Biasing Response in Fitts' Law Tasks

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Abstract
Fitts' law, relating the time to acquire a target to the target size and the distance from the target, is an effective and widely used predictor of performance in feedback controlled human motor targeting tasks. Beyond target size, however, movement time also varies according to a subject controlled mental trade-off between speed and accuracy for a given task. To adjust for this trade-off, researchers often use the "effective target width", the target width normalized for variations in movement speed, as a predictor of movement time. In this paper, we describe on-going work on analyzing factors affecting the speed-accuracy tradeoff for Fitts' tasks in subjects, exploring both incentives and penalties to manipulate subject accuracy. We also describe our work on measurable parameters of motion that correlate with the speed-accuracy trade-off.

Keywords
Fitts' Law, Signal, Speed, Accuracy

ACM Classification Keywords
H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

Introduction
Fitts' Law, describing target acquisition time based on the distance and size of a target, has proved an

enduring law of human motion [1]. One challenge, however, in its direct application has been variations in precision exhibited by different subjects performing tasks. To address this, many researchers have adopted the use of an "effective target size", specifically a normalization of target size in light of underlying pointing precision [2, 6].

This paper highlights our on-going work in analyzing techniques to manipulate relative precision by subjects. We examine both incentive-based and penalty-based approaches to controlling the accuracy of target acquisition, with the goal of developing a better understanding of what motivates caution in subject performance of tasks in interfaces. It is our hope that understanding what motivates caution may guide us to techniques that encourage exploration and reduce nervousness, particularly for novice computer users. Based on observed motion endpoints, we also examine target utilization as a correlate for incentive and penalty functions.

In our work, we find that incentive-based approaches, specifically more reward for more accurate targeting, is a more effective mechanism for controlling subject accuracy then is penalty-based approaches. As well, we note an interesting correlation between relative reward and subject accuracy.

Background

The information-theoretic approach to Fitts' target acquisition tasks considers movement amplitude a signal produced by the user and endpoint variability noise associated with the signal. Human physiological acts exhibit naturally occurring noise, or lack of precision, related to amplitude. The lack of precision results in motion endpoints that are normally distributed around the center of a target.

While the full details of the information-theoretic analysis of Fitts' Law is beyond the scope of this paper, a target of size, W, is considered fully utilized if 96% of all motion endpoints fall inside the target. In those cases where either less than or more than 96% of endpoints lie inside the target, researchers typically analyze the distribution of gesture endpoints and adopt an effective target width, W_e, defined by assuming normally distributed endpoints and adjusting target size such that 4% of gestures would fall outside the target area. For a subject who values accuracy over speed, the subject's effective target is smaller than the actual target in size; the inverse is true for a subject who values speed over accuracy. Variation in subject accuracy has also been observed in steering tasks, for example in the analysis of precision in lasso selection gestures [3].

In recent work, Zhai et al. contrast the use of effective to actual target size to model subject motion [6]. Subject accuracy is manipulated by encouraging subjects that are too accurate to speed up, and subjects that are two inaccurate to slow down. Zhai's study notes that, although effective target width can be used to correlate across differing levels of accuracy (i.e. to achieve better correlation of Fitts' parameters between careful and sloppy subjects), within any one level of accuracy the nominal target size correlates better with observed user speed. This result is not surprising, as the nominal target is the stimulus that causes initial subject response.

One weakness of Zhai's work is that subject bias is manipulated discretely under experimenter control. In actual pointing precision tasks, subjects, themselves, make an implicit decision on the relative importance of speed versus accuracy. The weakness involved in experimenter control of factors is one of experimental bias. Subjects are moving too slowly (making too few errors), so we encourage subjects to speed up. We then measure time as a function of error rate. Care must be taken, as the signal to "speed-up" directly manipulates the dependent variable. This leads to a risk of confounded experimental measurement. As well, discrete signals to the user to either increase or decrease speed result in an instantaneous change in user behavior. As a result, the overall behavior of the subject may not be consistent, i.e. the subject is first too cautious and then after a signal is too inaccurate, and never performs at the desired level of accuracy.

Given the desire to understand user behavior in interfaces, a better experimental approach would be to manipulate users at the overall response selection level. One approach to this, drawn from Psychophysics, is the manipulation of criterion functions in signal detection theory [5]. The field of signal detection theory deals with subject response to stimuli. The purpose of the work described here is to determine appropriate criterion functions to suitably bias subject response, thus eliminating direct experimental control of subject bias.

Experimental Design

We formulate our experimental design as one of biased response. Given a pointing task, the target presented to the subject can be viewed as a stimulus. The subject's response to this stimulus is a movement of subject-controlled amplitude in the direction of the target. The goal of our experiments is to manipulate incentives or penalties to bias subject response toward accuracy or speed, specifically to determine criteria a subject uses to select an appropriate speed for the targeting task.

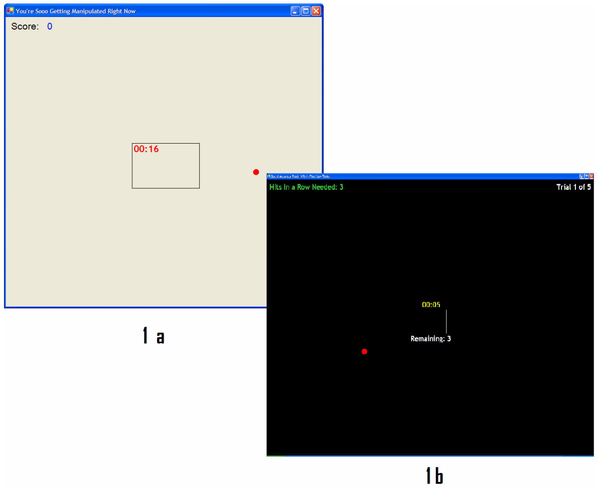

Figure 1: Interfaces for incentive (1a) and penalty (1b) based approaches to speed accuracy.

We performed our experiment using two different conditions. Figure 1 displays the interface that we used in our targeting tasks. Figure 1a represents an incentive-based approach to bias subject response, while Figure 1b represents a penalty-based approach. In an incentive-based treatment, a subject's desire to do better, specifically to score higher, increases care. In a penalty-based treatment, a subject's desire to avoid extra work motivates increasing care.

Incentive-Based Approach

In our first experiment, analyzing incentives for accuracy, subjects began by clicking inside the square in the center of the screen. A small red circle 20 pixels in diameter was then displayed on a 1600X1200 pixel laptop monitor. A subject would click on the circle. Then, to continue they would return to the center of the screen and click in the square again. Each time subjects correctly hit the target, they received a varying number of points depending on their proximity to the center of the circular target. Target location was varied randomly around the square region in the center of the screen.

To manipulate criterion for response selection, we vary the per-pixel cost of the distance from the center of the red target, similar to a game of darts. A pilot study found that using values for perfect targeting of the center of the circular target of 50 points, with per pixel reductions of 1, 3, 5, 10, and 20 points worked well in varying subject response. For example, with a 20 point per pixel reduction, subjects who contacted the target three pixels from the center of the circle received -10 points. There is, therefore, an incentive to acquire, as accurately as possible, the center of the target.

We conducted an experiment where ten users performed targeting tasks. Users were given two minutes with each scoring condition, and tried to maximize their score in the interface. Scoring conditions were presented in order from least to greatest point reduction. Target size was fixed at 20 pixels, and distances were varied between 200 and 700 pixels. Based on two minute trials in each condition for each of ten users, 2381 individual gestures were collected and analyzed.

Results

Table 1 summarizes the effect of varying point values on user accuracy across all users. Penalty values is the per pixel cost of distance from target center. Distance is the average distance users clicked from the center of the target. We note a consistent increase in targeting care of users across point value conditions. The higher the penalty, the more accurately users tried to target the center of the target. Anova of these values indicates statistically significant effect of varying user penalty ($f_{4, 5} = 18.42$, $p < 0.01$).

Penalty	1	3	5	10	20
Distance	3.26	2.71	2.48	2.3	2.09

Table 1: Effect of penalty on distance from target center.

An interesting and unexpected observation is a strong inverse linear correlation between penalty value and distance from the center of the target, $r^2 = -0.85$. While we did expect a significant effect of penalty on distance, we did not anticipate a linear relationship between penalty and proximity.

Penalty	1	3	5	10	20
Nominal	0.08	0.17	-0.01	0.06	0.18
Effective	0.28	0.33	0.16	0.28	0.18
Id_m	0.27	0.32	0.16	0.28	0.17

Table 2: Correlation of time across indices of difficulty, ID, using nominal target size, effective target size, and a modified ID based on Zhai's observations[6].

We also compared correlation of time taken for an individual targeting task with Index of Difficulty (ID) values for that task calculated based on the nominal target size, in this case 20 pixels, the effective target size (based on endpoint distribution), and a modified value, ID_m, proposed by Zhai [6]. Table 2 summarizes these results. We note weak correlations, though effective target size and Zhai's modified index of difficulty both perform better than nominal target size.

Penalty-Based Approach

In our second experiment, we introduced a penalty for target misses. As shown in Figure 1b, subjects began by clicking a square target area in the center of the screen. They would then, as in the first experiment, click on a circular red target. The red target would vanish, and they would return to the center of the screen and click inside the square. At this point the next target would appear.

The penalty associated with a target miss was temporal. In the top left corner of the display, a varying number of repeated targeting events was displayed, and the number of remaining target events in the current block was counted down directly under the center square (see Figure 1b). Each number of repeated targeting events represents a trial block. If a subject missed a target at any point in time during a block, he or she started the entire block again. All experiments were conducted on a laptop computer with a display resolution of 1400 X 1050 pixels using an attached USB optical mouse on an over-sized mouse pad. Circular target diameter was 10 pixels. When subjects correctly targeted, a quiet bell sounded; when they missed the target, a louder buzzer sounded. Subjects were given 2 minutes of un-timed practice to familiarize them with the bell, buzzer, and mouse acceleration parameters prior to beginning the experiment. Mouse acceleration parameters were set to Windows default.

The number of repeated targeting tasks was set to either 8, 12, 16, or 20, and distances were set to either 200, 300, 400, or 500 pixels in an individual block. A 4X4 Latin square design was used to counterbalance number of repeated tasks and distance. Each subject performed four different conditions (i.e. one condition is a specific number of repetitions at a fixed distance). Each condition was repeated 3 times by a subject to cross-validate. Eight subjects in total, therefore, performed 12 blocks each. Each individual subject performed a total of 168 targeting tasks, so the total number of targeting tasks analyzed was 1344. Testing took approximately 8 minutes per subject[1].

Results

Penalties had surprisingly little effect on varying the accuracy of users. Figure 2 is a plot of the effect potential cost of an error on time taken. Four lines in Figure 2 represent the average time taken at each iteration for each of the 8, 12, 16 and 20 repetitions required. These plots were generated by dividing time taken by task Index of Difficulty.

Anova indicates an effect on time taken based on current iteration (i.e. whether the user was clicking on the first target, second, third, fourth, etc. of the repeated targets), but not for number of repetitions

[1] Subjects could rest at any time after an individual targeting task to avoid fatigue confounding the experiment.

required, nor for the interaction of repetitions and current iteration. Post-hoc analysis indicates that only the first iteration varied significantly from the others, and it was slower, as shown on the graph.

We also looked at the effect current repetition and total required repetitions had on proximity to the center of the target. We note a main effect for total repetitions required, but post-hoc analysis indicates that significant differences exist only between 20 (closest to center of target) and 12 (furthest from center of target), leaving this relationship suspect.

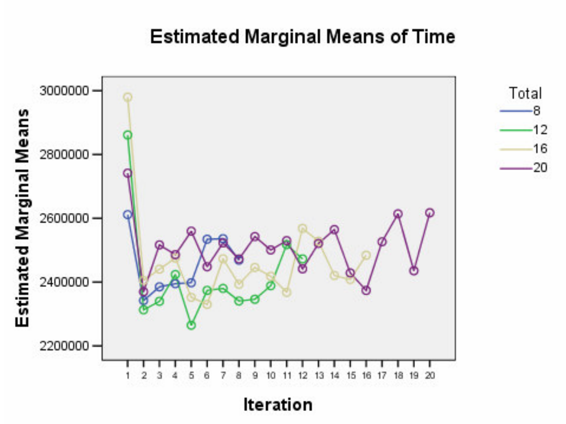

Figure 2: For eight, twelve, sixteen, and twenty targeting tasks, plots show the average time taken for each targeting task.

Conclusion

In this paper, we describe on-going work in manipulation of the speed-accuracy trade-off in Fitts' Law tasks. We describe early explorations into both incentive and penalty mechanisms.

Our results, while very early, indicate that incentive-based mechanisms may be of use in biasing subjects toward either speed or accuracy. As well, we note an interesting correlation between incentive and endpoint variability.

One cautionary note involves the scoring mechanism in our first experiment, which biases subjects toward shrinking effective target size. We continue to explore additional variants on incentives and penalties with the goal of better understanding factors that bias subjects toward either speed or accuracy.

Acknowledgements

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Citations

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