A Discrete Movement Model For Cursor Tracking Validated in the Context of a Dual-Task Experiment

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Understanding human cursor tracking behavior is essential in understanding human motor control. Though tracking has been hypothesized as a sequence of discrete movements, better data is needed to support the theory. By analyzing moment-to-moment tracking data, this paper shows that discrete, non-ballistic movements exist throughout a tracking task, and that these short submovements can be characterized by either Fitts' law or a linear model. A cognitive model was built to incorporate the characteristics of these discrete movements into a dual task. Using parameters estimated through linear regression of the movement data, the model achieves a good fit to the overall performance measures of the dual-task experiment. This research investigates the characteristics of human motor control in tracking tasks, improves modeling techniques by providing a new method for estimating tracking parameters, and advances the science of motor control with new evidence for the discrete movement tracking hypothesis. The discrete movement model presented here offers an excellent alternative to established control theory models that are used to simulate steering in cognitive models of driving.

Tracking is a class of tasks in which people use their hands to guide the position of a pointer (such as a cursor) with respect to a target. Driving is a tracking task because a driver uses a steering wheel to guide the position of a car to track the changing curvature of the road. Many other tasks such as controlling mechanical arms or putting out a fire with a hose involve tracking as well. Because tracking is an essential component of human-machine interaction, it has attracted researchers' attention since World War II. Through the decades, researchers have gained considerable insights into human motor control, which has helped in the design of systems that enhance the speed and accuracy of tracking (Jagacinski & Flach, 2003).

Kieras, Meyer, Ballas, and Lauber (2000) proposed that a laboratory tracking task can be modeled as a series of discrete aimed movements that, like other aimed movements such as pointing, adhere to Fitts' law (Fitts, 1954). This discrete movement model was implemented in the EPIC cognitive architecture (Executive Process-Interactive Control; Kieras & Meyer, 1997), which consists of software modules that simulate many aspects of human perceptual, cognitive, and motor information processing in fine-grained details.

In Kieras et al.'s discrete movement model, EPIC's ocular motor module simulates the eye movements that keep the foveal vision onto the moving target, and EPIC's manual motor module simulates the pointing movements that move the cursor to the target. With these parts of the task handled by the cognitive architecture, Kieras et al's implementation of the discrete movement model is straightforward: The model is a set of rules that tells the architecture to initiate a pointing movement whenever the tracking target and cursor are visible to the simulated human and the manual module is not executing another pointing movement or movements for other tasks. Consequently, when there are no other tasks, this model would use contiguous pointing movements to achieve smooth tracking performance; when there are other tasks that need visual or manual processing, this tracking model may be interrupted by models of other tasks, thereby simulating task interference effects exist in multitasking performance.

Kieras et al. applied the discrete movement tracking model to a dual-task experiment, and they found that the model was able to fit the overall observed root-mean-squared (RMS) tracking error very well, with a minimum 4% average absolute error.

Although the discrete pointing movement model may fit an overall tracking performance measure well, it is unclear whether such a model is able to accurately capture tracking dynamics from moment to moment. Analysis of overall tracking performance measures such as the RMS tracking error cannot provide the two pieces of evidence that are key to verify the discrete movement model: (a) whether there are distinguishable individual movements in the human tracking data, and (b) if such movements exist, whether they can be described by Fitts' law. Although studies have shown that Fitts' law can apply to rapid movements to a target that moves at a constant velocity (Jagacinski, Repperger, Ward, & Moran, 1980), it is questionable whether this extends to the tracking task, in which the target moves in an unpredictable manner. To show that tracking is truly comprised of discrete aimed movements, more detailed analysis is needed.

Applying the discrete movement model also requires a more reliable procedure for estimating the slope and intercept parameters of the Fitts' law equation. Currently, if the default parameter values in the EPIC architecture are inappropriate for certain tracking task conditions, analysts need to reestimate them by running the whole model of a task and then comparing the predicted summary statistics such as the RMS tracking error with the observed data. If the prediction does not fit the observed data very well, the analyst needs to manually adjust the parameters and rerun the model.

This method of estimating parameter values based on overall RMS error suffers from three drawbacks: First, many other parameters may contribute to the RMS tracking error in a multitasking scenario, and when multiple parameters are present, an incorrect configuration of the parameter values may still lead to correct RMS tracking error. For example, a large RMS tracking error might occur because a participant responds to the moving target slowly, or because another difficult visual task delays tracking. Second, because there is often not a direct relationship between the parameter values and the predicted RMS tracking error, it can take many iterations of parameter adjustments to arrive at a satisfactory fit. Third, a good fit to the RMS tracking error will not provide much support for the tracking model considering that

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only a few RMS tracking error data points might be collected from an experiment (one data point per session) and a two-parameter Fitts' law equation can easily fit them all. A better procedure would use other data to estimate the parameters, and leave the RMS tracking error for overall model evaluation.

This paper provides new evidence that a discrete movement model is capable of capturing the moment-to-moment tracking dynamics, and presents a robust procedure for estimating parameters from the tracking error data. To utilize the parameter estimation procedure, a new model is developed based on Kieras et al's (2000) tracking model, but with a slightly different assumption about the nature of the individual tracking movements. Though the model was implemented in EPIC, the ACT-R architecture (adaptive control of thought-rational; Anderson et al., 2004) should benefit from it as well, because ACT-R's approach to simulating motor behavior is derived from EPIC. The new discrete movement model and the parameter estimation procedure were validated in the context of a dual-task experiment, discussed next.

METHOD

Experiment

A dual-task experiment (Hornof, Zhang, & Halverson 2010) was conducted that collected tracking data in a multitasking scenario. In this experiment, a choice-reaction task was presented concurrently with a tracking task on opposite sides of the screen. On the left side of the screen, a series of icons moved down the display with different shapes, colors, speed and direction. In some sessions, auditory alerts signaled the statuses of these moving stimuli such as their initial appearances. In a window on the right side of the screen, an airplane-shaped tracking target (30 pixels by 12 pixels) moved constantly within the window. One degree of visual angle spanned 40 pixels. The moving path of the target was predetermined by combining several sinusoids, and appeared to be random to the participant.

Each participant used a keypad to classify the icons on the left display as hostile or neutral based on their appearances and moving velocities, and interleaved with this activity, they used a joystick to keep a tracking cursor as close as possible to the target. The position of the joystick was sampled every 83 ms and was integrated by the experimental software to produce a mixture of first- and second-order control, i.e. the joystick position influenced the tracking cursor's velocity and acceleration. The positions of the target and the cursor were also refreshed every 83 ms, and were recorded to a log file.

Twelve participants from the University of Oregon and surrounding communities completed the experiment, and ten of them met the criteria for this analysis of tracking performance (an overall mean tracking error of under 30 pixels). The participants completed four eight-minute sessions of the experiment on each of three consecutive days. Two factors were manipulated across the four daily sessions: (a) the availability of the auditory alerts for the choice-reaction task, and (b) the visibility of the not-currently-looked-at display (controlled using an eye tracker and a gaze-contingent display). Participants were financially motivated to perform quickly and accurately. For the tracking task, participants gained monetary rewards only when the cursor was kept within 20 pixels from the target, and lost rewards when the tracking error was larger than 50 pixels. Cursor color changed in real time to indicate the immediate reward or loss state. Given the practice and motivation, the participants' performance by the third day likely approached that of an expert. The data from the third day are used in this analysis.

Extract discrete movements

To determine whether there are distinct movements in the empirical tracking data to support a discrete movement model, we examined how the tracking error changed over time in the dual-task experiment. Figure 1 shows a glimpse of how the tracking error typically fluctuated over an eight-second period in one experiment session. The participant happened to be looking at the tracking display for the entire eight seconds. As can be seen, within this short time period, there were three steep descents (marked by gray lines) that began as a large tracking error above 50 pixels and eventually came down to below 20 pixels. These descents were likely caused by the participant's manual movements because they were uninterrupted drops that lasted several hundred milliseconds and ended with the cursor in the region in which participants could gain rewards. These trends can be seen consistently throughout all participant data.

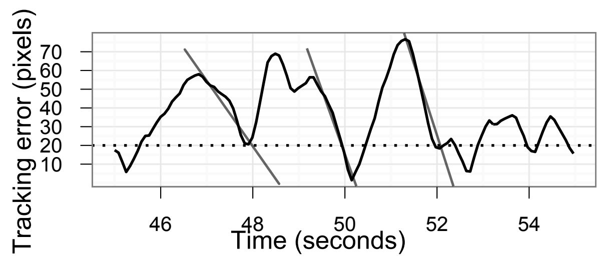

Figure 1. Tracking error data over eight seconds of a dual-task experiment session. The solid line shows the moment-to-moment tracking error, and the black dashed line marks the threshold below which the participant would gain rewards. Regressions were calculated for each downward slope that dropped at least 10 pixels and ended below 20. The gray lines mark three examples of such downward slopes.

If we can show that the steep descents in Figure 1 persist throughout the tracking task data, it can support the hypothesis that tracking is comprised of discrete movements. Based on this reasoning, we developed an algorithm to find descents with similar characteristics to those in Figure 1. Specifically, to qualify as a tracking movement, a decent must be an uninterrupted decrease of tracking error that reduces tracking error by more than 10 pixels and ends below 20 pixels. With these criteria, descents that were solely introduced by the random movements of the target should be eliminated. Thus, the extracted descents were treated as participants' discrete movements in subsequent analysis.

Estimate parameters

To further support the discrete movement model, it needs to be shown that there is a regular pattern in the movement data so that a simple function with a few free parameters can describe them. Kieras et al.'s (2000) tracking model assumed that the tracking movements can be described by Fitts' law, but provided no direct evidence to support this hypothesis. With the extracted movement data, it is possible to evaluate Kieras et al.'s assumption by examining how well the Fitt' law equation fits the data. The particular Fitts' law equation used by Kieras et al. is Welford's equation (1968), which is adopted in the EPIC cognitive architecture for calculating the movement time of pointing movements:

$$MT = a + b \log_2(A/W + 0.5),$$

where MT is the movement time, A is the movement amplitude, W is the target width, and a and b are parameters determined through linear regression. The logarithmic term, $\log_2(A/W + 0.5)$, is also referred to as *index of difficulty*. The target width W is set to 20 pixels because the participants only had to keep the tracking error below this value to gain reward. For movement amplitude A, we chose to use the tracking error at the moment that a movement is initiated instead of the ultimate distance that the cursor is actually moved. This is because a movement might change its course to follow the shifting of the target, which leads to variable and unpredictable moving distances. Using tracking error as A was also done in Kieras et al's model and in Jagacinski et al.'s (1980) study that investigated how well Fitts' law explains pursuit movements to a target with a constant velocity, as opposed to targets with a variable velocity as used in the tracking task.

The above procedure can determine the goodness-of-fit of a Fitts' law equation to the tracking data and can also be used to estimate the slope and intercept parameters of the equation to maximize the fit of the equation to the movement data. This parameter estimation procedure is more robust than the previous method that maximizes the fit to the RMS tracking error, because more factors contribute to the RMS tracking error than the slope and the intercept.

The discrete pursuit model

To use the parameters estimated with the above procedure, Kieras et al.'s discrete movement model needs to be modified slightly. Figure 2 illustrates how the movement in Kieras et al.'s model proceeds (dashed arrows and circles) and how the movement in the modified, discrete pursuit model proceeds (solid arrows and circles). As can be seen, in Kieras et al.'s model, a movement is ballistic in that once initiated, the movement cannot change its direction even if the target position changes. In the discrete pursuit model, however, a movement can change its course to follow the shifting of the target. The smoothness of the descents found in Figure 1 suggests that individual movements may be able to follow the motion of the target, because otherwise the random movement of the target would increase the tracking error from time to time and likely create a jagged pattern in the descents. In fact, we attempted to use the ballistic movement model with the estimated parameters, but the resulting RMS tracking error was inflated due to the failure to correct tracking direction during the movements. This suggests that iterative directional adjustments were performed.

A non-ballistic movement model has been adopted by many other motor control theories. For example, Meyer, Abrams, Kornblum, Wright, and Smith (1988) showed that

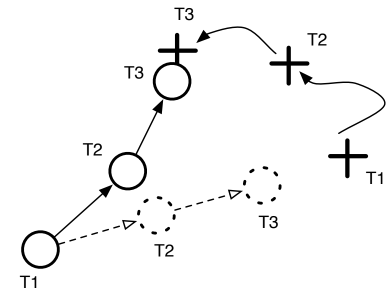

Figure 2. An illustration of how a ballistic tracking movement and a pursuit tracking movement proceed. The cross represents the target, and the circle represents the cursor. The arrows mark the paths of the target and cursor, from time T1 to time T3. Dashed lines represent the ballistic movement, and solid lines represent the pursuit movement.

rapid aimed movements to stationary targets, such as moving a mouse cursor to a button, can be described by a stochastic optimized-submovement model, which assumes that an aimed movement consists of a fast primary submovement and one or more corrective submovements. If humans are capable of making corrective submovements during a rapid aimed movement, which lasts only a few hundred milliseconds, it is likely that they can also respond to the motion of the tracking target within a similarly short period of time.

To validate the discrete pursuit model, we incorporated it into our EPIC model for the dual-task experiment and compared the predicted tracking data with the empirical data. The dual-task model was built based on Hornof and Zhang's (2010) moderately-overlapped model, which achieved a great deal of concurrent processing between the tracking task and the choice-reaction task, and which accurately explained the observed performance within and across the two tasks.

RESULTS

This section first presents the results from the analysis of the movement data to provide direct support for the discrete pursuit model, and then shows the goodness-of-fit of the model to the dual-task experiment tracking data.

Movement data

An average of 235 movements was extracted from each of the 40 eight-minute sessions, with a mean movement duration of 503 ms. These tracking movements accounted for 30% of the time spent on the tracking task. Considering that the extracted movements did not include small movements (those that reduced tracking error by fewer than 10 pixels), the discrete movements made up a substantial portion of the tracking task. This empirical result supports the basic assumption that tracking behavior is comprised of a series of discrete movements.

Figure 3 gives an example of running a linear regression on one session's tracking movement data. The distance reduced by each pursuit movement was rounded to its nearest integer, and movements that reduced the same amount of tracking error were collapsed into a single data point. The duration of the movement is plotted as a function of the index of difficulty, ($\log_2$ (*Tracking Error*/20 + 0.5)). As can be seen,

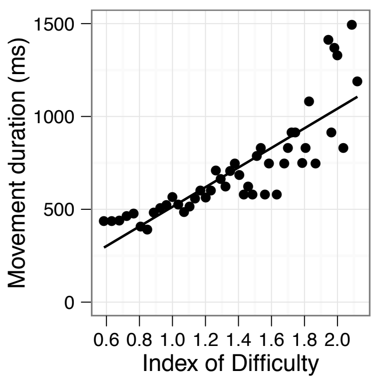

Figure 3. Durations of discrete movements as a function of the movements' index of difficulty for one session, and the best-fitting linear regression with an R2 of 0.68. The solid line is the regression line over the data points.

although the movement time and distance varied largely, the data points still lie roughly along the regression line. This suggests that the extracted movements can be approximated by Welford's equation.

Figure 4 shows the distribution of R^2 that resulted from fitting Welford's equation to the movement data of each of the 40 participant-sessions. The R^2 ranged from 0.19 to 0.69, but the majority fell between 0.4 and 0.6, with an average of 0.48. That is, on average, about half of the variance in the movement data can be explained by Welford's equation. Considering that the movement data itself has a large variability (as seen in Figure 3), that a two-parameter Fitts' law equation could account for about half of the variability suggests that these discrete movements adhere to Fitts' law.

Besides the Fitts' law model, a linear equation, $MT = a + b \times$ Tracking Error, was also fitted to the movement data, which resulted in R^2 similar to those of the Fitts' law model. The R^2 of the linear model ranged from 0.18 to 0.75, with an average of 0.48. The linear model probably achieved results similar to the Fitts' law model because the movements were small, typically between 10 pixels (the lower limit of our measurement) and 70 pixels. Within this range, the index of difficulty, $\log_2(\textit{Tracking Error}/20 + 0.5)$, is almost a linear function of the tracking error. However, because Fitts' law is used extensively in modeling manual movements, we chose to

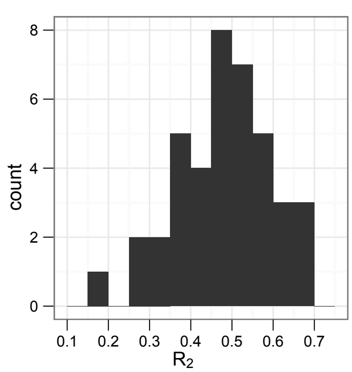

Figure 4. Distribution of R2 resulted from fitting Welford's equation to the movement data across 40 sessions. The majority of the R2 is distributed between 0.4 and 0.6.

adopt Fitts' law in the discrete pursuit model.

Tracking parameters and model predictions

Figure 5 shows all the Fitts' law parameter values estimated for the 40 sessions. For each of the ten participants, four sets of parameters were estimated, one for each session. The top panel shows the values of the intercept parameter across participants, and the bottom panel shows the values of

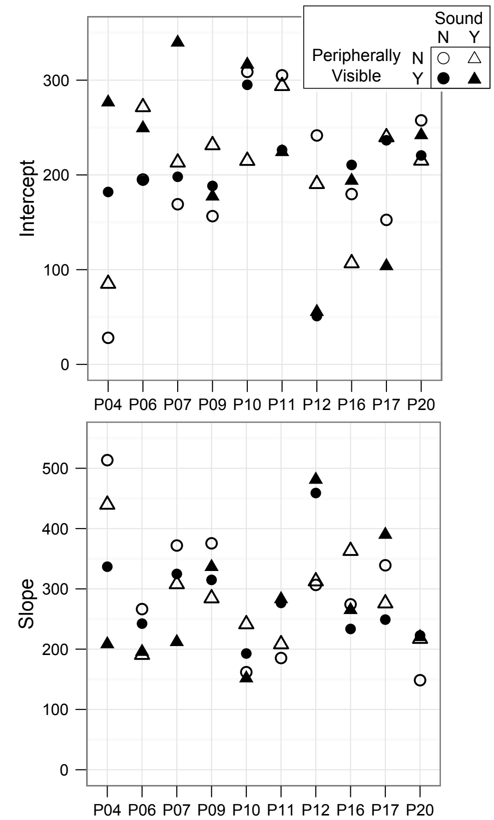

Figure 5. The best-fitting Fitts' law intercept and slope parameters estimated from the movement data across 40 participant-sessions.

the slope parameter. That the majority of the intercept values were between 150 and 250 ms suggests that the minimum tracking time might be the participants' simple reaction time. From the graph, it seems that participants varied their parameters considerably across sessions.

Using the EPIC cognitive architecture and the parameters in Figure 5, models that incorporate the discrete pursuit tracking component were built for the dual-task experiment. The RMS tracking error and the reaction time for the choice-reaction task were calculated for the simulation of each experimental session. The overall average predicted RMS tracking error is 21 pixels, which is very close to the average observed RMS tracking error of 22 pixels. Figure 6 shows the absolute percentage error between the predicted and observed RMS tracking error across participants and sessions. As can be seen, the majority of the predicted RMS tracking error is within 10% range of the observed RMS tracking error, which we accept as a good data fit for predictive modeling. The model also explained the observed data for the other nontracking task in the dual task experiment, suggesting that the proposed parameter estimation procedure can lead to correct tracking parameter values without overfitting the RMS tracking error.

DISCUSSION

The results from the movement data analysis support the basic assumption of the discrete movement model, that tracking behavior can be approximated by a sequence of discrete Fitts' law movements. Clear evidence of the discrete

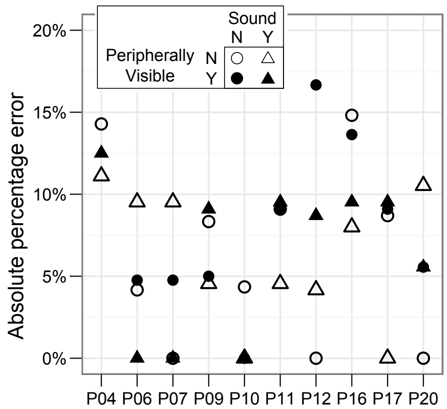

Figure 6. Absolute percentage error of models' RMS tracking error compared to the empirical data across the forty participant-sessions.

movements were found throughout participants' tracking data, such as shown in Figure 1. Each discrete movement represents an uninterrupted reduction of tracking error over a few hundred milliseconds.

The results suggest that overall tracking performance can be accurately modeled using Fitts' law parameters that are estimated based on individual movements. Using the parameters estimated with this procedure, the cognitive models for the dual-task experiment accurately predict the performance of both tasks. By assessing the model's fit to both tasks simultaneously, we have reduced the possibility that the parameters of one task were incorrectly adjusted to compensate the model's fit to the other task.

The data plots and the good fits of the discrete pursuit model support a hypothesis that tracking is comprised of non-ballistic movements whose directions can be altered to follow the movements of the target. Tracking movements extracted from the dual-task experimental data lasted on average about 500 ms, which is much longer than simple reaction time. The long duration of pursuit movements should allow participants to perceive the shifting of the target and to change their manual output to the controller device during a movement.

Implementing the discrete pursuit model within EPIC, as we have done, shows that it is possible to leverage the architecture's existing perceptual, cognitive, and motor modules to simulate the details of human information processing involved in tracking and other tasks. As a result, the model could accurately account for the tracking performance in a dual-task scenario.

Though the discrete pursuit model is validated here with a tracking task with control dynamics of first- and second-order control, it is likely that the model applies to other control dynamics as well. As control theory studies suggest (see Jagacinski & Flach, 2003 for a review), regardless of the actual control dynamics of a device, humans tend to adapt their manual movements to the dynamics of the device to make the response of the system behave as if it were a first-order control. As a result, regardless of the dynamics of the device, it always appears to the human operator that the tracking error drives the velocity of the system response, and larger tracking error leads to increasingly faster human movements. This is in fact in accordance with the discrete pursuit model proposed here because of the logarithmic function for calculating movement duration. Thus, the discrete pursuit model and the control theory seem to, albeit from different perspectives, describe the same phenomenon in tracking, and this phenomenon should not be dramatically affected by the control dynamics of the device.

The discrete pursuit model can potentially be applied to more complex, real-world tracking tasks such as driving. Eye tracking studies of driving (e.g., Land & Lee, 1994) suggest that humans use, as the error signal to guide steering during curve negotiation, the angular difference between (a) the forward line of sight and (b) the line of sight to the tangent point of the upcoming curve. A few models have been proposed to use the error signal to predict the steering angle (Salvucci, 2006) or vehicle lateral velocity (Brumby, Salvucci, & Howes, 2009), but these models are based on the control theory. Perhaps the discrete pursuit model could be used to predict the steering movement time in a dual task setting because, unlike control theory models that assume continuous tracking responses, the discrete movement model offers a straightforward means of interleaving steering with other tasks.

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