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Effects of Peripheral Visual Cues in Simulator-Based Training of Multimodal Control Skills

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This paper describes a training experiment performed in the SIMONA Research Simulator at Delft University of Technology to evaluate the effectiveness of peripheral visual cues as a substitute for physical motion feedback during the development of multimodal control skills. Twenty task-naive participants were divided in two experimental groups and performed a skill-based compensatory roll tracking task. Both groups were trained in a fixed-base setting, but one group was provided with additional out-of-the-window peripheral visual (roll rate) cues. After training, participants were transferred to a moving-base condition where pure roll motion cues were provided. The development of skills in both groups throughout the experiment was studied and compared using fits of a multimodal human operator model with an error and a roll feedback response, to explicitly quantify operators' use of all supplied feedbacks. As expected, the group that had access to peripheral visual cues attained better tracking performance during training and showed the development of multimodal control behavior. However, no evident transfer of this developed multimodal control strategy to a motion setting was observed. This suggests that training with peripheral visual cues is not an effective substitute for training the multimodal skills human operators use when motion feedback is available.

I. Introduction

In order to control and steer any vehicle, whether it is a bicycle, a car or an aircraft, humans depend on their sensory systems to perceive their surroundings and thereby gather information relevant for control. In general, visual and physical motion stimuli are the most relevant control inputs and control proficiency is attained through learned responses to what the visual and vestibular systems perceive.¹ In case of an aircraft, a large part of pilots' learning process is nowadays performed in full flight simulators, which replicate flight reality to ensure pilots develop realistic and effective control skills. The control skills acquired by pilots during simulator training need to be applied directly when transferred to a real-world setting and flying an actual aircraft. Understanding what changes in pilots' responses to their sensory systems inputs throughout their learning process, together with why and how those changes occur, will result in improved flight simulators, pilot training, and ultimately pilot skills.

Insight into the effectiveness of certain training paradigm or simulator type can be gained from transfer-of-training experiments, in which the transfer of control behavior acquired in a training condition (e.g., a flight simulator) to the evaluation setting (e.g., a real aircraft) is investigated and directly assessed. However, given the cost and effort involved with "true" transfer-of-training studies, the majority of experimental work in fact focuses on quasi-transfer-of-training experiments, where the evaluation setting is not true reality but a more realistic simulation environment.² The learning of skill-based manual control is characterized by the development of low-level automated responses to continuous environmental feedback signals,³ and the extent to which trained behavior transfers to a different environment is mainly defined by the environmental dependency of the applied skills.^{4,5} Multiple transfer-of-training experiments were performed to understand what are the effects of different types of simulator cues on humans' learning of control behavior and how these cues affect skill transfer. Most of them focused on the training effectiveness of motion cues, having found that motion feedback is required for effective simulator-based training of manual control skills.⁶⁻⁸ This happens because motion feedback strongly influences human operators' behavior, especially when the controlled dynamics require lead equalization.⁹⁻¹¹

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Recent studies with compensatory tracking tasks have shown that peripheral visual cues are utilized by human operators to support a human feedback control organization similar to the one observed in tasks with physical motion cues.^{12,13} It was proven that the presence of a strong outside visual scene provides lead information on the controlled dynamics in a similar way as achieved by the physical motion feedback, though perhaps not as effectively.^{1,13,14} If these findings are taken into consideration from a perspective of simulator-based training, similarities in the way human operators deal with both sensory inputs suggest that outside visual cues might be used as a substitute for true physical motion feedback during initial simulator-based training, as they might create and establish an equivalent feedback channel in the human operator without the need of actual physical motion cues. At this point, such a transfer of multimodal control skills has never been studied explicitly. This paper tests the hypothesis that the additional feedback channel human operators develop with a peripheral visual scene is indeed effective for also developing multimodal manual control skills in a moving-base setting.

This paper thus aims to verify the extent to which peripheral visual cues are effective in developing multimodal control skills, as would be adopted in a moving-base setting, during simulator-based pilot training. To achieve this goal, a quasi-transfer-of-training experiment was conducted in the SIMONA Research Simulator at Delft University of Technology with twenty fully task-naive participants. The participants were asked to perform a compensatory roll attitude tracking task, similar to multiple earlier training and tracking experiments.^{8,13,15,16} Subjects were divided in two experimental groups and performed 100 training runs, either with the simulator outside visual system off (“no-visuals”) or on (“visuals”). After this training phase, participants were transferred to the evaluation setting, where both groups performed 100 more runs with pure roll motion provided by the simulator and without a peripheral visual scene. Learning and transfer were analyzed by calculating tracking performance, control activity, and fitted human operator control models for each performed tracking run. The overall evolution of all control behavior metrics throughout the transfer-of-training experiment provides unique direct insight into the effectiveness of peripheral visual cues in using physical motion cues during simulator-based training of manual piloting skills.

This paper is structured as follows. The methods, the organization of the experiment, and the hypotheses are described in Section II. Section III presents the experiment data. The paper ends with a discussion and conclusions.

II. Methods

II.A. Control Task

The human-in-the-loop training experiment focused on a compensatory roll-axis tracking task, following the same procedures as various earlier investigations on skill-based manual control training.^{8,13,15,16} In Figure 1 this task is schematically represented. The human controller was asked to follow a target roll angle, specified by the tracking signal f_t , as accurately as possible. Simultaneously, the human operator had to reject disturbances on the controlled system H_c , which were induced by the disturbance signal f_d . This disturbance signal was added to the human operator’s input, u . In order to identify and model the multi-channel human operator response, characterized by H_{p_e} and H_{p_ϕ} , the disturbance signal f_d and the target signal f_t were independent sum-of-sines signals.^{17–19} Given the quasi-linear human operator model used, the control input had contributions from the error response, u_e , the roll response, u_ϕ , and a remnant n accounting for nonlinear behavior and measurement noise.

The experiment was performed in the SIMONA Research Simulator (SRS) at TU Delft, see Fig. 2(a). For the experiment, the simulator’s Primary Flight Display (PFD) presented participants with a compensatory display that resembled a basic artificial horizon, see Fig. 2(b). This compensatory display showed the roll error e between the

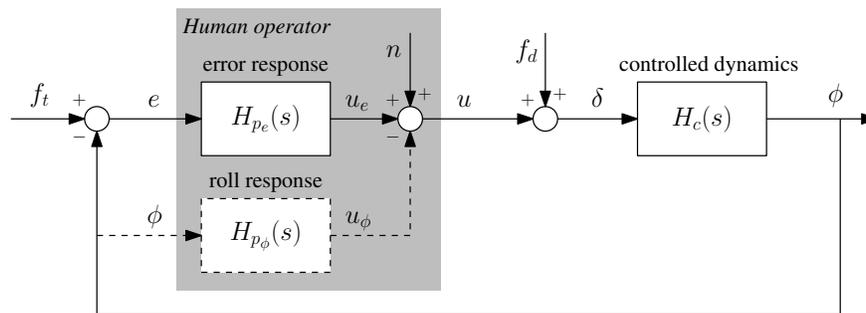


Figure 1. Schematic representation of the roll tracking task.

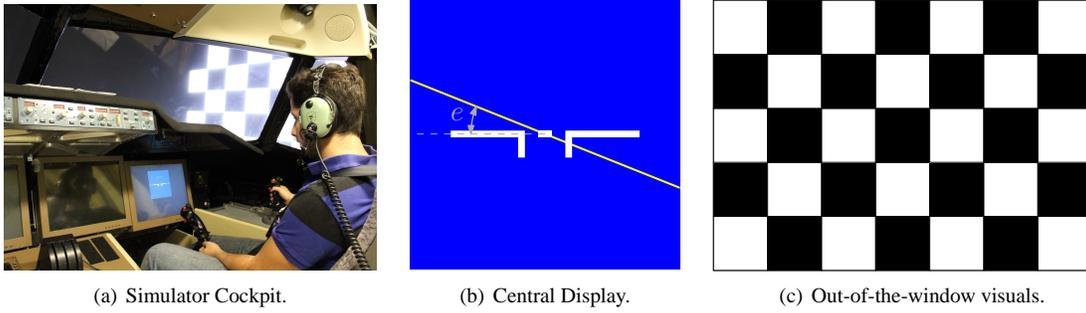


Figure 2. Simulator cockpit, central display and the out-of-the-window scene.

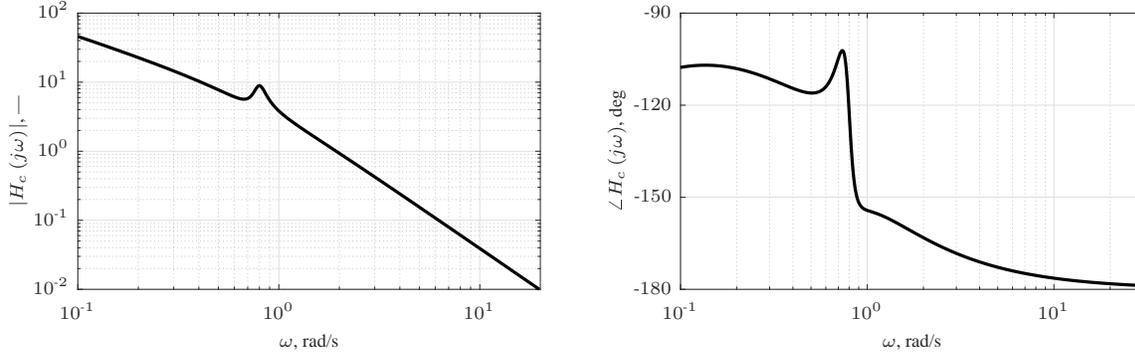


Figure 3. Frequency response of the controlled element dynamics.

current aircraft roll angle (ϕ) and the target roll angle (f_t) as the rotation of the reference line with respect to a static aircraft symbol.

The out-of-the-window peripheral visual cues used in this experiment were based on earlier experiments^{1,13,20,21} and consisted of two vertically moving checkerboard panels (see Fig. 2(c)) positioned in participants right and left peripheral visual field, providing a strong roll motion (roll rate) sensation without giving reference of roll-attitude. In the moving-base condition pure roll motion was provided, thus without any washout or lateral specific force compensation.

The controlled dynamics H_c were the dynamics used in Ref. 16 and presented in Eq. (1), multiplied by a gain of 5. These dynamics correspond to a mid-size twin-engine commercial transport aircraft with a gross weight of 185,800 lbs, linearized in a flight condition close to the stall point, at an altitude of 41,000 ft and an airspeed of 150 kts.

$$H_c(s) = 3.91040 \frac{(s^2 + 0.2175s + 0.5861)}{(s + 0.7599)(s - 0.02004)(s^2 + 0.1133s + 0.6375)} \quad (1)$$

As is clear from Eq. (1), these roll dynamics have a mildly unstable pole (spiral) in this flight condition. The dynamics approximate a single integrator ($\frac{1}{s}$) at low frequencies (< 0.75 rad/s) and a double integrator ($\frac{1}{s^2}$) at frequencies higher than 0.75 rad/s, as seen in Fig. 3, due to the effect of the pole at 0.7599 rad/s.

Human operator control behavior was modeled in this compensatory tracking task using a quasi-linear model.^{22,23} As shown in Fig. 1, the output of the human operator, the control input signal u , is the sum of a linear response and a remnant signal n . The linear response has two contributions, H_{p_e} and H_{p_ϕ} , which respectively model the response to the roll tracking error (available from the PFD) and the response to the roll feedback (available from the out-of-the-window cues or the simulator's physical motion).^{24,25} The remnant signal accounts for measurement noise and nonlinearities which are not described by the linear response functions. Determining the form of the transfer functions H_{p_e} and H_{p_ϕ} and the evolution of their parameters throughout the progress of a training experiment has proven to be of great help in understanding and quantifying the learning process of both visual and motion cues by the initially task-naive participants.^{8,16,26}

Table 1. Experiment forcing function (disturbance and target) data

Disturbance signal, f_d								Target signal, f_t							
n_d	ω_d , rad/s	A_d , deg	$\phi_{d,1}$, rad	$\phi_{d,2}$, rad	$\phi_{d,3}$, rad	$\phi_{d,4}$, rad	$\phi_{d,5}$, rad	n_t	ω_t , rad	A_t , deg	$\phi_{t,1}$, rad	$\phi_{t,2}$, rad	$\phi_{t,3}$, rad	$\phi_{t,4}$, rad	$\phi_{t,5}$, rad
2	0.15	0.03	6.28	3.52	2.64	2.83	2.96	5	0.38	0.51	5.68	3.99	3.92	6.00	4.39
3	0.23	0.05	1.25	5.41	2.07	5.64	1.00	6	0.46	0.49	0.83	4.35	1.42	5.23	5.77
9	0.69	0.13	1.46	2.16	5.64	5.18	4.57	13	1.00	0.34	0.54	5.35	5.17	4.75	4.93
10	0.77	0.09	5.45	0.11	3.78	5.70	1.51	14	1.07	0.33	1.14	5.92	1.57	6.28	4.23
22	1.69	0.27	1.96	0.66	4.94	4.09	1.81	27	2.07	0.16	2.93	3.84	4.05	2.88	4.01
23	1.76	0.28	3.29	2.88	0.38	4.65	4.04	28	2.15	0.15	2.83	3.48	6.24	1.23	2.39
36	2.76	0.36	2.62	1.96	1.88	4.43	3.33	41	3.14	0.08	6.02	4.99	4.04	1.21	2.91
37	2.84	0.36	4.28	5.61	4.38	4.98	3.45	42	3.22	0.08	1.74	4.97	2.71	0.29	0.46
49	3.76	0.40	6.28	5.63	0.73	3.80	4.31	53	4.07	0.06	3.90	4.26	1.71	1.88	2.56
50	3.83	0.41	3.93	0.31	2.07	2.35	5.67	54	4.14	0.05	0.74	1.00	4.03	4.62	2.08
69	5.29	0.47	4.39	0.65	4.09	3.60	1.54	73	5.60	0.03	5.65	4.69	0.67	0.89	4.56
70	5.37	0.48	0.65	1.14	4.42	4.20	1.80	74	5.68	0.03	3.70	5.01	5.85	0.97	3.33
97	7.44	0.59	6.17	0.35	2.82	0.34	6.24	103	7.90	0.02	3.63	5.44	5.13	0.74	1.43
99	7.59	0.60	2.17	2.92	2.69	5.85	0.84	104	7.98	0.02	1.42	5.78	4.14	5.81	1.44
135	10.35	0.79	3.80	2.27	4.91	4.54	3.25	139	10.66	0.02	3.64	0.86	2.66	5.21	5.97
136	10.43	0.80	2.58	2.57	4.31	2.20	1.43	140	10.74	0.02	5.94	2.05	5.65	1.08	4.55
169	12.96	1.03	2.84	6.07	4.46	6.16	4.57	193	14.80	0.01	4.74	2.03	4.28	0.70	5.76
170	13.04	1.04	4.11	2.98	4.22	3.94	0.44	194	14.88	0.01	3.72	2.88	1.92	2.81	5.28
224	17.18	1.53	4.98	0.77	4.69	2.20	3.57	229	17.56	0.01	4.32	3.01	1.03	4.44	2.67
225	17.26	1.54	5.67	3.90	4.70	4.16	5.20	230	17.64	0.01	2.15	2.93	3.21	0.53	2.50

II.B. Forcing Functions

The disturbance and target forcing functions, f_d and f_t , were independent sum-of-sines signals defined by Eq. (2), as used in a number of previous tracking studies.^{17,18,27}

$$f_{d,t}(t) = \sum_{k=1}^{N_{d,t}} A_{d,t}[k] \sin(\omega_{d,t}[k]t + \phi_{d,t}[k]) \quad (2)$$

In Eq. (2), $A_{d,t}[k]$, $\omega_{d,t}[k]$ and $\phi_{d,t}(k)$ respectively indicate the amplitude, frequency and phase of the k -th sine in the forcing function. $N_{d,t}$ is the number of sine waves constituting the forcing function. In this experiment, both the disturbance and target forcing functions were the sum of $N_{d,t} = 20$ individual sinusoids, each with different amplitudes, frequencies and phases. In Table 1 a list of all the parameters used to generate the forcing functions can be found.

The frequencies of the sinusoids, $\omega_{d,t}[k]$, were purposely defined as integer multiples of the measurement time base frequency, $\omega_{d,t}[k] = n_{d,t}[k] \omega_m$, where $\omega_m = 2\pi/T_m = 0.0767$ rad/s and $T_m = 2^{13} = 8192$ ms is the measurement time, counting from the end of the run (each run had 95 seconds and only the last 81.92 seconds were used, using a sampling frequency of 100 Hz). The selected integer multiples were used in previous studies,⁸ guaranteeing the twenty sinusoid frequencies covered the frequency range of human control at regular intervals on a logarithmic scale. Moreover, the integer multiples were chosen in consecutive pairs, creating double bands of input frequencies so that coherence between the control signal produced by the human operator u and the forcing functions f_d and f_t could be calculated.²⁸

A second-order low-pass filter was used to calculate the amplitudes of the individual sines, in similarity with previous studies.^{8,27} The purpose of this second-order filter was to reduce the magnitude of the amplitudes at higher frequencies, which results in a not extremely difficult tracking task. Also matching earlier experiments,^{8,27} the amplitude distributions were scaled so that the target forcing function power was 25% of that of the disturbance forcing function, which made this task predominantly a disturbance-rejection task.

Five realizations of f_d and f_t were used, differing only by their initial sinusoidal phases $\phi_{d,t}$ of the individual sine-components. The set of phases chosen yielded signals with a Gaussian-like distribution and an average crest factor.²⁹ This was done in order to prevent subjects from recognizing parts of the signals because of the repeated exposure inherent to performing 200 tracking runs. With a combination of five disturbance signals and five target signals, randomly assigned to consecutive tracking runs following a latin-square distribution, it was virtually impossible for the subjects to memorize the signals.

The disturbance signal was preshaped by the inverse of the aircraft dynamics to compensate for the fact that it is actually inserted before H_c (see Fig. 1).

II.C. Experiment Setup

The experiment was divided in two phases, referred to as the *training* phase and the *evaluation* phase. During the training phase, the task-naive participants received initial fixed-base training in the roll tracking task. They were subsequently transferred to the evaluation phase where the same roll tracking task was performed in a moving-base setting.

As shown in Fig. 4, participants were divided in two experimental groups. The first group, **Group NV**, was trained with only the PFD and thus without out-of-the-window visuals and motion cues (i.e., NV NM), and transferred to an evaluation condition with access to the PFD and motion feedback (i.e., NV M). The second group, referred to as **Group V**, was trained without motion, but with the PFD and the out-of-the-window visual cues (i.e., V NM). Group V was transferred to the same evaluation configuration as Group NV (NV M). Therefore, the only difference between the two experimental groups was the presence of out-of-the-window visual cues in the training phase.

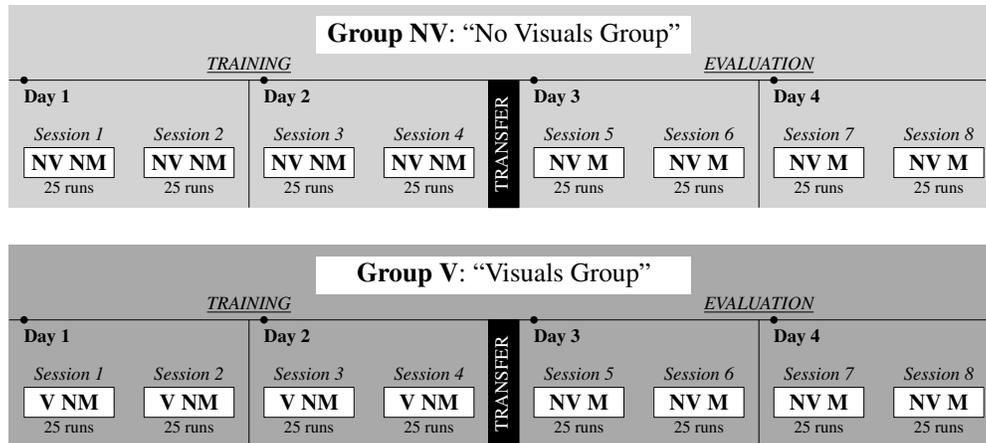


Figure 4. Quasi-transfer-of-training experiment design.

Each phase of the experiment consisted of a fixed number of 100 tracking runs, therefore each subject performed 200 runs in total. The 95-second runs were performed in eight sessions of 25 runs each. The eight sessions were performed in four consecutive days, therefore two sessions on each day, with a 20-minute break between sessions (subjects left the simulator between sessions). This experimental configuration allowed convergence of manual control skills in both experimental phases, with a consolidation of the acquired control skills in between simulator sessions, an effect known as offline learning.³⁰ This setup also respected the optimum retention time between low-level control skill training sessions of 24 hours.³¹

The experiment was ran for five weeks, on four consecutive working days of each week. With the four-day experiment design of Fig. 4, this means four participants performed the experiment in each week. On the four experiment days, subjects performed their sessions at the same time of the day, i.e., two subjects performed their two daily sessions in the morning, while two other subjects performed their two daily sessions in the afternoon. To guarantee the balancing of the times at which simulator sessions were performed between groups, every subject in one week was placed in the same group. Therefore, two weeks had subjects from Group NV, two weeks had subjects from Group V, and in the fifth week two participants from both groups were tested.

After each tracking run, the researcher informed the participant of his/her performance score in that run (the score was expressed as the root mean square value of the tracking error signal) and asked if the participant was ready for the next run. In case of an affirmative answer, the next run would be started. Otherwise, a brief break in between runs to was taken, to ensure subjects' concentration levels were high and as constant throughout the experiment as possible.

II.D. Apparatus

The quasi-transfer-of-training experiment was performed in the SIMONA Research Simulator (SRS) at the Aerospace Engineering Faculty at Delft University of Technology. Both the SRS's motion and outside visual systems were used, depending on the phase of the experiment. The SRS motion system is a hexapod with hydraulic actuators (Fig. 5), providing a six degrees-of-freedom motion system that reproduces the aircraft's motion with a time delay of 30 ms.³² Given that the task performed was a pure roll tracking task, only rotational roll motion was provided. The SRS workspace in terms of roll rotation is $\pm 25.9^\circ$, and in this experiment no roll motion filter was used, thus the controlled

roll attitude ϕ was reproduced one-to-one, without washout filtering. Matching the setup of Ref. 13, the visual system of the SRS was used to show the two checkerboard panels on the left and right window views of the simulator cockpit. The visual system delay is approximately 30 ms and all displays were ran at a 60 Hz refresh rate.³³

Participants sat in the simulator's (right) co-pilot seat and used a right-handed sidestick to control the roll rotation of the aircraft. The pitch axis of the sidestick was locked so that only roll commands could be given. In roll, the active stick was set to have a linear force-deflection characteristic of 0.75 N/deg without breakout-force. The simulator rolling motion was performed around an axis aligned with the center of the right pilot seat to ensure pure roll cueing. The compensatory display was located in front of the participant's seat.

Each subject adjusted both the height of the seat and the distance of the seat to the sidestick to ensure their comfort and the correct positioning with respect to the checkerboards in their peripheral field of vision. These seat settings were kept constant for each subject throughout the experiment. Furthermore, participants wore noise-canceling headphones with an additional masking aircraft engine sound to ensure they could not hear the acoustic noise caused by the actuators of SRS motion system.

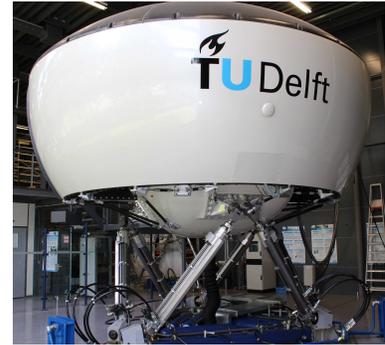


Figure 5. The SIMONA Research Simulator.

II.E. Participants

The experiment was performed by twenty fully task-naive participants, who gave their written informed consent to participate in this study prior to their participation. A total of ten subjects were included in each group. The participants were between 18 and 23 years old and included seventeen male and three female participants (two placed in Group NV and one in Group V). Two more subjects also performed the experiment, but due to severe motivation and performance inconsistencies their data were omitted from the final data set.

Each subject chose a time slot (8 sessions of 1 hour each spread over four consecutive working days) and this defined the group in which they were placed. Thus, no explicit pre-selection or distribution of the subjects over the experimental groups was performed, i.e., to actively balance the experiment groups.

II.F. Data Analysis

II.F.1. Human Operator Modeling

To understand how human operators acquire control skills throughout their learning process, their control behavior was modeled and identified in each tracking run using multimodal human operator modeling techniques. For every experiment run, the defining parameters of both the error response transfer function H_{p_e} and the roll feedback response transfer function H_{p_ϕ} (see Fig. 1) were determined using identification and optimization algorithms. The models used for H_{p_e} and H_{p_ϕ} were successfully applied in earlier studies.^{12,16,27} The considered model for the human operator error response H_{p_e} is given by:

$$H_{p_e}(s) = K_e (T_{lead}s + 1) e^{-\tau_e s} H_{nm}(s) \quad (3)$$

with H_{nm} being the neuromuscular dynamics modeled by:

$$H_{nm}(s) = \frac{\omega_{nm}^2}{s^2 + 2\zeta_{nm}\omega_{nm}s + \omega_{nm}^2} \quad (4)$$

For this roll tracking task with the considered controlled element dynamics, the error response model included a gain K_e , a lead equalization term T_{lead} , a human operator response delay τ_e , and the neuromuscular dynamics H_{nm} , modeled as a second-order mass-spring-damper system with a neuromuscular frequency ω_{nm} and a neuromuscular damping ratio ζ_{nm} . The considered structure of H_{p_e} is explained by the fact that human operators needed to generate lead, because the controlled dynamics approximated a double integrator in the frequency range where the human operator crossover frequency was expected to be for compensatory tracking (1 to 5 rad/s).^{16,22} The human operator roll response H_{p_ϕ} is modeled by:

$$H_{p_\phi}(s) = sK_\phi e^{-\tau_\phi s} H_{nm}(s) \quad (5)$$

The roll response included a pure derivative term and an equalization gain K_ϕ , modeling human operator limitations with a roll response delay τ_ϕ and the neuromuscular system, modeled as in H_{p_e} . It should be noted that H_{p_ϕ}

characterized the sum of multiple and separate feedback channels, namely the ones related with motion feedback, i.e., angular accelerations detected by the semicircular canals, linear accelerations detected by the otoliths, and motion cues from the somatosensory system.¹⁶ For similar tasks, this model structure has been successfully applied in earlier investigations.³⁴ The same human operator model was used for experimental conditions in which either motion or out-of-the-window cues were available. This allowed a direct assessment of how well out-of-the-window visual cues can replace motion cues.

The multi-channel pilot model defined in Eqs. (3) to (5) contained seven free parameters (K_e , T_{lead} , τ_e , K_ϕ , τ_ϕ , ω_{nm} , and ζ_{nm}), which were estimated from the collected experimental data (the time-domain signals e , ϕ , and u) using the time-domain parameter estimation technique of Ref. 19. For the training phase data of Group NV only H_{p_e} was fitted, as no out-of-the-window visual or motion cues were available. Firstly, ten repetitions of a genetic algorithm optimization were performed in order to obtain ten initial rough estimates of the parameters, which were the starting point of a Gauss-Newton optimization algorithm, yielding ten estimates for the set of parameters. The estimate yielding the lowest value of the likelihood function was selected as the one describing the control activity of the human operator in that run. If the lowest likelihood solution failed to satisfy the physical restrictions inherent to the model (neuromuscular frequency between 0 and 30 rad/s and neuromuscular damping ratio between 0 and 1), another solution from the set of ten Gauss-Newton estimates was considered. If none of the Gauss-Newton estimates was in the domain of the model parameters, the genetic algorithm solution holding the lowest likelihood was considered as the identified model of that run, with the validity of this lower likelihood solution being carefully analyzed. Should this model describe the human operator control behavior with an unacceptable low quality, the respective run would be omitted from the final data set. This procedure was applied to the 200 runs in the training and evaluation phases of each of the twenty subjects who performed the experiment, and from the set of 4000 tracking runs that compose the experiment, three were omitted from the final data set.

The Variance Accounted For (VAF) was calculated as a measure of the human operator model accuracy in describing the measured control signals. It is common practice to average tracking task data over a certain number of runs, to attenuate noise in the measured data and thus improving the model quality.²⁷ However, given the need to evaluate the development of control skills over individual runs, such averaging was not performed for the current experiment. Therefore, also consistently lower VAF values were obtained due to comparatively higher noise levels. Nevertheless, runs with abnormally low model VAFs (lower than 40%) were considered as identification outliers and excluded from the final data set, so that they would not influence the group average results shown in Section III. A total of 56 runs were excluded from the final data set due to this reason (i.e., only 1.4% of all performed runs), which is similar to exclusions required for an earlier training experiment with task-naive participants.⁸

The validity of the final model estimates was further analyzed with independently estimated frequency-domain describing functions for H_{p_e} and H_{p_ϕ} , obtained with a black-box multiloop identification method based on Fourier coefficients, described in detail in Refs. 18, 35 and 36.

II.F.2. Other Dependent Variables

To further evaluate the progress of every subject and the effectiveness of training cues in the evaluation setting, several additional dependent variables were calculated from the collected data. Operator control activity and performance were evaluated, in the time domain, with the variance of the control input, σ_u^2 , and the roll tracking error, σ_e^2 , respectively, in accordance to previous training studies.^{8,16} A decomposition on the sources (disturbance, target or remnant) of these variances was also made.

In the frequency domain, pilot performance in rejecting the disturbance forcing function and following the target signal was determined by the crossover frequencies and phase margins of the disturbance and target open-loop dynamics, respectively.³⁷ The disturbance and target open-loop dynamics are given by (see Fig. 1):

$$H_{ol,d}(s) = [H_{p_e}(s) + H_{p_\phi}(s)] H_c(s) \quad (6)$$

$$H_{ol,t}(s) = \frac{H_{p_e}(s)H_c(s)}{1 + H_{p_\phi}(s)H_c(s)} \quad (7)$$

The disturbance and target crossover frequencies $\omega_{c,d}$ and $\omega_{c,t}$ are the frequencies where the magnitude of the disturbance and target open-loop frequency responses is unity (0 dB). The phase differences from -180 degrees at these crossover frequencies are the corresponding phase margins $\phi_{m,d}$ and $\phi_{m,t}$.

II.F.3. Learning Curve Modeling

To give a quantitative insight on how operators' control behavior changed during training and after transfer to the evaluation condition, exponential learning curves were fitted to the dependent measures described above. The learning curve model used is given by Eq. (8):

$$y_{lc}(n) = p_a + (1 - F)^n(p_0 - p_a) \quad (8)$$

The exponential learning curve model in Eq. (8) is determined by the initial value p_0 , the asymptotic value p_a , and the learning rate F .⁶ These parameters were calculated using a non-linear optimization procedure (Matlab `fminsearch`) to minimize the summed squared error between the experimental data and the learning curve model. For each dependent variable, two learning curves were fit; one for the training phase and one for the evaluation phase. Pearson's linear correlation coefficient ρ was determined to evaluate the quality-of-fit of fitted learning curves. Only for $\rho > 0.5$ the correlation of the learning curve and data was deemed sufficient to present the learning curve fit in this paper.

II.F.4. Statistical Analysis

Statistical analysis of the dependent data σ_e^2 and σ_u^2 was performed to compare different phases of the experiment. Three pairwise comparisons (dependent t -tests) were performed for each variable, corresponding to the expected evolutions throughout the different parts of the experiment. The *training* comparison compared the average of each subject on runs 1-5 and 96-100. The *transfer* comparison considered the average of each subject on runs 96-100 and 101-105. For the *evaluation* comparison, the average of each subject on runs 101-105 and 196-200 was compared. The statistical test utilized for these comparisons was the nonparametric Wilcoxon signed-rank test, as the considered data were mostly not normally distributed due to large between-subject variability.

II.G. Hypotheses

Based on a number of previous tracking experiments where the effects of both out-of-the-window and motion cues were studied, together with earlier quasi-transfer-of-training studies, the following hypotheses were formulated for this experiment:

- H1:** *Training causes an improvement in performance and task proficiency in both experimental groups.* Clear effects of training were expected to occur in both experimental groups during the training phase, as seen in a number of previous training experiments (Refs. 7, 8, 16 and 38), which are visible in improved performance (lower σ_e^2), increased control activity (higher σ_u^2), and higher crossover frequencies and phase margins. In the human operator modeling results, it was expected to see adjustments in parameters that are known to be related to improved performance (increased K_e , K_ϕ , lower human operator delays).
- H2:** *The presence of peripheral visual cues in training of control skills provides a feedback channel of the controlled dynamics output.* For the group trained with visual conditions (Group V), previous studies (Refs. 1, 13 and 14) suggest that visual cues available in the training phase provide a feedback channel for the roll angle and this was expected to be visible in better performance (lower σ_e^2) and in the human operator parameters describing the response to roll angle feedback. The roll gain K_ϕ and the roll delay τ_ϕ were expected to be different from zero in the training phase of Group V.
- H3:** *In the evaluation phase, the presence of motion allows reaching better task performance levels.* It is known that the addition of motion cues in a tracking task allows reaching better levels of task performance than in a fixed-base setting.^{8,9,16} This effect was expected to be mainly visible in performance metrics with lower σ_e^2 and higher σ_u^2 . In the human operator parameters, higher gains (K_e and K_ϕ), lower delays (τ_e and τ_ϕ), and especially lower values of T_{lead} were expected as a consequence of the lead information provided by the motion feedback.
- H4:** *Adaption to motion conditions is faster for subjects who were trained with out-of-the-window visual cues.* It was expected that subjects in both groups would, at the end of the evaluation phase, reach the same level of task proficiency, as a result of the extensive repetition of the evaluation conditions with physical motion. However, this level of task proficiency was expected to be reached earlier by subjects in Group V, meaning less hours of training would be needed in a flight simulator with motion conditions. This would happen because transfer

of control skills to a motion condition was expected to be more effective for subjects who trained with the presence of out-of-the-window visuals, as these cues would have created a roll feedback response in training phase. This is supported by earlier findings that human operators use out-of-the-window visuals to formulate a similar additional feedback response as they do with physical motion feedback.¹² Therefore, this easier transfer of skills would be visible in higher learning rates in the evaluation condition for subjects in Group V when compared to subjects in Group NV and better task performance in Group V immediately after transfer.

III. Results

This section presents all experiment results. All figures in this section show the data from Group NV in blue and data from Group V in red. In plots where data evolution over the full 200 runs of the experiment is shown, a black vertical line indicates the transfer after run 100. When learning curves are fitted to the data, which is done when Pearson's correlation coefficient is higher than 0.5, Pearson's correlation coefficients for comparison of the learning curve model and the data are shown in the figure legend with the following organization $\rho = [\rho_{\text{training}}, \rho_{\text{evaluation}}]$. Gray error bars indicate the 95% confidence intervals of the mean data for plots showing data from all experiment runs.

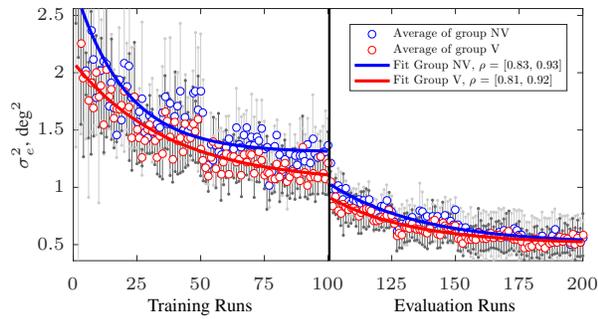
III.A. Tracking Performance

Tracking performance was measured with the variance of the roll error, i.e., the error presented to the human operator on the PFD. The lower the value of σ_e^2 , the better task was performed. Figure 6(a) shows the average variance of the tracking error per experiment run, together with fitted learning curves and the 95% confidence intervals of the mean data. Furthermore, to evaluate the performance improvement throughout the experiment, a decomposition in components of tracking error variance was made, separating the contributions from the disturbance forcing function, the target forcing function, and the remnant noise.³⁷ These results are shown, respectively, in Figs. 6(b), 6(c), and 6(d). The parameters of the fitted learning curves in Fig. 6 are presented on the left side of Tables 2 to 5.

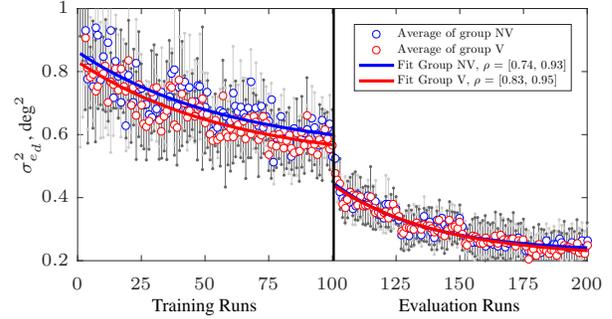
Some important conclusions can be drawn when looking at the tracking error results presented in Fig. 6. In the *training* phase, the performance level of Group V was always better than the performance level reached by Group NV in every component of the tracking error, suggesting that the presence of out-of-the-window visual cues indeed improved human operator performance, as expected from previous studies.^{12,13} In Fig. 6(a), it can be seen that Group NV showed a steeper improvement in performance during the training phase, whereas the learning curve for Group V was smoother, mainly because of the contribution of the remnant error seen in Fig. 6(d). This is also seen in the learning rates in Table 2, as F in the training phase was higher for Group NV. However, while Group NV stabilized their performance approximately at $\sigma_e^2 = 1.32 \text{ deg}^2$ around run 60, Group V kept a steady improvement throughout the 100 training runs, reaching $\sigma_e^2 = 1.09 \text{ deg}^2$ at the end of the training phase. This suggests it took longer to adapt to the peripheral visual scene but the information it provided allowed better performance, even in the first runs where a clear difference between groups was already visible. Statistical data shown in Tables 2-5 for the training phase confirm the significant improvements in performance.

Upon *transfer*, both groups showed a similar evolution in tracking performance, with an instantaneous decrease in total error variance of 0.3 deg^2 in Group NV and 0.2 deg^2 in Group V. This effect is also seen in the statistical analysis, reporting a significant difference in compared samples of total error and disturbance components both groups. However, this did not hold for the target error for Group V and for the remnant component of σ_e^2 in both groups, where no significant difference was found after transfer. This difference between groups suggests a better adaptation to motion cues by Group V, given that no significant difference was found in the target error component. This seems to suggest that some positive transfer of control skills did occur when the subjects in Group V were transferred to the motion conditions.

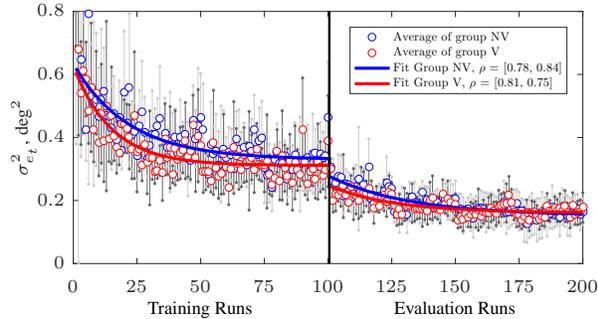
For the *evaluation* phase, it can be seen that, as reported by numerous previous studies,^{8,9,13} motion cues were more effective and they allowed for notable improvements in performance levels of subjects in both groups. Both groups ended in the same level of asymptotic task proficiency in terms of performance (total error of around 0.51 deg^2), showing a convergence of control skills, a necessary premise to validate the results of any training experiment. The confidence intervals for the evaluation phase were much smaller in amplitude and the Pearson's coefficients of the learning curves were also higher in this phase, which suggest lower subject variability as the experiment approached its end and subjects became more proficient in the task. Group NV had a lower evaluation learning rate in the total error, target error, and remnant error than Group V, which means Group V was faster in learning how to use motion cues. The improvement in performance for both groups during the evaluation phase was validated by the statistical analysis. It can also be seen that, even though the target error and the remnant error components decreased with motion, the



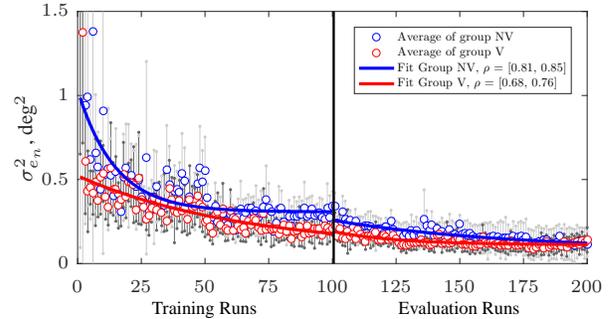
(a) Total tracking error variance.



(b) Disturbance tracking error variance.



(c) Target tracking error variance.



(d) Remnant tracking error variance.

Figure 6. Measured tracking error variance and the disturbance, target, and remnant contributions.

Table 2. Learning curve parameters and statistical analysis for total tracking error.

σ_e^2	Learning Curve Parameters						Statistical Significance					
	Training Phase			Evaluation Phase			Training		Transfer		Evaluation	
	p_0, deg^2	p_a, deg^2	$F(\times 10^{-2})$	p_0, deg^2	p_a, deg^2	$F(\times 10^{-2})$	W_s	Sig.	W_s	Sig.	W_s	Sig.
Group NV	2.94	1.32	5.42	1.04	0.51	2.72	55	**	51	*	55	**
Group V	2.26	1.09	1.38	0.93	0.51	3.05	55	**	55	**	55	**

Table 3. Learning curve parameters and statistical analysis for disturbance tracking error.

$\sigma_{e_d}^2$	Learning Curve Parameters						Statistical Significance					
	Training Phase			Evaluation Phase			Training		Transfer		Evaluation	
	p_0, deg^2	p_a, deg^2	$F(\times 10^{-2})$	p_0, deg^2	p_a, deg^2	$F(\times 10^{-2})$	W_s	Sig.	W_s	Sig.	W_s	Sig.
Group NV	0.89	0.57	2.15	0.45	0.23	2.79	55	**	51	**	54	**
Group V	0.86	0.54	2.17	0.44	0.21	2.38	55	**	55	**	55	**

Table 4. Learning curve parameters and statistical analysis for target tracking error.

$\sigma_{e_t}^2$	Learning Curve Parameters						Statistical Significance					
	Training Phase			Evaluation Phase			Training		Transfer		Evaluation	
	p_0, deg^2	p_a, deg^2	$F(\times 10^{-2})$	p_0, deg^2	p_a, deg^2	$F(\times 10^{-2})$	W_s	Sig.	W_s	Sig.	W_s	Sig.
Group NV	0.66	0.33	4.94	0.28	0.15	3.12	53	**	49	*	55	**
Group V	0.66	0.31	6.49	0.26	0.16	4.63	54	**	41	—	55	**

Table 5. Learning curve parameters and statistical analysis for remnant tracking error.

$\sigma_{e_n}^2$	Learning Curve Parameters						Statistical Significance					
	Training Phase			Evaluation Phase			Training		Transfer		Evaluation	
	p_0, deg^2	p_a, deg^2	$F(\times 10^{-2})$	p_0, deg^2	p_a, deg^2	$F(\times 10^{-2})$	W_s	Sig.	W_s	Sig.	W_s	Sig.
Group NV	1.13	0.31	7.35	0.26	0.08	1.41	55	**	30	—	54	**
Group V	0.57	0.15	2.33	0.19	0.11	3.73	55	**	45	—	47	*

Legend: ** = highly-significant ($p < 0.01$)
 * = significant ($0.01 \leq p < 0.05$)
 — = not significant ($p \geq 0.05$)

main effect of motion feedback was to decrease the disturbance tracking error. This was also observed in previous tracking tasks.^{13,27}

III.B. Control Activity

Figure 7 shows the evolution of the human operator control input throughout the 200 runs performed. Table 6 shows, on the left side, the fitted learning curves parameters and on the right side the corresponding statistical analysis results.

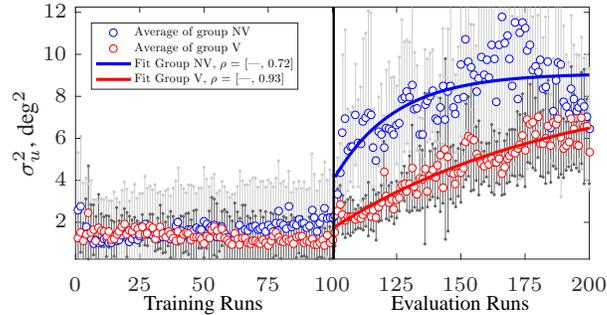


Figure 7. Average control input variance.

Table 6. Learning curve parameters and statistical analysis for control input.

σ_u^2	Learning Curve Parameters						Statistical Significance					
	Training Phase			Evaluation Phase			Training		Transfer		Evaluation	
	p_0, deg^2	p_a, deg^2	$F(\times 10^{-2})$	p_0, deg^2	p_a, deg^2	$F(\times 10^{-2})$	W_s	Sig.	W_s	Sig.	W_s	Sig.
Group NV	n/a	n/a	n/a	3.94	9.10	4.14	23	—	0	**	14	—
Group V	n/a	n/a	n/a	1.67	8.59	1.18	33	—	5	*	0	**

Legend: ** = highly-significant ($p < 0.01$)
 * = significant ($0.01 \leq p < 0.05$)
 — = not significant ($p \geq 0.05$)

Fig. 7 shows that the improvement in performance attained by both groups during *training* was achieved with approximately constant control activity throughout the runs, as no significant variation in σ_u^2 is observed. Learning curves were not fitted to the training phase data, as Pearson's correlation coefficients were below 0.5 for the data from both groups.

After the *transfer*, Group NV immediately showed a notable increase in control activity, whereas Group V showed a much smaller increase. Looking at the transfer column in Table 6, it is seen that both increases were statistically significant.

For the *evaluation* phase, an increase in control activity because of motion was expected for the performed disturbance-rejection task.^{8,13,27} Group NV showed much higher control activity than Group V. However, in the last runs, a drop in σ_u^2 is visible for Group NV, approaching the level of Group V. This drop was not fit by the learning curve, with a lower Pearson's coefficient as a result. However, it was visible in the statistical analysis in Table 6 where there was no statistical significant difference between σ_u^2 at the beginning and at the end of evaluation, due to the considerable spread in the data.

III.C. Human Operator Modeling Results

The development of skill-based control behavior during training, transfer and evaluation was further analyzed by identifying the human operator model shown in Fig. 1 for every run performed by every subject. An assessment of the quality of the fitted models was performed in three steps. First, single Bode diagram plots for the human response are presented, where the model fits are compared to independently estimated frequency-domain describing functions. Then, the VAFs of all estimated models are presented. Finally the averaged results of the parameter estimation are shown, followed by the evolution of the crossover frequencies and phase margins.

III.C.1. Model Fits and Describing Functions

Figure 8 presents Bode plots containing the frequency response of both response functions (error and roll response) of the human operator control model for one subject in Group V. The upper row of plots in Fig. 8 shows the data concerning the initial and final training runs, and the bottom row of plots shows data concerning the initial and final evaluation runs. In each Bode plot, the frequency response as calculated with the identified model is plotted with a continuous line, and the corresponding describing function estimates, calculated with the Fourier coefficients of the time signals, are plotted with circular markers. These plots represent the general obtained results and are similar to the data from the remaining participants.

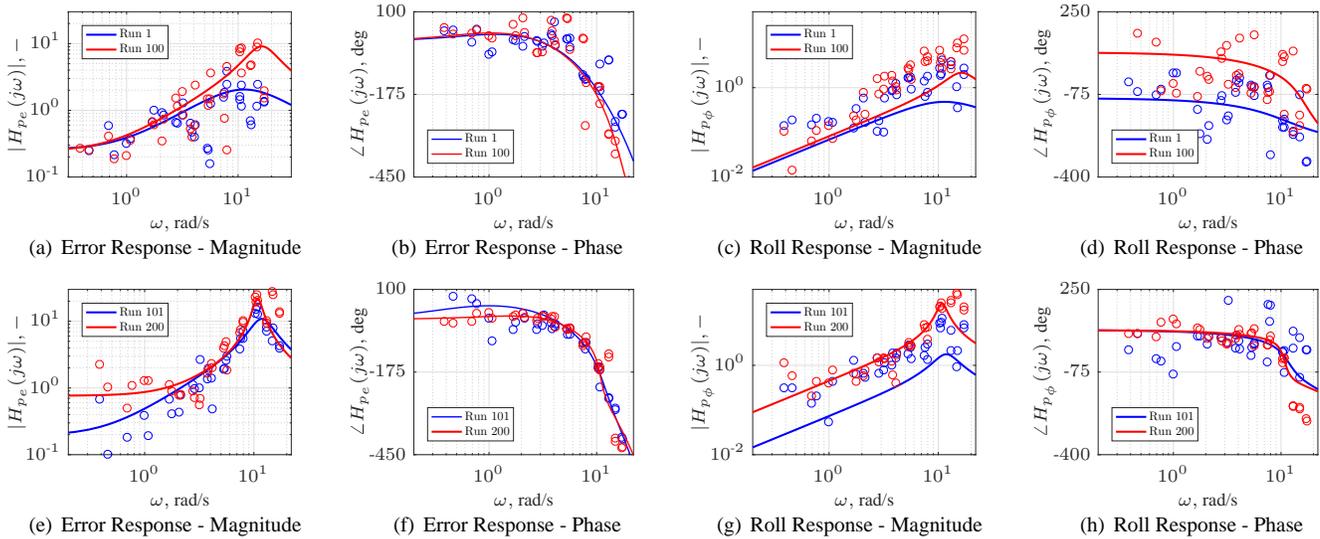


Figure 8. Frequency Response of Error and Roll channels in the human operator control model.

Comparing the error and roll responses in the upper row of plots in Fig. 8, a large variation is observed in the describing functions, together with discrepancies between the model and the respective describing function. This indicates reduced consistency and linearity of control behavior, which was expected given the naivety of the participants in the earlier training runs. Comparing the blue and red lines in Figs. 8(a) and 8(c), higher gains were seen in both responses at the end of training, the neuromuscular frequency increased, and the neuromuscular damping ratio decreased, which is a typical evolution in the acquisition of manual control skills by task-naive controllers.^{26,38}

Comparing the top (Run 1 and 100) and bottom (Run 101 and 200) rows of Fig. 8, it is clear that the quality of the human operator modeling data increased throughout the experiment, as the circular markers corresponding to the describing functions are closer to the corresponding model lines for the evaluation phase (Run 101 and 200) data. This means the model became better in describing the human control behavior, which is expected as people behave more linearly with increased training. In part, this can also be explained by the fact that in runs 101 and 200 motion cues were available, which is known to improve the prominence of the roll feedback response. Fig. 8 also shows that from run 101 to 200, human operators increased their error and roll gains, reduced the lead time constant, and lowered the neuromuscular damping ratio.

III.C.2. Variance Accounted For

The results for the average VAF in each group throughout the experimental runs are shown in Fig. 9. Values for the VAF in tracking experiments are usually around 80% and 90% when human operator data is averaged between repeated measurements.¹⁹ In a training experiment, the evolution in the model throughout the runs is crucial to evaluate the acquisition and development of control skills and averaging results would mask that effect. Therefore, a model was fit to each individual run without any averaging, lowering its VAF due to higher remnant noise. In this experiment, the majority of the models obtained had VAFs between 60% and 80%, which is in accordance with previous training studies.⁸ The reduced consistency and linearity seen when comparing initial and final runs of both experiment phases in Fig. 8 translated to lower VAFs, especially in the earlier runs of each phase. Furthermore, especially low values of VAF (around 40% and 50%) are seen throughout training phase.

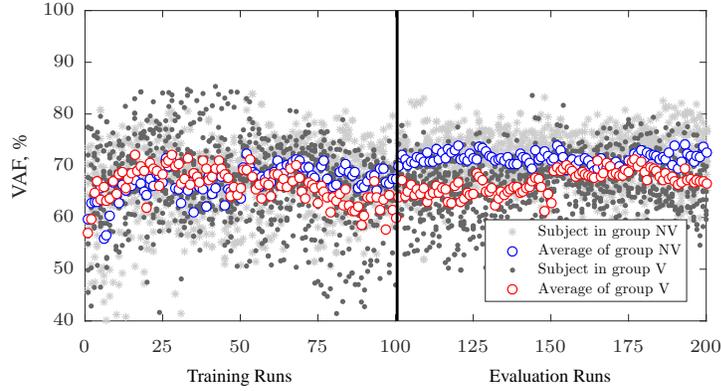


Figure 9. Average Variance Accounted For of the estimated model.

III.C.3. Human Operator Model Parameters

In the previous sections an assessment of the fitness quality of the human operator model was performed. It was concluded that the quality of the data increases with the number of runs performed, which is expected for any training experiment with task-naive participants. In Fig. 10, the estimated parameters of the error response, the roll response and the neuromuscular dynamics are presented. Fitted curves were included to show learning trends whenever the respective Pearson's coefficient was significant, with the parameters for all fits made shown in Table 7. Surprisingly, with clearly improving task performance, the average parameter estimation results do not show a clear learning trend in any parameter over the training phase. Therefore, no learning curves are presented for this phase in Fig. 10 and Table 7.

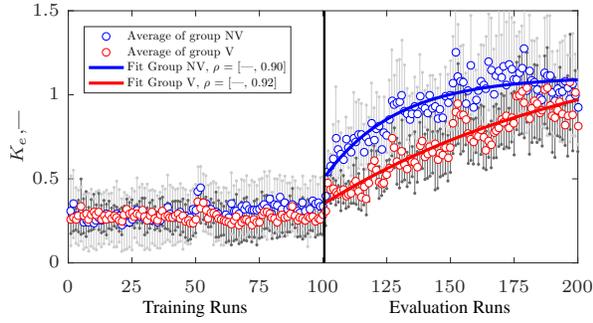
Table 7. Parameters for the evaluation phase learning curves shown in Fig. 10.

	K_e			$T_{lead}, (s)$			K_ϕ			$\sigma_{u_\phi}^2 / \sigma_a^2, \%$		
	$p_0, -$	$p_a, -$	$F (\times 10^{-2})$	p_0, s	p_a, s	$F (\times 10^{-2})$	$p_0, -$	$p_a, -$	$F (\times 10^{-2})$	$p_0, \%$	$p_a, \%$	$F (\times 10^{-2})$
Group NV	0.50	1.11	3.46	1.04	0.38	5.75	0.16	0.65	4.91	13.80	79.57	3.91
Group V	0.34	1.37	0.94	1.10	0.41	3.04	0.12	0.70	1.91	10.49	111.02	1.04

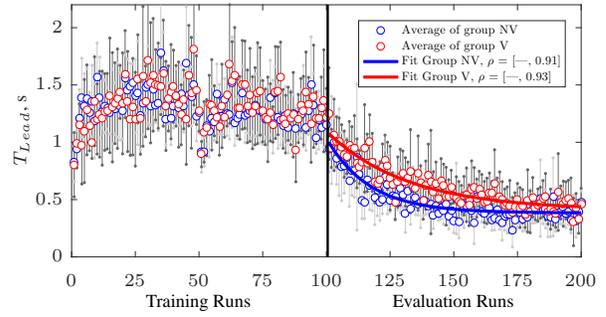
Considering the human operator error response parameters in the *training* phase, Fig. 10 shows that the error gain, the lead time constant and the error response delay did not show any consistent variation, remaining approximately constant throughout the 100 runs. This is consistent with the results of Ref. 16, where a similar task with the same controlled dynamics was performed. These evolutions are also consistent to what was found in control input metrics, in Fig. 7. Similarities between both groups indicate that peripheral visual cues do not affect the response in this channel. For the evaluation phase, the presence of motion induced a significant increase in the error gain for both groups, whereas the lead time constant decreased, as expected given the lead information motion provides.⁹⁻¹¹ For the evaluation phase, the learning curve parameters are shown in Table 7, where it can be seen that Group V had notably lower learning rates in K_ϕ and T_{lead} suggesting less transfer of skills for Group V.

With respect to the neuromuscular system parameters, shown in Fig. 10, no effects of learning were observed in the neuromuscular frequency, which was higher for Group V in training and it increased after transfer. This was an expected effect of experimental conditions with motion and can be seen as the human arm getting stiffer in motion conditions, corresponding to the contraction of the arm and hand muscle.²⁷ The neuromuscular damping ratio decreased throughout the experiment, which was also expected and it is a sign of task proficiency because with decreasing damping ratios phase lag is slightly lower in the frequencies where the human operator is actively controlling (frequencies around the crossover frequency).

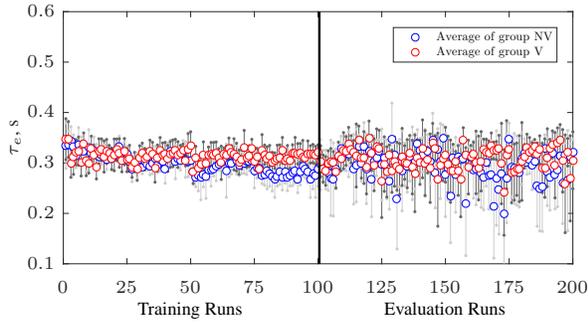
Finally, Fig. 10 shows that participants' use of the roll feedback channel was much reduced during the training than in the moving-base evaluation, suggesting that out-of-the-window visual cues were not as effective in providing a roll feedback channel as motion. Increasing roll gains were, however, observed in Group V during training: K_ϕ was initially around zero, but consistently above zero at the end of training. The roll response delay does not have any effect on the human operator model's response when the roll gain is zero, which explains the large variability in early



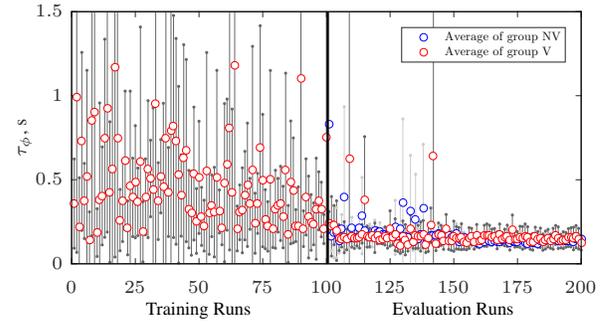
(a) Error gain.



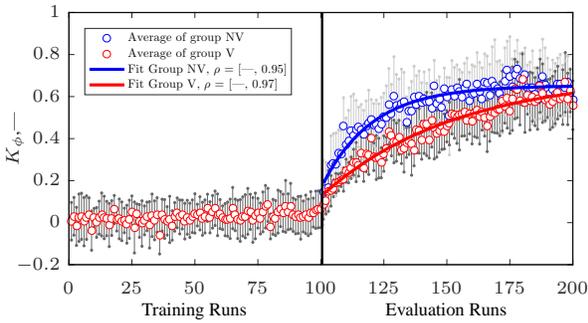
(b) Error lead time constant.



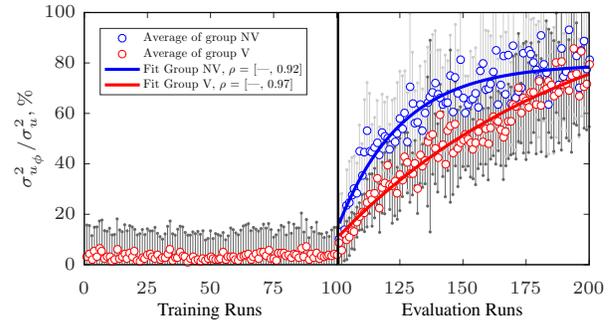
(c) Error Delay.



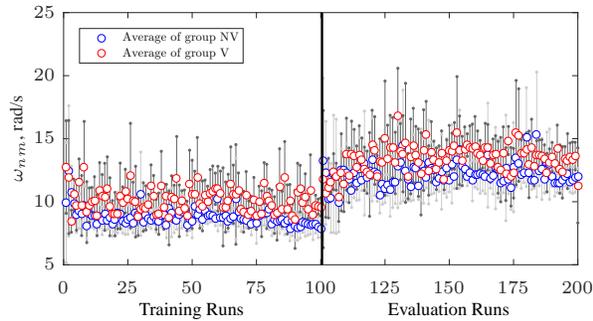
(d) Roll Delay.



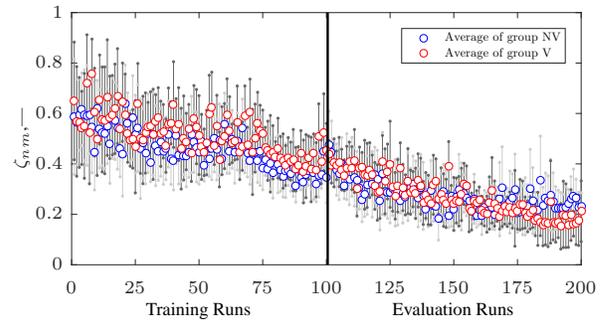
(e) Roll Gain.



(f) Roll channel variance fraction.



(g) Neuromuscular frequency.



(h) Neuromuscular damping ratio.

Figure 10. Average estimated human operator model parameters.

training runs. In the final training runs a decreasing trend was seen and its values seem to converge to the ones in the evaluation phase.

In Figure 10(f), the contribution of the roll feedback channel in the total control input is shown. A modest and approximately constant motion contribution was seen in training phase, which means peripheral visual cues slightly contributed for the development of a roll feedback channel. In the evaluation phase, there was a clear and increasing dominance of the roll feedback, and the final values (around 80%) were higher than what is usually expected for this type of tasks,⁸ suggesting that this unstable dynamics required an extensive use of motion cues.

III.D. Crossover Frequencies and Phase Margins

Figure 11 shows the average crossover frequencies and phase margins in the disturbance and target open loops for both groups, calculated considering the identified model.

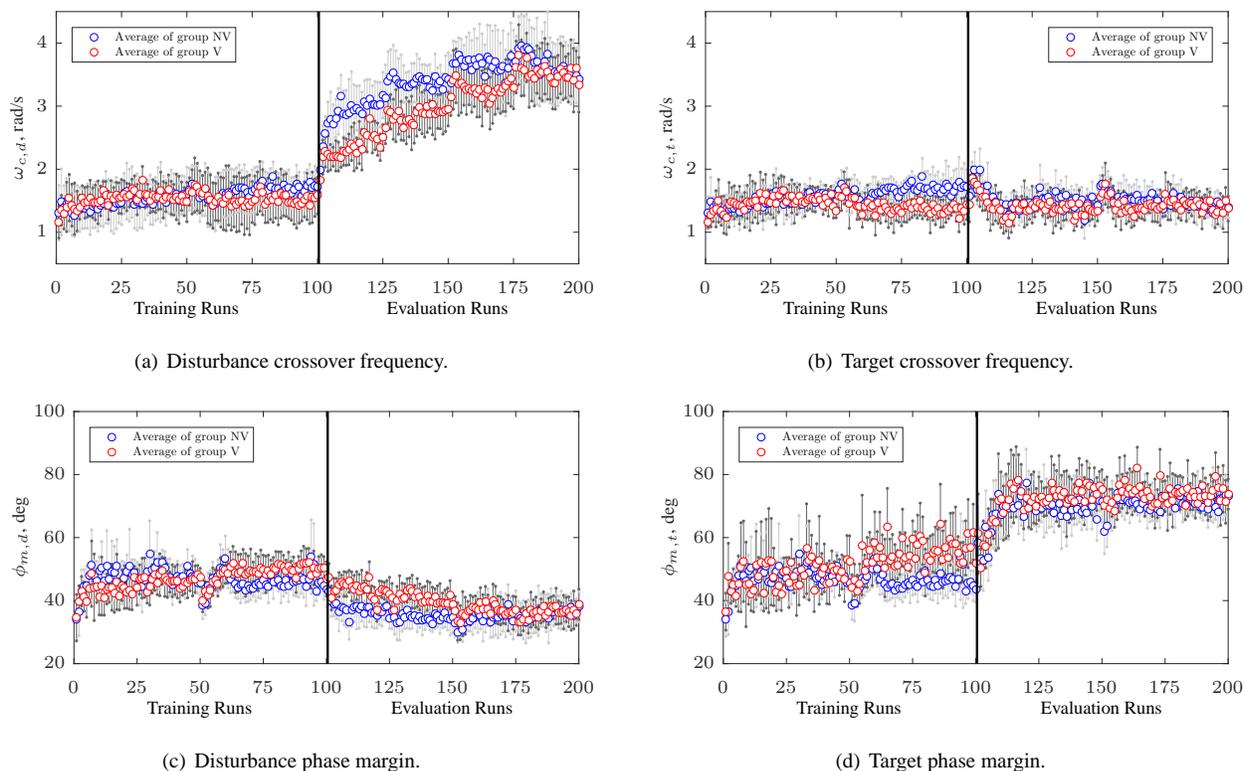


Figure 11. Average disturbance and target crossover frequencies and phase margins.

For the disturbance crossover frequency (Fig. 11(a)), small yet consistent increase was seen in both groups throughout training, which was congruent with the observed improvement in tracking performance. In the final runs of the training phase Group NV had a slightly higher disturbance crossover frequency than Group V, explained by the also slight difference in control activity in the final runs of the training phase. When transferred to the evaluation conditions, motion increased disturbance crossover frequency in both groups, which was an effect found in previous tracking experiments.^{13,27} Disturbance crossover frequency is higher for Group NV, following the control activity results. For the target crossover frequency (Fig. 11(b)), the results suggest again a slight increase throughout the training runs for both groups, with higher crossover frequencies for Group NV in the training phase, and no significant difference was seen after transfer.

With respect to the disturbance phase margin (Fig. 11(c)), a slight increase was seen in both groups throughout training phase, with Group V showing higher values of phase margin in the end of training phase. In evaluation, motion was seen to decrease disturbance phase margin. For the target phase margin (Fig. 11(d)), Group V had higher values in the end of training phase, following the results of the disturbance phase margin, and in the evaluation phase motion cues caused an increase in ϕ_{m_t} of both groups. Regarding the training phase, the differences existing between groups

in both disturbance and target phase margins were not significant to allow any conclusions. Looking at the evaluation phase, effects of motion in disturbance and target phase margins were expected given previous tracking studies.^{13,27}

IV. Discussion

The goal of the research project analyzed in this paper was to evaluate the effectiveness of out-of-the-window visual cues as a substitute for the development of multimodal manual control skills in the presence of motion feedback, by fully task-naive controllers. This was achieved by measuring tracking behavior in a roll tracking task, with a controlled element that required significant human operator lead equalization, in a quasi-transfer-of-training experiment performed in the SIMONA Research Simulator at TU Delft. The twenty participants were divided in two experimental groups and different cues were given according to the group and the experiment phase. Group NV was trained with only a PFD showing the tracking error whereas Group V was trained with both the PFD and an out-of-the-window (peripheral) visual roll rate stimulus. Both groups were then transferred to the same moving-base evaluation condition with pure roll motion feedback. Tracking performance, control effort, crossover frequencies, phase margins, and human operator modeling results in each run and for each subject were used to evaluate the evolution of human operator control behavior from the initial fully naive task exposure to the final task proficiency.

Based on findings from previous training experiments, clear effects of skill development were expected to be visible in the training phase in both groups (Hypothesis H1).^{8,26,38} Indeed, the first 100 runs showed a positive evolution in terms of task performance, with a decrease in tracking error variance due to a consistent reduction in the disturbance-rejection, target-tracking and remnant error variance contributions. The decrease in remnant error variance indicates that the task-naive participants successfully increased their linearity, which is a clear training effect. No clear variation in control activity was observed during training, which was consistent with the human operator model parameters whose average estimates were also approximately constant for the first 100 runs. This was not expected considering previous training experiments with task-naive participants, but it was congruent with the findings for the training experiment described in Ref. 16, where the controlled dynamics were the same as used here. Therefore, for the considered roll tracking task, training causes an improvement in task proficiency, but not necessarily in terms of human control dynamics, whose parameters remained approximately constant throughout training. However, these parameters describe the human control behavior progressively better as the human operator linearity increases with the number of training runs.

Based on results from earlier studies investigating the effect of out-of-the-window visual cues on tracking task performance and human control behavior, it was hypothesized that subjects in Group V would develop during training a roll feedback channel similar as the one created when motion cues are available (Hypothesis H2). Analyzing the results obtained in this experiment, out-of-the-window visuals helped subjects performing the control task, as Group V had a lower tracking error variance in the training phase. However, the average estimates of the motion gain K_ϕ were close to zero throughout training, meaning no strong roll feedback channel was used. This relatively weak roll feedback channel created with peripheral visual cues is not entirely consistent with observations from previous studies on the effect of out-of-the-window visual cues. A reason for this to happen might be due to the fact that the roll stimulus provided by the checkerboards was perhaps weaker than the yaw visual stimulus provided in Ref. 12. Furthermore, in Ref. 12, participants were not task-naive but experienced subjects who logically attain better performance easier. Another cause might be the different dynamics controlled, as the unstable roll dynamics used here require a control strategy with a stronger need for lead equalization.

When transferring to motion conditions in the evaluation phase, both groups were seen to achieve better performance using stronger control activity (Hypothesis 3). A clear evolution in the human model parameters was also seen, with higher error and roll gains and lower lead time constants, as a consequence of the lead information motion feedback provides. Therefore, motion significantly helped human operators performing this control tracking task, therefore confirming Hypothesis 3. Great differences were, however, found when groups were compared, with motion and visual gains being higher for Group NV, together with lower lead constants. This is explained with the significant differences in control activity levels between the groups in the evaluation phase, as Group NV adopted a significantly stronger control activity. Stronger inputs mean the dynamics are being more excited and thus better perceived by the human operator. Therefore, stronger control inputs increase the benefits from motion feedback. No clear explanation for this difference in control strategy was found, but the control strategy of Group NV was less consistent than the one of Group V. The data spread was notably larger for Group NV and the average control variance decreased in the end of evaluation, showing an unusual parabolic shape in this phase of the experiment.

As a consequence of the absence of a roll feedback channel with visual cues in the training phase, the benefit of training with visual cues was also not verified when transferring to motion (Hypothesis H4). On one side, supporting

this hypothesis, lower tracking errors and higher learning rates in tracking error data were indeed found for subjects in Group V when compared to subjects in Group NV, but on the other side this tendency was not confirmed by the human operator model parameters, where higher learning rates were in fact found for Group NV in the evaluation phase.

Looking at the overall experiment data, an unfortunate between-group imbalance seems to exist in the data set. As mentioned, no explicit group assignment and pre-selection (e.g., based on entry skill level) was made and this seems to have led to uneven groups in terms of manual control proficiency. Considering control activity, Group NV had, in evaluation phase, a significant in-group variance as some subjects had an abnormally high control activity, making Group NV's average significantly higher than Group V's average. This result propagated to the model parameter estimations, biasing the group comparison. To avoid this effect, a suggestion for future training experiments is to perform a brief inquiry to the participants to evaluate their propensity on developing manual control skills, and then assign them evenly in the experimental groups, avoiding confounding factors. Another solution to this problem is increasing the number of subjects performing the experiment, guaranteeing more samples in each group, which in this experiment was not possible given the limited availability of the SRS. This same factor justified the experimental setup chosen, with 50 tracking runs performed by each subject in each day, which might have been too intensive for the subjects and might have led to concentration issues that directly affected the results. It is advisable to make shorter sessions, without however reducing the amount of runs in each experiment phase, as 100 runs seem to be the necessary amount of practice needed to achieve task proficiency in a specific condition.

Finally, looking at the evaluation phase of both groups, the fact that a great improvement was achieved with respect to training suggests an ineffective training setup. The control skills learned in a fixed-base environment showed limited direct transfer to the moving-base condition, which had been described in previous experiments for the case where no visual scene was provided.^{8,26,38} The data collected in this experiment supports the conclusion that manual control skills developed during training with a peripheral visual scene also do not positively transfer to a motion condition. While peripheral visual cues are beneficial in terms of performance and simulator realism, they seem to not effectively create the feedback channel motion utilizes and therefore they should not be used as a direct substitute for true physical motion feedback during simulator-based manual control skill training.

V. Conclusions

To verify the extent to which out-of-the-window (peripheral) visual cues are an effective substitute for true physical motion feedback in simulator-based manual control skill training, a quasi-transfer-of-training experiment was performed, in which twenty fully task-naive participants were trained for a compensatory roll tracking task. Some transfer of control skills developed in a simulator with out-of-the-window cues was expected, given that with such additional visual cues human operators are known to develop a similar multimodal control organization – characterized by the use of an additional roll (rate) feedback channel – as with physical motion feedback. The twenty participants were divided in two groups: one group received training with out-of-the-window visual cues providing roll rate information present, while the other (control) group was trained without these additional visual cues. After training, both groups were transferred to a moving-base condition where pure roll motion feedback was provided. All individual tracking runs were analyzed for changes in tracking performance and control activity during training and transfer. Furthermore, multimodal human operator modeling techniques were used to explicitly quantify the progress in learned manual control skills. A clear difference between groups was seen in terms of performance during training, as the group trained with peripheral visual cues showed superior tracking performance. However, the analysis of human operator control behavior showed that only a very weak roll feedback response – with average roll response gain estimates only marginally above zero – was developed in the presence of the peripheral visual cues. In the evaluation phase, the participants trained with peripheral visual cues showed somewhat faster convergence to their final performance level, but human operator modeling results did not reveal any clear signs of positive skill transfer. Overall, this indicates that multimodal control skills developed in the presence of a peripheral visual scene do not show meaningful transfer to a setting where physical motion feedback drives a similar multimodal control organization. Therefore, this experiment shows that peripheral visual cues are not an effective substitute for physical motion feedback in simulator-based training of manual control skills.

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