Assessment of Maximum Unnoticeable Added Lag-Lead or Lead-Lag Dynamics with a Cybernetic Approach

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This paper investigates the human controllers’ sensitivity to added first-order lag-lead and lead-lag dynamics in the controlled system dynamics using a cybernetic approach and a dedicated human-in-the-loop experiment. The extent to which human controllers will adapt their control dynamics to these added dynamics is objectively determined and explicitly compared to Maximum Unnoticeable Added Dynamics (MUAD) envelopes from literature. Human control adaptation to added lag-lead and lead-lag dynamics is predicted for a wide range of lead and lag time-constants using offline human control model simulations, while a smaller subset of eight added dynamics settings, supplemented with a baseline condition, is tested in the experiment. Both the simulation predictions and experiment data show that human controllers will significantly adapt their control gains and lead time-constants to added lag-lead or lead-lag dynamics. Overall stronger adaptation is observed with added lag (i.e., high added dynamics lag time constants), which requires human controllers to generate more compensating lead equalization and results in degraded task performance. Collected subjective rating data also confirmed that added lag-lead dynamics were more noticeable for human controllers than added lead-lag. While overall these findings correspond well with literature, our experiment data shows that even for some conditions with added dynamics that remained within the MUAD boundaries statistically significant changes in human control gain and lead time-constants, compared to the baseline condition, occur.

I. Introduction

The adaptive nature of human manual control behavior to critical task-defining parameters is still of interest for many engineering applications.1–4 For example, the critical factor in many handling qualities investigations is the extent to which, and how, human controllers adapt their control dynamics to those of the controlled vehicle to achieve satisfactory combined system performance. The limits on this adaptation, i.e., determining when changes to controlled vehicle dynamics become noticeable to human controllers, have been studied extensively to validate the approximation of a vehicle’s true dynamics with a Low Order Equivalent System (LOES).5,6 which is often adopted in handling qualities assessments. As the allowable mismatch was found to be frequency-dependent, the “noticeability” limits were specified in the frequency domain and are referred to as Maximum Unnoticeable Added Dynamics (MUAD) envelopes6,7 or Allowable Error (AE) envelopes.8 The original MUAD envelopes were defined by Wood and Hodgkinson in 1980,7 who combined in-flight data from a number of earlier handling qualities investigations, such as the well-known Neal-Smith experiment of 1970.9

The available MUAD and AE envelopes, which were derived from subjective noticeability assessments of a larger number of added dynamics,6–8 consist of (generally asymmetrical) upper- and lower boundaries defined in the frequency domain. All added dynamics (e.g., control systems, delays, etc.) compared to original controlled dynamics that are contained within both boundaries will remain unnoticed by human controllers. Consistent with McRuer et al.’s crossover model theory,1,2 these envelopes are generally narrow in the crossover region that is critical to manual control performance, while they fan out at lower and higher frequencies. This paper is part of a recent research effort to investigate the concept of MUAD using a “cybernetic” approach4 to this problem, that is, to objectively measure
human control behavior adaptations to added dynamics in tracking tasks and characterize the adaptation using human controller modeling techniques. In earlier work, we have mostly focused on evaluating the effects of added dipole dynamics on manual control behavior.

The goal of this paper is to extend recent research into human control adaptation to added (dipole) dynamics, by following the same methodology to assess the effects of added first-order lag-lead and lead-lag dynamics. For this, human controllers’ adaptation to such added dynamics is both predicted using offline simulations and measured in a dedicated human-in-the-loop experiment, performed in the fixed-base simulator setup of TU Delft’s Human-Machine Interaction Laboratory (HMILab). Both the simulations and experiment are centered on a compensatory pitch tracking task, where a LOES representative for high-bandwidth conventional aircraft pitch dynamics is controlled, with different variations of added lag-lead and lead-lag dynamics. Data analysis is focused on objective measurement of human control adaptation using human controller modeling techniques (i.e., a “cybernetic” approach), yet in the experiment also subjective noticeability ratings were collected for reference.

This paper is structured as follows. First, Section II provides the details of the considered tracking task, the controlled dynamics, and the human controller model used for the offline model predictions as well as experiment data analysis. Next, Section III presents the two sets of offline simulations performed for quantitative prediction of human controller adaptation to added lag-lead and lead-lag dynamics. Section IV covers the methodology of the human-in-the-loop experiment, including the performed analysis of the experiment data. The collected subjective rating data, human control performance metrics (RMS($e$) and RMS($u$)), and estimated human controller model parameters are presented in Section V and compared across the experiment conditions. The paper ends with a discussion and conclusions.

II. Control Task

II.A. Compensatory Pitch Tracking Task

In this paper, the extent to which human controllers adapt their control behavior to added lead-lag or lag-lead dynamics is studied in a compensatory pitch tracking task matching the earlier human-in-the-loop experiment of Ref. 11. This control task is schematically represented in Figure 1.

As shown in Fig. 1, the human controller controls the pitch angle $\theta$ of the controlled (aircraft) dynamics. The human controller is instructed to ensure that the pitch angle follows the target signal $f_t$ as closely as possible, in order to minimize the Root Mean Square (RMS) of the tracking error signal $e$. In this paper, the controlled dynamics consist of fixed baseline dynamics ($H_{\text{baseline}}(s)$ in Fig. 1), combined with possible added dynamics, $H_{\text{added}}(s)$. This paper focuses on added dynamics that are first order lag-lead or lead-lag filters, for which the lead and lag time-constants will be varied to investigate the effect of $H_{\text{added}}(s)$ on human controllers. The human controller, whose linear control dynamics are given by $H_p(s)$, gives control inputs $u$ with a side-stick. The elevator control input $\delta_e$ to the controlled dynamics is obtained from applying a scaling gain $K_s$ to $u$, where in this study $K_s = 1$.

II.B. Forcing Function

Equivalent to earlier experiments, the target forcing function signal $f_t$ for the pitch tracking task was defined as a multisine signal, consisting of $N_t = 10$ sine waves with independent frequencies that spanned the frequency range of interest for manual control:

$$f_t(t) = \sum_{k=1}^{N_t} A_t[k] \sin(\omega_t[k]t + \phi_t[k])$$  (1)
The settings for the sinuoid amplitudes $A_t$, frequencies $\omega_t$, and phase shifts $\phi_t$ were identical to those used in previous experiment.\textsuperscript{10} To allow for accurate describing function estimates at $\omega_t$, all frequencies were chosen as integer multiples of the measurement time base frequency $\omega_0 = 2\pi/T_{\text{meas}}$, with $T_{\text{meas}} = 81.92$ s. Table 1 lists all forcing function signal parameters, including the integer frequency multiples $n_t$, for each sine wave $k$.

<table>
<thead>
<tr>
<th>$k$</th>
<th>$n_t$</th>
<th>$\omega_t$, rad/s</th>
<th>$A_t$, deg</th>
<th>$\phi_t$, rad</th>
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<tbody>
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<td>17.564</td>
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<td>3.479</td>
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II.C. Controlled Dynamics Settings

II.C.1. Baseline Dynamics

For the baseline dynamics $H_{\text{baseline}}(s)$, see Fig. 1, the high-bandwidth baseline that was used in the earlier experiment of Matamoros et al.\textsuperscript{11} was selected. These baseline dynamics represent a Low Order Equivalent System (LOES) of typical aircraft pitch dynamics and was also considered by Mitchell et al.\textsuperscript{8} The transfer function of these baseline dynamics is given by Eq. (2):

$$H_{\text{baseline}}(s) = M_{\delta_e} \frac{M_q}{s(s + M_q)}$$

In Eq. (2), $M_{\delta_e}$ is the elevator control effectiveness coefficient and $M_q$ is the pitch damping coefficient. For both parameters fixed values of $M_{\delta_e} = -1.5$ and $M_q = 3$ rad/s were chosen for the high bandwidth setting of Ref. 11.

II.C.2. Added Dynamics

For the added dynamics $H_{\text{added}}(s)$, see Fig. 1, first-order lag-lead, and lead-lag dynamics were selected. This choice was mainly based on the fact that the frequency response of such dynamics approximates, at high frequencies, the fanned-out shape of the magnitude MUAD-envelope of Ref. 7. The transfer function of the considered added lead-lag or lead-lag dynamics is given by Eq. (3):

$$H_{\text{added}}(s) = \frac{T_{\text{lag}}s + 1}{T_{\text{lead}}s + 1}$$

In Eq. (3), $T_{\text{lag}}$ represents the added dynamics’ lag time-constant and $T_{\text{lead}}$ is the lead time-constant. A dominant lead term, i.e., $T_{\text{lag}} > T_{\text{lead}}$, will make the controlled dynamics more responsive and easier to control, while a dominant lag term ($T_{\text{lag}} > T_{\text{lead}}$) results in more sluggish dynamics that require human controllers to generate more compensating lead, which is related to higher work load.\textsuperscript{2}

II.C.3. Controlled Dynamics Conditions

For the experimental work described in this paper, a set of nine controlled dynamics conditions, consisting of a baseline setting (B) and eight different settings for $H_{\text{added}}(s)$, was selected. The added dynamics conditions consisted of matching sets of four lead-lag and four lag-lag dynamics that both included added dynamics that fell within and outside the MUAD-envelope limits.\textsuperscript{7} Figure 2 shows the added dynamics’ FRFs for all nine conditions, along with the MUAD envelopes of Ref. 7 (top graphs), as well as the FRFs of the resulting total controlled dynamics $H_{\text{tot}}(s) = H_{\text{baseline}}(s)H_{\text{added}}(s)$ (bottom graphs). Table 2 lists the detailed lag and lead time-constant settings for all conditions.
Figure 2. Bode plots of added dynamics conditions tested in the experiment.

Table 2. Lead and lag time-constant settings for all conditions.

<table>
<thead>
<tr>
<th>Lag-Lead Dynamics</th>
<th>Lead-Lag Dynamics</th>
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<tr>
<td>Condition</td>
<td>$T_{lag}$ [s]</td>
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<tr>
<td>C1</td>
<td>0.20</td>
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<tr>
<td>C2</td>
<td>0.13</td>
</tr>
<tr>
<td>C3</td>
<td>0.08</td>
</tr>
<tr>
<td>C4</td>
<td>0.05</td>
</tr>
<tr>
<td>B</td>
<td>-</td>
</tr>
</tbody>
</table>

| Condition        | $T_{lag}$ [s]    | $T_{lead}$ [s] |
|------------------|------------------|
| C5               | 0.03             | 0.05           |
| C6               | 0.03             | 0.08           |
| C7               | 0.03             | 0.13           |
| C8               | 0.03             | 0.20           |
For both the lag-lead and lead-lag added dynamics, it was chosen to select the secondary (non-dominant) term to always have a corner frequency of 30 rad/s ($T_{lag}$ or $T_{lead} = 0.03$ s), as this matches the frequency where the high-frequency fanning-out of the magnitude MUAD-envelope terminates and the envelope boundary levels off, see Fig. 2. The maximum added lead or lag time-constants were limited to 0.2 s (corner frequency of 5 rad/s), as these added dynamics are well outside the MUAD and would certainly require human controller adaptation to retain adequate task performance. The three other tested values for the dominant $T_{lag}$ or $T_{lead}$ were chosen based on a logarithmic spacing between 0.03 s (resulting in the baseline) and 0.2 s (the maximum), which resulted in time constant settings of 0.05 s, 0.08 s, and 0.13 s. As can be verified from Figure 2, the chosen set of time-constants results in two lead-lag and lag-lead conditions that fall outside the MUAD-envelope (C1, C2, C7, and C8) and two lead-lag and lag-lead conditions that fall inside the MUAD (C3, C4, C5, and C6). For the conditions outside the MUAD it is expected that human operators will certainly notice the change in controlled dynamics and will show adapted control dynamics $H_p(s)$.

### II.D. Human Controller Dynamics

It is well-known that in tracking tasks human controllers adapt their own control dynamics $H_p(s)$ (see Fig. 1) to those of the controlled system. In tracking tasks with the baseline dynamics given by Eq. (2), human controllers would need to generate lead to compensate for the lag induced by $M_q$. Furthermore, as can be verified from Fig. 2, for the range of tested $T_{lag}$ and $T_{lead}$ settings the total controlled dynamics may increase or reduce this need for human controller lead equalization, but will not require additional equalization (e.g., lag) by the human controller. Hence, the following human controller model, which was also used by Matamoros et al. in a similar investigation, can describe the human control dynamics for the conditions listed in Table 2:

$$H_p(s) = K_v(T_L s + 1)e^{-\tau_v} \frac{\omega_{nm}^2}{s^2 + 2\zeta_{nm}\omega_{nm}s + \omega_{nm}^2}$$

In Eq. (4), $K_v$ indicates the human operator control gain. The subscript “v” here stands for “visual”, for consistency in notation with related work, where also human controller motion feedback responses were analyzed. The human controller’s lead time-constant and response delay are indicated with $T_L$ and $\tau_v$, respectively. The neuromuscular system is modelled as a second-order mass-spring-damper system with undamped natural frequency and damping ratio parameterized by $\omega_{nm}$ and $\zeta_{nm}$, respectively. The human controller model of Eq. (4) thus has a total of five free human controller parameters that may be adapted to different $H_{added}(s)$ settings.

### III. Offline Simulations

Before collecting experiment data on human controllers’ adaptation to the set of added lag-lead and lead-lag dynamics listed in Table 2, an offline simulation analysis based on the task details provided in Section II was performed. For the offline analysis, a wider range of added lag-lead and lead-lag added dynamics was considered, for which variations in task performance and changes in human control behavior were predicted. Two different offline simulation predictions were generated: in the “no-adaptation prediction” the human control dynamics were assumed to remain constant at the baseline setting independent of the added dynamics, while in the “human-adaptation prediction” the human controller’s gain $K_v$ and visual lead time-constant $T_L$ were free parameters.

### III.A. Setup

For both performed model predictions, a grid search method was used to cover the desired range of added dynamics’ lag and lead time-constants. For the predictions presented in this paper, both $T_{lag}$ and $T_{lead}$ ranged from 0 to 0.2 s in steps of 0.01 s. Overall, this results in $21 \times 21 = 441$ different conditions, of which 421 are in fact unique (multiple instances of $T_{lag} = T_{lead}$ excluded). For both the no-adaptation and human-adaptation predictions, the variation in task performance and control effort variations due the added dynamics. For the human-adaptation predictions, also the human control gain $K_v$ and lead time-constant $T_L$ were calculated as outcome variables as a function of $T_{lag}$ and $T_{lead}$.

For both predictions, the experiment data of the precursor study of Ref. 11 was used to obtain reference human control model parameter settings appropriate for control of the baseline dynamics considered in this paper. For the same baseline dynamics as given by Eq. (2), Matamoros et al. measured average values of $K_v = 1.2$, $T_L = 0.4$ s, $\tau_v = 0.25$ s, $\omega_{nm} = 9$ rad/s, and $\zeta_{nm} = 0.2$ from real human controllers. In both the no-adaptation and human-adaptation predictions, the neuromuscular parameters and the human controller delay were kept constant at the values.
from Ref. 11. For the human-adaptation analysis, $K_v$ and $T_L$ were free parameters, while they were also considered constants in the no-adaptation prediction.

The human-adaptive prediction was implemented as a grid search across a pre-defined grid of $K_v$ and $T_L$ values. For the human controller gain $K_v$ representative values ranging between 0.1 and 2.5 in steps of 0.1 were considered, while the lead time-constant $T_L$ was varied between 0.0 s and 3.0 s in steps of 0.1 s. Overall, this resulted in 775 unique combinations of the human controller’s equalization settings from which the human-adaptive prediction selected the best fit to a given added dynamics setting. This selection was performed using the following cost function:

$$J_{sim}(K_v, T_L) = \sigma^2_e(K_v, T_L) + K_u\sigma^2_u(K_v, T_L)$$

where $\sigma^2_e$ and $\sigma^2_u$ represent the variances of the error and control signals, respectively, and $K_u$ is the “control effort weight gain” parameter. The cost function defined by Eq. (5) is equivalent to those used to predict human performance in earlier studies, where the fact that human controllers weigh attaining good performance (i.e., low $\sigma^2_e$) and limiting the exerted control effort (i.e., low $\sigma^2_u$) to determine their control behavior. In the human-adaptation prediction, both these variances are a function of the free parameters of the optimization, i.e., $K_v$ and $T_L$. The value of $K_u$ used for the predictions was determined to achieve the best possible match with the experiment data from Ref. 11 for the baseline condition, as shown in detail in Section III.B.2.

III.B. Results

III.B.1. No-Adaptation Prediction

Fig. 3 shows the variation in RMS($e$) and RMS($u$) for all 411 added dynamics settings assuming no human control adaptation. The red crosses superimposed on the heatmaps indicate the selected test conditions listed in Table 2. As shown explicitly in Fig. 3, the values along the heatmaps’ diagonal axes correspond to the baseline condition, which is obtained when $T_{lag} = T_{lead}$.

![RMS($e$) and RMS($u$) for No-Adaptation Prediction](image)

**Figure 3.** No-adaptation prediction results for RMS($e$) and RMS($u$) due to varying $T_{lag}$ and $T_{lead}$.

Fig. 3 shows that when $T_{lag}$ is larger than $T_{lead}$ (i.e., added lag-lead dynamics, left of or above the diagonal), both RMS($e$) and RMS($u$) increase compared to the baseline values. For the most extreme lag-lead condition (C1), no adaptation of human control dynamics would result in a 22% degradation of tracking performance and around 14% higher control effort. On the other hand, for added lead-lag dynamics (right of or below the diagonal) both RMS($e$) and RMS($u$) are seen to consistently decrease. For C8 ($T_{lag} = 0.03$ s and $T_{lead} = 0.2$ s), a 16% improvement in tracking performance results, combined with approximately 9% less control effort. Overall, the no-adaptation prediction data in Fig. 3 show that added lag-lead and lead-lag dynamics with a constant human controller would result in approximately linear changes in tracking performance and control activity with increasing $T_{lag}$ and $T_{lead}$, respectively. Furthermore, the consequences of added lag-lead dynamics for RMS($e$) and RMS($u$) are consistently larger in magnitude than observed for added lead-lag dynamics.
III.B.2. Human-Adaptation Prediction: Control Effort Weight Factor

To predict realistic adaptation of the human controller’s gain $K_v$ and lead time-constant $T_L$ in response to added lag-lead and lead-lag dynamics, first the control effort weight factor $K_u$ in Eq. (5) needed to be determined. For this, the measured baseline experiment data for RMS($e$) and RMS($u$) from Ref. 11 was compared to the outcomes of the human-adaptation prediction analysis. Fig. 4 shows the variation in RMS($e$) and RMS($u$) simulated for all the 775 possible combinations of $K_v$ and $T_L$ for the baseline condition. It should be noted that many combinations of $K_v$ and $T_L$ (i.e., both high) will cause the closed-loop dynamics to become unstable, for which no RMS($e$) and RMS($u$) prediction data is shown in Fig. 4.

![Figure 4. Human-adaptation prediction results for the baseline condition with optimal $K_v$ and $T_L$ predicted for varying $K_u$ settings.](image)

The red crosses in Fig. 4 indicate the reference experiment data from Ref. 11. The red traces show the optimal combinations of $K_v$ and $T_L$ selected by the human-adaptive prediction using the cost function of Eq. (5) and $K_u$ ranging from 0 to 1 with steps of 0.01. The final result of the human-adaptation prediction with $K_u = 0$ (optimal performance only) is indicated with a red circular marker. As is clear from Fig. 4, this results in predicted performance that is better (lower RMS($e$)) and control activity that is much higher (increased RMS($u$)) than for the reference experiment data. The optimal control effort weight factor setting that results in a human-adaptation prediction that closely approximates the experiment data was found to be $K_u = 0.05$, which is indicated with the red plus-marker in Fig. 4. Hence, this value for $K_u$ is used for the final human-adaptation predictions presented in this paper.

III.B.3. Human-Adaptation Prediction: Results

Fig. 5 shows the final predictions of RMS($e$), RMS($u$), $K_v$, and $T_L$ obtained from the human-adaptation prediction for all considered combinations of $T_{lag}$ and $T_{lead}$ of the added dynamics. Matching the presentation of the no-adaptation prediction in Fig. 3, the selected experimental conditions (see Table 2) are indicated with red crosses, while the diagonal in all figures represents the baseline condition for which $T_{lag} = T_{lead}$.

Fig. 5(a) shows that overall the attained tracking performance for all lag-lead or lead-lag added dynamics settings is better than obtained for the no-adaptation prediction in Fig. 3. This is an expected result, as in the human-adaptation prediction the human controller adapts his control behaviour to the controlled dynamics, as a real human controller would also do. Furthermore, Fig. 5(a) shows also for the human-adaptation prediction the level of task performance is worse with added lag-lead dynamics (a 16% increase in RMS($e$) compared to the baseline for condition C1) than added lead-lag dynamics (a 21% performance improvement for condition C8 compared to the baseline). Compared to the no-adaptation prediction data of Fig. 3(b), Fig. 5(b) shows less variation in predicted RMS($u$) for the human-adaptation data, as well as a “noiser” prediction result. For the extreme test conditions C1 and C8, a small increase (5%) and decrease (6%) in RMS($u$) are predicted, respectively. Finally, Fig. 5(b) shows an clear increase in RMS($u$) with added lead-lag dynamics for $T_{lead} > 0.08$ s, compared to the consistent reduction in RMS($u$) observed for the no-adaptation prediction (Fig. 3(b)).

The predicted adaptation of the human controller gain $K_v$ and visual lead time-constant $T_L$ is shown in Figures 5(c) and (d), respectively. It can be observed from Fig. 5(c) that an increase in human controller gain $K_v$ is predicted
Figure 5. Human-adaptation predictions for RMS(\(e\)), RMS(\(u\)), \(K_v\), and \(T_L\) for varying \(T_{lag}\) and \(T_{lead}\) settings.
for added lead-lag dynamics (C5-C8) compared to the baseline case, while $K_v$ reduces with added lag-lead dynamics (C1-C4). For the strongest lag-lead and lead-lag experiment conditions (C1 and C8), $K_v$ is around 35% lower or higher, respectively, than for the baseline. Fig. 5(d) shows that the predicted adaptation of $T_L$ is even stronger, and also less symmetric. Added lag-lead is seen to result in strong increase in $T_L$ (89% for C1), while a more moderate decrease in $T_L$ is predicted with added lead-lag (33% for condition C8) compared to the baseline. It should be noted that all predicted trends are consistent with the crossover model theorem\(^1\) and reflect a human controller adapting his equalization dynamics to ensure approximately single integrator dynamics around crossover.

IV. Experiment

IV.A. Apparatus

To collect human-in-the-loop experiment data of how human controllers adapt the added lead-lag and lag-lead dynamics in the controlled element, an experiment was performed in the fixed-base flight simulator setup of the Human-Machine Interaction Laboratory (HMILab) at the faculty of Aerospace Engineering of TU Delft. As shown in Fig. 6(a), the experiment was performed in the right pilot seat, where the fore-aft axis of a hydraulic side-stick was used to perform the pitch control task introduced in Section II. During the experiment, the lateral axis of the side-stick was locked in its neutral position. The participants received visual feedback of their pitch tracking error using the compensatory display shown in Fig. 6(b), which was shown on the Primary Flight Display (PFD) in the simulator cockpit. On the display, which was also used in a number of earlier experiments\(^{10,11,13}\) the vertical displacement of the yellow horizon line with respect to the fixed aircraft symbol indicates the tracking error $e$. No other visual cues (e.g., outside visual) were provided during the experiment trials.

![Figure 6. The fixed-base flight simulator of the TU Delft Human-Machine Interaction Laboratory (HMILab) (a) and the compensatory display (b) used for the experiment.](image)

IV.B. Experimental Procedure

Nine participants volunteered to perform the human-in-the-loop experiment. All participants were students or staff of the Faculty of Aerospace Engineering of TU Delft and had prior experience with similar control tasks from earlier human-in-the-loop experiments. Before the start of the experiment, the participants received a short briefing to explain their task and the experiment procedures.

After the briefing, each participant was first trained for the pitch tracking task by performing around five tracking runs with the baseline condition (B). When participants’ performance in the task had stabilized, the actual experiment was started, in which participants tested all nine experiment conditions sequentially. Per condition, three consecutive tracking runs were performed, followed by a tracking run with the baseline dynamics. After this baseline run, participants gave a subjective rating of the noticeability any difference of the tested dynamics and the baseline, using the four-point rating scale listed in Table 3.\(^{10,14}\) Of the three runs performed for each condition, the first was discarded as participants may have needed to adjust their control behavior for each condition transition. The last two measured runs were used for data analysis. The tracking task was ran with a sample frequency of 100 Hz and one tracking run lasted 90 seconds, of which the final 81.92 seconds were used for data analysis.

To balance out order effects (e.g., fatigue and continued training) in the collected dataset, the order of condition presentation was randomized over all participants according to a 9 x 9 Latin square, see Table 4. In Table 4, all lag-lead conditions (C1-C4) have white backgrounds, the corresponding lead-lag conditions (C5-C8) have dark-grey
backgrounds, and the baseline condition (B) is indicated with a light-grey background. The experiment was performed in three sessions, where each session consisted out of three rounds, with a short break (i.e., 15-20 minutes) in-between sessions. The full experiment took 2-3 hours to complete with every participant.

### Table 3. Four-point subjective rating scale for rating the noticeability with respect to the baseline controlled system.

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<thead>
<tr>
<th>Rating</th>
<th>Interpretation</th>
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<tr>
<td>0</td>
<td>No difference</td>
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<tr>
<td>1</td>
<td>Difference, but not really noticeable</td>
</tr>
<tr>
<td>2</td>
<td>Noticeably different</td>
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<tr>
<td>3</td>
<td>Completely different</td>
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### Table 4. Experiment Latin square design.

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<th>sub.</th>
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<th>session II</th>
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<td>B C4 C8 C5 C6 C2</td>
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<td>B</td>
<td>C8 C6 B</td>
<td>C2 C1 C5 C3 C4 C7</td>
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<td>B</td>
<td>B C1 C3</td>
<td>C6 C5 C2 C7 C8 C4</td>
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<td>B</td>
<td>C4 C8 C2</td>
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<td>B</td>
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<tr>
<td>6</td>
<td>B</td>
<td>C2 C6 C8</td>
<td>C4 C3 C7 B C5 C1</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>B</td>
<td>C1 C5 C7</td>
<td>C3 C2 C6 C4 B C8</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>B</td>
<td>C6 C3 B</td>
<td>C8 C7 C4 C1 C2 C5</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>B</td>
<td>C7 C4 C5</td>
<td>C1 C8 B C2 C3 C6</td>
<td></td>
</tr>
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</table>

### IV.C. Dependent Variables and Data Analysis

For determining the extent to which the participants in the human-in-the-loop experiment adapted their control behavior to the nine tested experiment conditions (see Table 2), a number of different dependent variables were considered:

1. **Subjective ratings:**

2. **Performance and control activity:** To match the offline analysis of Section III, the RMS of the error ($e$) and control ($u$) signals were considered as measures of task performance and control activity, respectively. These RMS values were calculated for each of the two tracking runs used as measurement data for each condition per participant and then averaged for statistical comparison of the data.

3. **Human controller model parameters:** To explicitly quantify the human control dynamics $H_p(s)$ used by participants for all conditions, the five parameters of the human controller model of Eq. (4) were determined by fitting the model to the measured data. For fitting the model, first a frequency-domain describing function of the human control dynamics estimated at each frequency of the multisine target signal $\omega_t$ according to:

$$\hat{H}_p(j\omega_t) = \frac{U(j\omega_t)}{E(j\omega_t)}$$

where $U$ and $E$ represent the Fourier transforms of the time-domain averages of the two recorded sequences of the control ($u$) and error ($e$) signals, respectively. The human control model parameters were estimated by finding the parameter set $\theta$ that provided the best fit to the describing function according to the following complex squared cost function:

$$J_{exp}(\theta) = \sum_{k=1}^{N_t} |\hat{H}_p(j\omega_t[k]) - H_p(j\omega_t[k], \theta)|^2$$

This optimization problem was solved with Matlab’s “fminsearch” solver. To verify whether the fitted human controller models accurately modeled the measured control signals $u$, the Variance Accounted For (VAF) was used as an interpretable measure of quality-of-fit, as also done in earlier investigations.10, 13, 17

For all dependent variables except the subjective ratings statistical analysis was performed. As for most dependent variables the participants’ data for at least two conditions was not normally distributed, nonparametric tests were used for statistical comparisons. First, an overall significant effect across all tested conditions was verified with a Friedman test. In case of a significant overall effect, pairwise comparisons of all lead-lag and lag-lead conditions with the baseline were performed with Wilcoxon signed-rank tests.
IV.D. Hypotheses

Based on comparison with available MUAD envelopes\(^7\) and the performed offline simulation analysis (see Section III), three main hypotheses were formulated for the experiment:

**H1** Added lag-lead dynamics result in degraded task performance (higher RMS\((e)\)), a decrease in control gain \(K_v\), and increased lead equalization \(T_L\) compared to the baseline condition. The opposite effects will occur for added lead-lag dynamics. With added lag-lead dynamics (conditions C1-C4), the controlled dynamics become more sluggish and more difficult to control. As also predicted with the offline simulation, this will result in degraded task performance and increased compensating lead equalization by the human controller. In addition, the high-frequency gain of the controlled system is reduced by the added lag-lead, which will induce human controllers to increase their own control gain \(K_v\). The offline simulations of Section III predict no consistent change in human control activity (RMS\((u)\)). Consistent also with classical theory on manual control adaptation to the controlled system,\(^9\) our simulation predictions indicate that the opposite effects for RMS\((e)\), \(K_v\), and \(T_L\) will occur with added lead-lag dynamics (conditions C5-C8).

**H2** Added lag-lead dynamics are more noticeable and will induce stronger human control adaptation than added lead-lag dynamics. For the experiment, the tested lag-lead and lead-lag dynamics were on purpose selected to be symmetrical, as is clear from Fig. 2. However, as added lag-lead and lead-lag dynamics will effectively cause a slower (i.e., more difficult) or quicker (i.e., easier) response of the controlled element, respectively, the induced effects on human control behavior are not expected to show the same symmetry. Based on the offline simulations of Section III it is expected that the changes in the visual lead time constant \(T_L\) will be larger in magnitude for added lag-lead than for added lead-lag. This asymmetry is also consistent with the high-frequency shape of the MUAD envelope of Ref. 7, for which the upper boundary (i.e., for added lead-lag) is much closer to the 0 dB line than the lower boundary (i.e., for added lag-lead). As a result, it is also expected that subjective noticeability ratings for added lag-lead dynamics are higher (see Table 3) than for added lead-lag dynamics.

**H3** Only added dynamics for which the frequency response falls outside the MUAD of Ref. 7 will cause a significant adaptation of human controllers’ behavior. This research aims to investigate the difference between available MUAD envelopes,\(^7\) which indicate boundaries of human noticeability in frequency domain, and the limitations on human control behavior adaptation. To verify this correspondence, conditions C1, C2, C7, and C8 were deliberately chosen to have parts of their frequency response outside the MUAD, which implies that human controllers would be expected to notice the added dynamics. Conversely, conditions C3-C6 were purposefully selected to have frequency responses fully inside the MUAD envelope of Ref. 7. Here, without further evidence to the contrary, it is hypothesized that only noticeable added dynamics (i.e., C1, C2, C7, and C8) will result in significant adaptation of human controllers’ dynamics. For the considered added lag-lead and lead-lag dynamics, this adaptation of \(H_p(s)\) is expected to be evident from adjusted \(K_v\) and \(T_L\) values.

V. Results

V.A. Subjective Ratings

For each tested experiment condition, participants were asked to provide a subjective rating, using the rating scale of Table 3, of the noticeability of any differences in controlled dynamics due to (possible) added dynamics compared to the baseline dynamics. Fig. 7 presents the subjective ratings provided by all nine experiment participants for each condition (bars), as well as the median rating for all conditions (black line).

Fig. 7 shows that while the baseline condition (B) received the lowest ratings, still more than half of the participants did not provide a rating of 0 ("No difference"). Furthermore, it can be observed that added lag-lead dynamics (conditions C1-C4) are indeed more noticeable than the added lead-lag dynamics (C5-C8), as the former received higher ratings on average. For the lag-lead conditions even a consistent increase in median rating with increasing \(T_{lag}\) is observed from Fig. 7, while the overall increase in ratings with increasing \(T_{lead}\) for the lead-lag conditions is weaker and less consistent. Overall, despite the significant spread in the rating data, Fig. 7 shows the expected reduced noticeability of added lead-lag dynamics compared to added lag-lead dynamics (Hypothesis H2).

V.B. Performance and Control Activity

Fig. 8a shows the measured RMS\((e)\) and RMS\((u)\) data, here considered as measures of task performance and control activity, respectively, for all tested experiment conditions. The measured data are presented as boxplots. In addition,
Fig. 7. Subjective noticeability ratings for all experiment conditions.

Fig. 8a shows the outcomes of the no-adaptation and human-adaptation predictions from Section III, indicated with the solid green and red lines, respectively. As will be shown in Section V.C, the human controller delay \( \tau_v \) was found to be slightly higher in the current experiment than in the reference experiment of Ref. 11, i.e., around 0.3 s instead of the \( \tau_v = 0.25 \) s assumed for the human-adaptation prediction. For this reason, Fig. 8a shows a second human-adaptation prediction result (dashed red line), which was obtained with \( \tau_v = 0.3 \) s assumed for the simulation prediction.

Fig. 8(a) shows that compared to the baseline data the tracking performance consistently degrades for the lag-lead added dynamics with increasing \( T_{lag} \) (C4 to C1). For the added lead-lag dynamics, a slight reduction in RMS(\( e \)) is observed, but this reduction is smaller in magnitude and less consistent. Overall, the measured variation in RMS(\( e \)) is statistically significant, \( \chi^2(8) = 42.87, p < 0.05 \) (Friedman test). The pairwise comparison data in Table 5 confirms that only the degraded performance measured for the lag-lead added dynamics compared to the baseline data is statistically significant. Overall, the relative change in RMS(\( e \)) over all conditions is predicted well by all predictions shown in Fig. 8(a). However, the predicted performance level is consistently better than observed from the experiment data, which is explained by the fact that human controller remnant was not included in our predictions. With \( \tau_v = 0.25 \)
s the human-adaptation prediction is seen to further over-estimate the human performance level, as would be expected for a human controller who reacts more quickly to the visual input.

Fig. 8(b) shows that the control activity shows a similar, though less consistent, variation with added $T_{lag}$ or added $T_{lead}$, with increased and decreased control activity for added lag-lead and lead-lag dynamics, respectively. A Friedman test performed on the RMS$(u)$ data confirms a statistically significant variation across all experiment conditions: $\chi^2(8) = 35.39, p < 0.05$. With more spread compared to the RMS$(e)$ data, only the pairwise comparisons of the baseline data and the added dynamics with the highest $T_{lag}$ and $T_{lead}$ (C1 and C8) are statistically significant, see Table 5. As is clear from Fig. 8(b), the relative change in RMS$(u)$ over all conditions is reasonably well predicted by the no-adaptation simulation data, while the human-adaptation predictions both are approximately constant for all conditions. Again, the offsets in RMS$(u)$ between experiment data and simulation predictions can be explained by the fact that remnant was not included in the predictions.

V.C. Human Controller Model Parameters

Fig. 9 shows the human controller model parameters estimated for all experiment conditions using the frequency-domain parameter estimation approach explained in Section IV.C. Overall, the VAF of the fitted human control models for all participants and conditions was around 80%. Hence, the estimated human controller model parameters presented in Fig. 9 can be considered an accurate quantification of the measured control behavior. Using the same format as Fig. 8, Fig. 9 also shows the assumed constant settings or the predicted parameter variations from the no-adaptation and human-adaptation predictions introduced in Section III.

Fig. 9(a) shows that compared to average human controller gain of around 1.2 for the baseline condition, $K_v$ decreases with added lag-lead dynamics (C1-C4). For added lead-lag dynamics, no consistent change in $K_v$ is found. Overall, the observed variation in $K_v$ across all conditions was found to be statistically significant, $\chi^2(8) = 28.53, p < 0.05$ (Friedman test). The estimated human controller lead time-constants $T_L$ in Fig. 9(b) show clearly increased lead equalization with increasing $T_{lag}$ for the added lag-lead dynamics and reduced $T_L$ with the added lead-lag dynamics, as expected (Hypothesis H1). Also these changes in $T_L$ across all experiment conditions are statistically significant, $\chi^2(8) = 63.01, p < 0.05$. For both parameters, the results of post-hoc Wilcoxon tests performed to test for differences between all conditions and the baseline data (Table 6) suggest that only for the strongest lag-lead and lead-lag added dynamics statistically significant differences are found. Fig. 9(a) and (b) further show that the assumed constant values for $K_v$ and $T_L$ in the no-adaptation prediction (green data) are a very good match to the current measurement data for the baseline condition (B). Furthermore, the human-adaptation prediction results for both parameters show similar, but slightly stronger, trends than those observed with the experimental data. This indicates that the magnitude of the real human adaptation is slightly overestimated by our human-adaptation prediction.

Fig. 9(c), (d), and (e) show the estimated values for the human controller delay $\tau_v$, the neuromuscular frequency $\omega_{nm}$, and the neuromuscular damping ratio $\zeta_{nm}$. For $\tau_v$ and $\omega_{nm}$, approximately constant values across all tested conditions are found, which is confirmed by statistical analysis outcomes ($\chi^2(8) = 14.24, p > 0.05$ and $\chi^2(8) = 12.84, p > 0.05$, respectively), which indicate no significant overall variation for both parameters. For the neuromuscular frequency (Fig. 9(e)), however, a slight drop of around 0.5 rad/s is observed for the strongest lag-lead dynamics compared to the average value of the baseline condition. In addition, with added lead-lag dynamics (C5-C8) an increase in $\omega_{nm}$ of around 0.5 rad/s is visible. A Friedman test on the $\omega_{nm}$ indeed confirms an overall significant effect ($\chi^2(8) = 25.86, p < 0.05$), which post-hoc tests (see Table 6) indicate is mostly attributable to the increased $\omega_{nm}$ for condition C8. For both neuromuscular parameters, Fig. 9 shows close agreement of the experiment data and the assumed (constant) values used for the no-adaptation and human-adaptation predictions. Fig. 9(c) motivates why the human-adaptation prediction was also performed with a higher value for $\tau_v$ of 0.3 s, as this matches better with the current experiment data.

Table 6. Wilcoxon signed-rank test results for pairwise comparisons for $K_v$, $T_L$, and $\omega_{nm}$ with the baseline condition data (B). * indicates $p < 0.05$ and ** indicates $p < 0.01$. 

<table>
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<th>Sig.</th>
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<th>R</th>
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Figure 9. Estimated human controller model parameters compared to no-adaptation and human-adaptation predictions.
VI. Discussion

This paper investigated the adaptation of human controllers’ control behavior to added lag-lead and lead-lag dynamics in the controlled system. This was done by considering human controller behavior in a compensatory pitch attitude tracking task. Expected human adaptation was predicted using offline simulations and measured in a human-in-the-loop tracking experiment with nine skilled participants.

Based on the well-known adaptation of human operators to increased lag or lead in the controlled element as well as our simulation predictions from Section III, our Hypothesis H1 indicated that with added lag-lead dynamics we expected to find increased RMS($e$) (i.e., worse performance) and $T_L$ values and reduced human operator control gains $K_v$. In addition, the opposite effects in all three metrics were expected for added lead-lag dynamics, which reduce the phase lag of the baseline controlled dynamics. The collected experiment data indeed confirm these expected effects, with statistically significant trends over all experiment conditions for RMS($e$), $K_v$, and $T_L$. While these three metrics reflect the main human controller adaptation to lag-lead and lead-lag added dynamics, our experiment data also showed that the participants in the experiment also varied their neuromuscular system natural frequency $\omega_{nm}$, another statistically significant effect. While the change in $\omega_{nm}$ is modest – ±0.5 rad/s compared to the average $\omega_{nm} \approx 9.5$ rad/s found for the baseline condition – a similar dependency of human controllers’ neuromuscular frequency on the phase lag (or bandwidth) of the controlled system was also reported in Ref. 11.

Due to the fact that added lag has greater consequences for task performance in closed-loop control tasks than added lead, it was expected (Hypothesis H2) that added lag-lead dynamics would be more noticeable for human controllers and would result in stronger behavior adaptation than lead-lag added dynamics. Such asymmetric human controller adaptation was also predicted by the human-adaptation predictive simulations of Section III. In terms of subjective noticeability, the subjective rating data collected in the experiment indeed confirms this hypothesis, as the (median) ratings for the lag-lead conditions (C1-C4) were on average consistently higher (i.e., indicating more noticeable differences with the baseline dynamics) than those for the lead-lag conditions (C5-C8). Also for the estimated human controller gain $K_v$ and lead time-constant $T_L$ the measured changes were notably stronger with added lag-lead dynamics than for added lead-lag, as confirmed from statistical pairwise comparisons with the baseline condition data using Wilcoxon signed-rank tests. Overall, this hypothesis is thus accepted, which implies that the generally asymmetric high-frequency limits of available MUAD envelopes is reasonable.

The final expected outcome of the experiment (Hypothesis H3) was that only for conditions whose added dynamics’ frequency response falls outside of the MUAD of Ref. 7 a significant adaptation of human controllers’ behavior would be found. In other words, no significant human controller adaptation was expected to the conditions with only moderate added lag or lead whose dynamics remained inside of the MUAD, i.e., C3, C4, C5, and C6. Overall, the collected experiment data show that the observed changes in human control behavior and task performance due to added lag-lead and lead-lag dynamics are continuous and do not only occur for added dynamics with time-constants above a certain critical value. Especially added lag-lead dynamics were found to result in significantly degraded task performance and increased lead-time constants also for very low $T_{lag}$. Hence, Hypothesis H3 is rejected, which implies that for the development of objective “manual control adaptation” envelopes with discrete envelope limits such as the MUAD of Ref. 7, extreme care needs to be taken in settings limits on the likely continuous human control behavior adaptations.

For quantitative analysis of human controllers’ adaptation to added lag-lead and lead-lag dynamics, we performed predictive offline “human-adaptation” simulations – for a more finely spaced range of added dynamics than tested experimentally – based on closed-loop human operator model simulations of the considered pitch tracking task. Overall, very close agreement between the simulation predictions and experiment data was attained, as especially the relative changes in human controller parameters and task performance were matched closely. A potential further step that can be taken to improve the “human-adaptation predictions” presented in this paper is, for example, the addition of remnant noise to the simulations. In other investigations where similar model predictions were presented, the inclusion of simulated remnant was found to improve the quality of the model predictions. In addition, as in the experiment data presented in this paper also participants’ neuromuscular frequency $\omega_{nm}$ varied over the different tested experiment conditions, it should be investigated whether including $\omega_{nm}$ in the “free” parameters of the human-adaptation predictions would further improve the predictive power.

Overall, the results presented in this paper contribute to the further development of objective “manual control adaptation” envelopes, as also proposed in earlier papers. An important next step, given the hypothesized dependency of human noticeability of added dynamics ($H_{\text{added}}(s)$) on the baseline controlled system ($H_{\text{baseline}}(s)$), an important next step is to also consider the baseline controlled dynamics as an additional degree-of-freedom. The agreement between simulation predictions and experiment data in this paper suggests that a first-order estimate of the effects of varying $H_{\text{baseline}}(s)$ can be obtained from a similar offline simulation analysis. Furthermore, given the
inherent practical limitations on the number of test conditions that can be included in human-in-the-loop experiments, predictive simulations can also provide higher resolution data on human adaptation to added dynamics than can feasibly be obtained for experiment data. Both a broad range of added and baseline dynamics, as well as a high-resolution variation in their parameters, are required for the development of widely applicable “manual control adaptation” envelopes.12

VII. Conclusion

To verify human controllers’ sensitivity to added lag-lead and lead-lag dynamics as captured in Maximum Unnoticed Added Dynamics envelopes as developed by Wood and Hodgkinson,7 this paper described the results of a human-in-the-loop and linked offline simulation analysis. For both, a cybernetic approach, for which human control behavior was quantitatively and objectively analyzed in a pitch attitude tracking task, was considered. The results from both the simulation predictions and the experiment indicate that human controllers significantly adapt their control gain and lead time-constants when additional lag-lead or lead-lag dynamics are introduced in their controlled system. The control adaptation is found to be strongest for added lag-lead dynamics, which due to the added lag in the controlled dynamics require human controllers to perform more lead equalization, results in degraded task performance, and in a subjectively more noticeable change in the controlled system. Furthermore, this characteristic adaptation of control behavior is also found to occur for part of the test conditions which had added dynamics that remained fully inside of the MUAD envelope boundaries. This thus warrants the further development of recently proposed “manual control adaptation envelopes” that may be used to quantify the limits of human control adaptation to changes in the controlled system dynamics.

References