Article:

Louw, T orcid.org/0000-0001-6577-6369, Markkula, G orcid.org/0000-0003-0244-1582, Boer, E et al. (3 more authors) (2017) Coming back into the loop: Drivers' perceptual-motor performance in critical events after automated driving. Accident Analysis and Prevention, 108. pp. 9-18. ISSN 0001-4575

https://doi.org/10.1016/j.aap.2017.08.011

Coming Back into the Loop: Drivers' Perceptual-Motor Performance in Critical Events after Automated Driving

Tyron Louw*, Gustav Markkula, Erwin Boer, Ruth Madigan, Oliver Carsten, Natasha Merat

Institute for Transport Studies, University of Leeds, LS2 9JT, Leeds, United Kingdom

Abstract

This driving simulator study, conducted as part of the EU AdaptIVe project, investigated drivers' performance in critical traffic events, during the resumption of control from an automated driving system. Prior to the critical events, using a between-participant design, 75 drivers were exposed to various screen manipulations that varied the amount of available visual information from the road environment and automation state, which aimed to take them progressively further 'out-of-the-loop' (OoTL). The current paper presents an analysis of the timing, type, and rate of drivers' collision avoidance response, also investigating how these were influenced by the criticality of the unfolding situation. Results showed that the amount of visual information available to drivers during automation impacted on how quickly they resumed manual control, with less information associated with slower take-over times, however, this did not influence the timing of when drivers began a collision avoidance manoeuvre. Instead, the observed behaviour is in line with recent accounts emphasising the role of scenario kinematics in the timing of driver avoidance response. When considering collision incidents in particular, avoidance manoeuvres were initiated when the situation criticality exceeded an Inverse Time To Collision value of ≈ 0.3 s^{-1}. Our results suggest that take-over time and timing and quality of avoidance response appear to be largely independent, and while long take-over time did not predict collision outcome, kinematically late initiation of avoidance did. Hence, system design should focus on achieving kinematically early avoidance initiation, rather than short take-over times.

Keywords: driver behaviour, automated driving, situation awareness, reaction time, critical event kinematics

*Corresponding author

1. Introduction

The advent of automated vehicles promises a number of benefits, including an increase in the flow and capacity of the road network (Kesting *et al.,* 2008, Ntousakis *et al.,* 2015), a wide range of economic benefits (Fagnant and Kockelman, 2015), an increase in shared mobility (Fagnant and Kockelman, 2015), and a reduction in energy consumption (Anderson *et al.,* 2014). Many of these forecasts have received a great deal of attention in recent years, including those predicting that vehicle automation will result in a reduction in road traffic accidents (Bertoncello and Wee, 2015).

The aim of partial (SAE, 2016; Level 2; L2) automated driving systems is to relieve drivers of the moment-to-moment demands of the control (lateral and longitudinal), yet not supervision, of the driving task. In conditional (SAE Level 3; L3) automated driving systems, drivers can relinquish both control and supervision of the driving task. However, drivers are still expected to be responsible for the safety of the vehicle when operating these systems, and should be available to resume manual control, should the system reach some limit, for example, due to poorly marked lane boundaries. During automated driving, drivers may shift their attention away from information relevant to the driving task, for instance, the traffic environment or the status of the automated driving system, to one of a range of non-driving related activities (Carsten et al., 2012). This shift in attention potentially impairs drivers' ability to perceive, comprehend, and predict events in the road scene, diminishing their situation awareness (SA) (Endsley, 1995, De Winter et al., 2014). A key human factors concern regarding L2 and L3 systems is that drivers with deteriorated SA may be ill-prepared to regain the attention and motor control necessary to safely navigate the vehicle, if a system limit is reached and manual intervention (or 'take-over') is required; an issue often referred to as the out-of-the-loop (OoTL) performance problem (Endsley and Kiris, 1995).

There is evidence to suggest that the non-driving related task drivers engage in during automation may affect how quickly moreover, safely they can resume control (Gold et al., 2013; Zeeb, Buchner, and Schrauf, 2015; Radlmayr et al., 2014; Merat et al., 2014; Louw et al., 2015), though there is little consensus. For instance, Merat et al. (2012) compared drivers' responses to critical incident scenarios, while engaging in a verbal "20 Questions Task" (TQT). Compared to when drivers were not engaging in the TQT, the TQT had no effect on how long it took drivers to start the lane change, but it did affect their ability to reduce the vehicle's speed to a safe level quickly. In contrast, Neubauer et al. (2012) found that drivers engaging in a mobile phone conversation during a take-over, had shorter brake reaction times to a lead vehicle, compared to those who were not engaging in a mobile phone conversation. This lack of consensus is not surprising as studies have employed different experimental traffic scenarios (Naujoks et al., 2014, Radlmayr et al., 2014), with varying time-budgets (Gold et al., 2013; Damböck et al., 2012; van den Beukel and van der Voort, 2013), and human-machine interfaces (HMI), and in simulators of varying degrees of fidelity. As non-driving related tasks demand different levels of drivers' visual attention, it is important to compare the effect of a range of tasks.

In this study, conducted as part of the EU AdaptIVe project, we aimed to systematically take drives OoTL, by applying a number of screen manipulations that, to varying degrees, limited the amount of system and environmental information available to drivers during automation, before presenting critical and non-critical take-over events. During these events, instead of a 'take-over request', we used an 'uncertainty' alert, which required drivers to monitor the road scene and determine whether there was a need to resume control from automation. These manipulations were introduced by Louw et al. (2015, 2016) and Louw and Merat (2017), and are detailed further below. Previously, we showed that, during automated driving, drivers' eye-gaze concentration was differentially affected by the OoTL manipulations (Louw and Merat, 2017), as was the location of drivers' first eye-fixations in the road scene, after the manipulations ceased (Louw et al., 2016). However, these differences resolved within 2 s of the manipulations ceasing. While these studies have illustrated how vehicle automation affects drivers' visual attention when 'coming back into the loop', precisely whether and how the degree of visual information available to drivers during automation affects their perceptual-motor performance during the take-over is not clear, nor is what constitutes 'good' performance, in this context. This study aimed to investigate these issues.

A number of measures and metrics have been used to study drivers' take-over process once they have resumed control, including time to hands-on the steering wheel (Zeeb, Buchner, and Schrauf, 2015), time to disengage automation (take-over time; Damböck et al., 2014; Gold et al., 2014; Zeeb, Buchner, and Schrauf, 2015, 2016), reaction time to an obstacle (Neubauer et al., 2012), first gaze to the road centre (Gold et al., 2013; Louw et al., 2016). Take-over time in particular has been used widely to judge driver performance during the resumption of control (for a review see Eriksson and Stanton, 2017). However, we have previously argued that take-over time measures may not be the most appropriate indicator of drivers' preparedness for, or appreciation of the unfolding situation (Louw et al., 2015), as drivers could simply be reacting to take-over requests (TOR) from the system. Indeed, as reported in studies on braking behaviours in manual driving, there exists a driver-related delay between initial brake application and full emergency braking (Ising et al., 2012; Hirose et al., 2008; Perron et al., 2001; Kiesewetter et al., 1999; Yoshida et al., 1998). Therefore, the current study analysed not only drivers' take-over time, but also, the time it takes for them to react to a threat in the road environment, as was considered by others, such as Petermeijer et al. (2017).

While understanding the timing (Gold et al., 2013) and sequence (Zeeb, Buchner, and Schrauf, 2016) of behaviours during the take-over is important, there is also a need to understand whether, and how, automation affects the *quality* of drivers' vehicle control following a take-over, as drivers do not mitigate all risk just by resuming control or initiating a manoeuvre. Quality of vehicle control has previously be described by vehicle-based measures, such as maximum accelerations during vehicle control in the transition (Gold et al., 2013; Zeeb, Buchner, and Schrauf, 2015; Hergeth et al., 2016), minimum Time To Collision (TTC; Gold et al., 2013, Louw et al., 2015), minimum time headway to an obstacle (Merat and Jamson, 2009; Merat et al., 2014; Louw et al., 2015). However, their interpretation is often constrained to the particular scenario under investigation. Therefore, to provide scenario-independent measures of drivers' capabilities for vehicle control, and thus take-over quality, a possible solution is to analyse drivers' responses in relation to the kinematics of an unfolding situation, i.e. the criticality at the point at which they respond. Inverse Time To Collision (invTTC), for example, is a measure that accounts for the visual looming effect of a braking lead vehicle (Lee, 1976; Summala et al., 1998; Groeger, 2000; Kiefer et al., 2003, 2005), and is an important crash risk indicator (Kondoh et al., 2008). The looming argument is closely related to the tau hypothesis. Inverse tau is the ratio between the lead vehicle's optical expansion rate on the driver's retina, and its optical size, therefore, describing visual looming. Inverse tau is simply a visually available estimate of invTTC (Lee, 1976), though the latter was used in the current paper due to it being easier to calculate.

Victor et al. (2015) and Markkula et al. (2016) used this measure to show that a majority of drivers involved in naturalistic crash and near-crash scenarios during manual driving, reacted within 1 s of the kinematic urgency of the scenario, reaching values of invTTC ≈ 0.2 s^{-1}, which suggests that the *timing* and *response rate* of drivers' initial response appears to be anchored to the criticality of the unfolding event. Based on their findings, Markkula et al. (2016) proposed that how drivers make use of and act on visual looming information from a lead vehicle in manual driving may also explain drivers' response processes when suddenly brought back into the control loop in automated driving. Some evidence of this in automation may be found in an extended interpretation of the work of Gold et al. (2013). The authors found that drivers who were given longer time budgets in a take-over scenario took longer to intervene. However, it may be that the visual looming effect played some part in when drivers decided to intervene, and the current paper seeks to investigate this in more detail. If not being in physical vehicle control due to automation causes a mismatch between drivers' internal model of a vehicle's dynamics and the actual vehicle dynamics (Russell et al., 2016), then their ability to respond in manner that is appropriate for the criticality of the situation in hand may be impaired (cf. Fajen and Devaney, 2006; Fajen, 2008; Markkula et al., 2016).

The current study sought to evaluate this hypothesis, by analysing the timing and rate of drivers' responses (i.e. how fast they move brake pedal and steering wheel) in relation to the kinematics of the unfolding situation, and how this interacts with the degree of visual information available to drivers pre-take-over.

We hypothesised that drivers deprived of all visual information from the system and road environment would be furthest OoTL and, therefore, take-over control later and have the least consistent perceptual-motor control, than those who performed visual and non-visual tasks pre-take-over. However, drivers who had access to all visual information during automation were hypothesised to be the most in the loop and would, therefore, take-over control the earliest and have the most consistent perceptual-motor control during the transition.

2. Methods

2.1. Participants

Following ethical approval from the University of Leeds Research Ethics Committee (Reference Number: LTTRAN-054, seventy-five drivers (41 male), aged 21-69 years (M=36, SD=12) were recruited via the participant database of the University of Leeds Driving Simulator (UoLDS) and were reimbursed £20 for participation. Participants had normal or corrected-to-normal vision. Their average annual mileage was 8290 miles (SD=6723), and all participants had held a full driving licence for at least three years (M=16, SD=12) and drove at least twice a week. Participants details for each group are displayed in Table 1.

2.2. Materials

The experiment was conducted in the fully motion-based UoLDS, which consists of a Jaguar S-type cab housed in a 4m spherical projection dome with a 300° field-of-view

Table 1: Participant demographics for each OoTL condition.

Condition	No. years holding a full UK driving license (SD)	Mean annual mileage (SD)	Mean age (SD)	Number of Male participants	Number of Female participants
No Fog	16.07 (9.76)	9236 (12037)	36 (9)	8	7
No Fog + n-back	15.2 (10.29)	8780 (2392)	37 (11)	9	6
Light Fog	19.57 (14.13)	9967 (6650)	38 (13)	10	5
Heavy Fog	19.73 (16.5)	7800 (4068)	39 (15)	10	5
Heavy Fog + Task	9.89 (7.19)	5333 (3590)	29 (10)	4	11

projection system. A v4.5 Seeing Machines faceLAB eye-tracker was used to record eye movements at 60Hz.

2.3. OoTL Manipulations

To vary the degree to which drivers had access to visual information from the system and road environment during automation, we applied one of five OoTL manipulation techniques, which have been described previously in Louw et al. (2015, 2016) and Louw and Merat (2017), but are repeated in Table 2 and shown in Figure 1. As outlined in Figure 1, it was anticipated that drivers in the No Fog conditions would be the most *in the loop* and drivers in the Heavy Fog + Task condition would the most *out of the loop* (See Table 2). For the conditions that used a fog manipulation, we drew a canvass over the existing screens to change the brightness. The colour of the canvass was set to RGB 0.5 0.5 0.5 and the transparency was set to 0.0 for Heavy Fog and 0.09 for Light Fog, where 0.0 is no transparency and 1.0 is full transparency. In the two task conditions, participants were expected to engage with the tasks. However, in the other conditions, participants were not instructed to behave in any particular way.

2.4. Automated driving system

The automated driving system was only available when the vehicle was travelling between 65 and 75 mph in the centre of the middle lane. Drivers could engage the system by pressing a button on the steering wheel. When automation was engaged, and drivers' hands and feet were off the controls, automation could be disengaged by either pressing a button on the steering wheel, turning the steering wheel more than 2°, or depressing the brake pedal. If participants did not engage automation within 5 s of maintaining the vehicle position in the centre of the middle lane, the system engaged automatically. Once engaged, the system assumed lateral and longitudinal

Table 2: Description of the OoTL conditions.

Condition	Description	Motivation/Aim
No Fog	The road scene was not manipulated in any way.	This served as a baseline condition, where drivers had access to all visual information from the system and road environment during automation.
No Fog + n-back	The road scene was not manipulated in any way, but participants completed the 1-back task (Mehler et al., 2011) during automation, where they heard a sequence of single digit numbers and were expected to repeat out loud the last number presented.	The aim was to simulate situations where drivers had access to all visual information from the system and road, but they were engaged in a non-visual task.
Light Fog	A translucent grey filter was superimposed on the road scene.	The aim was to give drivers the opportunity to perceive elements in the immediate vicinity of the road environment but not further afield, and to hinder their ability to accurately predict how road events might unfold in the future.
Heavy Fog	An opaque grey filter overlaid the road scene blocking all visual information from the road environment.	The aim was to simulate situations where drivers are completely looking away from the road scene and are unaware of the traffic conditions but not engaged in any other activity.
Heavy Fog + Task	An opaque grey filter overlaid the road scene blocking all visual information from the road environment. A visually presented secondary task was projected onto the front scene, which involved a series of web-based multiple-choice IQ test questions requiring verbal answers. Questions related to visuo-spatial shape-matching, general knowledge questions, and moderately challenging mathematics.	The aim was to simulate situations where drivers are not attending to visual information from the system or road environment, due to interaction with a visual secondary task.

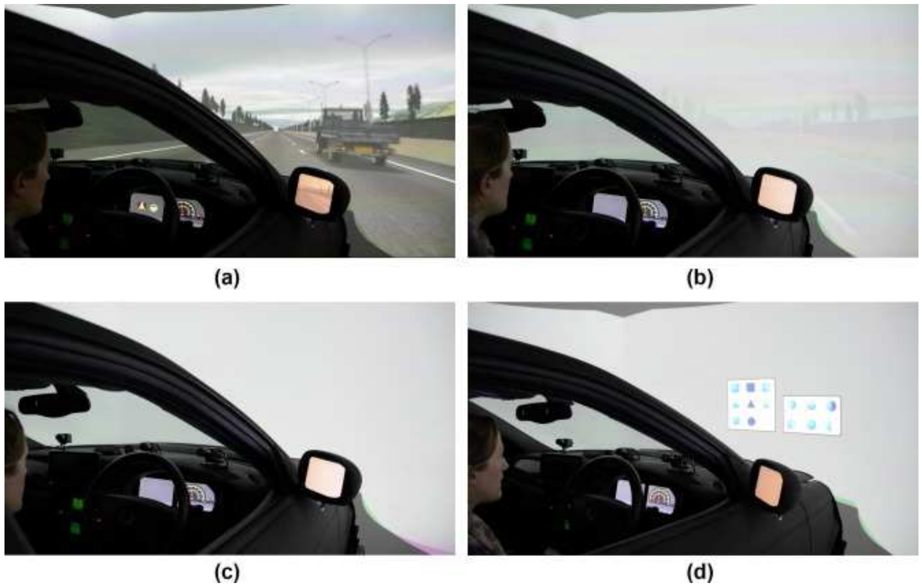

Figure 1: An example of drivers' view in the (a) no fog, no fog + n-back, (b) light fog, (c) heavy fog, and (d) heavy fog + task conditions..

control and adjusted the vehicle's speed to maintain 70 mph, which is the national speed limit for dual carriageways and motorways in the UK. All participants were told in the pre-experiment briefing session that they were to follow the normal rules of the road.

2.5. Human-machine interface

The human-machine interface (HMI) used for automation status related to the colour of a steering wheel symbol located in the vehicle's central display unit (Figure 2). This was solid grey when automation was unavailable, flashed green when available, and appeared solid green when active. For each event (see below), at the end of the OoTL manipulations, instead of a take-over request, drivers were presented with an 'uncertainty alert'. This was indicated by a flashing yellow symbol, which invited drivers to monitor the roadway and intervene, if they deemed necessary. If the driver deactivated the automation, the symbol appeared solid red for 2 s. Automation activation and deactivation were accompanied by an auditory tone (1000Hz, 0.2 s). In all conditions, a Forward Collision Warning (FCW) symbol included to the left of the automation status symbol gave drivers a visual estimate of the lead vehicle headway and a continuous alarm sounded if drivers reached an acceleration-based time-to-collision (TTC) of 2 s.

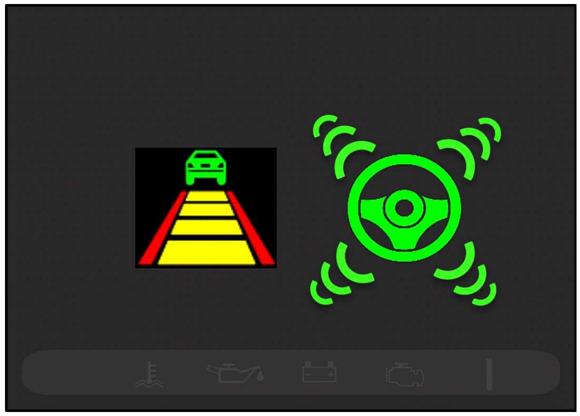

Figure 2: An example of the in-vehicle HMI with the Forward Collision Warning symbol on the left and the Automation Status Symbol on the right (flashing green in this example).

2.6. Experimental and Scenario Design

Five groups of 15 participants each were recruited for this study. All participants conducted an automated and manual (without the OoTL manipulations) drive, which were counterbalanced across participants. However, given the scope of this paper, only results of performance during the automated drive is included here. A 5 X 2 repeated-measures mixed design was used, with OoTL Manipulation (No Fog, Light Fog, Heavy Fog, Heavy Fog+Quiz, No Fog+n-back) as a between-participant factor and Event Number (1-6) as a within-participant factor.

Each experimental drive lasted about 20 minutes and encompassed six discrete car-following events, within a free-flowing three-lane motorway, with ambient traffic. As shown in Figure 3, each drive contained two critical events (2,6) and four non-critical events (1,3,4,5). For all events, 7 s before the uncertainty alert, a vehicle entered the lane ahead, from the right. In the critical events, after 3 s of the OoTL manipulations ending, the lead vehicle decelerated at a rate of 5.0 m/s^2. This resulted in a collision if, after 3 s from the lead vehicle brake onset, there was no driver action. In the non-critical events, after 3 s of the OoTL manipulations ending, the lead vehicle either sped up or changed lane to the left, nullifying the event criticality.

2.7. Procedure

Upon arrival, participants read a hand-out which contained details of the experiment, but which did not include information on the critical situations. After signing the consent form, participants completed a 15-minute familiarisation drive, consisting of non-critical events only. This began with a short manual drive. Once familiar with the simulator controls, participants practised activating/deactivating

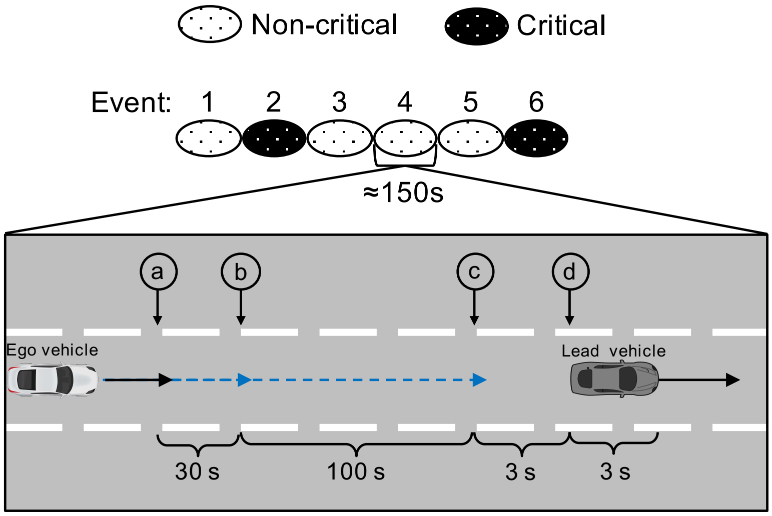

Figure 3: Schematic representation of each discrete event in the experimental drive. (a) to (d) represent various phases of the drive, where (a) denotes automation being engaged, (b) denotes the start of the OoTL manipulations, (c) denotes the end of the OoTL manipulations and the start of the uncertainty alert, and (d) denotes the start of the lead vehicle braking in the critical event.

the automation, were shown how the HMI communicated automation states, and experienced the OoTL manipulations. Participants then completed the experimental drive described in the previous section and shown in Figure 3. Each event began with a 30 s period of automated driving with no OoTL manipulation, after which the manipulations would be active for 100 s before ceasing and being replaced by an uncertainty alert. Participants completed a post-experiment survey, which probed aspects relating to trust and acceptance of the automated driving system. However, no interesting results emerged, therefore, and in the interest of space and scope of the paper, they are not included here.

2.8. Analysis of drivers' perceptual-motor performance

Reaction time measures

Two metrics were adopted for quantifying timing measures during the take-over process: The *first* was take-over time ($t_{take-over}$), which was defined as a measure of the time between the end of the OoTL manipulations and a driver's disengagement of the automated driving system (by either pressing a button on a steering wheel, turning the steering wheel more than 2°, or depressing the brake pedal). We also computed action time (t_{action}), which was defined as the time from the end of the OoTL manipulation, to when the driver started a significant deceleration or steering action that was clearly intended to mitigate the impending crash. It is worth noting that participants were not given any instruction as to how they should deal with a potential collision scenario.

During our studies, we have found that, in many cases, drivers touched the steering wheel but did not initiate an evasive steering action, and similarly, they often pressed the brake pedal but did not engage in an evasive braking action. Therefore, we looked for a clear steering or braking action and then searched for the starting point of this committed action. We developed a MATLAB (version R2015b, MathWorks) tool to allow the experimenter to judge when the driver committed to their response action. The following steps were taken to analyse t_{action} for the braking and steering responses, collected at a sampling rate of 60 Hz:

1. The brake pedal signal and steering wheel signal were each filtered with a 1st order low-pass Butterworth filter, with a cut-off frequency of 3 Hz for braking, and 6 Hz for steering.

2. (a) For braking, the first local maximum brake pedal sample greater than 4 was identified (Red diamond marker in Figure 4). The brake pedal sample represented a unit-less value of brake effort, on a scale of 0 to 450.

   (b) For steering, the local maxima and minima values with an amplitude threshold of $\pm 2.5°$ were first identified, as per Schmidt et al. (2014). Then, the global maximum steering wheel angle amplitude prior to the lane change manoeuvre was identified (Red diamond marker in Figure 5).

3. To identify the start point of the manoeuvre (t_{action}), two criteria were used. First, we identified the end of the plateau in brake or steering signal before the point identified above, such that there was less than a 0.0005 difference in values between consecutive samples (Red square markers in Figures 4 and 5). Second, to ensure accuracy, each start point was manually confirmed on a case-by-case basis, based on changes to the vehicle's speed and longitudinal acceleration, for braking, and the vehicle's offset and lateral acceleration, for steering. Minor adjustments to the location of the start points were made where necessary.

4. t_{action} was calculated as the time from the end of the OoTL screen manipulations (Figure 3) to the time corresponding to the start point identified in the previous step.

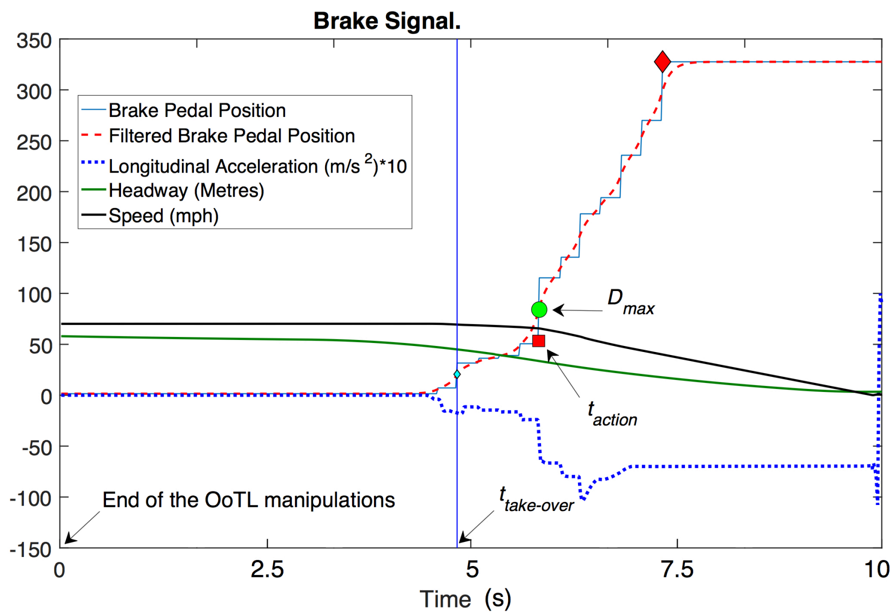

Figure 4: Example plot from the analysis of a brake signal, to determine t_{action}. Longitudinal acceleration values are multiplied by 10 for illustration purposes.

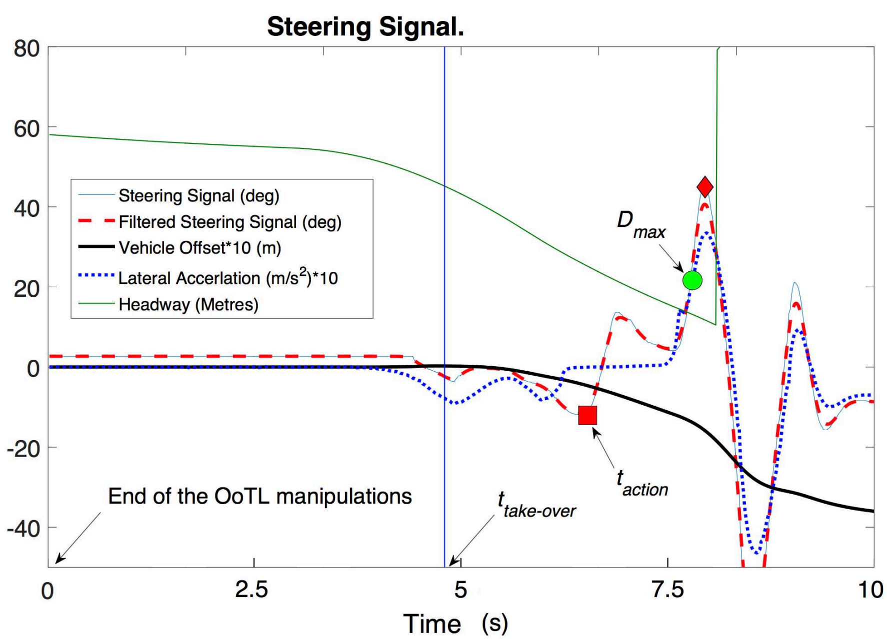

Figure 5: Example plot from the analysis of a steering signal, to determine t_{action}. Lateral acceleration and vehicle offset values are multiplied by 10 for illustration purposes.

Vehicle control

To determine the quality of drivers' vehicle control after resuming control, we considered whether drivers were able to scale the rate of their collision avoidance response to the event criticality. For this, we calculated and correlated two different measures.

The *first* measure was Inverse Time To Collision (invTTC; Kiefer et al., 2003, 2005) at t_{action}, and was used to quantify the criticality of the unfolding event at the point drivers began their collision avoidance manoeuvre. invTTC was calculated as relative speed divided by distance gap between the ego and lead vehicle, which takes the lead vehicle deceleration into account.

The *second* measure was the maximum derivative (D_{max}) of the control input that drivers used to avoid the collision, and was used to assess the rate and force of drivers' response to the critical event (Green circle marker in Figure 4 and Figure 5). D_{max} was taken from the time period between the response onset (t_{action}) and the maximum value of the respective control input. If drivers changed lane, then steering wheel angle was used, and if they braked, then brake pedal position was used. If drivers braked then steered, then steering wheel angle was used. For both steering avoidance (Markkula et al., 2014) and braking avoidance (Markkula et al., 2016), drivers scale the rate of their avoidance manoeuvre (i.e. D_{max}), to looming, as measured by invTTC. By correlating invTTC at t_{action} and D_{max}, we aimed to assess (i) whether similar situation-adaptive control behaviour would be present just after a take-over from automated driving, and if so, (ii) whether it would be affected by the OoTL manipulations. Specifically, as suggested in the Introduction, that drivers who had access to less visual information during automation, would generally have a more scattered correlation between invTTC at t_{action} and D_{max}.

As braking and steering inputs are measured in different units, they could not be analysed as a single data set, without first being transformed. To achieve this, separate regression equations were calculated for the steering and braking responses between invTTC and t_{action}. Next, the D_{max} values of the braking responses were transformed such that the intercept and slope of the regression equation was the same as that of the steering responses, allowing for the comparison of braking and steering responses.

Statistical analyses

The data were not normally distributed, therefore, Kendall's non-parametric rank correlation was used on the correlations between $t_{take-over}$ and t_{action}, and between invTTC at t_{action} and D_{max}. In addition, Kendall's rank correlation was used because, compared to Spearman's rank correlation, its p values are more accurate with smaller sample sizes (Howell, 2012). Kendall's rank correlation coefficient τ was used here as a measure of goodness of fit. This was calculated using the *cor.test* R function in the 'MASS' package using the "kendall" method (Venables and Ripley, 2002). For illustration purposes, the approximate slopes and intercepts of the various factors were also calculated using robust linear regression, using the *rlm* R function in the 'MASS' package with default settings (Venables and Ripley, 2002). To test for an effect of the OoTL manipulations on $t_{take-over}$ and t_{action}, Kruskal-Wallis H tests were conducted using SPSS V.21 (IBM, Armonk, NY, USA).

Included in this study, based on 15 participants in each of the five OoTL manipulation groups and two critical events per participant, there were 150 transition cases considered for the analysis. However, twenty-six cases were excluded for various reasons. In 13 cases, drivers avoided a collision by changing lane but, at the point of automation disengagement, the initial steering wheel angle exceed $\pm 5°$ (which was possible because the steering wheel was not self-correcting) and there were no subsequent salient steering inputs. This indicated the lane change was due to a slow drift and the driver's intentional response could not be determined confidently. In 11 cases, drivers steered while braking hard and thus skidded such that steering had no effect. In 1 case, a driver did not respond at all, and in another the driver's response could not be determined using the method described above.

3. Results and Discussion

The results from this study will be presented with the aid of two types of graphs: the first graph relates to the timing of drivers' response and shows take-over time (x-axis, $t_{take-over}$) relative to action time (y-axis, t_{action}), for example as illustrated in Figure 6. If a data point falls on the dashed grey diagonal line, it indicates that the driver began a collision avoidance manoeuvre at the same time as they resumed control. The greater the distance along the y-axis between the data point and the dashed diagonal line, the longer the time between when drivers resumed control and initiated a manoeuvre. The red dashed lines on the x- and y-axes indicate the onset of the vehicle brake light. The second graph relates to vehicle control and shows D_{max} (y-axis) relative to invTTC at the start of drivers' response (x-axis), for example as presented in Figure 7. This figure attempts to demonstrate the rate of drivers' steering or braking input, during their collision avoidance manoeuvre, in relation to the kinematic urgency faced by drivers when they began their manoeuvre (i.e. the visual looming from the lead vehicle).

Table 3: Mean (SD) of take-over time and action time for the five OoTL conditions.

	No Fog	**No Fog + n-back**	**Light Fog**	**Heavy Fog + Task**	**Heavy Fog**
$t_{take-over}$ **(s)**	3.70 (1.22)	4.11 (1.07)	4.13 (1.11)	4.39 (1.03)	4.53 (0.51)
t_{action} **(s)**	4.95 (0.91)	4.93 (0.99)	4.68 (0.72)	4.96 (1.02)	5.10 (0.87)

Results from a Kruskal-Wallis H test showed that, the lower the degree of visual information available to drivers during automation (from left to right in Figure 6), the slower they tended to take-over control ($t_{take-over}$, $\chi^2(4) = 9.820$, p <0.05; Table 3). However, an additional Kruskal-Wallis H test showed there was no difference between the groups regarding when drivers began their collision avoidance manoeuvre (t_{action}, $\chi^2(4) = 1.927$, p = .749; Table 3), which suggests that, the further OoTL drivers were, the higher the likelihood of a simultaneous take-over and manoeuvre initiation.

Figure 6 also shows that drivers who had access to all visual information pre-take-over (No Fog group), were most likely to resume control before the onset of the lead vehicle braking, suggesting more anticipatory responses. However, when drivers were either engaged in a non-driving related task and/or had some or all visual information withheld from them pre-take-over, they were more likely to resume control after the lead vehicle braked. These results suggest that the more OoTL drivers were, the more they reacted to external traffic than to system information, following the cessation of the OoTL manipulations.

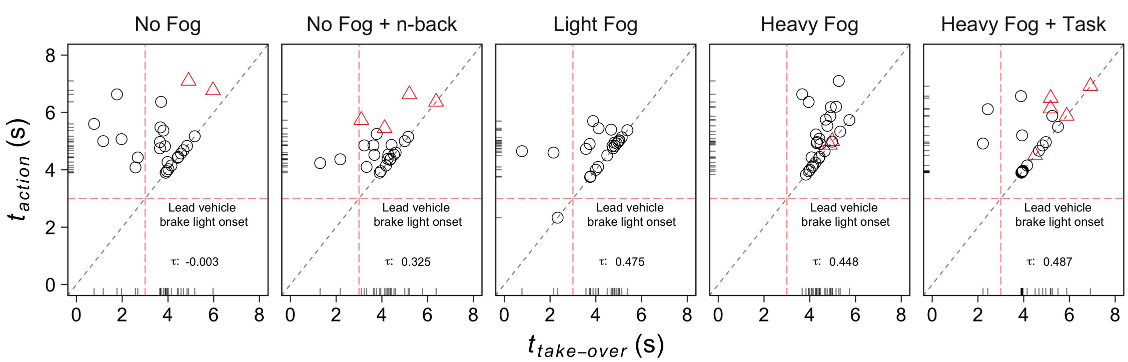

Figure 6: t_{action} relative to $t_{take-over}$ for the five OoTL conditions in both critical events. Red triangles show collisions and black circles show non-collisions. Note how, from leftmost to rightmost panel, the general pattern is that cases group further to the right in the panel, indicating later $t_{take-over}$ for more OoTL drivers whereas the scatter in the vertical direction remains largely unchanged (no statistically significant effect of the OoTL manipulations).

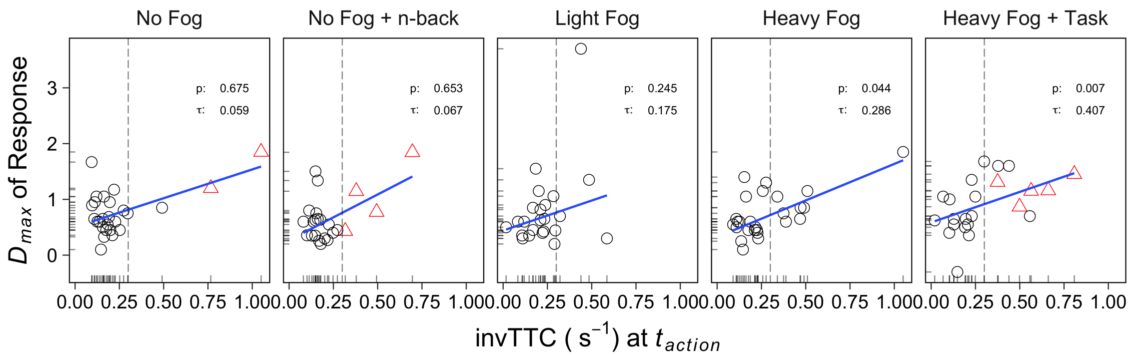

Figure 7: D_{max} of response relative to invTTC at t_{action} for the five OoTL conditions in both critical events. Triangles show collisions and circles show non-collisions. The blue lines are for illustration purposes only, showing the outcome of robust linear regression.

Taking the situation kinematics into account, it is clear from Figure 7 that the lower the degree of visual information available to drivers, the more likely they were to respond at invTTC of over 0.3 s^{-1}. It is also evident that the majority of drivers across the groups responded before the criticality of the situation reached a value of invTTC $\approx$ 0.3 s^{-1}. This is consistent with the findings of Victor et al. (2015) and Markkula et al. (2016), who showed that, during manual driving, drivers reacted within 1 s of the kinematic urgency of the scenario, reaching values of invTTC $\approx$ 0.2 s^{-1}. Overall, as the situation became increasingly critical, drivers scaled the rate of their avoidance response to the criticality of the situation, just as in manual driving, both for braking (Markkula et al., 2016) and steering (Markkula et al., 2014). Tau values shown in Figure 7 suggest that the rates of drivers' responses were less scattered the lower the degree of available visual information, which goes against our hypotheses. We proposed that Tau may be a good measure of scatter, however, considering the distribution of the data across the groups, Tau may not be the ideal measure, as it is sensitive to how much of the invTTC range is covered. Therefore, larger data sets with better coverage of the invTTC spectrum and/or more detailed analysis methods might clarify this further. Qualitative inspection of the plots in Figure 7 suggest that the general nature of the perceptual-motor scaling, in terms of slope and intercept, was rather similar between the OoTL manipulations.

For all cases that resulted in a collision, drivers began their avoidance manoeuvre when the situation criticality exceeded invTTC $\approx$ 0.3 s^{-1}. However, this cannot fully account for why drivers crashed in some cases, as in other cases drivers responded at the same criticality and avoided a collision. Further explanation can be derived from the type of response adopted by drivers after the take-over.

Results showed that, in the majority of cases, drivers mainly steered in response to the lead vehicle (68/124), while in 36/124 cases drivers mainly braked, and in 20/124 cases drivers braked then steered (Figure 8). This is consistent with findings of Gold et al. (2013) and Blommer et al. (2017), who also found that a high proportion of drivers steered in crash-imminent situations, following a take-over, despite the fact that previous studies have shown braking to be the more common response in manual driving (Adams, 1994). Figure 9 shows that drivers who braked after the situation criticality reached invTTC ≈ 0.3 s^{-1}, were unable to avoid a collision, despite clearly scaling the rate of their brake response to the higher criticality of the situation. This is not surprising, as it is a well known aspect of road vehicle dynamics that steering collision avoidance remains a feasible option for a longer time than braking avoidance, during the run-up to a potential collision (Rice and Dell'Amico, 1974; Lechner and Malaterre, 2015).

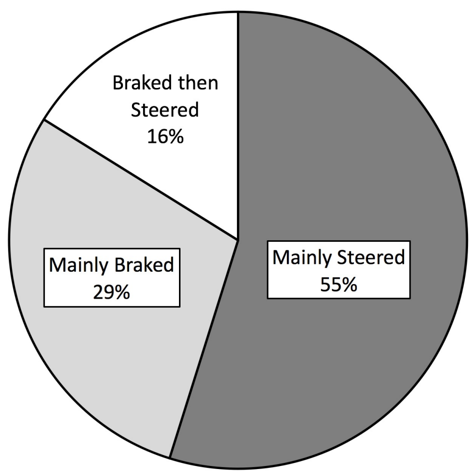

Figure 8: Combined frequency of drivers' responses in CE1 and CE2.

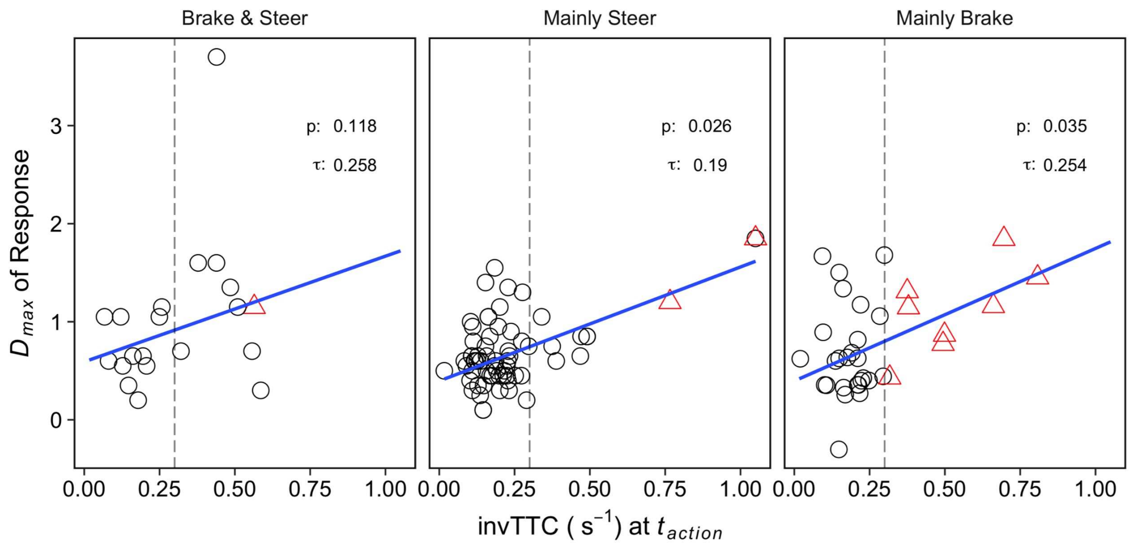

Figure 9: D_{max} of response relative to invTTC at t_{action} for the three response categories. Triangles show collisions and circles show non-collisions. The blue lines are for illustration purposes only, showing the outcome of robust linear regression.

In terms of actual number of collisions with the lead vehicle, Figure 10 shows that all collisions occurred in Critical Event 1 (CE1). While there were five cases in Critical Event 2 (CE2) where drivers responded after the criticality reached invTTC ≈ 0.3 s^{-1}, it is likely that the previous exposure might have helped these drivers make the correct decision to apply steering. In none of the cases that resulted in collisions, did drivers resume control or initiate a response before the onset of the lead vehicle braking, which could indicate increased decision-making time to take-over control. However, in 14 of the 108 non-collision, drivers resumed control (13 cases) or initiated a response (1 case) before the onset of the lead vehicle braking, which could indicate more anticipatory responses. Finally, Figure 10 shows that regressions were similar between the CE1 and CE2, which suggests that drivers' motor-control was largely unaffected by whether they had previously experienced a critical event.

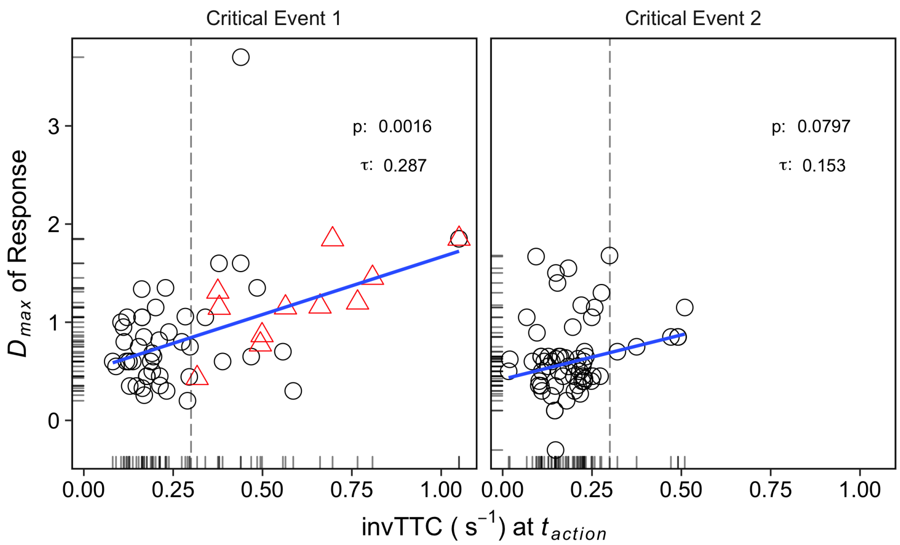

Figure 10: D_{max} of response relative to invTTC at t_{action} for Critical Event 1 and Critical Event 2. Triangles show collisions and circles show non-collisions. The blue lines are for illustration purposes only, showing the outcome of robust linear regression.

4. Conclusions

The analyses presented here builds on the work of Gold et al. (2013), Zeeb, Buchner, and Schrauf (2016), and Petermeijer et al. (2015), by providing some insights into the importance of visual information for drivers' perceptual-motor performance in critical situations during the resumption of control from automation.

Previously, we reported that the OoTL manipulations influenced the location of drivers' first eye-fixations after the manipulations ended, but that the effects resolved within 2 s (Louw et al., 2016). However, it was not clear whether the effect of the manipulations ended there or if they had an effect on drivers' perceptual-motor control. One important finding from the current analysis is that, despite there being no differences regarding where drivers directed their visual attention, the less visual information available to drivers during automation, the later they took over control. We hypothesised that the more OoTL drivers were, the less consistent their perceptual-motor performance. However, there was no difference between the OoTL groups regarding how long it took drivers to begin a collision avoidance manoeuvre, or, indeed, whether they would experience a crash.

In addition, our subsequent kinematic analysis showed that the degree of visual information available to drivers pre-take-over did not influence whether and how drivers scaled the rate of their response to the situation criticality, at least not in any way that could be detected with the present data and analyses. This suggests that the level of drivers' situation awareness during automation has an impact on the timing of their take-over ($t_{take-over}$), but not necessarily on when they began a collision avoidance manoeuvre (t_{action}) or the quality of their subsequent vehicle control (D_{max}). These results are in contrast to the findings of Zeeb, Buchner, and Schrauf (2016), who found that engaging in various secondary tasks did not delay how long it took drivers to return their hands to the steering wheel, following a take-over request, but it did cause a small delay in how long it took them to intervene in vehicle control.This brings into question the usefulness of take-over time as a measure of 'good' performance in the take-over.

Another finding is that the majority of drivers responded below invTTC ≈ 0.3 s^{-1}, which was common for cases that avoided a collision, while all cases that resulted in a collision shared the following characteristics: *First*, for all collisions, drivers began their evasive manoeuvre when the situation criticality was above invTTC ≈ 0.3 s^{-1}. *Second*, drivers who crashed only braked instead of only steering, or braking then steering. *Third*, all collisions occurred in the first critical event, which is in line with previous findings that drivers' familiarisation with the event and experience with the system, results in fewer interaction errors, and safer outcomes (Engström et al., 2010; Lee et al., 2002; Benderius et al., 2014).

Our results are generally in line with those of Gold et al. (2013) and others, who have found that drivers who are given less time to respond to a take-over request react faster but subsequent vehicle control results in higher accelerations. Gold et al. (2013) argued that this indicated that lane changes were riskier and, therefore, that take-over quality was worse. However, regarding defining drivers' capabilities and limitations in such scenarios, based on our analysis, we conclude that drivers' responses following a take-over are generally appropriately scaled to the criticality of the unfolding situation, even though highly critical situations may not be desirable from a safety point of view. Therefore, we use take-over 'quality' to refer to drivers' performance in relation to the situation, rather than to the criticality of the situation itself.

Taken together, our results suggest that it is important that, following a take-over, drivers act on any threat as early as possible in the kinematic scenario. While in the current study the usefulness of take-over time has been questioned, situations giving rise to take-over event will likely vary widely, and what is important is that drivers are able to respond to system feedback promptly. Therefore, the fact that the OoTL manipulations influenced how quickly drivers disengaged the automated driving systems has important HMI design implications for automated vehicles. For instance, HMIs that emphasise situation-relevant information before the take-over may facilitate safer take-over situations.

With increasing situation criticality, drivers clearly attempted to adjust the rate of their collision avoidance response. Despite this, in many cases, drivers were unsuccessful at avoiding a collision. This indicates that, should a system-initiated take-over be required, automated driving systems must support drivers during the transfer of physical vehicle control, by providing either advanced warning or vehicle control that reduces the situation criticality, via, for example, haptic shared control, Collision Mitigation by Braking (CMbB) or Emergency Steer Assist (ESA). A supportive HMI could also encourage drivers who respond late in the kinematic scenario to apply steering avoidance (the situation permitting, such as the one under investigation here).

There are a number of limitations in the present study. First, all drivers performed a manual drive identical in design to the automated drive, where they experienced two non-critical lead vehicle braking events. The order in which participants experienced the manual and automated drives were counterbalanced, which means that half of the participants would have experienced the manual drive first. This may have influenced the timing and magnitude of drivers' responses in the following automated drive, which suggests that our results potentially underestimate the effect of automation on performance. This is especially relevant when one considers that all collisions in the automated drives occurred in Critical Event 1, and 75% of these were when the automated drive was performed first. Second, though there was no direct instruction for drivers to resume control, the additional warnings from the lead vehicle brake light and the FCW alarm may have had some impact on when drivers responded. Thus, the looming effect was not the only cue of criticality. Finally, the small sample size in the present study meant that driver characteristics such as age, gender, and experience, could not be considered in detail. However, the sample was selected to be as representative of the general population as possible.

The current study sets out some avenues for future work. For example, the scattered gaze-fixations of colliders (Louw et al., 2016), possibly contributed to their braking response starting late in the situation kinematics, and further work is required to ratify this link, which, if found to be true, strengthens the argument for an HMI that is able to direct drivers' attention to relevant information. Furthermore, what constitutes '*quality*' regarding driver performance in the transition will vary according to the level of responsibility being transferred as well as the road traffic situation itself, which motivates the need to evaluate a range of real-world take-over scenarios.

Finally, it is important to understand further how automation impacts on the kinematic-dependencies of driver responses to critical events, as recent work by Blommer et al. (2017) has shown that avoidance responses come later after a transition out of automated driving than in manual driving. It remains an open question whether or not drivers' scaling of avoidance responses to kinematics also change between manual and automated modes of driving.

5. Acknowledgements

This research was conducted as part of the AdaptIVe project, co-funded by the European Union under the 7th Framework Programme, grant agreement number 610428.

6. References

Adams, L. (1994). Review of the literature on obstacle avoidance maneuvers: Braking versus steering (UMTRI-94-19). Ann Arbor, MI: University of Michigan Transportation Research Institute (UMTRI).

Anderson, J. M., Nidhi, K., Stanley, K. D., Sorensen, P., Samaras, C., and Oluwatola, O. A. (2014). Autonomous vehicle technology: A guide for policymakers. Rand Corporation.

Benderius, O., Markkula, G., Wolff, K., and Wahde, M. (2014). Driver behaviour in unexpected critical events and in repeated exposures-a comparison. European Transport Research Review, 6, 51-60.

Bertoncello, M., and Wee, D. (2015). Ten ways autonomous driving could redefine the automotive world. Market evaluation on development of autonomous vehicles. Retrieved from `http://www. mckinsey. com/insights/automotive_and_assembly/ten_ways_autonomous_ driving_could_redefine_the_automotive_world`.

van den Beukel, A. P., and van der Voort, M. C. (2013). The influence of time-criticality on situation awareness when retrieving human control after automated driving. In 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013) (pp. 2000-2005). IEEE.

Blommer, M., Curry, R., Swaminathan, R., Tijerina, L., Talamonti, W., and Kochhar, D. (2017). Driver brake vs. steer response to sudden forward collision scenario in manual and automated driving modes. Transportation research part F: traffic psychology and behaviour, 45, 93-101.

Carsten, O., Lai, F. C. H., Barnard, Y., Jamson, A. H., and Merat, N. (2012). Control task substitution in semi-automated driving: Does it matter what aspects are automated? Human Factors, 54, 747-761.

Damböck, D., Bengler, K., Farid, M., and Tönert, L. (2012). Übernahmezeiten beim hochautomatisierten fahren. Tagung Fahrerassistenz. München, 15, 16.

De Winter, J. C., Happee, R., Martens, M. H., and Stanton, N. A. (2014). Effects of adaptive cruise control and highly automated driving on workload and situation awareness: A review of the empirical evidence. Transportation research part F: traffic psychology and behaviour, 27, 196-217.

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. Human Factors: The Journal of the Human Factors and Ergonomics Society, 37, 32-64.

Endsley, M. R., and Kiris, E. O. (1995). The out-of-the-loop performance problem and level of control in automation. Human Factors: The Journal of the Human Factors and Ergonomics Society, 37, 381-394.

Engström, J., Aust, M. L., and Viström, M. (2010). Effects of working memory load and repeated scenario exposure on emergency braking performance. Human Factors: The Journal of the Human Factors and Ergonomics Society, 52, 551-559.

Fagnant, D. J., and Kockelman, K. (2015). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transportation Research Part A: Policy and Practice, 77, 167-181.

Fajen, B. R. (2008). Perceptual learning and the visual control of braking. Perception and Psychophysics, 70, 1117-1129.

Fajen, B. R., and Devaney, M. C. (2006). Learning to control collisions: the role of perceptual attunement and action boundaries. Journal of Experimental Psychology: Human Perception and Performance, 32, 300.

Gold, C., Damböck, D., Lorenz, L., and Bengler, K. (2013). "Take over!" how long does it take to get the driver back into the loop? In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (pp. 1938-1942). SAGE Publications volume 57.

Gold, C., Lorenz, L., and Bengler, K. (2014). Influence of automated brake application on take-over situations in highly automated driving scenarios. In Proceedings of the FISITA 2014 World Automotive Congress..

Groeger, J. A. (2000). Understanding driving: Applying cognitive psychology to a complex everyday task. Psychology Press.

Hergeth, S., Lorenz, L., Vilimek, R., and Krems, J. F. (2016). Keep your scanners peeled gaze behavior as a measure of automation trust during highly auto- mated driving. Human Factors: The Journal of the Human Factors and Ergonomics Society, 58, 509-519.

Hirose, T., Taniguchi, T., Hatano, T., Takahashi, K., and Tanaka, N. (2008). A study on the effect of brake assist systems (bas). SAE International Journal of Passenger Cars-Mechanical Systems, 1, 729-735.

Howell, D. C. (2012). Statistical methods for psychology. Cengage Learning.

Ising, K. W., Droll, J. A., Kroeker, S. G., D'Addario, P. M., and Goulet, J.-F. (2012). Driver-related delay in emergency braking response to a laterally incurring hazard. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (pp. 705-709). Sage Publications volume 56.

Kesting, A., Treiber, M., Schönhof, M., and Helbing, D. (2008). Adaptive cruise control design for active congestion avoidance. Transportation Research Part C: Emerging Technologies, 16, 668-683.

Kiefer, R. J., Cassar, M. T., Flannagan, C. A., LeBlanc, D. J., Palmer, M. D., Deering, R. K., and Shulman, M. A. (2003). Forward collision warning requirements project: refining the CAMP crash alert timing approach by examining" last-second" braking and lane change maneuvers under various kinematic conditions (No. HS-809 574,).

Kiefer, R. J., LeBlanc, D. J., and Flannagan, C. A. (2005). Developing an inverse time-to-collision crash alert timing approach based on drivers' last-second braking and steering judgements. Accident Analysis and Prevention, 37, 295-303.

Kiesewetter, W., Klinkner, W., Reichelt, W., and Steiner, M. (1999). The new brake assist of mercedes-benz active driver support in emergency braking situations. Vehicle Performance: Understanding Human Monitoring and Assessment, (pp. 67-83).

Kondoh, T., Yamamura, T., Kitazaki, S., Kuge, N., and Boer, E. R. (2008). Identification of visual cues and quantification of drivers' perception of proximity risk to the lead vehicle in car-following situations. Journal of Mechanical Systems for Transportation and Logistics, 1, 170-180.

Lechner, D., and Malaterre, G. (2015). Emergency Manuever Experimentation Using a Driving Simulator. Technical Report SAE Technical Paper.

Lee, D. N. (1976). A theory of visual control of braking based on information about time-to-collision. Perception, 5, 437-459.

Lee, J. D., McGehee, D. V., Brown, T. L., and Reyes, M. L. (2002). Collision warning timing, driver distraction, and driver response to imminent rear-end collisions in a high-fidelity driving simulator. Human Factors: The Journal of the Human Factors and Ergonomics Society, 44, 314-334.

Louw, T., Merat, N., and Jamson, H. (2015). Engaging with highly automated driving: To be or not to be in the loop? In 8th International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design, At Salt Lake City, Utah, USA.

Louw, T., Kountouriotis, G., Carsten, O., and Merat, N. (2015). Driver inattention during vehicle automation: How does driver engagement affect resumption of control? In Proceedings of the International Conference on Driver Distraction and Inattention. ARRB Group.

Louw, T., Madigan, R., Carsten, O., and Merat, N. (2016). Were they in the loop during automated driving? Links between visual attention and crash potential. Injury prevention. DOI: 10.1136/injuryprev-2016-042155

Louw, T., and Merat, N. (2017). Are you in the loop? using gaze dispersion to understand driver visual attention during vehicle automation. Transportation Research Part C: Emerging Technologies, 76, 35-50.

Macadam, C. C. (2003). Understanding and modelling the human driver. Vehicle System Dynamics, 40(1-3), 101-134.

Markkula, G., Benderius, O., and Wahde, M. (2014). Comparing and validating models of driver steering behaviour in collision avoidance and vehicle stabilisation. Vehicle System Dynamics, 52, 1658-1680.

Markkula, G., Engström, J., Lodin, J., Brgman, J., and Victor, T. (2016). A farewell to brake reaction times? kinematics-dependent brake response in naturalistic rear-end emergencies. Accident Analysis & Prevention, 95, 209-226.

Mehler, B., Reimer, B., and Dusek, J. (2011). Mit agelab delayed digit recall task (n-back). Cambridge, MA: Massachusetts Institute of Technology.

Merat, N., and Jamson, A. H. (2009). How do drivers behave in a highly automated car. In Proceedings of the 5th International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design (pp. 514-521).

Merat, N., Jamson, A. H., Lai, F. C., and Carsten, O. (2012). Highly automated driving, secondary task performance, and driver state. Human Factors: The Journal of the Human Factors and Ergonomics Society, 54, 762-771.

Merat, N., Jamson, A. H., Lai, F. C., Daly, M., and Carsten, O. M. (2014). Transition to manual: Driver behaviour when resuming control from a highly automated vehicle. Transportation research part F: traffic psychology and behaviour, 27, 274-282.

Naujoks, F., Mai, C., and Neukum, A. (2014). The effect of urgency of take-over requests during highly automated driving under distraction conditions. Advances in Human Aspects of Transportation, (p. 431).

Neubauer, C., Matthews, G., and Saxby, D. (2012, September). The effects of cell phone use and automation on driver performance and subjective state in simulated driving. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 56, No. 1, pp. 1987-1991). Sage CA: Los Angeles, CA: Sage Publications.

Perron, T., Kassaagi, M., and Brissart, G. (2001). Active safety experiments with common drivers for the specification of active safety systems. In 17th International Technical Conference on Enhanced Safety of Vehicles, Amsterdam.(Paper Number 427) Retrieved from `http://www-nrd.nhtsa.gov/database/nrd-01/esv/asp/esvpdf.asp`.

Petermeijer, S., Bazilinskyy, P., Bengler, K., and de Winter, J. (2017). Take-over again: Investigating multimodal and directional TORs to get the driver back into the loop. Applied Ergonomics, 62, 204-215.

Radlmayr, J., Gold, C., Lorenz, L., Farid, M., and Bengler, K. (2014). How traffic situations and non-driving related tasks affect the take-over quality in highly automated driving. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (pp. 2063-2067). Sage Publications volume 58.

Rice, R. S., and Dell'Amico, F. (1974). An Experimental Study of Automobile Driver Characteristics and Capabilities. Technical Report DTIC Document.

SAE (2016). Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems (J3016). Technical Report Technical report, SAE International.

Russell, H. E., Harbott, L. K., Nisky, I., Pan, S., Okamura, A. M., and Gerdes, J. C. (2016). Motor learning affects car-to-driver handover in automated vehicles. Science Robotics, 1(1), eaah5682.

Schmidt, K., Beggiato, M., Hoffmann, K. H., and Krems, J. F. (2014). A mathematical model for predicting lane changes using the steering wheel angle. Journal of safety research, 49, 85-e1.

Summala, H., Lamble, D., and Laakso, M. (1998). Driving experience and perception of the lead car's braking when looking at in-car targets. Accident Analysis & Prevention, 30, 401-407.

Venables, W. N., and Ripley, B. D. (2002). Random and mixed effects. In Modern Applied Statistics with S (pp. 271-300). Springer.

Victor, T., Dozza, M., Bärgman, J., Boda, C.-N., Engström, J., Flannagan, C., Lee, J. D., and Markkula, G. (2015). Analysis of naturalistic driving study data: Safer glances, driver inattention, and crash risk. Technical Report.

Yoshida, H., Sugitani, T., Ohta, M., Kizaki, J., Yamamotoz, A., and Shirai, K. (1998). Development of the brake assist system. Technical Report SAE Technical Paper.

Zeeb, K., Buchner, A., and Schrauf, M. (2015). What determines the take-over time? An integrated model approach of driver take-over after automated driving. Accident Analysis & Prevention, 78, 212-221.

Zeeb, K., Buchner, A., and Schrauf, M. (2016). Is take-over time all that matters? The impact of visual-cognitive load on driver take-over quality after conditionally automated driving. Accident Analysis & Prevention, 92, 230-239.