Deriving Steering Time Models for Paths with Corners of Varying Curvature Based on Preview-Based Velocity Control

Koyo Motoe
Meiji University
Nakano-ku, Tokyo, Japan
ev220558@meiji.ac.jp

Nobuhito Kasahara
Meiji University
Nakano-ku, Tokyo, Japan
cs242009@meiji.ac.jp

Shota Yamanaka
LY Corporation
Chiyoda-ku, Tokyo, Japan
syamanak@lycorp.co.jp

Wolfgang Stuerzlinger
SIAT, Simon Fraser University
Vancouver, BC, Canada
w.s@sfu.ca

Homei Miyashita
Meiji University
Nakano-ku, Tokyo, Japan
homei@homei.com

Abstract

Steering operations, such as menu navigation and drawing, constitute fundamental GUI interactions. The conventional Steering Law estimates movement times by accumulating the local width of the path, but it suffers from limited predictive accuracy for paths with varying curvature. In contrast, humans tend to adjust their speed by anticipating the path ahead (e.g., when driving). This study proposes a new Preview-based Model, which integrates geometric properties with visual constraints further along the path. Our experimental results show that our model achieved a higher adjusted R^2 (0.983) on curve-included paths than existing models. Furthermore, a simplified formulation without additional parameter tuning also exhibited comparable accuracy (adjusted $R^2 = 0.972$), confirming its effectiveness as a practical difficulty metric.

CCS Concepts

• **Human-centered computing → HCI theory, concepts and models**.

Keywords

Steering law, human-computer interaction, Interaction Design, velocity control, preview control

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1 Introduction

In HCI, steering a cursor along a path is a fundamental interaction, appearing in tasks such as hierarchical menu navigation and drawing. Accot and Zhai's Steering Law can predict movement time MT or speed V for such operations [1]. However, their models rely solely on local path width and ignore anticipatory speed adjustments based on the geometry of the path ahead.

Zhai et al. suggested in their study of driving tasks in VR environments that humans adjust their speed based on changes in curvature and their view in the direction of movement [22]. They also observed that participants shifted their gaze farther ahead in visually open segments, whereas they focused on nearer regions in narrow segments. This indicates that dynamic anticipatory control is performed, such as decelerating in advance when approaching sharp curves and accelerating in straight segments [22]. Existing models do not sufficiently represent this continuous speed correction, making it difficult to predict task difficulty accurately for complex composite paths.

This study introduces the concept of the (path) *Preview* to derive steering-time models. Conceptually, this represents how users "look ahead": an intuitive behavior where, for instance, drivers slow down before entering a corner because they anticipate the upcoming constraint. Our Preview-based Model takes two factors into account: the physical preview distance and the upper bound on speed imposed by human neuromotor capabilities. The results of our experiment showed significantly better prediction accuracy in terms of adjusted R^2 and AIC than the baselines.

2 Related Work

Humans anticipate the future route while driving. Drivers steer based on the preview time, defined as the ratio of gaze distance L to vehicle speed V ($T = L/V$) [9]. Subsequently, hierarchical models separating immediate stabilization and future anticipation were proposed [4, 16]. However, in our study, mouse-based steering operations impose fewer physical constraints (e.g., no inertia) and hence do not require such hierarchical structures. Thus, we leverage the fundamental definition of $T = L/V$ [9] and adopt a model in which a single preview time determines speed control.

Drury showed that MT for path-steering is linearly related to the ratio of path length A to width W (A/W), and that V is proportional to W [5]. Later, Accot and Zhai proposed the global Steering Law for paths of arbitrary shape by integrating the instantaneous index of difficulty [1]:

$$MT = a + b \cdot ID, \text{ where } ID = \int_C \frac{ds}{W(s)} \text{ or } ID = \int_C \frac{ds}{V(s)}. \quad (1)$$

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where a and b are empirical constants, and s is a point on the path C. In this formulation, $\int \frac{ds}{W(s)}$ represents the difficulty as a static geometric constraint, while $\int \frac{ds}{V(s)}$ reflects the fundamental physical accumulation of time. Accot and Zhai assumed a local linear relationship $V(s) \propto W(s)$, thereby enabling the prediction of MT from path geometry alone. While conventional studies have primarily relied on the static $W(s)$ term, our work leverages the velocity-based term by dynamically predicting $V(s)$ through a preview-based control mechanism.

Some studies also focused on the visual information regarding the direction of movement. Yamanaka et al. showed that, in situations where the forward field of view is restricted by the hand or frame, V is constrained by the forward visible distance S [20]. Although this is similar to our Preview concept, their model incorporates the field of view as a static geometric constraint; in a straight path, the speed is limited to $V \leq bS$. In contrast, our model assumes that users dynamically adjust V when approaching/leaving a corner, based on their preview of the path geometry ahead.

Pastel showed that MT increases for paths containing corners compared to straight paths, and proposed a composite model combining Fitts' law [6] for directional changes with the Steering Law [15]. Furthermore, for motor control, V and curvature radius R satisfy the one-third power law $V \propto R^{1/3}$ [11].[1] Based on this, Nancel and Lank's model assumes V is proportional to both W and $R^{1/3}$ [14], while Yamanaka et al.'s model assumes V decreases linearly with $1/R$ [18]. These approaches extended the applicability of the Steering Law to curved paths. Furthermore, Chen et al. improved predictive accuracy by adding the cumulative curvature K of the path [3]. Although these studies advanced modeling by incorporating curvature effects, they do not sufficiently address the dynamic speed adjustment mechanism based on the Preview in the direction of movement. In reality, users anticipate future path shape [14, 19].

3 Derivation of the Preview-based Model and Validation Conditions

Parameters: The following variables are used throughout the paper: **path width** W, **inner radius** r, **central turn angle** θ, **geometric preview distance** L, **constant preview time** t, and **predicted velocity** V. These are visually defined in Figure 1. For model validation, our experiment uses a composite path consisting of a straight–curve–straight configuration (Figure 1 (a)). A trial starts from the upper-left end and progresses to the lower-right end. The total path length A is defined as the sum of each of the straight-curve-straight segments, and the path width W is constant. As Figure 1 (c) shows, the preview distance L along the path center is calculated from W and the inner radius r as $L = \sqrt{rW + \frac{3}{4}W^2}$. Thus, L is defined as the Euclidean distance from the current point to the outer boundary of the path along the tangent vector direction. For computational convenience, we divide the path into sufficiently short pieces, and calculate L at each point i ($i = 0, \ldots, 1000$) as L_i, which varies dynamically as the task progresses. Figure 2 illustrates that the model captures the moment when L_i decreases and the operator anticipates the upcoming constraint.

[1] In this paper, we distinguish between the general path center radius R and the inner curve radius r used in the experimental conditions.

While driving, humans perform preview by anticipating future road information; drivers fixate on a point ahead at a distance L proportional to the speed V, and this ratio is called the preview time ($T = L/V$) [9]. For stylus- and mouse-based steering, users also attempt to maintain a constant preview time t [12, 13]. That is, to operate safely at the current speed V, a preview distance of at least $t \cdot V$ is required; otherwise, users have to reduce their speed.

To represent this behavior, we define the maximum feasible speed V_i given the width W_i at point i as follows:

$$V_i = k \cdot W_i \cdot \min\left(1, \left(\frac{L_i}{t \cdot V_{i-1}}\right)^p\right), \tag{2}$$

where k is the constant of the speed-form of the Steering Law ($V = k \cdot W$) [1, 5] and represents the maximum speed per unit width. In Eq. 2, V_i, W_i, L_i, t, and V_{i-1} represent predicted speed, path width, preview distance, preview time, and previous speed, respectively. This equation expresses that when L_i exceeds the required distance $t \cdot V_{i-1}$, the speed reaches the maximum value for the given W_i (saturated state), whereas when it falls below this threshold, the speed is reduced (suppressed state). The recursive dependence on V_{i-1} reflects the continuous feedback-based adjustment of speed during steering.

When the speed is restricted before/in a corner, Equation 2 indicates $V \propto L^p$, and from $L = \sqrt{rW + \frac{3}{4}W^2}$ (see Figure 1c), we can approximate $L \propto r^{1/2}$. In comparison, the one-third power law suggests $V \propto r^{1/3}$ under a corner [11]. Thus, to ensure consistency with existing findings, we set $(r^{1/2})^p = r^{1/3}$, which yields $p = 2/3$. This model ensures $V_i \neq 0$ even at the limit $r \to 0$ (sharp curve), and that V_i does not diverge for straight paths ($r \to \infty$) due to saturation.

Since the Preview-based Model calculates V_i recursively (Equation 2), which requires an explicit initial speed at the start of the simulation, we confirmed that an arbitrarily low initial value (e.g., $V_0 = 1.0$) and iteratively updating it 100 times yield an appropriate initial steady-state speed V_{start} (Figure 2, Left).

We now obtain a **General Preview-based Model**:

$$V_i = k \cdot W_i \cdot \min\left(1, \left(\frac{L_i}{t \cdot V_{i-1}}\right)^{2/3}\right), \quad ID_{General} = \sum_{i=1}^{N} \frac{\Delta s}{V_i} \tag{3}$$

If we can assume that a path would reasonably narrow and the speed never reaches saturation, i.e., L_i is always smaller than the required distance $t \cdot V_{i-1}$, we also have a **Simplified Preview-based Model**:

$$V'_i = k \cdot W_i \cdot \left(\frac{L_i}{V'_{i-1}}\right)^{2/3}, \quad ID_{Simplified} = \sum_{i=1}^{N} \frac{\Delta s}{V'_i} \tag{4}$$

This model enables task difficulty computation solely based on path geometry. This simplified formulation is particularly significant for practitioners. While technically recursive, it eliminates the need to experimentally calibrate the preview time t. This makes the model straightforwardly applicable for interface evaluation, as designers can compute a path's difficulty index $ID_{Simplified}$ using only its static geometric coordinates (W, L_i) through a single-pass calculation. In the form $MT = a + b \cdot ID$, k is absorbed into the slope b. Thus, the General Preview-based Model has three free parameters

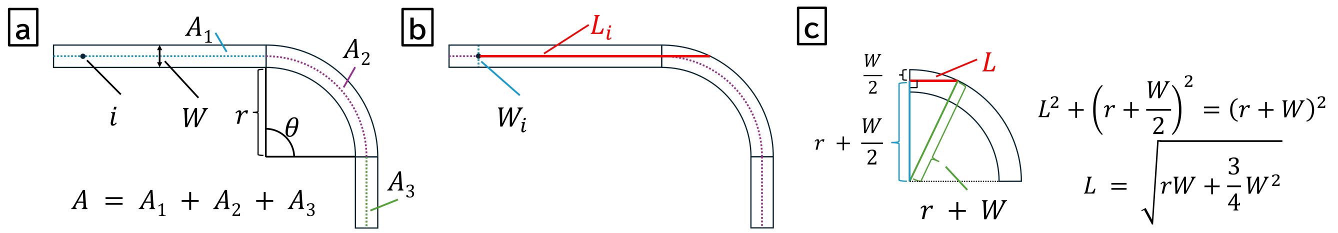

Figure 1: Definition of the experimental paths: (a) Global parameters including total length A, path width W, inner radius r, and turn angle θ. (b) Local parameters at point i, where W_i is the local width and L_i is the geometric preview distance. (c) Geometry of the preview distance L, defined by the tangent distance to the outer boundary.

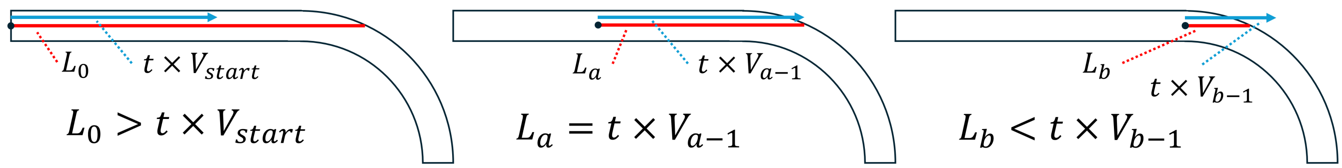

Figure 2: Recursive velocity control: (Left) Initial state at $i = 0$ where $L_0 > t \cdot V_{start}$ (converged via "warm-up"). (Center) Deceleration starts when $L_a = t \cdot V_{a-1}$. (Right) Velocity is suppressed when $L_b < t \cdot V_{b-1}$.

(a, b, and t), whereas the Simplified model introduces *no additional free parameters* relative to the baseline Steering Law.

4 Experiment

Apparatus: We used a **Logitech G304** mouse (**1600 DPI**, **1000 Hz** polling rate), a **Logitech G640** cloth mouse pad, and a **15.6-inch** display (1920×1080). The system, developed in Unity, ran at **150 Hz**. In this experiment, participants held the mouse button and moved the cursor from the green start to the blue end area along a white path (Figure 3). They were instructed to move as quickly and accurately as possible. The start-area width was set to 0.1 units (1 Unity unit = 16 mm) to ensure accurate acceleration measurement from zero speed. Visual feedback (red trace) indicated deviations, requiring participants to return to the path immediately. Invalid trials involving accidental releases or significant cut-offs were redone from the start.

Participants: Ten right-handed students (**8 male, 2 female**; mean age 21.8 ± 1.5) participated. All were daily PC users, though three primarily used touchpads instead of a mouse.

Design: We used a within-subjects design with three factors: (1) **path width** $W \in \{0.3, 0.5, 0.8\}$; (2) **central angle** $\theta \in \{45°, 90°, 135°\}$; and (3) **inner radius** r (10 levels from 0 to 4 with 0.125 steps). The **total path length** A was fixed at 6π units ($\approx$ 30.2 cm), with straight segments before and after the curve distributed in a 3:1 ratio. Each condition was repeated five times, yielding a total of 450 randomized trials ($3W \times 3\theta \times 10r \times 5$ repetitions). We measured MT from exiting the start area to entering the end area and included error trials in the analysis, as the task was eventually completed.

5 Results

Trials in which deviation(s) occurred were treated as error trials. Such error trials were also included when analyzing MT [8, 10, 17, 21, 23], because the task was still completed. After outlier removal based on the 1.5 IQR criterion for MT for each condition for each participant, 34 trials were excluded. We used RM-ANOVA with Bonferroni correction.

Experimental data that are not directly related to our research goal of comparing models' accuracy, such as ANOVA results on MT and error rate, are included in the supplementary materials. In summary, as expected, MT increased significantly for larger θ and narrower W. Note that MT also increased for larger r; this is because the total path length was fixed, and larger curves reduced the proportion of high-speed straight sections (Figure 4). The MT results thus appropriately varied depending on the task conditions. Therefore, we analyze the prediction accuracy of candidate models.

5.1 Model Definitions and Derivation of *ID*

As a benchmark, we analyze the fit of the baseline Steering Law (Model 1, Equation 5), as well as the curvature-aware models proposed by Yamanaka et al. [18] and Chen et al. [3] (Models 2–4, respectively, Equations 6–8). The ID for each model was defined as follows. **Model 1 (Steering Law)** is based on the global steering model that considers only the path width and length. **Model 2 (Yamanaka et al.)** incorporates the local curvature $1/R = 1/(r + W/2)$ and treats the lengths of straight and curved segments separately (A_{str} and A_{crv}, respectively) [18]. Since both models take the form $MT = a + b \cdot X$, the variable term X was directly used as the difficulty index ID.

$$ID_{Model1} = \frac{A}{W} \quad (5), \quad ID_{Model2} = \frac{A_{str}}{W} + \frac{A_{crv}}{W + c/R + d(W/R)} \quad (6)$$

Models 3 and 4 (Chen et al.): These global models incorporate cumulative curvature K [3]. Originally, these models were formulated as multiple regression models with A/W and K as predictors. To enable comparison and visualization using a single ID, we factorized each term by the coefficient b of the main term A/W, and

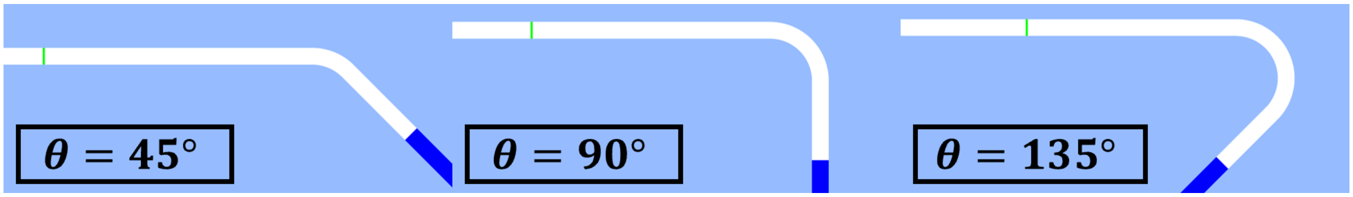

Figure 3: Path shapes for all central angle θ conditions with $W = 0.8$ and $r = 2$. Participants performed a dragging operation from the green start area to the blue end area.

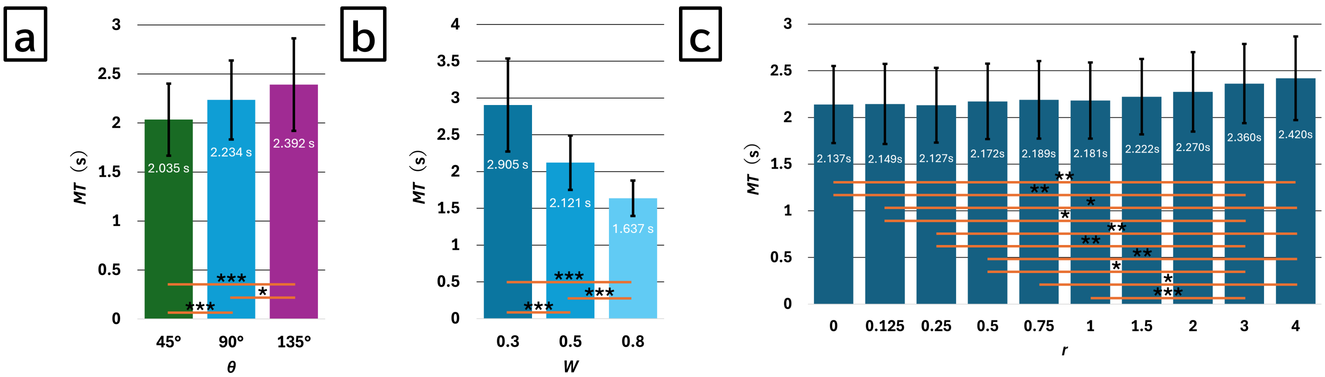

Figure 4: Mean MTs for each (a) central angle θ, (b) W, and (c) r. Error bars represent SD. Asterisks indicate statistically significant differences, with *: $p < 0.05$, **: $p < 0.01$, and ***: $p < 0.001$.

normalized the equations into the form $MT = a + b \cdot ID$ to define ID.

$$ID_{Model_3} = \frac{A}{W} + \frac{c}{b}K + \frac{d}{b}\left(\frac{A}{W}K\right) \tag{7}$$

$$ID_{Model_4} = \frac{A}{W} + \frac{c}{b}\log_2(K+1) + \frac{d}{b}\left(\frac{A}{W}K\right) \tag{8}$$

where the coefficients c and d were obtained from multiple regression analysis.

5.2 Comparison of Model Fit

Figure 5 summarizes the regression results. We use adjusted R^2 (higher is better) and AIC (lower is better; a difference > 10 indicates a significant difference [2]) as model-fit metrics. Existing geometric summation models (Models 1 and 2) showed limited fit ($Adj\ R^2 = 0.851$–0.870). While curvature-aware models (Models 3 and 4) improved accuracy to $Adj\ R^2 = 0.935$–0.937, the proposed Preview-based Models outperformed them. The Simplified version (Model 5) achieved $Adj\ R^2 = 0.972$ without introducing any additional parameters beyond those of the baseline Steering Law. Furthermore, the General one (Model 6) recorded the highest $Adj\ R^2$ (0.983) and the lowest AIC (−467.80), demonstrating superior statistical fit for complex paths.

6 Discussion

6.1 Comparison with Existing Models

Models 1 and 2 achieved goodness-of-fit values only in the 0.8 range. This result suggests that for tasks involving dynamic changes in difficulty, such as those examined in this experiment, simple additive combinations of geometric primitives have inherent limitations in predictive power. Models 3 and 4 improved their fit by incorporating cumulative curvature information, but they still fell short of the proposed models.

The primary reason why the proposed models achieved significantly better goodness of fit ($Adj\ R^2 > 0.97$ with AIC < -423) lies in the introduction of a velocity suppression mechanism based on the preview distance L and the preview time t. Humans continuously adjust their speed not only based on local width and curvature but also according to the forward visibility along the direction of motion [9, 22]. By mathematically incorporating this property, the proposed models successfully provide a unified description of motion ranging from sharp curves to gentle curves. Furthermore, our error analysis revealed a nuanced insight into the user's strategy: while path width W and radius r significantly affected error rates, the turn angle θ did not ($p = 0.568$). This suggests an accuracy-maintenance strategy where users effectively trade off speed for accuracy by slowing down sufficiently for longer turns, although the physical tightness of the radius (r) eventually limits their control capacity.

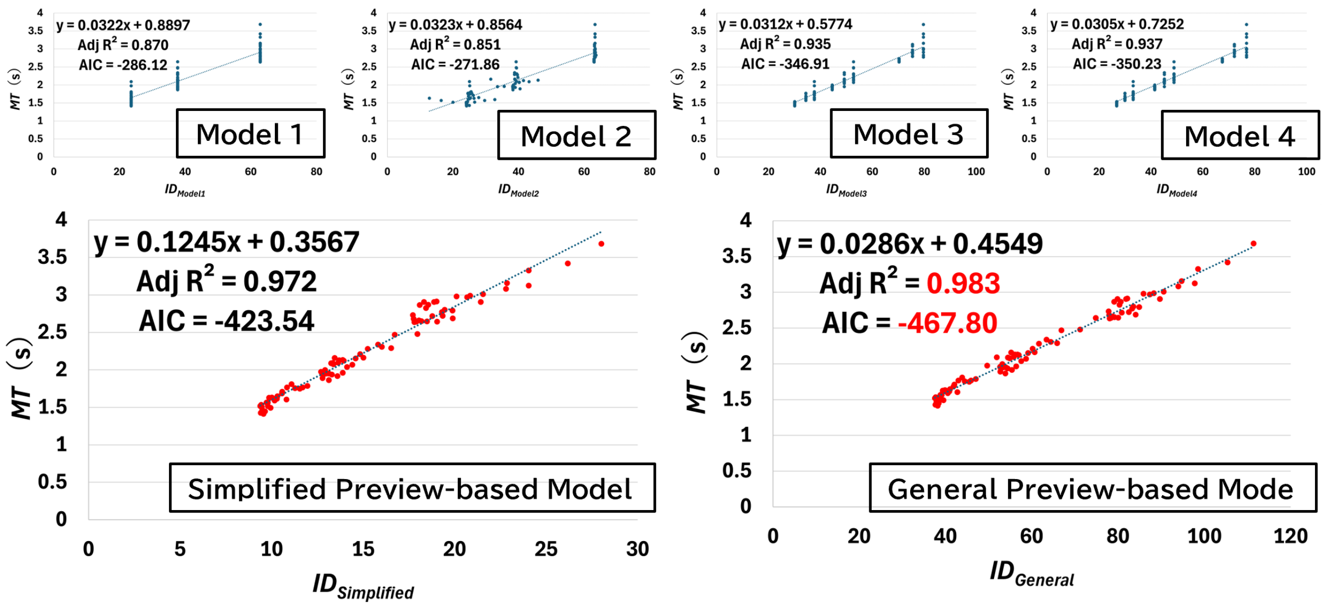

Figure 5: Relationship between ID and the mean MT for each model. Compared to existing formulations of Models 1–4, our proposed Preview-based Models (Models 5 and 6) showed higher $Adj\ R^2$ and significantly lower AIC values. Note that the Simplified Model (Model 5) provides a superior fit even without additional free parameter tuning.

6.2 Comparison Between the Proposed Models and the Significance of Parameters

The fact that the General Preview-based Model (Model 6) outperformed the Simplified one (Model 5) can be attributed to its ability to better account for physiological speed saturation (i.e., the ceiling effect of maximum speed) in straight segments. Notably, the Simplified Model (Model 5) outperformed the best existing model (Model 4) despite having no additional free parameters beyond those of the baseline Steering Law (a, b) , achieving a higher adjusted R^2 (0.972 vs. 0.937) and a significantly lower AIC (-423.54 vs. -350.23). This result indicates that geometric preview information alone can yield highly accurate predictions, even without additional parameter tuning, making the model particularly useful for practical applications such as interface design. Together, these findings suggest that the Preview-based Models, which integrate geometric preview and physical constraints, have superior validity compared to existing approaches for describing MT in paths with complex shapes.

6.3 Limitations and Future Work

A primary limitation of this study is the relatively small participant pool ($N = 10$). Additionally, while our model excels at single curves, future work should evaluate its performance on more complex UI paths, such as S-shapes or multiple successive corners. Since our models compute acceleration based on local width changes, they predict no deceleration until immediately before a narrow segment in "bottleneck-shaped" paths, where the width suddenly decreases. Yet, in reality, humans decelerate well before the narrow-width segment to avoid errors [19]. As a future direction, instead of relying solely on the local actual width, introducing the concept of a "mentally assumed width," which decreases as a function of the distance to the entrance of a narrow region, is expected to better predict human-like deceleration behavior. Moreover, when transitioning from a sharp curve to a straight segment, the geometric preview distance may increase discontinuously (depending on the segmentation precision), causing the predicted speed to jump instantaneously and resulting in infinite acceleration in the model. However, prior research showed that human movements are planned to minimize the integral of jerk (the rate of change of acceleration), producing smooth, bell-shaped velocity profiles [7]. The discontinuous velocity changes observed in the current model contradict such biological smoothness. Thus, in future work, instead of just imposing a constraint via the maximum acceleration, it would be beneficial to introduce a smoothing process that explicitly accounts for jerk, predicting more physiologically plausible movements.

7 Conclusion

In this work, we propose a Preview-based Model inspired by preview control in car driving, aiming to provide a unified description of steering task difficulty along paths with corners having different angles and curvature radii. Based on the experimental validation, the proposed models exhibited significantly high predictive accuracy for MT. While the goodness of fit of conventional steering laws and existing curvature-aware models ranged approximately from $Adj\ R^2 = 0.85$ to 0.94, the proposed models achieved $Adj\ R^2 > 0.97$. This supports the hypothesis that humans continuously regulate their speed not only based on local path width but also according to the forward "preview" and "preview time." Further, although the Simplified Preview-based Model requires no task-specific parameter tuning, it outperformed the best existing model with multiple parameters. This indicates that highly accurate task difficulty prediction is possible using only geometric preview information. In summary, the Preview-based Model effectively enhances our understanding of path-steering behavior in complex tasks and provides a valid foundational theory for predicting MT.

References

[1] Johnny Accot and Shumin Zhai. 1997. Beyond Fitts' Law: Models for Trajectory-Based HCI Tasks. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems* (Atlanta, Georgia, USA) *(CHI '97)*. Association for Computing Machinery, New York, NY, USA, 295–302. doi:10.1145/258549.258760

[2] Kenneth P Burnham and David R Anderson. 2003. *Model selection and multimodel inference: a practical information-theoretic approach*. Springer Science & Business Media, Heidelberg, Germany.

[3] Jennie J. Y. Chen and Sidney S. Fels. 2025. Curves Ahead: Enhancing the Steering Law for Complex Curved Trajectories. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '25)*. Association for Computing Machinery, New York, NY, USA, Article 975, 12 pages. doi:10.1145/3706598.3713102

[4] Edmund Donges. 1978. A Two-Level Model of Driver Steering Behavior. *Human Factors* 20, 6 (1978), 691–707. doi:10.1177/001872087802000607

[5] C. G. Drury. 1971. Movements with Lateral Constraint. *Ergonomics* 14, 2 (1971), 293–305. doi:10.1080/00140137108931246

[6] Paul M. Fitts. 1954. The information capacity of the human motor system in controlling the amplitude of movement. *Journal of Experimental Psychology* 47, 6 (1954), 381–391. doi:10.1037/h0055392

[7] T. Flash and N. Hogan. 1985. The Coordination of Arm Movements: An Experimentally Confirmed Mathematical Model. *Journal of Neuroscience* 5, 7 (1985), 1688–1703. doi:10.1523/JNEUROSCI.05-07-01688.1985

[8] Nobuhito Kasahara, Yosuke Oba, Shota Yamanaka, Anil Ufuk Batmaz, Wolfgang Stuerzlinger, and Homei Miyashita. 2024. Better Definition and Calculation of Throughput and Effective Parameters for Steering to Account for Subjective Speed–Accuracy Tradeoffs. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 722, 18 pages. doi:10.1145/3613904.3642084

[9] Masaichi Kondo and Akio Ajimine. 1968. Driver's Sight Point and Dynamics of the Driver-Vehicle-System Related to It. In *1968 Automotive Engineering Congress and Exposition*. SAE International. doi:10.4271/680104

[10] Sergey Kulikov, I. Scott MacKenzie, and Wolfgang Stuerzlinger. 2005. Measuring the Effective Parameters of Steering Motions. In *CHI '05 Extended Abstracts on Human Factors in Computing Systems* (Portland, OR, USA) *(CHI EA '05)*. Association for Computing Machinery, New York, NY, USA, 1569–1572. doi:10.1145/1056808.1056968

[11] Francesco Lacquaniti, Carlo Terzuolo, and Paolo Viviani. 1983. The Law Relating the Kinematic and Figural Aspects of Drawing Movements. *Acta Psychologica* 54, 1 (1983), 115–130. doi:10.1016/0001-6918(83)90027-6

[12] Ray F. Lin and Chih-Hsiang Hsu. 2014. Measuring individual corrective reaction time using the intermittent illumination model. *Ergonomics* 57, 9 (2014), 1337–1352. doi:10.1080/00140139.2014.933268

[13] M. A. Montazer, C. G. Drury, and M. H. Karwan. 1988. An optimization model for self-paced tracking on circular courses. *IEEE Transactions on Systems, Man, and Cybernetics* 18, 6 (Nov 1988), 908–916. doi:10.1109/21.23090

[14] Mathieu Nancel and Edward Lank. 2017. Modeling User Performance on Curved Constrained Paths. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 244–254. doi:10.1145/3025453.3025951

[15] Robert Pastel. 2006. Measuring the Difficulty of Steering Through Corners. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Montréal, Québec, Canada) *(CHI '06)*. Association for Computing Machinery, New York, NY, USA, 1087–1096. doi:10.1145/1124772.1124934

[16] Dario D. Salvucci and Rob Gray. 2004. A Two-Point Visual Control Model of Steering. *Perception* 33, 10 (2004), 1233–1248. doi:10.1068/p5343

[17] Shota Yamanaka. 2024. Sample-Size and Repetition Effects on the Prediction Accuracy of Time and Error-Rate Models in Steering Tasks. *Journal of Information Processing* 32 (2024), 247–255. doi:10.2197/ipsjjip.32.247

[18] Shota Yamanaka and Homei Miyashita. 2019. Modeling Pen Steering Performance in a Single Constant-Width Curved Path. In *Proceedings of the 2019 ACM International Conference on Interactive Surfaces and Spaces* (Daejeon, Republic of Korea) *(ISS '19)*. Association for Computing Machinery, New York, NY, USA, 65–76. doi:10.1145/3343055.3359697

[19] Shota Yamanaka, Wolfgang Stuerzlinger, and Homei Miyashita. 2017. Steering Through Sequential Linear Path Segments. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. ACM, New York, NY, USA, 232–243. doi:10.1145/3025453.3025836

[20] Shota Yamanaka, Hiroki Usuba, Haruki Takahashi, and Homei Miyashita. 2020. Peephole Steering: Speed Limitation Models for Steering Performance in Restricted View Sizes. In *Proceedings of Graphics Interface 2020* (Toronto, Ontario, Canada) *(GI 2020)*. Canadian Human-Computer Communications Society, 461–469. doi:10.20380/GI2020.46

[21] Shota Yamanaka, Hiroki Usuba, Haruki Takahashi, and Homei Miyashita. 2024. Predicting Success Rates in Steering Through Linear and Circular Paths by the Servo-Gaussian Model. *International Journal of Human–Computer Interaction* 40, 16 (2024), 4300–4318. doi:10.1080/10447318.2023.2212221

[22] Shumin Zhai, Johnny Accot, and Rogier Woltjer. 2004. Human Action Laws in Electronic Virtual Worlds: An Empirical Study of Path Steering Performance in VR. *Presence: Teleoper. Virtual Environ.* 13, 2 (April 2004), 113–127. doi:10.1162/1054746041382393

[23] Xiaolei Zhou and Xiangshi Ren. 2010. An Investigation of Subjective Operational Biases in Steering Tasks Evaluation. *Behaviour & Information Technology* 29, 2 (2010), 125–135.