ENHANCED TARGETING IN A HAPTIC USER INTERFACE
FOR THE PHYSICALLY DISABLED USING
A FORCE FEEDBACK MOUSE

by

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ABSTRACT

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Although the human computer interface continues to evolve by engaging sight, voice, sound, and touch to manipulate the environment, the marriage between mouse and graphic based operating systems remains one of the primary relationships through which we interact with the computer. With the advent of haptics it has become possible to enhance the GUI/mouse relationship with the sense of touch using a haptic mouse, opening new avenues of interaction, in particular for those with disabilities.

For the majority of users the mouse is an effective and proven device for human computer interaction. However it is not as well suited for particular groups with physical disabilities, leaving those with disabilities in search of an alternative input

device. The haptic mouse can exist as one of those alternatives if an effective interface can be designed that compensates for the disability of the user.

An environment has been constructed that uses haptic effects, movement profiles, and a prediction algorithm to improve targeting for a group of users with physical disabilities. The research presented 23 individuals with motor disabilities affecting the arms with varying haptic and non-haptic desktop-like interfaces. Results of the experiments found greatly improved performance for most individuals in the haptic condition over the non-haptic when the target was a known quantity. In conditions where prediction was used to apply the haptic effect, results varied based on proximity to the actual target. Predictions made within two objects of the target resulted in either no effect or improved performance among individuals, while predictions made further than two objects from the target resulted in no effect or decreased performance. Analysis of the prediction algorithm has identified areas where improvement would be possible given the data collected during the experiments with the disabled group. This research concluded with a better understanding of how disabled individuals interact with a haptic computer mouse, Fitts' Law evaluation of the haptic mouse, effectiveness of compound haptic effects, and a new algorithm for predicting targets in a multi-columned multi-rowed environment, that results in improved performance for a group of disabled individuals in a desktop interface using a haptic mouse.

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CHAPTER 1

INTRODUCTION

This research is designed to provide improved targeting for the physically disabled in an n-columned multi-target haptic user interface. Individuals in this group of disabled users often find themselves in search of an effective input device for interacting with the computer. Since most standard input devices do not account for disability and since special purpose input modalities are frequently very expensive and difficult to integrate into common computer applications which are mostly designed specifically for use with the standard devices, this dissertation investigates the possibility of haptics to enhance the common mouse interface in the hopes of provide a cost effective alternative to special purpose devices. As computer desktops are not natively designed for use with haptics, this requires the design and construction of a haptic interface. Construction of this interface, in turn, requires haptic device selection, haptic effect construction, experimental design considerations, and a prediction algorithm to determine the target of the user's movements. In this dissertation, the results of this research will be presented.

1.1 Why a Haptic Mouse?

Human-computer interaction (HCI) for the past two decades has been dominated by the graphical user interface/mouse relationship. As a result operating systems and applications have, for the most part, been designed for manipulation with a mouse. To augment this HCI, the addition of haptic or tactile cues to a graphical user interface (GUI) has been an area of increasing interest. Tactile feedback is any feedback from a device that is perceived through the sense of touch. Force feedback is a form of tactile feedback that provides force vectors from a haptic device. The amount of force and the number of possible vectors can vary among devices.

The range of haptic devices available allows for many differing ways of interacting with a computer interface, mostly in a three dimensional capacity. However, these devices are typically special purpose devices not suited for prolonged use with a GUI operating system. Two major drawbacks for a majority of haptic devices to be suited to mass production for prolonged daily use are their special purpose design which is unfamiliar to the user and the high cost of the hardware. Prices for many of the special purpose three dimensional haptic devices range from $15,000 to $60,000+. The first logical step for adapting haptic devices for everyday use is to reduce cost. Reducing cost typically means reducing functionality, sensitivity, strength of the device, and/or mass production with production refinement. The haptic mouse is an example of reduced functionality that still provides an effective input device. For a short time Logitech and a few other companies produced affordable haptic mice, mainly for the gamming industry, capable of effects ranging from vibrating feedback to full force feedback. The Logitech Wingman™ Force Feedback Mouse, while discontinued, was and is an inexpensive force feedback device (they can still be bought used and new from various sources for approximately $100.00).

As use of the haptic interface grows, a larger range of effects will be applied to the Haptic User Interface (HUI) [25]. Haptics helping with the selection of folders and files, with drawing circles, navigating tunnels, and manipulating GUI objects would require new and different effects to be designed for each particular task. Well designed haptic effects could enhance the HCI to the point of allowing users with physical disabilities to interact with the GUI in ways that would not be possible without the addition of haptic interaction. However, it is important to quantify the effect a haptic interface can have on human-computer interaction and determine if the widely accepted and tested principles of graphic interface design can be applied to a haptic interface.

The benefits of enhancing human-computer interaction in a GUI [2] with haptic interactions depends on the device, effect used, and the tasks performed [1]. It has been shown that enhancement of the input channels can improve human-computer interaction including for those with disabilities [15]. However, it is important to consider that haptics can defy accepted targeting laws and impede the targeting process [1]. Therefore, it is important to study the haptic effects used and quantify the results in terms of current HCI principles in order to construct an environment with the highest possibility of being beneficial to the target group.

The haptic mouse combines the familiarity of a mouse with the power of a full force feedback device. It is a goal of this research to construct an n-columned multi-object environment that will realize these two properties is such a way as to enhance targeting in a GUI for a group of individuals with physical disabilities.

1.2 The Wingman™ Mouse

The Wingman™ mouse is a force feedback device which can produce force vectors in two dimensions. Several properties define what forces each haptic device can produce and in how many dimensions. Vibrations do not require extended force vectors, can be produced easily in three dimensions, even in a mouse, and are very popular in most video game controllers. Extended force vectors, on the other hand, can be difficult to produce mechanically at varying levels of strength, but over a duration of time they can be used to create virtual objects, define the boundaries of the environment, simulate the consistency and texture of materials, and be used to create a whole range of effects not yet discovered. As a full force feedback device the Wingman™ can produce force vectors capable of creating all of these effects in two dimensions. One limitation of the Wingman™ is that it is not capable of measuring the pressure or force exerted by the user [11].

The Wingman™ has a wide range of effects that can be designed to enhance the interface. In this research a series of pilot studies were employed to identify beneficial effect designs for the Wingman™ to be used in the final experiment involving a movement impaired group of individuals. There has been extensive research in the area of haptics in a GUI environment using the expensive and special purpose haptic devices, such as the Phantom™, showing improved performance with the addition of haptic cues [2][18][19] and there has been research that identified haptic effects that proved detrimental to human-computer interaction [1]. It is clear that haptics can be either beneficial or detrimental to an interface based on the device used, the effect design, and the environment in which it is used, making careful effect design of the haptic interface crucial. An additional concern is ergonomics. Because many of the special purpose three dimensional devices require the user to hold their hands in unfamiliar and at times awkward positions, prolonged use can result in fatigue [18]. The mouse is a proven input device which has been a part of the GUI interface since its inception and the next logical step is to enhance that interface with tactile cues.

1.3 Related Research

There has been an abundance of research performed in recent years [3][10][20] investigating the mouse, general targeting, and targeting of objects on a desktop. The research presented in this chapter was selected because the methodologies and conclusions presented by each were directly related to the research in this dissertation and were useful in designing and implementing a haptic interface for the disabled.

Kabbash et al [14] investigate the effects of cursor size in selection tasks. In their research they reduce target size to a point (still visible) and increase the cursor width. By increasing the width of the cursor they were able to reproduce selection times consistent with a typical cursor and target of equal width. Furthermore they investigated the ability of Fitts' Law [8] to describe the relationship between cursor width and targets of a fixed size. It was found that there was a linear relationship between the movement time (*MT*) and index of difficulty (*ID*) when cursor size was varied. This conformation of Fitts' Law for cursor width shows the robust nature of the law and its ability to describe a number of selection tasks.

In recent studies, Langdon et al [15] have engaged in a number of experiments designed to investigate the haptic effect for enhancing a GUI for use with the physically disabled. Like much of the research investigating haptics in a GUI, the researchers compare haptically enhanced tasks vs. non-haptically enhanced tasks citing differences between movement times and error rates to quantify the differences. The difficulty with this approach is that without confirmation that Fitts' Law applies to the haptic condition it cannot be asserted that the relationships described in the research will hold for all distances and target sizes. The relationship between *ID* and *MT* must be established.

The results and conclusions reported by Kabbash et al [14] and Langdon et al [15] provide insight as to how the experimental interface for collecting targeting data should be designed. However, there is still a question of which haptic effects would be beneficial to the research in this dissertation. To address this, previous research studies [1][16][27] that employ haptic effects and evaluate performance were reviewed. Results of these studies were then used to establish what effects exist, which of those effects improves performance, and which effects are a good fit for the target group.

Langdon et al performed a series of experiments investigating the use of gravity wells and force channels with a group of disabled individuals [16]. Using the Wingman™ mouse they performed two experiments investigating each of these haptic effects. The first experiment placed multiple haptically enhanced targets within the environment. Each target was enhanced with a gravity well the size of which was varied. What they found was that competitive gravity wells increased average movement time up to the point of overlap. In the next experiment they compared force channels of varying width. A force channel provides free movement within the channel but restricts movement outside the channel. What they found were mixed results favoring a zero width channel.

Abbot et al performed an experiment to investigate the use of haptics in a surgical environment with non-disabled individuals [1]. In this experiment using a stylus type haptic device they created force ellipses to guide the user when drawing. The implications were originally intended for making incisions remotely, however the results were pertinent to this research. What they found was two fold. First they discovered that the use of ellipse type haptic effects, which create boundaries around areas, increased the performance of tracing tasks. Secondly they found that weaker assistive forces were more effective than more rigid forces.

Williams et al investigated the use of dampening with a group of non-disabled individuals [27]. In their experiments they applied inverted dampening to a stylus type haptic device and studied performance during targeting tasks. Inverted dampening as described by the researchers is an inverse relationship of force to velocity, so the faster the subject moved their hands the less force was applied. What they found was improved completion times in the inverted dampening environment compared to no dampening and regular dampening.

The results and conclusions of the studies presented in this chapter influenced and shaped how the experimental interface would be designed and which haptic effects would be investigated for inclusion in the final experiment of this research.

1.4 The Process

The ultimate goal of this research is to create a haptic environment capable of improving targeting in a GUI. The implications of this would be to provide users with movement disabilities an additional tool with which to interact with the computer. The process of developing an interface capable of integrating several haptic effects within an environment containing multiple targets for use by individuals with disabilities requires in depth knowledge of the device being used, the haptic effects to be included, and the target group which will use the system. In order to better understand these three aspects of the interface a series of pilot studies were performed.

The first task of this research was to identify haptic effects that were thought to be beneficial to the target group. Research has shown that gravity wells and resistance can have a positive effect when used in a GUI with disabled individuals [7] [15] [25]. The Wingman™ mouse is capable of both effects in the form of a spring and damper. In addition to the spring and damper effects, I believe that ellipse and funnel effects (which will be described later) could be of benefit to this research. Once designed, the effects were individually tested with targets of varying distances for comparison with the control (no effect) condition.

The second task of this research was to evaluate each haptic effect designed with the Wingman™ mouse. This first in a series of pilot studies allowed us to evaluate the experimental interface, evaluate effect design, and to collect movement profiles. In order to make meaningful assertions about performance within the system being developed I first needed to establish the relationships present within the system. There were three relationships that needed to be studied before research could move forward: (i) does the movement profile of the target group match that of subjects without movement disabilities, (ii) does the mouse with the haptic effect conform to Fitts' Law, and (iii) how will distractions be limited with multiple haptically enhanced targets. I intended to answer the first two questions through a series of pilot studies, at least one of which would involve members of the target group and to address the final issue using prediction techniques.

The third and final task of this research was to integrate the knowledge obtained during the pilot studies and construct an environment beneficial to the target group. A final experiment was constructed in which the subject experienced a combination of haptic effects while the environment attempts to minimize the number of distractions and performed a series of tasks designed to evaluate targeting performance.

Individuals with movement disabilities need inexpensive accessible input devices that allow them to interact with the computer in its intended fashion. The mouse continues to be the choice of input device for individuals without disability, and research that will be presented later has shown that it could be the choice of disabled individuals if a few hurdles could be overcome. It is through the use of haptics that I believe the mouse can be adapted for use by this group of users. The remainder of this document describes and discusses the science of targeting evaluation, the prediction algorithm, results of the experiments, and future directions.

CHAPTER 2

HAPTIC EFFECT DESIGN AND TARGETING MOVEMENTS

The construction of a multi-target haptic environment that is beneficial to disabled users requires the incorporation of beneficial effects, a model that describes the movement characteristics of the user's mouse movements, and a means of reducing distracting effects through the use of prediction, which will be discussed in Chapter 3. In order to accomplish this, an interface containing multiple haptic conditions has to be constructed. The different conditions should be designed to isolate targeting movements and measure movement times in a controlled environment to evaluate targeting performance when the user experienced no haptic effect, haptic effect applied to only the target, and haptic effect applied to the currently predicted target. To more completely understand the use of haptic effects less structured conditions should be employed to evaluate user performance in a more realistic environment. Construction of the more controlled environments should be motivated by Fitts' Law and designed to collect data capable of being evaluated in a Fitts' Law model. The less structured conditions do not provide targeting direction to the user resulting in data artifacts that make Fitts' Law evaluation difficult. However, these less controlled environments provide information about the use of this system as a whole and in a more realistic setting. The remainder of this chapter will describe research that motivated the decisions made for construction of the interfaces and the pilot studies undertaken.

A series of pilot studies were completed to collect data about targeting, the Wingman™ mouse, haptic effects, the experimental interface, and finally the target group. What follows is a description of each study and a discussion about the results. The three primary metrics for evaluation of performance for this research are movement time to evaluate efficiency, error rates to evaluate accuracy, and velocity peaks to evaluate smoothness. Movement time and error rates are common measures of performance. On the other hand, peaks in velocity are studied in conjunction with cursor traces to evaluate how the haptic effect changes a person's movement characteristics. In addition the target size vs. distance data is evaluated for correlation to a straight line. The purpose of this final evaluation is to verify the experiment was successful in isolating and capturing the targeting moves of the subjects.

2.1 Haptic effects

Having researched and found a number of haptic effects that were felt beneficial to targeting and groups with disability, four different haptic effects were designed for use with the Wingman™ mouse. The four selected effects were the gravity well, damper, ellipse, and force tunnel. For this research they are referred to as spring, damper, ellipse, and funnel respectively, based on the names given to them by Immersion Corporation, creator of the effect design tool.

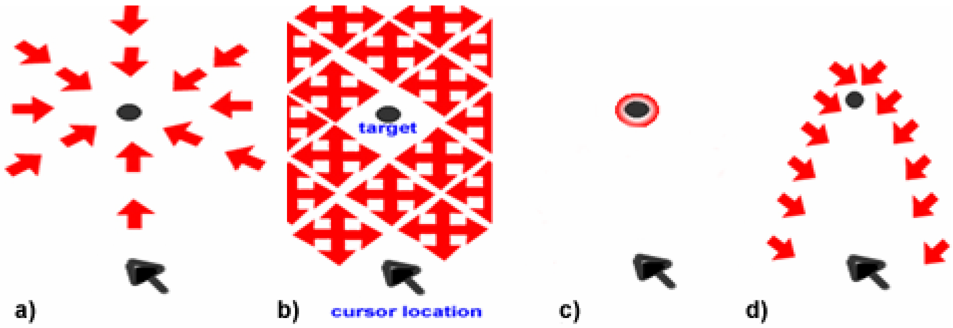

Figure 2.1 Haptic effects a)spring b)damper c)ellipse d)funnel

The spring effect provides force vectors in the direction of the target from all locations in the environment. While the Langdon et al [16] study presented earlier in Section 1.3 describes decreased performance when confronted with multiple competing gravity wells, it was felt this group of individuals would benefit from a much larger gravity well effect that would draw them toward the target from a much larger distance. A solution to the decreased performance from competing gravity wells could be a prediction algorithm capable of focusing the haptic effect on a single target within the environment (Prediction will be discussed in detail in Chapter 3). The damper effect provides force vectors in the opposite direction of the vector of travel. As the planned target group displays spasms and tremors, it was felt resistance added to the environment would steady user movement and provide a stabilizing force within the environment [24]. The ellipse effect creates a boundary around the target which is easy to enter but more difficult to leave. It was felt this effect would be beneficial to the target group in helping them remain over the target during target selection. Finally, the funnel effect provides force vectors on the edge of a tunnel. As long as the user remains in the middle of the tunnel no haptic effects would be experienced. However, any deviation from the tunnel would result in resistance. These four haptic effects were prepared and implemented in a series of pilot studies which will now be discussed.

2.2 Pilot Study 1

Having identified a haptic device that was affordable and capable of force feedback and haptic effects that might prove beneficial to targeting, the next step was to do a limited study of the system to determine its operational characteristics.

Figure 2.2 Data collection interface

Figure 2.2 illustrates the experimental interface which was designed to look and behave like a video game. The game-like interface was used to motivate the subject to perform as quickly and accurately as possible while maintaining a level of interest in the experiment. The system was implemented on a Windows XP computer using the Wingman™ Force Feedback Mouse as the input device. Since the mouse had been discontinued for some time and no official Windows XP drivers existed it was important to evaluate the performance of the mouse on XP. It was also important to evaluate the Java libraries provided by Immersion Corporation for programming the mouse in this environment. Like the mouse, the Java SDK from Immersion had not been updated for Windows XP and needed to be evaluated for stability. In addition the spring haptic effect was incorporated to evaluate the subject's reaction to the application of haptic effects. Data was collected, from four individuals in the UTA artificial intelligence lab, in the form of mouse locations read at ~1000Hz, movement time in ms, and errors recorded as clicks not on the target.

While no formal evaluation of the data was performed, it was found that the Windows 2000 drivers provided for the mouse were compatible with the Windows XP operating system, the Java libraries performed with no errors, the subjects quickly acclimated to the haptic effect, and the data collection methodology could operate at a lower granularity of 100Hz..

2.3 Pilot Study 2

Given the data collected from the first pilot study it was necessary to perform the experiment with more subjects and with more haptic effects and to evaluate the data collected. Evaluation of the data consisted of movement time for efficiency, error rates for accuracy, movement peaks for smoothness, and correlation to a straight line signifying a relationship between distance and target size as described by Fitts [8].

In this study the test environment consisted of a Pentium based computer running Windows XP, a Wingman™ mouse and a 17” monitor set to a resolution of 1152 by 864 pixels. The subjects were asked too sit in front of the computer and were given a brief explanation of the experiment, informing them of what to expect from the mouse and the interface to help eliminate any surprises. The test subjects were 29 Business students from Spring Hill College's Introduction to Computers course.

The interface (shown in Figure 2.2) contains a GUI frame containing a space ship console to display game information and circular alien torpedoes which act as target objects. The subject is asked to click on the target as soon as it appears. Each target object is 24 pixels in size and appears randomly in one of 5 locations as soon as the previous target object is selected. The only restriction is it cannot spawn at the same location it was last located.

Each subject participated in four identical GUI interfaces each with a different haptic condition. Between each of the conditions was a "boss level" where no data is collected and no haptic enhancement incorporated to help keep the subject interested. The interface was constructed using Java 1.5 and the Touch Sense Developer Toolkit from Immersion Corporation. One of the conditions has no haptic enhancement and serves as the control for the experiment. The other conditions consist of a spring, a damper, and an ellipse effect. Each experiment presents the four different conditions in random order.

The interface consists of five possible locations for target objects and measures time from selection of the previous target to the selection of the next target. The subjects complete four levels of the game, each with a different haptic effect, and data is collected. Since the effects were presented in random order, learning should not be an issue in the pooled data. Furthermore, while it would be desirable to have tested more than three haptic effects the experiment was already at ~10 minutes per subject. Therefore an educated guess had to be made as to which three effects would most benefit our target group for inclusion in the study.

2.3.1 Pilot Study 2 results

As the subject selected one target in the interface a new one would spawn in one of the four remaining unoccupied spawn locations. Movement time was measured from the end of the previous targeting task until the subject selected the new target object. This methodology captured the entire targeting process (locating the target, transversing the interface to the target, and target selection).

Table 2.1 Average movement times

Effect	Average Time (s)	P(T<=t) two-tail
No Effect (control)	1.368	
Spring Effect	1.045	0.0000000171
Ellipse Effect	1.397	0.700483
Damper Effect	1.317	0.26158

Movement times for each effect and the significance values when compared to the control (no effect) are presented in Table 2.1. Since the spring effect was the only one to provide vector haptic feedback toward the target object it was not surprising to see it have the greatest effect on movement time. A significant difference in favor of the spring environment was found when compared to the control. A surprising result was the damper effect. It was expected the damper would increase the time to target objects in the interface. However, there was no significant difference between the damper environment and the control with respect to movement time. Finally, no significant difference was found between the ellipse effect and the control. Since the ellipse effect only affects the final targeting process, total movement time is not an accurate measure of its effectiveness. The target selection process is in the range of ~200ms [1] and a significant change in that portion of the movement time may not show as significant when looking at the movement time as a whole. This data shows that the effects used here result in an increased or unchanged efficiency of the target move.

In addition to the movement times, the average number of velocity peaks were computed from the movement data to provide a means of measuring smoothness of the targeting movement. Peaks in velocity are identified by large changes in distance between readings. A change of 25 pixels in distance between readings (10ms granularity), identifying that the user is moving the cursor at more than 2.5 pixels/ms, is considered high in this research because values greater than that comprise less than 1% of all velocities. The average number of peaks for each movement per effect is presented in Table 2.2.

Table 2.2 Velocity peaks

Effect	Peaks	P(T<=t) two-tail
No Effect (control)	0.27	
Spring Effect	0.66	0.007
Eclipse Effect	0.39	0.115
Damper Effect	0.03	0.0000171

It is the belief of this research that while the haptic forces of the mouse are comparatively weak relative to the force of a tremor or spasm [15], it may be possible to determine when a tremor or spasm is occurring or to make the movements more predictable by dampening the tremors or spasms. It was believed a tremor or spasm would display sudden increases in velocity, making it important to identify which haptic effects might affect normal sudden increases in velocity. Table 2.2 contains the average number of peaks per movement. Ultimately this data was instrumental in determining values to be used in the prediction algorithm (presented in Chapter 3) and brought to light one of the benefits of the damper effect.

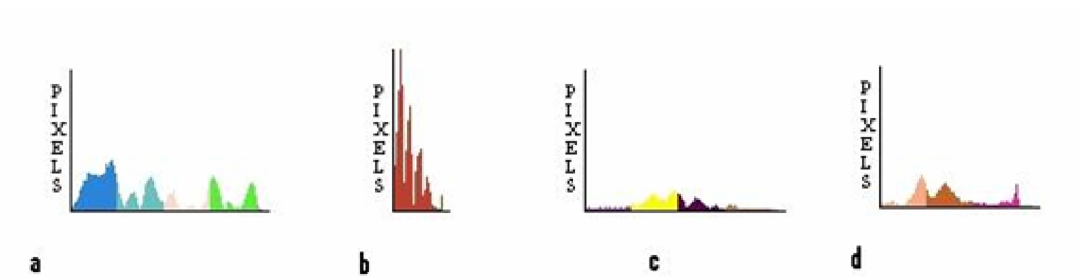

Figure 2.3 Representative movement peaks (Δ pixels per 10ms)
a) no effect b) spring effect c) damper effect d) ellipse effect

Representative movement peak profiles are presented in Figure 2.3 and color changes in the Figure occur every 100ms of the movement. The profiles are captured from a single subject and were selected due to their similarity to the majority of profiles observed for each effect. While the ellipse effect had no significant difference from the control, the spring and damper effect had significant differences in velocity peaks compared to the control. Figure 2.3 b) illustrates how the spring effect influences the subject, resulting in high rates of movement followed by short pauses, significantly increasing the number of velocity peaks from the control. The damper effect had the most significant difference in velocity peaks when compared to the control. It greatly reduced, and in many cases eliminated, peaks in velocity. When looking at the data for the damper effect as a whole it may be possible to eliminate peaks in velocity without adversely affecting movement times. This, in turn, could make targeting movements much more predictable, potentially further improving the capabilities and performance of an integrated HUI.

Besides movement time and velocity peak data presented above, cursor traces were collected and grouped by button and data from all subjects aggregated to create 20 distinct movement profiles for each effect (80 total movement profiles). Cursor traces were collected in order to identify distinct movements which would be indicative of where the user planned to move the cursor. Select results are presented in the following figures for discussion.

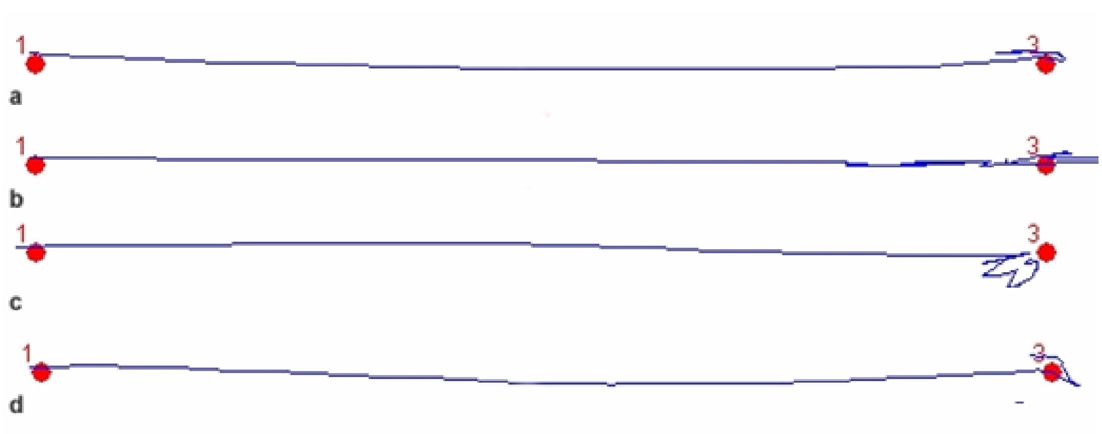

Figure 2.4 Average movements, from target 1 to 3
a) no effect b) spring effect c) damper effect d) ellipse effect

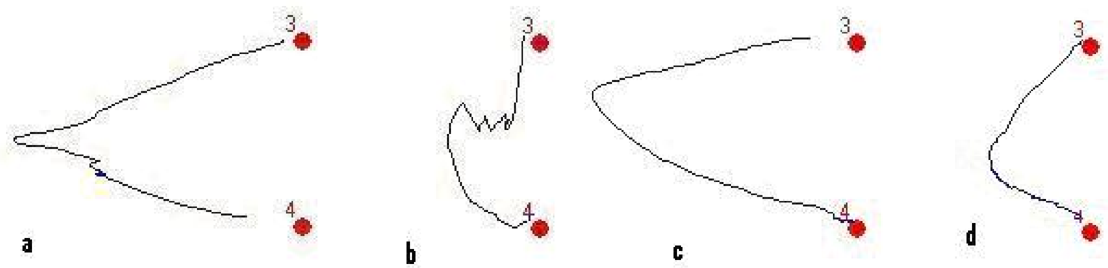

Figure 2.5 Average movement, from target 3 to 4
a) no effect b) spring effect c) damper effect d) ellipse effect

Figures 2.4 and 2.5 contain aggregated cursor traces for a select number of movements. The cursor traces presented were selected because they illustrate a phenomenon that was unexpected. It was discovered that cursor traces of vertical movement drifted toward the center of the interface before moving toward the target object. As each subject located the next target visually they appeared to be moving the mouse toward the center of the interface in anticipation of the next target's location. Since it is unclear when the subject actually knows where the target object is and when they are simply drifting, identifying intended direction becomes difficult at the early stages of movement. However, the ability to capture and identify movement characteristics from the cursor traces was confirmed. It was clear that another pilot study would be needed to address the problem of drifting, but analysis of the movement characteristics was still performed on the collected data to analyze its correlation to Fitts' Law, a law generally used to model targeting data.

2.3.1.1 Fitts' Law

> If the amplitude and tolerance limits of a task are controlled by E, and S is instructed to work at his maximum rate, then the average time per response will be directly proportional to the minimum average amount of information per response demanded by the particular conditions of amplitude and tolerance.
>
> Fitts, *The Information Capacity of the Human Motor System in Controlling the Amplitude of Movement*

Fitts, a psychologist at Ohio State University in the 1950's, studied the information capacity of the human motor system. In his classic paper quoted above Fitts theorizes that there is a fixed information-transmission capacity of the human motor system which can be quantified through experimentation. The motor system described by Fitts is comprised of visual and proprioceptive components.

In his most well known experiment Fitts asks the subjects to repeatedly tap plates of varying width at varying distances from each other with a stylus as accurately as possible. By varying the amplitude of movement and the size of the plates Fitts is able to isolate the visual and proprioceptive components of target selection. The capacity of this system is described by Fitts as the index of performance (*IP*). The *IP* is calculated using the index of difficulty (*ID*) and the movement time (*MT*).

(2.1) $IP = ID/MT$

ID is based on amplitude (*A*) and tolerance (*W*). Amplitude refers to the distance between the starting location of the movement and the middle of the target and tolerance refers to the width of the target.

(2.2) $ID = Log_2(2A/W)$

What is considered Fitts' Law can now be used to compute *MT*.

(2.3) $MT = a + b * ID$

The *MT* from Equation 2.1 is experimentally derived as the average *MT* collected during repeated trails with identical *ID*. By varying *ID*, a linear relationship can be established and *a* and *b* calculated. While *IP* is shown to be *ID/MT* by Fitts, it has been discovered that for low *ID* (< 3) alternative methods for computing *IP* are necessary. Wellford [26] offers an alternative for calculating *IP* which makes the relationship more linear and creates values of *ID* that are always greater than zero [25].

(2.4) $ID = (A/W) + .5$

The motivation for an alternative method for calculating *IP* is believed to be due to ballistic movements which are not subject to the proprioceptive feedback loop [10]. Ballistic movements are defined as small involuntary or reflexive movements which do not involve visual feedback in order to be performed. Low *ID* movements are primarily made up of ballistic movements and therefore subject to the relationship described by Gan and Hoffman [10].

Finally the information capacity (*IC*) of the motor system can be calculated from the data.

(2.5) $IC = 1/b$

The original motivation for Fitts research was to study the information capacity of the human motor system. That research has now become one of the foundations on which we study targeting characteristics in HCI.

2.3.1.2 Fitts' Law in research

As early as 1978 Fitts' Law was being used to evaluate performance in HCI tasks. In one of the earliest evaluations of the mouse, Card et al [3] used Fitts' Law to evaluate performance and *IP* of a mouse and joystick in selection tasks. It was found that the mouse used in that experiment had an *IP* of *10 bits/s* which is comparable to the stylus used in Fitts' original experiment. Of great interest to this research, it was discovered the joystick studied had an *IP* of *~5 bits/s* which demonstrates the effect an input device can have on the index of performance in selection tasks.

It is one of the goals of this research to verify the certainty with which Fitts' Law can accurately describe the movement times and error rates of targeting tasks in a GUI using the Wingman™ Force Feedback Mouse from Logitech with a range of haptic effects. By asking the subjects to perform a series of targeting tasks of differing *ID* under the influence of four different haptic conditions models can be constructed from the *MT* and error data collected and compared for correlation to Fitts' Law.

2.3.2 Pilot Study 2 Fitts' evaluation

An analysis of the data evaluating the relationship of distance to target size was performed. By separating the average *MTs* by distance slope, y-intercept, and correlation coefficients could be computed. The results are presented in Table 2.3.

Table 2.3 Slope, y-intercept, and correlation coefficient for each condition

	Control	**Spring**	**Damper**
b(s)	0.060	0.024	0.085
a(s)	1.135	0.984	0.974
r	0.41	0.38	0.75

The analysis resulted in relatively flat slopes, high intercepts, and low correlations. These results would seem to indicate the Wingman™ mouse does not conform to the targeting laws put forth by Fitts. If it did, the slopes would be steeper, the y-intercept would be ~0, and the correlation coefficient would be in the ~90% range. Since there is a large body of work verifying the mouse as a Fitts' compliant input device it was difficult to accept the Wingman™ Force Feedback mouse as non-compliant in the non-haptic condition.

Therefore a closer look at the methodology for the experiment was undertaken and it was decided a game-like interface was not a controlled enough environment to collect the data needed. In particular, as stated in the evaluation of the cursor traces, the use of a game environment led to initial drifting movements toward the center of the game region during the time used by the subject to locate the next target, and did not provide a means to separate these drift parts of the movement from the actual targeting movement. A new interface was designed which limited the subject's movements to allow for this separation. By restricting the data collection to the period after the target had been identified it was felt only the targeting movements described by Fitts' would be captured. The resulting experimental interface is described in Pilot Study 3.

2.4 Pilot Study 3

Two irregularities were discovered in the data collected during Pilot Study 2. The cursor traces for vertical movements contained unexplained drift toward the middle of the environment and the *ID* vs. time plots for the non-haptic conditions showed no correlation. To correct the issues identified, a more controlled interface was developed which requires the user to identify the target through the use of colored targets before the targeting move is begun. The new study was also used as an opportunity to investigate another haptic effect, so for this experiment the ellipse effect was replaced by a funnel effect. A full description of the interface and results of the experiment follow.

The testing environment for the experiment was identical to the one described for Pilot Study 2. The test subjects were 20 freshmen students from Spring Hill College's Introduction to Computer Applications course. The interface is comprised of a GUI frame containing a space ship console to display game information, 4 large (55 pixel) circular primer buttons around the edges, each of a different color, and small (24 pixel) circular alien torpedoes which act as target objects. Each target object appears randomly in one of the 3 furthest target locations across from one of the four primer buttons, except for every 10th target, which is randomly chosen from the 3 closest possible target locations. The new target color matches one of the primer button colors and target selection cannot occur until the subject first clicks on the matching primer button. It was believed this aspect of the experiment would correct the irregularities experienced in the last study by eliminating the drift component of the movements. As soon as a target object is selected, a new one spawns within the field of play. The only restriction is that the same primer button cannot be used in successive attempts.

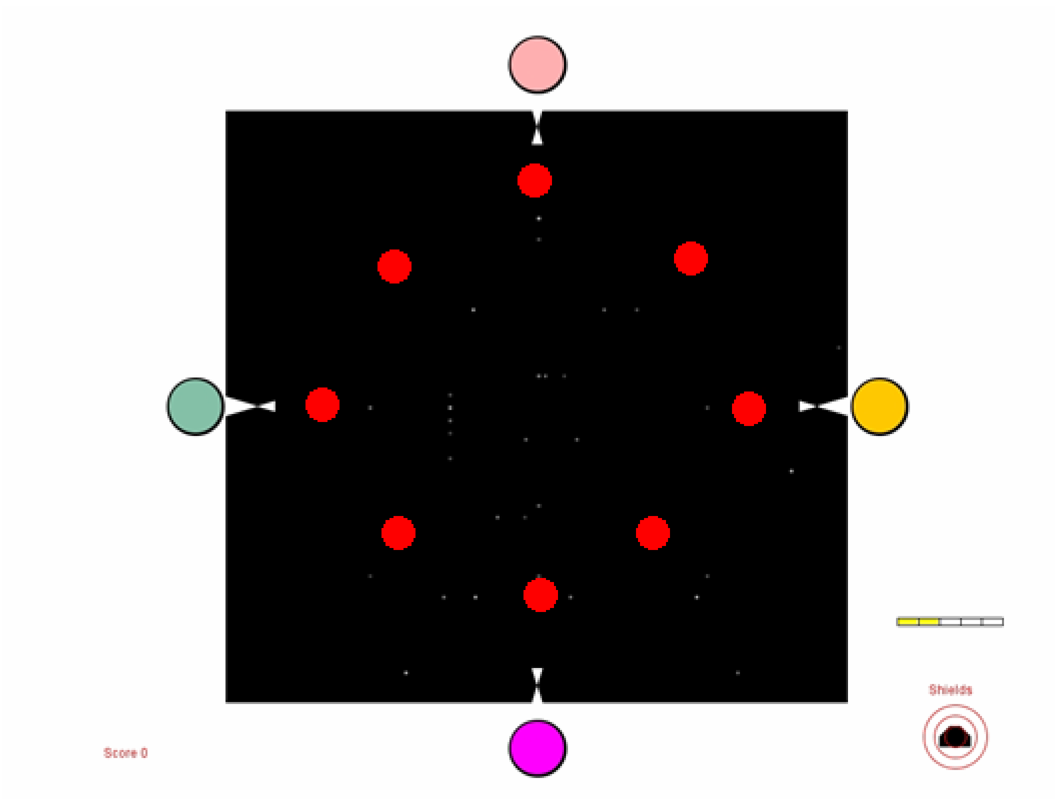

Figure 2.6 Data collection interface.

Each subject participated in four identical GUI interfaces, each with a different haptic condition. One of the conditions had no haptic enhancement and serves as the control for the experiment. The other three conditions consisted of a spring, damper, and funnel effect. Each experiment presented the four conditions in random order to remove any influence of a learning effect from the data.

Movement time is measured from selection of the primer button to selection of the target. Subjects were asked to emphasize accuracy over speed. The subject completed four trials of 20 targets each with a different haptic effect for each trial.

2.4.1 Pilot Study 3 results

The main goal of this third pilot study was to correct irregularities in data collection discovered in the second pilot study. These irregularities resulted in unexpected artifacts in the vertical cursor traces and deviation from a straight line in the Fitts' regression analysis of the *ID* to *MT* data. In order to study the effectiveness of the corrective measures taken, the data from this pilot study was evaluated using regression analysis and cursor trace observation.

Using the Fitts formulation ($ID>3$) *ID* was calculated for each amplitude and plotted against average *MT* for the non-haptic, spring, damper, and funnel effects. A straight line was then fit to the data using the models built from Equation 2.3 and regression analysis was performed.

From the data presented in Figure 2.7 the spring effect trend line shows a significant decrease in $MT\ (P(T<=t)=.048,\ p<.05)$ in the HUI and the damper effect has no significant impact on the $MT\ (P(T<=t)=.49,\ p>.05)$.

The average number of errors was recorded as clicks not on the target during a trial. Results are presented in Table 2.4.

Table 2.4 Average error

Effect	**Average Error**	**P(T<=t) two-tail**
No Effect (control)	1.8	
Spring Effect	0.6	0.002251
Funnel Effect	1.76	0.466378
Damper Effect	1.35	0.276954

What was found was a significant difference in error rate between the Control and Spring conditions *(P(T<=t)=.002,p<.05)* in favor of the spring effect.

However, the benefit of haptic effects can go beyond *MT* and error rates. In the case of the damper effect movements are smoothed and movement rate regulated, as was realized in the results from Pilot Study 2 and again here in Table 2.5.

Table 2.5 Average velocity peaks

Effect	Peaks	P(T<=t) two-tail
No Effect (control)	1.31	
Spring Effect	1.22	0.169648
Damper Effect	0.89	0.000023
Funnel Effect	1.27	0.348471

What was found was a significantly lower *(P(T<=t)=0.00002),p<.05)* number of average velocity peaks in the damper condition when compared to the control.

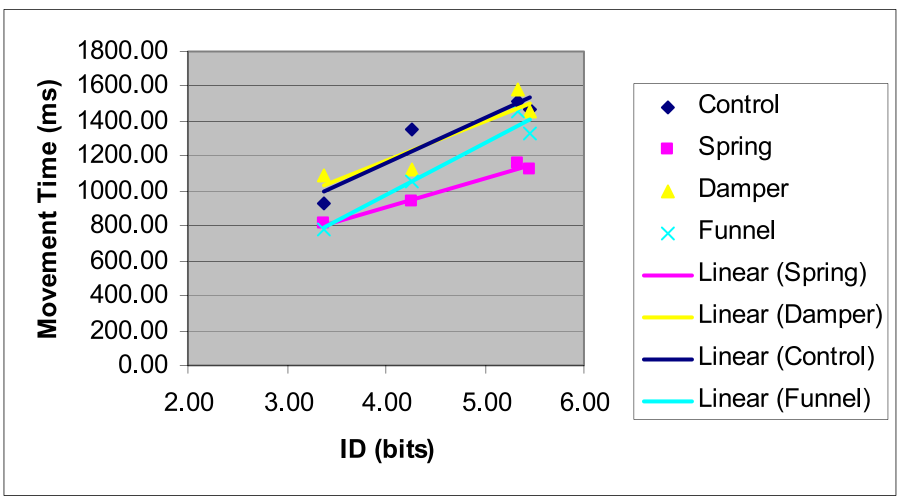

Figure 2.7 Relationship between movement time and index of difficulty with regression lines for all conditions.

Figure 2.8 shows aggregated cursor traces from the non-haptic condition in which it appears movements tend to move in relatively straight lines to the targets as was confirmed by an average radius of curvature > 50.

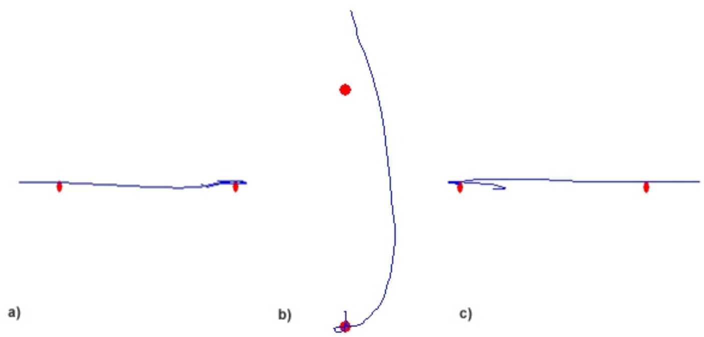

Figure 2.8 Cursor traces from Study 3
a) left to right b) top to bottom c) right to left

According to Fitts' Law, two tasks of equal amplitude (target distance) and equal tolerance (target size) should have equal *IP*. To test this assumption in the context of haptic effects, the *IP* for each condition is calculated using the Fitts' methodology for calculating *ID* (only the first amplitude and tolerance values result in an *ID* near the threshold reported by Gan and Hoffman [10]) and results are reported in Table 2.6.

Table 2.6 Fitts' IP all conditions

	IP			
ID	**Control**	**Spring**	**Damper**	**Funnel**
3.38	3.65	4.17	3.10	4.34
4.27	3.15	4.53	3.81	4.02
5.34	3.54	4.60	3.38	3.68
5.45	3.71	4.87	3.74	4.09

What was found was a differing *IP* when haptics was included in the GUI, where the *IP* appears to be relatively constant within an effect condition but differs across effects. A significant increase in *IP* can be seen in the spring and funnel enhanced HUI. Since there is differing *IP* with identical target width and distance, it appears as if the HUI does not conform to the Fitts' postulate for calculating *IP*.

The end result of Fitts' experiments was to determine the *IC* of the human motor system. Therefore, it was important to compare the *IC* for each condition of the experiment and the results are reported in Table 2.7.

Table 2.7 Fitts' calculated *IC (1/b)* for each condition

Fitts *IC*			
Control	**Spring**	**Damper**	**Funnel**
3.90	6.11	4.36	3.34

What was discovered was a different *IC* for each condition. While the *IC* for the damper and funnel effects was not significantly different from the control condition the *IC* for the spring effect enhanced tasks showed a 56% increase in *IC*. In Fitts' original work he stated:

The concept of a fixed information-transmission capacity of the motor system not only accounts for such divergent results but also suggests a way of relating quantitatively the amplitude, duration, and variability of motor responses. The concept leads to the expectation that if repetitive movements of a fixed average amplitude are speeded up, then on the average each movement can provide less information, and movement variability will increase by a specified amount. Similarly, it suggests that if average movement amplitude should be increased then variability and/or average duration will also increase.

Fitts, *The Information Capacity of the Human Motor System in Controlling the Amplitude of Movement*

Again it appears as if the HUI does not conform to Fitts' theory on information capacity, as the data shows increased *IC* with a decrease in *MT* and decrease in error rate *(P(T<=t)=0.0022)*. This seems to make sense if you ignore the fixed-transmission capacity theory, because as you increase *IC* you would expect to see decreases in the time taken to complete a task and decreases in error rates. So was Fitts wrong about the fixed *IC* of the human motor system? I do not believe this is the case, instead I believed the addition of haptic feedback has increased the *IC* of the HUI system (in a similar way as the mouse does compared to the use of a joystick [3]) allowing for increases in movement amplitude without increasing variability and/or average duration. The effect of increasing *IC* would then explain the increase in *IP* for the spring effect.

To support this hypothesis one just needs to look at the regression analysis of the data collected for each condition.

Table 2.8 Slope (b), intercept (a), and correlation coefficients (r) for each condition

	Control	**Spring**	**Damper**	**Funnel**
b (s)	0.256	0.163	0.229	0.299
a (s)	0.131	0.253	0.254	-0.225
r	0.94	0.99	0.92	0.98

From Table 2.8 it is clear that, while *IC* is not a fixed quantity in this system, strong correlation coefficients are found between *ID* and *MT* within all conditions suggesting there remains a relationship between *MT* and *ID* which is described by Fitts' Law.

The purpose of Pilot Study 3 was to make adjustments to the experimental interface to correct what was felt were errors in methodology from the previous Pilot Study. As indicated by the results, low y-intercepts with high correlation coefficients and normal cursor traces, the interface for Pilot Study 3 was able to measure the isolate the targeting movements and capture movement times accurately. The interface was ready for the target group.

2.5 Pilot Study 4

Feeling there was a sufficient number of haptic effects studied and that the experimental design was capable of isolating and measuring performance in the interface it was felt a study with the target group was necessary before design of the final experiment would take place. In addition to collecting preliminary data on the target group some preliminary data about how the target group may interact with a prediction algorithm and compound haptic effect was collected.

Pilot Study 4 was conducted under the same conditions as the previous study with the addition of a combined haptic effect and prediction condition. In this condition the spring and damper effect are focused on one of the eight target locations based on several conditions. Haptic effect strength is (i) inversely proportional to the velocity of the cursor, (ii) inversely proportional to the acceleration of the cursor, and (iii) proportional to the proximity of the target. The combined haptic effect consisted of spring and damper effects both varied equally by the prediction algorithm.

Due to the difficult nature of collecting subjects from the target group [15] it was felt an initial pilot study consisting of 4 to 5 subjects would supply sufficient data for comparison to the non-disabled data and prepare the system for a larger study. Movement times and cursor traces of the target group were collected for cursory comparison to the data collected in the previous studies. While a large *n* for this experiment may be desirable it is not a realistic goal. There are very few locations at which the target group gathers, and attempts to collect data have proven difficult. Given the limited accessibility of the target group it was decided to focus efforts on collecting subjects for the final experiment and find a small number of participants for this study. Observations of the data collected from the target group follow.

The aggregated cursor traces from the five individual in non-haptic conditions are shown in Figure 2.9.

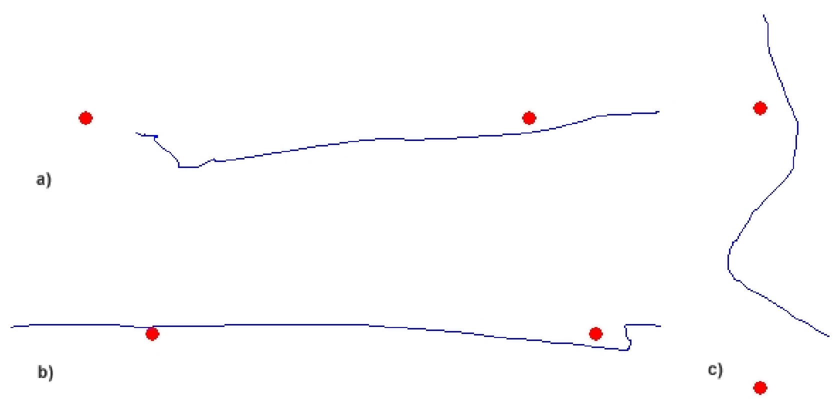

Figure 2.9 Cursor traces from Study 4
a) from right to left b) from left to right c) from top to bottom

The aggregated data from the cursor traces of the disabled and non-disabled groups are almost indistinguishable from each other and an average radius of curvature >50 confirm mostly straight line movements. Cursory observations of individual cursor traces showed what looked like very normal vectors from the disability group until they neared the target. The majority of the difference in movement vectors did not seem to occur until over the target.

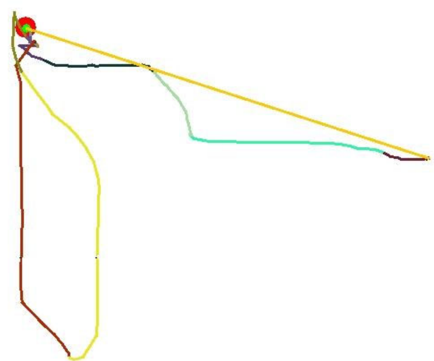

Figure 2.10 Select representative cursor trace (color changes every ~100ms)

Figure 2.10 shows a prevalent trend where the target group would diverge from a non-disabled user's movement profile. In the figure you can see the subject moves from the point on the right to the target (a straight line from the start location to the target is also included for comparison), then has difficulty remaining over the target when it comes time to make the selection. The process of target selection often resulted in the subject losing control of the mouse and struggling to regain control. In the figure the subject moves downward away from the target then regains control and moves back to the target. It was believed that through haptic effects designed to assist the user in remaining on top of the target this difficulty could be overcome.

One of the goals of this pilot study was to discover how the movement profiles of the target group differ from a non-disabled user to assist in determining which characteristics of the target group might effect the creation of a prediction algorithm. It was found that while the movement vectors were very similar there was a large difference in the movement times for the disability group when compared to the non-disabled group.

Table 2.9 Movement times for the disability group (seconds)

	Control	Spring	Damper	Funnel	Prediction
subject 1	5.543	3.272	3.344	3.445	2.842
subject 2	2.990	2.575	2.911	3.003	2.244
subject 3	2.625	2.956	3.982	2.385	4.647
subject 4	2.003	1.547	2.569	2.048	2.598
subject 5	7.756	3.132	6.907	8.269	11.223
average	4.183	2.696	3.942	3.830	4.710

When compared to the average *MT* from Table 2.1 there is a noticeable difference in the means of the two groups. The disability group takes on average 2 to 3 times longer to target than the non-disabled group. Additionally it appears there are large differences in *MT* within the group, as can be seen in subject 5 vs. subject 4. The results of the prediction condition were mixed. Subject 1 displayed a significant decrease in *MT* when under the compound/prediction condition; however Subject 5 displayed significant increase in *MT* under the same condition.

The results of Pilot Study 4 helped shape the final experiment and the design of the prediction algorithm. It was felt the differences between the target group and the control were understood and design of the final interface would account for those differences in both haptic effect design and prediction algorithm. In hindsight there was a variability issue that was missed when analyzing this data. Subject 5 displayed a very high variability between the spring and prediction conditions and within each condition. Training that will be discussed in Chapter 3 for the prediction algorithm was designed to account for variability between individuals but the possibility of significantly different variances between conditions was not expected. It may have been beneficial to look at variability within conditions to better understand the target group and how to use the training data. However, with the small sample size and majority of subjects displaying reasonable variability it was decided to move forward with the experiment.

2.6 Pilot study conclusion

Having performed a series of pilot studies it was felt sufficient data and information for the design of a prediction algorithm had been gathered and it was time to move forward with the final interface design and experiment under the following assumptions. Movement times of the target group are significantly higher than those of non-disabled individuals, movement trajectories should be relatively similar to those of non-disabled individuals resulting in straight movements toward the target, there is a large variability between individuals from the target group, and a prediction algorithm that trains itself for each user is the solution to that variability.

CHAPTER 3

PREDICTION

Predicting targets in a GUI is not a new concept. There is a wealth of research employing a number of differing approaches to prediction available [5][17][20]. The desire to predict the target in this instance is due to distractions created from overlapping haptic effects that occur in multiple target environments. If a successful prediction algorithm could be developed it reduces the multiple target problem to a single target making the application of haptic effects much less complex. Where this research differs from most is that the target group is comprised of disabled individuals in a multi-target environment, further complicating the problem. Using movement profiles collected during the pilot studies and information drawn from previous prediction algorithms a new prediction technique was devised for this research that fits the target group. The following is a description of prediction techniques that influenced the technique created for this research and a description of the prediction algorithm developed.

3.1 Related Prediction Research

In their paper *Guidelines for the Design of Haptic Widgets,* Oakley et al investigate the idea of multiple haptic targets within the same environment [20]. They cite several sources that use both anecdotal and quantitative arguments to dissuade the use of prediction in applying haptic effects in multi-target environments.

Dennerlein et al [5] describe an experiment in which the subjects are presented with multiple targets and asked to select one. As the trial progressed the researcher manually controlled the number of haptic distracters in the environment between the subject and the desired target. This simulated the different accuracies of prediction. While the timing and accuracy results of the experiment were mixed they maintained that partially successful prediction algorithms had negative subjective results on the user experience [5].

The experiment conducted by Oakley et al [20] consisted of a simulated desktop interface, depicted in Figure 3.1, with many possible haptically enhanced objects. The pointing device used was a PHANToM™ stylus from SensAble Technologies.

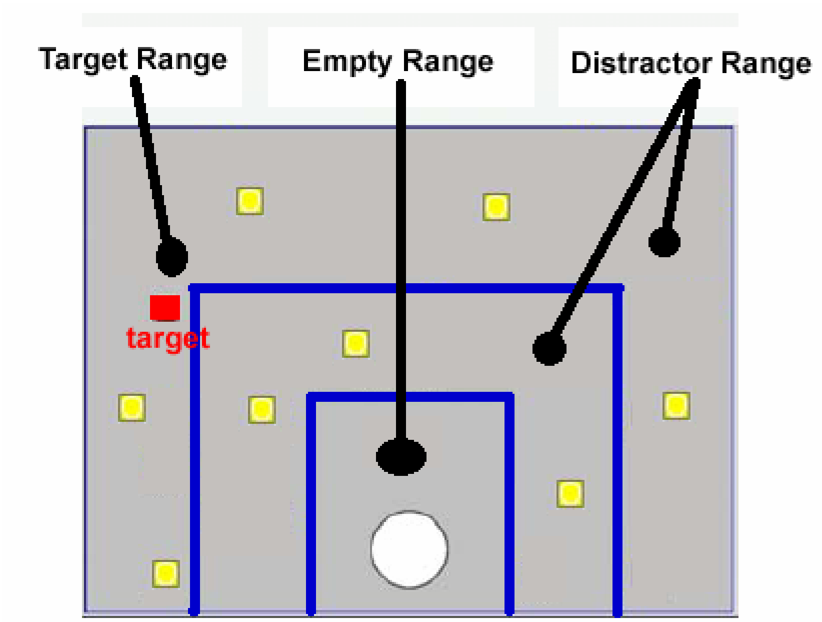

Figure 3.1 Prediction interface

The subject was asked to select targets on the outside range of the interface while starting from the middle white range. As the cursor passes over the non-target objects distracter forces are felt through the haptic interface. One possible approach to overcoming the interference caused by distracters would be to predict the target and then focus the haptic effect on the predicted target. However, as detailed earlier Oakley et al [20] cite research that contradicts the use of prediction algorithms because of the partially successful nature they display. They also believed the only successful prediction algorithm would be those requiring extensive training of the system for each particular task and input device. The solution proposed by Oakley et al was to forego a prediction altogether and to create an adjusted haptic effect that would have a high probability of overcoming the distracter effect while avoiding the negative subjective results experienced from partially successful prediction algorithms. The haptic effect would be adjusted based on three conditions:

1. Reduce the maximum force applied if a user is moving slowly (beneath 2 cm per second) to a minimum of one third of its normal value.
2. If a user is moving rapidly (above 2 cm per second) and has only been on a target for a short time (less than 100 ms) reduce the maximum applied force by a factor of two.

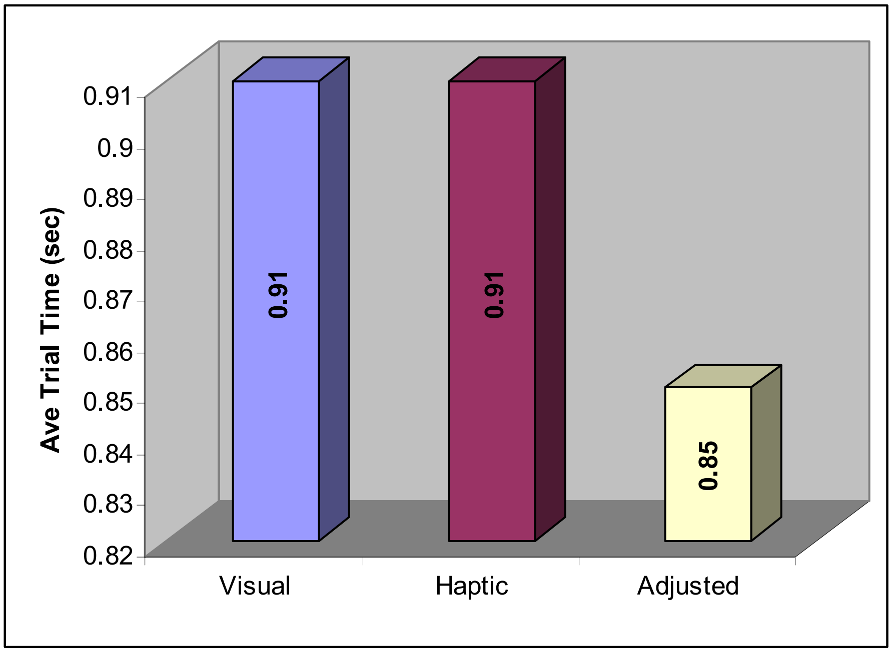

Figure 3.2 Average MT: Visual, Haptic, and Adjusted Haptic conditions

3. Increase the maximum force applied to three times its original amount if a user has begun to perform a click (by depressing the PHANToM's button) and reduce the force back to normal levels when the click is completed (by releasing the button). [20]

What they found was a decrease in *MT* for the adjusted haptic condition over both the haptic and non-haptic (visual) condition, as depicted in Figure 3.2.

Several types of errors were recorded. What was found was a lower error rate in the visual condition for misses than for either of the other two conditions but a decrease in errors compared to the haptic condition for the adjusted condition. Results are depicted in Figure 3.3.

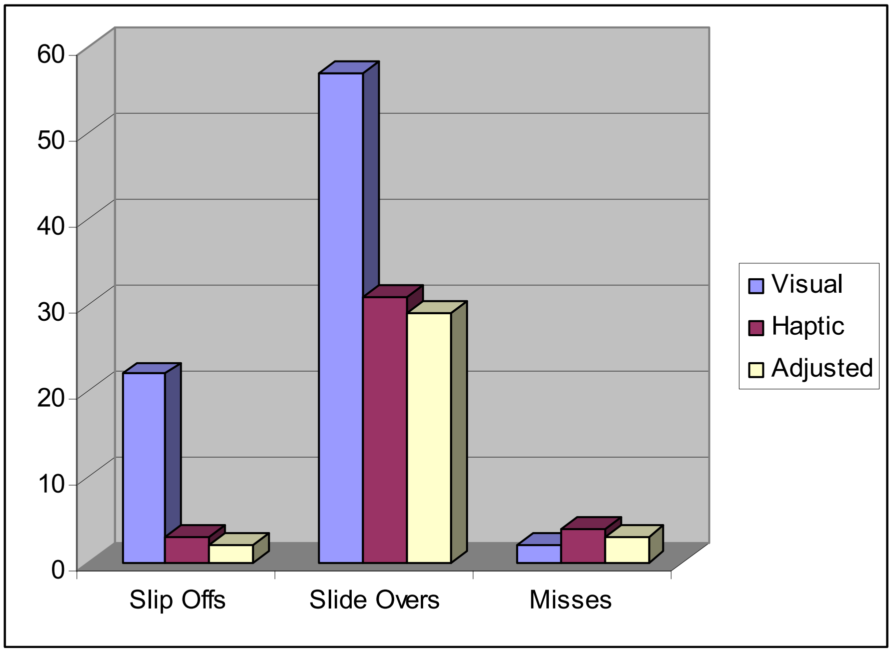

Figure 3.3 Error: Visual, Haptic, and Adjusted Haptic

For the slip off and slide over types of errors both haptic conditions showed far fewer errors than the visual condition and in each of those instances the adjusted haptic condition outperformed the haptic condition.

While the experiment described does not address the issue of applying haptic effects at distance, the researcher does provide a partial solution to the prediction algorithm. Oakley et al make an interesting argument against using prediction in the application of haptic interaction with multiple GUI objects but it would have been a far more complete study had they compared the adjusted condition to some form of prediction algorithm. However, the research was effective in presenting an alternative methodology to prediction which was incorporated into the algorithm employed by this research.

3.1.1 Vector Based Prediction

Murata describes a vector based method of target prediction in a desktop GUI environment [17]. In their approach they use vectors and angles to determine which target within the environment is the intended target. Figure 3.4 illustrates both the experimental interface and the proposed prediction algorithm that was used for the research. In this algorithm two vector types are constructed. The first vector type is constructed using consecutive cursor readings from the subject. The second vector type is constructed using the last cursor reading and the center of each target. The number of mouse samples is represented by *n* with a sampling interval represented by *st* (~1/60 second). The difference between the cursor/cursor angles and the cursor/target angles are computed at then end of each *st* and accumulated. The time to predict is the product of *n* and *st*. The cumulative difference in angle between the cursor/cursor vector and the cursor/target vector are computed for each target. The target is then predicted to be the target with the smallest cumulative angle. The larger *n* and *st* are the more accurate the prediction, however it also takes longer to create the prediction.

The experiment consisted of several trials of varying distance (*d*) between objects, *n*, and *st*. Figure 3.5 contains the *MT* data collected for each trial and a

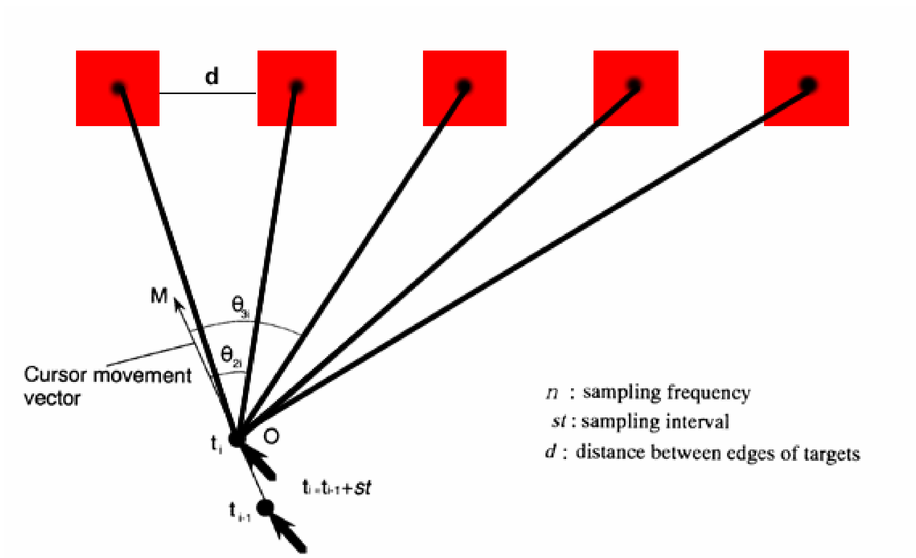

Figure 3.4 Experimental Interface and Prediction Algorithm

comparative chart for the Control vs. Prediction conditions. Figure 3.6 contains the prediction accuracy data from an experiment performed with non-disabled individuals [17].

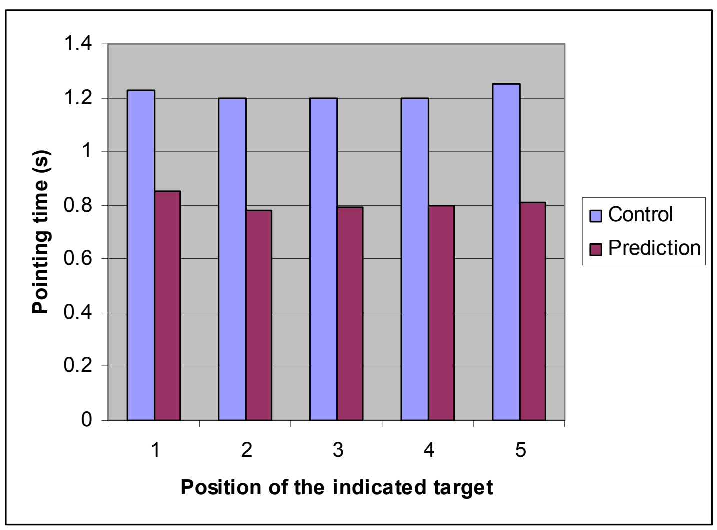

Figure 3.5 MT for Control and Prediction trials

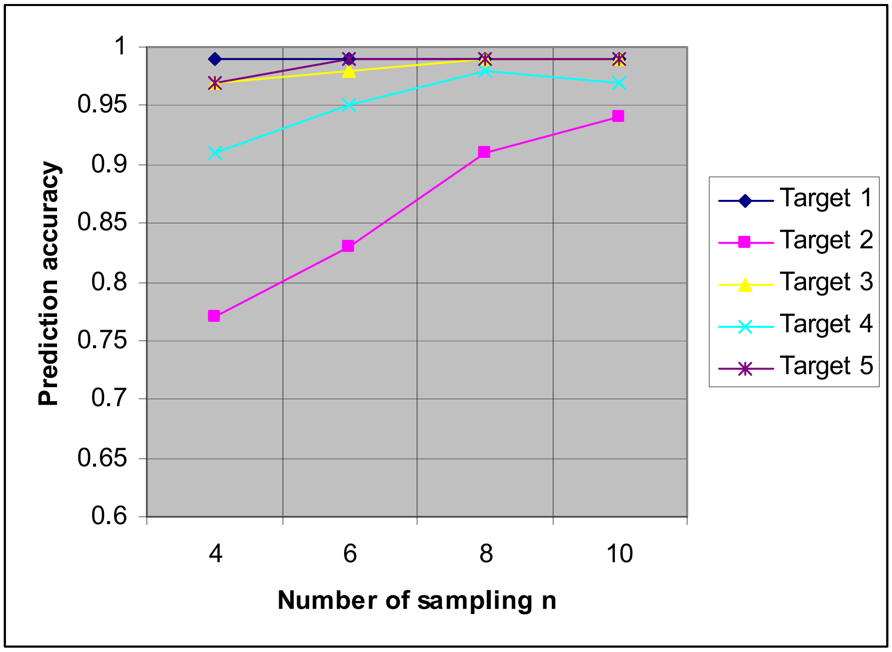

Figure 3.6 Prediction Accuracy

During these experiments the mouse cursor would jump to the predicted target as soon as a prediction was made, therefore the data from Figure 3.5 could be considered predefined by the system since the only variables would be computational on the computers part and click time by the subject. From the data in Figure 3.6 it is apparent that target position is directly related to prediction accuracy in the vector based system. Finally, Murata performed a comparison of prediction accuracy to distance between objects, the result of which is presented in Figure 3.7.

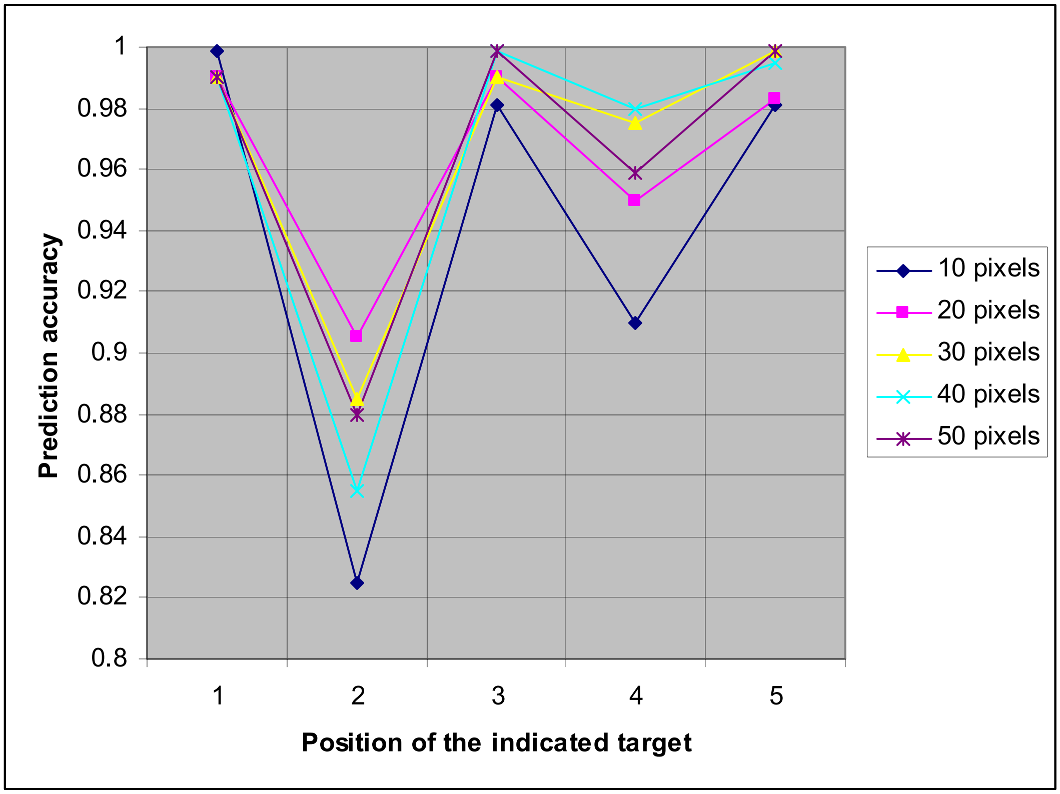

Figure 3.7 Distance vs. Prediction Accuracy

The results presented in Figure 3.7 do not seem to indicate a consistent relationship between distance between targets and predictability; you have a 40 pixel distance as the 2nd worst prediction distance for the target at position 2 and the 50 pixel distance as the 3rd worst prediction distance at target position 3. However, this data does indicate distance between difficult to predict targets as having a significant effect on predictability.

The vector based prediction algorithm appears to have a relatively high success rate when confronted with multiple targets within the environment. Based on the problems predicting targets 2 and 4 it was surprising to find a high prediction success for target 3. This would seem to indicate a vector based approach favors straight line vectors (target 3 was directly above the start location). It is also unclear how this approach would deal with multiple targets along the same vector. While this prediction algorithm may be an incomplete solution for a real desktop environment, it became the basis for a part of the prediction algorithm designed for this research.

3.2 The Prediction Algorithm

When applying haptic effects there are a number of considerations that must be made, the most important of which is to determine if the effect is beneficial to the user. Through a series of pilot studies performed as part of this research, it was determined the most beneficial haptic effect, of those selected, in a single haptic target environment was the spring effect (gravity well). While the desire to incorporate the spring effect is high, the implication of multiple spring effects overlapping is not at all desirable. The spring effect draws the user toward the target from all directions from all locations in the environment. In order to incorporate the spring effect it was determined a prediction algorithm of some sort must be constructed.

Prediction algorithm design for GUI based targeting tasks is a daunting enough task in itself, but when trying to predict for a disabled group of users that task becomes much more difficult. The literature discussed earlier in this chapter took two basic approaches to prediction, the first basically assumed 0% prediction accuracy and only addressed the prediction on top of possible targets, and the second predicted targets based completely on angles to the target with no design contingency for bad predictions. In order to construct a prediction algorithm for the target group it was necessary to identify what parts of the existing prediction literature was useful, where existing algorithms fell short, what could be done to address the shortcomings of existing algorithms, and how the disability of the target group would effect existing prediction algorithms.

3.2.1 Target Group Characteristics

When creating this prediction algorithm it was important to realize how the target group was similar to or different from a non-disabled group of users. Murata's [17] motivation for his vector based approach was an assumption that targeting movements tend to follow a straight line. Oakley et al believe that adjustments made to the haptic effect while over the target object could increase performance. Let us examine how each of these algorithms correlates to our target group.

While Murata does not provide evidence to support his assumption, he was never the less correct to a point. To understand what is meant by "correct to a point" there must be a distinguishing of movement types. During a normal targeting task there are typically two types of movement, targeting and corrective. Targeting movements are designed to move the user from distance to the target in one relatively long movement ($ID > 3$). Corrective movements are typically very short ($ID < 3$) movements meant to compensate for over or undershoot of the desired target object and can be ballistic in nature [26]. According to the data collected during this research the majority of targeting movements are straight lines (radius of curvature > 50 [12]), while corrective movements are a mixture of both straight and curved movements (varying radius of curvature > 50). If Murata's algorithm depends on straight line movement it should be effective for targeting movements, but will lose accuracy during corrective movements.

Oakley et al [20] describe an algorithm that adjusts haptic effect strength based on instantaneous movement data collected while over objects in the environment, mainly increasing haptic effect when clicking begins. One major difference between the target group and non-disabled individuals is the ability to make the clicking motion without causing a spasm. Therefore, it was not considered a good fit for our prediction algorithm, however the idea of modifying the strength of the haptic effect while over the an object based on instantaneous data still makes sense for our research, and will be discussed in the next section.

3.2.2 The Algorithm

After careful consideration it was determined a two phased approach to prediction would be taken. The prediction algorithm behaves similarly to the Murata algorithm at distance and similarly to the Oakley algorithm once within a cluster of objects. As mentioned previously both algorithms were not complete or perfect fits for our target groups so modifications have been made to each in order to maximize the potential of success.

3.2.2.1 At a Distance

The Murata algorithm with non-disabled users resulted in relatively high prediction accuracy, above 80%, for one column of objects with distances between them above 10 pixels. However, the algorithm lacks a robustness required for deployment in a realistic environment. In addition to the assumption that all movement will be relatively straight it cannot distinguish between two targets along the same angle. It is necessary for the algorithm to be able to distinguish distance as well as angle to the target in a multi-column environment. It is also a concern that the target group this algorithm is intended for use with does not display movements toward the target on a consistent basis; some contingency should be in place.

The algorithm designed for this research first looks for patterns in movement that indicate targeting movements and then segregates those movements for the construction of likelihood models. The models are used to estimate the likelihood of the current movement being a targeting move based on velocity, curvature, and directional data collected during the training condition. The models are custom made specifically for the individual performing the targeting task to account for the variability believed to exist between target group individuals.

To achieve a robust prediction, training of the algorithm is required and probabilities are used to make decisions about prediction and haptic effect application. Training of the data occurred in the non-haptic condition of the experiment, which will be described later. It is sufficient right now to mention that there are multiple conditions to the experimental interface, one of which asks the subject to select known targets without the benefit of haptic interaction. Movement data collected from the non-haptic condition is segregated into targeting and corrective movements.

Movement segregation is achieved by simply looking for increases in average velocity across 5 readings (50ms) of more than 60% to identify the beginning of a new movement and decreases in velocity of more than 60% to indicate the end of a movement. A minimum value of .5 pixels/ms was placed on the gross average velocities to reduce the sensitivity of the readings. The values used were extracted from the data collected during the first two pilot studies. In all cases, including the final experiment with the target group, this methodology has been successful in separating the movements. It was determined from the data collected during the first two pilot studies that the first movement with velocity greater than 2 pixels/ms was a targeting movement. Training takes place on the first targeting move of each task.

The segregated and smoothed targeting movements were transformed into 3 different model components which together form a model of a characteristic targeting move. The models are constructed in phase space to eliminate the effect of delayed movement onset or target selection, and normalized over the movement distance to allow for a uniform model for varying target distances. The underlying assumption, verified in the previous pilot studies, was that movement direction did not significantly affect the characteristics of a particular user. The 3 model components represent the velocity, curvature, and directional characteristics of the targeting movement, respectively, and are then used to probabilistically evaluate the likelihood that a particular object in the GUI is the target of the current mouse movement. The models are represented as follows:

- The velocity model is represented by:
  - an average normalized velocity profile in phase space (represented by a sequence of distance/velocity pairs $\{(d_1=0, v_1), (d_2, v_2), \ldots(d_n=1, v_n)\}$),

- a corresponding variance model for the normalized velocity profiles (represented by a sequence of distance/variance pairs {$(d_1=0, \sigma^2_{v1}), (d_2, \sigma^2_{v2}), \ldots (d_n=1, \sigma^2_{vn})$}),
- and a distribution of velocity scaling parameters (represented by a mean scaling parameter (mean peak velocity) s_v, and corresponding variance σ^2_{sv}).

- A curvature model represented by:
  - an average normalized curvature profile in phase space ({$(d_1=0, c_1), (d_2, c_2), \ldots (d_n=1, c_n)$})
  - and a corresponding variance model for the normalized curvature profiles ({$(d_1=0, \sigma^2_{c1}), (d_2, \sigma^2_{c2}), \ldots (d_n=1, \sigma^2_{cn})$}).
- A direction model represented by:
  - a distribution of angles ($\llcorner_i$) between the (known) target direction and the mouse movement vector (represented by an average difference angle Φ and a corresponding variance σ^2_Φ).

Assuming that deviations in movement velocity and curvatures are normally distributed, the above models represent a probability distribution for the targeting velocity and curvature for each current movement at distance d_i and the probability density for an observed normalized velocity of v_j is the value of the Gaussian distribution of v_j at d_i:

(3.1) $P(v_j) = G_{v_i, \sigma^2_{v_i}}(v_j)$

Similarly, the probability density for a curvature c_j at d_i is given by

(3.2) $P(c_j) = G_{c_i,\sigma^2_{c_i}}(c_j)$

And the density for an angle ∟$_j$ is given by

(3.3) $P(\angle_j) = G_{\Phi_i,\sigma^2_{\Phi_i}}(\angle_j)$

Given this set of probability distributions the likelihood of a given movement by the user being directed at a particular target can be computed using the smoothed partial current movement given as a time sequence of velocities, curvatures, and directions p_{cur} = $\{(t_1=0, pv_1), (t_2, pv_2), \ldots (t_k, pv_k)\}, \{(t_1=0, pc_1), (t_2, pc_2), \ldots (t_k, pc_k)\}, \{(t_1=0, \theta_1), (t_2, \theta_2), \ldots (t_k, \theta_k)\}$. Since the distance to each target is known, the velocity and curvature components can be converted into phase space and distances normalized. This results in the normalized partial sequences $\{(d_1=0, pv_1), (d_2/d, pv_2), \ldots (d_k/d, pv_k)\}$ and $\{(d_1=0, pc_1), (d_2/d, pc_2), \ldots (d_k/d, pc_k)\}$ for each target at distance d. Now it is possible to compute for each of the velocity scaling factors ps_v the likelihood that the observed partial targeting movement could belong to each target T.

$$P_T(p_{cur}, ps_v) = G_{S_v,\sigma^2_v}(ps_v) \cdot \prod_{n=0}^{k} G_{v_{(d_n/d)},\sigma^2_{v(d_n/d)}}(v_n / ps_v) \cdot$$

(3.4) $$\prod_{n=0}^{k} G_{c_{(d_n/d)},\sigma^2_{c(d_n/d)}}(pc_n) \cdot \prod_{n=0}^{k} G_{\Phi,\sigma^2_\Phi}(\angle_n)$$

Given this, the maximum likelihood of the observed partial movement to belong to a given target can be determined as the maximum likelihood for this target over all velocity scaling factors:

(3.5) $P_T(p_{cur}) = \max_{ps_v} P_T(p_{cur}, ps_v)$

The best predicted target is simply the one with the highest probability. For the following experiment (presented in Chapter 4), the assumption was made that the haptic prediction condition should always use the prediction, independent of the likelihood value. The main reason for this is that the previous experiments did not allow for the determination of the amount of benefit a correct prediction had and the amount of detriment from incorrect predictions. In Section 4.3.2.2, we will discuss and analyze an additional decision criterion that could be used to determine if a prediction should be made. Once a prediction is made, it is used to attach a spring effect to the predicted target. Once within close proximity to the objects in the environment control is turned over to another algorithm, described in the next section.

3.2.2.2 Close Proximity

One hundred percent accuracy in an algorithm predicting GUI targets in a desktop interface may one day be achievable but at this time is not a realistic goal. Therefore, in any prediction algorithm, especially one that applies haptic forces, there should be some contingency planned for wrong predictions.

The prediction algorithm described above trains itself on targeting moves and requires a five reading window (50ms) at a minimum before it can begin to make a prediction of the intended target. Corrective movements are typically shorter movements *(ID<3)* some lasting less than 100ms. It was felt that given the duration of corrective movements a different algorithm should be used for predicting targets that are in close proximity to the cursor. Considering objects in this environment were 38 pixels in width and spaced 38 pixels apart, control was turned over to a close proximity algorithm when the cursor was within 38 pixels of an object. This guarantees the algorithm to run as long as the subject is within the cluster of objects. This portion of the algorithm adjusts the haptic effects based on three criteria: velocity, acceleration, and distance from an object. Full discussion about these effects can be found in the pilot study chapter (Chapter 2) of this document.

- Velocity over 1 pixel/ms results in the damper effect alone being applied, at full strength.
- Positive acceleration results in proportionally weaker ellipse and spring effects, while negative acceleration results in proportionally stronger effects reaching their maximum at 0 pixels/ms.
- Distance from the target of more than 19 pixels results in the haptic effects changing focus to the next closest target to the cursor.

The values used in this algorithm were derived from numbers observed during the pilot studies. Since the majority of the data in the pilot studies was collected from non-disabled individuals it would be possible to readjust these values based on the data collected from the target group individuals during the final experiment to improve performance.

3.3 Prediction Summary

A two phased approach to prediction was developed. The first phase of the algorithm assists the user in moving to the general area of the predicted target and the second phase of the algorithm attempts to make navigation through the cluster of haptically enhanced objects as easy as possible while still assisting them while over the target.

Results of the prediction algorithm are reported with the analysis of the final experiment.

CHAPTER 4

EXPERIMENT: A DESKTOP ENVIRONMENT FOR THE DISABLED

The culmination of the four pilot studies is a simulated desktop environment capable of providing haptic enhancement to the targeting tasks of individuals with motor function disabilities. Each subject experienced multiple columns and rows of objects, compound haptic effects, and a prediction algorithm. A description of the experiment and analysis of the data collected follows.

4.1 The Target Group

While the original intention of this research was not to focus on a particular group of disabled individuals but rather a particular disability, the reality of the data collection process led to data being gathered from only one group of disabled individuals. Twenty-three individuals from United Cerebral Palsy of Alabama of varying degrees of physical disability participated in this research, with nineteen of them completing the experiment.

Cerebral Palsy describes a range of non-progressive neurological disorders that cause disability in movement and posture affecting approximately 500,000 individuals in the United States [6]. Cerebral Palsy is divided into four classifications based on how the disability effects movements which is usually directly related to the area of the brain damaged.

Spastic is by far the most common form of movement disability, affecting 70-80% of all individuals with Cerebral Palsy. Spasticity refers to a condition where certain muscles are continuously contracted. They typically display tightness of the musculature and have a neuromuscular condition stemming from damage to the corticospinal tract, motor cortex, or pyramidal tract affecting the nervous system's ability to process amino butyric acid at the locations of the spastic activity. Spastic Cerebral Palsy is further classified by region of the body affected. Spastic hemiplegia causes one side of the body to display limited functionality due to spasticity. Spastic diplegia affects the entire body of the individual but more so in the lower extremities resulting in overall weakness of the muscles. In addition people with Spastic diplegia commonly display strabismus (crossed eyes) due to a lack of strength in the muscles controlling the eyes. Spastic Quadriplegia refers to individuals with the entire body affected equally by muscle weakness. Individuals displaying Spastic Quadriplegia are sometimes affected by uncontrollable shaking in the limbs on one side of the body. Ataxia affects approximately 10% of those with Cerebral Palsy as a result of damage to the cerebellum. Individuals with ataxia typically display hypotonia and tremors. Athetoid is used to refer to individuals displaying mixed muscle tone, both hypertonia and hypotonia, due to damage to the extrapyramidal motor system and/or pyramidal tract and to the basal ganglia. About 25% of individuals with Cerebral Palsy display Athetoid. Individuals with Athetoid are also known to display tremor. The fourth and final form is a mixture of the previous three. [4]

A study performed at Sofia University's Special hospital for residential treatment of prolonged therapy and rehabilitation of children with cerebral palsy found that for children with Cerebral Palsy and other motor disabilities the mouse is the preferred input device. Ivanov et al found that for children with these disabilities the benefits of using a mouse include [13]:

- Handicapped children are enabled to work with the same equipment as the healthy children and thus they don't feel different.
- The mouse is configurable and comes with many options.
- The mouse is preferred to the track-ball because the hand position when using the mouse allows them to use the surface on which the mouse rests to steady movements.
- The mouse is preferred to the Joystick due to difficulties in spatial orientation due to disability and the three-dimensional movement of the Joystick.

The difficulties in using a mouse were identified as:

- Most children can not distance themselves from the mouse and believe the mouse pad defines the boundaries of movement.
- Due to visual thinking deficits most of the children can not make the connection that moving the mouse on the mouse pad corresponds to moving the cursor on the screen.
- The disability makes it difficult to keep the cursor in one position on the screen.
- Combinations of tasks such as clicking and dragging are difficult.

As a solution to these difficulties we suggest the Wingman™ be used. The mouse operates within a fixed area so the first issue actually becomes true. While the second issue is one of training, the use of haptics can assist in that training process. Different haptic effects can be employed to hold the cursor in place over targets and provide additional support to the hand for stability. The final issue is one which we observed in our own research, the solution to which might be a more accessible mouse which contains a more accessible button and straps for the hand.

Research centered on steadying of tremor and spasm has found resistance to be beneficial in the suppression of tremor and spasm. Abbot et al studied the effect of resistance on fine motor movements in non-disabled users and found that increases in performance were achievable given resistance. In an article published in 1992, MIT researchers report up to 80% reduction in tremors and spastic movement when resistance is applied to the arms of individuals with disabilities displaying those symptoms [24]. In addition to the applications in research, there are an abundance of devices designed to add resistance to the activities of these individuals, and it is well within the range of haptic effects for the haptic mouse to provide such resistance.

One realization made during this research is that within a group of disabled individuals with the same disability there can be significant differences. As described earlier, the number and variability of the neurological abnormalities makes every disabled individual unique. This is an issue that will be discussed later when describing the construction of the prediction algorithm and difficulties experienced with respect to the results. However, these individuals are trying to interface with the computer often using one of the standard input devices, with a desire to use a mouse.

4.2 The Experimental Interface

For this experiment the test environment consisted of a Pentium based computer running Windows XP, a Wingman™ mouse and a 17” monitor set to a resolution of 1152 by 864 pixels. The subjects were asked too sit in front of the computer and were given a brief explanation about the experiment, informing them of what to expect from the mouse and the interface to help eliminate any surprises. The test subjects were 23 disabled individuals from United Cerebral Palsy of Mobile Alabama and ranged in age from 17 to 54.

Two similar interfaces are used for data collection and each is comprised of a GUI frame containing 30 (38 pixel) circular objects arranged in 3 columns of 10 rows on the left side of the frame, a message area centered at the top of the frame, and either a column of 3 equally spaced trash can icons on the right side of the screen or one trashcan icon in the bottom right corner, as depicted in Figure 4.1. Figure 4.1 a) depicts the interface used in the first three conditions of the experiment and contains 30 objects on the left and 3 trash can icons on the right. Figure 4.1 b) depicts the interface used in the final two conditions and consists of 30 objects on the left and one trash can icon on the right. Each target object is selected from the 30 objects on the left of the interface.

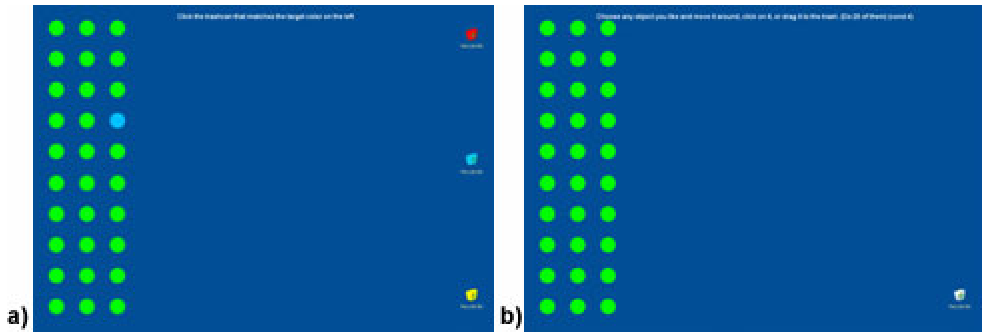

Figure 4.1 Data collection interfaces
a) Conditions 1, 2, and 3 b) Conditions 4 and 5

The subjects participated in five similar GUI interfaces, each with a different haptic condition or task set. The interface was constructed using Java 1.5 and the Touch Sense Developer Toolkit from Immersion Corporation. Two of the conditions have no haptic enhancement and serve as controls for the experiment. For the first three conditions the interface indicates the target to be selected by a change in color of the target. In the second condition the haptic effect is applied to the known target object, while in condition three the prediction algorithm applies the haptic effect simulating an unknown target object. The final two conditions do not direct the subject as to which object they should select. The five conditions consist of:

1. Condition 1: Directed targeting with no haptic effect.
2. Condition 2: Directed targeting, known target, with compound haptic effect.
3. Condition 3: Directed targeting, unknown target, compound haptic effect applied by prediction algorithm.
4. Condition 4: Undirected targeting, unknown target, no haptic effect.
5. Condition 5: Undirected targeting, unknown target, compound haptic effect applied by prediction algorithm.

Each experiment presents the conditions in such a way as to reflect the training involved while still varying some of the conditions to mitigate artifacts introduced by subject learning. Condition 1 serves as the prediction algorithm training condition but can be presented as either the first or second condition. Condition 2 can be presented as either the first or second condition. Condition 3 is always presented as the third condition. Condition 4 and Condition 5 can be presented as either the 4^{th} or 5^{th} condition. The presentation order for either Conditions 1 and 2 or Conditions 4 and 5 is determined randomly between trials.

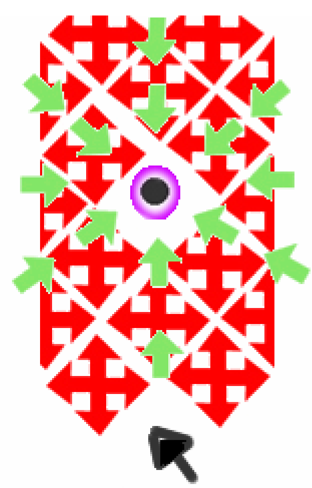

Figure 4.2 Compound Haptic effect

The compound haptic effect is composed of three different individual haptic effects, as seen in Figure 4.2. The spring effect drags the cursor toward the target and is intended to assist the user in navigating to the target and once there to remain on top of that target. The damper effect introduces resistance throughout the environment and is intended to assist the subject in self steadying to reduce spasms and tremors. The ellipse effect creates a boundary around the target which is easy to enter but difficult to leave and is intended to keep the user over the object as the clicking motion progresses. A fourth effect was studied, the funnel, however the added complexity of managing a fourth haptic effect outweighed the possible benefits it may have provided. The strength of each of these effects can be varied from 0, indicating no force, to 10000 indicating maximum force. When applied during Condition 2 all forces are set to maximum and applied to the known target object. For Conditions 3 and 5 the force from each effect is varied according to the phase of the prediction algorithm.

The interface for Conditions 1-3 consists of thirty possible locations for target objects and three possible trashcan icons, each of a different color. Each time a new target is created in the interface it would match one of the randomly chosen trashcan colors. The subject is asked to find the matching trashcan color, click it, and then select the target. A message box at the top of the screen indicates where the subject is in the selection process. Movement time is measured from selection of the trashcan to selection of the target. Subjects are asked to emphasize accuracy over speed [8]. The subject completes four trials of 20 targets each with a different haptic effect for each trial.

The only differences between Conditions 1, 2, and 3 is in how the haptic effects are applied. For Condition 1 there are no haptic effects applied. For Condition 2 the full force of all three haptic effects is applied to the target object. Application of the haptic effects for Condition 3 varied according to the phase of the prediction algorithm and behavior of the subject.

The interface for Conditions 4 and 5 consists of 30 possible locations for target objects at the start of each trial and one trashcan icon. The subject is asked to complete 20 targeting tasks of their choice with the restriction that objects selected on the left of the screen should be moved to the right. The trashcan icon on the lower right of the environment also behaves like a typical trashcan found on a GUI desktop. Icons dragged and dropped on top the trashcan icon disappear from the environment until the next trial. Movement times are recorded from mouse release to mouse click and capture the entire task performed. For Condition 4 there was no haptic effect provided and for Condition 5 the haptic effects were applied via the prediction algorithm.

4.3 Results and conclusions

In order to evaluate the results of this research it is important to understand the three variables influencing them. The first variable to study is the haptic effect and how it affects *MT*, error rates, and smoothness of movement. The second variable is target group dynamics, i.e. how different is the target group from people without disabilities and how different are they from each other. Finally the prediction algorithm is a variable which must be evaluated, how well did it perform and can it be improved. The remainder of this chapter is an evaluation of how each of these variables affects targeting performance in a haptic user interface.

4.3.1 Performance

Since Fitts first described his targeting experiments in the 1950's two measures of performance have been the basis for most evaluation of input devices, movement time and error rate. As the results of the second pilot study confirm, isolation and capture of targeting movements must be done in a highly structured environment. Because Conditions 3 and 4 are not structured in the same way as the other conditions, Conditions 1 (Control), 2 (Haptic), and 3 (Haptic(p)) will be compared to one another and Conditions 4 (Free) and 5 (Free(p)) compared, but no comparison between either Conditions 4 or 5 will be made to Conditions 1, 2, or 3.

Movement time for the Control, Haptic, and Haptic(p) conditions is measured from the time the subject clicks the trashcan until the selection of the color indicated target. Average *MT* is reported for all three conditions in Table 4.1.

Table 4.1 Average movement time (s)

	Control	Haptic	Haptic(P)	Free	Free(p)
Ave MT(s)	6.33	2.48	5.91	4.80	3.14

The average *MT* for the Haptic condition is nearly one third the value of the Control condition, however standard statistical analysis of the data results in no significant difference detected between either of the conditions and the Control condition. To investigate why the significance tests were not able to detect what looked to be a clearly significant difference between movement times, f-tests were conducted for each of the experimental conditions and the Control condition to determine if the variances were the same. When the conditions were compared a significant difference was found between the Haptic condition variances and the Control condition variances ($P(F<=f) = 2.92*10^{-13}$) and a significant difference was found between the Haptic(p) condition variances and the Control condition variances ($P(F<=f) = 0.03$). Given the significant differences between variances it was determined that Log_{10} data transformation [21] would be needed to normalize all the values. After data transformation, significantly lower *MTs* were found for the Haptic condition when compared to the Control (*P(T<=t) = 0.002*), however no significant difference was found between the Haptic(p) and the Control conditions (*P(T<=t) = 0.14*).

The average movement times are reported in Table 4.1 and significance testing between groups was applied. The results of the significance tests found the Haptic condition to result in significantly lower *MTs* than in the control condition. Based on the pilot studies this result was not a surprise, the spring effect, which was part of the compound effect used in the experiment, consistently resulted in lower average *MTs* for individuals. Not only was there a significant improvement but the average is a 60% improvement in average *MT*. The average *MT* for the Haptic(p) condition did not show any significant difference from the control condition, however average *MT* was lower than the control by about half a second. Given the prediction algorithm was an unknown going into the experiment it was not surprising to see only slightly lower average *MTs* for the Haptic(p) condition, and discussion about that will follow later in the document. For the Free and Free(p) conditions there was no significant difference found between them although the Free(p) condition mean *MT* was 1.66s lower than the Free *MT*. The lower *MTs* in the Free(p) condition could be due to training on the prediction algorithm (which will be discussed later) or due simply to the subject allowing it to choose the target.

Errors recorded as mouse clicks not over the target were recorded and averages computed. The results are reported in Table 4.2.

Table 4.2 Average error

	Control	Haptic	Haptic(P)	Free	Free(p)
Ave Error	4.89	2.42	3.75	5.58	3.47

Significance testing of the Haptic condition and the Control condition found significantly fewer errors in the Haptic condition than in the Control (*P(T<=t) = 0.01*), however no significance was found between the Haptic(p) condition and the Control condition (*P(T<=t) = 0.19*).

The average error was computed as the average number of clicks not on the indicated target. For the Haptic condition there were significantly fewer errors per targeting movement than in the Control. Once again this is not a surprising result, the data from the pilot studies showed significantly fewer errors for nearly every haptic effect evaluated. The average errors for the Haptic(p) condition was not found to be significantly lower than the Control, however the mean was 1.4 errors lower than the Control. Given the slightly higher average error than found in the Haptic condition it is possible there was some aspect of the Haptic(p) condition causing the user to err, or possibly the condition was just not as effective at reducing error as the Haptic condition. To determine if the higher error rate is due to prediction a study of errors during correct predictions vs. wrong predictions could be done. If the higher error rate remains in the correctly predicted targets then it is possible effect application could be to blame. The Free(p) condition had significantly fewer errors than the Free condition, however it was almost identical to the error rate from the Haptic(p) condition. This means that for at least some tasks on a desktop the prediction algorithm significantly improved error rate over no prediction.

Peaks in velocity were collected and averaged to study the smoothness of the targeting movements. Velocities higher than 2 pixels/ms were considered to be peaks in velocity. This number was experimentally derived as the average of the highest velocity per movement during the pilot studies. Average velocity peaks are reported in Table 4.3.

Table 4.3 Average Velocity Peaks

	Control	**Haptic**	**Haptic(P)**	**Free**	**Free(p)**
Ave Velocity Peaks	2.80	2.08	5.33	2.07	3.54

Significance testing of the data reveals significantly fewer velocity peaks in the Haptic condition when compared to the Control condition ($P(T<=t) = 0.006$). Significance testing of the Haptic(p) condition compared to the Control condition show significantly fewer velocity peaks associated with the Control condition ($P(T<=t) = 5.29*10^{-07}$).

The average number of peaks per movement from Table 4.3 showed a significantly lower number of peaks in the Haptic condition. Since the compound effect contains the damper, it is not surprising to see a decrease in peaks. During the pilot study it nearly eliminated peaks in movement. What was surprising was the significantly higher number of movement peaks seen in the Haptic(p) condition. Since the damper effect was consistently on to provide pressure to the subject it would be expected the average peaks would be fewer. It is possible the higher number of peaks is due to wrong predictions and the user fighting against the haptic effects that are attempting to hold them in place. This could be determined by looking at the average peak movements during correct prediction compared to those during wrong predictions. There was also a significant increase in average movement peaks in the Free(p) condition, probably from the same phenomenon that caused them in the Haptic(p) condition.

Significance testing between the Free and Free(p) conditions reveals no significant difference between the *MT* ($P(T<=t) = 0.17$), a significant decrease in error rate for the Free(p) condition ($P(T<=t) = 0.002$), and a significant increase in velocity peaks for the Free(p) condition ($P(T<=t) = 2.06*10^{-07}$). From this point forward the Free and Free(p) conditions will only be addressed were relevant, the nature of the data collection for these conditions does not allow for meaningful pairing of the data for direct comparison.

4.3.1.1 Groups and Individuals

Given the mixed results from the significance testing and higher than expected variances, a closer look at individual performance during the experiment seems necessary to determine if and where the Haptic and Haptic(p) conditions were more or less effective.

Using the average *MT* and *ID* values from Pilot Study 3 the average *MT* for the Control condition at average *ID* of 6.02 was computed to be 1.613s. The subjects where then separated based on Control condition average *MT* into two groups, those less than 4 times the expected average (group 1) and those greater than 4 times the expected average (group 2). The average *MTs* for each group under each condition are displayed in Table 4.4.

Table 4.4 Ave *MT* grouped

	Ave MT (s) Grouped by Control Condition Performance	
	Group 1 (Control *MT* < *6.455*)	**Group 2 (Control *MT* > *6.455*)**
Control	3.009	24.063
Haptic	2.511	3.740
Haptic(p)	6.191	18.727

The first significance test compares the two groups within each condition to determine if these groups perform significantly different from each other. Significantly lower *MTs* were found in group 1 when compared to those in group 2 for both the Control (*P(T<=t) = 0.03*) and Haptic(p) (*P(T<=t) = 0.02*) conditions. However no significant difference was found within the Haptic condition between the two groups.

The probability values for each haptic condition comparison to the Control condition separated by group can be found in Table 4.5.

Table 4.5 Within group probabilities

(P(T<=t)	**group 1**	**group 2**
Haptic	0.0003	0.07
Haptic(p)	0.08	0.39

From the data found in Table 4.5 the only significant difference is between the Haptic and Control conditions of group 1. This group displays much lower average *MTs* in the Haptic condition than they do in the Control condition.

In order to investigate the differences between groups the subjects were split into two groups based on average *MT*. A metric was defined based on four times the average expected *MT* for tasks of the same ID, as calculated using the data from Pilot Study 3, the results of this separation are listed in Table 4.4. A significant difference was found between the two groups in the Control and Haptic(p) conditions but not in the Haptic condition. What this means is that even though the groups are significantly different in disability, with the proper haptic effect application those differences can be overcome. The only significance within the groups was found in the group 1 Haptic condition. Given the extreme difference between the group 2 Control *MT* and Haptic *MT*, the group 2 control was 650% higher than the group 2 haptic, variability must have spoiled the test. It even appears there is a significant difference in group 2 *MT* between the Control and Haptic(p) condition, 24.063s vs. 18.727s respectively. The between and within group data shows the power of haptics by equalizing two significantly different groups. Even if the Haptic(p) condition was significantly better than the Control, 18s is a very high average *MT* and probably too high to make mouse use reasonable for this group. However, looking at the Haptic condition it is clear that if the effects could be fully realized, mouse use for group 2 would be attainable.

Table 4.6 compares each individual's performance in the Haptic and Haptic(p) conditions to their performance in the Control condition.

Table 4.6 Individual probabilities

Ave MT	*Subject 1*	*Subject 2*	*Subject 3*	*Subject 4*	*Subject 5*
Control	5244.97	4631.67	2777.03	1977.35	1627.25
Haptic	2735.54	3423.57	1439.96	1897.50	1155.59
Haptic(p)	5324.10	7363.87	2506.75	2048.61	2396.93
P(T<=t)					
Haptic	**0.011943**	**0.009556**	**0.000009**	0.372888	**0.001194**
Haptic(p)	0.482472	**0.030918**	0.178501	0.394143	**0.029846**

Ave MT	*Subject 6*	*Subject 7*	*Subject 8*	*Subject 9*	*Subject 10*
Control	2477.31	2819.51	4041.84	3750.01	2977.39
Haptic	2194.77	2805.14	2742.95	1961.31	2031.17
Haptic(p)	2906.93	2281.85	5177.77	2516.79	2784.89
P(T<=t)					
Haptic	0.138970	0.489433	**0.018221**	**0.011204**	**0.018849**
Haptic(p)	0.123858	**0.040513**	0.090453	**0.055049**	0.343390

Ave MT	*Subject 11*	*Subject 12*	*Subject 13*	*Subject 14*	*Subject 15*
Control	2313.87	2580.32	2982.43	2923.63	2231.23
Haptic	1382.96	1493.01	3200.31	2175.70	1369.75
Haptic(p)	2954.69	2180.04	3389.88	2597.45	2889.44
P(T<=t)					
Haptic	**0.000008**	**0.000047**	0.334867	**0.044511**	**0.001330**
Haptic(p)	**0.021266**	0.084381	0.115528	0.205632	0.102007

Ave MT	*Subject 16*	*Subject 17*	*Subject 18*	*Subject 19*	
Control	2794.79	10061.76	50924.08	11203.99	
Haptic	3929.15	6804.01	2444.48	1970.89	
Haptic(p)	6709.98	14132.99	31842.40	10205.77	
P(T<=t)					
Haptic	0.206948	**0.011308**	**0.000053**	**0.0000002**	
Haptic(p)	**0.026858**	0.095883	**0.038334**	0.312881	

In Table 4.6 bold values represent significant decreases in targeting time for the Haptic or Haptic(p) condition while bold and underlined values represent significant increases in targeting time. Fourteen of the nineteen subjects experienced significant decreases in *MT* in the Haptic condition with no significant increases in *MT* observed. Three of nineteen subjects experienced significant decreases in *MT* in the Haptic(p) condition while four of the nineteen subjects experienced significant increases in *MT* in the Haptic(p) condition.

The data for each individual per condition is listed in Table 4.6. This data was separated to see what the effect on each individual was for each condition. What was found was found was that fourteen subjects had significantly lower *MTs* from the Haptic condition, two had significantly lower *MTs* in the Haptic(p) condition, and four had significantly higher *MTs* in the Haptic(p) condition. What this means is that almost everyone in the study benefited from the Haptic condition, and at least fifteen individuals saw significant decreases in *MT* or no effect at all in the Haptic(p) condition. Given there is room for improvement in the prediction algorithm (as will be talked about shortly) it is encouraging to see these numbers.

4.3.1.2 Fitts' Law Model

In order to better understand the relationships of *ID* and *MT* for the target group the average *MT* data for each distance is used to calculate the slope, intercept, and correlation coefficients used to calculate *IP* and *IC*. Figure 4.3 shows the plot of *MT* to *ID*.

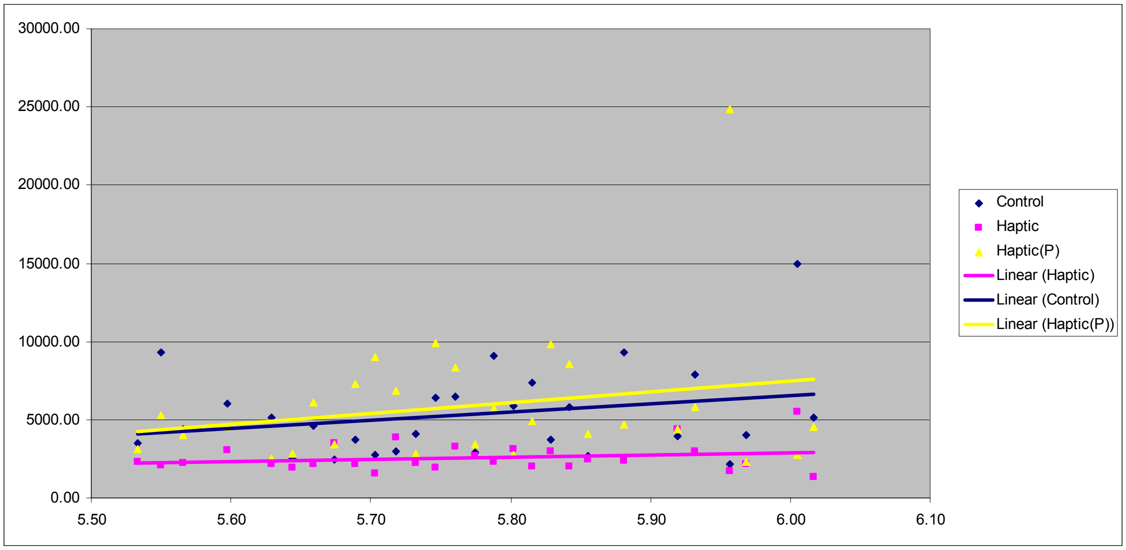

Figure 4.3 *MT* vs. *ID* plot

There are 28 different values of *ID* representing distances ranging from 880 pixels to 1230 pixels. The plot of the untransformed average *MT* data illustrates the variance issues that have plagued this data, in addition as the *ID* increases so does the variability of the data. Slope, intercept, and correlation coefficients are reported in Table 4.7.

Table 4.7 Slope (b), intercept (a), and correlation coefficient (r)

	Control	**Haptic**	**Haptic(P)**
b	5.213	1.357	6.862
a	-24.759	-5.245	-33.722
r	0.25	0.21	0.22

With intercept values ranging from -5.245 seconds to -33.722 seconds the variability of the data has resulted in Fitts' Law coefficients that do not appear realistic. In an attempt to fit this data into a Fitts' Law model the Fitts' coefficients were calculated again using the transformed data and results are reported in Table 4.8.

Table 4.8 Fitts' coefficients transformed data

	Control	Haptic	Haptic(P)
b	0.0192	0.0130	0.0168
a	0.108	0.550	0.250
r	0.19	0.12	0.13

The result from the transformed *MT* data is reasonable however the intercepts for the Haptic and Haptic(p) conditions are still well above the expected value of 0 and the correlation coefficients indicate no linear relationship ($r<.90$). If these results are correct, which will be talked about shortly, there is no linear relationship between task difficulty and *MT* as described by Fitts' for the target group.

The data was put into Fitts' Law models and evaluated for correlation. The result was flat slope, unreasonable intercepts, and low correlation. However, I do not believe this means there is no Fitts' relationship in this data; the number of *ID* points was so high (28) that there were probably not enough movements at each *ID* to create good averages. This resulted in the skewed charts and data. One possible solution would be to aggregate the *ID* values to create better averages and then analyze for correlation.

4.3.2 Prediction Performance

In this section the prediction algorithm is evaluated as well as each subject's performance under the prediction algorithm. The raw prediction data per individual is reported in Table 4.9. Table 4.9 contains the following breakdown of the prediction numbers:

- Ave Good – gives the average *MT* for good predictions

- Ave Bad – gives the average *MT* for bad predictions
- P(T<=t) Good – probability that there is a difference in *MT* between a good prediction and the Control condition
- P(T<=t) Bad – probability that there is a difference in *MT* between a bad prediction and the Control condition
- Prediction % - gives the percentage of correct predictions for this subject

Table 4.9 Prediction numbers

	Subject 1	*Subject 2*	*Subject 3*	*Subject 4*	*Subject 5*
Control	5.245	4.632	2.777	1.977	1.627
Ave Good	2.015	2.862	2.232	1.788	1.418
Ave Bad	5.529	7.249	3.130	2.115	2.585
P(T<=t) Good	**0.001288**	**0.000107**	**0.012164**	0.280458	0.116857
P(T<=t) Bad	0.436675	**0.020857**	0.249681	0.306672	**0.021178**
Prediction %	15.00%	15.00%	45.00%	25.00%	20.00%

	Subject 6	*Subject 7*	*Subject 8*	*Subject 9*	*Subject 10*
Control	2.477	2.820	4.042	3.750	2.977
Ave Good	2.117	2.030	2.076	2.079	1.746
Ave Bad	3.463	2.387	4.348	2.854	3.009
P(T<=t) Good	0.125463	**0.011310**	0.164017	**0.016357**	**0.004839**
P(T<=t) Bad	**0.029390**	0.091404	0.210306	0.128075	0.472756
Prediction %	40.00%	25.00%	5.00%	40.00%	15.00%

	Subject 11	*Subject 12*	*Subject 13*	*Subject 14*	*Subject 15*
Control	2.314	2.580	2.982	2.924	2.231
Ave Good	1.371	1.724	2.862	1.746	1.703
Ave Bad	3.243	2.199	3.842	2.748	3.579
P(T<=t) Good	**0.000725**	**0.001062**	0.373939	**0.002275**	**0.011378**
P(T<=t) Bad	**0.001290**	0.482479	**0.021252**	0.385654	**0.025523**
Prediction %	10.00%	45.00%	40.00%	15.00%	35.00%

	Subject 16	*Subject 17*	*Subject 18*	*Subject 19*	
Control	2.795	10.062	50.924	11.204	
Ave Good	3.491		5.686	6.820	
Ave Bad	8.470	13.494	31.769	9.217	
P(T<=t) Good	0.101189	0.237139	**0.000098**	**0.001114**	
P(T<=t) Bad	**0.020815**	0.104412	0.070809	0.347416	
Prediction %	35.00%	0.00%	10.00%	15.00%	

The rate of correctly predicted targets is 23%, the average *MT* for correct predictions is 2.532s, and the average *MT* for wrong predictions is 4.238s. Significance testing of the Control condition and the average *MT* of predictions shows a significant decrease in MT for correct predictions ($P(T<=t) = 0.0002$) and a significant increase in *MT* for wrong predictions ($P(T<=t) = 0.04$).

The data is separated by subject and compares individual performance in the Control condition to good and bad prediction in the Haptic(p) condition. Significantly lower average *MTs* than the Control are in bold and significantly higher average *MTs* are in bold and underlined. Twelve of nineteen subjects have significantly lower *MTs* during a good prediction than in the Control condition, while seven of nineteen subjects have significantly higher *MTs* from bad predictions when compared to the Control.

Table 4.9 contains the prediction data listing the raw prediction percentage, the good prediction average time and the bad prediction average time. What this data can tell us is what the possible outcomes would be if we are able to increase the accuracy of the prediction algorithm. Given the prediction rate of 23%, the performance of this prediction interface could be improved significantly if the number of incorrect predictions could be lowered. The average *MT* from good prediction was found to be significantly lower than the Control condition *MTs*. That means it is possible to increase performance to a significant level if prediction rate could be raised sufficiently. It was also found that bad predictions had significantly higher *MTs* than the Control. So increased prediction rates should again decrease the *MT*. It was also not surprising to find that for every individual with a significant difference in *MT* from bad predictions it was for increases and for every individual with significant differences in good prediction *MT* they were for decreases in *MT*. One other piece of data to look at in Table 4.9 is that the prediction rate depended on the individual. Individual prediction percentages ranged from 0-45% with all the better predictions occurring with individuals of low average *MT* (~3s) while those with the largest Control condition *MTs* were the hardest to predict, probably due to the high variability of their movements.

To further understand the performance of the prediction algorithm, average *MT* for the first 10 targeting moves of the Haptic(p) condition was compared to the average *MT* for the last 10 targeting moves of the Haptic(p) condition. This was to determine if there was an initial distracting effect of the changing haptic effects encountered during the Haptic(p) condition due to changing prediction conditions, that was adjusted to by individuals over time. What was found were significantly lower ($P(T<=t) = 0.0004$) *MTs* in the second half of the Haptic(p) condition. Significance testing of the second 10 *MT* averages to the Control condition did not show any difference between the groups ($P(T<=t) = 0.36$) even though the Haptic(p) mean (5.2s) was 1.06s lower than the Control mean (6.3s). Nevertheless, this suggests that the users adjusted to the prediction algorithm and learned to ignore its distracting characteristics and to utilize it to their advantage. There is no indication, however, as to how much training with the prediction algorithm could improve *MTs*.

Evaluation of the prediction algorithm would not be complete without looking at the area around the target to see if the prediction algorithm got the subject within the vicinity of the target (if not on the target). This can also be interpreted as asking how much the prediction accuracy would have improved had the targets been placed further apart. Table 4.10 lists the prediction times and percentages by prediction proximity to the target.

Table 4.10 Prediction zones

	Subject 1	*Subject 2*	*Subject 3*	*Subject 4*	*Subject 5*
Pred %	15.00%	15.00%	45.00%	25.00%	20.00%
Pred MT 1st zone	7657	6451	2526	2069	3058
Pred % 1st zone	35.00%	45.00%	60.00%	55.00%	45.00%
1st P(T<=t)	0.273010	0.122990	0.209578	0.366284	**0.034783**
Pred MT 2nd zone	5670	5746	2604	1961	2776
Pred % 2nd zone	65.00%	60.00%	65.00%	85.00%	65.00%
2nd P(T<=t)	0.424760	0.179576	0.286796	0.473602	**0.022609**

	Subject 6	*Subject 7*	*Subject 8*	*Subject 9*	*Subject 10*
Pred %	40.00%	25.00%	5.00%	40.00%	15.00%
Pred MT 1st zone	2517	2547	5338	2394	2751
Pred % 1st zone	60.00%	50.00%	25.00%	60.00%	40.00%
1st P(T<=t)	0.460106	0.217994	0.269710	**0.041985**	0.366519
Pred MT 2nd zone	2664	2307	4754	2390	2769
Pred % 2nd zone	95.00%	70.00%	40.00%	80.00%	55.00%
2nd P(T<=t)	0.117109	**0.057998**	0.295348	**0.038574**	0.353871

	Subject 11	*Subject 12*	*Subject 13*	*Subject 14*	*Subject 15*
Pred %	10.00%	45.00%	40.00%	15.00%	35.00%
Pred MT 1st zone	2417	1842	3315	2439	2933
Pred % 1st zone	15.00%	80.00%	65.00%	65.00%	65.00%
1st P(T<=t)	0.465381	0.062843	0.199001	0.125876	0.138003
Pred MT 2nd zone	2699	2193	3342	2523	2432
Pred % 2nd zone	30.00%	85.00%	80.00%	85.00%	95.00%
2nd P(T<=t)	0.242465	0.090859	0.149555	0.160010	0.173753

	Subject 16	*Subject 17*	*Subject 18*	*Subject 19*	*Ave*
Pred %	35.00%	0.00%	10.00%	15.00%	23.68%
Pred MT 1st zone	3472	12999	21741	7414	5046
Pred % 1st zone	60.00%	15.00%	40.00%	30.00%	47.89%
1st P(T<=t)	0.080936	0.370279	0.083407	**0.002636**	
Pred MT 2nd zone	6110	11507	30934	7802	5431
Pred % 2nd zone	80.00%	30.00%	45.00%	35.00%	65.53%
2nd P(T<=t)	**0.054964**	0.363071	**0.052453**	**0.006472**	

Table 4.10 shows the prediction percentages for three size target areas of three, the associated average *MT*, and the significant difference between the prediction average *MT* and the Control condition average *MT*. Probabilities in bold represent predictions with significantly lower *MT*. There are no significantly higher average *MTs* for these three zones of prediction.

The three zones of prediction include the one over the target, one within at least one object of the target (1^{st} zone), and one within at least two objects of the target (2^{nd} zone). For predictions within one object of the target (47%) there are no significantly higher *MTs* for any subject, however only three subjects recorded significantly lower *MTs* when compared to the Control. For predictions within two objects of the target (65%) there remain no significantly higher *MTs* for any subject and there are six subjects experiencing significantly lower *MTs* when compared to the Control.

While a 23% prediction rate is not ideal, it is important to understand the accuracy of the prediction in relation to the environment. To study this, the predictions were grouped by those within one object of the actual target and then within 2 objects of the target. The most striking information from Table 4.10 is the fact that none of the individuals had significantly higher *MTs* if the target was predicted within two objects of the target and three individuals had significantly lower *MTs* than the Control. With 65% accuracy of at least doing no harm it has given a much larger area to aim for with the prediction. It seems as long as all the predictions can be made within two objects of the target no significant increases in *MT* will be present. One strange data point was that the predictions within two objects had more significantly lower *MTs* for individuals than the predictions that miss by one object. This is probably due to the prediction algorithm over the target attempting to hold the user in place. When they pull away from the wrong prediction a slingshot effect would probably cause them to shoot past the closer objects onto the next. If the prediction algorithm over the targets could be tweaked to cause less slingshot the within one object prediction times may greatly improve.

Finally, Table 4.11 lists the prediction percentages by target.

Table 4.11 Prediction percentages per object

Object	Percentage	Object	Percentage	Object	Percentage	Average
0	0.00%	**10**	20.00%	**20**	45.45%	21.82%
1	16.67%	**11**	25.00%	**21**	14.29%	18.65%
2	7.69%	**12**	15.38%	**22**	10.00%	11.03%
3	11.11%	**13**	7.69%	**23**	27.27%	15.36%
4	25.00%	**14**	16.67%	**24**	38.89%	26.85%
5	9.09%	**15**	0.00%	**25**	66.67%	25.25%
6	26.67%	**16**	27.27%	**26**	46.67%	33.54%
7	18.18%	**17**	0.00%	**27**	50.00%	22.73%
8	7.14%	**18**	23.08%	**28**	38.46%	22.89%
9	18.18%	**19**	22.22%	**29**	90.00%	43.47%
Average	13.97%		15.73%		42.77%	

The front column of objects has a much higher prediction percentage than the other two columns. There also appears to be a dip in predictability in the upper left corner of the cluster of objects. A scatter plot is included to help illustrate the differences in prediction accuracy due to location in the cluster of objects.

Prediction percentages per target were categorized in Table 4.11. The reason this was done was to see if there was something about the environment that affected prediction percentage. It is clear the front row of the cluster was predicted at a much higher rate than the back or middle rows. What caused this may have been an artifact of

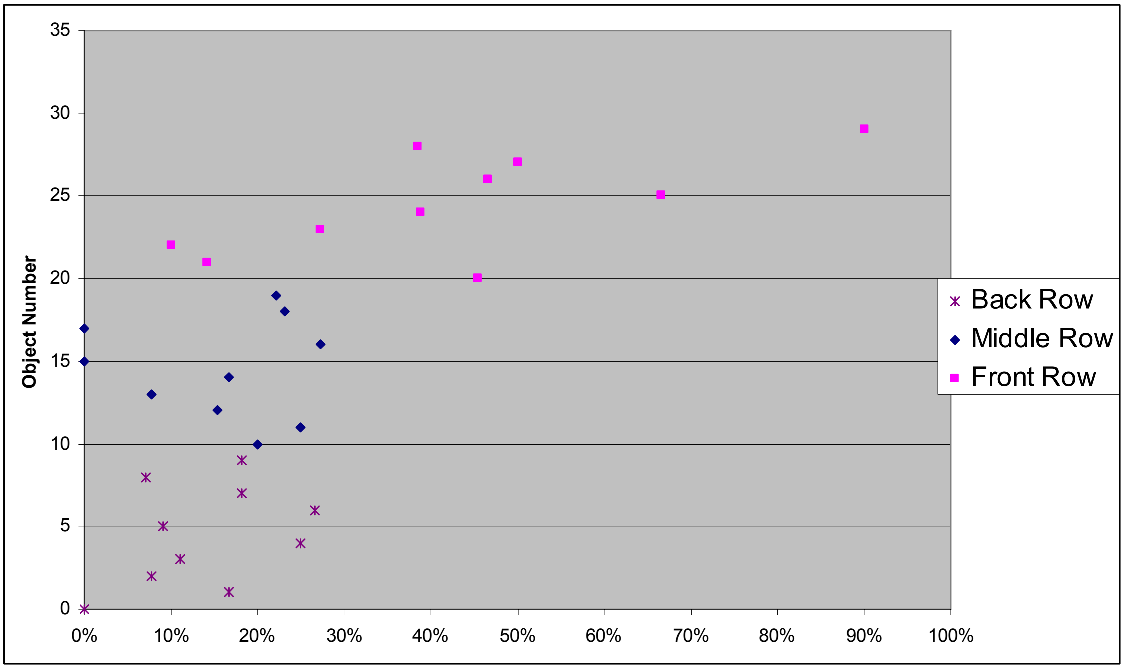

Figure 4.4 Prediction percentages per object

training of the prediction algorithm on the Control condition while the haptic effects were influencing movement in the prediction condition. If the application of the haptic effect changed the profile of the user in such a way that there was always undershoot of the prediction, the first row would end up being favored over the other two more distant rows. In the end it is hard to tell what caused this phenomenon, but it is definitely something to consider when revising the algorithm.

4.3.2.1 Murata comparison

To better understand how the prediction algorithm performed, a comparison to the Murata algorithm was performed. Predictions were performed on both the Control and Haptic(p) conditions of the disabled group data collected during the final experiment. Unlike in Murata's original experiment, the prediction is made here after the first 50ms of the targeting move to compare predictions over the same set of data as the results reported for the prediction algorithm used for this research.

The first data to have the Murata algorithm applied to it was the Control condition of the final experiment with the disabled individuals. The results where collected for correct predictions, predictions within one object, and predictions within two objects. What was found was 6% correct target predictions, 36% within one of the target, and 60% within two of the target. The very low correct prediction percentage is probably due to targets on the two more distant columns being shielded by the closest column of objects. The much higher within one and within two prediction percentages would seem to support the idea of the first column shielding the target from prediction.

The data from the Haptic(p) condition of the final experiment with the disabled individuals had the Murata algorithm applied to it. This data was collected to study how vector based prediction is affected by the application of haptic effects. The results were 4% prediction on the target, 28% predicted within one of the target, and 49% predicted within two of the target.

Given the much higher target prediction accuracy (23%) of the prediction algorithm developed in this research but about equal within one (47%) and within two (65%) accuracies it is reasonable to believe the algorithm used for this research is more effective at identifying targets within the cluster than a simple vector based algorithm. The within one and within two data supports the ability of the algorithm developed here to better predict targets within the cluster since the two algorithms perform about the same when considering the two zones. Meaning both algorithms are equally effective at getting the user to the area, just the one developed here is better at picking the correct one out of that area.

The comparison of the Murata algorithm to the one developed here has identified some possible avenues to increase accuracy or at least efficiency of the algorithm described by this research. The near equal within one and within two data for the experimental prediction algorithm when compared to the Murata algorithm would suggest it may not be necessary to compute the distance of the movement when predicting an area. There are two components modeling vector angles in this research, one which is the difference in angle from the start location to each target and the other is a difference in angles between subsequent vectors. Since both are components of the Murata algorithm and they have approximately the same success rate in predicting within one and within two it may be possible to remove the distance portion of the probability model during area predictions.

It seems given the per-target prediction percentages detailed in Table 4.11 there was favoritism for the closest row of targets, something which should have been avoidable using the distance model. However, once again the velocity model built during the control condition may have become disjoint from the movement data once haptic effects were applied. If there was a fundamental shift toward slower movements, as might occur if the damper effect was applied, the model would favor closer targets resulting in regular undershoots in prediction distance. As a solution to this problem the algorithm could be trained on haptic conditions and those models used once haptic effects are being applied in the environment.

4.3.2.2 Credibility

Because the prediction algorithm described in this research uses probability models, it not only calculates a prediction but also provides an estimate of the reliability, or credibility of the prediction. In particular, using Bayes law, the prediction value from Equation 3.2 for all objects, it is possible to determine the likelihood with which the predicted target is the correct target under the assumption that all objects are equally likely and that the user is actually targeting one of the objects:

$$P(T|p_{cur}) = \frac{P_T(p_{cur})P(T)}{P(p_{cur})} = \frac{P_T(p_{cur})}{\sum_t P_t(p_{cur})} \tag{4.1}$$

This value can in turn be used to make the decision when to apply haptic effects. To evaluate the reliability of this predicted accuracy value, its value was computed for correct, within one, and within two predictions. Figure 4.5 contains the experimental relation between this credibility (predicted accuracy) and the probability of correct predictions for the given credibility values. To provide more stable numbers, the data is presented as a histogram over predicted likelihood intervals of width 0.1.

Figure 4.5 contains the credibility for correct predictions.

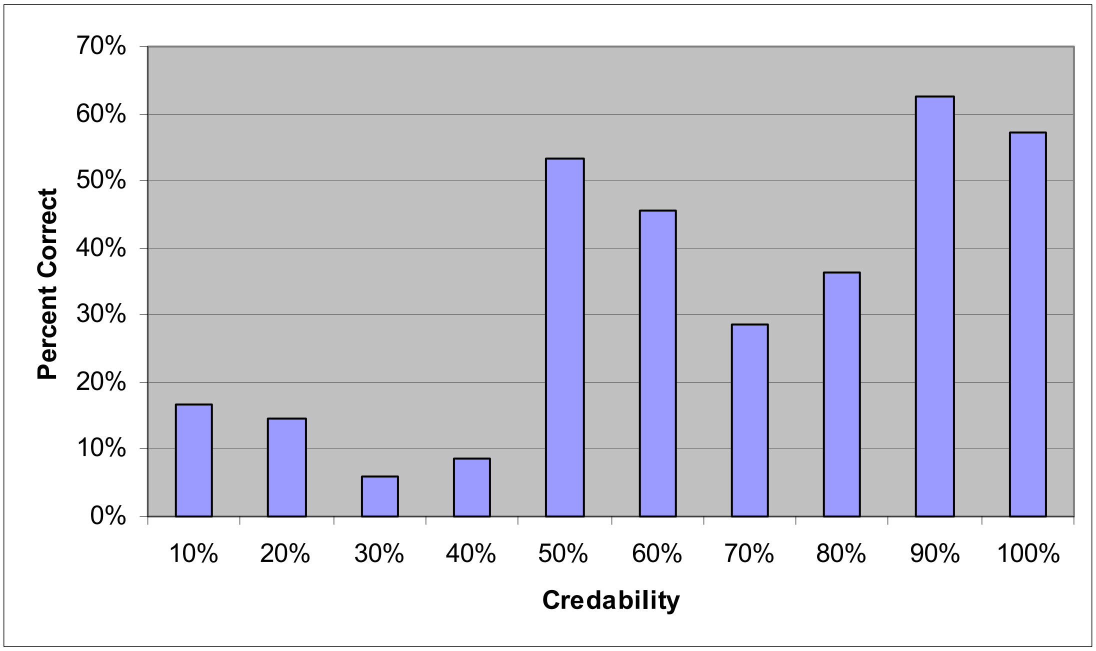

Figure 4.5 Correct prediction accuracy vs. credibility

From Figure 4.5 it is clear making a decision about when to apply haptic effects based on the predicted target could be beneficial. At about 50% credibility the prediction accuracy greatly increases. However, since 77% of the predictions were made below 50% credibility that would mean throwing away most of the predictions, both good and bad. As a result, a simple decision to not make predictions when the predicted credibility of the prediction falls below 50% would not be beneficial but rather a more complex criterion would be needed that also takes into account within one and within two prediction accuracies since these did not show detrimental effects on *MT.*

The credibilities for objects within one of the target are displayed in Figure 4.6.

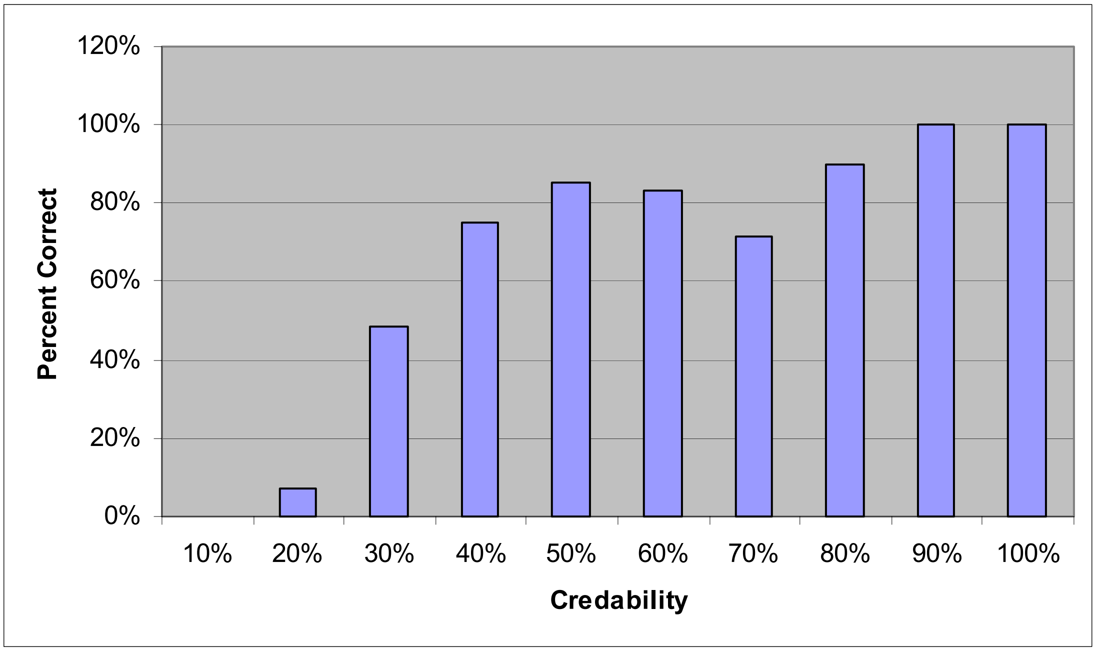

Figure 4.6 Prediction accuracy vs. credibility for within one object of target

The predicted credibilities for within one show a stronger effect than the ones for correct predictions. There is a definite shift correlating credibility to correct predictions. With the relatively high correct prediction rate for 40% credibility, the decision threshold could be lowered allowing for more predictions to be made. If the threshold was 40% credibility, 36% of the time predictions would be made at 83% accuracy (within one of the target).

The credibilities for the within two data is presented in Figure 4.7.

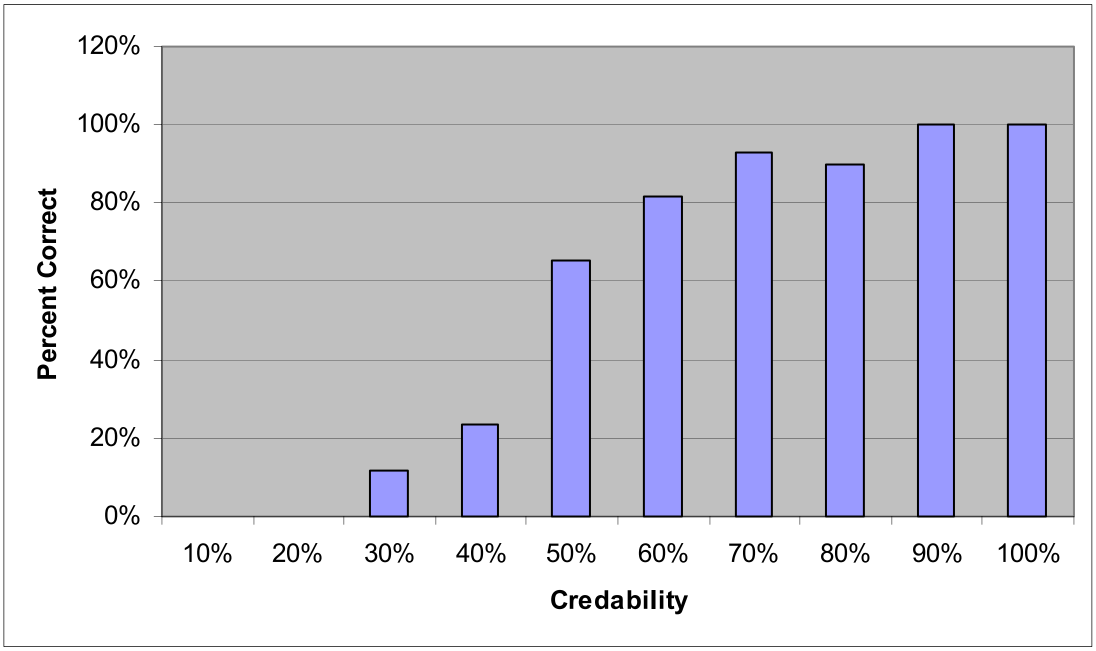

Figure 4.7 Prediction accuracy vs. credibility for within two objects of target

The credibilities within two show very few correct predictions below 50% credibility. If the threshold for making predictions was set at 50% credibility then 81% of predictions would be made at 88% accuracy. The results of these last two studies are very encouraging.

While the target prediction rate remains relatively low (23%) for this prediction algorithm, as noted earlier, only predictions not within two objects of the target resulted in significantly higher *MTs* for any individual. Given the data presented in this section here it is clear that if no haptic effects were applied when the predicted credibility for the target being within two of the actual target was lower than 50% almost all incorrect predictions for the within two target region could be eliminated. This would remove most negative results of the application of haptic effects during wrong predictions, which could greatly improve the performance of the system.

The number of predictions made with low credibility for the correct prediction and within one prediction data makes the use of those credibilities, as a sole decision criterion, to reduce the effects of bad predictions less valuable. However, what that data does reveal is a lower than expected correlation between the current movement and the prediction models. This supports my belief that haptic effect applied during the prediction conditions caused a significant shift in movement profile. Since the within two credibilities are very effective at segregating wrong from correct predictions and only discard 19% of the predictions it is possible to use these credibilities to reduce the number of detrimental predictions. The within two credibilities are more effective in increasing performance because it throws away far fewer correct predictions than the within one credibilities and allows predictions to be made at a much higher percentage than the within one or on target credibilities.

4.4 Summary

With the data collected from 4 pilot studies, one of which contained target group members, as a guide an effective tool for evaluating performance in a haptic environment was created. This tool was administered to twenty-three individuals displaying varying levels of motor disability, nineteen of which completed the experiment. The results of the final experiment were mixed, mainly due to variability differences between and within subjects. Evaluation of the prediction algorithm shows many positive indications that accuracy can be increased and the negative impact of wrong predictions reduced when attempting to apply haptic effects in an environment where the target object is not a know quantity. A deeper understanding of the target group should allow modifications to the methodology and algorithms used during this research to create an environment that closely resembles the ideal haptic performance increases, seen in the Haptic condition, in a real desktop environment.

CHAPTER 5

CONCLUSION

This dissertation examines the state of haptic devices and their availability, the need for careful effect design, and the possibilities for a haptic mouse. It also details the characteristics of individuals with Cerebral Palsy and describes their accessibility needs. When talking about computer science it may be tempting for the reader to think, “What is a detailed description of Cerebral Palsy doing in a Computer Science dissertation?”, and honestly early drafts of this document did not contain that section. However, by the time the second round of data collection with the target group was completed it was clear how uniquely each disability manifests itself within the individual. But for those who still aren’t convinced, let the computer science begin. The document describes the Wingman™ mouse and gives insight into the art of haptic effect design and presents a methodology for the creation of a haptic interface and collection of targeting data.

This document also presents necessary background information to understand why certain decisions were made in interface and prediction algorithm design. Discussion of Fitts’ Law is essential in any simple targeting task experiment as it has been the basis of most targeting performance evaluation with the mouse since it was first used with a mouse in the 1970’s. Understanding of Fitts’ Law will help the reader understand why certain interface and task decisions were made. Fitts’ Law influenced a number of interface decisions, the first of which was round targets. Round targets were used to give uniform amplitude and tolerance to the target when computing Fitts' Law coefficients. In addition since Fitts' Law does not make any assertion that direction of movement affects movement time (*MT*) or error rate there was no concern in using an interface where the targets were all located on the same side, like most uncluttered GUI desktops. Finally Fitts' Law was instrumental in the decision to use a color system to ensure the subject had located the target prior to beginning the task in order to remove any timing artifacts introduced due to difficult locating the target. Although little of the prediction algorithms that were discussed played a major roll in the algorithm designed for this research, the principles of each were used to shape aspects of it. Both the decision to use a series of readings to determine direction and a target based approach once inside the cluster were influenced by the research discussed in Chapter 2.

The prediction algorithm design attempts to take into account the differences between individual disability and at the same time provide a universal approach to over target behavior. At a distance the prediction algorithm uses training from the non-haptic Control condition to create probabilities at each distance the mouse travels. Training of the algorithm was chosen over a more general approach because it was believed each individual of the target group would display different movement profiles. The decision to switch algorithms once within a certain distance of an object was made because, much like Oakley et al claim [20], at some point bad predictions would have to be handled. By switching to and algorithm focused on behavior over the target effort was able to be focused on the decision to hold a user in place based on a smaller number of readings. In the end the algorithm could have used a period of adjustment with the target group which will be discussed later.

A series of pilot studies were performed for guidance in designing haptic effects, evaluate data collection methods, collect cursor traces, and evaluate the target group. The first three pilot studies were used to build and refine the experimental interface. Data collected during the first three pilot studies were from non-disabled individuals in a single target environment. These three pilot studies resulted in a number of interface refinements, effect changes, and methodology evaluation. The final pilot study was performed with five target group individuals and contained a simple prediction algorithm in a simulated multi-haptic target environment. The movement time, cursor traces, and error rates of the target group individuals were compared to the times of the non-disabled subjects. The results of those comparisons indicated the target group moved much slower than a non-disabled group but the movement trajectories were basically the same. The target group also displayed relatively high error rates due to spasms experienced when attempting to click on the target, these spasms were noted in the cursor traces and motivation for a strong haptic effect to help the subject remain over the target during clicking.

The final experiment consisted of five conditions, three very controlled conditions to capture Fitts' style *MTs*, and two conditions which allowed the subject to move freely through the environment. In hindsight the last two conditions could have been more structured in the task that was performed, which would have allowed for more analysis of the differences between the conditions, but the motivation was to move away from the heavily structured tasks in the previous three conditions. It may have been beneficial to evaluate the haptic effects individually however there was concern that if the experiment took too long fatigue would become a factor. The final experimental interface looked and behaved somewhat differently from what was originally expected, however confidence was high that it would be capable of capturing the affects of haptics and prediction on the target group. During administration of the experiment only one major deficiency was apparent and that was the trashcan icons. There was no haptic enhancement of those icons and it would have made the experiment much less frustrating to the participants had they been enhanced. The length of the experiment appeared to be right at the limit of attention span for people performing repetitive pointing tasks as they became fidgety toward the end. The experimental interface performed beyond expectations, the subjects were entertained by the changing colors and even tried drawing pictures with the targets in the last two free movement conditions.

The data collected was of several types, movement time, error rate, movement peaks, and predicted target. Performance evaluation for this research is based solely on subjective data collected from the interface. Movement time and error rate are the most important factors to take into account when evaluating performance in this system, the peaks in movement and prediction rate data are really measures of less consequence to performance evaluation and mainly used to evaluate the *MT* and error rate data. The data analysis turned out to be more extensive because extremely high variances between individuals, within conditions, and between conditions existed. A common method used to assist in the evaluation of data with high variances is to use transformations. Of the common data transformations the best treatment for this data was a $\log_{10}$ conversion.

Even though the statistical analysis of the data collected for this experiment was difficult there were some significant performance increases due to haptic effects displayed for most subjects. Even the data that did not show significance often showed improved average performance over the no effect condition. In addition to the performance increases, a wealth of data about the target group was gathered and a new prediction algorithm was developed. The future of this research is promising and should be the first step in developing a complete haptic desktop interface for the physically disabled.

5.1 Future Directions

One of the main issues I found during this research was interaction of the target group with the mouse design. Often the individuals would have trouble griping the mouse is such a way that clicking or clicking and dragging were difficult. While the basic design of the mouse remains desirable the placement of the buttons and the shape of the body could be more accessible. In addition the design of the haptic mouse could benefit from stronger haptic effects and since it is fixed to a pad an adjustable mouse body so that when the user would need to approach the mouse from different directions, due to wheel chair or other assistive device, they could easily position the mouse in a comfortable position.

The prediction algorithm could use adjustment. There is a lot of room for improvement but given the data collected from this experiment it should be possible to better design the algorithm to result in higher prediction rates and less adverse impact from wrong predictions. In particular, given the data evaluated here, improved training conditions as well as the addition of a decision criterion based on predicted credibility values of the predictions appear very promising and capable of significantly improving the performance of the haptic environment in the predictive condition.

This research has explored one area of desktop interaction. There still remains at a minimum a study with menus that must be undertaken to develop a complete desktop solution. Since menus are considered tunnels and behave a little differently than desktop targeting they will probably require a different set of haptic effects and prediction algorithms.

Finally, research conducted with the disabled individuals has proven very difficult. Not only does the disability result in highly variable individual performance but the need for attendants and lack of public meeting locations makes the data collection process nearly impossible. Without some funding to assist with either providing transportation to or a common experimental lab near an area the group is required to visit, repeated data collection from a significant number of individuals will be difficult to attain.

APPENDIX A

RAW AND TRANSFORMED DATA

Distance, ID, average MT, IP

Dist		ID	Control	Haptic	Haptic(P)	Control-IP	Haptic-IP	Haptic(P)-IP
880	46.32	5.53	3522	2344	3142	1.57	2.36	1.76
890	46.84	5.55	9318	2095	5311	0.60	2.65	1.90
900	47.37	5.57	4368	2265	3999	1.27	2.46	1.39
920	48.42	5.60	6000	3042	4531	0.93	1.84	1.24
940	49.47	5.63	5121	2155	2511	1.10	2.61	2.24
950	50.00	5.64	2510	1948	2850	2.25	2.90	1.98
960	50.53	5.66	4643	2176	6135	1.22	2.60	1.11
970	51.05	5.67	2441	3463	3429	2.32	1.64	1.65
980	51.58	5.69	3690	2149	7314	1.54	2.65	1.27
990	52.11	5.70	2737	1599	9019	2.08	3.57	1.43
1000	52.63	5.72	2954	3853	6862	1.94	1.48	1.25
1010	53.16	5.73	4094	2230	2843	1.40	2.57	2.02
1020	53.68	5.75	6377	1942	9918	0.90	2.96	0.72
1030	54.21	5.76	6478	3241	8364	0.89	1.78	1.21
1040	54.74	5.77	2891	2708	3447	2.00	2.13	1.68
1050	55.26	5.79	9098	2276	5721	0.64	2.54	1.18
1060	55.79	5.80	5911	3097	2730	0.98	1.87	2.13
1070	56.32	5.82	7365	2007	4921	0.79	2.90	1.18
1080	56.84	5.83	3694	2977	9791	1.58	1.96	1.14
1090	57.37	5.84	5781	1984	8576	1.01	2.94	2.16
1100	57.89	5.86	2700	2493	4059	2.17	2.35	1.44
1120	58.95	5.88	9335	2371	4675	0.63	2.48	1.26
1150	60.53	5.92	3981	4363	4363	1.49	1.36	1.36
1160	61.05	5.93	7884	2962	5827	0.75	2.00	1.66
1180	62.11	5.96	2166	1712	24846	2.75	3.48	1.38
1190	62.63	5.97	4022	2180	2277	1.48	2.74	2.62
1220	64.21	6.00	14978	5480	2735	0.40	1.10	2.20
1230	64.74	6.02	5114	1363	4524	1.18	4.41	1.33

Transformed MT values

Control	Haptic	Haptic(P)
3.5467598	3.3698804	3.49717955
3.9693353	3.3211654	3.72518578
3.6403281	3.3551364	3.60199595
3.7781438	3.4831046	3.65623076
3.709324	3.3334756	3.3997772
3.3997456	3.2896695	3.45484833
3.6667914	3.3377014	3.78784125
3.3875207	3.5393987	3.53513094
3.567026	3.3322372	3.86418088
3.4371985	3.2038773	3.95517726
3.4704528	3.5857566	3.83648216
3.6121614	3.3483932	3.45371397
3.8045977	3.2882693	3.99642566
3.8114361	3.5106705	3.92240255
3.4609771	3.4326307	3.53740837
3.9589423	3.3572021	3.7574878
3.7716396	3.4909227	3.43610233
3.867171	3.3025337	3.69201356
3.567511	3.4737469	3.99082194
3.761974	3.2975529	3.9333014
3.4313109	3.396754	3.60842052
3.9701182	3.3749247	3.66980135
3.5999548	3.6397376	3.63973757
3.8967563	3.4715619	3.7654238
3.3356729	3.2335697	4.39526386
3.6044299	3.3384372	3.35742686
4.1754558	3.7387568	3.43700775
3.7087345	3.1344749	3.65548567

Transformed MT, Error Rates, Velocity Peaks

Transformed Movement time

Control	3.72	3.67	3.44	3.30	3.21	3.39	3.45	3.61	3.57	3.47	3.36	3.41	3.47	3.47	3.35	3.45	4.00	4.71	4.05
Haptic	3.44	3.53	3.16	3.28	3.06	3.34	3.45	3.44	3.29	3.31	3.14	3.17	3.51	3.34	3.14	3.59	3.83	3.39	3.29
Haptic(p)	3.73	3.87	3.40	3.31	3.38	3.46	3.36	3.71	3.40	3.44	3.47	3.34	3.53	3.41	3.46	3.83	4.15	4.50	4.01
Free	3.61	3.70	3.15	3.24	3.15	3.36	3.24	3.36	3.38	3.39	3.28	3.38	3.65	3.21	3.35	3.42	3.94	4.48	4.09
Free(p)	3.34	3.80	3.36	3.28	3.23	3.30	3.32	3.28	3.48	3.32	3.29	3.32	3.60	3.28	3.37	3.64	3.79	3.86	3.62
Haptic(p) front	3.77	4.16	3.49	3.31	3.34	4.50	3.42	3.77	3.42	3.43	3.52	3.35	3.57	3.49	4.15	3.97	3.53	3.93	3.57
Haptic(p) back	3.61	3.88	3.37	3.31	3.40	4.52	3.30	3.63	3.39	3.47	3.45	3.34	3.50	3.42	4.11	3.62	3.39	3.68	3.32
Ave Good	3.30	3.46	3.35	3.25	3.15	3.33	3.31	3.32	3.32	3.24	3.14	3.24	3.46	3.24	3.23	3.54	3.37	3.75	3.83
Ave Bad	3.74	3.86	3.50	3.33	3.41	3.54	3.38	3.66	3.46	3.48	3.51	3.34	3.58	3.44	3.55	3.93	4.13	4.50	3.96
1st zone MT	3.88	3.81	3.40	3.32	3.49	3.40	3.41	3.73	3.38	3.44	3.38	3.27	3.52	3.39	3.47	3.54	4.11	4.34	3.87
2nd zone MT	3.75	3.76	3.42	3.29	3.44	3.43	3.36	3.68	3.38	3.44	3.43	3.34	3.52	3.40	3.39	3.79	4.06	4.49	3.89

Transformed Error Rates

Control	1.20	0.00	0.78	0.78	0.30	0.00	1.48	1.34	1.66	0.48	0.60	0.70	0.00	0.70	0.78	0.00	1.00	0.70	0.60
Haptic	1.04	0.00	0.30	0.48	0.00	0.30	1.58	1.28	0.00	0.48	0.00	0.00	0.00	0.00	0.30	1.04	0.48	0.00	0.00
Haptic(p)	1.11	0.00	0.95	0.30	0.00	0.30	1.36	0.90	0.00	0.00	0.00	0.78	0.30	0.00	0.60	1.04	1.18	1.04	1.04
Free	1.18	1.26	0.30	0.90	0.70	0.78	1.00	0.78	0.48	0.00	0.00	1.00	0.60	0.95	0.48	0.70	0.90	1.34	0.85
Free(p)	0.60	1.18	0.30	0.48	0.00	0.48	0.30	0.60	0.48	0.30	0.00	0.85	0.85	0.60	0.30	0.60	0.60	1.28	0.48

Transformed Velocity Peaks

Control	0.57	0.24	0.38	0.30	0.36	0.40	0.42	0.39	0.37	0.37	0.30	0.47	0.33	0.61	0.34	0.27	0.59	1.11	0.67
Haptic	0.51	0.30	0.32	0.11	0.32	0.37	0.38	0.40	0.15	0.39	0.30	0.33	0.26	0.22	0.38	0.32	0.33	0.34	0.30
Haptic(p)	0.77	0.84	0.71	0.57	0.67	0.33	0.62	0.87	0.58	0.70	0.77	0.61	0.57	0.64	0.80	0.71	0.87	1.16	1.04
Free	0.27	0.37	0.05	0.14	0.40	0.43	0.30	0.08	0.22	0.30	0.40	0.28	0.27	0.26	0.40	0.11	0.22	1.03	0.47
Free(p)	0.50	0.60	0.57	0.52	0.59	0.60	0.55	0.36	0.46	0.60	0.56	0.56	0.56	0.51	0.69	0.43	0.38	0.94	0.45

Control MT per distance

Control																			
1 to 0						2193		4751			1943		5470				92103	
1 to 1																			
1 to 2			4166	2211	1073		4790	4074	2216	2578									
1 to 3			2118																
1 to 4			1879		1704													32833	15814
1 to 5															2406	2213	7031	20156	
1 to 6			3261					3529				2488		1797	3766				
1 to 7			2685	1759						2199		2307						23956	
1 to 8			2702		1613										2183				
1 to 9		3557	3425	2016				3127			1927		2265					88529	
1 to 10						2832						3159					7032		5625
1 to 11					1698							3383							
1 to 12	2829	3262		1673			3110	2582										36890	11664
1 to 13				2871				5112				2144			1687	1557			
1 to 14	4560			1639											3517				
1 to 15	4727								3614				3239	2976					
1 to 16						2424			3149							5101		79908	
1 to 17	2592						1881												
1 to 18													3233	3037		2143			
1 to 19			2728		2759	2333		3176		2640	2151			2978		3583		79036	
1 to 20	1969		1642		1271								4021						
1 to 21										1928						2640			
1 to 22											1591								
1 to 23							1950	7620				1680					10800		
1 to 24	3310	2743						2665											
1 to 25	6158		1551	2213			1983		3183										
1 to 26												2007							
1 to 27	2921								3535		3023	3037						9853	
1 to 28						2135								4813			17980		
1 to 29				1623		1928				2706	2977		3216		2935				
2 to 0		6357									3031			1350		3549		17290	5999
2 to 1		3877									2885								14415
2 to 2			2486		888					2585									11620
2 to 3	4124			1312		1600					1648	1727							
2 to 4					3093										2062	2912			7230
2 to 5				1536										1677					
2 to 6								3466								2121	6335		
2 to 7													5431				21957		
2 to 8								3366		2696	3239					2344			15071
2 to 9					1224		1586				2727						15220		
2 to 10	4014	4800								2329									
2 to 11																			
2 to 12	1718		3807		1430				2764						1281		3644		
2 to 13		4351								2896			3174		1480				
2 to 14												1886					5874		
2 to 15												2154							10263
2 to 16												2686	3086	3208		4061			
2 to 17				1527					2757				2151						
2 to 18					1735						1343	2622			3237				
2 to 19	17885						3550									3943	9990		
2 to 20					1607			2010				2374							14492
2 to 21	2976											2615		1710	2024				
2 to 22					1734	2663	2420						2911	1895			9876		
2 to 23		5247		1386					2886		2033								
2 to 24				1935		1362			1846					3101					
2 to 25								2184							2351				
2 to 26								3096								1912		74930	
2 to 27			2832				3896				2448	3892			1639				9351
2 to 28	5041		2079	1464				2640					1741					76589	
2 to 29				1538		2462	3914							1977	2399				
3 to 0	6639				1856	2408			3791						1559		12482		7060
3 to 1															2602			1424	8040
3 to 2					1657										1103				
3 to 3	10038	3769				3865	3221				1839			1529					

Control MT per distance (cont)

3 to 4	6696														1705				
3 to 5			4901										2487						
3 to 6						3560								6785					
3 to 7		3646	2181					2919		2551			1968	1680					
3 to 8									1982				2583	2638					
3 to 9		4420			1352				2225					5065					
3 to 10			4382				2910	9234	2215				3128			2447	7207		
3 to 11									2079	2496								79441	26081
3 to 12										2521			2646						
3 to 13		6247	2298						13900			1422							12892
3 to 14																			8072
3 to 15						2487							3422						
3 to 16		9013		2309		1858				8350							7575		
3 to 17				1389		3006	2050				2385								
3 to 18				5191	1447	2600				3985							5607		
3 to 19		3983																	
3 to 20		4404	2328								1774								
3 to 21								7914	6856	2201					2080				
3 to 22					1150												8758		
3 to 23						3406											8199		
3 to 24			2090				2022												
3 to 25	6213						3636									1416			7600
3 to 26																			
3 to 27		2480															9816		
3 to 28		4511				1662											15790		
3 to 29		6702										5500		1863	2605	2777			10382
Ave	5245	4632	2777	1977	1627	2477	2820	4042	3750	2977	2314	2580	2982	2924	2231	2795	10062	50924	11204

Haptic MT per distance

1 to 20			1123	1403								1427							
1 to 21		2331	1136											2259					
1 to 22									1545		1187								
1 to 23						1959			1347	1339		2320					7210		
1 to 24		2859					2163									21440			1331
1 to 25					891						1443				971	1304			
1 to 26					1043								2875	1544	1243				
1 to 27							1723		2059			1355							
1 to 28					1031														
1 to 29				1971			1635								1093				
2 to 0		1835							2163								3899	2379	
2 to 1				2355			8610	2099			1171								
2 to 2		2581						4066		1931		1459							2971
2 to 3									2331				3155	3915				1352	
2 to 4																	8762	3027	1571
2 to 5					1183					2563			3827				12985		2147
2 to 6										2111								2267	
2 to 7									1955		1963			2395			6326	4810	
2 to 8				2984		1003			1683						1032				
2 to 9	667		3970		1251					1267									
2 to 10	3275		1419												4538	1763			
2 to 11	1395					2551		1755			995				1003				
2 to 12	4066					2859													
2 to 13		4458						2331									3898	2043	
2 to 14					971							1867							
2 to 15										1895						1682			
2 to 16	5450				1048			2011											
2 to 17								1728		1291	1683								
2 to 18											1481			1203				2403	
2 to 19														1595	923				1615
2 to 20						1624			2376	1755						1843		3179	
2 to 21			1339											1571		1251			1387
2 to 22													1915	1427	1195		5962		
2 to 23				1643			2587					1227			1747				2723
2 to 24								5435											
2 to 25					1139							1259							
2 to 26	2375										1123		1971						
2 to 27	1512				923								2155	1107				1028	
2 to 28			1339						1616			1672				2875			
2 to 29				1475		1096		2107	2019						1299				
3 to 0											1443	1283							
3 to 1						1587	3479			2523								1131	
3 to 2					1480			2763							1131		14561		

Haptic MT per distance (cont)

3 to 3	1467										995					2019		1571	
3 to 4					1683									3643					
3 to 5			1427										2171						
3 to 6	1755					2043	7566						1811					3627	
3 to 7		5698		2161			2063		1288			1573						2995	
3 to 8						2831	1912			2264						4114			
3 to 9				1547									2655						
3 to 10				1795			1592	2347									4642		
3 to 11				1928						2107				3867			7482		
3 to 12	5319					3115	2859												
3 to 13		2395										1395		2227					
3 to 14				1347	1283					1891	1419			1619		1979	9311		
3 to 15								3853											
3 to 16		6538						2363			1003				1827				
3 to 17		3099		1723					2963		1064								
3 to 18	1363		1475	1955								1136				2603			2019
3 to 19																			2368
3 to 20						4570	2211				1579		9622		1123				1415
3 to 21	2483									2595			3251			1787	4421		1275
3 to 22																			
3 to 23		2108	1735	1315		2200							2491						
3 to 24						2403				2187			2291	1803			6786		
3 to 25		2531																3155	
3 to 26						2387			2127										
3 to 27		3059					3735	3019								4434		1779	
3 to 28	1187				1240									1611			5478		
3 to 29								2619						1027					
Ave	2736	3424	1440	1898	1156	2195	2805	2743	1961	2031	1383	1493	3200	2176	1370	3929	6804	2444	1971

Haptic(p) MT per distance

1 to 21	1863	4959		1503	3911						1263				1575	1883			
1 to 22																2772			4551
1 to 23						2040			1807			2023							
1 to 24						1152		8070								1935			
1 to 25														1552					
1 to 26		2751		1783			1575			1799			3620			19666		12447	
1 to 27					1143			3007	3115				3251			2607			
1 to 28				2847			3823			1919			2593			5959	6607		
1 to 29				1583				3447		1519									
2 to 0		3047			1659			8630											
2 to 1							1835			2303								6746	
2 to 2	1639		2579												4914	8190			
2 to 3						2863		9163					2831			4991	5223		5695
2 to 4		4492		1847						2623								82493	
2 to 5				1904												5815	5908	13550	
2 to 6						2167			3095										
2 to 7					1431	2650		3764											
2 to 8									2719		3415		2935		3564		28323		
2 to 9	3975																	28904	
2 to 10	2511							5007			1663								
2 to 11		6758							1782		4383				1463				
2 to 12		6204	2039		1287					3504		1920			5619				
2 to 13		9102			1631							2423				3404			
2 to 14							1356							1863			26291		32171
2 to 15															1767				
2 to 16		15005	2420	2287				2076				2095		3287				32570	
2 to 17	4703				5751	4455													
2 to 18			4271		6223		3727							2175					7898
2 to 19	29070												5479						
2 to 20			1687				2916			2903			2632	2415					
2 to 21																	5823		17605
2 to 22	3103													1823			25547		
2 to 23													2380						
2 to 24			3918			2092							2528						14949
2 to 25			2135								2583								
2 to 26	2543			1856						2303					2135				7854
2 to 27				1452						2175	1479				1279				
2 to 28		3887		1803				2687						2751					
2 to 29			2312	1151															
3 to 0									4447					3055		6069			
3 to 1	3285				1477									2188	2159				
3 to 2										2943			5447	3087					
3 to 3		2936								3007	3583								

Haptic(p) MT per distance (cont)

3 to 4						2327		2775										15341	
3 to 5					1839		3415				3083		3203		1319				
3 to 6					1512				2279	3447				2147	1558		45560		
3 to 7	5567	3602		2680			1431	4119				1447							7774
3 to 8			2902		1696	5879			2367					3151					
3 to 9						4447						2775							
3 to 10			1640									2119	2400					20061	
3 to 11				3927					1903								5015		
3 to 12																	12310	31315	
3 to 13	3351										2448				5103			26775	16573
3 to 14							1935				3491								6703
3 to 15			1567	1399					3887								14793	12665	
3 to 16													2631				4359	41737	
3 to 17							1940							2975	2303	3911			
3 to 18					4791					6015					8835				7126
3 to 19															2360				8350
3 to 20																			5935
3 to 21						2039	1623												
3 to 22					1543	2983		3804									4071		7518
3 to 23								3946	2206		2408		4831	2975					
3 to 24	3187	17213	2271					6247			2491	1751				2519			6455
3 to 25												2039		1823					
3 to 26			2279		1421											3159			
3 to 27					1799				1887									31907	
3 to 28			2540				2767												6207
3 to 29				2599								1567	1919			3359		4627	
Ave	5324	7364	2507	2049	2397	2907	2282	5178	2517	2785	2955	2180	3390	2597	2889	6710	14133	31842	10206

Free, Free(p), Misses, Peaks

Free Move																			
Ave Time	4082	5055	1404	1755	1416	2310	1754	2291	2390	2438	1888	2420	4418	1621	2254	2604	8655	30084	12334
Free Move(P)																			
Ave Time	2180	6241	2309	1896	1703	2016	2076	1913	3031	2068	1967	2075	3973	1902	2357	4414	6168	7171	4205
Misses																			
Control	15	0	5	5	1	0	29	21	45	2	3	4	0	4	5	0	9	4	3
Haptic	10	0	1	2	0	1	37	18	0	2	0	0	0	0	1	10	2	0	0
Haptic (P)	12	0	8	1	0	1	22	7	0	0	0	5	1	0	3	10	14	10	10
Free Move	14	17	1	7	4	5	9	5	2	0	0	9	3	8	2	4	7	21	6
Free Move (P)	3	14	1	2	0	2	1	3	2	1	0	6	6	3	1	3	3	18	2
Peaks																			
Control	3	1	2	2	2	2	2	2	2	2	2	2	2	4	2	1	3	12	4
Haptic	3	2	2	1	2	2	2	2	1	2	2	2	1	1	2	2	2	2	2
Haptic (P)	5	6	5	3	4	2	4	7	3	5	5	4	3	4	6	5	7	14	10
Free Move	1	2	1	1	2	2	2	1	1	2	2	1	1	1	2	1	1	10	2
Free Move (P)	3	4	3	3	3	4	3	2	2	4	3	3	3	3	4	2	2	8	2

Prediction per target

Predictions

Target	27	24	11	20	25	11	2	2	3	18	21	27	27	12	18	4	16	21	21
Prediction	29	24	27	20	25	11	13	29	28	28	15	27	27	26	19	26	29	1	26
Time	3095	2820	6510	1751	1500	3359	2951	3631	4515	2754	4294	1599	4606	8070	4891	7710	9278	30883	34350
Target	26	7	8	28	2	8	26	16	27	26	24	23	2	14	8	6	3	9	14
Prediction	26	5	29	29	12	17	26	16	28	29	9	14	27	14	29	26	6	25	29
Time	2543	3879	3543	1803	3399	5878	1575	2076	4239	2303	2490	2023	5446	1863	3563	34242	5222	28903	32171
Target	9	0	18	16	7	6	1	7	6	20	6	20	28	2	13	21	4	14	19
Prediction	29	25	28	17	28	26	3	3	6	28	1	20	28	12	23	22	6	21	29
Time	3975	3047	4270	2287	1431	6686	2103	3763	3095	2903	5031	1455	2593	3087	5102	1882	9190	66957	8350
Target	10	16	0	26	21	4	14	19	23	26	25	25	16	0	12	26	15	4	7
Prediction	24	17	27	26	13	4	18	23	23	26	5	27	29	24	16	29	9	20	29
Time	2511	15005	4343	1855	3911	2327	2167	7822	2308	1799	2583	2039	2631	3055	5618	19665	14165	15341	10134
Target	9	24	25	5	10	17	17	3	27	14	23	19	26	15	21	5	22	15	24
Prediction	19	29	25	26	10	29	9	16	27	26	9	29	26	25	23	5	21	28	29
Time	3884	17212	2135	1903	1372	4454	1940	9163	1990	2199	2407	4319	3619	4311	1575	5814	4070	12665	6455
Target	19	13	20	29	12	24	18	27	20	15	5	9	8	22	27	2	7	13	3
Prediction	29	2	20	29	15	24	19	25	20	27	9	28	28	23	27	23	29	29	29
Time	29070	9102	1687	1583	1287	1207	3726	3007	2207	3503	3055	3095	2935	1823	1279	8190	15837	26774	7118
Target	13	4	10	7	18	3	7	15	8	12	11	24	27	5	1	13	6	29	24
Prediction	17	3	29	28	29	27	6	14	29	27	5	24	25	25	1	24	29	29	29
Time	3315	4492	1639	2679	4790	2863	2031	12581	2367	3655	4382	1751	3250	2475	2159	3404	45560	4626	14949
Target	7	11	28	2	6	24	11	22	11	27	13	10	23	2	26	28	28	8	22
Prediction	29	6	28	23	10	25	2	8	24	26	9	23	23	13	26	26	29	21	29
Time	3119	10541	2540	1847	1511	2092	2783	3804	1780	2175	2447	2398	2380	1903	2135	5958	6606	68476	7518
Target	6	7	4	26	1	19	28	0	20	6	3	13	10	20	18	26	3	27	18
Prediction	28	8	4	27	7	19	19	6	20	17	9	3	10	22	28	26	27	29	18
Time	3359	4135	2476	1783	1476	2379	3822	8630	1447	3447	4862	2422	2399	2415	8835	3159	6963	31906	7678
Target	2	28	12	29	0	7	14	11	3	28	11	4	6	14	6	3	12	10	20
Prediction	2	26	13	29	25	7	9	24	3	28	1	12	6	27	6	25	5	29	29
Time	1639	3887	2038	2598	1659	2359	1703	2671	1911	1919	4510	2671	2852	3391	1548	4991	12309	20060	5935
Target	1	3	16	21	17	22	3	29	11	12	7	10	5	17	6	17	15	16	18
Prediction	15	9	16	25	28	29	3	24	11	16	28	24	15	29	8	27	18	25	18
Time	3711	2743	2420	1503	5750	2983	2100	3447	1783	3351	3303	1839	3202	2975	1567	3910	15421	32570	6575
Target	24	11	9	27	26	23	21	24	23	29	14	9	3	23	11	0	16	5	18
Prediction	23	11	9	29	8	23	26	29	22	29	18	6	14	25	11	15	29	15	29
Time	2135	2975	1990	1451	1420	2039	1623	8070	1807	1519	3419	2535	2831	2975	1463	4950	4358	13549	7898
Target	7	19	2	15	8	6	14	7	27	3	17	12	12	16	17	24	21	11	7
Prediction	16	1	26	27	19	6	14	9	27	8	22	12	22	26	6	25	24	21	18
Time	5567	7491	2578	1399	1695	2167	1863	4119	1887	3007	2038	1920	5470	3287	2303	1935	5822	33893	7775

Prediction per target (cont)

Target	21	7	24	9	27	24	5	12	8	1	8	9	17	1	19	0	14	1	3
Prediction	21	7	14	18	8	24	8	21	27	5	5	9	25	2	19	29	22	1	27
Time	1863	2791	3918	2383	1799	1095	3415	4342	2719	2847	3414	2454	4191	2188	1959	7187	26291	6745	4272
Target	15	3	26	29	22	8	28	23	0	1	21	9	24	8	13	10	11	15	21
Prediction	25	5	29	29	25	29	28	8	24	3	21	19	24	29	24	20	13	11	29
Time	8758	3127	2278	1151	1543	1847	2767	3946	4446	2743	1263	2830	2527	3151	2719	6091	5014	68440	17604
Target	22	12	24	28	13	21	7	28	11	4	10	29	7	28	15	13	5	15	28
Prediction	25	23	24	29	16	29	9	29	25	7	5	29	16	18	18	13	12	21	28
Time	3103	6203	2271	2847	1631	2039	1431	2687	1903	2623	1663	1567	3214	2751	1767	4206	5907	16956	6207
Target	17	19	15	11	5	9	1	4	6	2	3	7	9	25	5	27	8	26	22
Prediction	29	20	28	16	29	29	5	9	27	18	1	7	19	25	17	27	9	21	29
Time	4703	10533	1567	3927	1839	4446	1834	2775	2279	2943	3055	1446	5478	1823	1319	2607	28322	12446	4551
Target	1	26	8	20	18	6	14	8	15	11	3	16	23	6	2	22	3	16	14
Prediction	6	3	8	22	28	24	6	28	25	12	9	16	26	8	15	22	17	28	27
Time	2859	2751	2259	1351	6222	2974	1356	4215	3887	2383	2303	2095	4830	2146	4914	2772	4155	41737	6702
Target	0	21	29	4	27	7	18	24	23	18	5	13	20	25	7	29	1	4	26
Prediction	24	25	29	26	27	8	18	17	24	29	9	3	23	25	7	29	29	14	29
Time	6591	4958	2311	1847	1143	2620	1847	6246	2167	6014	3111	2358	2631	1551	1376	3359	19844	82493	7854
Target	24	13	2	7	4	7	20	10	23	1	27	12	29	18	19	24	22	12	13
Prediction	28	0	25	16	4	18	27	0	25	27	27	12	29	29	9	24	29	28	28
Time	4239	14125	1751	2719	1655	2679	2915	5006	2142	2303	1479	1231	1919	2175	2359	2519	25547	31314	16573

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Brian Holbert has completed degrees in B.S. in Biology, M.S. in Computer Science, and PhD in Computer Science. His interests are in accessibility technology focused on the use of haptics. He is currently an assistant professor of computer science and intends to stay in academics researching assistive technologies.