

# A COMPARISON OF INPUT DEVICES IN ELEMENTAL POINTING AND DRAGGING TASKS

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## ABSTRACT

An experiment is described comparing three devices (a mouse, a trackball, and a stylus with tablet) in the performance of pointing and dragging tasks. During pointing, movement times were shorter and error rates were lower than during dragging. It is shown that Fitts' law can model both tasks, and that within devices the index of performance is higher when pointing than when dragging. Device differences also appeared. The stylus displayed a higher rate of information processing than the mouse during pointing but not during dragging. The trackball ranked third for both tasks.

**KEYWORDS:** Input devices, input tasks, performance modeling.

## INTRODUCTION

The actions of *pointing* and *dragging* are fundamental, low-level operations in direct manipulation interfaces. While pointing tasks have been studied extensively (see, for example, the surveys by Milner, 1988 and Greenstein & Arnaut, 1988), the same is not true for dragging. The present study addresses this imbalance. It is driven by a belief that the human factors of the full range of direct manipulation tasks must be better understood. With such understanding emerges the ability to develop better predictive and analytic models, for example by extending the Keystroke-Level Model of Card, Moran, and Newell (1980) to handle this mode of interaction.

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This paper has two main contributions. First, it shows that dragging is a variation of pointing, and consequently, that Fitts' law can be applied to it. Second, it establishes that the performance of input devices in *each* of these two tasks should be considered in characterizing the human-factors of devices.

We present an experiment comparing three devices (a mouse, a tablet, and a trackball) in both a pointing and a dragging task. Each is modelled after Fitts' reciprocal tapping task (Fitts, 1954).

## FITTS' LAW: AN OVERVIEW

Pointing (target acquisition) tasks have been studied extensively. Much of this work is based on a robust model of human movement known as *Fitts' law* (Fitts, 1954). The law predicts that the time to acquire a target is logarithmically related to the distance over the target size. More formally, the time ( $MT$ ) to move to a target of width  $W$  which lies at distance (or amplitude)  $A$  is

$$MT = a + b \log_2(2A / W) \quad (1)$$

where  $a$  and  $b$  are empirical constants determined through linear regression. A variation proposed by Welford (1968) is also widely used:

$$MT = a + b \log_2(A / W + 0.5). \quad (2)$$

The log term is called the index of difficulty ( $ID$ ) and carries the units "bits" (because the base is "2"). The reciprocal of  $b$  is the index of performance ( $IP$ ) in bits/s. This is purportedly the human rate of information processing for the movement task under investigation. Card, English, and Burr (1978) found  $IP = 10.4$  bits/s for the mouse in a text

selection task. This is similar to values obtained by Fitts (1954) but is higher than usual. For example, ten devices were tested in studies by Epps (1986), Jagacinski and Monk (1985), and Kantowitz and Elvers (1988). Performance indices ranged from 1.1 to 5.0 bits/s.

There is recent evidence that the following formulation is more theoretically sound and yields a better fit with empirical data (MacKenzie, 1989):

$$MT = a + b \log_2(A / W + 1). \quad (3)$$

In an analysis of data from Fitts' (1954) experiments, Equation 3 was shown to yield higher correlations than those obtained using the Fitts or Welford formulation. Another benefit of Equation 3 is that the index of difficulty cannot be negative, unlike the log term in Equation 1 or 2. Studies by Card et al. (1978), Gillan, Holden, Adam, Rudisill, and Magee (1990), and Ware and Mikaelian (1987), for example, yielded a negative index of difficulty under some conditions. Typically this results when wide, short targets (viz., words) are approached from above or below at close range. Under such conditions,  $A$  is small,  $W$  is large, and the index of difficulty, computed using Equation 1 or 2, is often negative. A negative index is theoretically unsound and diminishes some of the potential benefits of the model.

Fitts' original experiments used reciprocal tapping tasks where one alternately tapped on two rectangular targets. The controlled variables were target width and the distance between targets; however, the motion was one dimensional (back and forth). Extending the model to two dimensions (which better fits pointing tasks in computer usage) has been discussed by Card et al. (1978) and Jagacinski and Monk (1985), among others.

### DRAGGING

There is little in the literature addressing human performance in dragging tasks. One exception is the study by Gillan et al. (1990). Like them, we extend Fitts' law to dragging. However, their study deals with text selection and is confounded on issues such as approach angle. Our work is at a lower level, and pays closer attention to device performance in the respective tasks and to the formulation of the mathematical model.

Using Fitts' law to model dragging is best explained using an example. Consider the case of deleting a file on the Apple Macintosh. First, the user acquires the icon for the file in question. This point/select operation is a classic two-dimensional target acquisition task. Then, while holding the mouse button down, the icon is dragged to the trashcan. This also is a target acquisition task. One is really just acquiring the trashcan icon. In this case, however, the task is performed with the mouse button depressed.

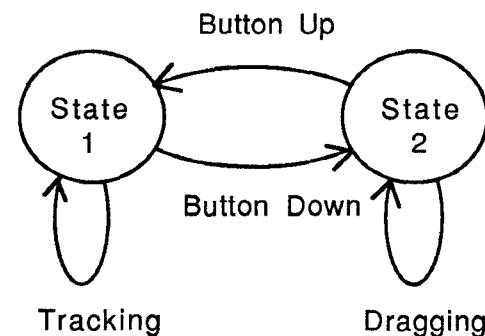
From the perspective of motor performance, the only difference is whether the tasks are performed with the mouse

button released or held down. (In both cases, the target is an icon of approximately the same size.) These classes of action are characterized as *State 1* and *State 2* by Buxton (1990), as illustrated in Figure 1.

State 2 motion on most input devices requires active maintenance of the state (e.g., by holding down a button), generally restricting the freedom of movement.<sup>1</sup> Given the frequency of State 2 actions in direct manipulation systems, we feel the following are important:

- to evaluate devices in *both* State 1 and State 2 tasks (unlike prior emphasis on the former), and
- to show that an established model (i.e., Fitts' law) can apply to this additional, State 2, case.

Achieving these two goals was our main motivation. Mean movement time, error rate, and Fitts' law were used to compare performance on three input devices in both State 1 and State 2 tasks.



**Figure 1.** Simple 2-State Interaction

*In State 1, mouse motion moves the tracking symbol. Pressing and releasing the mouse button over an icon selects the icon and leaves the user in State 1. Depressing the mouse button over an icon and moving the mouse drags the icon. This is a State 2 action. Releasing the mouse button returns to the tracking state, State 1 (from Buxton, 1990).*

### METHOD

#### Subjects

Twelve computer literate subjects (11 male, 1 female) from a local college served as paid volunteers. Subjects used their preferred hand.

#### Equipment

Tasks were performed on an Apple Macintosh II using three input devices:

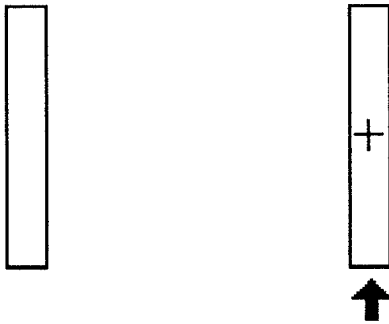
- Macintosh mouse
- Wacom tablet and stylus

<sup>1</sup> While maintenance of State 2 may exacerbate movement, the continued proprioceptive feedback can prevent mode errors (see Sellen, Kurtenbach, & Buxton, 1990).

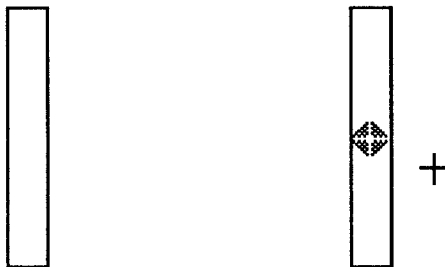
- Kensington trackball

**Procedure**

*Pointing Task:* Two targets appeared on each side of the screen (see Figure 2) with an arrow indicating where to begin. Subjects proceeded to point and click alternately between the two targets as quickly and accurately as possible, ten times in a row. A beep was heard if selection occurred outside the target. On each click a box at the top of the screen turned black while in State 2. (This additional feedback was important with the stylus to help judge the amount of pressure needed.) Following a one second pause the next condition appeared.



**Figure 2. State 1 Pointing Task**  
*Subjects started at the target marked by the arrow and alternately selected the targets as quickly and accurately as possible. The cross tracked the movement of the input device.*



**Figure 3. State 2 Dragging Task**  
*By placing the cross over the object inside the target, the object could be acquired and dragged to the other target. State 2 was maintained by holding the mouse button down.*

*Dragging Task:* The dragging task was similar except an "object" (see Figure 3) was acquired by pressing and holding down the button (on the mouse and trackball) or maintaining pressure on the stylus to "drag" the object to the other target. The object was dropped by releasing the button or pressure. The new object to be selected appeared

immediately in the centre of the target in which the old object was just dropped.

The dragging task can be likened to an inside-out pointing task: During pointing, movement occurred with the mouse button up and a down-up action terminated a move (and initiated the next); during dragging, movement occurred with the mouse button down and an up-down action terminated a move (and initiated the next).

Although instructed to move as quickly and accurately as possible, performance feedback was not provided. Subjects were told that an error rate of one miss in every 25 trials was optimal.

**Design**

Both tasks used four target amplitudes ( $A = 8, 16, 32,$  or  $64$  units; 1 unit = 8 pixels) fully crossed with four target widths ( $W = 1, 2, 4,$  or  $8$  units). Each  $A-W$  combination initiated a block of ten trials, each being one pointing or dragging task. Sixteen randomized blocks constituted one session. Five sessions were completed for each device for each task.

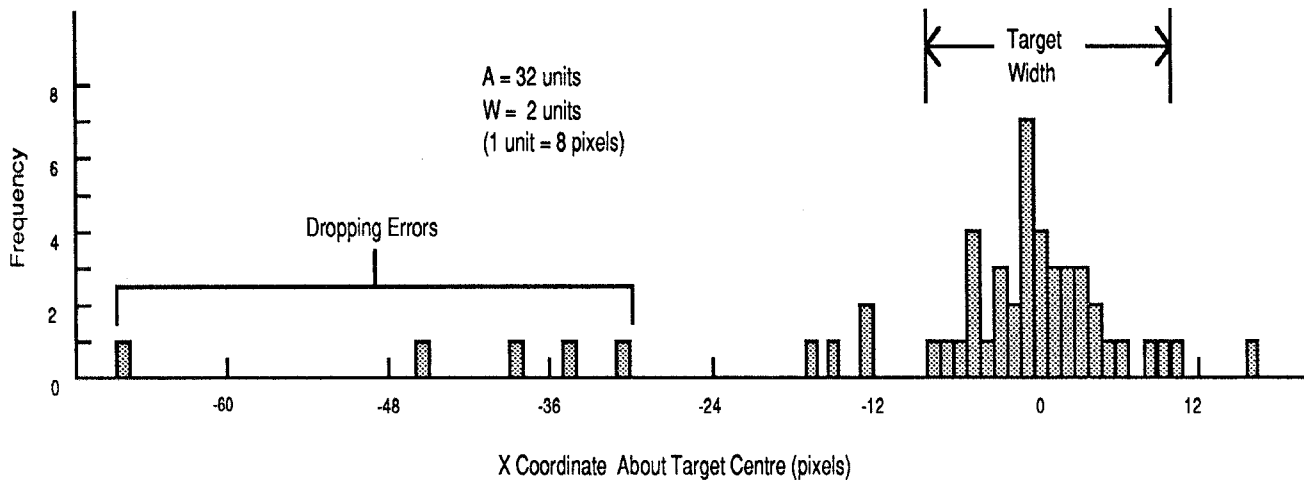
The task and device factors were within-subjects — each subject performed both pointing and dragging on all three devices. Ordering of devices was counterbalanced. Within devices, a random process determined the initial task (dragging or pointing) and tasks alternated for each session thereafter.

Prior to each new device-task condition, subjects were given a practice block. Breaks were allowed between blocks and sessions, but subjects completed all ten sessions on each device in a single sitting. Three sittings over three days, for a total of about three hours, were necessary to complete all conditions.

**RESULTS**

**Adjustment of Data**

Subjects were observed to occasionally "drop" the object during the dragging task, not through normal motor variability, but because of difficulty in sustaining State 2 motion. (This was particularly evident with the trackball.) Thus "dropping errors" were distinguished from motor variability errors. Examining the distribution of "hits" (the  $X$  coordinates) confirmed this source of error. Figure 4 shows a sample distribution of responses around the target for one subject during dragging. The data reveal deviate responses at very short movement distances distinct from the normal variability expected.



**Figure 4.** Dropping Errors

The distribution of X coordinates for one subject showing deviate responses classified as "dropping errors". Shown are 50 trials for the trackball during dragging with  $A = 32$  and  $W = 2$ .

Because dropping errors are considered a distinct behavior, we adjusted the data by eliminating trials with an X coordinate more than three standard deviations from the mean. Means and standard deviations were calculated separately for each subject, and for each combination of width ( $W$ ), amplitude ( $A$ ), device, and task.

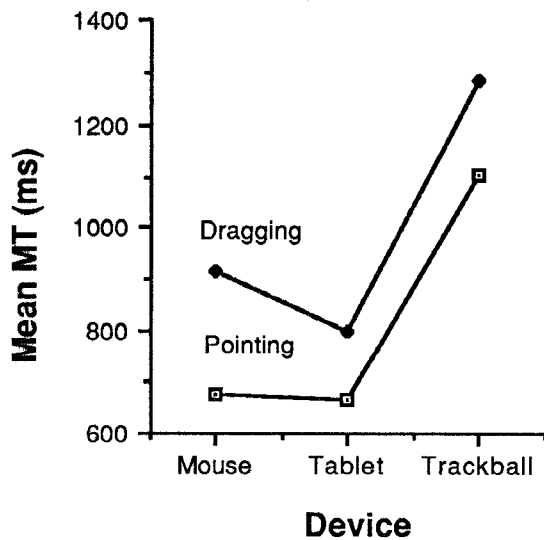
We also eliminated trials immediately following deviate trials. The literature on response times for repetitive, self-paced, serial tasks shows that deviate responses are disruptive events and can cause unusually long response

times on the following trial (e.g., Rabbitt, 1968).

A multiple comparisons test indicated a significant drop in movement time after the first session ( $p < .05$ ), but no significant difference in movement time over the last four sessions. Therefore, the first session for each subject for each device-task condition was also removed. Henceforth, "adjusted" results are those subject to the above modifications.

**Movement Time**

Mean movement times for the mouse, tablet, and trackball respectively were 674, 665, and 1101 ms during pointing and 916, 802, and 1284 ms during dragging. There was a significant main effect for task, with pointing faster than dragging ( $F_{1,11} = 72.4, p < .001$ ). This is shown in Figure 5. Devices also differed in movement time ( $F_{2,22} = 264.0, p < .001$ ). The trackball was the slowest in both pointing and dragging; however, there was a significant task-by-device interaction ( $F_{2,22} = 4.76, p < .05$ ). While the mouse and tablet were comparable for pointing, performance was more degraded for the mouse than for the tablet or trackball when the task changed to dragging. Adjusting for dropping errors had minimal effect on movement time.



**Figure 5.** Mean Movement Time by Device and Task

**Errors**

An error was defined as selecting outside the target while pointing, or relinquishing the object outside the target while dragging. Unadjusted error rates for pointing were in the desired range of 4% with means of 3.5% for the mouse, 4.0% for the tablet, and 3.9% for the trackball. However, in the case of dragging, error rates were considerably higher, with means of 10.8% for the mouse, 13.6% for the tablet, and 17.3% for the trackball.

Figure 6 shows the mean percentage errors by device and task, both adjusted and unadjusted. The unadjusted data showed a significant main effect of task, with the dragging task yielding many more errors than the pointing task

( $F_{1,11} = 45.28, p < .001$ ). In addition there was a significant main effect of device ( $F_{2,22} = 7.57, p < .001$ ). This effect, however, was entirely due to the dragging task as shown by a significant interaction ( $F_{2,22} = 16.04, p < .001$ ). While there was no difference in error rate across devices in the pointing task, error rate in the dragging task was dependent on device, with the trackball yielding the most errors and the mouse the fewest.

Adjusting for errors, not surprisingly, had a profound effect on dragging. By definition, no dropping errors occur in the pointing task; however, the same criterion was applied for consistency. If valid, not as many errors would be eliminated in the pointing task. As evident in Figure 6, this was the case.

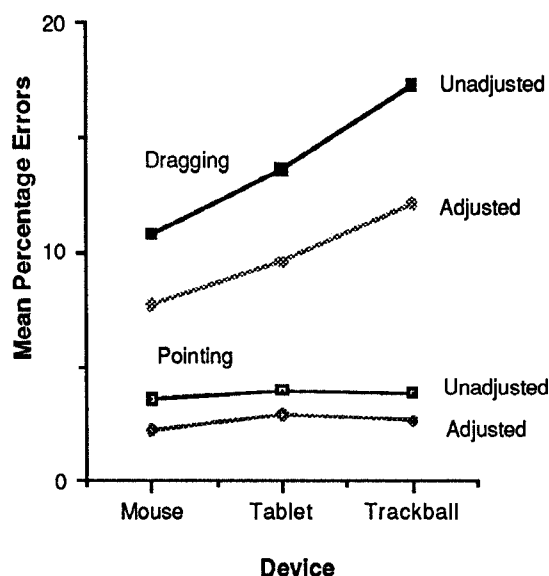


Figure 6. Mean Percentage Errors by Device and Task

#### Fit of the Model

A goal of this experiment was to compare the performance of several device-task combinations using Fitts' information processing model. Although Fitts' index of performance ( $IP$ , in bits/s) is considered an important performance metric, the disparity in error rates diminishes the validity of comparisons across device-task conditions. Clearly (see Figures 5 & 6), subjects were performing at different points on the speed-accuracy continuum for each device-task condition.

We applied Welford's (1968, p. 147) technique for normalizing response variability based on subjects' error rate. For each A-W condition, target width was transformed into an effective target width ( $W_e$ ) — for a nominal error rate of 4% — and  $ID$  was re-computed. Then,  $MT$  was regressed on the "effective"  $ID$ . Performance differences emerging from normalized data should be more indicative of

inherent device-task properties. Figure 7 shows the results of such an analysis.

There were consistently high correlations ( $r$ ) between movement time ( $MT$ ) and the index of task difficulty ( $ID$ , computed using Equation 3) for all device-task combinations.<sup>2</sup> The performance indices ( $IP$ ), obtained through linear regression, were less than those found by Card et al. (1978), but are comparable to those cited earlier. The rank order of devices changed across tasks, with the tablet outperformed the mouse during pointing but not during dragging. The differences, however, were slight. The trackball, third for both tasks, had a particularly low rating of  $IP = 1.5$  bits/s during dragging.

Five of the intercepts were close to the origin (within 135 ms); however, a large, negative intercept appeared for the trackball-dragging combination (-349 ms). With a negative intercept, the possibility of a negative predicted movement time looms. However, the chance of such an erroneous prediction is remote because of the large slope coefficients. For example, under the latter condition, a negative prediction would only occur for  $ID < 0.5$  bits.

Device	$r^a$	Regression Coefficients		
		Intercept, $a$ (ms)	Slope, $b$ (ms/bit)	$IP$ (bits/s) <sup>b</sup>
<i>Pointing</i>				
Mouse	.990	-107	223	4.5
Tablet	.988	-55	204	4.9
Trackball	.981	75	300	3.3
<i>Dragging</i>				
Mouse	.992	135	249	4.0
Tablet	.992	-27	276	3.6
Trackball	.923	-349	688	1.5

<sup>a</sup> $n = 16, p < .001$

<sup>b</sup> $IP$  (index of performance) =  $1/b$

#### Figure 7. Fitts' Law Models

A regression analysis for each device-task combination shows the correlation ( $r$ ), intercept ( $a$ ), slope ( $b$ ), and index of performance ( $IP = 1/b$ ). Prediction equations are of the form  $MT = a + b ID$ , where  $ID = \log_2(A/W + 1)$ .

#### CONCLUSION

This experiment confirmed the Card et al. (1978) finding of the superb performance of the mouse for pointing tasks, although the performance was comparable using a stylus and tablet.

The experiment showed a clear difference with devices in performing State 1 (pointing) and State 2 (dragging) tasks. For State 2 tasks, movement times are longer and error

<sup>2</sup>The correlations in all cases were slightly lower when computed using Equation 1 or 2.

rates are higher. The degradation between states differs across devices.

The trackball was a poor performer for both tasks, and had a very high error rate during dragging. This can be explained by noting the extent of muscle and limb interaction required to maintain State 2 motion and to execute state transitions. The button on the trackball was operated with the thumb while the ball was rolled with the fingers. It was particularly difficult to hold the ball stationary with the fingers while executing a state transition with the thumb: The interaction between muscle and limb groups was considerable. This was not the case with the mouse or tablet which afford separation of the means to effect action. Motion was realized through the wrist or forearm with state transitions executed via the index finger (mouse) or the application of pressure (tablet). Clearly, in the design of direct manipulation systems employing State 2 actions, the performance of devices in both states should be considered.

The experiment also showed that Fitts' law can model both dragging and pointing tasks; however, performance indices within devices were higher while pointing. Overall, *IP* ranged from 1.5 to 4.9 bits/s, somewhat less than the values found by Card et al. (1978) but comparable to values in other studies.

Of the devices tested, the highest index of performance was for the tablet during pointing and for the mouse during dragging. It is felt that a stylus, despite the requirement of additional, non-standard hardware, has the potential to perform as well as the mouse in direct manipulation systems, and may out-perform the mouse when user activities include, for example, drawing or gesture recognition.

Clearly, the work is not complete, and issues such as extending Fitts' law to accommodate approach angle need further investigation.

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