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Who's the Boss? Arbitrating Control Authority between a Human Driver and Automation System

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Abstract

Progress toward the fully automated highway will first require that manual and automatic control be successfully combined. Determining a combination that preserves the best performance features of human and automatic control yet allows either driver to cover for the faults of the other is a challenging problem. In this study, we invited 11 participants to drive a simulated vehicle through a course with obstacles to investigate the ability of human-automation teams to cover for human and automation faults. We developed the automation system using model predictive control and implemented three schemes under which the human would share control with the automation. In *Autopilot*, the human driver initiated a takeover with a button press whereas in *Active Safety* the automation initiated a takeover when it anticipated an obstacle collision. In *Haptic Shared Control* the hu-

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man was free to invoke a transition by activating or relaxing muscles. In addition, we included two baseline conditions in which control was given in whole to either the human or the automation. We compared performance in the five conditions by analyzing obstacle hits and metrics related to driving maneuvers around the obstacles that were avoided. Relative to individual human or automatic driver performance, we found that control sharing reduced obstacle hits under fault conditions but also occasionally resulted in obstacle hits under no-fault conditions. Our findings further indicated that team performance suffered most under *Autopilot* for automation faults and suffered most under *Active Safety* for human faults. *Haptic Shared Control* supported the best overall team performance.
Keywords: Haptic shared control, Human-automation interaction, Intelligent transportation systems, Human Factors

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1. Introduction

Human error accounts for an estimated 92% to 96% of traffic accidents [1]. The self-driving car promises to address this problem by removing human drivers from the control loop. Undeniably, automation systems are capable of faster response times, able to handle greater amounts of information, and able to process information more quickly and in a more repeatable fashion than human drivers. However, automation systems are subject to faults and misses as well, even if these rates have not been established given the short time self-driving cars have been on the road. It is also likely that society will not tolerate automation faults at the same high rates it currently tolerates human faults. Human drivers are therefore retained in a supervisory role or asked to remain available for immediate control take-over, oftentimes without warning [2]. Indeed, until self-driving cars are reliable in all foreseeable and even unforeseeable situations on the road, occasions will arise in which control must be transferred back to a human driver, perhaps on short notice.

Humans bring capabilities for driving a vehicle that are in large part complementary to the capabilities of automation systems. The human driver offers superior perception and judgment, is capable of making high-level decisions, brings rich prior experience, and brings an ability to generalize from one type of experience to another. To combine the capabilities of human and automatic drivers, one might imagine a scheme in which control authority is given to whichever agent outperforms the other in each traffic situation or time interval on the road. Ideally, safety would be guaranteed and the addition of automation would free attention for the human driver. However, a clean division and means of transitioning control authority is difficult to find.

Various schemes for combining the capabilities of human and automatic drivers have been proposed, differing primarily according to the manner in which control authority is transitioned between the two agents. Most commonly, transitions involve complete transfers of control authority that take place at discrete instants of time. That is, control authority is transferred as a lumped whole from human to automation system or back to human. Depending on the scheme, transfers may be initiated by the human driver, by the automation system, or by a separate arbitration algorithm [3, 4, 5].

In one common scheme, which here we call *Autopilot*, the human driver initiates the transitions, engaging and disengaging automatic control with a button-press or other trigger. For example, cruise control is conventionally engaged with a button press and disengaged with another button press or tap on the brake. Flight automation systems are likewise engaged by the pilot at discrete instants of time. In a second scheme, which we call *Active Safety*, it is the automation system that initiates a transition of control authority. For example, automated emergency braking can be initiated when the automation system detects an impending collision for which human reaction time is too short [6]. Active safety systems have also been proposed that decouple the steering rack from the steering wheel during avoidance maneuvers [7, 8].

However, smooth transfer of control authority between an automation system and human is notoriously difficult. From experience in deploying automation in aviation systems, we know that human/automation teams are particularly prone to errors during transfers of control authority [9]. Issues surrounding control transfer include a protracted time interval required for full transfer, mis-interpretation or mis-appropriation of responsibility (called mode errors), and incomplete understanding of vehicle or environment state (loss of situation awareness) [10, 11, 12]. Transitions involving such issues are often called "bumpy", and are implicated in compromises to safety [13, 14].

To support smooth transfers of authority and harness the complementary features of human and automatic control, researchers have proposed various schemes under which control may be shared between human and automation. Rather than complete transfers of control authority that occur at discrete instants of time, these schemes attempt to form a cooperative team that involves the human and automation system working together simultaneously. Ideally, team performance would exceed the performance of either agent acting alone and cognitive workload would be reduced for the human [15, 16, 17, 18, 19, 20].

The control sharing scheme called *Haptic Shared Control* takes its inspiration from two humans cooperating on a manual task, for example moving a piece of furniture [21, 22]. In shared control of steering, the automation system acts through an instrumented and motorized steering wheel, but by design acts with a mechanical impedance that is roughly matched to the impedance of the human driver. The human driver can increase the impedance by increasing the steering grip and co-contracting the muscles to override the automation system, and can reduce the impedance by decreasing the steering grip and relaxing the muscles (while keeping hands on the wheel) to yield control to the automation system. Whether active or relaxed, the human driver can monitor the actions of the automation system through haptic feedback [23, 24, 25, 26]. At all times, the final steering maneuver in *Haptic Shared Control* depends on the actions and the relative impedance of both the human driver and the automation system. The automation is generally designed to have a constant finite impedance but it can also be equipped with the ability to vary its impedance and to adjust its relative driving authority [22, 25].

While the underlying processes and degrees may differ, it is clear that both human drivers and automation systems are subject to misses, faults, or errors. A given scheme for combining human and automatic control must be robust to unanticipated conditions, misses, faults, and errors. As Bainbridge [27] noted, adding automation may expand rather than reduce problems for the human operator, especially when faults occur.

Operators left with the task of monitoring the driving situation and automation behavior are challenged precisely where their skills are poor—in maintaining vigilance [28]. Taking over control from an automation system in unexpected conditions usually requires additional cognitive rather than manual skills, and skills that may be difficult to develop and maintain [27]. Few studies have compared the response to faults of different control sharing schemes. Yet studies comparing performance across schemes are critical to determine gross sensitivities to unexpected conditions. Because faults are often sudden occurrences, schemes that support rapid transitions such as button presses may hold advantages. On the other hand, schemes that use the steering wheel as the interface for changing the balance of control authority rather than a button press might support smoother or earlier transitions.

For example, according to Itoh et al. [29], control sharing methods like *Haptic Shared Control* are effective at supporting smooth shifts of authority during automation-induced faults. The hypothesized mechanism is that the haptic feedback present in *Haptic Shared Control* enables the human driver to quickly understand and fix automation errors or faults by modulating their impedance [29]. In a 2016 survey conducted by Wolf on 1000 respondents [30], it was found that a majority of human drivers would not wish to completely relinquish control to an automation system. *Haptic Shared Control* also fulfills this requirement by giving neither the human nor the automation system full authority at any point of time while driving.

A majority of *Haptic Shared Control* designs are only concerned with human automation cooperation at the "operational level" (or the "control level") [31, 32]. In automotive systems, cooperation at the "operational level" involves collaboratively generating a trajectory or a path using both the automation and driver inputs to determine the final steering wheel angle [31]. Although such embodiments of *Haptic Shared Control* still provide a smooth shift of authority during driving, they can suffer from conflicts between the driver and the automation that arise when there is a difference between the actions and intentions of the human driver and the automation system. Conflicts are undesirable as they can cause annoyance, can deteriorate driving performance and, in worst-case scenarios, can result in accidents [29, 31].

Even though the conflicts can be dangerous, Itoh et al. [29] maintain that neither human nor machine should be given the full authority during driving and that control should still be shared. One way to manage conflicts while also sharing control is to perform cooperation at a higher "tactical" level as suggested in [31, 32]. For example, in [26], Mars et al. integrated the design of *Haptic Shared Control* system with a driver model that led to fewer conflicts and more agreements between the driver and the automation [33].

The surveys in [3] and [4] review the literature on control sharing schemes such as *Autopilot* and *Active Safety* that have appeared in commercialized vehicles. but do not include an assessment of schemes like *Haptic Shared Control* in which control authority is graded on a continuum between human and automation. Rather than comparing performance across schemes, studies on control transitions appearing to date have investigated the dependence of performance under one scheme to variation in certain parameters. For example, Ericksson and Stanton [34] found less erratic driver steering input in the first 20 seconds after taking over from automation in self-paced conditions than in automation-paced conditions. Desmond et al. [35] found similar degraded performance in the first 20 seconds after resuming control from automated driving following an automation failure compared to compensating for a wind gust in manual driving.

In this paper we pit the schemes *Autopilot*, *Active Safety* and *Haptic Shared Control* against one another in a simulated driving scenario in which faults occur at fixed rates but at unpredictable times. We induce faults simply by making obstacles invisible to either the human driver or the automation system. Similar to the implementation in [8, 31] our automation system is based on Model Predictive Control (MPC) and takes the current steering angle as an input to plan a path that conforms to the intention of the human driver to reduce conflicts. In Section 2 we present the details of our MPC-based automation system and our driving simulator and elaborate on our implementation of *Autopilot*, *Active Safety* and *Haptic Shared Control*. We describe an experiment in which we asked 11 participants to drive with the assist of the automation system under these three control sharing schemes. To establish baseline performance, we also asked the same participants to drive the course independently (*Manual Control*). The automation system also drove the course independently (*Automatic Control*). In Section 3 we present experimental results and follow this with a Discussion and Conclusion in Sections 4 and 5.

2. Methods

2.1. Participants

Eleven test participants (10 male and 1 female) between the ages of 23 and 40 years were recruited for the study. Participants did not receive compensation. All participants had normal or corrected-to-normal vision and signed informed consent in accordance with University of Michigan human participant protection policies.

Each participant was instructed on the four conditions *Manual Control*, *Active Safety*, *Autopilot*, and *Haptic Shared Control* and given a chance to familiarize themselves with these conditions in a training session up to 15 minutes long. The name of each condition was displayed on the corner of the screen during each run. Each participant was asked to complete the four experimental conditions with three repetitions each. The order of conditions including repetitions was randomized. The vehicle speed was set constant at 10 m/s, and each test run was about 90 s long.

Participants were informed about the existence of obstacles that would be invisible to them or not detected by the automation system. They were instructed that the automation system might be able to help them avoid obstacles that were invisible to them and that they might be able to avoid obstacles that were not detected by the automation system.

2.2. Apparatus

We developed a low-fidelity fixed-base driving simulator featuring a motorized steering wheel (see Fig. 1). A DC motor (AmpFlow A28-150, Belmont, CA) was coupled to the steering wheel (Speedway 38 cm solid aluminum wheel, Lincoln, NE) through a timing belt with a 72:15 mechanical advantage, making up to 66 Nm torque available to be imposed on the human driver. A 10,000 count per revolution optical encoder (US Digital HB6M, Vancouver, WA) was attached to the steering shaft and the motor was equipped with a 2048 count per revolution optical encoder (US Digital HB6M). In addition, the steering wheel was equipped with a red button within easy reach of a participant's thumb on the steering wheel. The virtual driving environment was displayed on a 50 cm LCD Widescreen monitor positioned about 140 cm from the participant.

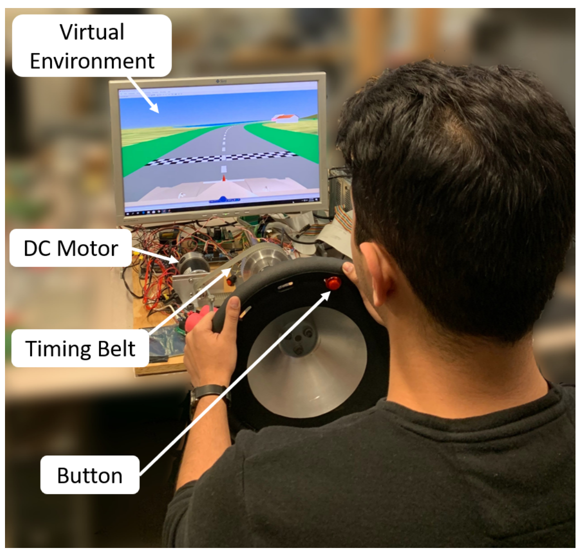


Figure 1: Fixed base driving simulator: experimental setup.

The computational hardware supporting the driving simulator included two computers: a PC (Intel Core i7-3770) to support the automation system and a second PC (Intel Core i5) to support the vehicle model, virtual driving environment, and control of the motorized steering wheel. Additional Arduino micro-controllers (Arduino Mega 2560) supported encoder reading and production of pulse-width-modulated (PWM) signals for the motor amplifier (Robot Power OSMC, Olympia, WA). The Arduino code was cycled at 350 Hz. The two PCs communicated every 10 ms through a dedicated User Datagram Protocol (UDP) link. The automation computer received vehicle states including steering angle and obstacle positions and responded with a steering angle setpoint. Data including vehicle position and heading, steering wheel angle, obstacle positions, and motor commands were logged at 100 Hz. The graphical display was rendered at 20 Hz.

The virtual environment was adapted from [36]. It was created using the Matlab-Simulink Virtual Reality Toolbox, and appeared as shown in Fig. 2. It contained a notional High Mobility Multipurpose Wheeled Vehicle (HMMWV) and a road with various landmarks that provided motion cues during driving. The vehicle traveled at a constant speed of 10 m/s, and neither the participant nor the automation system had any control over speed. The road (in gray) was 8 m wide with a white dashed centerline. Shoulders of 6 m width (in dark green) were located on either side of the road. The entire track was 850 m long, with 5 left turns and 4 right turns. An overview of the track is shown in Fig. 2 (A). Ten cylindrical obstacles with a 2 m diameter and 0.5 m height were distributed along the track's centerline at intervals that were set randomly between 40 and 50 m. A red notch was visible on the vehicle's hood as a center reference.

2.3. Automation System Design

We used Model Predictive Control (MPC) to develop an automation system capable of steering the vehicle along the track centerline while avoiding obstacles. The nonlinear MPC formulation described in [37, 38] was adopted.

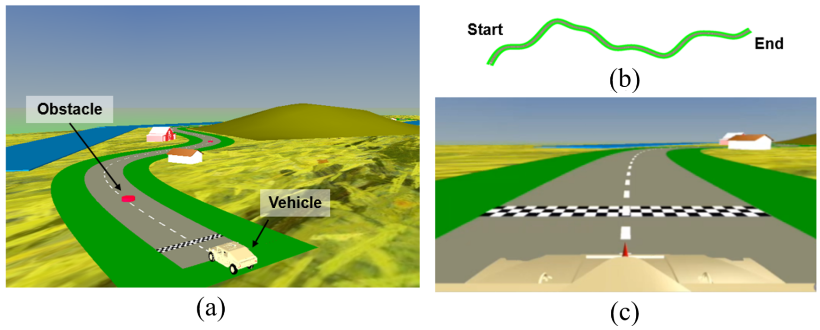


Figure 2: (a) Vehicle, track, landmarks, and obstacles in the virtual environment; (b) An overview of the track; (c) Scene visible to participants.

Input to this system included the vehicle's state, the position and size of the obstacles, and data describing the track. To capture the dynamics of the vehicle, the 3 degrees of freedom dynamic model developed in [39] was used. This vehicle model has seven states and uses a pure-slip Pacejka tire model [40] to calculate the lateral forces on the tires. The states include the vehicle's global position (x, y), lateral speed $V(t)$, yaw rate $\omega_z(t)$, heading angle $\Psi(t)$, steering angle $\delta(t)$, and longitudinal speed $U(t)$; the control input is the steering rate $\dot{\delta}(t)$. To prevent rollover, the vertical loads on the tires were constrained to be greater than 1000 N. Load transfer effects were accounted for in the vertical tire force computations.

The cost function included two terms: a first term to minimize the steering rate control effort $\dot{\delta}(t)$ and a second term to minimize the distance between position coordinates of the vehicle (x, y) and the coordinates of a closest target point on the track centerline (x_t, y_t). The cost function is expressed as follows:

$$J = w_{\dot{\delta}} \int_{t_0}^{t_0+t_p} \dot{\delta}(t)\mathrm{d}t + w_{\text{path}} \int_{t_0}^{t_0+t_p} (x(t) - x_t(t))^2 + (y(t) - y_t(t))^2 \mathrm{d}t, \tag{1}$$

where $w_{\dot{\delta}}$ and w_{path} were constant weighing terms set to 0.05 and 10.0, respectively, t_0 indicated the time at which each MPC computation began, and t_p encoded a time horizon of 6 s.

Elliptical hard constraints ensured that the vehicle avoided collisions with perceived obstacles [38]. These obstacle avoidance constraints were expressed as

$$(x(t) - \mathbf{x_{obs}}[i])^2 + (y(t) - \mathbf{y_{obs}}[i])^2 > (r_{\text{obs}} + sm)^2, \quad i = 1, 2, \dots Q, \tag{2}$$

where r_{obs} is the obstacle radius, sm is a safety margin that accounts for the vehicle's size and Q is the total number of obstacles. The vectors $\mathbf{x_{obs}}$ and $\mathbf{y_{obs}}$ contain the position and radii of the obstacles that are shown to the automation system. An implementation of the trapezoidal method in `NLOptControl` [41] directly transcribed the optimization problem into a nonlinear programming problem, which was then solved using KNITRO [42].

At the beginning $t = t_0$ of computations, the states of the vehicle, steering angle θ, and coordinates of obstacles visible to automation were sent from the driving simulator computer to the automation computer over the network connection using the User Datagram Protocol (UDP). At $t = t_0 + t_s$, where $t_s = 0.3$ s, the computed cost-minimizing steering trajectory θ_{A} was passed back to the driving simulator and used as a setpoint trajectory for the steering wheel. While this setpoint trajectory was used for a period of another $t_s = 0.3$ s, the vehicle state and steering angle were sampled again and the prediction horizon was shifted forward in time. Using the new values, the next cost-minimizing steering trajectory was delivered with the next iteration of the MPC algorithm.

A simple proportional-integral (PI) control law was used to generate the motor command torque τ_A as a function of the setpoint trajectory θ_A generated by the automation system and the current steering angle θ:

$$\tau_\mathrm{A}(t) = k_\mathrm{p}(\theta_\mathrm{A}(t) - \theta(t)) + k_\mathrm{i} \int_{t_\mathrm{eq}}^{t} [\theta_\mathrm{A}(T) - \theta(T)] dT, \tag{3}$$

where k_p and k_i are the proportional and integral gains. t_eq is defined as the time instant at which the steering angle $\theta(t)$ was found to be equal to the setpoint trajectory $\theta_\mathrm{A}(t)$ for at least five consecutive sampling instances. At t_eq, the integral term in the control law was reset to zero to prevent unnecessary accumulation of past errors in the commanded torque. Finally, the steering controller command τ_A was passed to the Arduino micro-controller where a PWM signal was generated and applied to the motor amplifier that produced the command torque at the motor.

2.4. Experimental Conditions

Our experiment involved three conditions in which control was shared between a human and automation, called *Active Safety*, *Haptic Shared Control*, and *Autopilot*. In addition, we included two conditions in which control was given in whole (without transitions) to either the human, called *Manual Control*, or the automation, called *Automatic Control*.

Under each condition, participants were asked to follow the road, keeping as close as possible to the centerline, but to avoid obstacles. Obstacles were invisible until the vehicle was within 40 meters range. Therefore, with a constant speed of 10 m/s, the participant had about 4 s to recognize and avoid an obstacle.

Ten obstacles were encountered on each run, though 2 obstacles chosen at random were made invisible to the driver (by not showing them on the monitor). These events were termed "Human Faults". Another 2 obstacles on each run were not detected by the automation system (their coordinates were not passed across the UDP link). These events were termed "Automation Faults". That is, of the 10 obstacles encountered in each run, only 6 were "No Fault" obstacles while 2 were "Human Fault" and another 2 were "Automation Fault" obstacles. The particular obstacles falling into each of these three bins were randomized in each run. The driver was informed that 2 of the 10 obstacles would not be visible on the screen but would be detected by the automation system and of the remaining 8 visible obstacles, 2 would not be detected by the automation.

2.4.1. Manual Control

In the *Manual Control* condition the driver was solely responsible for steering the vehicle; the automation system was not involved. The only torque feedback that the driver received from the motorized steering wheel was a self-aligning torque associated with the simulated tire-road interaction.

Table 1: Steering Control Parameters for the Control Conditions

Control Condition	k_p (V/rad)	k_i (V/rad/s)
Manual Control	–	–
Active Safety	55	100
Haptic Shared Control	40	80
Autopilot	40	80
Automatic Control	40	80

2.4.2. Automatic Control

To characterize the performance of the automation system alone, the MPC-based automation system described above in Section 2.3 drove the course without any human intervention. The automation system acted on the physical steering wheel through the motor, producing a steering trajectory that included the influence of the simulator hardware dynamics and PI control. The control gains listed in Table 1 were used.

2.4.3. Active Safety

In the *Active Safety* condition, the automation system took over complete control in the presence of obstacles that it detected and deemed likely to be hit without intervention. The automation system utilized the MPC algorithm described in Section 2.3. The gains in Table 1 rendered the automation desired steering angle with a high impedance and ensured that the automation system could wrest control from the driver whose hands remained on the steering wheel. The automation system in the active safety condition was not designed to bring the vehicle back to the path after passing the obstacle. In fact, once the vehicle successfully avoided a given obstacle, the automation system turned off and the driver became responsible for steering the vehicle back to the centerline.

2.4.4. Autopilot

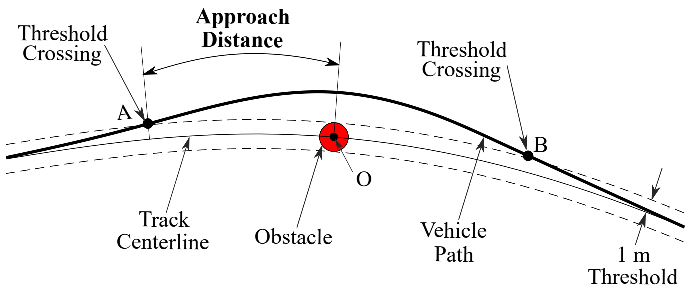
The *Autopilot* system utilized the same automation system as the *Automatic Control* system, except in this case the human was charged with monitoring system performance and intervening if they thought the automation system did not recognize an obstacle. The human could intervene by grasping the steering wheel and pressing the red button to disengage the automation system. That is, when the red button was pressed, the control task was given completely to the human. After driving around the obstacle in question the human driver could re-engage *Automatic Control* by pressing the red button again. A status symbol on the screen indicated whether the automation system was engaged or disengaged. When the automation system was engaged, the motor acted on the steering wheel with the PI gains shown in Table 1. During such periods, the participant could either relax and let the motor action determine the steering trajectory or could let go of the steering wheel.

2.4.5. Haptic Shared Control

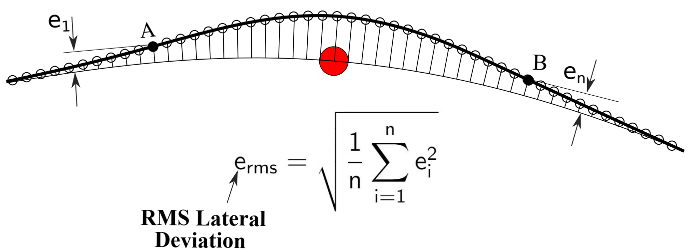
In the *Haptic Shared Control* condition, the participant kept both hands on the steering wheel and was free to act at any time. Likewise, the automation system was free to apply torque throughout a run. When the driver decided to take over control, they could increase their impedance and impose higher torques on the steering wheel. Conversely, the driver could yield control to the automation system by decreasing their impedance (relaxing) and applying a lower torque on the steering wheel. As in the other conditions, the automation system used the vehicle states as inputs to its MPC algorithm to generate control action using the motor coupled to the steering wheel. The steering controller gains were selected so that the participant could easily override, or "edit" the automation system's command (see Table 1).

2.5. Performance Metrics

Three metrics were defined to quantify driving performance and enable comparison across conditions and participants. The first metric, Obstacle Hits, was simply the number of obstacle collisions that occurred within a given run. Another two metrics, called Approach Distance and RMS Lateral Deviation, were defined to characterize driving performance around the obstacles that were successfully avoided as shown in Fig. 3. Both Approach Distance and RMS Lateral Deviation were defined with reference to points A and B, A being the point at which the vehicle trajectory first deviates by more than 1 m from the centerline, and B the point at which the vehicle trajectory arrives again within 1 m of the centerline (see Fig. 3). The Approach Distance is defined as the distance along the centerline from point A to the center of the obstacle O. For each point sampled at 10 ms along the vehicle trajectory, the closest point on the centerline was interpolated. Lateral deviation was then defined as the closest distance to the centerline, for each evenly sampled point on the vehicle trajectory. The RMS Lateral Deviation was the root mean square of the lateral deviation between points A and B. Note that Approach Distance and RMS Lateral Deviation were computed only for obstacles that were not hit.



(a)



(b)

Figure 3: A typical obstacle avoidance trajectory taken by a participant is used to define the performance metrics Approach Distance and RMS Lateral Deviation. (a) The track centerline and vehicle path are used to define the location of points A and B that lie on the vehicle path at a lateral distance of 1 m from centerline when the vehicle approaches and departs the obstacle. The distance between point A and obstacle center O along the centerline is defined as the Approach Distance. (b) Starting at point A on the vehicle path, the lateral deviation is denoted by e_1, then e_2 and so on until the lateral deviation at point B is denoted by e_n. RMS Lateral Deviation is then the root mean square of the values of lateral deviation between points A and B.

2.6. Data Analysis

The present study employed a 3 × 3 factorial design, with the two factors being: Control Sharing Condition (*Active Safety*, *Haptic Shared Control*, and *Autopilot*) and Fault Type (No Fault, Human Fault, and Automation Fault). The Control Sharing condition was varied between trials and the Fault condition was varied within trials. The dependent measures were: (1) the percentage of Obstacle Hits, (2) the RMS Lateral Deviation, and (3) the Approach Distance. Data analysis was performed using Generalized Linear Mixed Modeling method in IBM SPSS Statistics version 25. The Obstacle Hit metric was analyzed using the binary logistic regression procedure whereas the RMS Lateral Deviation and Approach Distance were analyzed using the linear modeling procedure. The Control Sharing condition and Fault Type were chosen as independent factors. A p-value of 0.05 was set to determine significance. Post-hoc, sequential Bonferroni method was applied to determine significant differences.

3. Results

3.1. Obstacle Hits

Each of our eleven participants and the automation system, when driving by themselves, were able to drive the course keeping close to the centerline and without hitting obstacles. And as expected, without seeing or detecting obstacles, our eleven participants and the automation system drove right through the obstacles located on the centerline. Thus the best case scenario for forming a human-automation team under conditions in which at least one agent saw every obstacle could be expected to produce perfect performance. However, this was not the case.

As shown in Table 2 and Table 3, a lower percentage of obstacles were hit in the three Control Sharing conditions in comparison to the 20% obstacles

Table 2: Obstacle Hits for each Control Sharing Condition separated by Fault Conditions

	No Fault		Human Fault		Automation Fault		**All Fault Conditions**	
	Obstacles Hit	%Hits	Obstacles Hit	%Hits	Obstacles Hit	%Hits	**Obstacles Hit**	**%Hits**
Active Safety	3/198	1.5%	19/66	28.8%	0/66	0%	**22/330**	**6.7%**
Haptic Shared Control	1/198	0.5%	3/66	4.5%	2/66	3%	**6/330**	**1.8%**
Autopilot	5/198	2.5%	4/66	6.1%	1/66	1.5%	**10/330**	**3%**
All Control Conditions	**9/594**	**1.5%**	**26/198**	**13.1%**	**3/198**	**1.5%**	**38/990**	**3.8%**

Table 3: Obstacles Hits for Baseline Conditions separated by Fault Conditions

	No Fault		Human Fault		Automation Fault		**All Fault Conditions**	
	Obstacles Hit	%Hits	Obstacles Hit	%Hits	Obstacles Hit	%Hits	**Obstacles Hit**	**%Hits**
Manual	0/264	0%	66/66	100%	–	–	**66/330**	20%
Automatic	0/24	0%	–	–	6/6	100%	**6/30**	20%

that were hit in both the *Manual Control* and the *Automatic Control* conditions. Considering only Fault Conditions, in the *Manual Control* condition, 100% of the obstacles that simulated Human Faults were hit whereas only 4.5% were hit in the *Haptic Shared Control*, 6.1% were hit in the *Autopilot*, and 28.8% were hit in the *Active Safety* condition. Likewise, in the *Automatic Control* condition 100% of the obstacles that simulated Automation Fault were hit whereas only 3% were hit in the *Haptic Shared Control*, 1.5% were hit in the *Autopilot*, and no obstacles were hit in the *Active Safety* condition. Between control sharing conditions, the *Active Safety* condition resulted in the highest percentage of obstacle hits (6.7%) whereas the *Haptic Shared Control* condition resulted in the lowest percentage of hits (1.8%). On the other hand, between Fault Conditions, Human Fault resulted in the

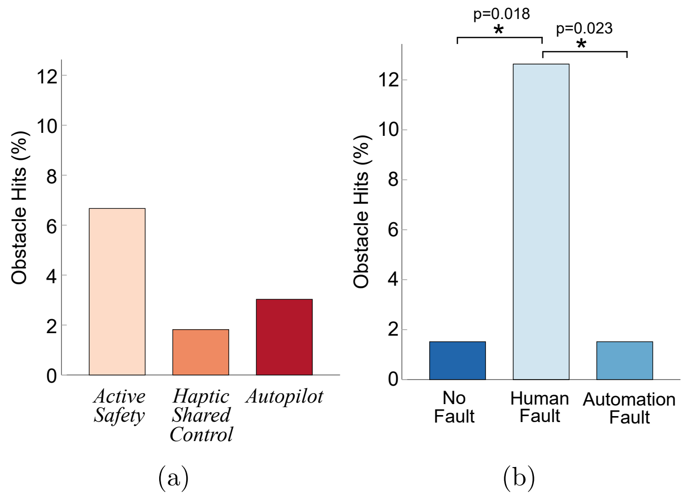


Figure 4: (a) Percent obstacle hits by Control Condition, (b) Percent obstacle hits by Fault Condition. The asterisks on the lines linking two bars indicate a significant difference between two conditions.

highest percentage (13.1%) whereas both Automation Fault and No Fault resulted in an equal percentage of hits (1.5%).

Analysis on the Obstacle Hit data indicated that the Control Sharing condition was not a significant predictor of an obstacle hit ($F(2, 981) = 0.923, p = 0.398$). Fault Condition, on the other hand, had a significant main effect on the likelihood of a hit ($F(2, 981) = 6.555, p = 0.001$). Post-hoc comparisons indicated that the possibility of an obstacle hit for the Human Fault condition was significantly higher than for both the Automation Fault ($p = 0.023$) and for the No Fault ($p = 0.018$) conditions (also indicated in Fig. 4 (b)). However, since the interaction effect between Fault Condition and Control Sharing condition was also found to be significant ($F(4, 981) = 2.579, p = 0.036$), it was difficult to generalize the effect of Fault Condition

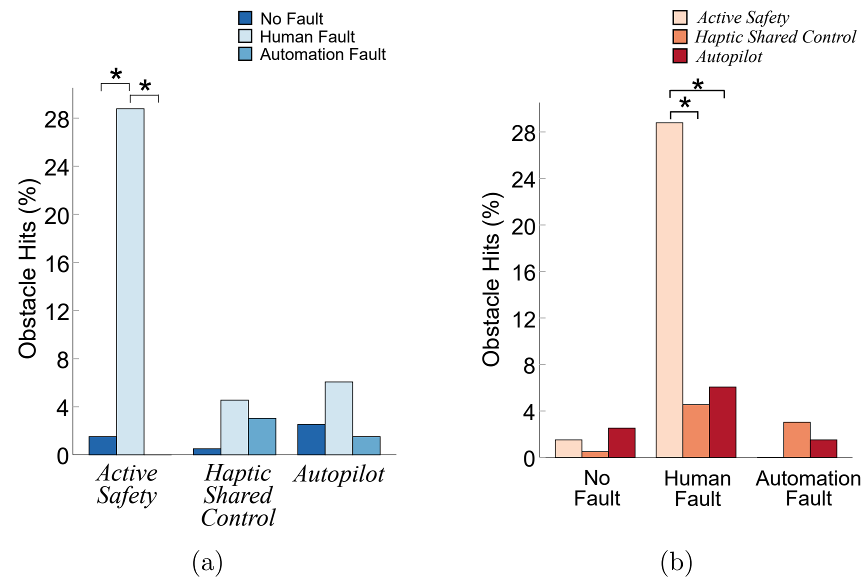


Figure 5: Percent Obstacle Hits (a) for each Fault Condition grouped by Control Condition and (b) for each Control Condition grouped by Fault Condition. The asterisks on the lines linking two bars indicate a significant difference between two conditions.

on all control conditions. To further understand this, we looked at the simple main effect of Control Sharing condition on obstacle hits for each of the three Fault Conditions and of Fault Condition on obstacle hits for each of the three Control Sharing conditions.

Our analysis showed that only for the Human Fault condition, Control Sharing condition had a significant effect on the likelihood of a hit ($F(2, 981) = 7.265, p = 0.0007$). Post-hoc sequential Bonferroni test revealed that for the Human Fault condition, *Active Safety* had a higher likelihood of an obstacle hit than *Autopilot* ($p = 0.001$) and *Haptic Shared Control* ($p = 0.0007$) conditions. For any other Fault Type, the Control Sharing Condition had no effect. Likewise, only for the *Active Safety* condition, the

Fault Condition had a significant effect on obstacle hits ($F(2, 981) = 10.032$, $p < 0.0005$). Post-hoc test revealed that for *Active Safety*, the Human Fault condition was found to result in a higher number of hits than Automation Fault ($p < 0.0005$) and No Fault ($p < 0.0005$) conditions. The results of post-hoc tests for the simple main effects analysis are summarized in Figure 5. Hence the main effect of Fault Type was only due to the large number of hits in the *Active Safety* condition for Human Fault and therefore this effect could not be generalized to the *Haptic Shared Control* and *Autopilot* conditions.

3.2. RMS Lateral Deviation

The RMS Lateral Deviation was used to gauge which control sharing condition resulted in the most "efficient" maneuver around the obstacles. The means of RMS Lateral Deviation are presented in Table 4 for all the Control Sharing conditions including *Manual* and *Automatic* conditions. As mentioned earlier, the RMS Lateral Deviation was only computed for obstacles that were successfully avoided. Therefore a lower value of RMS Lateral Deviation for a condition indicates that the participant found it relatively easier to use that control scheme to make an efficient maneuver around the obstacle. This becomes more apparent when we look at the trajectories presented in Fig. 6 and compare them with the numbers in Table 4. A lower mean value of RMS Lateral Deviation for a condition in Table 4 corresponds to a lower spread (indicated in grey) of trajectories for that condition in Fig. 6, and to an average trajectory (indicated by black solid line) that deviates less from the centerline.

Since the case of Automation Fault was not possible in the *Manual Con-*

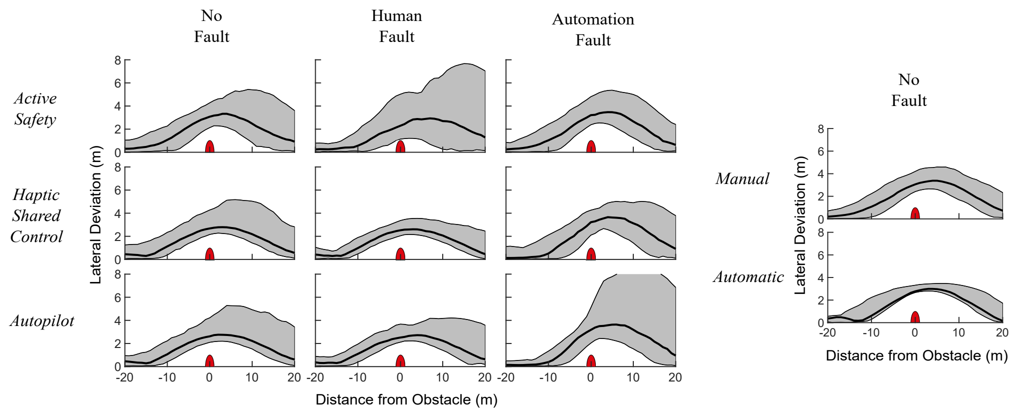


Figure 6: Plots depicting driving trajectories around the obstacles computed across all 11 participants for each control condition and fault condition. The black solid line indicates the 50^{th} percentile of lateral deviation. Two traces enveloping the black solid line shade the 5^{th} to 95^{th} percentile intervals for the lateral deviation. Obstacles are shown to scale by red half ellipses.

Table 4: Means and Standard Errors (S.E.) of RMS Lateral Deviation for all Control Conditions separated by Fault Conditions

	No Fault		Human Fault		Automation Fault		**All Fault Conditions**	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	**Mean**	**S.E.**
Active Safety	2.71	0.07	2.83	0.12	2.69	0.10	**2.74**	**0.07**
Haptic Shared Control	2.41	0.07	2.17	0.10	2.87	0.10	**2.48**	**0.07**
Autopilot	2.40	0.07	2.33	0.10	3.15	0.10	**2.63**	**0.07**
All Control Conditions	**2.51**	**0.05**	**2.44**	**0.08**	**2.90**	**0.08**	**2.62**	**0.06**

	No Fault	
	Mean	S.E.
Manual	2.63	0.025
Automatic	2.41	0.063

trol condition (because automation was absent), and the case of Human Fault - which resulted in hits - was removed while computing the metric, only the case of No Fault was pertinent for the *Manual Control* condition. Likewise, only the case of No Fault was pertinent for the *Automatic Control* condition. Looking at the means presented in Table 4, in the No Fault case, RMS Lateral

Deviation values with *Haptic Shared Control* and *Autopilot* were lower than *Manual Control* condition and was similar to the *Automatic Control* condition whereas RMS Lateral Deviation with *Active Safety* was higher than all other control conditions. These observations indicate that sharing control using schemes such as *Haptic Shared Control* and *Autopilot* can indeed maintain or reduce RMS Lateral Deviation when compared with *Automatic* and *Manual* driving.

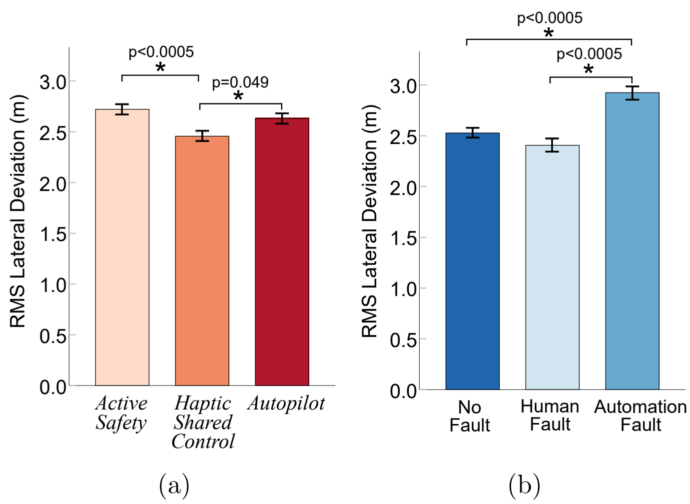


Figure 7: Mean RMS Lateral Deviation. The RMS Lateral Deviation is defined in Fig. 3. (a) Mean RMS Lateral Deviation for the three control conditions, (b) Mean RMS Lateral Deviation for the three Fault Conditions. Error bars are $\pm$ 1 standard error of the mean. The asterisks on the lines linking two bars indicate a significant difference between two conditions along with the respective p values.

Unlike Obstacle Hits, the Control Sharing Condition significantly affected the RMS Lateral Deviation ($F(2, 915) = 7.709, p < 0.0005$). As shown in Fig. 7 (a), between the three Control Sharing conditions, *Haptic Shared Control* had significantly lower RMS Lateral Deviation and consequently

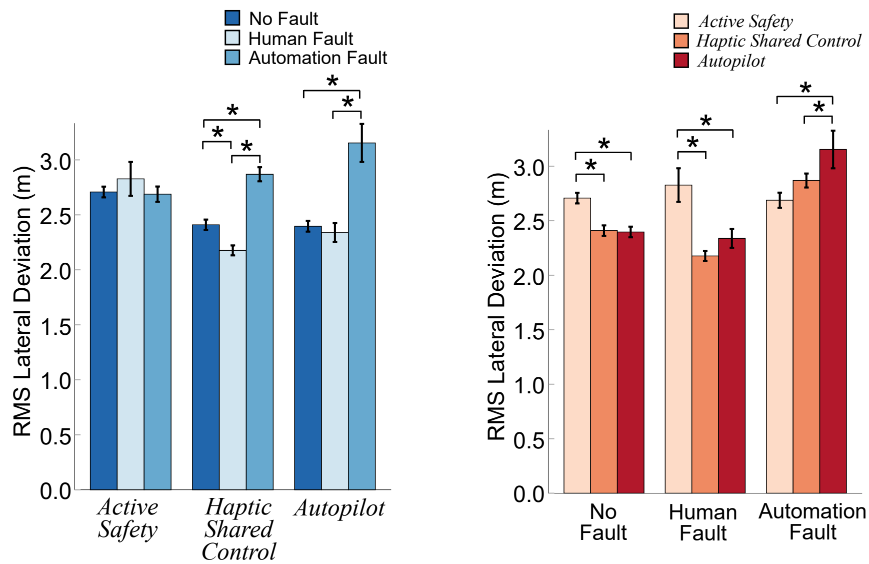


Figure 8: Mean RMS Lateral Deviation (a) for each Fault Condition grouped by Control Condition and (b) for each Control Condition grouped by Fault Condition. Error bars are ± 1 standard error of the mean. The asterisks on the lines linking two bars indicate a significant difference between two conditions.

better maneuvering efficiency than *Active Safety* ($p < 0.0005$) and *Autopilot* ($p = 0.049$). Fault Condition also had a main effect on RMS Lateral Deviation ($F(2, 915) = 26.04, p < 0.0005$) and, as shown in Fig. 7 (b), the RMS Lateral Deviation for the Automation Fault condition was significantly higher compared to the Human Fault ($p < 0.0005$) and No Fault ($p < 0.0005$) conditions. The effect of interactions on the RMS Lateral Deviation was also found to be significant ($F(4, 915) = 9.83, p < 0.0005$). Simple main effects analysis showed that the Control Sharing Condition had a significant effect on RMS Lateral Deviation for each Fault Condition: Human Fault ($F(2, 915) = 11.681, p < 0.0005$), Automation Fault ($F(4, 915) =$

$6.727, p = 0.001$), and No Fault ($F(4, 915) = 12.125, p < 0.0005$). Moreover, Fault Condition had a significant effect on RMS Lateral Deviation for *Autopilot* ($F(2, 915) = 29.284$, $p < 0.0005$) and *Haptic Shared Control* ($F(4, 915) = 6.727, p = 0.001$) conditions.

Post-hoc analysis indicated that *Active Safety* had significantly better maneuvering efficiency than *Autopilot* ($p = 0.0009$) around the obstacles that simulated Automation Faults whereas *Autopilot* had significantly better maneuvering efficiency than *Active Safety* around the obstacles that simulated Human Faults ($p = 0.0008$) and in the cases of No Fault ($p < 0.0005$) (Fig. 8 (b)). However, overall differences (averaged over three fault conditions) between *Active Safety* and *Autopilot* were found to be insignificant ($p = 0.087$) (Fig. 7 (a)). Other significant differences resulting from the post-hoc tests for the simple main effects analysis are summarized in Fig. 8.

3.3. Approach Distance

The Approach Distance was used to gauge the human driver's preparedness to give up or take over the driving authority during obstacle avoidance. The value of approach distance indicated how early the human-automation team deviated from the track to avoid the obstacle. For instance, a lower approach distance implied that during obstacle avoidance, the human-automation team took more time to deviate from the track. However, since the behavior of automation near the obstacles was fixed, a lower Approach Distance indicated that the human driver was primarily responsible for the additional delay in deviating from the track. In particular, the driver was either unprepared to take over the driving authority or was unprepared to give away the driving authority to automation which resulted in late deviation from the track. The means of Approach Distance for all conditions are summarized in Table 5. Note that the mean Approach Distance for a condition corresponds to the Approach Distance value of the mean driver trajectory for that condition in Fig. 6.

Table 5: Means and Standard Errors (S.E.) of Approach Distance for all Control Conditions separated by Fault Conditions

	No Fault		Human Fault		Automation Fault		**All Fault Conditions**	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	**Mean**	**S.E.**
Active Safety	11.52	0.47	8.98	0.70	11.00	0.62	**10.50**	**0.47**
Haptic Shared Control	12.12	0.47	11.92	0.62	9.73	0.62	**11.25**	**0.45**
Autopilot	11.62	0.47	11.24	0.62	8.30	0.63	**10.39**	**0.46**
All Control Conditions	**11.75**	**0.31**	**10.72**	**0.48**	**9.68**	**0.47**	**10.72**	**0.41**

	No Fault	
	Mean	S.E.
Manual	11.38	0.26
Automatic	10.32	1.12

Looking at the means of Approach Distance presented in Table 5, we see that out of all Control Conditions, the *Haptic Shared Control* condition had the highest Approach Distance whereas the *Automatic Control* had the lowest Approach Distance value. Note that the Approach Distance was low in *Automatic Control* condition not because automation was "unprepared" but because it was designed to minimize the lane keeping error. Therefore, the Approach Distance metric only indicates the behavior of automation near the obstacles but does not tell much about the performance of automation in the *Automatic Control* condition. The second highest mean Approach Distance after the *Haptic Shared Control* condition was seen in the *Autopilot* condition which was followed by the *Active Safety* and the *Manual* condition. These observations indicate that sharing control using any scheme increases the Approach Distance when compared with *Automatic* and *Manual* driving.

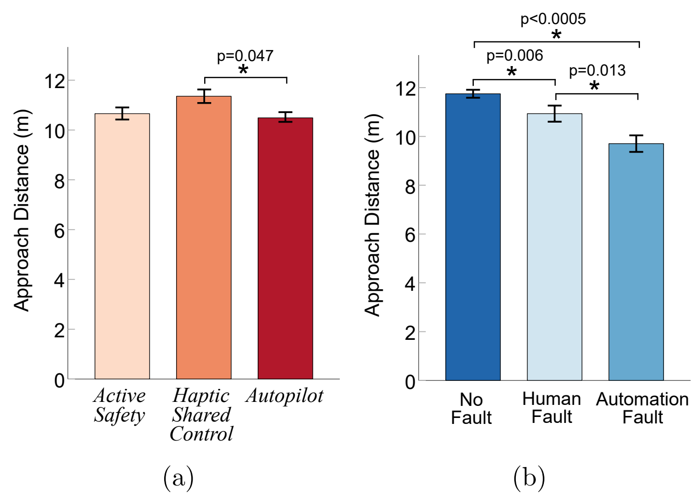


Figure 9: Mean Approach Distance. The Approach Distance is defined in Fig. 3. (a) Mean Approach Distance for the three Control Sharing Conditions (b) Mean Approach Distance for the three visibility conditions. Error bars are $\pm$ 1 standard error of the mean. The asterisks on the lines linking two bars indicate a significant difference between two conditions along with the respective p values.

The results for the analysis of Approach Distance are summarized in Fig. 9 and Fig. 10. The effect of control condition on Approach Distance was found to be statistically significant ($F(2, 915) = 3.43, p = 0.033$). Through the post-hoc tests it was found that the mean Approach Distance for the *Haptic Shared Control* condition was significantly higher than the *Autopilot* condition ($p = 0.047$). The Fault condition also had a significant effect on Approach Distance ($F(2, 915) = 21.07, p < 0.0005$). The post-hoc tests revealed that all three Fault conditions were significantly different from each other. The Automation Fault condition was found to have a significantly lower Approach Distance than the Human Fault ($p = 0.013$) and the No Fault ($p < 0.0005$) conditions. Furthermore, Approach Distance for the Human

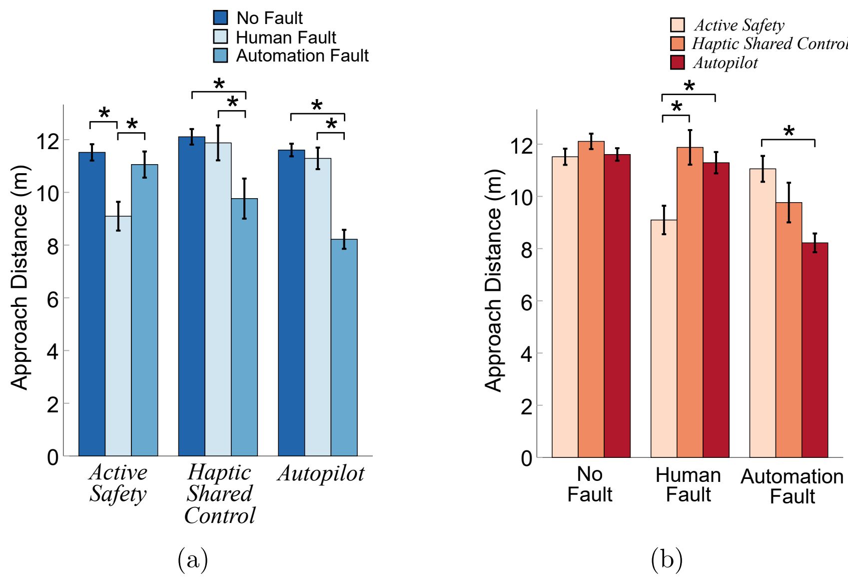


Figure 10: Mean Approach Distance (a) for each Fault Condition grouped by Control Condition and (b) for each Control Condition grouped by Fault Condition. Error bars are ± 1 standard error of the mean. The asterisks on the lines linking two bars indicate a significant difference between two conditions.

Fault condition was significantly lower than the No Fault condition ($p = 0.006$). Finally, the effect of interaction of the independent factors was also found to be significant ($F(2, 915) = 6.67, p < 0.0005$). Through simple main effect analysis, it was found that Control Sharing Condition had a significant effect on Approach Distance both for Human Fault condition ($F(2, 915) = 7.618, p = 0.0006$) and for Automation Fault condition ($F(2, 915) = 7.34, p = 0.0008$). Post-hoc tests for Control Condition further revealed that in the case of Automation Faults, the *Autopilot* condition had significantly lower Approach Distance than the *Active Safety* ($p < 0.0005$) condition. In the case of Human Faults however, the *Active Safety* condition had significantly lower Approach Distance than both the *Autopilot* ($p = 0.007$) and the *Haptic*

Shared Control ($p < 0.0005$) conditions. These results are summarized in Fig. 10 (b). Fault Condition also had a significant effect on the Approach Distance for all the Control Sharing Conditions. The post-hoc results for Fault Conditions are summarized in Fig. 10 (a).

4. Discussion

In this driving simulator study our goal was to compare the obstacle avoidance performance of human/automation teams under three Control Sharing Conditions in the presence of simulated *faults*. Faults were simulated by partitioning the visibility of obstacles among the human driver and the automation system. That is, certain obstacles were visible to the automation but invisible to the human (Human Fault), certain obstacles were visible to the human but invisible to the automation (Automation Fault) while the rest were visible to both human and automation (No Fault). Performance under the three Control Sharing Conditions and under the three Fault Conditions were then analyzed in a 3×3 study. To further understand the role of each agent in the Control Sharing Conditions, they were compared against two baseline driving conditions that did not involve any control sharing: *Manual Control* and *Automatic Control*. All analyses were undertaken on three performance metrics that focused on distinct aspects of the obstacle avoidance task. The Obstacle Hits metric was used to compare driving safety; higher obstacle hits corresponded to lower safety. Approach Distance was used to gauge the human driver's preparedness to give up or take over driving authority during obstacle avoidance; a lower approach distance indicated that around the obstacle the human driver was either unprepared to take over the driving authority or was unprepared to give away the driving authority to automation. Finally, RMS Lateral Deviation was used to compare the driver's maneuvering efficiency around the obstacle; lower RMS lateral deviation indicated that the maneuver was performed more efficiently without excessive lateral deviation from the centerline.

In terms of Obstacle Hits, two agents driving together were found to be better than either agent driving alone. With only one agent driving (as in the Manual and Automatic baseline conditions), a fault led unconditionally (100%) to an obstacle hit. With two agents sharing control, between 0% and 28.8% of faults led to an obstacle hit, depending on the Fault Condition and the Control Sharing Condition (see Table 2). In one sense this was encouraging, but in another quite disappointing. If each obstacle was seen by at least one agent in the Control Sharing Conditions, and each agent acting alone was capable of avoiding No Fault obstacles, as established in the baseline conditions, one might have expected zero obstacles to be hit in the Control Sharing conditions. It appears that transitions of control and an associated need for time to acquire situation awareness, communication, or negotiation between the two agents led to difficulties in handling Human Fault or Automation Fault obstacles.

But note further, adding a second agent had an alarming effect on the perfect single-agent record for No Fault obstacles, as between 0.5% and 2.5% of No Fault obstacles were hit in the Control Sharing Conditions. Like a back-seat driver may be blamed for distracting and inducing errors rather than helping, adding automation can be blamed for inducing errors. For that matter, adding a human to automatic driving might also be blamed for inducing automation errors.

In contrast, adding a second agent seemed to enhance the Approach Distance. This is supported by Table 5 where it can be observed that, for the No Fault Condition, all Control Sharing conditions had higher values of Approach Distance than the baseline conditions. Moreover, the *Manual* condition had a larger Approach Distance than the *Automatic* condition. This indicates that when faced with an obstacle, human drivers preferred to deviate earlier from the center-line than the automation system. Recall that the automation was designed to have a lower approach distance to minimize the deviation from the center-line. For the Control Sharing conditions, this might mean that while sharing control, our participants most likely reacted before the automation to avoid an obstacle. Likewise, as shown in Table 4, adding a second agent with the *Haptic Shared Control* and the *Autopilot* conditions also reduced or maintained the RMS Lateral Deviation, and therefore improved or maintained the maneuvering efficiency over the baseline conditions. In addition, since the *Automatic Control* condition had lower RMS Lateral Deviation than the *Manual* condition it is likely that our participants let the automation be more active in *Haptic Shared Control* and *Autopilot* while maneuvering around the obstacle. On the other hand, since RMS Lateral Deviation for the *Active Safety* condition was higher than the baseline conditions it might indicate that the human was still more involved during the obstacle avoidance maneuver than the automation system, which resulted in reduced maneuvering efficiency. Note, however, that our baseline conditions could not be statistically compared with our control sharing conditions because they had different levels of Fault Conditions. Therefore these results merit further exploration in future studies.

Looking at Obstacle Hits across Control Sharing and Fault conditions, we found that significantly more Human Fault obstacles were hit in the *Active Safety* condition than in the *Haptic Shared Control* or *Autopilot* conditions. It was observed that during the Human Fault condition in *Active Safety*, when the automation intervened to avoid the obstacle, our participants were oftentimes unwilling to let go of the steering wheel and give away the driving authority to automation. As a result, they either inadvertently crashed into an obstacle that they could not see or reacted very late and barely avoided the obstacle with an inefficient and potentially unsafe maneuver around the obstacle (see Fig. 6). Consequently, in the condition of Human Faults, *Active Safety* produced significantly more obstacle hits, lower Approach distance and larger RMS Lateral Deviation than the other two control sharing conditions. On the other hand, during the Human Fault condition in *Autopilot*, since the automation was already performing the driving task, our participants did not intervene and simply let the automation avoid the obstacle.

In contrast, in the case of Automation Faults, the *Autopilot* condition resulted in significantly larger RMS Lateral Deviation than the *Active Safety* condition and the *Haptic Shared Control* condition, and significantly lower Approach Distance than the *Active Safety* condition. For Automation Faults in *Autopilot*, we found our participants unprepared to take over the driving authority; they took additional time to acknowledge that the automation had failed and to press the button to take over the driving authority. This delay also resulted in more inefficient and uncontrolled obstacle avoidance maneuvers as shown in Fig. 6. Such a delay was absent in *Active Safety* where our participants were already performing the driving task and were not required to take over control from automation to avoid the obstacle (similar to *Manual* driving).

Contemporary research on transitions in control indicate that externally-paced (automation initiated) transitions lead to reduced performance relative to human-paced transitions in human takeovers from automation. Reduced performance is associated with lower “levels of control”, in particular so-called “scrambled control”, characterized by urgent selection of control actions seemingly at random [43, 34]. Note that in this study we investigated urgent human-paced takeovers from automation (*Autopilot*) and urgent externally-paced takeovers from human drivers (*Active Safety*). These takeovers were all necessary because of fault conditions induced artificially at constant high rates but at random times. Faults were not accompanied by alarms or announcements. Extensions to the current study could be undertaken to determine the effects of factors such as the time required to press a button or the potential delays associated with committing to transition when that transition takes the form of a lumped or total transfer of control authority.

Between *Active Safety* and *Autopilot*, we therefore see that there is a reduction in overall driving performance (higher hits, higher RMS Lateral Deviation, lower Approach Distance) when the primary agent responsible for lane keeping cannot see the obstacle: *Active Safety* does not perform well when the primary driver, human, cannot see the obstacle and *Autopilot* does not perform well when the primary driver, automation, cannot see the obstacle. In other words, it can be said that *Active Safety* behaves similar to the

Manual condition whereas *Autopilot* behaves similar to the *Automatic* condition. This observation is further reinforced by Table 4 where the mean RMS Lateral Deviation for *Active Safety* is closer to *Manual* condition and for *Autopilot* is closer to *Automatic* condition. This indicates that even though *Active Safety* and *Autopilot* conditions are designed to support control sharing between human and automation, they apparently still perform similar to single agent driving schemes.

Theoretically, therefore, driving performance could still be enhanced by increasing the involvement of the secondary agent in the primary driving task. This was facilitated in the *Haptic Shared Control* condition by having the driver actively hold the steering wheel while the automation performed the lane keeping task. Our results showed that overall, averaging over all fault conditions, *Haptic Shared Control* had significantly lower RMS Lateral Deviation than both *Active Safety* and *Autopilot* conditions and had significantly higher Approach Distance than the *Autopilot* condition and higher (if not "significantly" higher) Approach Distance than the *Active Safety* condition. Moreover, for each individual Fault Condition, with respect to the three metrics, the driving performance with *Haptic Shared Control* was never significantly lower than the *Active Safety* and the *Autopilot* conditions. This indicated that regardless of the Fault Condition we could expect *Haptic Shared Control* to perform at least as well as the other control sharing conditions.

The improvement in driving performance with *Haptic Shared Control* can be attributed to the more gradual nature of collaboration in *Haptic Shared Control* as compared to the other Control Conditions. In the *Haptic Shared Control* condition, the automation continuously communicated its control efforts to the driver through torque feedback on the steering wheel. The driver used this feedback to adopt a driving responsibility or assign a driving responsibility to the automation by activating or relaxing his/her muscles [17, 21, 44, 45]. For example, as seen in Table 4 and Table 5, since the Approach Distance of *Haptic Shared Control* was closer to the *Manual* condition than the *Automatic* condition, we can say that when faced with an obstacle, the human activated his/her muscles and overpowered the automation to deviate earlier from the centerline. Whereas, since the RMS Lateral Deviation of *Haptic Shared Control* was closer to the *Automatic* condition than the *Manual* condition, we can say that while maneuvering around the obstacle, the human relaxed and let the automation take control to perform the maneuever efficiently.

Based on the analysis of our performance metrics, our results indicate that sharing control under *Haptic Shared Control* promotes safer driving, enhances driver preparedness to take over or give away the driving authority, and promotes more efficient driving maneuvers around obstacles than sharing control between two agents with fixed and predefined primary and secondary driving roles. These results support the benefits of control sharing with haptic shared control that have been previously published in the literature [17, 21, 25, 24, 46, 47, 48]. Complementing previous research, this study demonstrates how shared driving with continuous transitions involving haptic feedback can help improve driving performance in the event of human errors or automation dropouts over control sharing techniques with discrete transitions that are currently available in production vehicles.

Finally, looking at the differences between the Fault Conditions based on the Control Conditions, we found that for *Autopilot* and *Haptic Shared Control*, the Automation Fault condition produced significantly larger RMS lateral deviation and lower Approach Distance than both the Human Fault and No Fault conditions. In other words, when only the driver could see the obstacle, in *Autopilot* and *Haptic Shared Control*, the automation's inaction was more detrimental to the driver's maneuvering efficiency and the driver's preparedness to take over or give up the driving authority than the automation's action when the driver could not see the obstacle or when both agents could see the obstacle. Since in both *Autopilot* and *Haptic Shared Control*, the automation was active most/all of the time, we think that the reduction in driving performance was probably because our participants mistook the Automation Fault obstacle for a No Fault obstacle and relied excessively on the automation system to avoid it. Such an over-reliance on automation or *misuse* of automation system has been referred to as automation-induced "complacency" in the shared control literature in the past [49, 10, 15].

Lower driving performance during Automation Fault, especially for the *Haptic Shared Control* condition, might also be a function of the high value of control gains that we used to implement the automation's authority (impedance) in our *Haptic Shared Control* design. As mentioned in the literature previously, high automation impedance is detrimental to the shared task performance in the case of Automation Faults [17]. We suspect that our design gave automation more control over driving than the driver. In future studies it would be interesting to examine if our results hold true for other levels of automation impedance (for instance a lower automation impedance) or for an *Adaptive Haptic Shared Control* design [17] where impedance values vary based on the driver's neuromuscular involvement.

5. Conclusion

This study investigated the ability of human-automation teams to avoid obstacles missed by an automation system (Automation Faults) and obstacles missed by human drivers (Human Faults) under three control sharing schemes. We hypothesized that *Haptic Shared Control*, designed to support graded and gradual transitions of control authority and enable the human driver to monitor automation actions through torque feedback on the steering wheel, would outperform the *Autopilot* and *Active Safety* schemes that feature lumped and instantaneous transitions of control authority.

We found the lowest team performance under *Autopilot* for automation faults and under *Active Safety* for human faults. *Haptic Shared Control* supported the best overall team performance. Relative to individual human or automatic driver performance, we found that control sharing improved obstacle hit rates, maneuvering efficiency, and driver's preparedness to take over or give up the driving authority during obstacle encounters. While both human drivers and the automation system were able to avoid most (but still not all) of the obstacles missed by the other when teamed together, forming a team with control transitions also introduced errors in conditions without faults. Obstacle collisions under No-Fault conditions were not observed when human drivers or the automation system drove alone.

While the timing of faults was unpredictable in the current study, the fault rates were constant and rather high. Handling of a seldom occurring fault likely differs significantly from a fault that occurs at an expected high rate of 20%. Also, in the present study, there was barely time to recover from the previous obstacle or fault before another obstacle or fault appeared. Future research could investigate the compounding effects of deteriorating vigilance when faults cannot be anticipated. Future research could also investigate whether announcing a fault through visual, audio, or haptic feedback could improve performance.

Certainly the results in the present study depend on the particular implementation of each control sharing scheme. Additional research will be required to determine the dependence of performance to parameters within a particular scheme. For example, the limited ability of *Active Safety* to wrest control from the human driver while his or her hands remained on the steering wheel would be very different in a steer-by-wire implementation, where automation actions can be executed without backdriving the human. On the other hand, handing back control to the driver after executing such automation actions could require increased time.

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References

[1] S. Singh, Critical reasons for crashes investigated in the national motor vehicle crash causation survey, Tech. rep., National Highway Traffic Safety Administration (2015).

[2] SAE On-Road Automated Vehicle Standards Committee, Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems, SAE International.

[3] Z. Lu, R. Happee, C. D. Cabrall, M. Kyriakidis, J. C. de Winter, Human factors of transitions in automated driving: A general framework and literature survey, Transportation Research Part F: Traffic Psychology and Behaviour 43 (2016) 183–198.

[4] J. W. Son, M. O. Park, et al., Situation awareness and transitions in highly automated driving a framework and mini-review, Journal of Ergonomics.

[5] A. P. van den Beukel, M. C. van der Voort, A. O. Eger, Towards a framework for testing drivers' interaction with partially automated driving, in: 2015 IEEE 18th International Conference on Intelligent Transportation Systems, IEEE, 2015, pp. 1902–1907.

[6] C. Grover, I. Knight, F. Okoro, I. Simmons, G. Couper, P. Massie, B. Smith, Automated emergency brake systems: Technical requirements, costs and benefits, Tech. rep., Crowthorne: Transportation Research Library (2008).

[7] M. Heesen, M. Dziennus, T. Hesse, A. Schieben, C. Brunken, C. Lper, J. Kelsch, M. Baumann, Interaction design of automatic steering for collision avoidance: challenges and potentials of driver decoupling, IET Intelligent Transport Systems 9 (1) (2015) 95–104.

[8] S. M. Erlien, S. Fujita, J. C. Gerdes, Shared steering control using safe envelopes for obstacle avoidance and vehicle stability, IEEE Transactions on Intelligent Transportation Systems 17 (2) (2016) 441–451.

[9] N. B. Sarter, D. D. Woods, C. E. Billings, Automation surprises, Handbook of Human Factors and Ergonomics 2 (1926-1943).

[10] R. Parasuraman, V. Riley, Humans and automation: Use, misuse, disuse, abuse, Human factors 39 (2) (1997) 230–253.

[11] F. Flemisch, M. Heesen, T. Hesse, J. Kelsch, A. Schieben, J. Beller, Towards a dynamic balance between humans and automation: Authority, ability, responsibility and control in shared and cooperative control situations, Cognition, Technology and Work 14 (1) (2012) 3–18.

[12] Z. Lu, R. Happee, C. D. Cabrall, M. Kyriakidis, J. C. de Winter, Human factors of transitions in automated driving: A general framework and literature survey, Transportation Research Part F: Traffic Psychology and Behaviour 43 (2016) 183–198.

[13] K. L. Mosier, Automation and cognition: Maintaining coherence in the electronic cockpit, in: Advances in Human Performance and Cognitive Engineering research, Emerald Group Publishing Limited, 2002, pp. 93–121.

[14] J. S. Rubinstein, D. E. Meyer, J. E. Evans, Executive control of cognitive processes in task switching., Journal of Experimental Psychology: Human Perception and Performance 27 (4) (2001) 763.

[15] D. A. Norman, The problem with automation: inappropriate feedback and interaction, not over-automation, Philosophical Transactions of the Royal Society of London. B, Biological Sciences 327 (1241) (1990) 585–593.

[16] C. E. Billings, Aviation Automation: The Search For a Human-centered Approach, CRC Press, 2018.

[17] D. A. Abbink, M. Mulder, E. R. Boer, Haptic shared control: smoothly shifting control authority?, Cognition, Technology and Work 14 (1) (2012) 19–28.

[18] M. Goodrich, On maximizing fan-out: Towards controlling multiple unmanned vehicles, Human-Robot Interactions in Future Military Operations (2010) 375–395.

[19] M. A. Goodrich, J. W. Crandall, E. Barakova, Teleoperation and beyond for assistive humanoid robots, Reviews of Human Factors and Ergonomics 9 (1) (2013) 175–226.

[20] J. Y. Chen, M. J. Barnes, Human–agent teaming for multirobot control: A review of human factors issues, IEEE Transactions on Human-Machine Systems 44 (1) (2014) 13–29.

[21] P. G. Griffiths, R. B. Gillespie, Sharing control between humans and

automation using haptic interface: primary and secondary task performance benefits, Human Factors: The Journal of the Human Factors and Ergonomics Society 47 (3) (2005) 574–590.

[22] D. Abbink, M. Mulder, Neuromuscular analysis as a guideline in designing shared control, Advances in Haptics (2010) 499–517.

[23] D. A. Abbink, M. Mulder, E. R. Boer, Haptic shared control: smoothly shifting control authority?, Cognition, Technology & Work 14 (1) (2012) 19–28.

[24] F. Mars, D. Mathieu, J.-M. Hoc, Analysis of human-machine cooperation when driving with different degrees of haptic shared control, IEEE Transactions on Haptics 1412 (c) (2014) 1–1.

[25] R. Nishimura, T. Wada, S. Sugiyama, Haptic shared control in steering operation based on cooperative status between a driver and a driver assistance system, Journal of Human-Robot Interaction 4 (3) (2015) 19–37.

[26] F. Mars, P. Chevrel, Modelling human control of steering for the design of advanced driver assistance systems, Annual Reviews in Control 44 (2017) 292–302.

[27] L. Bainbridge, Ironies of automation, in: Analysis, Design and Evaluation of Man–Machine Systems, Elsevier, 1983, pp. 129–135.

[28] R. Molloy, R. Parasuraman, Monitoring an automated system for a single failure: Vigilance and task complexity effects, Human Factors 38 (2) (1996) 311–322.

[29] M. Itoh, F. Flemisch, D. Abbink, A hierarchical framework to analyze shared control conflicts between human and machine, IFAC-PapersOnLine 49 (19) (2016) 96–101.

[30] I. Wolf, The interaction between humans and autonomous agents, in: Autonomous driving, Springer, 2016, pp. 103–124.

[31] C. Guo, C. Sentouh, J.-B. Haué, J.-C. Popieul, Driver–vehicle cooperation: a hierarchical cooperative control architecture for automated driving systems, Cognition, Technology & Work (2019) 1–14.

[32] F. Flemisch, D. Abbink, M. Itoh, M.-P. Pacaux-Lemoine, G. Weßel, Shared control is the sharp end of cooperation: Towards a common framework of joint action, shared control and human machine cooperation, IFAC-PapersOnLine 49 (19) (2016) 72–77.

[33] L. Saleh, P. Chevrel, F. Mars, J.-F. Lafay, F. Claveau, Human-like cybernetic driver model for lane keeping, IFAC Proceedings Volumes 44 (1) (2011) 4368–4373.

[34] A. Eriksson, N. A. Stanton, Driving performance after self-regulated control transitions in highly automated vehicles, Human Factors 59 (8) (2017) 1233–1248.

[35] P. A. Desmond, P. A. Hancock, J. L. Monette, Fatigue and automation-induced impairments in simulated driving performance, Transportation Research Record 1628 (1) (1998) 8–14.

[36] Y. Zheng, M. J. Brudnak, P. Jayakumar, J. L. Stein, T. Ersal, An experimental evaluation of a model-free predictor framework in teleoperated

vehicles, in: IFAC Workshop on Time Delay Systems, Vol. 49, 2016, pp. 157–164.

[37] J. Liu, P. Jayakumar, J. Stein, T. Ersal, Combined speed and steering control in high speed autonomous ground vehicles for obstacle avoidance using model predictive control, IEEE Transactions on Vehicular Technology.

[38] H. Febbo, J. Liu, P. Jayakumar, J. L. Stein, T. Ersal, Moving obstacle avoidance for large, high-speed autonomous ground vehicles, in: 2017 American Control Conference (ACC), IEEE, 2017, pp. 5568–5573.

[39] J. Liu, P. Jayakumar, J. L. Stein, T. Ersal, A study on model fidelity for model predictive control-based obstacle avoidance in high-speed autonomous ground vehicles, Vehicle System Dynamics 54 (11) (2016) 1629–1650.

[40] H. Pacejka, Tire and Vehicle Dynamics, Elsevier, 2005.

[41] H. Febbo, NLOptControl, `https://github.com/JuliaMPC/NLOptControl.jl` (2017).

[42] R. H. Byrd, J. Nocedal, R. A. Waltz, K nitro: An integrated package for nonlinear optimization, in: Large-scale Nonlinear Optimization, Springer, 2006, pp. 35–59.

[43] E. Hollnagel, D. D. Woods, Joint Cognitive Systems: Foundations of Cognitive Systems Engineering, CRC Press, 2005.

[44] D. A. Abbink, D. Cleij, M. Mulder, M. M. van Paassen, The importance of including knowledge of neuromuscular behaviour in haptic shared control, in: Systems, Man, and Cybernetics (SMC), 2012 IEEE International Conference on, IEEE, 2012, pp. 3350–3355.

[45] M. Mulder, D. a. Abbink, E. R. Boer, Sharing control with haptics: seamless driver support from manual to automatic control, Human Factors: The Journal of the Human Factors and Ergonomics Society 54 (5) (2012) 786–798. doi:10.1177/0018720812443984.

[46] M. A. Benloucif, A.-T. Nguyen, C. Sentouh, J.-C. Popieul, A new scheme for haptic shared lateral control in highway driving using trajectory planning, IFAC-PapersOnLine 50 (1) (2017) 13834–13840.

[47] H. Boessenkool, D. A. Abbink, C. J. Heemskerk, F. C. van der Helm, J. G. Wildenbeest, A task-specific analysis of the benefit of haptic shared control during telemanipulation, IEEE Transactions on Haptics 6 (1) (2013) 2–12.

[48] C. Masone, P. R. Giordano, H. H. Bülthoff, A. Franchi, Semi-autonomous trajectory generation for mobile robots with integral haptic shared control, in: 2014 IEEE International Conference on Robotics and Automation (ICRA), IEEE, 2014, pp. 6468–6475.

[49] R. Parasuraman, R. Molloy, I. L. Singh, Performance consequences of automation-induced 'complacency', The International Journal of Aviation Psychology 3 (1) (1993) 1–23.