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Effects of Preview Time on Human Control Behavior in Rate Tracking Tasks

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Abstract: In many practical control tasks, human controllers (HC) can preview the trajectory they must follow in the near future. This paper investigates the effects of the length of previewed target trajectory, or preview time, on HC behavior in rate tracking tasks. To do so, a human-in-the-loop experiment was performed, consisting of a combined target-tracking and disturbance-rejection task. Between conditions the preview time was varied between 0, 0.1, 0.25 0.5 0.75 or 1 s, capturing the complete human control-behavioral adaptation from zero- to full-preview tasks, where the performance remains constant. The measurements were analyzed by fitting a HC model for preview tracking tasks to the data. Results show that optimal performance is attained when the displayed preview time is higher than 0.5 s. When the preview time increases, subjects exhibit more phase lead in their target response dynamics. They respond to a single point on the target ahead when the preview time is below 0.5 s and generally to two different points when more preview is displayed. As the model tightly fits to the measurement data, its validity is extended to different preview times.

Keywords: Manual Control, Target Tracking, Preview, Parameter Estimation, Human Factors

1. INTRODUCTION

Much research has been conducted to increase our understanding of human manual control behavior since the 1960's. Despite great advancements for simple tasks, especially compensatory tracking (McRuer et al., 1965), the mechanisms underlying manual control behavior in more complex tasks with preview are still relatively unclear. Examples of such tasks include car driving, where the road ahead is visible through the windshield (Kondo and Ajimine, 1968), and flying an aircraft through a displayed tunnel-in-the-sky (Mulder and Mulder, 2005). In these tasks, a human controller (HC) can see and anticipate the future trajectory to follow, allowing for a more advanced control strategy that involves both feedforward and feedback (Sheridan, 1966; Ito and Ito, 1975; Van der El et al., 2015). Recently, Van der El et al. (2015) derived a new HC model for preview tracking with a physical foundation, enabling a more in-depth analysis on how humans exactly use preview information for control.

The effect of the previewed target trajectory's length (referred to as the preview time) on HC behavior has been abundantly studied (Reid and Drewell, 1972; Tomizuka and Whitney, 1973; Poulton, 1974; Ito and Ito, 1975; Van Lunteren, 1979). These authors report that HCs are able to track the target much better, and that the optimal performance in rate tracking tasks is already achieved with 0.5 s preview. The effect of additional preview beyond this so-called *critical preview time* is small, and tracking performance does not improve any further. However, using their new model, Van der El et al. (2015) found that HCs respond to a point on the target well *beyond* this critical preview time, in rate tracking tasks with 1 s of preview. It is unclear why HCs respond to the target further ahead when a similar performance is obtained with lower preview times.

The goal of this paper is to systematically analyze the effect of the displayed preview time on HC behavior in rate tracking tasks. To do so, we performed a human-in-the-loop experiment with integrator controlled element (CE) dynamics. Six conditions were tested, presenting 0, 0.1, 0.25, 0.5, 0.75 and 1 s of previewed target on the display, to capture the full human control-behavioral transition between situations without any preview to preview well beyond the reported critical preview time. First, the results are used to confirm previous findings that tracking performance improves with higher preview times. Then, the model from (Van der El et al., 2015) is fitted to the data to obtain the HC dynamics, including estimates of the points on the target responded to. These allow us to better explain how subjects use preview information. Finally, the Variance Accounted For (VAF) is calculated to confirm the model's validity in tasks with different preview times.

This paper is structured as follows. First, the new HC model for preview tracking is explained in Section 2, and an introduction to preview tracking is given. The parameter estimation method, used for fitting the model to the data, is explained in Section 3. Details of the experiment and its outcomes are presented in Sections 4 and 5. Finally, a discussion and our conclusions are presented in Sections 6 and 7.

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2. BACKGROUND

2.1 Manual Preview Tracking

The preview display used for the considered preview tracking task is shown in Fig. 1. The amount of preview information of the target signal $f_t([t, t+\tau_p])$ that is visible ahead is characterized by the preview time τ_p. When τ_p equals zero, only the *current* target $f_t(t)$ is visible and the display reduces to what is referred to as a pursuit display (Wasicko et al., 1966).

The HC's task is to give control inputs $u(t)$ that drive the CE output $x(t)$ as close as possible to the current value of the target signal. In other words, subjects are to reduce tracking error, defined by $e(t) = f_t(t) - x(t)$. Only the lateral displacement of the CE is controlled; the previewed target signal moves down over the screen, so the current target also moves laterally. The CE (with dynamics $H_{ce}(j\omega)$) is additionally perturbed by a disturbance $f_d(t)$. Fig. 2 shows a schematic overview of the task.

2.2 Human Controller Model for Preview Tracking

Van der El et al. (2015) showed that HCs in preview tracking tasks can be modeled using a quasi-linear framework. This means that most of the HC's output is *linearly* related to the inputs. The remaining non-linearities and noise elements are modeled as filtered white noise (referred to as the remnant $n(t)$) added to the linear control output. The complete model is shown in Fig. 3.

The model's inner loop is similar to McRuer's simplified precision model for compensatory tracking task (McRuer et al., 1965). As such, the HC's structural adaptation to the CE dynamics is captured by $H_{o_{e^\star}}(j\omega)$, the *internal* error response, which is a pure gain $K_{e^\star}$ for an integrator CE:

$$H_{o_{e^\star}}(j\omega) = K_{e^\star}. \tag{1}$$

The inner loop further incorporates the human's physical limitations: τ_v represents the HC visual response time delay and H_{nms} the neuromuscular system dynamics. The latter are modeled as:

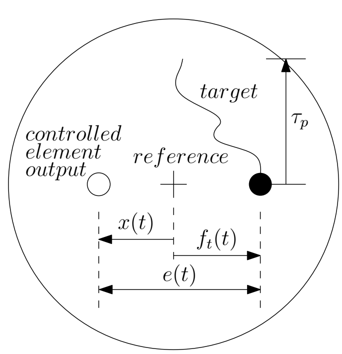

Fig. 1. Preview display.

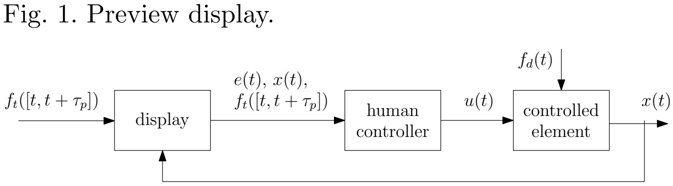

Fig. 2. Control task layout.

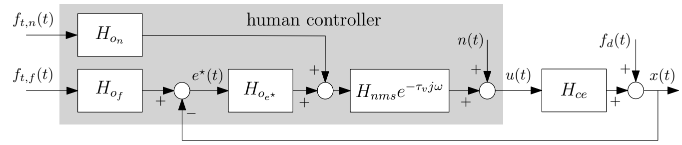

Fig. 3. Human controller model for preview tracking.

$$H_{nms}(j\omega) = \frac{\omega_{nms}^2}{(j\omega)^2 + 2\zeta_{nms}\omega_{nms}j\omega + \omega_{nms}^2}, \tag{2}$$

with natural frequency ω_{nms} and damping ratio ζ_{nms}.

For preview tracking tasks, the simplified precision model is extended with two responses with respect to different points on the previewed target. This near- and far-point ($f_{t,n}(t)$ and $f_{t,f}(t)$) are located τ_n and τ_f s ahead:

$$f_{t,n}(t) = f_t(t+\tau_n), \qquad f_{t,f}(t) = f_t(t+\tau_f). \tag{3}$$

By responding to the target ahead, HCs effectively introduce *negative* delays into the system, hence corresponding *phase lead*. This can be beneficial when used to compensate for their own response lags and the CE's inherent lag.

The far point is used to track to the slow changes (low frequencies) of the target signal. Its filtering dynamics $H_{o_f}(j\omega)$ thus has low-pass characteristics:

$$H_{o_f}(j\omega) = K_f \frac{1}{T_{l,f}j\omega + 1}, \tag{4}$$

with K_f and $T_{l,f}$ the far-point gain and lag time-constant, respectively. From the resulting filtered target signal HCs calculate the internal error $e^\star$, which in the frequency domain is given by

$$E^\star = H_{o_f}(j\omega)F_{t,f(j\omega)} - X(j\omega). \tag{5}$$

The capitals indicate the Fourier transforms of the respective signals.

The parallel near-point response $H_{o_n}(j\omega)$ was originally modeled as a high-pass filter. However, its estimated lag time-constant generally indicated a break frequency around 10 rad/s for tasks with integrator CE dynamics, which is in the region where the neuromuscular system dynamics also become dominant. Therefore, we omit the lag filter here, resulting in the following near-point response:

$$H_{o_n}(j\omega) = K_n j\omega, \tag{6}$$

with K_n the near-point gain.

Van der El et al. (2015) further showed that the model can be rewritten into an equivalent two-channel structure (see Fig. 4), which is more convenient for analytical analysis. The target and CE output response dynamics in this model, $H_{o_t}(j\omega)$ and $H_{o_x}(j\omega)$, are given by:

$$\begin{aligned} H_{o_t}(j\omega) = [&H_{o_f}(j\omega)H_{o_{e^\star}}(j\omega)e^{\tau_f j\omega} \\ &+ H_{o_n}(j\omega)e^{\tau_n j\omega}]H_{nms}(j\omega)e^{-\tau_v j\omega}, \end{aligned} \tag{7}$$

$$H_{o_x}(j\omega) = H_{o_{e^\star}}(j\omega)H_{nms}(j\omega)e^{-\tau_v j\omega}. \tag{8}$$

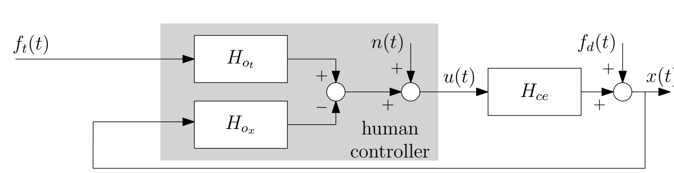

Fig. 4. Simplified control diagram of the preview model.