An Extensible Platform for the Interactive Exploration of Fitts' Law and Other Movement Time Models

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ABSTRACT

This paper describes a new software platform for the interactive exploration of movement time models such as Fitts' law. The software is written in Java and provides a flexible environment for HCI education and research. It is specifically designed using a patterns-based object model to provide maximum extensibility in terms of new models, task types, and selection modes.

Categories and Subject Descriptors

H.5.2 [**INFORMATION INTERFACES AND PRESENTATION**]: User Interfaces – *Input devices and strategies.*

General Terms

Measurement, Design, Experimentation, Human Factors, Fitts' Law.

Keywords

Fitts' law, HCI education, human performance modeling, input device evaluation, completion time predictions

1. INTRODUCTION

While many *ad hoc* utilities have been developed to capture data for the evaluation of input devices, throughput, and movement time predictions, few of the presently available tools represent an actual research platform on which scientific experimentation can be conducted. A standard, interactive platform for designing, executing, and analyzing experiments is required. The *Movement Time Evaluator (MTE)* described in this paper represents such a platform.

In addition to providing HCI researchers with a configurable environment for exploring the characteristics of input devices, user interface controls, and the rapid evaluation of new performance models, it also allows HCI students to conduct experiments and through that gain an understanding of the role of science in HCI.

The *MTE* platform is written in Java and represents a modern experimental toolkit for exploring Fitts' Law and other movement time models [1,4,6,7,9,10]. While several other tools have been created [11], *MTE* is constructed upon an extensible object-oriented framework and a comprehensive graphical user interface. Data files generated by *MTE* are exportable to many statistical analysis packages.

2. MOVEMENT TIME MODELS

Understanding the processes that guide human motor performance is critical in the engineering of usable computer systems. In particular, being able to quantify the production of rapid aiming movements with hands, arms, and fingers has important consequences for interface design. The advancement of engineering models that accurately predict human motor behavior is of great interest to HCI developers. Rapid aiming movements, such as guiding a pointing device to a particular location in a graphical user interface (GUI), are among the most important interaction mechanisms. Movement tasks in GUIs are either spatially or temporally constrained. Spatially constrained movement tasks are those where a target must be hit as accurately as possible while minimizing the average movement times. In contrast, in a temporally constrained movement task, the movement must end at a particular point and must be completed in a certain period of time. Most GUI selection tasks fall into the category of spatially constrained movement tasks. Spatial constraints can be along one dimension (univariate aiming tasks) or two dimensions (bivariate aiming tasks).

One of the earliest and most broadly applied engineering models is Fitts' Law [4]. In his groundbreaking work, Fitts discovered a logarithmic relationship between the spatial accuracy and the duration of rapid limb movements for univariate pointing. The mathematical quantification of speed versus accuracy has established itself as a cornerstone technique for the evaluation of human-computer interfaces. Card, English, and Burr [2] were among the first to apply Fitts' discoveries to man-machine interfaces when they used Fitts' Law to correctly predict word selection performance in a word processor using either a mouse or a keyboard.

Since the original publication of the work by Card *et al.*, Fitts' law has been successfully applied to a variety of HCI domains. Additionally, Fitts' Law has spawned an entire field of research that has resulted in a number of additional engineering models for HCI [1,4,6,7,9,10]. It is imperative that HCI researchers have a unified platform for analyzing various movement time models under different conditions and input device characteristics and therefore be in a position to make meaningful comparisons.

The generalized formulation of Fitts' law has the following relationship between movement time (MT), the amplitude (distance to the target) of the movement (A), and the width of the target (W):

$$MT = a + b \log_2\left(\frac{A}{W} + \varepsilon\right) \quad (1)$$

where the value of $\varepsilon \in \{½, 1, A/W\}$, and a and b are experimentally derived regression coefficients. The logarithm part of equation (1) is commonly referred to as the *Index of Difficulty* or *ID* of the movement.

In addition to Fitts' law and its variations, such as the Shannon formulation by MacKenzie [7], several other movement time models have been proposed, including those by Meyer *et al.* [9], Accot and Zhai [1] and Kvålseth [6]. The *MTE* platform allows researchers to test conformance with all of the above models as well as new ones.

The target width W is the smaller of the horizontal or vertical extent of the target for univariate pointing or the width along the approach vector for bivariate pointing. Additionally, MacKenzie [7] argues that the width of the target must be normalized to a standard error rate so that comparisons between input devices are meaningful. He proposes an effective width (W_e) that is either increased or decreased to provide a value that would result in a 4% standard error rate. The *MTE* platform can automatically adjust to an effective width.

The throughput (*TP*) of an input device is a measure of its efficiency and is calculated as the ratio of the mean *ID* and the mean *MT*, although sometime the inverse of the regression coefficient b is used as well. However, that definition of the throughout does not consider the reaction time captured by the regression coefficient a.

3. PLATFORM DESIGN

The *MTE* architecture is based upon an object-oriented design that takes advantage of many design patterns, such as *Strategy*, to simplify extensibility.

To make the control of experiments more efficient, the platform is remotely configurable, allowing a researcher to control the experiment from one workstation while the subject interacts with the software on a different workstation. The connectivity is through a standard TCP/IP connection and therefore can be distributed across any distance.

3.1 Configurability

The configuration of experiments is a two-step process. The researcher first creates an experiment setup which specifies session invariant parameters, such as target extent, target shape type (rectangular, oval, text, vibrating, moving, or expanding), home region placement (center of screen, random, coordinate system origin, or none), target position distribution (uniformly random, static, or reciprocal), feedback (auditory and visual), the number of repetitions, the type of movement (point-and-click versus drag) and the type of information that is be recorded for each movement, such as movement velocity. The configuration file is then saved for later use. When the researcher decides to run an experiment, the previously recorded configuration is selected from a list of stored setups. Before the experiment begins, a number of session specific items are recorded, such as subject information, posture (sitting, standing, walking, bracing), arm-body angle, environmental factors, input device type, screen dimension, probe characteristics, gain settings for the input device, as well as any other relevant *ad hoc* information. For each subject, several data points can be recorded including age, gender, height, and handedness.

3.2 Evaluation and Analysis

To assist in the rapid evaluation and interactive exploration of movement models and input devices, basic statistical analysis is built into the platform. The recorded data can be easily exported to many statistical packages for more sophisticated analysis. *MTE* supports correlation analysis and linear regression, as well as configurable scatter plots and distribution graphs. In addition, the raw data and the trajectory of the individual acquisition movements during a session can be viewed so that the movement patterns for different input devices can be studied. Lastly, a table comparing the correlation coefficients of various movement time models, including the different formulations of Fitts' law and the models by Meyer *et al.* [7], Kvalseth [4], and Accot and Zhai [1], is displayed.

The linear regression coefficients and the correlation coefficient (R) can be computed either on the raw observations or averaged *MT* values across ranges of *ID*, consistent in how much of the data has been published on Fitts' law [10]. In our experience, using raw observations yields R values in the range of 0.556 to 0.830 for all of the models, whereas using binned data for analysis results in R values of 0.90 or higher, consistent with what has been reported in the literature.

3.3 Extension and Customization

The *MTE* platform can be extended by adding new static as well as dynamic (moving) shape types, target position distributions, movement time models, and data export formats. Many of the extensions require minimal integration. The software architecture uses a number of design patterns, including Strategy, Singleton, Decorator, Factory, Mediator, and Prototype to facilitate extensibility and customization.

Of particular interest to the HCI researcher is the facility to add new movement time models by subclassing the *MovementTimeModel* abstract class and implementing the ID method as well as the tunable parameter sheet. This approach allows HCI researchers to quickly test new hypotheses and speed the process of discovery and learning.

3.4 Exporting to Other Tools

The tool records many data points for each movement using Java object serialization, including sampled coordinates and velocity along the movement trajectory. The data recorded in this format can be exported as CSV files for import into Microsoft Excel, relational databases, and statistical analysis packages. The format of the exported data can be controlled and customized.

3.5 Availability

The *MTE* platform is available under the GNU Public License (GPL) as open source software. An executable version that runs under Java 1.4.1 and later on Linux and Windows 98/XP can be obtained at http://www.cs.uml.edu/~mschedlb/mte.

4. EXPERIMENTAL RESULTS

4.1 Configuration

This section demonstrates how *MTE* can be used to evaluate several input devices with a particular focus on their motion characteristics. For that purpose one might want to configure two experiments, one as a univariate reciprocal pointing task similar to the classic Fitts experiment ("Experiment I") [4,7] and the other as a bivariate pointing task using an oval target shape ("Experiment II"). For each experiment the number of movement trials, target shape type, and target extent must be specified. The amplitude of the movement can be randomly varied, but the same positions will need to be displayed in the same order in all trials. So, the tool's *FixedRandomDistribution* positioning strategy is chosen. This results in a set of random target positions that is the same in all runs of this experiment. The seed for the random function and the can be adjusted in an external resource file. Other distribution functions consist of random placement with a random seed, reciprocal placement where the target moves back and forth between the left and the right side of the home position, and a static distribution where targets are displayed at fixed and pre-programmable positions, although the order of display can be randomized to mitigate the effects of learning in repeated trials.

In both experiments, the subject must first tap a home region before moving to the target, simulating a point-and-click task. A tap may actually be a finger touch, an input device click, or a stylus or pen tap. *MTE* allows the researcher to choose whether to display the target immediately or only once the home region is tapped. Deferring the display of the target implies that the recorded target acquisition time includes not only the movement time, but also the reaction time.

Each of the two experiments must now be carried out by several subjects, once for each input device. Figure 1 shows a screen shot of an actual trial run with experiment configuration I, Fitts' reciprocal tapping task, while Figure 2contains a screen shot of an interaction with experiment II. The second experiment has been set up to display as well as record the actual trajectory of the movement, along with the momentary speed at each mouse movement sample. In addition, the present mouse location is sampled and recorded at intervals of 10ms. This provides detailed acceleration information to the researcher.

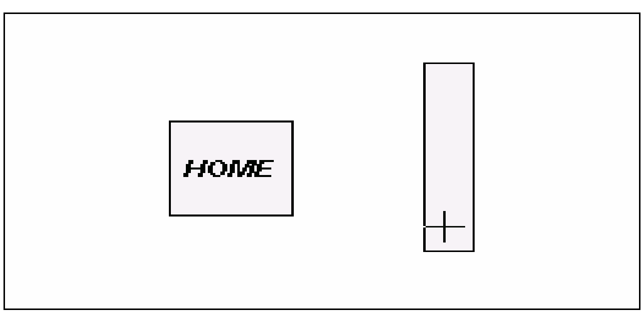

Figure 1. Acquisition of a target in Experiment I (Fitts Reciprocal Tapping).

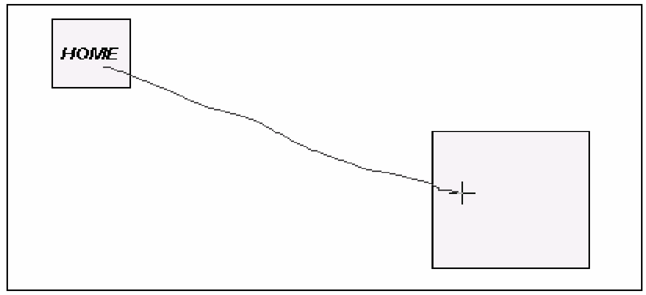

Figure 2. Acquisition of a square target in Experiment II (Bivariate Pointing). Trajectory of the movement path is shown in this configuration.

4.2 Exploration and Evaluation

After the raw data is gathered, different data sets can be merged into a single combined data set for exploration or a summarized data set that combines the means of the individual experiments. Data sets can be explored in their raw form or a "scrubbed" form in which data is binned (grouped and averaged) and outliers are removed.

Figure 3shows a scatter plot of the raw data for an experiment session along with the linear regression equation for the MacKenzie (Shannon) [7] formulation of Fitts' law. Movement time (*MT*) is along the Y axis and the Index of Difficulty (*ID*) is along the X axis. The tool allows any recorded parameter to be plotted against any other recorded parameter, *e.g.* amplitude against movement time or target angle against *ID*. To facilitate the comparison of different experiments, multiple data sets can be plotted side-by-side or overlaid. Figure 4 shows a scatter plot that contains two data sets collected through two different sessions of experiment II. In one run, a wireless mouse was used whereas in the second run a trackball was used. The trackball movements were markedly slower showing the cluster of trackball acquisitions above the mouse acquisitions.

Figure 5 summarizes the correlation results and throughput calculations for several movement time models. It shows the correlation coefficient (R) and the coefficient of determination (R^2) for each model using the Euclidean distance between the targets as the amplitude as well as the length of the cursor trajectory. Furthermore, the movement model panel displays minimum, maximum, and mean *ID* in addition to the minimum, maximum, and mean movement time *MT*. The models can be supplied the effective width W_e [7] or the width along the approach trajectory [12] instead of the nominal width along the horizontal and researchers can immediately see the effect on the correlation. Additionally, the width used in the model calculations can be increased by the width of the probe as proposed by Hoffmann and Sheikh [5].

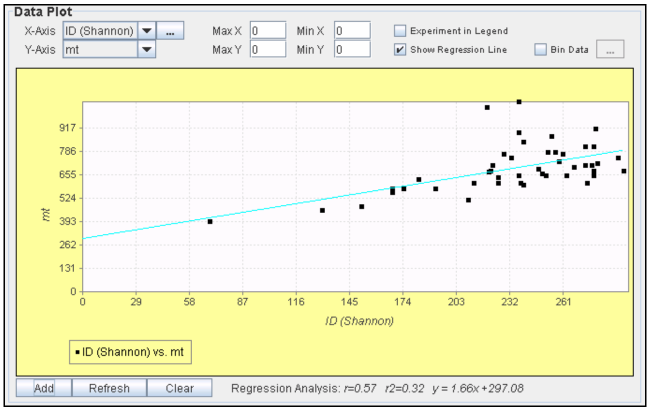

Figure 3. Scatter Plot of ID (Shannon formulation) versus MT with correlation coefficient (Pearson moment) and linear regression equation.

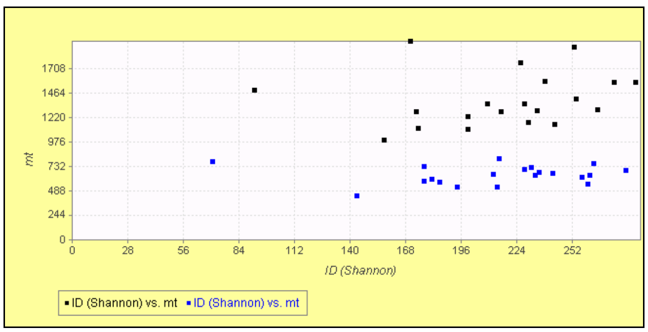

Figure 4. Scatter plot of ID (Shannon formulation) versus MT of two runs of the same experiment, one using a mouse and one using a trackball.

	Simple	Fitts	Welford	Shannon/M...	Meyer et al.	Kvalseth	Accot-Zhai
R (A, W)	0.69	0.74	0.74	0.73	0.72	0.69	0.74
R (D, W)	0.72	0.77	0.76	0.76	0.75	0.72	0.76
R2 (A, W)	0.47	0.55	0.54	0.53	0.52	0.47	0.55
R2 (D, W)	0.52	0.59	0.58	0.57	0.56	0.52	0.58
TP (bps)	4.60	3.82	2.65	3.05	2.69	4.60	4.90
Mean (ID)	2.75	2.28	1.58	1.82	1.61	2.75	2.93
Max (ID)	4.74	3.24	2.39	2.52	2.18	4.74	3.77
Min (ID)	0.73	0.54	0.29	0.79	0.85	0.73	1.55
Mean (MT)	598.40	598.40	598.40	598.40	598.40	598.40	598.40
Max (MT)	828.00	828.00	828.00	828.00	828.00	828.00	828.00
Min (MT)	344.00	344.00	344.00	344.00	344.00	344.00	344.00

Figure 5. Table comparing several movement time models.

To better understand the movement characteristics of the different input devices, the researcher can investigate the trajectory paths for each experiment. The plot in Figure 6 contains the starting position of the movement, the position at which the target was successfully acquired, the direct path to the target, and the actual path traveled. A different view of a single movement from the home position to the target is shown in Figure 7 as a plot of the speed along the trajectory path. Note how the movement is initially accelerating, and then slows down as the cursor moves toward the target.

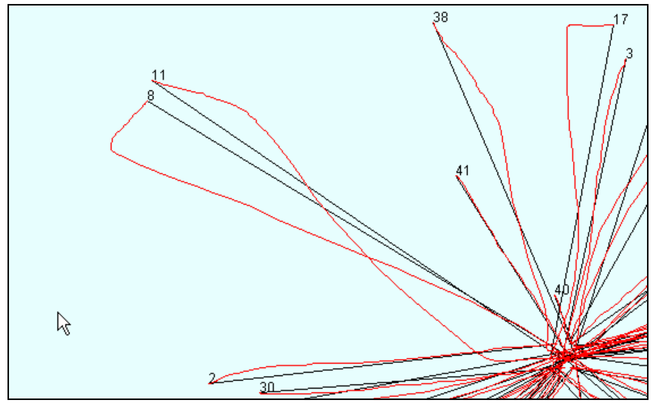

Figure 6. Plot of the actual trajectory of the mouse movement for some of the target acquisitions in Experiment II.

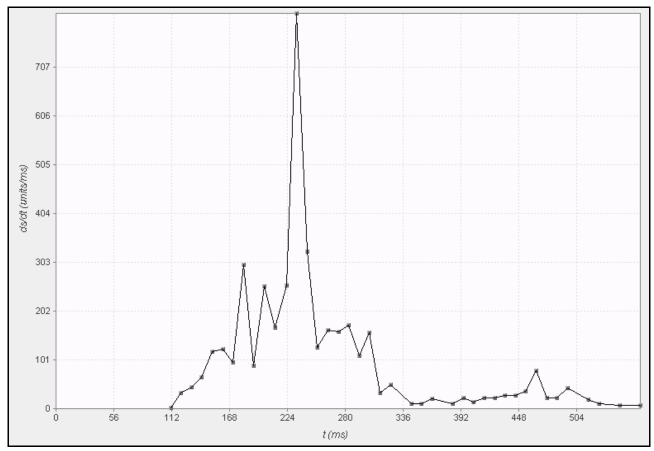

Figure 7. Graph of time since start of movement versus speed (ds/dt) for trajectory 8 of the acquisition movements of Experiment II.

5. FUTURE WORK

Work is undergoing in expanding the capabilities of *MTE* through the inclusion of additional movement time models. Additional performance models, such as those for measuring reaction time and learning, are being considered for *MTE*.

6. CONCLUSION

The *MTE* platform represents an easy-to-use environment for the exploration of movement time models. It is well-suited to HCI education since it provides an interactive means for teaching students about models such as Fitts' law and helping them understand the role of science in HCI. The tool's immediate feedback and exploratory make it a valuable resource for students and researchers. While the statistical mechanisms built into MTE are certainly useful, they do not represent a substitute for the more rigorous statistical analysis provided by specialized tools, such as the "R" and "S" statistics packages.

7. ACKNOWLEDGMENTS

We express our gratitude to the students and faculty of the Department of Computer Science for assisting in the usability testing of the software and their participation in evaluation experiments.

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