Modeling Speed-Accuracy Tradeoff in Trajectory-based Tasks with Subjective Bias and Temporal Constraint for User Interface Design

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Abstract

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Speed-accuracy tradeoff is a very common phenomenon in many types of human motor control tasks. In general, the more accurate the task to be accomplished, the longer it takes and vice versa. In Human-Computer Interaction (HCI), trajectory-based task (e.g., navigation through a cascade menu, drawing, writing, or steering through a 3D space, etc) is one of the most basic task paradigms, which likewise obeys the speed-accuracy tradeoff rule. The study on speed-accuracy tradeoff model can be efficiently used for predicting user performance, evaluating input device and instructing user interface design and so on.

Steering law is the widely accepted model for trajectory-based task (or steering task) in HCI and has got so many applications. The steering law obeys certain speed-accuracy tradeoff rule, i.e., the time of a movement tends to become longer when its accuracy increases and vice versa. It models the speed-accuracy tradeoff effect only by objective spatial task parameters, i.e., tunnel amplitude and tunnel width. Tasks in the real world, however, are not as simple as the steering tasks. Besides the objective spatial parameters, more parameters (subjective or objective, internal or external, temporal or spatial, etc.) may affect the human motor tasks, which results in different human performance and different description of speed-accuracy tradeoff.

In this thesis, based on the traditional steering tasks, we first investigated the trajectory-based task with subjective operational bias toward speed or accuracy through a controlled experiment. By analyzing the human performance data (i.e., resulting time and accuracy), we established a new model accommodating objective and subjective factors in steering tasks. Empirical results showed that the new model was more predictive and robust than the traditional steering law.

Following above study, we then investigated another trajectory-based task with objective temporal constraint through a controlled experiment. Different from above experiment, movement time was specified in advance for this study, and the accuracy should be measured. By analyzing the obtained human performance data, we established a new model predicting the relationship between accuracy and speed. Experimental results confirm that the new model fit the empirical data well.

In addition, we also investigate the maximal path width that the traditional steering law holds for, the effect of different start positions on human performance and the effect of age (younger and older people) on speed-accuracy tradeoff.

In theory, this work will contribute to considering more factors (subjective bias factor, objective temporal factor, movement direction and age-related effects) in modeling human performance and speed-accuracy tradeoff. In practice, all these results will provide new sights for future interface design and input device evaluation in HCI.

key words Human-computer interaction, speed-accuracy tradeoff, trajectory-based task, performance model, steering law, subjective operational bias, objective temporal constraint, age effect.

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Chapter 1

Introduction

1.1 Research Motivation

Human-Computer Interaction (HCI) is the study of how people interact with computer and how to design computer systems that are easy, quick and productive for people to use. It is an interdisciplinary subject, relating computer science with many other fields of study, such as physiology, psychology, motor control, philosophy and so on. For a long time, researchers in HCI have mainly focused on novel input device and user interface designs. Some typical task paradigms, such as pointing, steering, crossing and gesture, help users to accomplish various complex tasks when interacting with computers. To quantitatively evaluate the efficiency of these input devices and interfaces, accuracy and speed of task completion are usually measured.

A user can either perform the task very fast with a large number of errors or very slow with very few errors. When asked to perform a task as well as possible, people will apply various strategies that may optimize speed, optimize accuracy, or combine the two. For this reason, comparing the performance of 2 users cannot be done on the basis of speed or accuracy alone, but both need to be known. Under some testing situations, people can be instructed to optimize either speed or accuracy, and they will effectively adopt the appropriate strategy. However, results can be extremely hard to compare, because time differences between a person who made zero errors and a person who made one error can be dramatic. For this reason, in situations where a speed-accuracy tradeoff exists, the relationship between speed and accuracy needs to be mapped out. In the area of HCI, the relationship to be mapped out is called as model, which can be used to generalize studies on instructing user interface design, evaluating input device, predicting human performance and so on.

Target-based task and Trajectory-based task are two main and basic task paradigms in human computer interaction. Compared to the target-based task, models studies on trajectory-based task is not enough. One of the reason for that maybe the appearance of the first model for trajectory-based task was in 1997 [1], much later than the first model for target-based task in 1954 [18]. Another reason is that modeling the performance in HCI has always been a tough job. Table1.1 shows two by two taxonomy of model for speed-accuracy tradeoff.

One dimension of the taxonomy is the task stimulus in two categories: A. *Target*, and B. *Trajectory*. The other dimension is the constraint placed on I. *Spatial characteristics of the task*, or II. *Temporal characteristics of the task*. By constraint we mean the independent variables controlled in the task. In tasks in I row of Table 1.1, the independent variables are the spatial characteristics of the task, controlled and systematically manipulated in the experiments. The dependent variables, i.e., human performance measurements, are temporal (time or speed). In tasks in II row of Table 1.1, the independent variables are the temporal characteristics of the task, controlled and systematically manipulated in the experiments. The dependent variables, i.e., human performance measurements, are spatial (movement amplitude or standard deviation in space). Commutativity between dependent and independent variables in human performance laws poses an interesting theoretical issue to the psychological science.

Until now, the famous model for trajectory-based task is still steering law [1]. Steering law models a relationship between the steering time of trajectory-based tasks and the task difficulty, which is decided by the tunnel amplitude and tunnel width

Table 1.1 A taxonomy of speed-accuracy tradeoff model.

Models	Target-based Movement	Trajectory-based Movement
Spatial Constraint	Fitts' law [18] (deterministic iterative-corrections model [14] [31]*), ID_e model [68] [27], power law [49] (Stochastic optimized-submovement model [50] *), SH-model [61], SH-model with learning effect [62], Peephole pointing [10], Magic lens pointing [63]	Crossing model (semi-trajectory based) [4] , Steering law [1], (Steering + bias) law [78], CLC model (free-hand drawing) [9]
Temporal Constraint	Schmidt law [66] (impulse variability model [66]*), Error Model [69]	Ongoing model by the authors [79]

** attached represents motor control model of the corresponding law*

through mathematical deduction and experimental verification. During the paradigm experiment, subjects were asked to steer in the tunnel with amplitude A and width W as fast and as accurately as possible.

$$MT = a + b(\frac{A}{W}) \tag{1.1}$$

In Equation 1.1, MT is the movement time, A and W represent the tunnel amplitude and tunnel width respectively, a and b are two regression coefficients. The steering law obeys certain speed-accuracy tradeoff rule, i.e., the time of a movement tends to become longer when its accuracy *1 increases and vice versa. It models the speed-accuracy tradeoff effect in trajectory-based tasks by objective task parameters, i.e., tunnel amplitude and tunnel width.

Tasks in the real world, however, are not as simple as the above steering tasks. Besides the spatial constraint parameters, more parameters (subjective or objective, internal or external, etc.) affect the human motor tasks, which results in different human performance and different description of speed-accuracy tradeoff. These parameters may include physical factor of subject (younger or older, impaired or sound), environment (touch or hover), subjective bias (fast or slow), temporal constraint (500ms or 1000ms) and so on. So, new models or descriptions for speed-accuracy tradeoff in human motor tasks are needed.

1.2 Background Knowledge

Most models in HCI can be categorized into two groups: the descriptive models with metaphoric characteristics (such as Guiard's model of bimanual control [25] and Buxton's three-state model [8]) and the predictive models with mathematics rigors [35]. Simply speaking, "the descriptive models provide a framework or context for thinking about or describing a problem or situation" [40]. It is not the focus in this dissertation.

Predictive models are sometimes called *engineering models* or *performance models* [13] [45]. In HCI, predictive models allow metrics of human performance (speed or accuracy) to be determined analytically without undertaking time-consuming and resource-intensive experiments [40]. This dissertation focuses on predictive models, especially speed-accuracy tradeoff nature of predictive models.

Speed-accuracy tradeoffs in human motor control tasks have been studied for more

*1 In the traditional steering law, more accurate task generally means narrower tunnel width.

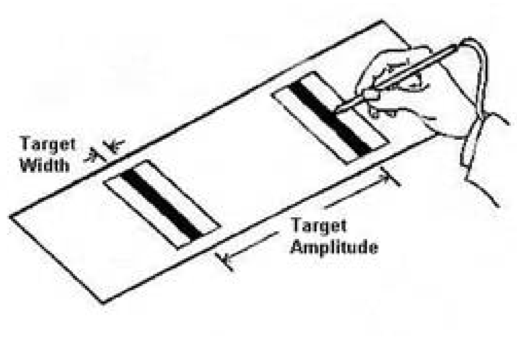

Fig. 1.1 Fitts' law reciprocal pointing paradigm [18].

than a century, resulting in well established experimental protocols and empirical laws relating movement amplitude, speed and accuracy. Woodworth [70] demonstrated that the accuracy of a line-drawing movement depended on the movement velocity. This was the earliest systematic study on speed-accuracy tradeoff. However, he did not formulate the speed-accuracy tradeoff. Since then many researchers have investigated models for speed-accuracy tradeoff. Depending on the nature of the task and the type of the constraint, these researches can be divided into four categories as follows:

1.2.1 Target-based Task with Spatial Constraint

Fitts' law is a model of human psychomotor behavior developed in 1954 [18], formulating speed-accuracy tradeoffs in rapid aimed movement (not drawing or writing). In Fitts' paradigmatic experiment, subjects used a pen to reciprocally point to two strips separated from each other by some distance on a platform (see Fig.1.1).

According to Fitts' Law, the time to move and point to a target of width W at a distance A is a logarithmic function of the spatial relative error ($\frac{2A}{W}$) [18] [19], that is:

$$MT = a + b\log_2(\frac{2A}{W}) \tag{1.2}$$

where, MT is the movement time. a and b are empirically determined constants, that are device dependent. A is the distance (or amplitude) of movement from start to target center. W is the width of the target, which corresponds to "accuracy". The term $\log_2(\frac{2A}{W})$ is called the index of difficulty (ID) of the movement. It describes the difficulty of the motor tasks. $1/b$ is called the index of performance (IP) in "bits/second", and measures the information capacity of the human motor system.

Extending Shannon's theorem [67] in information theory (a formulation of effective information capacity of a communication channel), now the most popular form of Fitts' law [38] is:

$$MT = a + b\log_2(\frac{A}{W} + 1) \tag{1.3}$$

Fitts' law is an effective quantitative method of modeling user performance in rapid, aimed movements, where one appendage (like a hand) starts at a specific start position, and moves to rest within a target area. Fitt's law has been verified to hold for a variety of circumstances [37] [32] [33]. Card et al. [11] reported the first comparative evaluation of the mouse, and also the first use of Fitts' Law in Human-Computer Interaction. Fitts' Law is an intensively used theory in Human-Computer Interaction. It can be used in assisting interface designs and in interface evaluation [28] [54] [60].

In addition, one explanation of motor control theory for Fitts' law was proposed by Crossman and Goodeve [14], and later refined by Keele [30]. It was described as an iterative-corrections model. This model attributes the law to closed-loop feedback control of a movement. It assumes that the whole movement is made up of a series of discrete submovements, each of which takes the user closer to the target and is triggered by feedback indicating the target is not yet attained.

Zhai et al. [77] investigated the speed-accuracy tradeoff based on participants' operational biases toward speed or accuracy, and attempted to derive a model incorporating not only objective task parameters but also subjective biases towards speed or accuracy. However, a simple and linear model was not found by the empirical studies. Consequently, Ren et al. [61] established the SH-Model involving both the system and subjective factors based on the distribution of the actual movement time, which is different from the traditional Fitts' law based on the spatial distribution of end points. The SH-Model then was experimentally verified to hold for several input devices [34]. Although the strong predictive power of SH-Model, it doesn't take learning effects into account. Ren et al. [62] proposed new model that reflected the learning effect on movement time based on the SH-Model in the pointing tasks.

1.2.2 Target-based Task with Temporal Constraint

Schmidt's law [66] is closely related to Fitts' law. In their study, movement amplitude and time were manipulated, and the standard deviation of end points distribution was measured. Schmidt's law described a strong linear relationship between the movement speed and the standard deviation of the end points distribution as shown in Equation 1.4.

$$W_e = b(\frac{A}{MT}) \tag{1.4}$$

where, W_e represents the standard deviation of end points, A is the amplitude of the movement, and MT (an independent variable) is the movement time as specified by the metronome. Therefore A/MT characterizes the average movement speed. In this experiment, the target is a target line with zero width.

Similarly, an impulse variability model was proposed from the perspective of motor control theory [66]. This model attributes Schmidt's law almost entirely to a single ballistic movement delivered by the muscles, driving the limb from its starting point towards the target.

From the above summary, we can see that target acquisition tasks with spatial constraint are characterized by logarithmic speed-accuracy tradeoff (Fitts' law), while target acquisition tasks with temporal constraint are characterized by linear speed-accuracy tradeoff (Schmidt's law) [48] [69] [72]. In order to investigate the coexistence of spatial and temporal constraints in one motor task, Zelaznik et al. [74] manipulated movement time, amplitude and target width (not target line) and discovered a similar linear speed-accuracy tradeoff, i.e., the target width did not affect the nature of the speed-accuracy tradeoff relation. In addition, Zelaznik et al. [75] also observed linear relations between speed and accuracy when attention is occupied with a secondary task.

A motor control model that explains both the linear speed-accuracy tradeoff and the logarithmic speed-accuracy tradeoff was the stochastic optimized dual-submovement model [49]. This model combined both open-loop and close-loop submovements, and described the speed-accuracy tradeoff as a power relationship.

In addition to researches that look at end point distribution, Wobbrock et al. [69] derived a predictive model for error rate through an experiment that manipulated target size, target distance and movement time. A logarithmic speed-accuracy tradeoff was found instead.

1.2.3 Trajectory-based Task with Spatial Constraint

The steering law is a predictive model of how quickly one may navigate, or steer, through a 2-dimensional tunnel. The tunnel can be thought of as a path or trajectory on a plane that has an associated thickness or width, where the width can vary along the tunnel. The goal of a steering task is to navigate from one end of the tunnel to the other as quickly as possible, without touching the boundaries of the tunnel. A real world example that approximates this task is driving a car down a road that may have twists and turns, where the car must navigate the road as quickly as possible without touching the sides of the road. Within human-computer interaction, the law was discovered by Accot and Zhai [1] in 1997, who mathematically derived it in a novel way from Fitts' law using integral calculus, experimentally verified it for a class of tasks, and developed the most general mathematical statement of it. In this context, the steering law is a predictive model of human movement, concerning the speed and total time with which a user may steer a pointing device (such as a mouse or stylus) through a 2D tunnel presented on a screen (i.e. with a bird's eye view of the tunnel), where the user must travel from one end of the path to the other as quickly as possible, while staying within the confines of the path. One potential practical application of this law is in modeling a user's performance in navigating a hierarchical cascading menu.

Many researchers in human-computer interaction, including Accot himself, find it surprising or even amazing that the steering law model predicts performance as well as it does, given the almost purely mathematical way in which it was derived.

In its general form, the steering law can be expressed as

$$MT = a + b \int_C \frac{ds}{W(s)} \tag{1.5}$$

where MT is the average time to navigate through the path, C is the path parameterized by s, $W(s)$ is the width of the path at s, and a and b are experimentally fitted constants. In general, the path may have a complicated curvilinear shape (such as a spiral) with variable thickness $W(s)$.

Simpler paths allow for mathematical simplifications of the general form of the law. For example, if the path is a straight tunnel of constant width W, the equation reduces to Equation 1.1. We see, especially in this simplified form, a speed-accuracy tradeoff, somewhat similar to that in Fitts' law.

We can also differentiate both sides of the integral equation with respect to s to obtain the local, or instantaneous, form of the law:

$$\frac{ds}{dT} = \frac{W(s)}{b} \tag{1.6}$$

which says that the instantaneous speed of the user is proportional to the width of the tunnel. This makes intuitive sense if we consider the analogous task of driving a car down a road: the wider the road, the faster we can drive and still stay on the road, even if there are curves in the road.

Subsequently, extensive researches have been done based on the steering law, such as models for steering through corners [56], and steering within above-the-surface interaction layers using the tracking state of the stylus [29]. In addition, a pen stroke gesture model for predicting completion time of free hand trajectory drawing tasks has also been proposed [9]. One aim in this paper is to investigate the effect of subjective factor on human performance and establish a new human performance model including both system and human factors.

1.2.4 Trajectory-based Task with Temporal Constraint

So far, trajectory-based tasks with temporal constraint has not been investigated and modeled. Another aim in this paper is to investigate the trajectory accuracy when the movement time is considered as an independent variable in trajectory-based tasks, which will fill the void in human performance modeling research.

1.3 Objectives and Research Issues

First of all, we will explore the problems existing in modeling trajectory-based tasks with spatial constraint from analyzing the human or subjective factor in human performance (resulting speed or accuracy). Therefore, we will carry out a special controlled experiment to observe the human steering performance with different levels of speed and accuracy inclinations incurred by performers. Through revealing the nature of speed-accuracy tradeoff in trajectory-based tasks and the impacts of objective factor and subjective factor on human performance, we will establish a new speed-accuracy tradeoff model accommodating both objective and subjective parameters.

Then we will go on to investigate speed-accuracy tradeoff nature in trajectory-based tasks from the perspective of objective temporal constraint. We will conduct a special controlled experiment to observe the human performance with different levels of temporal constraint. The experiment will help us testify the objective task parameters and objective temporal constraint affect the relationship between speed and accuracy and their respective impact on human performance. Through the analysis of experimental result, we will establish another new speed-accuracy tradeoff model involving objective task parameters and temporal constraint.

We will also try to resolve other related questions in trajectory-based tasks, including maximal path width of the steering law, the effect of different start positions on speed-accuracy tradeoff in the steering tasks, and the effects of aging on performance difference (movement time and accuracy) in steering tasks when interacting with computer interfaces and the physical and psychological characteristic of older people.

All these studies will afford us an opportunity to understand the features of trajectory-based tasks and the nature of speed-accuracy tradeoff phenomenon in motor tasks comprehensively. The results will be instructive to study about other kinds of motor behaviors in HCI.

1.4 Dissertation Structure

The structure of this dissertation is shown in Fig.1.2.

Chapter 2 in this dissertation scrutinizes the effects of the objective task parameters and subjective operational biases on human performance based on the statistical analysis of authentic experimental data. The results of a controlled experiment will be reported to help us observe the subjects steering performance with different level

1.4 Dissertation Structure

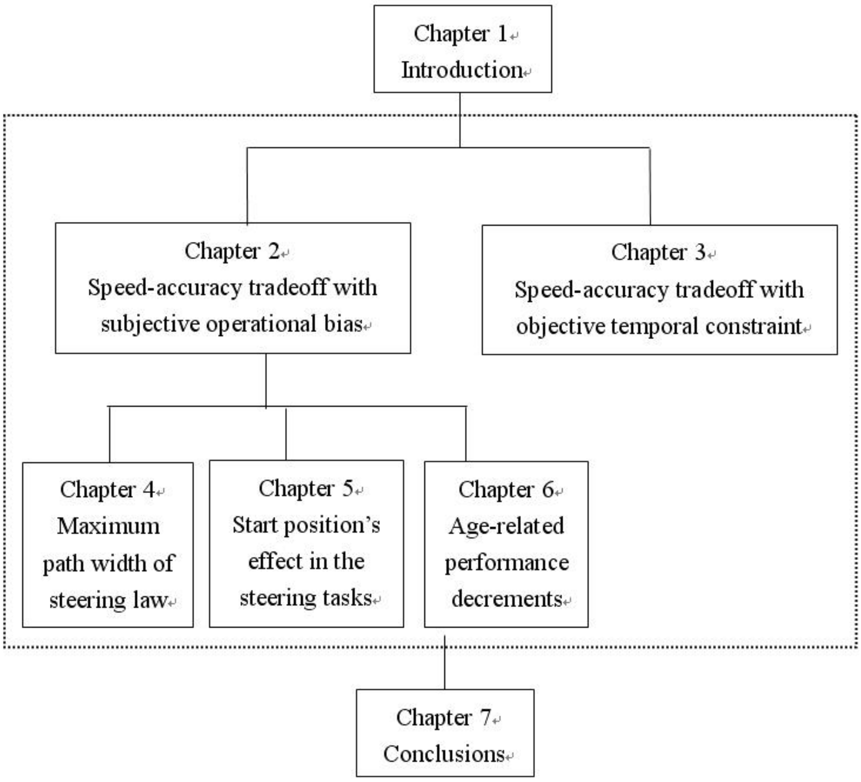

Fig. 1.2 The dissertation structure.

of speed and accuracy inclinations incurred by experimenters instructions. The experiment will help us testify both the objective task parameters and subjective operational biases affect the relationship between speed and accuracy and their respective impact on human performance. Finally, we will establish a new speed-accuracy tradeoff model accommodating both objective and subjective parameters.

Chapter 3 will explore the speed-accuracy tradeoff from the perspective of objective temporal constraint through a controlled experiment. A new speed-accuracy tradeoff model, in which movement time considered as a controlled variable and accuracy as measurement, will be established. If the speed specification in Chapter 2 is subjective, it will be objective in the Chapter 3. The robust of the proposed model will be verified by R^2 method.

The study in Chapter 2 will inspire us to do the studies in the following chapters

(Chapter 4, Chapter 5 and Chapter 6). Some basic issues of the steering law model are discussed.

1.5 Summary

Trajectory-based task is one of the most basic and main task paradigms in human computer interaction. Modeling for speed-accuracy tradeoff in trajectory-based tasks helps people understand human performance. This understanding will be instructive for not only input device evaluation but also user interface design. The studies developed with this theme will contribute to the modeling work mainly from the aspect of considering subjective operational bias and objective temporal constraint in modeling the performance.

These works will motivate much more explorations of speed-accuracy tradeoff in modeling for trajectory-based tasks with both the physiological and psychological information and factor. The knowledge will be instructive for UI design comprehensively.

With the fantastic development speed of science and technology, many novel input devices and user interfaces will appear. For the future work, it is necessary to carry out the model related researches about the application of human performance model on new input technology. Because few models have been established in the trajectory-based tasks, our study on human performance models will give evaluation of those previously and lately developed hardware and software, and further motivate more researchers to model human performance in the area of human computer interaction.

1.5 Summary

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Chapter 2

Speed-Accuracy Tradeoff in Trajectory-based Task with Subjective Operational Bias

The steering law is an excellent performance model for trajectory-based tasks, such as drawing and writing in GUIs. Current studies on steering tasks focus on the effect of system factors (i.e., path width and amplitude) on the movement time and steering law's related applications. In this chapter, we conducted a controlled experiment to further explore the effect of different operational biases (bias speed or accuracy) on steering completion time and standard deviation for two steering trajectory shapes, i.e., a straight steering task and a circular steering task, and then, establish a new model accommodating system and subjective factor in steering tasks. Empirical results showed that the new model is more predictive and robust than the traditional steering law.

2.1 Introduction

An important research branch in Human Computer Interaction (HCI) community is to seek to develop formal models [12] [18] [25] useful for predicting or describing human behavior in interactions with computer systems. Fitts' law [18] [19] is a very powerful model for pointing task evaluation and has found many uses in HCI [16] [43] [44]. Fitts' tasks follow certain speed-accuracy tradeoff rules, i.e., the more accurate the task to be accomplished, the longer it takes and vice versa.

In 1997, Accot and Zhai developed a new model for trajectory-based tasks, called steering law [1], deduced from Fitts' law. Similarly, steering law also follows certain speed-accuracy tradeoff rules and has been used for a number of studies [2] [3] [15] [56] [76]. But still, there exist some issues with the steering model. For example, current studies about the steering model pay little attention to the subjective factor, i.e., the subject's operational biases toward speed or accuracy. If the stroke is drawn as accurately as possible, steering completion time may increase. Conversely, if the stroke is drawn as fast as possible, steering completion time may decrease. So, the traditional steering law only involving system factors, i.e., tunnel amplitude and tunnel width, is not precise enough to model human performance accurately.

The objective of this chapter is to explore the comprehensive effect of different operational human biases in trajectory-based tasks and attempt to establish a new steering model involving not only system factors but also subjective factors.

2.2 Related Work

Literature about motor behavior models in human-computer interaction can be found in Mackenzie's paper [40], which gave a good summary of models of human movement relevant to HCI. However, subjective operational biases were not involved in it.

Recent studies about the effect of subjective operational biases in computer interaction tasks include the work of Zhai, Kong and Ren [77]. In that paper, the different operational biases of subjects towards speed or accuracy in Fitts' target acquisition tasks were systematically and completely discussed. A series of related experiments had been conducted to explore the relationships between target utilization, task specification and subjective operational biases. Experimental results showed that target utilization was not only affected by operational biases, but also by target width and distance. Moreover, the effect of width was more significant than the effect of distance. W_e model *1 [39] could partly compensate for the subjective layer's effect, but not completely. A complete model which can predict the relationships between the subjective and objective layers does not exist.

The above mentioned study about different operational biases is based on spatial variability, i.e. the normal distribution of end-points, which lacks theoretical and empirical foundations. Based on temporal constraint (distribution of movement time data), a new model, called SH-Model [61], was presented to include system and human effects in Fitts' target acquisition tasks. Empirical analysis showed that the SH-Model is stronger than the Shannon model *2 [38] and W_e model.

According to the definition of "effective target width" [39] in Fitts' tasks, Kulikov et al. introduced spatial variability into steering tasks for straight tunnels and established "effective tunnel width" [36] of steering motions. Empirical results manifested that the newly built model is stronger and more natural than traditional steering law. Effective tunnel width partly reflected what the subject actually did, but the different biases of operations were not been systematically and comprehensively discussed and varieties in the shape of the tunnel had not been considered in that paper, e.g. considered that the natural arc motion of the hand warranted that a curved tunnel or round tunnel be included.

*1 W_e model, i.e., "effective target width" model is: $MT = a + blog_2(A/W_e + 1)$, where $W_e = 4.133SD$

*2 Shannon model is: $MT = a + blog_2(A/W + 1)$. For both models, a and b are empirically determined constants, A is the pointing distance, W is the target width and MT the mean time of task completion. SD is the standard deviation of end-points distribution.

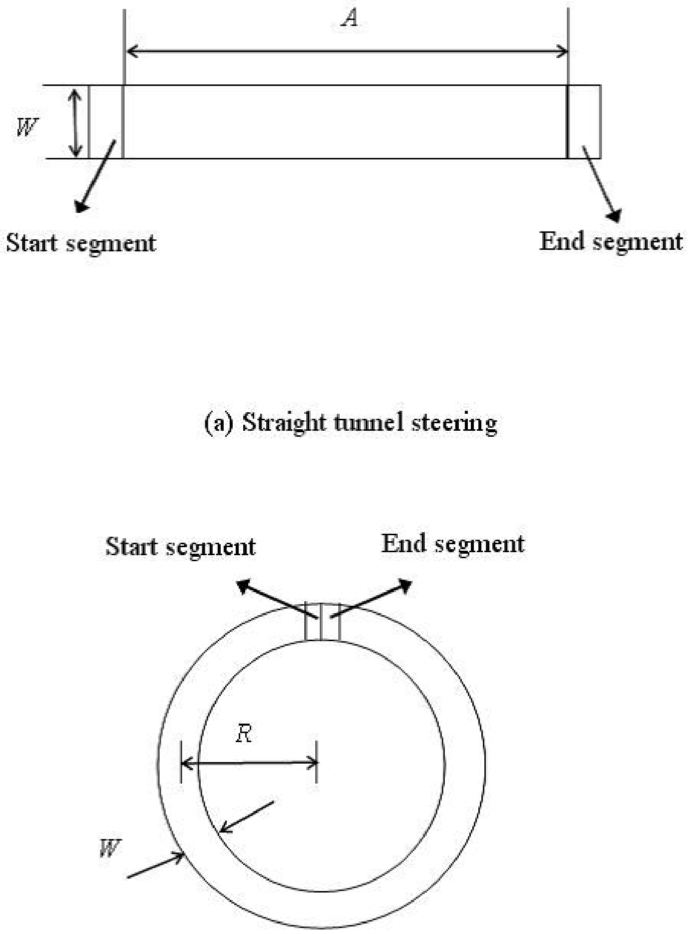
This chapter further comprehensively investigates the effect of five different operational biases on two steering tasks, i.e., a straight steering task and a circular steering task and introduces standard deviation as subjective factor. Finally, a new steering model is attempted to establish reflecting not only system factors but also subjective factors.

2.3 Experiment

2.3.1 Task

Our experiment takes a straight tunnel and a circular tunnel as two steering tasks (see Fig. 2.1). Although there are a great number of shapes that can be studied, only a few need to be used for practical purposes [2]. We decided to limit ourselves in this study to two shapes: straight tunnels (see Fig. 2.1a) and circular tunnels (see Fig. 2.1b). Although they do not necessarily represent all trajectory shapes found while interacting with a computer, these two shapes of tunnels allow us to investigate human different operational biases in both linear and non-linear movements. The representative nature of the two shapes of tasks, as well as the simplicity of their steering models made them the ideal candidates for standard evaluation of human operational conditions in trajectory-based tasks.

The difficulty for steering through a straight tunnel (see Fig. 2.1a) is $ID_s = A/W$, where A is the length of the tunnel, and W its width. For a circular tunnel, the movement amplitude A is equal to the circle circumference $2\pi R$, where R is the circle radius, so the difficulty for steering through a circular tunnel (see Fig. 2.1b) is $ID_c = 2\pi R/W$. Steering law that models the relationship between completion time MT and tasks difficulty ID can be expressed in the following form: $MT = a + b \times ID_s$ for a straight tunnel, and $MT = a + b \times ID_c$ for a circular tunnel.



(a) Straight tunnel steering

(b) Circular tunnel steering

Fig. 2.1 Two steering tasks.

2.3.2 Bias

The earliest study about the operational biases of subjects was the work of Fitts and Radford [20]. They systematically manipulated the operational biases of three subjects towards accuracy (A), neutrality (N), and speed (S), by means of monetary award and penalty at 1 cent per point. Fitts' thesis was that human information capacity in motor responses is relatively constant despite different experimental manipulations, so their paper did not focus on the effect of W_e correction.

In the work of Zhai, Kong and Ren [77], the different operational biases of subjects, towards speed or accuracy, were systematically and completely discussed in Fitts' target acquisition tasks; while the subject of our research is the effect of subjective operational biases in trajectory-based tasks.

Although the instruction of traditional steering law [1] is "make a stroke along the tunnel as fast and accurately as possible, and avoid crossing the tunnel border", the focus of this study is to investigate the effect of subjects' operational biases on the human performance of two steering tasks.

We would like to comprehensively investigate the effect of five different operational biases on the above two steering tasks. They are extremely accurate (EA), accurate (A), neutral (N), fast (F) and extremely fast (EF). The following verbal instructions corresponding to each operational bias are given by the experimenter to the participants: "Make a stroke along the tunnel as accurately as possible and do not worry about time or speed; try to avoid any error" in Condition EA; "as accurately as possible but keep some speed" in Condition A; "as accurately as possible and as fast as possible" in Condition N; "as fast as possible but keep some accuracy" in Condition F; and "as fast as possible and some errors are acceptable" in Condition EF.

2.3.3 Subjects

Ten subjects (7 male, 3 female, aged from 21 to 31) participated in the experiment. All participants had normal or corrected to normal sight. The participants performed the test using their preferred hand (all right handed).

2.3.4 Apparatus

The experiment was conducted on an IBM ThinkPad X41 Tablet PC with a stylus as the input device, running Windows XP. The screen size was 12.1 inches, with 1024×768 resolutions. Experimental software was developed with Java.

2.3.5 Design

The experiment was a 3×3 within-subjects factorial design. The within-subject factors were task (linear vs. circular), amplitude (250, 350, 450 pixels), and width (10, 25, 40 pixels). The direction of a linear task was towards right, and the direction of a circular task was clockwise.

10 participants were randomly divided into two groups, with 5 participants for each group. The participants in Group 1 first performed a linear task, while those in Group 2 did a circular task first. Each subject was instructed to repeat the experiment five times with different operational strategies, i.e., extremely accurate (EA), accurate (A), neutral (N), fast (F) and extremely fast (EF). The aforementioned verbal instructions corresponding to each operational bias were given by the experimenter to the participants before performing experiment.

The order of the EA, A, N, F, EF conditions was balanced by a Latin square pattern across each group of subjects. The order of the nine amplitude and width combinations was presented in random order to the participants in each operational bias. Each subject performed 9 strokes for each Amplitude/Width combination in each operational bias of the two tasks. So the total stroke number was 3 (tunnel amplitudes) $\times$ 3 (tunnel widths) $\times$ 9 (strokes) $\times$ 5 (operational biases) $\times$ 2 (tasks) $\times$ 10 (subjects) = 8,100.

2.3.6 Procedure

The participants were first briefed on the purpose of the experiment. With the stylus as the input device, the subjects were allowed to place the Tablet PC on their knees or on the desktop, which ever was more comfortable. But during the experiment, all of them chose to place the Tablet PC on the desktop. Before the test, all subjects were allowed to perform some warm-up trials in each operational bias until they felt that they could begin the experiments.

Subjects performed two types of steering tasks: straight tunnel steering and circular tunnel steering (see Fig. 2.1). At the beginning of each trial, the path to be steered was presented on the screen, in black. After placing the cursor to the left of the start segment and depressing the tip of the stylus, the subject began to draw a green line on the computer screen, showing the stylus trajectory. When the cursor crossed the start segment, left to right, the line turned blue, as a signal that the task had begun, the time was being recorded and the stylus trajectory was being sampled. When the cursor crossed the end segment, also left to right, the current tunnel disappeared and a new tunnel was presented to the subject. Lifting the pen tip up from the Tablet PC surface after crossing the start segment and before crossing the end segment would result in an invalid trial and that trial needed to be repeated. When the cursor crossed the borders of the path, the line turned red, as a signal that the stylus trajectory was outside of the tunnel, but the current trial did not need to be redone.

2.3.7 Measurements

While the stroke was being made, the position of the cursor was sampled in intervals of 10 milliseconds. The dependent variables were: MT (time taken to move the cursor from the start line to the end line), SD (Standard Deviation: for the linear tunnel, SD

Table 2.1 Mean MT with two tasks for each bias (EA, A, N, F and EF).

MT (ms)	EA	A	N	F	EF
Linear steering task	2173.0	1538.1	1080.8	840.3	421.8
Circular steering task	4433.4	2939.8	2273.2	1780.3	1044.8

is computed using the sampled y-values between the start line and the end line; for the circular tunnel, SD is computed using the distances between the sampled points and the center of the circular tunnel), and OPM (Out of Path Movement, percentage of sample points outside the tunnel border). For example, if 100 points were sampled and 10 of those points were outside the tunnel border, then OPM would be 10%.

2.4 Results

2.4.1 Movement time

Repeated measures ANOVA showed that there was a significant effect of bias ($F_{4,405} = 121.96, p < .00001$ for linear tasks, $F_{4,405} = 227.29, p < .00001$ for circular tasks) upon steering time. Mean steering time for EA, A, N, F and EF biases were respectively 2173.0, 1538.1, 1080.8, 840.3, and 421.8 milliseconds for linear steering tasks and 4433.4, 2939.8, 2273.2, 1780.3, and 1044.8 for circular steering tasks (see Table 2.1 or Fig. 2.2). The circular steering task was significantly more difficult than the linear task, although the two shared the same tunnel amplitudes and tunnel widths.

Further ANOVA analysis showed that there was a significant interaction between index of difficulty and biases ($F_{32,405} = 4.42, p < .00001$ for linear tasks, $F_{32,405} = 4.98, p < .00001$ for circular tasks) (see Fig. 2.3).

In linear steering, linear regression between steering index of difficulty and steering

2.4 Results

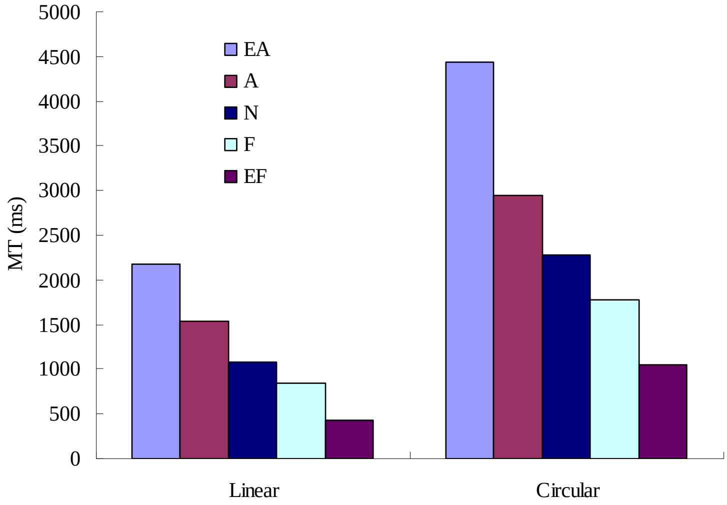


Fig. 2.2 Mean completion time with two tasks for each bias (EA, A, N, F and EF).

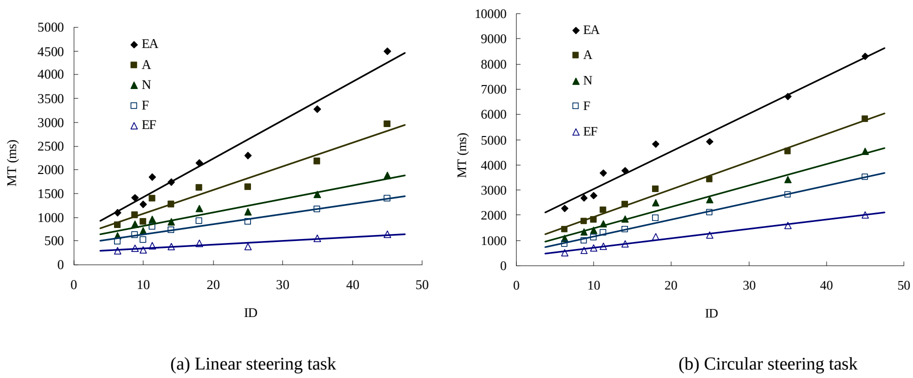


Fig. 2.3 Mean completion time for each bias (EA, A, N, F and EF) as a function of difficulty in both linear and circular steering tasks.

time (expressed in milliseconds) produced the following equations for each bias:

EA: $MT = 80.68 * ID + 619.92 \quad (R^2 = 0.963)$

A: $MT = 50.05 * ID + 574.69 \quad (R^2 = 0.947)$

N: $MT = 28.64 * ID + 529.43 \quad (R^2 = 0.931)$

F: $MT = 21.41 * ID + 428.22 \quad (R^2 = 0.926)$

EF: $MT = 8.01 * ID + 267.73 \quad (R^2 = 0.871)$

For circular steering, the equations were:

EA: $MT = 148.96 * ID + 1565.9 \quad (R^2 = 0.974)$

A: $MT = 109.27 * ID + 836.33 \quad (R^2 = 0.992)$

N: $MT = 84.32 * ID + 650 \quad (R^2 = 0.981)$

F: $MT = 67.57 * ID + 479.62 \quad (R^2 = 0.993)$

EF: $MT = 37.42 * ID + 324.44 \quad (R^2 = 0.985)$

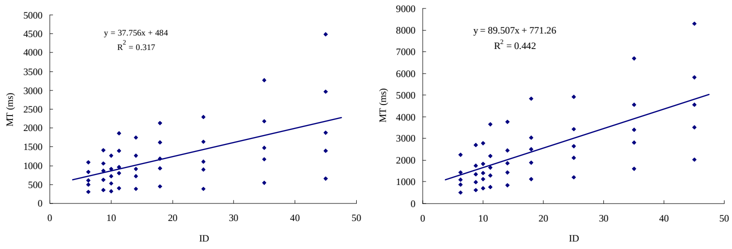
For linear steering tasks, there was an interesting tendency that the more risky (faster paced) the operational condition was, the weaker the correlation between MT vs. ID was. That is to say, the R^2 values between MT vs. ID from EA to EF declined, respectively 0.963, 0.947, 0.931, 0.926 and 0.871. This phenomenon was reverse compared with pointing task trials [77]. In pointing tasks, the values of R^2 are 0.904, 0.899, 0.961, 0.995 and 0.992 respectively for biases EA, A, N, F and EF.

Although the instructions were very different and hence there were very different levels of steering completion time, the R^2 values of MT vs. ID linear regression were all above 0.92 except the bias EF (0.871). For circular steering tasks, the R^2 values of MT vs. ID linear regression were all above 0.97 for each operational condition.

ID was indeed shown to be a remarkably robust determinant of the mean pointing time within each condition, but the correlation between MT and ID became much weaker when data from all the operational biases were merged in one regression (see Fig. 2.4). For linear steering tasks, ID accounted for only 31.7% of the variance of mean trial completion time caused by both different levels of ID and the quite different five operational biases. For circular steering, ID could also account for only 44.2%. The correlation between MT vs. ID in both linear and circular steering tasks is weaker than that in one-dimensional pointing tasks ($R^2 = 0.46$) [77].

2.4.2 Standard Deviation (SD)

Repeated measures ANOVA analysis showed that there was a significant effect of bias ($F_{4,135} = 21.09, p < .00001$ for linear tasks, $F_{4,135} = 54.33, p < .00001$ for circular



(a) Linear steering task

(b) Circular steering task

Fig. 2.4 Mean completion time for all biases combined as a function of difficulty in both linear and circular steering tasks.

Table 2.2 Mean SD with two tasks for each bias (EA, A, N, F and EF).

SD (pixels)	EA	A	N	F	EF
Linear steering task	1.340	1.42	1.64	1.70	2.07
Circular steering task	2.09	2.41	2.66	2.89	3.78

tasks) upon standard deviation. Mean standard deviation for EA, A, N, F and EF biases were respectively 1.34, 1.42, 1.64, 1.70, and 2.07 for linear steering and 2.09, 2.41, 2.66, 2.89, and 3.78 for circular steering (see Table 2.2 or Fig. 2.5).

SD varied irregularly with the increase of ID for both linear and circular steering tasks (see Fig. 2.6). So we further examined the influence on SD separately by tunnel amplitude and width (see Fig. 2.7 and Fig. 2.8 respectively).

Repeated measures ANOVA analysis showed that there was a significant effect of amplitude ($F_{2,135} = 19.56, p < .00001$ for linear tasks, $F_{2,135} = 11.64, p < .00001$ for circular tasks) upon standard deviation. Mean standard deviation for 250, 350, and 450 pixel amplitudes were respectively 1.41, 1.65, and 1.83 for linear steering and 2.55, 2.79, and 2.96 for circular steering (see Fig. 2.7).

In linear steering, linear regression between amplitude and SD produced the following equations for each bias:

2.4 Results

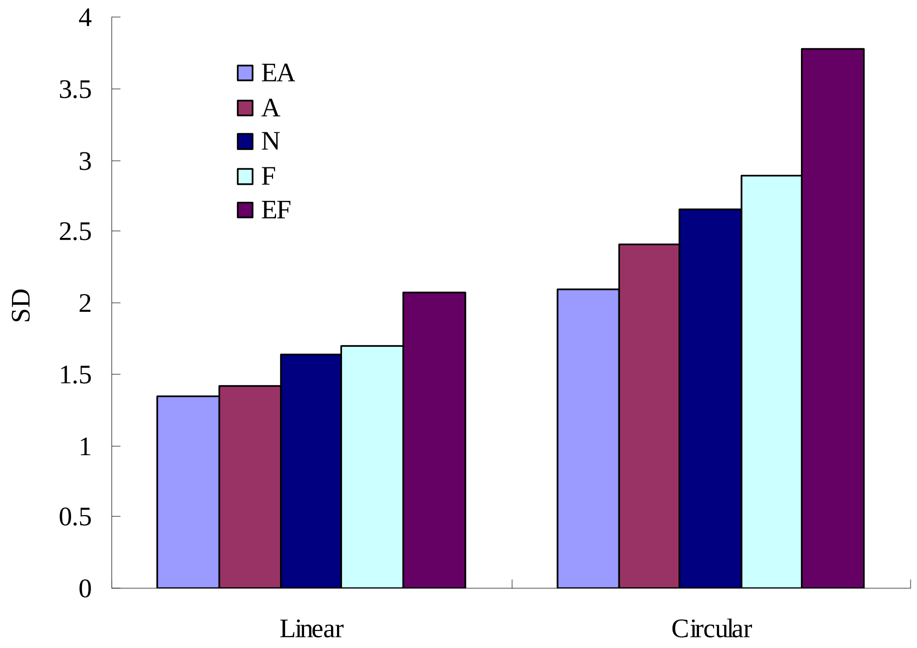


Fig. 2.5 Mean SD with two tasks for each bias.

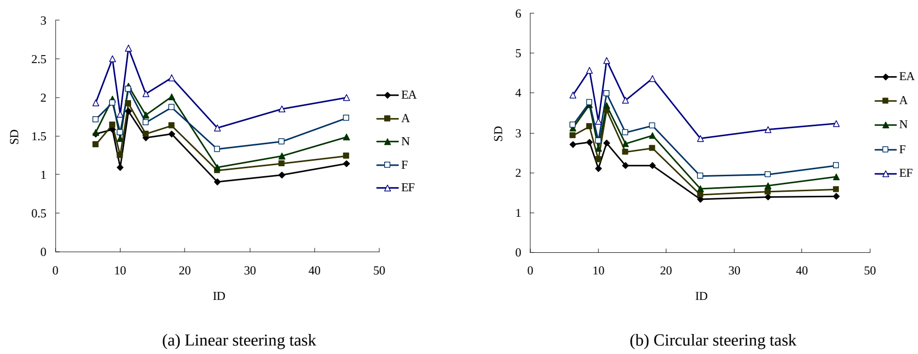


Fig. 2.6 Mean SD vs. ID for each bias in both linear and circular steering tasks.

EA: $SD = 0.002 * A + 0.78 \quad (R^2 = 0.996)$

A: $SD = 0.002 * A + 0.78 \quad (R^2 = 0.995)$

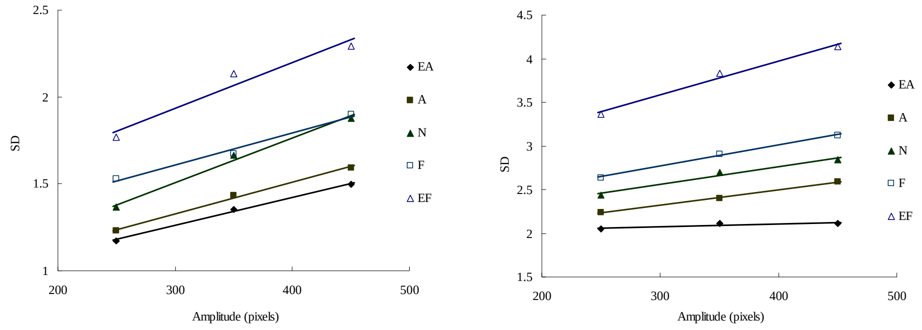
N: $SD = 0.003 * A + 0.74 \quad (R^2 = 0.992)$

F: $SD = 0.002 * A + 1.05 \quad (R^2 = 0.985)$

EF: $SD = 0.003 * A + 1.15 \quad (R^2 = 0.952)$

For circular steering, the equations were:

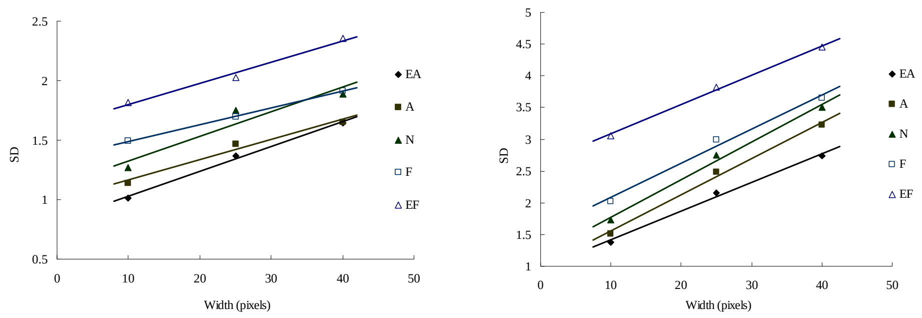
EA: $SD = 0.0003 * A + 1.983 \quad (R^2 = 0.777)$



(a) Linear steering task

(b) Circular steering task

Fig. 2.7 Mean SD vs. Amplitude for each bias in both linear and circular steering tasks.



(a) Linear steering task

(b) Circular steering task

Fig. 2.8 Mean SD vs. Width for each bias in both linear and circular steering tasks.

A: $SD = 0.002 * A + 1.792 \quad (R^2 = 0.998)$

N: $SD = 0.002 * A + 1.96 \quad (R^2 = 0.972)$

F: $SD = 0.002 * A + 2.05 \quad (R^2 = 0.995)$

EF: $SD = 0.004 * A + 2.428 \quad (R^2 = 0.986)$

There was a significant effect of width ($F_{2,135} = 32.29, p < .00001$ for linear tasks, $F_{2,135} = 138.01, p < .00001$ for circular tasks) upon standard deviation. Mean standard deviation for 10, 25, and 40 pixels width were respectively 1.35, 1.66, and 1.89 for linear steering and 1.94, 2.84, and 3.51 for circular steering (see Fig. 2.8).

In linear steering, linear regression between width and SD produced the following equations for each bias:

EA: $SD = 0.02 * W + 0.82 \quad (R^2 = 0.995)$

A: $SD = 0.02 * W + 0.99 \quad (R^2 = 0.973)$

N: $SD = 0.02 * W + 1.12 \quad (R^2 = 0.908)$

F: $SD = 0.01 * W + 1.35 \quad (R^2 = 0.999)$

EF: $SD = 0.02 * W + 1.62 \quad (R^2 = 0.984)$

For circular steering, the equations were:

EA: $SD = 0.05 * W + 0.964 \quad (R^2 = 0.992)$

A: $SD = 0.06 * W + 0.983 \quad (R^2 = 0.994)$

N: $SD = 0.06 * W + 1.178 \quad (R^2 = 0.991)$

F: $SD = 0.05 * W + 1.538 \quad (R^2 = 0.987)$

EF: $SD = 0.05 * W + 2.618 \quad (R^2 = 0.997)$

But ANOVA analysis showed that there was no significant interaction between bias and tunnel width ($F_{8,135} = 0.38, p = 0.93$ for linear tasks, $F_{8,135} = 0.42, p = 0.91$ for circular tasks) upon standard deviation. And there was also no significant interaction between bias and tunnel amplitude ($F_{8,135} = 0.27, p = 0.97$ for linear tasks, $F_{8,135} = 0.90, p = 0.52$ for circular tasks) upon standard deviation.

Although there was a significant effect of amplitude on SD, it was smaller than the significant effect of width since only 30% and 16% enhancements of SD for linear steering and circular steering respectively were observed for the amplitude from 250 to 450 pixels, while 40% and 81% for the width from 10 to 40 pixels. That is to say, only 30 pixel changes in width resulted in larger enhancement of SD (SD varied from 1.35 to 1.89 for linear steering, and 1.94 to 3.51 for circular steering), while 200 pixel changes in amplitudes resulted in smaller enhancement of SD (SD varied from 1.41 to 1.83 for linear steering, and 2.55 to 2.96 for circular steering). So, SD was mainly affected by operational biases and tunnel widths (ignoring the smaller effect of amplitude).

From Fig. 2.7 and Fig. 2.8 in this part, we could clearly observe that SD increased in line with operational biases from EA to EF and with widths from 10 to 40 pixels.

Table 2.3 Mean OPM with two tasks for each bias (EA, A, N, F and EF).

OPM	EA	A	N	F	EF
Linear steering task	0.03%	0.27%	0.45%	1.46%	3.73%
Circular steering task	0.12%	0.21%	0.9%	1.83%	5.7%

2.4.3 Out of Path Movement (OPM)

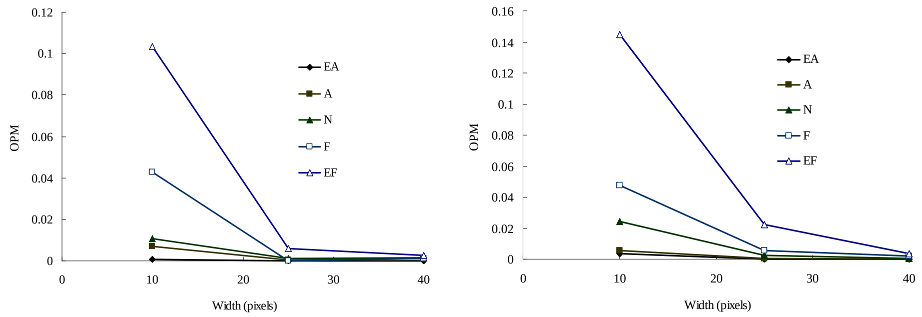
Repeated measures ANOVA analysis showed that there was a significant effect of bias ($F_{4,135} = 19.75, p < .00001$ for linear tasks, $F_{4,135} = 26.10, p < .00001$ for circular tasks) upon OPM. Mean OPM for EA, A, N, F and EF biases were respectively 0.03%, 0.27%, 0.45%, 1.46%, and 3.73% for linear steering and 0.12%, 0.21%, 0.9%, 1.83%, and 5.7% for circular steering (see Table 2.3).

There was a significant effect of width ($F_{2,135} = 47.15, p < .00001$ for linear tasks, $F_{2,135} = 46.87, p < .00001$ for circular tasks) upon OPM. Mean OPM for 10, 25, and 40 pixels were respectively 3.29%, 0.15%, and 0.12% for linear steering and 4.51%, 0.62%, and 0.13% for circular steering.

ANOVA analysis also showed that there was a significant interaction between width and bias ($F_{8,135} = 16.04, p < .00001$ for linear tasks, $F_{8,135} = 15.59, p < .00001$ for circular tasks) on OPM. Our OPM vs. Width plots for each operational bias (see Fig. 2.9) had the same tendency as Mackenzie's [36].

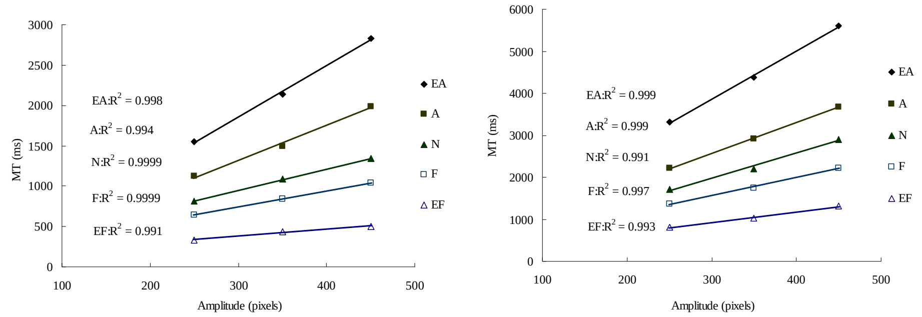
2.5 Model Deduction and Verification

Now, in order to find out a new steering model, we would like to further examine the effects on performance of MT with operational biases from EA to EF separately by tunnel amplitudes and widths for both linear and circular steering tasks (see Fig. 2.10 and Fig. 2.11, respectively).



(a) Linear steering task (b) Circular steering task

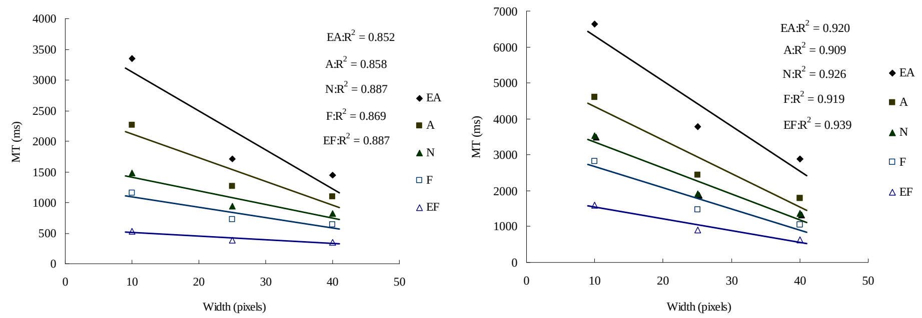
Fig. 2.9 Mean OPM vs. Width for each bias in both linear and circular steering tasks.



(a) Linear steering task (b) Circular steering task

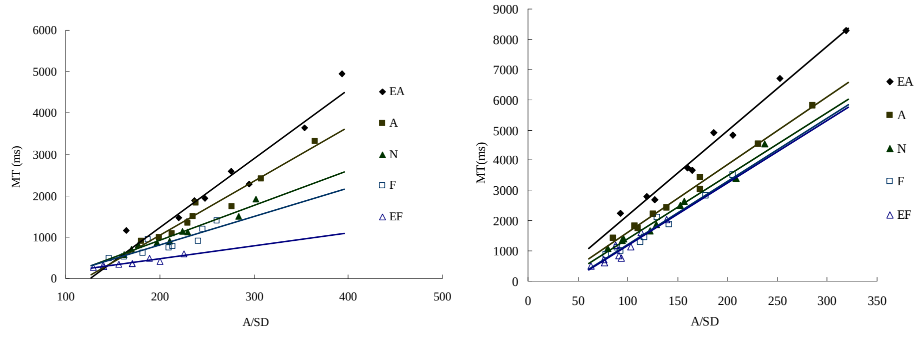
Fig. 2.10 Mean MT vs. Amplitude for each bias in both linear and circular steering tasks.

It was shown that, in Fig. 2.10 and Fig. 2.11, MT decreased in line with operational biases from EA to EF and with width from 10 to 40 pixels for both steering tasks, which had opposite changes tendency compared with SD, while increased in line with



(a) Linear steering task (b) Circular steering task

Fig. 2.11 Mean MT vs. Width for each bias in both linear and circular steering tasks.



(a) Linear steering task (b) Circular steering task

Fig. 2.12 Mean MT vs. A/SD for each bias in both linear and circular steering tasks.

amplitude from 250 to 450 pixels for both steering tasks.

According to foregoing analysis, it is presumably predicted that more MT is needed with the increased tunnel amplitude, while less MT is needed with the increased SD. So, the following hypothetic equation is given:

$$MT = a + b * ID_n \tag{2.1}$$

Where, ID_n is a new index of difficulty and formulated as:

$$ID_n = A/SD \tag{2.2}$$

where, SD is the standard deviation of sampled points.

Next, we would examine the predictive power of this newly proposed model for both linear and circular steering tasks in each operational bias and across all the operational biases (see Fig. 2.12 and Fig. 2.13 respectively).

In linear steering, linear regression between the new steering index of difficulty (A/SD) and steering time produced the following equations for each bias:

EA: $MT = 16.65 * (A/SD) - 2105.4 \quad (R^2 = 0.919)$

A: $MT = 13.09 * (A/SD) - 1582.3 \quad (R^2 = 0.953)$

N: $MT = 8.47 * (A/SD) - 777.84 \quad (R^2 = 0.959)$

F: $MT = 6.84 * (A/SD) - 559.09 \quad (R^2 = 0.787)$

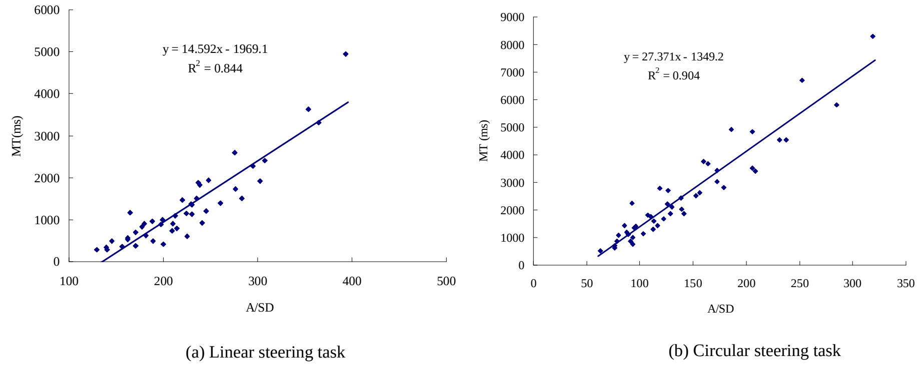


Fig. 2.13 Mean MT vs. A/SD for all biases combined in both linear and circular steering tasks.

EF: $MT = 3.04 * (A/SD) - 125.43 \quad (R^2 = 0.889)$

For circular steering, the equations were:

EA: $MT = 28.03 * (A/SD) - 626.92 \quad (R^2 = 0.984)$

A: $MT = 22.4 * (A/SD) - 613.95 \quad (R^2 = 0.993)$

N: $MT = 20.96 * (A/SD) - 700.61 \quad (R^2 = 0.978)$

F: $MT = 20.88 * (A/SD) - 876.9 \quad (R^2 = 0.967)$

EF: $MT = 20.71 * (A/SD) - 897.02 \quad (R^2 = 0.887)$

From Fig. 2.13, we could clearly observe that the new index of difficulty ID_n was a stronger determinant than ID when data from all conditions were merged in one regression. ID_n could account for 84.4% and 90.4%, respectively for linear and circular steering, of the variance of mean trial completion time caused by both different levels of ID_n and the quite different five operational biases.

An interesting discovery is that the R^2 values of MT vs. ID_n linear regression in biases A, N and EF were even higher than their corresponding R^2 values of MT vs. ID in the same bias in linear steering tasks. In circular steering tasks, the R^2 values of MT vs. ID_n linear regression in biases EA and A were higher than their corresponding R^2 values of MT vs. ID in the same bias (see Fig. 2.12, Tables 2.4 and 2.5).

Table 2.4 Summary of the two models regression (R^2) for linear steering tasks.

Model	EA	A	N	F	EF
ID vs. MT	0.963	0.947	0.931	0.926	0.871
ID_n vs. MT	0.919	0.953	0.959	0.787	0.889

Table 2.5 Summary of the two models regression (R^2) for circular steering tasks.

Model	EA	A	N	F	EF
ID vs. MT	0.974	0.992	0.981	0.993	0.985
ID_n vs. MT	0.984	0.993	0.978	0.967	0.887

We further compared the new steering model with the "effective tunnel width" steering model, in which tunnel width was adjusted to be $4.133SD$. The two models showed the same predictive ability in performance. So, another more interesting discovery was that the concept of "effective width" in steering tasks seemed much more robust than in pointing tasks. In pointing task experiments, the R^2 values between MT vs. "effective index of difficulty" (which replaces target width by $4.133SD$) in each bias (EA, A, N, F, EF) were all lower (all below 0.9 except 0.926 in bias F) than their corresponding R^2 values between MT vs. ID in the same bias [77]. Moreover, when all the operational biases were merged in one regression, the R^2 value between MT vs. "effective index of difficulty" was only 0.783, which is significantly lower than both 0.844 in linear steering tasks and 0.904 in circular steering tasks.

In fact, SD is equivalent to "effective tunnel width", since only the coefficient is different. But the steering model with SD has the following advantages: firstly, the calculation is simpler with SD than with "effective tunnel width", with which one must remember the coefficient 4.133; secondly, the concept of "effective width" was derived from the theory of normal distribution, which has no empirical or theoretical foundations and may be more complex in steering tasks than in pointing tasks; finally, SD reflects what subjects actually performed.

2.6 Conclusions

We have systematically explored the effect of different operational biases of subjects (toward to speed or accuracy) on steering tasks for both straight and circular movements. Experimental results showed that the effect of subjective factors indeed existed. Different operational biases would result in different levels of SD, which was mainly affected by the different operational biases of subjects and by tunnel widths. Then, we deduced a new steering model involving system and subjective factors, which was shown to have the same predictive power as the "effective tunnel width" steering model.

Three interesting discoveries in our investigation were, firstly, the effect of subjective factor indeed existed in steering tasks, which was reflected by different levels of SD and MT; secondly, our newly proposed model was still shown to be a robust determinant of the mean steering time within each operational bias for both linear and circular steering tasks. When all the operational conditions were merged in one regression, the new model was shown to be a much more predictive determinant of the mean steering time than the traditional steering model; thirdly, although the concept of "effective tunnel width" in steering tasks was directly, without explanation, derived from "effective target width" in pointing tasks, it seemed more robust in steering tasks than in pointing tasks.

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Chapter 3

Speed-Accuracy Tradeoff in Trajectory-based Task with Objective Temporal Constraint

Speed-accuracy tradeoff is a common phenomenon in many types of human motor tasks. In general, the more accurately the task is to be accomplished, the more time it takes, and vice versa. In particular, when users attempt to complete the task with a specified amount of time, the accuracy of the task can be considered as a dependent variable to measure user performance. In this chapter, we investigate speed-accuracy tradeoff in trajectory-based tasks with temporal constraint, through a controlled experiment that manipulates the movement time (MT) in addition to the tunnel amplitude (A) and width (W). A quantitative model is proposed and validated to predict the task accuracy in terms of lateral standard deviation (SD) of the trajectory.

3.1 Introduction

An important research branch of human-computer interaction is to develop predictive models for human performance in fundamental interaction tasks. One of such tasks is the trajectory-based "steering" task, in which the user uses the input device such as a stylus to produce a trajectory ("stroke") through a "tunnel" with set amplitude (length) A and width W. The movement time (MT) of the steering tasks has been modeled by the steering law [1]: $MT = a + b(A/W)$, where a and b are empirically determined constants, and A/W (index of difficulty or ID) characterizes the difficulty of the task. The steering law has been verified with several input devices [2], in different scales [3] and in simulated driving tasks [76].

The steering law models the relationship between the movement time of trajectory-based tasks and the task difficulty, determined by the tunnel amplitude A and tunnel width W. In the steering law, the movement time MT is the dependent variable. The more accurate the task is required (the narrower the tunnel width W is), the longer the resulting movement time is. However, if we want to consider the opposite direction, i.e. inferring the actual trajectory accuracy given a specific movement time (or speed), the steering law does not enable us to make this prediction.

Given the bidirectional relationship between time and accuracy, it is worthwhile to establish a model that predicts the trajectory accuracy by considering the movement time as an independent variable. Such a model will supplement the steering law, and enrich our understanding of the speed-accuracy tradeoff in trajectory-based tasks. On the other hand, a prediction model of the trajectory accuracy also has practical implications. For example, pen gestures have been widely used to trigger commands. Such a model may allow us to estimate the deviation of the actual gesture stroke from the standard template at different drawing speeds, and improve the recognition and interpretation of the gestures. In a real world scenario, we may determine the optimal road width according to the marked driving speed.

Although speed-accuracy tradeoff have been widely studied [49] [48] [57] [66], these works have mostly focused on target acquisition tasks. In this chapter, we sought to investigate the speed-accuracy tradeoff in trajectory-based tasks through a controlled experiment, and derive a quantitative model for predicting accuracy.

Previous studies on speed-accuracy tradeoff have involved experimental protocols with two types of constraints: spatial constraint and temporal constraint, which differentiate the nature of the task. For example, in rapid aimed hand movements with spatial constraints, participants are required to move as quickly as possible to reach the target with width W placed at distance A. The movement time is measured to reflect the task performance. This is a target acquisition task (also known as time-minimization task) and has been modeled by Fitts' law [18]. In rapid aimed hand movements with temporal constraints, participants are required to reach the target with a specified movement time. This is a paced reaching task (also known as a time-matching movement task) [66]. It is similar to the standard target acquisition task, except that the movement time MT now becomes an independent variable. In this type of tasks, movement time is controlled and spatial variability of the movement is measured to reflect the accuracy. Similarly, in trajectory-based movements with spatial constraints, participants are required to produce a trajectory through a tunnel with length A and width W as quickly as possible. This is the standard steering task and has been modeled by the steering law [1]. However, if participants are required to produce a trajectory through a tunnel with length A and width W with a specified movement time, does regularity exist in the relationship between the trajectory accuracy and the task parameters? What kind of speed-accuracy tradeoff can be observed from trajectory-based task with temporal constraint? What are the differences between trajectory-based movements with temporal constraint and with spatial constraint? We sought to answer these questions in this chapter.

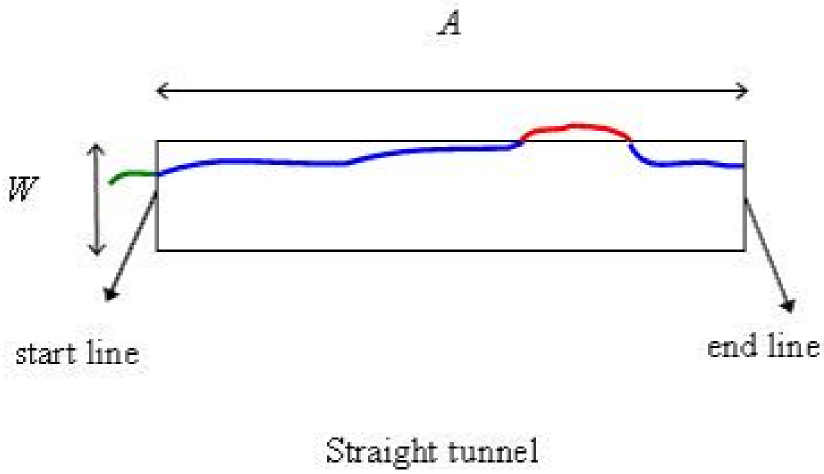

Fig. 3.1 Experimental task.

3.2 Problem Definition & Hypothesis

In this chapter, we investigate the trajectory-based task of steering through a straight tunnel with temporal constraint (Fig. 3.1). The user is required to complete the task with a specified movement time (within a tolerance range). Although the tunnel does have a finite width W that the user supposedly stays within, this spatial constraint is not strictly enforced, i.e. the user may move outside the sides of the tunnel without failing the task.

We are interested in establishing a quantitative model for the trajectory accuracy described by the amount of lateral deviation throughout the trajectory produced. In practice this is represented by SD, the standard deviation of the y-coordinates (in the case of a horizontal tunnel) along the entire trajectory. The larger SD is, the less accurate the trajectory is. Note that in contrast to the target acquisition task where accuracy is measured by the statistical distribution of a set of trials, here SD describes the accuracy of a single steering movement trajectory.

In both Schmidt et al.'s study ($W = 0$) [66] and Zelaznik et al.'s study ($W > 0$) [74] on target acquisition tasks with temporal constraint, the standard deviation of the end point distribution is linearly related to the average movement speed. The effect of the target width on the accuracy was small and not included in their speed-accuracy tradeoff models. This might be explained as that in the target acquisition task, the target width only constrains the final corrective submovement but not the initial ballistic submovement (as discussed by Meyer et al. [49]). In contrast, in trajectory-based tasks the tunnel width constrains the entire movement, as the user is expected to produce a trajectory that stays within the tunnel all the time. Consequently, we hypothesize that in trajectory-based tasks with temporal constraint, not only is SD related to the average movement speed (A/MT), but also the tunnel width W will have a considerable influence on it. In order to provide a holistic understanding of all affecting factors, our speed-accuracy for trajectory-based tasks model should incorporate the impacts of both factors. The correctness of this hypothesis will be verified through our experiment.

3.3 Experiment

3.3.1 Apparatus

The experiment was conducted on an IBM ThinkPad X41 Tablet PC with a 12.1-inch screen at the resolution of 1024×768, and a stylus as the input device. The experimental software was developed in Java.

3.3.2 Task

The experiment used a basic trajectory-based task, that is steering through a horizontal straight tunnel with amplitude A and width W (see Fig. 3.1). The participant was required to move the stylus from the start line rightward to the end line through the tunnel, with a specified movement time (denoted as *movement time goal* or *MT goal* hereafter to distinguish from the *actual movement time* observed). A percentage *tempo-*

ral error tolerance parameter determined the acceptable range for the actual movement time. For example, if *movement time goal* was 200ms and *temporal error tolerance* was 10%, the actual movement time was allowed to range between 180ms and 220ms to be accepted. The participants were instructed that their movement time should be anywhere within the specified range.

Before the experiment began, the instructions were explained to the participants, who then conducted training trials until they fully understood the requirements and felt comfortable with the task. At the beginning of each trial, the tunnel to be steered was presented in black. After placing the stylus tip to the left of the start line, the subject began to move the stylus rightward. A green line was displayed to show the stylus trajectory produced by the participant. When the stylus crossed the start line, the trajectory line turned blue to signal that the task had begun. When the stylus crossed the end line, the task ended, and the actual movement time taken was displayed as feedback to the participant.

If the actual movement time was within the acceptable range, the trial was considered successful. Otherwise, the trial needed to be repeated until the actual movement time was within the acceptable range. For unsuccessful trials, the system indicated the percentage by which the trial was too fast or too slow, to help the participant adjust the movement time to meet the requirement.

Lifting the stylus between the start line and the end line was considered invalid and the trial needed to be repeated. The participant was instructed to try to keep the stylus within the upper and lower borders of the tunnel throughout the task. If the stylus was outside the tunnel borders during the trial, the trajectory part that was outside the borders was displayed in red as a warning (see Fig. 3.1), but the trial was not considered invalid.

3.3.3 Measurements

For each successful trial, the stylus position along the trajectory was sampled in intervals of 10ms. Based on these sample points, we calculated SD (standard deviation of y-coordinates of the sample points), and OPM (Out of Path Movement, percentage of sample points outside the tunnel). Calculated from the same set of data, both SD and OPM describe the accuracy of the trajectory, but from slightly different perspectives. SD describes the original user behavior (lateral deviation) under the current stimuli, and provides understandings about the fundamental human capabilities; while OPM evaluates how the user behavior satisfies the accuracy requirement (tunnel width) set by the particular task, and its implications are more on the user interaction side. For both SD and OPM, higher values indicate lower accuracy.

In addition to the accuracy metrics, we recorded the *actual movement time* (or *actual MT*) for each successful trial to understand participants' performance on matching the *movement time goal*. The *actual movement time* is the time taken to move the stylus between the start line and the end line.

3.3.4 Design & Procedure

The experiment employed a mixed factorial design and combined within- and between-subject factors. The within-subject factors were A (300, 600, 800 pixels), W (10, 25, 40, 55, 70 pixels), and *MT goal* (300, 500, 2000, 3500, 5000ms). The values of *MT goal* were chosen according to the preliminary results of a pilot study.

The between-subject factor was *temporal error tolerance* (10%, 20%, and 40%). Previous research [66] [75] on temporally-constrained tasks usually used a single level of temporal error tolerance of 10%. Zelaznik et al. [74] adopted 3 levels of temporal error tolerance to investigate the effect of temporal precision on the nature of the speed-accuracy tradeoff. In our experiment, we also chose 3 levels in order to investigate whether and how different levels of *temporal error tolerance* might affect the human performance and the nature of speed-accuracy tradeoff.

The participant was first briefed on the purpose of the experiment. Then 5 experiment sessions corresponding to the 5 *MT goal* conditions were tested in sequence. Within each session, the participant performed 3 successful trials for each condition combination of A and W respectively. Before each session began, the participant was informed of the current *MT goal* and the relevant acceptable range of the *actual movement time*, and was allowed to perform practice trials until s/he felt comfortable.

The order of the *MT goal* conditions was counterbalanced using a Latin square pattern across participants. The order of the A and W conditions was randomized within each *MT goal* condition.

3.3.5 Participants

Thirty righted-handed people, aged from 21 to 34, participated in the experiment. They were assigned randomly to one of three *temporal error tolerance* groups (10%, 20% and 40%), with 10 participants (8 males and 2 females) per group. All participants had normal or corrected to normal sight.

Therefore, the total number of successful trials performed was:

3 (trials) $\times$ 3 (tunnel amplitude A) $\times$ 5 (tunnel width W) $\times$ 5 (*MT goal*) $\times$ 3 (*temporal error tolerance* group)$\times$ 10 (participants per group) = 6,750

3.4 Results

3.4.1 Actual Movement Time

The *actual movement time (actual MT)* varied significantly with both the between-subject factor *temporal error tolerance* ($F_{2,27} = 8.97, p = .001$), and all the within-subject factors: *MT goal* ($F_{4,108} = 6584.77, p < .001$), W ($F_{4,108} = 13.01, p < .001$), and A ($F_{2,54} = 249.24, p < .001$). The mean *actual MT* for the 10%, 20% and 40% *temporal error tolerance* groups were 2250ms, 2226ms and 2089ms respectively. A significant interaction between *temporal error tolerance* and *MT goal* was observed on *actual MT* ($F_{8,108} = 6.35, p < .001$) (see Fig. 3.2). For 10% and 20% groups, the mean *actual MT* values approximated the *MT goals*. However, such was not the case for the 40% group. The mean *actual MTs* for the 300ms to 5000ms conditions were 312, 495, 1910, 3205, and 4522 ms respectively. Post hoc pair-wise comparisons showed that *actual MTs* were almost equivalent with the *MT goals* for the 10% and 20% groups. However, for the 40% group, the *actual MTs* were equivalent with the other two groups only under the 300ms and 500ms condition, and significantly lower *actual MTs* were observed than the other two groups under the 2000, 3500 and 5000ms conditions ($p < 0.05$).

Similar to the results obtained by [74], the results of MT for the 40% group also indicated a range effect [58]: longer-duration tasks exhibit an *actual MT* shorter than the *MT goal*, indicating the participant moving at a more natural speed, faster than the speed dictated. The looser temporal constraint in the 40% group allowed this range effect to be observed, while the tighter constraints in the other two groups effectively eliminated the range effect.

Another phenomenon was the significant interaction for *temporal error tolerance* $\times$ W ($F_{8,108} = 4.36, p < .001$), and *temporal error tolerance* $\times$ A ($F_{4,54} = 57.39, p < .001$). In the 10% *temporal error tolerance* group, W did not have a significant effect on

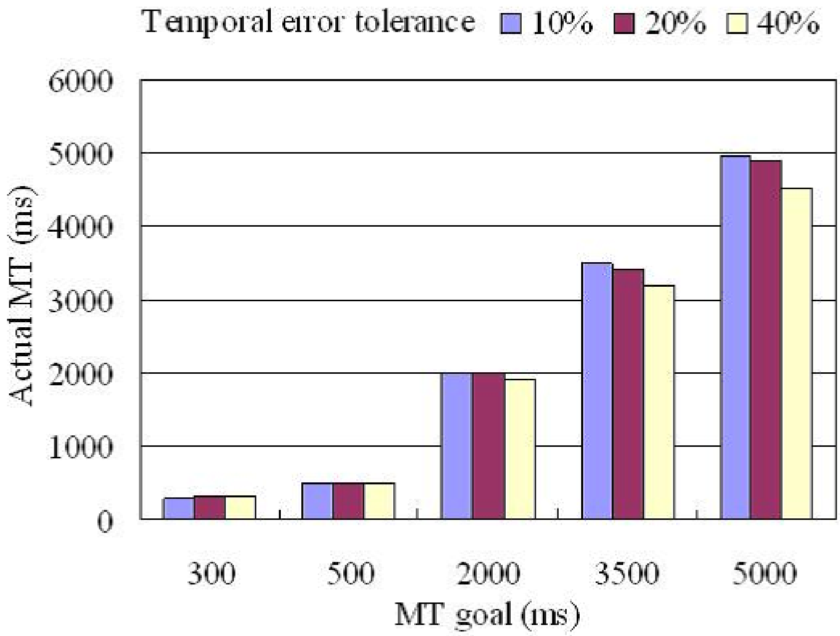

Fig. 3.2 *Actual MT* vs. *MT goal* for each *temporal error tolerance.*

actual MT ($F_{4,36} = 1.68, p = .176$). However, in both of the other two groups, W had significant effects on *actual MT* ($F_{4,36} = 4.91, p = .003$ for 20% group; $F_{4,36} = 8.49, p < .001$ for 40% group), in that *actual MT* decreased as W increased. Similarly, in the 10% group pair-wise comparisons revealed no significant difference of *actual MT* between the $A = 600$ pixels and $A = 800$ pixels conditions ($p = 0.673$). But in both the 20% and the 40% group, significant differences of *actual MT* were found among all three levels of A ($p = 0.003$), showing that *actual MT* increased as A increased. In the 20% and 40% groups the effects of A and W displayed the similar trends discovered by the steering law research [1], i.e., MT increases with A and decreases with W. Not surprisingly, because of the temporal constraints, the trends shown in our experiment were not strong enough to follow the linear relationship dictated by the steering law. Nevertheless, this is an interesting finding that even when people intentionally attempt to match a specific movement time, the underlying motor control mechanism still regulates the

Table 3.1 Main effects on SD.

MT *goal* (ms)	300	500	2000	3500	5000
SD (pixels)	4.15	3.50	2.40	2.16	2.04

W (pixels)	10	25	40	55	70
SD (pixels)	2.33	2.50	2.86	3.19	3.38

A (pixels)	300		600		800
SD (pixels)	1.87		2.92		3.76

motion subconsciously within the allowable range and cannot be completely overridden. Again, in the 10% group, the strict temporal constraint prevented the trends from being observable.

3.4.2 Trajectory Accuracy (SD)

SD measures the lateral deviation of the trajectory, as an indication of the trajectory accuracy. The grand mean of SD was 2.85 pixels. SD did not vary significantly with the between-subject factor *temporal error tolerance* ($F_{2,27} = 1.36, p = .275$), but varied significantly with all the within-subject factors: MT *goal* ($F_{4,108} = 121.04, p < .001$), W ($F_{4,108} = 82.22, p < .001$), and A ($F_{2,54} = 292.42, p < .001$). SD decreased as MT *goal* increased, showing that a longer movement time enabled participants to be more accurate. SD increased as W increased, showing that a wider tunnel allowed for less accurate movement. SD also increased as A increased, showing that a longer path (hence higher movement speed when other factors remain the same) resulted in less accurate movement. Table 3.1 summarizes these.

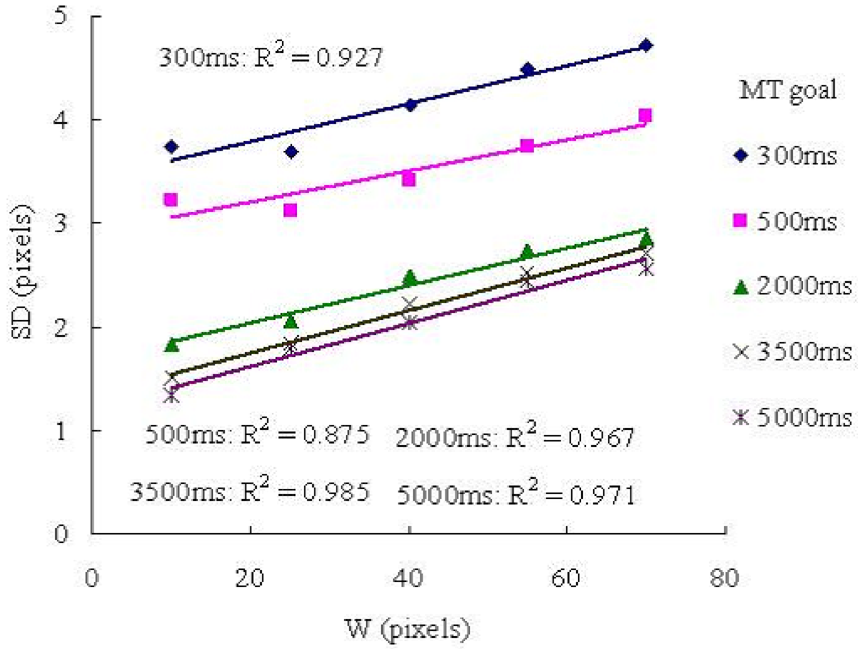

Fig. 3.3 Mean *SD* vs. *W* for each *MT goal*.

Since no significant difference of SD was observed among the three *temporal error tolerance* groups, we combined the data sets from the three groups in further analysis of the interaction effects between *MT goal*, A and W. No significant interaction between *MT goal* and W ($F_{16,144} = 1.669, p = .059$) was observed on SD, as shown in Fig. 3.3 by the fact that the five regression lines are almost parallel, meaning that the effects of *MT goal* and W were independent. In addition, the correlations (R^2) between SD and W are high ($0.875 \sim 0.985$) for each *MT goal*, showing that SD follows a strong linear relationship with W when other variables are factored out.

Similarly, no significant interaction between W and A were observed on SD, indicating that the effects of W and A were independent as well.

A significant interaction between *MT goal* and A ($F_{8,72} = 45.216, p < .001$) was observed on SD (see Fig. 3.4). The effect of A increased as *MT goal* decreased, as shown by the slopes of the regression lines. This is an intuitive observation if we consider the

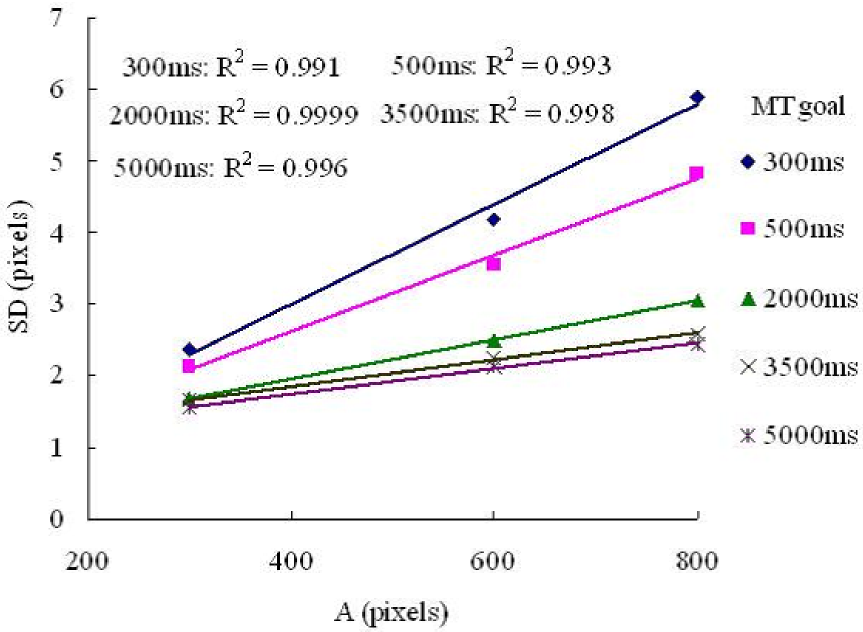

Fig. 3.4 Mean SD vs. A for each *MT goal*.

average movement speed that is A/MT. Smaller *MT goal* resulted in larger changes on the anticipated movement speed for the same amount of change over A, and in turn larger changes on the movement accuracy. Similar to W, the correlations (R^2) between SD and A are high for each *MT goal* in Fig. 3.4, showing that SD follows a strong linear relationship with A when other variables are factored out.

3.4.3 Out of Path Movement (OPM)

OPM measures the percentage of the trajectory outside the tunnel, indicating how well the spatial constraint was satisfied. The grand mean of OPM was 3.4%. OPM did not vary significantly with the between-subject factor *temporal error tolerance* ($F_{2,27} = 1.77, p = .189$), but varied significantly with all within-subject factors: *MT goal* ($F_{4,108} = 148.53, p < .001$), W ($F_{4,108} = 315.58, p < .001$), and A ($F_{2,54} = 128.88, p < .001$). Table 3.2 summarizes mean OPM under different conditions. Similar to SD,

Table 3.2 Main effects on OPM.

$MT\ goal$ (ms)	300	500	2000	3500	5000
OPM (%)	8.6	6.6	1.3	0.5	0.2

W (pixels)	10	25	40	55	70
OPM (%)	14.3	2.3	0.4	0.2	0.1

A (pixels)	300	600	800
OPM (%)	1.3	3.3	5.7

OPM decreased as $MT\ goal$ increased, and increased as A increased. However, different from SD, OPM decreased as W increased. It was easier for participants to keep the stylus inside a wider tunnel, despite that the produced trajectory itself becomes more relaxed (resulting in higher SD).

Given that no significant difference of OPM was observed among the three *temporal error tolerance* groups, we combined the data set from these three groups in further analysis on OPM. Significant interaction between $MT\ goal$ and W ($F_{16,144} = 190.31, p < .001$) was observed on OPM (Fig. 3.5). The effect of W increased as $MT\ goal$ decreased. As known from the analysis of SD, smaller $MT\ goal$ resulted in larger lateral deviation (SD) in the trajectory, which contributed to the variety of OPM values that depended heavily on the tunnel width. However when $MT\ goal$ is larger, the resulting smaller SD meant most of the trajectory would stay inside the tunnel, and in turn caused the uniformly small OPM. This finding is similar to the study results on subjective bias in steering tasks [79]. Significant interactions also exist in $A \times MT\ goal$ ($F_{8,72} = 35.31, p < .001$) and $A \times W$ ($F_{8,72} = 115.86, p < .001$).

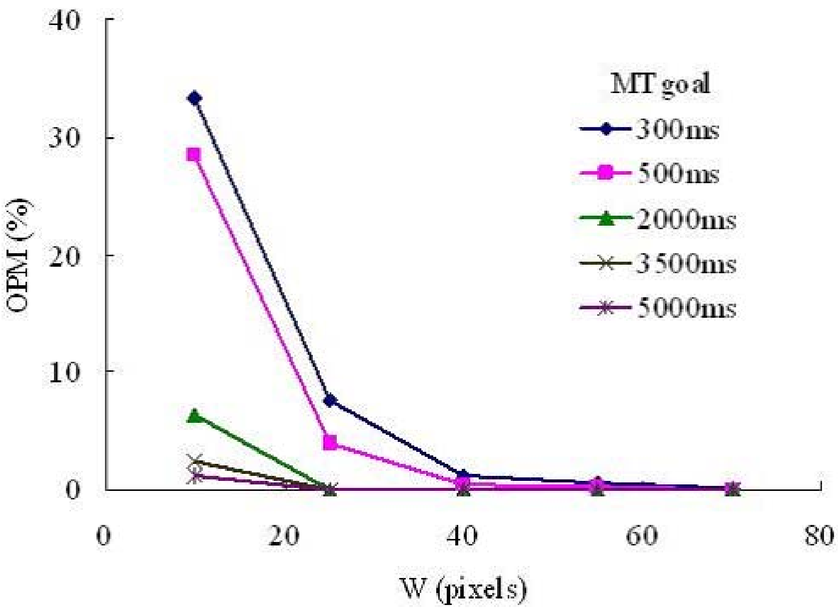

Fig. 3.5 Mean OPM vs. W for each MT *goal*.

3.5 Model Deduction and Verification

Based on the experimental results, we now attempt to establish a speed-accuracy tradeoff model that quantitatively predicts SD from A, W and MT *goal*. Based on our analysis of SD, we concluded that:

- SD is significantly affected by tunnel width W, tunnel amplitude A and MT *goal*.
- SD increases as A and W increase, and decreases as MT *goal* increase.
- The relationship between SD and W is linear when other variables remain constant. Same for the relationship between SD and A.
- The effects of W and MT *goal* on SD are independent of each other (i.e. additive). Same for the effects of W and A. The effects of A and MT *goal* on SD are not independent (i.e. not additive)

Table 3.3 Regression results of the proposed model 3.1.

temporal error tolerance	a	b	c	R^2
All	1.08	0.0185	1.44	0.857
10%	0.985	0.0209	1.20	0.800
20%	1.25	0.0164	1.41	0.826
40%	1.02	0.0181	1.71	0.880

Considering all these properties, we speculated the following model to describe the speed-accuracy tradeoff in trajectory-based tasks with temporal constraint:

$$SD = a + bW + c(A/MT) \tag{3.1}$$

where W is the tunnel width, A is the tunnel amplitude, MT is the specified movement time (i.e. MT *goal*), and SD is the lateral standard deviation of the trajectory. a, b and c are empirically determined constants. The A/MT also represents the average movement speed.

To verify the above model, we fit it to our experimental data using least-square regression. In addition to fitting to the entire data set, we also fit the model to the data from each *temporal error tolerance* group individually to test its performance under different conditions. Table 3.3 summarizes the regression coefficients and R^2 values for each fitting result.

The model had a good fit with the entire data set ($R^2 = 0.857$), as well as with data from all individual *temporal error tolerance* groups ($R^2 \geq 0.800$). This confirmed the validity of our model.

This model also confirmed our initial hypothesis that in trajectory-based tasks with temporal constraint, SD is not only related to the average movement speed (A/MT),

Table 3.4 Regression results of the proposed model 3.2.

temporal error tolerance	a'	b'	R^2
All	1.82	1.44	0.764
10%	1.82	1.20	0.654
20%	1.90	1.41	0.751
40%	1.74	1.71	0.813

but also related to the tunnel width W. In order to further consolidate our model by comparing its performance with simpler alternatives, we tested an alternate model that ignored the effect of W in model 3.1, i.e.:

$$SD = a' + b'(A/MT) \tag{3.2}$$

Again, the alternative model 3.2 was fit to both the entire data set and the individual *temporal error tolerance* groups. The regression coefficients and R^2 values of model 3.2 are summarized in Table 3.4.

The R^2 values for model 3.2 are considerably lower than those of model 3.1 in all cases, therefore not considered a valid model. Unlike in target acquisition tasks, the effect of W on SD cannot be ignored in trajectory-based tasks. As such, we conclude that model 3.1 best describes the speed-accuracy tradeoff in trajectory-based tasks with temporal constraint.

3.6 Discussion

In our model, SD measures the "average" accuracy throughout the entire trajectory. This is consistent with our original problem setup of a straight tunnel with uniform width W, and A/MT is the "average" movement speed. However, if we consider the more general case in which both the tunnel width and the movement speed can vary throughout the trajectory, we could let W_P and V_P represent the local tunnel width and instant movement speed at a given point on the trajectory. As a result, $SD_P = a + bW_P + cV_P$ might be used to predict the local expected lateral deviation at the point. This might help us design and analyze interactions using trajectories or tunnels of various shapes and properties, and understand them at a finer level.

Our experiment used a setup with relatively strict temporal constraint and non-strict spatial constraint. We could naturally consider the other variant where there is no explicit spatial constraint at all (i.e. tunnel width $W = 0$), which essentially becomes a line tracing task. This is the analogy of Schmidt et al.'s study [66] where the target is a thin line with nominally zero width. Fortunately, we might predict the user performance under this case by setting $W = 0$ in our current model, which then becomes $SD = a + c(A/MT)$. This means the lateral deviation is linearly related to the movement speed only, a similar result to Schmidt's law. Obviously, this conclusion would need real experimental data to be validated.

The two accuracy metrics we used, SD and OPM, are highly correlated since they are both calculated from the trajectory. In fact, if we know the tunnel width W and assume the y-coordinates of the trajectory follow a normal distribution, we can calculate the OPM value from SD by utilizing the properties of normal distributions, and vice versa. This may prove useful in practice, e.g., after predicting the SD for a particular trajectory-based task, we can further predict the associated error rate by calculating the OPM. Conversely, knowing the SD value we could calculate the "effective tunnel width" as the width of an imaginative tunnel for which an anticipated OPM (e.g. 4%) would be achieved. This may guide us to choose the optimal tunnel width depending on the speed and accuracy requirements for particular trajectory-based interactions, such as navigating a hierarchical menu or triggering a hover widget [24]. Our model for trajectory accuracy may also have implications in scenarios beyond human-computer interaction, e.g., to decide optimal road widths for different driving speeds in road planning.

Throughout this paper we have been referring to previous research on speed-accuracy tradeoff in target acquisition tasks as an analogy. However, we also want to emphasize the differences between trajectory-based tasks and target acquisition tasks, especially in terms of the notion of accuracy. In a target acquisition task, the movement accuracy is solely determined by the destination (end point) of the movement, for which we call the "destination accuracy". The spatial error in the destination is mainly caused by the ballistic nature of the movement, and is collinear to the movement. In contrast, in a trajectory-based task, the movement accuracy is determined by the entire process (trajectory) of the movement, for which we call the "process accuracy". The spatial error in the trajectory is mainly caused by the motor instability in the movement, and is perpendicular to the movement. These differences also contributed to the different forms of speed-accuracy tradeoff models for the two types of tasks. Similar comparisons can be made with other motor control tasks, For example, in a crossing task, destination accuracy and perpendicular error coexist, which may result in yet another form of speed-accuracy tradeoff.

Since participants could not possibly finish a task with exactly the specified movement time, *temporal error tolerance* was introduced to define the range of acceptable movement time. Although our choice of testing multiple levels of *temporal error tolerance* did not result in observable effects on the trajectory accuracy, it did provide us with interesting observations on user behaviors in terms of the actual movement time taken. In particular, from the groups with higher *temporal error tolerance* values, we observed that the steering law as a fundamental motor control mechanism still affects the movement time, even when people consciously follow an explicit temporal requirement. We suspect that a similar effect might be present in other types of motor control tasks as well. This suggests that in practical time-critical applications, we cannot overlook the inherent properties of the tasks and expect users to be able to perform at an arbitrary rate, even when accuracy is not the priority. On the other hand, in our experiment we used a post hoc feedback mechanism about the participant's temporal performance. How real-time feedback mechanisms (e.g. progressively filling the tunnel with color to indicate the elapsing of time) might affect the participants' behaviors remains an interesting question for further investigations.

3.7 Conclusion

As the result of our investigation, we now can answer the questions we raised in the beginning: In trajectory-based tasks with temporal constraints, regularity does exist in the relationship between the trajectory accuracy and the task parameters, which is described by the speed-accuracy tradeoff model: $SD = a + bW + c(A/MT)$, where W is the tunnel width, A is the tunnel amplitude, MT is the specified movement time, and SD represents the lateral standard deviation of the trajectory. SD forms a linear relationship with both the tunnel width W and the average movement speed (A/MT).

Regarding the comparison between temporally- and spatially- constrained trajectory-based movements, both of them reflect a linear speed-accuracy tradeoff. As investigated by Zhou and Ren [79], in spatially-constrained tasks with subjective biases, the lateral deviation of trajectory (SD) is mainly affected by the tunnel width W and the subjective bias. In comparison, in temporally-constrained tasks the accuracy of trajectory (SD) is affected by both the tunnel width W and the average steering speed (A/MT).

In this chapter we experimentally investigated the speed-accuracy tradeoff in trajectory-based tasks with temporal constraint. A quantitative model has been established and validated by the experimental data. This work may enrich the research on human performance modeling, and enhance the understanding of speed-accuracy tradeoff in fundamental interaction tasks. This understanding would help guide the design and evaluation of trajectory-based user interfaces as well as relevant input devices. We hope this work will motivate further explorations in this direction.

3.8 Future Work

In the future, we plan to extend our investigation to trajectory-based tasks with zero tunnel width, non-uniform tunnel with, as well as trajectories of other shapes such as a circle. We would also like to test our model using other input devices such as a mouse, other forms of temporal feedback, or other reward-penalty mechanisms for the temporal constraint. In addition to spatial accuracy, we are also interested in systematically investigating the temporal accuracy, which describes human capabilities in matching the temporal constraints. Finally, we plan to investigate individual differences in terms of perception, estimation, and preference of the time constraints, especially for different age groups.

3.8 Future Work

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Chapter 4

An Investigation on Maximal Path Width for Steering Tasks

Steering law is a robust performance model for studying steering tasks in Human-Computer Interaction (HCI), such as drawing, writing and navigating a cascade menu. In this chapter, we investigated the maximum path width for steering law with stylus and mouse as two different input devices for both straight and circular steering tasks. Experimental results showed that the maximum path with size was 70 pixels for both stylus and mouse in the straight steering task, while 60 pixels for stylus and 50 pixels for mouse in the circular steering task. So, the maximum path width range is 50 $\sim$ 70 pixels (12.1 $\sim$ 16.9 mm).

4.1 Introduction

As referred in chapters 2 and 3, the steering law [1] has been a robust model for studying steering tasks in human-computer interaction, such as drawing, writing, navigating through a cascade menu, steering through a 3D space, etc. A daily example of the steering task is driving an automobile without crossing the road boundaries. The classical steering task paradigm is that steering a certain pointing device (such as a mouse or a pen) from the start segment of a tunnel to the end segment as quickly as possible, while staying within the boundaries of the tunnel (see Fig. 2.1).

The steering law quantifies the difficulty of a trajectory task with an index ID (Index of Difficulty), and relates tunnel steering time with the index in a linear fashion. The difficulty for steering through a straight tunnel (see Fig. 2.1a) is $ID_s = A/W$, where A is the length of the tunnel, and W is its width. For a circular tunnel, the movement amplitude A is equal to the circle circumference $2\pi R$, where R is the circle radius, so the difficulty for steering through a circular tunnel (see Fig. 2.1b) is $ID_c = 2\pi R/W$. Steering law that models the relationship between completion time MT and tasks difficulty ID can be expressed in the following form: $MT = a + b \times ID_s$ for a straight tunnel, and $MT = a + b \times ID_c$ for a circular tunnel.

From the mathematical formulation of the steering law, we can see that when the path width W goes to infinity, the steering time MT will go to a constant a. Moreover, Accot and Zhai [1] reported that the steering law would lose its predictability power as the path width exceeded certain upper bound limit on a display [5]. But so far, no literature has reported the maximum path width for the steering law holding. In this chapter, we will explore the maximum path width for the steering law. Investigation on this issue will contribute to a further understanding of the steering law and user behavior, and provide new insight on user interface design and evaluation.

4.2 Experiment

The aim of this experiment is to explore the maximum path width of the steering law with a stylus and a mouse respectively as input devices on both straight and circular steering tasks.

4.2.1 Task

The experimental task was steering a stylus or a mouse through straight and circular tunnels with different sizes (see Fig. 2.1) along a certain direction as fast and as accurately as possible. The two typical steering tunnels are often used in the researches related to steering tasks [2], [3], [76].

4.2.2 Subjects

In the experiment, 20 young subjects were recruited from local university and randomly divided into 2 groups with 10 subjects for each group. The first group performed both straight and circular steering tasks with a stylus as input device, while the second group with a mouse as input device. All subjects were right-handed and experienced mouse and stylus users.

4.2.3 Apparatus

The experiment was conducted on an IBM ThinkPad X41 Tablet PC with a stylus and a Microsoft Optical Wheel mouse respectively as the input devices, running Windows XP. The screen size was 12.1 inches, with 1024×768 resolutions. Experimental software was developed with Java.

4.2.4 Procedure

With the stylus and the mouse as two kinds of input devices, the subjects placed the Tablet PC on the desktop. Before the test, all subjects were allowed to perform some warm-up trials with the input devices assigned to them until they felt that they could begin the experiments.

Following the protocols pointed out by [2], [3], subjects performed two types of steering tasks: straight and circular tunnel steering. At the beginning of each trial, the path to be steered was presented on the screen, in black. After placing the cursor to the left of the start line and depressing the tip of the stylus or the left button of the mouse, the subject began to draw a green line on the computer screen, showing the cursor's trajectory. When the cursor crossed the start line, left to right, the cursor trajectory turned blue, as a signal that the task had begun, the time was being recorded and the cursor's trajectory was being sampled. When the cursor crossed the end line, also left to right, the current tunnel disappeared and a new tunnel was presented to the subject. Lifting the pen tip up or releasing the mouse left button from the Tablet PC surface after crossing the start line and before crossing the end line would result in an invalid trial and that trial needed to be repeated. When the cursor crossed the borders of the path, the line turned red, as a signal that the cursor trajectory was outside of the tunnel, but the current trial did not need to be redone. Subjects were instructed to steer through the tunnel as fast and accurate as possible. The steering direction of straight tunnel was rightward; as for circular tunnel, it was clockwise.

4.2.5 Design

Input device was a between-subject factor with two levels (mouse and stylus, with 10 subjects for each input device). The within-subject variables included: tunnel shape (straight tunnel and circular tunnel); tunnel Amplitude (100-700 pixels with 100 pixels increment), tunnel Width (10-300 pixels with 10 pixels increment) for straight tunnel; tunnel Amplitude (100-800 pixels with 100 pixels increment), tunnel Width (10-100 pixels with 10 pixels increment) for circular tunnel. The order of tunnel amplitude and width combinations was in random presented to the subjects in each trial. 3 repetitions were made for each tunnel amplitude and width combination. Two shapes of steering tunnel were balanced by Latin Square between 10 subjects of each group, i.e., five subjects had trials of circular tunnels first followed by those of straight tunnels, and the other half of the subjects had the reverse order.

4.2.6 Measurements

While the stroke was being made, the position of the cursor was sampled in intervals of 10 milliseconds. The dependent variables were: MT (Movement Time: time taken to move the cursor from the start line to the end line), SD (Standard Deviation: for the straight tunnel, SD is computed using the sampled y-values between the start line and the end line; for the circular tunnel, SD is computed using the distances between the sampled points and the center of the circular tunnel), and OPM (Out of Path Movement: percentage of sample points outside the tunnel border). For example, if 100 points were sampled and 10 of those points were outside the tunnel border, then OPM would be 10%.

4.3 Results

4.3.1 Movement Time (MT)

For the stylus as input device, experimental results showed that the R^2 values of MT vs. ID (Index of Difficulty) linear regression were all above 0.94 for all the tunnel widths on both straight (see Fig. 4.1) and circular tunnel steering. The traditional steering law still holds for all the path widths tested in this experiment. Here we only reported two path widths of straight tunnel steering at the smallest (10 pixels) and largest values (300 pixels) since the limitation of space.

However, Turkey HSD analysis showed that MT was significantly different between 10-60 pixels group and 70-300 pixels group for straight tunnel steering, and between 10-50 pixels group and 60-100 pixels group for circular tunnel steering (see Fig. 4.2). That

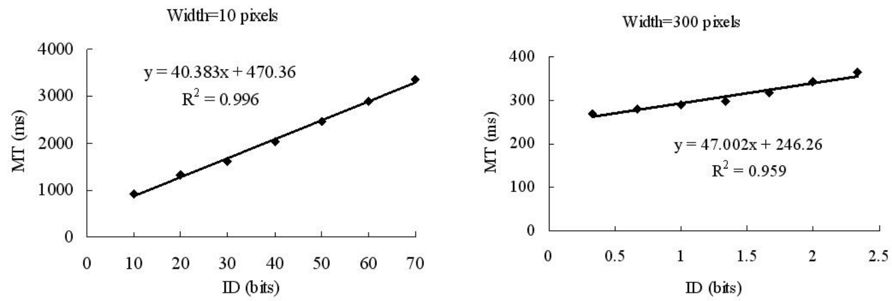
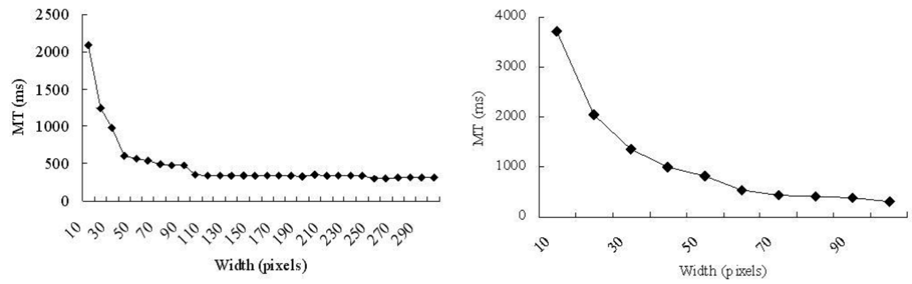


Fig. 4.1 MT vs. ID for widths 10 and 300 pixels in the straight tunnel steering (stylus as input device).



(a) straight tunnel steering (b) circular tunnel steering

Fig. 4.2 MT vs. Width for straight tunnel (a) and circular tunnel (b) steering (stylus as input device).

is to say, MT was not significantly affected by path width when the width size was over 70 pixels for straight tunnel steering and over 60 pixels for circular tunnel steering.

For the mouse as input device, the traditional steering law still holds for all the path widths ($R^2 > 0.95$) on both straight and circular tunnel steering. Turkey HSD analysis results showed that MT was not significantly affected by path width when the width size was over 70 pixels for straight tunnel steering and over 50 pixels for circular tunnel steering (see Fig. 4.3).

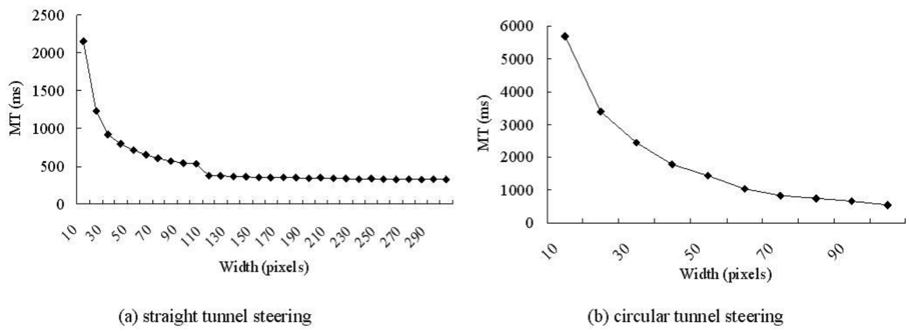


Fig. 4.3 MT vs. Width for straight tunnel (a) and circular tunnel (b) steering (mouse as input device).

4.3.2 Standard Deviation (SD)

For the stylus as input device, ANOVA analysis showed that SD was significantly affected by path width ($F_{29,270} = 10.6, p < 0.001$) for the straight tunnel steering. The value of SD increased with increasing path width (see Fig. 4.4a). The same result was observed for the circular tunnel steering. For the mouse as input device, the case was also the same.

4.3.3 Out of Path Movement (OPM)

For the stylus as input device, ANOVA analysis showed that OPM was significantly affected by path width ($F_{29,270} = 20.65, p < 0.001$) for the straight tunnel steering. The value of OPM rapidly decreased with increasing width when path width was smaller (see Fig. 4.4b). The same result was observed for the circular tunnel steering. For the mouse as input device, the case was also the same.

4.4 Discussion

From the experimental results of this chapter, we could see that the steering law still held for all the tunnel widths ($R^2 > 0.9$) for both straight and circular steering

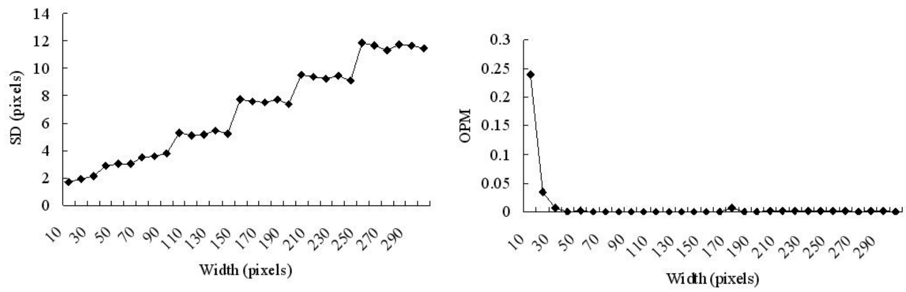


Fig. 4.4 SD vs. Width (a) and OPM vs. Width (b) for straight tunnel steering (stylus as input device).

tunnels. The reason for this maybe the limitation of apparatus size. Further Turkey HSD analysis showed that when the tunnel width exceeded a certain size, movement time (MT) would not be significantly affected by tunnel width. Here, we specified the certain size as the maximal path width for steering law under some situations. So, the maximum path width was 70 pixels for both stylus and mouse in the straight steering task, while 60 pixels for stylus and 50 pixels for mouse in the circular steering task.

In general, the wider the tunnel width, the less time one may take. From our experimental results, however, the tunnel width can not be widened infinitely. In the user interface design of handheld devices, like tablet PC, it is enough for the tunnel width to set as 70 pixels. Much wider tunnel size will not only take more space, but also not contribute to the reduction of movement time.

4.5 Conclusions

In this chapter, one basic issue related to the traditional steering law/tasks was investigated, i.e., the maximum path width for the steering law with a stylus and a mouse as input device on both straight and circular steering tasks. Experimental results showed that the maximum path width was 70 pixels (16.9 mm) for both stylus and mouse in the straight steering task, while 60 pixels (14.5 mm) for stylus and 50 pixels (12.1

mm) for mouse in the circular steering task. That is to say, when path width exceeds a certain value, MT will not change. The maximum path width range is $50 \sim 70$ pixels ($12.1 \sim 16.9$ mm). This result will be instructive for user interface design.

4.5 Conclusions

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Chapter 5

Effect of Different Start Positions on Human Performance in Steering Tasks

In this chapter, based on the maximal path width obtained in the above chapter, we investigated the effect of four different start positions on human performance in steering task. Experimental results showed that no statistically significant differences of the human performance, such as MT (Movement Time), SD (Standard Deviation), and OPM (Out of Path Movement) were observed among the four start positions in the circular steering task. However, there was a significant difference in SD among the four start positions in the straight steering task. Vertical steering resulted in more SD than horizontal steering. These results will be useful for further research and experiment design.

5.1 Introduction

The steering law, proposed by Accot and Zhai in 1997 [1], has been a robust model for studying steering tasks in human-computer interaction, such as drawing, writing and navigating through a menu and its nested menus. A daily example of the steering task is driving an automobile without crossing the road boundaries. Examples of the steering task performed with input devices in current GUI (Graphical User Interface) include steering through a menu and moving a scroll bar of a window, etc.

So far, the steering law has been widely studied. It has been verified with several input devices [2], such as stylus, mouse, isometric joystick, touch pad, and trackball, in different scale [3] and in locomotion [76]. Consequently, some extensive researches about the steering task have been done based on the steering law, such as the model of steering through tunnel with corner [56], steering within above-the-surface interaction layers for time prediction in the tracking state of the stylus [29], and study of subjective biases toward speed or accuracy in the steering tasks [79]. In addition, the pen stroke gesture model for time prediction in free hand drawing tasks has also been established [9]. A similar study to ours is Dennerlein et al.'s [15], which concluded that vertical movements required more time to complete than horizontal screen movement for the conventional mouse. The input device they used was indirect. We don't know whether the direct input device, such as stylus, had the same performance.

Through above literature, we see that little attention has been paid to the influence of different start positions on human performance. Investigations on this issue will rich in the content of the steering law and further enhance the understanding of user behaviors and instruct user interface design. In this chapter, we specify four kinds of start position for both straight and circular steering tasks, i.e., the left, right, top and bottom of the tunnel. For the circular tunnel steering, both clockwise and anti-clockwise directions' movement are performed.

5.2 Experiment

The aim of this experiment is to investigate the effect of four kinds of start position (top, bottom, left and right) on human performance with a stylus as input device on

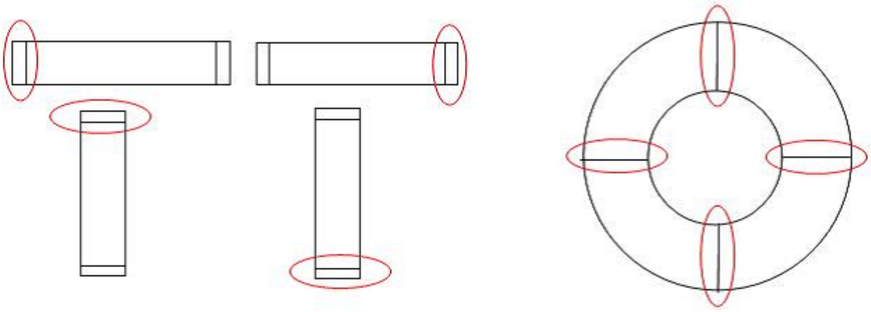


Fig. 5.1 Four kinds of start position (in the red ellipse).

both straight and circular steering tasks.

5.2.1 Tasks

The same as chapter 4, we also take a straight tunnel and a circular tunnel as two steering tasks. Different from the experiment in chapter 4, four start positions are specified in this experiment. The four start positions for the straight and circular tunnel are respectively at the left, right, top and bottom of the path (see Fig. 5.1). The red ellipses in Fig. 5.1 show different start positions. For the straight tunnel, different start position represents different steering direction. For example, the left start position represents rightward steering. For the circular tunnel, however, two steering directions, i.e., clockwise and anticlockwise are specified for each of the four start positions.

5.2.2 Subjects

10 subjects were recruited from local university to participate in this experiment. All subjects were right-handed.

5.2.3 Apparatus

The experiment was conducted on an IBM ThinkPad X41 Tablet PC with a stylus as the input device, running Windows XP. The screen size was 12.1 inches, with 1024×768 resolutions. Experimental software was developed with Java.

5.2.4 Design

A fully-crossed, within-subject factorial design was used. The independent variables included: tunnel Width (10, 20, 30, 40 and 50 pixels) and tunnel Amplitude (150, 250, 350 and 450 pixels) for straight tunnel, tunnel Width (10, 25 and 40 pixels) and tunnel Amplitude (250, 350 and 450 pixels) for circular tunnel, start position (left, right, top and bottom) for both straight and circular tunnel. The order of start position, tunnel amplitude and width combinations was in random presented to the subjects in each trial, with each combination repeating 3 times. Two shapes of steering tunnel were balanced by Latin Square between 10 subjects.

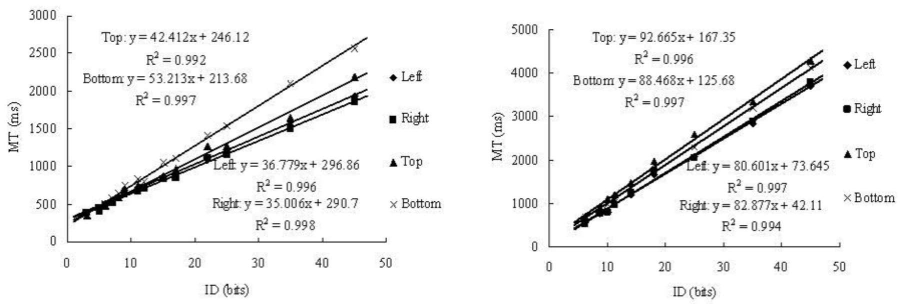
5.2.5 Procedure

The participants were first briefed on the purpose of the experiment. With the stylus as the input device, the subjects were allowed to place the Tablet PC on their knees or on the desktop, which ever was more comfortable. But during the experiment, all of them chose to place the Tablet PC on the desktop. Before the test, all subjects were allowed to perform some warm-up trials in each steering start position until they felt that they could begin the experiments. The experimental instruction was "Make a stroke as accurately as possible and as fast as possible along the tunnel".

All subjects performed two types of steering tasks: straight tunnel steering and circular tunnel steering. At the beginning of each trial, the path to be steered was presented with steering start position hint on the screen, in black. After placing the cursor at start position (red ellipse) and depressing the tip of the stylus, the subject began to draw a green line on the computer screen, showing the stylus trajectory. When the cursor crossed the start segment or start position line, the pen trajectory turned blue, as a signal that the task had begun, the time was being recorded and the stylus trajectory was being sampled. When the cursor crossed the end line, the current tunnel disappeared and a new tunnel was presented to the subject. Lifting the pen tip up from the Tablet PC surface after crossing the start line and before crossing the end line would result in an invalid trial and that trial needed to be repeated. When the cursor crossed the borders of the path, the trajectory turned red, as a signal that the stylus trajectory was outside of the tunnel, but the current trial did not need to be redone.

5.2.6 Measurements

While the stroke was being made, the position of the cursor was sampled in intervals of 10 milliseconds. The dependent variables were: MT (Movement Time: time taken to move the cursor from the start line to the end line), SD (Standard Deviation: for the straight tunnel, SD is computed using the sampled y-values between the start line and the end line; for the circular tunnel, SD is computed using the distances between the sampled points and the center of the circular tunnel), and OPM (Out of Path Movement: percentage of sample points outside the tunnel border). For example, if 100 points were sampled and 10 of those points were outside the tunnel border, then OPM would be 10%.



(a) straight tunnel steering

(b) circular tunnel steering (clockwise)

Fig. 5.2 MT vs. ID for both straight and circular tunnels.

5.3 Results

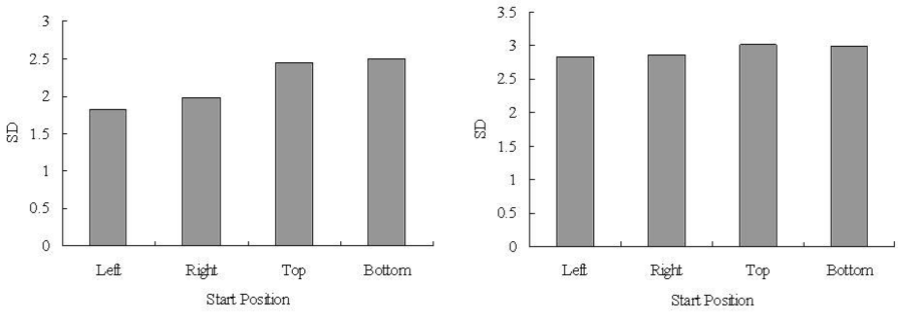
5.3.1 Movement Time (MT)

Repeated measures ANOVA showed that no significant effect of start position ($F_{3,39} = 2.87, p = 0.35$ for straight tasks, $F_{3,39} = 2.87, p = 0.23$ for clockwise direction and $F_{3,39} = 2.87, p = 0.63$ for anticlockwise direction of circular tasks) upon steering time was observed. Mean steering time for left, right, top and bottom start positions were respectively 790.1, 761.7, 814.7, and 930.5 ms for straight steering tasks and 1625.2, 1639.6, 1937.3, and 1828.7 ms for clockwise direction and 1901.0 1944.7, 1788.8, and 2062.1 ms for anticlockwise direction of circular steering tasks. Moreover, MT was not significantly different between clockwise and anticlockwise directions of circular steering tasks.

The steering law still holds for the four kinds of start position in both straight and circular steering tasks with all $R^2 > 0.99$ (see Fig. 5.2).

5.3.2 Standard Deviation (SD)

Repeated measures ANOVA showed that there was significant effect of start position ($F_{3,39} = 2.87, p < 0.001$) upon SD for straight steering tasks. Mean SD for left,



(a) straight tunnel steering (b) circular tunnel steering (clockwise)

Fig. 5.3 SD for four kinds of start position in both straight and circular tunnel steering.

right, top and bottom start positions were respectively 1.82, 1.98, 2.44, and 2.50 (see Fig. 5.3a). However, no significant effect of start position ($F_{3,39} = 2.87, p > 0.5$) upon SD was observed for clockwise and anticlockwise directions of circular steering tasks. Mean SD for left, right, top and bottom start positions were respectively 2.84, 2.87, 3.02, and 2.99 (see Fig. 5.3b) at the clockwise direction and 2.93, 3.01, 2.99 and 2.93 at the anticlockwise direction. Moreover, SD was not significantly different between clockwise and anticlockwise directions of circular steering tasks.

In addition, pairwise comparisons showed no significant differences between top and bottom ($p = 0.731$), and between left and right ($p = 0.296$) start positions for straight tunnel steering, which meant that horizontal and vertical steering resulted in significantly different SD. The mean SDs for horizontal and vertical steering were respectively 2.86 and 3. Vertical steering produced larger SD than horizontal steering. This indicates that user performs horizontal movement more accurate than performing vertical movement.

The reason for the difference of the effect of start positions on SD maybe that in the straight tunnel different start positions represent different drawing directions; the movements of wrist are different in the different drawing directions, especially at the horizontal direction and vertical direction; while in the circular tunnel the movements

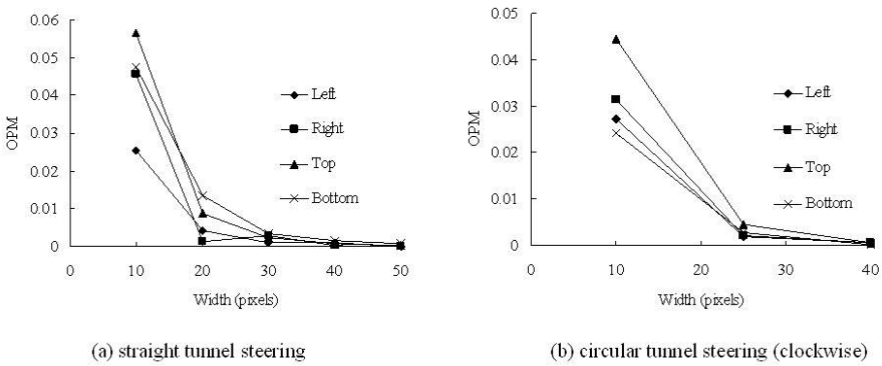


Fig. 5.4 OPM vs. Width for four kinds of start position in both straight and circular tunnel steering.

of wrist are the same in spite of different start positions.

5.3.3 Out of Path Movement (OPM)

Repeated measures ANOVA showed that there was no significant effect of start position ($F_{3,39} = 2.87, p = 0.40$ for straight tasks, $F_{3,39} = 2.87, p = 0.41$ for clockwise direction and $F_{3,39} = 2.87, p = 0.84$ for anticlockwise direction of circular tasks) upon OPM. Mean OPM for left, right, top and bottom start positions were respectively 0.64%, 1.01%, 1.38%, and 1.33% for straight steering tasks and 1%, 1.14%, 1.57%, and 0.92% for clockwise direction of circular steering tasks. Moreover, OPM was not significantly different between clockwise and anticlockwise directions of circular steering tasks. Fig. 5.4 showed that OPM decreased with increasing tunnel width for all four kinds of start position in both straight and circular tunnel steering, which was consistent with [36].

5.4 Discussion

In the circular tunnel steering tasks, start position didn't have significant effect on human performance for both clockwise and anti-clockwise steering directions. This indicates that the wrist rotation movement of human is very flexible, which can easily perform clockwise or anti-clockwise movement from different start points.

In the straight tunnel steering tasks, horizontal movement led to more accurate than vertical movement. For example, in the menu item design, the designer should arrange the items in row not in column as possible.

5.5 Conclusions

In this chapter, we investigated the effect of four start positions on human performance for both straight and circular steering tasks. Experimental results showed that no statistically significant differences of the human performance, such as MT (Movement Time), SD (Standard Deviation), and OPM (Out of Path Movement) were observed among the four start positions in the circular steering task. However, there was significant difference in the values of SD among the four start positions in the straight steering task. Vertical steering resulted in more SD than horizontal steering. That means a user performs horizontal movement more accurately than performing vertical movement. It will be instructive for user interface design. For example, user interface should let user perform horizontal movement as much as possible.

Future work includes further comparing the difference between visual-guided movements and free-hand drawing with the effect of drawing directions.

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Chapter 6

Assessing Age-Related Performance Decrements in User Interface Tasks

As the computer and internet generations age, there is an increasing need to develop appropriate interfaces for the elderly that can accommodate age-related changes in manual dexterity, visual acuity, and cognitive abilities. Assessment of age effects is typically a necessary first step in designing age-appropriate interfaces, but assessment of age related effects may be complicated by a bias towards accuracy in the elderly or by other differences in how the tradeoff between speed and accuracy is handled by different people. In this paper, we attempt to investigate the effects of aging on performance difference in interacting with computer interfaces. An experiment was conducted to examine age related effects in a steering task. In order to assess the impact of a possible speed-accuracy tradeoff, performance was observed under three different instructional sets i.e., *accuracy (A)*, *neutral (N)*, and *speed (S)* when steering on a circular track. Experimental results showed that the elderly group performed significantly less accurately for all three instruction sets. The younger subjects were more influenced by instructions to perform faster, or with more accuracy. Cluster analysis of the empirical data individually for both the old and younger participants showed that variability among subjects was much greater in older users than younger users. Implications for user interface design for older users, and for the evaluation of age effects in HCI generally, are discussed.

6.1 Introduction

In the past, elderly users have tended to have low computer literacy and design of information technologies for the aged has received little emphasis. However, the situation is set to change as the baby boomer generation reaches retirement age, where large numbers of retiring people, particularly in developed countries, will both highly educated and experienced computer users. In spite of their greater technical proficiency, baby boomers and subsequent generations will still be subject to the physiological and psychological changes that occur with aging, including reductions in manual dexterity, visual acuity, hearing sensitivity and cognitive complexity, etc., which affect control of user interfaces in particular [6] [73] [80].

In order to meet the needs of aging computer users, novel interfaces are required for the elderly so that they can contribute to and function in a society that is increasingly dominated by information technology.

In this chapter, we attempt to investigate the effects of aging by a bias towards speed or accuracy in the elderly or by other performance differences in how the trade-off between speed and accuracy is handled by different people. An experiment was conducted to examine age related effects under three different instructional sets i.e., *accuracy (A)*, *neutral (N)*, and *speed (S)* when steering on a circular track. The reason that we chose the steering task was that this was a task that has been extensively studied in past research, and as [2] pointed out, straight and circular steering tunnels are two basic and representative steering tasks in HCI. Examples of steering task in HCI include navigation through a cascade menu, drawing, writing, or steering through a 3D space, etc. These are also tasks that require fine motor control and where age effects may be expected to occur. According to the experimental results, implications for user interface design for older users, and for the evaluation of age effects in HCI generally are discussed.

6.2 Related Work

The study of age effects in HCI is complicated by a tendency for the elderly to focus more on accuracy at the expense of speed [64]. This suggests that potential speed-accuracy tradeoffs [42] [77] need to be considered when age effects are examined in HCI.

The research reported in this chapter focuses on assessing age effects on a common HCI task in visual interfaces: navigating, or steering the cursor through a 2-dimensional tunnel, which can be modeled using steering law [1]. Many studies have been performed in the past on the verification of the steering law for various input devices [2], scales [3], and parameters of steering motion [36]. However, the participants in previous studies were young adults, mostly involving students from universities. The present study sought to address this deficiency in the literature by providing findings on the effect of aging on the steering task, while also serving as a case study of how to examine the impact of speed-accuracy tradeoffs in HCI evaluations.

Aging effects have been examined in other HCI tasks. For instance, it has been reported that older users position the cursor much more slowly than younger users and have great difficulty making targeted movements to small targets [71]. Novel interaction techniques have been proposed (e.g., use of proxy targets [26], area cursors and sticky icons [71]) to overcome this difficulty and improving the accessibility of user interface or web usability for older people. Other recommended changes to user interfaces involve changes to content aspects such as font type and size for enhanced legibility [7]. Moffatt et al. [52] [51] [53] conducted a controlled laboratory experiment to examine target acquisition difficulties across the lifespan (younger, pre-old, and old people) during two tasks: multi-dimension tapping and menu selection, and attempted to address these difficulties by using appropriate interactive techniques for older people. In addition, adaptive interface for older people or motor impaired person [21] [22], and systematic theory framework research for web design or user interface design [73] were also investigated. However, research investigating age related effects in steering tasks that also considers the possible impact of age-related differences in the speed accuracy trade-off has yet to be carried out. The following experiment was designed to address that deficiency.

6.3 Experiment

6.3.1 Speed and Accuracy

In steering tasks, speed is typically represented by the time spent to accomplish a task, or movement time (MT). Accuracy may be measured as the standard deviation of sampled points in a trajectory made by a user, or by the number of points that are outside the specified area be steered within. We used both measurements for accuracy in this research. In this paper, the effect of three different instructional sets on performance in the circular steering tasks is contrasted for younger vs. older users. The following instructional sets were used: accuracy emphasis (A) where users were asked to focus on accuracy only; neutral (N) where users were asked to focus on both speed and accuracy; speed emphasis (S) where users were asked to focus on speed only.

6.3.2 Subjects

12 younger participants (3 females and 9 males; 20 to 27 years old, mean age 21.3; all right-handed), and 12 older participants (4 females and 8 males, 61 to 72 years old, mean age 65.8; all right-handed) were recruited to participate in this experiment. The younger people were students, and the older people were educated (two graduated from college, and others from middle school) and from a local "Older People's Center". The older people investigated in this paper are healthy older people, who don't appear disabled, but their functionality, needs and wants are different from those they had when they were younger [23].

6.3.3 Apparatus

The experiment was conducted on an IBM ThinkPad X41 Tablet PC running Microsoft Windows XP tablet edition, using a stylus as input. The screen size was 12.1 inches (1024×768 pixels resolution). The experimental software was developed in Java 6.0.

6.3.4 Task

Fig. 6.1 illustrates the experimental task for both user groups. Users were asked to perform steering tasks in a circular tunnel from the start line to the end line. R was the radius of the circular tunnel and W was its width. The movement amplitude A was equal to the circle circumference $2\pi R$.

6.3.5 Design

The experiment used a mixed design. User group was the only between-subject factor with two levels (young vs. old). The three within-subject factors were: Amplitude

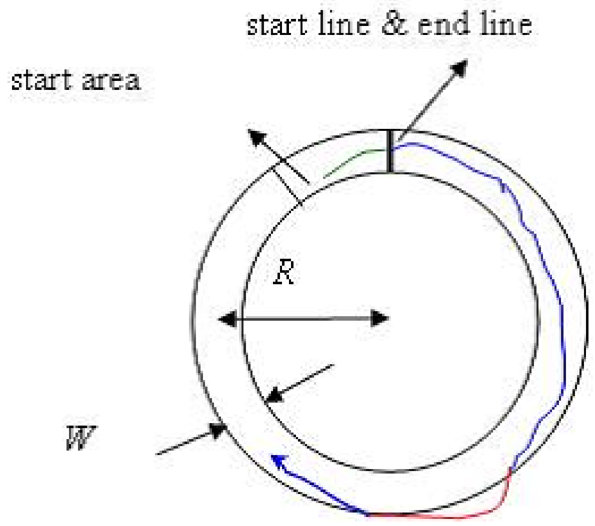


Fig. 6.1 Circle tunnel steering.

(300, 600, 800 pixels), Width (20, 30, 40, 50, and 60 pixels), and Instructional set (A, N, and S, as defined above). The direction of the circular steering task was clockwise. Similar designs were used previously [2] [3].

Each subject repeated the experiment three times with the different instructional sets, i.e., A, N, and S. Instructions corresponding to each instructional set were given by the experimenter before each experiment.

The order of the three instructional sets, A, N, S, was balanced using a Latin square. The order of the 15 amplitude and width combinations was presented in random order to the participants within each instructional set. Each subject performed 3 strokes for each Amplitude/Width combination within each instructional set of the circular steering tasks. Subjects completed the experiment in one session of about 30 minutes. In summary, the experiment design involved 24 subjects $\times$ 3 (tunnel amplitudes) $\times$ 5 (tunnel widths) $\times$ 3 (strokes) $\times$ 3 (instructional sets) = 3240 for the total number of trials.

6.3.6 Procedure

Warm-up trials were performed before each instructional set was used for the first time by each subject, leading to three sets of warm-up trials.

For each trial, subjects were instructed to trace a circular path from the start line to the end line in one clockwise motion. The trajectory of the stylus' movement was displayed in real time as feedback to users. The color of the trajectory was green if the stylus was inside the start area and had not entered the tunnel, blue if the movement of the stylus had crossed the start line and was inside the tunnel, and red if the stylus moved outside the path boundaries. Users completed the entire circle by passing the stylus across the end line from left to right, after which the tunnel disappeared. During this task, the tip of the stylus was required to stay in contact with the touchscreen. The same trial was repeated if the pen lifted off the touchscreen surface during this process.

6.3.7 Measurements

The position of the stylus was sampled every 10 milliseconds for each trial. The movement time (MT) required for users to trace the entire circle, from beginning to end, along with standard deviation (SD) of the distances from the center of the circular tunnel to the sampled points in pixel units, and the out of path movement (OPM), measured as the percentage of sample points outside the tunnel border were measured.

6.4 Results

Since the focus of this study was on the speed-accuracy tradeoff, the effects of amplitude and width are not reported below. The main effect of instruction set (as expected) was significant on movement time, SD, and OPM ($p < .001$ in all the three cases), demonstrating that the subjects changed their performance in response to the

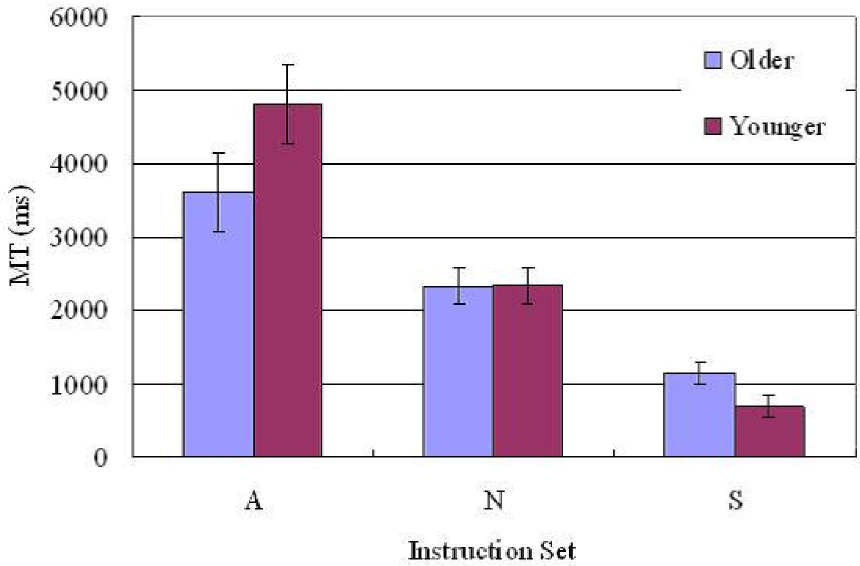


Fig. 6.2 Mean MT in instruction set A, N, and S for both older and younger user groups (with standard error bars).

instructions provided to them. In the following subsections the results of more detailed analysis will be reported.

6.4.1 Movement Time (MT)

ANOVA analysis showed a significant interaction effect of age group and instruction set on movement times ($F_{1.25,44} = 4.43, p < .05$) [*1] , but no main effect of age group ($p > .05$). As can be seen in Fig. 6.2, while movement times vary with instructional set for both age groups, the change is more dramatic for the younger group.

[*1] Note that non-integer values for degrees of freedom indicate that the sphericity assumption was violated and that the Huyn-Feldt adjustment to the effect degrees of freedom was used, as is recommended practice in such cases.

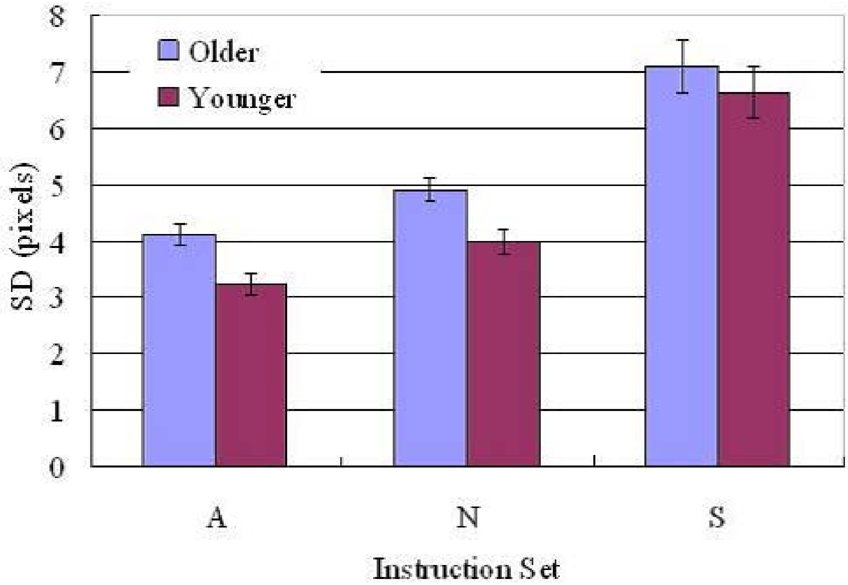


Fig. 6.3 Mean SD in instruction set A, N, and S for both older and younger user groups (with standard error bars).

6.4.2 Standard Deviation(SD)

ANOVA analysis showed no significant interaction between instruction set and age group on SD ($F < 1$), but there was a significant main effect of Age group on SD ($F_{1,22} = 4.94, p < .05$). On average the younger group was more accurate for all three of the instructional sets (see Fig. 6.3).

6.4.3 Out of Path Movement (OPM)

ANOVA analysis showed no significant effect on OPM is found for user group ($p >$ .05). Mean $OPMs$ for older and younger groups were 3.3% and 2.0% respectively. No significant interaction effect between instructional set and user group was observed ($p >$ .05). These showed that both older and younger users' behaviours could equivalently follow the requirement (tunnel width) the task set. A significant interaction between

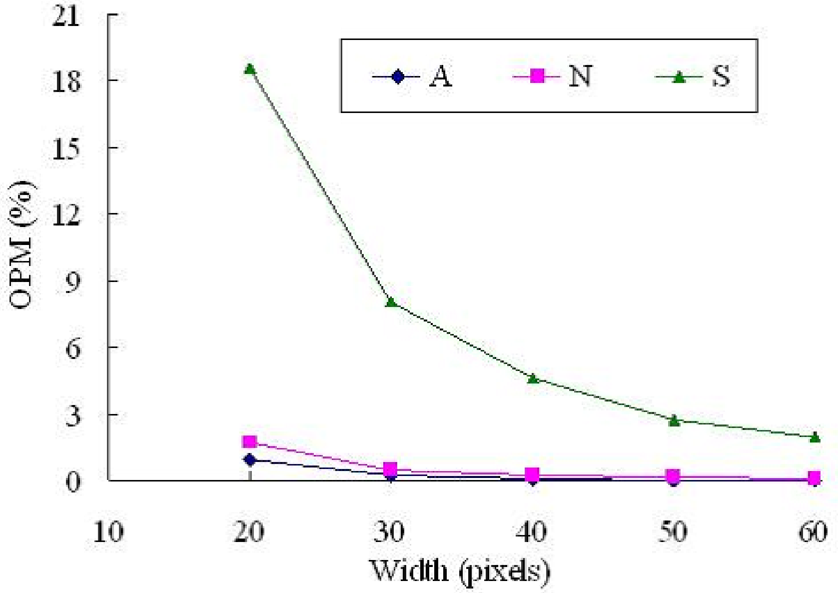


Fig. 6.4 OPM vs. W for instruction set A, N, and S - with older and younger user groups averaged.

instructional set and W was observed on OPM ($F_{8,176} = 49.79, p < .01$) (see Fig. 6.4). The effect of W on OPM is larger in condition S (when speed is the only concern) than that in condition A and N.

6.4.4 Cluster Analysis of Individual Differences

Individual differences are known to increase with age [59]. Here we investigated the individual difference for both older and younger people by the cluster analysis.

We found that the older group were overall less accurate in terms of the SD measure, and were also less responsive to instructional set. In order to better understand the nature of these effects, cluster analysis was carried out to determine the extent to which individual differences occurred within the two age groups, and how strongly such differences might have affected the results obtained.

Since there was both a strong age effect and a strong instruction set effect on accuracy, cluster analysis was carried out to examine how individual differences may have mediated the observed relationships between age, instruction set, and accuracy.

The average accuracies in terms of pixel SD were calculated across all combinations of the 24 participants and the three instructional sets. The accuracies were then converted into z-score units with the normalization being carried out for the data pooled across all instructional sets and participants. K-means analysis clustering was then carried out, with two, three, and four cluster solutions being examined. The four cluster solution was chosen for further study based on its interpretability.

Accuracy values across the three instruction sets are shown for each of the clusters in Fig. 6.5. Members of cluster 1 consisted of three older people and one younger people. They displayed very little change in accuracy in response to instruction set (with accuracy remaining within one half standard deviation of the experiment average across all three instruction sets). Cluster 4 contained only older (five) people. The people in this cluster were generally less accurate, and particularly so in the speed instruction set (with average SD in this case being over two standard deviations above the average for the experiment). Eight of the nine people in clusters 1 and 4 were older people. In contrast, six of the eight people in cluster 2 were younger, and five of the seven people in cluster 3 were younger. Clusters 2 and 3 both had high accuracy when instructed to be accurate and a fairly good level of accuracy in the neutral condition, but they differed in that cluster 3 subjects retained an accuracy level close to the experimental average, whereas SD increased to almost 1.5 standard deviation units above the average for cluster 2 subjects.

The clusters described above were identified based on the accuracy data, could they also predict differences in movement time across the different instruction sets?

This question was addressed by turning the four clusters into four levels of a corresponding "Cluster" pseudo factor and again running mixed ANOVA, but this time using

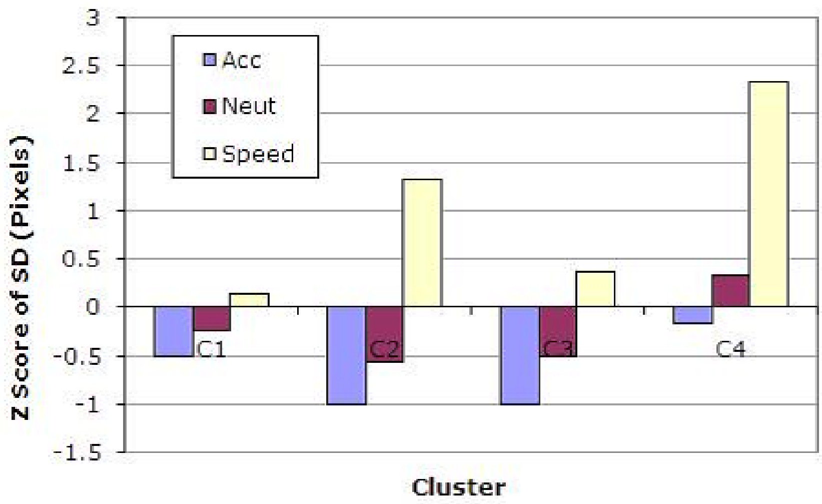


Fig. 6.5 Cluster centre values for z-score of SD across the four clusters (clusters one through four in left to right order).

the Cluster factor in place of the age group factor. There was a significant interaction between cluster and instruction set on movement time ($F_{4.78,40} = 4.135, p < .01$).

It can be seen in Fig. 6.6 that the an increasing instruction set for accuracy slowed movement times down in all four clusters, but that this effect was more pronounced for the "younger" clusters, i.e., clusters 2 and 3. By comparing Fig. 6.5 and Fig. 6.6, it can also be seen that subjects in cluster 2 responded more aggressively to the instructions, slowing down more in the accurate condition (but with no benefit to accuracy as compared with that obtained in cluster 3) and speeding up more in the speed condition (but at a relatively high cost to accuracy). Similarly it can be seen for the "older clusters (1 and 4)" that the fast movement times achieved in cluster 4 came at the expense of a substantial loss of accuracy.

6.5 Discussion

In general the more accurately a task is performed, the longer it takes and vice versa, with a characteristic s-shaped curve often being observed [55]. The relationship between

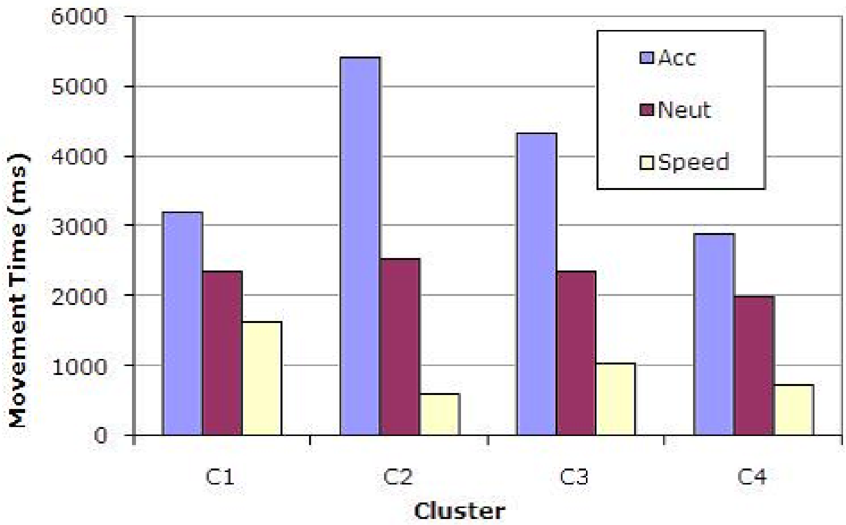


Fig. 6.6 The effect of instruction set on average movement time across the four clusters.

SD and MT was fitted as a power function separately for both older and younger groups. As indicated by the power curve goodness of fits shown in Fig. 6.7, there was a more consistent speed-accuracy relationship for the younger subjects ($R^2 = 0.861$ vs. 0.699 for the older subjects). The effect of instruction set can be seen vividly in Fig. 6.7, where the triangles (speed set) tend to be above and to the left of the squares (neutral) which in turn tend to be above and to the left of the circles (accurate set). It can also be seen that the speed-accuracy tradeoff is more strongly defined for the younger subjects.

Individual differences tend to increase with age [59]. We found that the older group were overall less accurate in terms of the SD measure, and were also less responsive to instructional set. When analyzing the data individually for both the old and younger participants, we found that variability among subjects was much greater in older users than younger users. Using cluster analysis based on SD over the three different instruction sets, we found that four of the elderly group showed a pattern of performance that was characteristic of the younger group, whilst only one of the younger group exhibited "older" performance.

The overall results showed that aging significantly diminishes performance on the steering task in terms of accuracy but not movement time. However, the speed-accuracy tradeoff induced by differences in instruction set was much stronger for the younger subjects.

6.6 Implications for Interface Design

While older users tend to have accuracy bias, in this study older users produced larger SD (greater deviation from the centre of the tunnel) than did younger users. In the user interface design for older users, one obvious strategy for dealing with this age effect would be to use larger tunnel size or target size.

It is generally more difficult for older users to perform a trajectory tracing task. In our experiment we observed that slow but precise movement of the stylus required firm but stable grasp of the stylus, which was difficult for older users' due to hand tremor. Fast movement of the stylus required good hand dexterity, which was also difficult for older users.

The older subjects showed less variability in movement time in spite of the instruction set. When older users did attempt to speed up a lot, there was a disastrous loss of accuracy. The inability of at least some of the older subjects to perform both fast and accurately may be partly due to the effects of reduced hand dexterity.

Recently, there has been considerable interest in gesture-based interfaces for pen-based computing. Many of these interfaces designed for efficient performance, especially by expert users. However, our results suggest that the utility of an interaction technique may be influenced by age. Many innovative techniques are currently tested only with younger users and age effects are ignored. Since gestural interfaces often rely on steering tasks of one sort or another, the differences found in our results indicate that some of the advantages exhibited by these interfaces in a younger user group may not apply to older users. Empirical studies are needed to reassess the effectiveness of these interfaces for an older population. Some of these techniques may need to be redesigned or enhanced by special interactive techniques such as force feedback, and area cursors to make steering tasks more manageable for older users.

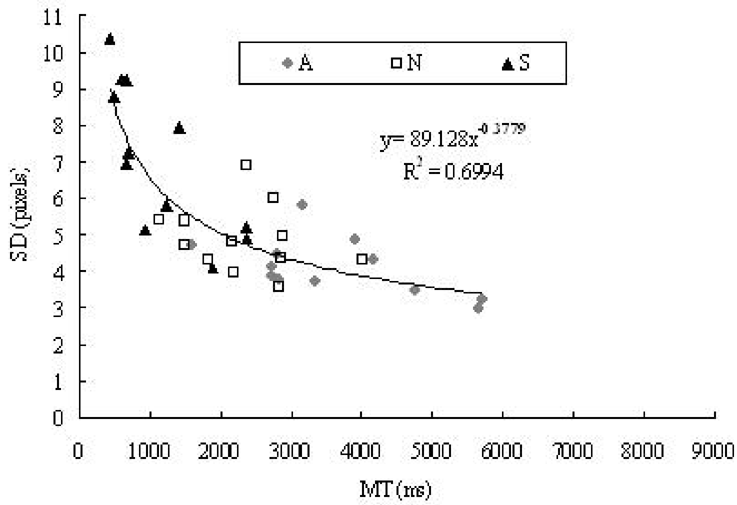
Observations made in our experiment also point out issues that need to be considered while conducting age related evaluation. Our experiment shows that relying on chronological age in studying age effects may be misleading. A distinction needs to be made between elderly users who perform like younger people and more typical elderly users who show the effects of age in their performance.

In addition, the effects of implied or explicit instruction sets on performance need to be carefully controlled in studies involving age effects. In general younger people may show a greater effect of instruction set on their performance. Thus depending on the instruction set younger users may appear to speed up or slow down (or become more or less accurate) relative to older subjects.

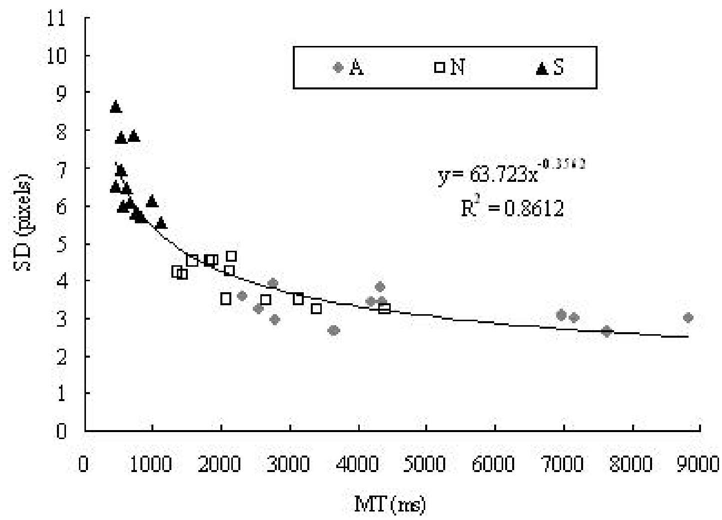
6.7 Conclusion

As Salthouse has pointed out [65], as people age, their cognitive, perceptual, and motor abilities decline, with negative effects on their ability to perform many tasks. However, as the present results demonstrate, aging effects need to be evaluated carefully. While it seems clear that aging has a negative impact on the steering task (and likely on many other HCI tasks as well), the situation is complicated both by speed-accuracy tradeoff effects and also by the heterogeneous nature of elderly populations. In any tasks there are likely to be some elderly people that can perform like younger people, and for those people an interface design specifically for the elderly might be annoying and inefficient. With respect to speed versus accuracy, researchers need to be careful about how much they stress speed or accuracy in performing experimental tasks. It is possible that relatively subtle changes in instructional set may lead to radically different apparent age effects. Where possible, it may be useful, as carried out in the present paper, to examine explicitly speed-accuracy tradeoffs and the effect of individual differences on performance. It would seem that analysis of aging effects in HCI may require more careful and detailed analysis of the experimental data and the subtle patterns and effects obtained therein.

This chapter shows how interpretation of age effects in HCI is complicated by the different way in which speed is traded off against accuracy in older people, the tendency of older people to stress accuracy at the expense of speed, and to have greater individual differences in performance, enriching our knowledge of how aging effects are likely to impact evaluations in HCI. In the future, we would like to perform further analysis to systematically investigate the individual effects of visual acuity, manual dexterity, and possibly other factors (such as hearing and cognitive abilities) on the steering task and other common user interface tasks.



(a) Older user group



(b) Younger user group

Fig. 6.7 Changes in speed (MT) and accuracy (SD) - for (a) older user group and (b) younger user group. Points corresponding to different instruction sets are labeled with differed shapes.

6.7 Conclusion

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Chapter 7

General Conclusions and Future Directions

This chapter summarizes the researches that were carried out, addresses the main contributions of this dissertation and views the future directions.

7.1 General Conclusions and Contributions

Modeling speed-accuracy tradeoff nature for trajectory-based tasks is the most fundamental work for human performance prediction, devices selection and user interface design. In the traditional steering law for trajectory-based tasks, only the objective spatial parameters of the task itself are considered. In real user interface tasks, however, some physiological and psychological effects of human beings and other subjective or objective factors also may affect the human performance and the formulation of speed-accuracy tradeoff model, which have not been emphasized enough in early studies. That is to say, the traditional steering law may not hold in some of these situations when more factors are considered.

The subjective operational bias towards speed or accuracy in the steering tasks had been studied in detail in Chapter 2. A controlled experiment was conducted involving five levels of subjective bias (EA, A, N, F, EF). Empirical data showed that subjective operational bias indeed had significant effect on human performance (movement time or accuracy). Analysis of interaction effect between subjective bias and objective spatial parameters (tunnel amplitude and width) indicated that accuracy SD was mainly affected by subjective bias and tunnel width. Then, we deduced a new steering time model (Equation 2.1) involving system and subjective factors, which was shown to have more robust predictive power than the traditional steering law.

Given that subjective speed or accuracy specification in Chapter 2, we explored the objective temporal (speed) constraint in trajectory-based tasks for modeling speed-accuracy tradeoff in Chapter 3. This study mainly discussed how the objective temporal constraint and objective spatial parameters of tasks affects human performance and the nature of speed-accuracy tradeoff. The experimental results showed that the accuracy of trajectory (SD) was affected by tunnel width and average movement speed and a quantitative accuracy model was proposed (Equation 3.1). In addition, we also discussed the differences of speed-accuracy tradeoff nature and motor mechanism in target-based tasks and trajectory based tasks.

We also investigated the maximal path width in the traditional steering law for both straight and circular tunnel steering with a stylus and a mouse respectively in Chapter 4, and experimental results showed that the maximum sizes of path width was 70 pixels (16.9 mm) for both stylus and mouse in the straight steering task, while 60 pixels (14.5 mm) for stylus and 50 pixels (12.1 mm) for mouse in the circular steering task. That is to say, when path width exceeds a certain value, MT will not change. The maximum path width range is $50 \sim 70$ pixels ($12.1 \sim 16.9$ mm).

In Chapter 5, we investigated the effect of different start positions (left, right, top and bottom) on human performance in straight and circular trajectory-based tasks. In the circular steering tasks, drawing direction for the four kinds of start position is clockwise and anticlockwise. Experimental results showed that only in the straight trajectory-based tasks, significant difference of accuracy of the trajectory was observed among different start positions, in which top and bottom start positions produce less accuracy of trajectory than left and right start positions. That is to say, horizontal movement is more accurate than vertical movement.

Finally, we investigated the effects of aging on performance difference in interacting with computer interfaces in Chapter 6. An experiment was conducted to examine age related effects in a steering task. In order to assess the impact of a possible speed-accuracy tradeoff, performance was observed under three different instructional sets, i.e., accuracy (A), neutral (N), and speed (S) when steering on a circular track. Experimental results showed that the elderly group performed significantly less accurately for all three instruction sets. The younger subjects were more influenced by instructions to perform faster, or with more accuracy. Cluster analysis of the empirical data individually for both the old and younger participants showed that variability among subjects was much greater in older users than younger users.

Comprehensively, the main contributions of this dissertation are as follows:

- Modeling speed-accuracy tradeoff nature in trajectory-based tasks (Chapters 2 and 3): From subjective operational bias, the performance model is: $MT = a + b(A/SD)$;

  From objective temporal constraint, the performance model is: $SD = a + bW + c(A/MT)$
- Exploring the maximum path width in the steering law (Chapter 4): In steering task, when path width exceeds a certain value, movement time (MT) will not change. The maximum path width is $12.1 \sim 16.9$ mm.
- Steering direction choice (Chapter 5): The accuracy of horizontal movement is higher than that of vertical movement, which is instructive for user interface design.
- Assessing age-related performance declining in trajectory-based tasks: The younger

subjects were more influenced by instructions to perform faster, or with more accuracy; variability among subjects was much greater in older users than younger users.

7.2 Future Directions

We aim to establish the speed-accuracy tradeoff models which can accurately include the human physiological and psychological information, temporal constraint parameters into the mathematical equations. Such speed-accuracy tradeoff models will be reliable and applicable for devices selection and user interface evaluation.

These works will motivate much more explorations of speed-accuracy tradeoff in modeling for trajectory-based tasks with both the physiological and psychological information and factor. The knowledge will be instructive for UI design comprehensively. All these works can assist us to know whether the existing devices or user interfaces are appropriate for a certain user group or under a certain situation.

With the fantastic development speed of science and technology, many novel input devices and user interfaces will appear. For the future work, it is necessary to carry out the model related researches about the application of human performance model on new input technology. Because few models have been established in the trajectory-based tasks, our study on human performance models will give evaluation of those previously and lately developed hardware and software, and further motivate more researchers to model human performance in the area of human computer interaction.

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Appendix A

Publications

A.1 Articles in or submitted to refereed journals

1. Zhou, X., Ren, X. 2009. An investigation of subjective operational biases in steering tasks evaluation. *To appear in Behaviour & Information Technology, Taylor & Francis.* (Terada Paper Award)

2. Zhou, X., Ren, X. 2009. Speed-accuracy Tradeoff Models in Target-based and Trajectory-based Movements. *To appear in the International Journal of Innovative Computing, Information and Control.* Vol.5 No.12.

3. Zhou, X., Ren, X. 2009. A comparison of pressure and tilt input techniques for cursor control. *To appear in The Institute of Electronics Information and Communication Engineers (IEICE).* Vol.E92-D No.9.

4. Ren, X., Zhou, X. 2009. The Optimal Size of Handwriting Character Input Boxes on PDAs. *Accepted for publication in the International Journal of Human-Computer Interaction, Taylor & Francis.*

5. Ren, X., Zhou, X. 2009. An investigation of the usability of the stylus pen for various age groups on PDAs. *Accepted with minor revision in Behaviour & Information Technology.*

6. Zhou, X., Cao, X., Ren, X. 2009. Modeling Speed-Accuracy Tradeoff in Trajectory-Based Tasks with Temporal Constraint. *To submit to Behaviour & Information Technology, Taylor & Francis.*

7. Zhou, X., Zhao, S., Chignell, M., Ren, X. 2009. Assessing Age-Related Performance Decrements in User Interface Tasks. *To submit to Computers in Human Behavior, Elsevier.*

A.2 Articles in full paper refereed international conference proceedings

8. Ren, X., Zhou, X., Liu, Z. 2007. An Empirical Evaluation of Seven Mice for Scrolling Tasks. *In Proceedings of the IEEE International Conference on Mechatronics and Automation (ICMA), Harbin, China.* pp. 582-586.

9. Zhou, X., Ren, X. 2008. Effect of Start Position on Human Performance in Steering Tasks.*In Proceedings of the International Conference on Computer Science and Software Engineering (CSSE), Wuhan, China.* pp.1098-1101.

10. Zhou, X., Ren, X., and Hui, Y. 2008. Empirical Study of Pen-pressure and Pen-tilt Input Techniques. *In Proceedings of the 2008 International Conference on Intelligent Pervasive Computing (IPC), Sydney, Australia.* pp.982-989.

11. Zhou, X., Cao, X., Ren, X. 2009. Speed-Accuracy Tradeoff in Trajectory-Based Tasks with Temporal Constraint. *Accepted by the 12th IFIP conference on Human-Computer Interaction (Interact2009), Uppsala, Sweden.*

A.3 Articles in abstract refereed international conference proceedings

12. Zhou, X., Fukutoku, F., Ren, X. 2008. An Investigation of Different Start Positions in Steering Tasks. *In Adjunct Proceedings of the 8th Asia-Pacific Conference on Computer-Human Interaction (APCHI), Seoul, Korea.* pp.121-122.

13. Fukutoku, F., Zhou, X., Ren, X. 2008. An Evaluation of the Maximal Path Width for the Steering Law. *In Adjunct Proceedings of the 8th Asia-Pacific Conference on Computer-Human Interaction (APCHI), Seoul, Korea.* pp.116-118.

14. Fukutoku, F., Ren, X., Zhou, X. 2007. An Empirical Evaluation of Upper Bound Limit of Width for Steering Task. *In Proceedings of International Conference on Next Era Information Networking (NEINE), Shanghai, China.*

15. Zhou, X., Ren, X. 2008. An Empirical Study of Operational Bias in Steering Tasks for Different User Groups. *In Proceedings of International Conference on Next Era Information Networking (NEINE), Kochi, Japan.* pp.384-385.

A.4 Articles in local conference proceedings

16. Zhou, X., Ren, X. 2007. An Investigation of Subjective Operational Biases in Steering Tasks Evaluation. *In Proceedings of SJCIEE2007. (Tokushima, Japan, September 29, 2007)*

17. Fukutoku, F., Ren, X., Zhou, X. 2007. The Upper Limit Size of Path Width for the Steering law. *In Proceedings of SJCIEE2007. (Tokushima, Japan, September 29, 2007)*

18. Higaki, T., Ren, X., Zhou, X. 2007. An Investigation of Influence of Different Start Position for Steering Tasks. *In Proceedings of SJCIEE2007. (Tokushima, Japan, September 29, 2007)*

19. Zhou, X., Ren, X. 2008. Effect of Different Steering Direction on Human Performance in Steering Tasks. *In Proceedings of SJCIEE2008. (Tokushima, Japan, September 27, 2008)*

20. Zhou, X., Zhao, S., Chignell, M., Ren, X. 2009. An Empirical Investigation of Age-related Performance in Computer Interface Tasks. *Accepted by Fukusi Engineering*

A.4 Articles in local conference proceedings

Symposium 2009, Kochi, Japan.