Effect of Automation Instructions and Vehicle Control Algorithms on Eye Behavior in Highly Automated Vehicles

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ABSTRACT: Increasingly vehicle automation may convey greater capability than it actually possesses. The emergence of highly capable vehicle automation (e.g., SAE Level 4) and the promise of driverless vehicles in the near future can lead drivers to inappropriately cede responsibility for driving to the vehicle with less capable automation (e.g., SAE Level 2). This inappropriate reliance on automation can compromise safety, and so we investigated how algorithms and instructions might mitigate overreliance. Seventy-two drivers, balanced by gender, between the ages of 25 and 55, participated in this study using a fixed-base driving simulator. Drivers were exposed to one of three vehicle steering algorithms: lane centering, lane keeping, or an adaptive combination. A gaze tracker was used to track eye glance behavior. While automation was engaged, participants were told they could interact with an email sorting task on a tablet positioned near the center stack. Changes in roadway demand—traffic approaching in the adjacent lane—varied across the drive. Instructions indicating the driver was responsible, in combination with the adaptive algorithm, led drivers to be particularly attentive to the road as the traffic approached them. These results also have implications for evaluating more capable automation (SAE Levels 4 and 5), where drivers need not attend to the road: unnecessary attention to roadway demands might indicate lack of trust and acceptance of control algorithms that guide driverless vehicles.

KEY WORDS: safety, vehicle automation, vehicle control algorithms, joint control, trust [C1]

1. Introduction

With advancing vehicle technology, drivers are beginning to share control with automation. However over the next decade, these technologies will still require monitoring and intermittent control (1). The Society of Automotive Engineers (SAE) has defined this technology in terms of levels of automation (2). At the highest level, (SAE Level 5), drivers cede responsibility to the automation and shift from being drivers to riders. This shift between Levels 1 and 5 is clear and easy for drivers to understand, but less so between the other levels.

At lower levels (SAE Levels 2-4), the allocation of primary responsibility can be unclear to drivers. In vehicles classified as SAE Level 2, the automation controls both the lateral and longitudinal vehicle motion subtasks of the dynamic driving task, with the expectation that the driver completes the object and event detection and response subtask and supervises the automation. Primary responsibility therefore is with the driver. SAE Level 3 shifts more responsibility to the automation, meaning all of the dynamic driving subtasks (e.g., lateral control, longitudinal control, and object and event detection), and only requires that the driver to be vigilant for automation failures and receptive and able to respond to vehicle requests to intervene. Arguably, responsibility is with the automation. With SAE Level 4 primary responsibility for driving is clearly with the automation. Within a limited operational domain, the automation remains in control even if the driver does not respond to requests to intervene when the vehicle reaches the edge of its operational domain. SAE Level 5 requires no driver intervention and the automation has full responsibility for driving in all operational domains. Although it is appropriate for drivers to cede responsibility with Level 5, they might confuse Level 2 and Level 3 and neglect driving with Level 2. Although the SAE levels precisely define the role of people and avoid designating responsibility (driver versus automation), people typically adopt simplifying distinctions and heuristics to guide behavior (3).

A prominent failure mode of automation is responsibility diffusion, which leads people to reduce their engagement when supported by automation (4). Responsibility diffusion occurs when it is unclear if the driver or the automation is primarily responsible for vehicle monitoring and control (5). Responsibility diffusion stems from a poor understanding and trust of automation capabilities (6). Responsibility diffusion can lead drivers to fail to recognize when the automation is reaching its operating limits or has diminished capability, requiring the driver to resume monitoring or control. Designers often neglect responsibility diffusion and assume that drivers will remain attentive to the road, but drivers may assume that the automation frees them to attend to non-driving tasks.

Although designers might easily differentiate between the capabilities of Level 2 and Level 3 automation, drivers might struggle. To better align designers’ and drivers’ expectations, instructions regarding vehicle capabilities can be given to drivers (7). Instructions might take the form of guidance in the owner’s manual, video explanations, product naming, and product promotional material.

Instructions could prove beneficial; however further steps should be taken to continuously demonstrate the capability of the automation to drivers (8). Consistent with related research in human-robot interaction (9), vehicle control algorithms are a promising solution to conveying vehicle capabilities and limits to drivers (10). Vehicle control algorithms are the control laws that govern vehicle motion. Most simply, two vehicle control algorithms might indicate different capability of the automation: lane centering and lane keeping. Lane centering algorithms track the center of the lane, whereas lane keeping algorithms allow the vehicle to drift within the lane boundaries. Even in a
fixed-base simulator, adjusting algorithms to vary between lane keeping and lane centering strongly influenced driver trust in the automation. Algorithms that track the center of the lane garnered more trust, which would be appropriate for highly capable automation (e.g., Level 4). A combination of instructions and control algorithms might help establish appropriate trust in automation and attention to the road.

Although highly automated vehicles present the opportunity for drivers to engage in non-driving tasks, lower levels of automation still require driver engagement. By removing the driving demands, drivers may be tempted to engage in distracting activities. There is some evidence that drivers of highly automated vehicles can modulate their attention, engaging in secondary tasks when roadway demands are low and attending to the road when demands are high. This is consistent with research that has shown drivers sample the forward roadway more intensely as uncertainty in the road situation increases. As responsibility diffuses from drivers to the vehicle, drivers’ attention to demanding situations may decline. A critical design challenge concerns how to engage driver attention to roadway demands, particularly with automation that assumes drivers will remain responsible for monitoring and intervention.

There is strong evidence that eye gaze and movements are closely linked to driver’s visual attention. Gaze behavior has been used to predict readiness to take over control of an automated vehicle, and patterns of drivers’ eye fixations can predict successful takeovers. More generally, drivers’ horizontal and vertical gaze dispersion have been used to index levels of engagement. However, little research has considered how instructions regarding the capability of the automation and vehicle control algorithms affect gaze behavior. We investigate whether instructions and vehicle control algorithms can help drivers modulate their attention so that they look to the road during high-demand situations. Three general hypotheses guide this analysis. First, we expect vehicle control algorithms to positively influence gaze behavior, resulting in increased attention to the road. Second, we expect instructions, which indicate whether or not the driver has primary responsibility, will have little effect on gaze behavior. Third, we expect increased roadway demand will increase attention to the road.

2. Methods

2.1. Experimental Design

A (3 X 2) X 4 X 3 mixed between and within-subjects factorial design was used to assess drivers’ attention to the road when driving a highly automated vehicle. The experimental design combined three algorithms (lane centering, lane keeping, or adaptive) and two levels of instructed responsibility (automation or driver) as between subject conditions (Table 1), for a total of 72 participants between 25 to 55 years of age. Participants were recruited from the Madison, WI area using online postings and flyers and were screened before participation. Participants were required to drive a minimum of 2,000 miles per year, possess a valid driver’s license for at least two years, and be in relatively good health. Total participation time for each driver was 90 minutes. Participants were paid $30/hr. for full participation. This experiment was reviewed and approved by the University of Wisconsin-Madison Internal Review Board (IRB) and was ethically conducted (Protocol ID: 2015-1029).

Table 1. Between subjects combination of algorithms and primary responsibility

| Algorithms | Primary Responsibility |
|------------|-------------------------|
| Lane Centering (LC) | SAE Level 2 | SAE Level 3 |
| Lane Keeping (LK) | LC/Driver | LC/Automation |
| Adaptive (LC/Driver) | LCLK/Driver | LCLK/Automation |

2.2. Participants

There were 12 participants, balanced by gender, in each between subject condition (Table 1), for a total of 72 participants. Each participant completed a single drive.

2.3. Apparatus

The National Advanced Driving Simulator (NADS) MiniSim™ was used for this study. The MiniSim™ consists of one 65-inch screen placed 4.5 feet from the driver. The simulated roadway was a four-lane divided highway. The same scenario was used for all experimental conditions.

2.4. Gaze Tracker

The Autoliv Driver Monitoring System was used to track participants’ gaze over the duration of the drive. The tracker determines head pose and uses this to differentiate between eyes on road and eyes off road. This stream of dichotomous data (eyes on road, eyes off road) was fed to the NADS MiniSim™ and used to guide the adaptive algorithms in real time.

2.5. Vehicle Control Algorithms

The vehicle control algorithms were developed using Matlab Simulink™ and interfaced with the NADS Dyna, the vehicle dynamics module of the simulator. Using findings from a previous study, the steering behavior of the automation was controlled using a proportional-integral-derivative (PID) controller. The steering angle was calculated using the instantaneous lateral error of the vehicle’s center of gravity from the lane center. The steering angle was adjusted only when the error exceeded the specified deadband value on either side of the lane center. A deadband (DB) is the range of the error where the control output is zero.

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The lane centering algorithm used a deadband value of zero feet from the lane center. The lane keeping used a deadband value of one foot on either side of the lane center. The adaptive algorithm varied between the two deadband values. When drivers had their eyes on the road the steering behavior would be consistent with lane centering (DB = zero feet). However, when drivers’ eyes were off the road for more than five seconds, the vehicle’s steering behavior would change from lane centering (DB = zero feet) to lane keeping (DB = one foot, 0.3 meters), to convey diminished capability. Fig. 2 shows examples of algorithm behavior.

2.6. Secondary Task
Participants completed an email sorting task on a tablet that was mounted to the right of the participants in the MiniSim™ cab. Participants sorted emails into one of three categories (Work, Family and Friends, and Trash) by selecting up to five emails at a time. The task did not allow for scrolling and the emails were listed on the same page. Two distinct sounds indicated if the emails were sorted properly or not. A count of emails at a time. The task did not allow for scrolling and the emails were listed on the same page. Two distinct sounds indicated if the emails were sorted properly or not. A count of each email type was updated at the top of the screen as the participants sorted the email. Participants were instructed to engage with the secondary task only if and when they thought appropriate. If participants did not want to engage with the secondary task, they were not required to.

2.7. Traffic Demand
Traffic demand was calculated using Equation 1, which is an exponential function of the distance, in feet, between the driver and traffic on the oncoming lane. The equation relates the intensity of a physical stimulus (e.g., proximity of the oncoming cars) to the sensation (e.g., the potential threat) (20). Traffic demand was zero when there were no cars approaching and traffic demand was equal to one when vehicles were passing in the opposing lane. An instance of traffic is the period in which traffic demand starts at zero (when oncoming traffic is not present), peaks at one (when oncoming traffic is passing the driver) and drops to zero. This sequence was coded as: pre-demand, onset, peak demand and post-demand.

\[
\text{Traffic Demand} = \beta e^{\theta \cdot \text{distance}} \quad \beta = 1.0, \theta = -0.001 \quad (1)
\]

2.8. Procedure
Upon arrival, each participant’s license was checked and participants were asked to review and sign the informed consent. Participants then completed a driving demographics questionnaire, wellness questionnaire, tendency to trust survey, as well as the susceptibility to driving distraction survey. After all questionnaires and surveys were complete, participants were given instructions about the capability of the vehicle they would be driving. Participants were instructed that if they felt that the vehicle was not able to handle any situation, they should press the button, brake pedal, or accelerator pedal to switch from automated driving back to manual driving. Following the instructions, each participant completed a four-minute practice drive where they manually drove for one minute, switched to automation for two minutes and then switched back to manual driving for one minute to become familiar with the simulator. During the two minutes of automated driving, participants practiced the email sorting task. When driving manually, participants were asked to drive in the left-most lane at a constant speed of 88.5 km/h (55 mph), ambient traffic was present in the scenario.

After the practice drive was complete, instructions about the capability of the vehicle and regaining control were given and then participants began the experiment. Participants began driving manually. After two minutes the vehicle prompted them to switch to automated mode. After 20 minutes of driving, participants were prompted to switch back to manual driving and then they drove for another two minutes. At the end of the experiment, participants completed a short exit questionnaire regarding their trust of the automation (21).

3. Results
This paper only reports those results associated with the effect of vehicle control algorithms, level of responsibility, and demand of traffic on drivers’ eye glance behavior. All manual driving data collected in this study was excluded from these results.

Fig. 3 shows timelines of the drives for each between subject experimental condition. The graph summarizes data from 72 participants. Because each facet of the graph represents a between subjects experimental condition, each point in each of the 6 graphs is the mean value based on 12 participants. The vertical axis represents the mean proportion of the time the drivers’ eyes were on the road. This was calculated by taking the mean of participants’ eyes on road time for each second across the drive for each experimental condition. The graphs in the left column show data from drivers who were told the automation was primarily responsible for driving and the right column shows graphs for those who were told they were primarily responsible for driving. The rows indicate the three algorithms: lane centering, lane keeping, and adaptive.

The grey spikes show the 14 instances of traffic demand and the black dots show the mean proportion of time the eyes were on the road, averaged over participants. The horizontal line indicates the mean of the eyes on road time for each condition. The graph shows a distinct association of attention to the road and traffic demand. The horizontal line shows the mean value for each condition, which indicate that attention also depends on the instructed responsibility and the algorithm.

Fig. 4 shows the data aggregated across instances of traffic demand. The grey profile indicates traffic demand, and the black lines indicate the mean proportion of eyes on road. This graph shows a large effect of traffic demand, and also suggests that the effect is more pronounced when drivers are told they are primarily responsible for vehicle control.
Fig. 3. Instances of traffic demand (grey spikes) and mean proportion of time the drivers’ eyes were on the road (black dots) over the duration of the drive. The horizontal lines represent the mean proportion of eyes on road for each condition. The left column represents the condition where the automation had primary responsibility for the driving task and the right column represents the condition where the driver had primary responsibility.

Fig. 4. Traffic demand (grey profile) and mean proportion of time the eyes were on the road (black line). The columns indicate whether the driver or the automation was primarily responsible for driving and the rows indicate the control algorithm.
Fig. 5 directly evaluates the association between traffic demand and the proportion of time the eyes were on the road. The grey line is a regression model fit to the entire dataset. The blue line is a LOESS (Locally Weighted Scatterplot Smoothing) fit to the data from each of the six conditions. The intercepts show that in the low-demand periods, those drivers in the lane centering and adaptive conditions, who were told they were primarily responsible for driving, look to the road a similar amount compared to those who were told the automation was primarily responsible. In contrast, drivers with the lane keeping algorithm who were told they were responsible look to the road more even in the low-demand situation. In all cases as the demand of traffic increased, so did the proportion of time that drivers’ eyes were on the road.

The slope of the LOESS lines is steeper when drivers were told they were responsible for driving, indicating their attention to the road is more sensitive to traffic demand than drivers who were told the automation was responsible. The slope is greatest for drivers with the adaptive algorithm.

Fig. 6 and the associated ANOVA (Table 2) provide a comprehensive description of the effects seen in the preceding graphs, as well as the statistical significance of these effects and their interactions. The previous graphs suggest that the effect of the algorithms depends on responsibility assigned to the drivers and the traffic demand. Fig. 6 shows drivers’ response also changed from the beginning to the end of the drive.

A three-way interaction (Algorithm X Traffic Demand X Instance) and the four-way interaction are statistically significant and are most easily seen by comparing the patterns of rising and falling attention to the road in the upper left quadrant of Fig. 6 to those in the lower right. Moving from automation being indicated as primarily responsible to the driver as primarily responsible and from lane centering to the adaptive algorithm leads to increasing eyes on road during the peak demand period relative to the pre and post demand periods. Drivers who were primarily responsible for vehicle control and had the adaptive algorithm were particularly attentive during the peak traffic demand.
Table 2. ANOVA of algorithm, level of responsibility, traffic demand, and instance of traffic.

|                      | num Df | den Df | F    | Pr(>F) |
|----------------------|--------|--------|------|--------|
| Algorithm X Responsibility | 2.00   | 66.00  | 0.22 | 0.80   |
| Responsibility       | 1.00   | 66.00  | 4.70 | 0.03   |
| Algorithm X Responsibility X Traffic Demand | 2.00   | 107.98 | 2.41 | 0.10   |
| Traffic Demand       | 1.64   | 107.98 | 86.81| <0.001 |
| Algorithm X Traffic Demand | 3.27   | 107.98 | 0.64 | 0.60   |
| Responsibility X Traffic Demand | 1.64   | 107.98 | 8.87 | 0.00   |
| Algorithm X Responsibility X Traffic Demand | 3.27   | 107.98 | 1.42 | 0.24   |
| Instance             | 1.85   | 121.97 | 0.30 | 0.73   |
| Algorithm X Instance | 3.70   | 121.97 | 4.75 | <0.001 |
| Responsibility X Instance | 1.85   | 121.97 | 0.95 | 0.38   |
| Algorithm X Responsibility X Instance | 3.70   | 121.97 | 1.11 | 0.35   |
| Traffic Demand X Instance | 47.79  | 315.98 | 7.36 | <0.001 |
| Algorithm X Traffic Demand X Instance | 9.58   | 315.98 | 2.27 | 0.02   |
| Responsibility X Traffic Demand X Instance | 4.79   | 315.98 | 0.85 | 0.51   |
| Algorithm X Responsibility X Traffic Demand X Instance | 9.58   | 315.98 | 2.07 | 0.03   |

Table 2 summarizes the statistical model that assessed the effects of the independent variables on drivers’ attention to the road. The fractional numerator and denominator degrees of freedom reflect Greenhouse-Geisser corrections for violations of sphericity. The rightmost column indicates the p-value of the test of each effect: we used an alpha of 0.05 as the threshold of statistical significance. Consistent with Fig. 6, responsibility and traffic demand were significant main effects. Drivers who were told they were primarily responsible for control of the vehicle looked at the road more, as did drivers when traffic demand was high. The two-way interactions between responsibility and traffic demand, algorithm and instance of traffic demand and traffic demand and instance of traffic demand were statistically significant. The three-way interaction between algorithm, traffic demand and instance of traffic demand and the four-way interaction were statistically significant which is also consistent with Fig. 6 where drivers’ attention to the road was highest when the driver was primarily responsible, experiencing the adaptive algorithm and traffic was present.

4. Conclusion

4.1. Discussion of Results

This study investigated the effects of vehicle control algorithms on gaze behavior with the aim of using vehicle control algorithms to promote driver attention to the road, addressing the critical design challenge of how to engage driver attention to roadway demands.

Changes in traffic demand increased attention to the road. Instructions that indicated whether or not the driver had primary responsibility (level of responsibility), also increased attention to the road. Vehicle control algorithms alone did not significantly influence gaze behavior. However, the interaction between vehicle control algorithms, level of responsibility, traffic demand, and instance of traffic demand indicates that control algorithms combine with instructions and the traffic situation to direct drivers’ attention to the road.

As a consequence of this interaction, eyes on road time was highest with the adaptive algorithm, when drivers were told they had primary responsibility, and traffic was present. Drivers in this condition, attended to the road more during the peak of traffic demand. This is consistent with findings from a study that found that with high levels of automation drivers had a higher propensity to become involved with in-vehicle tasks, but were still receptive to the demands of heavy traffic, devoting more attention to the roadway in such conditions (12). Our results suggest control algorithms combined with instructions regarding the locus of responsibility can enhance or diminish driver attention to critical roadway demands.

4.2. Vehicle Design Implications

Generalizing from these results to guide vehicle design merits caution. Vehicle control algorithms used in this study were experienced in a fixed-base simulator where drivers received no vestibular or haptic cues of the lateral motion, limiting their potency. This might underestimate the effect of the vehicle control algorithms implemented in actual cars. Haptic and vestibular cues might be particularly salient indicators of control behavior, particularly short-time constant micro adjustments to vehicle trajectory.

Because haptic and vestibular cues are particularly salient, they might redirect drivers’ attention to the road, but might also annoy drivers. Designers must balance effectiveness with comfort. The lane keeping and adaptive algorithms, combined with instructions, were effective in directing attention to the road. However, the lane keeping algorithm was perceived as untrustworthy in a previous study (10), and the haptic and vestibular cues that would accompany these algorithms in actual cars could accentuate this discomfort. In addition, extended exposure to this behavior might lead drivers to reject these algorithms, a possibility that the short exposure to the algorithm in this study failed to address.

With higher levels of automation (Levels 4 and 5) there is no need to direct drivers’ attention to the roadway. Instead, trustworthy algorithms (10) that do not draw drivers attention to roadway demands, but might also annoy drivers. Designers must balance effectiveness with comfort. The lane keeping and adaptive algorithms, combined with instructions, were effective in directing attention to the road. However, the lane keeping algorithm was perceived as untrustworthy in a previous study (10), and the haptic and vestibular cues that would accompany these algorithms in actual cars could accentuate this discomfort. In addition, extended exposure to this behavior might lead drivers to reject these algorithms, a possibility that the short exposure to the algorithm in this study failed to address.

4.3. Automation Instruction and Naming

Instructions were provided to participants about the level of responsibility immediately before performing the experiment, leading to maximum potency. Generalizing these results to behavior with actual vehicles likely overestimates the true effect of instructions. In this experiment, we explicitly described the capabilities and limitations of the automation to the participants. Participants then immediately experienced the automation. With actual cars, people are unlikely to receive clear instructions about the capabilities and limits of their vehicle and then immediately drive. Instead drivers might not read the manual, might receive inaccurate information from salespeople, and the name used for the automation might fail to specify its intended use. A recent study found that Tesla service representatives provided conflicting and inconsistent...
information about the capabilities and limitations of the autopilot (22). Although the instructions in this study helped to orient driver attention to the road, its potency in actual situations is likely to be less than what was observed in this study.

Beyond instructions, branding and naming might strongly influence behavior. Terms such as “autopilot” might suggest the automation is primarily responsible. This, combined with a very consistent steering algorithm, could lead to a diffusion of responsibility. In the recent fatal Tesla crash, the driver had the autopilot engaged for 37.5 minutes and during this time had his hands on the wheel for a total of 25 seconds. This behavior suggests a substantial diffusion of responsibility, even though Tesla provided instructions in their owner’s manual and in its release notes for new software releases (23). This information competes with the product’s name, media coverage of automated driving, and daily experience to guide driver expectations. One study showed the owner’s manual for the Tesla Model S did not fully explain details of the automation, requiring the driver to rely on trial-and-error experience to determine how the automation behaves in different driving conditions (22). The intended responsibility of the automation, behavior of the algorithms, and messages about the automation should align to avoid inappropriate diffusion of responsibility and overreliance.

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References

(1) NHTSA: Preliminary statement of policy concerning automated vehicles. (2013).
(2) SAE: Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems (J3016), (2014).
(3) Tversky A. & Kahneman D.: Judgement under Uncertainty: Heuristics and Biases. Science. Vol. 185, No. 4157, pp. 1124–1131, (1974).
(4) Lee J., Wicken C., Liu Y., et al.: Designing for People: An Introduction to Human Factors Engineering. CreateSpace, (2017).
(5) Gibson, M., Lee, J., Venkatraman, V., Price, M., Lewis, J., Montgomery, O., & Foley, J.: Situation awareness, scenarios, and secondary tasks: measuring driver performance and safety margins in highly automated vehicles. SAE International Journal of Passenger Cars-Electronic and Electrical Systems, Vol. 9, SAE Technical Paper No. 2016-01-0145, pp. 237-242, (2016).
(6) Lee J. & See K.: Trust in automation: designing for appropriate reliance. Hum. Factors, Vol. 46, pp. 50–80, (2004).
(7) Stanton N. & Young M.: Driver Behaviour with Adaptive Cruise Control. Ergonomics Vol. 48, pp. 1294–1313, (2005).
(8) Seppelt B. & Lee, J.: Making adaptive cruise control (ACC) limits visible. Int. J. Hum. Comput. Stud. Vol. 65, pp. 192–205, (2007).
(9) Brule R. van den, Bijlstra G., Dotsch R., et al.: Warning Signals for Poor Performance Improve Human-Robot Interaction Warning Signals for Poor Performance Improve Human-Robot Interaction. J. Human-Robot Interact. Vol. 5, pp. 69–89, (2016).
(10) Price, M., Venkatraman, V., Gibson, M., Lee, J., & Mutlu, B.:Psychophysics of Trust in Vehicle Control Algorithms, SAE Technical Paper No. 2016-01-0144, (2016).
(11) Merat N. & Lee J.: Preface to the Special Section on Human Factors and Automation in Vehicles: Designing Highly Automated Vehicles With the Driver in Mind. Hum. Factors J. Hum. Factors Ergon. Soc. Vol. 54, pp. 681–686, (2012).
(12) Jamson A., Merat N., Carsten O., et al.: Behavioral changes in drivers experiencing highly-automated vehicle control in varying traffic conditions. Transp. Res. Part C Emerg. Technol. Vol. 30, pp. 116–125. Elsevier Ltd, (2013).
(13) Senders J., Kistofferson A., Levison W., et al.: The attentional demand of automobile driving. Highw. Res. Rec. Vol. 195, pp. 15–33, (1966).
(14) Crundall D. & Underwood G.: Effects of experience and processing demands on visual information acquisition in drivers. Ergonomics Vol. 41, pp. 448–458, (1998).
(15) Konstantopoulos P., Chapman, P. & Crundal, D.: Driver’s visual attention as a function of driving experience and visibility. Using a driving simulator to explore drivers’ eye movements in day, night and rain driving. Accid. Anal. Prev. Vol. 42, pp. 825–832. Elsevier Ltd, (2010).
(16) Zeeb K., Buchner, A. & Schrauf, M.: What determines the take-over time? An integrated model approach of driver take-over after automated driving. Accid. Anal. Prev. Vol. 78, pp. 212–221. Elsevier Ltd, (2015).
(17) Merat N., Jamson H., Lai F., et al.: Transition to manual: Driver behaviour when resuming control from a highly automated vehicle. Transp. Res. Part F Traffic Psychol. Behav. Vol. 27, pp. 274–282. Elsevier Ltd, (2014).
(18) Louw T. & Merat N.: Are you in the loop? Using gaze dispersion to understand driver visual attention during vehicle automation. Transp. Res. Part C Vol. 76, pp. 35–50. Elsevier Ltd, (2017).
(19) Karlsson J., Apoy C., Lind H., et al.: Eyes On Road - An anti-distraction Field Operational Test. Stockholm, (2016).
(20) Stevens S.: On the psychophysical law. Psychol. Rev. Vol. 64, pp. 153–181, (1957).
(21) Muir, B. & Moray N.: Trust in automation. Part II. Experimental studies of trust and human intervention in a process control simulation. Ergonomics Vol. 39, pp. 429–460, (1996).
(22) Endsley M.: Autonomous Driving Systems: A Preliminary Naturalistic Study of the Tesla Model S. J. Cogn. Eng. Decis. Mak, (2017).
(23) Kareem Habib: Failure Report Summary (Tesla Crash). Washington D.C., (2017) .