2D-BayesPointer: An Implicit Moving Target Selection Technique Enabled by Human Performance Modeling

Nianlong Li[1, 2, 3]
linianlong16@mails.ucas.ac.cn

Feng Tian[1, 2]
tianfeng@iscas.ac.cn

Jin Huang[1, 2, 3]
huangjin@iscas.ac.cn

Xiangmin Fan[1, 2]
xiangmin@iscas.ac.cn

Hongan Wang[1, 2]
hongan@iscas.ac.cn

[1]State Key Laboratory of Computer Science, Institute of Software, Chinese Academy of Sciences, Beijing, China

[2]Beijing Key Lab of Human-Computer Interaction, Institute of Software, Chinese Academy of Sciences, Beijing, China

[3]School of Computer and Control Engineering, University of Chinese Academy of Sciences, Beijing, China

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Abstract
Interactive systems with dynamic content are becoming ubiquitous nowadays. However, it is challenging to select small and fast-moving targets in such environment. We present 2D-BayesPointer, a novel interaction technique to assist moving target selection in 2D space. Compared with previous techniques, our method provides implicit support without modifying the original interface design. Moreover, the algorithmic parameters are determined by probabilistic modeling of human performance in moving target selection tasks. The preliminary results from a pilot study have shown that this technique can significantly improve both selection speed and accuracy.

Author Keywords
Moving Target Selection, Endpoint Distribution, Statistical Criterion, Human Performance Modeling.

ACM Classification Keywords
H.5.2 [**Information interfaces and presentation**]: User interfaces – *theory and methods*; H.1.2 [**Models and principles**]: User/machine systems – *human factors*.

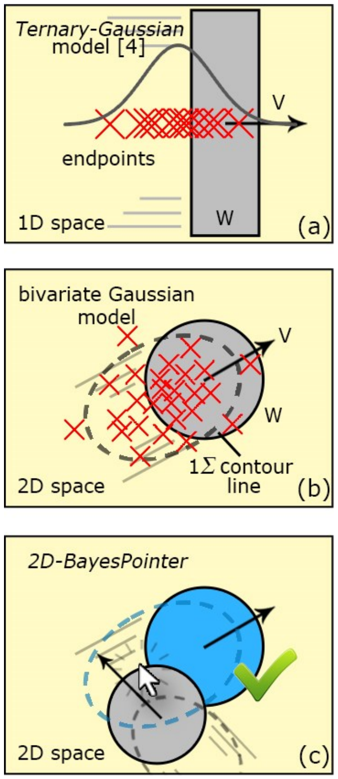

Figure 1. A snapshot of our work. (a) The *Ternary-Gaussian* model describing endpoint distribution in 1D space. (b) We build a bivariate Gaussian model to extend and validate prior work in 2D space. (c) We propose *2D-BayesPointer*, a moving target selection technique which determines the intended target based on statistical criterion derived from selection endpoint distribution, rather than the physical boundaries.

Introduction

Moving target selection is a common task in interactive systems with dynamic content such as games, Virtual Reality (VR) and Augmented Reality (AR) applications. For instance, in traffic control displays, users select a vehicle to view detailed information. In first-person shooter games, players point at the moving enemies to attack them. These tasks are challenging because users need to continuously track the target and simultaneously plan the timing for selection, which impose high sensory-motor coordination demand on users. A number of assist techniques have been proposed to address this challenge. *Comet* and *Target Ghost* [3], for example, improve selection accuracy by either enlarging the target's activation area or reducing target speed. Although these techniques were proved to be effective, they either modify the original interface design or need additional operations from users.

We recently proposed an implicit interaction technique, BayesPointer [4], to assist moving target selection in 1D space. The technique was built upon a Ternary-Gaussian model that describes the selection endpoint distribution (Figure 1.a). Specifically, BayesPointer determines the intended target based on the statistical criterion derived from the endpoint distribution, rather than merely relying on the physical boundaries. Since this technique does not modify the original interface design, it is transparent to users. However, BayesPointer and its underlying model have only been validated in 1D space. Moreover, there has been no formal comparisons between BayesPointer and other state-of-the-art techniques.

In this work, we extend our prior work in 2D space to make it applicable to more diverse interaction scenarios. Specifically, we make the following three contributions. First, we extend and validate the Ternary-Gaussian model to describe endpoint distribution in 2D moving target selection tasks (Figure 1.b). Second, we use this model as statistical criterion and build *2D-BayesPointer*, an implicit target selection technique that works in 2D space (Figure 1.c). Third, we conducted formal comparisons between our technique with other state-of-the-art techniques (i.e. *Bubble Cursor* and *Comet*). The results showed that *2D-BayesPointer* outperformed *Comet* in selection accuracy, and outperformed *Bubble Cursor* in both speed and accuracy.

Related Work

Novel Selection Techniques

Researchers proposed both cursor enhancement methods and target enhancement methods to assist selection. *Area Cursor* [5] is one of the most well-known cursor enhancement techniques. It uses an area, rather than a point, to represent cursor, which can increase the effective selection area. However, it suffers when the area cursor overlaps with multiple selectable objects. *Bubble Cursor* [2] addresses this problem by dynamically changing the selection area based on the surrounding targets. As a target enhancement technique, *Comet* [3] adds a tail to each target based on its speed and width thus to enlarge the its activation area. *Target Ghost* [3] reduces the target speed to zero by pausing the whole scene and creating static proxies of objects. Although these techniques have been proved to be beneficial, they result in either modifications of the original interface design or additional demand for user input (e.g., button press [3]).

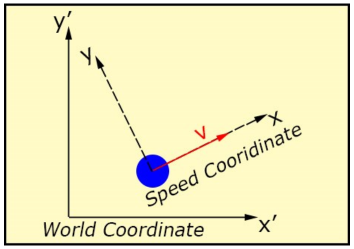

Figure 2. The illustration of the coordinate system used in this work.

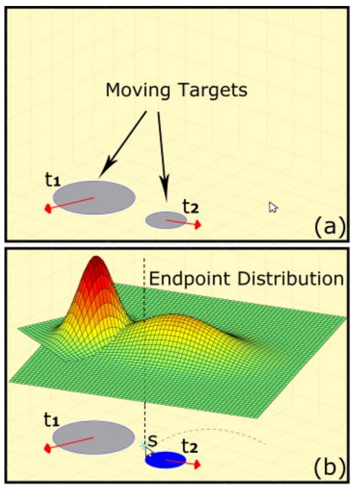

Figure 3. A concrete example illustrating how *2D-BayesPointer* works in practice. (a) Two moving targets with different widths and speed levels; (b) *t2* is determined as the intended target because *P(s|t2) > P(s|t1)*.

Statistical Criterion (Human Performance Modeling)
Researchers also explored assisting target selection via statistical criterion derived from human performance modeling. Bayesian Touch [1] combines Bayes' rule and a dual Gaussian distribution hypothesis to improve the accuracy of target selection for finger touch. However, this work only focuses on static targets. We proposed a *Ternary-Gaussian* model in our prior work [4] to describe the endpoint distribution in 1D moving target selection. We found that the shape of the distribution as characterized by μ and σ in the Gaussian model were primarily determined by the speed (V) and size of the moving target (W):

$$\mu = a + bV + cW \tag{1}$$

$$\sigma^2 = d + eV^2 + fW^2 + g\frac{V^2}{W^2} \tag{2}$$

The model fitted the empirical data well with 0.95 and 0.94 R^2 values for μ and σ, respectively. Based on this model, we further proposed *BayesPointer* which identified the intended target based on the probability density function (PDF) of endpoint distribution as the likelihood function in Bayes' rule. However, the model and selection technique in our previous study are limited to 1D space, and lack of formal comparisons with existing assist techniques.

Methods

Bivariate Gaussian Model
We first extend the *Ternary-Gaussian* model from 1D space to 2D space. We define the two axes of the *Speed Coordinate* space as follows (Figure 2):

- X-axis: the axis parallel with the moving direction;
- Y-axis: the axis perpendicular to the moving direction.

Assuming that the distributions in these two axes are independent, we get a bivariate Gaussian distribution $X \sim N(\mu, \Sigma)$ as follows:

$$\mu = \begin{pmatrix} \mu_x \\ \mu_y \end{pmatrix} \qquad \Sigma = \begin{pmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{pmatrix} \tag{3}$$

Where μ_x and μ_y, σ_x and σ_y are means and standard deviations in the two axes, respectively. By decomposing the speed vector along the two axes, we can adopt the *Ternary-Gaussian* in each axis.

For x-axis, note that the decomposed speed $V_x=V$, and the formulations of μ_x and σ_x can be written as:

$$\mu_x = a_x + b_x V + c_x W \tag{4}$$

$$\sigma^2{}_x = d_x + e_x V^2 + f_x W^2 + g_x \frac{V^2}{W^2} \tag{5}$$

For y-axis, the decomposed speed $V_y=0$, and the endpoints-shifting effect which reflected by the expectation value is minimal, thus we set μ_y to zero. However, for σ_y, the overall target speed brings uncertainty to user's movement even in the vertical direction as it required a quicker "click" action. Therefore, we kept the formulation consist with x-axis with different constants:

$$\mu_y = 0 \tag{6}$$

$$\sigma^2{}_y = d_y + e_y V^2 + f_y W^2 + g_y \frac{V^2}{W^2} \tag{7}$$

Model Fitting
We collected data to estimate the parameters in the bivariate Gaussian model from 12 subjects (average age = 25, 6 females). The study included 16 conditions corresponding to 4 levels of target width W (24, 48, 96

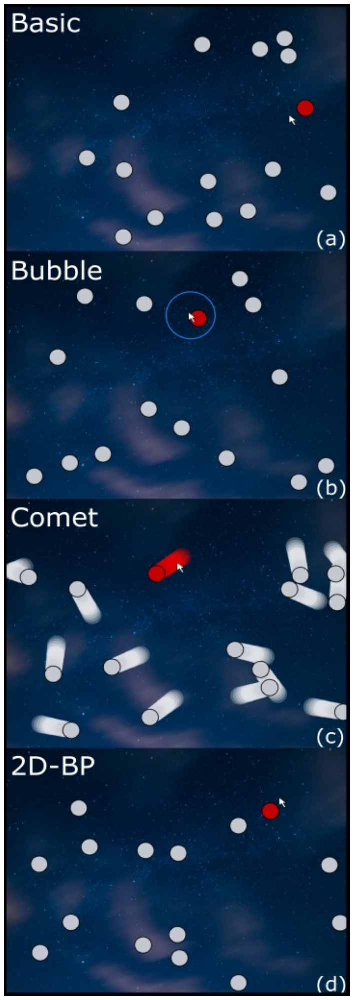

Figure 4. Four techniques explored in the study (from top to bottom: *Basic, Bubble, Comet* and *2D-BayesPointer*).

and 144 pixels) × 4 levels of target speed *V* (96, 192, 288, 384 pixels/second). Each condition included 10 trials, and each subject performed 160 trials in total. By applying least square regression, the model fit the data well with 0.961, 0.938, 0.955 R^2 values for μ_x, σ_x and σ_y, respectively. For μ_y, we do not use R^2 value to evaluate it as it was arbitrarily set to zero. Alternatively, mean absolute error (MAE) was computed, and a 1.05 pixels MAE of it showed that it is very close to the actual values.

2D-BayesPointer

We then integrated the bivariate Gaussian model into Bayes' rule to derive the decision-making strategy of *2D-BayesPointer*. Assuming there are n targets $\{t_1, t_2, \ldots, t_n\}$, and an endpoint s. According Bayes' rule, we can get the probability of selecting target t given endpoint s:

$$P(t \mid s) = \frac{P(s \mid t)P(t)}{P(s)} \tag{8}$$

where $P(t)$ is the priori probability to select target t, $P(s)$ is the normalization constant, and $P(s|t)$ is the likelihood function that express how probable the touch point s is if t is the intended target, which can be calculate through the PDF of our bivariate Gaussian model. Our goal is to find t^* (the intended target) that maximizes $P(t|s)$. We let each target have the same priori probability to be selected, then the target with a highest $P(s|t)$ will be treated as the intended target. To avoid always returning a target even when user intentionally clicks on a blank space, clicks falling outside of 3Σ contour line of the corresponding distribution will be ignored. Figure 3 shows an example illustrating how *2D-BayesPointer* works in practice.

Experiment

We conducted a study to answer the following three questions: 1) whether the performance of *2D-BayesPointer* is better than Windows basic selection technique (i.e. *Basic*) and other existing selection techniques (i.e. *Bubble Cursor* and *Comet*); 2) how these techniques perform with varied target sizes and speed levels; and 3) do users prefer the implicit manner enabled by our technique?

We recruited 16 subjects (average age = 26, 6 females) in this study. All of them were right-handed. We ran the experiment on a Lenovo P318 computer, with an Intel Core i7 4 Quad core CPU at 2.6GHz and a 23-inch (533.2×312mm) LED display at 1,920×1,080 resolution. The pointing device was a Dell MS111 mouse (1000 dpi). The experimental environment was developed with Unity3D. Figure 4 shows the four techniques in this comparative study.

Independent variables

We used a within-subjects design to compare between 4 techniques, 4 target widths, and 4 speed levels:

- Technique (*Tech*): *Basic, Bubble Cursor [2], Comet [3] and 2D-BayesPointer*
- Target Width (*W*): 24 pixels, 48 pixels, 96 pixels, 144 pixels
- Target Velocity (*V*): 96 pixels/sec, 192 pixels/sec, 288 pixels/sec, 384 pixels/sec

Each subject performed 10 trials in each condition. In total, we had 4×4×4×10×16= 10240 trials. Participates could practice before starting and could rest anytime they wanted in between. The order of techniques was counterbalanced across participants.

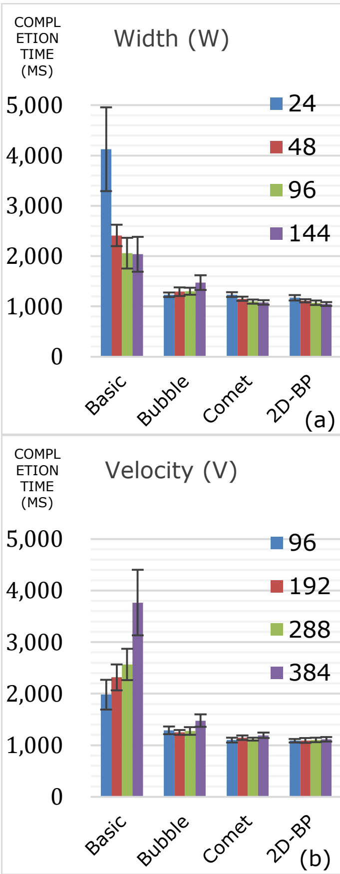

Figure 5. Completion time across techniques by (a) different widths and (b) different speed levels.

Tasks
After a user started a certain technique, 15 balls appeared at random positions within the window (1,024×768 resolution) and moved toward random directions with the same pre-determined target size and speed. The red ball was the target and participants were asked to select it as accurately as possible and as fast as possible. The other white balls were interfering objects (Figure 2). Balls bounced off when they hit the edge of the interface. Participants completed a trial when they successfully selected the red target.

Measures
We collected the completion time and error rates for all *W*×*V* conditions. Completion time was the time duration from trial start to a successful selection. Error rate was recorded if users clicked the mouse button but failed to select the target. We also collected post-surveys to gather subjective feedback.

Results

We used the repeated-measures ANOVA test for the following analyses.

Completion Time
All three variables *Tech* ($F_{3,45}=30.688$, $p<.001$), *W* ($F_{3,45}=6.545$, $p=.001$) and *V* ($F_{3,45}=8.436$, $p<.001$) exhibited significant effects on completion time. Pairwise comparisons using the Bonferroni adjustment yielded significant differences across all pairs of techniques ($p<.05$) except *2D-BayesPointer* vs. *Comet* ($p=1.0$). *2D-BayesPointer* had the lowest average completion time (1099ms), followed by *Comet* (1138ms), *Bubble Cursor* (1324ms) and *Basic* (2657ms). Figure 5 shows the average completion time across *Tech* with varied *W* and *V*.

Error Rates
All three variables *Tech* ($F_{3,45}=75.306$, $p<.001$), *W* ($F_{3,45}=3.537$, $p=.022$) and *V* ($F_{3,45}=12.462$, $p<.001$) exhibited significant effects on error rate. Pairwise comparisons showed significant differences across all pairs of techniques ($p<.05$). The lowest error rate was achieved by *2D-BayesPointer* (14.0%), followed by *Comet* (20.9%), *Bubble Cursor* (32.7%) and *Basic* (54.7%). Figure 6 shows error rates across *Tech* with varied *W* and *V*.

Performance of Varying Sizes and Speed Levels
We tested the effects of *W* and *V* on speed and accuracy of each technique separately. Results showed that W or V could make significant or marginal significant effect on the performance of *Basic, Bubble Cursor* and *Comet.* On the contrary, neither *W* nor *V* exhibited significant effect on performance of *2D-BayesPointer* (Table 1). Therefore, the speed and accuracy performances of our technique is robust across varied target sizes and speed levels.

Technique	Completion Time		Error Rates	
	Width	Velocity	Width	Velocity
Basic	0.004*	0.001*	0.028*	0.002*
Bubble	0.141	0.023*	0.048*	0.057
Comet	0.004*	0.127	0.037*	0.089
2D-BP	0.065	0.809	0.613	0.427

Table 1: p-values of W and V effects on performance of the four techniques, * marked a significant level of p<.05.

In addition, we found *Bubble Cursor* suffers a decline on speed and accuracy when target size increases. We attribute this to the fact that bigger target size

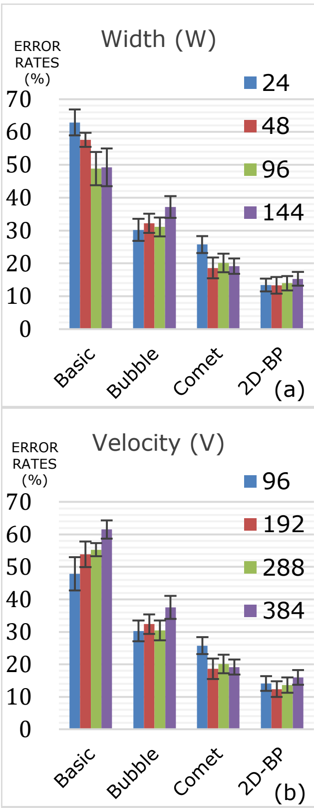

Figure 6. Error rates across techniques by (a) different widths and (b) different speed levels.

increases the chance of multi targets overlap on each other, thus it is difficult for *Bubble Cursor* to pick out the intended one in such situation.

Subject Feedback

A 7-points Likert scale for soliciting users' preference showed that they preferred *2D-BayesPointer* (M=5.82, SD=0.98) more than *Comet* (M=5.72, SD=1.34), *Bubble Cursor* (M=5.36, SD=1.43) and *Basic* (M=2.73, SD=1.55). Sample responses include:

- *"The 2D-BayesPointer technique looks the same with Basic, but it is much quicker." [S12]*
- *"The Bubble Cursor is fast, but it hard to use in big and dense targets." [S1]*

Conclusion and Future Work

In this paper, we presented *2D-BayesPointer*, an implicit moving target selection technique using statistical criterion derived from human performance modeling. We conducted a controlled experiment to evaluate our technique. Results showed that *2D-BayesPointer* outperformed *Comet* in selection accuracy, and it outperformed *Bubble Cursor* in both speed and accuracy. Our technique works in an implicit manner and it is robust across varied target sizes and speed levels. We believe that this technique can be useful to improve interaction efficiency in interactive systems with dynamic content.

In the future, we will validate our technique in real world scenarios and explore applying *2D-BayesPointer* on different input devices. We are also interested in extending this technique for moving target selection in 3D environment, which might be more inspirational for VR and AR developers and practitioners.

Acknowledgements

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