to complete a given task or compensating with their less impaired limb their decision will either strengthen or weaken their learned nonuse habits.

Constraint induced therapy address this problem by requiring participants to wear a movement impeding mitt on their less impaired hand for ~90% of the their waking day. However, a similar effect might be achieved by incentivizing use of the more impaired limb instead of de-incentivizing use of the less-impaired limb. Pedometers have proven to be an effective tool for incentivizing walking in sedentary populations [48], and it has also been shown that providing stroke survivors with feedback of their walking speed during training significantly improves their performance [49]. Although the diversity of upper extremity use makes it more difficult to monitor than walking, initial attempts have been made to create activity monitors capable of providing meaningful information about upper extremity use.

Starting with the early clinical trials evaluating constraint induced therapy, wrist accelerometry has long been used by experimenters to quantify the extent to which stroke survivors use their impaired upper extremity in their day to day lives [50]. Although wrist accelerometry has been used to great effect as a technology for quantifying motor impairment and daily use habits [51]–[53], it is a somewhat limited technology. Many of the early studies using wrist accelerometry relied on threshold filters that simply distinguished between periods of activity and periods of inactivity without concern for the amount, type, or quality of the activity [54]. Although processing methods have become a bit more refined, wrist accelerometry still describes amount of activity more than it describes the type or quality of that activity [51], [55]. More importantly, wrist accelerometry is only able to detect movement of the wrist. As such, it is unable to directly quantify hand use. Given the importance of hand use for many activities of daily living the ability to directly measure hand use could greatly improve the utility of the technology. Specific knowledge of hand use would be particularly important for an augmented feedback system designed to encourage hand use.
To address these needs and to improve upon the existing state of accelerometry, we introduce a new device, called the manumeter, for monitoring activity of the arm and hand outside the laboratory.

1.4 Outline

The content of this dissertation discusses two complementary technologies for addressing the problem of learned nonuse after stroke.

The remainder of this dissertation discusses the application of robotic assistance and wearable sensing systems to the problem of learned nonuse after stroke. As such, the dissertation is split into two halves with the first half focusing on robotic therapy and the second half focusing on the development and testing of a new wearable device for monitoring arm and hand use after stroke.

Chapter 2 of the dissertation will introduce FINGER, a robotic exoskeleton designed to assist in hand rehabilitation, and chapter three will describe a clinical trial in which this device was used to study the effects of motor practice at high success rates versus low success rates. We hypothesized that experiencing higher levels of success during training with FINGER would improve motor performance by 1) motivating participants to use their impaired limbs, and 2) providing participants with large sensory inputs synchronized with their desired motor outputs.

The second half of the thesis will focus on the development and testing of a wearable sensing system designed to address nonuse by providing stroke survivors with augmented feedback describing how much they use their impaired limb in their day to day lives. The design of this device, which we will refer to as the manumeter, is described in Chapter 4. Chapter 5 describes the initial testing of the manumeter on a cohort of unimpaired subjects. One of the primary innovations of the manumeter is that it is able to distinguish between arm use and hand use. To verify that this distinction is in fact valuable, Chapter 6 describes an experiment examining the relationship between arm use and hand use. Finally, Chapter 7 describes a number of improvements made to the initial design of the manumeter which 1) increase the accuracy of
Chapter 2 A device for motivating impaired limb use via robotic assistance: Design and initial testing of the FINGER robot

Portions of this chapter have been reproduced from the following publications [56], [57].

2.1 Introduction
Development in the field of neuro-motor rehabilitation is currently being driven by a need for technologies and methods that reduce the cost of rehabilitation therapy while simultaneously extending its benefits beyond the modest gains that have become familiar in the past two decades. To address this need, an increasing number of research groups have begun to focus on the development of robotic devices to add automation, objectivity, and control to the rehabilitation process [58]–[61]. Although the devices themselves are currently expensive, evidence suggests that by providing intensive therapy with a reduced dependence on continuous and laborious therapist attention such devices can improve the cost effectiveness of rehabilitation therapy [62]. In addition to reducing both the cost therapy and the strain placed on the therapists, robotic devices also enable deeper insights into the mechanisms of neurorehabilitation [13], [25], [41].

Currently, the approach of most robotic rehabilitation systems is to provide stroke survivors with the appropriate amount of assistance to enable them to complete movements that they would not otherwise be able to complete on their own [58], [59]. In this paradigm, the robot adopts the role of a physical therapist performing “active assist” exercises. Although robotic active assist therapy has been shown to improve motor function, the exact mechanisms by which it works are not fully understood.
One possibility is that active assist therapy might work by allowing the motor outputs of the CNS to result in the rich sensory response that accompanies a successful movement. This idea is consistent with the hypothesis that plasticity in the CNS is driven largely by Hebbian-like learning rules. Hebbian learning states that the strength of each synapse in a network is modulated according to the level of correlation between its inputs and its outputs [63]. To strengthen a synapse between two adjacent neurons, those neurons must fire at the same time many times in a row. The more often they fire at the same time, the stronger the synaptic weight describing the influence of the input neuron on the output neuron will be. As such, to develop connections to facilitate fluid movement of the impaired limb, the Hebbian learning rule would prescribe a large number of movement attempts in which the sensory feedback describing a successful movement are time correlated with the patient’s volitional input. Since active assist therapy enables participants to perform a large number of successful movements, the effectiveness of the therapy could be, in part, due to Hebbian learning [64].

In addition to this Hebbian learning process, it is also possible that active assist therapy works, in part at least, by correcting learned nonuse. Stroke survivors develop nonuse when their attempts to use their impaired limbs repeatedly result in exhaustion, failure, or some other form of punishment. Active assist therapy, in contrast, enables repetitive and successful practice with the impaired limb. If the successes experienced during active assist therapy is sufficient to outweigh the failures experienced outside of therapy, and if the success experienced during active assist therapy is not simply attributed to the robot providing the therapy, then active assist therapy could reduce the effects of learned nonuse. This can be thought of as the motivational value of robot assisted therapy.

To test the roles of these two mechanisms in robotic active assist therapy, we have developed a flexible robotic platform for hand rehabilitation after stroke. Because of the high sensory capacity of the hand and its importance for many activities of daily living, this robotic platform, which we refer to as FINGER (Finger INdividuation Grasp Exercise Robot), was designed to study and manipulate individuated movement of the index and middle fingers. To ensure that FINGER
would be able to facilitate both active assist therapy as well as therapies focusing on error
driven learning, FINGER uses high fidelity servo tube actuators. Like pneumatic actuators, these
servo tube actuators are back drivable and inherently compliant. However, unlike pneumatic
actuators, servo tube actuators are very responsive and easy to control. The design of the
FINGER robot was completed in collaboration with researchers at the University of Idaho, and a
thorough presentation of the design and performance of the system has been published
elsewhere [56], [65]. This chapter will give an overview of the functionality and design of the
device, but will focus on a pilot experiment in which we used the device to examine the effect
of practicing at low, medium, and high success rates on patient engagement. We also
demonstrate the capabilities of the robot as a device for obtaining objective outcome measures
of hand recovery.

2.2 The FINGER robot
FINGER (Finger INdividuation Grasp Exercise Robot) is a two degree of freedom robotic device
for assisting and monitoring finger rehabilitation after a neurological injury. The device consists
of a pair of stacked, single degree of freedom eight bar mechanisms, which can each control the
angle and position of the proximal phalanx and the position of the medial phalanx of a single
finger. These eight bar mechanisms were designed to follow the natural curling motions of the
index and middle fingers during grasping movements [56].
Each mechanism is actuated by a high speed linear motor (Dunkermotoren STA116-168-S-S03C) capable of producing a continuous force of 26.75N and a peak force of 91.9N. The actuators are easily back-drivable and can move the finger mechanisms at speeds up to 8 Hz with negligible attenuation [56]. The actuators are controlled using the Mathworks xPCTarget operating system. Tasks related to the control and safety of the robot are managed by a target computer which communicates with the robot through a data acquisition card, and therapeutic video games running on a host computer communicate with the target computer through a TCP network connection.

2.3 Measuring finger individuation and task engagement with the FINGER exoskeleton

To validate the FINGER robot as a device for obtaining meaningful outcome measures for rehabilitation therapy, the robot was used to perform an experiment in which both finger individuation and real-time task engagement were quantified.

Our goal was to develop an engaging task for assessing finger movement ability, and to develop a method for providing assistance so that individuals at a wide range of impairment levels, including more severe levels, could engage in the task. Within this context, we sought to understand whether the amount of assistance provided affected the subject engagement. We also sought to develop measures of finger movement, including finger individuation.
In accordance with this goal, we performed an experiment in which FINGER was used to test the hypothesis that subjects will be most engaged in the rehabilitation therapy presented to them when they are at their optimal challenge level. To test this hypothesis, FINGER was used to assist subjects in playing a custom-designed game similar to Guitar Hero. This game requires subjects to play along with a song by attempting to hit notes streaming down a visual display as shown in Figure 2.

In order to hit these notes, the subjects were required to flex their fingers to a desired angle and stop at the correct time. During the game, subjects were presented with three types of notes corresponding to flexion of the index finger, the middle finger and both fingers together. After successfully hitting a note, the subjects were required to extend their fingers back to a neutral position before the game would credit them with hitting future notes. While subjects attempted to flex their fingers to the correct positions, small colored balls hovering above the fret board were displayed to provide the subjects with visual feedback of their finger position (see Figure 2). The song used in this experiment was “Happy Together” by the Turtles, and it required 104 notes to be hit over the course of a 160 second gaming session.

### 2.3.1 Subjects

Sixteen volunteers with stroke related motor impairment participated in the study (average age of 57.8 +/- 12.5 SD). Level of impairment was assessed using both the upper extremity Fugl-Meyer (FM) test and the box and blocks (BB) test [65], [66]. For the FM test, a trained therapist asked subjects to perform 33 test movements and scored them 0 (can’t do), 1 (can do partially), or 2 (can do), then summed the scores. For the BB test, subjects moved as many blocks as possible over a divider in a one minute period. The average FM scores for the group were found to be 41.6±15.8 SD out of 66, and average BB scores were found to be 25.1±21.9 (compared to a score of 75.2±11.9 reported in literature for healthy subjects) [66]. Based on these scores, nine of the subjects were classified as highly impaired (FM < 40 & BB< 20), and the remaining seven subjects were classified as moderately impaired. For comparison, four healthy subjects (3 male/1 female, average age 33.5 ± 9.4 SD) were also included in the study. All
subjects provided informed consent, and all procedures were approved by the Institutional Review Board at U.C. Irvine.

2.3.2 Success rate algorithm

During the game, FINGER was used to both assist the subjects in completing the desired task and to monitor their performance. Although FINGER can be operated under a variety of control paradigms, this experiment used a PD controller whose gains were intermittently updated by an algorithm which attempted to control the subjects' probability of hitting notes successfully [67]. Our contention was that by controlling subjects’ success rate, we would be able to control their challenge level. According to the Challenge Point Framework (CPF) from the motor learning literature, determining the optimal challenge level is crucial to optimality of motor learning, particularly in rehabilitation [68]. CPF states there is an ideal amount of information which when presented to the learner will optimize the learning process. In other words, to achieve the best learning rate, the task shouldn’t be too easy or too difficult. This ideal amount of information varies with the skill level of the learner. By adaptively modifying the controller gains, we can set the game difficulty and hence the level of challenge the subjects experience, regardless of their impairment level.

Determining the optimal challenge point for a particular task is difficult because it requires measuring long-term learning at a variety of challenge levels in a large number of subjects. However, one determinant of the optimal challenge point is likely engagement – i.e. the more engaged a subject is, the more learning will likely occur. Engagement can be measured in real-time and thus has the potential to serve as a means to identify when conditions are at least partially conducive for learning. Thus, we studied how task engagement, quantified by how much effort the subjects exerted during the game (see below), varied with success rate.

The success rate algorithm mentioned above works as follows. For each successful note, the algorithm reduced the gains on the corresponding finger by an amount $\rho$, and for every missed note the gains on the corresponding finger were increased by an amount $\alpha \cdot \rho$. As shown in [67],
this simple algorithm eventually forces the subjects’ probability of success to converge on a value dependent only on $\alpha$ as shown in Eq. 1 below.

$$\hat{p}_{t\to\infty} = \frac{\alpha}{\alpha+1}$$

Eq. 1

Subjects were seated in front of a visual display, and the proximal and medial phalanges of their index and middle fingers were securely attached to the end effectors of the FINGER robot. Subjects were then instructed how to play the game and were asked to familiarize themselves with the task by playing through a song at a success rate of 75%. Data from this initial trial were excluded from the final analysis.

After the familiarization task, the robot was used to measure the subjects’ range of motion and maximum isometric force in both flexion and extension. Measurements were taken from the index and middle fingers both individually and together. These measurements were repeated at the end of the experiment. Then subjects were asked to play through the same song twice at each of the three randomly presented success rates (50%, 75%, and 99%).

On a randomly selected subset consisting of roughly 15% of the notes in every song, the robot's gains were set to a fixed, high value and by doing so the robot was used to block the subject’s movements instead of assisting them. During these blocked trials, the amount of force exerted against the robot was taken as a measure of the subject’s engagement in the task. Subject performance during these trials was not used to adapt the robot’s gains, and once the blocked notes passed the control gains were returned to their previous values.

2.3.3 Measuring finger individuation and engagement

The instantaneous success rate at each note was calculated by dividing the number of successful trials within a moving window containing the 25 preceding notes by the size of the window. The peak force applied against the robot during blocked trials was used to quantify subject engagement by normalizing it to the subject’s maximum force for the corresponding finger as measured during isometric trials. An unbalanced 2 factor mixed measures ANOVA with
repeated measures applied to the success rate variable was used to test the effects of success rate and impairment level on subjects’ engagement.

During blocked notes for the index and middle fingers, the robot restricted the motion of both the correct and the incorrect fingers. An estimate of finger individuation was thus obtained by comparing the force generated by the finger that was supposed to move to the force generated by the finger that was not. Forces measured from both fingers were first normalized by their corresponding maximum force values from isometric trials. A measure of individuation was then calculated by dividing the average maximum normalized force applied by the incorrect finger by that of the correct finger. For blocked notes in which the force applied by the incorrect finger was greater than 1.25 times the force applied by the correct finger, it was assumed that the subject accidentally tried to hit the wrong note. Similarly, for trials in which the subjects did not apply any measurable force with either finger, it was assumed the notes were completely missed. These blocked notes were not included in the individuation analysis. An unbalanced three factor mixed measures ANOVA with repeated measures on the finger variable and the success rate variable was used to determine whether finger, success rate, or impairment level had any significant effect on the subject's individuation value.

2.3.4 Results

Average probability of success in hitting correct notes during gameplay versus time for the sixteen impaired and the four healthy subjects is shown in Figure 3. At the desired success rates of 50%, 75% and 99% the impaired subjects converged to the average actual success rates of 47.7+/−9.6%, 73.8+/−7.1%, and 97.6+/−1.9%. However, the unimpaired subjects converged to the average actual success rates of 72.2+/−19.5%, 79.3+/−4%, and 99+/−1.1%. 
This result shows that the success rate algorithm is successful in assisting subjects to achieve a desired success rate. It is not surprising that the healthy subjects could achieve success rates higher than algorithm’s desired success rate, because the algorithm doesn’t prevent subjects from hitting more correct notes than desired. In order to effectively challenge the unimpaired subjects, the algorithm would need to have been able to make the game more difficult than it would naturally be with the assistance turned completely off. This is not necessary for the impaired subjects, whose reduced neuromuscular ability provided the increased difficulty.
We also measured how success rate and impairment level affected the subjects’ engagement while playing the game. Success rate was found to have a significant effect on subjects’ engagement (\( p = 0.0024 \)). The effects of impairment level on engagement, approached but not achieve significance (\( p = 0.0785 \)). As shown in Figure 4, engagement decreased when subjects’ success rate increased.

Figure 5 shows the effects of impairment level and the finger being used on finger individuation. Both the finger being used and

![Figure 6](image-url)  
*Figure 6  Finger individuation for both the index and middle fingers at each success rate for each impairment level. Individuation was measured during blocked trials as the normalized amount of force produced by the incorrect finger divided by the normalized amount of force produced by the correct finger.*

impairment level were found to have a significant effect on finger individuation (\( p = .0001 \) and \( p = .0062 \) respectively). As can be seen in Figure 5, individuation scores of the index finger were consistently better (i.e. lower) than those of the middle finger. This means that when the subject tried to move the index finger, he was more successful at moving the index finger only, as compared to when he tried to move the middle finger in isolation.
2.4 Discussion
This chapter described the design and pilot testing of FINGER (Finger Individuating rasp Exercise Robot). We designed FINGER to be a high-performance robotic platform for implementing and testing control strategies for hand rehabilitation. Our goal is to better identify the behavioral factors associated with training in robotic devices that may help promote functional recovery after stroke. We also designed FINGER to have a high level of control fidelity to allow testing of the greatest possible range of training strategies. To achieve these goals, we designed a lightweight planar mechanism to guide each finger through a naturalistic grasping motion, actuated by a backdriveable, low friction, and high-bandwidth linear electric actuator.

The control fidelity of FINGER makes it a viable candidate for assisting patients in therapy tasks requiring precise timing. Therefore, we implemented a music game environment similar to Guitar Hero, in which subjects attempted to perform finger movements to match the timing of musical notes. This type of gameplay has the additional advantage of being engaging even for repetitive motions.

2.4.1 Controlling success using the FINGER robot
Since the level of success during game play is likely an important factor that influences effort and engagement during movement training [66], we devised a way to control success at the Guitar Hero game with FINGER. Specifically, during game play, we used FINGER to provide assistance to the subjects based on their in-game performance. By modulating the gains of a standard position feedback controller, we accurately controlled the stroke subjects’ success level. However, the unimpaired subjects achieved higher success levels than desired. This is likely due to a combination of the subjects’ inherent ability to perform the task without assistance and the fact that FINGER was programmed to assist subjects rather than resisting them.
2.4.2 Effects of success on participant engagement

Given a way to control success levels, we hypothesized that the level of success that subject’s experienced would modulate their engagement in the task. Specifically, based on previous studies that found that individuals with a neurologic impairment slacked when robot therapy devices over-assisted their movements [41], [67], we expected that subjects would exert less effort if they were too successful at the task. Our observation that the effort of both high level and low level subjects decreased when their success rate increased confirms this hypothesis. However, according to CPF, there should be an intermediate success rate at which practice is most productive. We did not find a success level at which the effort of our participants was optimized. One possibility is that effort may not decrease unless success is below 50%, the lowest level we tested.

Although significant, the effect of success rate on engagement was relatively small compared to the difference between the high impairment group and the moderate impairment group. The initial finding of this study were published in an EMBC conference paper[57], and at the time of publication we had only run 8 of the 16 chronic stroke participants included in this study. Before the continuation, we were not able to detect a significant effect of impairment level on participant engagement. The drop in effort of the unimpaired group was also significantly lower than that of the groups with motor impairments. Furthermore, the engagement of the severely impaired group was lower than that of the moderately impaired group both before and after the continuation. Since the effort measured during the blocked notes was normalized by the maximum force that the subjects could produce, this difference is likely not due to strength, but due to either 1) a true lack of engagement, or 2) inability of the participants to produce large forces quickly on demand. Given this confound, it might not be reasonable to equate effort and engagement for individuals with severe motor impairments.

2.4.3 Effect of impairment level on finger individuation

These tests also demonstrated the ability of FINGER to quantify finger individuation. Using measurements during blocked trials based on patients’ force applied by the wrong finger, we
found that patients with higher impairment levels individuated less than those with lower levels of impairment. This result supports the findings in the previous literature on individuation that found that stroke reduced the ability to perform selective individuated finger motions, and specifically that the independence of the middle finger is more impaired than that of the index finger[68], [69]. Significantly, we were able to quantify individuation during the normal course of game play of the game similar to Guitar Hero®. The possibility of generating quantitative measures of movement ability while therapy is delivered may increase the frequency at which these measures can be obtained. The results of the preliminary tests with FINGER demonstrate its unique capabilities to study and implement finger therapy after stroke. Additional testing with FINGER may add insight to the effects of success rate on motor learning and finger movement recovery.

2.5 Conclusion
In this chapter we introduce the FINGER robot as a platform for running experiments to test the importance of a variety of factors on motor recovery after stroke. In particular, we demonstrate that the device can enable participants with a wide range of motor impairments to successfully play musical games that require precise timing. We also demonstrate a simple algorithm that allows us to adaptively select control gains to guide our participants to desired success rates.

In this chapter, we used this algorithm to test the effects of practicing at high verses low success rates on participant engagement and we found that participants produced significantly less force (as normalized by their own maximal value) when practicing at high success rates. Although the effect was small, this might suggest that practicing at high assistance levels (and thus high success) rates might be less beneficial than practicing at lower assistance levels (and thus lower success rates). However, enabling participants to complete movements that they would not otherwise be able to complete on their own might have the added benefit of providing their brains with large sensory inputs time correlated with their own motor outputs – thereby encouraging Hebbian plasticity. It is also possible that the motivational benefits of high
success therapy might outweigh its potential disadvantages by encouraging use of the more impaired hand.

In the next chapter we will test these ideas by using a system very similar to the one described here to test the long term effect of high verses low robot assisted practice on both motor capacity and motivation after three weeks of practice.

Chapter 3 Benefits of robotic assistance for retraining finger movement ability after chronic stroke

3.1 Introduction
We have proposed that using robotic devices to enable successful practice after stroke could improve motor outcomes, in part, by correcting the effects of learned nonuse and driving Hebbian plasticity. However, there is some concern that using robotic assistance to reduce errors and enable successful practice could interfere with the error driven learning processes of the CNS.

Motor learning in unimpaired populations is widely believed to be driven by the minimization of error and effort [24], [25]. By using robotic assistance to allow successful movements that, without assistance, would result in high-error failures, it is possible that we might not only be masking a valuable training signal but also de-incentivizing exploration. Many of the models used to describe the iterative, error driven learning process of the CNS use the size of the previous error to update the motor commands for each upcoming movement. The importance of these errors in guiding the exploration of the CNS has even inspired some groups to use robots to amplify errors instead of reducing them [40].
In addition to minimizing error, there is also evidence that the CNS continuously learns to minimize the metabolic cost of its movements [24], [25]. Indeed, in our pilot testing of the Finger robot, we found some evidence that participants, and especially less-impaired participants, exerted significantly less effort per their own maximum when receiving high levels of robot assistance. This effort minimization mechanism is concerning for robotic assistance during stroke movement therapy given that studies comparing active therapy to passive movement therapy have consistently found effortful engagement to be necessary to drive positive plastic change [70], [71]. Because the human motor system is constantly seeking to minimize its effort, and because robot assistance often allows the motor system to “slack” without incurring an error penalty, there is some concern that practicing with robotic assistance might not be active enough to drive activity dependent plasticity [41].

However, while error and effort driven learning might be very important for the participants of most motor learning studies they might be less relevant for individuals with severe motor impairments. Studies comparing error reduction to error amplification are inconclusive. Some suggest that error amplification might be better even for highly impaired subjects [40], whereas others suggest that error amplification might be better only for skilled individuals [72]. Furthermore, models incorporating the error and effort minimization mechanisms of the CNS suggest that, below a certain motor ability threshold, these mechanisms do not facilitate positive plastic change but rather contribute to learned nonuse [21]. For individuals with severe motor impairments, the easiest way for the CNS to minimize the error and effort of a desired movement is to simply compensate with the less impaired limb.

This finding that error and effort driven learning mechanisms might only be beneficial above a certain threshold is consistent with the challenge point framework proposed by Guadagnoli and Lee [66]. The Challenge point framework suggests that motor practice should be most beneficial when the difficulty of the tasks has been tuned to optimize the amount of information that the learner can extract from it [66]. If the task is too difficult, as unassisted practice might be for many stroke survivors, then their errors will not provide them with any
actionable information but will rather contribute to their growing sense of futility. On the other hand, if the task is too easy, as robotic assistance might be for individuals with little to no motor impairment, then they might not make enough errors to guide further improvement.

If there is a threshold beneath which normal learning processes do not contribute to recovery but rather drive maladaptive change in the damaged CNS, then robot assisted therapy that reduces errors and enables successful practice could fill a vital role in the recovery process. However, if the challenge point framework is correct, then there might be a point at which this high success therapy becomes less beneficial.

To determine whether the advantages of high success practice outweigh its potential disadvantages, we have run a blinded, dose controlled clinical trial comparing the effects of high success (high assistance) versus low assistance (low assistance) robot assisted practice on motor recovery and motivation after stroke. Many studies have now demonstrated the benefits of active assist therapy [34]–[39], but to our knowledge there are no studies that compare the effects of high success versus low success therapy in a dose controlled fashion. In this experiment both groups received the same dose of therapy (in terms of duration, amplitude, and number of movements), and the rate at which those movements were successful was controlled by continuously adjusting the level of the robotic assistance.

### 3.2 Methods

#### 3.2.1 Study design and participants

In this experiment we used the FINGER exoskeleton to provide varying levels of assistance to participants with stroke related hand impairments while they played a musical computer game in the style of Guitar Hero. We divided these participants into a high success group and a low success group and then dynamically adjusted the amount of robotic assistance to drive participants towards their targeted success rate. Participants in the high success group were guided towards a success rate of 85% and participants in the low success group were guided towards a success rate of 50%.
We enrolled a total of 30 chronic stroke participants to participate in the study. To be included in the study, participants had to meet the following criteria: 1) history of unilateral stroke at least six months prior, 2) age between 18-73 years, able to score at least three blocks on the box and blocks test.

Once enrolled, an experienced evaluator assessed participants using a set of clinical outcome measures listed. To ensure that the participants were at a stable baseline at the time of enrollment, participants returned one week after their preliminary evaluation to repeat the Box and Blocks test. Two weeks after their preliminary evaluation participants began therapy in the FINGER robot. Therapy was given for three weeks at a dose of three one hour visits per week. Within each session there were 1065 possible movements. At the end of every week, we measured the self-efficacy of the participants with respect to the box and box task by asking them to report their confidence (on a scale from 0% to 100% in increments of 10%) that they could score at least 4, 6, 8, 10, 13, 20, 30, 40, and 50 blocks. At the end of the three week period, participants repeated the initial battery of outcome measures, and at one month the participants repeated outcome measures again to test long-term retention.

3.2.2 Robotic training program

FINGER uses a pair of independently actuated 8-bar mechanisms to assist the index and middle fingers of the impaired hand in moving through a natural curling motion. In this study we used the finger robot to assist participants in playing a musical game in the style of Guitar Hero. During each training session, participants played five songs two times each. In each song, note objects corresponding to the beat and general inflexion of the melody scrolled across the screen in the direction of finger flexion (e.g. left to right for left hand impairments) (Figure 7). These notes were distributed across three rows and moved towards color-coordinated targets located on the opposite side of the screen. Notes in the top row were green and corresponded to flexion of the index (top) finger. Notes in the bottom row were yellow and corresponded to flexion of the middle (bottom) finger. Notes in the middle row were blue and corresponded to movement of both fingers together. In addition to the notes and the targets, each row also
contained a ball indicating the position of the row’s corresponding finger. Participants were instructed to try to hit each note by moving the corresponding ball so as to stop inside of the target at the same moment that the note passed through the target. The size of the target (referred to as the hit window) corresponded to a physical distance of 20% of the robot’s range of motion. When participants hit a note correctly, the game played a satisfying animation of the note exploding. After attempting to hit a note, participants were instructed to move their fingers back behind a green line corresponding to 80% of full extension. To discourage participants from simply slamming their fingers into the hard-stop on the robot, the targets were placed at 80% of the robot’s full range of motion. This placed the hard stop of the robot just outside of the target’s hit window, thereby requiring participants to make controlled, graceful movements rather than wild, slamming movements.

Figure 7  During therapy, subjects played a game similar to guitar hero by completing individuated flexion and extension movements with their index and middle fingers. Targets were placed at 80% of full flexion, and between trials, the game prompted players to return to at least 20% of full extension.
As they played the game, the FIGNER robot provided corrective forces guiding players along desired trajectories. However, the robot only provided these forces if the participants initiated the movements themselves. We detected movement initiation using small load cells placed between the exoskeleton and the fingers; forces exceeding 1.75 times the measured noise threshold of the load cells were sufficient to trigger movement. As soon as a movement was triggered the robot calculated a minimum jerk trajectory that would move the finger from its starting position to the target position with a movement duration that would place the finger in the middle of the target at the same moment as the note the participant was trying to hit. A mirror trajectory would then guide the finger back to full extension. If a participant tried to initiate a movement when there was no upcoming note corresponding to that movement, the robot would not change its desired trajectory and would thus resist the erroneous movement. To determine if there was an upcoming note corresponding to an attempted movement and to prevent movements from overlapping, we restricted the maximum flexion duration to 0.8 seconds. To prevent the robot from moving at speeds that might surprise participants, we also defined a minimum flexion duration of 0.15 seconds.

Assistive forces guiding participants toward the desired trajectory were calculated using a proportional-derivative position controller, and the gains for the controller were selected adaptively to guide participants toward a desired success rate. The algorithm used to control success rate has been described in the previous chapter. Participants in the high success group were guided towards a desired success rate of 85%, and participants in the low success group were guided towards a success rate of 50%. The algorithm adapted gains separately for each finger and for both flexion and extension. However, adaptive gain selection was only turned on during the first visit of each week. During subsequent visits, the gains remained at the final value from the previous visit. As such, during the next two visits the participants had a chance to improve their scores without the robot increasing or decreasing its assistance to compensate. Because the last song in the set was significantly harder than the other songs (0.9
notes per second for the last song versus. an average of 0.5 notes per second for the other songs), the gain adaptation was not turned on for that song.

3.2.3 Outcome measures and data collection

We assessed the motor capacity of our participants one week before beginning training, shortly after completing training, and one month after completing training using standard clinical outcomes performed by a trained, blinded physical therapist. All participants were in the chronic stage of their injury, but to confirm that they were at a stable baseline we repeated our primary outcome measure one week after our initial assessment. Our primary outcome measure for the study was the Box and Blocks Test (BB), and our secondary outcome was the Fugl-Meyer test (FM). In addition, we also performed the Nine Hole Peg Test (NHPT), Lateral and Three Jaw Pinch Strength (PS) measurements, the NIH Stroke Scale (NIHSS), the Finger Tap Test (FT), the Action Research Arm Test (ARAT), the Modified Ashworth Scale of Spasticity (MASS), the Motor Activity Log (MAL), the Geriatric Depression Scale (GDS), and the Beck Hopelessness Scale (BHS).
After each robotic therapy session the participants also completed a subset of the Intrinsic Motivation Index questionnaire (IMI). A list of the included statements and their corresponding subscales is given in Table 1. Participants were instructed to evaluate the truth of each statement on a scale from 1 to 7 as pertaining to the therapy given with the FINGER robot.

### Table 1 A list of the Intrinsic Motivation Index (IMI) questions used for the FINGER study

<table>
<thead>
<tr>
<th>Statement to be evaluated</th>
<th>subscale</th>
<th>Reversed</th>
</tr>
</thead>
<tbody>
<tr>
<td>I think that this activity was boring.</td>
<td>Interest</td>
<td>Yes</td>
</tr>
<tr>
<td>I enjoyed doing this activity very much.</td>
<td>Interest</td>
<td>No</td>
</tr>
<tr>
<td>I thought that this activity was quite enjoyable.</td>
<td>Interest</td>
<td>No</td>
</tr>
<tr>
<td>This activity did not hold my attention at all.</td>
<td>Interest</td>
<td>No</td>
</tr>
<tr>
<td>I would be willing to do this activity again because it has some value to me.</td>
<td>Value</td>
<td>No</td>
</tr>
<tr>
<td>I believe that doing this activity could be beneficial to me.</td>
<td>Value</td>
<td>No</td>
</tr>
<tr>
<td>I think this is an important activity.</td>
<td>Value</td>
<td>No</td>
</tr>
<tr>
<td>I felt very tense while doing this activity.</td>
<td>Pressure</td>
<td>No</td>
</tr>
<tr>
<td>I felt pressure while doing this activity.</td>
<td>Pressure</td>
<td>No</td>
</tr>
<tr>
<td>I was anxious while working on this activity.</td>
<td>Pressure</td>
<td>No</td>
</tr>
<tr>
<td>I was very relaxed in doing this task.</td>
<td>Pressure</td>
<td>Yes</td>
</tr>
<tr>
<td>I felt like I had to do this.</td>
<td>Choice</td>
<td>Yes</td>
</tr>
<tr>
<td>I did this activity because I wanted to.</td>
<td>Choice</td>
<td>No</td>
</tr>
<tr>
<td>I put a lot of effort into this.</td>
<td>Effort</td>
<td>No</td>
</tr>
<tr>
<td>It was important to me to do well at this task.</td>
<td>Effort</td>
<td>No</td>
</tr>
<tr>
<td>I did not try very hard to do well at this activity</td>
<td>Effort</td>
<td>Yes</td>
</tr>
<tr>
<td>I think I am pretty good at this activity.</td>
<td>Competence</td>
<td>No</td>
</tr>
<tr>
<td>After working on this activity for a while I felt pretty competent.</td>
<td>Competence</td>
<td>No</td>
</tr>
<tr>
<td>This was an activity that I could not do very well</td>
<td>Competence</td>
<td>Yes</td>
</tr>
</tbody>
</table>

### 3.2.4 Data Analysis

To determine the effect of training in the FINGER robot at high and low success rates, we tested the significance of time, success group, and the time-group interaction on all of our outcomes using linear mixed-effect models. The model allowed random intercepts for each participant to account for the fact that the participants spanned a wide range of impairment levels. After fitting each model, we performed model comparison analyses by using the Bayesian Information Criterion (BIC) to prune away terms that substantially reduced the fit of the model.
(as marked by an increase in the BIC score of 5 or more points). To verify that the normality requirements for the tests were being satisfied we used quantile-quantile (Q-Q) plots to graphically compare our model residuals to normally distributed data. Data for models that did not natively yield normally distributed residuals were transformed towards normality using Box-Cox power transformations. However a few of the outcomes could not be corrected to yield normal residuals. For these outcome measures we used Friedman tests to evaluate the effect of time on the outcome. All statistical analyses were performed in R.

When interpreting these models, it is important to realize that the data that they are testing describes the state of the groups before and after treatment. As such, the time factor tested whether the treatment led to a significant change in the outcome being examined irrespective of group. Similarly, the time-group interaction tested whether the change over time varied significantly between groups. These were the two factors that were of most interest to us. The group factor tested whether there was a significant, measurable difference between the groups irrespective of time.

We used a similar approach to study the effects of the high and low success training on the participants’ motivation as revealed by the intrinsic motivation index (IMI). As with the clinical data, we used a linear mixed model to test the effect of time and grouping. We used the same methods described above, but in addition to time, group and the time group interaction, we added baseline Box and Blocks score as a potential covariate. Despite the similarity in the methods, the results of the tests must be interpreted differently due to differences in the data itself. Unlike the clinical data, all of the IMI data was collected after training. Thus, a significant effect on the group factor would indicate that training at high versus low success rates yielded a significant difference in the subscale being tested.
The Intrinsic Motivation Index (IMI) is a multidimensional assessment designed to measure six different variables either directly or indirectly related to motivation. To obtain a single, generic variable describing the participant’s motivation we first normalized the data and then used principal component analysis to reduce the full IMI datasets to their first principal components.

Table 2: Significance of each outcome measure included in the finger study.

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Test</th>
<th>Time</th>
<th>Group</th>
<th>Time:Group</th>
<th>Change Post</th>
<th>Change Follow-up</th>
</tr>
</thead>
<tbody>
<tr>
<td>BB</td>
<td>LME</td>
<td>P=0.014</td>
<td>P=0.651</td>
<td>NI</td>
<td>4.5+/-.28</td>
<td>2.3+/-.37</td>
</tr>
<tr>
<td>FM</td>
<td>LME</td>
<td>P&lt;0.001</td>
<td>P=0.986</td>
<td>P=0.052</td>
<td>2.7+/-.26</td>
<td>3.7+/-.33</td>
</tr>
<tr>
<td>ARAT</td>
<td>LME(^1)</td>
<td>P=0.001</td>
<td>P=0.734</td>
<td>NI</td>
<td>3.4+/-.44</td>
<td>2.5+/-.37</td>
</tr>
<tr>
<td>NHP(^2)</td>
<td>Fried</td>
<td>P=0.229</td>
<td>Na</td>
<td>Na</td>
<td>0+/-.05</td>
<td>.01+/-.04</td>
</tr>
<tr>
<td>Lateral(^3)</td>
<td>LME(^1)</td>
<td>P=0.001</td>
<td>P=0.820</td>
<td>P=0.016</td>
<td>0.5+/-.06</td>
<td>0.1+/-.06</td>
</tr>
<tr>
<td>3 jaw(^3)</td>
<td>Fried</td>
<td>P=0.293</td>
<td>Na</td>
<td>Na</td>
<td>0.1+/-.04</td>
<td>0.3+/-.05</td>
</tr>
<tr>
<td>FT</td>
<td>LME(^1)</td>
<td>P=0.0191</td>
<td>P=0.801</td>
<td>NI</td>
<td>2.6+/-.3.5</td>
<td>2.1+/-.3.3</td>
</tr>
<tr>
<td>MAL-hm</td>
<td>LME</td>
<td>P&lt;0.001</td>
<td>P=0.92</td>
<td>NI</td>
<td>0.5+/-.06</td>
<td>0.3+/-.06</td>
</tr>
<tr>
<td>MAL-hw</td>
<td>LME</td>
<td>P&lt;0.001</td>
<td>P=0.851</td>
<td>NI</td>
<td>0.5+/-.06</td>
<td>0.3+/-.06</td>
</tr>
<tr>
<td>NIHSS(^4)</td>
<td>LME</td>
<td>P=0.069</td>
<td>P=0.914</td>
<td>NI</td>
<td>-0.3+/-.06</td>
<td>-0.3+/-.11</td>
</tr>
<tr>
<td>BHS(^4)</td>
<td>LME(^1)</td>
<td>P=0.012</td>
<td>P=0.925</td>
<td>NI</td>
<td>0.8+/-.18</td>
<td>-0.8+/-.13</td>
</tr>
<tr>
<td>GDS(^4)</td>
<td>LME(^1)</td>
<td>P=0.003</td>
<td>P=0.605</td>
<td>NI</td>
<td>-0.8+/-.2</td>
<td>-1.7+/-.2</td>
</tr>
</tbody>
</table>

1. Box-Cox transformed
2. in Kg
3. in pegs per second
4. lower is better

Na – not applicable to this model
NI – not included – pruned based on BIC criteria
We also used a linear mixed model to test the effects of time (number of weeks post therapy), treatment group (high success verses low success), and their interaction on the self-efficacy of the participants as measured with respect to the box and blocks test.

Finally, we tested baseline Fugl-Meyer score as a predictor of the change in Fugl-Meyer score to determine whether robot assisted practice was more or less successful for low level subjects than for high level subjects. We ran two separate tests: one for the post therapy evaluation and one for the follow up evaluation. For each test we used a general linear model with change in Fugl-Meyer as the output and baseline Fugl-Meyer, group, and the interaction of baseline Fugl-Meyer as predictors.

3.3 Results
Both groups performed an equivalent number of movements (p<0.001) as shown in Figure 8. The actual average success rate at the end of the final song in the set was 82 +/- 7 % for the high success group and 54+/- 6% for the low success group, close to the desired values of 85% and 50%.

Figure 8  (Top) Average of the total number of movements performed by each group across the duration of the finger study. (middle) The average success rate for the last song for both the high success group and the low success group. (bottom) Success rates for unassisted trials.
All of the outcome measures except for the NHP test and the NIHSS improved significantly over
the course of the experiment. For many of the outcome measures (FM, MAL, FT, LP) the high-
success group trended towards higher recovery than the low success group, but this trend was
only significant for the Fugl-Meyer test and the Lateral Pinch Strength Test. Table 2 holds the
results of the statistical analysis, and Figure 9 shows the change in the primary outcomes over
the course of the experiment.

We observed similar trends in the IMI data. To examine the overall motivation of the
participants, we used principal component analysis to reduce the IMI dataset to its directions of
most variance and took the first principal component (a weighted mixture of the individual IMI
subscales) as an indicator of overall motivation. This value was significantly higher for
participants in the high-success group than for those in the low-success group (p<0.001).
Motivation also increased significantly over time irrespective of group, but the change was
small. Of the individual subscales, the only one for which we found a significant group effect
was the effort subscale. Surprisingly, participants in the high-success group felt that they were
expending more effort than those in the low success group despite the fact that they were
receiving more robotic assistance per their own need. The value, interest, and effort subscales
all increased significantly over the course of the experiment. Perceived competence was the
only IMI subscale for which baseline Box and Blocks score was a significant factor.

<table>
<thead>
<tr>
<th>IMI Sub-scale</th>
<th>Time</th>
<th>Group</th>
<th>Baseline</th>
<th>Grp:Baseline</th>
<th>High Success</th>
<th>Low Success</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pressure</td>
<td>P=0.172</td>
<td>P=0.123</td>
<td>Ni</td>
<td>Ni</td>
<td>2.2+/−1.3</td>
<td>3.1+/−1.6</td>
</tr>
<tr>
<td>Competence</td>
<td>P=0.833</td>
<td>P=0.235</td>
<td>P=0.054</td>
<td>Ni</td>
<td>5.2+/−1.2</td>
<td>4.5+/−1.6</td>
</tr>
<tr>
<td>Value</td>
<td>P&lt;0.001</td>
<td>P=0.358</td>
<td>P=0.811</td>
<td>P=0.503</td>
<td>6.6+/−0.8</td>
<td>6.3+/−1.1</td>
</tr>
<tr>
<td>Choice</td>
<td>P=0.197</td>
<td>P=0.122</td>
<td>Ni</td>
<td>Ni</td>
<td>6.1+/−1.4</td>
<td>5.3+/−1.5</td>
</tr>
<tr>
<td>Interest</td>
<td>P=0.052</td>
<td>P=0.851</td>
<td>P=0.152</td>
<td>P=0.605</td>
<td>6.1+/−1.1</td>
<td>5.9+/−1.2</td>
</tr>
<tr>
<td>Effort</td>
<td>P=0.006</td>
<td>P=0.002</td>
<td>P=0.99</td>
<td>Ni</td>
<td>6.7+/−0.6</td>
<td>5.7+/−1.3</td>
</tr>
<tr>
<td>First PC</td>
<td>P=0.027</td>
<td>P&lt;0.001</td>
<td>Ni</td>
<td>Ni</td>
<td>-0.5+/−1.3</td>
<td>0.5+/−1.7</td>
</tr>
</tbody>
</table>
We also used a set of generalized linear models to determine if high success therapy was any more or less effective for low highly impaired subjects than for less impaired subjects. For these tests, we treated the change in FM at post therapy and follow up as outputs and baseline FM, group, and their interaction as inputs. At both time points we found that baseline FM was a significant predictor of the change in FM (p<<0.001 post therapy and p=0.002 at follow up). At the post therapy evaluation neither the intercepts nor the slopes of the lines relating baseline FM to delta FM were significantly different. However, at follow-up the intercept of the High success group was significantly higher than that of the low success group (p=0.03) and the difference in slopes trended towards significance (p=0.13). The lines of best fit for this analysis are shown in Figure 10.

The self-efficacy of both groups with respect to the box and blocks test improved significantly over the duration of the therapy (p=0.038), but there was not significant effect due to treatment group or the interaction of time and treatment group.

3.4 Discussion
The purpose of this study was to evaluate the effects of successful versus unsuccessful practice during the chronic stage of post-stroke motor recovery. We did this by adaptively varying the
assistance provided by a robotic device to drive some participants to a low (50%) success rate and other participants to a high (85%) success rate while they played a rhythm game similar to guitar hero. After three weeks of therapy, during which participants participated in three one hour practice sessions, both groups recovered significantly across all outcome measures except for the NIHSS and the NHP test. There was no significant difference between the Box and Blocks scores of the high success group and those of the low success group at any time point. However, the high success group retained its improvements at the one month follow-up more than the low success group as measured by the Fugl-Meyer test and the lateral pinch test. We observed the same trend for the Motor Activity Log and the finger tap test, but the effect was not significant.

After each therapy session, our participants completed an IMI questionnaire to estimate 1) the value that they assigned to their therapy, 2) their interest in the therapy, 3) their perceived competence, 4) their level of choice or freedom, 5) the amount of pressure that they felt that the therapy put on them, and 6) the amount of effort that they felt they invested in the therapy. These subscales of the IMI are all considered to be either directly or indirectly related to the intrinsic motivation of the teste. We also used principal component analysis to reduce this multidimensional dataset into a single vector describing overall intrinsic motivation.

Participants in the high success group scored significantly higher on our measure of overall motivation. However, the only individual outcome measure for which a significant difference was measured between the groups was the effort subscale. Surprisingly, participants in the high success group believed that they were investing more effort than participants in the low success group despite the fact that they were actually receiving more robotic assistance. Despite feeling that they were not working hard enough, participants in the low success group valued the therapy just as much as those in the high success group and derived just as much interest/enjoyment from the therapy. Participants in the low success group reported slightly higher levels of pressure, and slightly lower levels of choice and competence but these differences were not significant. The only subscale that varied significantly with baseline ability
(as measured by the box and blocks test) was the competence subscale. This suggests that participant’s baseline motor ability did affect their perceived competence at the therapeutic video game, but did not affect any other aspect of their motivation. The interaction between success grouping and baseline ability was not significant for any of the subscales, so it is unlikely that response to the high or low success grouping depended on the participant’s baseline ability.

3.4.1 Relevance to the Challenge Point Hypothesis

Overall, these results suggest that practicing at high success rates is at least as clinically effective as practicing at low success rates and possibly more effective. It is clear, however, that practicing at high success rates is more intrinsically motivating than practicing at low success rates. The import of these results can best be understood within the context of the challenge point hypothesis proposed by Guadagnoli and Lee [66].

According to the challenge point hypothesis, motor learning/relearning should be most effective when learners are able to practice at a challenge level that allows them to extract the highest amount of new, actionable information from their task[66]. When a task is too broad, difficult, or opaque, extracting meaningful information from exploration can be frustrating. Similarly, when a task is too specific, simple, or route attempting to extract new information can be boring.

Finding this ideal scope could be particularly important within the context of stroke rehabilitation. Without any scoping, motor recovery can often become a prohibitively difficult task in which practice does not yield understandable results at a humanly perceptible rate. Learners do not see the effects of their efforts, and as such they report that they are less motivated to perform the thousands of repetitions that would be needed for them to produce tangible results[33]. Furthermore, because they have the option to bypass this experimentation by compensating with their less impaired limb, failures that would normally serve to guide
them away from old methods and encourage them to explore new methods can instead guide them towards compensation, inactivity, and ultimately learned nonuse[20], [28], [29].

3.4.2 Motivational benefits of high assistance practice

In our study, we found that participants that practiced at higher success rates found their therapy more motivating than those that practiced at lower success rates. Motivation is widely considered to be important for motor recovery, and is even used to evaluate patients candidacy for therapy[73]–[75]. Although motivation is not always well defined in clinical settings, there is a general consensus that motivation represents the proclivity of the participants to continue therapy in the absence of external motivators [73]. This emphasis on motivation is consistent with the challenge point hypothesis. Motivation is necessary in order for participants to continue exploring the capabilities of their post stroke motor systems. It is important to note that the motivation measured in this study pertained only to the therapy performed in the FINGER robot, not the participants general motivation for using their impaired limb. Nevertheless, this result suggests that there is value in using robotic devices to enable high success practice.

We also found that participants in the high-success, high-motivation group thought that they were exerting more effort than those in the lower motivation, low success group. This is surprising given that in our pilot testing of the finger robot we found that participants exerted less effort per their own maximum when they were playing at high success rates than they did when playing at low success rates. Although the effect in the pilot study was small, and was much more pronounced for the unimpaired participants than the impaired participants, it is surprising that the participants in the current study believed that were working harder when trends from the pilot study would predict that they would work less.

It is unclear whether the participants in the current study simply believed that they were working hard because they were doing well, whether they felt more comfortable reporting that they were working hard because they were doing well, or whether the extra success afforded
by the robotic assistance actually motivated them to try harder. Regardless, one of the longstanding arguments against using robotic devices to assist in neuro-rehabilitation has been that augmenting participants with robot assistance might make them less engaged in their therapy [67], [76]. However, this result suggests that the participants who received the most robotic assistance per their own need believed that they were more effortfully engaged in the therapy. It is possible that by augmenting the participants’ natural abilities we were giving them inaccurate (and thus less meaningful) feedback about their actions. However, the participants did improve over the course of the experiment (Figure 11), and participants in the high success group did not do worse than those in the low success group.

![Figure 11 Evolution of unassisted game success over the course of the experiment. Robotic assistance was completely turned off for these trials. The high assistance group is shown in red and the low assistance group is shown in blue.](image)

### 3.4.3 The relationship between motivation and recovery

Despite being more motivating and seeming to be more engaging, we did not find strong evidence that the high-success therapy was more clinically effective than the low-success therapy. This finding is not necessarily out of line with the Challenge Point Hypothesis. Motivation is important to encourage exploration and engagement, but in order for that exploration to be effective it needs to provide learners with information that can help guide them to new solutions. It is possible that using robot assistance to augment the learners’ natural abilities might be giving them inaccurate, and thus ineffective, feedback about their
actions. However, the fact that the participants improved over the course of the therapy makes this unlikely.

It is possible that training with the robot assistance simply served to reward participants for attempting to move without actually teaching them how to move. Some of our evidence is consistent with this idea. Participants did report more use of their impaired limbs suggesting that the therapy encouraged them to use their impaired limbs more at home. These changes could have been a result of their increase in motor capacity, but the fact that the participants retained their MAL changes better than their capacity changes suggests that the two might not be directly related.

It is also possible that the difference in the success rates of the groups was not high enough to produce a measurable difference in the clinical outcomes. Even at the 50% success rate most of the participants were practicing at a success rate that exceeded their own un-augmented abilities. As such, it is possible that even the low success practice was sufficiently motivating for the participants to benefit from the therapy.

3.4.4 Intrinsic verses extrinsic motivation

It has recently been demonstrated that external monetary and verbal rewards can significantly increase the clinical effectiveness of some forms of therapy [77]. If the results of our two studies are to be considered comparable, it is possible that their external rewards were more effective because they gave participants a compelling reason to work harder on their assigned task instead of just making the task easier. The fact that external rewards can be given without affecting the task itself is somewhat attractive. However, it is not very practical to provide individuals in the real world with monetary rewards for participating in physical therapy. It is also important to note that the participants in [77] received robotic assistance in addition to their external motivators. It is unclear whether the external motivators alone would have been sufficient to drive recovery without the scoping provided by the robotic assistance.
3.5 Conclusion
In conclusion, we found that participants who practiced at high success rates were significantly more motivated during practice than those that practiced at low success rates. We also found the practicing at high success rates was at least as effective as, and in some outcome measures more effective than, practicing at low success rates at promoting motor recovery. Motor activity log scores for participants who practiced at high success rates trended towards being higher than those that practiced at low success rates, but the effect was not quite significant. Furthermore, at the one month followup, Fugl-Meyer scores for the high success group were significantly higher than those for the low success group and highly impaired participants benefitted from high success practice more than less impaired participants. These results suggest that at least some of the gains associated with robotic active assist therapy might be due to motivational benefits of practicing at high success rates. The results are also consistent with the challenge point framework, which hypothesizes that easier, low error practice should be better for novices than for skilled learners.

Chapter 4 The Manumeter: a non-obtrusive wearable device for monitoring and changing spontaneous use habits of the wrist and fingers

Portions of this chapter have been reconstructed from the following publications [78], [79].

4.1 Introduction
Although robotic devices such as the FINGER robot discussed in the previous chapters have proven to be reasonably effective at improving motor function after stroke, one of the limitations of these devices is that they can only reasonably be used in clinics or research laboratories. With a few notable exceptions [80], most robotic devices are either too weak or too large, bulky, and unsafe to use in daily life. This severely limits the amount of therapy they can deliver.
One alternative to using robotic devices to improve motor performance and encourage upper limb use after stroke is to use wearable sensing systems to provide stroke survivors with augmented feedback describing how they use their impaired limbs in their day to day lives. Outside the field of neurorehabilitation, giving members of sedentary populations feedback describing how many steps they take on a given day has proven to encourage activity [48], and in the field of neurorehabilitation it has been shown that stroke survivors who are given feedback of their walking speed improve more than those that are not [49].

However, although there are a variety of technologies for measuring use of the lower extremities outside of the lab, no comparable device exists for the hand. Such a device would be beneficial not only to stroke survivors as an augmented feedback device, but also to clinicians as an outcome measure for monitoring improvement and evaluating therapies.

An important goal of stroke motor rehabilitation is to improve patients’ ability to use their upper extremity to perform needed activities of daily living. However, measuring individuals’ ability to use their impaired limb in the real world can be challenging. Measurements of upper extremity motor function performed in the clinic or laboratory may not accurately reflect actual use of the limb [20], [81]. Two standard tools for addressing this problem are the Motor Activity Log (MAL) and accelerometry, which have been used to estimate spontaneous use of the upper extremity in the real world [29], [31], [82], [83]. The MAL involves an interview in which subjects are asked to report how often (amount) and how well (quality of use) they believe that they use their impaired limb for a set of common daily tasks [84], [85]. Although the MAL is attractive because of its simplicity, it is subjective because it is self-reported. The MAL also relies on the memory and comprehension of the subject, making it difficult for some patients [86]. Like other self-reported measures of activity, the MAL is only moderately correlated with direct measures of hand use such as accelerometry [85], [86].

Accelerometry can be a more objective means of measuring spontaneous use of the impaired hand [50], [55]. A common way to use accelerometry to quantify use of the upper extremity is
to require subjects to wear a data-logging accelerometer enclosed in a watch-like unit. Accelerations recorded by these units are typically integrated over short time intervals to create an arbitrary unit called a raw count [50]. Although it has been demonstrated that the raw counts produced by an accelerometer worn at the wrist correlate well with movement speed and duration when averaged across subjects [30], [54], the measure is too noisy to provide reliable data on an individual basis [54], [87]. This noise can be reduced by using a threshold filter to increment a movement score only if accelerations measured at the wrist exceed a predefined threshold within a given time epoch [50], [54]. Using the threshold filter approach, such scores have been shown to correlate well with the total time spent moving the arm in daily living and to have good test-retest reliability for various upper extremity movement tasks [54].

Unfortunately, the noise reduction gained by using the threshold filtering of acceleration reduces sensitivity to movement quality and features. Small movements can be overlooked, and any combination of movements large enough to push the accelerations over the threshold will result in the same score for an epoch [54]. Moreover, because the sensors are worn at the wrist, accelerometry is insensitive to fine movements of the wrist and hand, such as writing or typing [54]. Given the importance of the wrist, hand, and fingers in many activities of daily living, it would be desirable to estimate their actual use.

In the laboratory, datagloves, goniometers, and motion capture systems can be used to quantify use of the wrist and hand [88]–[96]. However, such devices are typically not designed for long-term data-logging in an uncontrolled environment. They can be difficult for individuals with a physical impairment to don and doff, may restrict natural movement of the hand, and may be too cumbersome to wear for long periods of time. Such issues can be reduced through appropriate engineering (e.g. [91]), but still there is no device to our knowledge for measuring wrist, hand, and finger movement that is as unobtrusive as a normal garment or piece of jewelry.
To address these limitations we developed a non-obtrusive device to monitor daily use of the hand and wrist in an uncontrolled environment. Here, we use the new term “Manumeter” to refer to a device used to measure the (angular) distance traveled by joints of the hand (Latin: “manus”), mimicking the existing term “pedometer”, which refers to a device that measures the distance travelled by foot (Latin: “pedites”). The Manumeter described here uses a magnetic sensing system that is packaged in a socially acceptable ring and watch-like unit (Fig. 1). In this paper we first discuss the design of the Manumeter and how we use it to infer wrist and finger joint angles. We then present results from an experiment that tested its accuracy and repeatability in monitoring amount of wrist and finger movements.

4.2 Working principle of the manumeter
The manumeter uses a magnetic ring worn on the index finger and a pair of magnetometers worn in a wristband to estimate the wrist radial/ulnar deviation, wrist flexion/extension, and finger flexion/extension (Figure 12, left). Changes in the position and orientation of the magnetic ring relative to the wrist are reflected in the magnetometer data collected by the manumeter. We use radial basis function networks to invert this relationship by mapping magnetometer measurements to their corresponding joint angles. The battery powered device logs data from two tri-axial magnetometers (Honeywell HMC5843) located in the watch-like enclosure, and stores that data on a microSD card. The magnetometers are located on the proximal and distal sides of the data-logger board (Figure 13) and measure the magnetic field produced by a N50 neodymium magnetic ring with a field strength of 0.3 Gauss at 15 cm (roughly the distance from the metacarpal-phalangeal (MCP) joint of the ring finger to the wrist). The device also contains an accelerometer, but for the experiments reported here the accelerometer was not used. The Manumeter can be slid into a docking station (Figure 12, middle) that recharges the battery, transfers the logged data to an Android tablet, and estimates and displays amount of wrist flexion/extension, radial/ulnar deviation, and finger flexion/extension achieved while the device was worn (Figure 12, right).
4.2.1 Firmware design

Firmware was programmed on a PIC24FJ64GB002 Microchip microcontroller. When powered, the firmware first checks whether the USB is connected to a computer. If there is no USB connection, the Manumeter enters the data-logger mode. The microSD mass storage is enabled and a new text file is created. Data are then read from the two triaxial magnetometers and a triaxial accelerometer. The magnetometers are programmed to sense magnetic field strength at a range of +/- 3.2 gauss with 12 bits of resolution. The sensor array and a time stamp are then written to the microSD card.
4.2.2 Electrical design

The custom designed printed circuit board of the Manumeter (Figure 13) measures 39.4mm (height) x 22.6mm (width) x 1.55mm (thickness) and has a maximum thickness of 5.1 mm with components. There are two main states to the power and recharge circuit.

In the condition that the Manumeter is not connected to the computer through a USB cable, the microcontroller is powered by a 3.7V, 450mAh lithium polymer battery. Once connected through the Micro-USB connector, an auto-switching power multiplexer disconnects the battery and switches to the power supplied by the USB host. At a sample rate of 25 Hz per channel (a rate fast enough to capture human movement [91], [97], [98]), the Manumeter draws on average 20.5mA at 3.3V from the lithium polymer battery and can be powered for a maximum of 21.5 hours between charges. The battery recharges at 1C and reaches full capacity after a two and a half hour charge.

The Manumeter writes to an on-board 4GB microSD card (maximum card size is 64GB). At a sampling frequency of 25Hz, the Manumeter writes 1.8 megabytes of data per hour and can log data for over 90 days before filling the current 4GB memory capacity.

4.2.3 Extracting joint angles from magnetometer data

Although the magnetic field measurements taken by the manumeter do natively reflect the amount of movement of the hand and ring, additional processing is needed to convert the raw manumeter data into a more meaningful form.
Figure 14 shows an overview of the process we developed to convert the raw magnetometer signals from the manumeter into joint angle estimates. This process involves taking a differential measurement from the two magnetometers and then using a radial basis function network to map field measurements to joint angles.

4.2.4 Canceling the effects of the earth’s magnetic field

Because the strength of the ring’s magnetic field as measured at the watch is comparable to that of the earth, moving the watch relative to the earth introduces artifacts into the magnetometer data that are indistinguishable from the desired effects caused by movement of the ring relative to the watch. These artifacts need to be removed before the magnetometer data collected by the manumeter can be used to estimate joint angles of the wrist and hand. To accomplish this goal we take advantage of the fact that the earth’s magnetic field does not change much over short distances whereas the fields produced by smaller, nearby magnets (like the magnetic ring) do. By taking a differential measurement between the two
magnetometers located on either side of the data-logging board (roughly 3 cm apart), we are able to exclude the components of our measurement that affect both sensors equally. While this does confound the magnetic field measurements produced by the magnetic ring to some extent, it will effectively eliminate the effects of large, distant magnetic field sources like the earth.

4.2.5 Calibrating the magnetometers using the earth’s magnetic field

Before taking the differential signal, the magnetometers must first be calibrated and registered to one another to ensure that they respond uniformly. This calibration is performed using the earth’s magnetic field as a reference as described by [99]. Since the earth’s magnetic field should not change appreciably over the course of the calibration, sampling this vector while moving the manometer through many different orientations should sweep out a spherical cloud of data-points in the magnetometers’ input space. However, small magnetic distortions caused by the battery and ferromagnetic components located on the data-logger board cause the magnetometers to respond more strongly in some directions than in others. Under the influence of these distortions, rotating the manometer relative to the earth’s magnetic field will form an ellipsoid rather than a perfect sphere. These distortions can be modeled and accounted for by finding the non-uniform transformation necessary to translate, scale, and rotate the ellipsoidal magnetometer data such that it conforms as closely as possible to a sphere centered at the origin of the magnetometer’s frame of reference.

Figure 15 Left: Magnetic field measurements of the triaxial magnetometer as the Manumeter was rotated in random orientations for 30 seconds away from ferrous or magnetic materials. The non-symmetrical ellipse about the x, y, and z axes is a product of magnetic field distortions from ferrous and EMF producing components on the Manumeter PCB. Right: after calibration, signal artifacts are removed and the magnetometer measures the same magnitude regardless of its orientation when mapped in 3D space.
This transformation matrix can be found using the process described by [100]. To summarize their method, we will assume that there is a matrix $A$ and a translation vector $b$ satisfying the relationship

$$h = A \ast (\hat{h} - b). \quad \text{Eq. 2}$$

Where $\hat{h}$ represents the distorted magnetometer data and $h$ represents the calibrated/undistorted magnetometer data. To calibrate the magnetometer, we need to find values for $A$ and $b$ such that the magnitude of the vector $h$ is always equal to the magnitude of the earth's magnetic field ($H_{\text{earth}}$) as shown in Eq. 3.

$$0 = \|h\|^2 - H_{\text{earth}}^2 \quad \text{Eq. 3}$$

$$0 = h^T h - H_{\text{earth}}^2 .$$

By substituting $h$ from Eq. 2 into Eq. 3, we obtain the equation for an ellipsoid as shown in Eq. 4.

$$0 = (\hat{h} - b)^T A^T A (\hat{h} - b) - H_{\text{earth}}^2$$

$$H_{\text{earth}}^2 = (\hat{h} - b)^T Q (\hat{h} - b) \quad \text{Eq. 4}$$

As such, by finding the values for $Q$ and $b$ that optimally fit an ellipse to our raw magnetometer data, we can indirectly obtain the matrix $A$ and the translation vector $b$ needed to transform our data into a sphere [99].

To calibrate the front magnetometer, an ellipse is fit to a set of training data using the method described in [100]. Figure 15 shows a set of magnetometer training data plotted in vector space before (top) and after (bottom) being calibrated using this method.

### 4.2.6 Magnetometer registration

Since we intend to take a differential signal between our two magnetometers, it is essential that they perform as uniformly as possible. Any differences measured between the two magnetometers in the absence of an externally applied magnetic field will introduce noise into our system. As such, rather than calibrating the rear magnetometer using the same method
described above, we instead look for the affine transformation matrix that optimally aligns the data from the rear magnetometer with the calibrated data from the front magnetometer as shown in Eq. 5.

\[
\begin{align*}
\text{Mag}_1 &= \begin{bmatrix} A & b \end{bmatrix} \text{Mag}_2 + \epsilon \\
\begin{bmatrix} x_1 \\ y_1 \\ z_1 \\ 1 \end{bmatrix} &= \begin{bmatrix} A_{11} & A_{12} & A_{13} & A_{14} \\ A_{21} & A_{22} & A_{23} & A_{24} \\ A_{31} & A_{32} & A_{33} & A_{34} \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \hat{x}_2 \\ \hat{y}_2 \\ \hat{z}_2 \\ 1 \end{bmatrix} + \epsilon
\end{align*}
\]

Eq. 5

To find the transformation matrix which minimizes the difference between the two magnetometers, the variables are re-arranged into a single-output, linear equation as shown in Eq. 6.

\[
\begin{align*}
\begin{bmatrix} x_{11} \\ y_{11} \\ z_{11} \\ x_{12} \\ y_{12} \\ z_{12} \\ \vdots \\ x_{1n} \\ y_{1n} \\ z_{1n} \end{bmatrix} &= \begin{bmatrix} x_{21} & y_{21} & z_{21} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & x_{21} & y_{21} & z_{21} & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & x_{21} & y_{21} & z_{21} & 0 & 0 & 1 \\ x_{22} & y_{22} & z_{22} & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & x_{22} & y_{22} & z_{22} & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & x_{22} & y_{22} & z_{22} & 0 & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{2n} & y_{2n} & z_{2n} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & x_{2n} & y_{2n} & z_{2n} & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & x_{2n} & y_{2n} & z_{2n} & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} A_{11} \\ A_{12} \\ A_{13} \\ A_{14} \\ A_{21} \\ A_{22} \\ A_{23} \\ A_{24} \\ A_{31} \\ A_{32} \\ A_{33} \\ A_{34} \end{bmatrix} \\
y &= Mw
\end{align*}
\]

Eq. 6
The parameters of the affine transformation matrix inside the vector were then found by using linear-least squares to minimize the error between the two magnetometers. Figure 16 shows the response of the magnetometers before and after the calibration and registration process.

Once the front magnetometer has been calibrated and the rear magnetometer has been transformed to match the front, the differential signal can be taken between the two sensors. To take the differential signal, measurements of the x, y, and z components of the magnetic field collected by the second magnetometer are subtracted from those of the first magnetometer. Since the two magnetometers are located 3 cm inches apart, the effects of the ring’s magnetic field are felt more strongly by the first magnetometer than by the second. As such, taking the differential signal allows these effects to be isolated.

A radial basis function (RBF) network is then used to map field measurements to their corresponding hand orientations.

4.2.7 Estimating joint angles using a radial basis function network

Radial Basis Function networks are a class of single layer neural networks capable of acting as universal function approximators [101]. Each neuron in a radial basis function network is represented by a function that decays to zero on either side of a central point. Although many
types of basis functions exist [101], [102], the Gaussian function is one of the most commonly used radial basis functions.

\[ RBF(x) = \exp \left( \frac{-(x - \mu)^2}{\sigma^2} \right) \]

In the Gaussian function shown in Eq. 7, \( \mu \) defines the function’s center position and \( \sigma \) defines its width. Most radial basis function networks contain a large number of these neurons with centers distributed over the entire input space. All neurons then feed into an output layer in which they are scaled by weights before being summed together to create a single output. This process is illustrated in Figure 17.

### 4.2.8 Training the RBF network

The RBF network used to map differential magnetometer measurements to joint angles is slightly more complicated than the system shown in

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**Figure 17** An overview of the process by which RBF networks can be used for function approximation. The top figure shows the structure of a 1 input, 1 output RBF net, and the bottom plot shows how a weighted combination of a sufficient number of radial basis functions can approximate the behavior of an arbitrary function.
Figure 17 in that it is a three input, three output system (see Figure 18).

For a radial basis function network with three inputs, a single Gaussian RBF can be described by the equation,

\[ rbf(x, y, z) = \exp\left(\frac{-(x-\mu_x)^2-(y-\mu_y)^2-(z-\mu_z)^2}{\sigma^2}\right) \]  

Eq. 8

In which \( \mu_x, \mu_y, \) and \( \mu_z, \) define the center position of the RBF in the 3D input space of the network and \( \sigma \) defines the width of the radial basis function. We divided the process of fully training our radial basis function network into two steps. We first used a set of unstructured learning processes to find effective values for the center and width of each RBF in the network, and then used a modified form of linear least squares to minimize the error between the output of our network and a training set of joint angles measured using the passive exoskeleton shown in Figure 20.

4.2.8.1 Finding RBF centers and widths

We found centers for the radial basis functions within the input space using a simple K-means clustering algorithm as shown in Figure 19. This algorithm initially selects K random cluster positions (where K was the number of RBFs in the network - we used 25 RBFs for most testing). Each data point in the training set is then allocated to its
nearest cluster center. Once the data points have all been allocated, the position of each cluster is then set to the center of mass of the data points allocated to it in the previous step. This process is repeated until the cluster centers stop moving [103]. Once the centers were known, we set the width of each RBF to the average of its distance from its $P$ nearest neighbors in the network (using $P=10$).

4.2.8.2 Finding RBF Weights

We found the weights for each RBF by using linear least squares to minimize the error between the joint angles measured by the passive exoskeleton and those predicted by the network. However, to prevent over-fitting, we added a weight decay term has been added to the optimization. That is, for the RBF network described by the equation

$$f(x, y, z) = \sum_{j=1}^{m} w_j RBF_j(x, y, z)$$

Eq. 9

In which $x$, $y$, and $z$ are the inputs from the manumeter, $RBF_j(x,y,z)$ are the outputs of our radial basis functions, and $w_j$ are the weights, instead of minimizing the error function

$$error = \sum_{i=1}^{p} (\hat{y}_i - f(x, y, z))^2$$

Eq. 10

In which $\hat{y}_i$ is the training data collected by the mechanical exoskeleton and $f(x, y, z)$ is the output of the network, we will minimize the cost function

$$cost = \sum_{i=1}^{p} (\hat{y}_i - f(x, y, z))^2 - \sum_{j=1}^{m} \lambda w_j.$$  

Eq. 11

This technique is referred to as ridge regression (or weight decay), and it allows the network to fit true trends while overlooking noise that can often lead to over-fitting [104]. Ridge regression accomplishes this by reducing the variance of the model's fitting error at the expense of accepting some bias. In the same way that reducing the number of neurons in the model will
smooth out its output by making it impossible for it to fit all of the data, adding the weight decay term to the optimization prevents over-fitting by forcing the optimization to accept some bias error. Using this method, the amount of bias accepted in the fit is controlled by the weight decay factor $\lambda$. Increasing the value of $\lambda$ will increase the amount of bias error accepted by the model, and decreasing $\lambda$ will decrease it.

Using standard linear-least squares regression, the weights for the radial basis functions can be found by first defining the variance matrix

$$A = RBFs^T RBFs$$

where $RBFs$ is the $N_{\text{samples}} \times N_{\text{RBFs}}$ design matrix containing the un-weighted output of the radial basis functions. The weights themselves can then be found using the familiar formula

$$w = A^{-1} RBFs^T y.$$  

Eq. 13

However, to implement the ridge regression described above, a weight decay factor is added to the variance matrix as shown below.

$$A = RBFs^T RBFs + \lambda I_m$$

Eq. 14

### 4.2.8.3 Finding the optimal weight decay factor $\lambda$

Given its role in reducing over-fitting in a model, the ideal value for $\lambda$ would be the value which maximizes the model's generalization capabilities. A common method for measuring the generalization capabilities of a model is through a cross validation process in which the set of training data is split into two sections. One of these sections is used to train the model while the other is used to test how well the model fits non-training data. However, this method is not ideal in that it does not take advantage of all of the recorded data. If important trends are relegated to the testing section, then blind-spots will be introduced into the newly trained
model. Conversely, if important trends are left out of the testing section then the test will not provide a true representation of the model's generalization ability [101].

An alternative to splitting the data into a single training set and a single evaluation set is to create and test many different partitions of the data and then aggregate the fitting error from all of the training subsets that are tested. Using this method, data which might be used for evaluation in one partition will be used for training in another, so there will be no blind spots in either the training or the evaluation data. One of the most common data partitioning strategies is leave-one-out cross validation. For a training set with p data points, LOO creates p different partitions of the data in which p-1 points are used for training and the remaining point is used to evaluate the model. Although LOO cross validation is effective, it is very slow to compute. As such, we used a very similar cross validation metric called generalized gross validation (GCV) as the primary measure of our network's generalization ability [105].

The GCV of the model is calculated analytically using the following formula

$$\hat{\sigma}_{GCV}^2 = \frac{py^T p^{(2)} y}{\text{trace}(P)^2}$$  \hspace{1cm} \text{Eq. 15}

in which p is the number of points in the training set, y is the training data, and P

$$P = I_p - RBFS A^{-1} RBFS^T$$  \hspace{1cm} \text{Eq. 16}

is the projection matrix of the model [101].

This measure of the model's cross validation ability is then used to find the optimal value of λ which allows the model to match as much data as well as possible while reducing over-fitting effects due to random variance in the data.

Normally finding the optimal lambda would require a potentially slow nonlinear optimization. However, one of the elegant advantages of using GCV to indicate the generalization ability of
the model is that it allows us to find the optimal $\lambda$ using the following re-estimation formula [101].

$$
\lambda = \frac{y^T P^2 y \text{trace}(A^{-1} - \hat{\lambda} A^{-2})}{w^T A^{-1} w \text{trace}(P)}
$$

Eq. 17

A derivation of this formula can be found in [53]. After selecting an initial guess for lambda, the variance matrix $A$ is obtained using Eq. 14, the weight vector $w$ is obtained using Eq. 13, and the projection matrix $P$ is obtained using Eq. 16. These values are then used to update the estimate for $\lambda$ using Eq. 17. This process is then repeated until the value for $\lambda$ stops changing.

### 4.2.9 Validating the RBF net training procedure

To determine whether the steps of the training process described above improved the performance of the RBF networks, the process was compared to eleven alternative training procedures in which one or more of the components of the primary training procedure were turned off. Table shows the active and inactive components for each of the 12 training procedures.

To evaluate these training procedures, the manumeter and the calibration goniometer were attached to the forearm of a test subject and used to collect both six training sets and six corresponding test sets. During each training set, the subject repeatedly moved his wrist and finger through its full range of motion for 1 minute. During the test set, the subject moved his wrist and hand freely without any instruction. Each training set was then submitted to each of the twelve training procedures shown in Table 3.

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Table 3 Training procedures used to evaluate calibration process.
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For trials in which the K-means center selection was turned off, the RBF centers were placed in an evenly distributed grid covering the input space. Similarly, for trials in which the P nearest neighbor width selection was turned off, the width of each RBF was set to the volume of the rectangular box bounding the input data divided by the number of RBFs in the network. For the trials in which ridge regression was turned off, normal least squares regression was used, and for trials in which λ re-estimation was turned off, a constant value was used for λ. Because λ re-estimation can only be performed in cooperation with ridge regression, permutations of the training components in which λ re-estimation was turned on but ridge regression was turned off were left out of the experiment.

In order to create an evenly spaced 3D grid (for trials not using K-means to pick centers), the number of RBFs in the network had to be an even cube. As such, we used 27 RBFs for all trials.

After each training procedure, the resulting mean squared error (MSE) of both the training set and the test set were recorded. Figure 21

![Figure 21](image)

Figure 21 Average mean squared error (MSE) for six trials. Training data from each trial was submitted to 12 different training procedures. After each training procedure, the network was applied to a set of test data and the resulting MSE was recorded. The top graph shows which components of the training main process were used for each of the 12 training procedures. White blocks indicate active components.
shows the average MSE for the test data using each of the 12 training procedures. We used a repeated measures ANOVA to test the effects of the training procedure used on the MSE score of the model, and Bonferroni tests were used to perform post-hoc testing between the groups.

For radial/ulnar deviation and wrist flexion/extension, the training conditions were found to have a significant effect on the MSE for the dataset. Bonferroni tests revealed that trials using PNN width selection led to significantly lower MSE than trials in which the widths were set based on the estimated volume of the input space and the number of RBFs. For finger flexion/extension, training settings were found to have a significant effect, but the Bonferroni tests did not reveal that any single training conditions was significantly better than the others.

To determine which combination of training procedures was most effective, the MSE scores for each of the three measured degrees of freedom were normalized and combined to produce a single score for each training condition. The training condition in which K-means center selection and PNN width selection were turned on but ridge-regression and λ re-estimation were turned off led to the best (lowest) score. However, the difference between this group and other groups in which PNN width selection was used was not significant. This result does not necessarily suggest that ridge-regression and λ re-estimation should be abandoned. Ridge regression was used to improve reduce over-fitting and improve the generalization ability of the model. It is possible that the tests described above were not sufficient to demonstrate the benefits of the ridge regression technique. The components are the training procedure were selected because they made the most sense and because they have been proven in existing literature to be fast and effective [101].

4.3 Proof of concept testing
To demonstrate that the manumeter can be used to track movement of the wrist, hand, and fingers, we performed a series of tests on a single subject. A more in depth evaluation of the device will follow in the next chapter of this document. For this test, we compared the data collected by the manumeter to that collected using the calibration exoskeleton. Prior to the first
test, the magnetometers were calibrated and the RBF network was trained using the methods described above. Immediately after calibration, we collected 15 minutes worth of data in which we collected joint angle estimates from both devices simultaneously. To ensure that the data collected from both devices were properly synchronized, we sampled the devices at regular intervals using a host computer. During this 15 minute period, the participant was instructed to explore the full range of motion of his wrist and fingers. After the 15 minute period, the participant removed and replaced the device without recalibration. The participant then began a one hour trial to evaluate the performance of the sensor over a longer period of time.

To determine the accuracy of the manumeter, we combined the manumeter estimates of wrist radial/ulnar deviation, wrist flexion/extension, and finger flexion/extension with their corresponding exoskeleton measurements to form three N by 2 datasets in which N was the number of samples. We then used principal component analysis to find the primary and

**Figure 22** (Left column) Angle estimates from the last three minutes of a 1 hour test of the manumeter. Estimates taken using the manumeter are shown in solid dashed red, and estimates taken with the manumeter are shown in solid blue. (Right column) Correlations between the two measurement devices. The minor axes of the ellipses fit to the data enclose 95% of the data in the error direction as defined using principal component analysis (r = radial, u = ulnar deviation; f = flexion, e = extension).
secondary directions of variance in each dataset. We took the change within the first principal
direction to be indicative of true signal within the data, and we took change within the second
principal component to be indicative of noise within the dataset. We then found the range of
angle estimate errors enclosing 95% by taking twice the standard deviation of the data in the
error direction. To identify changes in hand use over the course of the measurement period, we
calculated the distance traveled by the hand within one minute bins.

For the 15 minute trial, 95% of the angle estimates for wrist radial/ulnar deviation, wrist
flexion/extension, and finger flexion extension were within +/- 1.4, 6.4, and 4.7 degrees
respectively, of the “gold standard” values from the exoskeleton. For the one hour trial, we did
not recalibrate the device and instead used the calibration performed before the 15 minute
trial. For this longer trial, 95% of the estimates were within +/- 2.4, 5.8, and 4.7 degrees
respectively (Figure 22). Estimates of the distance traveled in radial/ulnar deviation, wrist

![Figure 23](image)

*Figure 23* (Left column) Distance traveled estimates taken using the data from the passive exoskeleton (wide blue) and the manumeter
(narrow green). Plots in the right column show the correlation between the estimates taken from the manumeter and the estimates taken
from the passive exoskeleton. (Right column) Correlation coefficients for the distance traveled estimates of wrist radial/ulnar deviation,
wrist flexion/extension, and finger flexion extension were 0.97, 0.90, and 0.8 respectively
flexion/extension, and finger flexion/extension during the hour long test as measured by the manumeter were significantly correlated with estimates taken using the exoskeleton (P < .001 all, R² = 0.90, 0.89, and 0.92 respectively Fig. 5). The total distance traveled in radial/ulnar deviation, wrist flexion/extension, and finger flexion/extension as measured by the manumeter were within 10.4%, 4.5%, and 14.3 % of their actual values as measured using the passive exoskeleton.

4.4 Discussion

This chapter provides a proof of the concept that movement of the magnetic field produced by a magnetic ring worn on the finger can be detected at the wrist and processed to estimate wrist flexion/extension, radial/ulnar deviation, and finger flexion extension about the metacarpophalangeal joint. We show here in a pilot study that the manumeter can be used to reliably estimate joint angles and total angular distance traveled in a one hour trial. By using a permanent magnet to produce signals at the finger and a pair of magnetometers to receive those signals at the wrist we have created an un-tethered sensing mechanism that can be incorporated into common, socially accepted accessories (a ring and a watch-like band).

It may be possible to further improve the resolution of the device. Errors in the angle measurement are sometimes exhibited as offsets (Figure 22) that appear to be due to metal components on the PC board in the watch-like unit. These metal components distort the ring’s magnetic field and can become magnetized over time, causing the raw magnetometer signals to slowly drift as guided by the previous history of movement of the magnet. Such errors can be reduced in future designs by increasing the distance between metal components and the sensors.

The results of the proof of concept test described here need to be verified with more subjects, both unimpaired and impaired, who wear the device for a longer duration in the real world. A key issue for future research is the effect of environmental ferromagnetic material, such as elevators, car doors, or metal utensils on the device readings. It should be possible to identify
close interactions with metal because such interactions often cause the magnetometer readings to vary in ways not possible due to anatomical movement of the magnetic ring alone. Important safety considerations include avoiding close proximity to sharp ferrous objects, MRI machines, and other strong electromagnets, and analyzing possible effects on pacemakers.

4.5 Conclusion
In this chapter we describe the design of the device and the results of initial pilot testing. To our knowledge, the manumeter is the only unteathered wearable sensing device capable of measuring movement of the wrist and hand. The device is non-obtrusive, and is capable of estimating wrist radial/ulnar deviation, wrist flexion/extension, and finger flexion/extension within 10.4%, 4.5%, and 14.3% of their gold standard values. Here we reported data from a single subject. In the next chapter we test the device more thoroughly on a population of participants with no known motor impairments.

Chapter 5 Evaluating the accuracy and reliability of the manumeter as a device for long term observation of hand use

Portions of this chapter have been reconstructed from the following publication [79].

5.1 Introduction
In the previous chapter, we described the operating principles of the manumeter, a non-obtrusive, wearable device for monitoring hand and arm use outside the lab. In this chapter, we will describe an experiment evaluating the accuracy and repeatability of the manumeter in unimpaired participants over a set of predefined tasks.

The aim of this experiment was to determine: 1) the accuracy of the Manumeter in monitoring finger flexion/extension, wrist flexion/extension, and wrist ulnar/radial deviation during a series of range of motion and functional upper-extremity tasks; 2) the accuracy in estimating different levels of movement activity; and 3) the test-retest reliability of these measurements over three
separate sessions separated by days using only the initial calibration from the first session. 7 healthy individuals, all males, with an average age of 23.3 ± 3.4SD years with no upper-extremity movement disorders participated in the study. The Manumeter system was tested on the right hand for all subjects; one of the subjects was left-hand dominant. All subjects provided written consent, and all procedures were approved by the Institutional Review Board of UC Irvine.

5.2 Accuracy and reliability testing
At the beginning of each session we calibrated the magnetometers for each participant as described above. The participants then donned the magnetic ring and exoskeleton and were instructed to move their fingers and wrist randomly through their full range of motion for two minutes. We used this data to train the radial basis function network to map magnetometer values to the joint angles measured by the exoskeleton. Participants were then instructed to complete a set of 12 tasks three times, at either a low, medium, or high intensity. Subjects were randomly assigned to experience the three intensity conditions in random order. The set of tasks that we instructed participants to complete at the low intensity condition were:

1. Simulate eating 10 Goldfish crackers one at a time
2. Flex and extend your fingers through your maximum range of motion 10 times
3. Move 30 standard index playing cards one at a time
4. Take 5 bills and 10 coins out of the provided wallet and put the money back in the wallet one at a time
5. Open and close a door 8 times
6. Pour 6oz of water from one 16oz cup into an identical 16oz cup spaced 12 inches apart 8 times
7. Perform a radial and ulnar deviation through your maximum range of motion 10 times
8. Tie/untie the shoelaces from the provided shoe 3 times
9. Type the phrase “The quick brown fox jumped over the lazy dogs” 6 times
10. Lay your hand and arm flat on the table and remain still
11. Flex and extend your wrist through your maximum range of motion 10 times
12. Write the phrase “The quick brown fox jumped over the lazy dogs” 3 times

For the medium intensity condition, participants were instructed to make twice as many repetitions as in the low intensity condition, and for the high intensity condition they performed three times as many repetitions. For example, participants simulated eating 20 goldfish crackers in the medium intensity condition, and 30 goldfish crackers in the high intensity condition. Subjects completed the same tasks in the same order for all intensity conditions varying only the
quantity of movement. They completed a total of three sessions spaced 1-2 days apart between session 1 and 2, and 6-8 days apart between sessions 2 and 3.

In order to match for the duration of each task for the three conditions, subjects were allotted one and a half minutes to complete each task. This duration was selected to give subjects enough time to complete the specified number of repetitions in the high intensity condition. In the common event that a task was completed before time expired, subjects were asked to lay their hand and arm flat on the table and remain still. In the rare event that the task was not completed before the allotted time, subjects were instructed to finish the task. A computer program guided the participants through each task by displaying how to complete the task and the amount of time remaining for the given task. A trained individual provided supplementary guidance and helped to count the number of repetitions remaining in each task.

5.2.1 Results of accuracy and reliability testing

The distance traveled estimates obtained by the manumeter were well correlated with those collected using the passive exoskeleton estimates. Regressing the manumeter and exoskeleton angular distance traveled estimates resulted in $R^2$ values of 0.86-0.91 for wrist flexion/extension.

![Figure 24](image.png)

Figure 24 Estimates of total angular distance traveled with the Manumeter are plotted against estimates from the exoskeleton goniometer for wrist flexion/extension (Wrist FE, left), radial/ulnar deviation (Wrist Dev., middle) and finger flexion/extension (Finger FE, right).
and wrist radial/ulnar deviation, across all three training days with all regressions being highly significant (P<0.0001) (Figure 24). Regressions were still significant for finger flexion, but the R² values were 0.39-0.61.

To determine whether the Manumeter could detect amount of hand use in a fixed period, we summed the total angular distance traveled for all tasks completed for all joints at each intensity condition. Since the design of the experiment mandated that the amount of movement in the low intensity condition should double and triple in the medium and high intensity conditions, we defined predicted values for the Manumeter and calibrator by doubling and tripling their distance traveled estimates at the low intensity condition. The Manumeter estimates were on average 83-94% of their predicted values including at the 6-8 day post follow up session, while the calibrator estimates were 89-99% of the predicted values (Figure 25).

There was an offset in the estimate of the Manumeter with respect to that of the exoskeleton. In practice, this offset could be measured during the initial calibration of the device on Day 1 for each subject, and then subtracted for the following days. We therefore calculated the offset from the first 12 tasks on Day 1 of the experiment and applied that offset to all intensity conditions on all days. With the offset correction applied to the Manumeter estimates, the total distance

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**Figure 25** Total angular distance summed across all 12 tasks and all 3 joint angles are shown at each intensity condition for Day 1 (left), Day 2 (middle, 2-3 days later) and Day 3 (right, 6-8 days later). Data from the Manumeter and calibrator are shown by the solid gray and black lines respectively. Dashed lines show predictions calculated by doubling and tripling the values measured at the low intensity condition. Error bars show 1 SD.
traveled summed across, all tasks, all conditions, and at all joint angles, were on average 92.5% ± 28.4, 98.3% ± 23.3, and 94.7% ± 19.3 of the exoskeleton estimates for Day 1, Day 2, and Day 3 respectively. The accuracy of total distance travelled estimates of the Manumeter compared to the exoskeleton values with offset correction for each intensity level, movement DOF, and testing day are shown in.

### 5.2.2 Effects of ferrous metals on manumeter error

Given the likelihood that Manumeter users will encounter ferrous objects in their daily routines, we measured how these interactions affect the Manumeter. A lab member attached the ring and watch unit to a rigid plastic frame mimicking a fixed hand orientation. We then slowly moved the plastic frame towards a cast-iron dumbbell (radius=15cm, height = 2.5cm), measuring the position of the dumbbell and Manumeter using an optical motion capture system (PhaseSpace Impulse X2) that had been calibrated to a resolution of ~1mm. We repeated this step 15 times over the course of 1 and a half minutes. We defined the threshold for interference as occurring

<table>
<thead>
<tr>
<th>Intensity</th>
<th>Movement</th>
<th>Low</th>
<th>SD</th>
<th>Medium</th>
<th>SD</th>
<th>High</th>
<th>SD</th>
</tr>
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<tbody>
<tr>
<td>Day 1</td>
<td>Wfe</td>
<td>74.6</td>
<td>17.9</td>
<td>96.8</td>
<td>12.9</td>
<td>100.6</td>
<td>8.6</td>
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<tr>
<td></td>
<td>Wru</td>
<td>137.5</td>
<td>34.1</td>
<td>110.3</td>
<td>17.3</td>
<td>101.8</td>
<td>5.7</td>
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<tr>
<td></td>
<td>Ffe</td>
<td>71.2</td>
<td>53.7</td>
<td>54.1</td>
<td>35.3</td>
<td>96.7</td>
<td>31.4</td>
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<tr>
<td>Average</td>
<td></td>
<td>84.1</td>
<td>27.7</td>
<td>94.3</td>
<td>9.4</td>
<td>99.1</td>
<td>6.3</td>
</tr>
<tr>
<td>Day 2</td>
<td>Wfe</td>
<td>66.1</td>
<td>30.1</td>
<td>93.7</td>
<td>26.2</td>
<td>97.1</td>
<td>29.6</td>
</tr>
<tr>
<td></td>
<td>Wru</td>
<td>154.4</td>
<td>36.5</td>
<td>128.7</td>
<td>27.2</td>
<td>124.6</td>
<td>26.3</td>
</tr>
<tr>
<td></td>
<td>Ffe</td>
<td>72.9</td>
<td>88.3</td>
<td>102.3</td>
<td>88.8</td>
<td>152.4</td>
<td>102.7</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>82.2</td>
<td>28.8</td>
<td>99.9</td>
<td>22.4</td>
<td>112.8</td>
<td>19.0</td>
</tr>
<tr>
<td>Day 3</td>
<td>Wfe</td>
<td>83.5</td>
<td>25.1</td>
<td>96.7</td>
<td>15.2</td>
<td>104.9</td>
<td>12.6</td>
</tr>
<tr>
<td></td>
<td>Wru</td>
<td>132.7</td>
<td>41.5</td>
<td>122.4</td>
<td>34.9</td>
<td>109.7</td>
<td>29.4</td>
</tr>
<tr>
<td></td>
<td>Ffe</td>
<td>47.0</td>
<td>80.4</td>
<td>79.6</td>
<td>55.3</td>
<td>99.9</td>
<td>50.3</td>
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<td>82.6</td>
<td>28.40</td>
<td>96.9</td>
<td>23.0</td>
<td>104.2</td>
<td>19.3</td>
</tr>
</tbody>
</table>

% is defined as the total angular distance estimates summed across all 12 tasks for manumeter compared to goniometer exoskeleton. Wfe = Wrist flexion/extension, Wru = Wrist radial ulnar deviation, Ffe = Finger flexion/extension
when the manumeter reading exceeded four standard deviations of the normal variance of the readings, which corresponds to a sensor reading outside of 99.99% of normal readings.

5.3 Discussion
Data from the testing described above suggests that magnetic sensing is a viable technology for tracking hand movement over extended periods of time. By using a permanent magnet to produce signals at the finger and a pair of magnetometers to receive those signals at the wrist we have created an un-tethered sensing mechanism that can be incorporated into common, socially accepted accessories (a ring and a watch-like band).
It may be possible to further improve the resolution of the device. Errors in the angle measurement are sometimes exhibited as offsets (Fig. 4) that appear to be due to metal components on the PC board in the watch-like unit. These metal components distort the ring’s magnetic field and can become magnetized over time, causing the raw magnetometer signals to slowly drift as guided by the previous history of movement of the magnet. Such errors can be reduced in future designs by increasing the distance between metal components and the sensors. However, we note that the distance traveled measurement is already relatively insensitive to this drift, as the changes in the resulting offsets were small relative to the total distance traveled within an epoch.

We envision the manumeter aiding clinical practice and research in several ways. Healthcare providers could use the manumeter to gather objective information about the user’s daily movement habits to administer appropriate, personalized therapy. For research, the manumeter may improve estimates of how much subjects use their impaired limbs in their daily lives. Unlike estimates of spontaneous use obtained using accelerometry, the manumeter can convey detailed, quantitative information regarding how the wrist and hand are actually being used.

Perhaps most importantly, the manumeter may also be useful as a therapeutic tool, as it could be used to provide a daily report of hand and arm use that informs the user whether he or she is meeting daily movement goals. Simple forms of feedback about movement performance can improve recovery of motor function in people with stroke [106]. By providing chronic stroke survivors with augmented feedback describing how much they are using their impaired limbs we hope to nudge them out of their learned nonuse cycle and drastically increase the dose of goal oriented movements that they perform with their impaired hand on a daily basis. In conjunction with daily movement monitoring, the manumeter could also be used as a real-time input device for therapeutic video games to provide supplementary movement practice.
Chapter 6 The variable relationship between arm and hand use: a rationale for using finger magnetometry to complement wrist accelerometry when measuring daily use of the upper extremity

Portions of this chapter have been reconstructed from the following publication [107].

6.1 Introduction

The primary innovation of the manumeter over existing devices for monitoring upper extremity use in uncontrolled environments is that the manumeter includes a mechanism for specifically targeting hand use. While there are certainly some applications for which specific knowledge of hand use in important, for many applications a more comprehensive description of upper extremity use might be desirable. For these reason, the manumeter collects accelerometry data in addition to the magnetometer data used to estimate hand activity.

However, for these more general applications in which a comprehensive picture of upper extremity use is preferred over specific information regarding hand use it is unclear whether the added functionality of the manumeter is important or desirable.

Following the development of low cost, low power mems accelerometers, wrist accelerometry has become a standard practice for monitoring how individuals with motor impairments use their impaired limbs in daily life [54], [82]–[84], [108]. In wrist accelerometry, non-obtrusive data-loggers worn on the wrists of one or both arms are used to measure and record the accelerations of the arms over extended periods of time [108]. In some implementations, the amount of use is determined from the magnitude of the accelerations observed, and in others movement is treated as a Boolean value and the devices are used to determine what percent of the time the accelerations were above a predetermined threshold [108].
One potential limitation of wrist accelerometry is that it does not measure the joint movements of the wrist and fingers, which are regularly used in functional activity. If the accelerometers are worn on the hand rather than the wrist, it is still not possible to isolate the joint movements of the wrist and fingers, as the accelerations and orientation changes are due to both proximal and distal joint movement. Sensing systems spanning multiple finger joints can measure finger movement [109], but are obtrusive, making it difficult to use them to measure long term daily use outside the lab.

We propose that the manumeter might address these concerns by adding information concerning hand use to the general information about arm use collected via wrist accelerometry. However, the value of this additional information depends on the relationship between arm use and hand use. It is possible that periods of high arm activity often correspond to periods of hand use, or that arm use can be used to predict hand use within a reasonable margin of error. If this is the case, then the information provided by the manumeter might be redundant. However, if the relationship between arm use and hand use is variable or is too complex to model then the additional information provided by the manumeter might be very valuable. Thus, the goals of the present study were to 1) determine the relationship between arm and hand use and 2) determine to what extent adding an estimate of hand use adds information beyond that obtained using wrist accelerometry.

6.2 Methods

6.2.1 In-lab testing with unimpaired participants

Measures of arm use and hand use were collected from seven unimpaired male subjects (23.3 ± 3.4 years of age) as they performed the following twelve activities, which were chosen on an ad hoc basis to represent typical daily activities involving the upper extremity:

1. Simulated eating of 10 goldfish crackers one at a time.
2. Fully flex and extend fingers 10 times.
3. Remove and replace five bills and ten coins from a wallet one at a time.
4. Flip and deal 30 playing cards to new pile.
5. Open and close a door eight times.
6. Pour 6 oz. of water from one cup to another spaced 12 inches away 8 times.
7. Move wrist through full radial/ulnar deviation 10 times.
8. Tie and untie the shoelaces of a provided shoe 3 times.
9. Type the phrase “The quick brown fox jumped over the lazy dogs” 6 times.
10. Lay the hand flat and remaining still for two minutes.
11. Fully flex and extend the wrist 10 times.
12. Writing the phrase “The quick brown fox jumped over the lazy dogs” 3 times.

Subjects performed the entire set of tasks three times at three different intensity levels. The number of repetitions indicated above for each task defined the number of movements for the low intensity level. At the medium intensity level, the number of repetitions was doubled and at the high intensity level the number of repetitions was tripled. To reduce order and learning effects, the presentation order of the three intensity levels was randomized across subjects. During all tasks, the subjects wore a custom built device for monitoring arm and hand use called the manumeter (Figure 28). The manumeter includes a tri-axial accelerometer (Analog Devices adxl335) used to obtain estimates of gross arm use. It also has a pair of tri-axial magnetometers (Honeywell hmc5883l) which are used in combination with a magnetic ring to obtain estimates of wrist and hand use, as described in [78]. All raw data for this experiment were collected at a rate of 30Hz and were stored locally on the manumeter before being copied to a computer at the end of each trial.

6.2.2 Data collection and analysis

Estimates of arm use were obtained using the accelerometer. Data from the accelerometer were sampled by a microcontroller on the manumeter and stored locally on an sd-card. Once collected, the data from the accelerometer were processed using a widely-used method.
similar to that described by [55]. Typical factory values for the device’s sensitivities and offsets were used to convert the raw voltage measurements into units of Earth’s acceleration due to gravity (g). After converting the data, we used a low pass Butterworth filter with a cutoff frequency of 5 Hz to remove high frequency noise unrelated to arm movement. We then calculated the magnitude of each accelerometer measurement and subtracted off the expected 1g of acceleration due to the earth’s gravity. By computing the magnitude of the acceleration measurements we isolated the movement related changes in the signal from the orientation related changes. Finally we segmented the accelerometer data into two second long epochs and summed it. For epochs in which the summed magnitude did not exceed a threshold of 2g the score for that epoch was set to zero. Otherwise, the score for the epoch was set to the integrated magnitude. We defined the total arm use score for a trial as the sum of the scores for each epoch.

Estimates of hand use were obtained using data collected from the two magnetometers located on either end of the manometer. These magnetometers measured changes in the local magnetic field caused by movement of a magnetic ring worn on the index finger. To isolate the signal changes due to movement of the ring from those caused by movement of the manometer relative to the earth’s magnetic field, we subtracted the field measurements collected by the rear magnetometer from those collected by the front magnetometer. This allowed us to reject any fields affecting both sensors equally without losing the signals produced by smaller and more local magnetic fields.

We processed the data collected from the magnetometers to obtain estimates of the distance traveled by the finger in flexion/extension and by wrist in both flexion/extension and radial/ulnar deviation (see [78] for details). Briefly, we fed the differential signal taken between
the two magnetometers into a radial basis function network trained to map magnetometer measurements to joint angle estimates. We then took the sum of the absolute value of the change in joint angle to get the distance traveled by each joint. Finally, we defined the total distance traveled across all measured degrees of freedom as the indicator of hand use.

6.2.3 Monitoring Daily use of stroke subjects

In addition to the in-lab testing performed with the seven unimpaired subjects, manumeters were given to four stroke subjects to use at home on a daily basis for approximately one month. Their ages were 57, 55, 57, and 59, and their Box and Blocks (BB) scores were 43, 25, 8, and 3. The BB assessment tests how many blocks they could transport in a 1 minute period; a normal score is about 70. In addition to the manumeter, the subjects were given an Android tablet computer capable of copying data off of a manumeter, processing that data, and providing the subjects with feedback of their hand use (Figure 27). Subjects were instructed to wear the device for six hours a day and to switch back and forth between wearing the device on their impaired and less impaired hand at the beginning of every day.

Before sending them home with the subjects, the devices were calibrated to measure the subjects' hand movements using the methods described in [78]. Separate calibrations were made for each hand and for each of the two possible orientations of the magnetic ring (positive pole facing the tip of the index finger vs positive pole facing the base of the index finger) — resulting in a total of four calibrations. The collected data were processed in 15 minute batches, and the calibration used for each batch was selected by computing the distance between the mean of the differential magnetometer data for the given batch to that of the data used to create each calibration and then picking the closest calibration.
For the in-lab data, we used a mixed-measures-ANOVA to test the relationship between arm use and hand use and to determine whether the task being performed and/or the subject performing the task affected this relationship. Hand use was treated as the response of the ANOVA model. Arm use, the task being performed, and the subject performing the task were all treated as factors. Random effects were applied to the arm use and subject factors, and repeated measures were applied to the subject factor.

To analyze the data collected from stroke subjects outside the lab, we first segmented each data set into five minute bins. For each bin we used the accelerometry data to estimate arm use and the magnetometer data to estimate hand use. To determine the relationship between arm and hand use we ran regression tests for each subject using arm use as the predictor and hand use as the response. We used Pierce’s criteria [16] to identify and remove outliers caused by wearing the manumeter incorrectly (e.g. wearing the watch backwards or without the ring). Two datasets were flagged and removed for subject 2 and one subject 4.

Figure 29 Results from lab-based testing. The left plot shows average estimates of hand use via magnetometry vs arm use via accelerometry for each of the twelve tasks. The bottom plot shows the slopes of the lines fit to the hand vs arm use data for each task. The error bars on the bottom plot show the confidence intervals of the line fits, and the colors of the lines in the top plot match their corresponding bars in the bottom plot.
6.3 Results
For the in-lab testing with unimpaired participants, the amount of arm use and the task being performed made statistically significant contributions to the model’s ability to predict hand use (p = 0.002 and 0.003, respectively). This result suggests that although there is a relationship between arm use and hand use, the nature of this relationship varies depending on the task being performed. As illustrated in Figure 29, the slope of hand to arm use for fine manipulation tasks like typing and flipping a deck of cards was ~12 times higher than the slope for arm movement oriented tasks writing.

For the community-based testing with the stroke participants, there was a wide spread in the relationship between hand and arm use, consistent with the concept that the relationship depended on the tasks being performed in the measured 5 min epoch (Figure 30, R^2 < 0.2 for all). For subjects 1-3 the average amount of arm use for the unimpaired limb was significantly higher than that of the impaired limb, however, the opposite was true of subject 4 (p < 0.001), paired Student’s t-test). Subject 4 was also unique because he exhibited significantly less arm movement overall than any of the other three for the unimpaired arm (p < 0.001). For all subjects the total amount of hand use of the unimpaired limb was significantly higher than that of the impaired limb. The relationship between arm and hand use was significant for both hands for all subjects (p < 0.001).

6.4 Discussion
We examined the relationship between arm use as measured using wrist accelerometry and hand use as measured using finger magnetometry, which are both sufficiently non-obtrusive to be used outside the lab on a daily basis. In both the clearly defined motor tasks performed in the lab by unimpaired subjects, and in the unconstrained upper extremity use sampled from the daily lives of stroke subjects outside of the lab, accelerometry and magnetometry proved to be complementary technologies.
For the in-lab testing, arm use significantly predicted hand use. However, the slope of hand versus arm use varied substantially (by more than a factor of 12) with the task being performed. Thus, there are some behaviors that wrist accelerometry measures well, but other behaviors that finger magnetometry is much more sensitive at measuring. This suggests that the two sensing approaches complement one another. Not only can the one fill in the other’s blind spots, but when considered together they give better insight into the type of task being performed. For example, a higher slope indicates a greater use of distal joints of the upper limb, and thus provides insight into patterns of recovery after stroke.

The task-dependent relationship between arm and hand use observed in the lab can be used to interpret the unrestricted daily use pattern of the upper extremity by subjects with stroke. The coefficient of determinations ($R^2$) for the relationship between hand and arm use were low for all subjects and arms, indicating a high amount of unexplained variance in the model. We would expect this wide spread given the dependence of this relationship on the task being performed, and the fact that the individuals with stroke performed many tasks throughout the day.

Figure 30 The left column shows arm use vs hand use estimates obtained using the magnetometers and accelerometer respectively for the impaired and unimpaired arms of four stroke subjects. The right column shows the means and variances of each of the point clouds in the left column. The box and blocks scores of these four subjects (in order) were 43, 25, 8, and 3.
We note that both modalities still have a key limitation because they rely on the assumption that more movement means more use. Although this is often the case, it is not universally true because the arm and hand are often used without moving them. This is illustrated by the results of the hand writing task shown in Figure 29. Despite the fact that handwriting clearly requires hand function, the actual wrist and finger movements involved in handwriting are small. Thus, the estimates of hand use measured by the manumeter for the handwriting task were relatively low despite the fact that it was one of the most hand-use intensive tasks in the set.

6.5 Conclusion
In conclusion, we found that arm use as detected by a wrist accelerometer correlates with hand use as detected by finger magnetometry for individual tasks, but the slope of the relationship depends on the task being performed. This helps explain our further finding that individuals with stroke exhibit a wide spread in the relationship between hand and arm use in daily life. Quantifying and analyzing the shape of this spread will likely give more insight into recovery than wrist accelerometry or finger manumetry alone because it relates to the content of the daily tasks performed and the relative frequency of hand versus arm movement (via the spread) as well as the amount of upper extremity use (via the centroid).

Chapter 7 Improving on the initial design of the manumeter

7.1 Introduction
In the preceding chapters we have described the design and initial testing of the manumeter, a wearable device for monitoring activity of the arm and hand outside the lab. This device uses a pair of magnetometers located in a non-obtrusive wristband in combination with a magnetic ring worn on the index finger to estimate flexion/extension and radial/ulnar deviation of the wrist in addition to flexion/extension of the index finger. Although the accuracy of the device proved to be comparable to other daily activity monitoring devices (such as pedometers), initial
testing revealed opportunities for improvements to both the hardware and the technique used to extract joint angle estimates from the raw magnetometer data [79].

One of the most pressing limitations of the original device was that it had to be trained on a subject to subject basis. While the idea of subject specific training sets might sound attractive, it introduces extra opportunity for overfitting during the training process and makes the device considerably less practical. Obtaining training sets that cover a representative portion of the user’s range of motion can be difficult for users with motor impairments, and requiring users to train the device before use limits its practicality and its potential for widespread adoption.

Initial testing also revealed that the device’s finger flexion estimates were consistently less accurate than its wrist flexion/extension and radial/ulnar deviation estimates [79]. While the overall accuracy of the device was still suitable for many applications, it was undesirable that the metric most closely related to grasping was the device’s primary source of error. Improving the accuracy of the device would decrease the number of subjects required to make meaningful observations, and would increase the number of application for which it could be used.

In addition to these major concerns, initial testing on users with motor impairments highlighted the need for many minor practical improvements as well. The majority of these concerns were related to the training process, the aesthetics of the device, the material used for the magnetic rings, and the data saving process.

### 7.2 Improvements upon the initial design

To correct many of the limitations of the original manumeter, we made three major changes to the design and operation of the device. The first of these changes was guided by a desire to switch from a subject specific training procedure to a one-size-fits-all training procedure, and it involved training the device to estimate the position and orientation of the magnet instead of training it to estimate joint angles directly. The second and third major changes were guided by a desire to improve the accuracy of the device, and they involved adding a third magnetometer
to the device and using a second optimization process to refine the selections of the center positions and widths used for the radial basis function network.

7.2.1 One size fits all training method

In the initial design of the manumeter, the device was trained to map differential magnetometer measurements directly to joint angles. This training process ensured that the subject specific information describing the biomechanics of the wearer’s hand was represented in the trained model. However, the method also introduced additional risk of overfitting.

By training the model to account for the kinematics of the user’s hand, we also inadvertently trained the model to expect a very specific placement of the manumeter and ring relative to the user’s hand. Incorrect placement of the manumeter on the wrist, or misalignment of the passive exoskeleton could introduce error into the resulting joint angle estimates. Since it is not reasonable to expect users with motor impairments to always don the device in a consistent way, it is also not reasonable to use a model that assumes little to no variability in the placement of the device. Errors of this type can be considered as overfitting errors since the model is learning context dependent information about the system but treating that information as if it is fundamental to the system.

In general, the solution to this problem is to remove the context dependent information from the model. In the case of the manumeter, this meant removing information specific to the placement of the device, and, by extension, information related to the biomechanics of the wearer’s hand. To exclude this information from the model, we trained the model to relate differential magnetometer measurements to the position and orientation of the magnetic ring instead of training it to predict joint angles directly.

The relationship between the pose of the magnet and the differential measurements that it produces are the same for all hands and all device placements. In effect, this training method produces a one-size-fits-all model that could be used out of the box on any hand. A second
inverse kinematic model informed by simple measurements of the wearer’s hand could then be used to obtain joint angle estimates from the marker position data.

7.2.1.1 Training the manumeter to estimate the position and orientation of the magnetic ring

To train the manumeter to estimate the pose of the magnetic ring instead of estimating joint angles directly, we simply changed the training measurements supplied to our model. Instead of training the model to minimize the error between its outputs and joint angles measurements obtained from a passive exoskeleton, we trained it to minimize the error between its outputs and position and orientation estimates obtained using a phasespace motion capture system.

Since the goal of this new training process was to create a model that could be used out of the box on many different hands, it was important that the training data cover a sufficient area to describe many different hand sizes. Rather than finding participants with many different hand sizes, we simply made an adjustable artificial hand with a range of motion similar to that of an actual human hand. All testing of the new system was performed using this artificial hand.

7.2.2 Incorporating a third magnetometer

Radial basis function networks are ultimately tools for function approximation. Consequently, for RBF networks to accurately model the behavior of a system, the output of that system must be a valid function of the inputs supplied to the RBF net. If there are instances in which the system being modeled can have two different possible outputs that correspond to the same (or
close to the same) inputs, then attempting to minimize the error to one output will simply increase the error to the other output and the training process will yield unsatisfactory results. In such scenarios the system being modeled can be called ill-conditioned.

The simplest scenario in which the one-to-one relationship between inputs and outputs can be broken for the manumeter is when the measured signal corresponding to a change in an output is close to the noise threshold of the sensors. This can occur when the magnet is far away from
the sensors or when the output being modeled does not have a large effect on the inputs relative to the measurement noise in the system.

Figure 31 shows that the one-to-one relationship between inputs and outputs did not hold when using the manumeter to map differential magnetometer measurements to finger flexion extension angles. This observation is consistent with the error consistently observed in the finger FE estimates of the original manumeter.

Due to the symmetry of the magnetic fields produced by the ring, it is also possible to create situations in which the same set of inputs from a 2 magnetometer manumeter can correspond to two different outputs. For example, consider the scenario shown in Figure 32 in which a magnet is moving in the same plane as the two magnetometers being used to observe it. In this simulation, the magnetic moment of the magnet is always in line with the z axes of the magnetometers. The Magnetic field measured at the magnetometers can be estimated using the magnetic dipole equation.

Figure 32 (top) A scenario in which using only two magnetometers allows a single input to correspond to multiple outputs. M0 and m1 represent the position of two magnetometers, and the green dots represent the path of a magnet. In this simulation the magnetic moment of the magnet is aligned with the z axis of the magnetometers. (bottom) A demonstration that there are two possible y position for each set of inputs (only the z input matters, the rest are zero).
\[
\begin{align*}
\vec{B} &= \frac{1}{4 \pi} \left( \frac{3 \vec{r}(\vec{M} \cdot \vec{r})}{||r^{5}||} - \frac{\vec{M}}{||r^{3}||} \right) \\
\text{Eq. 18}
\end{align*}
\]

In which M is the magnetic moment of the magnet, \( \vec{r} \) is the vector from the magnet to the sensor, and B is the field measured at the sensor.

When M is exclusively in the Z direction and \( \vec{r} \) is exclusively in the XY plane, the resulting magnetic fields will all be exclusively in the Z direction as well. The magnitude of B will depend on the distance (|r|) between the magnet and the sensor, but all magnet positions along a given radius will look identical to the sensor. Consequently, rotating the magnet around the front sensor as shown in Figure 32 will have no measurable effect of the field measured by that sensor. Since the distance from the magnet to the second sensor will change, the differential measurement between the two sensors will not be zero. However, while movement in the x direction will create unique differential measurements, the differential measurements corresponding to different y positions will be redundant due to the fact that the distances to symmetric points on either side of the x axis will be the same (as shown in Figure 32).

Many of the problems that break the one-to-one correspondence between the inputs and outputs of the manumeter can be solved or attenuated by increasing the number of sensors. Adding a third sensor outside the line created by the first two would correct the symmetry-induced problem illustrated above and would allow for unique inputs for each y position. Similarly measuring from more locations can reduce the number of locations in which the magnet is outside the clean range of the sensors. Finally, if the measurement noise affecting the sensors is Gaussian then including more measurements should reduce the overall noise in the system. As such, we hypothesized that adding a third magnetometer to the manumeter would increase the accuracy of its magnet pose estimates.

### 7.2.3 Using partial swarm optimization to refine the RBF networks

In addition to addressing the modeling errors due to breakdown of the one-to-one relationship between model inputs and training outputs, it is also possible that the accuracy of the
manumeter’s estimates could be improved by improving the process used to train the
manumeter. As discussed in chapter 4, the manumeter estimates its outputs (either joint angles
as discussed in chapter 4 or magnet positions as discussed in this chapter) using radial basis
function networks. These networks have to be trained to learn the relationship between the
differential magnetometer measurements used as inputs and the network’s various outputs.
For a RBF net the parameters that have to be trained during the optimization process are the
center positions of the individual radial basis functions, the widths of the radial basis functions,
and the weights applied to each radial basis function. Although the method used to find
weights for the radial basis function network used a true optimization, the methods used to
find the center positions and the widths of the radial basis functions relied on heuristics. We
have demonstrated that these heuristics do reduce improve the accuracy of the model
(especially the heuristic for selecting widths – see chapter 4), however, it is possible that using
an actual optimization to find these parameters would further increase the accuracy of the
device.

Unluckily it is not possible to solve for the optimal centers and widths using the same
linear least squares optimization used to find the weights. Applying a nonlinear gradient based
method would also be very difficult due to the scope of the problem and the number of
parameters being optimized. Probabilistic search algorithms such as particle swarm
optimization, however, are well suited to large problems with many possible local minima such
as the tuning of neural networks  [110]–[112].

Particle swarm optimization (PSO) was inspired by the swarm intelligence exhibited by many
species in the natural world. Many creatures such as fish, birds, and bees explore the world as a
group and share information between individuals to make their exploration more productive.
PSO attempts to utilize this concept of swarm intelligence to explore parameter spaces for
solutions to large optimization problems. In practice, PSO algorithms are similar to genetic
algorithms in that they gradually modify a large number of randomly generated parameter sets
in an attempt to find the parameter set that either minimizes a cost function or maximizes a
fitness function. In genetic algorithms, these parameter sets are called genomes, in each iteration of the algorithm new genomes are formed by randomly combining and mutating the genomes of the most performant members of the set. In particle swarm optimization, however, these parameter sets are called particles, and over the course of the optimization these particles fly through the parameter space until they settle in the position that maximizes their guiding fitness function. Each particle starts with a random velocity, which dictates the change in the particle’s position within the parameter space during the next update phase. In addition to its position in the parameter space and its velocity, each particle also has a memory vector that keeps track of the best position in the parameter space that it has seen so far. The algorithm is divided into an evaluation phase and an update phase. In the evaluation phase, the current fitness value is calculated for each particle, the memories of each particle are updated as needed based off of the new values, and the current, global best memory from across the entire group is selected. In the update phase, the particles are moved to the new position indicated by their velocities, and their velocities are updated using the equation

\[
V_{i,t} = (1 - \xi) \times V_{i,t-1} + c_1 \times r_1 \times (M_i - P_i) + c_2 \times r_2 \times (G - P_i)
\]

Eq. 19

In which \(V\) is the velocity of the particle being updated, \(\xi\) is the damping factor applied to the particle’s previous velocity, \(M_i\) is the position of the particle’s best memory, \(G\) is the best position observed across the entire swarm, and \(P_i\) is the current position of the particle. \(c_1\) and \(c_2\) are weights that determine how much each particle values its own knowledge vs the knowledge of the group as a whole. Similarly, \(r_1\) and \(r_2\) are random numbers that introduce variability into the influence of each term.

We used PSO to find the radial basis function widths and centers that would minimize the cross validation error of our model. Instead of using leave one out cross validation as we did when selecting the ridge regression parameter for the original manumeter training paradigm, we elected to use K-fold cross validation (with K=10). Not only did this reduce the number of test cycles, but it placed greater demands on the generalization ability of the model.
Each particle consisted of a list of RBF center positions and widths. For a radial basis function with six inputs there were thus seven parameters in each particle. Discounting the weights, this meant that for a full network of 22 RBFs there were a total of 154 parameter to be optimized. During the evaluation phase of each PSO iteration we used linear least squares to find the optimal weights for each particle and computed the mean squared cross validation error for each resulting network. We then updated the global best memory and the best memories of each particle, updated the position of the particles in the parameter space, and calculated their new velocities using Eq. 19.

7.3 Quantifying improvement due to the new design
To verify that the improvements made to the manumeter were working as desired and to evaluate their impact on the accuracy of the device, we performed a brief experiment comparing the accuracy of the device with and without each new component. The components included in this test were the one-size-fits-all (OSFA) calibration method, the addition of the third magnetometer (3Mag), and the particle swarm optimization (PSO). The optimization was set to terminate if the difference between the cost values of each particle went below 0.75 (a value picked by experimentation). The optimization would also terminate if the net velocity of the particles became sufficiently close to zero or if the number of iteration exceeded 125.

7.3.1 Methods
We performed all of the tests for this experiment using the artificial plastic hand shown in Figure 33. This artificial hand was designed to have a range of motion of -20° to 35° in radial/ulnar deviation, +/- 70° in wrist flexion/extension, and 90°/-5° degrees in finger flexion/extension. It was also possible to adjust the size of the hand.

Figure 33 Artificial hand used to approximate range of motion of many different hand sizes
along the dimensions shown in Figure 33. During each trial we collected data from the manumeter while simultaneously recording the positions and orientations of the manumeter and the magnet using a Phasespace motion capture system.

<table>
<thead>
<tr>
<th>configuration</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>OSFA</td>
<td>Off</td>
<td>Off</td>
<td>Off</td>
<td>Off</td>
<td>On</td>
<td>On</td>
<td>On</td>
<td>On</td>
</tr>
<tr>
<td>3rd Mag</td>
<td>Off</td>
<td>Off</td>
<td>On</td>
<td>On</td>
<td>Off</td>
<td>Off</td>
<td>On</td>
<td>On</td>
</tr>
<tr>
<td>PSO</td>
<td>Off</td>
<td>On</td>
<td>Off</td>
<td>On</td>
<td>Off</td>
<td>On</td>
<td>Off</td>
<td>On</td>
</tr>
</tbody>
</table>

To evaluate the new training method, we collected two separate sets of data at each of eight different possible hand sizes. The first set collected at each hand size was considered a training set, and the second was considered a test set. Using this data we trained the manumeter using a total of eight different possible methods. These methods are listed in Table 5.

When the one-size-fits-all (OSFA) mode was on, we trained the manumeter using the data collected from all eight hand sizes and then tested each of the eight test sets individually. Conversely, when the OSFA mode was off we trained and tested the manumeter using only the data for a particular hand size. When the third magnetometer was on, we took two differential measurements – each using the rear magnetometer as the reference – and used these as the inputs to the RBF net. In contrast, when the 3rd magnetometer option was off, we only used two of the magnetometers. Finally, when PSO was on, we used particle swarm optimization to select center positions and widths. When it was off, we used the original heuristics to select center positions and widths.
To ensure that the error measurements used to evaluate the three new approaches accounted for overfitting effects, we trained the manumeter using only the training datasets and tested the manumeter using only the test sets.

### 7.3.2 Results

To evaluate the contributions of the one size fits all (OSFA) training method, the addition of the third magnetometer (Mag3), and the use of particle swarm optimization (PSO) for center and width selection, we used a linear mixed model to test the effects of these three factors and their interactions.

![Figure 34 RMS error for each condition. A black grid in the top row indicates that the corresponding component is not used and a white grid indicates that it is used.](image)
on the RMS error measured from each test set. Since multiple experiments were performed at each hand size, we included hand size as a random effects factor in the model. For the X and Z directions, the addition of the third magnetometer and the interaction of PSO and the third magnetometer were both significant ($p<0.001$ and $p<0.05$ respectively). For the Y direction, the third magnetometer still had a significant effect ($p<0.001$), but the interaction of the third magnetometer and PSO did not. Instead, the effect of PSO in isolation proved to be significant ($p=0.02$). Neither the OSFA factor nor any of its interactions had a significant effect on the RMS error for any of the directions. These results suggest that adding the third magnetometer

![Figure 35 Ring position estimates in the x, y, and z directions collected using the motion capture system (black) and the manumeter (red). Manumeter estimates were obtained using all of the improved methods – one size fits all calibration, the third magnetometer, and the PSO based network refinement were all used. Manumeter estimates were within 1cm of the mocap measurements for all hand sizes.](image)
significantly improved the accuracy of the system. Using PSO to select centers and widths improved the accuracy of the system, but only when using the third magnetometer. Figure 34 shows the error values measured using each of the eight possible training methods. Figure 35 shows example data from one particular test set.

The RMS error values measured from trials using the OSFA training method were comparable to those measured from trials in which the manumeter was specifically trained for each hand size. Although the OSFA training method did not significantly improve the accuracy of the system, the OSFA method greatly improves the practicality of the manumeter. This result suggests that it is not necessary to train the manumeter for each individual that uses it. Instead, a single, all-encompassing training set can be used to create RBF networks that will accurately predict magnet positions for many different hand sizes.

7.4 Discussion
The three improvements discussed in this chapter address many of the limitations of the original manumeter. They increase the accuracy of the device to within a centimeter of the true value, and they make it possible for users to collect meaningful data from the device without going through a calibration process that could be difficult and error prone for individuals with motor impairments.

7.5 Practical improvements to the magnetic rings
In addition to the major improvements to the training process, we also made a number of simple, but impactful, changes to the ring used to generate the magnetic fields measured by the manumeter.

The original rings used for the manumeter were made of solid neodymium. Since neodymium is a ceramic material, these rings were too fragile to stand up to daily use by individuals with motor impairments. Furthermore the rings were very rigid, and inconsistent swelling in the users’ fingers made the rings uncomfortable and difficult to size. To accommodate different finger sizes it was necessary to use many different ring sizes. This made it difficult to compare
raw magnetometer data between individuals. Many users also complained about ferromagnetic objects sticking to the inside of their hands. To address all of these concerns, we switched from using solid neodymium rings to using non-rigid silicon rings with disk magnets embedded in them. Because the rings were rubber, they could expand and contract comfortably to account for swelling. The same magnet could also be used for all ring sizes, and the magnetic component of the ring could be relegated to the back of the hand – thereby reducing contact with ferromagnetic objects.

7.6 Grip type classification: an alternative manumeter application
Unlike a pedometer, which only has to detect a single, well defined activity, the ideal device for monitoring hand use should be capable of recognizing and quantifying many different applications of the hand. Thus far we have used the manumeter to quantify hand use based off of the amount of movement of the hand. However, while hand use often involves movement of the hand, the two terms are not synonymous. Hand use does not always require movement and movement does not always necessarily imply active use. For example, while grasping an object might involve movement of the hand, holding on to an object might not.

One alternative way to quantify hand use would be to track the amount of time spent in different grip types or hand postures. This technique could be particularly useful for individuals with stroke related motor impairments since they often converge into a familiar static posture known as a flexion contracture. Measuring the amount of time spent in and out of their flexion contracture could provide valuable insight into the extent of their motor impairments. Since the raw data collected by the manumeter is directly informed by the posture of the hand, the manumeter can be used to classify a limited set of unique hand postures. Here we give a proof of concept example of this new application of the manumeter.

In this proof of concept trial, we use a support vector machine to distinguish between differential magnetometer measurements corresponding to hand open versus hand closed. We collected data from a single subject using the two magnetometer version of the manumeter
and a single N-40 neodymium magnet (10mm diameter 4mm thick). To compare the ability of the manumeter to distinguish between hand states to that of a gold standard, we also used a phasespace motion capture system to record the position of the tip of the thumb and the middle phalanx of the index finger. Using these two sources of data, we trained two support vector machines (SVMs) to classify hand postures. The first SVM was trained to find the optimal hyperplane separating the differential magnetometer measurements describing hand open and hand closed, and the second SVM did the same for the vector from the thumb to the index finger obtained by the motion capture system. To synchronize the data collected by the manumeter and the motion capture system, we used the manumeter’s serial interface and simultaneously streamed data from both devices at 30 Hz.

To reduce impact of overfitting effects on our accuracy estimates we collected separate testing and training datasets. During the training datasets, the participant followed instructions provided on a monitor dictating which posture they should adopt. The monitor then instructed the participant to explore the full range of motion of his wrist while maintaining the desired hand posture. This process was repeated four times for each hand posture. During each of these trials the computer collected data for eight seconds.

We used the nuSVC support vector machine implementation included in the scikit-learn python library [113] which is in turn based on libsvm [114]. NuSCV classifiers have two primary parameters that can be adjusted to customize their performance. The parameter nu is a value between zero and 1 that defines the upper bound on training errors and a lower bound on the fraction of support vectors. If nu is high, then the classifier will tolerate more training errors, but will use fewer support vectors (thereby reducing the risk of overfitting). In contrast, if nu is low then the classifier will not tolerate many training errors, but will use more support vectors. The parameter gamma (when using a radial basis function kernel) affects the radius of influence of the model’s support vectors. If gamma is high, then the support vectors will have a very low radius of influence, and if it is low then they will have a very high radius of influence. We used particle swarm optimization to find the values for nu and gamma that maximized the receiver-
operator-curve cross validation score of our classifier. We used two fold cross validation to obtain this score.

After training the classifiers we tested them on completely naive data. During the trial used to collected the test data the user was not required to follow prompts given by the data collection program, but was rather instructed to switch between the hand open and the hand closed posture at will. We then compared the decisions of the manumeter based classifier to those of the mocap classifier. We found 94% agreement between the decision of the mocap based

Figure 36: The manumeter can reliably tell when the hand is open or closed. The top plot shows as a “gold standard” reference the distance between a marker on the tip of the forefinger, and another marker on the tip of the thumb, measured with optical motion capture. The bottom plot shows the output the Manumeter, implementing a binary classifier fed with differential magnetometer sensor readings. The blue line is the real-time distance to the hyper-plane that was found to optimally separate the hand open and hand closed clusters during classifier training (reference to the left-side y-axis in the graph). The red line is the binary state of the hand (open or closed) identified by the classifier (referenced to the right-side y-axis). Note that the Manumeter reliably detects the hand open and hand closed states, which is something that wrist accelerometry cannot do.
classifier and the manumeter based classifier. Figure 36 shows the output of the manumeter SVM as it relates to the hand aperture measured by the motion capture system.

Chapter 8 Conclusion

Although it is known that rehabilitation therapy can reduce the effects of post stroke motor impairments, the amount of therapy required for individuals to recover to their full potential can be very daunting. Attaining the required dose of practice can be frustrating and exhausting. It is much easier for individuals with severe motor impairments to see the individual failures from each practice movement than it is for them to see their gradual progress. Because practicing with their impaired limbs is so frustrating, and because it is often easier for them to simply compensate for the weakness in their impaired limb by using their less impaired limb, it is common for these individuals to underutilize their impaired limbs in their daily lives and fail to recover to their full potential.

In the first half of this dissertation we discuss experimental results with the FINGER robot as a device for motivating impaired limb use by enabling successful practice, and in the second half we discuss development of the manumeter as a wearable sensing system for motivating impaired limb use by providing users with augmented feedback of their use.

8.1 The FINGER robot – using robotic devices to motivate impaired limb

In the first two chapters of this dissertation we introduce the FINGER robot – a versatile robotic platform for assisting in finger individuation after stroke. To our knowledge, FINGER is the only robotic exoskeleton capable of facilitating individuated, high speed movement of the index and middle fingers. In our pilot testing for the FINGER robot, we successfully demonstrated a simple algorithm for controlling the success rate of a task by adaptively varying the level of assistance provided, by modifying the robot impedance from trial to trial. However, we also found that practicing at high success rates could cause participants to contribute less effort to their task. This finding is consistent with the observation that participants of robot assisted therapy tend
to slack[24], [67], [76], and it is concerning because effort is widely considered to be important for neurorehabilitation [43], [70]. This effect was small though, and was more prominent for the unimpaired participants of the experiment than for the impaired participants. This suggests that the motivating nature of the musical game tends to prevent the tendency to slack for more impaired participants.

In our subsequent clinical trial we used a similar process to test the long term effects of practicing at high verses low assistance levels on both motor capacity and motivation. Most clinical trials examining the benefits of robot assisted therapy control the dose of therapy as defined by the duration of the therapy. However, because the robotic assistance can allow participants to complete more movements than they would normally be able to complete using traditional methods, this introduces a dose confound into the results. By contrast, this study directly compared high verses low assistance robot therapy using the same task and the same number of movements. Based on the results of our pilot testing it was unclear whether the added sensory and motivational benefits of practicing at high success rates would be sufficient to outweigh any negative consequences due to slacking or the lack of task errors. However, we found that high assistance therapy was at least as clinically effective as low success therapy, and possibly more effective for some outcome measures. Moreover, the high success therapy trended towards being more effective for the highly impaired participants than for the less impaired participants. This finding is consistent with the Challenge Point Hypothesis, which would predict that more impaired participants would need more assistance in order to scale the difficulty of their task down to a level that could facilitate meaningful exploration and practice. For more impaired participants a reduction in effort might not be detrimental since the effort required by unassisted practice might normally be beyond their capability (or at least beyond their capability for sustained practice). Similarly, the reduction in task errors might not be too detrimental for highly impaired participants because, without assistance, their errors might be so large that they would lead to frustration instead of learning.
We also found that participants in the high assistance group found the therapy more motivating than those in the low success group. This suggests that high assistance therapy might be an effective tool for encouraging participants to complete the large dose of practice needed for them to recover to their full potential. However, there is an inherent limit to the dose of practice that can be supplied in a clinic regardless of whether a robotic device is used. As such, this dissertation also discusses the use of wearable sensing systems for monitoring and incentivizing impaired limb use outside the lab.

8.2 The Manumeter – a wearable device for collecting augmented feedback of arm and hand use

Chapters four through eight describe the design and testing of the manumeter, a wearable device for monitoring arm and hand use in an uncontrolled environment. Unlike other activity monitors, the manumeter estimates movement of the wrist and hand using an array of magnetometers and a magnetic ring. Because there is no physical connection between the ring and the sensing platform, the device is considerably less obtrusive than any of the datagloves that offer equivalent data.

Pilot testing of the device showed that the device was able to estimate distance traveled in wrist flexion/extension, wrist radial/ulnar deviation, and finger flexion/extension within 10.4%, 4.5%, and 14.3 % of their goniometrically measured values at all times. Subsequent testing on a population of unimpaired participants showed that the accuracy of the device was comparable to that of the most accurate pedometers. For the entire population, estimates total distance traveled estimates were 92.5% ± 28.4, 98.3% ± 23.3, and 94.7% ± 19.3 accurate for three sequential days of testing.

The primary innovation of the manumeter is that it can directly monitor hand use - an achievement that is not possible using wrist accelerometry. However, the manumeter is more complicated than the elegant data-loggers used for wrist accelerometry. To determine whether the added complexity of the manumeter offered meaningful benefits over accelerometry alone
we ran an experiment to determine whether arm use could be used as a reasonable predictor of hand use. We found that arm use could predict hand use, but that the relationship between the two depended on the task being performed. For some tasks arm use was dominant, and for others hand use was dominant. These results suggest that the additional information provided by the manumeter is valuable and complements the data provided by wrist accelerometry.

After our initial testing of the device, we made a number of improvements to the manumeter to make the device more practical and more accurate. Most significantly, we altered the design of the device to allow one-size-fits-all calibrations. Not only does this reduce the possibility of subject specific overfitting effects, but it allows the device to be used “out of the box” without the need for a subject specific calibration process. Since it is more difficult to obtain high quality calibrations from users with severe motor impairments than from users with moderate to light impairments, the use of a single model for all subjects also reduces the risk of impairment level confounds in the manumeter data.

We also switched from a two magnetometer to a three magnetometer system and used particle swarm optimization to refine the width and position of the radial basis functions in the model. Both changes significantly improved the accuracy of the system, but the improvements due to the optimization were only significant when also using the third magnetometer.

8.3 The interaction of learned nonuse and the challenge point hypothesis

To fully understand the relationship of robotic assistance and augmented activity feedback to the problem of learned nonuse, it is important to first understand the interaction between learned nonuse and the Challenge Point Hypothesis proposed by [66]. This interaction can perhaps be best understood via metaphor. To this end, we will refer to the climax of the film Wargames, which is considered a classic movie by computer hackers.

At the end of the movie, the young protagonist, David Lightman, saves the world by forcing the artificially intelligent “WOPR” super computer to play Tic-tac-toe against itself. Because Tic-tac-
toe is a predictable game with a challenge level that is not conducive to meaningful exploration, every match ends in a draw - leaving no way for either side to win. This introduces the concept of futility to the computer, and it quickly realizes that similar principles apply to thermonuclear warfare. By continually failing over and over again, the computer quickly learns that “the only winning move is not to play”.

Like Tic-tac-toe and thermonuclear warfare, the challenge of recovering motor function after stroke for a severely impaired person is typically not set to a level that allows meaningful exploration or practice. However, unlike Tic-tac-toe, which offers too little challenge, recovering motor function offers too much challenge for a person with substantial impairment. In order for individuals with stroke related motor impairments to recover after their injuries they have to practice extensively with their impaired limbs. However, because they have the option to compensate with their less impaired limbs, choosing to practice with their impaired limbs can be difficult. Because the challenge level of the task does not facilitate meaningful exploration, compensation and nonuse can seem to patients and therapists like the only viable option.

The goal of the robot assisted therapy provided in the present work was to reframe the challenge level of impaired hand use to make it look more like “a nice game of chess”. Not only should this enable optimal practice according to the challenge point hypothesis, but it should also address the root cause of learned nonuse.

Similarly, just as the goal of the FINGER robot was to redefine the challenge level of motor practice by providing assistance, the goal of the manumeter is to redefine the challenge level of motor practice by providing feedback information to the user. In the original Challenge Point Framework [66], the ideal challenge point of a task is defined as the point at which the learners can extract the most meaningful information from their practice. As such, using augmented feedback to provide learners with useful information that would not otherwise be available to them might be sufficient to make an excessively challenging task seem more manageable. With the correct feedback, impaired limb use might not seem quite so futile or punishing.
8.4 Future work

8.4.1 Wearable robotic devices for enabling and motivating impaired limb use

Results from the Finger study were encouraging, and suggest that robotic assistance is a useful tool for motivating and restoring hand use after stroke. However, one limitation to robotic devices such as the Finger robot is that they are only usable within the context of a lab or clinic. One of the unique features of the Finger robot was that the mechanism responsible for moving the fingers through their desired trajectory sat strictly behind the hand—thereby leaving the palm and fingers open to interact with physical objects. This feature would be very useful for a wearable exoskeleton designed to motivate and assist in activities of daily living. However, there are a number of large hurdles to be overcome before such a device could be practical.

The first issue that would need to be addressed would be that of the added encumbrance. Even the Finger mechanisms without the added weight of the actuators, light and backdrivable as they are, are slightly too heavy and bulky to support daily use. Because the device is attached to the hand, a distal body segment that needs to be moved frequently, adding additional weight might dissuade use of the hand by increase the metabolic cost of using the device.

The next hurdle is that of actuation. The amount of force required to open the hand of patients with severe motor impairments can be quite large. Supplying the necessary force without adding a prohibitive encumbrance would be very difficult. Furthermore, because the bandwidth of hand use is relatively high, the actuators used to control the robotic device would need to be very responsive in order to keep up. Although the current actuators used by the Finger robot are strong and sufficiently responsive, they are bulky. Working them into a wearable system is an important challenge for future research.

In addition to new actuators, the system would also need new strategies for controlling those actuators. The current controllers used for most robotic devices rely heavily on the fact that that “target” of movements performed during robotic therapy is known. This is not a problem
when the devices are being used to interact with a video game because the game can supply the target information. In daily life, however, the target is less clear. Perhaps the admittance control schemes used by devices like the Gentle/s robot could be adapted[115], [116]. Such schemes focus on following the forces generated by the users rather than only on moving the user to a desired location.

Although there are many challenges to be overcome before such a device could exist, the benefits of a wearable device for assisting in hand use might justify the work. The results of the present work suggest that assisting in hand use would not interfere with recovery (especially for highly impaired users), but would rather facilitate recovery. Such a device would be the opposite to the mitts used in constraint induced therapy. Rather than blocking use of the unimpaired limb in daily life, a wearable exoskeleton would enable use of the less impaired limb.

8.4.2 Future of the manumeter
A key direction for future work with the manumeter is to obtain more results from users with stroke related motor impairments. Although we demonstrate the accuracy and repeatability of the device, additional work needs to be done to demonstrate the utility of the device both as an outcome measure for monitoring progress and as a motivation tool for providing augmented feedback of impaired limb use.

Furthermore, many of the improvements discussed in chapter 7 utilized a development version of the manumeter that only supported data streaming – not long term data storage. These improvements would need to be ported over to a more permanent device.

One desirable feature for a future version of the manumeter is the ability to notify users when they are failing to achieve preset movement milestones. The device could also be used to facilitate short, repetitive movement practice sessions distributed throughout the day. In much the same way that a wearable robotic device could function as a positive analog of the mitts used by constraining induced therapy, the manumeter could be used to show individuals with
stroke related motor impairments how much they are choosing to use their impaired limb verses the unimpaired limb – thereby incentivizing motor practice habits that might decrease learned nonuse and allow users to approach their full potential.

Chapter 9 References

“Always ... no, no ... Never ... forget to check your references.”
- Dr. Meredith (Real Genius, 1985)


[37] S. Hesse, C. Werner, M. Pohl, S. Rueckriem, J. Mehrholz, and M. L. Lingnau, “Computerized arm training improves the motor control of the severely affected arm after


