ABSTRACT

The steering law is a model for predicting the time and speed for passing through a constrained path. When people can view only a limited range of a path forward, they have to limit their speed in preparation of possibly needing (e.g.) to turn at a corner. However, only a few studies have focused on how limited views affect steering performance, and no quantitative models have been established. The results of a mouse steering study showed that speed was linearly limited by the path width and limited by the square root of viewable forward distance as well. While a baseline model showed an adjusted $R^2 = 0.144$ for predicting the speed, our best-fit model showed an adjusted $R^2 = 0.975$ with only one additional coefficient, which demonstrated a comparatively higher prediction accuracy among given viewable forward distances.

Author Keywords

Steering law; graphical user interfaces; motor performance modeling; Fitts’ law; anticipation strategy.

CCS Concepts

• Human-centered computing → HCI theory, concepts and models; Pointing; Empirical studies in HCI;

INTRODUCTION

The steering law [2, 17, 33] is a model for predicting the time and speed for passing through a constrained path, such as navigation through hierarchical menus. In HCI, the validity of the steering law has been typically confirmed in a desktop environment, such as by maneuvering a mouse cursor or stylus tip through a path drawn on a display (e.g., [3, 38]). Under such conditions, participants can view an entire path or enough of the path forward before a trial begins, and they can determine the appropriate movement speed for a given path width.

However, conditions under which users can view enough of a long path forward create the ideal situation. Imagine that we move a character in a 3D action game with a thumbstick (Figure 1a). When the character moves forwards toward the screen, the viewable forward distance (towards the camera/player) is limited due to the camera view. Therefore, the character might fall from the bridge if the movement speed is too high to safely turn at the corner. The time remaining after the corner appears to safely tilt the thumbstick rightwards decreases as the viewable forward distance decreases, and thus, players have to move the character at lower speed.

Therefore, for path steering tasks, we assume that the viewable forward distance would limit the movement speed in addition to the path width. This negative effect of the viewable forward distance would be true for other steering operations, including lassoing selections (Figure 1b), 3D drawing with head-mounted displays (HMDs) [8], 3D tube-steering tasks with HMDs like surgery training systems [27], playing on a night course in racing games [1], and driving simulators [48].

Although the effect of limited view sizes has sometimes been investigated in HCI [13, 19, 24, 36], the main interest has been on target selection. Also, for steering tasks, while the view of the forward path can be limited, we found few papers on this topic including map navigation tasks with a magnified view (Figure 1c, [21]). If we can derive models on the relationship between task conditions and outcomes — path width and viewable forward distance vs. movement speed — it would contribute to better understanding of human motor behavior.
Accurate prediction models can also contribute to the appropriate balancing of task difficulties, such as in racing video games. In addition, the steering law has been recently used for more complicated HCI-related tasks with a limited viewable range, such as lasso selection [46] and walk navigation in VR environments [31]. Hence, evaluating model robustness against an additional constraint (viewable forward distance) becomes more important, yet this has not been investigated well; this motivated us to conduct this work.

We conducted a path-steering study with a mouse. In developing refined models, this setup allowed us to fairly evaluate the effect of a new factor (viewable forward distance) while eliminating other factors such as view angles in 3D games. Our key contributions are as follows.

(a) Showing empirical evidence that the viewable forward distance $S$ significantly affected the steering speed. We also justify why the relationship between $S$ and speed is represented by the power law.

(b) Developing refined models for predicting the movement speed on the basis of the path width and $S$, which had significant main effects and interaction. Our model could predict the speed with an adjusted $R^2 > 0.97$. We also show that the movement time while steering through a view-limited area could be predicted with $R^2 > 0.97$.

We also discuss other findings, e.g., the reason a conclusion opposite that of previous studies was obtained; the speed increased with a narrower $S$ in peephole pointing [24].

RELATED WORK

Steering Law Models

Rashevsky [33, 34], Drury [17], and Accot and Zhai [2] proposed a mathematically equivalent model to predict the movement speed to pass through a constant-width path:

$$V = \text{const} \times W \quad (1)$$

where $V$ is the speed and $W$ is the path width. Typically, participants are instructed to perform a task as quickly and accurately as possible. Hence, there are several interpretations of $V$: the possible maximum safe speed $V_{\text{max}}$ in Rashevsky’s model, the average speed $V_{\text{avg}}$ in a given path length in Drury’s model (i.e., $V_{\text{avg}} = A/MT$, where the path length is $A$ and the movement time needed is $MT$), and an instantaneous speed at a certain moment in Accot and Zhai’s model.

The validity of this model ($V \propto W$) has been empirically confirmed for (e.g.) car driving [15, 18, 11], pen tablets [47], and mice [38, 45]. Because $V_{\text{avg}}$ is defined as $A/MT$, the following equation for predicting $MT$ is also valid [17, 23]:

$$MT = b(A/V_{\text{avg}}) \quad (2)$$

where $b$ is a constant (hereafter, $a$–$e$ with or without prime marks like $b'$ mean regression coefficients). Since $V_{\text{avg}} = \text{const} \times W$, Equation 2 can be as follows.

$$MT = b \frac{A}{\text{const} \times W} = b \frac{A}{W} \quad (let \ b' = b/\text{const}) \quad (3)$$

Both for predicting $V_{\text{avg}}$ and $MT$, these no-intercept forms are theoretically valid, while the contribution of the intercept is often statistically significant [23] as follows.

$$V_{\text{avg}} = a + bW \quad (4)$$

$$MT = a + b(A/V_{\text{avg}}) \quad (5)$$

$$MT = a + b(A/W) \quad (6)$$

The steering law models on $V_{\text{avg}}$ and $MT$ hold when $W$ is not too wide. Otherwise, users do not have to pay attention to path boundaries; thus, $W$ does not limit the speed [2, 23, 40].

Steering Operations with Cornering

To accurately predict the $MT$ for steering through a corner as shown in Figures 1a and c, Pastel [32] refined the model by adding Fitts’ law difficulty [20] as follows.

$$MT = a + b \frac{2A}{W} + cID \quad (7)$$

where the first and second path segments before/after the corner have the same length ($A$) and same width ($W$), and $ID$ is the index of difficulty of Fitts’ law (Pastel used the Shannon formulation [28]: $ID = \log_2(A/W + 1)$). Fitts’ law is originally a model for pointing to a target with width $W$ at distance $A$. Therefore, this model means that, in addition to the difficulty of steering in order to pass through an entire path, also considering the difficulty of decelerating in order to turn at a corner is required. However, if users cannot see the corner position due to the restricted view, starting to decelerate at an appropriate timing would be difficult.

Effect of Viewable Forward Distance on Task Performance

Bateman et al. tested the effects of viewable forward distance $S$ and camera position on $MT$s in video racing games [9]. They showed that the camera position (e.g., overhead vs. third-person views) affected the $MT$, but the $S$ did not. Hence, they reported no relationship models between $S$, path width, and $MT$. Note that they used only two $S$ values (11.1 and 22.2 m), and $MT$s for driving on the 360-m road were ~28 and 25 sec, respectively (no significant difference). If Bateman et al. had tested longer $S$ values like 100 m, $S$ might have significantly affected the results.

For real car driving, it is known that drivers keep on looking at the tangent of the inside curve [26, 42] and tend to use two view regions, 0–8 m and 10–20 m [37]. If the road is curved, the viewable forward distance decreases as the curvature increases, and thus, drivers must be more careful.

Peephole pointing [13, 24] or magic lens [36] are more relevant to our work. The most popular task for peephole pointing is map navigation. When users want to see information on a landmark on a map application via smartphones or PCs, they first scroll the map (search phase) and then select an intended location (selection phase). Because Fitts’ law [20] holds for 1D scrolling tasks done to capture a target into a view area [22], the $MT$ changes due to $S$, and the total time can be predicted by the sum of the search and selection phases [13, 36]. Models for peephole pointing have been validated with a mouse [13], spatially-aware phone [36], handheld projector [24, 19], and touchscreen [50].
Although the importance of user performance models for peep-hole situation is explained in these papers, unfortunately, the main focuses have been on target selection. An exception that studied the effect of viewable ranges in steering-law tasks was Gutwin and Skopik’s work [21]; an area around a cursor was zoomed in on by radar-view tools (see Figure 3 in [21]). The cursor and view window were concurrently moved, and users moved the window so that the cursor steered through a path.

There are two differences in Gutwin and Skopik’s work [21] from ours. First, they fixed the window size of the radar view, and thus, as the zoom level increased, the corresponding viewable forward distance $S$ decreased. In contrast, in our intended tasks (e.g., Figure 1a), the $S$ changed, but there was no zooming. They reported that the zoom levels did not largely change $MT$s, which was the opposite conclusion to the peephole pointing studies. Thus, a consistent effect of $S$ on $MT$ was not observed for steering and pointing; we will revisit this point in Discussion. Second is that the entire view was provided as a miniature view (see Figure 1c), which assisted the timing for decelerating in preparation for the next corner.

In summary, the quantitative relationship between steering performance ($V_{avg}$ or $MT$) and $S$ is unclear. Yet, it will be beneficial for understanding user behavior in restricted-view situations, which are realistic for some tasks as described in Introduction. We tackle this challenge through two studies.

**MODEL DEVELOPMENT FOR UNCERTAIN CORNERING TIMING**

As the baseline model to predict the movement speed, we will test Equation 4 ($V_{avg} = a + bW$) for our experimental data. Also, to check the effect of an additional task parameter (here, $S$) on the estimated result ($V_{avg}$), the simplest method is to add the additional factor and two predictor variables being multiplied (if the interaction term is significant) to the baseline model\(^1\). Thus we will test:

\[
V_{avg} = a + bW + cS \\
V_{avg} = a + bW + cS + dWS
\]

(8) (9)

Next, we discuss how the speed is limited when users prepare for a corner that would appear at an uncertain timing. As the first step towards deriving a more general model, in this study we fix the width of second path segment $W_2$, and let the experimental participants have the previous knowledge (PK) of $W_2$ being fixed. We incorporate Pastel’s model that users have to decelerate in the first path segment when approaching to the corner to safely enter the second path segment [32]. As a more general case, the first and second path segments have different lengths and widths as shown in Figure 2a. Pastel’s idea to integrate Fitts’ $ID$ is that the cursor must stop within the second path area that has the width of $W_2$ after traveling the first path segment. Hence, Equation 7 can be rewritten as:

\[
MT = a + b\frac{A_1}{W_1} + cID + d\frac{A_2}{W_2}
\]

(10)

\(^1\)This is explained in introductory statistics textbooks or websites, e.g., https://web.archive.org/web/20190617154149/https://www.cscu.cornell.edu/news/statnews/stnews46.pdf.

where $ID = \log_2 (A_1/W_2 + 1)$: the movement amplitude for pointing is the first path’s distance and the target size is the second path’s width.

As shown in Figure 2b, when a corner is not yet revealed from the forward mask, users can at least move for a viewable forward distance $S$. In the case that the corner is just beyond the viewable forward distance, users must adjust the speed as if the second path tolerance ranged from $S$ to $S + W_2$: the “target” center of second path segment is located at $S + 0.5W_2$ from the cursor position. The time needed to perform this pointing motion is modeled by, according to Pastel, Fitts’ law with $S + 0.5W_2$ as the target amplitude and $W_2$ as the width. Yet, another definition of Fitts’ law amplitude is that the distance to the closer edge of the target and this empirically holds [4, 5, 7]. Thus, using $S$ as the amplitude is a simpler choice and would not degrade model fitness.

If the $W_2$ is sufficiently wide, it would be possible that users can move the cursor to pen tip rapidly in the first path segment, because they can appropriately decelerate after they notice the corner. However, again, such a task is not considered a steering task in a constrained path, and it is necessary that the path widths ($W_1$ and $W_2$) are not extremely wide to hold the steering law [2, 17, 23]. Therefore, in this study we set a narrow $W_2$ requiring careful movements to safely turn at the corner.

Another model for pointing tasks is by Meyer et al. [30].

\[
MT = b \sqrt{A/W}
\]

(11)

The $A$ is the distance to the target center. While the mathematical equivalency between this power model and Fitts’ logarithmic model is questioned by Rioul and Guiard [35], they also agree that these models are well approximated.

On the basis of these discussions, we assume that the $MT$ for pointing to the second path segment, which might be just beyond the front mask, ranging from $S$ to $S + W_2$ can be regressed in practice as follows:

\[
MT = b \sqrt{S/W_2}
\]

(12)

![Figure 2. Steering operations with cornering where the first and second path segments have different sizes. (a) No-mask and (b) masked conditions. Left and right masks are actually opaque in study, not semi-transparent](image)
Again, Meyer et al.’s original model used the distance to the target center as the target amplitude \((S + 0.5W_2)\) but using \(S\) as amplitude would fit well. The average speed for this movement is defined as the distance to be traveled divided by the time needed as follows.

\[
V_{\text{avg}} = \frac{S}{MT} = \frac{S}{b'\sqrt{S/W_2}} = b' \sqrt{S \times W_2} \quad (\text{let } b' = 1/b) \quad (13)
\]

In our experiment, to focus on the new factor \(S\), we fixed the \(W_2\) value. Thus, Equation 14 can be simplified further:

\[
V_{\text{avg}} = b' \sqrt{S \times W_2} = b'' \sqrt{S} \quad (\text{let } b'' = b' \sqrt{W_2}) \quad (14)
\]

In summary, we hypothesize that when the viewable forward distance is limited to \(S\), users have to limit the speed in the case that the second path segment is just beyond the viewable forward distance, and this behavior is expected to be modeled as \(V_{\text{avg}} = b' \sqrt{S}\). While this is justified on the basis of existing theoretical and empirical evidence, we have to empirically test the validity of our hypothesis. Thus, we conducted a path-steering study to evaluate the models combined with the steering law.

**EXPERIMENT**

**Participants**

Twelve university students participated (3 females and 9 males; \(M = 21.6, SD = 1.32\) years). All were right-handed and had normal or corrected-to-normal vision. Six were daily mouse users.

**Apparatus**

The PC was a Sony Vaio Z (2.1 GHz; 8-GB RAM; Windows 7). The display was manufactured by I-O DATA (1920 \times 1080 pixels, 527.04 mm \times 296.46 mm; 60-Hz refresh rate). A Logitech optical mouse was used (model: G300r; 1000 dpi; 2.05-m cable) on a large mouse pad (42 cm \times 30 cm). The experimental system was implemented with Hot Soup Processor 3.5 and used in full-screen mode. The system read and processed input \(\sim 125\) times per sec.

The cursor speed was set to the default: the pointer-speed slider was set to the center in the Control Panel. Pointer acceleration, or the Enhance Pointer Precision setting in Windows 7, was enabled to perform mouse operations with higher ecological validity [14]. Using pointer acceleration does not violate Fitts’ and steering laws [3, 44]. The large mouse pad and long mouse cable were for avoiding clutching (repositioning of the mouse) during trials. This was to omit unwanted factors during model evaluation. If we had allowed clutching and a model’s fit were low, we could not discuss whether the low fit was due to the model formulation or clutching. No recognizable latency was reported by the participants.

**Task**

The participants had to click on the blue start line, horizontally steer through a white path of width \(W_1\), turn at a corner downwards, and then enter a green end area (Figure 3). After that, an orange area labeled “Next” appeared on the left-side screen edge, and entering this area began the next trial.

If the cursor entered gray out-of-path areas, a beep was sounded, and the trial was flagged as a steering error \(E_{\text{R steer}}\) and retried later. If the cursor did not deviate from the blue and white path segments, the trial was flagged as a success, and entering the green end area sounded a bell (no clicking was needed). The left and right masks moved alongside the cursor.

The participants were instructed to not make any errors and to move the cursor to the end area in as a short time as possible. In addition, we asked them to not perform clutching while steering. However, if participants accidentally clutched or if the mouse reached the right edge of the mouse pad, they were instructed to press the mouse button. Such trials were flagged as invalid and removed from data analysis. If steering errors and invalid trials were observed, a beep was sounded, and the trial was retried later within a randomized order.

The measurement area of distance \(A\) for recording \(MT\) and speed is shown in Figure 3c, that is, from (b) when the cursor reached the left edge of the white path to (c) when the viewable range reached one pixel before the second path segment. While in this area, the participants did not know the corner position and thus had to carefully move the cursor to avoid deviating from the path. We measured the \(MT\) spent in that measurement area, and the average speed was computed as \(V_{\text{avg}} = A/MT\) as the dependent variable. Note that, because in this measurement area the participants could not see the corner, the operation required in this area was only steering through a constrained path with a restricted view.

To avoid seeing the corner position before a trial began, (1) the cursor had to go to the “Next” area at the left edge of the screen at the end of every trial, and (2) the cursor had to stop at the blue start line and could not move further rightwards until it was clicked. We provided a run-up area of 50 pixels (Figure 3a) because the speed when clicking on the blue start area was zero. When the speed measurement began, the cursor had already moved at a certain speed.

**Design and Procedure**

This experiment had a \(6 \times 5\) within-subjects design with the following independent variable and levels. We tested six \(S\) values: 25, 50, 100, 200, and 400 pixels and the no-mask condition. The no-mask condition was included to measure the baseline performance. The \(W_1\) values were 19, 27, 37, 49, and 63 pixels. The movement time and speed were measured in
We found the main effects of \( \text{V}_{\text{avg}} = A/MT \) as the dependent variable.

The width of the end area \( W_2 \) was fixed to 19 pixels. To avoid participants noticing that the target appeared at several fixed positions, we used various \( A \) values, and the start line had a random offset from the left-side screen edge ranging from 100 to 400 pixels every trial. The y-coordinate of the white path center had a random offset ranging from \(-150\) to \(150\) pixels from the screen center. The \( A \) values for the measurement area were 300, 500, and 800 pixels and were not included as an independent variable. For the no-mask condition (baseline), the white-area distance was set to \( A + 400 + W_2 \) pixels (i.e., same as the largest \( S \) condition).

Among the combination of \( 6 \times 5 \times 3 \times 4 = 90 \) patterns, 10 trials were randomly selected as practice. Then, the participants attempted three sessions of 90 data-collection trials. In total, we recorded 90 patterns \( \times 3 \) sessions \( \times 12 \) participants = 3240 successful data points. This study took approximately 40 min per participant.

**Results**

For error rate analysis, we used a non-parametric ANOVA with Aligned Rank Transform (ART) [43] with Tukey’s method for p-value adjustment in posthoc comparisons. For the speed data analysis, we used repeated-measures ANOVA and Bonferroni correction as the p-value adjustment method. Note that ANOVA is robust even if experimental data are non-normal [10].

**Errors**

**Steering Error in the Entire Trial.** The numbers of \( \text{ER}_{\text{steer}} \) for smaller to wider \( S = 144, 103, 41, 49, 37, \) and 46, respectively. The numbers of \( \text{ER}_{\text{steer}} \) for smaller to wider \( W \) were 126, 85, 70, 74, and 65, respectively. The mean \( \text{ER}_{\text{steer}} \) rate was 11.5%, which was slightly high compared with previous work on mouse steering tasks (e.g., 9% [3]). On the basis of the experimenter’s observation, the point with the highest error was turning at the corner.

We observed the main effects of \( S \) (\( F_{5,55} = 7.830, p < 0.001, \eta^2_p = 0.42 \)) and \( W_1 \) (\( F_{4,44} = 3.529, p < 0.05, \eta^2_p = 0.24 \)) on the \( \text{ER}_{\text{steer}} \) rate in the entire trial. No significant interaction of \( S \times W_1 \) was found (\( F_{20,220} = 1.539, p = 0.07055, \eta^2_p = 0.12 \)).

**Steering Error in the Measurement Area.** The numbers of \( \text{ER}_{\text{steer}} \) for smaller to wider \( S = 12, 9, 18, 15, 9, \) and 10, respectively. The numbers of \( \text{ER}_{\text{steer}} \) for smaller to wider \( W \) were 40, 13, 9, 9, 2, respectively. The mean \( \text{ER}_{\text{steer}} \) rate was 22.0%. We observed the main effects of \( S \) (\( F_{5,55} = 15.05, p < 0.001, \eta^2_p = 0.58 \)) and \( W_1 \) (\( F_{4,44} = 9.362, p < 0.05, \eta^2_p = 0.46 \)) on the \( \text{ER}_{\text{steer}} \) rate in the measurement area. The interaction of \( S \times W \) was significant (\( F_{20,220} = 3.262, p < 0.001, \eta^2_p = 0.23 \)).

**Average Speed**

We found the main effects of \( S \) (\( F_{5,55} = 69.98, p < 0.001, \eta^2_p = 0.86 \)) and \( W_1 \) (\( F_{4,44} = 180.6, p < 0.001, \eta^2_p = 0.94 \)) on \( \text{V}_{\text{avg}} \). The \( \text{V}_{\text{avg}} \) values for \( S = 25-400 \) pixels and the no-mask condition were 154, 224, 320, 420, 520, and 545 pixels/sec, respectively. The \( \text{V}_{\text{avg}} \) values for \( W_1 = 19-63 \) pixels were 240, 302, 365, 428, and 485 pixels/sec, respectively.

The interaction of \( S \times W_1 \) was significant (\( F_{20,220} = 48.70, p < 0.001, \eta^2_p = 0.82 \)). As shown in Figure 4a, when the \( S \) was wide (\( S = 200 \) and 400 pixels, and no-mask), \( \text{V}_{\text{avg}} \) increased as \( W_1 \) increased. However, as \( S \) decreased, the effect of \( W_1 \) tended to be smaller, i.e., the \( \text{V}_{\text{avg}} \) differences became insignificant for more pairs. This indicates that the speed is more limited by \( W_1 \) following the steering law when \( S \) is wide, but \( S \) has a priority to limit the speed when \( S \) is narrow.

Also, Figure 4b shows that, for all five \( W_1 \) values, there were no significant differences between \( S = 400 \) pixels and the no-mask condition. Therefore, in our experimental condition, \( S = 400 \) pixels was sufficient for eliminating the effect of masks on \( \text{V}_{\text{avg}} \). However, if we had included longer \( A \) values, it could be possible that the \( \text{V}_{\text{avg}} \) for the no-mask condition would have been much higher. Thus, it is fair to avoid concluding that the steering performance for \( S = 400 \) pixels is equivalent to that for the no-mask condition.

To analyze the speed profiles in the measurement area, we resampled the cursor trajectory at every 25 pixels to reduce noise in the raw data. Figure 5a shows that speed changes every \( 5 \) pixels are not clearly seen under the narrowest \( S \), similarly to Figure 4a. Then, as \( S \) increases, the effects of \( W_1 \) on \( \text{V}_{\text{avg}} \) are exhibited more visually (Figures 5b and c). In the same manner, Figures 5d–f show that the effects of \( S \) become clearer as \( W_1 \) increases.

Figures 6a and b show that using the power model is more appropriate than the linear model for predicting \( \text{V}_{\text{avg}} \) with \( S \). Here, we merged five \( W_1 \) values only to see the prediction accurately when using \( S \) and \( \sqrt{S} \). Similarly, Figure 6c shows a high correlation between \( \text{V}_{\text{avg}} \) versus \( W_1 \) in restricted-view conditions, which merges the five \( S \) conditions (eliminating the no-mask condition). We also confirmed that the steering law of the \( \text{V}_{\text{avg}} = a + b \sqrt{S} \) form (Equation 4) fitted reasonably for each \( S \) as shown in Figure 7. This indicates that the steering law holds if a fixed-size \( S \) is used. In addition, the slopes decreased as \( S \) decreased; this means that a small \( S \) prohibits wider \( W_1 \)s from increasing \( \text{V}_{\text{avg}} \).

Figure 8 shows that the power law (\( \text{V}_{\text{avg}} = a + b \sqrt{S} \), Equation 14 with intercept) held for large \( W_1 \) values because the
of S and W1 were not significant contributors (p > 0.05). This means that the effects of S and W1 on increasing Vavg can be achieved by the interaction factor. Therefore, we also tested the fitness of Model #4. Model #5 was tested for the sake of completeness and consistency with the power model (described below).

Models #6 to #9 are power functions based on Equation 14 with an intercept. Models #6 and #7 are derived similarly to the linear ones. In Model #7, $\sqrt{S}$ was not a significant contributor ($p = 0.999$); Model #9 shows the fit after eliminating it. For consistent comparison with the linear models, we also tested an interaction-factor-only model (#8). Also, Model #5 was tested as a comparison with #9.

As a result, Models #7 and #9 are the best-fit models according to the lowest AIC values, whose difference was in actuality 1.997 (<2). Also, the difference in their adjusted R² values was less than 1%. If the prediction accuracy is not significantly different, a model with fewer free parameters has better utility, and thus, we recommend using Model #9 to predict $V_{avg}$.

By applying Model #9 to Equation 5 (i.e., $MT = a + b[A/V_{avg}]$), we can also predict the MT for the measurement area as follows.

$$MT = \frac{A}{c + dW_1 + eW_1 \sqrt{S}}$$
$$= a + \frac{b}{c} \times \frac{A}{e + W_1(d/e + \sqrt{S})}$$
$$= a + b' \left( \frac{A}{c' + W_1(d'/\sqrt{S})} \right) \quad (15)$$

For $N = 75$ data points ($S \times W_1 \times 3$), the baseline steering law model (Equation 5: $MT = a + b[A/W_1]$) showed a poor fit (Figure 9a). Our model where the new steering difficulty is $A/(c' + W_1[d'/\sqrt{S}])$, could predict the MT more accurately (Figure 9b).
Table 1. Model fitting results for predicting $V_{avg}$ for $N = 25$ data points (5s × 5w) with adjusted $R^2$ (higher is better) and AIC (lower is better) values. $a$–$d$ are estimated coefficients with their significance levels (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, and no-asterisk for $p > 0.05$) and 95% CIs [lower, upper].

<table>
<thead>
<tr>
<th>Model</th>
<th>$a$</th>
<th>$b$</th>
<th>$c$</th>
<th>$d$</th>
<th>Adj. $R^2$</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>(#1) a + b$W_1$</td>
<td>162 [-2.20, 327]</td>
<td>-4.24* [0.331, 8.15]</td>
<td></td>
<td></td>
<td>0.144</td>
<td>327</td>
</tr>
<tr>
<td>(#2) a + b$S + cW_1$</td>
<td>20.5 [-66.8, 108]</td>
<td>0.914*** [0.695, 1.13]</td>
<td>4.24*** [2.33, 6.16]</td>
<td></td>
<td>0.796</td>
<td>292</td>
</tr>
<tr>
<td>(#3) a + b$S + cW_1 + dW_1$</td>
<td>167*** [87.2, 248]</td>
<td>-0.0342 [-0.423, 0.355]</td>
<td>0.473 [-1.44, 2.38]</td>
<td>0.0243*** [0.0151, 0.0336]</td>
<td>0.912</td>
<td>272</td>
</tr>
<tr>
<td>(#4) a + b$W_1$</td>
<td>182*** [155, 208]</td>
<td>0.0241*** [0.0211, 0.0272]</td>
<td></td>
<td></td>
<td>0.916</td>
<td>269</td>
</tr>
<tr>
<td>(#5) a + b$W_1 + cW_1$</td>
<td>162*** [110, 214]</td>
<td>0.590 [0.746, 1.93]</td>
<td>0.0236*** [0.0202, 0.0269]</td>
<td></td>
<td>0.916</td>
<td>270</td>
</tr>
<tr>
<td>(#6) a + b$W_1 + cW_1 + dW_1$</td>
<td>162*** [95.3, 229]</td>
<td>0.00463 [-5.36, 5.37]</td>
<td>0.276*** [-4.35, -1.17]</td>
<td>0.622*** [0.495, 0.750]</td>
<td>0.974</td>
<td>241</td>
</tr>
<tr>
<td>(#7) a + b$S + cW_1 + dW_1$</td>
<td>95.5*** [62.8, 128]</td>
<td>0.529*** [0.467, 0.592]</td>
<td></td>
<td></td>
<td>0.927</td>
<td>265</td>
</tr>
<tr>
<td>(#8) a + b$W_1$</td>
<td>162*** [134, 190]</td>
<td>-2.76*** [-3.60, -1.91]</td>
<td>0.623*** [0.576, 0.669]</td>
<td></td>
<td>0.975</td>
<td>239</td>
</tr>
</tbody>
</table>

![Figure 9. (a, b) Model fitting results for $MT$. (c) Predicting $MT$ as mentioned in Discussion.](image)

**DISCUSSION**

**Findings and Result Validity**

In two previous studies on peephole pointing, the error rate was smallest for the smallest $S$ and greatest for the largest $S$ [13, 24]. It was assumed that the participants were over-careful for a small $S$ and over-relaxed for a large $S$ when selecting the target. In contrast, we observed that the error rates tended to be higher for smaller $S$ values. This inconsistency could be because of the different error definition; errors meant conventional pointing misses, and thus overshooting the target while aiming was permitted in the previous two studies, while we did not allow overshooting in the end of the first path segment (i.e., cornering misses).

Kaufmann and Ahlström also showed that the movement speed tended to decrease as $S$ increased both with and without prior knowledge (PK) on the target position [24]. They explained that the reason was “With small peepholes, participants were eager to uncover the target location by scanning the workspace as quickly as possible; accepting that they would overshoot.” Hence, without our work, in the HCI field, it has been believed that the speed decreases as $S$ increases for peephole interactions. Yet, in our experiment, users could not perform such “quick scanning” because they had to safely turn at a corner.

In previous studies on peephole pointing [13, 24], only the targets were drawn on the workspace, and thus, participants could easily recognize targets with such quick scanning. However, in peephole steering such as map navigation [21], quick scanning could not be performed; if users lose sight of the current road from a peephole window, they have to find the previous road from among several roads and then return to the navigation task. Therefore, we show the new finding on peephole interactions that a larger $S$ increases the speed in overshoot-avoided conditions [our results] but decreases the speed in overshoot-permitted conditions [13, 24], which contributes to better understanding of users’ strategies in the peephole situation.

**Other Experimental Design Choices**

Our research question was on the effect of viewable forward distance on the path-steering speed where users have to react to a corner. Instead, using a dead end is also possible: steering through a path and then stopping in front of a wall without overshooting. This is called a targeted-steering task [16, 25], where the stopping motion is modeled by Fitts’ law. Therefore, we assume that the appropriate model for this task will be somewhat similar to our proposed models, but this requires further experiments.

Using only the right-side mask was also possible for the experiment, while we depicted the left-side mask for consistency with the previous works on peephole pointing. Regarding a lasso selection task using a direct input pen tablet (Figure 1b), the width of a forward mask $W_{mask}$ would affect the speed because the hand would occlude the forward path, but beyond the hand, the path could be viewed.

While more various experimental designs are possible and the resultant speed would change, our experimental data were internally valid. Thus, the fact that “other experimental designs are possible” does not spoil the validity of our models. If user performance under new conditions were to show different conclusions, that would provide further contributions in the future.

**Implications for HCI-related Tasks**

As based on our findings, for mouse steering tasks, the speed and $MT$ should change with $S$, but a related work on map navigation with a radar view showed no clear changes in $MT$ [21]. Currently, we have no answer as to whether this inconsistency comes from the fact that they used a miniature view to show the entire map and/or used magnification, or from inaccuracies or blind spots in our own models. Also, the interaction between $S$ and magnification levels on $V_{avg}$ is unclear and thus should be investigated. As demonstrated in this discussion, our work motivates us to rethink the validity of existing work and opens up such new topics to be studied.
Our models would be beneficial to reducing the efforts made to measuring users’ operation speed under given screen sizes. Once test users operate a map application as in Gutwin and Skopik’s study [21] with several screen sizes, the resultant $V_{\text{avg}}$ values are recorded, and we can then predict the $V_{\text{avg}}$ for other screen sizes. For example, when we tested only $S = 25$ and 400 pixels ($N = 2S \times SW = 10$ data points), Model #9 yielded $a = 130$, $b = -2.47$, and $c = 0.622$ with $R^2 = 0.998$. Using these constants, we can predict $V_{\text{avg}}$ for $S = 50, 100, \text{and} 200$ pixels ($N = 15$), which showed $R^2 > 0.96$ for predicted vs. observed $V_{\text{avg}}$ values (Figure 9c). Hence, depending on the new screen sizes, the $V_{\text{avg}}$ for which test users can perform is accurately estimated. Importantly, as we showed that the relationship between $S$ and $V_{\text{avg}}$ was not linear and the interaction of $S \times W_1$ was significant, it is difficult to accurately predict $V_{\text{avg}}$ for a given $S$ and $W_1$ without our proposed model.

Limitations and Future Work

Our results and discussions are somewhat limited due to the task conditions used in the studies, e.g., circular paths were not tested. Also, the $A$ ranged from 300 to 800 pixels, but if $A$ is too short or $W_1$ is too wide, the task finishes before the speed reaches the potential maximum value [39, 41]. We limited these values so as not to be extremely short or wide to observe the effects of $S$. Investigating valid ranges of $S, W_1,$ and $A$ to hold our models is included in our future work.

The second path segment width $W_2$ was fixed to 19 pixels and thus was not dealt with as an independent variable. In the derivation around Equation 14 ($V_{\text{avg}} = b' \sqrt{S \times W_2} = b'' \sqrt{S}$), originally, $V_{\text{avg}}$ is assumed to increase with $W_2$. This could be true; if users know that $W_2$ is wide, such as 200 pixels, the necessity for quick deceleration would decrease. However, this depends on whether users have prior knowledge $PK$ on the $W_2$. If users do not know $W_2$, they have to begin to decelerate when a part of the end area is revealed in preparation for a narrow $W_2$. Hence, we have to account for human online response skills to a given visual stimulus [29, 49].

The $PK$ on the position or timing when a corner appears would also affect the speed. We tested only no-$PK$ conditions, which correspond to conditions such as playing a new stage in action games. In contrast, if players know the stage, controlling at much higher speeds is possible while maintaining safety. A kind of medium-$PK$ would also be possible in our experimental design. That is, although the participants did not know the $A$ beforehand, if the second path segment did not appear on the left half of the screen, the participants could notice that they had better decelerate because the corner must have been in the remaining space. Therefore, employing a complete no-$PK$ condition would be difficult for desktop or HMD environments to evaluate peephole pointing and steering, although this technical limitation has not been explicitly mentioned in the literature [13, 19, 24, 36].

Our future work includes conducting a study with driving simulators and racing games in order to validate our models. When driving at night, there are no clear boundaries between a viewable area and mask; rather, the forward view becomes gradually darker. Using clear boundaries is suitable for evaluating the effect of $S$, as in a study by Bateman et al., who used a wall instead of realistic fog in racing games [9]. More critically, the distance from when a brake pedal is pressed to when a car is completely stopped increases with $S^2$ (cf. thinking and braking distances), which would limit the speed more.

CONCLUSION

We presented an experiment done to investigate the effects of viewable forward distance $S$ on path-steering speeds. In path-steering tasks with cornering at an uncertain timing, the relationship between $S$ and the speed followed a power law (square root), and the interaction between path width $W_1$ and $S$ should be accounted for to accurately predict the speed. The best-fit model showed an adjusted $R^2 = 0.975$ with only one additional constant added to the baseline steering law, which also yielded an accurate model for task completion times. Interestingly, opposite conclusions were derived depending on the task requirements; a narrower $S$ increased the speed peephole pointing [13, 24] but decreased it in our path-steering experiment. Although not many studies have focused on the effects of $S$ on user performance, the importance will increase with the growth of devices with limited view areas such as smartphones and VR devices, and thus, we hope this topic is revisited by many more researchers in the future.

REFERENCES


