Modeling the Uncertainty in Pointing of Moving Targets with Arbitrary Shapes

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Abstract

When we try to acquire moving targets such as shooting enemies in computer games, the shapes of these targets are often varied. Considering the effects of target shape in moving target selection is essential for predicting user performances such as error rate in user interfaces involving dynamic content. In this paper, we propose a model to be descriptive of the endpoint uncertainty in pointing of moving targets with arbitrary shapes. The model combines the Gaussian mixture model (GMM) with a *Ternary-Gaussian* model to describe the impacts of target shape and target motion on selection endpoints of moving targets. Compared to the-state-of-the-art, our model achieved higher performance in the fitting of endpoint distribution and predicting selection error rate.
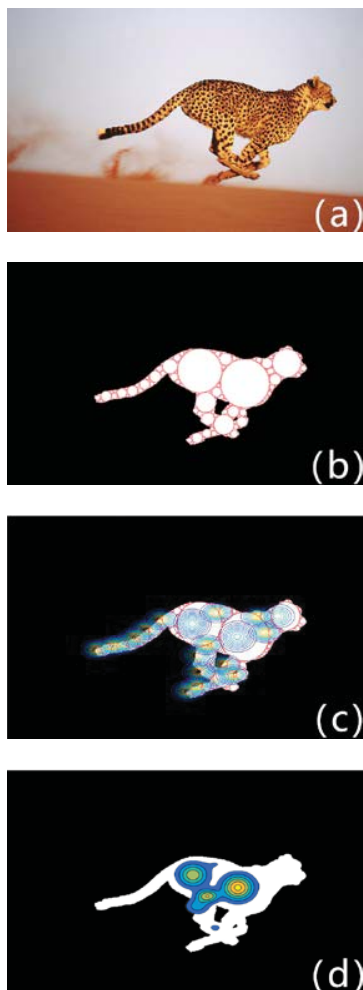
Author Keywords

Moving Target Selection; Arbitrary Shape; Endpoint Distribution; Error Rate

CSS Concepts

Human-centered computing → Human computer interaction (HCI) → HCI theory, concepts and models

Introduction

Moving target acquisition, as a fundamental research problem in HCI, has recently attracted more and more

Figure 1: Modeling the endpoint distribution of moving target with arbitrary shape.

attentions [8], [9], [10], [12]. Prior models that predict pointing uncertainty (i.e., the distribution of selection endpoints) in moving target selection show an important role in understanding user behaviors and predicting user performances in user interfaces involving dynamic content. However, as far as we know, there is no previous attempt try to consider the influence of target shape on modeling pointing uncertainty for moving targets. Such a model could be essential for explaining user performances for interfaces taking the shaped targets as major interaction objects like animation systems and virtual reality (VR) applications.

The influence of target shape on pointing static targets has been studied in HCI literature. Grossman and Balakrishnan et al. [4][5] proposed a probabilistic model to predict movement time (*MT*) for targets with arbitrary shapes by mapping endpoint distribution to the index of difficulty (*ID*) in Fitts' law [2], [13]. Their works suggest that the target shape has a significant impact on user performances, and the *MT* can be predicted by obtaining the selection center for each shaped target. However, their works do not predict the distributions of selection endpoints, leaving the selection uncertainty, the more fundamental factor in the pointing task affecting user performances [9], can only be observed from user's data. Further, the interaction between of target shape and target motion on endpoint distribution has not been studied.

In order to solve this problem, we combined a *Ternary-Gaussian* model [9], [10], one of the-state-of-the-arts in predicting endpoint distribution for moving targets, with the Gaussian mixture model (GMM) to model pointing of moving targets with arbitrary shapes.

Consider modeling the selection endpoints for a shaped target as shown in Figure 1 (a). We first split the target into sub-targets by iteratively selecting max inscribed circles of the target (Figure 1 (b)); then we used the *Ternary-Gaussian* model to generate endpoint distribution on each sub-target (Figure 1 (c)); finally, we used the Gaussian mixture model to mix these Gaussian distributions according to a weighting strategy (Figure 1 (d)). Compared with the original *Ternary-Gaussian* model, our approach achieved a higher fitting performance indicated by smaller *Hellinger Distance* [6] on moving targets with arbitrary shapes. By using the model to predict error rates of pointing moving targets, our model also outperformed the *Ternary-Gaussian* model with lower mean absolute error (MAE).

Related Work

In target acquisition, Fitts' law [2], [13], is one of the most widely accepted and robust models which precisely predict the time duration in pointing static targets. With the deepening of the Fitts' law research, it was extended to predict the user performance in higher dimension [1], [3]. However, Fitts' law and its variants cannot model the user performance for dynamic targets which become ubiquitous in modern user interfaces [7]. For dynamic targets, Jagacinski et al.'s model [11] is the most well-known approach that can estimate *MT* for moving targets by introducing the target speed as a term into Fitts' law. Recently, to further understand the uncertainty, a more fundamental factor in the pointing task affecting user performances, Huang et al. proposed a *Ternary-Gaussian* model that predicted the endpoint distribution for moving targets in 1D [9] and 2D [10] spaces. Although this model has been verified in multiple interaction scenarios, it is only adaptable for circular targets, which limits its application. In this
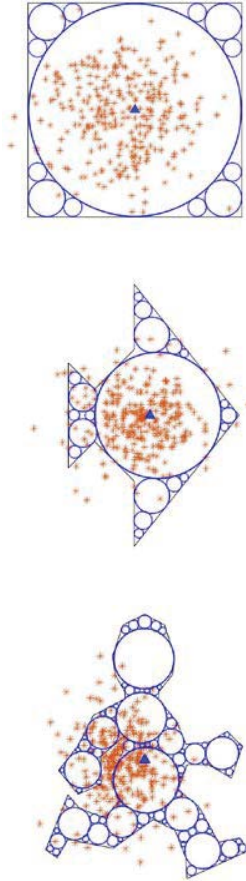
Figure 2: The endpoint distributions, polygon centroid and max inscribed circles of three shapes.

paper, we will try to extend this model to make it capable of modeling the endpoint distribution in pointing of moving targets with any shape.

Considering the shape effect on target acquisition, there are also many existing studies in HCI literature. For those targets with non-rectangular shape. Grossman and Balakrishnan et al. [3], [4] proposed a probabilistic model to predict *MT* of pointing at targets with arbitrary shapes by obtaining selection center and tolerance from endpoints and mapping them to the Fitts' *ID*. However, as Grossman and Balakrishnan's model did not directly predict the endpoint distribution, ones have to re-sample endpoints for new target when applying it. Besides, the assumption that the σ of endpoint distribution increased linearly with the distance may not hold in moving target selection. Evidence showed that the effect of initial distance is much smaller and usually negligible for *MT* [11] and pointing accuracy [9] when pointing moving targets with position control systems like mouse.

GMM-based Ternary Gaussian Framework

To extend the *Ternary-Gaussian* model capable of modeling endpoint distribution with arbitrary shapes, we 1) iteratively selected the maximum inscribed circle of the target to divide the target into multiple sub-targets, and 2) used the *Ternary-Gaussian* model to generate a speculative endpoint distribution for each sub-target. Finally, we 3) used the Gaussian mixture model to mix these speculative endpoint distributions according to a weighting strategy to obtain the final endpoint distribution of the shaped target.

For splitting the shaped target into sub-targets, we used the *Max Inscribed Circles* algorithm

in *ImageJ* [14] to get the max inscribed circles fill with each shape as shown in figure 2. The algorithm iteratively searched the circle with the largest tangent area to the edge inside of a polygon, to realize the segmentation of a polygon into sub-targets with multiple inscribed circles.

For generating speculative endpoint distribution, we used the 2D *Ternary-Gaussian* model [10] to calculate the corresponding distribution for each sub-target. 2D *Ternary-Gaussian* model described the selection endpoints of a circular target as a 2D Gaussian random variable with the mean and covariance associated with the size and speed of the target as shown in Equation 1 and 2.

$$\mu = \begin{pmatrix} a_t + b_t V + c_t W_t + x_i \\ y_i \end{pmatrix} \quad (1)$$

$$\Sigma = \begin{pmatrix} d_t + e_t V^2 + f_t W_t{}^2 + g_t \dfrac{V}{W_t} & 0 \\ 0 & d_n + e_n V^2 + f_n W_n{}^2 \end{pmatrix} \quad (2)$$

Where, *W* and *V* represented the size and speed of the target, (x_i , y_i) represented the center of the target, and $a_t, b_t, c_t, d_t, e_t, f_t, g_t, d_n$ were free parameters. The subscripts *t* and *n* represented the two axes of the endpoint coordinates, where *t* is the axis tangential to target velocity and *n* is the axis normal to it. W_t and W_n represent major minor axis of the elliptical target ($W_t = W_n$ for circular target).

For mixing the speculative endpoint distributions of sub-targets into final endpoint distribution, we used the *Gaussian mixture model* (GMM) to generate a mixture distribution composed by all the speculative (Gaussian) distributions ($N(x \,|\, \mu_i, \Sigma_i)$) of the sub-targets with weight

Figure 3: The experimental apparatus

Para.		Term	Value
u_t	a_t	-	9.1105
	b_t	V	-0.0987
	c_t	V	0.0508
σ_t	d_t	-	71.6353
	e_t	V^2	0.0029
	f_t	W^2	0.0249
	g_t	$\frac{V}{W}$	-0.1431
σ_n	d_n	-	63.8703
	e_n	V^2	0.0007
	f_n	W^2	0.0248

Table 1: Coefficients of the 2D *Ternary-Gaussian* model estimated by our data.

w_i. Thus, we have the final formulation of the GMM-based *Ternary Gaussian* framework as follow:

$$GTF(x) = \sum_{i=1}^{K} w_i N(x \mid \mu_i, \Sigma_i) \quad (\sum_{i=1}^{K} w_i = 1) \quad (3)$$

Where K represents the number of the speculative distributions. By stacking several Gaussian probability density functions with an appropriated weighting strategy determined each w_i, this framework can flexibly be used to approximate distributions in any form.

Based on the above GMM-based *Ternary Gaussian* framework (GTF), we proposed two candidate models differ by whether to consider the overall uncertainty of pointing the target independently. We describe the two candidate models in the next section.

Candidate Models

Model-1 is a two-part model in form of a weighted sum of a *Global Uncertainty* part $N(x \mid \mu, \Sigma)$ and a *Local Uncertainty* part $GTF(x)$ as shown in Equation 4:

$$P_{model-1}(x) = \alpha N(x \mid \mu, \Sigma) + (1-\alpha)GTF(x) \quad a \in [0,1] \quad (4)$$

$$Weighting\ strategy\ of\ GTF(x): \quad w_i = \frac{r_i^2}{\sum_{k=1}^{K} r_k^2} \quad (5)$$

For the *Global Uncertainty* part. We assumed that the user perceive the shaped target as an ellipse in a global perspective. Thus, we used the 2D *Ternary-Gaussian* model to approximate the *Global Uncertainty* part by calculating endpoint distribution of an ellipse target centering at the polygon centroid of the target. The major axis (W_t) and the minor axis (W_n) of the ellipse

was set as the width and height of the target's circumscribed rectangle.

For the *Local Uncertainty* part. A GTF was used to represent the influence of target shape. As people is more likely to click on a target with bigger size, the weight of each Gaussian distribution in the GTF was determined by the area of the corresponding sub-target πr^2. The constant π was eliminated when normalizing the weights.

The free parameter α is used to balance the weight of the parts of *Global Uncertainty* and *Local Uncertainty*, which is varied by targets. Generally, a smaller α value corresponds to a more irregular target, while a bigger one corresponds to a more regular target.

In contrast to splitting the global and local uncertainty into two parts, **Model-2** directly model the two parts with one single GTF (Equation 6). For doing that, we designed a weighting strategy of the GTF to reflect these two kinds of uncertainty as shown in Equation 7.

$$P_{model-2}(x) = GTF(x) \quad (6)$$

$$Weighting\ strategy\ of\ GTF(x): \quad w_i = \frac{r_i^2/d_i^\beta}{\sum_{k=1}^{K} r_k^2/d_k^\beta} \quad (7)$$

Based on considering the area of the sub-target, this the weighting strategy additionally took the distance between the sub-target and the target center into account. As a result, the weight of a sub-target decreases as the distance to the target center increases, and increases as its area increases.

According our prior observation. We found that the probability of a sub-target to be hit is nonlinearly declining with its distance to the target center. We used a power function d^β with a free parameter β to model this phenomenon. As a result, the weight is set as $\pi r^2/d^\beta$ as the effect of the distance is opposite to the area. Finally, normalizing the weights yields to an expression of the weighting strategy shown in Equation 7.

Experiment

We conducted an experiment to evaluate the performance of the proposed two candidate models. The experiment followed a within-subject design with four fully crossed variables, including 4 target shapes, 2 initial distances (192 and 384 pixels), 3 sizes (96, 192, 384 pixels), and 3 speeds (96, 192, 384 pixels/sec).

The four target shapes included a symmetrical square, a semi-symmetrical fish shape, and an asymmetric shape of a running man (Figure 2). A circular target was also included for achieving the parameters of 2D *Ternary-Gaussian* model. Widths of irregular target were determined by the diagonal length of the circumscribed rectangle.

We recruited 15 participants (6 females, 9 males, 25.5 years old on average). All the participants were right-handed. The experiment was conducted on a Lenovo JiaYue 30600I desktop computer, the display is a 23-inch Dell P2314H LED display with a resolution of 1920 ×1080, and the mouse is a Dell ms116t with 1000dpi.

In each trial, a participant clicked the start button located in the center of the window, and then a target with specified shape and size appeared on the screen and started moving with a fixed speed heading in a random direction. The initial position of the target was randomly set on the circumference of a certain radius from the start button. The participant was asked to click the target quickly and accurately as possible with the computer mouse. The participant could only attempt to acquire the target once. Selection endpoint was recorded no matter the target was hit or miss. Each condition repeated 10 times, yielding a total 15 participants × 4 shapes × 2 distances × 3 sizes × 3 speeds × 10 repeats = 10800 endpoints. The orders of the conditions were randomized.

Results and Discussion

For getting the coefficients of the 2D *Ternary-Gaussian* model in our experimental environment, we used the data of the circular target to train the model. All nine sets of endpoints with 300 samples in each set passed the normality test using 2D Kolmogorov-Smirnov with a confidence level of 95%. The coefficients estimated by the nlinfit function provided in MATLAB were shown in Table 1. After we had the coefficients of the 2D *Ternary-Gaussian* model, we built and evaluated the two candidate models (i.e., **Model-1** and **Model-2**) in the other three shapes. The free parameters α and β were estimated separately by shapes. The 2D *Ternary-Gaussian* model was also evaluated as a baseline.

We used two measures to evaluate the models. 1) The similarity measured by the Hellinger Distance [6] (HD) between the actual and predicted endpoint distributions; and 2) mean absolute error (MAE) from selecting error rates predicated by the models to the actual error rates. The HD was used to quantify the similarity between two probability distributions with the range from 0 to 1. A value 0 means the two
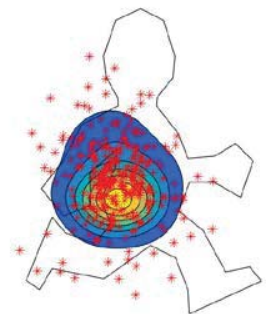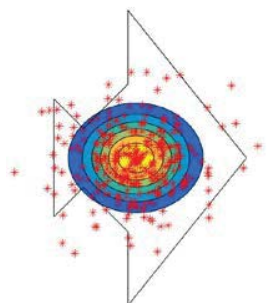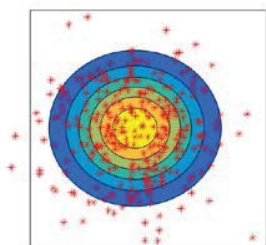
Figure 4: The actual endpoints and predicted endpoint distribution of Model-2.

Model	Square		Fish		Person	
	Distributions Similarity (HD)	Error Rate (MAE)	Distributions Similarity (HD)	Error Rate (MAE)	Distributions Similarity (HD)	Error Rate (MAE)
2D Ternary-Gaussian Model	0.158	1.45%	0.251	9.99%	0.267	11.98%
Model-1	**0.152**	0.85%	0.247	9.46%	0.267	11.98%
Model-2	0.153	**0.84%**	**0.192**	**1.68%**	**0.235**	**2.40%**

Table 2: The experimental results of the *2D Ternary-Gaussian* model and two candidate models in three shapes.

distributions are entirely consistent, and 1 means that they are completely inconsistent.

As shown in Table 2, for the square shape, the distribution similarity of the two candidate models was slightly better than the baseline (0.005 and 0.006 in HD). It may because the regularity of the square shape limited the advantages of the two candidate models. As a result, the improvements of the candidate models in predicting error rates were also marginal (0.60% and 0.61% in MAE). For the fish shape, the distribution similarity of **Model-2** was higher than the baseline (0.059 in HD), while only a negligible improvement of **Model-1** was found. Therefore, **Model-2** got a notable improvement in predicting error rates with 8.31% in MAE. We found similar results in the shape of the running man. Compared with the baseline, **Model-2** reduced 0.32 HD in distribution similarity while it reduced the 9.58% MAE of error rate prediction. **Model-1** got the same performance as the baseline in the shape of the running man. Therefore, we finally determined the **Model-2** as the winning candidate in this work. Figure 4 showed the actual endpoints and endpoint distribution predicted by our final model**.**

Conclusion and Future Work

In this paper, we proposed a GMM-based approach to model the uncertainty in pointing moving targets with arbitrary shape. We compared the performance of two candidate models and chose one as our final proposed model. Results showed that our model could better describe the endpoint distribution and predict the error rate for moving targets with arbitrary shapes.

However, this work is limited by the small number of tested types of shape. Some extreme shapes such as a thin stick or a ring were not evaluated. It is very interesting to find out how our model will adapt to these shapes and weather the free parameter of the model can reflect the characteristics of them. In the future, we also interested in verifying our model in more practical scenarios involving moving targets, such as vertical reality and gameplay. It may provide helpful insights for the design of these dynamical user interfaces.

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