Generalizability of Manual Control Skills between Control Tasks of Varying Difficulty

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Abstract: This paper presents the results of an experiment that was performed at NASA Ames Research Center using 18 participants in two different groups who trained a task for ten days, with the goal of identifying how skill generalization would occur between two similar tasks of varying difficulty. A cybernetic approach was used. The first group was trained in a simple one-dimensional tracking task and transferred to a difficult two-dimensional tracking task. For the second group, this was reversed. Training with a simple task before transferring to the difficult task resulted in a slower convergence to final performance. However, it did allow participants to start with a better initial performance in the difficult task. Furthermore, after training with a simple task, participants controlled with a higher gain and generated lower lead time constants. However, possibly due to the number of participants, this experiment did not find any statistical evidence to support the conclusion that training with a simple task version helps in learning a more complex task.

Keywords: Training, Manual Control, Cybernetics, Skill Generalizability, Man/Machine Interaction

1. INTRODUCTION

The goal of this experiment was to assess whether manual control skills generalize between tasks of different difficulty. It attempted to answer the following research question: *"How does training with a simpler task representation aid in generalizing skills to a difficult task and vice versa?"* This paper adds to the literature in two ways. Firstly, generalizability of manual control skills was investigated by looking at changes in operator control behavior. This paves the way for future applications in more real-life settings. Secondly, a method new to this domain was applied: a cybernetic approach [Pieters and Zaal (2019)]. This approach has been used in many (training) experiments before and allows to create models of human operators to identify their control strategy. It allowed to look at the concept of skill generalizability in a manner that could provide information on how an operator uses a generalizable skill.

2. EXPERIMENTAL SETUP

Two tasks were present in this experiment: a simple task with only horizontal control and a difficult task with both horizontal and vertical control. Because the focus lied on generalizability between tasks, two experimental groups were present in a between-subjects design. In group 1, participants trained with the simple task and were evaluated on the difficult task. In group 2, this was reversed. Fig. 1 summarizes this experimental design. Each participant performed 10 runs per day, on 5 consecutive days. Furthermore, on the sixth and seventh day no runs were taken, in order to facilitate the transfer of skills.

This design allowed to compare the learning of a complex manual control task to learning of said task while having already trained with a simpler generalizable variant. Furthermore, the reverse could be investigated: learning a simple task, compared to learning a simple task after already having learned a difficult task. The simple and difficult task were not compared with each other.

2.1 Manual Control Task

The task that the participants performed can be represented by the closed-loop control diagram in Fig. 2. A joystick was used to create a control input signal u. This signal was the input for the controlled dynamics $H_c(s)$,

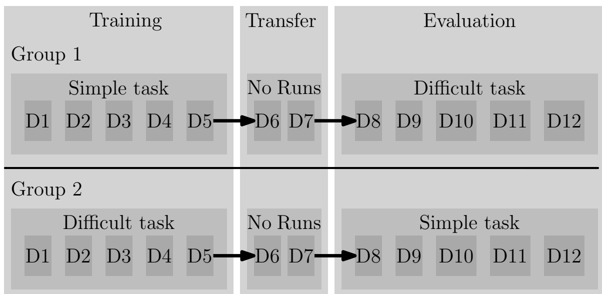

Fig. 1. Experimental design and procedure.

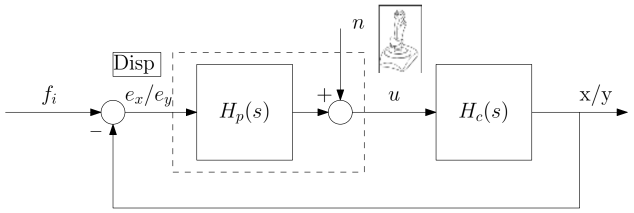

Fig. 2. Closed-loop compensatory tracking task, used in both x and y direction.

which subsequently delivered the system output. The operator perceived the error e between the system output x and the target signal f_i on the display depicted in Fig. 3. In compensatory tracking tasks such as this one, the human operator is typically modeled with a linear transfer function $H_p(s)$ and a remnant signal n which encapsulates human nonlinear behavior and noise in the control loop.

The remainder of this section provides more details on the different components of the control task in Fig. 2.

2.1.0.1. Controlled dynamics The controlled dynamics are defined in Equation 1. In this equation, K_d is the gain and ω_d is the break frequency. The value of ω_d was chosen at $\omega_d = 0.5\ rad/s$; below the crossover frequency normally observed for the human operator, which means that the controlled dynamics were similar to a double integrator. The gain was chosen to be $K_d = 2.0$. This resulted in a fairly difficult acceleration-based control task, while having sufficient control activity to achieve good performance. The task was deliberately made difficult to give participants a challenge, and to ensure they would have to exert effort into learning the task. The difficult task was significantly harder, as it required controlling in two directions.

$$H_c(s) = \frac{K_d}{s(s+\omega_d)} \tag{1}$$

2.1.0.2. Human operator model In compensatory tracking tasks, a human operator adjusts his or her control behavior such that the open loop characteristics of the human-vehicle $H_p(s)H_c(s)$ resemble a single integrator for a frequency range around the crossover frequency [McRuer and Jex (1967)]. Therefore, for the controlled dynamics described above, the human operator needs to generate lead. The model proposed is provided by Equation 2.

$$H_p(s) = \overbrace{K_p(1+T_L s)}^{equalization}\,\overbrace{e^{-\tau_v s}\frac{\omega_n^2}{\omega_n^2 + 2\zeta_n\omega_n s + s^2}}^{limitations} \tag{2}$$

In Equation 2, K_p is the operator visual gain; the relative weight that is put on the error signal e. T_L is the lead time constant. K_pT_L combined represents the relative weight that is put on the error rate $\dot{e}$. Together, K_p and T_L are the equalization parameters; the parameters the human operator uses to achieve stable closed-loop control. The remaining parameters are limitations found in humans. τ_v is the time delay constant that results from delays in perception, neural processing and action. The final two parameters represent the combined neuromuscular system and control interceptor dynamics, with ω_n as the frequency and ζ_n as the damping ratio.

2.1.0.3. Target signal The target signal f_i consisted of a sum of sines:

$$f_i(t) = \sum_{k=1}^{N_f} A_f(k) sin[\omega_f(k)t + \phi_f(k)] \tag{3}$$

In this equation $A_f(k)$, $\omega_f(k)$ and $\phi_f(k)$ represent the amplitude, frequency and phase of the k^{th} sine in f_i, respectively. N_f represents the number of sine waves, which was 10 in the current study. Furthermore, two different target signals were used: one in the x-direction and another in the y-direction. Table 1 presents the properties of both target signals.

Table 1. Forcing function properties.

f_{i_x}				f_{i_y}			
n_f -	ω_f rad/s	A_f deg	ϕ_f rad	n_f -	ω_f rad/s	A_f deg	ϕ_f rad
4	0.307	0.866	-2.220	6	0.460	0.506	0.458
9	0.690	0.742	-1.429	13	0.997	0.310	-0.205
17	1.304	0.447	-1.154	21	1.611	0.175	-1.588
25	1.918	0.256	2.296	29	2.224	0.108	1.830
41	3.145	0.138	-0.822	45	3.452	0.053	2.619
53	4.065	0.092	-0.086	56	4.295	0.037	-0.839
73	5.599	0.057	-0.902	76	5.829	0.024	-1.640
103	7.900	0.036	2.989	106	8.130	0.015	1.345
139	10.661	0.027	0.436	142	10.891	0.011	-2.511
194	14.880	0.021	1.468	195	14.956	0.009	2.191

The sinusoidal frequencies were all integer multiples n_f of the measurement time base frequency, $\omega_m = 2\pi/T_m = 0.0767\ rad/s$. The runs lasted for 90 seconds, but only the last 81.92 s of data were used, to eliminate the effects of participants adjusting to a constant control strategy. The two forcing function signals were used in a previous experiment [Zaal and Mobertz (2017)] and were approximately normally distributed and with average crest factors. The forcing function frequencies were selected to cover the range of manual control with relatively regular intervals on a logarithmic scale.

2.2 Apparatus

Participants were seated in front of a display and were instructed to perform the manual control task using a BG Systems joystick located on their right side, see Fig. 4.

The seat position was fixed and determined such that participants were able to control comfortably. The display showed a cross symbol, which participants controlled using the joystick. A fixed target circle was present in the center of the display and to more easily perceive the error between the cross and the target a horizontal and vertical line were drawn, see Fig. 3. The color of the background of the screen was black, in order to make it more comfortable for participants to look at the screen. The lines, cross and circle were the same shade of bright green. Prior to the experiment, participants received a briefing, explaining the

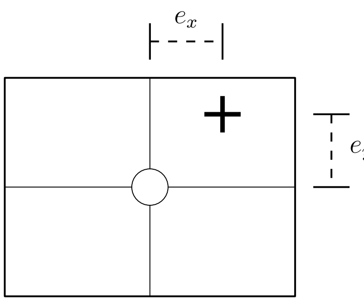

Fig. 3. Display with the errors indicated. For the simple task $e_y = 0$.

Fig. 4. Experimental setup.

task and how to operate the joystick. Participants were instructed to continuously minimize the error between the cross and the circle giving smooth, continuous inputs.

2.3 Participants

In total, 18 participants participated in this experiment, all task-naive before commencing training. All participants were comfortable with controlling a joystick with their right hand. Twelve pilots were used in the data analysis and 6 were eliminated because they performed below standards or used control inputs that did not allow for accurate pilot model parameter estimates. This left 6 pilots in group 1 and 6 pilots in group 2. The median ages of the final groups were 32 and 26, respectively, with standard deviations of 9.0 years and 3.9 years.

2.4 Dependent Variables

The goal of this experiment was to investigate in which manner generalization of manual control skills occurs between tasks of varying difficulty. Therefore, human control behavior and performance parameters were the variables of interest.

The root mean square (RMS) of the error signal RMS_e was used as a measure for tracking performance. A lower RMS_e indicates better tracking performance. The RMS of the control input RMS_u was used as a measure for control effort. A higher RMS_u indicates a higher control effort. For the difficult task, both these parameters were obtained separately for both directions.

Manual control behavior was characterized by the visual error position gain K_p, lead time constant T_L, time delay τ_v, neuromuscular frequency ω_{nm}, and neuromuscular damping ratio ζ_{nm}.

The parameters of the human manual control model presented in Equation 2 were obtained using a time-domain parameter estimation technique, based on maximum likelihood estimation [Zaal et al. (2009)]. A genetic algorithm was used to obtain initial parameter estimates, which were subsequently refined using a gradient-based Gauss-Newton estimation. For the difficult task, the pilot model in the x direction and y direction were determined separately.

To all dependent variables learning curves were fit to model learning effects during the runs.

$$y_{lc} = p_a + (p_0 - p_a)(1 - F)^x \tag{4}$$

This learning curve form has been used in previous experiments to capture learning effects, for example in Zaal et al. (2015) and Pool et al. (2016). The equation features three variables: the asymptotic performance p_a, the initial performance p_0 and the learning rate F. A least squares error minimization scheme was used to fit the curve to the dependent variables. Pearson's coefficient R was computed to assess the quality of fit.

2.5 Hypotheses

Training a simple task representation to proficiency can be argued to be equal to partially training for a real task. In this vein, the simple task can be seen as a generalizable skill, which can be applied to more specific and harder tasks. The learning rate F of the RMS_e learning curve is a measure of how fast a task is learned. Firstly, it was hypothesized that the learning rate F of RMS_e of the difficult task would be higher for the scenario where participants had already trained on a simple task (Hypothesis 1). This would indicate that the presence of a simple and generalizable task version helps in training for a real task.

Secondly, it was hypothesized that training with a simple task version would result in a better initial performance in the difficult task, as compared to not having had initial training at all (as is the case in group 2). For Hypothesis 2 the initial performance p_0 of the RMS_e is of importance. It is hypothesized that the initial performance in x direction would be better, as well as the initial performance in y direction (Hypothesis 2), even though for the latter no specific initial training with that direction was present, thus requiring generalizability of skills.

Thirdly, it was hypothesized that training on a simple task would allow participants to develop a more effective control strategy faster, and hence show a lower control activity for a higher performance, than if no training was present (Hypothesis 3). For this hypothesis, the RMS_u and its learning rate F_{RMS_u} were of importance.

It was hypothesized that if a generalizable skill would be present after training, it could be seen in the pilot model parameters K_p and T_L. The pilot error position gain K_p would show an increase, when comparing group 1 to group 2 (Hypothesis 4a), for the difficult task. This is consistent with an improvement in task performance and control activity, as described by McRuer and Jex (1967). Furthermore, the lead time constant T_L would show a decrease in group 1, compared to group 2 for the difficult task (Hypothesis 4b).

3. RESULTS

For all results the time-average of two runs was taken, in order to lower the noise present in the measurements and to increase the model identification quality. In order to test statistical significance a two-way mixed analysis of variance (ANOVA) was performed on the time-averaged first two and last two runs of each participant, for each of the tasks that were compared. Unless otherwise stated, the assumptions necessary for this statistical analysis were satisfied. The presence of outliers was determined with boxplots. Shapiro-Wilk's test ($p > .05$) was used to assess the normality of the dataset. Homogeneity of variances was assessed with Levene's test of homogeneity of variance ($p > .05$). Finally, homogeneity of covariances, was assessed by Box's test of equality of covariance matrices. Learning curves were fit to the averaged data. The goodness of fit was assessed by computing Pearson's coefficient R. For the purpose of this experiment, a minimum correlation of 0.3 was deemed strong enough, due to the relatively low number of participants and the considerable measurement noise which is typically present in this kind of data [Pool (2012)]. All learning curve fits with lower correlations were disregarded in further data analysis, since the data cannot be sufficiently explained by the learning curve fit. All figures in this section follow the structure of Fig. 1; the simple tasks are shown on the top left and bottom right and the difficult tasks on the top right and bottom left. The learning curve parameters are shown above the figures.

For the purpose of brevity, it was decided to omit the results of the limitation parameters τ_v, ζ_{nm} and ω_{nm}.

3.1 Tracking Performance and Control Activity

Fig. 5 shows participants' tracking performance in terms of the root mean square of the error signal. In the x direction data, there was no statistically significant interaction between training type (having trained with a simple generalizable skill or not) and the tracking performance, but the main effect of number of training runs showed a statistically significant difference in tracking performance over the length of the sessions ($F(1, 10) = 11.987$, $p = 0.006$, $\eta^2 = 0.545$); the performance thus improves with training. The main effect of experimental group showed that there was no statistically significant difference in tracking performance between groups. The learning curves showed similar initial and asymptotic performance, regardless of having received initial training, as can be seen in Fig. 5. For the y direction, there was no statistically significant interaction between training type and the tracking performance. The main effect of number of training runs showed a statistically significant difference in tracking performance over the length of the sessions ($F(1, 10) = 22.367$, $p = 0.001$, $\eta^2 = 0.691$). The main effect of experimental group showed that there was no statistically significant difference in tracking performance between groups. The presence or absence of a generalizable skill therefore is not visible in the initial performance, the final performance or the learning rate of the difficult task, in either direction. For the simple task, group 2 participants had a higher learning rate, but both their initial and final performance were worse. Group 1 participants showed a better initial performance and a better final performance. However, also here there was no significant interaction between training type and the tracking performance. The main effect of number of training runs did show a significant effect ($F(1, 10) = 15.741$, $p = 0.003$, $\eta^2 = 0.612$), indicating that participants improved their performance over the training sessions. The main effect of the difference in group showed a statistical interaction as well ($F(1, 10) = 5.903$, $p = 0.035$, $\eta^2 = 0.371$). Participants thus performed better on the simple task when they are task-naive, instead of having performed the difficult task first. Negative transfer was present in this case.

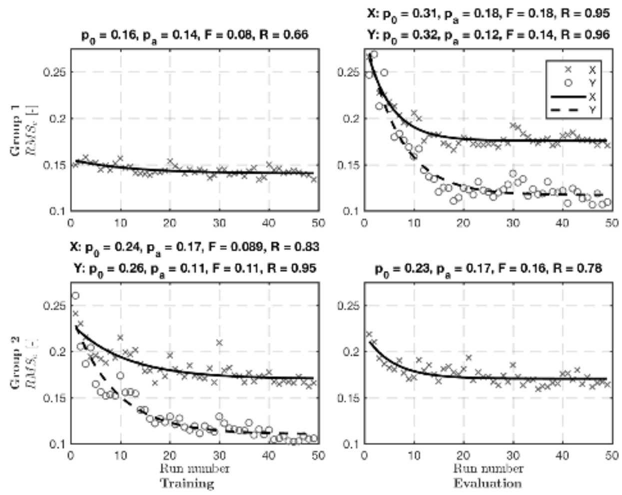

Fig. 5. Pilot performance.

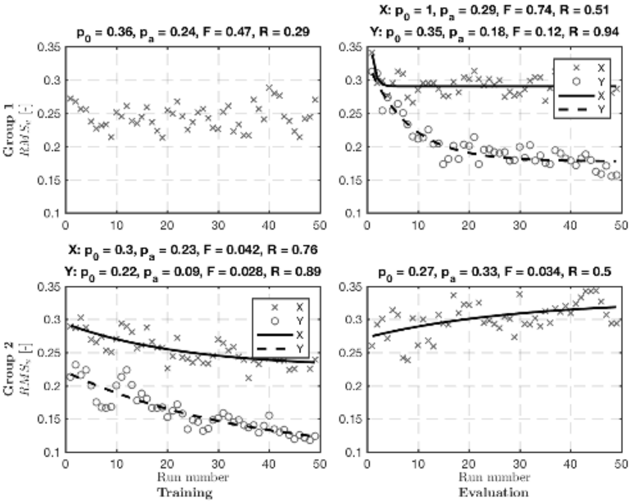

Fig. 6. Pilot control activity.

Fig. 6 shows the control activity in terms of the root mean square of the control input signal u. In the x direction of the difficult task, it can be observed that participants who trained with the simple task (group 1) controlled with less activity, especially after being fully trained. One outlier is present in the data of group 2. When comparing the results of the ANOVA with or without the outlier, little difference in the statistical analysis was seen. There was no significant interaction between training type and the control activity. The main effects of training runs and experimental groups did not show a significant effect either. Therefore, using these data it could not be concluded that there were differences in control activity between groups. Furthermore, control activity remained constant over the sessions, according to the statistical analysis. The learning curve of group 2 reflects this, as can be seen from the very low learning rate. The curve of group 1 however does show a gradual decrease in control activity. For the y direction, the results from the x direction were supported; the initial control activity was lower for pre-trained participants, as well as their final control activity. The pre-trained participants did have a lower learning

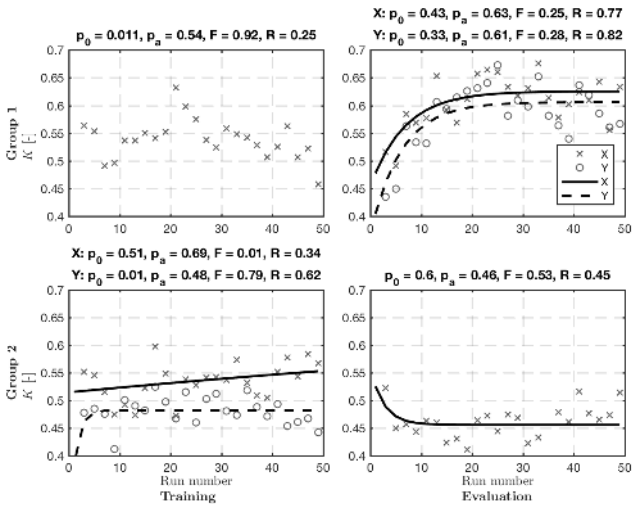

Fig. 7. Pilot model gain K_p.

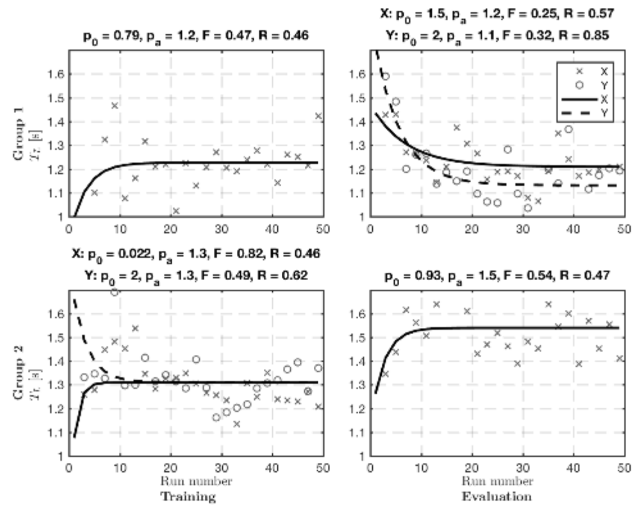

Fig. 8. Pilot model lead time constant T_L.

rate. There was no significant interaction between training type and tracking performance. The main effect of training runs did show a significant effect ($F(1, 10) = 18.086$, $p = 0.002$, $\eta^2 = 0.644$) and the main effect of experimental group showed no statistical interaction. For the simple task, the difference between participants who started the task without any experience (group 1) and those who trained with the difficult task (group 2) is clearly visible from the learning curves. Group 2 participants controlled with higher activities, especially after being fully adjusted to the task. This is reflected as well in a higher RMS_e, as can be seen from Fig. 5. However, statistical analysis showed that the interaction between training type and the tracking performance was not statistically significant. The main effect of training runs did not show a significant effect either, although Fig. 6 clearly shows an increase in control activity for group 2 participants over the runs. Finally, the main effect of the difference in training type showed no statistical interaction.

3.2 Control Behavior

Fig. 7 shows the pilot model gain K_p. Participants who had initial training on the simple task controlled with a higher asymptotic pilot model gain. It can be seen that the learning curve of group 2 participants showed a different trend from group 1 for the difficult task. Even though the figure shows that the pre-trained participants (group 1) controlled with a higher gain, no statistical significance between training type and pilot model gain was found. Furthermore, this dataset did not reveal an interaction of increasing gain over the number of training runs either, even though the learning curves adequately described the data and did show such an effect. No difference between groups was found. In the y direction the outcome of the statistical analysis was the same; no interaction was found between gain and training type, nor were the two main effects significant. For the simple task, it can be seen that the gain with which participants control is generally higher for group 1, where participants did not have any initial training. Participants who performed the difficult task before the simple one showed a lower pilot model gain. No statistically significant effects were found.

Fig. 8 shows the pilot model lead time constant T_L. Participants who had initial training on the simple task generated less lead. The x direction of the difficult task shows two different learning curve trends. Three outliers were present. The results of the ANOVA did not change when the outliers were removed. The data of the x direction did not reveal any statistical significance, which is reflected by relatively scattered data points. In the y direction the initial performance of both groups of participants was equal. However, the learning curve shows that the participants who were task-naive and had no initial training (group 2) generated more lead. Furthermore, they reached their asymptotic value quicker. Statistical analysis revealed no significant difference between training type and lead time constant. However, the main effect of the number of runs was significant ($F(1, 10) = 5.661$, $p = 0.039$, $\eta^2 = 0.361$), indicating that the lead time constant did change over the runs. No significance in the between-participant differences were found. For the simple task, the learning curve of the participants who had initially performed the difficult task (group 2) can be found above the curve of the task-naive participants, indicating that trained participants generate more lead time. The ANOVA did not discover any significant differences.

4. DISCUSSION

A human manual control behavior experiment, where participants had to learn one task and transfer to another with the goal of researching generalizability was performed. Eighteen participants divided over two groups performed a difficult tracking task either having received initial training or starting task-naive. In the final analysis six participants per experimental condition were present. Previous studies looking at learning effects, such as Pool et al. (2016), used 12 participants per group. Even though the ANOVA's showed no statistical significance in many of the dependent variables, the results and the learning curves still indicated interesting trends.

Looking at the difficult task, as the pre-trained participants showed lower learning rates, hypothesis 1 is rejected. Participants who had initially trained already reached a certain performance level and struggled to adapt to a more difficult version of the task. For the simple task these results were opposite, which suggested that it was easier to adapt to a new, more simple, task variation. In both the x direction and y direction of the difficult task, the learning curves indicated that the initial performance was lower for the pre-trained participants, which is in support of Hypothesis 2. This indicates that training with a simple task allowed participants to start with better performance, even for the y direction, which suggests the simple task was generalizable to the more difficult task.

For the difficult task, the control activity RMS_u mostly remained constant, or decreased over the runs. This decrease in RMS_u over runs was found to be significant in the y direction. In this direction, previously it was found that the performance significantly increased over the runs. Thus, both the RMS_u and the RMS_e decreased, showing that participants were able to track the signal better, while showing less control activity. For the x direction performance increased with constant control activity. Hypothesis 3 is thus accepted. The fact that the control activity did not display a significant change in x direction, but did show one in y direction might be due to the fact that the training was in x direction; the pre-trained participants thus already had a feel for the control task in this direction.

Looking at the pilot model parameters of the difficult task, the gain was higher in both directions in group 1 compared to group 2, as was hypothesized in Hypothesis 4a. Participants controlled with a higher gain when they pre-trained on a simple task compared to when they had no previous training at all. Due to the two different learning curve trends, it is difficult to infer information from the learning rate. Hypothesis 4a could therefore be accepted, however the ANOVA indicated that the data did not contain any significant interactions. The lead time constant T_L was hypothesized to be smaller in group 1, which Fig. 8 indeed reflects; participants have to generate less lead with the presence of a generalizable skill. Furthermore, adapting from the simple task seems to negatively impact the convergence of the lead time constant of the difficult task to the final value, in both the x direction and the y direction. Hypothesis 4b can not be accepted however, because also here no statistically significant interaction was found, apart from the main effect of the number of training runs in the y direction.

Apart from the gain in x direction, it seems that pre-training with a simple task variant negatively influences the learning rate of a difficult manual control task; in all other parameters the learning rates were lower when compared to a group of task-naive participants. Participants do seem to use the simple task as a generalizable skill, because of the increased gain and lower lead time. Both changes are consistent with McRuer and Jex (1967), however more research is required to support these results with statistical evidence.

Results in manual control experiments always involve high levels of noise due to between-subject variability, the effects of which could be mitigated by adding more participants. Due to the nature of the investigation, a between-subjects approach was chosen, which typically requires more participants to gather statistical power. Furthermore, several of the group 2 participants indicated that the switch from the difficult to the simple task challenged them in terms of their attention span: the simple task was deemed too simple after having performed the difficult one. If a follow-up experiment were to be executed, care should therefore be taken to have both tasks be sufficiently challenging.

5. CONCLUSION

This paper investigated the generalizability of manual control skills in two tasks with varying difficulty. Twelve participants divided over two experimental groups trained on a compensatory manual control task for five days, before switching to a different task. One group switched from a simple one-dimensional task to a difficult two-dimensional task and another group performed these two tasks in reverse order. The human operator gain showed an increase after initial training, compared to having no training, especially in the y direction, where the operator did not control before. The lead time constant showed a decrease after possession of a generalizable skill. Furthermore, training with a simpler generalizable skill variant lowered the convergence to final performance, as opposed to having no prior training at all. More research into generalizability of manual control tasks is required to be able to adjust training practices and to prove whether the results are statistically significant. Although no statistical evidence was found indicating that training simple generalizable skills helps the training of difficult operational tasks, application of the method was proven for looking at the problem of generalizability of training.

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