Master’s thesis

Learning a Slow Dynamic System: Training Enhancement by Haptic Shared Control

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Preface

The importance of the interaction between human and machine have always amazed me during my Master's study. The idea from Shared Control of combining the versatile human with the capabilities of an automated controller, have provided endless new opportunities for human-machine interaction. Where one of these new opportunities, is training the human to learn to control a slow dynamic system. The goal of this study is to learn humans how to control a slow dynamic system with the teaching support from haptic shared control.

The focus during my Master's thesis was on developing and executing the human factors experiment, which is extensively described in the research paper. The appendices provide background on the challenges encountered in developing this human factors experiment, and present extra results of this experiment.

Appendix A describes the development of the experimental setup, whereas Appendix B, C, and D presents the results of the initial pilots studies used in development of the experiment setup. Appendix E presents the extensive overview of the results from the human factor experiment. In Appendix F, a method on how the manipulator stiffness and guidance stiffness can be combined in haptic shared control is presented.

A USB-disk containing all raw measurement data, software, GUI's, literature, information, etc, has been submitted to the BioMechanical Engineering department depository, all of which is available on request.

Finally, I would like to thank all the people who have stimulated and supported me throughout this thesis.

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ABSTRACT

Humans learning to control slow dynamic systems (e.g. a large excavator) perceive complex system dynamics in combination with, the less intuitive, rate control method. Earlier research has described that humans control these systems by predicting the slow response on basis of an internal model of the system dynamics. Learning this internal model can be a long and therefore a costly process in practical applications as excavators. This paper presents a training method based on the concept of Haptic Shared Control to support learning of the system dynamics. Literature on learning with Haptic Shared Control has found no consensus if this improves learning performance. However, recent literature have shown that improved learning performance is possible in timing based tasks with guidance-as-needed support. This study hypothesis that providing Haptic Shared Control training trials, used for training the desired control input, will result in lower control activity and higher performance after training. Two groups (n=10 each) had to pursuit a trajectory by controlling the slow dynamic system with a 1-DOF manipulator. The results show that subjects learning with Haptic Shared Control had similar performance, and similar excessive control activity in the frequency domain. On the other hand also a noisier joystick input, which may indicate a less developed model of the system dynamics. It is concluded that the used form of Haptic Shared Control can be used to increase the safety and performance during the slow dynamic system learning process, but is ineffective as training method.

Index Terms: Slow Dynamic System, Learning, Haptic Shared Control, Rate Control

1 INTRODUCTION

Slow Dynamic System

The difficulty which the human operator face when controlling a slow dynamic system, is that the system has the tendency to not respond immediately to an input command. This dynamic characteristic, called control lag in manual control studies [22], is inherent in systems with the combination of large mass and relative low power (e.g. heavy (offshore) excavators or large cranes). Humans can control these kinds of systems by predicting the slow system behaviour on basis of internal model of the causal relation between the control input and slowly changing perceived system output [3]. The result of this increased control lag is a decrease in the short-term human-system performance [22]. The performance is especially low in the beginning and during the relative long learning process, for instance in the practical case of an excavator [15]. The learning process of an excavator is not only influenced by the control lag, but also due to the kinematics, time delay by hydraulic valves, and the rate control method. However, this study will focus on learning of controlling a system with control lag due to the dependency on using the internal model of the system dynamics. Using rate control is a common method to control both slow dynamic systems and excavators, and is still included in this research. The main downside from the rate control method used in slow dynamic systems is the longer learning period [11]. The relative similar system performance as for the position control method [16][28], and the infinite workspace make rate control a practical control method for slow dynamic systems. It is the interest of this study to see if it is possible to improve the performance during the learning process. Improving the performance during the learning process will reduce the costs related to a long learning process. The two main options for improving the performance during the learning process are: i) make the controlled system for the human simpler, or ii) use a training method. Making the controlled system simpler can be done in numerous ways as described within literature: i) change the control method from rate control to position control and thereby reduce the learning effect associated with rate control [15], ii) use (partially) automation, which also reduces the human operator mental effort [33], or iii) predict the future position and display this visually [22]. The downsides from the first method are the limited workspace, and the trade-off between low amplification-factor and ergonomic design. The downside from the second and third method is that it can make the human dependent on a form of support during and after the learning process. This dependency occurs because the support mechanism alters the perceived dynamics between control input and visualized output. Training the human has the advantage that the human can still use the practical rate control method and that it will stimulates the human to learn the actual system dynamics. By learning the system dynamics, it will make the human independent on the support mechanism for when the support mechanism fails. An interesting training method which is lately used in recent literature [5][20][21][23], is training with the help of Haptic Shared Control (HSC). In haptic shared control are haptic guidance forces used as a communication channel between the human operator and an automated controller of the system. This study will design a form of HSC to demonstrate in an experiment that these guidance forces can support the learning process.

Augmented Haptic Feedback

Literature has described many ways on how augmented haptic feedback can be used to enhance training, ranging from relative simple “perceptual overlays” as the virtual fixture approach [27] to more complex Haptic Shared Control paradigms [1][23]. Previous literature has identified three forms of augmented haptic feedback for enhancing learning performance [23]. These three types are: i) augmented haptic feedback based on the concept of virtual fixtures from Rosenberg [27], ii) passive augmented haptic feedback

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based on recording the control input from an expert operator and replaying the expert's control input for training a novice operator [9], and iii) Haptic Shared Control, an automatic controller determining the desired control input and communication this by the means of forces to the human. The differences between these methods are the ability to interact during training, and the function of the guidances forces. The virtual fixture approach base their guidance forces on the areas where either the manipulator, or the controlled system should not be. This method has an on-off approach due to perceptual overlay design, and therefore provides limited interacting opportunities. Both the "record-and-replay" and the HSC base there desired control input on experimental cues and that is normally an error between the desired system position and the actual position. HSC has the advantage over the "record-and-replay" method that it can interact with the human, because the desired control input is continuously determined and not beforehand. It is possible in HSC to define two steps in the process of converting environmental cues into guidance forces [1]. The first step describes how the environmental cues (e.g. the position of the system) can be related to a desired control input. This desired control input is determined by an automated controller, and the design of the controller determines how the augmented haptic feedback is perceived [8]. The second step in HSC relates how this desired control input can be converted into the guidance forces. The taxonomy of Powell [26] describes the different guidance paradigms which can be used for learning of a task. The taxonomy from Powell classifies on: i) whether the guidance forces resist or assist the human in completing the task, ii) how the task and guidance forces can be reconciled by the human, and iii) how the forces behave over time during the subjects performance. All these three taxonomy classifications result in different force strengths acting on the manipulator controlled by the human, and are the basis for large differences in learning performance.

Learning with Haptic Shared Control

One of the main critics on learning with any form of HSC, is that the guidance forces reduce the error which is one of the main driving factors in learning a dynamic task [30][34]. Multiple research have used this line of reasoning to show that reducing the error will result in reduced rate of adaptation in: a reaching task [31], or a target-hitting task [19]. New concepts were developed on basis of these results that reducing the error by a fixed guidance will reduce the rate of adaptation in the learning process. One of these new paradigms belonging to the first taxonomy of Powell, are guidance paradigms where the error was increased to improve learning. Examples in literature are: error-amplification [17], gross resistance [26], or progressive error-amplification [29]. Error-amplification has shown to either do not effect rate of adaptation in reaching movements by the human hand [31], to improve learning in a 2D-tracking task with a robotic arm [17], or to have similar performance as fixed haptic guidance in a timing based pinball-like task [21]. Another new concept belonging to the first and third taxonomy of Powell are the "assistance-as-needed" paradigms, where the strength of the guidance forces reduces over time. This provides humans with a demonstration of the required movement, and provides additional proprioceptive and somatosensory feedback on the task performance in the initial trials. Where the reduced strength of the haptic guidance in the later trials will ensure that humans will do the task itself, and cannot become dependent on the haptic support. This guidance paradigm is called either: "assistance-as-needed" [7], "guidance-as-needed" [5], or progressive fading guidance [19]. The results from reducing assistance have shown that this reduced guidance strength can improve performance in the case of a timing based steering task [20], but also have shown to decrease performance in a 2D-tracking task [17]. In another study, it was described that the performance with "guidance-as-needed" haptic forces improved performance in a steering task only for the subjects starting with a low skill-level [5]. In summary, improved performance is in literature only described for timing based tasks where subjects needed to predict the response of the system. Where the guidance-as-needed HSC paradigm can improve performance during and after the learning process.

Haptic Shared Control and Slow Dynamic System

As previously stated, it is the goal of this study to see if HSC can improve the learning of the internal model needed for controlling a slow dynamic system. There are two separate sub-goals in this main goal, which focus on different areas. The first sub-goal is to improve by training the performance of controlling a slow dynamic system. The performance increase is of interest due to the costly and long learning process. A performance increase is achieved in previous literature for timing based tasks with guidance-as-needed HSC. Timing is an important part in controlling of a slow dynamic system, because the human needs to predict when to initialize the control movement on basis of the internal model of the system dynamics. The second sub-goal is learning of the internal model, where the internal model concept and structure is developed in motor control studies [14]. The internal model consists out of feedforward motor command, which is a combination of an inverse model of the system dynamics and a forward model used for predicting the sensory feedback and updating the inverse model. The second component of the internal model is the feedback motor command which controls on the perceived error and also regulates by adjusting the neuromuscular properties in for instance the human arm. This internal model is primarily used in human movement studies, however the concept of internal model and more specific the inverse model is interesting to assess. The inverse model is the component which formalizes the knowledge of the system dynamics. This feedforward command is needed due to lagged visual feedback to the human. The visual feedback is lagging due to the control lag of the system. This means that the human needs to predict the system response on basis of the inverse model of the system dynamics, as also recognized in a previous study [3]. The concept of inverse model inherent in the internal model implicates that it is interesting to assess how close the human can come in forming of this inverse model. Learning with the help of haptic shared control can show the human how the task can be done with the perfect inverse model. The idea is that the human can observe the optimal control input, and has a faster feedback loop on the desired control input. Therefore the two main hypothesis are:

- Hyp. 1A It is hypothesized that humans training with haptic shared control will have a decreased error in post-learning trials.
- Hyp. 1B It is hypothesized that humans training with haptic shared control will have a decreased control activity in post-learning trials.

These two hypothesis will be tested in a human factors experiment. The experiment will use a pursuit task with preview where subjects have to track a desired trajectory with a slow dynamic system. A pursuit tracking task is comparable with literature [5], and provides the ability to evaluated how the human is controlling the system with the inverse model. The preview will give the subjects the ability to predict ahead what the required control input needs to be. The HSC design will be based on the "guidance-as-needed" HSC paradigm, with the difference that the guidance will not be based on the individual subjects performance. The experiment setup will use a limited number of HSC training trials to ensure that the human can learn from errors. The function of the HSC training trials is to stimulate the observational learning process.

2 Material and Methods

Subjects

Twenty right-handed students and employees from the Delft University of Technology participated voluntary in this study, of which fifteen men and five women. The mean age of the subjects was 25.9 ($\sigma = 3.55$) years, and the mean height was 1.82 ($\sigma = 0.0726$) m. Subjects were randomly divided between groups on basis of their application. Female participants were manually divided into groups to create equal gender groups. All subjects gave their informed consent and no financial compensation was given for their participation.

Experimental setup

The study was performed on a horizontal 1-DOF hydraulic manipulator, depicted in figure 1, used in previous research [6] to determine the neuromuscular properties of the human arm.

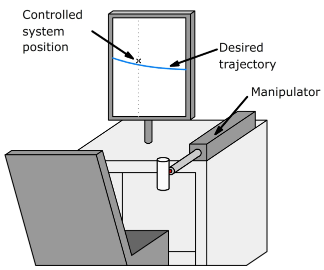

Figure 1: Display of the pursuit task with a preview of two seconds. Subjects had to minimize the distance between the controlled system represented by a black cross and the desired trajectory.

The values of the hydraulic manipulator could be varied between 0.6-20 kg for the mass M_j, 0.6-400 Ns/m for the damping B_j, and 0.6-250 N/m for the stiffness K_j. The maximum force from the manipulator was 200 N. The manipulator was designed in such a way that it mimics joystick behaviour. This implies that the manipulator had a centering stiffness to return the joystick to a zero position, which corresponds to a zero velocity rate input. The maximum input range boundaries were created by a stiff spring and a non-linear damper. The manipulator dynamics were set as a stiffness of 60 N/m, damping of 15 Ns/m, and mass of 1 kg. The maximum input range was set as $\pm$ 0.10 m. The direction coupling of the manipulator-visualisation was such that position in the pushed direction will result in a vertical velocity upwards of the controlled system. The hydraulic manipulator is controlled with dSPACE ControlDesk real-time operating system running at a sample frequency of 5000 Hz. The simulated environment could be designed in Matlab Simulink® and uploaded onto the real-time industrial pc. The visualisation of the task was displayed on a vertical orientated 19 inch LCD with 1280x1024 pixels. The visualisation had a refresh frequency of 64 Hz.

Task Description

The task for the subjects was to perform a classical pursuit task where subjects had to minimize the error between the desired trajectory and the controlled system position (see figure 1). The slow dynamic system was visualized with a 5 mm large black cross with a thickness of 2 pixels, and the desired trajectory was displayed as a two pixels thin blue line. Subjects could minimize the error in the vertical direction by moving the manipulator in the horizontal direction. The controlled system could not be moved in the horizontal direction. The visualisation provided a constant two seconds of preview, one second of history from the desired trajectory, and only the current state of the simulated slow dynamic system.

Desired Trajectory Design

The desired trajectories that the human needed to pursuit were designed off-line in the frequency domain to form unpredictable desired trajectories. The desired trajectory contained four perturbation signals from 0.0191 to, 0.0382, 0.0573, and 0.0764 Hz with a rectangular power spectra as depicted in figure 2. The lowest frequency was selected on basis of the preferred desired trajectory time of around one minute, and the highest to be lower than the undamped natural frequency of the controlled system. The phase of the four frequencies was randomized to create an unpredictable desired trajectory, and the cresting technique was applied to prevent large leaks in the time domain [24]. The desired trajectory was completed by adding smoothed inputs and outputs to the signal for starting and ending at a zero position, where the smoothed signal was a shifted cosinus with a frequency of 0.05 Hz. The complete desired trajectory had a duration of 75 seconds. Every trial in the experiment had its own unique desired trajectory made on basis of the frequency domain and a selecting procedure to limit the variance in maximum velocity of the trajectory. Every subject received the same combination and order of trials.

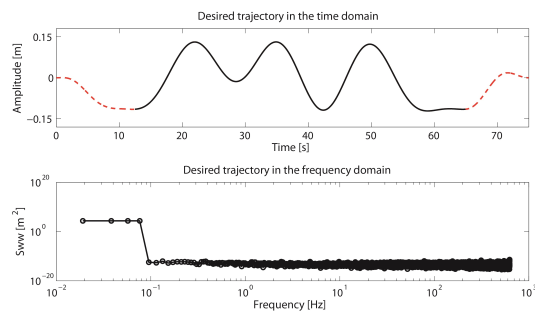

Figure 2: An example desired trajectory in both the time and frequency domain. The dashed red line in the time domain is the smooth function which is not a part of the displayed frequency domain. The black line in the time domain is the unpredictable desired trajectory used for data analysis.

System Dynamics

The total slow dynamic behaviour that the human perceives is dependent on the dynamic components that are between the joystick position input and the visualized system position output as depicted by figure 3. The slow dynamic system that is designed in as combination of a physical second-order system which is controlled in rate controlled fashion by a servo actuator. The servo actuator ensures by controlling the force output that the joystick position input, which corresponds due to the rate control method to a desired system velocity, and the realized system velocity will become equal. The servo actuator is divided into two parts (i.e. forward gain and error gain) to be able to adjust the behaviour of the controlled system in the maximum obtainable velocity and in the system response.

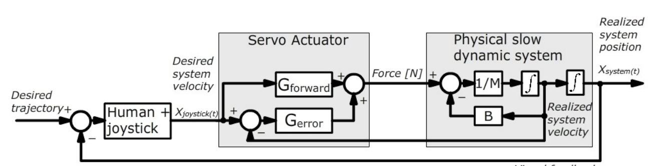

Figure 3: The perceived slow dynamic system divided into a physical second-order system, and a rate servo actuator which ensures that the system velocity output will match the desired velocity set by the joystick position.

The transfer function of the slow dynamic system (equation 1) includes the servo actuator settings, forward (G_f) and error (G_e) gain, and the mechanical properties from the physical system, mass (M) and damping (B). The forward and error gain were adjusted to ensure that the controlled system had the chosen difficulty. Where the chosen difficulty was defined as the ratio between the maximal velocity of the controlled system over the maximal velocity of the desired trajectory. This ratio determines the time to match the desired trajectory velocity, and influences the ability to correct delayed initialized control movements.

$$H(s) = \frac{X_{system}(s)}{X_{joystick}(s)} = \frac{G_f + G_e}{Ms^2 + Bs + G_e s} \tag{1}$$

The lag, due to the mass inherent in the physical system, and the relative low actuator strength will create the typical slow behaviour. This implies that it will take some time before the velocities match in the case of a desired velocity step input as depicted by figure 4.

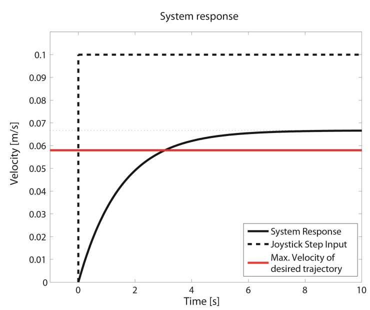

Figure 4: The system response on a maximal joystick step input. The system response has a rise time of 1.5 seconds, and the maximal system velocity is 1.15 times higher than the maximal velocity of the desired trajectory.

The control lag of the system can be described in the terms of the rise time and in the natural frequency of the system. Both the rise time [22] and undamped natural frequency [16] present an indication of the sluggishness of the system, and the amount of control lag. The chosen settings for the controlled systems are: M = 6 kg, B = 2 Ns/m , K_e = 2, and K_f = 0.6641. The chosen system dynamics used in this study has an undamped natural frequency of 0.106 Hz, and a rise time of 1.5 seconds. The undamped natural frequency can be described as a comparison for other realistic systems. For instance, the undamped natural frequency, or more specific in this case the location of the two system poles, of the transfer function between rudder input and heading angle output of a 200.000 tons supertanker are 0 Hz and 0.0006 Hz [32]. Other less extreme slow dynamic examples are: the undamped natural frequency of the Space Shuttle Remote Manipulator System (SRMS) while carrying a 14500 kg object is 0.027 Hz [16]; the undamped natural frequency of the reduced-order pitch dynamics from of a Cessna Citation plane flying at 160 kts is 0.44 Hz [25]; and the undamped natural frequency of the steering dynamics between steering angle input and lateral displacement of a 950 kg car driving at 25 m/s is 0.93 Hz [18].

Haptic Shared Control design

The design of the HSC consists out of the mapping relating the controlled system position into a desired control input, and a mapping relating the desired control input into a guidance force [1]. The first mapping consist out of the combination of the controlled system position sensor and a controller determining the desired control input. The desired control input is transformed by the means of a guidance stiffness into a force around this desired control input as can be seen in figure 5. During trials with HSC was the joystick centering stiffness disabled to ensure that subjects would perceive the desired control input as the zero force on the joystick.

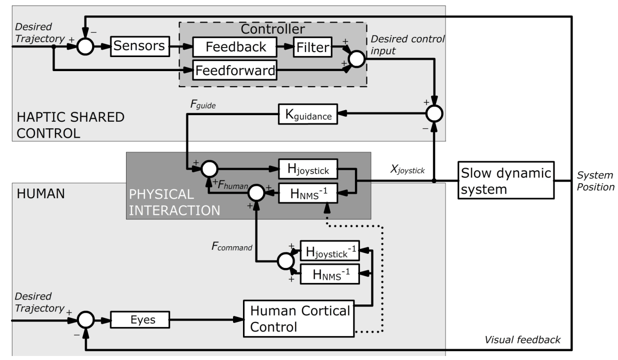

Figure 5: Representation of the haptic shared control system in combination with the human. Both perceive the system position by sensors and determine their own desired control input. Physical interaction occurs due to the guidance force from the haptic shared control, and the commanded force from the human based on the inverse model of the joystick ($H_{joystick}{}^{-1}$) and the neuromuscular system of the human arm ($H_{nms}{}^{-1}$). The human can adapt the neuromuscular properties of human arm (Diplayed by dotted line). (Adapted from Abbink [2])

Controller

The controller used to train the human in learning the system dynamics is a combination of a feedforward and feedback controller. The feedforward model calculates the optimal control input on basis of the exact inverse model of the slow dynamic system. The feedback control is added to provide the subject with the ability to interact and deviated from the optimal control input. The feedback controller is designed as a proportional controller on the current error between desired trajectory and system position, and a proportional controller on the look-ahead error between the future desired trajectory and the predicted system position. A second-order low-pass filter with a cut-off frequency of 8.5 Hz is applied over the response of the feedback to limit jerky behaviour of the joystick.

The feedback controller was tuned during pilots and simulations to assure that the feedback controller could overrule the feedforward control actions in the case of too large errors, and to ensure that maximal joystick input is given at a maximum allowed error. The maximum allowed error was 0.02 m for the current error resulting in a proportional gain of 5. Where the maximum allowed error at the look-ahead time of 0.75 s was 0.04 m, resulting in a proportional lookahead gain of 2.5. The maximum allowed desired control input determined by either the feedforward of feedback controller was limited to the maximum joystick input.

$$X_{desired} = P * E_{current} + P_{look} * E_{look} \tag{2}$$

Where $X_{desired}$ is the desired control input from the feedback controller, P is the proportional gain, $E_{current}$ is the error between desired trajectory and system position, P_{look} is the proportional gain at the look-ahead time, and E_{look} is the error at the look-ahead time between desired trajectory and predicted system position.

Guidance Stiffness Algorithm

The guidance stiffness converts the desired control input into guidance forces pushing the human arm towards the desired control input. This guidance stiffness is reduced exponentially in strength over the trials with HSC to stimulate the humans in doing the task itself. This behaviour is similar as in "guidance-as-needed" paradigm except that the exponentially reducing stiffness is not dependent on the subjects performance as can be seen in equation 3. The guidance stiffness is reduced in strength until it reaches at the last training trial a similar stiffness as the centering joystick stiffness.

$$K_{guidance}(n+1) = f_r * K_{guidance}(n) \tag{3}$$

Where $K_{guidance}$ is the stiffness guidance in training trial n which decreases from an initial stiffness of 338 N/m in the first training trial to 60 N/m in the last training trial. The forgetting factor f_r was set at 0.525.

Experimental Conditions

The subjects were divided into two groups (n = 10 each) with one condition per group. The conditions were different in the form of haptic guidance, namely the i) No Guidance condition where the subject did no receive any haptic guidance in any trial, and ii) Haptic Guidance condition where subjects received haptic guidance at a number of training trials to show how they could perform the task with minimal control activity.

Experiment Setup

The experiment consisted out of an instruction phase, familiarization phase, and the actual learning phase. In the instruction phase, subjects had the opportunity to see the required task of minimizing the error between desired trajectory and controlled system position. The familiarization phase was used to familiarize subjects with the hydraulic manipulator as joystick. Subjects could feel the maximum input boundaries, and see the direction coupling of the joystick with the controlled system. The perceived controlled system was modelled as a position controlled system in both the instruction and familiarization phase in order to minimize learning of the system dynamics in these trials. It was explicitly stated towards the subjects that the systems dynamics in the learning phase were different. Both conditions received the same instruction and familiarization.

The learning phase is the actual experiment consisting out of 40 trials in total as depicted in figure 6. The first three trials in the experiment were without any form of haptic guidance for both conditions to form the pre-guidance baseline. The pre-guidance baseline was used to assess the learning behaviour before the training trials with HSC started. Conceptual similar is the post-guidance baseline, which is used to assess the learned behaviour after training with HSC. The thirty trials between pre and post-guidance baseline are the Guidance Session where the Haptic Guidance condition received eight so called HSC training trials. The other twenty-two trials in the Guidance Session for the Haptic Guidance condition had no training with HSC. The distribution of HSC training trials was more dense in the beginning, to enhance the learning process in the area where the rate-of-learning is large.

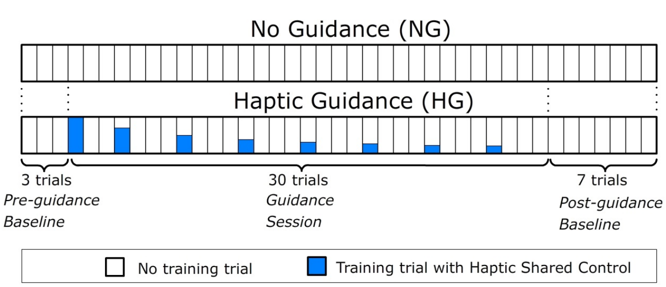

Figure 6: The two conditions, No Guidance and Haptic Guidance, and the experimental setup of pre-guidance baseline and post-guidance baseline to assess initial and final performance. Eight haptic guidance training trials were included for the Haptic Guidance condition to present how the task could be done.

The total duration of the experiment was between 1.5 and 2 hours. A break of around 10 minutes was included after the twentieth trial for every subject to reduce subject fatigue. The number of forty trials was chosen on basis of the performance learning curve in pilot studies.

Task Instruction

Subjects received a written task instruction, and the required task was also verbally explained. Subjects were instructed to keep the controlled system (black cross) as close as possible on the target during the 40 trials of the experiment. Feedback on the performance was given with a performance indication at the end of every trial. The performance indication was based on the absolute mean position error in the complete trial, and the performance indication varied linearly between 0% and 100%. 0% performance indicated a mean error of 0.02 m, and 100% a mean error of 0. Subjects received the instruction that 100% is the maximum perfect score, and that 90% is their achievable goal. Subjects with the Haptic Guidance condition received an extra instruction that is was their task to actively corporate with guidance to see how the automated system instructs them how they should do the task. The Haptic Guidance condition subjects were, before the any HSC training trial started, told if the haptic guidance would interact. At the tenth trial or third HSC training trial was explained that the guidance from the HSC was becoming weaker.

Data Analysis

The stored data of the experiment consisted out of 21 different variables, ranging from joystick position and force on joystick to internal optimal control positions and slow dynamic system states. All the variables were logged at the downsampled frequency of 1250 Hz. The six scales of the subjective NASA-TLX questionnaire were done after completing every trial, and the pair-wise comparisons were done only once after the first trial. The data analysis used only the desired trajectory that was designed in the frequency domain. The smoothed input and output desired trajectory were not processed in the data analysis to ensure that the trials all had the same difficulty. The mean of the first three trials is taken to form the pre-learning baseline metrics, and the mean of trial 34 to 40 is taken to form the post-learning baseline. Assessing the learning behaviour is done by comparing the pre-learning baseline with the post-learning baseline with the use of a paired T-test. The difference between conditions is compared with the use of an independent-samples T-test. α was for both statistical tests set at 0.05.

Metrics

The experimental data was evaluated for performance, control activity, and subjective mental load metrics.

Performance
The performance was evaluated with both the Absolute Mean Position Error (AMPE) and the Root Mean Squared Position Error (RMSPE) for the error between the desired and realized trajectory. The Absolute Mean Velocity Error (AMVE) assessed the velocity error between desired and realized trajectory velocity.

Learning curve
An individual learning curve was fitted on basis of the Absolute Mean Position Error of the subjects performance with a single exponential learning curve, described by equation 4. The learning curve parameters were fitted with the use of a non-linear least squares error function, and the quality of the fit was assessed by the square of the correlation between the error values and the predicted error values (R^2).

$$AMPE(n) = B_{exp} + A_{exp} * e^{-\gamma_{exp} * n} \tag{4}$$

Where AMPE is the Absolute Mean Position Error in trial n, B_{exp} represents the final asymptotic performance, A_{exp} represents the initial performance, and γ_{exp} represents the rate of learning. The learning curve was fitted for both conditions on the trials where the Haptic Guidance condition had no HSC training.

Joystick reversal
The joystick reversal rate, conceptual similar to the steering reversal rate [13], was determined by filtering the joystick input with a 2^{nd}-order ButterWorth low-pass filter with a cut-off frequency at 10 Hz. The reversal threshold was set at four different levels to see the influence of the reversal threshold. The used reversal thresholds are: 0.0075m, 0.01m, 0.02m, and 0.03m.

Excessive control activity: joystick input frequency analysis
The joystick input frequency analysis evaluated the power spectral density of the joystick input. The excessive control activity was analysed by summing the power spectral density of a certain frequency band. The main excessive control activity metric looked at the frequencies between the highest desired trajectory frequency (i.e. > 0.0764 Hz) and 1 Hz, where only noise was visible in the higher frequencies power spectrum. Other frequency bands were evaluated to see if there is a difference between the frequency bands. These frequency bands are displayed in table 1.

Table 1: The used frequency bands for assessing the control activity by summing the power spectral density.

Frequency band	Low freq. [Hz]	High freq. [Hz]
Excessive control activity	0.1	1
Useful control activity	0.0191	0.0764
Excessive control activity, medium range	0.1	0.4
Excessive control activity, high range	0.3	0.6
Peak PSD	0.0764	0.0764

System velocity reversal rate
The system velocity reversal rate was determined with the same technique as the joystick reversal rate, however now with the realized system trajectory velocity as input. The system velocity reversal rate was assessed to see if the corrections made by the joystick result in a velocity reverse of the system. Or will only result that the system inertia is compensated due to the slow dynamic behaviour.

NASA-TLX
The subjective NASA-Task Load Index questionnaire for the perceived workload [10]. The six different scales were weighted with the subjects weighting function, and result in a subjective workload ranging from 0 to 100.

3 Results

The experimental results of the experiment are divided into: pre-learning baseline, guidance session, and post-guidance baseline. One subject in the No Guidance condition achieved very low performance throughout the complete experiment. The performance in all the trials of the post-learning baseline was outside the 3σ of the other subjects. The highest performance achieved by this subject was an absolute mean position error of 0.0186 in one of the post-learning baseline trials. This subject was removed due to the extreme low performance, and this condition was redone with another subject to create equal groups of ten subjects.

Performance

Typical subjects
The performance of the two typical subjects, each for one condition, which achieved average performance can be seen in figure 7. The actual performance of trial 4 is shown for both subjects to present the difference in the first HSC training trial for the Haptic Guidance condition. The performance of the subject during all the trials of the experiment is shown to present the individual learning behaviour and includes the fitted exponential learning curve.

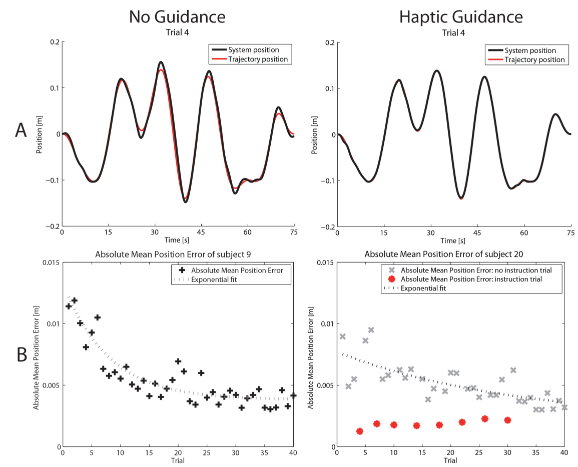

Figure 7: Performance evaluated by the absolute mean position error between the desired trajectory and the system trajectory of two typical subjects. **A)** The position of both the desired trajectory and the controlled system trajectory in trial 4, where training by haptic guidance was active for the Haptic Guidance subject. The figures show performance from a No Guidance typical subject and a Haptic Guidance typical subject. **B)** The absolute mean position error of both the typical subjects during the complete experiment. The dotted line is the exponential learning curve fitted through the subjects data (Quality of fit: No Guidance $R^2 = 0.84$, Haptic Guidance $R^2 = 0.55$).

Absolute Mean Position Error
In both conditions, the Absolute Mean Position Error (AMPE) decreased between the pre-learning baseline and the post-learning baseline (NG: $p < 0.001$, HG: $p < 0.005$) indication a learning process. Figure 8 shows that the absolute mean position error for both conditions decreases until it levelled near a constant value at the end of the experiment. Trials where HSC was added, the so called training trials displayed in red, show lower error.

Figure 9 shows the across subject mean of the AMPE in the post-guidance baseline, and the mean of all the trials in the post-guidance baseline. There is no difference between the two conditions in both the pre-guidance baseline (P=0.336, F=0.032), and in the post-guidance baseline (P=0.814, F=2.428).

Other metrics evaluating the performance, either the Root Mean Squared Position Error or the Absolute Mean Velocity Error, showed similar results. Both the different performance metrics showed a learning behaviour, and did not show difference between conditions for both the pre-learning baseline and the post-learning baseline.

Exponential learning curves
Individual learning curves, fitted on basis of the exponential learning curve described by equation 4, were fitted on the absolute mean position error of the subject's data. The quality of the fit was reasonable (R^2 μ = 0.7178, σ = 0.1488). The fitted parameters of the exponential showed no difference between conditions: initial per-

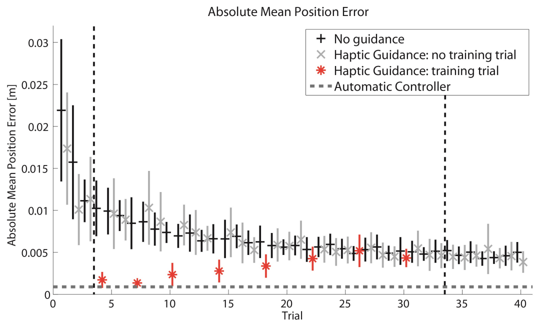

Figure 8: Across subject mean and 95% confidence interval of the subjects absolute mean position error for both conditions during the experiment. Note that the error where the Haptic Guidance subjects received HSC training, displayed with the red crosses, were lower than for the No Guidance condition. The error in these guidance trials increased over trials due to reduced haptic guidance. The error of the automatic controller was lower than the error made any of the subjects.

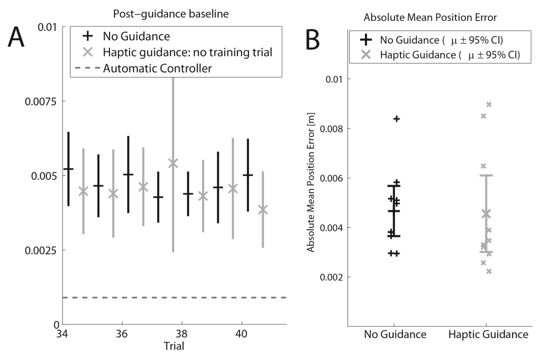

Figure 9: **A**) The across subjects mean and 95% confidence interval of the absolute mean position error from the post-learning baseline. **B**) The mean of the complete post-learning baseline. The absolute mean position error was not different between conditions in the post-learning baseline.

formance parameter (P=0.901, F=0.007), rate of learning parameter (P=0.675, F=1.183), and final asymptotic performance (P=0.240, F=1.195).

Control Activity

Typical subjects
The control activity of the same two typical subjects as for the performance, can be seen in figure 10. The data depicted in this figure displays: the joystick position in combination with optimal control input according to the feedforward controller; the power spectral density of the joystick input; and the summed power density between 0.1-1 Hz of the subjects complete experiment.

Control Activity: summed power spectral density
For both conditions the control activity evaluated with the summed power spectra density decreased between pre-guidance baseline and post-guidance baseline (NG: $P < 0.05$, HG: $P < 0.001$) as can be seen in figure 11. No difference between conditions is found for the pre-learning baseline (P=0.325, F=2.57), and the post-learning baseline (P=0.536, F=11.126).

The control activity evaluated by the power spectral density with other frequency ranges showed either no learning behavior (e.g. useful control activity, excessive control activity in the high range, or peak PSD) or learning behavior (e.g. excessive control activity in medium range). All the frequencies ranges showed no difference between conditions in both the pre-learning baseline and post-learning baseline.

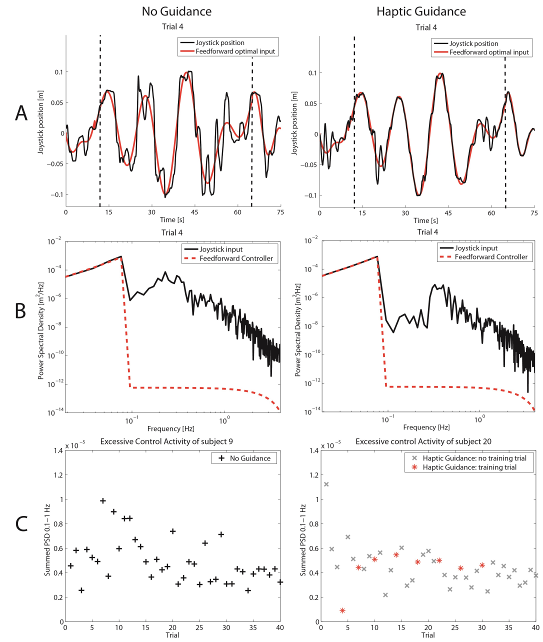

Figure 10: Control activity for two typical subjects. **A)** The position of both the subjects joystick input and the desired control input on basis of the feedforward controller for the first haptic guidance training trial. **B)** The power spectral density between 0 and 4 Hz for the joystick inputs is shown in A. The PSD of the desired control input from the feedforward is also displayed. **C)** The control activity, defined as the summation between 0.1-1 Hz, over the complete experiments for both typical subjects.

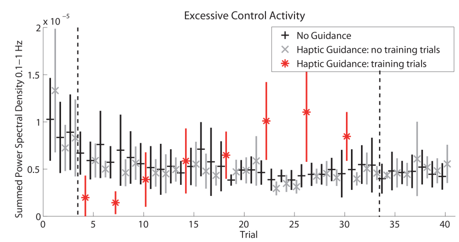

Figure 11: Across subjects mean and 95% confidence interval for the control activity evaluated by the summed power spectral density between 0.1-1 Hz.

Control Activity: Joystick Reversal Rate
The joystick reversal rate with a reversal threshold of 0.01 m is depicted in figure 12. The joystick reversal rate showed no learning behavior for both conditions (NG: P=0.796), (HG: P=0.092).

No difference between conditions was found for the pre-guidance baseline (P=0.450, F=0.035). However, a difference was found between conditions for the post-guidance baseline (P=0.035, F=0.052) depicted in figure 13. Similar results were found for the joystick reversal rate evaluated with the three other reversal thresholds.

Joystick error
The joystick error is the difference between the desired control input determined with the feedforward controller and the actual joystick input from the subject. The joystick error, depicted in figure 14, showed learning behavior for both conditions (NG:

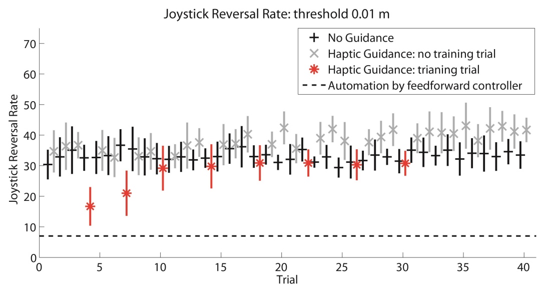

Figure 12: The across subjects mean and 95% confidence interval for the joystick reversal rate with a reversal threshold of 0.01 m for all subjects.

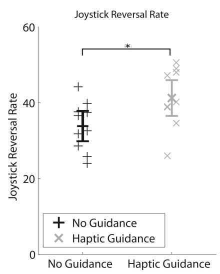

Figure 13: The mean of the post-learning baseline from the across subjects mean of the joystick reversal rate. The joystick reversal rate showed for this and the other reversal thresholds a difference between the conditions. Subjects with Haptic Guidance showed an increased joystick reversal rate.

P $<$ 0.05), (HG: $<$ 0.001). No difference was found between conditions for the pre-learning baseline (P=0.580, F=2.002) and the post-learning baseline (P=0.593, F=0.142).

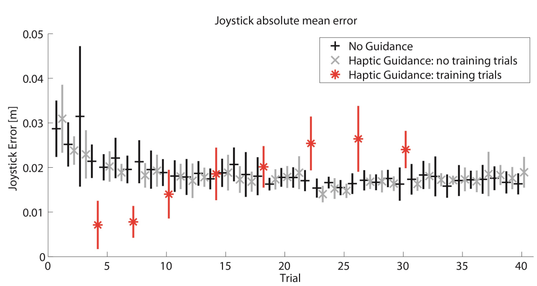

Figure 14: Error between the desired control input, determined by the feedforward controller on basis of the exact inverse model, and the actual subject joystick input. The across subjects mean and 95% confidence interval during the complete experiment.

System Velocity Reversal Rate

The system velocity reversal shows if the reversals inducted by a joystick reversal result in velocity reverval of the system, or in only in stabilizing the velocity. The system velocity reversal rate assessed with a reversal threshold of 0.0025 m/s is depicted in figure 15. The velocity reversal rate showed no learning behavior for the NG condition (P = 0.0279), but showed learning behavior for the HG condition (P $<$ 0.05). No difference between conditions was found for the pre-learning baseline (P=0.468, F=3.311) and for the post-learning baseline (P=0.558, F=2.932). The system velocity reversal rate assessed with a reversal threshold of 0.005 m/s showed similar results.

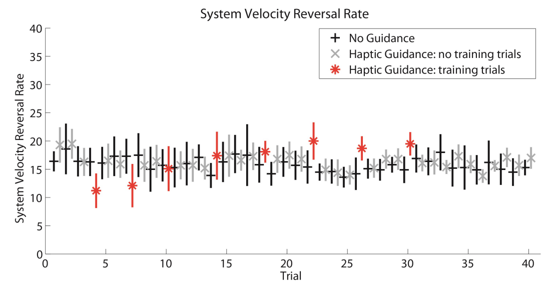

Figure 15: The across subjects mean and 95% confidence interval for the system velocity reversal rate with a threshold of 0.0025 m/s.

Subjective Mental Load

The mean and 95% confidence interval of the weighted NASA-TLX score during the experiment can be seen in figure 16. No learning effect was found for the No Guidance condition (P=0.091), and a learning effect was found for the Haptic Guidance condition (P $<$ 0.01). No difference between conditions was found for the pre-learning baseline (P=0.840, F=2.451), and the post-learning baseline (P=0.974, F=0.104).

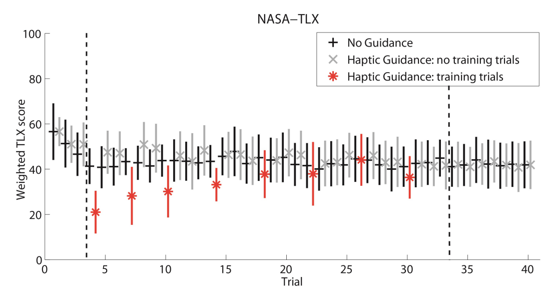

Figure 16: The mean and 95% confidence interval for the weighted NASA-TLX score for all subjects.

4 Discussion

The hypothesized results for this experiment were an increased performance and decreased control activity after training for the condition training with Haptic Shared Control (HSC). However, the experimental results did not show any difference between the two conditions. The performance after training showed no difference between conditions. The control activity after training showed no difference in the frequency domain, and showed the unexpected result of increased control activity evaluated by the joystick reversal rate.

Performance

The different metrics assessing the performance all showed the same result of similar performance after training for both conditions. The individual subject data shows a large variance in subject performance. However, the exponential learning curve can be seen and fitted with reasonable quality in the subjects performance. Even the low error in the initial HSC training trials, and the increasing error in the HSC training trials due to decreasing guidance stiffness can be observed in figure 8. The similar performance result in this experiment is different than the increased performance after training found for subjects learning a steering task with guidance-as-needed haptic guidance [5][20]. Also assessing the results for the low-skilled subjects in this study showed not the improved performance as found for the low-skilled subjects in a pinball-like timing task [21]. Both previous literature used a timing based task in combination with a haptic guidance throughout the complete experiment. The timing based task in both literature used a fixed trajectory or task, where this experiment used different unpredictable trajectories to assess the learning performance. This implies that the subjects in this study were not able to form the cognitive trick of knowing on basis of previous experience where to start the movement. Subjects in this study had learn the system dynamics for predicting when to initialize the control movement. This internal model could be formed due to error-based learning in the no training trials, and due to observational learning in the HSC training trials. Where subjects also received the force guidance from the faster feedback loop of the Shared Controller. However, providing the subjects with haptic guidance influences the perceived dynamics, and thereby affects learning of the system dynamics. That this disturbs the learning process can be seen in the error of the trials after the HSC training trials in figure 8. It can be seen that the subjects error makes a jump in error, and this error is the following trials reduced with stronger rate-of-learning than the NG subjects. This effect can be seen after most HSC training trials. It seems that haptic guidance disturbs the learning process by altering the perceived dynamics between the required force on joystick, and the position output. So, the forces from the HSC present to the human a different form of dynamics and thereby disturb the learning process.

Control Activity

The control activity was assessed in the frequency domain, and by the joystick reversal rate. Other less common metrics were added in the data analysis to see if these metrics could assess the behaviour in a different way. The results of the control activity in the frequency domain showed learned behaviour and no difference between conditions. The control activity evaluated by the joystick reversal rate showed not an effect by learning and a difference between conditions. The hypothesis for the control activity was that training the human with HSC will bring the control activity closer by the minimal control activity needed for controlling a slow dynamic system. Where the minimal control activity would be defined by a perfect inverse model of the system dynamics. The idea that humans could observe this optimal control strategy and thereby reduce their control activity was not found. However, there are multiple observations possible in the control activity. The first observation is the increased control activity in the HSC training trials in the later stage of the experiment as depicted in figure 11. It is interesting to see the forces applied by the human, before arguing what could be the cause of this increased control activity. The forces applied by the human are depicted in figure 17, and it can be observed that the human applied force does not decrease while the guidance stiffness reduces in strength. This means that the error between the desired control input and the actual joystick is becoming larger in the later HSC training trials.

It seems due to the combination of increased control activity and relative increased human applied force that the human disagrees more with the HSC. The disagreement can be seen in subject specific data where the human follows the desired control input with low control activity. It can be observed in the subject specific data that when the human disagrees by using more forces that then the control activity increases. The control activity from the desired control input can only be increased by the feedback controller of the HSC. The design of the feedback controller was such that the guidance was focussed on high performance, and this means that the feedback settings were too much focussed on the current error. In other words, the HSC in role as teacher was too much focussed on high performance. Where literature on teaching by interaction stated that a teacher should not care to much about performance, but should be focussed on removing itself as fast as possible [12][9].

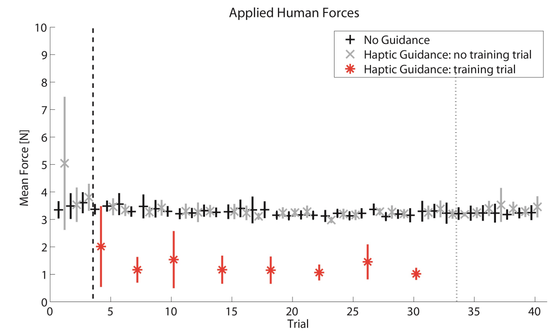

Figure 17: The across subjects mean and 95% confidence interval of the applied subjects force. The mean force in the HSC training trials is lower than in the other trials, and does not decrease while the guidance stiffness strength is reduced.

The second observation is that the control activity assessed in the frequency domain decreases with an almost similar rate-of-learning as the performance. The control activity is different than the control effort learning curve in previous literature [31]. It can be argued that the control activity in the frequency domain is decreased due to lower amplitude of the control inputs. It can be seen in subject specific data that subjects make in the first trial large and fast joystick movements to correct the large errors. Where in the later phases the human uses a slow main joystick movement, with fast and small corrections around this movement. Therefore, the control activity in the frequency domain decreases due to lower amplitude movements.

The last observation is the difference between the control activity in the frequency domain, and the joystick reversal rate. The joystick reversal rate resulted for a range of thresholds in a difference between conditions which was significantly large. These contradictory results can be argued with multiple statements: i) subjects have learned a more poor developed internal model, ii) subjects have learned to control in a more aggressive manner. In general, all the subjects in this experiment have not formed the exact inverse model resulting in the minimal control activity in the frequency domain and in the minimum reversal rate. It can be argued that the final result in the control activity is a combination of a less formed internal model and more aggressive behaviour. Subjects looked primarily on how to minimize the error at the current position, and making sure that high-velocity sections of the desired trajectories were nicely followed. The high-velocity sections of desired trajectories were difficult for the subjects, because it requires multiple seconds before the slow dynamic system matches the trajectory velocity. The aggressive behaviour from the proportional controller in the HSC feedback controller, also resulted that Haptic Guidance subjects received a training with a high performance target. This could have resulted that HG subjects became more focussed on the current errors, and therefore made more corrections as seen by the joystick reversal rate. Another possibility is that this form of guidance teaches the human to behave more aggressive in similar way as some pilots flying planes tend to be more aggressive. In similar way as the high-gain piloting behaviour described in literature [4]. However, no increase of frequency or amplitude are seen in this study. So, it can be argued that the Haptic Guidance subjects were more focussed on the current error, and thereby increased the control activity.

Subjects comments on Haptic Shared Control

One the main comments made by subjects learning with HSC was that they missed the manipulator stiffness during HSC training trials. One of the main downside of this form of HSC is that alters the perceived dynamics between human force input and system position output. It was assumed in this research that this was not a too large of a problem due to dominant slow dynamic system behavior, and that the human also perceives proprioceptive information about the manipulator position. However, some subjects stated that they liked the centering behavior of the manipulator as joystick, and that they missed this behavior and cue in the training trials. A more general comment is made by the subjects in the NASA-TLX performance scale. It is interesting to see that the variance in the post-learning baseline for the HG subjects is twice as large as for the NG subjects. It can be argued that high performance HSC training trials make some subjects less pleased with their own results.

Limitations and recommendations

This research is limited for the practical application of an excavator, because it only looks at the combination of rate control method and control lag. The second limitation is the investigation on tracking movements, and not on point-to-point movements. For further research it is interesting to see how point-to-point movements can be learned with HSC. The second limitation and therefore another recommendation, is the limited use in this study of the potential available in the frequency domain. Assessing the learning from the neuromuscular properties of the human arm would be a nice enhancement of this study. The last recommendation is to see if it is possible to keep the centering stiffness in haptic guidance trials by creating with the haptic guidance stiffness a local force dip around the desired control input.

5 CONCLUSION

The effect of Haptic Shared Control (HSC) with guidance-as-needed support on training the human to learn the system dynamics of a slow dynamic task is assessed by looking at performance, control activity, and subjective mental load. The human factors experiment compared the No Guidance condition (NG) with the Haptic Guidance condition (HG), and the following conclusions can be drawn on comparing the experimental results.

- Performance assessed by multiple metrics in the NG and HG conditions showed similar results.
- Control activity in the frequency domain in the NG and HG condition showed similar results. On the other hand, control activity assessed by the joystick reversal rate showed increased number of reversals for the HG in comparisons with the NG.
- Subjective mental load in the NG and HG condition showed similar result.

It is concluded that HSC with guidance-as-needed does not improve learning of the internal model of a slow dynamic system, and can even tend to make the human more aggressive. However, the results from this form of HSC have shown that the performance is improved in HSC training trials, and that this form of HSC does not reduces performance after training. In other words, the HSC can reduce the costs and increase the safety of the initial learning phase, and will result that the human learns large parts of the system dynamics for the when the haptic support fails. Therefore, this form of HSC is a good *support* option for this task, however it is not a suited *training* option.

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Appendices belonging to the Master's thesis:

Learning a Slow Dynamic System: Training Enhancement by Haptic Shared Control

V.Honing

CONTENTS

Appendix A: Experimental Setup

The experimental setup used for the human factors experiment is developed on the ProPrio manipulator depicted in figure A-1. The following sections will describe how the experimental setup is developed, and what the final settings are for the experiment. These sections contain information on how the ProPrio is programmed in order to control a slow dynamic system with the rate control method. Also information about the trajectory design, slow dynamic system behaviour, haptic guidance settings, and experimental instructions are added to describe how the experiment is designed.

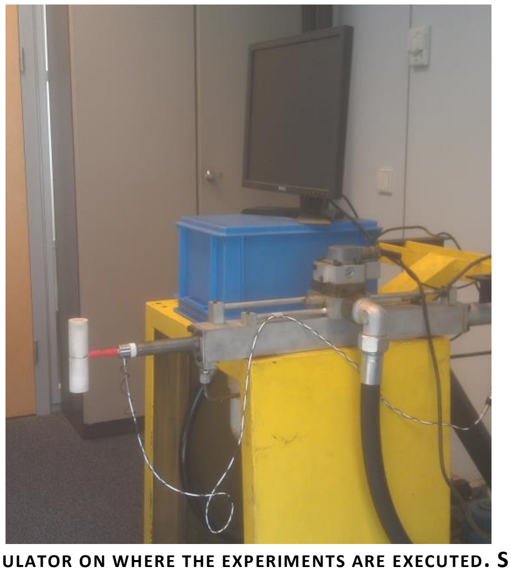


Figure A-1: The ProPrio Manipulator on where the experiments are executed. Subjects used the white handle to control the slow dynamic system which is visualized on the screen.

Slow Dynamic System

The slow dynamic system implemented in this study is a combination of a physical second-order system in combination with a servo actuator as can be seen in figure A-2. One of the important parts in this scheme is how the rate control is implemented. There are two methods of rate control described in literature: the common integrator approach, also called rate control with position servo (Kim, 1987), or the rate control method with velocity servo (Kim, 1987). The rate control method displayed here is the rate control with velocity servo. The rate control with velocity servo is chosen, because the rate control with position servo will become jerk-control if the undamped natural frequency goes to zero as described by Kim. The servo actuator in this study is separated into a forward gain, and error gain. This setup was chosen to have the flexibility in the system response (i.e. the control lag of system) and the maximum obtainable velocity of the system.

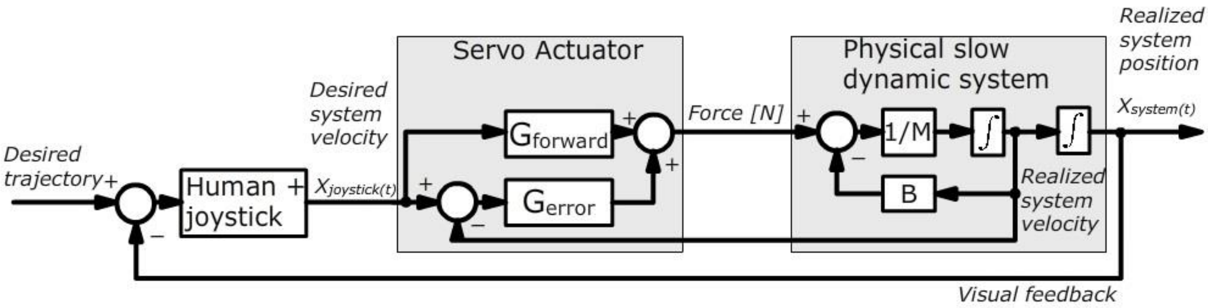


Figure A-2: Slow dynamic system as a combination of a physical second-order system in combination with a servo actuator . The servo actuator controls the force on the physical slow dynamic system in such a way that the desired system velocity (set by the joystick position) will become equal as the realized system velocity.

The corresponding transfer function of the described slow dynamic system can be seen below:

$$H_{system} = \frac{G_f + G_e}{Ms^2 + Bs + G_e s}$$

Where mass is M, damping is B, forward gain is G_f, and error gain is G_e. The response of the system is dependent on the parameters M, B, and G_e. And the maximum obtainable velocity is dependent on the ratio of G_f and G_e over B and G_e. A more simplified from of the dynamics can be described with:

$$H_{system\_2} = \frac{K_m}{Ms^2 + Bs}$$

Where mass is M, damping is B, and motor gain is K_m. This simplified system can be tuned in a similar way as the first system. However, the more complex form provides more insight in the working of the rate servo actuator. The implemented controller, which controls the force until the actual system velocity is equal to the desired system velocity, is a simple proportional controller. More complex controllers can be implemented, but they change how the human perceives the slow dynamic system. A more or less similar comment is applicable for the actuator producing force on the physical slow dynamic. A more complex hydraulic actuator, or clipped force outputs can be implemented. However, the focus in the study was to keep the slow dynamic system as simple as possible in order to see how close the human comes in learning the slow response of the system. The bode plot of the transfer function from H_{system} can be seen in figure A-3.

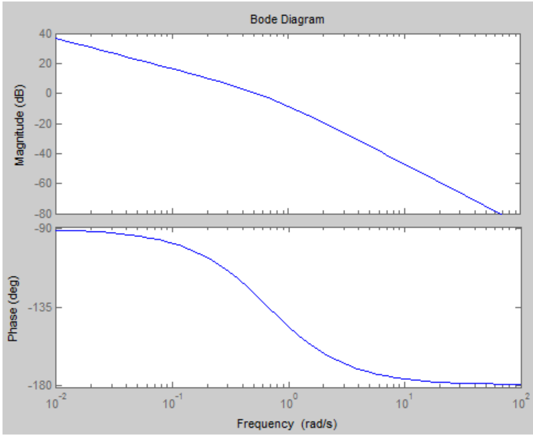


FIGURE A-3: BODE PLOT OF THE TRANSFER FUNCTION FROM THE SLOW DYNAMIC SYSTEM. THE POLE LOCATIONS OF THE DISPLAYED SYSTEM ARE AT 0 RAD/S AND 2/3 RAD/S.

The behaviour of the slow dynamic behaviour (i.e. amount of control lag) was designed on basis of the undamped natural frequency range from realistic systems (see Table A-1). And from the duration of the learning process of subjects during pilots.

TABLE A-1: TRANSFER FUNCTION AND UNDAMPED NATURAL FREQUENCY OF OTHER REALISTIC SYSTEMS.

System	Transfer function	Undamped Natural frequency [rad/s]	Reference
Supertanker: first-order equation beteen rudder angle input and heading angle output	$H_{\varphi,\delta}(s) = \frac{-0.05}{264s^2 + s}$	0.0038	Veldhuyzen, 1976
Space Shuttle Remote Manipulator System (SRMS) in with load of 14.500 kg	–	0.17	Kim et al, 1987
Plane: Cessna Citation reduced-order linearized pitch dynamics flying at 160 kts	$H_{\Theta,\delta_{e(s)}} = \frac{10.6189(s + 0.9906)}{s(s^2 + 2.756s + 7.612)}$	2.76	Pool et al, 2009
Car: transfer between steering angle input and lateral displacement of a 950 kg car driving at 25 m/s	$H_{y,\delta}(s) = \frac{K_1 s^2 + K_2 s^2 + K_3}{s^2(s^2 + 9.0655s + 34.2321)}$	5.85	Leqouis et al, 1986

Another criteria was that the desired trajectory could be completed by a feedforward controller with an inverse model of the system dynamics. The maximum obtainable velocity was tuned by the ratio between the maximal velocity of the controller over the maximum velocity of the desired trajectory. This ratio determines how strongly the human perceives the slow response, and how strongly the human can correct for errors. The response of the slow dynamic can be seen in figure A-4. Here it is clearly shown that it takes 3 seconds before the velocity will become equal in the extreme case of a step input. Changing the ratio between the velocities will increase or decrease this “time-to-match”, and thereby determines how strong the human *needs* to predict the slow dynamic behaviour. The ratio also determines how fast human made errors can be reduced.

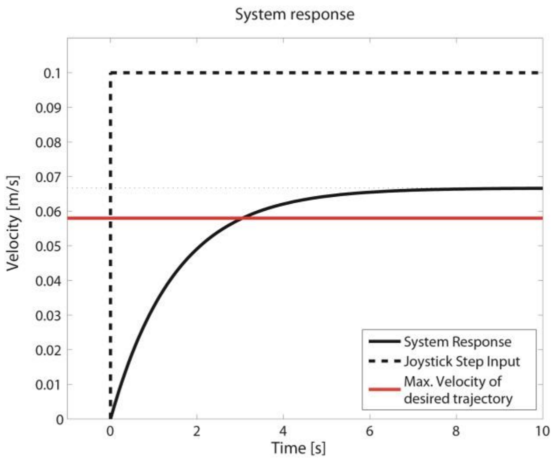


FIGURE A-4: RESPONSE OF THE SLOW DYNAMIC SYSTEM ON A JOYSTICK STEP INPUT. WHERE THE JOYSTICK INPUT CORRESPONDS TO A DESIRED SYSTEM VELOCITY DUE TO RATE CONTROL. THE RISE TIME OF THE SLOW DYNAMIC SYSTEM WAS 1.5 SECONDS. THE MAXIMAL VELOCITY OF THE CONTROLLED SYSTEMS WAS 1.15 TIMES THE MAXIMAL VELOCITY OF THE DESIRED TRAJECTORY VELOCITY.

The final settings of the slow dynamic system were a mass of 6 kg, damping (B) of 2 Ns/m, G_e of 2, and G_f of 0.6641. The two pole locations of this systems are 0 and 2/3 rad/s, and the rise time is 1.5 seconds. This slow dynamic system in combination with the trajectory design could just be controlled by the perfect inverse model of the system dynamics. And the learning curve seen during pilots was around forty trials of 75 seconds each.

ProPrio Hydraulic Manipulator

The chosen manipulator for this study was the ProPrio hydraulic manipulator. This manipulator was used in previous research to determine the neuromuscular properties of the human arm. The manipulator was chosen because the behaviour of the manipulator was highly tuneable, and the maximum produced force was 200 N which was above the required need for this experiment. The ProPrio was controlled with dSpace Controldesk software, where simulation environments could be designed with Matlab Simulink. This study programmed a Matlab GUI for control of the experiment, and a Simulink environment for controlling the trials in the experiment.

Simulink environment

The Simulink environment was used for controlling the interacting parts inherent in study. The inputs of this environment are the position and velocity of joystick, and the force on the joystick handle as can be seen in figure A-5. The output is the force on the joystick. There are five components which should be described independently:

A. Desired Trajectory
B. Desired control input controller
C. Guidance Stiffness
D. Controlled System
E. Manipulator Dynamics

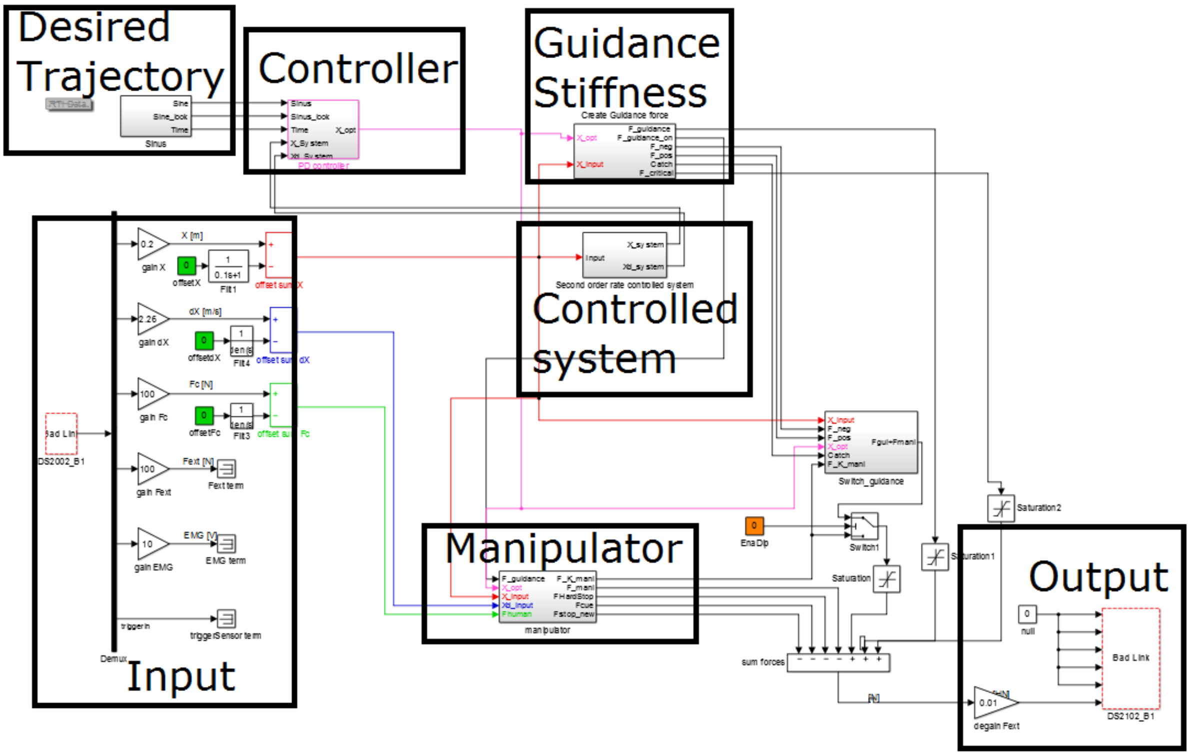


Figure A-5: Developed Simulink environment for control of the manipulator. The environment receives as inputs: the joystick position, joystick velocity, and the force on joystick from the human. The output is the force on the joystick from the manipulator. The manipulator dynamics is designed so that the ProPrio manipulator will mimic the behaviour of a joystick. Where the desired trajectory and controlled system are used to present the manual control task for the subjects. The desired control input controller and guidance stiffness are the components from Haptic Shared Control resulting in guidance forces.

In the Simulink environment are colours used to describe the function of Simulink blocks, or to describe the signal function. The colours used for the Simulink blocks are:

• Orange	(Safety) switches
• Light blue	Task settings
• Green	Variables set with a Matlab Command

The colours used for lines are:

• Red	Position of the joystick
• Blue	Velocity of the joystick
• Light green	Force on joystick
• Pink	Desired (optimal) control input

Desired Trajectory

The desired trajectory function in the Simulink environment determines: the time used in the simulation, the desired trajectory, and the desired trajectory at a certain look-ahead time. The clock determining the time is set and reset by a safety Matlab command. The desired trajectory is loaded from Matlab into the look-up tables used. The blue task gain blocks are tuned so that one cm movement in the desired trajectory in the simulation will correspond to one cm of movement in the visualisation.

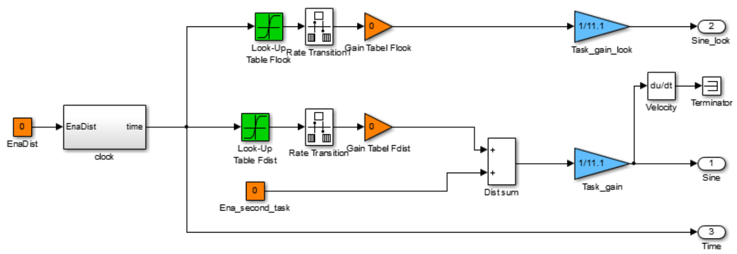


Figure A-6: Desired trajectory function block determining the time, and desired trajectory.

Desired control input controller

The desired control input is determined on basis of a feedforward controller and two feedback controllers. Where one of the feedback controller acts on the current error, and the other on the look-ahead error. The look-ahead position of the system is predicted on basis of the system velocity plus current position. All the controllers are limited to the maximum joystick input. The transfer function of the filter is based on the neuromuscular model of the human arm in a relax task (Schouten,2000) , and is implemented as a second-order filter with a cut-off frequency of around 8.5 Hz. The steady-state gain is one.

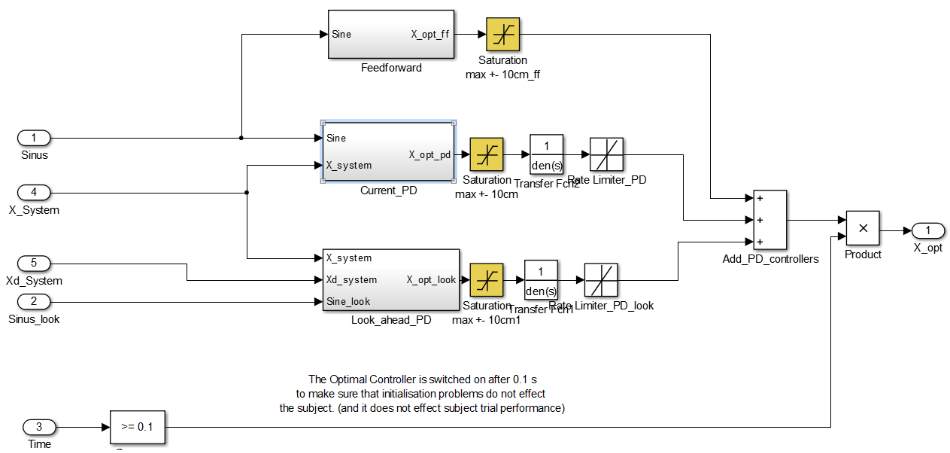


Figure A-7: Desired control input determined by a feedforward and two feedback controllers.

Guidance Stiffness

This function determines the amount of guidance force on basis of the desired control input. The used component in the experiment was only the guidance stiffness (i.e. the blue gain K_critical) transforming position into forces. This function contains also the inverse models of the manipulator and the MBK-model of the human arm (from Van der Helm (2002) and de Vlugt (2001) . Another part is the Force_dip block belonging to a different haptic guidance technique as described in Appendix F. Both the force_dip and the inverse models were implemented, but are not used in this study.

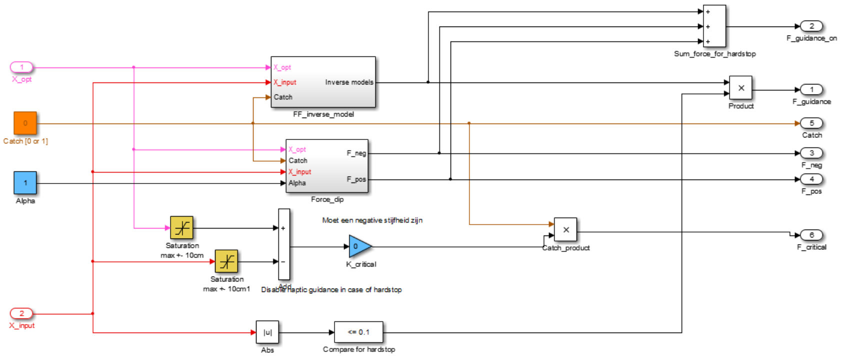


FIGURE A-8: SECOND MAPPING IN HSC WHICH CONVERTS THE DESIRED CONTROL INPUT IN GUIDANCE FORCES. THE EXPERIMENT ONLY USES A GUIDANCE STIFFNESS AROUND THE DESIRED CONTROL INPUT. HOWEVER, THIS FUNCTION IN SIMULINK ALSO HAS THE INVERSE MODELS OF THE MANIPULATOR AND THE INTRINSIC COMPONENTS OF THE HUMAN ARM, AND THE "FORCE-DIP" GUIDANCE METHOD.

Controlled System

Combination of the slow second-order rate controlled system and a position controlled system. The position controlled system is used in the instruction and familiarization phase. Both the systems are reset in position and velocity by doing of offset.

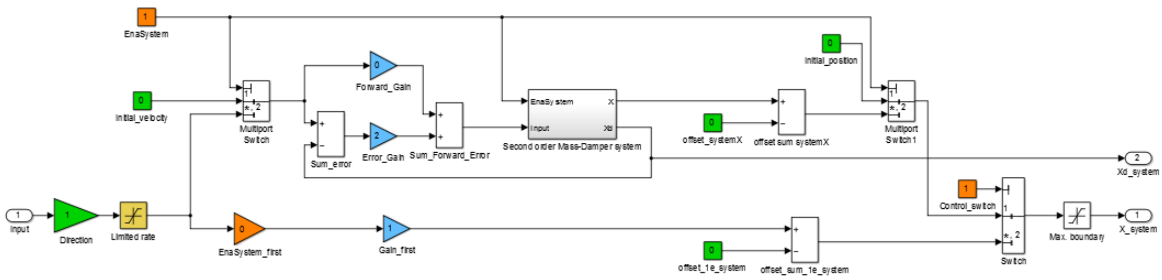


FIGURE A-9: DYNAMICS OF THE SLOW DYNAMIC SYSTEM, AND THE POSITION CONTROLLED SYSTEM USED IN THE INSTRUCTION AND FAMILIRIZATION PHASE.

Manipulator dynamics

The manipulator settings used in the experiment are a combination of: a mass-spring-damper system and maximum input boundaries. The simulation contains also a haptic cue for the zero position. However, this is not used because this will insert a non-linear effect in the experiments. The settings of the mass-spring-damper behaviour are chosen during the pilots. The required behaviour of the manipulator dynamics were designed to have a faster response than the slow dynamic system, and a centering stiffness. The centering stiffness was set at relative low value of 60 N/m due to the on-off switching in the case of HSC training trials, and due to a reducing guidance stiffness ending up at that value. Subjects preferred in pilots a higher value of the manipulators dynamics. The values of the maximum input boundaries are: stiffness of 1250 N/m times the distance to maximum input, and the velocity of joystick to the power of 5 with a damping gain of 1e7 Ns/m.

CONTROL OF MANIPULATOR

The Matlab GUI was developed to reduce the workload during the experiments for the experiment leader, and to provide a controlled experiment setup. The Matlab GUi called *control panel* consisted out of multiple components as can be seen in figure A-11:

- Main control panel
- Settings
- Plotted data

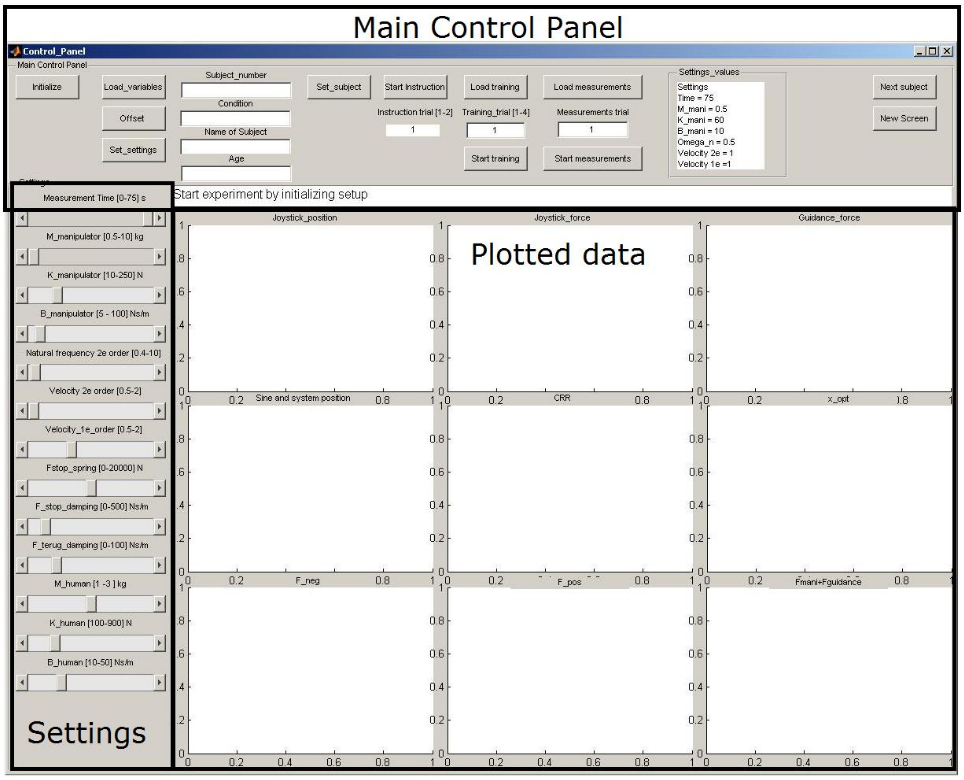


FIGURE A-11: MATLAB GUI FOR CONTROLLING THE EXPERIMENT

The main control panel works as follows:

A. **Initialize** loads the Simulink environment on the industrial pc and loads the pre-made desired trajectories.
B. **Load_variables** loads the variables to the Simulink environment, and loads the initial settings.
C. **Offset** offsets the manipulator position, velocity and force sensors.
D. **Set_settings** sets the settings in the Simulink environment.
E. **Input boxes** are used to choose subject number and corresponding condition. The subjects name and age is temporally stored.
F. **Set_subject** stores the settings used in experiment
G. **Start_instruction** starts the instruction trial
H. **Load training** and **Start training** loads and starts the training.
I. **Load Measurement** and **Start Measurement** loads and starts the actual experiment trials
J. **Next subject** resets the settings
K. **New screen** opens a new visualisation

HAPTIC SHARED CONTROL

Haptic Shared Control is used in this study to guide the human with the means of forces to the desired control input. Two steps, or mappings in the words of Abbink (2012), describe how the environmental cues are related to the guidance forces. Where the first steps transforms the environmental cues into the desired control input, and the second steps converts this desired control input into guidance forces.

In this research, it is the role of the Haptic Shared Control to behave as a teacher. Where the behaviour of the human transforms during the experiment from novice student to expert student. The Haptic Shared Control adapts through the learning process of the human by reducing the stiffness around the desired control input in a similar as the concept of "guidance-as-needed" of Crespo, 2008. The used form of Haptic Shared Control can be seen in figure A-12. The designed form of HSC does not contain information on the neuromuscular properties of the human. However, it is mentioned in previous literature that including neuromuscular knowledge would approve the design of the HSC (Abbink and Mulder, 2010)(Abbink et al., 2012). The main two reasons for not including this (available) neuromuscular knowledge are: in order to compare the results an almost similar approach is used as previous literature (Crespo, 2008(Milot, 2010), and ii) this inverse model of the physical interaction should also be increased during the learning process in order to have a similar approach as the reduced guidance stiffness. However, the centering stiffness from the joystick is removed during the HSC training trials. This is only possible in the case of the virtual stiffness used by the ProPrio, but real-life joysticks should use the inverse model of the stiffness to do this.

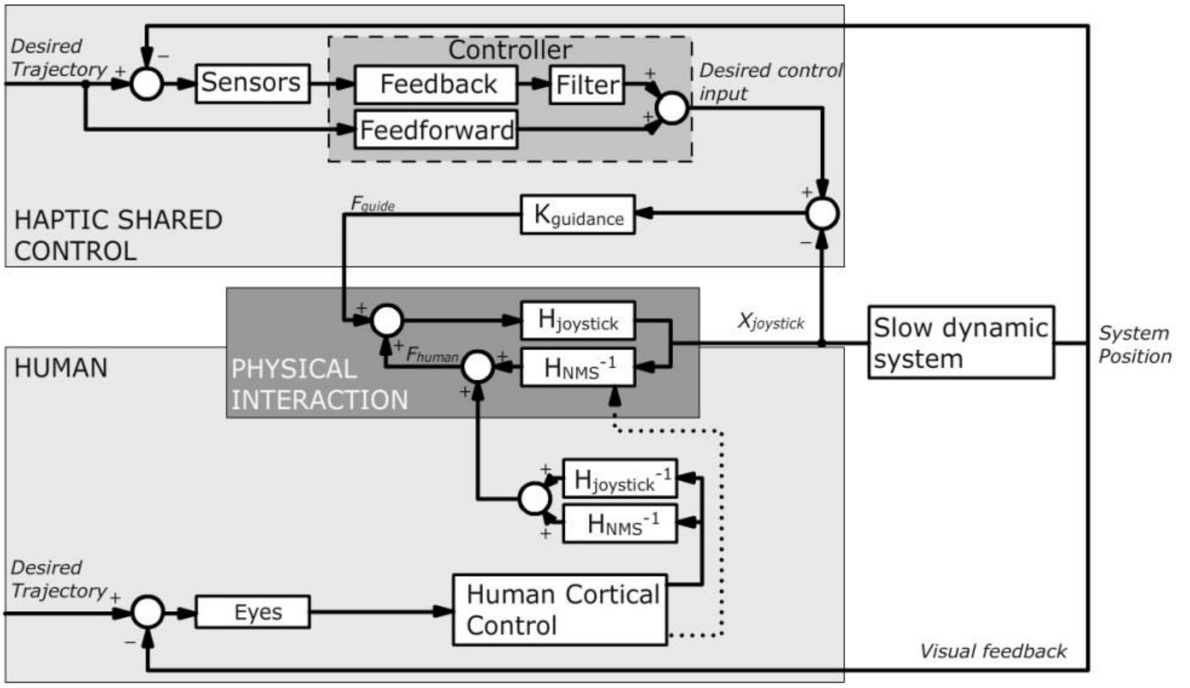


FIGURE A-12: USED IMPLEMENTATION OF HAPTIC SHARED CONTROL WHERE THE HUMAN INTERACTS WITH THE HAPTIC SHARED CONTROL BY COMMUNICATION WITH FORCES ON THE JOYSTICK. THE GUIDANCE FORCES ARE DETERMINED ON BASIS OF THE STIFFNESS AROUND A DESIRED CONTROL INPUT. WERE THE DESIRED CONTROL INPUT IS DETERMINED BY A FEEDFORWARD AND FEEDBACK CONTROLLER. NO NEUROMUSCULAR IS INCLUDED IN THE USED FORM OF HAPTIC SHARED CONTROL.(FIGURE ADAPTED FROM ABBINK, 2011.)

CONTROLLER DESIGN

Multiple controller design have been proposed and tested during the development phase leading to the actual controller in the final experiment. The final setup was a combination of a feedforward and a feedback controller. However, in earlier trials it was tried to design and optimize a feedback controller. Describing the different tested feedback controller will be needed for clarifying why a feedforward controller is required. Multiple feedback controller design are proposed during this study and are based on ideas from previous literature such as the predictive controller (Forsyth, 2006). Also the feedback design for the “guidance-as-needed” literature (Crespo, 2008) was tested. The components implemented at some point in the feedback controller were:

- P, PD, PID controller on the current error between trajectory and system position
- P and PD controller on the look-ahead error between trajectory in the future and predicted system position.
- P and PD controller on the angle towards the predicted position (Crespo, 2008)

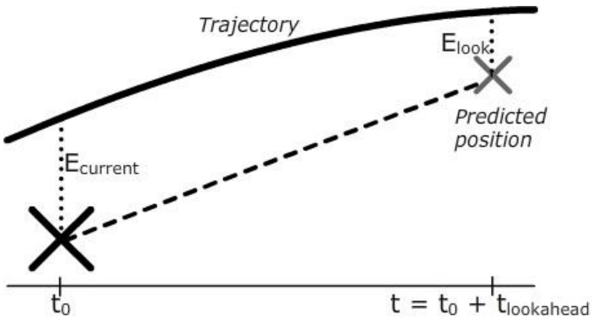


FIGURE A-13: ERRORS USED IN THE DIFFERENT FEEDBACK CONTROLLER DESIGNS.

The predicted system position was either determined on basis of the current position and velocity as done for the actual experiment, or with current position, velocity and acceleration.

A simple optimization was used to find the controller gains that resulted in the optimal control input. This simple optimization was a basic grid-search in order to provide insight in the results of the optimization. The optimization used a simulated model of the manipulator, example desired trajectory, controlled system, and the HSC. The optimization looked at the Absolute Mean Position Error, and number of control reversals (e.g. joystick reversal rate). The optimization parameters were the different controller settings including the look-ahead. A simple grid-search result can be seen in figure A-14.

The first component or the first mapping relates the environmental cues into the desired control input. This section will describe the process during the thesis of finding the proper controller, and the lessons learned during that process. The learned lessons during pilots, or during manual tuning sessions and simulation runs have contributed mostly to the final implementation of feedforward and feedback controller. This optimization only looked at relative low values for the gains of a PD controller, and show the results of the Absolute Mean Position Error. Higher controller gains were possible, however high control gains are not beneficial in the case of this setup of rate control with slow dynamic system.

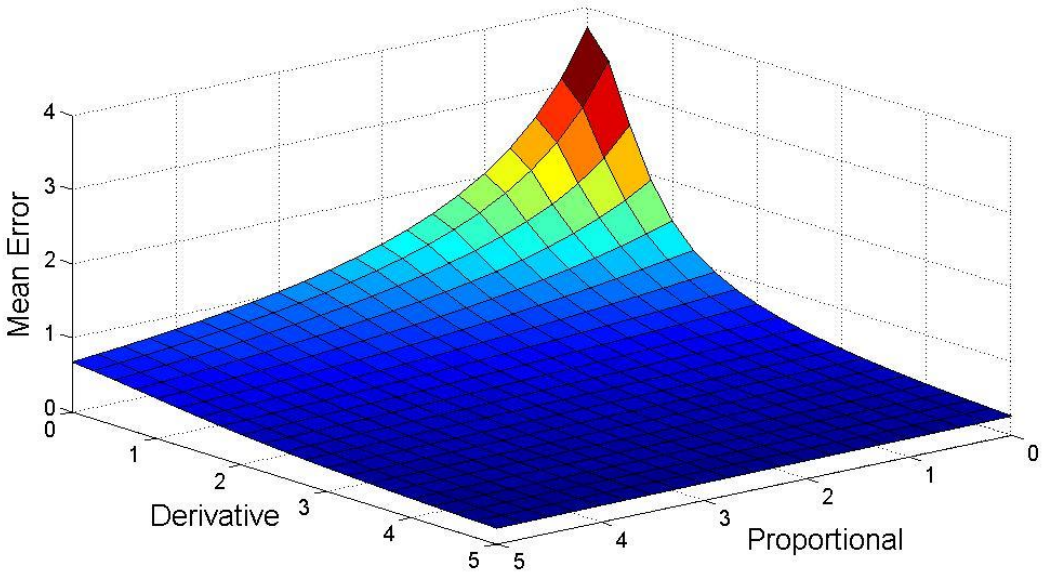


FIGURE A-13: RESULT OF A SIMPLE GRID-SEARCH FOR A PD-CONTROLLER ON THE CURRENT ERROR BETWEEN DESIRED TRAJECTORY AND SYSTEM POSITION. THE ABSOLUTE MEAN ERROR WILL EVEN MORE DECREASE FOR HIGHER PROPORTIONAL AND DERIVATIVES SETTINGS.

The main problem with the pure feedback controller design was that even relative low controller gains resulted in quite aggressive behavior. A better way to describe this behaviour is to describe a simple example. Where the important thing to keep in mind is that even the maximum inputs from the joystick will not immediately result in a decreased error. For instance, take the example of a pure proportional feedback controller on the current error with a gain of 5. This means that an error of 0.02 m on the screen will result in maximum output of the joystick. The problem with this example is that a proportional is not enough to result in low error, and will keep the controlled system around the trajectory. What often happened was that the proportional controlling was first at -0.02 m and a few moments later at 0.02 m. This was mainly the case on when the position of the desired trajectory was at a peak. Even including a look-ahead controller did not fix this problem, because at the peaks the controller should look ahead. However, at more straight sections should the look ahead time by reduced in order to not deviate too much from the desired trajectory. Also implementing a filter of the feedback control actions to limit too fast responses did not succeed. The final solutions was to use a feedforward controller for predicting the optimal control input for a certain trajectory and using a feedback controller for enabling the ability to interact. This impacted the optimization procedure, because the feedforward controller designed was perfect for the controlled task. The only reason that the error of the controller was not zero, was due to connection of the desired trajectory designed in the frequency domain with the smoothed inputs and outputs. The desired trajectory had an acceleration difference at these locations, that could not influence the measurement (due to the chosen data analysis range) but influenced the performance of the feedforward controller.

CONTROLLER TUNING

As described before, optimizing the controller design should be done on other criteria than the performance due to the included feedforward controller with the perfect inverse model. Therefore, the controller settings of the feedback controller, which is the only part which needed to be tuned, was done with the use of simulations and manually. In simulations the behaviour of the feedback controller was simulated by looking how the feedback controller would cope with a smoothed added error. Where the smoothed error would represented an error made by the human. Finally the choice of the feedback controller was made on basis of literature (Forsyth, 2006) and on response in simulations. The choice of parameters of this feedback controller was done by tuning on the ProPrio manipulator; by perceiving the maximum errors made by subjects in pilot studies; and to see when the feedback controller could overrule the feedforward controller in too large errors. The maximum allowed current error was thereby set at 0.02 m, and the look-ahead error at a time of 0.75 in the future was set at 0.04. For these situations should the joystick go to the maximal possible input.

Decreasing Guidance Stiffness

The decreasing stiffness was based on the concept of "guidance-as-needed" from Crespo (2008) and Emken (2008). This study uses that the concept, however with the two differences that: i) in guidance-as-needed is the controller integrated with the guidance stiffness, and ii) the decreasing stiffness is in the concept dependent on the performance of the subject. The research of Crespo (2010) uses that concept for a steering task with the similar limitation of fixed exponentially decreasing guidance. The used equation for the decreasing guidance is as follows:

$$K_{guidance}(n+1) = f_r * K_{guidance}(n)$$

Where $K_{guidance}$ is the stiffness in trial n relating the desired control input to the guidance force, and f_r is the forgetting factor. Emken (2008) describes how the forgetting factor should be designed in such a way that guidance will always be a step ahead of the human in order to stimulate that the learns the dynamics. He also describe simulations on how to determine the forgetting factor for rehabilitation of walking. However, in the research the task is learning to control a slow dynamic system. Thereby, the forgetting factor cannot be based on down regulating of the visuomotor gains during learning of the slow dynamics. This research tuned the initial guidance stiffness and the forgetting factor on multiple factors. First the information from the research done on the ProPrio for assessing the neuromuscular properties of the human arm (Schouten, 2008). Combining this with tuning of this initial guidance, resulted in the chosen value of 338 N/m. The forgetting factor is determined on basis of the number of HSC training trials, and the required behaviour that the guidance stiffness should end up with almost a similar stiffness as the manipulator in the last training trial.

TRAJECTORY DESIGN

The trajectory was designed in the frequency domain in order to design unpredictable trajectories which can be used for signal analysis. The main advantage of the frequency domain approach for this study was that it was able to form different trajectories with almost similar difficulty. The trajectories were made with a Matlab m-file written by D.A. Abbink called the '*DisturbanceGenerator_Wavelot_FullPower*' based on the multisine design of Pintelon and Schoukens (2004). The settings in this file were adjusted, and minor changes were made to the code. To start with the settings, the requirements for the desired trajectory were:

- A preferred length of around one minute
- The highest included frequency lower than the natural frequency of controlled system

The preferred length of one minute was chosen to have a trajectory based on multiple frequencies, and a trajectory short enough to assess the learning process with multiple trials. The highest frequency should be higher than the natural frequency of the controlled system in order to not present too difficult trajectories. The resulting four frequencies that could be included were: 0.0191, 0.0382, 0.0753, and 0.0764 Hz. The final duration of the signal was 52.42 seconds. The signal was sampled with a sample frequency of 1250 Hz, and contained 2^{16} points. An example of the trajectory can be seen in figure A-14.

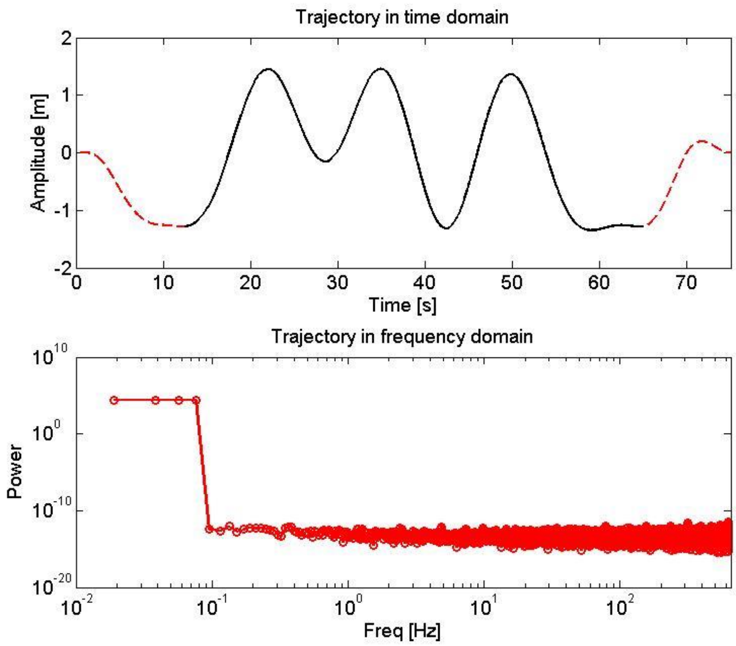


FIGURE A-14: TRAJECTORY DESIGN IN BOTH THE TIME DOMAIN AND IN THE FREQUENCY DOMAIN.

The trajectory signal was added with a smoothed input and output. Both the smoothed input and output was a shifted cosinus with a frequency of 0.5 Hz.

Two changes in the matlab script were made in order to make the trajectory suitable for slow dynamic systems. The first is that the data is not stored with the *cvswrite* command, but with the *dlmwrite* command. Csvwrite writes the signal in the matlab short length, while dlmwrite provides the option to write the signal in more decimals. Were 10 decimals are used in this study. Writing the signal with csvwrite caused problems when the signal needed to be differentiated for the differential controller, and the relating the desired control input with an inverse model (containing 2 differentiators) into the required force.

The second change made is too limit the velocity difference between the smooth input and output signal and the frequency domain signal. The current script assures that the position of the smooth input and the designed trajectory matches. However, there are velocity and acceleration differences which cause a jump in the control command for the guidance feedforward controller. The velocity difference is minimized in the Matlab script by shifting the desired trajectory in the frequency domain until the minimal velocity difference is found.

250 trajectory were designed in the frequency domain, and from these 250 trajectory were 41 trajectories selected on basis of their maximum velocity. This procedure was to done to minimize the variance in maximum velocity. Where the maximum velocity is important due to the difficulty of the system based on this velocity. The mean of the maximum velocity of the 250 trials was used to found the 41 trials that were the closest to this mean. The resulting 41 trials trajectories can be seen in figure A-15. Forty of these trials were used in the actual experiment, and one trials was used for the instruction and familiarization phase. All the trajectory had the limited design of four fast movements, two medium movements, and one relative strait section.

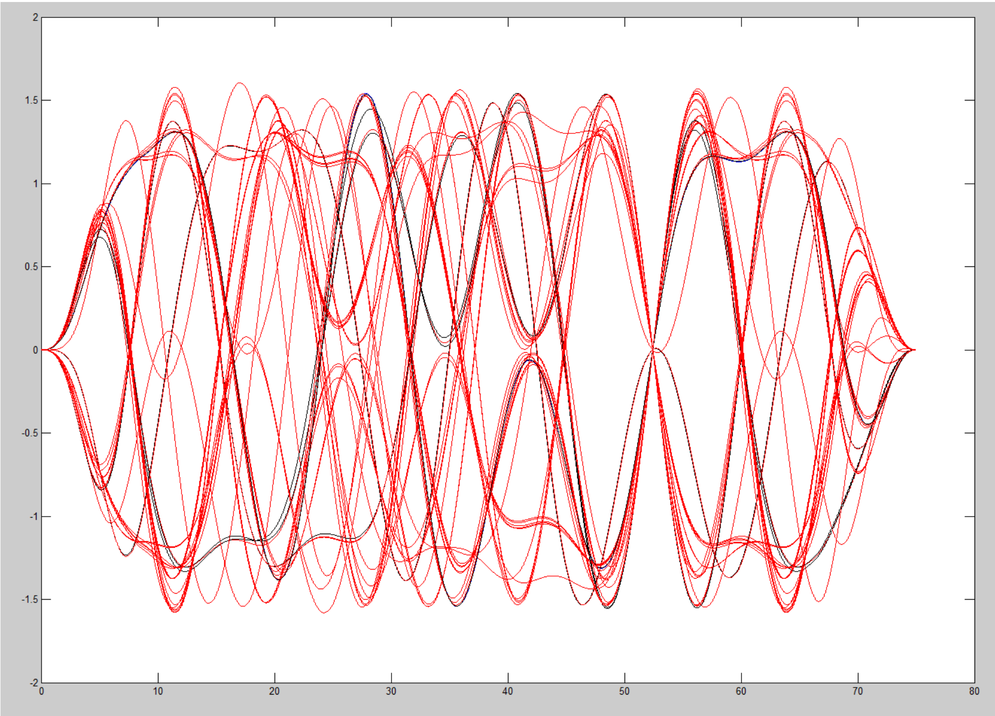


FIGURE A-15: POSITION OF ALL THE 41 DESIRED TRAJECTORIES USED IN THE EXPERIMENT

Experiment Instructions

The experiment instructions were given to subjects on paper in order to provide each subject with a similar set of instructions on the required task. The experimental instructions described the required task, behaviour of manipulator, experiment setup, and data storage procedure. There were two different experiment instructions: one for the No Guidance condition, and one for the Haptic Guidance conditions. Subjects with Haptic Guidance received a slightly different text, which included information about the haptic guidance which they received. All subjects confirmed in an informed consent that they have read the experiment instructions, and they were aware that they could stop with the experiment at any time.

Experiment Instructions (No Guidance)

Experiment instructions

You will participate in a manual control experiment were the goal is to learn the dynamics of an object. The simple objective in this experiment is to keep the controlled object (visualized by the cross) at the target line (figure 1). The object can be controlled in the vertical direction by moving the hydraulic actuator from the Proprio manipulator (figure 2). You will be controlling the hydraulic manipulator from a seated position during the 40 trials, with a length of 75 seconds each. Small rest periods will be possible during trials. The complete duration of the experiment will be around 1.5 hour.

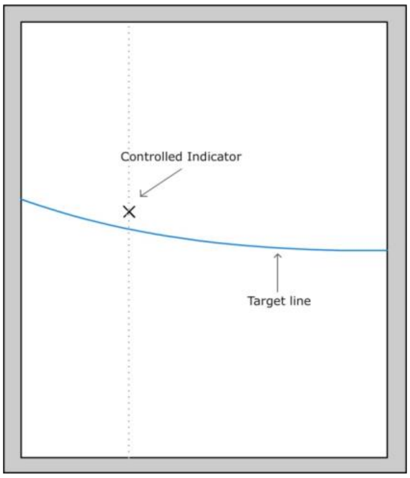


FIGURE 1: TASK ON SCREEN

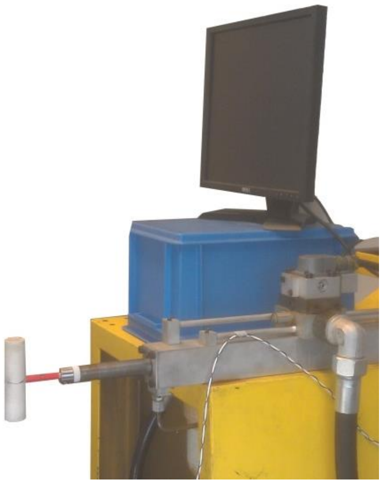


FIGURE 2: PROPRIO MANIPULATOR

The behavior of the Proprio is made in such a way that it mimics the behavior of a joystick. This implies that a forward position will result in a vertical **velocity** of the cross upwards; and vice-versa for the backward position. The special features of the Proprio are that it has a centering stiffness to return the manipulator towards a zero velocity input (see figure 3), and that it has a maximum input range. During the experiment it is preferred to use the maximum input as minimal as possible. You will have some time during the training phase to feel the centering stiffness, maximum input range, and direction of input.

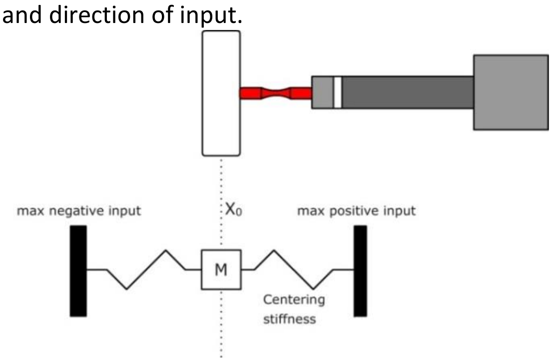


Figure 3: Proprio manipulator mimics joystick behavior with centering stiffness, and limited maximal inputs.

Before the experiment starts, the experiment leader will twice offset (set the zero position) of the hydraulic manipulator for your arm. Your task, for the first offset, is to find a position where your lower arm is horizontal . This can be seen in figure 4. A horizontal position can be found by adjusting the chair and by moving your arm. The experiment leader will help you with making the required seating position. The second offset requires that you release the handle. This makes it possible to offset the force sensor.

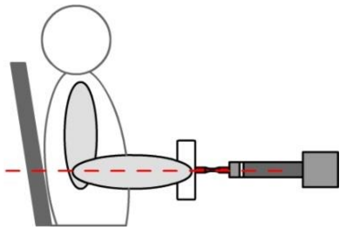


Figure 4: Required position for offset procedure

The experiment itself will consist out of three different phases:

In the **instruction phase,** the experiment leader will tell you what is expected from you. You do not need to grab the hydraulic actuator in this phase.
In the short **training phase,** you will have the time to feel the behavior of the manipulator. The duration of the training phase is ½ trial and the behavior of the controlled object (black cross on screen) is different than in the learning phase. However, this provides you with some time to feel the joystick behavior of the hydraulic actuator.
The **learning phase** will consist out of 40 trials and is the actual experiment were you will learn the dynamics of the object (visualized with the cross). After every trial a performance indication is given. It is your goal to reach, as close by as possible, the 100% score.

You will receive a questionnaire after completing every trial. This questionnaire consist out of six scales, and only after the first trial contains the questionnaire an extra fifteen pair-wise comparisons. The experiment leader will guide you through the questionnaire.

Short periods of rest (~10 sec) are available between trails, and a longer rest period is given after the twentieth trial. After 40 trials is the experiment done.

You can always ask the experiment leader for more instructions when needed.
Your first name, age, length, and performance during trials will be recorded for data processing. All personal data will only be visible for the experiment leader and the personal data will be removed after two months. Anonymized research data can be seen by a group of researchers.

Thank you for your assistance,

Experiment Instructions (Haptic Guidance)

For the Haptic Guidance condition experiment instruction was an extra instruction added to explain how the subjects should interact with the haptic guidance. This extra instruction was added to instructions belonging to the learning phase.

In certain trials, you will receive force guidance from manipulator which are meant as an example on how you can perform the task. During those trials it is your task to corporate with the force guidance and to feel how the guidance states that you should perform the task. The experiment leader will tell you when these trials occur.

Informed Consent

The informed consent presented and signed by all the subjects in this study can be seen below. The subject stated in the informed consent that he or she: had read the experiment instructions; understand what the required task was; was aware that at any point they could stop with the experiment; that personal data is stored for two months and is then removed; and that anonymized data, without any link to actual subject, can be seen by a group of researchers.

Informed Consent

Topic of research: Manual control of a slow dynamic systems

I confirm that I read and understood the written experiment instructions for the manual control experiment. I understand that my task is to do a manual control task for 90 minutes . I was able to ask questions, and I am satisfied with the answers to my questions.

I am aware that my participation is voluntary and that I can stop with the experiment at any time.

I know that personal data (first name, age, length of subject) is stored for two months and can only be accessed by the experiment leader (Vincent Honing). I am aware that my anonymized data can be seen by a group of researchers.

I agree in participating in this research.

Name participant: ____________________

Participant Signature: _________________________ Date: __/__/____

DATA MANAGEMENT

During the experiment was 9.5 Gb of data recorded for the twenty subjects. The data was divided into: 800 measurement trials, 40 training trials, 40 familiarization trials, 40 NASA-TLX questionnaires, 40 subject settings files, and 800 visual frequency data. The raw data is available from the repository as well as the script used to pre-process the data. Individual data can be assessed through the developed data-analysis Matlab GUI. Individual metrics scripts are provided to assess the data efficiently.

The stored data during the experiment consisted out of 22 variables ranging from external variables (e.g. position of joystick) to internal variables (e.g. position of controlled system). Some of the variables were redundant. The stored data contained:

#	Name of variable	Short Explanation
1	Vars.X	Position of the joystick
2	Vars.dX	Velocity of the joystick
3	Vars.Fc	Force on the joystick
4	Vars.X_system	Position of the controlled system
5	Vars.Xd_system	Velocity of the controlled system
6	Vars.Time	Time in the simulation
7	Vars.X_sine	Position of the desired trajectory
8	Vars.Xd_sine	Velocity of the desired trajectory
9	Vars.X_sine_look	Position of the desired trajectory at the lookahead time
10	Vars.X_predict	Predicted position of the controlled system at the lookahead time
11	Vars.Error_current	Error between desired trajectory and system position
12	Vars.Error_look	Error between lookahead desired trajectory and predicted system position
13	Vars.Xopt_pd	Desired control input on basis of proportional times error
14	Vars.Xopt_pd_look	Desired control input on basis of proportional times lookahead error
15	Vars.Xopt	Complete desired control input (feedforward and feedback)
16	Vars.Xdiff	Difference between joystick position and desired control input
17	Vars.F_DM_mani	Force used to create damping and inertia in joystick
18	Vars.F_K_mani	Force used to create centering behaviour of joystick
19	Vars.F_critical	Haptic Guidance force
20	Vars.Fstop	Force from the maximum inputs
21	Vars.Fsum	Total force exerted on the manipulator
22	Vars.Xoptff	Desired control input according to feedforward controller

INDIVIDUAL DATA PROCESSING

For the individual data processing a Matlab GUI was developed to assess the subject specific data in the pilots or in the experiments. The GUI provided the opportunity to assess and discuss the raw data. The individual data processing script is included in the delivered data.

The Matlab Data-analysis GUI works as following:

- Enter the maximal number of subjects (1-20)
- Enter the maximal number of trials (always 40)
- Press Load Subject and wait…
- All subjects performance and control activity will appear in box 3 and 6
- Choose subject and press Load Subject, data will appear in box 9 and 12
- Choose trial and press Plot Data, data will appear in the left boxes
- Large screen plots for: Joystick input, trial performance, Control effort, Fhuman, trail performance velocity, trial performance acceleration, and Trial PSD can be acquired by using the Plot Item with Create Figure

The Matlab Data-analysis GUI can be seen below.

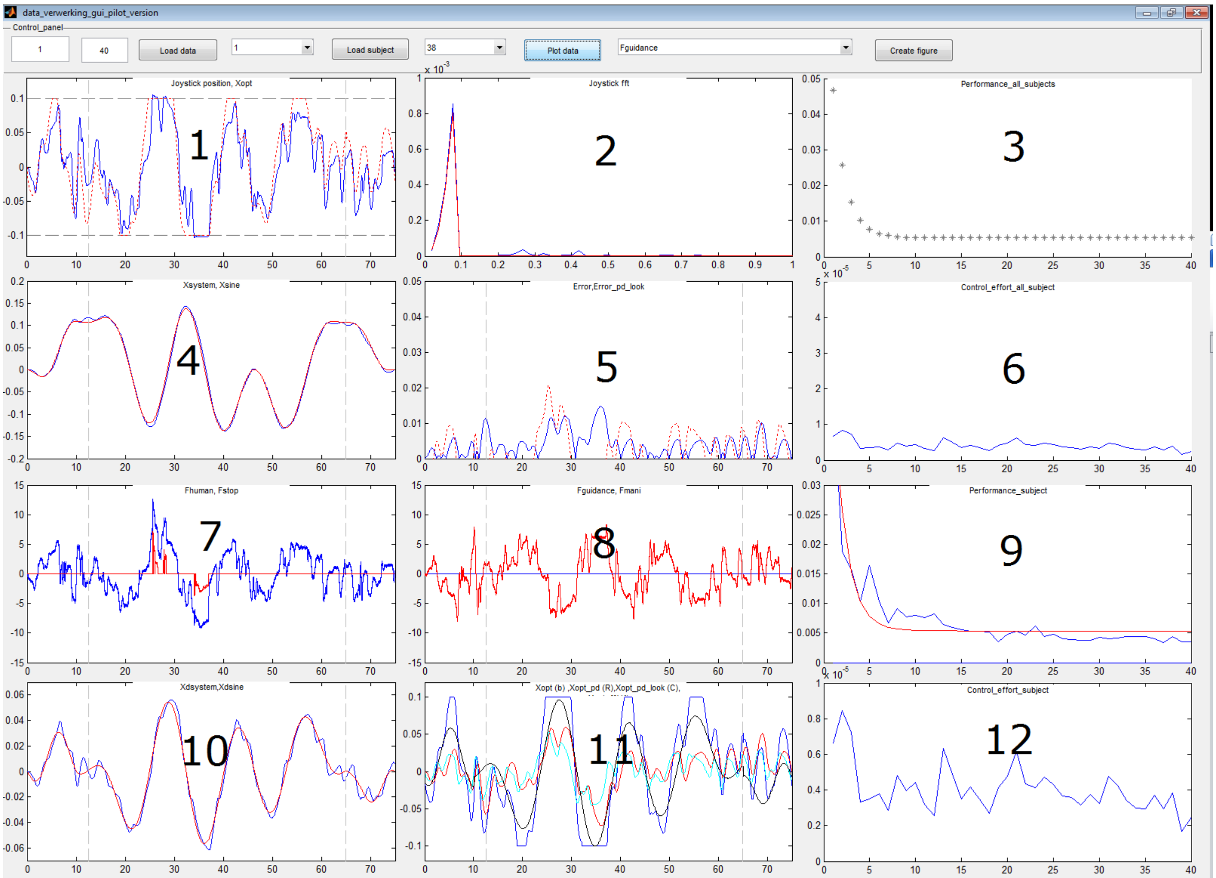


FIGURE A-16: MATLAB DATA-ANALYSIS GUI USED FOR INDIVIDUAL DATA ASSESSMENT.

The twelve different plots are used to assess:

Plot number	Data displayed
1	Joystick position (blue) optimal control input from feedforward controller (red)
2	PSD of the joystick input (blue), and the feedforward desired control input (red)
3	All subjects performance assessed by exponential learning curve
4	Controlled system position (blue) and desired trajectory (red)
5	Error between controlled system and desired trajectory (blue), and lookahead error (red)
6	All subjects control activity as the summation of the PSD
7	Human applied force (blue) and force from maximum inputs (red)
8	Joystick force (red) and guidance force (blue)
9	Performance of subject: Absolute mean position error (blue) and fitted learning curve
10	Velocity of controlled system (blue) and velocity of desired trajectory (red)
11	Desired control input: all (blue), FB_error (red), FB_lookahead (cyan), FF (black)
12	Control activity of the subject assessed by summation of PSD

Appendix B: Pilot A, Manual control behaviour study

The first preliminarily pilot was used to assess how the behaviour of the subjects changed under certain conditions. One of the important parts in this study were the comments from the subjects over the different settings used. The comments could range from difficulty of task to duration of task. This information was used to improve the experiment setup. The subjects data was also processed to assess the performance learning curves of the subject.

Goal	To assess the natural subject behaviour under different experiment setups. The goal of the pilot was to gain insight in the subject behaviour, and to collect comments about the experiment setup.
Sub-goals	Subject 1 (NG): to assess initial experiment setup Subject 2 (NG): to assess length of learning curve and behaviour in a pursuit task Subject 3 (NG): to assess length of learning curve and behaviour in a pursuit task with preview Subject 4 (HG): to assess effect of the initial HSC design Subject 5 (NG): to assess behaviour at a more difficult task and with vertical display
Subjects	Five subjects participated in this study. All subjects had no experience with this setup, and three of the subjects were right-handed.
Apparatus	ProPrio manipulator with horizontal or vertical display with and without preview of 2 seconds. The centering stiffness of the manipulator was either 60 N/m or 160 N/m for the later subjects. The manipulator had maximum input boundaries by a local position controller with release criteria, and a haptic cue at the zero position.
Task description	Subjects had to pursuit a desired trajectory by moving the hydraulic manipulator as in the actual experiment. The subjects received an instruction, either written or verbally, and had an instruction trial in combination with familiarization trials. The length of the experiment was: 20 trials (subject 1), 50 trials (subject 2), or 40 trials (subject 3,4, and 5).
Experiment design	The natural frequency of the controlled system was 0.5 rad/s, and the task difficulty by the velocity ratio was 2. The desired trajectory contained three frequencies in the power spectrum density. The HSC was designed on basis of a feedback controller, and the initial guidance stiffness was 169 N/m. Structure of the experiment: Instruction trial One or two familiarization trials 20, 40, or 50 experiment trials Where the Haptic Guidance condition had eight catch trials in the first thirty experiment trials to see how learning of the system dynamics progressed.
Metrics	Absolute Mean Position Error as performance metrics Control activity assessed in the data processing GUI

Performance results of pilot study A:

The first pilot study was executed to give insight in the proposed setup instruction trial, familiarization trial, and experiment trials. The results of this pilot study can be seen in figure B-1.

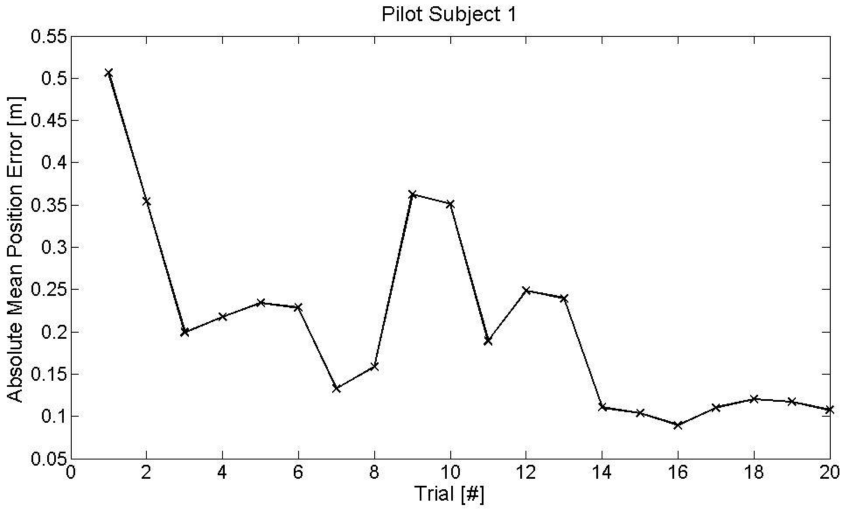


FIGURE B-1: THE ABSOLUTE MEAN POSITION ERROR OF THE FIRST PILOT SUBJECT. THE SUBJECT HAD TO PURSUIT WITHOUT PREVIEW A SLOW DYNAMIC WITH AN UNDAMPED NATURAL FREQUENCY OF 0.5 RAD/S. THIS FIRST PILOT STUDY WAS DONE TO SEE IF THE SETUP OF INSTRUCTION TRIALS, 2 TRAININGS TRIALS, AND 20 EXPERIMENT TRIALS RESULTED IN THE REQUIRED BEHAVIOUR. THE VISUALISATION WAS DONE WITH A 10 MM CROSS ON THE HORIZONTAL SCREEN. WHERE THE DESIRED TRAJECTORY WAS DISPLAYED WITH ONLY A BLUE LINE.

The second pilot study was used to see how long the learning curve would be for one particular setup. The subject in this study was highly motivated and the final result was a relative long learning process as depicted in figure B-2, and increasing control activity evaluated in the frequency domain. On basis of this increased control activity was determined to include a preview for the next pilot study.

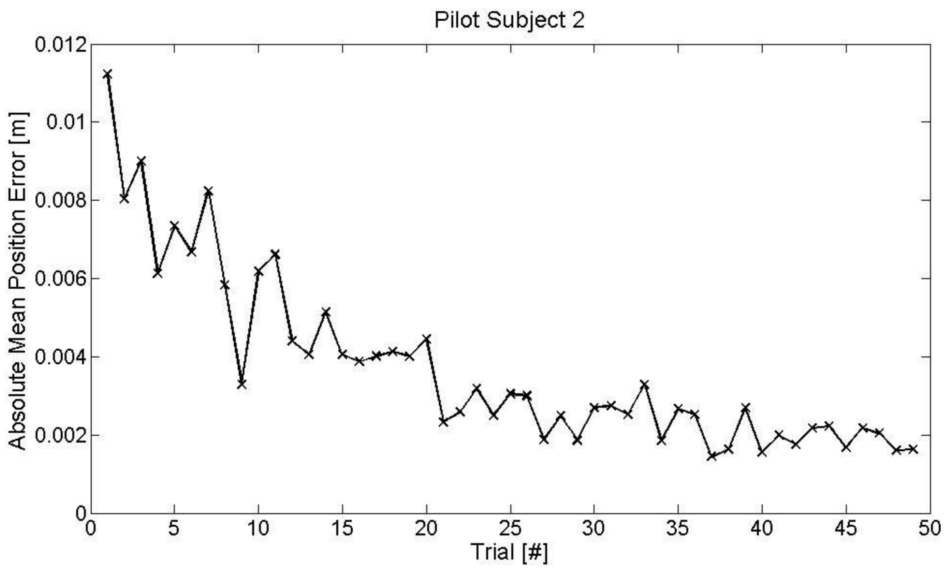


FIGURE B-2: THE ABSOLUTE MEAN POSITION ERROR OF THE SECOND PILOT SUBJECT. THE SUBJECT HAD THE SIMILAR TASK AS SUBJECT ONE. HOWEVER, THE GOAL OF THIS STUDY WAS TO SEE HOW THE SUBJECT PROGRESSED OVER 50-TRIAL LONG EXPERIMENT. THE RESULTS SHOW A LOW ERROR AND A LONG LEARNING CURVE. THE CONTROL ACTIVITY FOR THIS PILOT STUDY WAS HIGH, AND IN COMBINATION WITH THE COMMENTS OF THE SUBJECT IS WHAT DETERMINED TO IMPLEMENT A PREVIEW. THE DURATION OF 50 TRIALS WAS CONSIDERED RELATIVE LONG.

For the third pilot study a number a things was done differently. The main change was including a 2 seconds preview to the visualization in order to decrease the increasing control activity during the trials. The manipulator stiffness was also increased to 160 N/m in order to see if this had an effect on the control activity. The resulting performance learning curve assessed by the mean error can be seen in figure B-3, and the control activity was evaluated by the data processing GUI and showed limited improvement.

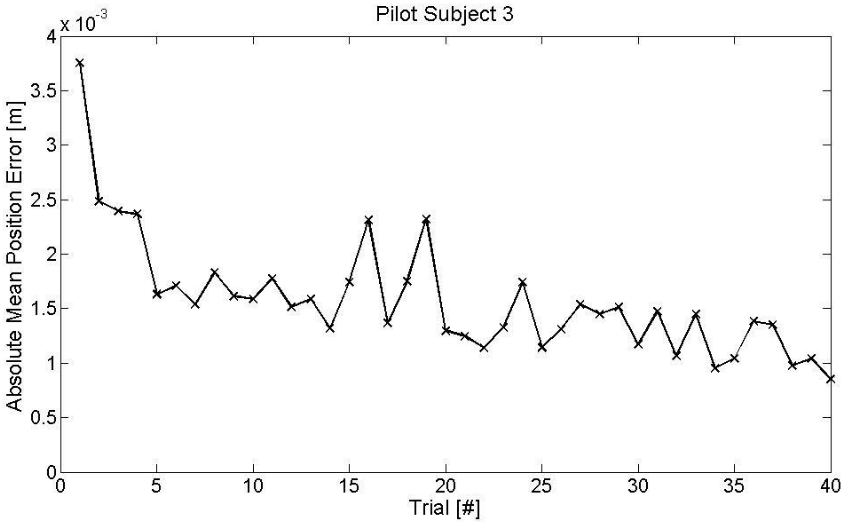


FIGURE B-3: THE ABSOLUTE MEAN POSITION ERROR OF THE LEFT-HANDED THIRD PILOT SUBJECT. A TWO SECONDS OF PREVIEW, AND A ONE SECONDS OF HISTORY WAS ADDED TO THE VISUALISATION. THE STIFFNESS OF THE MANIPULATOR INCREASED TO 160 N/M IN ORDER TO MINIMIZE THE CONTROL ACTIVITY. THE RESULTING PERFORMANCE CURVE IS NOT NEAR A CONSTANT VALUE AT THE END.

The goal of pilot study four was to see how a subject responded to a still not perfect tuned feedback controller. The experimental setup was based on the "catch-trial" design, where the subject had eight catch-trial to assess the learning performance. The initial guidance stiffness was 169 N/m. The main comment from the subject in catch-trial was: "Put the fancy support system on, why should I to this myself".

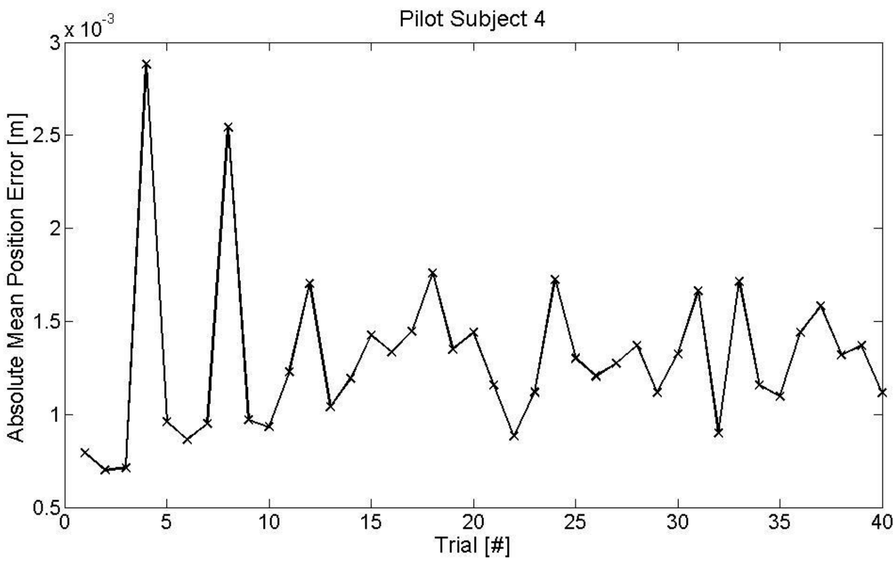


FIGURE B-4: THE FIRST RESULT OF THE ABSOLUTE MEAN POSITION ERROR FOR THE HAPTIC GUIDANCE CONDITION. THE DESIRED CONTROL INPUT WAS DETERMINED ON BASIS OF A FEEDBACK CONTROLLER. AND THE EXPERIMENT DESIGN CONSISTED OUT OF EIGHT SO CALLED "CATCH-TRIALS" WHERE THE HSC WAS NOT ACTIVE TO SEE HOW LEARNING OF THE SYSTEM DYNAMICS

PROGRESSED. THE EFFECT OF THESE "CATCH-TRIALS" CAN BE SEEN BY THE PEAKS AT FOR INSTANCE TRIAL 4 AND TRIAL 7. NO CATCH TRIALS WERE INCLUDED AFTER THE THIRTIETH TRIAL, TO FORM THE POST-LEARNING BASELINE. THE GUIDANCE STIFFNESS WAS SET AT 169 N/M FOR THE INITIAL LEARNING TRIALS, AND THIS SUBJECT COULD OVERRULE THIS STIFFNESS WITH EASE. THE FINAL PERFORMANCE IN THE POST-LEARNING BASELINE WAS NOT BETTER THAN PILOT SUBJECT 3.

The last pilot subject in Pilot study B was used to fine tune behaviour of the setup. The main change was rotating the display into the vertical direction. This provided the opportunity to increase the scale of the visualization in order to present larger errors. The performance result can be seen in figure B-5, and the required long learning curve was missing for this combination of subject and task. It was decided to decrease the size of the visualized controlled system depicted by a cross from 10 mm to 5 mm.

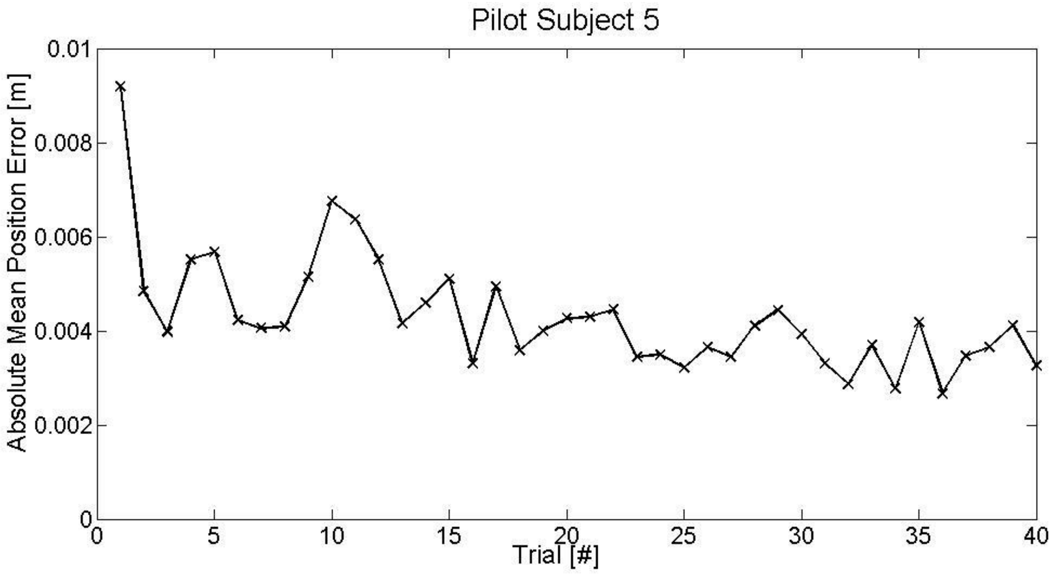


FIGURE B-5:THE ABSOLUTE MEAN POSITION ERROR OF FIFTH PILOT SUBJECT. FOR THIS FIFTH PILOT SUBJECT WAS THE DISPLAY ROTATED TO A VERTICAL POSITION, IN ORDER TO PRESENT LARGER MOVEMENTS THAN IN THE PREVIOUS PILOTS. THE SIZE OF THE CONTROLLED SYSTEM CROSS WAS STILL AROUND 10 MM, AND THE TASK DIFFICULTY WAS AROUND 2. WHERE THE TASK DIFFICULTY WAS STILL DEFINED AS THE RATIO BETWEEN THE MAXIMAL SYSTEM VELOCITY OVER THE DESIRED TRAJECTORY VELOCITY. THE PERFORMANCE INDICATION WAS IMPROVED FOR THIS PILOT. THE RESULTS OF THIS PILOT WERE ALMOST NEAR THE REQUIRED BEHAVIOUR IN THE ACTUAL EXPERIMENT. HOWEVER, THE TASK DIFFICULTY WAS SLIGHTLY TOO LOW. THIS CAN BE SEEN BY A RELATIVE CONSTANT PERFORMANCE AFTER TRIAL TWENTY.

APPENDIX C: PILOT B, SUBJECT BEHAVIOR STUDY WITH AND WITHOUT HSC.

Where pilot study A was used to give insight in the subject behaviour, it is was the goal of pilot study B to give insight if the proposed experimental setup resulted in the required results. The basic experimental setup was developed and assessed in pilot study A, and this study progressed on finalizing the tuning of the task difficulty and the HSC.

Goal	To assess if the proposed experimental setup will result in improved performance and lower control activity.
Sub-goals	Subject 5 (NG): assess the performance and control activity Subject 6 (HG): assess the behaviour of the HSC on performance and control activity, where the desired control input was determined with feedback controller Subject 7 (HG): assess the behaviour of the HSC on performance and control activity, where the desired control input was determined with feedback and feedforward controller.
Subjects	Three subjects participated in this pilot study. All subjects had no experience with this particularly setup, and all the subject were right-handed.
Apparatus	ProPrio manipulator with vertical display and preview of 2 seconds. The centering stiffness of the manipulator was 160 N/m. The manipulator had maximum input boundaries by a stiffness and non-linear damping. Combined with haptic cue and maximal inputs of 7.5 cm. System visualized by a cross of 5 mm.
Task description	Subjects had to pursuit a desired trajectory by moving the hydraulic manipulator as in the actual experiment. The subjects received an instruction, either written or verbally, and had an instruction trial in combination with familiarization trials. The length of the experiment was 40 trials.
Experiment design	The natural frequency of the controlled system was 0.5 rad/s, and the task difficulty by the velocity ratio was 2. The desired trajectory contained three frequencies in the power spectrum density. The haptic guidance was designed on basis of a PD controller on the current position, and a PD controller on the look-ahead position for subject 6. For subject 7 was the feedforward and feedback controller used. Initial guidance stiffness was 169 N/m. Structure of experiment: Instruction trial Familiarization trial 40 experiment trials
Metrics	Absolute Mean Position Error Control activity assessed in the frequency domain Joystick forces

Pilot B results subject 5.

The performance, control activity, and individual trial results were assessed to see if this setup had the required behaviour. The performance results were improved over the results from Pilot study A.

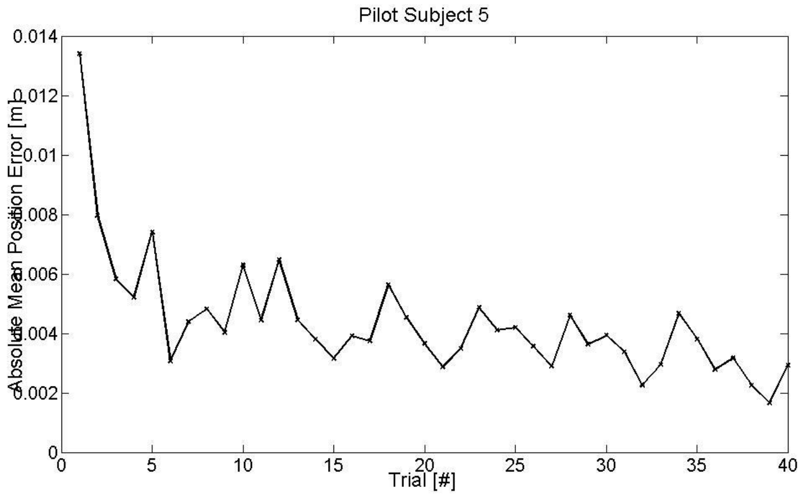


FIGURE C-1: ABSOLUTE MEAN POSITION ERROR OF PILOT SUBJECT 5 IN THE PILOT STUDY B. THE PERFORMANCE SHOWS FAST LEARNING IN THE INITIAL LEARNING TRIALS, AND AN ALMOST CONSTANT PERFORMANCE LEVEL AT THE LAST TRIALS.

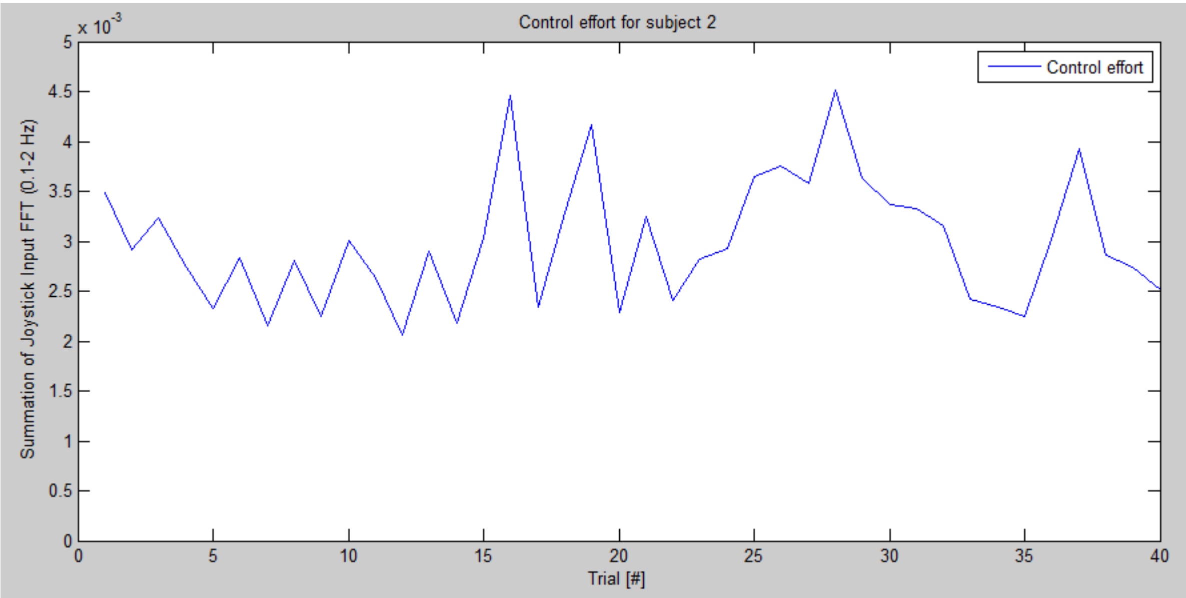


FIGURE C-2: CONTROL ACTIVITY EVALUATED IN THE FREQUENCY DOMAIN OF JOYSTICK INPUT. THE CONTROL ACTIVITY WAS DETERMINED AS A SUMMATION OVER THE JOYSTICK FOURIER TRANSFORM (0.1-2 HZ). THE CONTROL ACTIVITY STAYS AT A RELATIVE SIMILAR LEVEL.

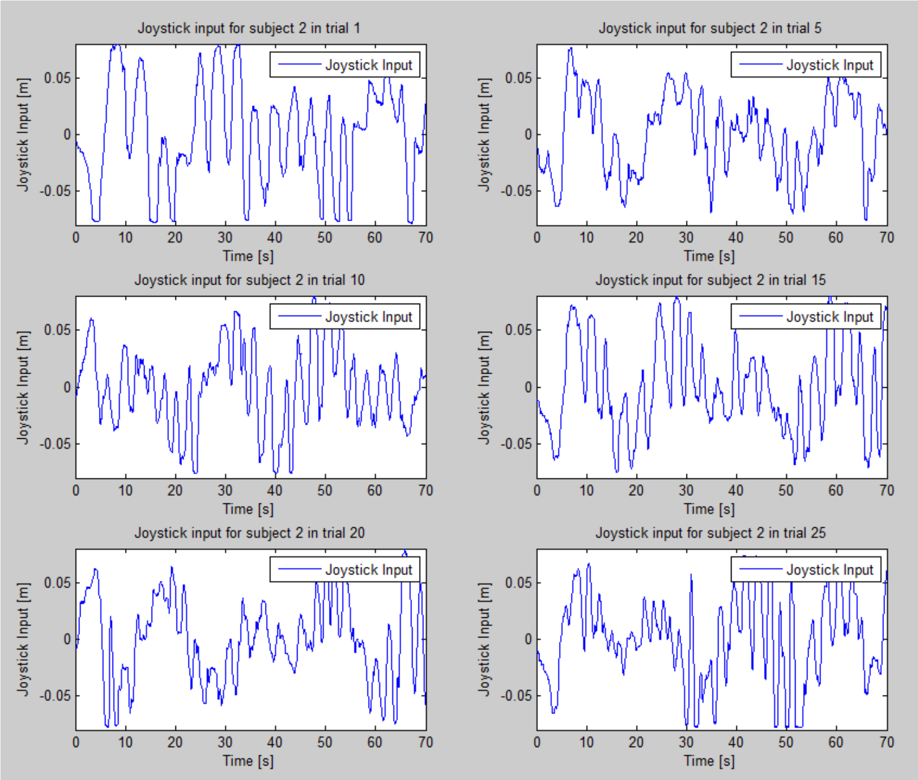


FIGURE C-3: JOYSTICK INPUT FROM SUBJECT 5 IN SIX EXAMPLE TRIALS THROUGHOUT THE EXPERIMENT. LARGE AMPLITUDE MOVEMENTS CAN STILL BE SEEN IN POST-LEARNING BASELINE TRIALS.

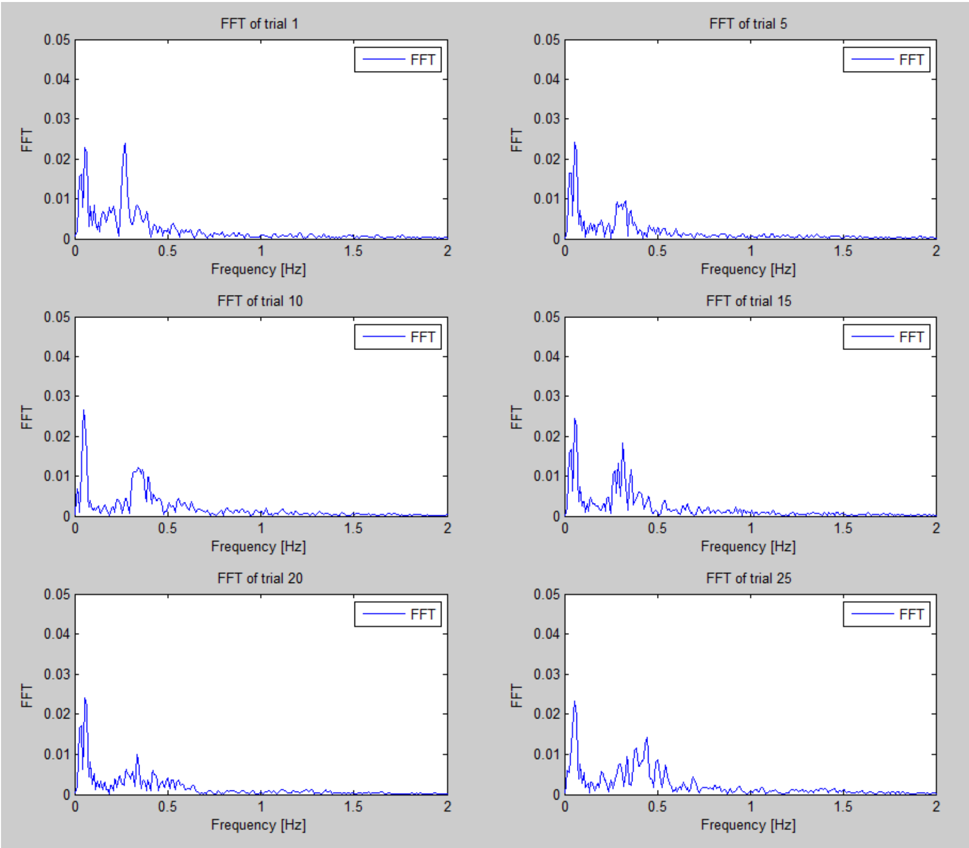


FIGURE C-4: FOURIER TRANSFORM OF THE JOYSTICK INPUT DISPLAYED IN FIGURE C-3. ONLY LIMITED CHANGES CAN BE SEEN IN THE FOURIER TRANSFORM.

Pilot B results subject 6 (HG)

The second pilot study was executed to see if the proposed HSC setup would work. However, the proposed feedback design was still not optimal and resulted in frustration of the subject.

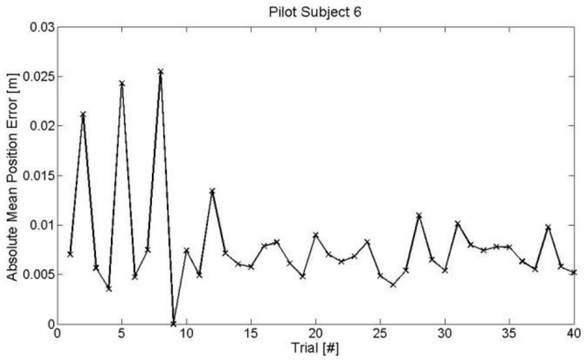


FIGURE C-5: THE ABSOLUTE MEAN POSITION ERROR FOR A HG SUBJECT. THE POOR DESIGN OF THE HSC CAN BE SEEN IN THE RELATIVE HIGH ERROR IN THE FIRST HSC TRIALS (E.G. 1,3). THE PEAKS CAN FROM THE CATCH-TRIAL DESIGN.

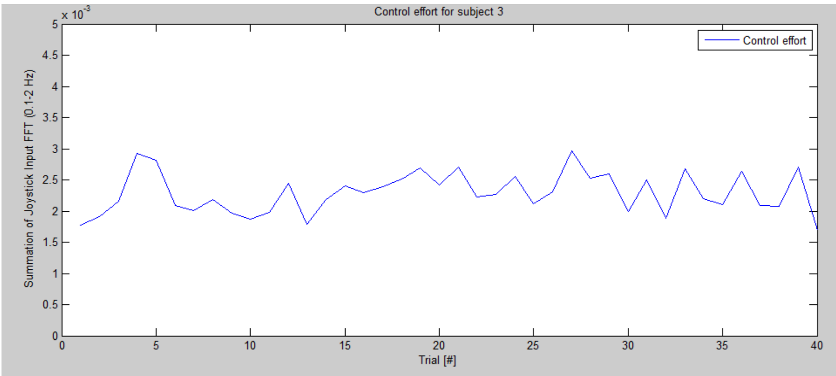


FIGURE C-6: CONTROL ACTIVITY ASSESSED IN THE FREQUENCY DOMAIN. THE POOR HSC DESIGN CAN BE SEEN IN THE CONTROL ACTIVITY, BECAUSE THE CONTROL ACTIVITY IS NOT LOWER THAN IN THE CATCH-TRIALS (E.G. TRIAL: 2,5,8,12)

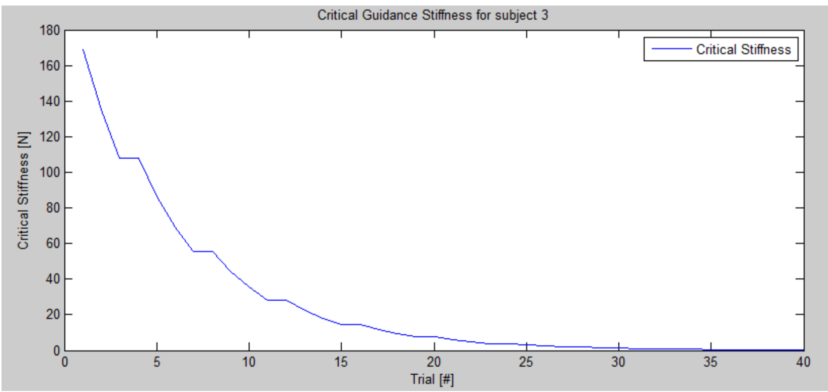


FIGURE C-7: THE GUIDANCE STIFFNESS USED IN THIS HSC DESIGN. THE INITIAL VALUE WAS 169 N/M, AND THIS VALUE DECREASED EXPONENTIALLY TO ZERO.

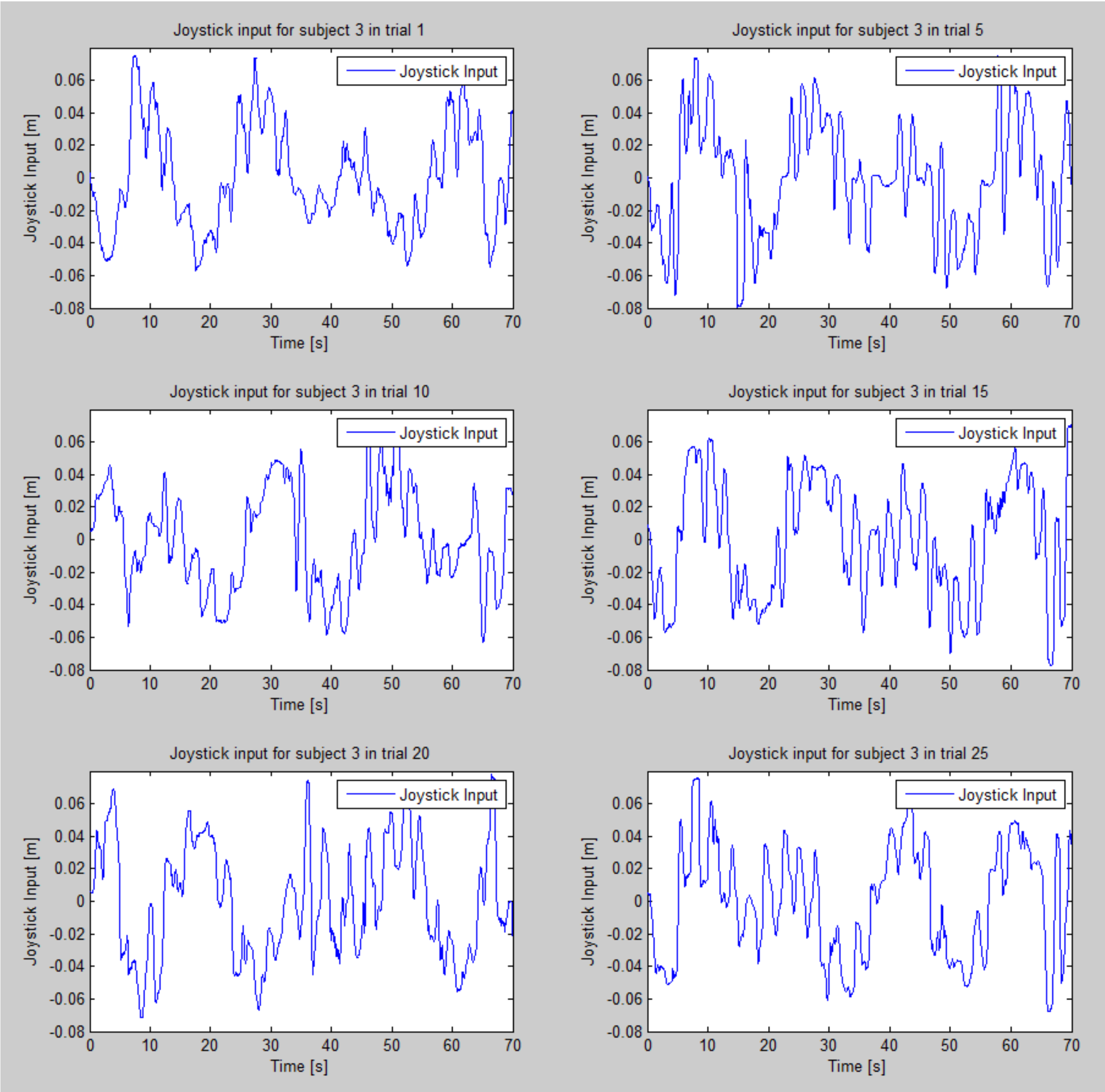


FIGURE C-8: JOYSTICK INPUT DURING SIX OF THE EXPERIMENT TRIALS.

Pilot B results subject 7 (HG)

Pilot subject 7 received many improvements over the pilot study done for subject 6. So was the feedforward controller introduced, an extra fourth frequency was added to the power spectrum of the desired trajectory, and the task difficulty was changed to 110%. Also the input range of the manipulator was increased to 0.10 m, and the duration of the trial was extended in order to include a lower frequencies in the smoothed input and output. The experiment design was still a combination of mainly trials with HSC, and eight catch-trials to assess the learning performance. The performance curve in figure C-9 shows clearly where the catch-trials during the experiment. The main comment of the subject during training with HSC was: “Can I release the handle? “. Improved performance was not shown for this “catch-trial” design, and therefore the choice was made in Pilot study C to converted this ratio. So there were eight HSC training trials instead of eight catch-trials.

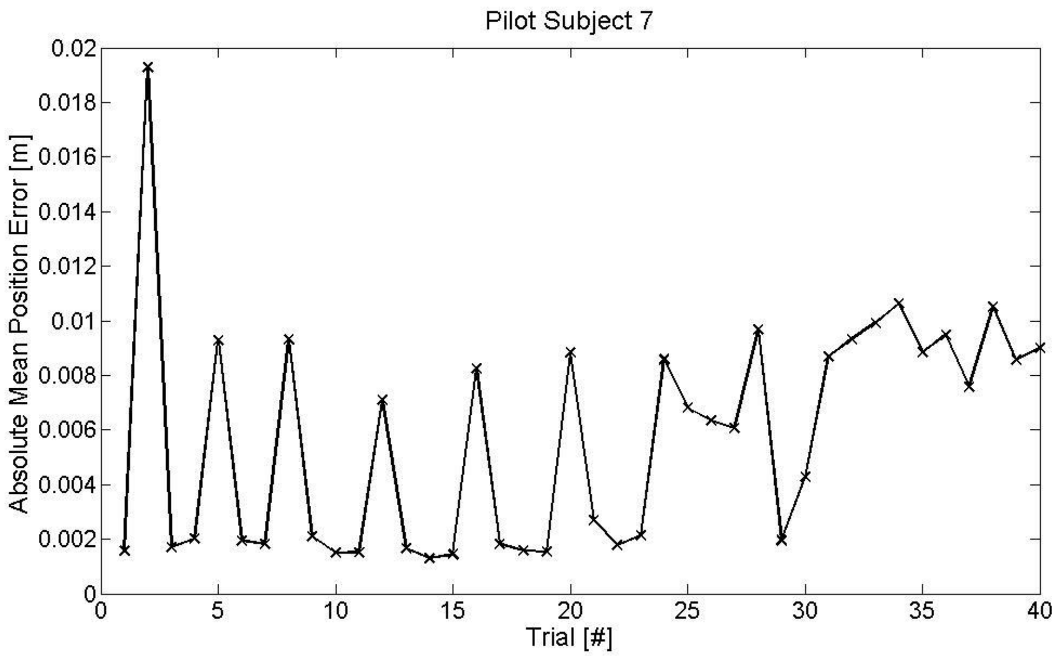


Figure C-9. Absolute Mean Position Error of subject seven with proper HSC design including feedforward controller. The effect of the catch-trials can be seen in the error, and the final result was very limited learning process.

Appendix D: Pilot C, Subject behaviour study with limited HSC training trials

The last pilot. All the settings were during previous pilot sessions tuned, and now the different approach was used of including eight HSC training trials. Pilot study C was a short experiment in order to see if this new approach including the already fined tuned settings had the required behaviour.

Goal	To assess limited HSC training trials approach.
Subjects	One right-handed subject participated in this study.
Apparatus	ProPrio manipulator tuned in the final experiment settings. Visualization on a vertical display with 2 seconds, and 5 mm cross displaying controlled system. Manipulator settings with a centering stiffness of 60 N/m and no haptic cue implemented. The maximal boundaries were ±0.10 m.
Task description	Subjects had to pursuit a desired trajectory by moving the hydraulic manipulator as in the actual experiment. The subjects received an instruction, either written or verbally, and had an instruction trial in combination with familiarization trials. The length of the experiment was 15 trials.
Experiment design	As in actual experiment.
Metrics	Absolute Mean Position Error as performance metrics Control Activity and forces assessed in the Matlab GUI.

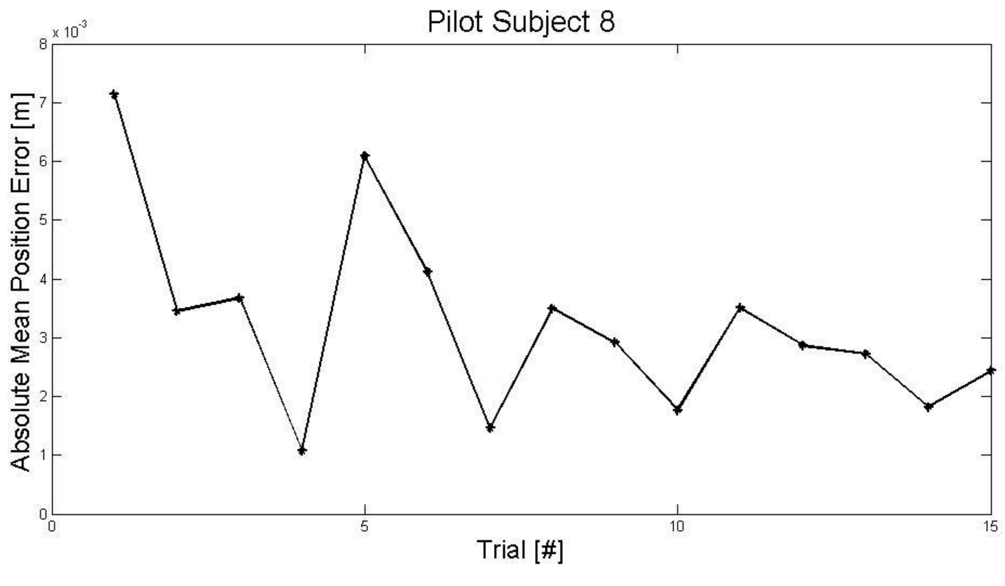


Figure D-1: The Absolute MEan Position Error of subject 8 in Pilot C. The HSC training trials were located at trial 4, 7, 10, and 14. The highest performance is set in the HSC training trials, and the error in these trials increases due to the reducing guidance stiffness. What can be noticed after doing the complete experiment, is that even this result shows the typical jump and recovery after a HSC training trials.

Appendix E. Experiment Results

This appendix shows extra experimental results of the experiment. This can be the experiment results which are not already described in the paper or the statistical results for all the T-tests done in this experiment.

Statistical results

Learning behavior between the pre-learning baseline and the post-learning baseline was compared with the use of a paired T-test. The pre-learning baseline was formed by taking the mean of the across subjects first three trials, and the post-learning baseline was formed by taking the mean of the across subject last seven trials. Difference between conditions was assessed by the individual samples T-test. Alpha was set on 0.05 for both statistical tests. All the statistical tests were performed with the use of IBM SPSS.

Metric	**Absolute Mean Position Error**
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.000)
Guidance	(P = 0.002)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.336 , F =0.032)
Post-guidance Baseline	(P = 0.814 , F =2.428)

Metric	**Root Mean squared Position Error**
Paired t-test results to assess learning in both conditions	
No Guidance	(P =0.001)
Guidance	(P =0.002)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P =0.293 , F =0.021)
Post-guidance Baseline	(P =0.090 , F =3.202)

Metric	**Absolute Mean Velocity Error**
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.000)
Guidance	(P = 0.000)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P =0.527 , F =0.005)
Post-guidance Baseline	(P = 0.904 , F = 2.641)

Metric	**Absolute Mean Position Error: Low Performance Group**
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.003)
Guidance	(P = 0.011)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.384 , F =0.957)
Post-guidance Baseline	(P = 0.806 , F =1.785)

Metric	**Learning curve:**
Independent Samples t-test to assess difference between condition	
Alpha	(P = 0.901 , F =0.007)
Beta	(P = 0.675 , F = 1.183)
Gamma	(P = 0.240 , F = 1.195)

Metric	**Control effort: 0.1-1 Hz**
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.034)
Guidance	(P = 0.008)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.871 , F = 0.000)
Post-guidance Baseline	(P =0.696 , F =0.012)

Metric	Control effort: 0-0.1 Hz
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.246)
Guidance	(P =0.739)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.325 , F = 2.57)
Post-guidance Baseline	(P =0.536, F =11.126)

Metric	Control effort: peak PSD
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.489)
Guidance	(P = 0.486)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.366 , F = 0.960)
Post-guidance Baseline	(P = 0.760 , F =6.310)

Metric	Control effort: 0.1-0.4 Hz
Paired t-test results to assess learning in both conditions	
No Guidance	(P =0.015)
Guidance	(P =0.007)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.839 , F = 0.274)
Post-guidance Baseline	(P = 0.815 , F = 1.375)

Metric	Control effort: 0.3-0.6 Hz
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.561)
Guidance	(P = 0.013)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.779 , F = 4.68)
Post-guidance Baseline	(P = 0.925 , F =5.128)

Metric	Joystick Reversal Rate: 0.01m
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.796)
Guidance	(P = 0.092)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.450 , F =0.035)
Post-guidance Baseline	(P = 0.035 , F = 0.052)

Metric	Joystick Reversal Rate: 0.0075 m
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.840)
Guidance	(P =0.104)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.428 , F = 0.059)
Post-guidance Baseline	(P = 0.035 , F = 0.016)

Metric	Joystick Reversal Rate: 0.02 m
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.873)
Guidance	(P = 0.165)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.510 , F = 0.001)
Post-guidance Baseline	(P = 0.017 , F =0.038)

Metric	Joystick Reversal Rate: 0.03 m
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.532)
Guidance	(P = 0.374)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.589 , F = 0.057)
Post-guidance Baseline	(P = 0.023 , F = 1.024)

Metric	Joystick error
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.017)
Guidance	(P = 0.000)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.580 , F = 2.002)
Post-guidance Baseline	(P = 0.593 , F =0.142)

Metric	Joystick velocity Reversal Rate: 0.0025 m/s
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.279)
Guidance	(P =0.049)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P =0.468 , F = 3.311)
Post-guidance Baseline	(P =0.558 , F =2.932)

Metric	Joystick velocity Reversal Rate: 0.005 m/s
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.174)
Guidance	(P = 0.006)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.0579 , F = 4.468)
Post-guidance Baseline	(P =0.883 , F = 4.285)

Metric	NASA-TLX
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.091)
Guidance	(P = 0.004)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P =0.840 , F =2.451)
Post-guidance Baseline	(P =0.974 , F =0.104)

Metric	Force
Paired t-test results to assess learning in both conditions	
No Guidance	(P = 0.268)
Guidance	(P = 0.109)
Independent Samples t-test to assess difference between condition	
Pre-guidance Baseline	(P = 0.278 , F =3.492)
Post-guidance Baseline	(P =0.453 , F =0.013)

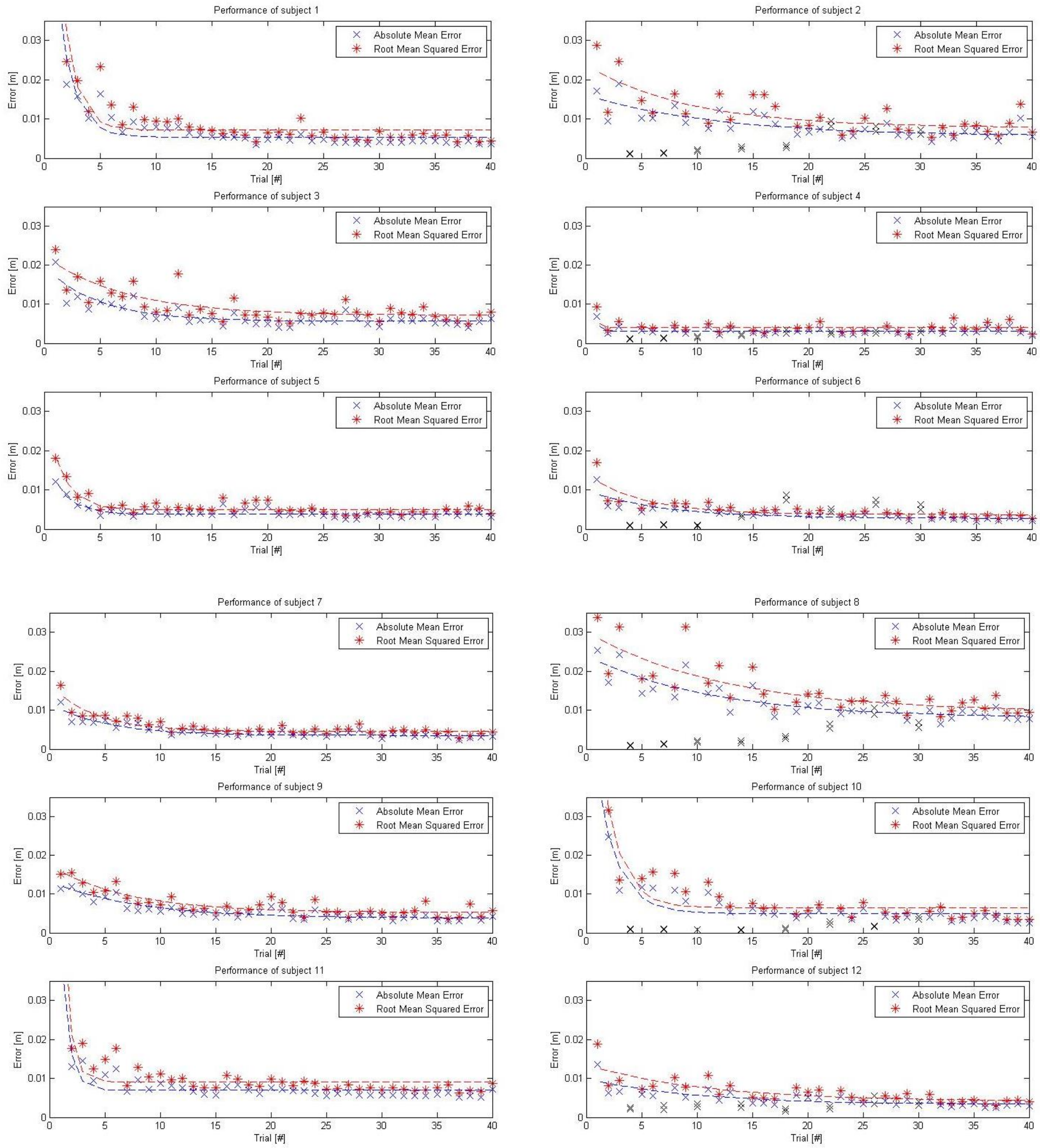
Metric	Distance moved of joystick
Independent Samples t-test to assess difference between condition	
Post-guidance Baseline	(P =0.111 , F =3.027)

EXPERIMENTAL DATA

This section shows more experimental results than already displayed in the results section of the paper. The extra performance results are: the individual subjects performance, low-performance subjects and high-performance subjects, or the performance assessed by the velocity. More (individual) and trial specific data are available through the data-analysis Matlab GUI. For the control activity are the other thresholds displayed.

PERFORMANCE

The individual performance plots show the Absolute Mean Position Error and the Root Mean Squared Error. For both conditions is an exponential learning curve fitted throughout the data points.



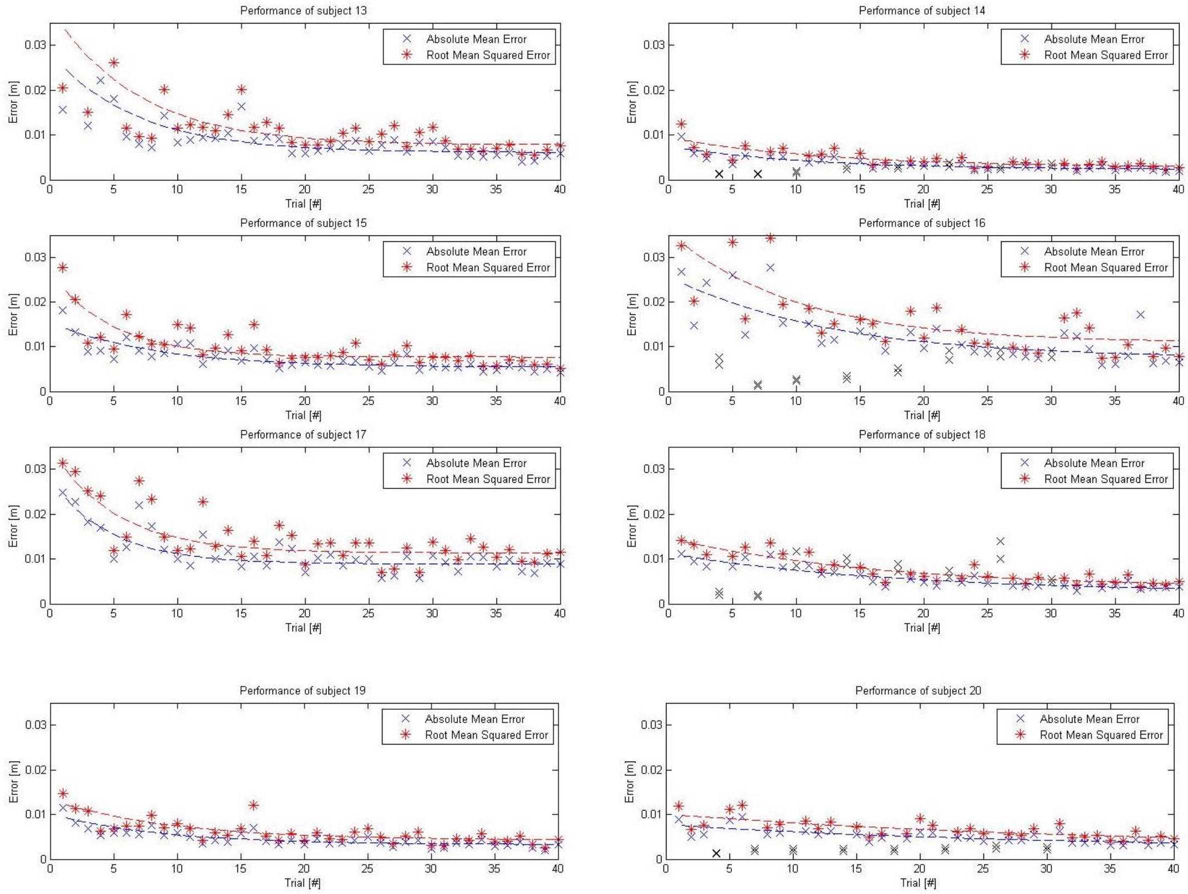


FIGURE E-1: INDIVIDUAL PERFORMANCE PLOTS FOR ALL SUBJECTS. THE PERFORMANCE IS ASSESSED BY THE ABSOLUTE MEAN POSITION ERROR (BLUE) AND THE ROOT MEAN SQUARED POSITION ERROR (RED). THE LEARNING CURVES ARE FITTED ON BOTH METRICS WITH AN EXPONENTIAL LEARNING CURVE.

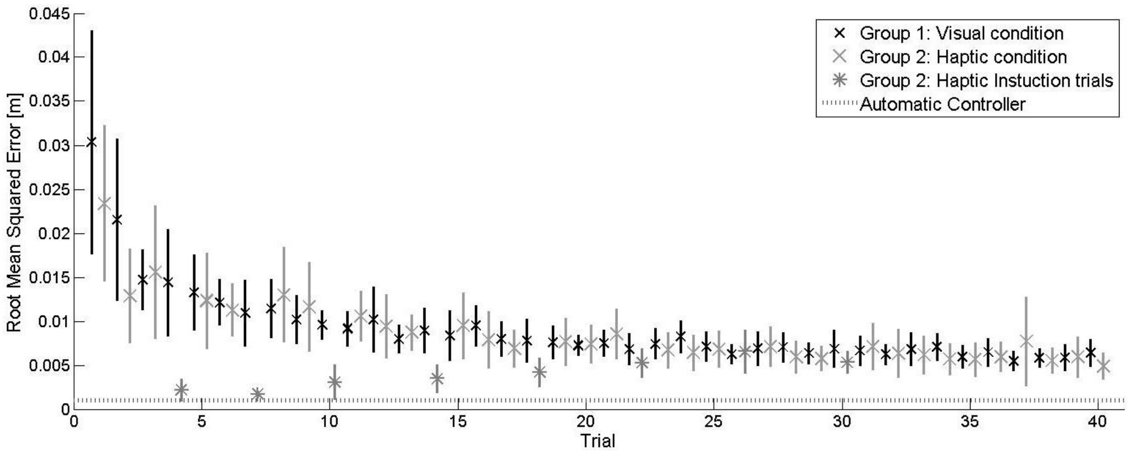


FIGURE E-2: THE ACROSS SUBJECTS MEAN OF THE ROOT MEAN SQUARED POSITION ERROR. THE ERROR BARS INDICATE THE 95% CONFIDENCE INTERVAL. THE HAPTIC INSTRUCTION TRIALS ARE THE TRIALS WHERE SUBJECTS LEARNED WITH HSC.

The Absolute Mean Position Error for the high-performance group, or in other words the top five performing subjects from the No Guidance and Haptic Guidance group.

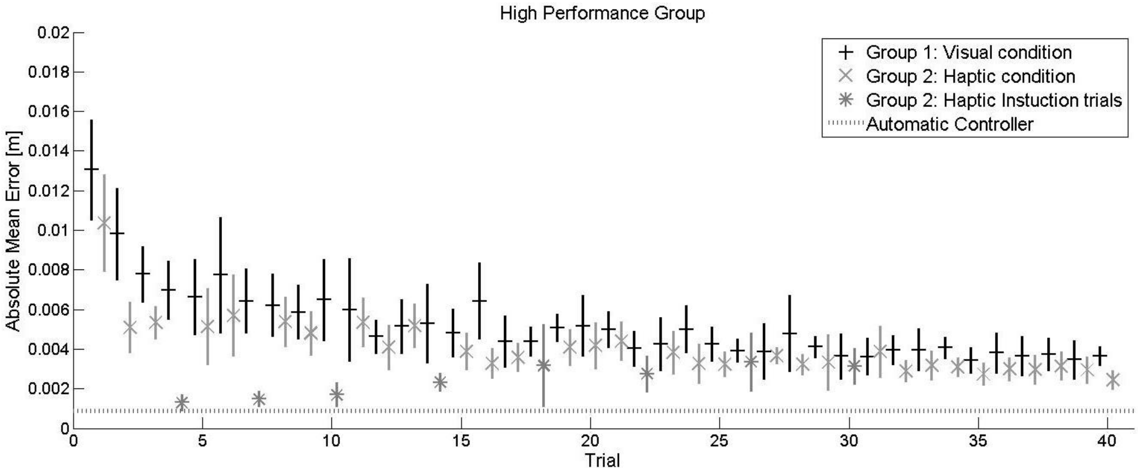


FIGURE E-3: THE ABSOLUTE MEAN POSITION ERROR FOR THE HIGH-PERFORMANCE SUBJECTS IN BOTH CONDITIONS. THE HIGH-PERFORMANCE SUBJECTS ARE: 4,5,6,7,9,12,14,15,19, AND 20. SELECTION IS MADE ON THE MEAN ERROR IN THE PRE-GUIDANCE BASELINE.

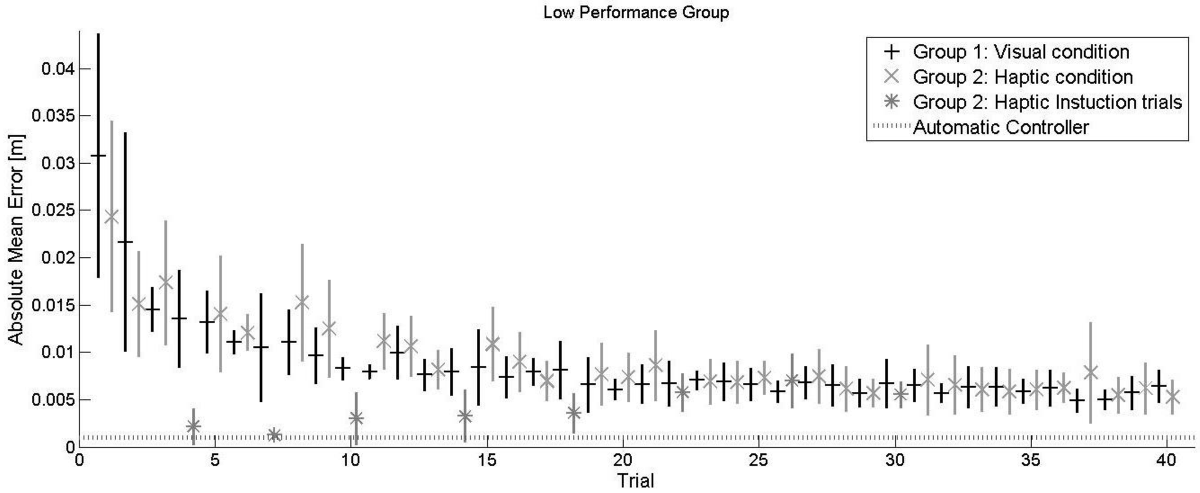


FIGURE E-4: THE ABSOLUTE MEAN POSITION ERROR FOR THE LOW-PERFORMANCE SUBJECTS IN BOTH CONDITIONS. THE LOW-PERFORMANCE SUBJECTS ARE: 1,2,3,8,10,11,13,16,17, AND 18. SELECTION IS MADE ON THE MEAN ERROR IN THE PRE-GUIDANCE BASELIN.

The performance defined as the velocity error between the desired trajectory velocity and the controlled system velocity. The velocity error is evaluated by the Absolute Mean Velocity Error and the Root Mean Squared Velocity Error. The root mean squared is evaluated as to see if there is primarily a decrease in large errors.

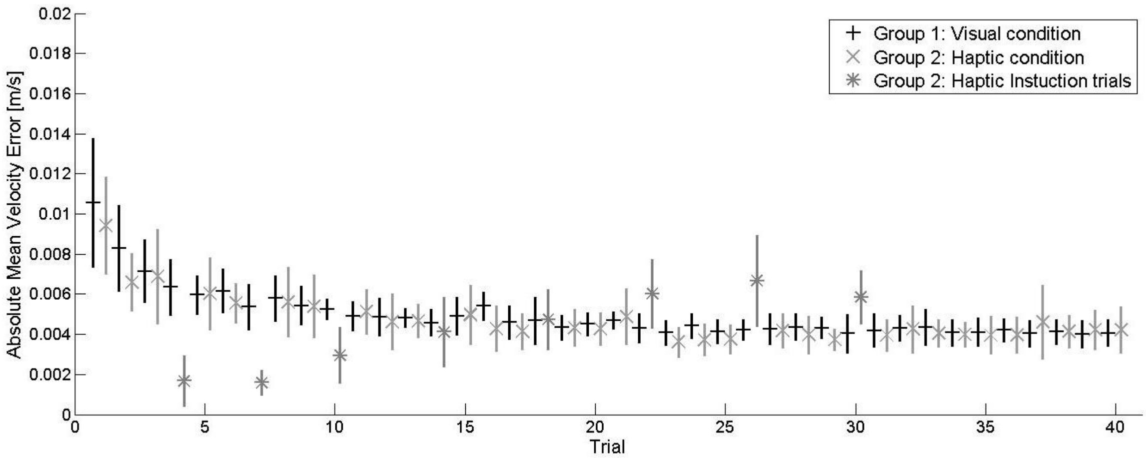


FIGURE E-5: ABSOLUTE MEAN VELOCITY ERROR OF THE ACROSS SUBJECTS MEAN.

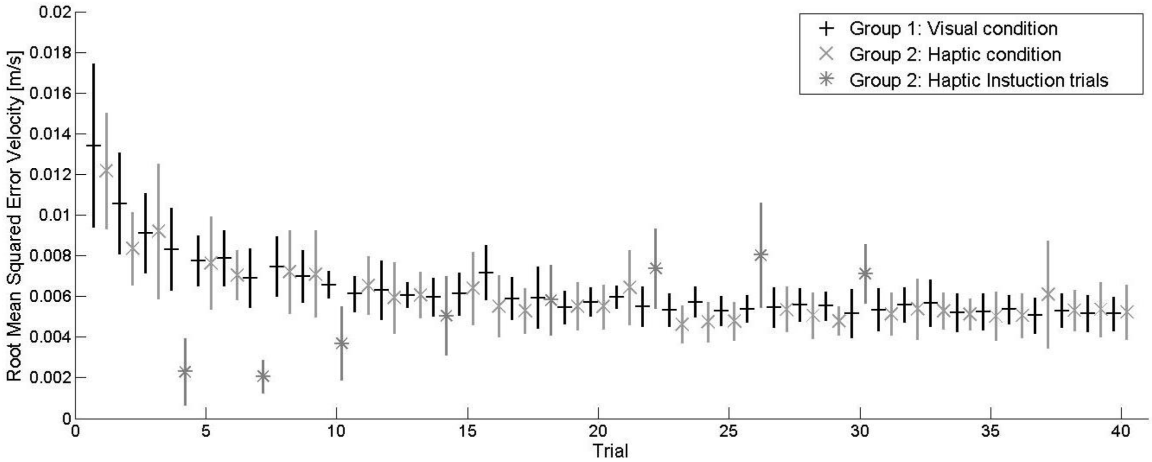


FIGURE E-6: ACROSS SUBJECTS MEAN OF THE ROOT MEAN SQUARED VELOCITY ERROR.

CONTROL ACTIVITY

Here are the results displayed from both the control activity evaluated in the frequency domain, and the control activity from the joystick reversal rate. The control activity results shown are a for the other frequency bands, or reversal threshold. For the frequency domain, the results of the: useful control activity, medium excessive control activity, high excessive control activity, and peak power spectral density will be shown. For the joystick reversal rate, the results of the three other reversal threshold (i.e. 0.0075, 0.02, or 0.03 m) will be displayed. Also the control activity in the frequency domain will be shown for the high-performance subjects, and the low-performance subjects.

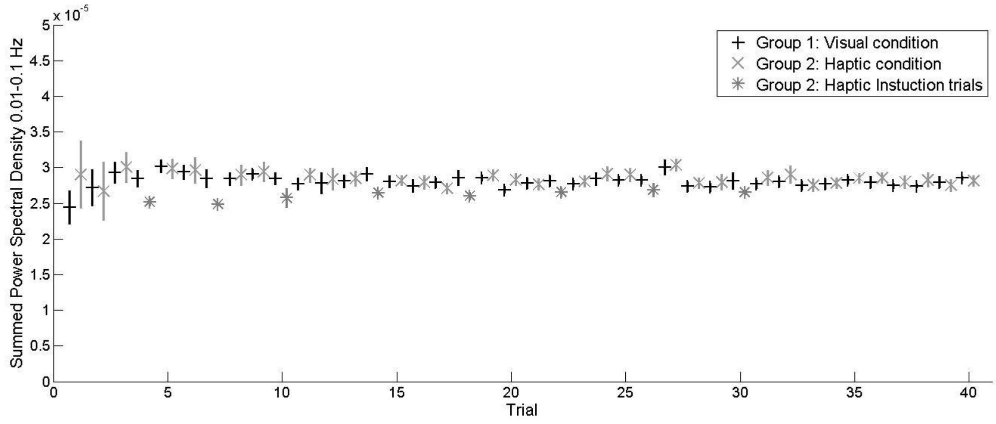


FIGURE E-7: ACROSS SUBJECTS MEAN OF THE USEFUL CONTROL ACTIVITY (FREQUENCY RANGE 0-0.1 HZ).

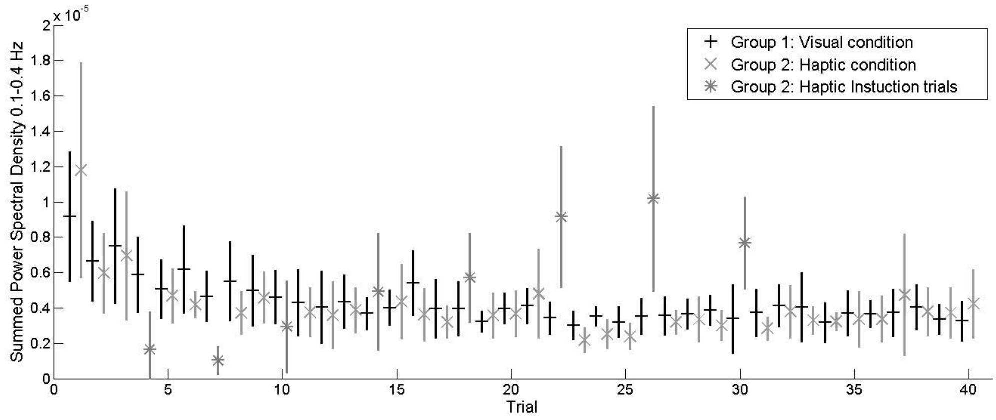


FIGURE E-8: ACROSS SUBJECTS MEAN OF THE MEDIUM EXCESSIVE CONTROL ACTIVITY (FREQUENCY RANGE 0.1-0.4 HZ).

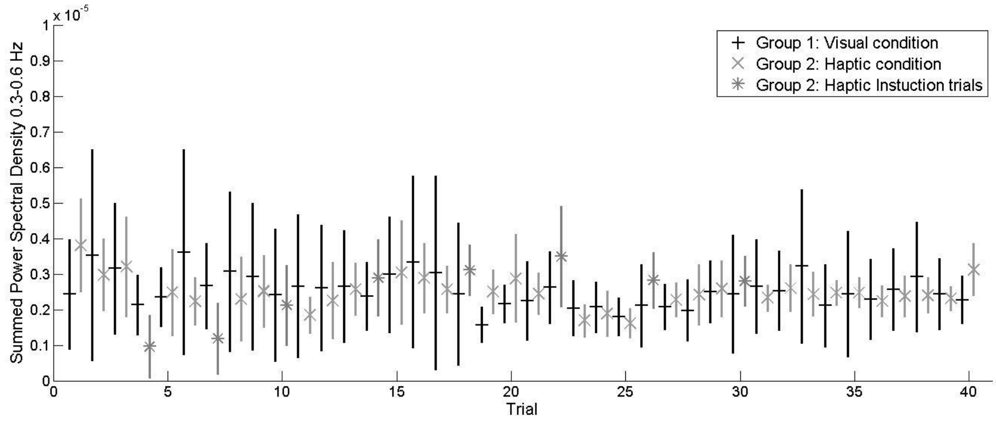


FIGURE E-9: : ACROSS SUBJECTS MEAN OF THE HIGH EXCESSIVE CONTROL ACTIVITY (FREQUENCY RANGE 0.3-0.6 HZ).

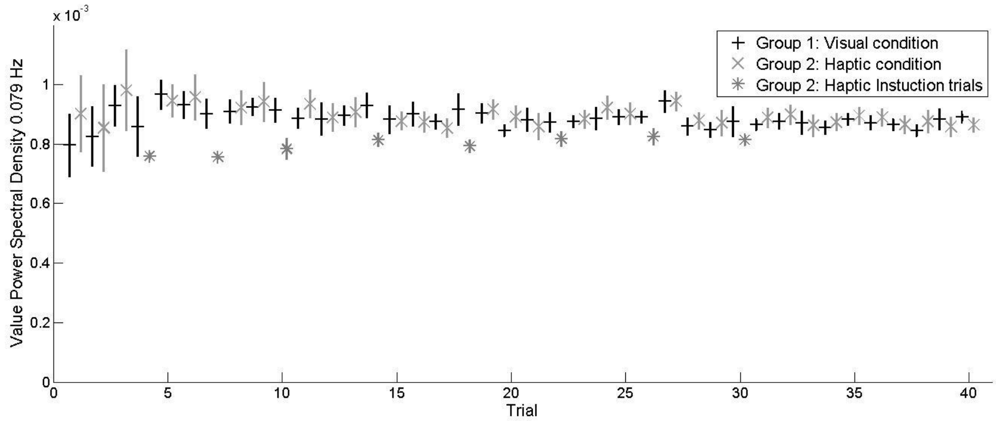


FIGURE E-10: ACROSS SUBJECTS MEAN OF THE PEAK POWER SPECTRAL DENSITY (0.0191 HZ)

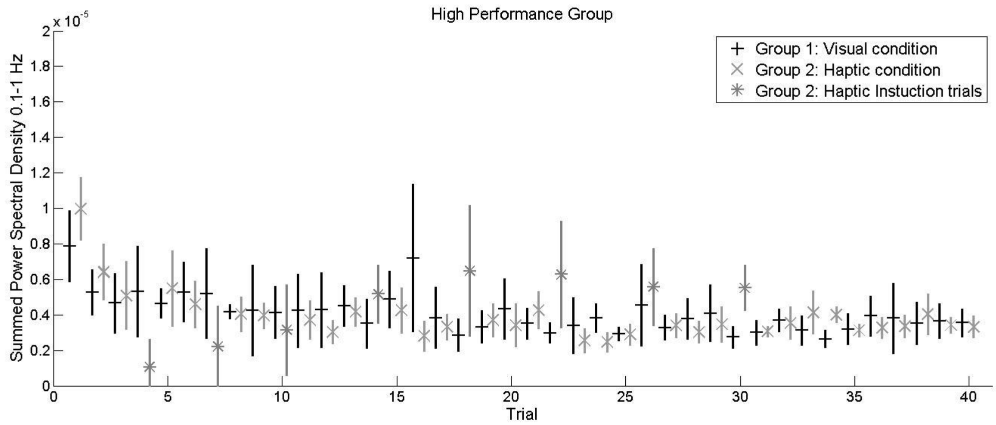


FIGURE E-11: ACROSS SUBJECTS MEAN OF CONTROL ACTIVITY IN THE FREQUENCY DOMAIN (0.1-1 HZ) FOR THE HIGH-PERFORMANCE GROUP (I.E. SUBJECTS: 4,5,6,7,9,12,14,15,19, AND 20).

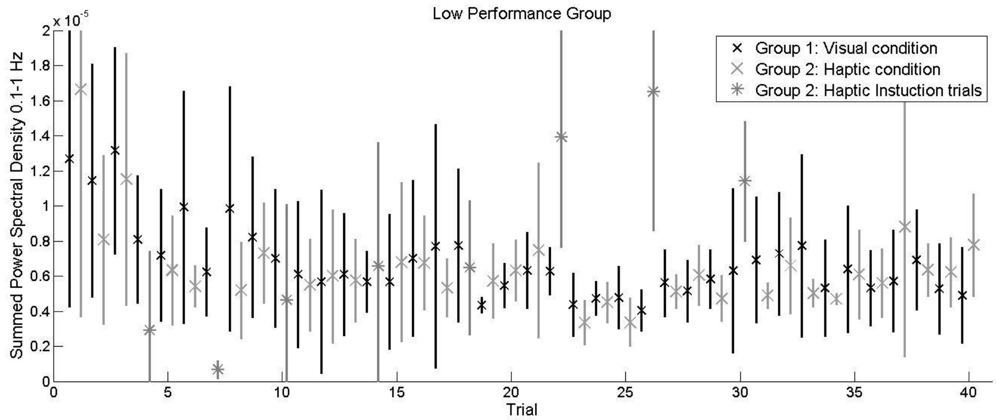


FIGURE E-12: ACROSS SUBJECTS MEAN OF CONTROL ACTIVITY IN THE FREQUENCY DOMAIN (0.1-1 HZ)FOR THE LOW-PERFORMANCE GROUP (I.E. SUBJECTS: : 1,2,3,8,10,11,13,16,17, AND 18).

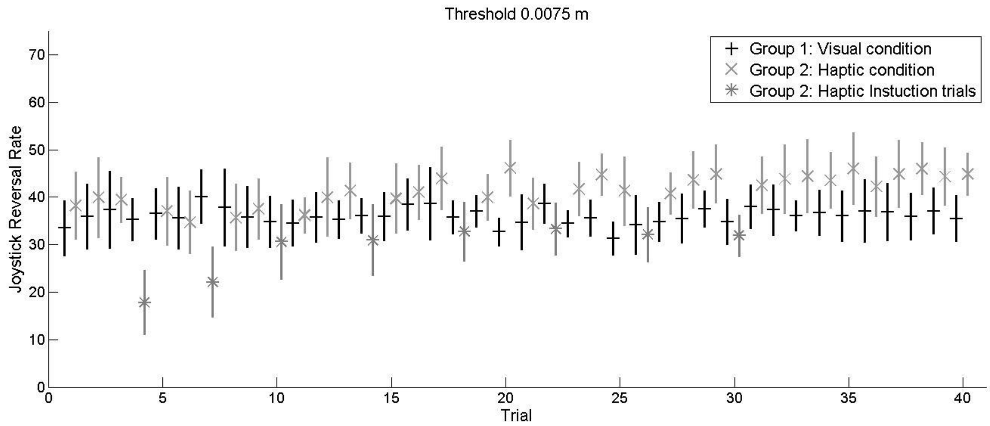


FIGURE E-13: ACROSS SUBJECT MEAN OF JRR WITH REVERSAL THRESHOLD 0.0075 M

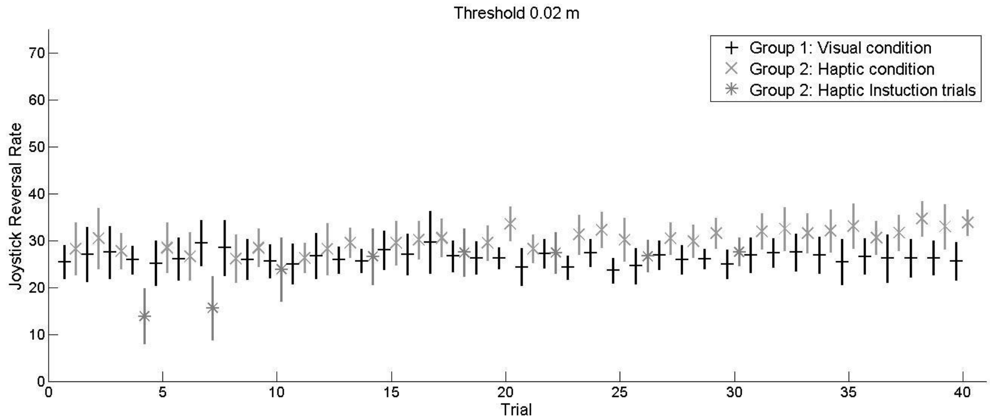


FIGURE E-14: ACROSS SUBJECT MEAN OF JRR WITH REVERSAL THRESHOLD 0.02 M

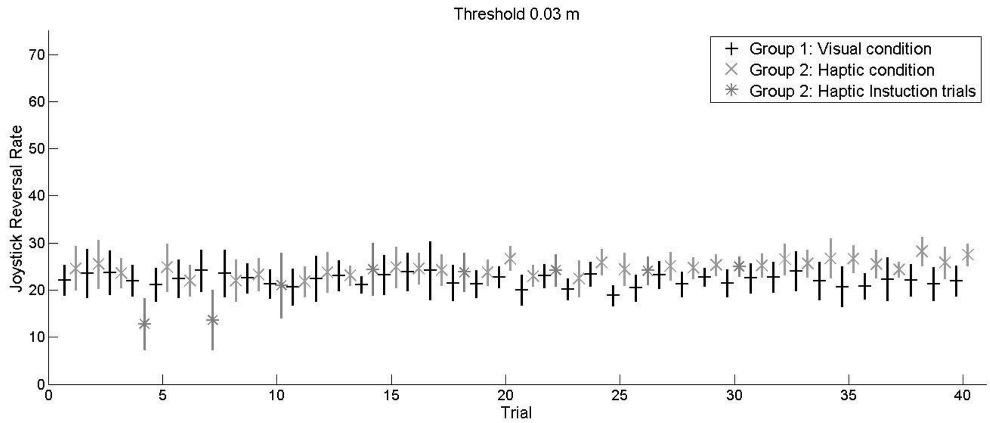


FIGURE E-15: ACROSS SUBJECT MEAN OF JRR WITH REVERSAL THRESHOLD 0.03 M

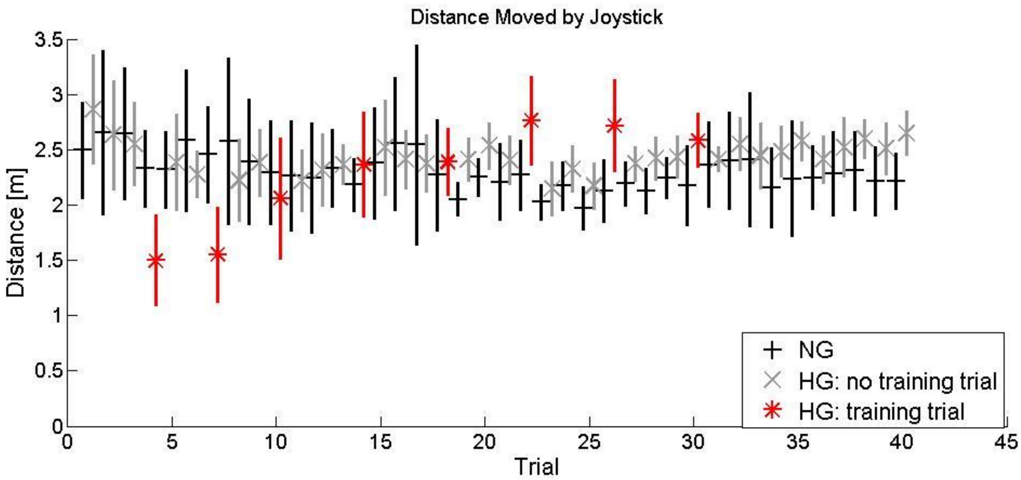


Figure E-16: Across subjects mean of the distance moved by the joystick.

Subjective Mental Load: NASA TLX

In the experiment subjects had to fill in the six scales of the NASA TLX. The results of the weighted final NASA TLX have be shown in the paper. However, the other independent scales are not presented yet. Here the six scales will be presented on how the subjects rated the task.

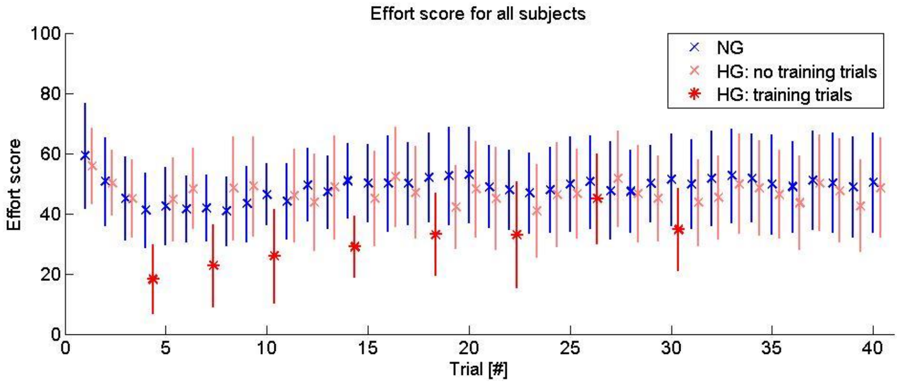


Figure E-17: Across subject mean of the effort scale of the subjective NASA-TLX.

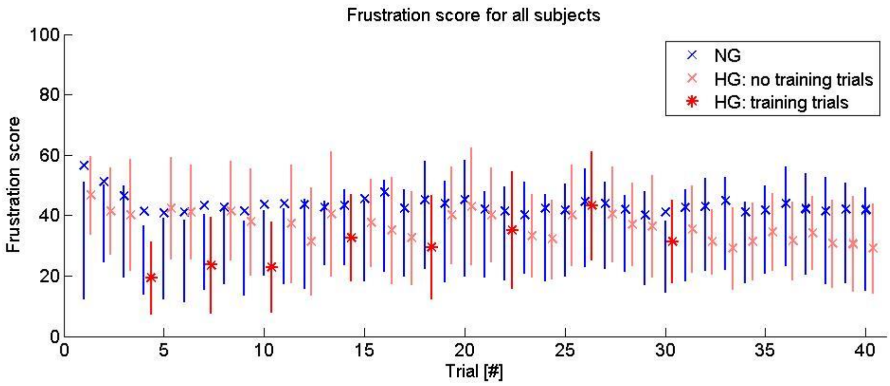


Figure E-18: Across subject mean of the frustration scale of the subjective NASA-TLX.

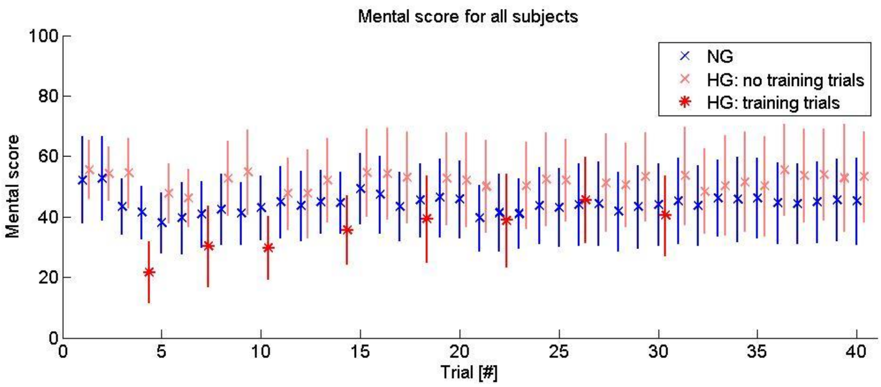


Figure E-19: Across subject mean of the Mental scale of the subjective NASA-TLX.

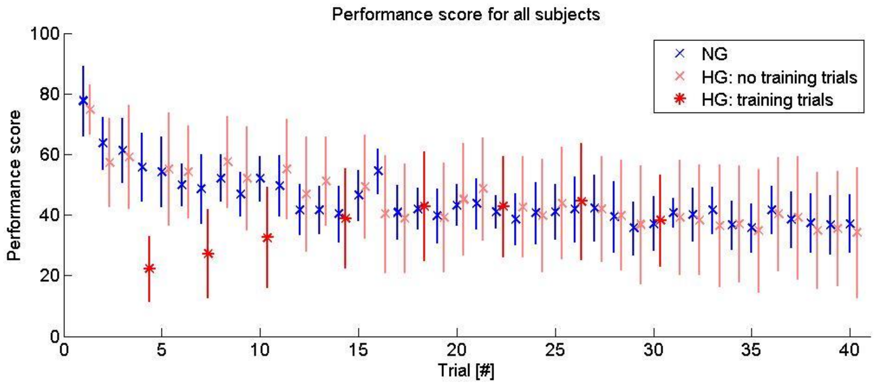


FIGURE E-20: ACROSS SUBJECT MEAN OF THE PERFORMANCE SCALE OF THE SUBJECTIVE NASA-TLX.

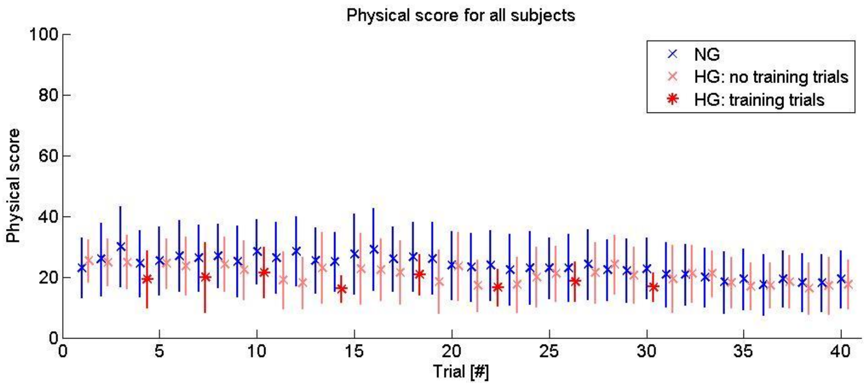


FIGURE E-21: ACROSS SUBJECT MEAN OF THE PHYSICAL SCALE OF THE SUBJECTIVE NASA-TLX.

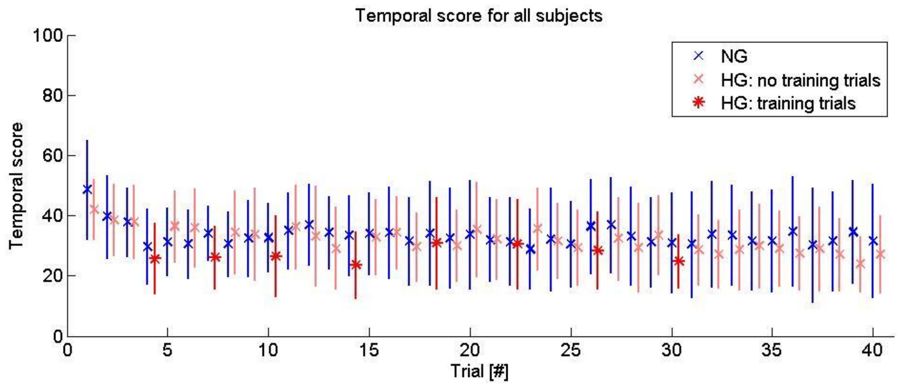


FIGURE E-22: ACROSS SUBJECT MEAN OF THE TEMPORAL SCALE OF THE SUBJECTIVE NASA-TLX.

Appendix F: Recommendation "Force-Dip" Guidance

During the master thesis was another haptic guidance method developed to cope with the combination of manipulator stiffness and guidance stiffness. A new idea was developed in cooperation with ir. R.J. Kuiper, and the concept was implemented in simulations and on the ProPrio Manipulator. The problem relating to this new concept can be seen in figure F-1, and the solutions is displayed in figure F-2. This haptic guidance method was not used in the actual experiment, due to the unknown effect of the multiple parameters on the subjects performance.

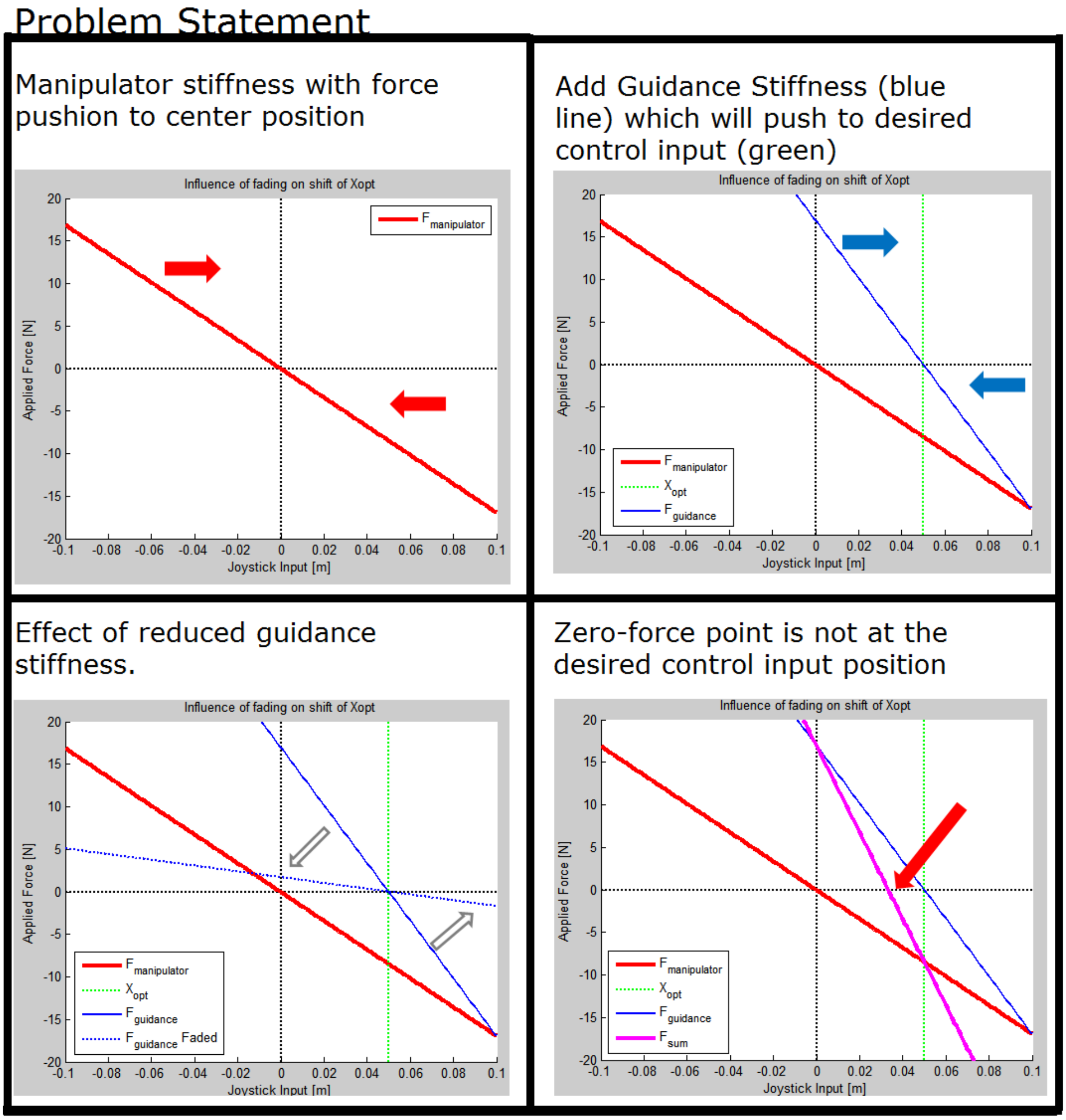


FIGURE F-1: "FORCE-DIP" IS DEVELOPED IN SHARED COOPERATION WITH IR.[2] R. KUIPER, BECAUSE IN THE CURRENT HAPTIC GUIDANCE SETUP IS NOT POSSIBLE TO COMBINE THE MANIPULATOR AND GUIDANCE STIFFNESS. A) THE MANIPULATOR STIFFNESS USED IN A JOYSTICK CAUSES THE MANIPULATOR TO CENTERING A THE ZERO POSITION, THAT CORRESPONDS FOR RATE CONTROL FOR A ZERO VELOCITY INPUT, B) THE GUIDANCE STIFFNESS WORKS AROUND THE DESIRED CONTROL INPUT AND PUSHES THE HUMAN TOWARDS THIS DESIRED CONTROL INPUT, C) REDUCING THE GUIDANCE STIFFNESS IS DONE IN "GUIDANCE-AS-NEEDED" PARADIGMS, D) ADDING THE MANIPULATOR STIFFNESS WITH THE GUIDANCE STIFFNESS. THE ZERO FORCE POINT IS AT A DIFFERENT LOCATION THAN THE DESIRED CONTROL INPUT.

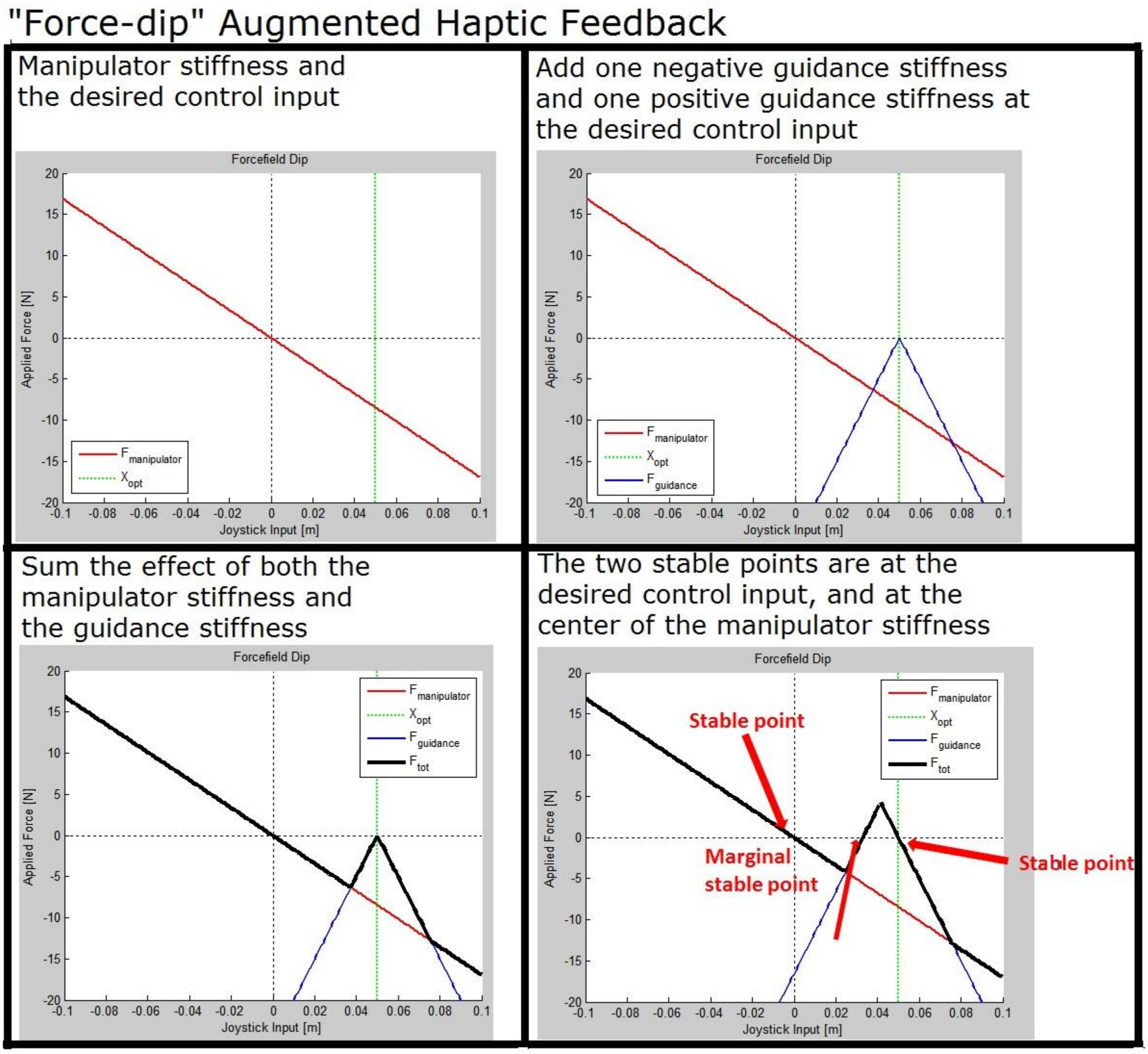


Figure F-2: “Force-Dip” Augmented Haptic Feedback implementation. A) Again, the combination of manipulator stiffness and the desired control input, B) Add one negative guidance Stiffness and one positive Guidance Stiffness around the desired control input in order to create a “dip”, C) Sum the effect of manipulator stiffness in combination with the Guidance STiffness, D) The final result of the “Force-Dip” Augemented Haptic Guidance with two stable locations, and one marginal stable position. Changing the location where the two guidance stiffness intersects can be used for the “guidance-as-needed” paradigm. The Intersecting point will then start in the positive Appied force field, and will during the trials be lowered until it reaches the manipulator stiffness line. Three parameters need to be tuned for the “guidance-as-needed” method. i) the start location of the intersecting point. ii) the strength of the guidance stiffness. iii) the forgetting factor, or how fast the intersecting point will be lowered to the manipulator stiffness line.

Feeling this “force-dip” on the ProPrio was quite interesting. You actually feel being sucked in to the desired control input when you start outside the range influenced by the guidance stiffness. Outside of this range you experience the normal manipulator stiffness. Another interesting behaviour is when the intersecting point is in the lower section or at the zero-force line of figure F-2C. Then the desired control input is not stable any more, and you perceive the mixed effect of the manipulator and guidance stiffness.

APPENDIX G: LITERATURE

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