Trajectory Prediction Model for Crossing-Based Target Selection

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ABSTRACT

In some cases, crossing-based target selection motion may gain a less error rates and a higher interactive speed. Most of the research in target selection fields focused on the analysis of interaction results. Moreover, trajectories play a much more important role in crossing-based target selection comparing to the other interactive techniques. And an ideal model for trajectories may help computer designers make predictions about interaction results during the process of target selection rather than at the end of the whole process. We proposed a trajectory prediction model for crossing-based target selection tasks referring to dynamic model theory. Simulation results show that our model performed well in the prediction of the trajectories, endpoints and the hitting time for target-selection motion, and the average error of trajectories, endpoints and hitting time values as 17.28%, 18.17 pixel and 11.50%.

KEYWORDS

Target Selection; Crossing-Based Selection; Trajectory Prediction;

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INTRODUCTION

Target selection has found notable interest in the human-computer interaction (HCI) community. In some cases, crossing-based selection can achieve a higher efficient comparing with conventional interactive techniques, for example, crossing-based selection reach a less error rates and a higher interactive speed for continuous crossing task with direction constraint. In the prior study, selecting targets by crossing a boundary "goal" instead of pointing inside targets has already been systematically investigated. However, most of the research on target selection lies in the analysis of interaction results—the endpoints of trajectory. Only a few researchers focused on the analysis of trajectories in the HCI community. A good understanding of the trajectories of target selection is important as it can provide insight and guidance on the effects of practice on performance, rational decision-making, and layout design in these user interfaces [1]. An ideal model for the whole target-selection motion process may help computer designers make predictions about interaction results during the process of selection target rather than at the end of the whole process. It is a much more challenging job to predict trajectory for crossing-based selection. The main concern is that users prefer to choose the longer side to cross the target due to the targets are stick-like rectangles. The main impact on trajectory is the bending of the path. As a result, the existing trajectory prediction model could not predict the trajectory for crossing-based selection well due to the lack of adequate thinking about the shape of target. Moreover, it is a challenging work to simulate the bending of trajectories. Feedback control models and dynamic models are usually used to simulate the motion process. All models quantities the places and velocity at every moment according to the control signal dynamically adjusted by the position and velocity feedback. Referring to the same core ideas of the prior models and correlation theories of dynamic models, our work contributes new model for crossing-based interaction techniques. Through the simulation results, we find that our model achieved a satisfied simulation results on trajectory similarity, endpoints and time fitting.

RELATED WORK

Crossing-based Target Selection

An early crossing-based selection experiment referring to a "goal passing task" was performed by Accot and Zhai, which laid the foundation for the Steering Law [2]. Apitz et al. named the six task conditions of indirect stylus input [3]. Luo and Vogel [4] summarized a generalizable and empirical support for application of crossing to touch input through the analysis of the six task conditions. However, among the basic research on target selection, most of the researchers focused on the study of duration and endpoints.

Trajectory Prediction Model

Besides the research lies in the endpoints analysis of target selection motion, there are a few works for the trajectories analysis. Huang et al. [5] built a target-selection motion model based on linearquadratic-Gaussian optimal feedback control (OFC) mechanism, their model can simulate trajectories of target selection tasks with no thought for fitting time. Quinn and Zhai [6] developed a production model which can predict users' timing performance while typing using word-gesture keyboards. Due to its specific application scenario, some other information, such as semantic information, would be helpful to the model, and it may be not suitable for general target selection tasks.

Dynamic models for reaching motion

Dynamic models represent the behavior of an object over time. It is widely used in the fields of dynamics simulations. Yekutieli et al. [7] used a dynamic model to simulate the reaching movement of octopus arm. Tahara et al. [8] built a musculo-skeletal redundant arm model to simulate the motion of human arms. Unlike the motion of arms, process of target selection is a more microscopic motion with complex psychological functions. Even a slight force may lead to a huge shocks of trajectories. In our work, we contributed to build a dynamic micro-model referring to the conception of social force model (SFM) [9], and represent the behavior of the cursor over time using Newton's Second Law to predict the moving trajectories in crossing-based target selection acquisition.

TRAJECTORY PREDICTION MODEL

To model crossing-based target selection motion, we build a mechanical model referring to the relevant dynamic models. We approximated the movement of the pointing devices by particle pushing with a controlled force, which can be formulated as Newton's second law [10]. The main forces that effect the motion of particle p will be introduced:

Desired force

In the process of moving towards a target, particle is willing to reach a moving destination with minimum velocity perturbation under user's commands. Referring to SFM, we introduce the conception of desired direction and desired velocity. The particle p of mass m_p tends to move with a desired speed v_p^0 into the moving target α with a changeable direction vector $\overrightarrow{e_{p\alpha}(t)}$, and therefore the particle is likely to correspondingly adapt its actual velocity $v(t)$ with a relaxation time τ_p. The desired force of the particle can be described by an acceleration term of the form

$$\overrightarrow{f_0(t)} = \frac{v_p^0 \overrightarrow{e_{p\alpha}(t)} - v(t)}{\tau_p}. \tag{1}$$

Inertial Losses

At the front part of the trajectory, there unavoidably exists inertia which may influence the subsequent frames of motion trajectory at the state of an accelerated motion. The inertial action will decrease as the particle gradually approach to the target, this is because a comparably lower velocity is needed for users to selection the moving target. For this reason, we introduce a linear inertial losses function to simulate the phenomenon of inertial losses, it is given by

$$\overrightarrow{f_{inertance}(t)} = w^k \frac{v_p^0 \overrightarrow{e_{p\alpha}(t)} - v(t)}{\tau_p}. \tag{2}$$

And the coefficient of inertial losses w^k is

$$w^k = w_{ini} - \frac{w_{ini} - w_{end}}{2k_{max}} k_t, \tag{3}$$

where w_{ini} and w_{end} are system parameters, k_{max} is the maximum number of trajectory's frames, k_t is the current frame of the motion process.

Boundary force

The particle also try to keep a certain distance from border of the screen. Users may feel uncomfortable as the stylus or fingers moving towards the boundary of the screen. Therefore, the boundary of the screen *b* evokes a repulsive effect that can be described by

$$\overrightarrow{f_{pb}(t)} = \left[A \exp\left(\frac{r_{pb}}{B}\right)\right] \overrightarrow{n_{pb}}, \tag{4}$$

where $\overrightarrow{n_{pb}}$ is the unit vector denotes the direction perpendicular to boundary, r_{pb} shows the distance between particle and boundary.

Interactive force

Crossing-based target selection has its specificity, the targets in this kind of interaction are stick- like rectangles, and users customarily choose the longer side to cross the target. In this case, we modify the general moving direction and the inserted angle towards target. Inspired by literature [11], we use angle to control the bending of the trajectory influenced by psychological factors. The intersection angle of moving direction between particle $\overrightarrow{e_p(t)}$ and target $\overrightarrow{e_\alpha(t)}$ is used as the reference standard. The intersection θ_V and the force to control moving direction are defined

$$\theta_v = < \overrightarrow{e_p(t)}, \overrightarrow{e_\alpha(t)} >, \tag{5}$$

$$\overrightarrow{f_v(t)} = C \ \exp\left[\frac{D\,(\theta_V)^E\, r_p}{F}\right], \tag{6}$$

Another reference intersection angle θ_i and the force to control inserted angle are given by

$$\theta_i = < \overrightarrow{e_{p\alpha}(t)}, \overrightarrow{n_{\alpha ori}} >, \tag{7}$$

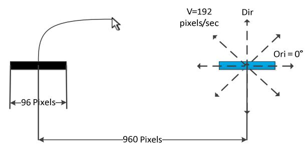
$$\overrightarrow{f_\iota(t)} = G \ exp\left[\frac{H\,(\theta_i)^I\, r_p}{F}\right], \tag{8}$$

where $\overrightarrow{n_{\alpha ori}}$ is the normal vector of orientation of target, r_p is the distance between target and particle. The model for crossing-based target selection motion is finally defined by

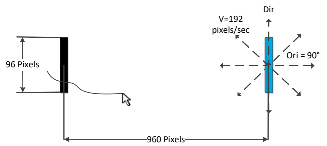
$$m_p \frac{dv_p}{dt} = m_p \overrightarrow{f_0(t)} + \overrightarrow{f_{inertance}(t)} + \overrightarrow{f_{pb}(t)} + \overrightarrow{f_v(t)} + \overrightarrow{f_\iota(t)}. \tag{9}$$

EXPERIMENTS AND SIMULATION

Experiment Design



(a)Target with an orientation of 0°



(b)Target with an orientation of 90°

Figure 1: Crossing-based selection task

Table 1: Optimization Parameters

Parameter	*Values*
A	1847.5
B	1157.4
C	$\begin{cases} -2099.5, < \overrightarrow{e_p(t)}, \overrightarrow{e_\alpha(t)} > \leq \theta_v \\ 1916.1, else \end{cases}$
D	$\begin{cases} -0.4793, < \overrightarrow{e_p(t)}, \overrightarrow{e_\alpha(t)} > \leq \theta_v \\ 2.4787, else \end{cases}$
E	$\begin{cases} 4.9962, < \overrightarrow{e_p(t)}, \overrightarrow{e_\alpha(t)} > \leq \theta_v \\ 4.8709, else \end{cases}$
F	1220.3
G	$\begin{cases} -1282.4, < \overrightarrow{e_{p\alpha}(t)}, \overrightarrow{n_{\alpha ori}} > \leq \theta_i \\ 1231.8, else \end{cases}$
H	$\begin{cases} 2.1322, < \overrightarrow{e_{p\alpha}(t)}, \overrightarrow{n_{\alpha ori}} > \leq \theta_i \\ 9.8106, else \end{cases}$
I	$\begin{cases} 0.4991, < \overrightarrow{e_{p\alpha}(t)}, \overrightarrow{n_{\alpha ori}} > \leq \theta_i \\ -1.5923, else \end{cases}$
w_{ini}	0.9
w_{end}	0.7
θ_v	0.1948
θ_i	-0.1907

To generate empirical data for estimating the parameters, we conducted a crossing-based selection task referring to the work of [9]. Participants used mouse to cross a moving target with 2 types of orientation (Ori), 8 types of the moving direction (Dir) width of 96 pixels and velocity of 192 pixels/sec, the initial distance between target and start point is 960 pixels. The crossing tasks are illustrated in Figure 1.

Participants

We recruited 15 participants (8 females and 7 males, with an average age of 27.3) in this study. All of them are familiar with computer and stylus. We ran the experiment on a regular desktop computer with a 13.3 inches display at 1,920×1,080. The stylus was 15.4 cm in length, 9mm in diameter at the barrel, and 10 g in weight.

Optimization Parameters

System parameter set $[A, B, C, D, E, F, G, H, I, w_{ini}, w_{end}, \theta_v, \theta_i]$ is selected according to the model defined in Section 3, which may significantly affect the similarity between the real data and the simulated one. We defined the sum total Euler distance per frame as the cost function to estimate the similarity value. We developed a Genetic Algorithm to gain the most appropriate parameter set, and the population size was set 50, the optimized parameter set is shown in Table 1.

Results of Endpoints

The average errors of the mean endpoint is 18.17 pixels, the maximum errors of endpoint is 27.71 pixels when Ori = 90°, Dir = 180°, while the minimum errors is 8.19 pixel when Ori = 90°, Dir = 45°

Simulation Results of Trajectory

To simulate a trajectory for task situation, we initialized the cursor at a mean state of $p_0 = [p_x(t_0); p_y(t_0); \dot{p}_x(t_0); \dot{p}_y(t_0); \tau_0; v_p^0]$, the moving target α’s position was set at $p_{\alpha 0} = [1120{,}540]$. Each simulation trial ended when the cursor hits the target or the target moving out of the screen.

The comparison of trajectories between simulation and real data is shown in Figure 2. As we can see from Figs 2, simulation results show that our model works better when the orientation is 90°, the average error of the mean trajectory is 981 pixels (17.28 % of the overall variability).

Results of Time Fitting

The Time Fitting results are shown in Table 2. Simulation results show that time is partly well-fitted. The average errors variability is 11.50%, and gain minimum value when Ori = 90°, Dir = 0° at 2.95%.

Discussion

As we can see from Figure 2, the bending of trajectories and the intersection angle show that users may adjust their direction to ensure that the long side is the boundary they choose to cross. Therefore, the existing trajectory prediction model could not simulate the bending of the trajectory due to the lack of adequate thinking about the shape of target. Furthermore, when Ori = 90°, the motion direction is vertical to the long side of target and only minor adjustments are needed for users to cross the target in a comfortable way.

CONCLUSIONS

Based on dynamic models, we proposed a trajectory prediction model for crossing-based target

Table 2: Comparison of Time fitting

$Ori(°)$	$Dir(°)$	$(T_r - T_s)/T_r(\%)$
0	-135	11.91
0	-90	12.88
0	-45	14.29
0	0	15.28
0	45	9.36
0	90	19.69
0	135	24.17
0	180	20.99
90	-135	10.91
90	-90	9.42
90	-45	6.16
90	0	2.95
90	45	4.54
90	90	7.73
90	135	7.22
90	180	6.46

selection. Experiments show that users prefer to select the long side of the target to cross. Simulation results show that our model performed well in the prediction of trajectories, endpoints and hitting time for crossing-based target selection. However, our model is still far from perfect. In the future, we will further analyze other parameters' impact on crossing-based target selection. At the same time, some other influence forces could be added into our model, such as the motion uncertainty. Our work may provide new perspectives for understanding target selection motion and other HCI research.

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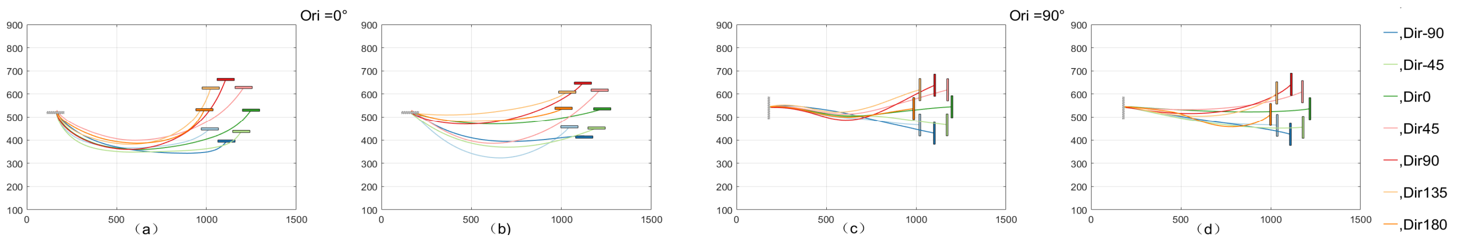

Figure 2: Comparison of trajectories. (Fig 2.(b), (d) are the predicted trajectories)