MASTER THESIS
JELLE HOFLAND

Evaluating trading and sharing control for constraint motion tasks in a domestic environment using a remote controlled semi-autonomous robot

TU Delft

Evaluating trading and sharing control for constraint motion tasks in a domestic environment using a remote controlled semi-autonomous robot

by

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Preface

This master is the results of a collaboration between the Haptics Lab, Interactive Intelligence and Heemskerk Innovative Technology (HIT). HIT provided a great business case with their care robot, interactive task simulator (ITS) and haption haptic device, to do research on the possibility of combining haptic shared control and coactive design.

The main objective of my research was to find out if HSC could perhaps be an addition to a coactive design approach for skill-based tasks. To do this I used a simulator to simulate my domestic environment en implemented a haptic shared controller and automatic controller of which control could be taken over. By creating translational offsets in 3 dimensions, I created a failure mode for the automatic controller, which I could also use as input to the haptic shared controller to make a fair comparison.

In this book you will find the paper containing my main findings and several appendices. Most of the appendices are dedicated to anyone who wants to continue my work or do further analysis on my data, you can find the design process, the data analysis, working with the simulator, the interdependence analysis and all the forms I used. For anyone who wants to continue on my work, the raw data, documents and Matlab code are available upon request on the BioMechanical Department.

I would like to thank everyone who contributed during my Master Thesis, but I do want to thank 5 persons in special. First of all, my Profs, David and Catholijn. Getting feedback from to two totally different backgrounds was not always easy, but did make it more interesting and eventually better. For all these monthly meetings and your enthusiasm, I would really like to thank you two. Next to this I want to thank the Jeroen and Jeroen. First Jeroen van Oosterhout, thanks for all your technical support when I had when having questions about ITS, even though you did not work for HIT or the TU anymore, without you I would probably still be struggling with the structure of ITS. Then Jeroen Wildenbeest, how had to disadvantage of sitting in the same office and therefore being the easiest victim for advice, thanks for all your comments on my work and for noticing and picking me up when I was fully stuck. Finally the last thanks for my other colleagues at HIT. I really liked the atmosphere of improving together, the numerous discussions, the two-weekly supervision meetings, the Friday afternoon drinks and the summer cycling trips. I would really like to thank Cock for the atmosphere he creates in the office. I can say that I learned a lot during my graduation, both from HIT as well from the supervision from David, Catholijn and Jeroen.

Jelle Hofland
Delft, December 2018

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Paper

Evaluating trading and sharing control for constraint motion tasks in a domestic environment using a remote controlled semi-autonomous robot

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***Abstract*—Automation in a domestic environment is not flawless and human interference will be necessary, for implementing robots in this environment. When remotely controlling semi-autonomous robots, proposed concepts can be divided into two main concepts: To trade control back and forth between the human and the operator and to share control continuously. However, a deep analysis lacks about when either of these methods is useful. This study focuses on comparing task completion time and task behavior Trading Control (TC) and Haptic Shared Control (HSC) using a mix of accurate models of the tasks and models with a small translational offset. These are examined in the current mix as well as separated into models that were accurate or did contain an offset. In remote execution of a constraint motion task, we hypothesize Haptic Shared control to have a lower task completion time compared to Trading Control when inaccuracies are present. When the model is fully accurate, on the other hand, we hypothesize Trading Control to have a lower task completion time compared to haptic shared control. Participants used a 6DOF haptic manipulator to control a virtual robot arm, in order to open a simulated drawer. An autonomous controller was developed based on a model that was perfectly accurate (50% of the time), or that had an effective endpoint error (50% of the time). Control over the automation was either traded by pressing a space bar or continuously shared through haptic shared control. In trials with a translational offset, Haptic shared control had a lower task completion time compared to trading control. In the trials with a perfectly accurate model of the task, Trading Control had the benefit of lowering peak collision force and increasing smoothness of the master input. Therefore more research is needed to better understand when trading control is beneficial compared to haptic shared control.**

***Keywords*—Human Robot Interaction, Haptic Shared Control, flawed automation, care robot, Teleoperation.**

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I. INTRODUCTION

The rise in artificial intelligence is bringing automation more in daily life. Whereas in the past robots were only introduced in highly controlled environments such as factories, now they are making their way into our daily lives, which can be seen in, for instance, the rapid increase of ”autonomous” vehicles such as Tesla, Google and Uber. However bringing automation more into a human-based environment poses some challenges [1]. A domestic environment is not specifically designed for robots. Robots have to interact with humans and since the environment is designed for humans it has to rely on the sensors on the robot itself, instead of having any information besides his own [2]. Therefore in this environment sensor accuracy is a limiting factor. If an inaccuracy is too big for the specific task, for instance when grasping a cup. If the perceived position and the actual position are off by a couple of centimeters, sending the arm to the perceived location does not help you to actually grasp a cup. These inaccuracies can lead to failed behavior depending on task specifications. To ensure task execution we need methods to deal with failures of automatic systems [3]. This was also pointed out in a recent book chapter of Sheridan, that very few systems are indeed fully autonomous and many systems still have some form of human supervision or oversight[4].

One method which has shown to be useful in the DARPA challenge was the coactive design method [5]. This was also referred to by other authors as a promising approach especially to answer the question what should be automated [6]. This method depends on an analysis of capacities, where each subtask gets as assigned a main actor, to ensure task completion. Also in this analysis improvements in efficiency are indicated. Their main focus during the DARPA challenge was to create a resilient robot that could do all the tasks. To achieve this their method Traded Control (TC) between agents between tasks. Still there is enough potential to improve since their robot was only approximately 20% of the operation time was robot motion during the trials[7]. In their reflection, they subscribe their success to design for teamwork instead of task work and rightsizing human teamwork instead of downsizing it [8].

A method that attempts to design for teamwork using a different approach is haptic shared control (HSC). In HSC there is no main actor, both actors and continuously engaged in the task and executing the task. To achieve this both entities, the human and the haptic shared controller exert force on a master device. Haptic shared control has the advantage of increased task performance and decreasing workload of a task, at the trade-off of keeping to keep the human continuously in the loop on 1 robot. In the nuclear sector haptic shared control has shown to be assistive for teleoperation, even with small translational errors in the model that underlined the shared controller [9]. However, if errors were too large performance would decrease compared to manual control. Currently, it unknown under what conditions HSC are TC might be beneficial.

In this study we are examining this for a care robot. The domestic environment is built for humans and not for robots, which proposes its difficulties, especially when sensor inaccuracies occur. For domestic robots, an accuracy of 0.05 m has to be taken into account [10]. A first desired function of a domestic care robot would be to support Activities of Daily Living (ADL) [11]. To be able to fetch and carry objects in the domestic environment you have to be able to open drawers and cabinets. This constraint motion tasks can be hard to do autonomously. Currently, there is one study concerning domestic care robots. This wanted to have as much as possible autonomous and used a trading control approach to develop their Human Robot Interaction [12].

In some tasks it seems evident to trade control. When an object is placed in front of 3 objects and asks the human operator which is the mug that has been grasped, clicking and selecting an object is a much simpler approach than taking over the robot to grasp one of these objects. This was also found by Kent et al. [13]. This however that the grasping strategy must work and the robot should have an accurate model of the task and should be able to execute the planned movement. When placing this kind of interference in the framework of Rasmussen, this intervention would be knowledge-based behavior [14]. But flaws can also occur on a lower skill-based level, for instance, if there is a translational offset in the model of the environment. In those instances, it becomes less evident how an intervention is the most convenient. Going to back to the example of the mug, in execution you are a couple of centimeters off, due to a sensor inaccuracy, how do you compensate for this. Do you direct the robot to move a couple of centimeters in a direction based on your own guess of this distance, or do you take over manually and deal with the difficulties of teleoperation or perhaps use haptic shared control to ease the task of teleoperation even tough information might be slightly flawed?

In this research, we will examine the simple task of opening a drawer using a telerobot to compare TC, HSC to Manual Control (MC) as a baseline. The TC will consist of supervisory control with humans taking over if they deem it necessary. We choose to give the controller the right location in 50% of the time and send the gripper to a wrong location in the other 50%, 4 cm of the path for opening. This results in unsuccessful grasping or jamming of the gripper when remained in autonomous behavior. In this research, we want to find out what determines when HSC and TC should be implemented and how human behavior changes when inaccuracies occur. For this experiment we hypothesize: Hypothesis 1: *For opening a drawer using a semi-autonomous domestic robot we expect haptic shared control to have a lower task completion time compared to Trading control when small inaccuracies are present in the model of the task.* Hypothesis 2: *For opening a drawer using a semi-autonomous domestic robot we expect Trading control to have a lower task completion time when the models are accurate*

II. Methods

A. Participants

In this research operators were controlling a haptic master device using their right hand. Twelve right-handed participants were recruited on the campus of the TU Delft. Nine participants were males and 3 females, age from 20 to 28 (mean: 24.2 $\pm$ 2.4). Participants did not get any financial reimbursement for their participation.

B. Materials

In this study was done in a virtual environment. This was simulated in an Interactive Task Simulator (ITS) that was also used in [9]. This is a rigid-body simulator, based on Nvidia PhysX 2.8.5. The virtual environment was simulated at 500 Hz and visualized on a TV screen 1.5 meters from the participants. Participants operated a Haption Virtuose 6D 35-45 master device.

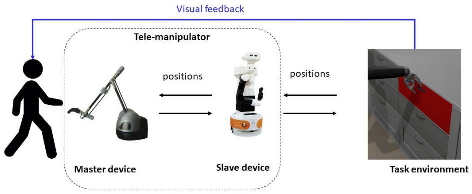

Fig. 1. The setup of the experiment for the manual control condition. There is a human operator operating the robot through a master device. This master device controls the slave device that manipulates the environment (a drawer). During the experiment, this was not only done trough telemanipulation but also trough Haptic Shared Control and Trading Control.

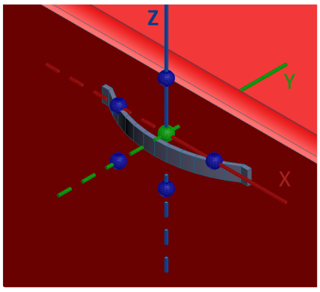

Fig. 2. The drawer positions available to the model of the automatic or haptic shared controller with the correct one (green) and 5 of the 6 offsets (blue) and the axis of the drawer.

C. Design

The experiment used a within-subjects design. The order of the 3 conditions was randomized to counterbalance a learning effect. The independent variable was the HRI used (TC, HSC or MC). The automatic controller was designed such that in 50% of the time it would be perfect and in 50 % there would be an offset. These were offsets along 3 axes of the drawer as can be seen in fig. 2. All these offsets had an amplitude of 4 cm. These offsets occurred 2 times each and were made unpredictable using an incomplete counterbalanced measures design.

To operate the robot, participants had 2 cameras, one in the head and a small one on the gripper. Both of these were visualized at the same time on the same screen. The closing function of the gripper was disabled, to ensure that forces were recorded. Participants were instructed to use a top grasp to open the drawer and open the drawer fast and safely. The opening in the middle of the handle was 4.5 cm. The width of the gripper was 2 cm at the front part, increasing to the end where it would reach 4 cm.

1) Haptic shared controller: The haptic shared controller was implemented as a perfect path. After completion, it was checked to be similar to a human expert path. The haptic shared controller provided a force using the perpendicular distance to the path. This is done using with a spring constant of 100 N/m and 3Nm/rad and was limited to 10N and 1 Nm. This was high enough to still provide guidance and low enough so people did not fight the system. A higher stiffness resulted in this behavior during the pilot study. This implementation had made a segmentation of the path of 2 mm. This was chosen to provide a smooth path, also during fine approach. The implementation used the same and implemented just as [9].

2) Trading control: The trading control condition used the same paths as the haptic shared controller. Only the stiffness of the controller was increased to 1000 N/m and 75 Nm/rad. These forces were damped with 10N/m/s and 2.5 Nm/rad/s. This was chosen to ensure that the path was followed. A force of 1 N dragged it downwards to provide forward momentum and on contact with the handle, a force of 60 N was put on the gripper in a direction perpendicular to the drawer. This force was found to be sufficient to open the drawer, whilst keep opening controlled and observable. Participants were able to intervene by hitting a space bar on the keyboard in front of them. When this was done, the scene was frozen and a countdown box was presented. This initialization time was removed afterwards from the data. After the take over participants had full control over the robot, just as they would have in the manual condition, without augmented haptic guidance.

D. Procedure

Before starting the experiment participants had to fill in the data form. People with prior knowledge and experience were excluded from the experiment, to ensure that people did not have any training on the task. To achieve the same entry level and for participants to get familiar with the setup, participants first got some training in opening a fridge. When they were able to open the fridge within 5 seconds on average over 5 trials, they would proceed to the experiment. When this would not be achieved within 10 minutes, participants would be excluded from the study. However, this was not found to be necessary during my experiment and no one was excluded. The experimental procedure is described in fig. 4. Then each condition would consist of 5 times training without any offsets. After this training they have to do 24 repetitions with offsets or 12 repetitions in the case of manual control, were no offsets occur. The haption was handed over in a consistent

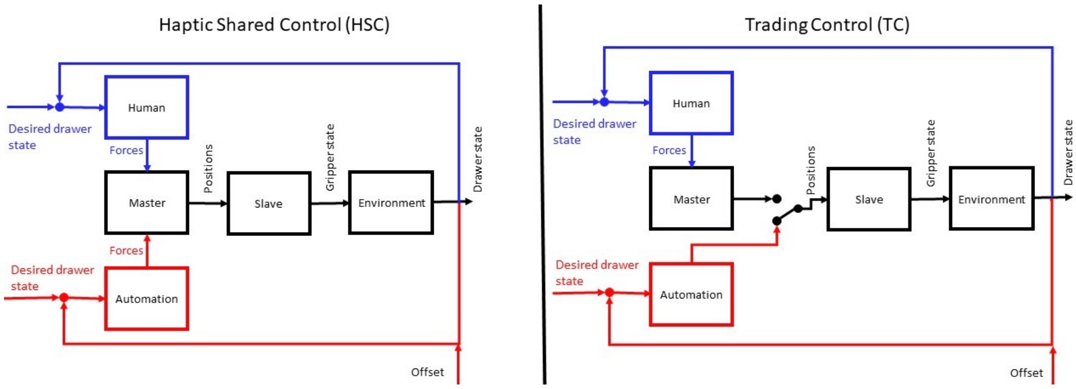

Fig. 3. Schematic overview of the assistive systems compared in this study. In both, the error can be introduced on the positions of the drawer. In HSC both systems provide a force on the master device. In TC control is traded through a switch between automatic and manual control. This switch was controlled by the human operator and was only able to switch from automatic control to manual control.

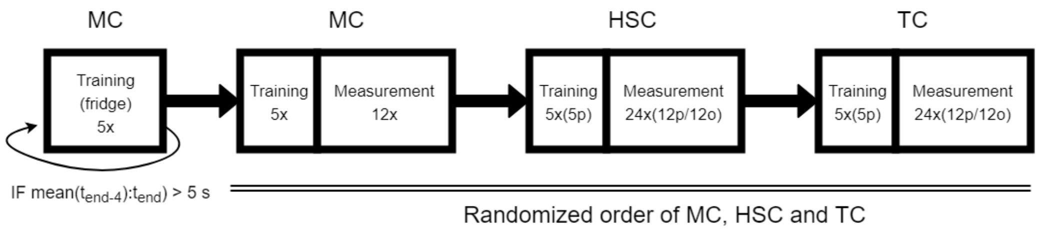

Fig. 4. The experimental design. Participants would keep on practicing on opening the fridge door until they were able to open it under 5 seconds on average over the last 5 trials. After that participants did 3 blocks in randomized order of MC, HSC, TC. These blocks start with 5 practice trials and then 12 (MC) or 24 (HSC, TC) repetitions

configuration, to ensure that execution of the task was possible without reconfiguration of the master. During the training of the trading control condition, participants were instructed to look at perfect execution the first 2 times and on the last 3 trials of the training to do a mandatory take over to ensure some experience with the task. At the end of each condition they were asked to fill in a VanderLaan questionnaire. At the end of the experiment participants were asked to answer two questions: What did they find hard and what condition did they liked the best.

E. Metrics

Data from the master, slave and haptic shared controller was logged at 500 Hz. The logger contains time, positions and orientations, velocities, forces, torques. To evaluate the performance we used the Task completion time[s]. Time only will provide a limited view of performance. There is a trade-off between speed and accuracy. Therefore we will quantify the accuracy using Collision force in the fine approach. Next to this, we will also examine the contact time with the table top. As can be seen in fig. 6 the tabletop lies on top of the drawer en contact with this top is most likely unintentional. Therefore contact time with the table top is also examined as an accuracy metric. To measure control effort a smoothness measurement is used on the master input, using the Spectral Arc Length. [15] This metric measures smoothness of movement on the master and will therefore provide us with an objective measurement for the control effort of the operators. In 2D reversal rate is shown to be correlated to control effort. [16] Reversal rate is easy for a straightforward task but becomes hard to judge in 6 DOF. Spectral Arc Length has shown to be a robust 3D measurement for smoothness [15] and we consider it our best option to quantify the physical effort.

Next, to these objective measurements, there also was a subjective measurement, using the VanDerLaan questionnaire about the usefulness of the system. This would provide a subjective insight in the participants and their acceptance of each system.

F. Data analysis

Data is first filtered using a 4th order Butterworth filter with a cutoff frequency of 200 Hz to remove any sudden peaks in the simulation. I started a trial when the gripper is moved for the first time. In the data analysis, a distinction is made in 3 subsections. The rough approach, fine approach, and constraint movement. These transitions between these subsections were defined as:

- Rough approach: Starts at the first movement of the gripper. It ends when a sphere with a radius of 11 cm around the handle is reached for the first time.
- Fine approach: The fine approach starts when the sphere is reached for the first time. This phase ends when a movement starts that is at least 80% in the direction of Y (therefore the constraint direction of the drawer) within the 82 and 86 cm above the ground (the height of the handle of the drawer).
- Constraint Translational Movement: When the velocity is more than 80% in the Y-direction within the height of the drawer, then the constraint movement is started, this ends when the drawer is opened slightly over 40 cm, which is almost a full opening of the drawer. On this position, the log was stopped automatically.

  First, the means for each participant were calculated over the 12 trials per condition and these were used for further analysis. When comparing the means of each participant first a KolmogorovSmirnov test will test if the data is parametric. After the KolmogorovSmirnov test confirmed that the data was parametric a repeated measures ANOVA was used. Then post-hoc, a Tukey Kramer test was performed to find if there was a significant difference between conditions. Results were considered significant below a p=0.05 value.

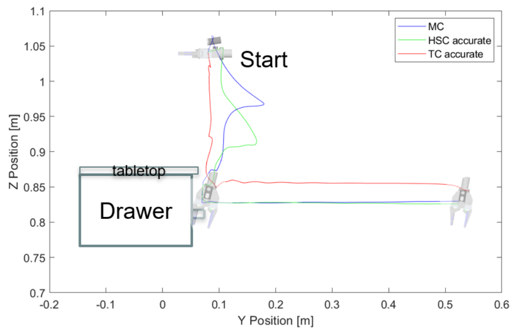

Fig. 5. Typical paths for the task from 1 participant viewed in the YZ plane. The blue line represents the Manual Control(MC) condition. The green line shows the Haptic Shared Control (HSC) condition. The trading control (TC) condition is represented by the red lines. In this graph, all the paths are visualized were the model of the task was accurate. During the experiment there was a mix of an accurate model of the task and models with a shifted effective endpoint.

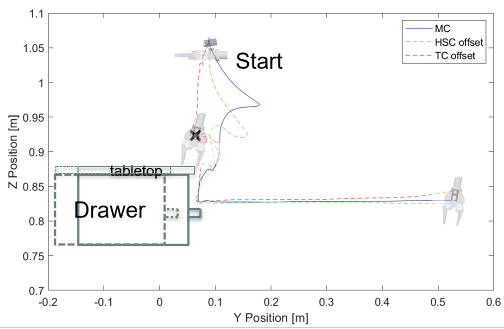

Fig. 6. Typical paths for the task from 1 participant viewed in the YZ plane. The blue line represents the Manual Control(MC) condition. The green line shows the Haptic Shared Control (HSC) condition. The trading control (TC) condition is represented by the red lines. In this graph an offset was introduced, therefore the effective endpoint of the model is shifted 4 cm in the negative Y direction, as visualized in the dashed drawer. Also visible in this graph is the take over position, where the gripper was jammed on the surface of the tabletop.

III. Results

In this experiment, 12 participants had to open a drawer trough Manual Control (MC), Trading Control (TC) and Haptic Shared Control (HSC). In 50% of the trials of HSC and TC, there was an offset in the automation which prevented fully autonomous opening of the drawer. For each participant, an average was calculated per condition. These averages of all participants are visualized as data points. The measured data is represented by the dark colors. Subsets of these measurements with and without an offset are represented using lighter colors. Comparisons are done between the conditions with and without offsets. In the figures, this is indicated using the bars across conditions. Manual control was always used as a baseline. Significant differences were denoted with */•, **/••, ***/• • • for respectively $p<0.05$, $p<0.01$, $p<0.001$.

fig. 6 Shows typical paths from 1 participant for all 5 conditions. The offsets were introduced in the negative Y-direction in both HSC and TC in this example.

In trading control with an accurate model, the automatic was able to open the drawer without interference. This was always recognized quite well by the participants, but 3 operators took over in either 1 or 2 of the 12 trials.

A. Completion time

In the current setup no differences were found ($F(2,22) = 2.92$, $p = .08$)). When there were no offsets present we found a difference ($F(2,22)=5.73$, $p=0.010$). Post hoc analysis

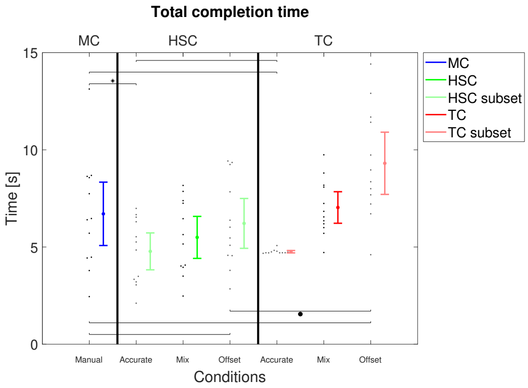

Fig. 7. The completion time of the entire task. When there are no offsets (accurate) HSC is faster compared to MC. When there are offsets TC takes has a longer task completion time then HSC. Significant differences were denoted with */●, **/●●, ***/●●● for respectively p<0.05, p<0.01, p<0.001

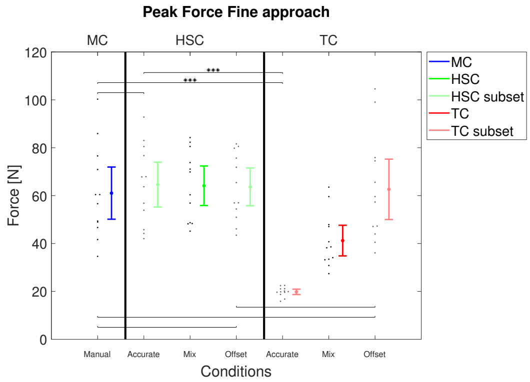

Fig. 8. The peak force in the fine approach. This was used as an indication of safety. Differences were found between the TC and MC, and TC and HSC.

showed that HSC was significantly faster compared to MC,(p=0.024)

When offsets were present also there was a difference found F(2,22)=7.52, p=0.0032. A post hoc analysis showed that TC was significantly slower with respect to HSC (p=0.014)

B. *Peak force*

We found that the peak collision force in the fine approach in the current setup was lower in TC compared to HSC and MC, with respectively p=0.00020 and p=0.011 (F(2,22)=12.65 p=0.00022). When we divide this into the trials were the model of the task was fully accurate and the ones with an offset, then we saw that there was no difference between conditions when offsets were present (F(2,22)=0.098, p=0.91). The difference came from the when the trials with the accurate model of the task (F(2,22)=39.68 p=5.03e-08). Post hoc analysis showed that TC applied significantly less force on the environment compared to HSC and MC, respectively p=4.80e-6 and 3.93e-5. It had to be noted that in 97% of the TC with an accurate model the movement was executed by the automatic controller.

C. *Master input smoothness*

In the current setup, we found a difference (F(2,22)=25.72, p=1.75e-06) in the smoothness of the master input. Post hoc analysis showed that the input of TC was smoother compared to HSC and MC, p=2.41e-05 and p=0.00027). There was no difference between conditions in when the model contained an offset in the model of the task. (F(2,22)=0.082, p=0.92). In trials with an accurate model of the task, there was a difference. (F(2,22)=85.91, p=4.03e-11). Post hoc analysis showed that TC was more smooth compared to HSC and MC, respectively p=1.02e-7 and p=9.27e-7.

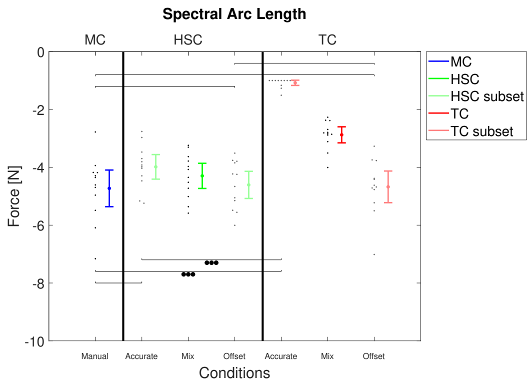

Fig. 9. Spectral Arc Length of the master for all conditions, only the automatic controller was statistically different from the other conditions, where there was almost no input

D. *Subjective measurement*

The van der Laan acceptance scale was used to evaluate the human effort in a subjective metric. No difference were found for the useful (F(2,22)=0.68, p=0.52) and satisfying scores(F(2,22)=0.39, p=0.68)

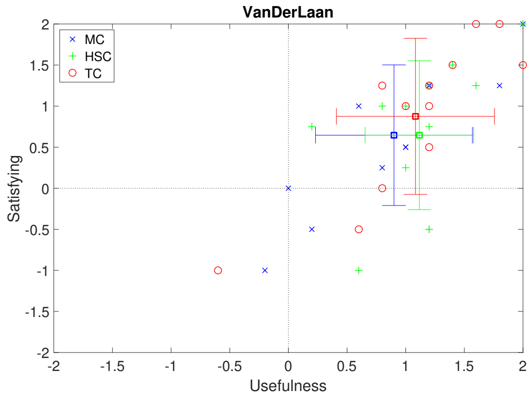

Fig. 10. The outcome of the VanderLaan questionnaire. No differences were found significant. All the conditions were ranked in the top right quarter as useful and satisfying

E. Contact time

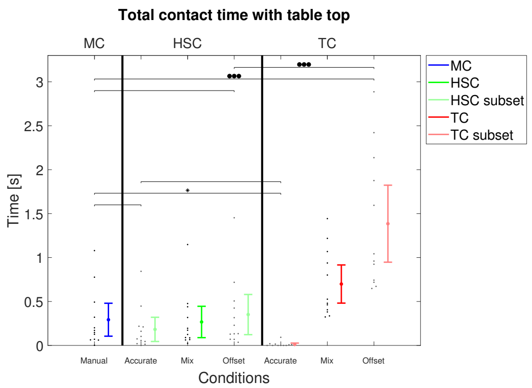

Fig. 11. Different tactics can be seen in the contact with the table top, an automatic controller does not need to use the table top as a guidance mechanism. Next to this when there are offsets, operators are not aware of the collision, because depth perception is limited. Resulting in a longer contact time compared to MC and HSC.

During the experiment, we noticed different behaviors between conditions. To quantify we this we examined the contact time with the table top. This found the have differences F(2,22)=9.23 p=0.0012). Post hoc analysis showed that the contact time was longer in TC compared to HSC and MC, respectively p=0.011 and p=0.031. Examining the subsets this was found to be different for both the accurate model of the task (F(2,22)=5.81, p=0.0094) as well as the model containing an offset (F(2,22)=20.83, p=8.40e-06). When the model was accurate TC the contact time was lower in TC compared to MC (p=0.037). When there was an offset TC took was longer in contact with the tabletop compared to MC and HSC, respectively p=0.0020 and p=0.0016.

IV. Discussion

In this experiment, we wanted to examine the differences between Manual Control (MC), Haptic Shared Control (HSC) and Trading Control (TC). Participants had to open a simulated drawer using MC or with assistance in HSC or TC. Task completion time, peak collision force in the fine approach, the spectral arc length of the input on the master device, contact time with the tabletop and acceptance were examined for these conditions.

We expected that HSC would have a lower task completion time compared to TC when small inaccuracies were present in the model of the task. When these offsets were presented only 50% of the time, we did not find any difference in task completion time and the Vanderlaan questionnaire. We did find a difference in peak collision force, a smoother master input and a longer contact time with the tabletop. To explain this results it is useful to divide trials in which there was an offset and the ones in which there wasn't. It has to be taken into account that the behavior visible corresponds to the current mix of this experiment. In the trials that contained an offset, no differences were found in peak collision force and the spectral arc length between TC and HSC. In the trials containing an offset we only found a difference between HSC and TC in contact time with the tabletop. In TC with offsets in the model of the task, the contact time with the tabletop was 3x times as long as in MC or HSC. This showed different behavior of the operators. These results indicate that operators had difficulties recognizing a collision in TC. An example of this is visible in fig. 6, wherein TC with an offset the controller jams on the tabletop and operators using HSC have compensated for this in an earlier stage. This behavior can be explained as a lack of situational awareness due to out of the loop behavior [17], which is a negative side effect of supervisory control. However no differences were found in the current setup, the trials containing offsets in the model of the task indicate that TC might not be the best approach for these trials and HSC seems a better approach for these trials.

We also expected that TC would have a lower task completion time compared to HSC when the model of the task was fully accurate. This was not found in our experiment. This can be explained by the design choice to limit the automation speed, to keep the robot observable and allow humans time to intervene. However, TC did have its advantages compared to HSC when the model of the task is accurate. We

TABLE I

RESULTS OF THE REPEATED MEASURES ANOVA WHEN THE MODEL WAS ACCURATE. ON THE LEFT THE MEANS AND 95% CONFIDENCE INTERVALS ARE DISPLAYED

	Means (95% CI)			ANOVA		Post-Hoc		
Metric	MC	HSC	TC	F	p	MC-HSC	MC-TC	HSC-TC
Total completion time	6.71(5.65)	4.78(3.29)	4.76(0.21)	5,76	0,010	0,024	0,094	0.999
Peak Collision Force	61.04(37.74)	64.61(32.44)	19.81(3.88)	39,68	5,03e-08	0,84	3,93e-05	4,80e-06
Spectral Arc Length	-4.73 (2.19)	-3.98 (1.47)	-1.08(0.31)	85.91	4.02e-11	0.089	9.27e-07	1.02e-07
Contact Time	0.29(0.65)	0.18(0.48)	0.01(0.05)	5,81	0,0094	0,36	0,0367	0,088

TABLE II

RESULTS OF THE REPEATED MEASURES ANOVA WHEN THE MODEL OF THE TASK CONTAINED A TRANSLATIONAL OFFSET. ON THE LEFT THE MEANS AND 95% CONFIDENCE INTERVALS ARE DISPLAYED.

	Means (95% CI)			ANOVA		Post-Hoc		
Metric	MC	HSC	TC	F	p	MC-HSC	MC-TC	HSC-TC
Total completion time	6.71(5.65)	6.22(4.44)	9.31(5.54)	7.52	0.0032	0.64	0.073	0.014
Peak Collision Force	61.04(37.74)	63.65(27.30)	62.62(43.68)	0.098	0.91	x	x	x
Spectral Arc Length	-4.73 (2.19)	-4.61(1.63)	-4.68(1.90)	0.082	0.92	x	x	x
Contact Time	0.29(0.65)	0.35(0.79)	1.39(1.52)	20.83	8.40e-06	0.71	0.0020	0.0016

found a lower collision force in the fine approach, a smoother input on the master device, which indicates less physical control effort and a shorter contact time with the environment. In this condition, the automatic controller did the entire execution of the robot in 97% of the time. Therefore we conclude that when an automatic controller is working perfectly, it can be better at tasks than human operators and therefore TC might be a better approach for those trials.

To validate our experiment we checked if the assistive systems were of help during our experiment. In the subset with an accurate model, HSC has shown to decrease the task completion time compared to MC. In TC this decrease was not significant. TC still had the advantage of lowering the peak force in the fine approach and having a smoother master input, which was used to quantify physical control effort. Also, the contact time with the tabletop decreased in TC compared to MC. The explanation for this is simple, because the automatic controller does not need to use the table top as a guidance mechanism, as human operators do need to. These show that in our experiment both support systems did provide assistance to improve task performance when the model was fully accurate.

To explain the differences we could place this in the HASO model of [18]. The slow response time is a result of the lower engagement in the model. Haptic shared control, on the other hand, might decrease the complexity of the task by providing guidance. This could even hold for small offsets, for instance in this study offsets were only present in 1 DOF, so therefore the guidance was accurate in the other 5 DOF. When offsets are too large, it might make the task even more complex than it originally was, which could decrease task performance.

A. Comparison to other studies

As far as we were concerned there has never been a study that compared HSC to TC. This actually surprises us since both try to solve the problem of semi-autonomy. Both methods are used already by Sheridan and Verplank [19].

To compare our findings on the haptic shared control, we compare our findings to the findings of Van Oosterhout et al. [9] and Boessenkool et al. [20]. Both studies found that HSC with an accurate model improved task performance compared to MC. Van Oosterhout et al. [9] found that using small translational offsets HSC could be beneficial compared to MC. In the study of Van Oosterhout et al. offsets were only introduced in along 1 axis, whereas in our study the offsets were introduced in 3 dimensions. Also quantitatively did the results match expectations. The study of van Oosterhout et al. [9] showed a 40% decrease of task completion time comparing HSC and MC, just as this study. The study of Boessenkool et al. [20] showed just a 24% increase of HSC, but this task was also different since it was only in 2D.

If we compare our results to the results found in the DARPA Robotics Challenge, TC worked good according to their first place in the Virtual Robotics Challenge and second place in the Robotics Challenge Trials. In the DARPA Robotics Challenge (DRC) team were encouraged to do as much as possible autonomous. A reason why HSC was not explored in the DRC might be due to bandwidth constraints and data delays, which oscillated (between 1Mb/s and 100 ms delay to 100kb/s and 1000ms delay)

[21]. However, this might have been a good idea for tasks, when inaccuracies would occur. When problems occurred at a higher level, for example not knowing how to grasp an object this is a problem on a tactical level. Given the high complexity of executing any task on these humanoid robots, trading becomes efficient easily.

B. Limitations

In this research, we chose a simple constraint motion task of opening a drawer. This task would occur often for a domestic care robot. Since this is an exemplary task for a constraint motion task. An important factor in transferring our results is the complexity of the task. Also, I will be interesting to see how our results translate to tasks with a softer constraint. For instance, when holding a cup of coffee, you want to keep the cup more or less upward, to prevent the spill of hot coffee. Therefore there is some play in this constraint. This should make the task easier in MC and therefore the gain from HSC and TC will be smaller. When transferring our results to the opening of a door, the constraint rotational instead of the translational. This might be a little more complex, due to the combination of rotation and translation in telemanipulation and therefore I expect HSC to perform even better.

When examining the point where TC, might be beneficial to HSC or MC, it has to be taken into account, that the current scenario was the best case scenario for the operator to take over. In this scenario, there was an operator that was actively engaged in the task, by intervening and following the movement. Also, the offsets occur often, when offsets would occur less often this would decrease the reaction time of operators will most likely increase due to less attention devoted to supervising the task. They will simply start to other things in the meantime. Endsley explains this as loss of situational awareness when humans are out of the loop [18].

As mentioned earlier all the conclusions are drawn, also for the subsets represent the behavior at the current mix. When this ratio would change, this would influence the results of the subsets. When the accuracy of the autonomy would increase, we would start to see more out of the loop behavior, such as loss of situational awareness[17]. Therefore we expect that when the percentage of trials with an accurate model of the task would increase the task completion and contact time would increase in TC. Since the speed of automation was tuned to keep the robot observable this cannot be increased before reaching 100% reliability. For HSC we do not expect a big drop in performance at any points because humans remain in the loop. However, research lacks to do a more in-depth prediction. In this research, we choose a mix of 50% of the time an offset and 50% without an offset, for 2 reasons. First of all, differences between HSC and TC in this mix, indicating that these differences would also occur when the accuracy percentage of the model of the task would increase when out of the loop behavior is expected to be more present. This is harder the other way around. Next to this ratio also had the advantage of getting a high statistical power, without too many trials. To gain more insight, research has to be done using higher accuracy ratios. To better understand when TC and HSC are beneficial more research has to be done, the previous study indicate that most likely the difference between accurate and trials containing an offset will increase more in TC compared to HSC.

Although we don't know the critical points when TC becomes beneficial compared to HSC, we do know what works better at the extreme ends of the spectrum. If an error is really uncommon, such as in factory robots TC seems to be the most convenient option. If on the other hand errors are really common and small in amplitude, such as in robotics surgery or nuclear maintenance, you want to have a human in the loop to react quickly to the errors.

C. Implications

In this experiment, participants received an accurate model or one with an offset. This offset had a fixed distance that would lead to failed behavior. However offsets in the real world have variable amplitudes and slightly smaller offsets, do not necessarily lead to failed behavior. This would most likely make judging of the system harder in trading of control. Next to this, there would most likely be smaller offsets, which based on the findings of [9] would decrease task completion time, when the amplitude of the offset decreases. Based on the combination it is harder to judge if automation is able to accomplish the task and increase of performance when the amplitude of offset decrease in HSC, I expect HSC to be more beneficial when offsets are more randomly distributed.

Based on the contact time with the table top, we can see that using HSC operators respond much faster to a collision than in TC. The lower in HSC compared to TC could be useful for tasks in which response time is critical. Therefore it is not surprising that in the nuclear field, where response time can be really critical, HSC is more widely spread. Also for the automotive industry HSC could help to not increase response whilst adding to task performance.

V. Conclusion

In this experiment we wanted to find out what determines human robot interaction when dealing with sensor inaccuracies. This was examined in a human factors experiment comparing Manual Control (MC), Haptic Shared Control (HSC) and Trading Control (TC) for opening a simulated drawer. The model of the task that was the input of HSC and TC was accurate in 50% of the time, in the other 50% it contained a small offset.

For the experimental conditions studied we can conclude:

- Although no differences in task completion time were found in the current mix, as hypothesized. However TC was slower in the trials containing an offset in the model of the task and were slower to react to contact with the environment, indicating that TC might not be the best solution to deal with inaccuracies.
- When the model of the task was perfectly accurate TC did have an advantage over HSC, although not by decreasing the task completion time as hypothesized, the found advantages can be assigned to the advantages of the automatic controller compared to manual control.

This research found that in trials that contained an offset in the model of the task, TC showed a decrease of performance compared to MC and HSC. When inaccuracies are really uncommon TC increases performance compared to HSC. HSC seems to be helpful when response time is critical and the offsets in the system are small. Also it seems useful to further research the effect of small inaccuracies with a lower prevalence and in a more random distribution on HSC, to find critical points where TC and HSC outperform one another.

Appendix

A. Apparatus

1) Computer: This experiment was done in a Virtual Environment. This was done using a Dell Precision Tower 3620, with an Intel i5-7600 CPU with 16 GB RAM and a Nvidia GeForce GTX 1060 3GB. This was simulated in an Interactive Task Simulator (ITS) also used in [9]. This is a rigid-body simulator, based on Nvidia PhysX 2.8.5. It simulates the virtual environment in this experiment with 500 Hz and visualizes this at 30 Hz in Unity. This visualization included shadows to provide some depth information for operators. This was displayed on a Sony Bravia TV screen with a diameter of 1.01 m. Participants were placed at 1.5 meter from this screen.

2) Master Device: The input device of the virtual scene was a Haption Virtuose 6D 35-45 master device. The Haption Virtuose 6D 35-45 has a workspace of 900 x 600 x 1016 mm, which effectively has a cubical workspace of 0.45m. This apparatus allowed for physical feedback in 6 Degrees of Freedom (DOF). This physical feedback was limited to 10 N and 1 Nm. These forces were transmitted from the Position Error controller of the virtuose with a maximum controller stiffness of 2000 N/m and 80 Nm/rad. The controller was damped with 40 N/m/s and 1 Nm/rad/s.

VI. Acknowledgments

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A

Appendix: Design Process

In the process of creating my thesis, I've made some choices along the way and ran into some problems that would most likely influence further work. This section is dedicated to these After I decided I want to compare Trading Control (TC) and Haptic Shared Control (HSC) ,my first idea was to start out comparing to methods of intervention by high level so controlling the robot through a control ring in Rviz as can be seen in fig. A.1, whilst inaccuracies occur. This was planned to work in the docker of HIT, containing a model of Robot Marco in Gazebo. This could either be controlled through a control ring and telemanipulation. After some time I found out that Gazebo was not accurate for force feedback and therefore haptic shared control was not really feasible to test trough this setup. However there was a solution, the Interactive Task Simulator (ITS).

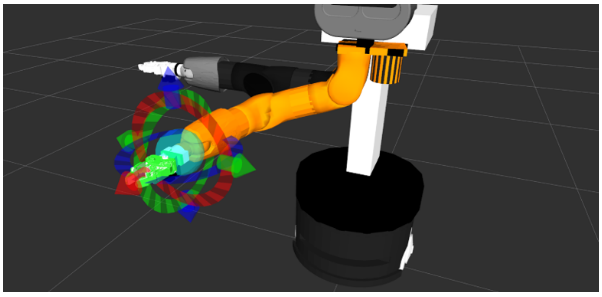


Figure A.1: The system envisioned to provide high level human feedback in TC.

Operating Marco would also be possible in ITS due to the work of a former student. He created a setup of ITS which used the whole body controller of PAL that drives the robot arm. This whole body controller was only available in Ubuntu and he connected a Windows machine and Ubuntu through Orocos, trough a following setup:

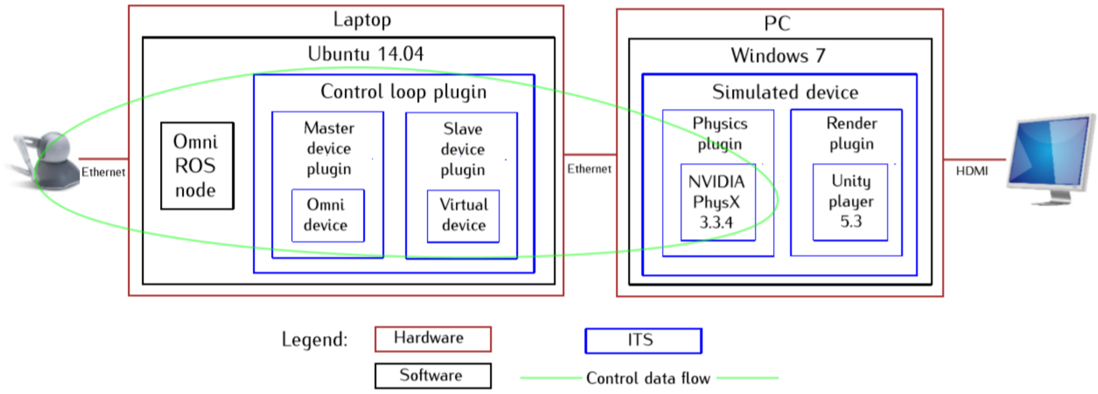


Figure A.2: Schematic overview of the simulator environment. Copied from Catarino [1]

Unfortunately help about understanding the system was limited and there was a lack of structure in the previous work. After some time I do was able to run this simulation in this setup, and start controlling the arm. Only there were two problems with this setup:

- Structure was lacking and naming seemed random. Therefore it was unclear what 3dsmax scene corresponded to what unity scenes and physx files. Scenes that I created myself were unable to run. This meant that I would be unable to create scenes myself and posed a big problem. In retrospect this was probably due to a wrong version of the physx plugin.
- The scenes that were created by Filipe did run but there was trouble in control. After some tuning the control was intuitive for 5 of 6 DOF, but roll remained uncontrollable, which made any task really hard
- Due to the limited understanding of the complex building blocks of this simulator (ITS on the windows side, the black box whole body controller from PAL robotics on the Ubuntu side and the difficult connection trough OROCOS) it was really hard to debug problems and unit test them

Next to this setup and scenes I also found an old scene of a kitchen that did not need a whole body controller and therefore would only need the windows computer running ITS. This simplified the setup very much and therefore I decided to proceed with this setup. By removing the Ubuntu part from the setup this also meant that the control ring I envisioned to use in TC disappeared. Therefore an alternative had to be found. The alternative became another form of trading control, trough supervisory control with a human taking over.

The next step was to have the kitchen scene working as envisioned for the experiment. Quite quick I changed the PhysX engine from 3.3 to 2.8.5. This was because PhysX is originally a gaming engine wich is optimez for computation speed, especially in 3.3. Although 2.8.5 was slower, it did run more stable compared to 3.3, which was required for the force feedback. At first I want the participants to re-position the base of the robot. However there was probably a constraint somewhere hidden, that caused the robot to sway when moving the base. Therefore this option was later removed. I also choose to fix the camera viewpoint of operators to remove variance between participants. After testing with the Geomagic touch I decided to move to the 6D Haption Virtuose. The Geomagic Touch was only able to provide force feedback in 3 DOF. For the experiment also orientation might play a big role in the tasks I choose and therefore use of a 6DOF haptic device would be better. Also findings of the 6DOF haptic device might transfer to a 3D DOF device, but this is harder to other way around. When no difference was found between HSC and MC on the Haption this would indicate that would also be no difference on the Geomagic Touch. The other way around this becomes harder, if no difference would be found the conclusions could either HSC doesn't work or apparently orientation guidance is also important to make HSC work. To ensure smooth rendering of the simulator I removed all the unnecessary objects from the scene to increase the simulation frequency from 100 Hz to 500 Hz. After having MC fully functioning, I started on implementing the augmented haptics. At first it was hard to actually get the image of the forces on the virtuose. This had to do with the layering of the controlloop in ITS, if the augmented haptics layer was added after the Position error controller, the forces of the augmented haptics get overwritten. After finding this out I was able to tune the controller. In tuning the controller I decided to use only one spline, since multiple splines resulted in unpredictable behavior in transition between paths.

I also choose to smooth the sharp edge near the handle to avoid erratic behavior around that point, which was annoying to participants. Also the look ahead time was removed because this could lead to instability. Creating the automatic controller was done using the haptic controller with high gains more then 10 times higher to ensure accurate path tracking. Since this force could not be applied directly to a controlled object, the gripper was linked to a different object out of sight and the force was applied on this one. A force was used to drag the gripper along, downwards. After contact between the gripper and the drawer, the direction and amplitude of the force was changed in the direction to open the drawer. To ensure that in all directions the offset would lead to consequent failed behavior I choose an offset of 4 cm. After tuning this I tested the data logger, this showed 2 problems. First of all there was a problem that because there were joints in the fingers not all the forces were logged. Since closing was not necessary for the task, I created together with a colleague a new gripper with the same shape in a solid U shape, to ensure all the forces were logged. This gripper was given 2 degrees of play and a spring to avoid unrealistic behavior, due to hard constraints. A second issue was that for the data logger would not log 2 control loops simultaneously when started a different moments. This would lead to empty data files in more or less 50% of the tasks. Therefore I choose to separate the loggers before and after take over and merge them later in the data analysis. To add some depth cues to my simulation I made shadows of the objects rendered to help participants perceive depth and make the simulation resemble real life. In actually doing the experiments I made some design choices as well. I started by handing over the haption for every trial to ensure consistency between trials and participants and having the task executable in the workspace of the master device without re-indexing.In the conditions I presented the offsets in a double balanced Latin square to have unpredictable random offsets in a 50/50 proportion.

After doing the pilot I made two last minute changes to use the VanDerLaan instead of NASA TLX since this would take to much time. I also decide to changed the decreased the stiffness of the haptic shared controller. Almost all participants rated the haptic shared controller as annoying in the pilot via the NASA TLX or VanDerLaan, Therefore I decreased the stiffness from 200N/m and 4Nm/rad to 100N/m and 3Nm/rad.

B

Appendix: ITS

B.1. Creating Scenes

To create scenes ITS has this basic setup from scene to human operated simulation:

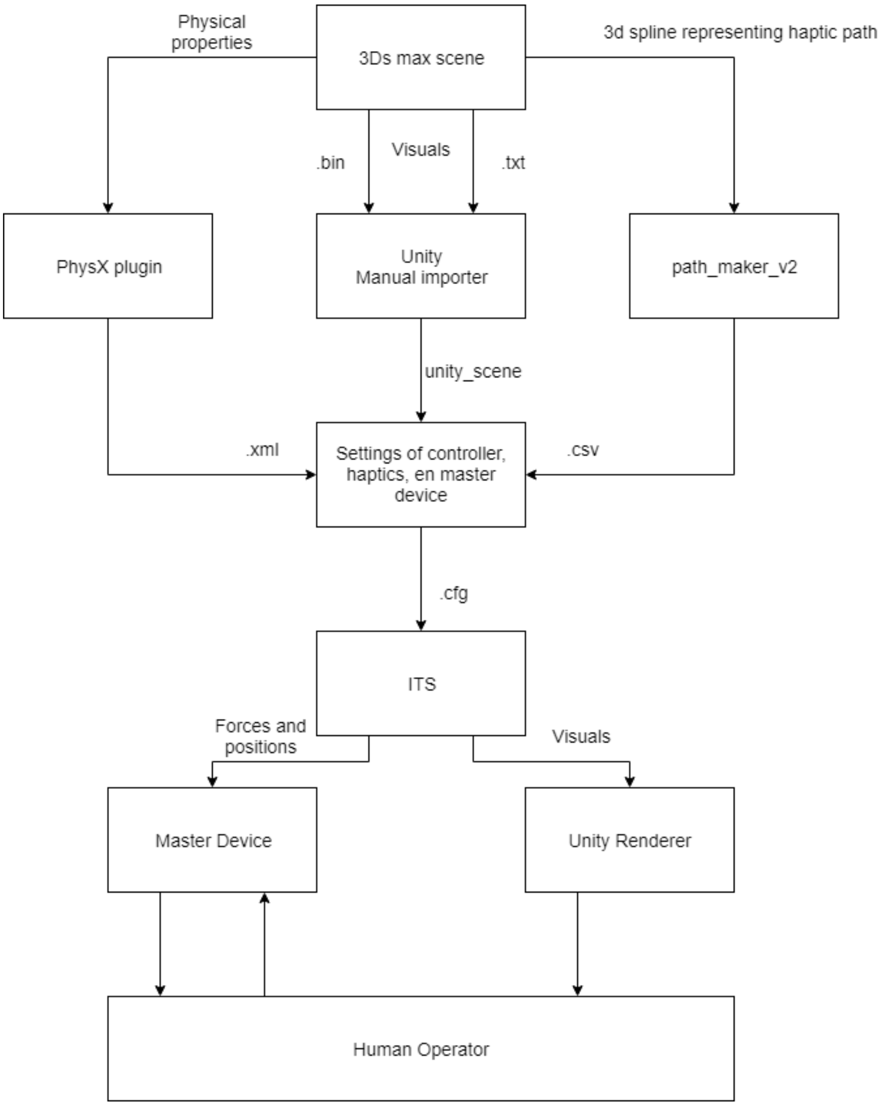


Figure B.1: The basic structure of creating scenes in ITS, from scene to using through a human operator

Starting with the scene of a kitchen, modifications were made on the environment, placement of the robot, changing of physical properties of the robot. For this thesis I started out with a scene of a robot. After placement of the robot at a desired location, several alterations were made in the 3dsmax scene. A haptic shared controller was implemented, more information about this is in appendix B.2. Other changes involved changing the bones of the gripper, to ensure that data was logged correctly, by removing most joints and the gripper and but still allow for realistic behavior and removing background noise to ensure high frequency simulation. Also a takeover mechanism was implemented to ensure that people could take over using one action. Instead of hitting a key and having to press enter before execution of the required action. From the 3ds max files exports were made for the visuals trough binary and text files to unity scenes and physx files into a xml. These were loaded in ITS and additional settings of the Position error controller, haptic shared controller, and data logger were set.

B.2. HSC

A haptic shared controller was made based on a method used by Van Oosterhout et al. [5]. A spline was created in 3ds max to replicate a path in 3d. These editable spline was converted in to a csv using the path_maker script of Jeroen van Oosterhout. The distance between blocks was 1 mm. The orientation of the gripper was provided by a dummy box in 3ds max. The orientation of the reference path was the same during the entire movement. The path roughly corresponds with the path and orientation of an expert. The path consisted of 4 tuning points. The starting point, a pre-grasp position just above the handle, the location of the handle itself and the end point. Also the curvature in between these points. Tuning these points was done to allow both the automatic controller to open the drawer consistently and to avoid sharp point that could introduce erratic behavior in the haptic shared controller.

This haptic shared controller is loaded into ITS using the controlloop. The controlloop contains layers of a haptic shared controller, world frame, offset frame, data logger and position error controller. It is important to first call the augmented haptics layer before the position error controller otherwise the augmented haptics get overwritten.

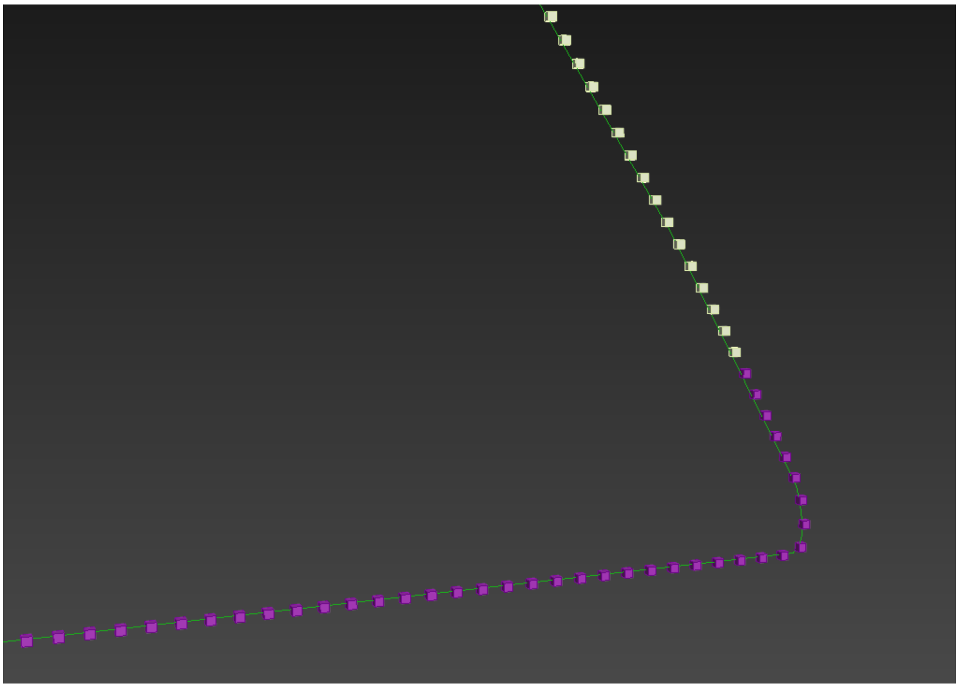


Figure B.2: A impression of the haptic shared controller that was created

C

Appendix: Pilot

During the pilot I wanted to check a couple of things. First if people do in fact benefit from HSC in the task of opening a drawer. A experienced operator was used to do the task in manual control and HSC. In the HSC condition the feedback was fully accurate. This was to test how the operator would benefit from the haptic guidance. Although an experienced operator (in manual control) he still was helped using the haptic shared control and increased his completion time, most of the time.

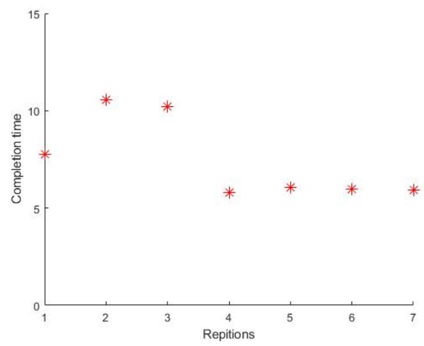


Figure C.1: First I wanted to check, how a learning effect would influence the results

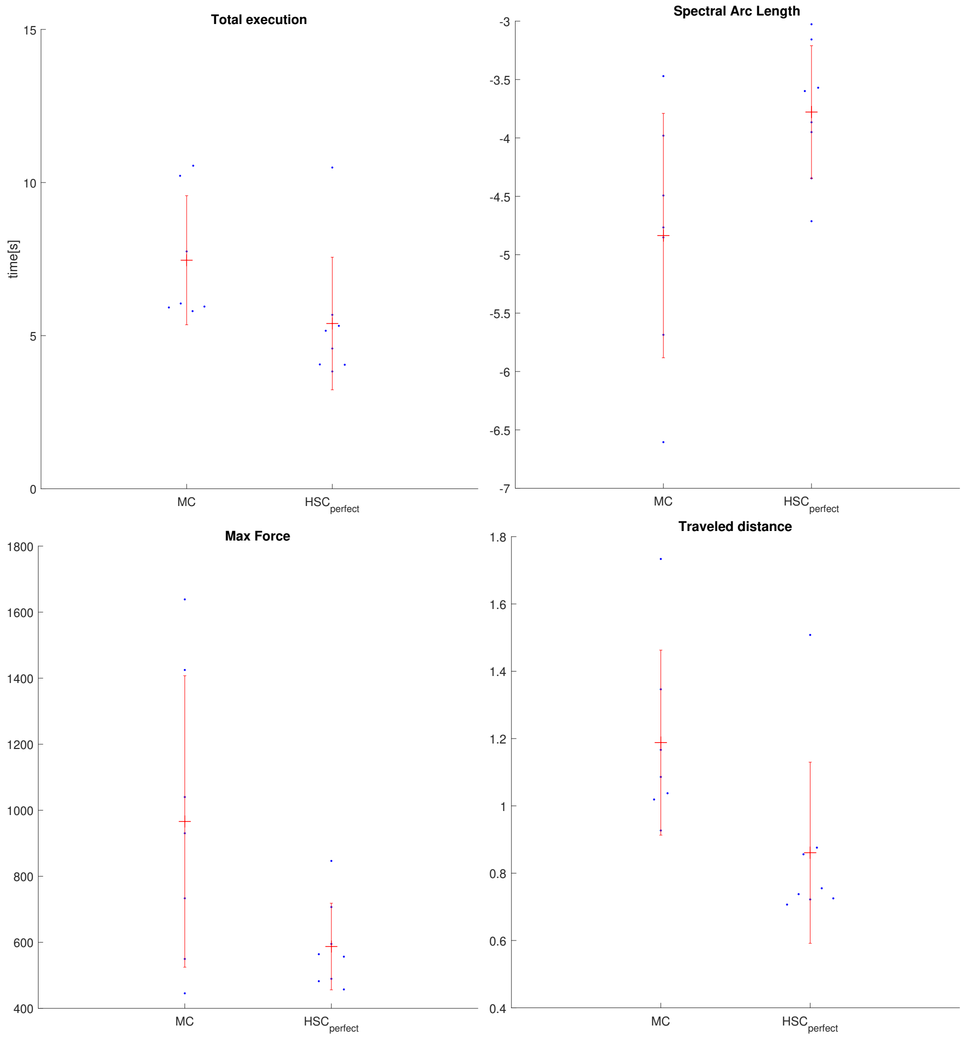


Figure C.2: Based on these results the HSC controller was assistive to the operator and could help the operator to improve task execution, to decrease execution time, decrease the force,traveled distance and increase smoothness

In the second part of the pilot I did the entire experiment fully, after this pilot I changed my data analysis from FAM-CT-CTM to rough-fine and CTM, since then take-overs would take place in the same subsection, which should make more sense. Also I changed from using the NASA-TLX to using a VanDerLaan questionnaire since this provided more insight in less time.

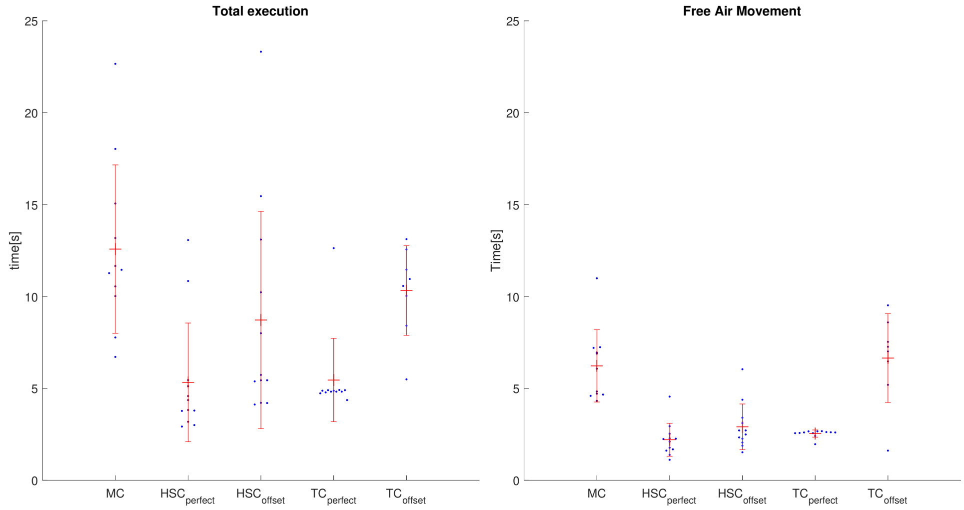


Figure C.3: In the pilot The HSC and seemed to be be beneficial even with offsets

Also during the pilot, the drawer was sliding over a drawer that would still open. Therefore some damping was added on the drawer. Next to this, there were some empty log files in the TC conditions. Therefore this data was not useful for my experiment.

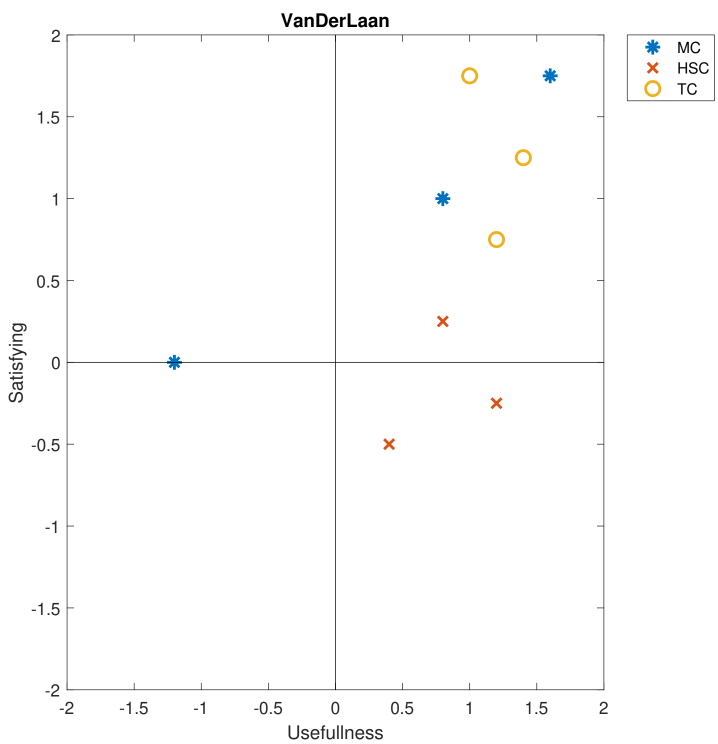


Figure C.4: Scores of the pilot in the VanDerLaan questionnaire. Next to participants reported fighting the system in the Haptic Shared Controller

	MC	HSC	TC	Weight factor
Mental Demand	35	40	20	2
Physical Demand	30	**55**	10	0
Temporal Demand	25	25	15	5
Performance	15	25	10	4
Effort	45	30	5	3
Frustration	15	**45**	5	1
Total Weighted	27	26	11.67	

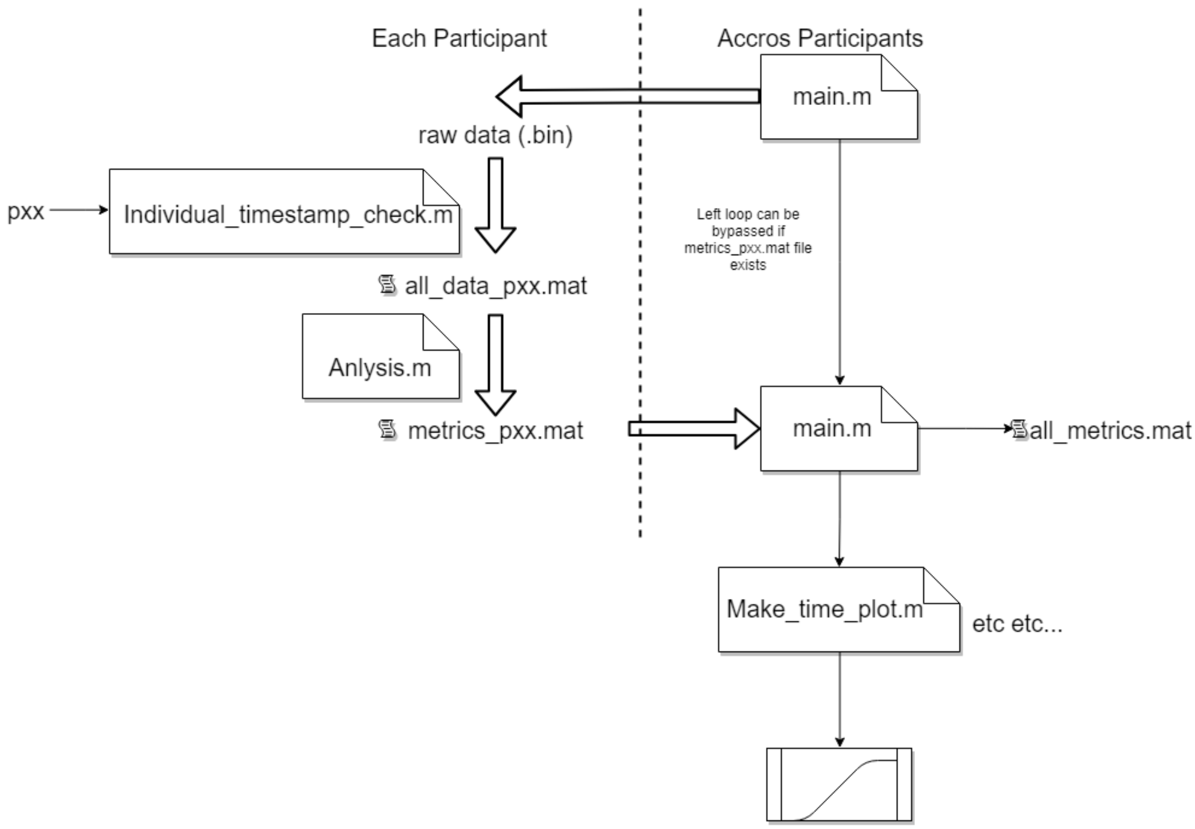
Table C.1: The scores of the NASA TLX for 1 participant, where frustration and physical demand were rated much higher in the HSC condition compared to the MC

During the pilot I found out that the stiffness of the haptic shared controller was quite high, resulting in participants really working against the haptic shared controller. Of course this was not intended and therefore after the pilot I decreased the stiffness to ensure that the guidance was less intense, but still present. The right stiffness for a haptic shared controller is, apparently, quite precise. This fighting against the system was also visible in the VanDerLaan, were participant rated the HSC as being useful but not satisfying.

D

Appendix: Data analysis

My data analysis was build up layer by layer. Per trial data was written out of the binary files, in to matlab structs. Because of trouble running 2 data loggers simultaneously, which came with loss of data, in individual_timestamp_check.m the data of trials was combined based on a indication of a takeover. After this a check was executed and a warning was displayed if the start times of the data logger that was combined was more then 15 seconds apart, because this should be an indication that under normal condition this files did not belong together. After this the trials of each participants were combined into all_data_pxx.mat. This data was loaded into analysis.m and provided a matlab struct containing all the metrics in a struct. This file can also be run separately. After this I created a main file to run individual_timestamp_check.m for all the participants. Together this give a struct containing all the metrics for all the participants, this was further for statistical analysis and used as input for several scripts to make plots.



	Performance	**Accuracy**	**Control effort**
Rough	Time	X	Spectral Arc Length (Master)
Fine	Time	Peak Force	Spectral Arc Length (Master)
CTM	Time	Shear Force	Spectral Arc Length (Master)
Total	Time	Total traveled path/ Average speed	Spectral Arc Length (Master)

Table D.1: Metrics objective

D.1. Metrics

Next to the objective metrics in table D.1 I will also record a subjective scale using the VanDerLaan questionnaire. This will be done using a matlab version of this.

Definition of sections:

- Rough approach: The rough approach starts at the first movement of the gripper. It ends when a sphere with a radius of 11 cm around the handle is reached for the first time.
- Fine approach: The fine approach starts when the sphere is reached for the first time. This phase ends when a movements starts that is at least 80% in the direction of Y (therefore the constraint direction of the drawer) within the 82 en 86 cm above the ground (the height of the handle of the drawer). By definition takeover should take place in this section, given that it is not able to full fill the requirement to end this. The time needed to move the Haption after taking over through the space bar was removed, since this initialization time should not be taken into account in the analysis.
- Constraint Translational Movement: When the velocity is more then 80% in the Y-direction within the height of the drawer, then the constraint movement is started, this ends when the drawer is opened for more or less 40 cm, which is almost a full opening of the drawer. This end is defined by a trigger box, triggering on contact with the drawer the end of the simulation.

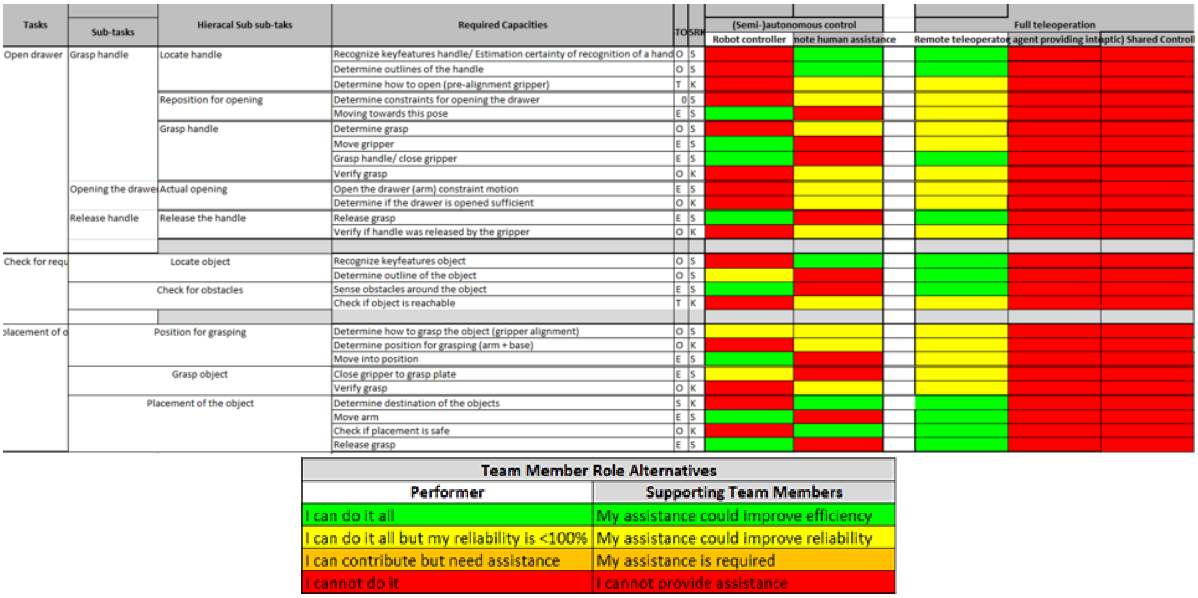
Definition of metrics:

- Time to completion: The time was started at first movement of the gripper and ended using a trigger box at almost full opening of the drawer. The same was done for the subsection as explained above.
- Peak Force: After the 200 Hz filtering the peak force was searched in the fine approach of the forces on the gripper
- Spectral Arc Length: The spectral arc length was a measurement for smoothness of the human operator. Master velocity data was used to calculate this.

E

Appendix: Interdependence analysis

In a first stage of my graduation and internship I tried to implement the coactive design method on robot ROSE. The task we choose in this assignment was a pick and place task. This a task that occurs quite often in a ADL tasks. The scenario that was chosen was grabbing an object from a cluttered drawer. Since the navigation can already be done autonomously robustly, this was not incorporated in the interdependence analysis. Due the problems with the autonomous controllers of the robot the interdependence had to be based on videos of the robot executing this task and discussing the current possibilities with Nicky (the Robotics Engineer).



Tasks	Sub-tasks	Hieracal Sub sub-taks	Required Capacities	TO	SRK
Open drawer	Grasp handle	Locate handle	Recognize keyfeatures handle/ Estimation certainty of recognition of a hand	O	S
			Determine outlines of the handle	O	S
			Determine how to open (pre-alignment gripper)	T	K
		Reposition for opening	Determine constraints for opening the drawer	0	S
			Moving towards this pose	E	S
		Grasp handle	Determine grasp	O	S
			Move gripper	E	S
			Grasp handle/ close gripper	E	S
			Verify grasp	O	K
	Opening the drawe	Actual opening	Open the drawer (arm) constraint motion	E	S
			Determine if the drawer is opened sufficient	O	K
	Release handle	Release the handle	Release grasp	E	S
			Verify if handle was released by the gripper	O	K
Check for requ		Locate object	Recognize keyfeatures object	O	S
			Determine outline of the object	O	S
		Check for obstacles	Sense obstacles around the object	E	S
			Check if object is reachable	T	K
lacement of o		Position for grasping	Determine how to grasp the object (gripper alignment)	O	S
			Determine position for grasping (arm + base)	O	K
			Move into position	E	S
		Grasp object	Close gripper to grasp plate	E	S
			Verify grasp	O	K
		Placement of the object	Determine destination of the objects	S	K
			Move arm	E	S
			Check if placement is safe	O	K
			Release grasp	E	S

(Semi-)autonomous control		Full teleoperation		
Robot controller	mote human assistance	Remote teleoperator	agent providing int	ptic) Shared Controll

Team Member Role Alternatives	
Performer	**Supporting Team Members**
I can do it all	My assistance could improve efficiency
I can do it all but my reliability is <100%	My assistance could improve reliability
I can contribute but need assistance	My assistance is required
I cannot do it	I cannot provide assistance

Figure E.1: An interdependence analysis was made for the task of retrieving an object from a drawer. The columns show if agents are capable of doing a task (first column of an alternative) or able to assist (other columns of an alternative) on a task

Next to the automated implementation we also assessed the human operators. In this process I saw that human operators are capable to operate the robot in a lot of ways but we tend to struggle with:

- Maneuvering of the gripper accurately
- Verification of grasps
- Self-collision of the robot or collision of the environment that can be hard to notice for the human operators.

In the interdependence analysis all the tasks and subtasks were classified according to the models of Michon [2] and Rasmussen [3]. This classification was later used to sort the interdependence analysis. Using this sorted IA I started looking at possible solutions to improve these groups of tasks. Here I made the following sub categories:

- Recognition of features
- Determine the outlines
- Determine the grasp
- Verification of grasp
- Free air movement
- Contact movement

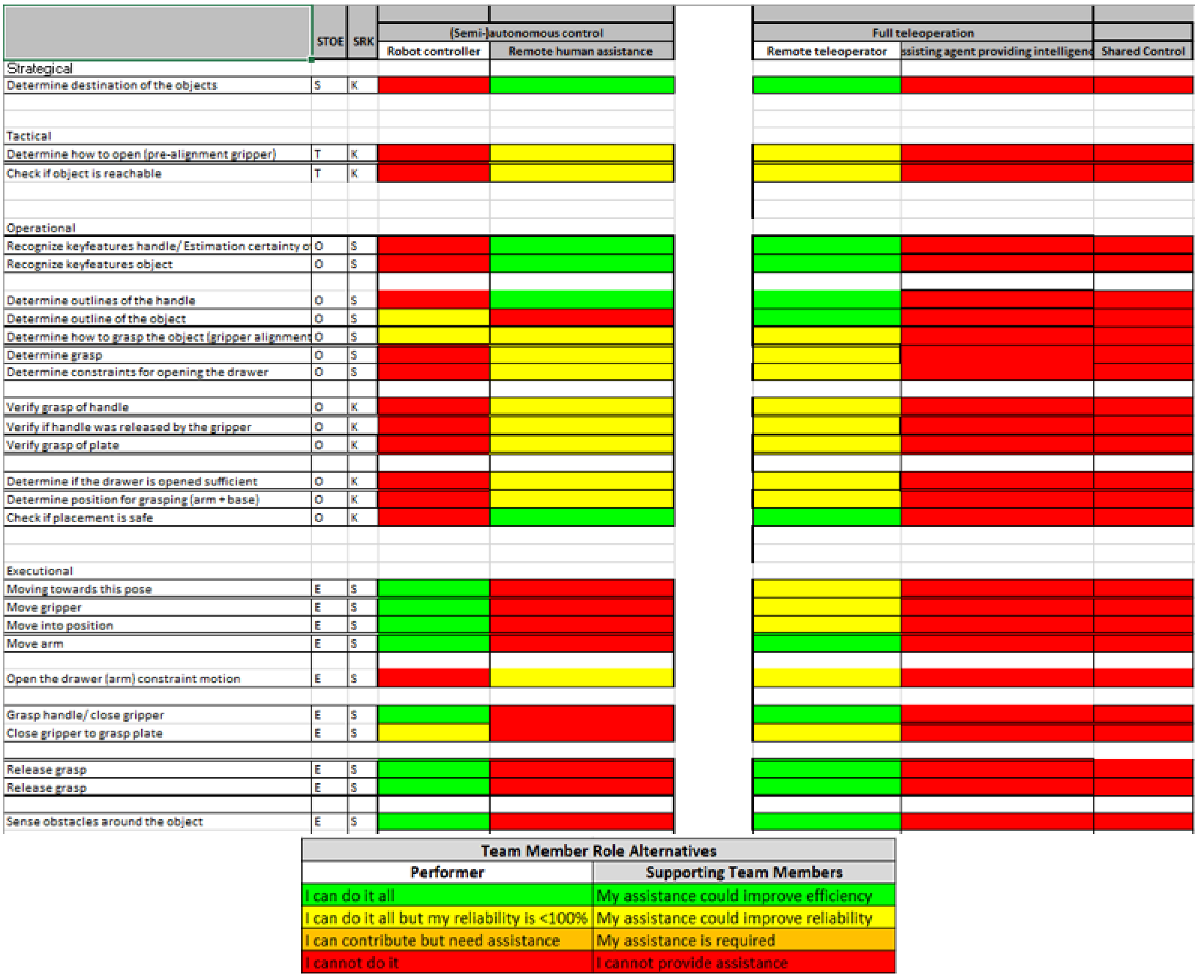


Figure E.2: To organize the interdependence analysis the frameworks of Michon [2] and Rasmussen [3] were used. This helped us to divide the tasks into different groups and clearly where there were some difficulties. As we can see that autonomously we can only do executional tasks robustly and other tasks turn out to be difficult.

- Recognition of features → Point and Click Interface
- Determine the outlines → Point Cloud
- Determine the grasp → Control ring on augmented gripper
- Verification of grasp → Augmented Gripper
- Free air movement → Works fine

- Contact movement → Small and specific problem

According to this IA the tasks that act on the executional level were performed robust. On the operational level this became more troubling. Therefore we wanted to implement a solution on this level. A possible solution for the problem of not correctly detecting an object or the possibility to not accurately find the contours of an object was a Point and Click interface. This interface allows the human to provide input on a higher level which allows the robot intelligence to execute the movement, which the robot is better at compared then human operators. In this point-and-click interface we wanted the robot to segment the object itself based on the point clicked upon. During the internship I did this using a following work scheme:

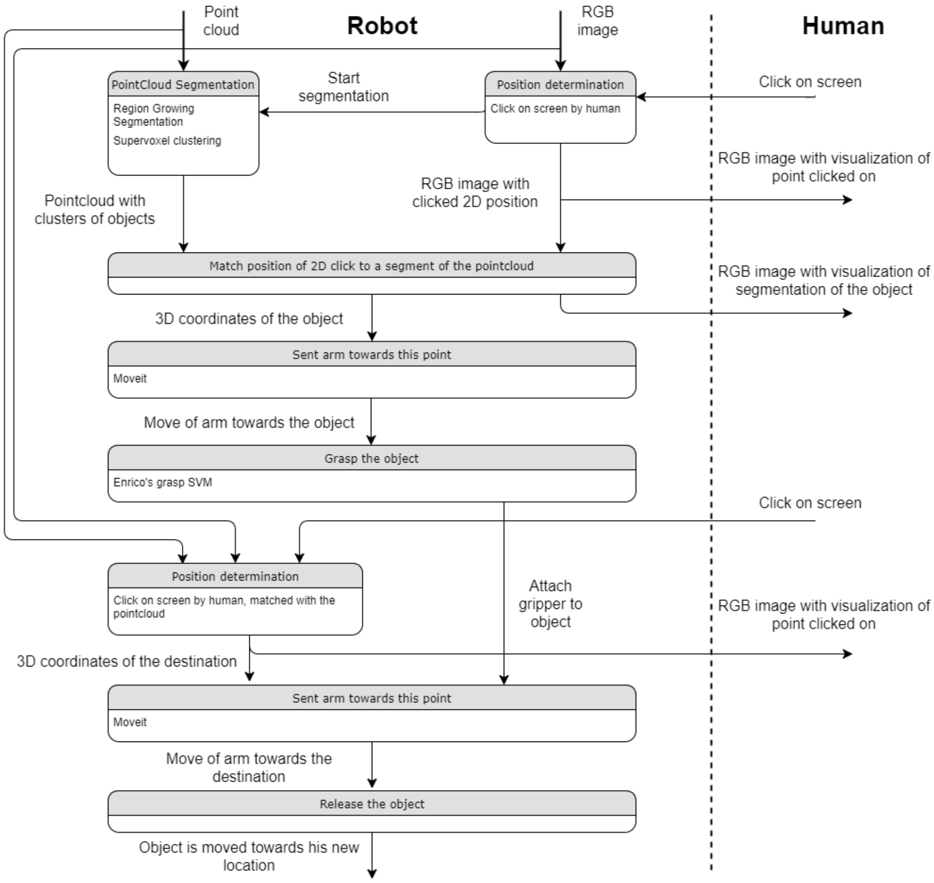


Figure E.3: To design the interface I had the following pipeline. Since the body controller on Moveit! and a grasp SVM already exist, I will focus on the top part, so the autonomous segmentation and the visualization of this segmentation.

The process of creating a point and click interface started with familiarizing myself with C++, ROS and Qt. My starting point was the current interface used for remote handling. First to make sure this would work a would remove unnecessary parts, this gave me a version of an interface which could connect to the robot and display the image of the head camera. The first problem was to retrieve the position on the screen when the user clicks on the image. I used the QMouseEvent to do this. The next step was to visualize this in the interface, so the user receives feedback on where he clicked, and to ensure this works correct. It turned out to be difficult to overlay these pixmaps, but eventually this worked, provided this was done in the same function. QPainter can draw over the image coming from the head cam. Then I subscribed to the topic that publishes the Point cloud coming from the depth camera in the head of the robot. Overlaying the Point cloud and the 2D RGB image gave me 3D locations of pixels.

Another important step was to publish the 3D coordinates into a ROS topic so it can be used by Moveit! to control the arm. In my case I choose to only publish one point the average of all the visible points of the object, because I wanted a global guess of the position of the center of mass, but this can be changed easily depending on the needs for an application.

The next step was to segment the image so that edges can be found of the object. To do this multiple segmentation algorithms were available in the Point Cloud Library, for instance Supervoxel Clustering, Euclidean Cluster Extraction, Plane model segmentation, Cylinder model segmentation, Difference of Normals Based Segmentation, but eventually I choose the region-growing segmentation. This segmentation method merges point that close enough in terms of the smoothness constraint. It does this based on the comparison of angles between normals of point. This normal estimation can be done in the point cloud according to, this is done with a plane PCA, just as in Teng and Xiao [4]. This method has the advantage that it doesn't assume a certain shape, such as Plane model segmentation, Cylinder model segmentation. Another advantage opposed to the Euclidean Cluster Extraction, that it can differentiate between objects, that have small difference in depth, using the normal estimation. A advantage of region growing with respect to Supervoxel Clustering is that accuracy doesn't go down. The last advantage of region growing segmentation is that it can use the point and only segment the cluster that was clicked on, which saves time compared to segmenting the entire Point cloud. Given that Moveit! and an SVM to grasp the object already work we will not focus on this. Integration of these parts would be nice, but this is not feasible within the duration of the internship.

E.1. Output of the point and click interface

The robot was first tested in a simulation environment. In the simulation environment the robot was standing in front of a table with multiple objects on it. When there was a click on the screen, the segmentation was started.

Figure E.4: In the left images the point clicked on was marked by a red dot. This started the segmentation, the result is shown in right pictures in cyan. This shows that in the simulation environment the object segmentation can accurately isolate an object

As can be seen by these examples the segmentation algorithm works really well in the simulation environment, and is able to find the edges of the object really accurately. Within a centimeter. The duration of the segmentation was more or less 10 seconds. Then we applied this on the real robot in the real world. This gave us the following results:

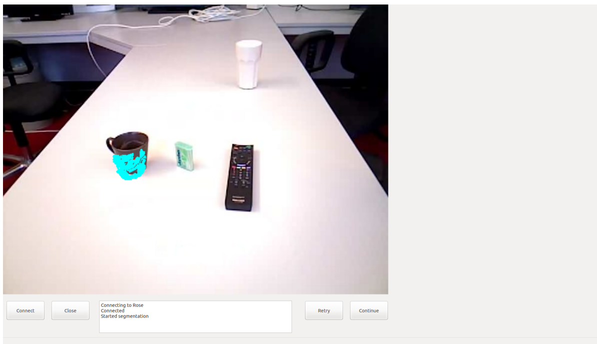


Figure E.5: When applying the segmentation algorithm on ROSE, we see that it works, but there is some noise and a slight offset away from the center of the screen

The P&C interface is able to segment the image in 10 seconds, without prior information about the object, also the result of the segmentation was clearly visualized so that the input of the grasping algorithm is understandable and therefore the motion is more predictable. Only the result in the real world case has some noise as can be seen in fig. E.5. This shows that even though the segmentation works perfectly accurate in the real world we suffer from sensor inaccuracies. This became really evident when overlaying the point cloud with the with rgb image and turning the image. This can be seen in fig. E.6.

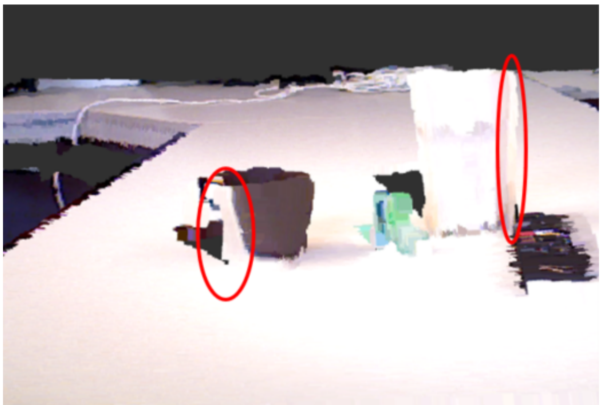


Figure E.6: In this figure we see the point cloud (depth map) overlaid with the RGB image. Here we see a small discrepancy between the 2 images

F

Appendix: Forms

Delft University of Technology
ETHICS REVIEW CHECKLIST FOR HUMAN RESEARCH
(Version 10.10.2017)

This checklist should be completed for every research study that involves human participants and should be submitted before potential participants are approached to take part in your research study.

In this checklist we will ask for additional information if need be. Please attach this as an Annex to the application.

Please upload the documents (go to [this page](#) for instructions).

Thank you and please check our [website](#) for guidelines, forms, best practices, meeting dates of the HREC, etc.

I. Basic Data

Project title:	**Comparing haptic shared control to trading of control for skill based tasks with an inaccurate model**
Name(s) of researcher(s):	**Jelle Hofland**
Research period (planning)	**September/Oktober 2018**
E-mail contact person	**j.hofland@student.tudelft.nl**
Faculty/Dept.	**3ME**
Position researcher(s):[1]	**Student**
Name of supervisor (if applicable):	**D. Abbink/ C. Jonker**
Role of supervisor (if applicable):	**Professor**

II. A) Summary Research

This research will compare sharing control to trading of control (supervisory control with the possibility to takeover) for low level control of a domestic care robot executing a skill based task (opening of a drawer). It compares the methods based on efficiency (smallest amount of time) and safety (smooth movement, low collisions forces) and operator workload (NASA-TLX). This experiment is done in virtual environment and all the data is collected in this virtual environment. 12 participants will take place in the experiment. Participants can control the virtual robot trough the Haption Virtuose 6DOF haptic device.

B) Risk assessment

The risk in taking part in this experiment is small. Since the experiment is done in a virtual environment, no data is stored that can be used to trace the participant. Also the Haption Virtuose has a deadman switch, so when the handle is released no forces are exerted on the joystick anymore. Which prevents the participant from getting hurt. Discomfort can arise from holding the joystick in a position, which can cause some fatigue.

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[1] For example: student, PhD, post-doc

III. Checklist

Question	Yes	No
1. Does the study involve participants who are particularly vulnerable or unable to give informed consent? (e.g., children, people with learning difficulties, patients, people receiving counselling, people living in care or nursing homes, people recruited through self-help groups).		x
2. Are the participants, outside the context of the research, in a dependent or subordinate position to the investigator (such as own children or own students)?[2]		x
3. Will it be necessary for participants to take part in the study without their knowledge and consent at the time? (e.g., covert observation of people in non-public places).		x
4. Will the study involve actively deceiving the participants? (e.g., will participants be deliberately falsely informed, will information be withheld from them or will they be misled in such a way that they are likely to object or show unease when debriefed about the study).		x
5. Personal data • Will the study involve discussion or collection of personal data? (e.g., BSN number, location, sexual activity, drug use, mental health). Please check the following definition (here link to data stewards website).		x
If yes': Did the data steward approve your data management plan? (Electronic Consent)		
6. Will drugs, placebos, or other substances (e.g., drinks, foods, food or drink constituents, dietary supplements) be administered to the study participants?		x
7. Will blood or tissue samples be obtained from participants?		x
8. Is pain or more than mild discomfort likely to result from the study?		x
9. Does the study risk causing psychological stress or anxiety or other harm or negative consequences beyond that normally encountered by the participants in their life outside research?		x
10. Will financial inducement (other than reasonable expenses and compensation for time) be offered to participants?		x
Important: if you answered 'yes' to any of the questions mentioned above, please submit a full application to HREC (see: website for forms or examples).		
11. Will the experiment collect and store videos, pictures, or other identifiable data of human subjects? [3]		x

[2] **Important note concerning questions 1 and 2.** Some intended studies involve research subjects who are particularly vulnerable or unable to give informed consent .Research involving participants who are in a dependent or unequal relationship with the researcher or research supervisor (e.g., the researcher's or research supervisor's students or staff) may also be regarded as a vulnerable group . If your study involves such participants, it is essential that you safeguard against possible adverse consequences of this situation (e.g., allowing a student's failure to complete their participation to your satisfaction to affect your evaluation of their coursework). This can be achieved by ensuring that participants remain anonymous to the individuals concerned (e.g., you do not seek names of students taking part in your study). If such safeguards are in place, or the research does not involve other potentially vulnerable groups or individuals unable to give informed consent, it is appropriate to check the NO box for questions 1 and 2. Please describe corresponding safeguards in the summary field.

[3] Note: you have to ensure that collected data is safeguarded physically and will not be accessible to anyone outside the study. Furthermore, the data has to be de-identified if possible and has to be destroyed after a

Question	Yes	No
If "yes", please fill in Annex 1 and make you sure you follow all requirements of the applicable data protection legislation. In addition, please provide proof by sending us a copy of the informed consent form.		
12. Will the experiment involve the use of devices that are not 'CE' certified? *Only, if 'yes': continue with the following questions:*		x
➢ Was the device built in-house?		
➢ Was it inspected by a safety expert at TU Delft? (*Please provide device report, see: HREC website*)		
➢ If it was not built in house and not CE-certified, was it inspected by some other, qualified authority in safety and approved? *(Please provide records of the inspection).*		
13. Has or will this research be submitted to a research ethics committee other than this one? (*if so, please provide details and a copy of the approval or submission).*		x

IV. Enclosures (tick if applicable)

- Full proposal (if 'yes' to any of the questions 1 until 10)
- Informed consent form (if 'yes' to question 11)
- Device report (if 'yes' to question 12)
- Approval other HREC-committee (if 'yes' to question 13)
- Any other information which might be relevant for decision making by HREC
- Data management plan approved by a data steward (if yes to question 5B)

V. Signature(s

Signature(s) of researcher(s)
Date:

Signature (or upload Electronic Consent) research supervisor (if applicable)
Date:

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scientifically appropriate period of time. Also ask explicitly for consent if anonymised data will be published as open data.

Date 01-10-2018
Contact person Ir. J.B.J. Groot Kormelink, secretary HREC
Telephone +31 152783260
E-mail j.b.j.grootkormelink@tudelft.nl

Human Research Ethics Committee
TU Delft
(http://hrec.tudelft.nl/)
Visiting address
Jaffalaan 5 (building 31)
2628 BX Delft
Postal address
P.O. Box 5015 2600 GA Delft
The Netherlands

Ethics Approval Application: Comparing haptic shared control to trading of control for skill based tasks with an inaccurate model
Applicant: Boessenkool, Henri

Dear Henri Boessenkool,

It is a pleasure to inform you that your application mentioned above has been approved.

Good luck with your research!

Sincerely,

Prof. Dr. Sabine Roeser
Chair Human Research Ethics Committee TU Delft

Prof.dr. Sabine Roeser
TU Delft
Head of the Ethics and Philosophy of Technology Section
Department of Values, Technology, and Innovation
Faculty of Technology, Policy and Management
Jaffalaan 5
2628 BX Delft
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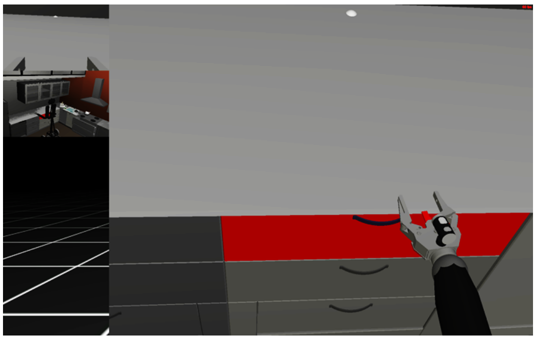
+31 (0) 15 2788779
S.Roeser@tudelft.nl
www.tbm.tudelft.nl/sroeser

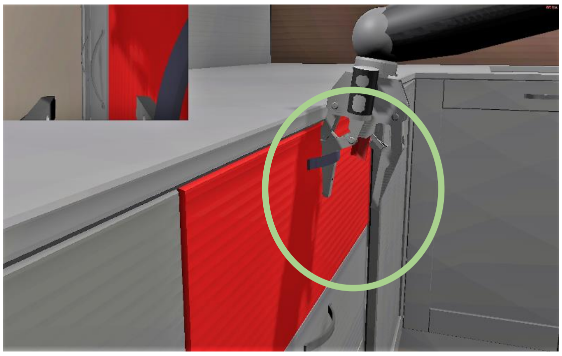
Study information



Today you will take the role of an operator of a domestic care robot. This robot operates (partly) autonomously, but for some tasks it relies on an operator to take over. You will support the robot in opening a drawer. Because operating a robot can be difficult we will first let you practice this a few times to get familiar with the controls and how the robot behaves. After the training the measurements will start where we repeat this movement 12 or 24 times per condition. The experiment will consist of 3 conditions. At the end of each condition you are asked to answer a small questionnaire about that condition.

Instruction

Open the red drawer in a safely manner. Don't exert to much force on the gripper or the gripper, or they might break. But make sure you don't take minutes to open a drawer, the patient is waiting! As you work near patients your movements should be smooth and predictable. In this experiment you are required to use a topgrasp, as can be seen I the figure.



The gripper can't be closed in this experiment. To extend your workspace you can use the red button to re-index the gripper. The functionality to re-index is there if you deem it necessary.

In the haptic shared control condition there are forces that guide towards a correct execution on the robot. During the training these forces are spot on, but in the experiment these forces might guide you towards the wrong location, so be aware.

The same goes for the trading control condition in this case the robot operates autonomously. During the training this works perfectly. Here you can see perfect execution of the autonomous robot. During the measurements the autonomous controller might fail to open the drawer. In such cases you should intervene by hitting the space button in front of you. When you do this controls are handed over to you after a small initialization time (1 second)

Consent Form for Comparing Trading of Control with Sharing Control for opening a drawer

Please tick the appropriate boxes	Yes	No
Taking part in the study		
I have read and understood the study information or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	○	○
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	○	○
I understand that taking part in the study involves doing a task in a virtual environment with an haptic interface and filling in a questionnaire. Also I will provide information about age/gender (without use of traceable participant information)	○	○
Risk associated with participating in the study		
I understand that taking part in the study involves the following risks: - Physical discomfort of staring to a screen - Physical discomfort of force from the Haption of 10 N at most - Physical discomfort of holding the joystick of the Haption in an uncomfortable position	○	○
Use of the information in the study		
I understand that information I provide will be used for a master thesis project and possibly for publication purposes. Results will be saved and made public in the TU Delft repository.	○	○
I understand that personal information collected about me that can identify me, such as (name or age), will not be shared beyond the study team and if necessary a control board.	○	○
I agree that my written comments made on the questionnaire can be used as anonymous quotes in research outputs	○	○
Future use and reuse of the information by others		
I give permission for the virtual position data and survey data that I provide to be archived in the TU Delft repository and HIT data archive so it can be used for future research and learning. This data will be anonymised by participant number so that no one except for the researcher can trace my data back to a specific person.	○	○

Signatures

________________________	________________________	_________
Name of participant	Signature	Date

I have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

Jelle Hofland___________	____________________	_________
Researcher name	Signature	Date

Study contact details for further information:

Jelle Hofland

+31 6 34 27 49 10

j.hofland@student.tudelft.nl

Participant data form

Research: Comparing trading and haptic shared control, a simulation study
Researcher: Jelle Hofland

Participant no.: __________
Date ______-______-________ (dd-mm-yyyy) Time: _____ : _____ (24hrs notation)
Age: __________
Gender: male / female
Handedness: left / right
Experience with video games: None / 1 hr / 10 hrs / 1 day / 10 days / 1 week / 10 weeks / more
Experience with telemanipulation: None / 1 hr / 10 hrs / 1 day / 10 days / 1 week / 10 weeks / more

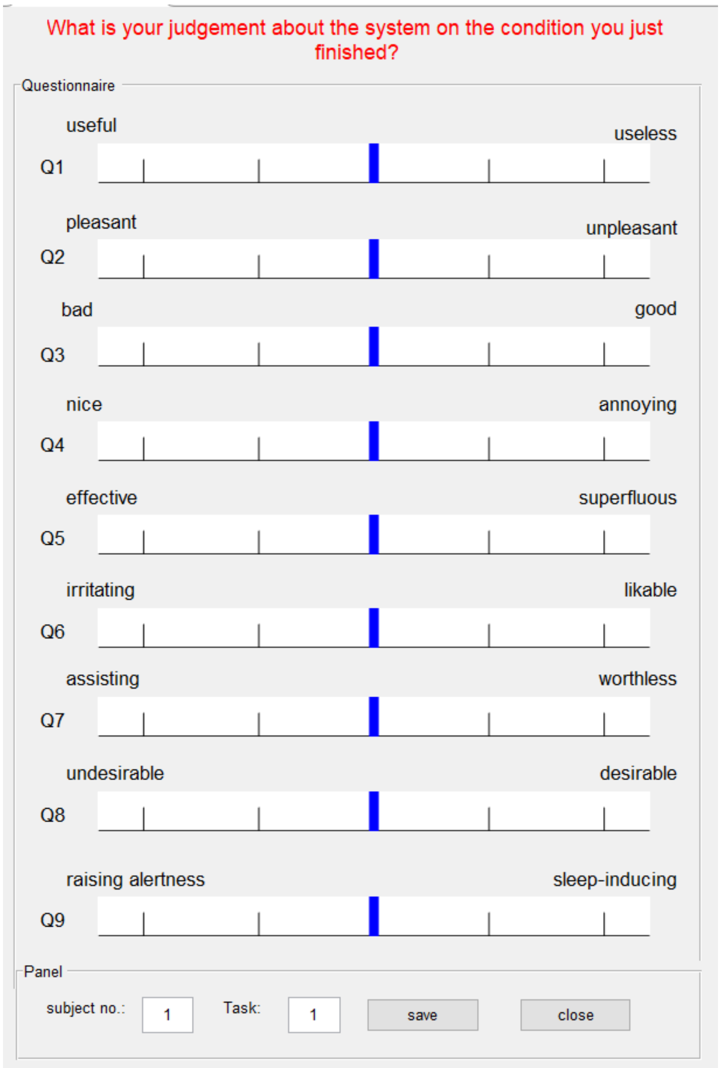
Open Questions:

What was hard?

What condition did you like the best?

Remarks:

VanDerLaan Questionnaire



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