Training Effectiveness of Flight Simulators with Outside Visual Cues

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Abstract

This paper reports a training experiment performed in the SIMONA Research Simulator at Delft University of Technology in which the effectiveness of outside visual cues during the development of multimodal control skills was evaluated. Twenty fully task-naïve 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 had additional out-of-the-window visual cues. After training, subjects were transferred to a motion-base condition where pure roll motion cues were provided. The development of skills in both groups throughout the experiment was studied and compared utilizing multiple derived variables. Specifically, to allow a direct evaluation of the effectiveness of outside visual cues as a source of roll feedback, the human operator multimodal structure was the same for both feedback sources, outside visual scene and physical motion. During training the group in which outside visual cues were available attained better tracking performance levels. However, no significant transfer of these superior control skills to the motion condition occurred, suggesting that training with outside visual cues might not be sufficiently effective for a subsequent transfer to motion settings.

Keywords: Flight Simulator, Cybernetics, Outside Visual Cues, Manual Control, Transfer of Training

1. 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 the surrounding reality and thereby gather information relevant for control. Visual and motion stimuli are the most relevant control inputs and control proficiency is attained by training responses to what the visual and vestibular systems perceive [1]. In case of an aircraft, pilots’ learning process usually includes a simulator-based phase in which simulators replicate flight reality for pilots to develop their control skills. The control skills acquired by a pilot in his simulator training are brought into use when transferred to a real-world setting as 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.

A cybernetic approach to understand these changes consists on 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 impracticability in performing transfer to real settings, the majority of the studies performed are in fact quasi-transfer-of-training experiments, where the evaluation setting is not true reality but a more realistic simulation environment [2]. 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 [3]. This happens because motion feedback strongly influences human operators’ behavior, especially when the controlled dynamics require lead equalization [4].

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 [5]. 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 not as effectively [6]. 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 for initial simulator-based training, as they might create and establish a feedback channel in the human operator without the need of actual physical
motion cues. At this point, such transfer has never been studied explicitly and it is thus hypothesized that the feedback channel created by the existence of a peripheral visual scene is effective in easing the developing of manual control skills in a motion condition.

The goal of the research described in this paper is to discover to which extent visual cues are effective in developing multimodal control skills 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 and it is hereby described and analyzed.

This paper is structured as follows. First, the methods, the organization of the experiment, and the hypotheses are described in Section 2. Section 3 contains the results of the experiment. A discussion follows in Section 4 and the paper ends with conclusions in Section 5.

2. Methods
In this section, the methods followed in this quasi-transfer-of-training experiment are given, explaining how the experiment was prepared, conducted and analyzed. The hypotheses to be tested with the experimental results are formulated in the end of this section.

2.1. Control Task
This human-in-the-loop training experiment considered a compensatory roll-axis tracking task, schematically represented in Fig. 2. The human controller was asked to follow a target roll angle, specified by the tracking signal \( f_t \), as accurately as possible, while simultaneously rejecting disturbances on the controlled system \( H_c \), which were induced by the disturbance signal \( f_d \). This disturbance signal was summed to the human operator's input, \( u \), and directly affected the controlled dynamics. In order to identify and model the multi-channel human operator response, characterized by \( H_{p_c} \) and \( H_{p_o} \), the disturbance signal \( f_d \) and the target signal \( f_t \) were independent sum-of-sines signals [7]. Given the quasi-linear human operator model used, the control input had contributions from the error response, \( u_e \), the roll response, \( u_o \), and a remnant \( n \) accounting for nonlinear behavior and measurement noise.

In the experiment (see Fig. 1(a)), the human operator perceived the dynamics being controlled with a compensatory display which resembled a basic Primary Flight Display (PFD), shown in Fig. 1(b). This compensatory display showed the deviation \( e \) between the current aircraft roll angle, \( \phi \), and the target roll angle, \( f_t \). The out-of-the-window peripheral visual cues used in this experiment were based on various compensatory roll-axis tracking experiments [6] and consisted of two vertically moving checkerboard panels, providing a strong roll motion 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.

Figure 1: Simulator cockpit and the central display.

The controlled dynamics \( H_c \) were the dynamics used in Ref. [8] 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. An obvious remark regarding the transfer function presented in Eq. (1) is that the roll dynamics of the aircraft are unstable in this flight condition. These dynamics approximate a single integrator \( \left( \frac{1}{s} \right) \) at low frequencies \(< 0.76 \text{ rad/s} \) and a double integrator \( \left( \frac{1}{s^2} \right) \) at frequencies higher than 0.76 rad/s, due to the effect of the pole at \( s = -0.76 \text{ rad/s} \).

\[
H_c(s) = 3.91 \frac{(s^2 + 0.22s + 0.59)}{(s + 0.76)(s - 0.02)(s^2 + 0.11s + 0.64)}
\]

(1)

The human operator control behavior was modeled in this compensatory tracking task using a quasi-linear model [9]. As shown in Fig. 2, 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, \( H_{p_c} \) and \( H_{p_o} \), which respectively model the response to the roll tracking error (available from the PFD) and the response to the roll feedback (available via the out-of-the-window cues or simulator’s motion) [10]. 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 \( H_{p_c} \) and \( H_{p_o} \) 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].
2.2. Experiment Setup

The experiment was divided in two phases, henceforth referred to as training and evaluation. During the training phase, the task-naive participants were trained in the roll tracking task previously described until their level of task performance stabilized. They were subsequently transferred to the evaluation phase where the same roll tracking task was performed with different cues being provided.

Participants were divided in two experimental groups. The first group, henceforth referred to as Group NV, was trained with only the PFD, thus without neither out-of-the-window visuals or motion cues (NV, NM), and they were transferred to evaluation conditions where they had access to the PFD and motion feedback (NV, M). The second group, henceforth referred to as Group V, was trained without motion but with the PFD and the out-of-the-window visual cues (V, NM), and it was transferred to the same evaluation configuration as the Group NV where the PFD and motion cues were available, without peripheral visual cues (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.

Each phase of the experiment consisted on 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 consecutive days, therefore two sessions on each day, with a 20 minutes 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 days happening outside the simulator, an effect known as offline learning [11], and it also respected the optimum retention time between training sessions of 24 hours [12].

The experiment was performed during five weeks on four consecutive working days of each week. Two subjects performed their two daily sessions in the morning and two subjects performed their two daily sessions in the afternoon, meaning a total of four subjects performed the experiment in each week. To guarantee the balancing between subjects in the 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 the fifth week had subjects from both groups.

In the end of each tracking run, the researcher informed the subject of their score in that run (the score being the root mean square value of the tracking error signal) and asked if they were ready for the following run. In case of an affirmative answer, the next run would start. Otherwise, some seconds could be taken as a small break in between runs to assure subjects’ concentration levels were high and as constant throughout the experiment as possible.

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 SRS motion and outside visual systems were used, depending on the phase of the experiment. The SRS motion system is a hexapod with hydraulic actuators, providing a six degrees-of-freedom hydraulic motion system which reproduces the aircraft’s motion with a time delay of 30 ms [13]. Given that the task performed was a pure roll tracking task, only SIMONA roll rotation was utilized. 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 $\phi$ was given one-to-one, without washout filtering. The visual system of the SRS consisted on two projectors generating 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 [13].
2.3. Participants
To perform this training experiment, subjects could neither have any type of previous piloting experience nor have participated in earlier tracking experiments. Another requirement the subjects had to comply with was to be right-handed. An initial group of twenty fully task-naive subjects, who gave their written consent to participate in this study, performed the experiment. A total of ten subjects were included in each group, considering people between 18 and 23 years old, with nine different nationalities and three females (two placed in Group NV and one in Group V). Two more subjects were tested in the experiment set, but due to performance inconsistencies were omitted from the final data set.

2.4. 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 a multimodal quasi-linear operator model. Namely, the defining parameters of both the error response transfer function \( H_{\text{pe}} \) and the roll feedback response transfer function \( H_{\text{po}} \) were determined using identification and optimization algorithms. The models used for \( H_{\text{pe}} \) and \( H_{\text{po}} \) were successfully used in earlier studies [14, 15].

The considered model for the human operator error response \( H_{\text{pe}} \) is given by:

\[
H_{\text{pe}}(s) = K_e (T_{\text{lead}} s + 1) e^{-\tau s} H_{\text{nm}}(s) \quad (2)
\]

With \( H_{\text{nm}} \) being the neuromuscular dynamics modeled by:

\[
H_{\text{nm}}(s) = \frac{\omega_{\text{nm}}^2}{s^2 + 2\zeta_{\text{nm}}\omega_{\text{nm}} s + \omega_{\text{nm}}^2} \quad (3)
\]

For this roll tracking task with the considered controlled element dynamics, the error response model included a gain \( K_e \), a lead equalization term \( T_{\text{lead}} \), a human operator response delay \( \tau_\phi \), and the neuromuscular dynamics \( H_{\text{nm}} \), modeled as a second-order mass-spring-damper system with a neuromuscular frequency \( \omega_{\text{nm}} \) and a neuromuscular damping ratio \( \zeta_{\text{nm}} \). The considered structure of \( H_{\text{pe}} \) 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 - 5 rad/s) [8].

The human operator roll response \( H_{\text{po}} \) is modeled by:

\[
H_{\text{po}}(s) = sK_\phi e^{-\tau_\phi s} H_{\text{nm}}(s) \quad (4)
\]

The roll response included a pure derivative term and an equalization gain \( K_\phi \), modeling human operator limitations with a roll response delay \( \tau_\phi \) and the neuromuscular system, modeled as in \( H_{\text{pe}} \). It is convenient to mention that \( H_{\text{pe}} \) 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 [8]. 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. (2) to (4) contained seven free parameters \( (K_e, T_{\text{lead}}, \tau_\phi, K_\phi, \tau_\phi, \omega_{\text{nm}}, \text{ and } \zeta_{\text{nm}}) \) which were estimated using maximum likelihood time-domain parameter estimation techniques, described in Ref. [7], on the collected experimental data (the time-domain signals \( e, \phi, \text{ and } u \)). Obviously, in the training phase of Group NV, only \( H_{\text{pe}} \) 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.

In every tracking run, the identified model Variance Accounted For (VAF) was calculated as a measure of the human operator model accuracy in describing the measured control signal. It is an usual practice in cybernetic studies to average the time
signals over a certain number of runs, to attenuate noise in the measured data and thus improving the model quality [14]. However, given the need to evaluate acquisition of control skills throughout individual runs, averaging was not an option and therefore slightly lower VAF values were obtained due to 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 considered, 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, which is a reduced percentage of excluded runs (1.4 %) for a training experiment with task-naive participants [3].

2.5. 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. [3, 8] and [16]), which are visible in improved performance (lower \( \sigma_r^2 \)), increased control activity (higher \( \sigma_u^2 \)), 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 \( K_c, K_\phi \), 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] and [6]) suggest that visual cues available in training provide a feedback channel for the roll angle and this was expected to be visible in better performance (lower \( \sigma_r^2 \)) and the human operator parameters describing the response to roll angle feedback. The roll gain \( K_\phi \) and the roll delay \( \tau_\phi \) 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. The addition of motion cues in a tracking task allows reaching better levels of task performance [3, 8, 17]. This effect was expected to be mainly visible in performance metrics with lower \( \sigma_r^2 \) and higher \( \sigma_u^2 \). In the human operator parameters, higher gains (\( K_r \) and \( K_\phi \)), lower delays (\( \tau_r \) and \( \tau_\phi \)), and especially lower values of \( T_{\text{load}} \) were expected as a consequence of the lead information provided by the motion feedback.

**H4:** Adaptation to motion conditions is faster for subjects who were trained with out-of-the-window visual cues. The final 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, as the 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. This is supported by earlier findings that out-of-the-window visuals function to a certain extent as a motion feedback channel [5]. This would be visible in higher learning rates in the evaluation condition for subjects in Group V and better performances of this group immediately after transfer.

3. Results

In the Figures of this section, data from Group NV is shown in blue and data from Group V in red. In plots where data evolution is shown over 200 runs, a black vertical line indicates the transfer after run 100. Learning curves are fitted to the data when Pearson’s correlation coefficient is higher than 0.5, with the Pearson’s correlation coefficients being shown in the plot’s legend with the following organization: \( \rho = [\rho_{\text{training}}, \rho_{\text{evaluation}}] \). Gray error bars are plotted indicating the 95% confidence intervals of mean data for plots showing the evolution with the runs.

3.1. 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 \( \sigma_r^2 \), the better the performance. Figure 3(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 [18]. Results are shown, respectively, in Figs. 3(b), 3(c), and 3(d). The parameters of the fitted learning curves in Fig. 3 are presented on the left side of Tables 1 to 4.

Some important conclusions can be drawn when looking at the tracking error results presented in Fig. 3. 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. In Fig. 3(a), it can be seen that Group NV showed a steeper improvement in per-
Table 1: Learning curve parameters and statistical analysis for total tracking error.

<table>
<thead>
<tr>
<th>Group</th>
<th>Learning Curve Parameters</th>
<th>Statistical Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Training Phase</td>
<td>Evaluation Phase</td>
</tr>
<tr>
<td>Group NV</td>
<td>$p_0$, deg</td>
<td>$p_0$, deg</td>
</tr>
<tr>
<td></td>
<td>$p_0$, deg</td>
<td>$p_0$, deg</td>
</tr>
<tr>
<td>Group NV</td>
<td>2.94</td>
<td>1.32</td>
</tr>
<tr>
<td>Group V</td>
<td>2.26</td>
<td>1.09</td>
</tr>
<tr>
<td>Group NV</td>
<td>0.78</td>
<td>0.17</td>
</tr>
<tr>
<td>Group V</td>
<td>0.86</td>
<td>0.54</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
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<th>Group</th>
<th>Learning Curve Parameters</th>
<th>Statistical Significance</th>
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<tbody>
<tr>
<td></td>
<td>Training Phase</td>
<td>Evaluation Phase</td>
</tr>
<tr>
<td>Group NV</td>
<td>$p_0$, deg</td>
<td>$p_0$, deg</td>
</tr>
<tr>
<td>Group NV</td>
<td>2.94</td>
<td>1.32</td>
</tr>
<tr>
<td>Group V</td>
<td>2.26</td>
<td>1.09</td>
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</tbody>
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Table 3: Learning curve parameters and statistical analysis for target tracking error.

<table>
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<tr>
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<tr>
<td></td>
<td>Training Phase</td>
<td>Evaluation Phase</td>
</tr>
<tr>
<td>Group NV</td>
<td>$p_0$, deg</td>
<td>$p_0$, deg</td>
</tr>
<tr>
<td>Group NV</td>
<td>2.94</td>
<td>1.32</td>
</tr>
<tr>
<td>Group V</td>
<td>2.26</td>
<td>1.09</td>
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</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Group</th>
<th>Learning Curve Parameters</th>
<th>Statistical Significance</th>
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<tbody>
<tr>
<td></td>
<td>Training Phase</td>
<td>Evaluation Phase</td>
</tr>
<tr>
<td>Group NV</td>
<td>$p_0$, deg</td>
<td>$p_0$, deg</td>
</tr>
<tr>
<td>Group NV</td>
<td>2.94</td>
<td>1.32</td>
</tr>
<tr>
<td>Group V</td>
<td>2.26</td>
<td>1.09</td>
</tr>
</tbody>
</table>

Legend:

** indicates highly significant ($p < 0.01$) statistical differences between compared samples.
* indicates significant (0.01 ≤ $p < 0.05$) statistical differences between compared samples.
— indicates no significant ($p ≥ 0.05$) statistical differences between compared samples.
formance 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. 3(d). This is also seen in the learning rates in Table 1, as $F$ in the training phase was higher for Group NV. However, while Group NV stabilized their performance approximately at $\sigma_e^2 = 1.32$ deg$^2$ around run 60, Group V kept a steady improvement throughout the 100 training runs, reaching $\sigma_e^2 = 1.09$ 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 1-4 for the training phase confirm the significant improvements in performance. It is also important to notice that the contribution of the disturbance forcing function was larger than the contribution of the target forcing function, as seen in a comparison of Figs. 3(b) and (c), given that the experiment had mainly a disturbance-rejection character.

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.

For the evaluation phase, it can be seen that, as reported by numerous previous studies [3, 6], motion cues were more effective and 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 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 correlation coefficient was lower for Group NV. However, while Group NV registered much stronger inputs than Group V, in spite of an unusually high spread of values. Notwithstanding, in the last runs, a leveling in the power of the control signal was visible, approaching the levels of Group V. This behavior was not portrayed by the learning curve, which translated in a lower Pearson’s coefficient.

3.3. Human Operator Model Parameters
In this section, the estimated parameters of the error response, the roll response and the neuromuscular system are presented. The average parameter estimation results do not show a learning trend in the training phase, and therefore learning curves are not shown for this phase.

Considering the human operator error parameters in the training phase, it is clear that both the gain, the lead time constant and the delay did not show any consistent trend, remaining approximately constant throughout the 100 runs. This is consistent with the results of Ref. [8], 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. 4. 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 [17, 19]. Comparing the learning curve shape of both groups, it is visible that Group V had lower learning rates in $K_e$ and $T_{\text{lead}}$ suggesting less transfer of skills for Group V.

With respect to the neuromuscular system parameters, no effects of learning were observed in

Figure 4: Average control input variance.
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 [14]. 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, for the roll gain, it is visible that the use of the roll feedback channel was much smaller in training than in evaluation, suggesting that out-of-the-window visual cues were not as effective in providing a roll feedback channel as motion. It was seen though a positive evolution in roll gain during training, which was initially zero and in the end of training was slightly greater than zero, but this effect is not significant enough to state an effective difference introduced by the presence of the outside visual scene.

4. Discussion
Considering the results from previous training experiments [3, 16, 20], it was expected to see clear effects of skill development in the training phase in both groups (Hypothesis H1). The progress seen in 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 of disturbance-rejection, target-tracking and remnant error variances. The decrease in remnant error variance means the initial task-naive participants increased their linearity, which is a clear training ef-

Figure 5: Human operator model parameters and roll channel variance fraction.
fect. In terms of control activity, no clear tendency existed during training, which was consistent with the human operator model parameters whose average estimates were approximately constant for the first 100 runs. Therefore, training causes an improvement in task proficiency but not necessarily in terms of human control dynamics, whose parameters remained constant throughout training. However, these parameters describe the human control behavior progressively better as the human operator linearity increases with the number of runs.

Based on results from earlier studies, such as Ref. [5], which investigated 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 $K_w$ were close to zero throughout training, meaning no strong roll feedback channel was used. This reduced effect of a roll feedback channel created with peripheral visual cues is not entirely consistent with 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 checkboard was weaker than the yaw visual stimulus provided in Ref. [5]. Furthermore, in Ref. [5], 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, both groups were seen to achieve better performance using stronger control activity (Hypothesis 3), following what was observed in previous studies, as in Refs. [6] and [8]. 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, 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.

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.

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. [3, 16, 20] 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 do not replace motion as a cue in an initial phase of simulator-based training.

5. Conclusion

A quasi-transfer-of-training experiment was performed to evaluate to which extent out-of-the-window visual cues are effective as an initial setting of simulator-based training, under the hypothesis that such cues ease the developing of manual control skills with physical motion. This easiness would be created because peripheral visual cues would develop a feedback channel similar to the one motion is known to introduce in human operator control strategy. Looking at the results from the experiment, training with peripheral visual cues caused lower tracking errors which can be seen as a clear benefit from this source of stimuli. However, when analyzing parameters describing human operator control behavior, a response to a roll feedback provided by peripheral visual cues was barely existent, which indicates that developing control skills with a peripheral visual scene does not hold any strong benefit when transferring to a motion condition. Physical motion is ultimately the most relevant cue in simulator-based training of piloting skills.
References


