IMPROVING MOUSE POINTING WITH EYE-GAZE TARGETING: APPLICATION IN RADIOLOGY

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Abstract

In current radiology workstations, a scroll mouse is typically used as the primary input device for navigating image slices and conducting operations on an image. Radiological analysis and diagnosis rely on careful observation and annotation of medical images. During analysis of 3D MRI and CT volumes thousands of mouse clicks are performed every day, which can cause wrist fatigue. This thesis presents a dynamic Control-to-Display (C-D) gain mouse movement method, controlled by an eye-gaze tracker as the target predictor. By adjusting the C-D gain according to the distance to the target, the target width in motor space is effectively enlarged, thus reducing the index of difficulty of the mouse movement. Results indicate that using eye-gaze to predict the target position, the dynamic C-D gain method can improve pointing performance and increase the accuracy over traditional mouse movement.

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Chapter 1

Introduction

Pointing is a daily issue for computer users, as the popularity of graphical interface in all kinds of computer systems increases. Due to the growing complexity of graphical interfaces, as well as the increasing resolution and size of the display monitor, how to increase the pointing accuracy and reduce the movement time come to the agenda.

In the field of radiology, radiologists often navigate through long sequences of 2D image slices generated from MR or CT volume data. For example, up to 1,000 images are generated by abdominal CT exams, and each image must be viewed [32].

The typical display mode seen in radiology shows an axial and coronal view spanning multiple monitors. Precise targeting is frequently needed in radiology tasks. For example, it is often necessary in MRI and CT scans to cross-reference small lesions (<10mm) between anatomic planes (axial, saggital and coronal). This is done with a mouse click on the lesion in one plane, which by nature of lesions' small size, must be precise. Furthermore, for MRI it is often necessary to cross-reference small lesions between different pulse sequences, to better understand the tissue characteristics. In the case where multiple images are shown simultaneously, it becomes necessary to routinely move the cursor from one monitor to another for cross-referencing [18]. It is easy to become fatigued and stressed after hundreds of such procedures, particularly when the target is small, and the distance to move is large, such as across two display monitors [31].

Figure 1.1: The Contour Design Shuttle Xpress jog & shuttle wheel.

1.1 Other Interactive Methods for Radiology Workstations

Other than using a typical scroll-wheel mouse, there are some alternative methods for the interaction with the radiology workstation such as trackball, tablet, gaming joystick. etc.

Sherbondy et al. [33] reported the use of alternative interaction devices for navigating through large CT data sets. Four devices were compared: a trackball, a tablet with two interactive techniques, a jog-shuttle wheel made by Contour Design (Figure 1.1), and a mouse. Each participant (four radiologists) looked for artificial targets in five different large CT data sets; each data set was viewed using a different interaction technique. Results showed that the trackball was significantly slower and less preferred over other methods, but there was no significant difference among the other methods. The trackball used in the study required participants to hold down a button while rotating the ball. Its poor performance was hypothesized to arise because users have to make large repetitive motions to traverse large numbers of slices; the authors speculate that it is possible that a different interaction technique which did not require the button might improve the ratings of the trackball.

Atkins et al. [3] considered three interaction techniques for image navigation during stack-mode viewing. Two involved different interactions using a scroll-wheel mouse, and one involved the Contour Design jog-shuttle wheel. They found that radiologists were faster using the unfamiliar jog-shuttle wheel, but most preferred the familiar scroll-wheel mouse. These results imply that people prefer the interactive method that they were familiar with.

Weiss et al. [37] conducted a study that required six radiologists to evaluate six alternative user interface devices (UIDs), including 5-button and 8-button mice, a gyroscopic mouse, a multimedia controller, a handheld mouse-and-keyboard combination device, and a gaming joystick. Each participant assessed each device during the real-time daily imaging interpretation of magnetic resonance, computed tomographic, and general X-ray studies over a 2-week period. Participants also completed a detailed questionnaire on the ease of use, comparative utility as an alternative device to mouse and QWERTY keyboard, efficiency, workflow, and the ease of customized programming. In this qualitative study, no single device was completely able to replace the mouse and keyboard in the estimation of participants, and the 5-button mouse was preferred over the 8-button mouse, although several participants noted that this might be a function of learning curves that exceeded the 2-week study period for each device. This result confirms that the mouse is the most preferred interactive method by radiologists.

The above studies indicate that although some alternative methods are shown to be more efficient in some circumstances, radiologists still prefer the scroll-wheel mouse that they are most familiar with.

1.2 To Be Expected

Pointing tasks are performed frequently and extensively as the most common used interactive method. We observed radiologists at work and noted that they typically use a regular scroll-wheel mouse to complete a pointing task. Consequently, reducing the time required for pointing tasks can enhance the usability of the interactive technology. Although alternative interactive methods have been developed [33, 37], most of these methods showed poor performance and were also less preferred by users. Therefore, we decided it was still meaningful to improve the performance of the regular scroll-wheel mouse, leading higher working efficiency. Moreover, scroll wheel mouse is still the most common used interactive device, so that this work can be easily extended to scenarios other than a radiology workstation.

In this thesis, we hypothesized we could improve the pointing performance by using the dynamic control-to-display (C-D) gain method in conjunction with eye-gaze targeting.

Control-to-Display Gain

The gain of the resulting cursor distance to the control (mouse) is called the control-to-display gain. Detail will be introduced in 2.4.1.

Eye-gaze Targeting

People look at what they are working on [20]. We believe that in a pointing task, the location of the target can be predicted by obtaining the user's eye-gaze location. Details will be introduced in 2.4.3.

1.3 Structure of the Thesis

The rest of the thesis is organized as following: chapter 2 explores the related work on methods which improve pointing performance, and details about the dynamic C-D gain method, as well as the eye-gaze targeting. Chapter 3 discusses the methodology and results of each of four studies: pilot study 1 in 3.1 evaluates the parameter of the dynamic C-D gain in 2-D space; pilot study 2 in 3.2 evaluates the accuracy of the eye-gaze tracker; study 1 in 3.3 develops a platform to simulate the radiology workstation operations and evaluates the performance of the dynamic C-D gain on known targets; study 2 in 3.4 evaluates the performance of the dynamic C-D gain + eye-gaze targeting on predicted targets. Chapter 4 concludes this thesis.

Chapter 2

Literature Review

Pointing tasks are performed frequently and extensively as the most common used interactive method. Consequently, reducing the time required for pointing tasks can enhance the usability of the interactive technology. Lots of studies have been contributed to this area.

In 2.1, 2.2 and 2.3, discussions are categorized into three groups: single pre-specified targets, multiple pre-specified targets and unspecified targets. Single pre-specified targets exist in an ideal experimental scenario. In this scenario, there is only one object to be chosen, which is considered the target. Both the user and the system know the location of the target.

In the scenario of multiple pre-specified targets, there are more than one objects and their locations are known to the system. Only one object is considered the target and known to the user, but unknown to the system.

In the scenario of unspecified targets, the system does not have any information about the target.

Section 2.4 introduces our method that uses the dynamic control-to-display (C-D) gain in conjunction with an eye-gaze tracker. Our method aimed to improve pointing performance in the scenario of unspecified targets, which is the most practical and the most difficult case.

Section 2.5 concludes this chapter and lists expected results and work to be done in later studies.

2.1 Single Pre-specified Targets

In the context that a single target is pre-specified at a time, studies to reduce the pointing time are in ideal experimental scenarios where the neighbor objects of the target are not considered.

Blanch, Guiard and Lafon proposed *Semantic Pointing* in which the control-display ratio changes according to the distance to the target [6]. The movement of the device in the physical world will be converted to a longer cursor movement on the display when the cursor is far away from the target, and a shorter cursor movement when the cursor is close to the target. This method reduces the pointing time by up to 17%.

In Blanch et al.'s method, the mapping method of the cursor movement to the physical movement affects the pointing time. Sawminathan and Sato [34] concluded that in the context of large displays "nonlinear mappings are too counterintuitive to be a general solution for pointer movement".

Blanch et al.'s method can be concluded as a dynamic mapping of the physical movement to the cursor movement on the display. Such method can also be interpreted as a dynamic magnification of the physical space where the mouse movements take place.

Similarly, fisheye views use magnification of the visual space. Fisheye views distort a visualization by magnifying a particular point [12]. This method is considered a visual expansion of the target. It has been applied to a variety of contexts but its impact on pointing performance is controversial. Cockburn et al. [9] showed that for small targets, visual expansion (that occurs only when the cursor crosses the targets motor boundary) is helpful because it provides visual feedback that the cursor is on the target. However, other studies showed that these visual-only expansions have been shown to be harmful to pointing performance [15], since they may fool users into thinking that the target is larger than it really is. Also, radiologists will not tolerate visual distortions [36]. Therefore, we tended to develop a method that uses motor expansion.

2.2 Multiple Pre-specified Targets

In the context in which multiple pre-specified targets exist, mostly in the so-called WIMP paradigm (Windows, Icons, Menus, and Pointers), locations of objects (icons, menus, etc.) are usually pre-specified and known to both the user and the system. At any time there is only one object to be chosen, which becomes the target. Some predictive methods have been proposed by taking advantage of pre-specified locations.

Guiard, Blanch and Lafon [14] proposed a method called *Object Pointing*. Traditional pointing can be modeled as selecting pixels in bitmap displays. Object pointing is a novel interaction technique based on a special screen cursor that skips empty spaces. It requires identifying the target object. This is achieved by analyzing the cursor's initial motion in angular terms. Once the instantaneous direction of motion has been identified, the system searches the new objects around this direction. Then the cursor jumps to the proximal boundary of the nearest object.

Atsuo Murata [29] proposed a similar method for the prediction of a target on the basis of the trajectory of the mouse cursor. This method compares the angle of the movement to the angles of the mouse to those potential targets. The target with the minimum difference with this angle is determined as the prediction target.

The above methods can dramatically reduce the pointing time in some circumstances. However, the object to which the cursor jumps is determined solely by the movement direction, and the nearest neighbor is always picked. Therefore, directional errors frequently happen, that is, the initial mouse movement may not follow the direction to the real target, leading the cursor jump to the wrong object. Also, with a number of objects lying on the same direction, both methods jump to non-target objects.

2.3 Unspecified Targets

In this section, we discuss the most difficult, and the most practical situation, that is, where the user wants to click is not known to the system. No objects are pre-specified as candidate targets.

The *Delphian Desktop* predicts the target location by the maximum velocity during the mouse movement [1]. For individual users, the target distance linearly corresponds to the peak velocity. The peak velocity is determined by sampling, and the mouse cursor jumps to the predicted location. It enables the user to warp sparse areas. But it requires the user to correct the cursor position after the warping. Sometimes users may lost track of the cursor because of the warping. Also, directional errors frequently happen in this method.

Eye-tracking utilizes eye movement to assist the pointing tasks. Scientists have shown that people continuously explore their environment by moving their eyes. They look around quickly and with little conscious effort. Researchers have also found that people look at what they are working on [20]. The eyes do not wander randomly. Thus the eye gaze can be used for pointing tasks as an input device. Murata [30] compared the usability of the eye-gaze input among three age groups (young, middle-aged, and older adults) and with that of a traditional PC mouse. The eye-gaze input system led to a faster pointing time as compared with mouse input for targets of 30 pixels in radius, especially for older adults. However, the overhead of eye-tracking is that a fixation does not tell us precisely where the user is looking because the fovea (the sharp area of focus) covers approximately one degree of visual angle [19], corresponding to about 20 pixels on the display. This feature causes the inaccuracy of eye-gaze targeting, making it inappropriate in circumstances where high accuracy is required.

To increase the accuracy, some efforts have been made. One approach uses target magnification [4] such that the user can increase the effective size of target objects by temporarily "zooming in" on the target area during a single selection. This technique is based on the principle of fisheye views [12, 2].

MAGIC Pointing [40] is an interactive technique in which pointing and selection remained a primarily a manual control task but are also aided by gaze tracking. The key idea is to use gaze to dynamically warp the "home" position of the cursor to be at the vicinity of the target, which by definition was what the user was looking at, thereby reducing the cursor movement amplitude needed for target selection. Once the cursor position had been warped, the user would need to only make a small movement to, and click on the target with a regular manual input device. Similarly to the *Delphian Desktop*, the cursor jumping might cause the user lose track of the cursor.

2.4 Dynamic C-D Gain with Eye-tracking

For radiology tasks, the target is unpredictable since suspicious features can lie anywhere in the image. Therefore, simply applying one or two of approaches in 2.1, 2.2 or 2.3 cannot effectively improve the pointing performance. We proposed a method called dynamic control-to-display (C-D) gain in conjunction with eye-gaze targeting to adaptively change the speed of the mouse, to make the target effectively larger.

2.4.1 C-D Gain

In an interactive system, movements of the mouse for a fixed distance causes the cursor to move a corresponding distance on the screen. The ratio of the resulting cursor distance to the control (mouse) is called the control-to-display (C-D) gain. Setting this gain high implies that small mouse movements cause larger cursor movements. The user can cross long screen distances with less effort but precise pointing can be difficult. Setting the C-D gain low has the inverse effect; long movements requires more effort but precise pointing is easier.

2.4.2 Fitts' Law

Fitts' law [11] states that the movement time (MT) in pointing to a target depends on the index of the difficulty (ID). The ID is controlled by the width (W) and distance (D) of the target.

$$MT = a + b \log_2 \frac{2D}{W} \tag{2.1}$$

where $ID = \log_2 \frac{2D}{W}$. Here a and b are constants characterizing the system and user.

Variations of the formulation have been proposed by Welford [38] and MacKenzie [23, 22], as shown in equations 2.2 and 2.3.

Using the Fitts' or Welford formulation (equations 2.1 and 2.2), the ID is negative if the distance is less than half the target width; that is, $D < \frac{W}{2}$.

$$MT = a + b \log_2 (\frac{D}{W} + 0.5) \tag{2.2}$$

Equation 2.3, known as the Shannon Formulation, always gives a positive rating for the ID; that is, as D approaches zero, ID approaches zero but never becomes negative.

$$MT = a + b \log_2 (\frac{D}{W} + 1) \tag{2.3}$$

In our later experiments, the case in which $D < \frac{W}{2}$ would be excluded. To simplify the calculation, we chose the Fitts formulation (equation 2.1). Hence Fitts' law links the movement time to acquire a target to the task's ID in one-dimension space.

To be generalized into two or three dimensions, other issues such as the shape of targets need to be considered [24].

From the equation: $ID = \log_2 \frac{2D}{W}$, it is seen that the distance to the target is a factor that affects the MT. As the resolution and size of displays increases, the number of pixels in one dimension has increased. Thus the visual distance and motor distance (under constant C-D gain) on a display screen also increases. Increasing the C-D gain can reduce the effective motor distance to the target, however, as the speed goes up, the accuracy simultaneously decreases [17]. This arises because while reducing the distance D by speeding up the cursor, the target width W is also affected. That is, when the C-D gain is increased to achieve a faster cursor speed, the relative width of the target is effectively reduced by the increase in the C-D gain. Therefore, simply increasing or decreasing the cursor speed would not improve the pointing performance.

Fitts' law has led people to develop techniques to facilitate pointing tasks by enlarging target width or reducing the distance [5, 7, 10, 28]. Control-to-Display Adaptation [21, 39, 10] is another approach to improve the pointing performance. When the mouse speed reaches a threshold, the C-D gain will be adapted, usually being doubled. This method is now used in some Windows operating systems, but to our knowledge, it has not been thoroughly analyzed by Fitts' law. A typical adaptation in current use is the so-called "acceleration", where the C-D gain is changed when the mouse cursor covers a certain number of pixels more quickly. However, most computer game players switch the "acceleration" off, turning the mouse into a pseudo absolute device to enhance pointing performance. Thus, adjusting C-D gain according to the position rather than to the acceleration might be more preferred in terms of pointing performance.

Bubble cursor [13] enlarges the cursor's activation area and the result showed that the average selection time for targets (pre-specified) can be shortened. However, the enlarged cursor activation area is not suitable for radiology tasks because any operations on an image need to be precise.

2.4.3 Dynamic C-D Gain

As seen in the Fitts' law equation, changing the cursor speed only cannot change the *ID* because D and W are affected simultaneously. The dynamic C-D gain method proposed that by adaptively changing the C-D gain during the mouse movement, the *ID* can be reduced as shown in the following section.

Dynamic C-D Gain in 1-D Space

The index of difficulty can be reduced by expanding just the target size in motor space [6]. The concept of the dynamic C-D gain is that by decreasing the C-D gain when the cursor is over the target, the target width becomes effectively bigger in motor space. This is because as the C-D gain decreases, crossing the same number of pixels on the screen requires a longer movement in motor space, thus enlarging the motor width of the target. This method has been shown to improve pointing performance [6].

On the other hand, when the cursor is not over the target, the C-D gain remains at the initial value. Therefore, the W (width) in Fitts' law increases while the D (distance) remains mostly as before, thus reducing the ID.

As seen in equation 2.4, once the cursor speed is reduced by dividing by the slowing down ratio R, the effective width of the target becomes WR. Additionally, the space in which the cursor speed is reduced will be called the slowing down area (quantified as S in diameter). If the cursor slows down just over the target, then the ID is reduced by subtracting $log_2 R$, as shown in equation 2.5. Theoretically, the greater R becomes, the more ID is decreased.

$$\begin{aligned} ID &= \log_2 \frac{2D}{WR}, \text{where R is the slowing down ratio} \qquad (2.4) \\ &= \log_2 \frac{2D}{W} - \log_2 R \qquad (2.5) \end{aligned}$$

Dynamic C-D Gain in 2-D Space

The dynamic C-D gain is proved to be effective to improve mouse performance. Some of the studies were conducted in 1-D space [6, 10, 8]. In 1-D space, the target width is strictly defined, and the cursor can easily follow the unique path to the target. Some studies were in 2-D space [21, 39]. These studies were usually icon-based, which means targets were pre-set. In the scenario of a radiology workstation, some targets can be pre-set such as icons or buttons. However, while making notes on suspicious areas on the image, the target is unpredictable and cannot be pre-set.

In 2-D space, the situation becomes more complicated. First of all, the target width is much harder to determine due to different target shapes and entry angles. Several methods have been proposed to solve this problem. One is called *STATUS QUO* [25], which uses the horizontal extent of the target. A second and more sophisticated method is to substitute

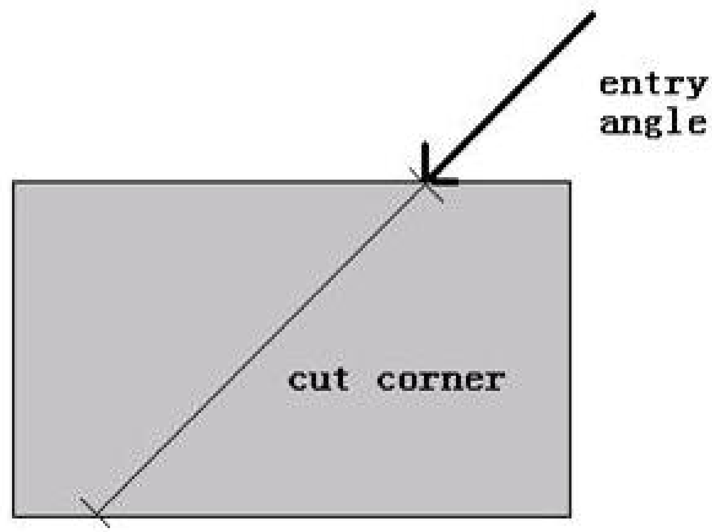


Figure 2.1: Using "cut corner" as target width

for W a measure more consistent with the 2-D nature of the task. It uses the "cut corners" (Figure 2.1) as the target width [25] . Another possible method is "the smaller of W or H". In this method, the target width is defined as the smaller of the two dimensions.

Secondly, path variation is another issue brought to 2-D space. In 1-D tasks, there is a unique path from the starting point to the target, that is, the target can be reached as long as the moving direction is correct. This important feature makes the dynamic C-D gain very effective in 1-D. For example, an average of 16.9% improvement was demonstrated [6]. In that case, the greater slowing down ratio R is, the less is ID. In 2-D tasks, path variations include target re-entry, task axis crossing, movement direction change and orthogonal direction change. The path variation can significantly affect the MT [26]. Therefore, only increasing the value of R may not enhance the pointing performance especially when targets are small (Figure 2.2) because the path variation might dominate the MT.

We proposed that if we were able to expand the slowing down area beyond the visual boundaries of the target, the influence of path variations could be reduced since the mouse cursor is relatively easily captured. In addition, the expanded slowing down area is able to tolerate inaccurate target prediction or acquisition, making the implementation more

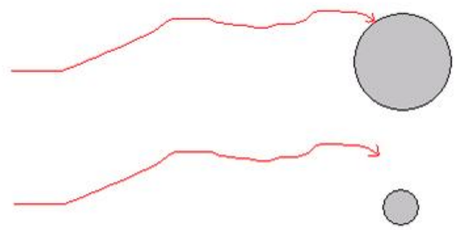


Figure 2.2: Path variation for big targets and small targets. With the same amount of path variation, the cursor can reach the big target but will miss the small target.

practical. For example, in some situations where potential targets are located close to each other, or where the target prediction is inaccurate, the actual target can still be covered by the expanded slowing down area based on the predicted target.

Equations 2.6 - 2.8 show that the new effective distance D' and new effective width W' increase together,

$$D' = \int_0^D CD(x)dx \tag{2.6}$$

$$= (D - \frac{S}{2}) \times CD + \frac{S}{2} \times CD \times R \tag{2.7}$$

$$W' = \int_0^W CD(x)dx = W \times CD \times R \tag{2.8}$$

where S is the width (diameter) of the expanded slowing down area and R is the slowing down ratio.

Equation 2.10 recalculate the ID based on D' and W'. Although we add some extra distance to move in motor space, it does not significantly affect the ID when D is large and W is small.

$$ID' = \log_2 \frac{2D'}{W'} = \log_2 \frac{2 \times ((D - \frac{S}{2}) + \frac{S}{2} \times R)}{W \times R} \tag{2.9}$$

$$ID' = \log_2 \frac{2D + S(R-1)}{W \times R} \tag{2.10}$$

Eye-gaze Targeting in Dynamic C-D Gain

As described above, people look at what they are working on [20]. Consequently, the target location predicted by an eye-gaze tracker can be used to dynamically adjust the C-D gain. Although the eye-gaze tracker is only accurate within approximately 1 cm (about 20 pixels) viewed at a distance of 50 cm, we expected that pointing performance can still be enhanced using the dynamic C-D gain. However, due to the limited accuracy of the eye-gaze tracker, an expanded slowing down area is needed.

2.5 Summary

In this chapter, we discussed previous studies that address single pre-specified targets, multiple pre-specified targets and unspecified targets. We found that only applying one or two of those methods cannot fit the need in the radiology where suspicious targets are unknown to the system. Thus we proposed a method that use the dynamic C-D gain in conjunction with an eye-gaze tracker to improve pointing performance in radiology tasks. There are two major reasons that we used an expanded slowing down area. First, an expanded slowing down area can more effectively capture the mouse cursor when the target to click is small. Second, inaccurate target predictions can be tolerated by the expanded slowing down area, thus making the dynamic C-D gain technique implementable.

However, when we expand the slowing down area, we inevitably increase the distance to travel. The extra distance can only be ignored when the size of the slowing down area is not too large and the slowing down ratio is not too big. This constraint might prevent us from using bigger R which can dramatically enlarge the target width.

In next chapter, we will talk about the studies we have conducted to evaluate this method.

Chapter 3

Experiments and Results

We ran two pilot studies and two studies. The pilot study 1 was designed to preliminary evaluate the performance improvement of the dynamic C-D gain method, finding out the optimal parameter S and R. The pilot study 2 was to analyze the accuracy of the Tobii 1750 eye-tracker. Next, two studies were performed separatedly by a period of several months, and featured different participants. Study 1 evaluated the optimal performance of the dynamic C-D gain method based on the parameter found in pilot study 1 by using predetermined targets. Study 2 evaluated the practical performance by using targets predicted by eye-gaze.

3.1 Pilot Study 1 - Determination of Optimal Parameters

3.1.1 Assumption

According to the new formula of calculating *ID'*(equation 2.10), increasing the value of R widens the target width in motor space, however, it also enlarges the distance. Further more, when S is small, increasing R could enlarge the target width and has little effect on the distance in motor space. But note that small S can not reduce the impact of path variation, as discussed in section 2.4.3. On the other hand, big S helps reduce the impact of path variation but leads to a longer distance.

The theoretical improvement was calculated by the reduction of *ID*. The quantity of the impact of path variation (small, medium and large) was based on our observations.

Tables 3.1, 3.2, 3.3 and 3.4 indicate the change of *ID* and the impact of path variation for different kinds of trials with different S and R. Table 3.1 shows the change of *ID* and the impact of path variation for big targets with short distance. As shown, the *ID* reduction is large with small impact of path variation. Table 3.2 shows the change of *ID* and the impact of path variation for big targets with long distance. The *ID* reduction is not as significant as for short distance but still, with small impact of path variation. Table 3.3 shows the change of *ID* and the impact of path variation for small targets with short distance. When the S is small (40 pixels), the *ID* reduction is very large, but leading to a big impact of path variation. When the S is enlarged to 60 pixels, the *ID* reduction is slightly affected but the impact of path variation is changed to normal. Table 3.4 shows the change of *ID* and the impact of path variation for small targets with long distance. Similarly, the *ID* reduction is significant with big impact of path variation when S is small. Increasing S can change the impact of path variation from big to normal, with a little cost of *ID* reduction.

Table 3.1: Pilot Study 1 - Expected Result: $W = 100$ pixels, $D = 200$ pixels, $ID = 2$

S	R	ID	ID'	Calculated Improvement	Impact of Path Variation
100	10	2	0.38	81%	small
150	10	2	0.80	60%	small
200	10	2	1.14	43%	small

Table 3.2: Pilot Study 1 - Expected Result: $W = 100$ pixels, $D = 800$ pixels, $ID = 4$

S	R	ID	ID'	Calculated Improvement	Impact of Path Variation
100	2	4	3.09	23%	small
150	2	4	3.13	22%	small
200	2	4	3.17	21%	small

3.1.2 Objective

Tables 3.1, 3.2, 3.3 and 3.4 gave us a coarse idea of how the performance varies from different parameter. However, since the impact of path variation is not well quantified, we still need

Table 3.3: Pilot Study 1 - Expected Result: $W = 20$ pixels, $D = 200$ pixels, $ID = 4.32$

S	R	ID	ID'	Calculated Improvement	Impact of Path Variation
40	10	4.32	1.57	64%	large
60	10	4.32	1.74	60%	medium
80	10	4.32	1.93	55%	medium

Table 3.4: Pilot Study 1 - Expected Result: $W = 20$ pixels, $D = 800$ pixels, $ID = 9.64$

S	R	ID	ID'	Calculated Improvement	Impact of Path Variation
40	2	9.64	5.34	45%	large
60	2	9.64	5.35	45%	medium
80	2	9.64	6.32	34%	medium

to conduct a pilot study to evaluate the actual performance of different combinations of S and R.

3.1.3 Method

We used the Windows XP Application Programming Interface (API) to access the C-D gain during the movement. By capturing the mouse movement events, the C-D gain was adjusted according to the current position of mouse cursor. Microsoft added the "acceleration" as a parameter for mouse movement. The effect of acceleration means that when the speed of the mouse reaches a certain threshold, the C-D gain will be changed, normally approximately doubling it. In order to control the variable during the experiment, we removed the built in "acceleration" during the experiment.

Microsoft scales the C-D gain on an abstract scale from 1 (slowest) to 20 (highest). By experiment we found that the C-D gain is linearly changed from the lowest to the highest. Thus, the new speed V' under certain slowing down ratio R could be $V' = \frac{V'}{R}$ where V is the current mouse speed. Similarly, the new C-D gain $CD' = \frac{CD}{R}$ where CD is the current C-D gain.

Task Setup

In this pilot study, targets were pre-set, that is, the system knows the location of the target. Thus the C-D gain was adjusted according to the distance between the current cursor location with the target location. We aimed to quantify the relationship between the movement time (MT) and the combination of S and R as shown in Figure 3.1. There were four independent variables for the study: target width W (100, 40, 20 and 10 pixels), target distance D (800, 400 and 200 pixels), slowing down area diameter S and slowing down ratio R.

Targets with $W \geq 40$ pixels were considered *Big*. Targets with $W < 40$ were considered *Small*. For the *Big* targets, we took the value of 2×, 1.5× and 1× of the W for S. Note that when the S was set to be equal to the W, the mouse cursor was only slowed down over the target. For *Small* targets, the value of slowing down area diameter (S) was taken 80, 60 and 40 pixels (Table 3.5). For both *Big* and *Small* targets, the R was set to 2, 3.3, 5 and 10. Note that we used different schemes of choosing S for *Big* targets and *Small* targets. The reason is that the eye-gaze tracker may not be accurate enough to achieve 40 pixels accuracy, so the dynamic C-D gain may not be effective if S is below 40 pixels. Further more, we believe that bigger S could help capture the mouse cursor for *Small* targets.

Table 3.5: Pilot Study 1: Experiment parameters

Parameter	Value
W	10, 20, 40, 100
D	200, 400 ,800
S	$2 \times W$, $1.5 \times W$, $1 \times W$ when $W \geq 40$
	80, 60, 40 when $W < 40$
R	2, 3.3, 5, 10

In this pilot study, for both *Big* and *Small* targets, there were 12 combinations of R and S plus the *Base* which used the constant C-D gain. For each combination of R and S, the participant first double-clicked the start point at the center of the screen, then left-clicked on the target randomly appeared. Except for the *Base*, the C-D gain was adjusted according to the distance to the target. Participants repeated the procedure with different Ws and Ds taken from the Table 3.5. Each participant performed the same sequence. A given (R,S)

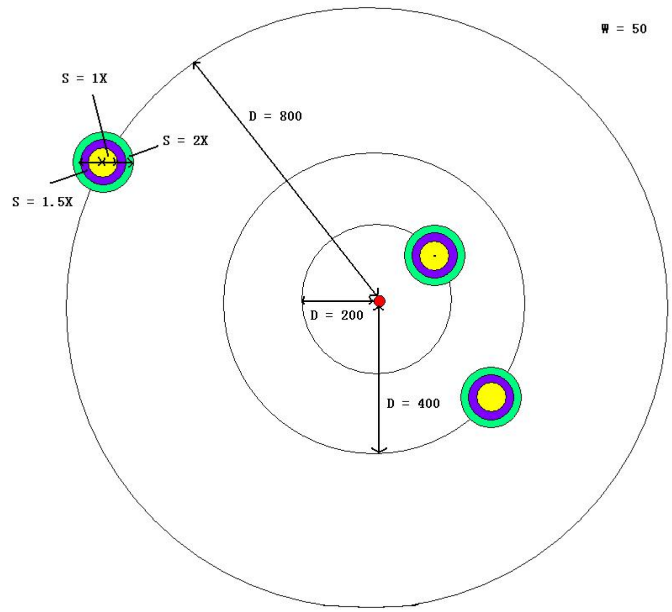


Figure 3.1: Pilot Study 1 - Experiment descriptions: target randomly appears at the orbit at distance of 200, 400 and 800 pixel. For each target, the slowing down area diameter varies from 1 time to 2 times target width. The red circle in the center is the starting point and the inner yellow circle is the target.

pair formed a set of trials with combinations of W and D.

Completing a target selection was defined as one *trial*. For each combination of D, W, S and R, the user performed 2 trials consecutively with targets in different positions. Therefore, the total number of trials was (12 (R,S) + 1 Base) $\times$ 3 widths $\times$ 4 distances $\times$ 2 targets = 312. The study lasted about 30 minutes. Note that during the study, the *Base* (constant C-D gain) was performed before other combinations of R and S

During the study, the movement time (MT) which was the lapsed time from target presentation to left-click completed was recorded, as well as the error clicks which corresponded to the click conducted outside the target.

Initially, the C-D gain was set to the value corresponding to mouse cursor speed 10 in Windows XP. In the base condition (constant C-D gain condition), the mouse cursor speed remained at 10 all the time. In the dynamic C-D gain condition, the mouse cursor speed was set to 5,3,2 and 1 according to the value of R= 2, 3.3, 5 and 10 while approaching targets.

The study was conducted on a computer running Windows XP SP2, with an AMD Athlon Dual core 2.4G, 2G memory and a 22 inch monitor with resolution of 1680×960.

Participants

There were two volunteer participants. Both were daily computer users (more than two hours everyday) and right-handed. Participant 1: Male, age 22, daily computer user . Participant 2: Female, age 24, daily computer user. During the study, participants were using a Logitech G1 laser mouse.

3.1.4 Result and Discussion

Figure 3.2 shows the average MT of the two participants in all combinations of R and S for *Big* targets. In Figure 3.2, the black line shows the average MT in the constant C-D gain condition (*Base*). After combinations of R and S with obviously poor performance were removed, we found that 5 conditions: R(2)S($2\times W$), R(2)S($1.5\times W$), R(3.3)S($1.5\times W$), R(2)S($1\times W$) and R(3.3)S($1\times W$), had some data points below the constant C-D gain condition. Among these, we found that R(2)S($1.5\times W$) and R(3.3)S($1\times W$) were best (Figure 3.3).

The result for *Big* targets indicates that big R cannot improve the pointing performance. Small R can sometimes improve the performance but needs to collaborate with small S. This result was expected since we knew that big R amplifies the D too much. When R is small, with big S it can still over-enlarge the D.

Figure 3.4 shows the average MT of the two participants in all combinations of R and S for *Small* targets. In Figure 3.4, the black line shows the average MT in the constant C-D gain condition (*Base*). After those combinations of R and S with obviously poor performance were removed, we found that 5 combinations: R(2)S(80), R(2)S(60), R(3.3)S(60),R(2)S(40) and R(3.3)S(40), had some data points below the constant C-D gain condition. Among these, we found that R(2)S(80), R(2)S(60) and R(2)S(40) were the best (Figure 3.5).

Similarly to the result for *Big* targets, big R was not preferred for *Small* targets.

Summary

Table 3.6 shows a summary of parameters with poor performance. We found that for *Big* targets, applying big R on the expanded slowing down area significantly decreased

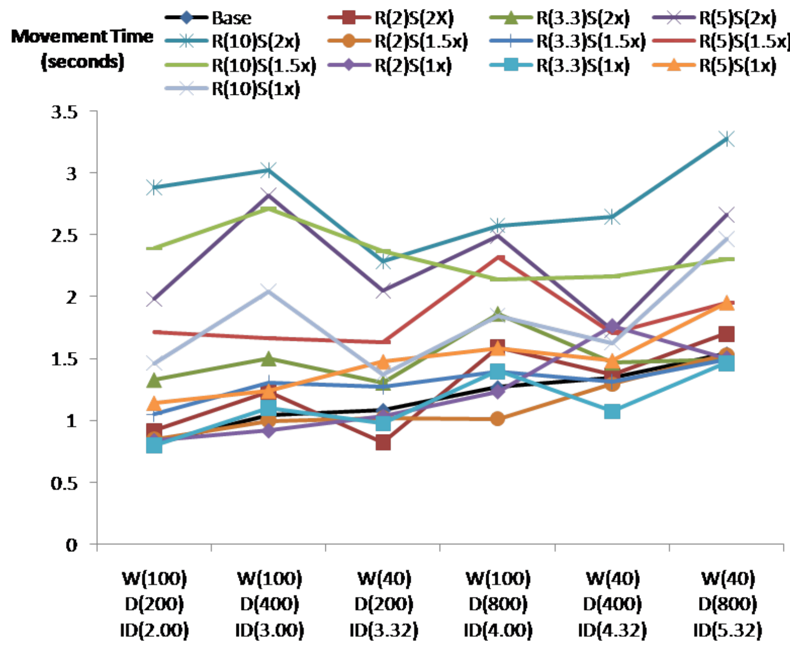


Figure 3.2: Pilot Study 1: The average MT of the two participants in all combinations of R and S for *Big* targets

the pointing performance. This result was expected since the distance in motor space was largely increased. Then the increase of D overwhelmed the enlargement of W, making trials more difficult.

Similarly for the *Small* targets, big R brought negative effect on the pointing performance since we only applied expanded slowing down area for *Small* targets. And, the big R over-enlarged the D.

Among the remaining combinations of R and S, R(2)S(1.5$\times W$) and R(3.3)S(1$\times W$) had the best performance for *Big* targets. R(2)S(80), R(2)S(60) and R(2)S(40) had the best performance for *Small* targets.

Note that during this pilot study, participants were asked to perform under the constant C-D gain (*Base*) first. The effect of fatigue might have affected the result in the later condition, as no break was given. From these results, we could expect that the dynamic C-D gain with certain combinations of S and R should be able to bring more improvement for the pointing performance.

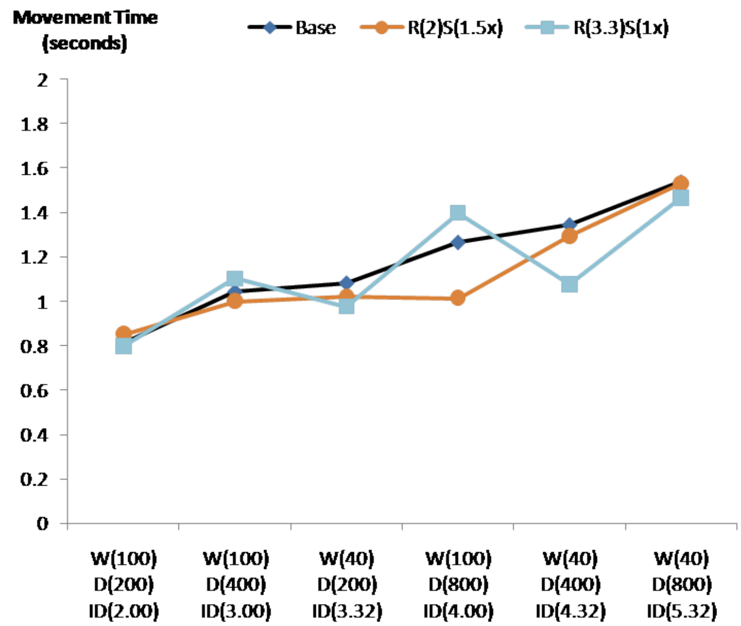


Figure 3.3: Pilot Study 1: The average MT of the two participants in combinations of R and S which have the best performance for *Big* targets

3.2 Pilot Study 2 - Evaluating Eye-gaze Targeting

3.2.1 Objective

The purpose of this pilot study was to evaluate how accurate the prediction by an eye-gaze tracker could be. As we found in the previous pilot study, some combinations of S and R could achieve a high upgrade of the pointing performance but small S requires an accurate prediction of targets. The result of this pilot study should indicate which of those combinations are practical to implement.

3.2.2 Method

The study setup was mostly the same as the previous pilot study, except there were some changes of the parameters. We chose combinations of S and R which were found helpful for the pointing performance in the previous study. The distance D varied by 200, 400 and 600 pixels. Width W was taken 10, 20 and 50 pixels. For the combinations of S and R, when W

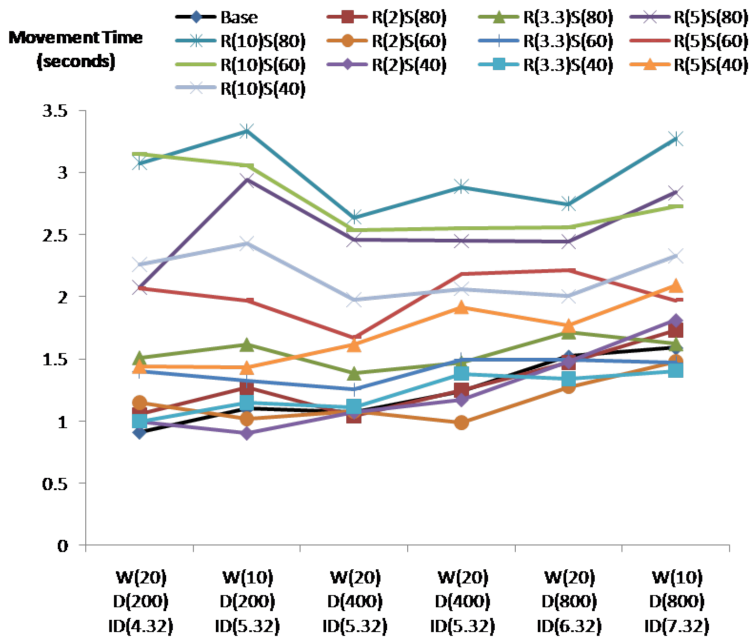


Figure 3.4: Pilot Study 1: The average MT of the two participants in all combinations of R and S for *Small* targets

was 10 or 20 pixels, combinations chosen are shown in Table 3.7. When W was 50 pixels, we took combinations shown in Table 3.8. For each combination of W, D, S and R, there was 1 trial. Thus there were 81 trials for each participant. We recruited 4 participants for this pilot study, so the total number of trials was $81 \times 4 = 324$.

Before the study, all participants needed to calibrate to the eye-gaze tracker.

3.2.3 Result and Discussion

Within the data we collected, there were 52 trials (out of 324 trials in total) with invalid gaze points. The data for those trials were recorded when the eye-gaze tracker lost track of participants' eyes. The reason causing this could be the significant change of the head position, or the eye-blinking. We excluded those trials from the analysis.

We found that the gaze points for one trial were distributed mostly in two areas: One around the starting point and one around the target (Figure 3.6), so for each trial, we excluded gaze points which were further than 200 pixels from the target and took the

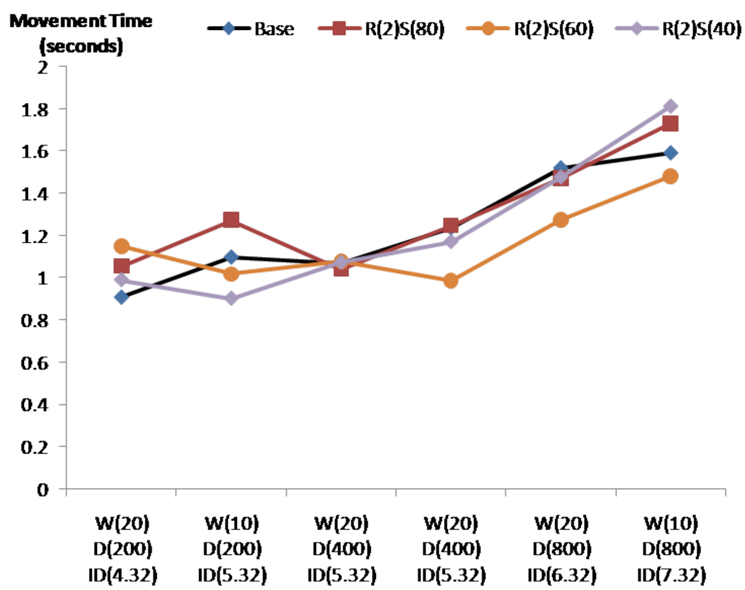


Figure 3.5: Pilot Study 1: The average MT of the two participants in combinations of R and S which have the best performance for *Small* targets

average of the remaining gaze points as the predicated location.

For the remaining trials, we divided them into two groups: *Big* targets ($W \geq 40$, 40 trials) and *Small* targets ($W < 40$, 232 trials).

In the group of *Big* targets, the average offset between the gaze point and the center of target for each trial was 29 ± 20 (standard deviation) pixels. Within this group, 16 trials (40%) had offset less than 20 pixels. 17 (43%) trials had offset between 20 and 40 pixels. 7 (17%) trials had offset larger than 40 pixels.

In the group of *Small* targets, the average offset between the gaze point and the center of target for each trial was 28 ± 17 (standard deviation) pixels. Within this group, 82 trials (35%) had offset less than 20 pixels. 101 trials (44%) had offset between 20 and 40 pixels. 49 trials (21%) had offset larger than 40 pixels.

The result of this pilot study showed that majority of the trials had offset between the fixation point and the target less than 40 pixels (about 80% of the trials with valid gaze points). For trials without valid gaze, we had no way distinguishing whether the data is lost. As long as the slowing down area has diameter larger than 40 pixels and the eye-gaze

Table 3.6: Pilot Study 1: Combinations of slowing down area diameter and ratio with poor performance.

	R	S
$W \geq 40$	3.3	$2\times W$
	5.0	$2\times W$, $1.5\times W$, $1\times W$
	10.0	$2\times W$, $1.5\times W$, $1\times W$
$W < 40$	3.3	80
	5.0	80, 60, 40
	10.0	80, 60, 40

Table 3.7: Pilot Study 2: Experiment parameters when $W = 10, 20$

R	S
5.0	20, 30
3.3	20, 30, 40
2.0	20, 30, 40
1.0	20, 30, 40

can be maintained, the mouse cursor could still be possibly slowed down while approaching the target.

3.3 Study 1 - Specified Target

3.3.1 Objective

As shown in Figure 3.5, all R(2)S(80), R(2)S(60) and R(2)S(40) boosted the pointing performance for *Small* targets. In consideration of the accuracy that the eye-gaze tracker can achieve, we took the R(2)S(80) as the optimal parameter for later studies.

We conducted a study to evaluate the performance of the dynamic C-D gain on *Small* targets [35]. In this study, all targets were pre-set and known to the system. The reason for using known targets was to determine the optimal improvement of the dynamic C-D gain method.

Table 3.8: Pilot Study 2: Experiment parameters when $W = 50$

R	S
10.0	$1{\times}W$
5.0	$1{\times}W$
3.3	$1{\times}W$
2.0	$1{\times}W$
1.0	$1{\times}W$

3.3.2 Method

The experimental screen shot is shown in Figure 3.7.

Tasks

Participants were required to use the mouse to point to targets on the MR images. Four sets of images were used. To begin each image set, participants first right-clicked anywhere on the screen to activate a popup menu, and selected "linking" from a menu. The software displayed a red target dot. After clicking on each target, a new dot appeared; there were 8 targets for each set of four images. When all 8 dots had been clicked, participants again right-clicked and selected "linking" to begin the next set. Image sets were blocked, with each set recurring four times per block. Note that since the location where the user clicked to activate the "linking" was varying, the D of the first trial in each set was no longer fixed. Thus we discarded the first trial of each set. Therefore, the total number of trials was 7 dots$\times$4sets$\times$4 blocks = 112 trials per participant. All mouse clicks were logged and time-stamped by the experimental software.

The order that the dots appear must be carefully arranged. If dots appear on the screen in a fixed order, participants might learn to predict the location of the next target, confounding the results. Appropriate dot order can also provide a balanced variety of movement distances and angles. In this study, there were four image sets in each block. Target dots appeared in one image at a time in pseudo-random positions at different distances and angles. Dots sequences for each set are shown in Figure 3.8 and distances for each direction are shown in Table 3.9. Table 3.10 shows how many targets were at each distance D. We applied this sequence to all four blocks.

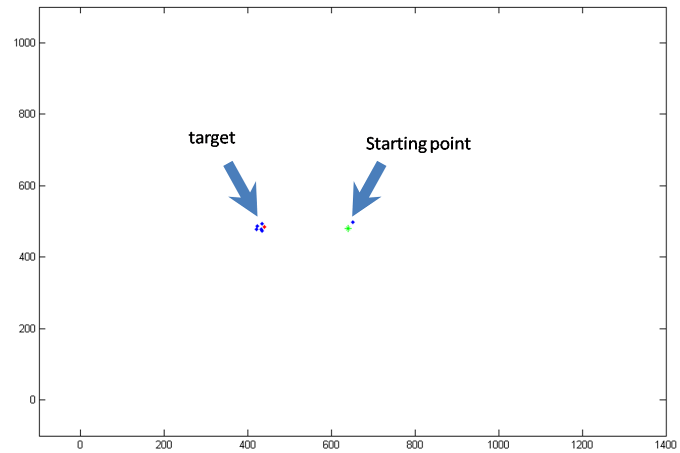


Figure 3.6: Pilot Study 2: The typical distribution of the gaze points for a typical trial.

The slowing down ratio we used was $R = 2$. The slowing down area was $S = 80$ pixels in diameter. The expected ID for different distances is shown in Table 3.11.

Participants

We recruited 12 participants for this study. Participants were all students with an average age of 24.8. The study was conducted following a strict written procedure, which did not give any indication of change of mouse settings (see Appendix A.1). The whole procedure was managed by the experiment administrator. Participants were first introduced to the mouse trials, and completed a general questionnaire to gain information regarding their age, education and experience of using a mouse (see Appendix B.1.1).

Procedure

All trials were performed under two conditions (constant C-D gain and dynamic C-D gain). In order to minimize the impact of fatigue, participants were required to have a short break every five minutes. Order of each condition was counterbalanced, with half of the participants performing the trials under constant C-D gain before the dynamic C-D, and vice-versa for the remaining half of the participants. After each condition, participants were

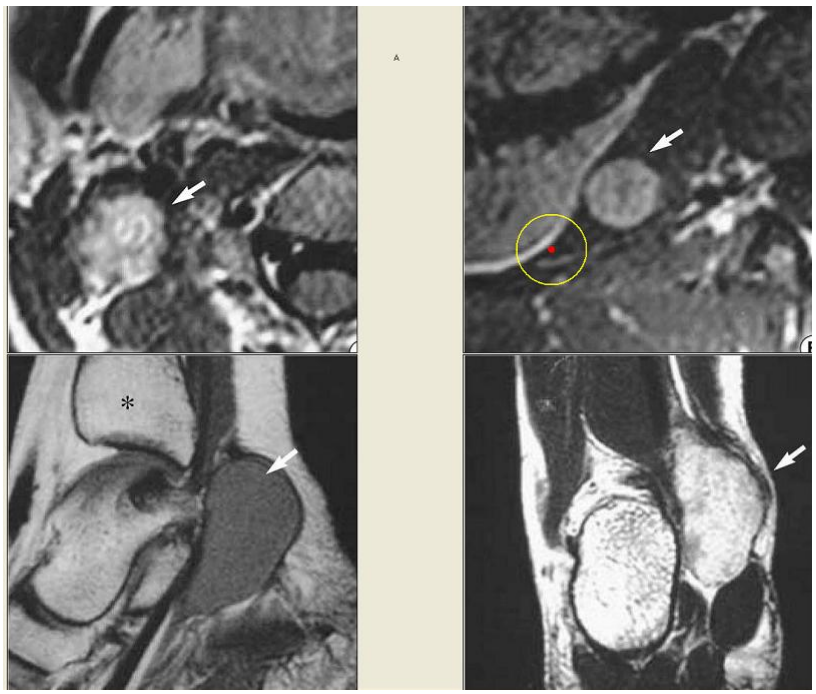


Figure 3.7: Study 1: The experiment platform layout (Participants were told to ignore the white cursor originally on each image)

requested to complete a questionnaire about the preceding condition. After completion of both conditions, each participant was given a questionnaire for subjectively comparing any perceived difference between the two conditions. The whole procedure was about 30 minutes.

3.3.3 Expected Improvement

Table 3.11 shows the theoretical improvement possibly brought from the dynamic C-D gain method. By the new equation of calculating the *ID'*, we estimated that the *MT* which linearly corresponds to the *ID* could be reduced by from 12.4% to 13.6%.

3.3.4 Result and Discussion

The analysis for this study consisted of controlling for learning, times accuracy and user preference.

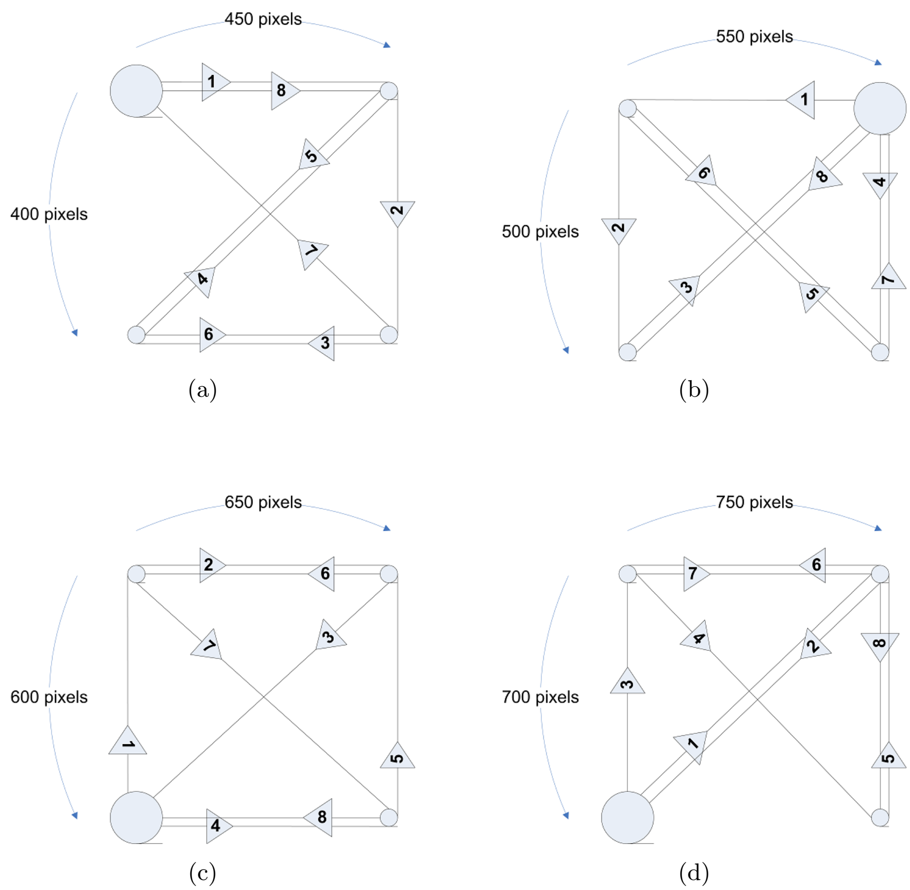


Figure 3.8: Study 1: The order in which targets appeared on the screen. The big circle indicates the starting point, however, participants may click other place to activate "linking"

Table 3.9: Study 1: The distances (pixel) between targets labeled in Figure 3.8.

	a	b	c	d
1	450	550	600	1025
2	400	500	650	1025
3	450	750	884	700
4	600	500	650	1025
5	600	750	600	700
6	450	750	650	750
7	600	500	884	750
8	450	750	650	700

Table 3.10: Study 1: Number of trials N for each distance D.

D	N
400	36
450	108
500	108
600	144
650	144
700	108
750	216
884	72
1025	72

Controlling For Learning

Since we did not provide any practice for participants before starting the experiment, the learning effects may influence the result. Then we should determine how many blocks participants required for learning. Because we counterbalanced the order of the two conditions during the experiment, there were 6 participants (participant 1, 3, 5, 7, 9, 11) firstly did the experiment under the constant C-D gain, and vice-versa for the others.

Figure 3.3.4 shows the average total completion time for each block over 12 participants under both constant and dynamic C-D gain. We observed that out of the four blocks in the overall procedure, the first block had the longest completion time under both constant C-D

Table 3.11: Study 1: Original ID vs new $ID' = \log_2 \frac{2D+(R-1)S}{W \times R}, R = 2, S = 80$

D (pixel)	W (pixel)	ID (bit)	ID' (bit)	Improvement
400	10	6.32	5.46	14%
450	10	6.49	5.61	14%
500	10	6.64	5.75	13%
600	10	6.91	6.00	13%
650	10	7.02	6.11	13%
700	10	7.13	6.21	13%
750	10	7.23	6.30	13%
884	10	7.47	6.53	13%
1025	10	7.68	6.73	12%

gain and dynamic C-D gain. Additionally, the remaining three blocks had a relatively stable performance. This result enabled us to conservatively assume that the duration of trials in the first block was enough for participants to adapt to the experimental platform and mouse movement trials. Moreover, Figure 3.10 shows the performance difference between training stage (the first block) and the remaining three blocks. We saw that in both constant C-D gain and dynamic C-D gain, the average total completion time over 12 participants during the training stage was longer than that during the remaining three blocks. This confirmed the assumption that the participants had already adapted to the experimental setup after the first block.

Times

As described above, we excluded the first block from the analysis and then evaluated the performance improvement on the remaining three blocks. Figure 3.11 shows the average MT and standard deviation corresponding to distances under constant C-D gain and dynamic C-D gain. We saw that the average MT under dynamic C-D gain was always shorter than that under constant C-D gain for all distances. Table 3.12 shows the average MT under both conditions, percentage improvement of the dynamic C-D gain, number of trials and the p-value. The p-value of the difference between constant and dynamic C-D gain is shown in the last column of Table 3.12. Most improvements were significant at the 0.01 level. The highest improvement is 19.2% which occurred at $D = 450$ pixels, while the lowest was 11.7%

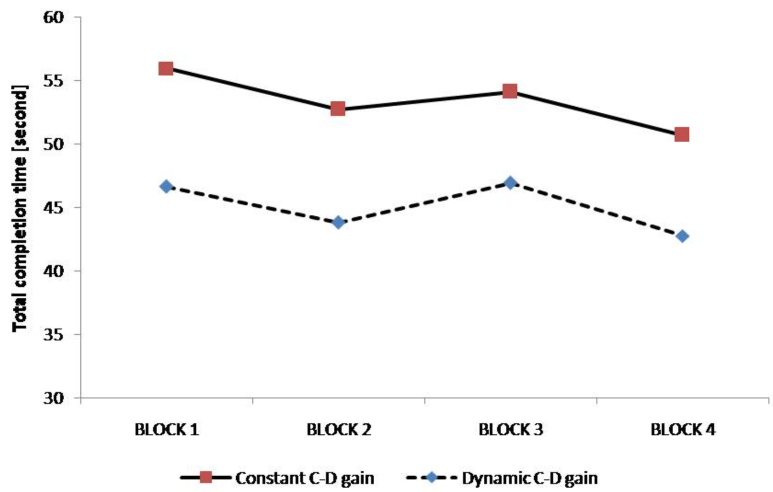
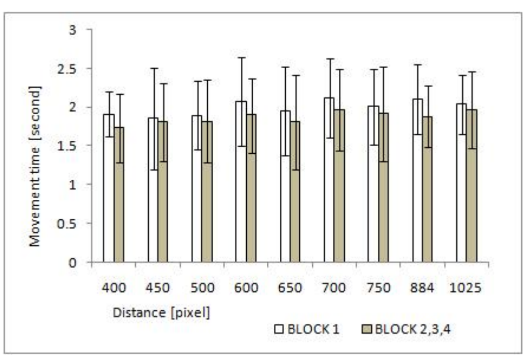
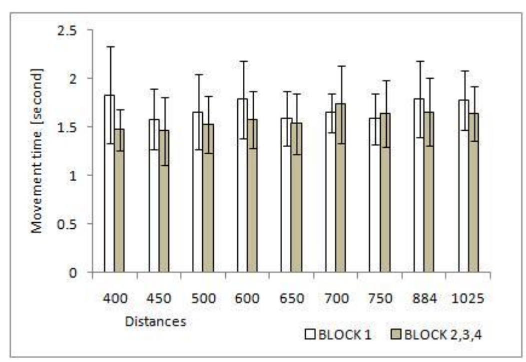


Figure 3.9: Study 1: The average total completion time for each block over 12 participants.



(a)



(b)

Figure 3.10: Study 1: The average movement time and standard deviation corresponding to distances. First block vs the remaining three blocks. The left figure is that under constant C-D gain, the right figure is that under dynamic C-D gain

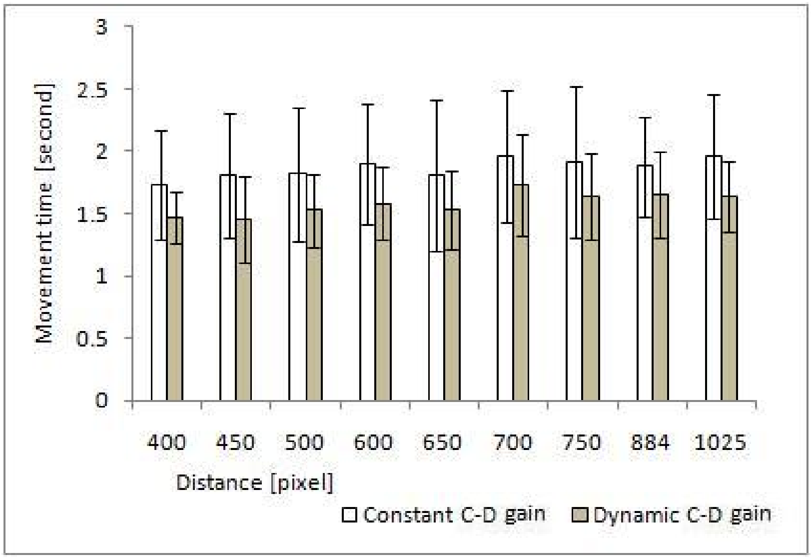


Figure 3.11: Study 1: Mean performance comparison for both conditions at each distance D. Error bar is the standard deviation.

which occurred at $D = 700$ pixels. This result was consistent with our prediction shown in Table 3.11 that the improved dynamic C-D gain would provide about 13% performance improvement.

By looking at the standard deviation in Figure 3.11 and Table 3.12, we found that the standard deviation for each distance was quite large. This could be explained by individual differences. Note that the standard deviation appears smaller for dynamic gain than constant gain. Also, by looking into the questionnaire, we found that some participants were left-handed mouse users. These left-handed users would certainly perform less accurately using the right-handed mouse, and spend more time on each trial. Some other people complained that the default mouse speed was not what they were familiar with, and claimed that they could perform much better under their own preferred mouse speed.

Accuracy

The cursor was displayed as a cross 20 pixel wide with an active area of a single pixel. We computed the percentage of error clicks (clicks outside the 10 pixels wide circular target) over all trials. The dynamic C-D gain always provided a lower error rate comparing to

Table 3.12: Study 1: The mean movement time (seconds), standard deviation and number of trials under both conditions for each distance D, and the p-value from the paired t-test.

D	Constant C-D	Dynamic C-D	Observed Improvement	df	p-value
400	1.73 ± 0.44	1.47 ± 0.21	15%	36	0.04
450	1.81 ± 0.50	1.46 ± 0.35	19%	108	0.02
500	1.82 ± 0.54	1.53 ± 0.29	16%	108	0.02
600	1.90 ± 0.48	1.58 ± 0.29	17%	144	0.01
650	1.81 ± 0.61	1.53 ± 0.31	15%	144	0.01
700	1.96 ± 0.52	1.73 ± 0.40	12%	108	0.01
750	1.92 ± 0.61	1.64 ± 0.34	15%	216	0.01
884	1.88 ± 0.40	1.65 ± 0.35	12%	72	0.01
1025	1.97 ± 0.50	1.64 ± 0.28	17%	72	0.00

constant C-D gain (Figure 3.12). The result was consistent with the questionnaire on that all participants claimed they could perform equally or more accurately under the dynamic C-D gain than the constant C-D gain.

User Preference

For the perceptibility, 8 participants out of 12 claimed that they did not perceive any differences between the two conditions (Questions can be found in Appendix B.1.4). For the remaining 4, all preferred the dynamic gain. Of interest was one participant who did not feel any difference but still ranked the dynamic gain above the constant gain. No participants preferred the constant gain.

3.3.5 Summary

This study indicated that dynamic gain improved the pointing time to a known target by 15%, with a lower error rate and higher user preference.

In this study, all targets were pre-set (known to the system). In the next study, we employed eye-gaze tracking for target prediction, which generalizes the dynamic C-D gain method to all kinds of mouse trials without any knowledge of the underlying interface or tasks.

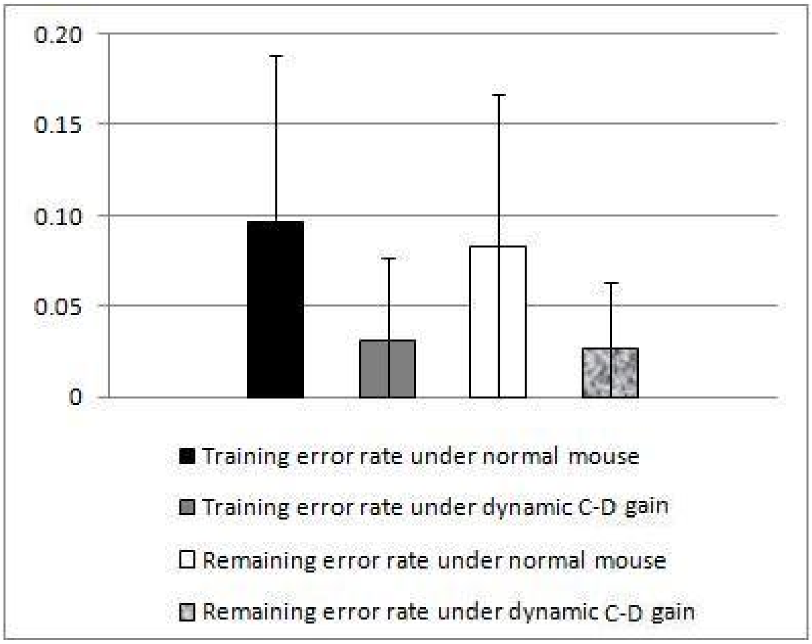


Figure 3.12: Study 1: The error rate for training (first block) and remaining (second,third and forth block)

3.4 Study 2 - Eye-gaze Prediction of Likely Target

3.4.1 Objective

The study 1 indicated an average of 15% performance improvement on the known targets. To fulfill the need for unknown targets in radiology, we conducted another study with predicted targets to get a practical result with comparison to the optimal result obtained from the study 1. The experiment setup for this study was identical to the study 1 except using gaze point data from the eye-gaze tracker.

3.4.2 Method

Tasks and Procedure

In this study, the real target location is unknown to the system and the mouse cursor was slowed down according to the target location predicted by the Tobii 1750 eye-tracker. The eye-gaze tracker was calibrated to the individual participant, even for the condition where the eye-gaze was not used to alter the C-D gain.

Participants

We recruited 12 participants for this study. Participants were all students at Simon Fraser University with an average age of 26. None of them participated in the pilot studies or study 1.

Gaze Data

The location of each sampled gaze point was used to adjust the C-D gain. Note that unusually, we did not use fixations of durations>150 msec, as taking the average of several gaze points would not leave enough time to slow the mouse down before it reached the target.

When the eye-gaze tracker lost the track of participants' eyes, participants were notified by noticeable beeping sound. So they could adjust their head position to resume the tracking.

3.4.3 Result and Discussion

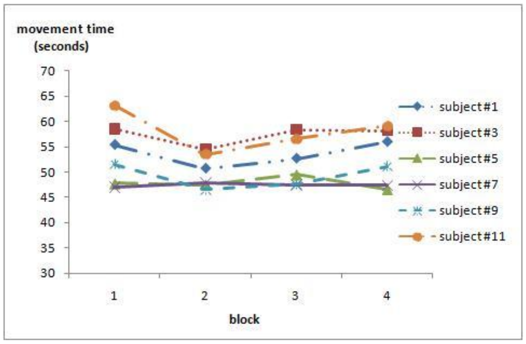
Controlling For Learning

The process for learning was mostly identical to the study 1.

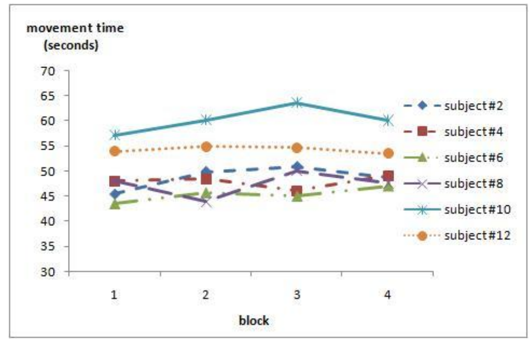
Figure 3.13(a) shows the completion time by block for participants who began with constant C-D gain. Figure 3.13(b) shows the completion time by block for participants who first did the experiment under dynamic C-D gain. Figure 3.13(a) shows a strong reduction in time from Block 1 to Block 2 for four of the six participants. The time for the remaining blocks is generally less than for the first block. In Figure 3.13(b), however, all participants have approximately the same completion time for each block. We have no explanation for the apparent absence of learning in this group. To reduce the confounding effect of learning, Block 1 was excluded from the analysis for all participants.

Times

Figure 3.14 shows the average MT with constant C-D gain and dynamic C-D gain. For trials with D>600 pixels, the average MT with dynamic C-D gain was always less than that with constant C-D gain. However, when we looked into the p-value through the paired



(a)



(b)

Figure 3.13: Study 2: The completion time of each block for each participant. (a) participants who performed under the constant C-D gain first. (b) participants who performed under the dynamic C-D gain first.

t-test as shown in Table 3.13, it does not indicate any statistically significant difference. The possible reason is that due to the imprecise prediction from the eye-gaze tracker, some trials with dynamic C-D gain had the gain adjusted in a region far from the actual target. Then the cursor might slow down within an improper area or it did not slow down at all. In order to get a more detailed result, we categorized the data by the precision of the target prediction.

For each trial we traced back the previous three gaze points, and use the average as the target fixation point. Each target fixation point was analyzed to see how far it was from the target. Trials were split into three categories. Trials with target prediction errors of less than 20 pixels were categorized as "*Precise*" (43% of the trials). For these trials, no matter where the area of reduced cursor speed was placed relative to the target, the cursor would still always be slowed for some distance (Column 1, Figure 3.15). Trials with prediction errors between 20 pixels and 40 pixels were categorized as "*Medium*" (34% of the trials). For such predictions, the cursor might not be slowed down in the worst case, as the worst case only occurs when the actual target lies between the predicted target location and the starting point (Column 2, Figure 3.15). The rest of the trials were categorized as "*Imprecise*" (23% of the trials). For prediction errors over 40 pixels, the actual target location will always be outside of the area of the reduced cursor speed (Column 3, Figure 3.15). All participants had some trials in every category.

The mean movement time for the "*Precise*" trials is shown in Table 3.14. The column *df*

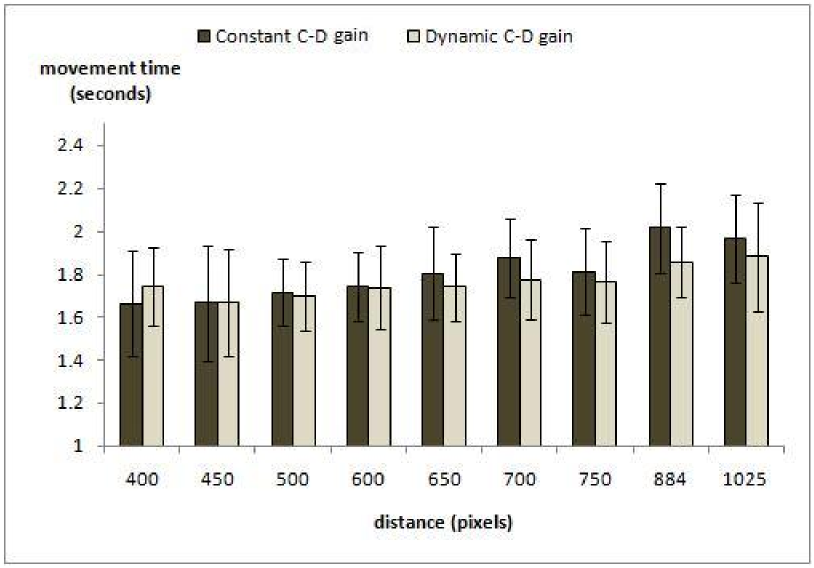


Figure 3.14: Study 2: Mean performance comparison for both conditions at each distance D. Error bar is the standard deviation.

(degree of freedom) in Table 3.14 was related to the number of participants involved in that D in "*Precise*", that is, if 5 participants out of 12 had trials in $D = 400$ in "*Precise*", the *df* for $D = 400$ is 4. The mean movement time with dynamic C-D gain for trials with 650 pixels$\leq D<1025$ pixels is significantly lower than for constant C-D gain. Overall, there is an average of 7.8% improvement for those trials. Furthermore, more statistically significant difference for the improvement is found in this group. We cannot explain why dynamic gain had no effect for trials with D=1025 pixels. Perhaps this distance was too large to cross with a single hand motion under the active mouse speed setting, requiring the user to physically re-position the mouse.

The mean movement time for the "*Medium*" trials is shown in Table 3.15. The performance under dynamic gain for all trials is faster than for constant gain. But the improvement are small and none is close to statistically significant. The lack of strong effect for these trials is expected, because dynamic gain is unreliable in this case, where the region of reduced cursor speed can be any direction from the actual target. If the slower region is on the line connecting the starting point and the target, the cursor slows as it approaches the target. If instead the predicted location is offset from the line, the dynamic gain has little to no

Table 3.13: Study 2: The mean movement time (seconds), standard deviation and number of trials under both conditions for each distance D, and the p-value from the paired t-test.

D	Constant C-D	Dynamic C-D	Observed Improvement	df	p-value
400	1.66 ± 0.24	1.74 ± 0.18	-5%	36	0.23
450	1.66 ± 0.27	1.67 ± 0.25	0%	108	0.48
500	1.72 ± 0.16	1.70 ± 0.16	1%	108	0.39
600	1.74 ± 0.16	1.74 ± 0.20	0%	144	0.48
650	1.80 ± 0.22	1.74 ± 0.16	4%	144	0.14
700	1.87 ± 0.18	1.77 ± 0.19	5%	108	0.04
750	1.81 ± 0.20	1.77 ± 0.19	3%	216	0.16
884	2.01 ± 0.21	1.86 ± 0.16	8%	72	0.04
1025	1.97 ± 0.20	1.88 ± 0.25	4%	72	0.21

effect on the cursor.

Since the target prediction for the "*Imprecise*" trials was completely incorrect, there should be no difference between trials with constant C-D gain and dynamic C-D gain in this group. The result in Table 3.16 shows that the average movement time in both conditions is almost identical and no significant difference was found, except for D=400 in which the dynamic C-D gain was significantly slower. This result is unreliable because of the small sample size

Accuracy

The cursor was displayed as a cross 20 pixels wide with an active area of a single pixel in the center. We computed the percentage of error clicks (clicks outside the 10 pixels wide circular target) over all trials. Figure 3.16 shows the error rates of each participant under each condition. The error rate under dynamic gain is mostly lower than that under constant gain. The average rate with constant gain was 8.20% versus 6.25% with dynamic gain (t=2.20, p<0.03, df=11).

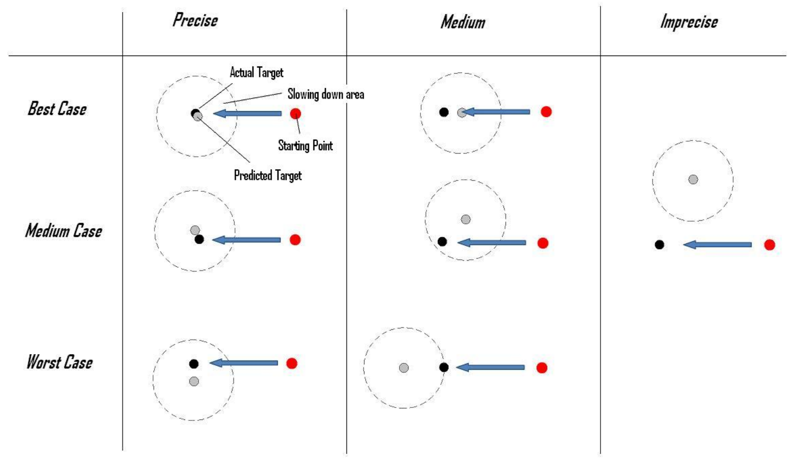


Figure 3.15: Study 2: The best, medium and worst case of predictions in *Precise*, *Medium* and *Imprecise*. The black circle is the actual target. The grey circle is the predicted target. Area inside the dotted circle is the slowing down area. The red circle is the starting point.

User Preference

Most participants (10/12) claimed that they did not perceive any differences between the two conditions. For the remaining 2, one preferred the dynamic gain and the other preferred the constant gain. This differs strongly from the preferences expressed by participants in study 1. One possible reason is that many trials in the dynamic gain condition were performed with medium or imprecise target prediction. The dynamic gain condition effectively mixed dynamic and constant-gain trials, reducing perceptibility of the dynamic gain.

3.4.4 Summary

In this more realistic condition, in which eye-gaze was used to predict the likely target location, improvement in pointing performance varied with prediction accuracy. For trials in which the prediction was within 20 pixels of the target, pointing time was improved 7.8% for distances larger than 600 pixels. However, no effect was found for the longest distance, 1025 pixels, perhaps because this distance required the user to re-position the mouse, overwhelming the effect of the dynamic gain.

For trials with moderately accurate prediction (error within 20 and 40 pixels), dynamic

Table 3.14: Study 2 - Group *Precise*: The mean movement time (seconds), standard deviation and degree of freedom (*df*) under both conditions for each distance D, and the p-value from the paired t-test.

D	Constant C-D	Dynamic C-D	Observed Improvement	df	p-value
400	1.68 ± 0.17	1.75 ± 0.25	-4%	6	0.29
450	1.74 ± 0.25	1.68 ± 0.32	3%	11	0.26
500	1.75 ± 0.26	1.63 ± 0.17	7%	11	0.06
600	1.78 ± 0.21	1.72 ± 0.18	3%	11	0.22
650	1.82 ± 0.34	1.65 ± 0.23	9%	11	0.04
700	1.89 ± 0.21	1.78 ± 0.12	6%	11	0.05
750	1.82 ± 0.25	1.74 ± 0.24	4%	11	0.06
884	2.02 ± 0.31	1.77 ± 0.18	12%	9	0.02
1025	1.95 ± 0.23	1.93 ± 0.25	1%	10	0.45

gain had essentially no effect. For trials with the most inaccurate prediction (error greater than 40 pixels), the effect of dynamic gain varied widely, in the worst case actually slowing the user's performance.

Dynamic gain also reduced the error rate slightly and was typically imperceptible to users.

3.5 Discussion

The result of pilot studies encouraged us to use $R = 2; S = 80$ as the parameter for small targets because the S(80) can be tolerated by the accuracy of the eye-gaze tracker which is 28±17 pixels. By using this parameter, we conducted a study (study 1) with 12 participants. We used known targets to estimate the optimal improvement possible with a dynamic C-D gain in a radiology context. From study 1, we found an average of 13.6% (p<0.01) improvement on the average movement time for known targets with a significantly lower error rate and higher user preference in study 1.

We also conducted a second study (study 2) with 12 different participants to evaluate the role of eye-gaze targeting in the realistic situation of unknown target positions. The result of the second study indicated the practical performance of the dynamic C-D gain

Table 3.15: Study 2 - Group *Medium*: The mean movement time (seconds), standard deviation and degree of freedom (*df*) under both conditions for each distance *D*, and the *p*-value from the paired *t*-test.

D	Constant C-D	Dynamic C-D	Observed Improvement	*df*	*p*-value
400	1.74 ± 0.39	1.64 ± 0.19	6%	6	0.28
450	1.68 ± 0.24	1.64 ± 0.20	2%	8	0.29
500	1.72 ± 0.29	1.67 ± 0.24	3%	10	0.31
600	1.74 ± 0.28	1.72 ± 0.20	1%	11	0.41
650	1.71 ± 0.21	1.70 ± 0.25	0%	11	0.48
700	1.83 ± 0.19	1.77 ± 0.23	3%	11	0.19
750	1.81 ± 0.23	1.77 ± 0.18	2%	11	0.30
884	1.83 ± 0.17	1.78 ± 0.27	3%	9	0.29
1025	1.92 ± 0.33	1.81 ± 0.27	6%	9	0.22

method with an eye-gaze tracker. Due to the imprecise prediction, we expected and found the result to be less promising than the study 1 which was the optimal. We found an average of 7.8% improvement for trials with distance larger than 600 pixels for trials with precise target prediction (error<20 pixels). However, no effect was found for the longest distance, 1025 pixels, perhaps because this distance required the user to re-position the mouse, overwhelming the effect of the dynamic gain. For trials with moderately accurate prediction (error within 20 and 40 pixels), dynamic gain had essentially no effect. For trials with the most inaccurate prediction (error>40pixels), the effect of dynamic gain varied widely, in the worst case actually slowing the user's performance. Furthermore, dynamic gain reduced the error rate over constant gain. Finally, there was no difference perceived by users.

Table 3.16: Study 2 - Group *Imprecise*: The mean movement time (seconds), standard deviation and degree of freedom (*df*) under both conditions for each distance D, and the p-value from the paired t-test.

D	Constant C-D	Dynamic C-D	Observed Improvement	*df*	p-value
400	1.53 ± 0.12	1.78 ± 0.22	-16%	3	0.05
450	1.70 ± 0.57	1.69 ± 0.36	0%	10	0.49
500	1.78 ± 0.41	1.81 ± 0.28	-2%	9	0.44
600	1.70 ± 0.20	1.77 ± 0.28	-4%	10	0.21
650	1.75 ± 0.26	1.82 ± 0.12	-4%	10	0.21
700	1.76 ± 0.24	1.74 ± 0.25	1%	9	0.41
750	1.78 ± 0.29	1.73 ± 0.16	3%	9	0.31
884	1.97 ± 0.46	2.02 ± 0.26	-2%	6	0.39
1025	1.96 ± 0.29	1.76 ± 0.29	11%	7	0.10

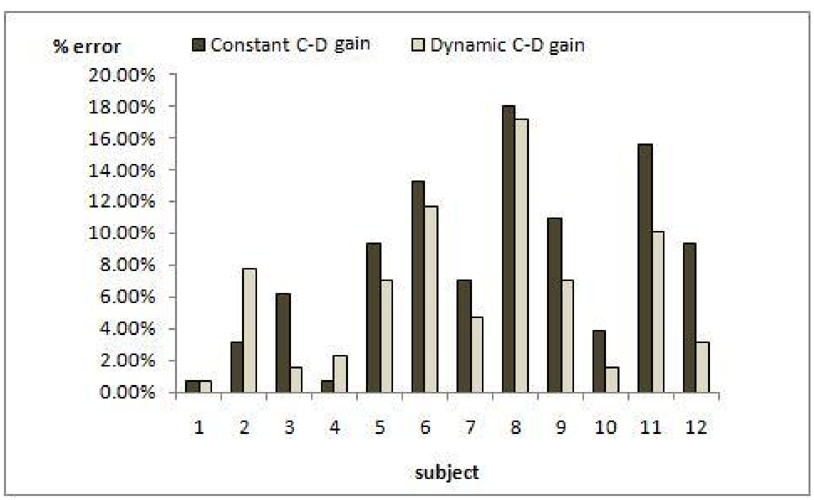


Figure 3.16: Study 2: The percentage error for every participant.

Chapter 4

Conclusion

This thesis makes an exploration of the feasibility of using the dynamic control-to-display (C-D) gain technique with an eye-gaze tracker to improve the pointing performance for radiology tasks.

Pointing tasks are performed frequently and extensively in radiology workstations. Reducing time required for pointing tasks can improve the usability of the interaction, upgrading the efficiency for radiologists. Among all existing interactive methods, the scroll-wheel mouse is the most preferred commonly used device. Although there are other methods shown to be more efficient in some circumstances than the scroll-wheel mouse, people still prefer the device that they are most familiar with.

We improved the dynamic C-D gain technique, integrating with an eye-gaze tracker, to improve the pointing performance using the traditional scroll-wheel mouse. The concept behind the dynamic C-D gain is that by dynamically adjusting the C-D gain, the index of the difficulty (ID) of a pointing task can be reduced. We slowed down the mouse cursor when it is close to the target, making the target effectively bigger in the motor space. In order to apply this method to the 2-D space, and make it more effective for small targets, we proposed an extended slowing down area instead of just slowing the cursor down over the target. Previous studies showed that people look at where they are working on. Based on this fact, we proposed that the gaze location of the user can be used to predict the target location. We used an Tobii 1750 eye-gaze tracker to obtain the gaze data from the user, and then dynamically changed the C-D gain according to the cursor location to the gaze location.

By experiments we found that $R = 2; S = 80$ are the best parameters; that is, the optimum value of the slowing down ratio R is 2, and the optimum value of the slowing down area diameter S is 80 pixels which can be tolerated by the accuracy of the eye-gaze tracker (28 ± 17 pixels). By using this parameter, we obtained an average of 13.6% improvement in pointing time from study 1 in which only known targets were used. Also in study 1, dynamic gain significantly reduced the error rate over constant gain. No differences between dynamic gain and constant gain were perceived by participants. Next, we conducted a second study (study 2) with 12 different participants to evaluate the role of eye-gaze targeting in the realistic situation of unknown target positions. We found an average of 7.8% improvement for trials with distance larger than 600 pixels for trials where the eye-gaze prediction of the target was precise (error<20 pixels). However, no effect was found for the longest distance, 1025 pixels, perhaps because this distance required the user to re-position the mouse, overwhelming the effect of the dynamic gain. For trials where the eye-gaze only predicted the target with moderate precision (error within 20 and 40 pixels), dynamic gain had essentially no effect. For trials with the most inaccurate prediction (error>40pixels), the effect of dynamic gain varied widely, in the worst case actually slowing the user's performance. Furthermore, dynamic gain reduced the error rate over constant gain. Finally, there was no difference perceived by users.

4.1 Difficulties

During the exploration, there were some major difficulties. The first difficulty is in determining how much the cursor should be slowed down (slowing down ratio R), and how big the slowing down area should be (slowing down area diameter S). Since both S and R can affect the *ID*, as well as the path variation, it's difficult to determine the best value for S and R by theoretical calculation. Therefore, we conducted a pilot study to coarsely evaluate different combinations of S and R. We found that R(2)S(80), R(2)S(60) and R(2)S(40) can improve the pointing performance.

Another challenge is how to balance the value of S with the accuracy of the eye-gaze tracker. As we found, if the S is too big, the distance D will be significantly affected; if the S is too small, the impact of path variation is high, so we cannot achieve the optimum performance. To solve this, we conducted another pilot study to evaluate the accuracy of the eye-gaze tracker. We found that there's an average of about 20 pixels offset between the target and the predicted target. Combining this result with the result from the first pilot study, $S = 80$ pixels and $R = 2$ were chosen.

4.2 Future Work

Currently, about 43% of the target predictions in our experiment were precise (error<20 pixels). This proportion of the trials brought the highest improvement for the pointing performance. We believe that with a better calibration procedure and a better real-time analysis method for the real time gaze data, the accuracy of the prediction can be improved. Also, we could combine the eye-gaze tracker with other target predicting methods, to get a more accurate and confident prediction. Candidate methods such as *Delphian Desktop* [1] should be able to handle unspecified targets. Once more than one predictive method is employed, the prediction from each method can be combined to the final prediction.

Moreover, only "slowing down" was applied in the current method. Theoretically, if the "speeding up" can be applied while the cursor is far away from the target, the *ID* can be reduced further. Besides, with "speeding up", tasks with longer distance can be completed with a single hand motion, thus potentially reducing the movement time.

In the future, the mouse path for each trial can be tracked to get a more detailed analysis. For example, we can compare trials of overshoot and undershoot, and directional bias. Also we can analyze the path variations.

Since we were constrained to just a single monitor because of our eye-gaze tracking equipment, in future, with different eye-gaze trackers, we would like to employ multiple monitors to test the more realistic situations encountered in radiology, and examine the performance improvements over much larger distances.

The dynamic C-D gain method is completely context-free. This feature is useful because our technique is applicable to any display without specific knowledge of the GUI system. Hence our method can actually be used on any system, instead of being applicable only radiology workstations. However, if we add our knowledge to a radiology workstation, taking advantage of known positions of icons, buttons etc., there might be a further boost in the improvement. For example, methods such as [14, 29] which can handle pre-specified targets will be eligible to combine with. Note that no matter what method is proposed in the future, validations with radiologists will be necessary.

Appendix A

Experiment Descriptions

Participants in study 1 and study 2 followed a strict written procedure, as shown in the following sections.

A.1 Study 1

Mouse pointing with control gain - User instructions

Dec 11th, 2008

Description of tasks

In this experiment, you will be using a standard mouse to perform clicking actions.

In this experiment, you will only need to use the mouse to click on circular targets shown as small red dots surrounded by a larger yellow ring.

- To begin, right-click anywhere on the screen, and select “linking” from the menu which appears.
- Then click on each red dot as they appear; there will be 8 dots in each set.
- When 8 dots have been clicked, please again right-click and select ”linking” to begin the next set.
- The experiment ends when 16 sets with each of 8 dots have been completed.

This procedure will be repeated twice. At the end of each, you need to fill up a questionnaire. This experiment may take approximately 10-15 minutes to complete.

Your performance will be timed; please try to work quickly, but also try to ensure you hit the targets accurately.

Please inform the experimenter if you wish to take a break; you are also free to withdraw from the experiment at any time.

Thank you for your participation!

A.2 Study 2

Mouse pointing with control gain - User instructions

Mar 6th, 2009

Description of task

In this study, you will be using a standard mouse to perform clicking actions.

In this study, you will only need to use the mouse to click on circular targets shown as small red dots surrounded by a larger yellow ring. Your eye-gaze fixations will be recorded. Note that you can ask for reversing the mouse keys if you are left-handed mouse user. The study has two experiments.

- Before each experiment, the eye-gaze tracker needs to be calibrated. Simply use your eyes to follow the blue ball on the screen.
- To begin, right-click anywhere on the screen, and select ”linking” from the menu which appears.
- Then click on each red dot as they appear; there will be 8 dots in each set.
- When 8 dots have been clicked, please again right-click and select ”linking” to begin the next set.
- The experiment ends when 16 sets each with 8 dots have been completed.

During the experiment, if your eye-gaze signal is lost, there will be a beeping sound. If you hear this sound, please adjust your head position until the beeping stops. This can usually be done by facing the eyetracking monitor squarely at the advised distance.

This experiment will be repeated twice. At the end of each, you will be asked to complete a questionnaire.

This study may take approximately 15-20 minutes to complete.

Your performance will be timed; please try to work quickly, but also try to ensure you hit the targets accurately.

Please inform the experimenter if you wish to take a break; you are also free to withdraw from the study at any time.

Thank you for your participation!

Appendix B

Questionnaires

During both study 1 and study 2, participants were given questionnaires before and after the experiment.

B.1 Study 1

B.1.1 Background Questionnaire

Background information

Before beginning the experiment, we would like to collect some general demographical information and to know your level of computer experience.

1. **Age:** ________ years

2. **Gender:** ________ Female
   ________ Male

3. Approximately how many hours per week do you use a computer (please check the closest answer)?

Less than half an hour a week	Less than 2 hours a week	Less than 7 hours a week	Less than 7 hours a week	14 or more hours a week

Experience:

4. How much do you use the mouse to point at and click on small targets (e.g. about the size of one letter on this sheet of paper)? Please check the most suitable answer.

Never	Rarely	Somewhat often	Frequently

5. Which hand do you prefer for using the mouse? ________ Right
________ Left
________ Either

6. Do you prefer to reverse the "left" and "right" mouse buttons? ________ No
________ Yes

Thank you for your responses. Please follow the instructions of the experimenter. Remember that you are free to take a break or withdraw from the study at any time.

B.1.2 Questionnaire After the Constant Gain Condition

Evaluation of experimental condition

For the experimental condition you have just completed, please rate your experience with respect to the following characteristics:

Please circle the number best matching your experience.

1. Speed of clicking the target:
(Slow) 1 2 3 4 5 6 7 (Quick)

2. Accuracy of clicking the target:
(Inaccurate) 1 2 3 4 5 6 7 (Accurate)

3. Comfort of using this interface:
(Uncomfortable) 1 2 3 4 5 6 7 (Comfortable)

4. How effectively did this interface support you to do the target pointing task?
(Poorly) 1 2 3 4 5 6 7 (Well)

B.1.3 Questionnaire After the Dynamic Gain Condition

Evaluation of experimental condition

For the experimental condition you have just completed, please rate your experience with respect to the following characteristics:

Please circle the number best matching your experience.

1. Speed of clicking the target:
   (Slow) 1 2 3 4 5 6 7 (Quick)

2. Accuracy of clicking the target:
   (Inaccurate) 1 2 3 4 5 6 7 (Accurate)

3. Comfort of using this interface:
   (Uncomfortable) 1 2 3 4 5 6 7 (Comfortable)

4. How effectively did this interface support you to do the target pointing task?
   (Poorly) 1 2 3 4 5 6 7 (Well)

B.1.4 Questionnaire After Both Conditions

Ranking & open-ended questions

Preference ranking

1. If you cannot remember or did not notice any difference between the two conditions, indicate this in the spaces provided below.
   ________ Cannot remember the conditions
   ________ No noticeable difference between the conditions

2. If you noticed a difference between the two conditions, please rank the two experimental conditions in order of your preference (1 = most preferred, 2 = least preferred).

Rank	Condition
	First
	Second

General feedback

3. Please give any comments you have in the space provided below:

This concludes the experimental session. Thank you for your participation. We appreciate your valuable time, please enjoy the refreshments before you leave.

B.2 Study 2

Background information

Before beginning the experiment, we would like to collect some general demographical information and to know your level of computer experience.

1. **Age:** ________ years

2. **Gender:** ________ Female

   ________ Male

3. Approximately how many hours per week do you use a computer (please check the closest answer)?

Less than half an hour a week	Less than 2 hours a week	Less than 7 hours a week	Less than 7 hours a week	14 or more hours a week

Experience:

4. How much do you use the mouse to point at and click on small targets (e.g. about the size of one letter on this sheet of paper)? Please check the most suitable answer.

Never	Rarely	Somewhat often	Frequently

5. Which hand do you prefer for using the mouse? ________ Right

   ________ Left

   ________ Either

6. Do you prefer to reverse the "left" and "right" mouse buttons? ________ No

   ________ Yes

7. Have you ever used an eye-gaze tracker before? ________ No

   ________ Yes

   If Yes, for how long? ________

Thank you for your responses. Please follow the instructions of the experimenter. Remember that you are free to take a break or withdraw from the study at any time.

B.2.1 Questionnaire After the Constant Gain Condition

Evaluation of experimental condition

For the experimental condition you have just completed, please rate your experience with respect to the following characteristics:

Please circle the number best matching your experience.

1. Speed of clicking the target:
   (Slow) 1 2 3 4 5 6 7 (Quick)

2. Accuracy of clicking the target:
   (Inaccurate) 1 2 3 4 5 6 7 (Accurate)

3. Comfort of using this interface:
   (Uncomfortable) 1 2 3 4 5 6 7 (Comfortable)

4. How effectively did this interface support you to do the target pointing task?
   (Poorly) 1 2 3 4 5 6 7 (Well)

B.2.2 Questionnaire After the Dynamic Gain Condition

Evaluation of experimental condition

For the experimental condition you have just completed, please rate your experience with respect to the following characteristics:

Please circle the number best matching your experience.

1. Speed of clicking the target:
   (Slow) 1 2 3 4 5 6 7 (Quick)

2. Accuracy of clicking the target:
   (Inaccurate) 1 2 3 4 5 6 7 (Accurate)

3. Comfort of using this interface:
   (Uncomfortable) 1 2 3 4 5 6 7 (Comfortable)

4. How effectively did this interface support you to do the target pointing task?
   (Poorly) 1 2 3 4 5 6 7 (Well)

B.2.3 Questionnaire After Both Conditions

Ranking & open-ended questions

Preference ranking

1. If you cannot remember or did not notice any difference between the two conditions, indicate this in the spaces provided below.
   ________ Cannot remember the conditions
   ________ No noticeable difference between the conditions

2. If you noticed a difference between the two conditions, please rank the two experimental conditions in order of your preference (1 = most preferred, 2 = least preferred).

Rank	Condition
	First
	Second

During the experiment, there was a beep noise notifying you when your eye-gaze signal is lost.

3. Please rate how noticeable the noise was:
   (very unnoticeable) 1 2 3 4 5 6 7 (very noticeable)

4. Please rate how intrusive the noise was:
   (very unintrusive) 1 2 3 4 5 6 7 (very intrusive)

5. Was it clear how you needed to readjust your posture to regain accurate eyetracking?
   (very unclear) 1 2 3 4 5 6 7 (very clear)

6. Was it easy to adjust and maintain your posture to regain accurate eyetracking?
   (very difficult) 1 2 3 4 5 6 7 (very easy)

General feedback

7. Please give any comments you have in the space provided below:

This concludes the study. Thank you for your participation. We appreciate your valuable time, please enjoy the refreshments before you leave.

Bibliography

[1] Takeshi Asano, Ehud Sharlin, Yoshifumi Kitamura, Kazuki Takashima, and Fumio Kishino. Predictive interaction using the Delphian Desktop. In *UIST '05: Proceedings of the 18th annual ACM symposium on User interface software and technology*, pages 133–141, New York, NY, USA, 2005. ACM.

[2] Michael Ashmore, Andrew T. Duchowski, and Garth Shoemaker. Efficient eye pointing with a fisheye lens. In *GI '05: Proceedings of Graphics Interface 2005*, pages 203–210, Victoria, British Columbia, 2005. Canadian Human-Computer Communications Society.

[3] M. Stella Atkins, Jennifer Fernquist, Arthur E. Kirkpatrick, and Bruch B. Forster. Evaluating interaction techniques for stack mode viewing. *Journal of Digital Imaging*, 22(4):369–382, 2008.

[4] Richard Bates and Howell Istance. Zooming interfaces!: enhancing the performance of eye controlled pointing devices. In *Assets '02: Proceedings of the fifth international ACM conference on Assistive technologies*, pages 119–126, Edinburgh, Scotland, 2002. ACM.

[5] Patrick Baudisch, Edward Cutrell, Dan Robbins, Mary Czerwinski, Peter Tandler, Benjamin Bederson, and Alex Zierlinger. Drag-and-pop and drag-and-pick: Techniques for accessing remote screen content on touch- and pen-operated systems. In *Proceedings of Interact 2003*, pages 57–64, August 2003.

[6] Renaud Blanch, Yves Guiard, and Michel Beaudouin-Lafon. Semantic pointing: improving target acquisition with control-display ratio adaptation. In *CHI '04: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 519–526, New York, NY, USA, 2004. ACM.

[7] Jack Callahan, Don Hopkins, Mark Weiser, and Ben Shneiderman. An empirical comparison of pie vs. linear menus. In *CHI '88: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 95–100, New York, NY, USA, 1988. ACM Press.

[8] Andy Cockburn and Stephen Brewster. Multimodal feedback for the acquisition of small targets. *Ergonomics*, 48(9), 2005.

[9] Andy Cockburn and Philip Brock. Human on-line response to visual and motor target expansion. In *GI '06: Proceedings of Graphics Interface 2006*, pages 81–87, Toronto, Ont., Canada, Canada, 2006. Canadian Information Processing Society.

[10] Andy Cockburn and Andrew Firth. Improving the acquisition of small targets. In *British HCI Conference*, pages 181–196. University of Canterbury. Computer Science and Software Engineering, 2003.

[11] Paul M. Fitts. The information capacity of the human motor system in controlling the amplitude of movement. 1954. *J Exp Psychol Gen*, 121(3):262–269, September 1992.

[12] George W. Furnas. Generalized fisheye views. In *CHI '86: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 16–23, New York, NY, USA, 1986. ACM.

[13] Tovi Grossman and Ravin Balakrishnan. The bubble cursor: enhancing target acquisition by dynamic resizing of the cursor's activation area. In *CHI '05: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 281–290, New York, NY, USA, 2005. ACM.

[14] Yves Guiard, Renaud Blanch, and Michel Beaudouin-Lafon. Object pointing: a complement to bitmap pointing in GUIs. In *GI '04: Proceedings of Graphics Interface 2004*, pages 9–16, London, Ontario, Canada, 2004. Canadian Human-Computer Communications Society.

[15] Carl Gutwin. Improving focus targeting in interactive fisheye views. In *CHI '02: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 267–274, New York, NY, USA, 2002. ACM.

[16] Carl Gutwin. Improving focus targeting in interactive fisheye views. In *CHI '02: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 267–274, New York, NY, USA, 2002. ACM.

[17] Peter A. Hancock and Karl M. Newell. The movement speed-accuracy relationship in space-time. In *Motor Behaviour: Programming, Control, and Acquisition*, pages 153–188, New York: Springer-Verlag, 1985.

[18] Bradley M. Hemminger, Anne Bauers, and Jian Yang. Comparison of navigation techniques for large digital images. *Journal of Digital Imaging*, July 2008.

[19] Robert J. K. Jacob. The use of eye movements in human-computer interaction techniques: what you look at is what you get. *ACM Trans. Inf. Syst.*, 9(2):152–169, 1991.

[20] Marcel Adam Just and Patricia A. Carpenter. Eye fixations and cognitive processes. *Cognitive Psychology*, 8:441–480, 1976.

[21] David V. Keyson. Dynamic cursor gain and tactual feedback in the capture of cursor movements. *Ergonomics*, 12:1287–1298, December 1997.

[22] I. Scott MacKenzie. A note on the information-theoretic basis for Fitts' law. *Journal of Motor Behavior*, 21:323–330, 1989.

[23] I. Scott MacKenzie. Fitts' law as a research and design tool in human-computer interaction. *Human-Computer Interaction*, 7(1):91–139, 1992.

[24] I. Scott MacKenzie. Movement time prediction in human-computer interfaces. *Human-computer interaction: toward the year 2000*, pages 483–492, 1995.

[25] I. Scott Mackenzie and William Buxton. Extending Fitts' law to two-dimensional tasks. In *CHI '92: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 219–226, Monterey, California, United States, 1992. ACM.

[26] I. Scott MacKenzie, Tatu Kauppinen, and Miika Silfverberg. Accuracy measures for evaluating computer pointing devices. In *CHI '01: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 9–16, New York, NY, USA, 2001. ACM.

[27] I. Scott Mackenzie and Stan Riddersma. Effects of output display and control-display gain on human performance in interactive systems. *Behaviour & Information Technology*, 13:328 – 337, 1994.

[28] Michael McGuffin and Ravin Balakrishnan. Acquisition of expanding targets. In *CHI '02: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 57–64, New York, NY, USA, 2002. ACM.

[29] Atsuo Murata. Improvement of pointing time by predicting targets in pointing with a PC mouse. *International Journal of Human-Computer Interaction*, 10:23–32, 1998.

[30] Atsuo Murata. Eye-gaze input versus mouse: Cursor control as a function of age. *International Journal of Human-Computer Interaction*, 21:1–14, 2006.

[31] Miguel A. Nacenta, Regan L. Mandryk, and Carl Gutwin. Targeting across displayless space. In *CHI '08: Proceeding of the twenty-sixth annual SIGCHI conference on Human factors in computing systems*, pages 777–786, New York, NY, USA, 2008. ACM.

[32] Bruce I. Reiner, Eliot L. Siegel, and Khan Siddiqui. Evolution of the digital revolution: a radiologist perspective. *Journal of Digital Imaging*, 16(4):324 – 330, 2003.

[33] Anthony J. Sherbondy, Djamila Holmlund, Geoffrey D. Rubin, and Pamela K. Schraedley. Alternative input devices for efficient navigation of large CT angiography data sets. *Radiology*, 234:391–398, 2005.

[34] Kishore Swaminathan and Steve Sato. Interaction design for large displays. *interactions*, 4(1):15–24, 1997.

[35] Yan Tan, Geoffrey Tien, Bruce B. Forster, and M. Stella Atkins. Improving mouse pointing for radiology tasks. In *SPIE medical imaging*, volume 7263, pages 72631I–72631I–11, 2009.

[36] J. E. van der Heyden, M. S. T. Carpendale, K. Inkpen, and M. S. Atkins. Visual presentation of magnetic resonance images. In *VIS '98: Proceedings of the conference on Visualization '98*, pages 423–426, Los Alamitos, CA, USA, 1998. IEEE Computer Society Press.

[37] David L. Weiss, Khan M. Siddiqui, and Joe Scopelliti. Radiologist assessment of PACS user interface devices. *Journal of the American College of Radiology*, 3:265–273, 2006.

[38] Alan T. Welford. *Fundamentals of skills.* Methuen, 1968.

[39] Aileen Worden, Nef Walker, Krishna Bharat, and Scott Hudson. Making computers easier for older adults to use: area cursors and sticky icons. In *CHI '97: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 266–271, New York, NY, USA, 1997. ACM.

[40] Shumin Zhai, Carlos Morimoto, and Steven Ihde. Manual and gaze input cascaded (MAGIC) pointing. In *CHI '99: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 246–253, New York, NY, USA, 1999. ACM.