

Supplementary Material: Model Refinement of Overshoot-avoiding Mouse-pointing Operations

In this Supplementary Material, the constants a – f with or without prime marks (e.g., b') mean regression coefficients. Table 1 lists the model fitting results described as follows. As a reminder, Fitts' law in the Shannon formulation is:

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

where MT is the time to point to the target, A is the distance to the target, and W is its size. a and b are empirically determined constants. The logarithmic term is called the index of difficulty (ID):

$$ID = \log_2(A/W + 1) \quad (2)$$

To model the effects of the T_{delay} and Gap on the MT , we modify models that capture the transmission Lag . Hoffmann derived the following model based on Fitts' law [4]:

$$MT = a + b(c + Lag)ID \quad (3)$$

where $c \neq 0$ for the case of no lag (the coefficient for ID cannot be zero). This equation can be converted into

$$\begin{aligned} MT &= a + bc \left(1 + \frac{Lag}{c}\right) ID \\ &= a + b'(1 + c' Lag)ID \quad (\text{let } b' = bc, c' = 1/c) \end{aligned} \quad (4)$$

MacKenzie and Ware proposed the following model [6]:

$$MT = a + (b + cLag)ID \quad (5)$$

where $b \neq 0$ for the same reason as in Equation 3, and c is a weight for the $Lag \times ID$ interaction. This can be converted into

$$\begin{aligned} MT &= a + b \left(1 + \frac{c}{b} Lag\right) ID \\ &= a + b(1 + c' Lag)ID \quad (\text{let } c' = c/b) \end{aligned} \quad (6)$$

which is the same as Equation 4. These models indicate that, if the Lag is large, each step of the feedback loop between a visual stimulus and a motor output requires a longer time [4]. As a result, the pointing speed decreases and the total time increases. The validity of these models has been confirmed by other researcher groups [3, 8, 9].

In general, the MT increased as the T_{delay} decreased in Experiment 1, so a short T_{delay} has the effect of slowing down the user's mouse operation speed throughout a corrective-movement phase, as shown in Figure 6 (speed profiles) in the

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main manuscript. Assuming that this slowing-down effect due to the T_{delay} is similar to the fact that the Lag on every frame decreases the movement speed and increases the MT , we can simply invert the Lag term in our model to capture the T_{delay} factor:

$$MT = a + b \left(1 + c \frac{1}{T_{delay}}\right) ID \quad (7)$$

To avoid mathematical error when $T_{delay} = 0$ sec, we add a constant d (> 0):

$$MT = a + b \left(1 + c \frac{1}{d + T_{delay}}\right) ID \quad (8)$$

When $T_{delay} = \infty$ sec (i.e., when there is no concern about overshooting, as in conventional Fitts tasks), Equation 8 matches the baseline formulation of $MT = a + bID$. When $T_{delay} = 0$ sec, which is the worst case for the MT , the ID value is multiplied by $(1 + c/d)$ as compared with the baseline formulation. This means that, while the IP for the baseline formula is $1/b$, the IP for Equation 8 is increased by “ $\times(1 + c/d)$ ” in the worst case.

According to Figure 5 (Fitts' law regressions) in the main manuscript, the experimental IP values for the baseline and the worst case were 7.19 and 5.63 bits/sec, respectively, so we assume that the value of $(1 + c/d)$ is approximately $7.19/5.63 = 1.277$. This is close to the actual model fitting: the result for Equation 8 in Table 1 in the main manuscript shows that $(1 + c/d) = (1 + 13.53/53.58) = 1.253$, giving a difference from the assumed value of $(1.277 - 1.253)/1.253 = 0.01915$, which is less than 2%. Thus, the term $(1 + c/d)$ adequately represents the performance degradation induced by the T_{delay} as compared with the baseline condition.

For the results of Experiment 2, similarly to the case of T_{delay} , we assume that a smaller Gap lowers the movement speed, and we replace the term T_{delay} in Equation 8 with Gap :

$$MT = a + b \left(1 + e \frac{1}{f + Gap}\right) ID \quad (9)$$

which also matches the baseline formulation when $Gap = \infty$ pixels.

From the results of Experiment 3, because we found no main effect of T_{delay} on MT , we reuse Equation 9. For the sake of completeness, however, we also check a model that includes both factors, T_{delay} and Gap :

$$MT = a + b \left(1 + c \frac{1}{d + T_{delay}} + e \frac{1}{f + Gap}\right) ID \quad (10)$$

Note that T_{delay} and Gap are independently added here because there was no significant interaction between them.

One problem here is that our refined models (Equations 8, 9, and 10) include additional free parameters for regression

Table 1. Model fitting results with adjusted R^2 and AIC values for the candidate models. MT and T_{delay} are in msec, and Gap is in pixels. The constants a, b, c, d, e , and f are estimated regression coefficients with 95% CIs [lower, upper].

Exp.	Eq.	a	b	c	d	e	f	Adj. R^2	AIC
1	1	176.8 [110.7, 242.9]	151.3 [132.0, 170.6]					0.8817	379.6
	8	175.6 [148.9, 202.4]	141.3 [133.0, 149.6]	13.53 [4.148, 22.92]	53.58 [20.04, 87.12]			0.9819	316.0
2	1	185.3 [139.2, 231.4]	153.2 [139.7, 166.7]					0.9400	353.6
	9	185.3 [162.3, 208.4]	141.7 [134.3, 149.1]			7.471 [1.528, 13.41]	47.52 [12.04, 83.00]	0.9859	305.3
3	1	172.4 [146.5, 198.4]	151.7 [144.1, 159.3]					0.9300	1186
	9	210.6 [176.2, 245.1]	118.6 [42.96, 194.2]			17.98 [-118.2, 154.2]	57.46 [-286.8, 401.7]	0.9358	1180
	10	210.7 [178.8, 242.7]	101.3 [11.38, 191.2]	77.96 [-272.9, 428.8]	395.3 [-685.8, 1476]	26.38 [-181.6, 234.4]	69.32 [-324.5, 463.1]	0.9457	1160

fitting, beyond the baseline model (Equation 1). For fair comparison among models with different numbers of constants, the Akaike information criterion (AIC) [1, 2] has been used in HCI [7, 11]. The AIC determines the comparatively best model on the basis of the following information: a model (a) with a lower AIC value is a better one, (b) with $AIC \leq (AIC_{min} + 2)$ should be compared with better models, and (c) with $AIC \geq (AIC_{min} + 10)$ is safely rejected.

For Experiments 1 and 2, taking the effects of T_{delay} and Gap into account improved the fitness: the adjusted R^2 increased from 0.8817 to 0.9819 for Experiment 1, and from 0.9400 to 0.9859 for Experiment 2. Also, their AIC differences were significant (> 10), so we can confirm that T_{delay} and Gap inversely affected MT , as explained by Equations 8 and 9.

For Experiment 3, however, we could not see a fitness improvement by the proposed model (Equation 9): the fitness improvement in adjusted R^2 was less than 1% and that in AIC was 6. Because these statistical indicators were not improved, regarding the utility, it seems better to use a model with a smaller number of coefficients, and thus we can conclude that the baseline model (Equation 1) already had sufficient prediction accuracy.

Equation 10 shows that accounting for the effect of T_{delay} improved the prediction accuracy. Although the improvement in adjusted R^2 was less than 1% from Equation 9, that in AIC was 20 by using six degrees of freedom. Hence, if we observe a significant main effect of T_{delay} owing to (e.g.) user group difference or pointing device difference, using Equation 10 may be a better choice.

Note that, we refined models just to work mathematically well (i.e., fitting well to the empirical data), and thus our models do not help with understanding either the phenomena or the user strategy. For example, Figure 6 (speed profiles) in the main manuscript shows a binary strategy but the models do not reflect this behavior; constants (a to f) are just weights of regression. Thus, we do not claim that the model refinement described in this Supplementary Material is our main contribution.

Yet, another contribution type in performance modeling is the prediction accuracy improvement internally to the experiment data. Even if a model for pointing tasks includes ten or more free parameters for all (co)variances (e.g., [5, 10]), it has been regarded to have a contribution because it fits to the measured data; values of the regression weights do not help to understand some phenomena. Hence, there are various areas of focus in performance modeling studies, and our model provides one of them (prediction accuracy improvement). We are aware that models to help understand other phenomena are required as well. If such models can be derived, they will provide an additional contribution in the future.

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