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Assessing Human Feedback Parameters for Disturbance-Rejection

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Abstract: Electromyography (EMG) interfaces are a promising alternative to traditional manual interfaces such as joysticks, mice, and touchscreens for applications such as prosthetics, rehabilitation, and human-computer interaction. McRuer's crossover model has been extensively studied to determine the impacts of dynamical systems on humans using manual interfaces; however, the same analysis has not been conducted with EMG interfaces or more complex dynamical systems. In this paper, we establish and assess changes in human parameters (gain and delay) and bandwidth for manual (joystick) and EMG interfaces when humans are tasked with controlling a first- and second-order dynamical system. We performed a secondary data analysis to estimate the human parameters for 11 participants by performing least-squares fitting on the error between empirical estimates (calculated from measured signals and system dynamics at specific frequencies) and parameterized models (developed from the McRuer's gain-margin crossover model). EMG delay was smaller than the manual delay for the first-order system and EMG delay was smaller with the first-order system than the second-order system. EMG bandwidth was also larger than the manual bandwidth for both first- and second-order systems. These results suggest that using an EMG interface improves the user's reaction time in a first-order system, and the EMG interface increases the bandwidth that the user can control for both first- and second-order systems compared to a manual interface. Understanding the differences in delays and bandwidth based on interfaces and system dynamics is useful for designing multimodal interfaces or for complex systems where the human delay or bandwidth is important.

Keywords: electromyography, delay estimation, human-machine interface, sensorimotor control.

1. INTRODUCTION

Electromyography (EMG) interfaces translate noninvasively measured electrical activity from muscles to signals that can be used for controlling machines and devices. Such interfaces are a promising alternative to traditional manual interfaces like joysticks, mice, and touchscreens in application areas like prosthetics (Zabre-Gonzalez et al., 2021; Zhuang et al., 2019), rehabilitation (Lobo-Prat et al., 2014; Ghassemi et al., 2019), and human-computer interfaces (Lu et al., 2014). EMG interfaces may enhance response speed to stimuli because EMG activity precedes movement and can be used to predict movement (Tabie and Kirchner, 2013; Wöhrle et al., 2017). As EMG interfaces become more ubiquitous for controlling machines and devices, it is important to establish models to quantify the benefits and drawbacks of EMG interfaces.

One interface model that has been particularly well-studied for continuous sinusoidal reference-tracking and disturbance-rejection tasks is McRuer's gain-margin crossover model (McRuer and Jex, 1967). In recent years, this model has been used to quantify the effects of different dynamical systems on human-machine interface performance (Zhang et al., 2020), quantify human behavior during predictable and unpredictable trajectory-tracking tasks (Yu et al., 2014), and identify differences in human delay between unimpaired participants and people with cerebellar ataxia (Zimmet et al., 2020). However, this model has primarily been used to quantify the effects of novel dynamical systems on manual interfaces like joysticks or sliders, and little is known about how the parameters of the gain-margin crossover model are affected by alternative interfaces like EMG interfaces.

A few studies have leveraged the gain-crossover model to compare EMG and manual interface performance. Yamagami et al. (2020) compared the effects of EMG and manual interfaces on feedforward model formulation, and found that humans have improved feedforward model formulation closer to the inversion of the controlled dynamical system when using an EMG interface to control a second-order system. However, they did not compare how human parameters (gain and delay) are affected by interface type and dynamical system. Corbett et al. (2011) and Lobo-Prat et al. (2014) compared EMG and manual interface performance when people are tasked with controlling a first-order dynamical system. Lobo-Prat et al. (2014) found that the EMG interfaces reduce tracking error, improve crossover frequency (i.e., increase control

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bandwidth), and have lower human delay compared to manual interfaces. However, they did not assess whether such performance improvements persist when humans are tasked with controlling more complex dynamical systems, such as second-order systems.

In this paper, we 1) established human *gain* and *delay* parameters for *manual* and *EMG* interfaces when humans are tasked with controlling a *first-* and *second-order* dynamical system and 2) assessed changes in human delay and crossover frequency between interfaces and dynamical systems. We hypothesized that regardless of dynamical system order, users will have a lower delay when using the EMG interface compared to the manual interface. The findings of this study may benefit future developments of human-machine systems that involve complex dynamics, such as teleoperating surgical robots or shared driving an intelligent vehicle, where understanding human delays is essential to optimizing human-machine interaction. In addition, the findings may suggest potential benefits of using one interface or another when different task dynamics are given. This will be particularly useful for interfaces that have both modalities (manual and EMG), where modalities can be switched to effectively conduct specific tasks.

2. METHODS

This study is a secondary data analysis of a larger study comparing the performance of a manual and an EMG interface as participants completed a trajectory-tracking and disturbance-rejection task (Yamagami et al., 2020). The goal of this secondary analysis is to establish human gain and delay parameters for manual and EMG interfaces as humans control a first- and second-order dynamical system and to quantify the effects of interface and controlled dynamical system on human delays.

2.1 Task Summary

Briefly summarizing the task from Yamagami et al. (2020), 11 participants used either a manual or EMG interface to track references and reject disturbances (Fig. 1). The trajectory of the path they followed was determined from a pseudo-random sum-of-sines, with eight stimulated frequencies below 1 Hz, $F = \{0.10, 0.15, 0.25, 0.35, 0.55, 0.65, 0.85, 0.95\}$ Hz. We define the stimulated frequencies in radians as $\Omega = \{2\pi f, f \in F\}$. For the manual interface, the users manipulated a one-degree-of-freedom slider with a 10 cm extent to control the cursor on the screen. For the EMG interface, the users activated their biceps and triceps to control the cursor on the screen. We used the Delsys Trigno EMG System (Delsys Inc. Massachusetts, USA) to collect EMG activity from participants' biceps and triceps.

Each trial lasted for 45 seconds, and each participant completed 30 trials for the two interfaces (manual or EMG; I_m, I_e respectively) and dynamical systems (first- or second-order; $\widehat{M}_{fo}(s) = \frac{1}{s}$, $\widehat{M}_{so}(s) = \frac{1}{s(s+1)}, s = j\omega, \omega \in \Omega$ respectively). Each of the four conditions were shown to the participants in a randomized order. User input from either the muscle or manual device $u(t)$, the reference $r(t)$ and disturbance $d(t)$ trajectories, and output cursor position $y(t)$ were recorded at 60 Hz during each trial.

Fig. 1. Participants controlled a purple cursor on a computer screen using either a manual slider (left) or muscle EMG (right) interface. Adapted from Yamagami et al. (2020).

All analyses were conducted on frequency-domain signal $\widehat{x}(\omega)$ and transformations $\widehat{T}(\omega)$ at stimulated frequencies, where $\omega \in \Omega$. The signal $\widehat{x}(\omega)$ was obtained by taking the Fast-Fourier Transform of the time-domain signal $x(t)$ over the last 40 seconds of each trial. For the purposes of this secondary analysis, we solely included performance data for the disturbance-rejection task as we were primarily interested in quantifying the differences in human delay between the EMG and manual interfaces. We disregarded the data from the reference-tracking task to avoid the effect of the human feedforward controller on the system, which we previously investigated (Yamagami et al., 2020).

2.2 Human-Machine Interface Model

To obtain a data-driven model of the manual and the EMG interfaces and to assess our hypothesis that participants have lower human delay with the EMG interface than the manual interface, we adapted the McRuer's gain-margin crossover model (McRuer and Jex, 1967) (Fig. 2). The model assumes that the human can be modeled with a gain k and a delay τ. A more detailed derivation can be found in Yamagami et al. (2021), but briefly, we estimated the human controller from data by assuming that the human was a *linear time-invariant system* (Åström and Murray, 2010, Ch. 3, pg. 4) and applying *block diagram algebra* (Åström and Murray, 2010, Sec. 2.2) to obtain the user input at the stimulated frequencies:

$$\widehat{u}(\omega) = \underbrace{\frac{-\widehat{M}(\omega)\widehat{H}(\omega)}{1 + \widehat{M}(\omega)\widehat{H}(\omega)}}_{\widehat{T}_{ud}(\omega)} \widehat{d}(\omega), \quad \omega \in \Omega. \tag{1}$$

where $\widehat{H}(\omega)$ is the human controller, $\widehat{M}(\omega)$ is a first- or second-order dynamical system that the person is tasked with controlling, and $\widehat{T}_{ud}(\omega)$ is the transformation between input and disturbance. We can then rearrange (1) to obtain empirical estimates of the human controller $\widehat{H}(\omega)$ from measured and prescribed signals $\widehat{u}(\omega)$, $\widehat{d}(\omega)$, $\widehat{M}(\omega)$ at the stimulated frequencies:

$$\widehat{H}(\omega) = -\widehat{M}^{-1}(\omega)\frac{\widehat{T}_{ud}(\omega)}{1 + \widehat{T}_{ud}(\omega)}, \quad \omega \in \Omega. \tag{2}$$

We can then compare these empirical estimates against the human controller models suggested by McRuer and Jex (1967) for first-order (fo) and second-order (so) systems:

$$\widehat{H}_{fo}(\omega) \approx k_{fo} e^{-j\omega\tau_{fo}}, \tag{3a}$$

$$\widehat{H}_{so}(\omega) \approx k_{so}(j\omega + 1) e^{-j\omega\tau_{so}}. \tag{3b}$$

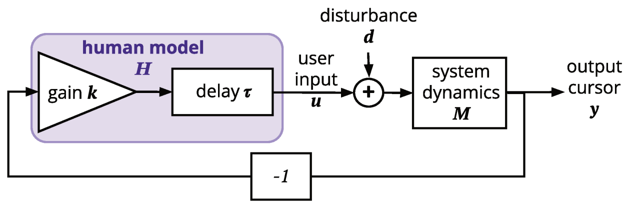

Fig. 2. Block diagram of the human-machine interface. The human, within the solid purple square, transforms the cursor output y with a scaled delay to produce the human input u. The system transform the sum of human input u and the external disturbance d to the output y via system dynamics M.

2.3 Parameter Estimation

One of our goals is to establish population ranges for human gain $k_{I,M}$ and delay $\tau_{I,M}$ parameters for manual and EMG interfaces $I \in \{m, e\}$ when humans are tasked with controlling first- and second-order dynamical systems $M \in \{fo, so\}$. Following the analysis outlined in Zimmet et al. (2020), we obtained the population parameter estimates for the first- and second-order gains for the manual interface $(k_{m,fo}, k_{m,so})$ and the EMG interface $(k_{e,fo}, k_{e,so})$. We also calculated the delays for the manual interface $(\tau_{m,fo}, \tau_{m,so})$ and the EMG interface $(\tau_{e,fo}, \tau_{e,so})$ for both dynamical systems. All population estimates were obtained by computing the parameter estimates for each of the 11 participants, then bootstrapping with replacement to compute a 95% confidence interval for each parameter.

We first obtained the empirical estimates of the human controller $\widehat{H}(\omega)$ for each participant by averaging the computed human controller values (2) across the last six trials, resulting in eight complex numbers for each participant corresponding to the eight stimulated frequencies for both the first- and second-order dynamical systems as well as the two interfaces (EMG and manual). We then computed the best-fit parameter estimates for each participant by performing a least-squares fit on the error between the empirical estimates (2) and parameterized models (3) such that for a given interface $I \in \{e, m\}$, the error for the first- and second-order dynamical systems, respectively, can be quantified as:

$$E_{I,fo}(k_{I,fo}, \tau_{I,fo}) = \sum_{\omega \in \Omega} |\widehat{H}_{I,fo}(\omega) - k_{I,fo} e^{-s\tau_{I,fo}}|^2, \tag{4a}$$

$$E_{I,so}(k_{I,so}, \tau_{I,so}) = \sum_{\omega \in \Omega} |\widehat{H}_{I,so}(\omega) - k_{I,so}(s+1) e^{-s\tau_{I,so}}|^2, \tag{4b}$$

where $s = j\omega$, $\omega \in \Omega$.

The model fitting resulted in gain and delay estimates for the manual and EMG interfaces as well as the first- and second-order systems for each of the 11 participants. We then used bootstrapping to compute the 95% confidence interface for each parameter (Efron and Tibshirani, 1993). We randomly sampled 11 times with replacement from the 11 parameter estimates and calculated the mean. We repeated this process 1000 times and then used the population of means to calculate the 95% confidence interval.

We additionally computed the 95% confidence interval for the crossover frequency [1] by minimizing the difference between the open-loop transfer function magnitude $|\frac{k}{s}|$ and 1 (i.e., minimize $\left| |\frac{k}{2\pi j f}| - 1 \right|, f \in F$ with respect to f) using the previously computed 95% confidence interval for the gain for each interface and system dynamics.

2.4 Statistical Analysis

To test the effects of interface and dynamical system order on the human delay, gain, and crossover frequency, we performed an independent sample t-test on the computed confidence intervals with $\alpha = 0.05$ (Yuen, 1974).

3. RESULTS

3.1 Parameter Estimates Approximate Experimental Data

The computed human gain and delay parameters (Table 1) approximately fit the empirical open-loop transfer function $\widehat{H}(\omega)\widehat{M}(\omega)$ across interfaces and dynamical system orders (Fig. 3). The computed parameters fit the phase of the empirical data better at higher frequencies than lower frequencies, but we saw no frequency dependence for the fit of the gain of the empirical data.

Table 1. Manual and EMG gains and delays for first- and second-order dynamical systems (mean ± standard deviation).

	first-order fo	second-order so
manual gain k_m	2.42 ± 0.57	2.75 ± 2.06
EMG gain k_e	3.22 ± 0.90	4.34 ± 2.31
manual delay τ_m (ms)	314 ± 44.8	321 ± 148.8
EMG delay τ_e (ms)	204 ± 107.3	320 ± 63.8

3.2 Interface and System Dynamics Affect Human Delay, Gain, and Crossover Frequency

Comparing the human delay between the manual and EMG interface, we found that the EMG interface decreases human delay when humans control a first-order dynamical system ($p < 0.01$) but not a second-order dynamical system ($p = 0.99$) (Fig. 4). This result led us to accept our hypothesis that the EMG interface has a lower delay than the manual interface for the first-order system but reject our hypothesis for the second-order system. Comparing the human delay between the first-order and second-order dynamical systems, we found that the EMG interface delay was higher with the second-order dynamical system than with the first-order ($p < 0.01$). We did not find a significant difference in human delay for the manual interface between the first- and second-order dynamical systems ($p = 0.89$).

We additionally compared the human gain between manual and EMG interfaces, and found that the human gain was significantly higher with the EMG interface than the manual interface for the first-order dynamical system ($p = 0.02$) (Fig. 5). There was no significant difference in human gain between the dynamical system order for either

[1] frequency at which the open-loop transfer function magnitude is below 1, $|\widehat{L}| = |\frac{k}{s} e^{-s\tau}| < 1, s = j\omega$ (McRuer and Jex, 1967)

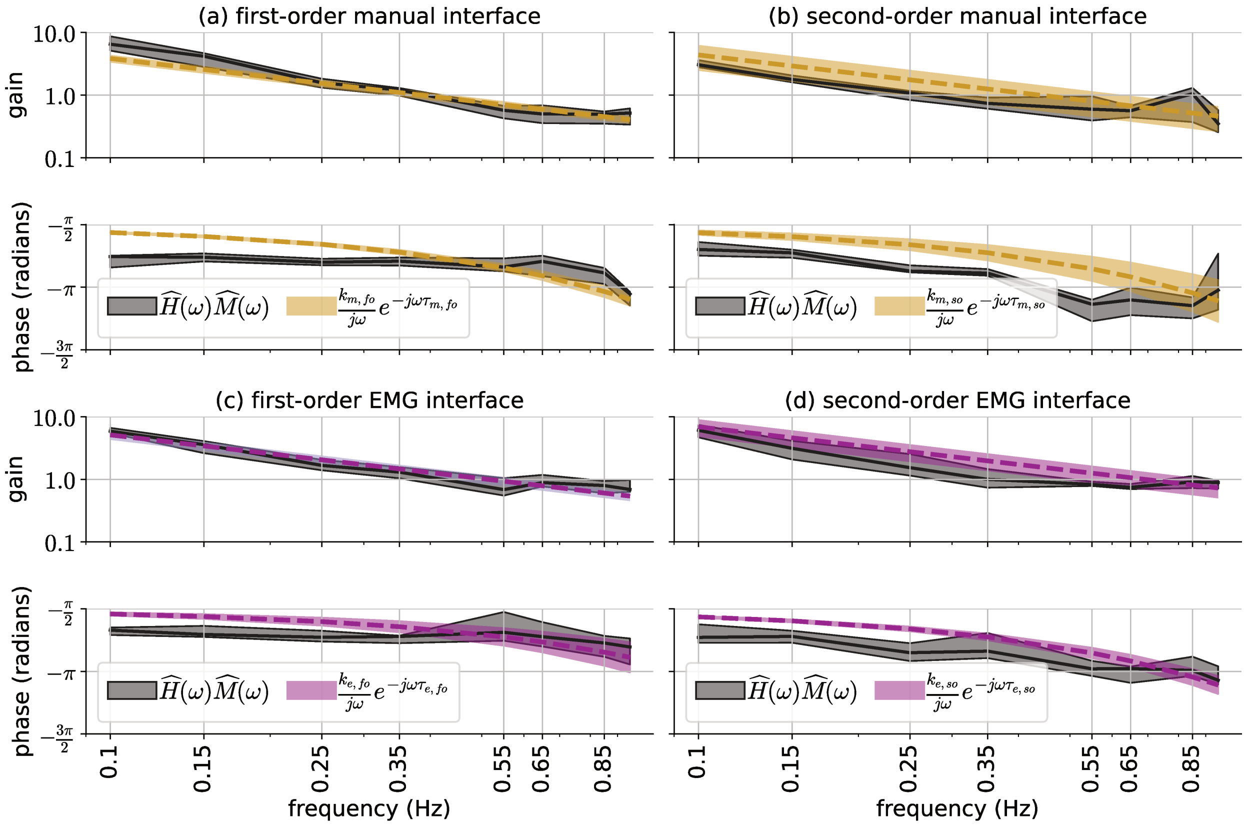

Fig. 3. Bode plots of the open-loop transfer function $\widehat{H}(\omega)\widehat{M}(\omega)$ for (a) first-order manual; (b) second-order manual; (c) first-order EMG; and (d) second-order EMG interfaces. The gold (manual) or purple (EMG) represent distributions of the open-loop transfer functions computed from 95% confidence interval parameter estimates k, τ. The gray represents the empirical estimates from data averages (median, interquartile, $N = 11$ participants).

interface ($p > 0.05$) or between manual and EMG interfaces for the second-order dynamical system ($p > 0.05$).

Finally, we compared the crossover frequency between manual and EMG interfaces, and found that the crossover frequency was signficantly higher with the EMG interface than the manual interface for both first- and second-order dynamical systems (Fig. 6, $p = 0.022$, $p = 0.045$, respectively). Further, we found that the crossover frequency of the second-order EMG interface was significantly higher than the crossover frequency of the first-order EMG interface ($p < 0.01$), but that there was no difference between the first- and second-order crossover frequencies with the manual interface.

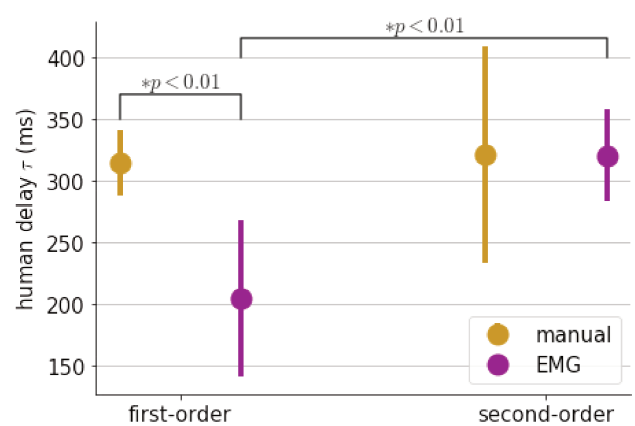

Fig. 4. The 95% confidence intervals for first- and second-order delay (τ) estimates for manual (gold) and EMG (purple) interfaces. Lower values represent a faster response time. Statistically significant differences are marked with their respective p values.

4. DISCUSSION

In this paper, we established human gain and delay parameters when humans are tasked with controlling first- and second-order systems with a manual or EMG interface. We found that our parameter estimates are a good fit for the magnitude of the empirical data and the phase at higher frequencies. We additionally demonstrated that humans have a lower delay with the EMG interface than the manual interface when tasked with controlling a first-order dynamical system, but have comparable delays when controlling a second-order system. Regardless of which dynamical system the human is controlling, crossover frequency, or bandwidth, was higher with the EMG interface than the manual interface.

Our study demonstrated that the order of the dynamical system that the human is tasked with controlling affects the human delay, but not the human gain parameter when using an EMG interface. Consistent with prior

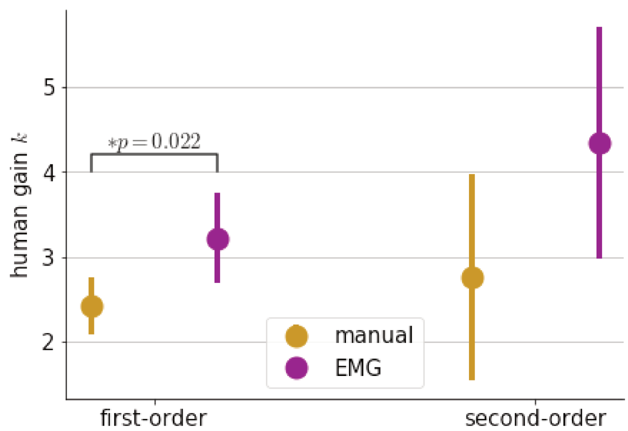

Fig. 5. The 95% confidence intervals for first- and second-order gain (k) estimates for manual (gold) and EMG (purple) interfaces. Lower values represent a smaller scaling factor. Statistically significant differences are marked with their respective p values.

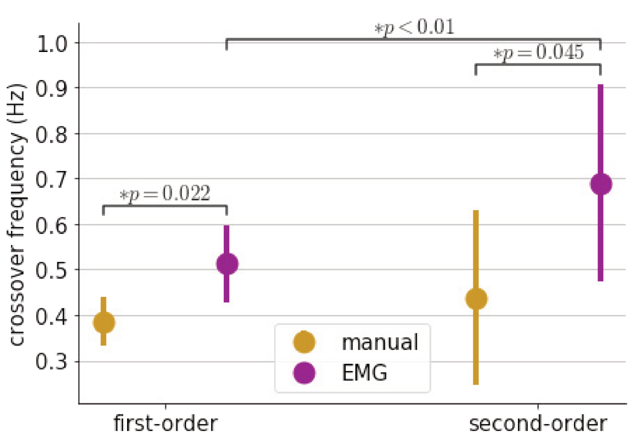

Fig. 6. The 95% confidence intervals for first- and second-order crossover frequency estimates for manual (gold) and EMG (purple) interfaces. Lower values represent a lower control bandwidth. Statistically significant differences are marked with their respective p values.

results from Lobo-Prat et al. (2014), we found that the human delay using an EMG interface was significantly lower for the first-order system compared to the manual interface. However, this trend did not hold when people were tasked with controlling a second-order dynamical system. Human delay when using an EMG interface was significantly higher when people controlled the second-order system compared to the first-order system, and the delays were comparable between the manual and EMG interface with the second-order dynamical system task. This was somewhat surprising to us because EMG is considered to be a measurement of force, and therefore directly proportional to acceleration and potentially makes controlling a second-order dynamical system easier for humans (De Luca, 1997). Further research is needed to elucidate the mechanisms behind how the human delay is affected by the dynamical system that the person is controlling.

Our results also suggest that using an EMG interface enables the user to respond more quickly to faster or higher-frequency stimuli due to the higher crossover frequency of the EMG interface compared to the manual interface. This is consistent with prior results from Lobo-Prat et al. (2014), where they demonstrated that an EMG interface has a higher crossover frequency compared to a manual interface for a first-order dynamical system. We further extended this result to a second-order dynamical system where we found that humans had a higher crossover frequency with the EMG interface compared to the manual interface, and that using an EMG interface to control a second-order system resulted in a larger crossover frequency than when controlling a first-order system. The larger crossover frequency enables the user to better perform disturbance-rejection tasks at higher frequencies, which suggests that tasks that require control at higher-frequencies (i.e., more rapid movements) may benefit from using an EMG interface over a manual interface.

Our results suggest new approaches to designing human-machine interfaces. For first-order systems, using either a combination of EMG and manual interfaces or only EMG interfaces may enhance performance by decreasing the human response time and increasing control bandwidth. This could be particularly useful when controlling systems that require a high amount of responsiveness and accuracy, such as prostheses (Scott, 1984). For second-order systems, the comparable human parameters between EMG and manual interfaces suggest that we can likely use the two interfaces interchangeably or combined, potentially improving human-machine interface performance (Rizzoglio et al., 2020). If we want to combine the two interfaces when designing a multimodal interface, we can possibly combine them directly because there are no differences in delays or gains. For either system order, systems that require the human to control a higher range of frequencies might be better controlled with an EMG interface than a manual interface.

For future work, examining different dynamics such as fourth-order systems (Zhang et al., 2017) or non-minimum phase systems (Zhang et al., 2020) and their effects when humans interact with different interfaces might provide additional insight as to how human model parameters are affected by dynamical system order and interface type (Yamagami et al., 2020). Our results that the dynamical system order affects human delay for EMG interfaces but not for manual interfaces suggests that there may be an interaction between the interface type and system dynamics that should be further investigated.

5. CONCLUSION

In this study, we modeled the humans as gains and delays in a human-machine system where participants used a manual or an EMG interface to control different system dynamics. We demonstrated that our human model with the estimated parameters (gains and delays) was a good approximation to the empirical data. We further investigated the estimated human delays between interfaces (EMG and manual) and dynamical systems (first- and second-order). Our results showed that the EMG interface significantly improved response time given the first-order task, while the two interfaces had similar response times given a second-order task. We additionally showed that the EMG interface had higher control bandwidth than the manual interface for both first- and second-order systems. These findings have implications for designing future human-machine interfaces for different system dynamics. However, further investigation is still needed to explain the mechanisms of how system dynamics and interface types influence the parameters of the human model.

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