Analysis of Performance in Precise 3D Curve Input Tasks in Virtual Reality

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1 Introduction

Predictive models for human performance, such as Fitts' Law [2] and the Steering Law [1], are useful tools for developers of interactive applications because they help guide us toward effective and efficient interface designs. In this poster, we present a mathematical model in this style that is meant to characterize performance in precise, continuous 3D input tasks, such as making an exact tracing of a 3D curve presented in virtual reality (VR).

This continuous, sweeping style of 3D input has important implications for interactive visualizations. We utilize within our group, direct input of curved 3D paths in several visualization contexts, for example, free-form modeling for designing scientific visualizations and creating 3D illustrations [3] and selecting streamlines and regions of interest in interactive 3D fluid flow visualizations. [5] In addition, a current project seeks to utilize haptic-guided input of 3D curved paths for querying 3D datasets and selecting fine detail within dense visualizations of neural fiber tracts in the brain. Increased knowledge of our ability to control precise 3D input is likely lead to improved interaction and more productive user experiences in these interactive visualizations.

One of the challenges in working with this style of input is that it can be difficult to control with precision. In a precursor to this work, we developed two new interaction techniques, a two-handed 3D tape drawing interface and a one-handed 3D drag drawing interface. Each significantly improves the precision of continuous 3D input as compared to standard modes of tracking a moving prop through the air. Full details of these interfaces and of the tracing experiment described briefly below have been presented elsewhere. [4] The novel contribution of the work presented here (and adapted from Daniel Keefe's dissertation [3]) is the derivation of a performance model for this style of input from theory in related disciplines and the verification of this model using experimental data from the tracing experiment.

2 High-Level Model Derivation

Our model draws heavily upon the structure of Accot and Zhai's Steering Law, [1] and we extend it based on theories of anisotropy in control of visually guided motion along 3D axes [7] and the relationship between drawing speed and curvature (the Power Law) described within the neuroscience literature. [6]

The Steering Law describes the time taken to steer (by drawing) through a "tunnel" constraint. A practical example is a File menu. The mouse starts at the top and traces a path downward without going outside the boundaries of the menu until it selects the appropriate item. Task completion time T is proportional to an index of difficulty D defined by the length of the tunnel A and its width W:

$$T = a + bD \text{ where } D = \frac{A}{W}. \tag{1}$$

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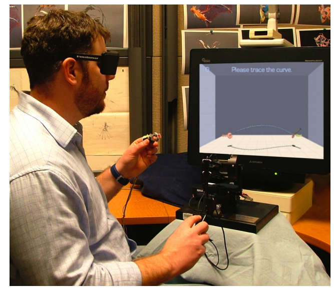

Figure 1: Experimental setup for the 3D tracing experiment.

Several variations on the law are possible, and more general forms can capture tunnels that follow curved paths and have varying widths. The Steering Law also has a local form:

$$v(s) = \frac{W(s)}{\tau} \tag{2}$$

where $v(s)$ is the drawing velocity at a point s along the path of the tunnel, $W(s)$ is the tunnel width at that point, and τ is an empirically determined time constant.

The Steering Law excels at describing input intended to be as fast as possible, but consider an alternative style of input, intended to be as precise as possible. Rather than drawing through a tunnel, consider an exact input task, such as tracing a thin line. In this situation, the width term of the Steering Law approaches zero as users try to be as exact in their input as possible. Since tunnel width is less useful in this situation, we are interested in identifying other factors that may be used to describe the difficulty of this task. We introduce two factors below and then show how they may be used within a refined local index of difficulty.

From literature on perception and studies of interactionwithin VR [7] we know that differences exist in human perception and motion along various axes. Specifically, errors in perception and motor control are largest by far along the depth axis and slightly larger along the vertical axis as compared to the horizontal. These differences suggest that the orientation of the input (the drawing direction) may play a role in the difficulty of the task. This leads us to the first of three revised local indices of difficulty, which we will compare in the next section. The first suggested local index of difficulty is a weighted sum of the components of the local direction of input $d(s)$:

$$D_1(s) = w_y|d_y(s)| + w_z(-d_z(s)). \tag{3}$$

A second factor that may contribute to a local index of difficulty is the local curvature of the input trajectory. This notion is supported by the Power Law within the neuroscience literature. [6] The Power Law describes a relationship between curvature of a drawing trajectory and the drawing speed. It has been shown that in rhythmic drawing and writing movements, the speed of drawing decreases in areas of high curvature according to the following relation:

$$v(s) = \frac{k}{K(s)^{\beta}} \tag{4}$$

where $v(s)$ is the local drawing speed, $K(s)$ is the local curvature, β is a constant, typically close to $1/3$, and k is a empirically determined velocity gain factor. The second suggested local index of difficulty adds this concept to the first:

$$D_2(s) = w_y|d_y(s)| + w_z(-d_z(s)) + w_k K(s)^{\beta}. \tag{5}$$

Finally, we introduce a third, more complete local index of difficulty that includes a cross-product term to account for potential interactions between local curve orientation and curvature.

$$\begin{aligned} D_3(s) =& w_y|d_y(s)| + w_z(-d_z(s)) + w_k K(s)^{\beta} \\ &+ K(s)^{\beta}(w_i|d_y(s)| + w_j(-d_z(s))). \end{aligned} \tag{6}$$

Since each model builds on the previous, we hypothesize that, of the three, model D_3 will be most closely correlated with experimental measures of task difficulty. In the next section we report on analysis designed to test this hypothesis and verify that each term in the model is significant.

3 Verification of the Model

In order to verify and compare the three models put forth for a local index of difficulty, we examine data from a 3D tracing experiment. [4] We briefly review the experimental design and measured data below before reporting on the correlations of the models with this data.

3D Tracing Experiment: The experimental setup for the 3D tracing experiment is shown in Figure 1. Twelve participants used a desktop-scale, stereoscopic, head-tracked VR environment to complete the study. A Phantom force-feedback device was used to input 3D trajectories. Four alternative interfaces for continuous 3D input were compared: 1. a novel, haptic-aided, two-handed, 3D tape drawing interface (*tape*), 2. a novel, one-handed version called drag drawing (*drag*), 3. a standard freehand 3D input technique (*free*), and 4. a haptic-aided freehand technique, called *sand* because a friction effect makes the stylus feel as though it is being moved through loose sand. Results in Figures 2 and 3 are categorized by these interfaces.

Each participant performed 100 trials consisting of tracing a randomly selected 3D curve presented in VR using one of the input techniques. Three measures of performance were recorded: drawing time, positional error, and directional error. Due to space limitations, in this abstract, we will present results from just local directional error, which is calculated as the mean angle between the tangents of the prompt curve and the curve drawn by the user over corresponding local samples of the tracing data.

Statistical Analysis: Figure 2 shows a scatter plot of samples from the experimental data. For each sample point a local index of difficulty is calculated according to the D_3 model and this is plotted against the measured local directional error averaged across subjects. We see a strong linear trend, indicating that there is a high correlation between the index of difficulty and the experimental data. Similar trends are seen for the other measures of task difficulty, positional error and drawing time.

Figure 3 compares the quality of the three models proposed above. The adjusted R^2 value is a measure of the amount of variance in the data explained by the model, corrected to account for differences in the number of degrees of freedom in each model. The staircase pattern in the graph suggests that we may confirm our hypothesis. Each successive model does improve upon the previous. Again, similar trends can be seen for the other measures not reported here.

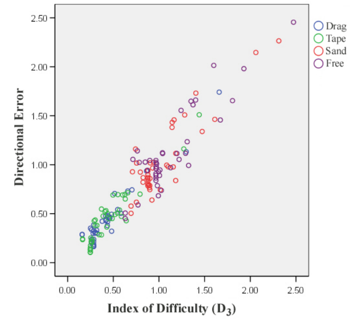

Figure 2: Experimental data describing local measured directional error are plotted against the local index of difficulty, D_3.

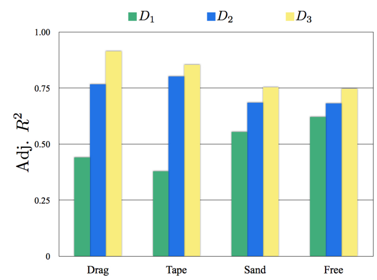

Figure 3: Comparison of model fit for directional error data adjusted for number of degrees of freedom in each model. Differences between models are significant. (Hierarchical multiple regression, F-Test on R-square change, $p < .05$.)

4 Conclusions and Future Work

Based on this analysis, we learn that both local direction and curvature of the input trajectory are important factors in quantifying and predicting the difficulty of precise 3D curve input. Additional analysis reveals that the relative importance of these two factors changes depending on the particular input technique used. Thus, we believe this expansion of the Steering Law model holds promise both as a tool for guiding design decisions in interactive applications and providing a framework for interface comparison. We are currently expanding this work by investigating global models formed by integrating the local formulations presented here along entire 3D curves.

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