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Measurement of finger coordination during a motor learning task

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ABSTRACT

MEASUREMENT OF FINGER COORDINATION DURING A MOTOR LEARNING TASK

by
Robert George Ebel

The focus of this study is to observe the changes in whole hand grasp strategy, in healthy subjects, over time in a series of isometric force control learning tasks. During a series of trials with real-time visual feedback of the five finger forces, subjects adapted their grasp strategy in order to reach the target in a time efficient manner. In early trials, it is very evident that subjects focus on controlling the force output of one finger at a time until they reach the goal. As the block of trials progresses, subjects alter their strategy to a more coordinated movement to reach the target faster as they learn the coordination task. Throughout the study, forces are measured using a custom designed force measurement device. Many stroke patients do not fully recover hand function after a stroke. It has previously been shown that stroke subjects have an increase in finger enslavement or an increase in unintended force production between adjacent fingers. Ideally, using a force measurement device and a grasp shaping task, as described here, could translate to a therapy for stroke subjects enabling a faster recovery and greater finger independence.

MEASUREMENT OF FINGER COORDINATION DURING A MOTOR LEARNING TASK

by
Robert Ebel

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APPROVAL PAGE

MEASUREMENT OF FINGER COORDINATION DURING A MOTOR LEARNING TASK

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This Thesis is dedicated to my loving parents.

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I would like to recognize the help and friendship provided by my peers over the years, especially Deep Patel, John Macaluso and Andrew House. Finally, I would like to thank all the Professors from whom I have had the privilege to learn during my time spent at NJIT.

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CHAPTER 1

INTRODUCTION

1.1 Objective

The purpose of this master's thesis is to analyze and document the changes in grasp strategies during a motor learning task. This was accomplished through measurement of each finger force over a series of repetitive, goal oriented, whole hand learning tasks. It was discovered that over the course of a learning trial, subjects alter their grasp strategy in different ways to reach the target more efficiently. This knowledge provides a better understanding of how people adapt during a learning task. The ultimate goal is to translate this knowledge to designing better stroke rehabilitation protocols. This study will serve as a baseline to compare to the learning pattern of stroke patients because loss of whole hand coordination is a major problem facing many stroke survivors.

1.2 Background Information

1.2.1 Stroke Sequela

Stroke is the leading cause of permanent disability in adults.[1] A stroke occurs when one of the arteries providing oxygenated blood to the brain is clogged.[2] When blood flow is cut off from any part of the brain for more than a couple of minutes, permanent damage occurs. Time is a critical element in the treatment of stroke. A longer time to reach critical care is associated with a poorer outcome because more damage occurs the longer neurons are deprived of oxygen. Some stroke victims do not survive while many others suffer from chronic disability. Following a stroke, patients will exhibit a decrease in range of motion and an abnormal posture on one side of the body due to neurological dysfunction. Weakness on one side of the body is called hemiplegia and occurs in 8 out of 10 stroke survivors.[3] Stoke survivors may have very little range of movement and will be restricted in their posture. The typical posture associated with hemiplegia from stroke is one of a hooked arm due to elbow flexion and a fisted hand from finger flexion. Abnormal postures following stroke are due to the neurological effects of stroke. The recovery process has varied outcomes where some patients experience spontaneous recovery and approach initial levels of functionality while others do not make a full recovery. It is possible to see improvements in strength and motion by going through therapy. Through therapy, subjects can also increase individual finger actuation but they may not fully regain coordinated grasping strategies, which is important in everyday function. It is important to note that there is a window of time to start rehabilitation therapy for it to be effective. Despite advances in rehabilitation methods, after six months to a year, there is generally little additional recovery even with rehabilitation.[4] This long-term disability is the focus of stroke rehabilitation as well as restoring quality of life.

1.2.2 Current Rehabilitation Methods

With a large population of subjects that do not fully recover from a stroke, there is an unmet need in patient care with many paths being pursued to fill this void. While a stroke is most likely to occur in an older population, it can occur at any age, making rehabilitation much more important for improving quality of life. The treatment of a stroke will vary depending on the specific symptoms. Current treatments for stroke patients run the gamut from simply pickup and placement of household objects, to advanced brain computer interfaces.

Following a stroke, a natural recovery process also helps the brain to regain its original function due to plasticity. It is not possible for the brain tissue to recover using the same mechanism of wound healing as it occurs elsewhere in the body due to the blood brain barrier and the nature of the injury. Neurons affected by a stroke are dead along with all of the connections they made. The only way the brain recovers is through neuroplasticity where functions that were lost can be remapped onto other healthy areas of brain tissue. The functional area surrounding stroke damaged tissue is remapped to take on the lost function based on the redundant connections in surviving neurons.[5] Remapping areas of the brain appears to use the same physiological mechanisms as in task learning. Time is critical in the rehabilitation of stroke because the brain is most plastic in the period directly following an injury. In an rat study, motor rehabilitation that was started in the first two weeks lead to a much better outcome than in the rats that started training 30 days post injury.[5]

In recent years, transcranial magnetic stimulation (TMS) has emerged as a fascinating research tool and a promising therapy for stroke rehabilitation. TMS is a noninvasive method of stimulating tissue such as muscles or neurons. Neurons can be electrically stimulated through the scalp from an induced current originating in a coil placed over the targeted area. A diagram of this is shown in Figure 1.1 below. When stimulation is directed over the primary motor cortex, a muscle contraction can be observed in a conscious subject without experiencing pain.[6] The biological response to a TMS pulse depends on several factors. In addition to basic parameters such as positioning and current of the coil, the shape, stimulation intensity and stimulation frequency all have an effect on the neuronal response.[6] Building on the brain's natural plasticity, TMS can provide additional stimulation to the area's surrounding a stroke lesion to enhance the effects of motor rehabilitation. Repetitive TMS at low frequency in conjunction with occupational therapy has shown some promise for improving the symptoms of hemiplegia in stroke.[7]

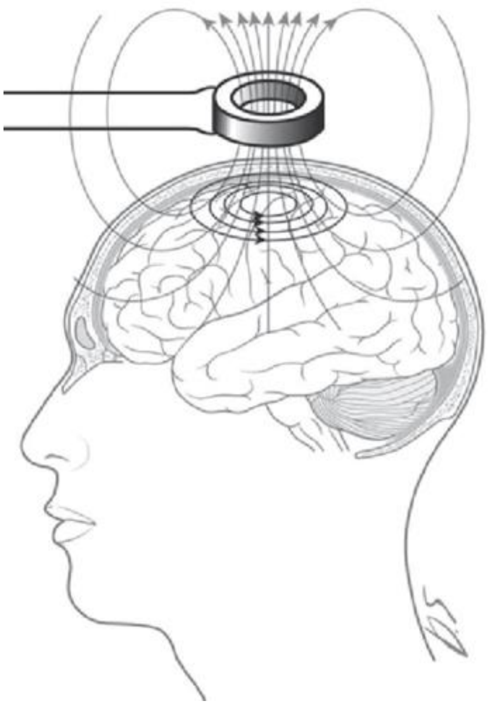

Figure 1.1 Transcranial magnetic stimulation diagram showing the coil, magnetic fields and the induced current beneath the scalp.

Source: https://www.researchgate.net/figure/303694440_fig1_Fig-1-Diagram-of-the-underlying-principle-of-transcranial-magnetic-stimulation-TMS

Virtual training is another promising method of treating the motor deficits after a stroke, which is already starting to be implemented in rehabilitation centers. At its most basic level, virtual training involves an interactive system including visual feedback and the software that processes and uses the data measured from the user. Systems that involve motion tracking, haptic feedback, audio feedback, virtual reality, and virtual environments are more immersive and provide a more engaging setting to the user. By using a virtual environment, there are limitless possibilities for modifying the virtual task to keep the task challenging and engaging. Virtual reality therapy can create improvements if the task is fun, engaging, and designed with a specific training in mind.[8] In addition, virtual rehabilitation provides a means for recording data during each session for in depth post processing. Finally, virtual rehabilitation is easily transferable from a clinical rehabilitation center to the home environment just by providing the user with the software and hardware they need. Training can continue at home, long after insurance has stopped paying for therapy. At home, more time can be spent on virtual rehabilitation than in a clinical setting.[9]

1.2.3 Muscle Synergies and Enslavement

The physiology of the human hand is very dexterous and allows for a great range of motion. Our dexterity comes about because each hand contains 27 degrees of freedom. This allows for very complicated motion patterns from playing musical instruments, to the daily exercises of typing. Every motion that is produced in the hand, or any part of the body, is directed by the primary motor cortex of the brain. As Andrea d'Avella has pointed out, the brain cannot act in a closed-loop feedback paradigm to generate movements.[10] With each movement, 27 degrees of freedom provide a nearly infinite number of solutions to simple motor problems. To simplify the problem, the brain chooses a solution from a smaller set of motions or postures called synergies. These synergies represent a pattern of muscle activation that varies with time. Using a weighted sum of a finite number of synergies, the entire range of fine motor motion can be generated. Several groups have published that about 90% of hand positions, can be generated from about six synergies.[11, 12] One of these studies also claimed that more than half of our regular hand movements could be described by two synergies across multiple subjects.[12] This significantly decreases the computational load on the brain. Instead of having to calculate each finger's joint angles for a given movement just based on visual integration, a grasp or pinch is sufficient to describe the desired motion.

According to Signe Brunnstrom, after a stroke, abnormal synergies are a key reason for hemiparetic disability.[13] After a stroke, the contralateral limb and hand become flaccid and due to temporary disuse and increased neuroplasticity abnormal synergies arise. It is also stated that normal synergies arise from basic reflexes that are present from a young age.[13] These reflexes are always present and can be used as a tool to restore function. Rehabilitation can be achieved by training the common synergies back into a patient's repertoire just as synergies are developed in a child.

Enslavement is an unintentional force produced in a finger that is not explicitly involved in a task.[14] The finger(s) that is explicitly involved in a task, is known as the master finger, while the other fingers are the slaves. These forces can have a mechanical connection and a neurological component.

"Motor 'learning' is used to mean the formation of a new motor pattern that occurs via longterm practice."[15] Using this definition from Amy Bastian, the task presented in this thesis would more accurately be described as a motor adaptation task. If we assume that synergies are not static, the process of motor learning is in essence the process of creating new synergies. Adaptation on the other hand, would represent modifying the current set of synergies to meet the demands specific to the task and to make reaching a goal easier. In a motor task, enslavement and synergies play a critical role in reaching a grasp target. When the perceived target is a close match to an existing synergy, the hand can match the target and reach the goal very rapidly. On the other hand, when the task involves motions or postures that are not regularly used, the subject may have a difficult time finding the appropriate combination of synergies to reach the target. In the case of a stroke survivor, the neural representations of the synergies they have used all their life are gone or severely damaged. Using the brain's plasticity, new synergies can be developed in heathy regions of the brain by remapping the function those neurons perform.

CHAPTER 2

MATERIALS AND METHODS

2.1 Experimental Setup

Data collection was performed in the same laboratory environment across all trials with minimal external stimulus for consistency. The experimental setup is shown in Figure 2.1. The entire setup consists of a computer running the data collection and user interface program in MATLAB, a custom force sensor array or rehabilitation device (RD), a chair, and a pillow for arm support. The RD was designed for a previous undergraduate senior design course and modified to meet the needs of this experiment. It was designed to be an inexpensive tool to measure finger forces, especially for stroke patients. The RD is made up of a baseboard, a vertical mounting board, 2 analog to digital amplifier boards, 5 force sensors, and accompanying 3D printed hardware to interface each sensor with a finger and to mount each sensor on the mounting board.

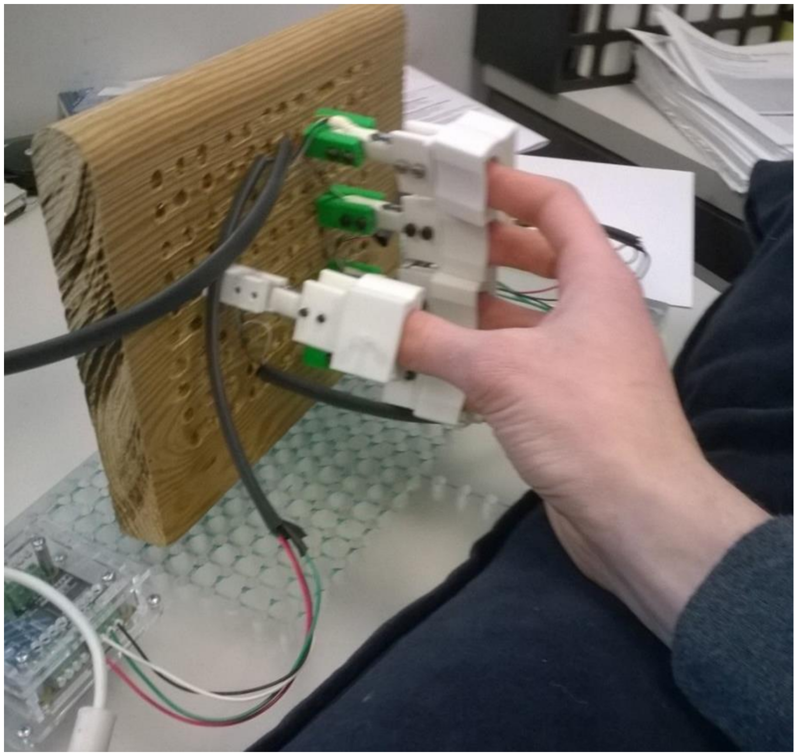

Figure 2.1 Experimental setup: Subject's arm is resting on a pillow and each finger is in a finger cup attached to a force sensor.

The components of the rehabilitation device are shown in Figure 2.2. Subjects interfaced with the force sensors via a set of 3D printed finger cups on the end of each strain gauge. A plastic sleeve was printed to fit over the finger cup. This sleeve clamps the finger between the cup and the sleeve and can be adjusted with a nylon screw on the back of the sleeve to fit fingers of any thickness. The cup and sleeve allows subjects to transition from flexion to extension without any force being lost to moving the sensor. At the other end of the force sensor, a plastic holster attaches each sensor to an aluminum rod (.25" diameter). The aluminum rod allows the sensor unit to be relocated anywhere on the wooden board and makes it adjustable for subjects with different hand sizes. Each plastic holster and finger cup is attached to the strain gauge with 2 M3 hex bolt. Both the electronic amplifier and force sensors were purchased from Phidgets (parts: 1046 and

3132, respectively).[16] The force sensors are resistive strain gauges arranged in a Wheatstone bridge configuration and are rated to 7.6N of force.

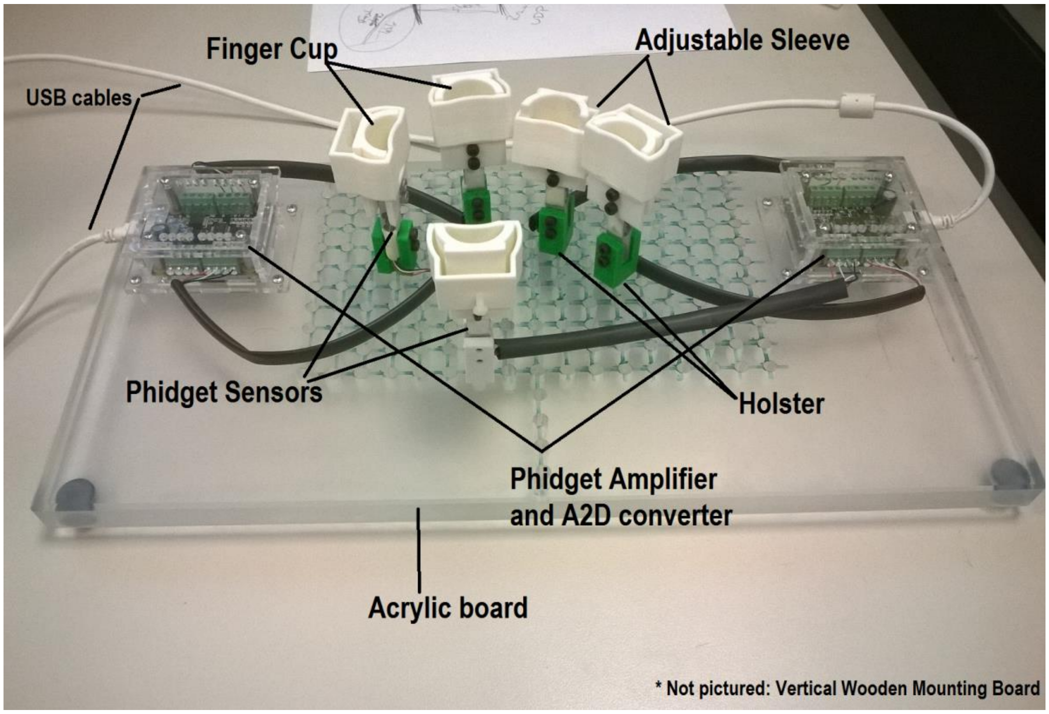

Figure 2.2 Rehabilitation device with all components labeled.

2.2 Subjects

Five healthy subjects were recruited for the study and each participated after signing the approved informed consent form. The only exclusions were if the subject had a history of seizures or if they had a recent upper extremity injury or surgery. All subjects were between the ages of 18 and 30 and all were right handed. Subjects were asked one question to gauge their level of finger control. All subjects responded with moderate levels of daily use of fine motor control including the use of a computer keyboard and some use in hobbies.

2.3 Data Collection Procedure

Each subject was seated comfortably facing the display monitor where the user interface and task are shown. The active arm rested on the table with a pillow to support the elbow, while the inactive arm rested on an armrest from the chair. The RD was oriented at approximately a 45° angle to the subject so the wrist is slightly extended. The finger tips were placed in their respective cups up to the distal interphalangeal joint and were tightened so there was no motion between the finger and cup when transitioning between flexion and extension. Sensors were set up to simulate a grasping pose, where the thumb was abducted and it opposed the force from the other four fingers. This can be seen in Figure 2.1. With variations in hand size, sensors were relocated on the board to maintain this orientation. Care was taken to prevent any part of the force sensor unit from touching each other. Interference between sensors results in an inaccurate reading of the applied force.

At the start of data collection, the first task was used to measure finger enslavement. Measurements were taken from all five sensors while the subject was instructed to squeeze with one finger that was instructed on the screen. There was no visual feedback provided at this point. This procedure was repeated again at the conclusion of the session.

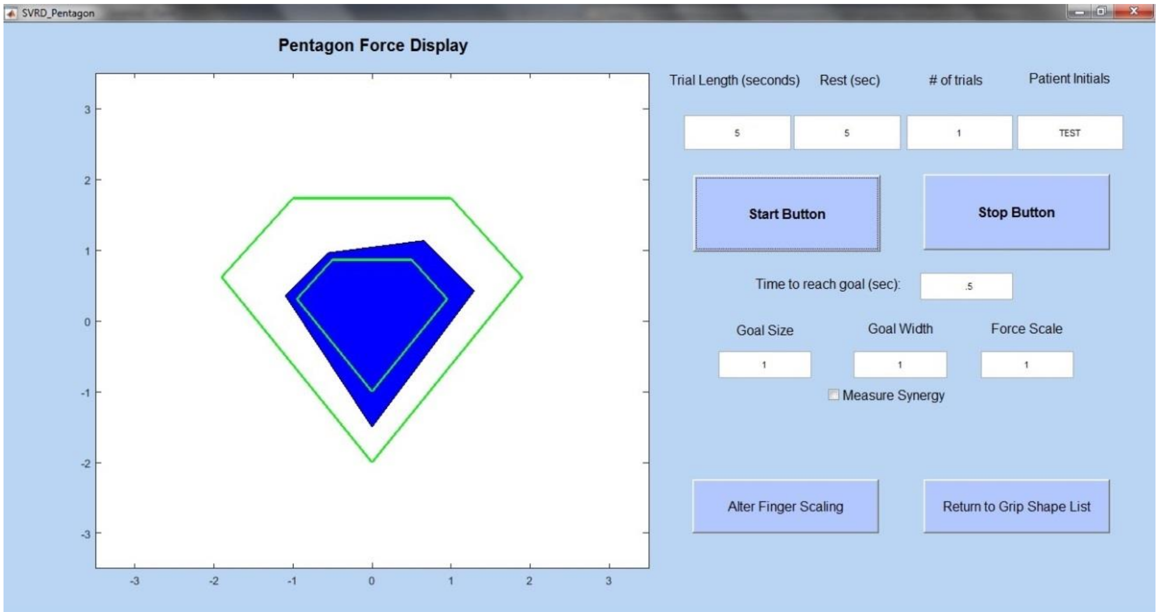

Figure 2.3 Force feedback user interface. This is a successful trial because all points on the polygon are within the goal range.

The software used for force measurement was developed as a part of this project. The learning task involved controlling a polygon in the user interface to reach a goal between two thresholds using the five force sensors. Each point on the polygon moved radially from the center based on the force measured on a corresponding finger. The motion on the monitor was directly proportional to force from each finger, measured in Newtons. To further simulate a grasping task, the polygon started with an initial size and would shrink when force is applied, as though it is being squeezed. The vertices were not labeled forcing the user to learn through use. As a starting point, each new subject was instructed that the thumb was the sharpest point on the diamond shape. Subjects were instructed to get the blue polygon between both goals as quickly as they could. The force for each finger had to be less than the outer goal line and greater than the inner line, seen in Figure 2.3. Initially, both of the goal diamonds are red and will turn green, for additional feedback, once all five points are on the correct side of the goal. Data collection for each trial stopped after the goal condition was met for half a second. The 500 millisecond minimum was put in place to ensure that the goal posture was met and that it was met in a transient crossing. Each data collection trial was followed by a 5 second rest period. Resting between trials, the subject relaxed their hand to avoid passively reaching the target by holding the previous grasp profile.

Each subject performed 100 learning trials, split into two blocks. In between the two blocks, one parameter was modified to create a similar task that the subject had to adapt to. For Subjects 1, 2, and 5 the target and force polygon were rotated 90°s clockwise, presenting the subject with the additional element of mentally rotating the image they had previously learned to a new orientation. All other parameters were left unmodified. The target orientation did not change for Subjects 3 and 4 but the goal width and a scaling factor were modified.

CHAPTER 3

RESULTS

3.1 Measurements of Success and Strategy

In order to analyze the level of success for a given trial, two different metrics were used. The simplest measure for analyzing each learned task is to determine how long it took the subject to reach the goal on a given trial. Taking this value for each trial and fitting an exponential to the data gives the rate of learning. Using the equation $y = a*e^{bx}$, the rate of learning used was the value b. A negative value means the y value decreases with trial number.

The second method used to measure how well the task was learned, was to look at how quickly all five fingers entered the goal. This measurement only measured the time between the first finger entering the goal region and the time the slowest finger reached the goal. This time was used even if there was an overshoot. If the motion was very coordinated, all five fingers would enter the goal within half a second, though, at least one could have overshot the target.

Categorizing what strategy was used over hundreds of trials by visually analyzing the data would be a large undertaking. The differentiation of each strategy was done programmatically. When all five fingers entered the goal within one second of each other and all fingers did not exit the goal again too many times, the trial was designated as a unified hand strategy. The threshold was set to 20 times entering or exiting the goal area because at a minimum there are 5 crossings and each time a finger exits the goal, it must return inside. When all fingers did not cross the goal area more than 20 times but they reached the goal separately, the trial was designated as an individual finger strategy. Finally, if all five fingers were not able to stay within the goal and kept entering and exiting, the strategy was designated a random exploration strategy. A sample of each strategy is provided in Figures 3.1-3.3

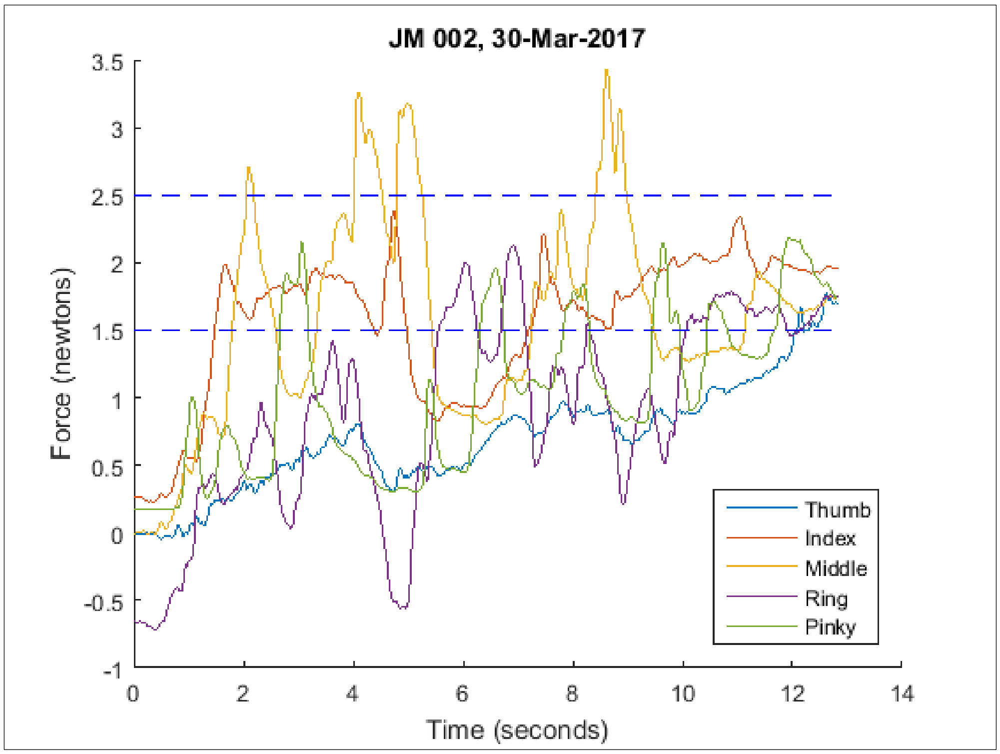

Figure 3.1 Random Exploration grasp strategy example. One finger is in the goal most of the time but when focus moves from one finger to another, the first finger leaves the goal area.

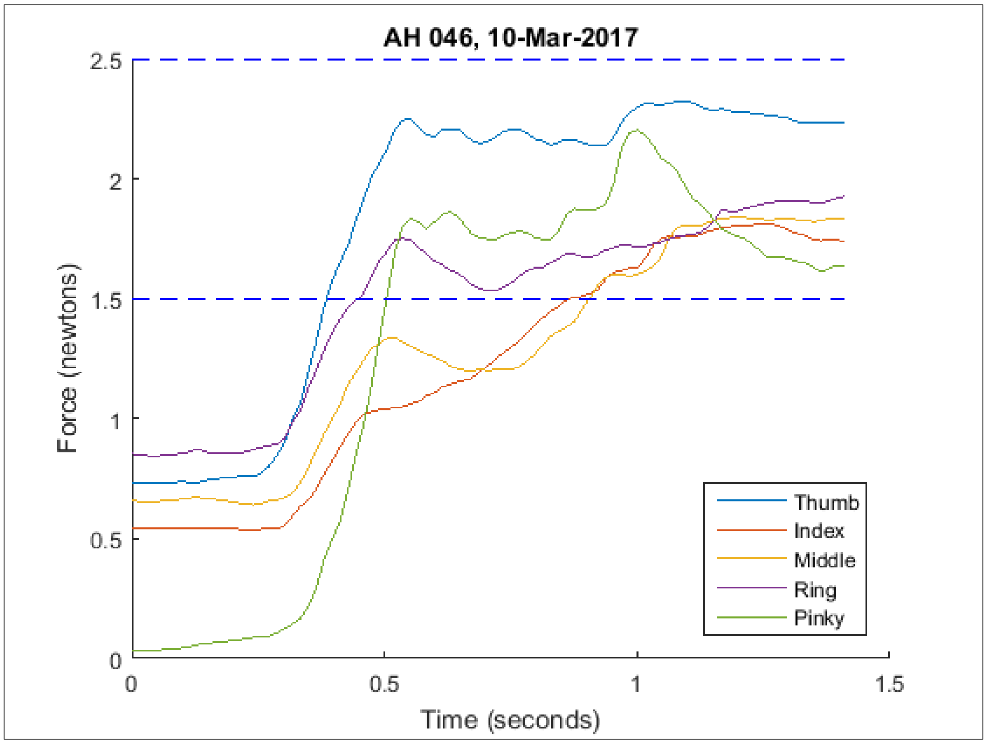

Figure 3.2 Unified hand strategy. All fingers move in unison and the goal is met rapidly.

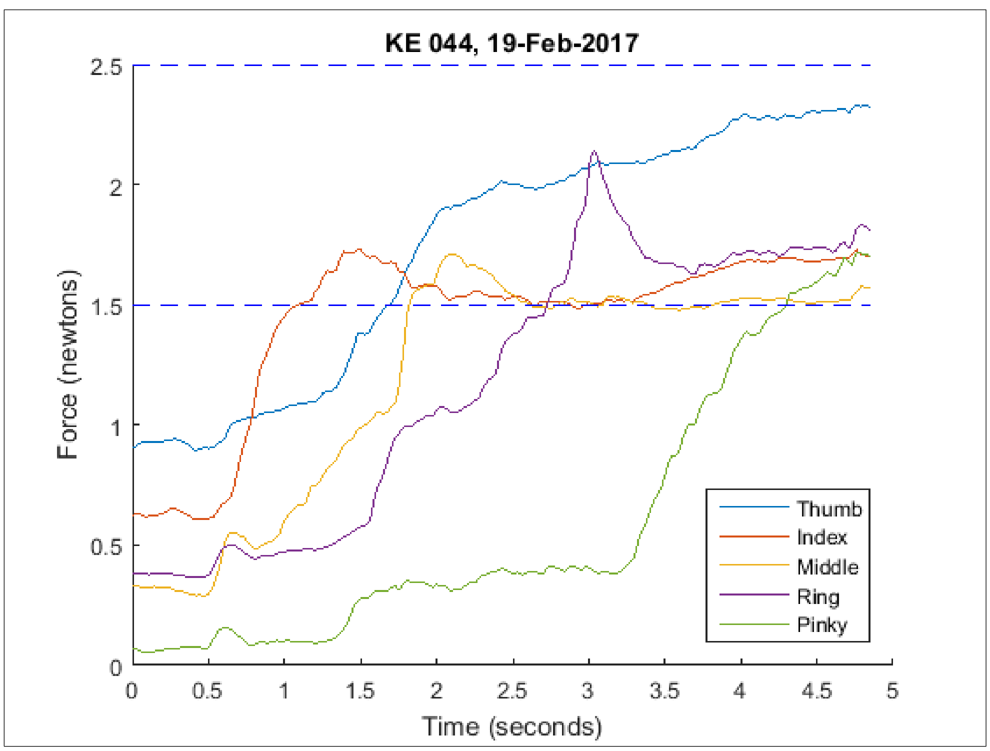

Figure 3.3 Individual finger strategy. Fingers are moved nearly independently and the goal is met easily without major corrections.

3.2 Subject Data

Table 3.1 Exponential Rates of Learning

Subject #	Time to reach goal: Block1	Time to reach goal: Block 2	Time for all fingers to reach goal: Block 1	Time for all fingers to reach goal: Block 2
1	-.008	-.28	-.001	-.035
2	-.023	-.007	-.038	-.017
3	-.021	.003	-.018	.010
4	-.022	.003	-.012	-.028
5	-.024	-.035	-.017	-.044

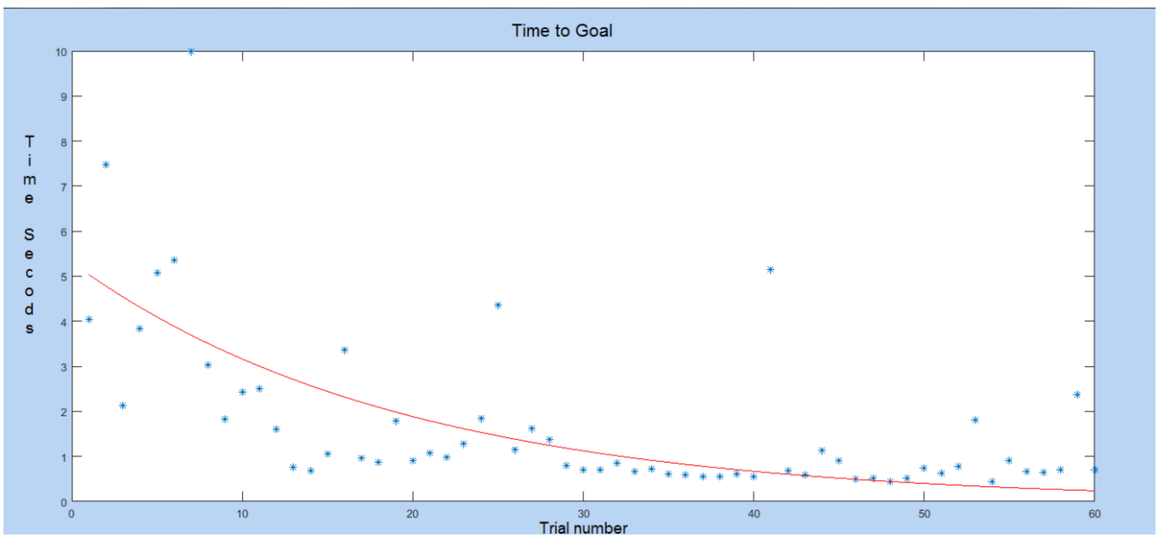

Figure 3.4 Preliminary data showing the time to reach the goal vs trial number. Data can be represented nicely by an exponential learning curve despite a few outliers. This was used to determine that 50 is the ideal number of trials in a block.

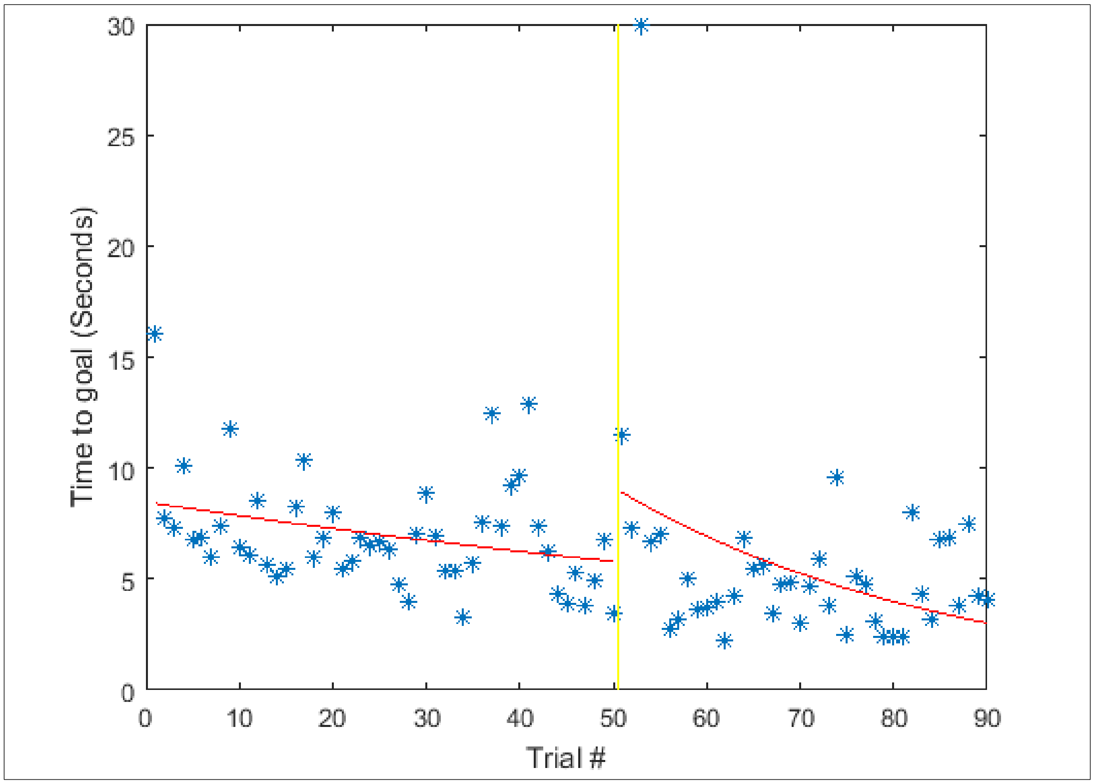

Figure 3.5 Subject 1 Time to reach the goal.

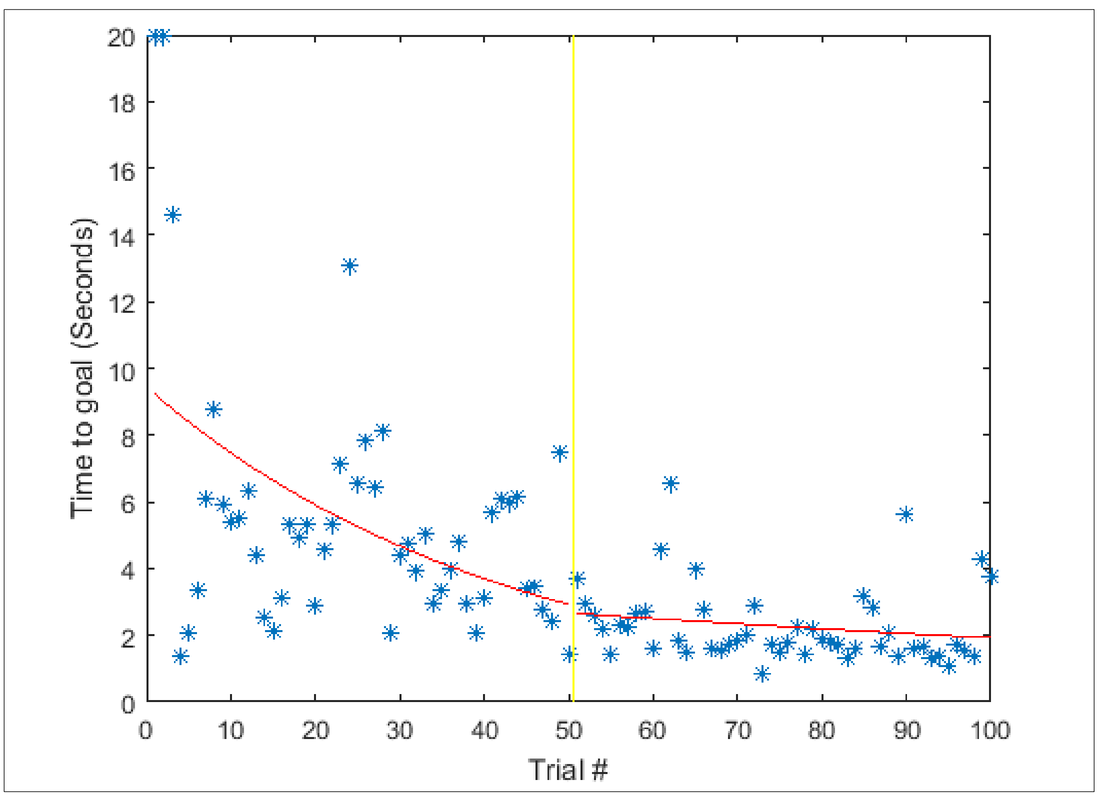

Figure 3.6 Subject 2 Time to reach the goal.

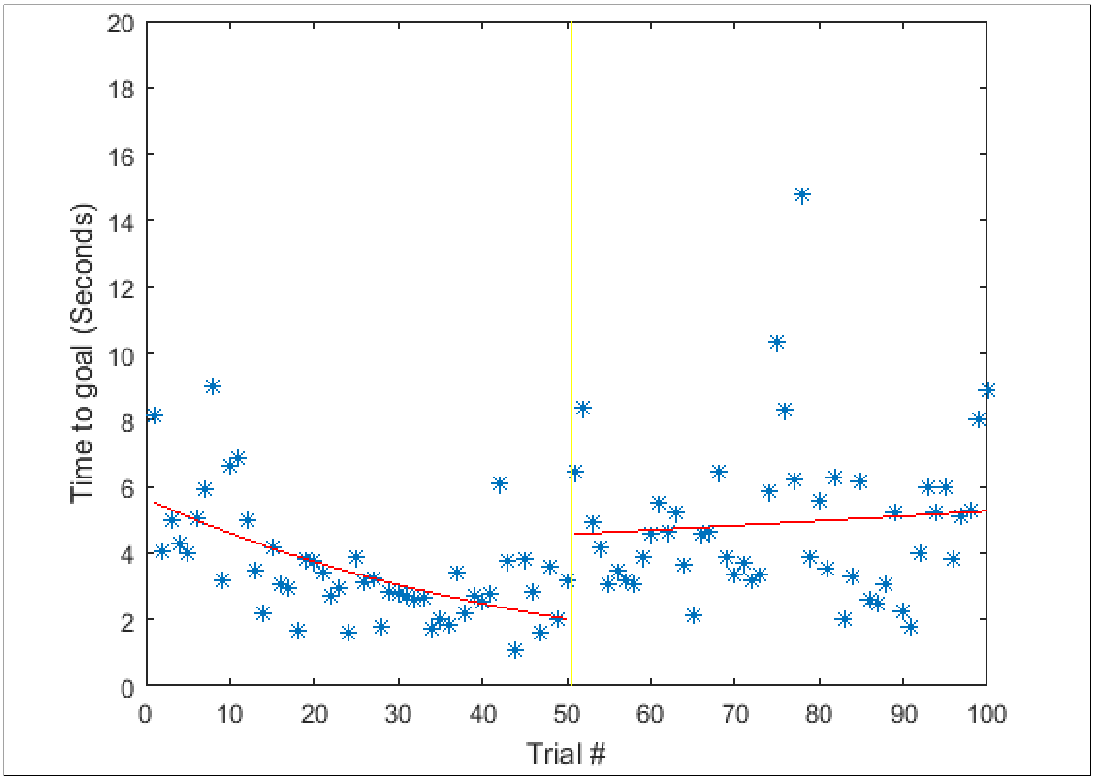

Figure 3.7 Subject 3 Time to reach the goal.

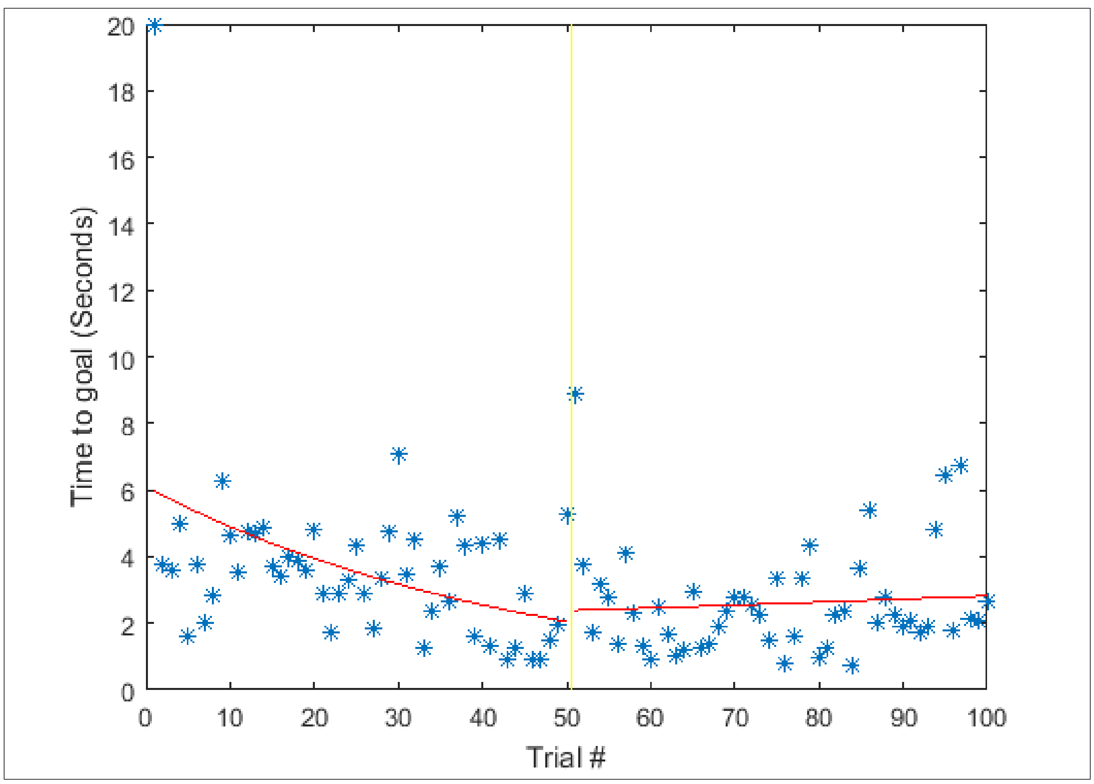

Figure 3.8 Subject 4 Time to reach the goal.

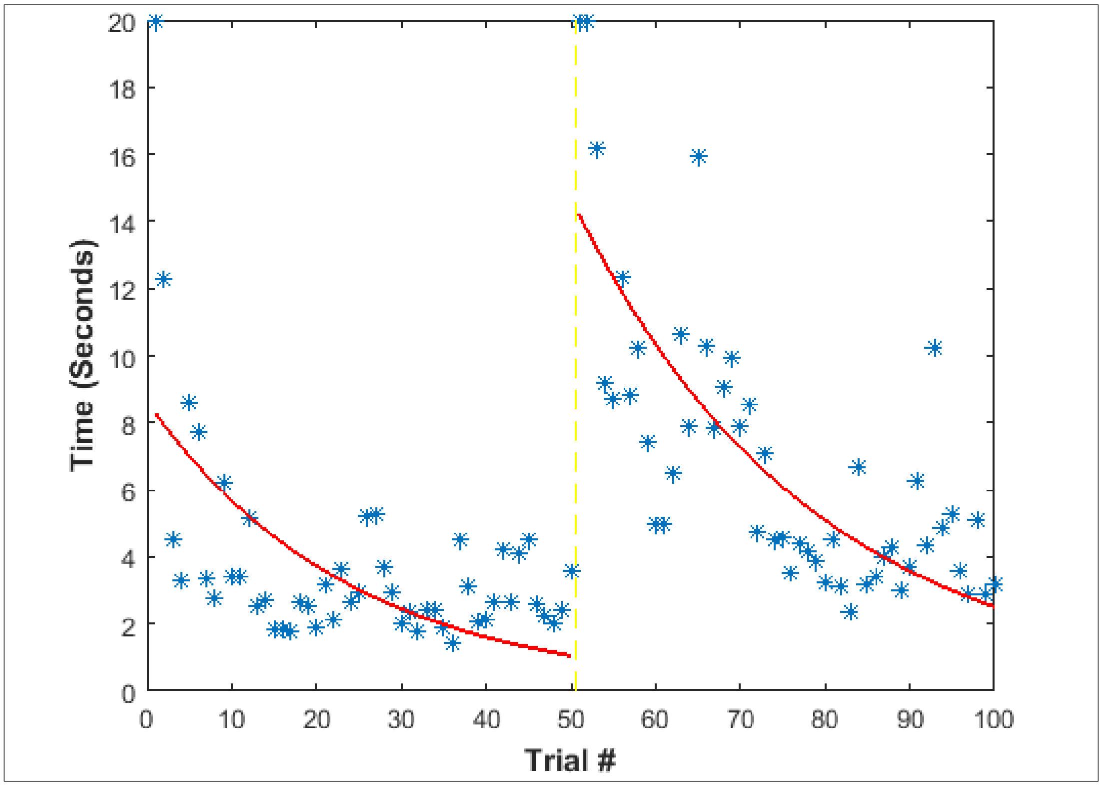

Figure 3.9 Subject 5 Time to reach the goal.

Table 3.2 Percent of Trials Using Each Strategy.

Subject #	Random Exploration	Individual	Whole hand
1	37	63	0
2	34	20	46
3	50	34	16
4	43	7	50
5	37	58	5

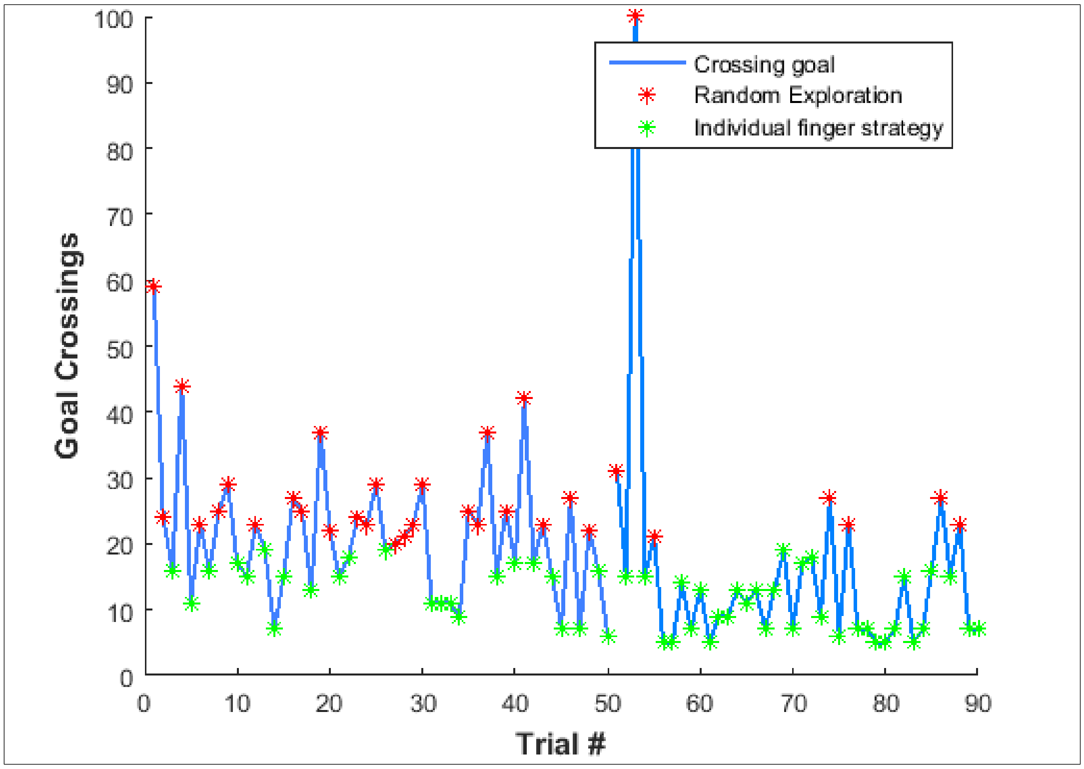

Figure 3.10 Subject 1 strategy. This subject focused on reaching the goal with single finger movements.

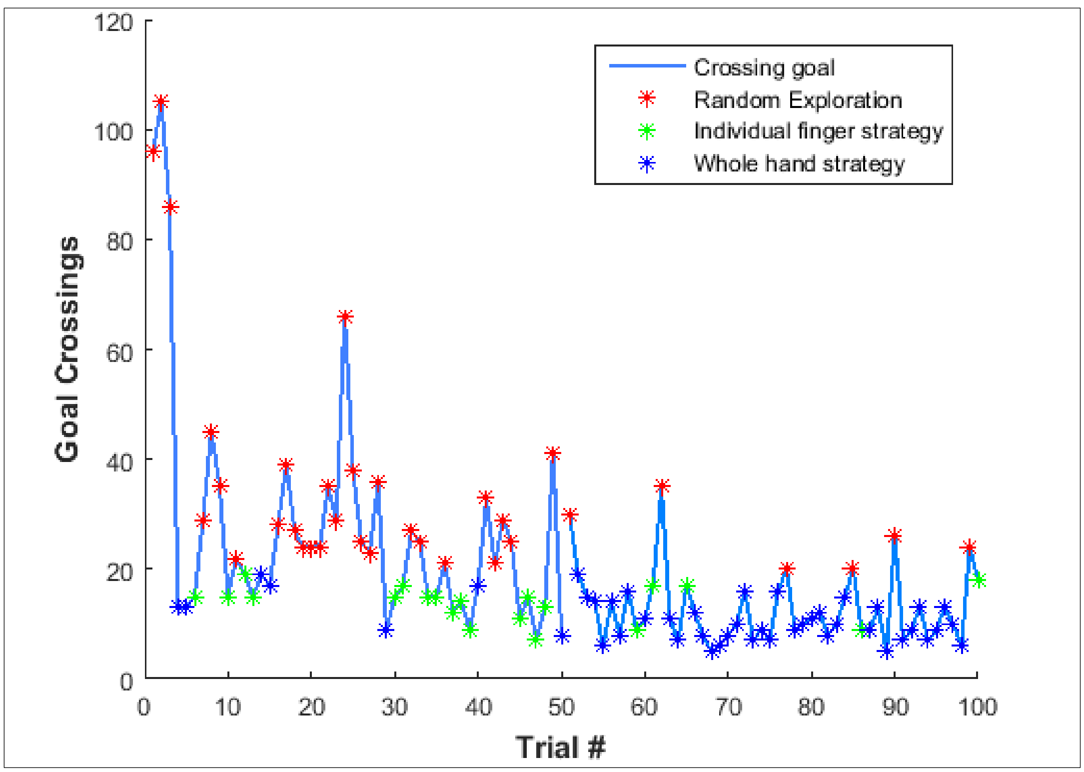

Figure 3.11 Subject 2 strategy. This subject varied their strategy until settling on a unified hand motion.

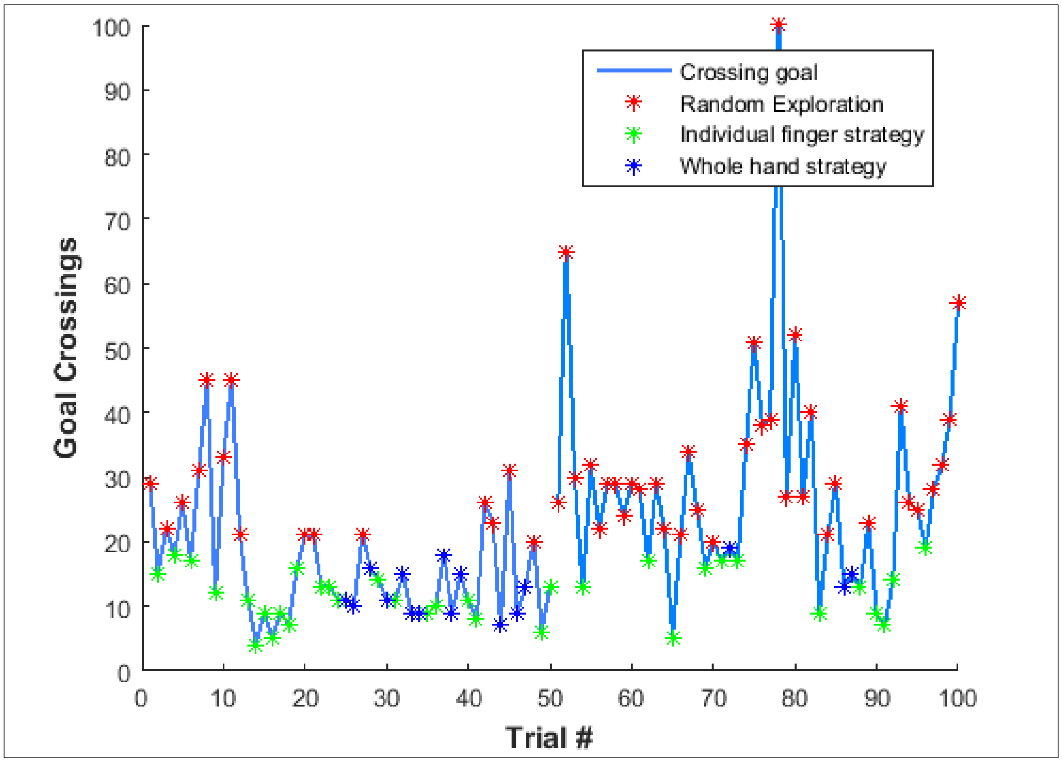

Figure 3.12 Subject 3 strategy. This subject did not find an optimal strategy for effectively reaching the goal.

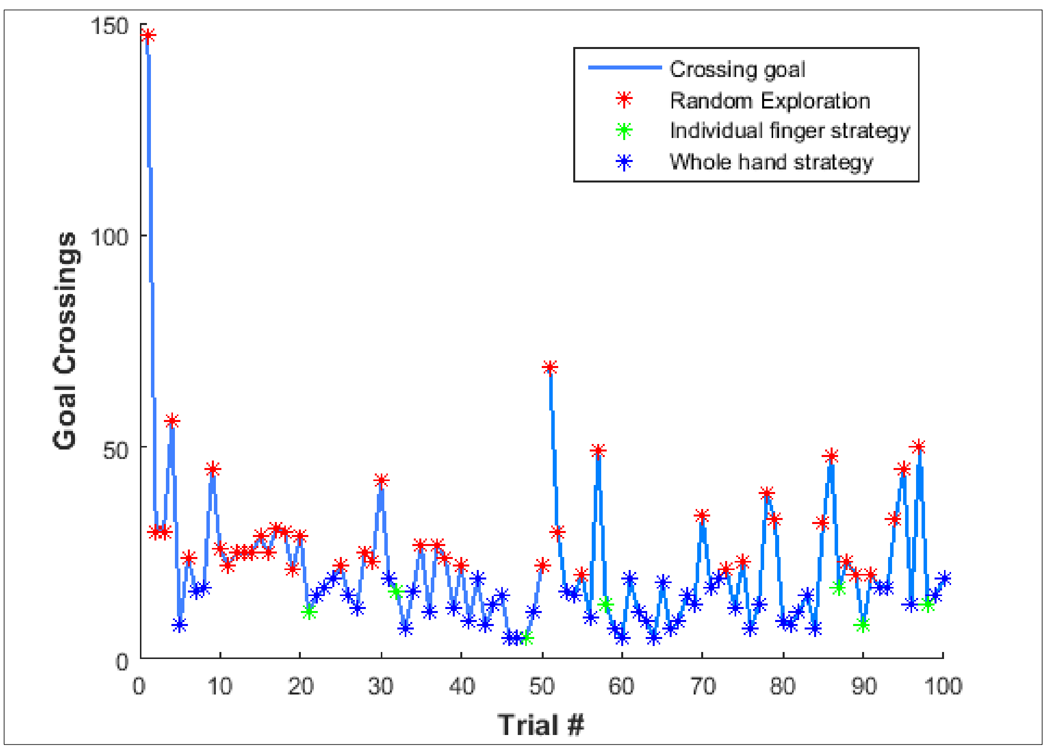

Figure 3.13 Subject 4 strategy. This subject mostly used a unified finger strategy.

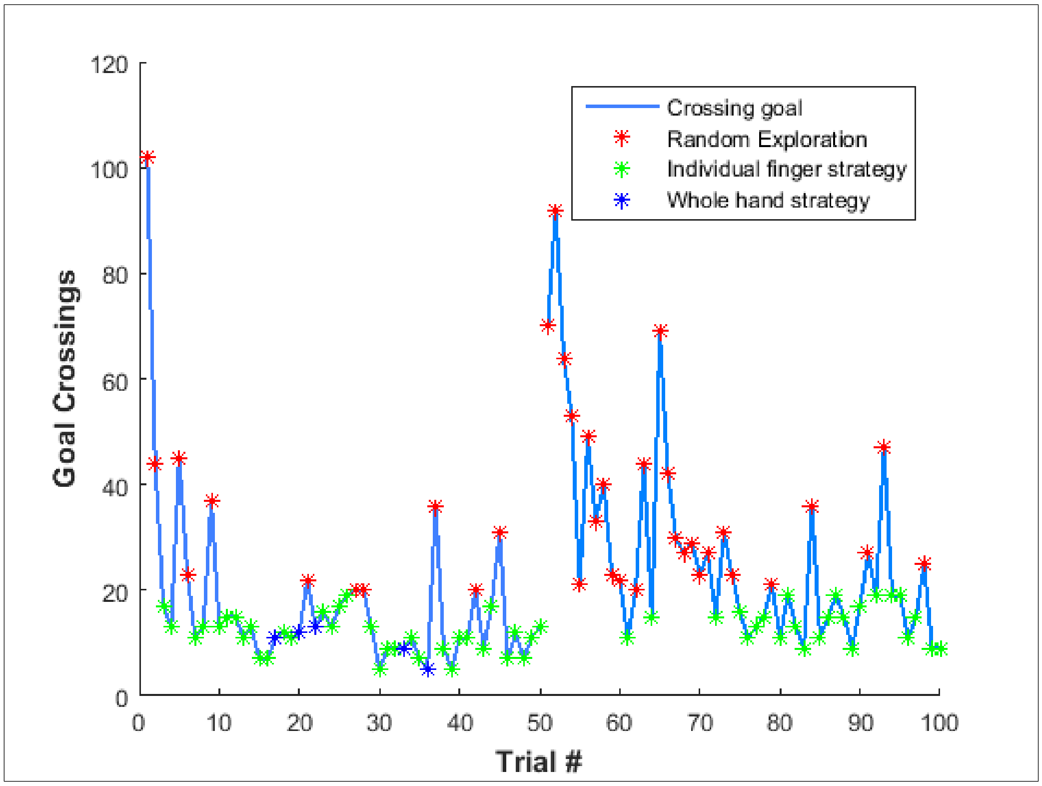

Figure 3.14 Subject 5 Strategy. This subject used an individual finger strategy.

3.3 Enslavement Data

Figures 3.16-3.23 display the enslavement data for each of the participants, both before and after they went through the learning experiment. The title for each subplot indicates the finger that was the master finger in each case. Positive force represents finger flexion, while a negative value shows a finger extension force.

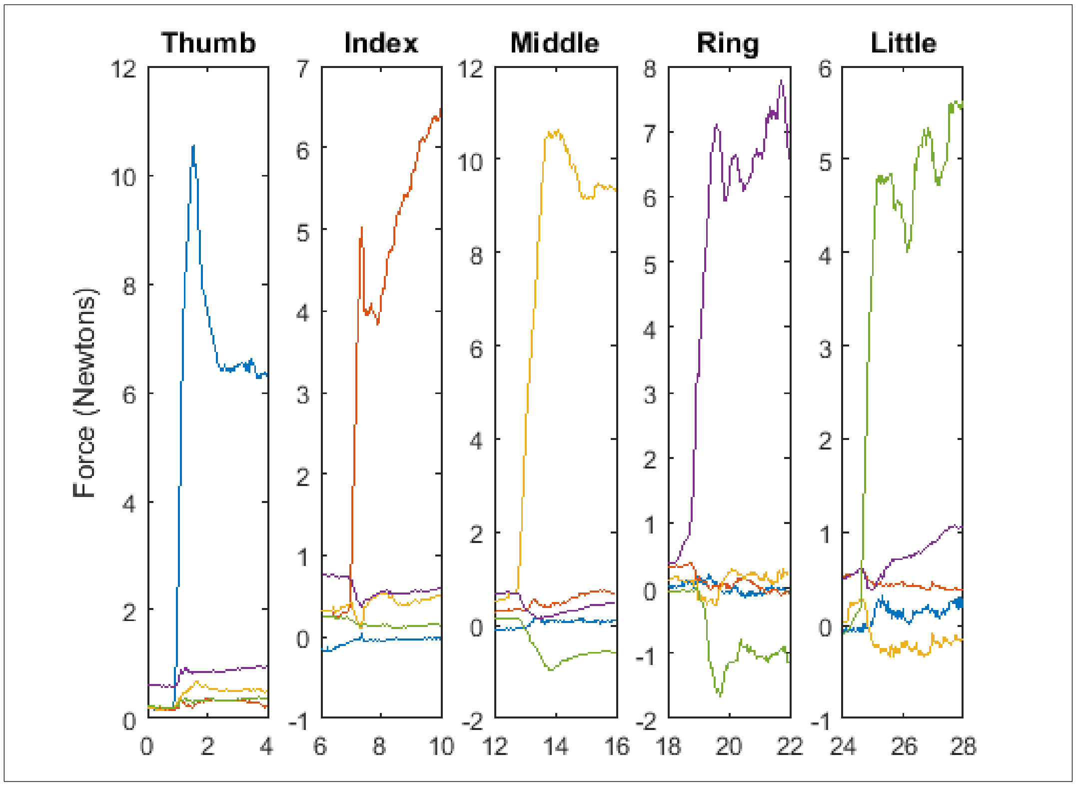

Figure 3.15 Preliminary enslavement data.

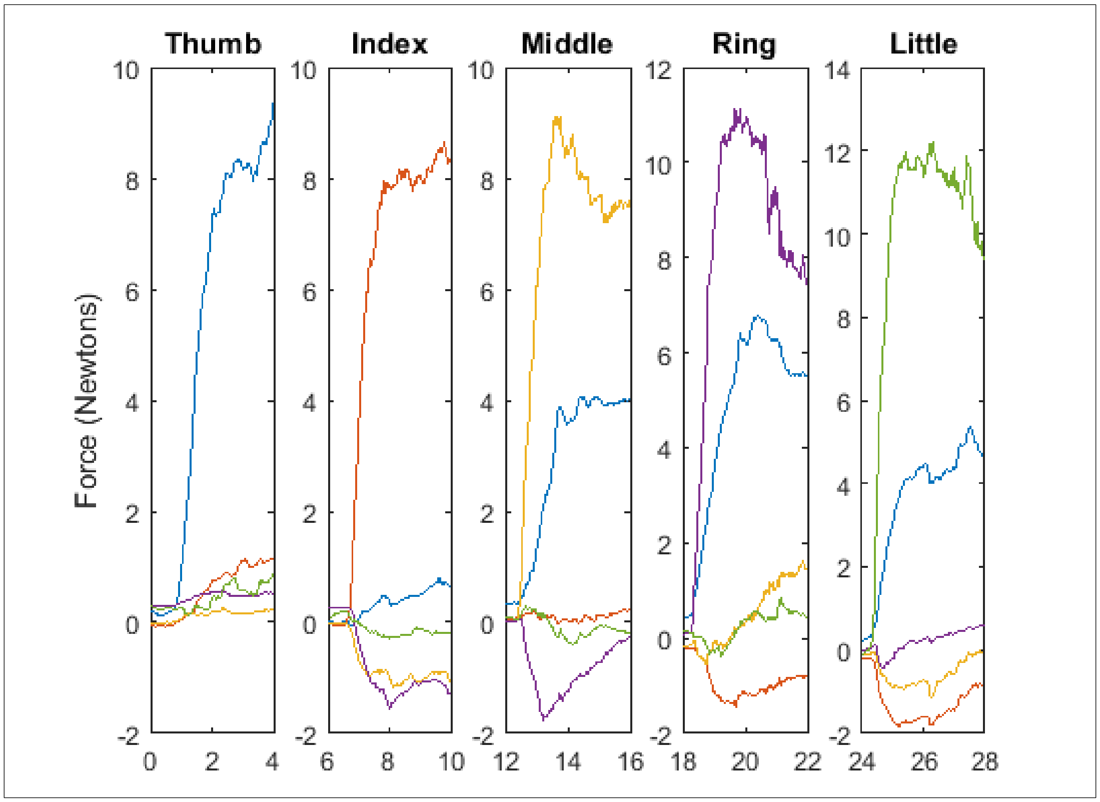

Figure 3.16 Subject 1, initial enslavement.

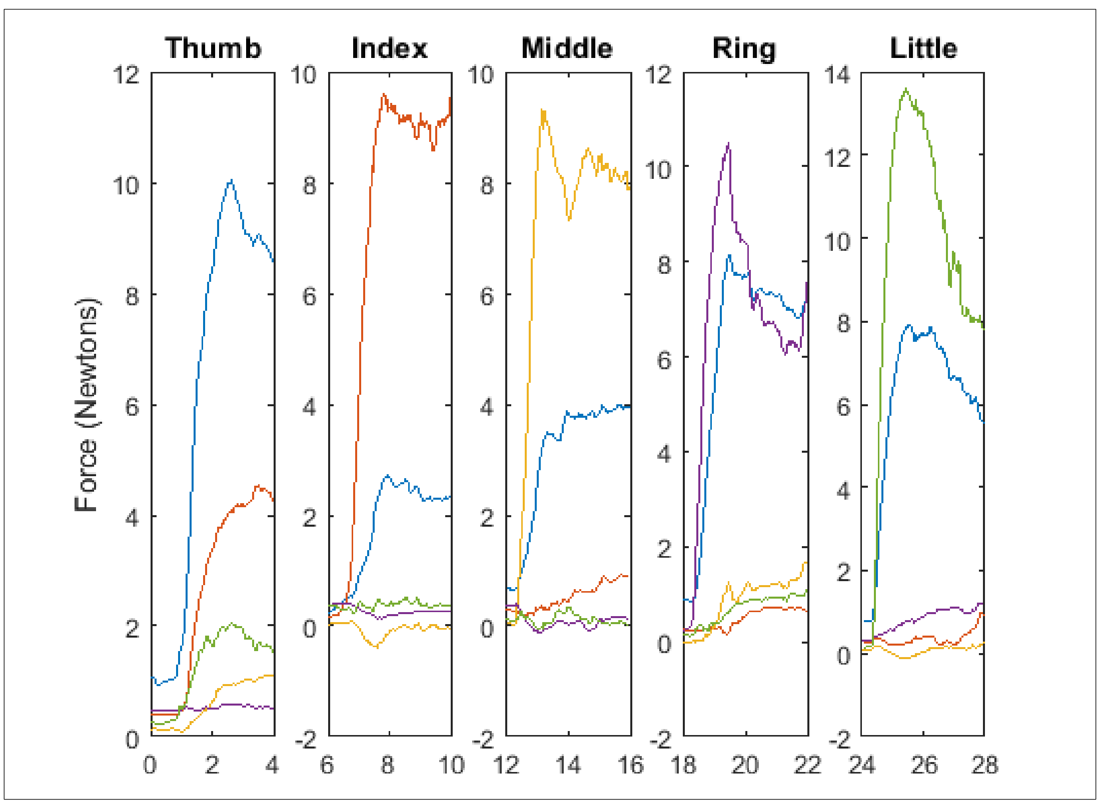

Figure 3.17 Subject 1, final enslavement.

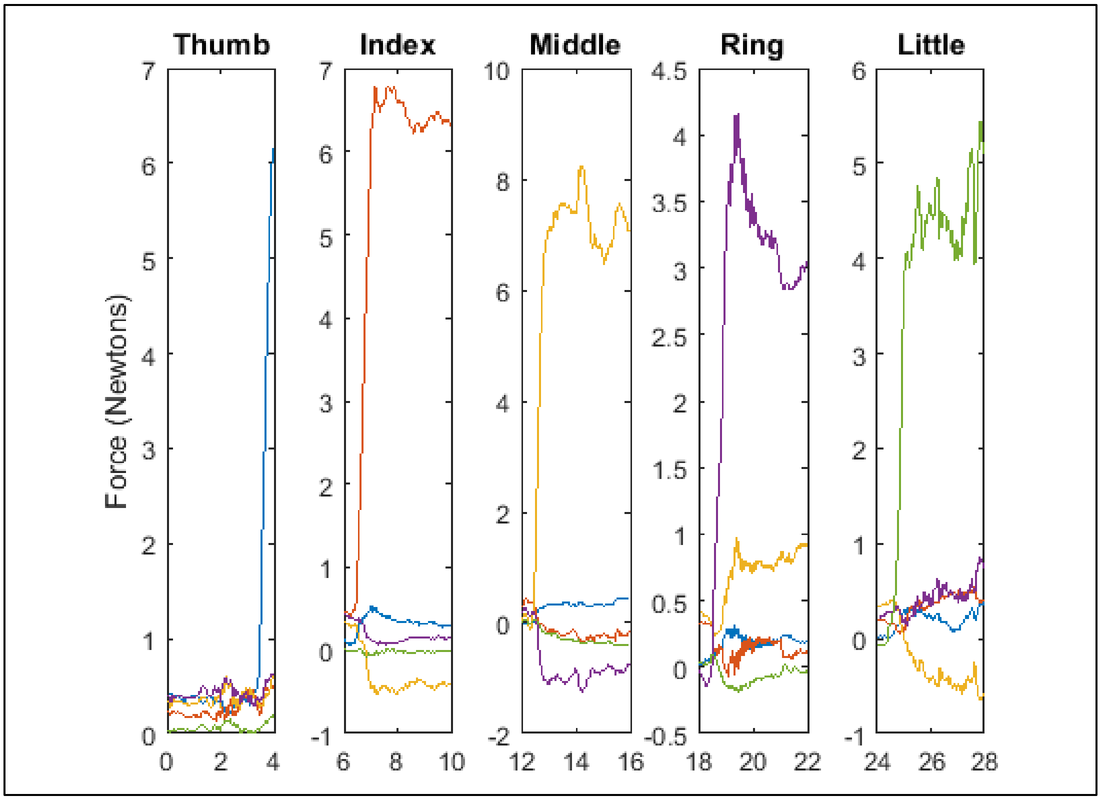

Figure 3.18 Subject 3, initial enslavement.

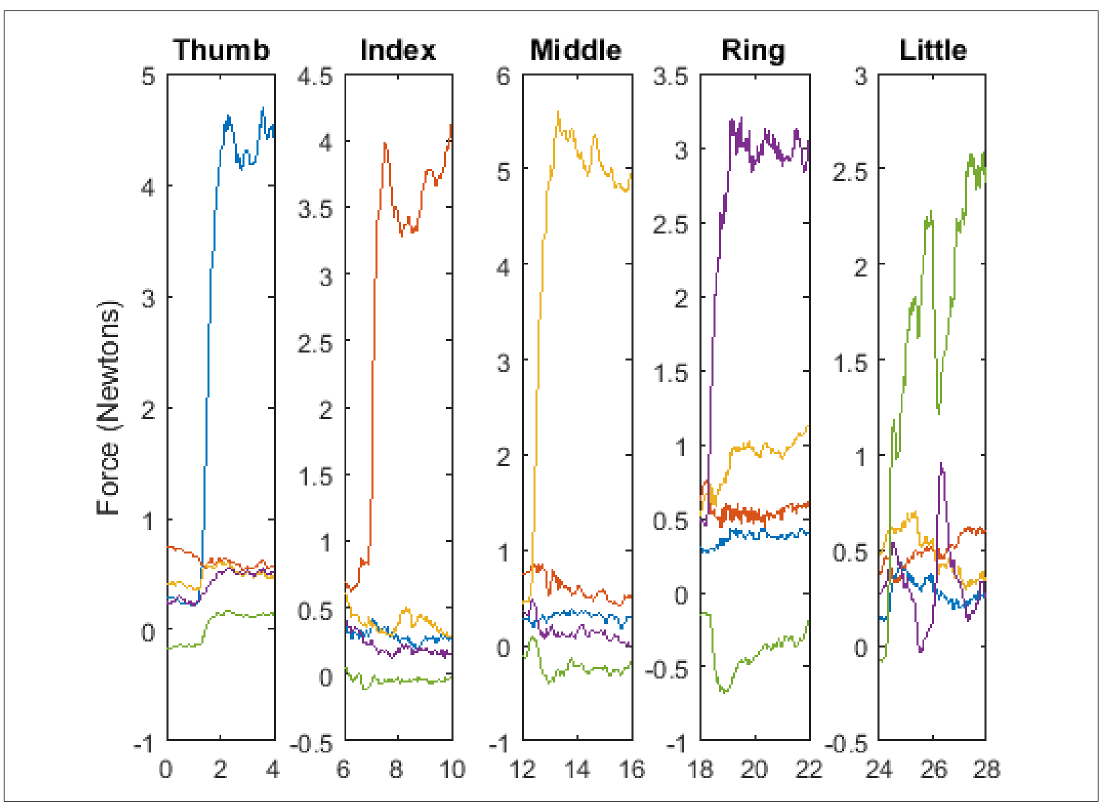

Figure 3.19 Subject 3, final enslavement.

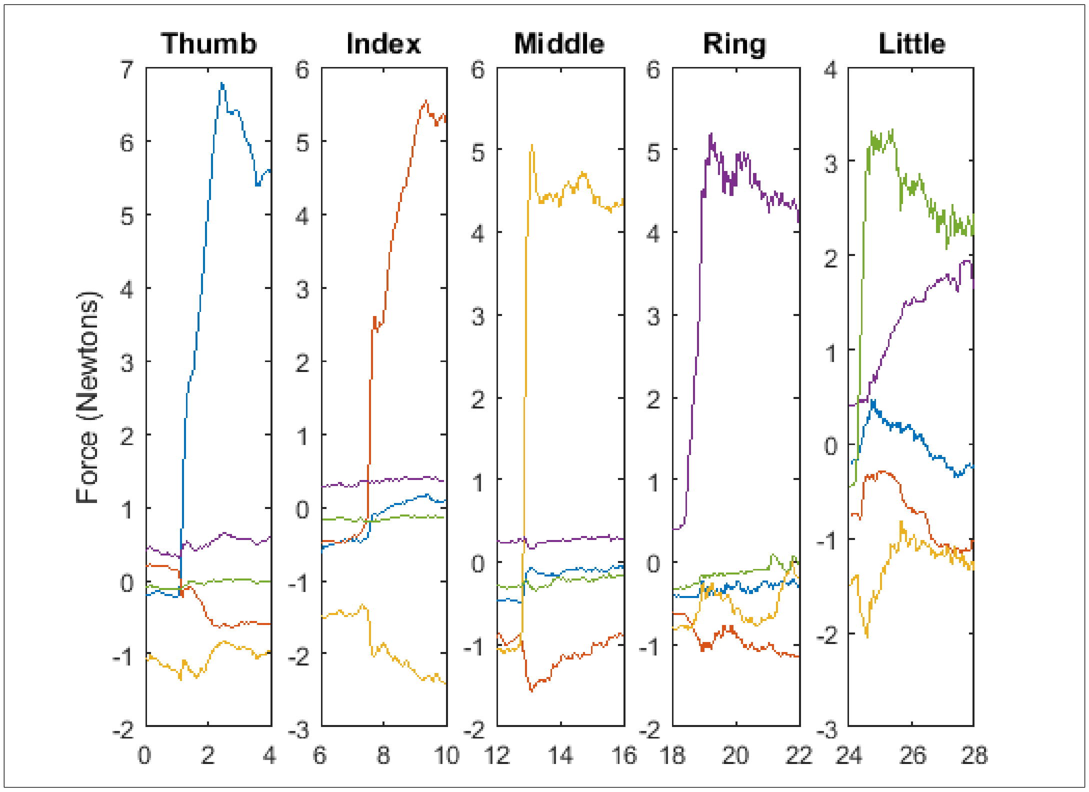

Figure 3.20 Subject 4, initial enslavement.

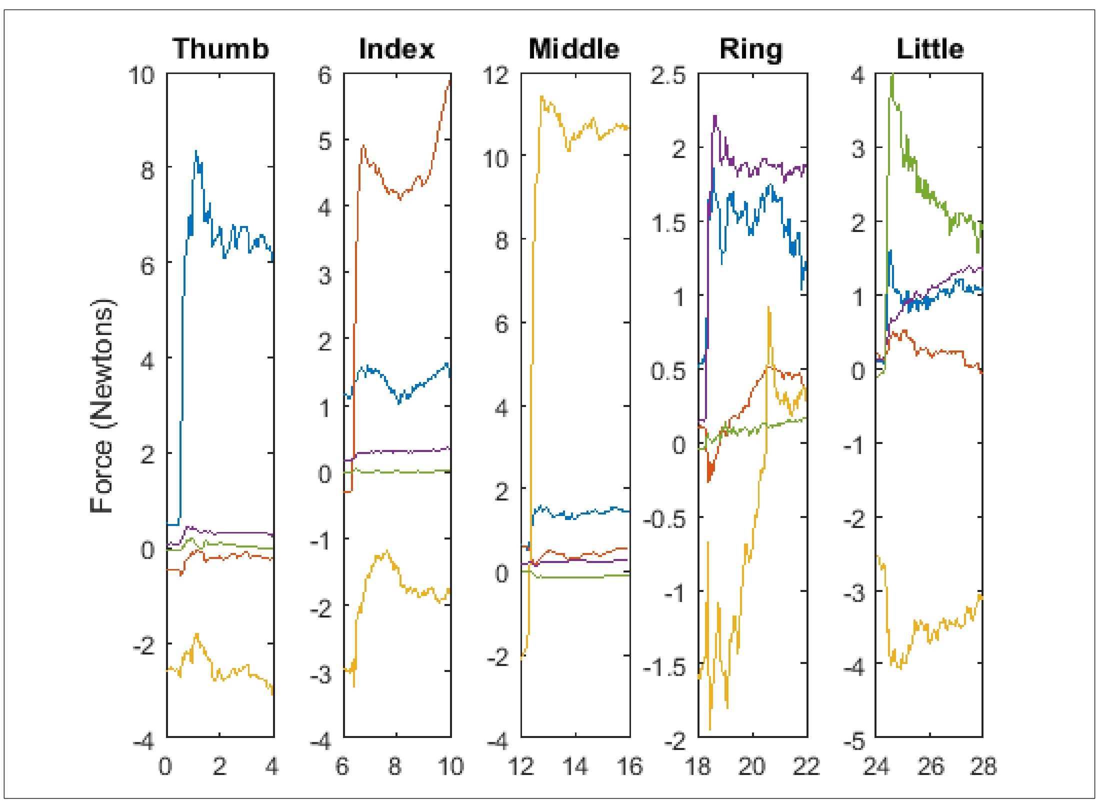

Figure 3.21 Subject 4, final enslavement.

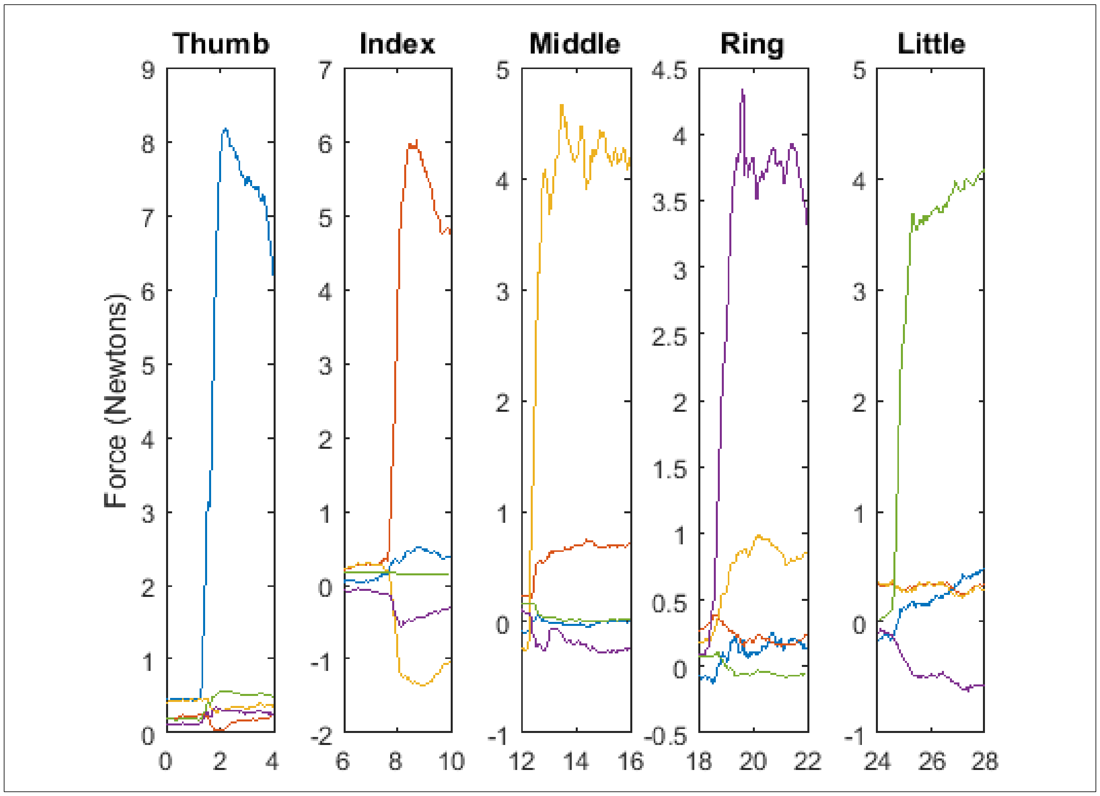

Figure 3.22 Subject 5, initial enslavement.

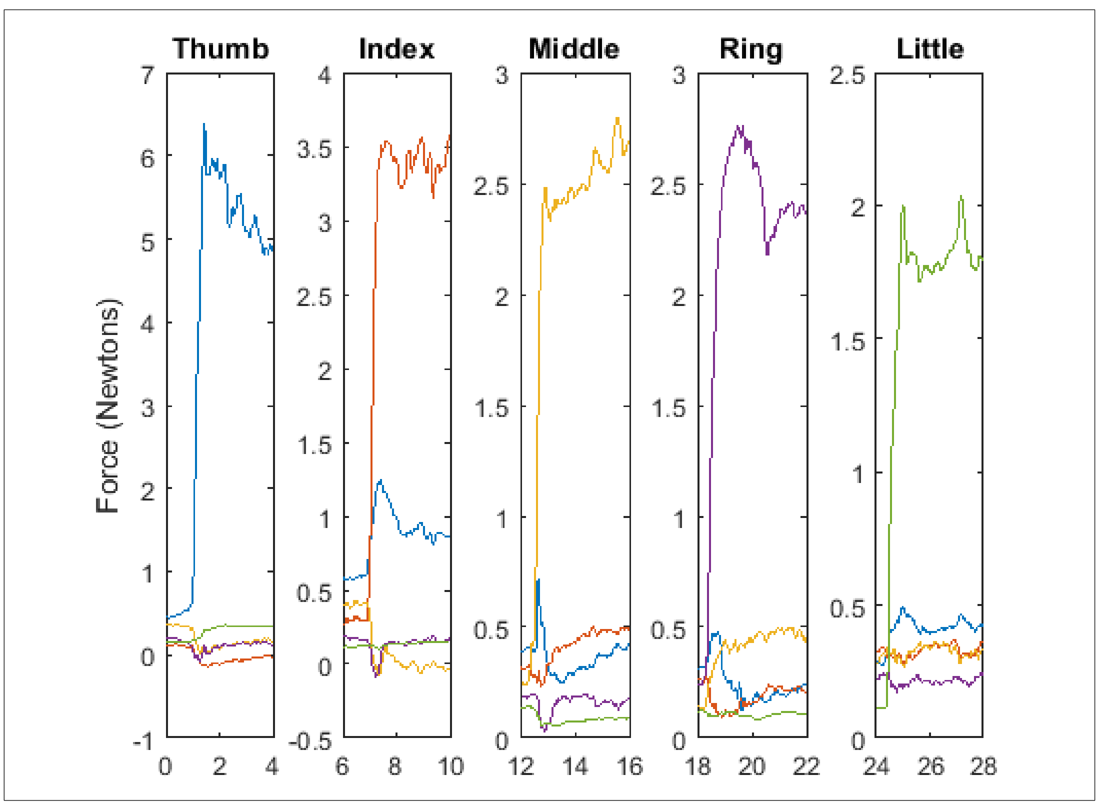

Figure 3.23 Subject 5, final enslavement.

CHAPTER 4

DISCUSSION

4.1 Adaptive Changes in Grasp Strategy

The different strategies the participants used are seen in Table 3.2 with examples shown in Figures 3.1-3.3. All participants spent a substantial amount of trials learning how to efficiently reach the goal. It was clear from observation during data collection that there were limited strategies for reaching the target. Early trials and some outliers followed a very basic strategy of random exploration to reach the goal. The random exploration strategy is characterized by getting one finger to reach the goal while unintentionally moving another finger out of the goal. These trials were the longest because subjects were perpetually making inadvertent movements out of the goal. The second more coordinated approach was where a subject focused on one finger at a time, but they were careful not to move any finger that had already reached the goal. This method is designated the individual finger strategy. The ideal strategy that arose was to move all five fingers in unison and make small corrections. As would be expected, random exploration is most common during the start of the block of trials. While the task is learned, the strategy will transition to either of the other two strategies. The challenge was to categorize each trial using only the data. Using these observations, categories were defined and translated to the analysis code for a systematic categorization of the data. After categorizing the trial data, several other observations became clear.

Fatigue can play a large role in the strategy used, as seen in Figure 3.12. The subject was able to learn the task and progressed to using a whole hand strategy at the end of the first block. They had only used the random exploration in 15 of the first 50 trials. During the second block of trials, they were experiencing muscle fatigue, which was when most of their exploration occurred. Fatigue was responsible for the increase in random exploration to be used in 35 of the trials in the second block. Since the goal for the subject is to reach the goal as quickly as possible, random exploration is not a desired strategy.

4.2 Observations

Despite choosing the goal range to be relatively small, requiring between 1.5-2.5 Newtons of force, subjects still exhibited mild fatigue by the last trials. This goal range was chosen for several reasons. In preliminary testing, one Newton as a minimum was found to be too low because the resting force measured before the subject reacted was up to .75 Newtons and did not elicit a large enough response. At a 2 Newton minimum, subjects would fatigue within a block of 50 trials. The maximum force was set one Newton past the minimum level because some trial subjects could not learn the task within the 50 block window. Subject four clearly showed signs of fatigue. The correlation between fingers is relatively high by the end, but the time to reach the goal increases.

The task presented was an achievable whole hand learning task. From Table 3.1, both the time to reach the goal and the time measured between the first and last fingers reaching the goal as measures show that there was improvement over time for all subjects. In the second block of trials, the rate of learning decreased because there was minor muscle fatigue. Subjects that did not experience fatigue were able to improve on their preliminary enslavement measures.

Another observation from the enslavement test was adjacent digits to the specified digit occasionally produce a force in the opposite direction. Adjacent fingers should have the highest enslavement forces if enslavement was a purely mechanical effect. This can be observed in Figure 3.18. Marc Schieber documented this activation of antagonist muscles in monkeys.[17] A large enough spillover between adjacent fingers causes an activation of antagonist muscles to prevent enslavement.[18] This raises a few questions regarding stroke subjects. What pattern are finger muscles activated in stroke subjects? That question is already answered. After exploring why stroke victims cannot extend their fingers easily, it was found that they have a higher spasticity because there is coactivation of the flexor and extensor muscles.[19] This research also explained that the increase in spasticity is purely a neurological fault and not a mechanical one.

4.3 Lessons Learned

Throughout the initial phases of this project, several other experimental designs were tested with minimal success. Early trials with the five-finger force production task were found to be too difficult or too easy. An attempt to make the task easier was made by summing the forces from all five fingers and having one goal for the whole hand. This task does a better job of representing grasping an object in real life. However, there was no real learning curve observed in these results. Another task was to run the whole hand goal without providing visual feedback. This modification made the task more difficult and would have provided a better sample of data for reaction force production. After several iterations of the pentagon task utilizing a combination of different goal shapes, different target forces, and different time limits, this task was chosen as the experiment.

CHAPTER 5

CONCLUSIONS

It was discovered that subjects will use different strategies to reach the same goal as they adapt to the task. Using a whole hand grasp is the fastest way to reach the goal. Another strategy is to apply force, finger by finger, to reach the goal in a controlled manner. In order to reach the target more effectively, the participant changed how they approached the task as it was learned. Some subjects will explicitly try to focus on using one strategy to reach the goal. Other users will only focus on reaching the goal and do not have a set strategy. The strategy is relative to the individual but as the task is learned, subjects will adopt either the whole hand or the individual finger strategy to reach the goal efficiently. During the analysis for stroke subjects, it is important to note that all of their movements will be much slower and more variable. Due to time constraints, the effects of the different parameter alterations were not fully studied. With more subjects, a comparison between the visual remapping due to a rotation of the goal and an alteration in force scaling could have fully been explored.

A future experiment would be to compare these results to that of stroke subjects. It would be necessary to modify the task for stroke patients so it is an achievable learning task. To make an achievable target, the force required to reach the goal should be decreased and the tolerance should both be increased to make an easier target. The time limit could also be increased to give subjects more time to reach the goal. It is also important to consider the static force from the abnormal posture due the stroke. Since the fist is the pose associated with the hand of a stroke subject, just fitting their hand onto each of the sensors will result in an applied force in the range of Newtons. A more beneficial therapy for stroke subjects would involve a task where the goal is to open the hand because this is often a difficult task.

A primary concern of rehabilitation is to increase the individuation of finger movements. Based on these results, even mild training can influence individual motions in the short term, provided the activity does not cause fatigue. Better results for reducing enslavement should be obtained by training to specifically increase fractionation. This virtual rehabilitation setup can be altered to focus on individual finger movements just by setting the goal for one finger to be different from the other goals.

Learning control over finger force output is important for everyday tasks, whether the task involves fine motor control such as tying a knot on a fishing line, or a coarse motion such as grasping a container. To improve these skills, virtual rehabilitation can be used to improve fine motor control. The task described in this thesis provides a basic framework for a rehabilitation tool. With fine tuning and development of an immersive experience, this can potentially be a valuable yet inexpensive tool for facilitating fine motor recovery.

APPENDIX

MATLAB SCRIPTS FOR DATA ANALYSIS

A.1 Calculation of the time to reach the goal.

```
function AveTime_Callback(hObject, eventdata, handles)
set(handles.text1,'String',sprintf('Time to Goal'))
% Time that the goal is first met.
global forceMat; global timeMat; global date; global numTrials; global
goalData; global goalSize;
global dur; global circles;
if (~isempty(goalData))
    for i = numTrials(1):numTrials(2)
        tempTime = []; inGoal = []; metGoal = []; Zcross = 0;
        tempTime = timeMat(:,:,i);
        tempTime = tempTime(1:find(tempTime,1,'last'));
        if isempty(circles) | (circles==0)
            metGoal =
(forceMat(:,:,i)>goalData(i,1,1))&(forceMat(:,:,i)<(goalData(i,1,1)+goa
lSize(i,2)));
            inGoal =
(metGoal(1,:)==1)&(metGoal(2,:)==1)&(metGoal(3,:)==1)&(metGoal(4,:)==1)
&(metGoal(5,:)==1);
            Fgoal = find(inGoal,1,'first');
            if isempty(Fgoal)
                T1 = length(tempTime)-1;
            else
                T1 = Fgoal;
            end
            Goalmet = 0;
            for k = 2:length(tempTime)
                if inGoal(k) ~= 1
                    if dur(i,1) < (tempTime(k)-tempTime(T1))
                        Goalmet = Goalmet + 1;
                        if Goalmet == 1
                            aveTime(i) = tempTime(T1);
                        end
                    end
                    T1 = k;
                end
                if sum(metGoal(:,k)) ~= sum(metGoal(:,k-1))
                    Zcross = Zcross+1;
                end
            end
            if dur(i,1) < (tempTime(k)- tempTime(T1))
                Goalmet = Goalmet + 1;
                if Goalmet == 1
                    aveTime(i) = tempTime(T1);
                end
            end
            if Goalmet == 0;
                aveTime(i) = tempTime(length(tempTime));
            end
```

```
        else
            radi = [];
            radi = sum(forceMat(:,:,i));
            inGoal =
(radi>goalData(i,1,1))&(radi<(goalData(i,1,1)+goalSize(i,2)));
            Fgoal = find(inGoal,1,'first');
            if isempty(Fgoal)
                T1 = length(tempTime)-1;
            else
                T1 = Fgoal;
            end
            Goalmet = 0;
            for k = T1+1:length(tempTime)
                if inGoal(k) ~= 1
                    if dur(i,1) < (tempTime(k)-tempTime(T1))
                        Goalmet = Goalmet + 1;
                        if Goalmet == 1
                            aveTime(i) = tempTime(T1);
                        end
                    end
                    T1 = k;
                end
            end
            if dur(i,1) < (tempTime(k)- tempTime(T1))
                Goalmet = Goalmet + 1;
                if Goalmet == 1
                    aveTime(i) = tempTime(T1);
                end
            end
            if Goalmet == 0;
                aveTime(i) = tempTime(length(tempTime));
            end
        end
    crossings(i) = Zcross;
    end
cla
X = numTrials(1):numTrials(2);
plot(X,aveTime(numTrials(1):numTrials(2)),'*')
hold on
cf = fit(X(numTrials(1):50)',aveTime(numTrials(1):50)','exp1')
plot((numTrials(1):50),cf(numTrials(1):50),'r')
cf = fit(X(50+1:numTrials(2))',aveTime(50+1:numTrials(2))','exp1')
plot((50+1:numTrials(2)),cf(50+1:numTrials(2)),'r')
set(handles.Yaxis,'String',sprintf('T\ni\nm\ne\n\nS\ne\nc\no\nd\ns'))
set(handles.Xaxis,'String',sprintf('Trial number'))
end
```

A.2 Code for sorting trials by category

```
function Strategy_Callback(hObject, eventdata, handles)
set(handles.text1,'String',sprintf('Grasp Strategy'))
% Time that the goal is first met.
global forceMat; global timeMat; global date; global numTrials; global
goalData; global goalSize;
global dur; global circles;
for i = numTrials(1):numTrials(2)
    tempTime = []; tempForce = []; inGoal = []; metGoal = []; Zcross =
0;
    tempTime = timeMat(:,:,i);
    tempTime = tempTime(1:find(tempTime,1,'last'));

    % Average time spent in goal
    metGoal = [0;0;0;0;0];
    tempForce = forceMat(:,:,i);
    currentLength = find(tempForce(1,:),1,'last');
    tempForce = tempForce(:,1:currentLength);
    tempTime = tempTime(1:currentLength);
    currentGoal(:,:) = goalData(i,:,1:find(goalData(i,1,:),1,'last'));
    goalSWS = goalSize(i,:);
    for k = 1:currentLength;
        metGoal(:,k) =
(abs(tempForce(:,k))>currentGoal')&(abs(tempForce(:,k))<(currentGoal'+g
oalSWS(2)));
    end
    total(i,:) = sum(metGoal,2);
    metGoal = [];
    success(i,:) = 100*(total(i,:)/currentLength);

    % Time to reach goal and # of zero crossings
    metGoal =
(forceMat(:,:,i)>goalData(i,1,1))&(forceMat(:,:,i)<(goalData(i,1,1)+goa
lSize(i,2)));
    FirstG =
[find(metGoal(1,:),1,'first'),find(metGoal(2,:),1,'first'),find(metGoal
(3,:),1,'first'),find(metGoal(4,:),1,'first'),find(metGoal(5,:),1,'firs
t')];
    FirstT(:,i) =
[timeMat(1,FirstG(1),i),timeMat(1,FirstG(2),i),timeMat(1,FirstG(3),i),t
imeMat(1,FirstG(4),i),timeMat(1,FirstG(5),i)];
    inGoal =
(metGoal(1,:)==1)&(metGoal(2,:)==1)&(metGoal(3,:)==1)&(metGoal(4,:)==1)
&(metGoal(5,:)==1);
    Fgoal = find(inGoal,1,'first');
    if isempty(Fgoal)
        T1 = length(tempTime)-1;
    else
        T1 = Fgoal;
    end
    Goalmet = 0;
    for k = 2:length(tempTime)
        if inGoal(k) ~= 1
            if dur(i,1) < (tempTime(k)-tempTime(T1))
                Goalmet = Goalmet + 1;
```

```
                if Goalmet == 1
                    aveTime(i) = tempTime(T1);
                end
            end
            T1 = k;
        end
        if sum(metGoal(:,k)) ~= sum(metGoal(:,k-1))
            Zcross = Zcross+1;
        end
    end
    if dur(i,1) < (tempTime(k)- tempTime(T1))
        Goalmet = Goalmet + 1;
        if Goalmet == 1
            aveTime(i) = tempTime(T1);
        end
    end
    if Goalmet == 0;
        aveTime(i) = tempTime(length(tempTime));
    end
    crossings(i) = Zcross; % number of zero crossings
end
goalPerc = mean(success');
FirstC = min(FirstT);
LastC = max(FirstT);
crossingDiff = LastC-FirstC;
cla
noStrat = crossings>=20;
individual = (crossings<20)&(crossingDiff>=1.1);
wholeHand = (crossings<20)&(crossingDiff<1.1);
assignin('base','noStrat', noStrat);
assignin('base','wholeHand',wholeHand);
assignin('base','individual',individual);

X = numTrials(1):numTrials(2);
hold on
set(handles.Yaxis,'String',sprintf('G\no\na\nl\n\nC\nr\no\ns\ns\ni\nn\n
g\ns'))
set(handles.Xaxis,'String',sprintf('Trial number'))
plot(X(1:50),crossings(1:50),'b','LineWidth',1.3)
plot(X((crossings>=20)),crossings((crossings>=20)),'r*')
plot(X((crossings<20)),crossings((crossings<20)),'g*')
plot(X((crossings<20)&(crossingDiff<1.1)),crossings((crossings<20)&(cro
ssingDiff<1.1)),'b*')
plot(X(51:end),crossings(51:end),'b','LineWidth',1.3)
legend('Crossing goal','Random Exploration','Individual finger
strategy','Unified hand strategy')
hold off

legend('Crossing goal','Random Exploration','Individual finger
strategy','Whole hand strategy')
xlabel('Trial #','FontSize',12,'FontWeight','bold')
ylabel('Goal Crossings','FontSize',12,'FontWeight','bold')
assignin('base', 'aveTime', aveTime);
assignin('base','crossings',crossings)
```

A.3 Code to Measuring Time Between First and Last Fingers Entering the Goal

```
%Executes on button press in TimeDiff.          "Time Difference"
function TimeDiff_Callback(hObject, eventdata, handles)
set(handles.text1,'String',sprintf('Time Difference'))
global forceMat; global timeMat; global date; global numTrials; global
goalData; global goalSize;
if (~isempty(goalData))
for i = numTrials(1):numTrials(2)
    tempTime = []; inGoal = []; metGoal = [];
    tempTime = timeMat(:,:,i);
    tempTime = tempTime(1:find(tempTime,1,'last'));
    metGoal =
(forceMat(:,:,i)>goalData(i,1,1))&(forceMat(:,:,i)<(goalData(i,1,1)+goa
lSize(i,2)));
    if
(sum(metGoal(1,:))~=0)&&(sum(metGoal(2,:))~=0)&&(sum(metGoal(3,:))~=0)&
&(sum(metGoal(4,:))~=0)&&(sum(metGoal(5,:))~=0)
    Ffinger(1) = find(metGoal(1,:),1,'first');
    Ffinger(2) = find(metGoal(2,:),1,'first');
    Ffinger(3) = find(metGoal(3,:),1,'first');
    Ffinger(4) = find(metGoal(4,:),1,'first');
    Ffinger(5) = find(metGoal(5,:),1,'first');
    T1 = tempTime(min(Ffinger));
    T2 = tempTime(max(Ffinger));
    if T2-T1 == 0;
        aveTime(i) = tempTime(length(tempTime));
    else
        aveTime(i) = T2-T1;
    end
    else
        aveTime(i) = NaN;
    end
end
cla
X = numTrials(1):numTrials(2);
plot(X,aveTime(numTrials(1):numTrials(2)),'*')
hold on
cf = fit(X(numTrials(1):50)',aveTime(numTrials(1):50)','exp1')
plot((numTrials(1):50),cf(numTrials(1):50),'r')
cf = fit(X(50+1:numTrials(2))',aveTime(50+1:numTrials(2))','exp1')
plot((50+1:numTrials(2)),cf(50+1:numTrials(2)),'r')
set(handles.Yaxis,'String',sprintf('T\ni\nm\ne\n\nS\ne\nc\no\nd\ns'))
set(handles.Xaxis,'String',sprintf('Trial number'))
hold off
figure
plot(X,aveTime(numTrials(1):numTrials(2)),'*')
hold on
cf = fit(X(numTrials(1):50)',aveTime(numTrials(1):50)','exp1')
plot((numTrials(1):50),cf(numTrials(1):50),'r')
cf = fit(X(50+1:numTrials(2))',aveTime(50+1:numTrials(2))','exp1')
plot((50+1:numTrials(2)),cf(50+1:numTrials(2)),'r')
hold off
assignin('base', 'aveTime', aveTime);
end
```

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