SCIENCE CHINA
Information Sciences

• MOOP •

April 2018, Vol. 61 044101:1–044101:3
https://doi.org/10.1007/s11432-017-9326-8

Modeling a target-selection motion by leveraging an optimal feedback control mechanism

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Received 27 September 2017/Accepted 29 December 2017/Published online 2 March 2018

Citation Huang J, Peng X L, Tian F, et al. Modeling a target-selection motion by leveraging an optimal feedback control mechanism. Sci China Inf Sci, 2018, 61(4): 044101, https://doi.org/10.1007/s11432-017-9326-8

Target selection has always been a popular research topic in the human-computer interaction (HCI) community. Systems with continuous interactive spaces, such as video games, augmented reality (AR), and virtual reality (VR), are becoming ubiquitous. A good understanding of the process properties (e.g., trajectory and speed profile) 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]. Despite extensive HCI investigations of human performance in target selection, most have focused on interaction results (e.g., duration [2] and endpoints [3]), and few have studied the process properties of target-selection motion.

The application of optimal control theory to modeling target selection motion is conceptually appealing. This theory describes movement based on the concurrent consideration of effort, speed, and accuracy, and is highly consistent with the common understanding of interaction behaviors. The optimal feedback control (OFC) system is a closed-loop optimal control system that makes decisions regarding the control of a plant at each time step based on feedback information. Compared to open-loop systems, it performs in a more human-like pattern characterized by a constant creation process in response to unpredictable fluctuations from the planned trajectory [4].

In contrast to traditional human performance models [2, 3], the output of an OFC system is a simulation set that contains multiple replications of a specified movement, and the adjustment and evaluation of this system relies on the similarity of the simulation and empirical data sets. However, to our knowledge, there is no such definition of similarity in the HCI literature, so a golden standard is needed.

In this article, we simulate target-selection motion with approximate profiles of the trajectory and motion uncertainties in the empirical data. We propose a framework based on the OFC system that describes target-selection motion. We investigated two kinds of typical interaction tasks—static- and moving-target selection—and (1) formulated these tasks as OFC systems; (2) measured their similarity to estimate key system parameters based on empirical data; and (3) used these estimated parameters in the system to simulate target-selection motions and evaluate the simulations. The experimental results show that the trajectory and variability of users' motions are well simulated by our framework, which can repro-

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duce many of the important characteristics of human motion in target selection, such as the speed-accuracy tradeoff [3] and feedback-decision uncertainty [5].

To model target-selection motion, we adopted a linear-quadratic-Gaussian OFC system [4]. We approximated the movement of the pointing devices by mass point pushing with a controlled force, which can be formulated as a linear dynamical system with the state $\boldsymbol{x}_t \in \mathbb{R}^m$, control $\boldsymbol{u}_t \in \mathbb{R}^n$, and feedback $\boldsymbol{y}_t \in \mathbb{R}^k$ in discrete time $t \in [1, N]$, as follows:

$$\begin{aligned} &\text{Dynamics} && \boldsymbol{x}_{t+1} = A\boldsymbol{x}_t + B\boldsymbol{u}_t + \boldsymbol{\xi}_t + \varepsilon_t C\boldsymbol{u}_t, \\ &\text{Feedback} && \boldsymbol{y}_{t+1} = H\boldsymbol{x}_t + \boldsymbol{\omega}_t, \\ &\text{Cost} && \sum_{t=1}^{n} \boldsymbol{x}_t^{\mathrm{T}} Q_t \boldsymbol{x}_t + \boldsymbol{u}_t^{\mathrm{T}} R \boldsymbol{u}_t. \end{aligned} \tag{1}$$

We developed formulations of the two types of interaction tasks and selected the system parameter set $\theta = [\sigma_c, \sigma_p, \sigma_v, \sigma_f, r, w_v, w_f]$ as key parameters to produce better simulations. We selected these parameters as they significantly affect the trajectory and trajectory variabilities of the simulation (see Appendix A.1 for more details). Inspired by the authors in [6], we defined a measurement for similarity that considers the errors of both the trajectory and the trajectory variability in the simulated and experimental trajectory sets. Then, we used this similarity value as a cost function to estimate the θ^* value that generates a simulation with the highest similarity to the empirical data.

$$\begin{aligned} &J(\theta) = \mathrm{trE} \times \mathrm{vaE}, \\ &\mathrm{trE} = \frac{1}{n}\sum_{i=1}^{n} ||\overline{p_i^s} - \overline{p_i^e}||, \\ &\mathrm{vaE} = \frac{1}{n}\sum_{i=1}^{n} ||\mathrm{var}_i^s - \mathrm{var}_i^e||, \end{aligned} \tag{2}$$

where trE and vaE are the average Euler distances between the mean point position and the variability along the trajectory, respectively. They measure the trajectory and variability similarities of the two trajectory sets. To estimate θ^*, we developed a random search algorithm that iteratively compares newly generated simulations with the data, the details of which are shown in Appendix A.2.

To generate empirical data for estimating the parameters, we conducted two experiments involving static- and moving-target selection. As pointing and feedback devices, we used a computer mouse and a 23-inch (533.2×312 mm) LED display at 1920×1080 resolution, respectively. In the static-target selection, for the target, we used a circle with a diameter of 48 pixels that was 480 pixels away from the center of the display. In the moving-target selection, we initialized the same target at the same position but moved it with speed of 144 pixels/s in eight directions, as shown in Figure 1(a).

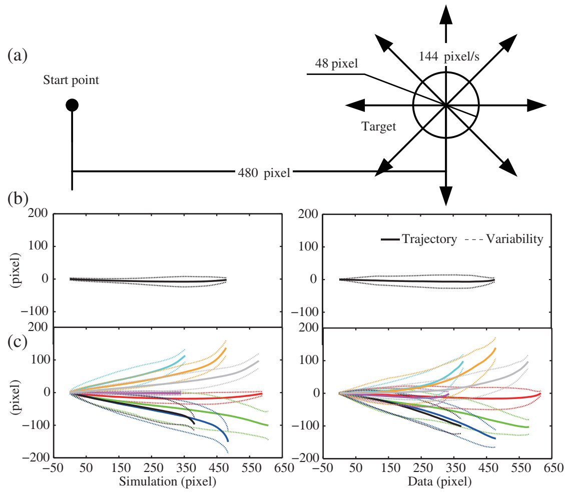

Figure 1 (Color online) Experiment and simulations. (a) Experimental setup for static- and moving-target selection; (b) simulation results and empirical data for static-target selection with the solid line representing the mean trajectory of movements and the dashed line representing the trajectory variability; (c) simulation results and empirical data for the eight directions (in different colors) of the moving-target selection.

We recruited twenty subjects (6 females and 14 males, with an average age of 26.3 years) to participate in the experiment. All were right-handed and had more than 2 years of experience using a computer and mouse. In each trial, the cursor was first fixed in the center of the display and the target appeared after a short time. Then, each participant was asked to move the cursor to acquire the target as quickly and accurately as possible. Participants had only one chance to select the target. If a participant failed to select the target, he/she had to perform the failed trial again. For the static-target selection, each participant completed six selection tasks. For the moving-target selection, each participant completed six selection tasks in each of the eight directions. All the trials in the moving-target selection experiment were randomly ordered.

We estimated the system parameters for the nine tasks. Beginning with the initial simulated data, the algorithm iteratively searches for θ^*. To accelerate the convergence, we set the initial searching range as $\boldsymbol{\mu} = [0\ 0\ 0\ 0\ 0\ 0\ \ 0]; \boldsymbol{\Delta} = [1000\ 1000\ 1000\ 1000\ 1000\ 1000\ 1000]$ for all the static- and moving-selection tasks. We set the coefficient of convergence φ to 0.05 and the maximum number of iterations to 20.

In the searching process, the algorithm must use the OFC system repeatedly to simulate a trajectory in a specific task setup. Specifically, in each iteration, we simulated trajectory sets containing equal numbers of experimental data to compute the cost function $J(\theta)$. To simulate a trajectory for one of the nine task situations, we initialized the cursor at a mean state of $\boldsymbol{x}_t = [0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ p_x^*(0)\ p_y^*(0)]$ with covariance Σ_1. For static-target selection, we fixed the target in the position (480×0) by $p_x^*(t) = 480$, $p_y^*(t) = 0$ $(t = 1, 2, \ldots, N)$, and for the moving-target selection, we set the target's position as $p_x^*(t) = 480 + t \times v_x$, $p_y^*(t) = 0 + t \times v_y$ $(t = 1, 2, \ldots, N)$, where $\boldsymbol{v} = [v_x, v_y]$ corresponded to the moving directions, for instance, $\boldsymbol{v} = [1.44, 0]$ for the right-hand direction. Each simulation trial ended when the condition $||p(t)-p^*(t)|| < 48$ was held for more than 0.5 s, that is, 50 time steps.

Figure B1 (Appendix B) shows the final estimated parameters for the static- and moving-target selections. For the moving-target selection, we used eight sets of parameters obtained from eight directions, and used their mean values as the final estimated parameters.

Using the above two parameter sets, we simulated 120 trajectories for each of the nine target selection tasks. Figures 1(b) and (c) show their mean trajectory and trajectory variability, respectively. As shown, our system closely simulated the mean trajectories and trajectory variabilities of all the experimental conditions. The trajectory error trE and variability vaE, in Table B2 (Appendix B), shows the quantitative similarity between our simulation and the data. For the static target, the average error of the mean trajectory is 9.86 pixel (1.70% of the trajectory length) and the variability is 17.89 pixel (3.86% of the overall variability). For the eight moving targets, the average errors are in the ranges of [22.14 pixel (6.59%), 52.07 pixel (10.56%)] and [27.03 pixel (3.28%), 49.75 pixel (5.60%)], respectively. These results indicate that the target-selection motions were well simulated by our framework.

Figures B1 and B2 (Appendix B) show all the simulation results for the static- and moving-target selections compared to the empirical data. In general, we found that users tend to combine predetermined and tracking actions while performing selection movements, initially moving the cursor in a relatively straight line to the expected position and then turning smoothly to the target. Our system recreated this behavior. On the other hand, users also display unconscious cursor turbulence and continuously correct their actions [5], which results in different movement trajectories but always success in acquiring the target. Our system also reproduced this behavioral property. In addition, our system recreated another well-known property of reaching movements, which are a trade-off between speed and accuracy [3], for which variability increases with increased moving speed.

In the future, our framework could be used for guiding the design of user interfaces. For example, by simulating users' motions on a shopping website, we can evaluate the complexity and efficiency of the purchasing of commodities on the website. Our study may also provide new perspectives for understanding other HCI research issues, such as complex interaction movements [7] and multimodal fusion and coordination [8].

Acknowledgements This work was supported by National Key R&D Program of China (Grant No. 2016YFB1001405), National Natural Science Foundation of China (Grant Nos. 61232013, 61422212), and Key Research Program of Frontier Sciences, CAS (Grant No. QYZDY-SSW-JSC041).

Supporting information Appendixes A and B. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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