

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

Butijn, Martin; Lu, Tao; Pool, Daan; van Paassen, Rene

DOI

[10.2514/6.2019-1229](https://doi.org/10.2514/6.2019-1229)

Publication date

2019

Document Version

Final published version

Published in

AIAA Scitech 2019 Forum

Citation (APA)

Butijn, M., Lu, T., Pool, D., & van Paassen, R. (2019). Assessment of Maximum Unnoticeable Added Lag-Lead or Lead-Lag Dynamics with a Cybernetic Approach. In *AIAA Scitech 2019 Forum: 7-11 January 2019, San Diego, California, USA* Article AIAA 2019-1229 <https://doi.org/10.2514/6.2019-1229>

Important note

To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.



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

M.C. Butijn,^{*} T. Lu,[†] D.M. Pool,[‡] and M.M. van Paassen[§]

Delft University of Technology, Delft, The Netherlands

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) envelopes^{6,7} 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

^{*}M.Sc. student, Control and Simulation Division, Faculty of Aerospace Engineering, P.O. Box 5058, 2600GB Delft, The Netherlands; martin-butijn92@hotmail.com

[†]Ph.D. student, Control and Simulation Division, Faculty of Aerospace Engineering, P.O. Box 5058, 2600GB Delft, The Netherlands; t.lu-3@tudelft.nl

[‡]Assistant Professor, Control and Simulation Division, Faculty of Aerospace Engineering, P.O. Box 5058, 2600GB Delft, The Netherlands; d.m.pool@tudelft.nl. Member AIAA.

[§]Associate Professor, Control and Simulation Division, Faculty of Aerospace Engineering, P.O. Box 5058, 2600GB Delft, The Netherlands; m.m.vanpaassen@tudelft.nl. Member AIAA.

human control behavior adaptations to added dynamics in tracking tasks and characterize the adaptation using human controller modeling techniques.^{10–12} In earlier work, we have mostly focused on evaluating the effects of added dipole dynamics on manual control behavior.^{10–12}

The goal of this paper is to extend recent research into human control adaptation to added (dipole) dynamics,^{10–12} 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^{8,11} 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" approach⁴), 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 ($\text{RMS}(e)$ and $\text{RMS}(u)$), 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.

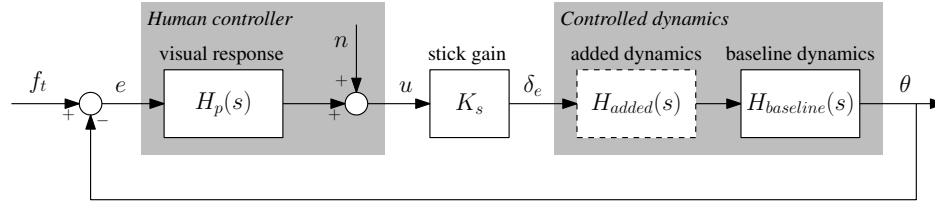


Figure 1. Schematic representation of the considered compensatory pitch tracking task with added dynamics.

As shown in Fig. 1, the human controller controls the pitch angle θ 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 ($H_{baseline}(s)$ in Fig. 1), combined with possible *added* dynamics, $H_{added}(s)$. 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 $H_{added}(s)$ 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 δ_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,^{10,11,13,14} 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:^{1,15}

$$f_t(t) = \sum_{k=1}^{N_t} A_t[k] \sin(\omega_t[k]t + \phi_t[k]) \quad (1)$$

The settings for the sinusoid amplitudes A_t , frequencies ω_t , and phase shifts ϕ_t were identical to those used in previous experiment.¹⁰ To allow for accurate describing function estimates at ω_t , all frequencies were chosen as integer multiples of the measurement time base frequency $\omega_0 = 2\pi/T_{meas}$, with $T_{meas} = 81.92$ s. Table 1 lists all forcing function signal parameters, including the integer frequency multiples n_t , for each sine wave k .

Table 1. Multisine forcing function properties as taken from Ref. 10.

k	n_t	ω_t , rad/s	A_t , deg	ϕ_t , rad
1	6	0.460	1.397	1.288
2	13	0.997	0.977	6.089
3	27	2.071	0.441	5.507
4	41	3.145	0.237	1.734
5	53	4.065	0.159	2.019
6	73	5.599	0.099	0.441
7	103	7.900	0.063	5.175
8	139	10.661	0.046	3.415
9	194	14.880	0.036	1.066
10	229	17.564	0.033	3.479

II.C. Controlled Dynamics Settings

II.C.1. Baseline Dynamics

For the baseline dynamics $H_{baseline}(s)$, see Fig. 1, the high-bandwidth baseline that was used in the earlier experiment of Matamoros et al.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.⁸ The transfer function of these baseline dynamics is given by Eq. (2):

$$H_{baseline}(s) = M_{\delta_e} \frac{M_q}{s(s + M_q)} \quad (2)$$

In Eq. (2), M_{δ_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 $H_{added}(s)$, 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):

$$H_{added}(s) = \frac{T_{lead}s + 1}{T_{lag}s + 1} \quad (3)$$

In Eq. (3), T_{lag} represents the added dynamics' lag time-constant and T_{lead} is the lead time-constant. A dominant lead term, i.e., $T_{lead} > T_{lag}$, will make the controlled dynamics more responsive and easier to control, while a dominant lag term ($T_{lag} > T_{lead}$) results in more sluggish dynamics that require human controllers to generate more compensating lead, which is related to higher work load.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 $H_{added}(s)$, was selected. The added dynamics conditions consisted of matching sets of four lead-lag and four lag-lead dynamics that both included added dynamics that fell within and outside the MUAD-envelope limits.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 $H_{tot}(s) = H_{baseline}(s)H_{added}(s)$ (bottom graphs). Table 2 lists the detailed lag and lead time-constant settings for all conditions.

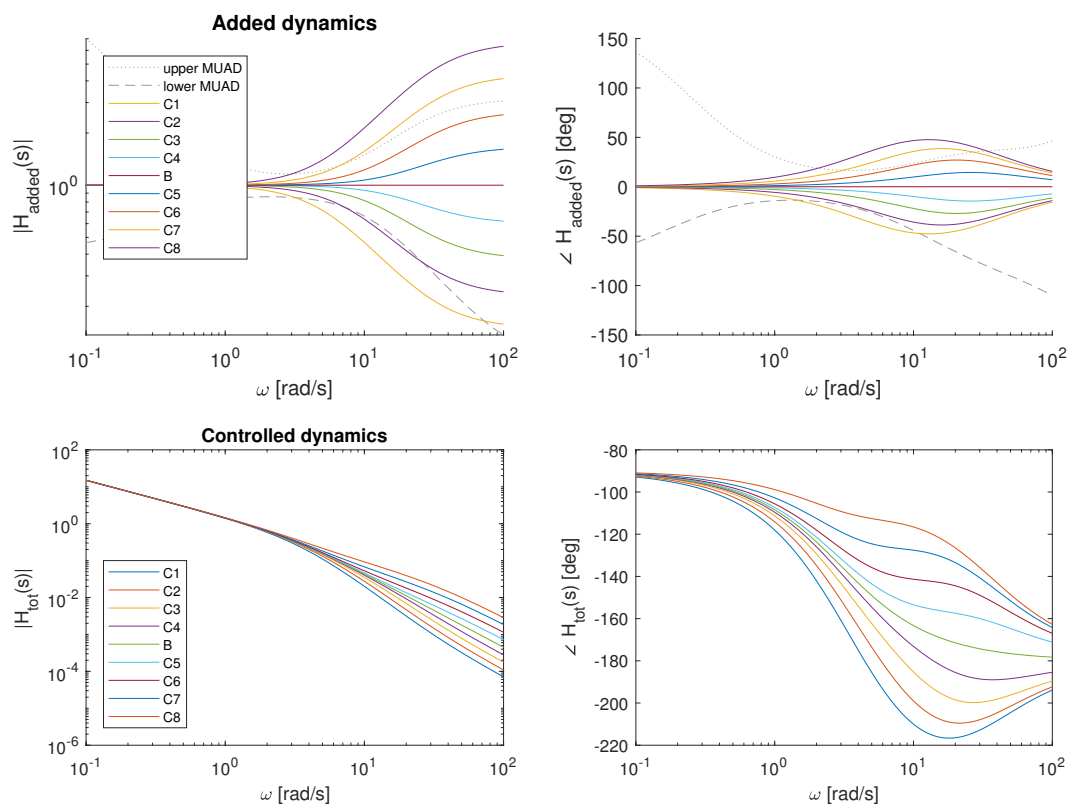


Figure 2. Bode plots of added dynamics conditions tested in the experiment.

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

Lag-Lead Dynamics			Lead-Lag Dynamics		
Condition	T_{lag} [s]	T_{lead} [s]	Condition	T_{lag} [s]	T_{lead} [s]
C1	0.20	0.03	C5	0.03	0.05
C2	0.13	0.03	C6	0.03	0.08
C3	0.08	0.03	C7	0.03	0.13
C4	0.05	0.03	C8	0.03	0.20
B	-	-			

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.^{1,2} 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 Matamoras et al.¹¹ in a similar investigation, can describe the human control dynamics for the conditions listed in Table 2:

$$H_p(s) = K_v(T_L s + 1)e^{-s\tau_v} \frac{\omega_{nm}^2}{s^2 + 2\zeta_{nm}\omega_{nm}s + \omega_{nm}^2} \quad (4)$$

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,^{10,12} 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 τ_v , respectively. The neuromuscular system is modelled as a second-order mass-spring-damper system with undamped natural frequency and damping ratio parameterized by ω_{nm} and ζ_{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 the Root Mean Square (RMS) of the error signal e and the control signal u was calculated to quantify 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), Matamoras et al.¹¹ 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:

$$J_{sim}(K_v, T_L) = \sigma_e^2(K_v, T_L) + K_u \sigma_u^2(K_v, T_L) \quad (5)$$

where σ_e^2 , and σ_u^2 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,^{13,16} where the fact that human controllers weigh attaining good performance (i.e., low σ_e^2) and limiting the exerted control effort (i.e., low σ_u^2) 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 $T_{lag} = T_{lead}$.

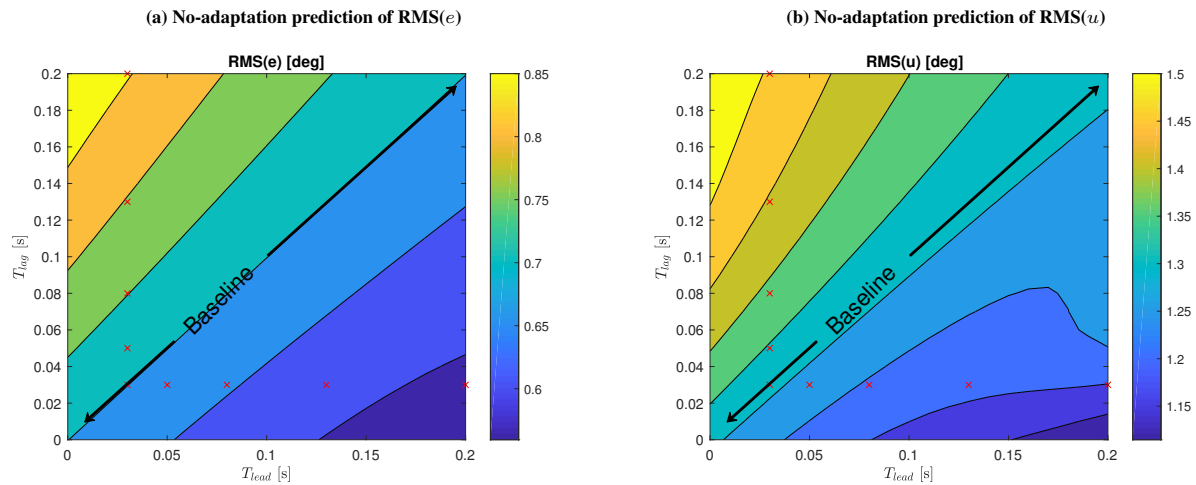


Figure 3. No-adaptation prediction results for $RMS(e)$ and $RMS(u)$ due to varying T_{lag} and T_{lead} .

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 $\text{RMS}(e)$ and $\text{RMS}(u)$ from Ref. 11 was compared to the outcomes of the human-adaptation prediction analysis. Fig. 4 shows the variation in $\text{RMS}(e)$ and $\text{RMS}(u)$ 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 $\text{RMS}(e)$ and $\text{RMS}(u)$ prediction data is shown in Fig. 4.

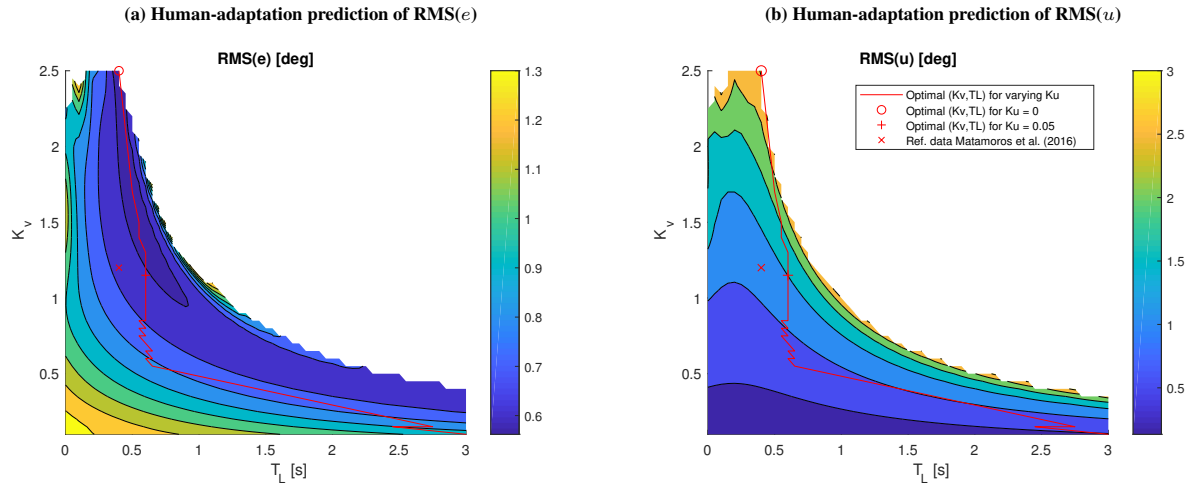


Figure 4. Human-adaptation prediction results for the baseline condition with optimal K_v and T_L predicted for varying K_u settings.

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 $\text{RMS}(e)$) and control activity that is much higher (increased $\text{RMS}(u)$) 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 $\text{RMS}(e)$, $\text{RMS}(u)$, 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 $\text{RMS}(e)$ 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 $\text{RMS}(u)$ 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 $\text{RMS}(u)$ are predicted, respectively. Finally, Fig. 5(b) shows an clear increase in $\text{RMS}(u)$ with added lead-lag dynamics for $T_{lead} > 0.08$ s, compared to the consistent reduction in $\text{RMS}(u)$ 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

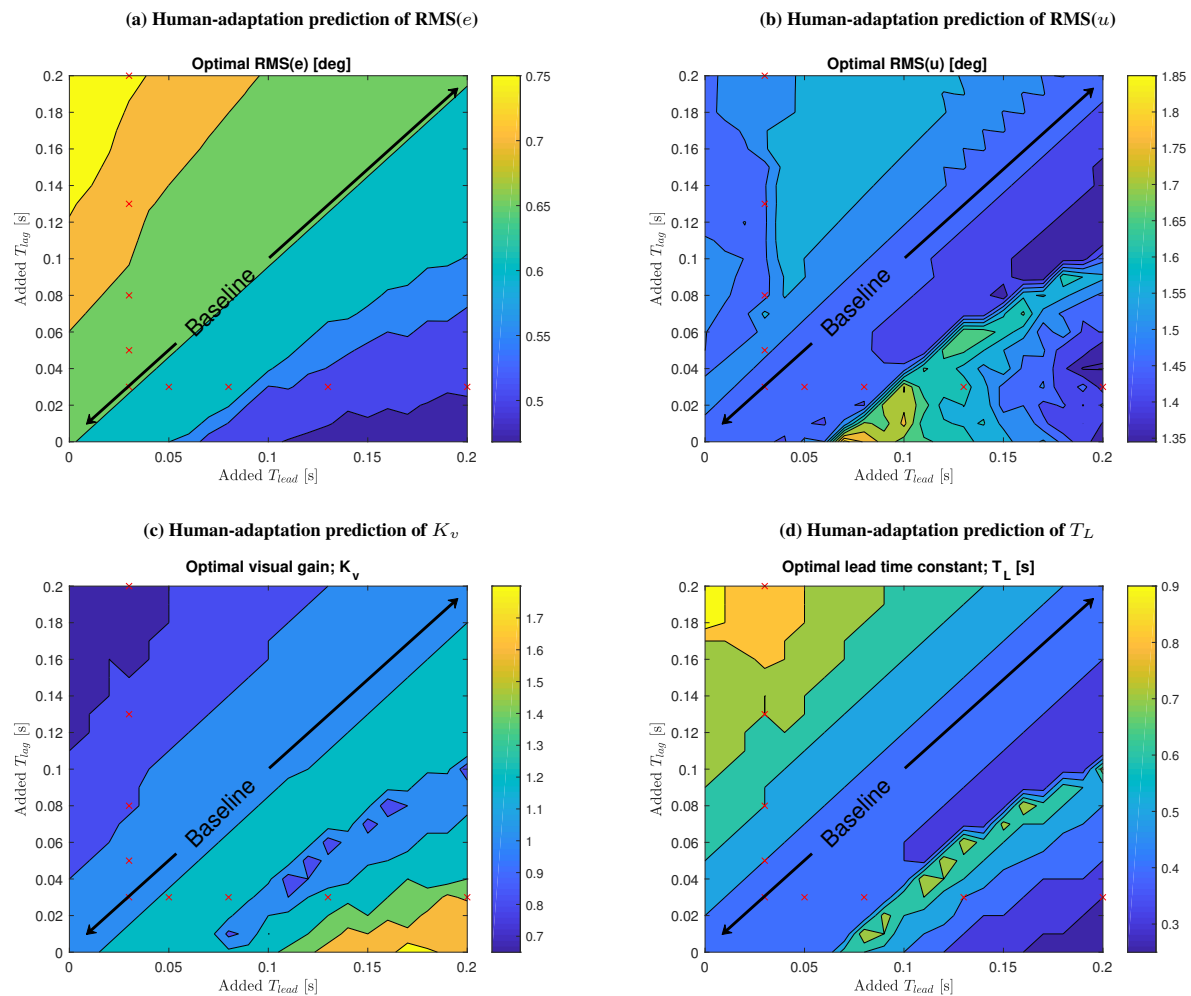


Figure 5. Human-adaptation predictions for $RMS(e)$, $RMS(u)$, K_v , and T_L for varying T_{lag} and T_{lead} settings.

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 theorem¹ 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.

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.

Rating	Interpretation
0	No difference
1	Difference, but not really noticeable
2	Noticeably different
3	Completely different

Table 4. Experiment Latin square design.

subj.	training	session I			session II			session III		
1	B	C3	C7	C1	B	C4	C8	C5	C6	C2
2	B	C8	B	C6	C2	C1	C5	C3	C4	C7
3	B	B	C1	C3	C6	C5	C2	C7	C8	C4
4	B	C4	C8	C2	C5	B	C1	C6	C7	C3
5	B	C5	C2	C4	C7	C6	C3	C8	C1	B
6	B	C2	C6	C8	C4	C3	C7	B	C5	C1
7	B	C1	C5	C7	C3	C2	C6	C4	B	C8
8	B	C6	C3	B	C8	C7	C4	C1	C2	C5
9	B	C7	C4	C5	C1	C8	B	C2	C3	C6

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 ω_t according to:

$$\hat{H}_p(j\omega_t) = \frac{U(j\omega_t)}{E(j\omega_t)} \quad (6)$$

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 θ that provided the best fit to the describing function according to the following complex squared cost function:

$$J_{exp}(\theta) = \sum_{k=1}^{N_t} |\hat{H}_p(j\omega_t[k]) - H_p(j\omega_t[k], \theta)|^2 \quad (7)$$

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 envelopes⁷ 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,¹ 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,

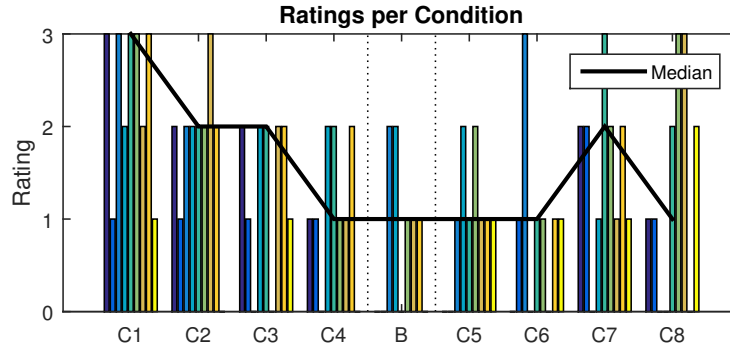


Figure 7. Subjective noticeability ratings for all experiment conditions.

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 τ_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.

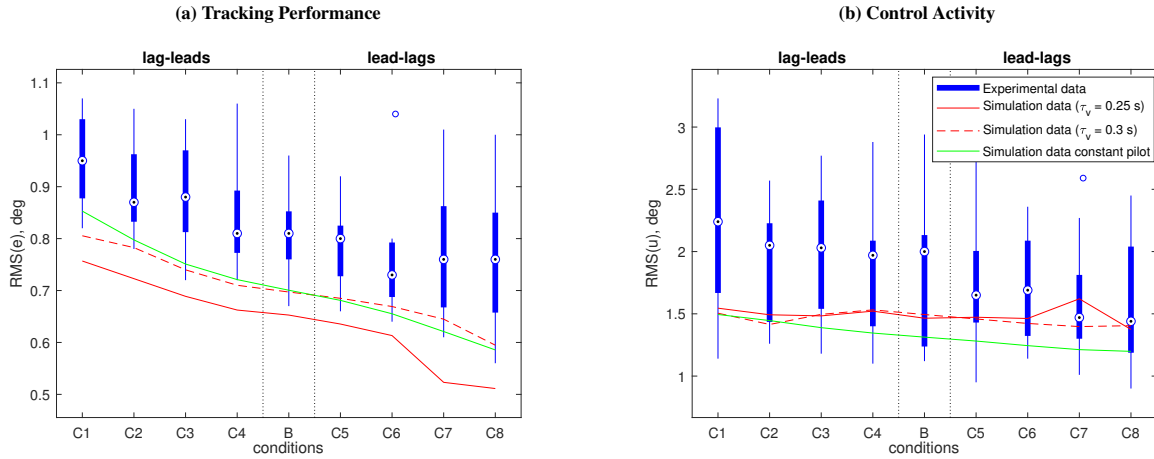


Figure 8. Measured performance ($RMS(e)$) and control activity ($RMS(u)$) compared to no-adaptation and human-adaptation predictions.

Table 5. Wilcoxon signed-rank test results for pairwise comparisons of $RMS(e)$ and $RMS(u)$ data with the baseline condition (B). * indicates $p < 0.05$ and ** indicates $p < 0.01$.

RMS(e)						RMS(u)					
lag-leads			lead-lags			lag-leads			lead-lags		
Cond.	R	Sig.	Cond.	R	Sig.	Cond.	R	Sig.	Cond.	R	Sig.
C1-B	45.0	**	C5-B	14.5	-	C1-B	45.0	**	C5-B	18.5	-
C2-B	44.0	**	C6-B	4.5	-	C2-B	30.0	-	C6-B	16.0	-
C3-B	40.5	*	C7-B	10.5	-	C3-B	36.0	-	C7-B	8.0	-
C4-B	32.5	*	C8-B	7.5	-	C4-B	12.5	-	C8-B	4.0	*

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 τ_v , the neuromuscular frequency ω_{nm} , and the neuromuscular damping ratio ζ_{nm} . For τ_v and ζ_{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 ω_{nm} of around 0.5 rad/s is visible. A Friedman test on the ω_{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 ω_{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 τ_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 ω_{nm} with the baseline condition data (B). * indicates $p < 0.05$ and ** indicates $p < 0.01$.

K_v						T_L						ω_{nm}					
lag-leads			lead-lags			lag-leads			lead-lags			lag-leads			lead-lags		
Cond.	R	Sig.	Cond.	R	Sig.	Cond.	R	Sig.	Cond.	R	Sig.	Cond.	R	Sig.	Cond.	R	Sig.
C1-B	3.0	*	C5-B	23.5	-	C1-B	45.0	**	C5-B	21.0	-	C1-B	10.0	-	C5-B	33.0	-
C2-B	5.0	*	C6-B	31.5	-	C2-B	43.5	*	C6-B	7.5	-	C2-B	14.0	-	C6-B	38.0	-
C3-B	11.0	-	C7-B	32.0	-	C3-B	43.0	*	C7-B	0.0	**	C3-B	10.0	-	C7-B	38.0	-
C4-B	8.5	-	C8-B	41.0	*	C4-B	36.0	-	C8-B	0.0	**	C4-B	26.0	-	C8-B	45.0	**

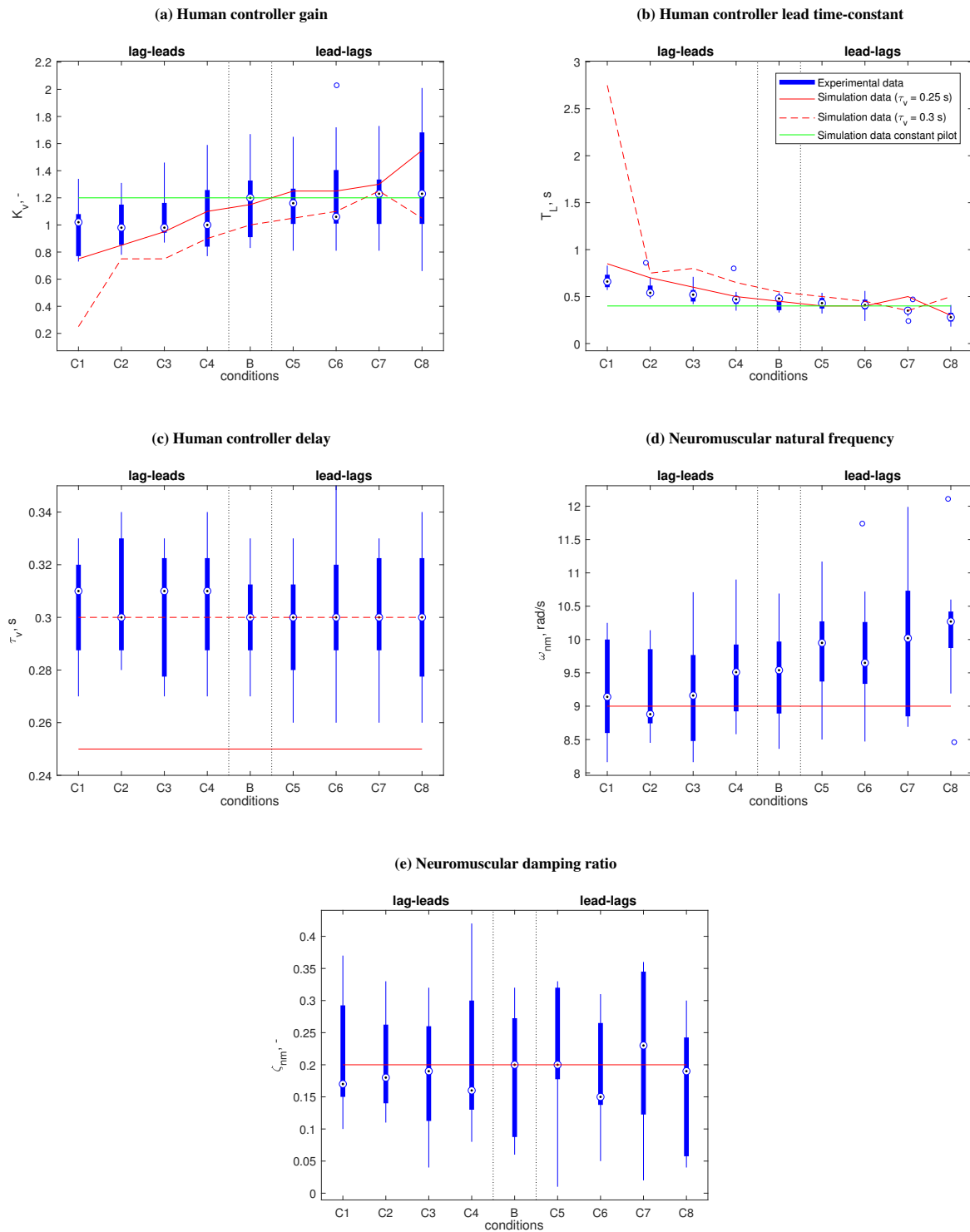


Figure 9. Estimated human controller model parameters compared to no-adaptation and human-adaptation predictions.

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 element² as well as our simulation predictions from Section III, our Hypothesis **H1** indicated that with added lag-lead dynamics we expected to find increased $\text{RMS}(e)$ (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 $\text{RMS}(e)$, 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 ω_{nm} , another statistically significant effect. While the change in ω_{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 envelopes⁷ 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,^{12,14} 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,^{10,13} 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 ω_{nm} varied over the different tested experiment conditions, it should be investigated whether including ω_{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.^{10–12,14} An important next step, given the hypothesized dependency of human noticeability of added dynamics ($H_{added}(s)$) on the the baseline controlled system ($H_{baseline}(s)$),^{8,11} 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 $H_{baseline}(s)$ 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

- ¹McRuer, D. T., Graham, D., Krendel, E. S., and Reisener, W. J., “Human Pilot Dynamics in Compensatory Systems, Theory Models and Experiments with Controlled Element and Forcing Function Variations,” Tech. Rep. AFFDL-TR-65-15, Air Force Flight Dynamics Laboratory, Wright-Patterson Air Force Base (OH), 1965.
- ²McRuer, D. T. and Jex, H. R., “A Review of Quasi-Linear Pilot Models,” *IEEE Transactions on Human Factors in Electronics*, Vol. HFE-8, No. 3, Sept. 1967, pp. 231–249.
- ³Young, L. R., “On Adaptive Manual Control,” *Ergonomics*, Vol. 12, No. 4, 1969, pp. 635–674.
- ⁴Mulder, M., Pool, D. M., Abbink, D. A., Boer, E. R., Zaal, P. M. T., Drop, F. M., van der El, K., and van Paassen, M. M., “Manual Control Cybernetics: State-of-the-Art and Current Trends,” *IEEE Transactions on Human-Machine Systems*, Vol. 48, No. 5, Oct. 2018, pp. 468–485.
- ⁵Hodgkinson, J., “History of Low-Order Equivalent Systems for Aircraft Flying Qualities,” *Journal of Guidance, Control, and Dynamics*, Vol. 28, No. 4, July-August 2005, pp. 577–583.
- ⁶Carpenter, C. G. and Hodgkinson, J., “V/STOL Equivalent Systems Analysis,” Tech. Rep. NADC-79141-60, United States Navy, Naval Air Development Center, Warminster, Pennsylvania 18974, May 1980.
- ⁷Wood, J. R. and Hodgkinson, J., “Definition of Acceptable Levels of Mismatch for Equivalent Systems of Augmented CTOL Aircraft,” Tech. Rep. MDC A6792, McDonnell Aircraft Company, St. Louis (MO), Dec. 1980.
- ⁸Mitchell, D. G., Hoh, R. H., He, C., and Strobe, K., “Determination of Maximum Unnoticeable Added Dynamics,” *Proceedings of the AIAA Atmospheric Flight Mechanics Conference and Exhibit, Keystone (CO)*, No. AIAA-2006-6492, 2006.
- ⁹Neal, T. P. and Smith, R. E., “An In-flight Investigation to Develop Control System Design Criteria for Fighter Airplanes,” Tech. Rep. AFFDL-TR-70-74, Volume 1, Air Force Flight Dynamics Laboratory, Dec. 1970.
- ¹⁰Lu, T., Pool, D. M., van Paassen, M. M., and Mulder, M., “Quantifying the Effects of Added Dynamics with Human Operator Control Behavior Measurements and Simulations,” *Proceedings of the AIAA Modeling and Simulation Technologies Conference, Denver (CO)*, No. AIAA-2017-3667, 2017.
- ¹¹Matamoros, I., Lu, T., van Paassen, M. M., and Pool, D. M., “A Cybernetic Analysis of Maximum Unnoticeable Added Dynamics for Different Baseline Controlled Systems,” *Proceedings of the the 20th IFAC World Congress, Toulouse, France*, Vol. 50 of *IFAC-PapersOnLine*, July 2017, pp. 15847–15852.
- ¹²Lu, T., *Objective Evaluation of Human Manual Control Adaptation Boundaries using a Cybernetic Approach*, Ph.D. thesis, Delft University of Technology, Faculty of Aerospace Engineering, April 2018.
- ¹³Zaal, P. M. T., Pool, D. M., de Bruin, J., Mulder, M., and van Paassen, M. M., “Use of Pitch and Heave Motion Cues in a Pitch Control Task,” *Journal of Guidance, Control, and Dynamics*, Vol. 32, No. 2, 2009, pp. 366–377.
- ¹⁴Fasiello, S., Lu, T., Pool, D. M., and van Paassen, M. M., “Manual Control Adaptation to Variations in Short-Period Natural Frequency and Damping,” *Proceedings of the AIAA Modeling and Simulation Technologies Conference, San Diego (CA)*, 2019.
- ¹⁵Damveld, H. J., Beerens, G. C., van Paassen, M. M., and Mulder, M., “Design of Forcing Functions for the Identification of Human Control Behavior,” *Journal of Guidance, Control, and Dynamics*, Vol. 33, No. 4, July 2010, pp. 1064–1081.
- ¹⁶Hosman, R. J. A. W., *Pilot’s Perception and Control of Aircraft Motions*, Ph.D. thesis, Delft University of Technology, Faculty of Aerospace Engineering, 1996.
- ¹⁷Zaal, P. M. T., Pool, D. M., Chu, Q. P., van Paassen, M. M., Mulder, M., and Mulder, J. A., “Modeling Human Multimodal Perception and Control Using Genetic Maximum Likelihood Estimation,” *Journal of Guidance, Control, and Dynamics*, Vol. 32, No. 4, 2009, pp. 1089–1099.