Buzz or Beep?

How Mode of Alert Influences Driver Takeover Following Automation Failure

by

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ABSTRACT

Highly automated vehicles require drivers to remain aware enough to takeover during critical events. Driver distraction is a key factor that prevents drivers from reacting adequately, and thus there is need for an alert to help drivers regain situational awareness and be able to act quickly and successfully should a critical event arise. This study examines two aspects of alerts that could help facilitate driver takeover: mode (auditory and tactile) and direction (towards and away). Auditory alerts appear to be somewhat more effective than tactile alerts, though both modes produce significantly faster reaction times than no alert. Alerts moving towards the driver also appear to be more effective than alerts moving away from the driver. Future research should examine how multimodal alerts differ from single mode, and see if higher fidelity alerts influence takeover times.

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INTRODUCTION

In late 2014, Tesla began an automotive revolution with the update of their Model S car. With a new camera and some complex software, the Model S became the first publicly available, private automobile with automated driving capabilities. Google had been the first to prove that such technology was plausible with their self-driving car back in 2009, but their cars have yet to be commercialized. Now, companies like Uber, BMW, Mercedes, Infinity, Ford, and others are beginning to develop and commercialize their own automated driving systems. Business Insider (2016) has predicted that by 2020 there will be as many as 10 million self-driving cars on the road. Such a swell in automated driving has a fair share of issues such as delegating blame in accidents involving automated driving, and how to train drivers to properly handle automated driving. One issue that is of particular import at this early stage is that of driver takeover following a failure in the automation.

On May 7, 2016, a Tesla Model S operating in autopilot mode crashed into a trailer and killed its 40-year-old driver. In the bright sunlight, the vehicle's camera failed to see the white trailer and thus did not engage the braking systems that would have prevented the accident. The investigators reported that the driver had seven seconds to take some sort of evasive action, but ultimately failed to do so (Golson, 2017). Such incidents serve only to highlight the need to understand how drivers interact with automated driving systems. The design of these systems should be tailored to fit the capabilities of those using them. Thus, we must first understand what those capabilities are. How quickly can a driver takeover following automation failure? How can we ensure they respond appropriately? How do distractions, such as cell phone use, influence that takeover time? And, ultimately, what can we do to facilitate a fast and appropriate takeover response?

Automation is still in relative infancy, and some issues must be considered in the design of any automated system. The first and foremost among these issues is the proper use of the automation. Use of automation is influenced by familiarity, training and system design. Misuse can be characterized by overreliance, underutilization, or inappropriate application (Parasuraman & Riley, 1997). System failure can be attributed to any of these. Familiarity with automated systems and their limitations is key to both early positive interactions and long-term performance (Hergeth, Lorenz & Krems, 2017). Training programs have yet to produce the sort of expertise needed for automated systems, and automated systems are still being designed to provide more aide than operators need and with interfaces that can hinder rather than help (Strauch, 2017). System failure can also be the result of poor operator performance or – far more rarely – imperfect automation (Sebok & Wickens, 2017). Finding the optimal design, the right interfaces, and the best training method to best facilitate human interaction with automated systems is one of the great challenges of modern research.

The operation of personal vehicles that make use of automation adds weight to the challenge of automation research. In their current state, highly automated vehicles—such as those made by companies like Tesla, Google, and others—require drivers to be alert and aware while the automation is handling operation of the vehicle. Driver takeover refers to the specific time that a driver takes full, manual control of the vehicle after the automation has been driving. This time is usually prefaced by a handover time wherein the automation typically signals the driver that it is transferring control of the vehicle.

Two potential problems are inherent to this system of trading-off between the driver and the automation: a lack of practice leading to a loss of driver's skill and dependency on the automation, and a system design that naturally leads to errors (Parasuraman & Manzey, 2010). These two potential problems lead to two challenges that must be faced in order to bring highly automated vehicles into common use. The first challenge is to create a design that will facilitate driver takeover in the event of automation failure. As automation systems tend to make the driver feel out of the loop, they will likely have low situational awareness at the point of takeover, and the system design needs to address that (Carsten, Lai, Bernard, Jamson & Merat, 2012). The second challenge is presented where performance is concerned. Takeover results in lower performance for the human compared to humans driving without the automation at all. This decrease in performance is further degraded by distractions that occupy the driver's attention. Automated driving systems, in their current state, should only be seen as developmental. To truly achieve the benefits that automation can provide automation must be total, but research into proper design and performance can still have impact in the short-term.

Driver distraction can also be a challenge when addressing automation in personal vehicles. A comparison of drivers operating under various states of automation revealed that the more the automation controlled, the more drivers tended to engage in secondary nondriving tasks (Carsten, Lai, Bernard, Jamson & Merat, 2012). Drivers become more willing to engage in these secondary tasks as they perceive the automation as being in greater control. Similarly, drivers have been shown to be more prone to shifting focus away from the road when they could not predict when automation failure would occur (Merat, Jamson, Lai, Daly & Carsten, 2014). When such a shift of focus occurs, driver takeover becomes more difficult and the time it takes for a driver to resume full control increases (Eriksson & Stanton, 2017). Thus, the design of highly automated driving systems needs to account for tendencies to shift attention from the task of driving, and be capable of regaining that attention for driver takeover when needed.

Two variables may serve as potential mediators when it comes to driver takeover: prior familiarization with automated driving, and how critical the takeover situation is. Most drivers today are unfamiliar with the handoff between highly automated vehicles and their operators. Drivers who become familiar with automated driving systems and requests for driver takeover, even when that familiarization occurs by only a brief experience, show an increase in automation trust and takeover performance (Hergeth, Lorenz & Krems, 2016). Perhaps over the long-term familiarization could lead to complacency, but at least initially it has a positive influence. In comparing critical and non-critical situations, we can see some measure of complacency, however. Drivers take longer to resume control in noncritical situations such as exiting a freeway than in critical situations (Eriksson & Stanton, 2017). These variances in the time required for driver takeover need to be accounted for in vehicle design.

A key piece of design in highly automated vehicles is the alert that initiates the request for driver takeover. Prior research has suggested that this is an area that could use some further research (Merat et al., 2014, Eriksson & Stanton, 2017). As trust may serve as a mediator between the alert and the reaction time should there be a false alarm (Chancey, Bliss, Yamani & Handley, 2017), ensuring that the alert can reliably acquire driver attention in any given situation is important for system success.

The mode of alert is a critical factor in facilitating driver takeover. Auditory alerts have long been in use in vehicles, and they have been demonstrated to be useful at gaining the driver's attention (Gold, Dambock, Lorenz, & Bengler, 2013, Melcher, Rauh, Diedrichs & Bauer, 2015). Vibrotactile alerts, or alerts that make use of vibration, also appear to be beneficial. Both alert types, however, have the potential to go unnoticed in the presence of other stimuli. Long duration or high intensity, which would ensure notice, may provide discomfort for drivers. Vibrotactile feedback has been be particularly effective at providing warnings to drivers, but using it alone is not recommended (Petermeijer, de Winter & Bengler, 2016). Visual alerts are particularly ineffective, yielding lower results than either auditory or vibrotactile alerts. Associating the mode of alert with the type of secondary task – such as an auditory alert during an auditory secondary task – does not have any significant effect. Auditory and vibrotactile alerts seem to be equally effective regardless of the secondary task (Petermeijer, Doubek & de Winter, 2017), though secondary tasks still represent a great risk.

While both auditory and vibrotactile warnings have been shown to be similarly effective, there is some disagreement as to which is most effective. Location may also play a role in this variance. Vibrotactile warnings delivered through a driver's abdomen produces shorter reaction times compared to similar audio or visual warnings (Scott & Gray, 2008). Vibrotactile warnings delivered to the shoulder are perceived as more urgent than vibrations at the lower back or waste (Li & Burns, 2013). As the effects of alerts varies with location and mode, there is a need to further examine this subject to ascertain the best designs for highly automated vehicles.

Informative warnings have also been shown to influence driver attention. Informative warnings come in two types: looming warnings, where the intensity of the alert increases to simulate an object approaching, and apparent motion warnings, which signal a direction, i.e. towards an object ahead. In forward collision warning systems, looming auditory warnings have been demonstrated to increase the perceived urgency of the threat and produce better brake reaction times than non-looming warnings (Gray, 2011). Vibrotactile warning signals have also been shown to be similarly effective, though a warning with two points of contact (tactors) – such as the hand and the shoulder – is more effective than a warning with a single point of contact – such as the waist (Gray, Ho & Spence, 2014). A single tactor simply does not convey the same directional influence as two tactors or an auditory warning.

Human-machine systems provide a complex and unique research subject, and many variables must be understood and operationalized before assessment can take place. For example, safety is a key issue in a human-machine system, but it is a multifaceted and complex idea. It could be defined as a lack of accidents, i.e., the better the safety, the less accidents occur. However, it could also be defined as efficient and successful performance, especially in critical scenarios where human lives are on the line. In such situations, one of the primary goals of the system is safety for those involved, thus performance is an indicator of safety (Stowers et al, 2017). Within human-vehicle systems, assessing the cognitive processes of the human are important to assure both safety and success of other system goals.

Attention and situation awareness are critical factors in such systems, and assessing them can be difficult. Several models have been suggested to help measure these factors and predict human performance (Johnson, Duda, Sheridan & Oman, 2016, Sebok & Wickens, 2016). The operationalization of situation awareness and attention is key in such models. Latent hazards are particularly effective for assessing situation awareness (Gibson et al., 2016). A latent hazard is an external danger that threatens system success. In automated driving, such a hazard may be road construction or traffic. These hazards pose a threat to safety and require drivers to understand the situation and take appropriate action. As such, they are effective at assessing the driver's situation awareness. Secondary tasks are an effective means at assessing attention (Zeep, Buchner & Schrauf, 2015). Secondary tasks are any task undertaken by the driver that is not directly related to driving, such as cell phone use. In automated driving scenarios, drivers who are occupied by secondary tasks have longer takeover times (Eriksson & Stanton, 2017). These times vary based on the involvement in the secondary task. Tasks that require more attention make it more difficult for drivers to return their attention to the road and regain situation awareness, thus secondary tasks are good for the assessment of attention. By operationalizing situation awareness and attention with latent hazards and secondary tasks, we can assess the performance of the system as it relates to safety.

It is the aim of this study to compare how auditory and vibrotactile alerts differ in their effect on driver takeover in highly automated driving scenarios. The study will include the use of locality to compare how perceived direction of alerts (either towards- or away-from the driver) as well as modality influences driver takeover time. It is hypothesized that vibrotactile alerts will be more effective than auditory alerts. Furthermore, based on research using forward collision warnings, it is predicted that takeover alerts which simulate motion towards the driver will be more effective when compared to those simulating motion towards the road.

METHOD

Design

This study had five conditions in a within-subjects design. The five conditions included the combination of two modalities (vibrotactile, auditory) and two directions (towards, away) plus a no alert control condition.

Participants

A power analysis based on previous research on takeover alerts (McNabb & Gray, 2017; power=0.8, $\eta_p^2 = .73$) resulted in a required sample size of 18. This sample was drawn from undergraduate students at ASU who were enrolled in HSE 101 and needed to participate in research as part of the course requirement. They were fluent in English and had a valid driver's license, and had normal or corrected-to-normal vision.

Materials

Alerts. These conditions preceded critical events wherein the drivers were required to make a choice. The difference in steering reaction times (SRT) and break reaction times (BRT) were compared. These reaction times represent the driver's attention. Shorter times show a better recovery of attention while longer times suggest poorer attention recovery. Situation awareness was examined by the choice made by the driver during the critical events, which are detailed below. These measures are consistent with the literature and similar research conducted at ASU. Internal validity will be addressed by randomization of the critical events and corresponding takeover request condition. To increase external validity, participants were encouraged to act as they would in a real-world situation, including the use of their phones or other potentially distracting tasks.

Driving Simulator. The primary tool for this study is the DS-600c Advanced Research Simulator by DriveSafety™ at ASU (see Figure 1). This simulator has been designed to feel as similar to a real personal vehicle as possible without causing discomfort to participants. The body of the simulator is the full-width automobile cab of a Ford Focus. Floor mounts enable the cab to move forward and backward to imitate acceleration and braking. Six monitors are placed in key positions: three large monitors in front of the windshield to give a broad front view, and three smaller monitors in positions where mirrors are in typical personal vehicles (rear-view, right wing and left wing). These monitors and the floor mountings are all controlled by a simulation program run by a computer near the simulator. This program also records speeds, braking, and steering as the participant inputs directions from the pedals and steering wheel at 60 Hz.

Figure 1: The Driving Simulator at Arizona State University

Takeover Request Conditions. The five different takeover request conditions were operationalized and compared as follows:

Auditory Away: A 250-hz tone was given for a total of 300msec to the right speaker (near driver's right hand) followed by 100msec of silence and then a 250-hz tone presented to the left speaker (left side of dash) for a total of 300msec.

Auditory Toward: A 250-hz tone was given for a total of 300msec to the left speaker (near dash) followed by 100msec of silence and then a 250-hz tone presented to the right speaker (near driver's right hand) for a total of 300msec.

Tactile Away: A 250-hz tone was given for a total of 300msec via a tactor that was velcroed onto the participant's right wrist, followed by 100msec pause, and then another 250-hz tone that was presented for 300msec to the left wrist.

Tactile Toward: A 250-hz tone was given for a total of 300msec via a tactor that was velcroed onto the participants left wrist, followed by 100msec pause and then another 250-hz tone that was presented for 300msec to the right wrist.

No Warning: No auditory or tactile alert.

One of these conditions occurred prior to each critical event. The variance of the location of the vibrotactile and auditory warnings was to simulate direction, either toward the driver or toward the road. This manipulation was made effective by placement of participants' hands. Their left hand was placed on the top-center of the steering wheel while their right held their smartphone near the gear shifter. With the sources of the warnings located near their hands (on their wrists for the tactile warnings and via speakers near those locations for the audio warnings), the perception of direction was a matter of where driver attention was focused. Videos on their smartphone, discussed later, kept attention at their right hand while attention to the road would have been closer to their left hand. Thus, an alert beginning at their left hand and moving to their right would have been perceived as approaching the participant while an alert beginning at their right hand and moving left would have been perceived as moving away.

The timing of alerts was based on similar research (Straughn, Gray, & Tan, 2009, Gray, 2011) which utilized the algorithm developed by Hirst and Graham (1997):

$$D_w = TTC_{\text{thres}} \times \frac{dD}{dt} + \text{SP} \times V_F.$$

This algorithm was designed to provide the driver with timely warnings based on distance before collision. D_{w} represents the distance between the driver and the lead vehicle when the warning is activated. This is determined by two system-set variables - the time-to-collision threshold (TTC_{thres}) and speed penalty (SP) – and two operator-inputs – the driver's vehicle speed (V_f) and the closure rate between the two vehicles (dD/dt). In the present study, the recommended values of 0.4905 for the SP and 3.0 for TTC_{thres} will be used (Hirst & Graham, 1997).

The simulator program randomized both the critical condition and the takeover request, and each participant experienced five critical events.

Procedure

Participants were introduced to the driving simulator very briefly. They were told they were participating in an automated driving simulation that would last 60 minutes: five 10-minute drives with breaks between to prevent simulator sickness and fatigue. Simple explanations of automated vehicles were provided to ensure all enter the simulator with similar familiarity. They were told that if the automation failed, an alert would be issued and they should try to avoid accidents by either swerving into an open lane if possible or by braking, as they see fit. Each driver completed a 3-minute practice trial to get acquainted with the simulator.

Following the practice drive, each driver chose from a selection of science-related videos to view on their smartphone. In order to ensure their attention was focused on this distraction and not on the road, they were instructed that they would be quizzed on the contents of the video following the driving task. Once they had selected a video and started it, they began the task.

The task consisted of automated driving performed by the simulator on a three-lane road with occasional construction. The automation from the simulator controlled the car’s lane position and speed along this straight road as it followed a lead car. At varied intervals (4-10 minutes) a critical event was programmed to occur. These events are designed to require the driver to make a decision about how to respond. They consisted of the lead car braking suddenly in response to lanes being blocked by construction. The automation triggered one of the takeover request conditions and the driver was required to take manual control of the car and decide whether to brake or swerve in a safe direction. The events contained some variation: some had two lanes closed with only one open lane (either left or right) while others had all three lanes closed. The reactions (SRT & BRT) of the driver and the results of the decision made were observed and recorded. Each driver experienced all five warning conditions throughout the experiment.

RESULTS

Over the course of the experiment, 90 take-over situations occurred. Response accuracy across all conditions was 100%, meaning when drivers were alerted and action was required, drivers who did turn were able to turn the correct direction. A one-way ANOVA was used to analyze BRT and SRT across the five conditions, and pairwise T-tests were used to compare individual effects.

		Aud_To	Aud_Aw	Tac_To	Tac_Aw	None
BRT	Mean	1.04	1.23	1.16	1.66	2.25
	SD	0.22	0.25	0.20	0.19	0.30
SRT	Mean	1.36	1.46	1.70	1.66	1.97
	SD	0.22	0.21	0.25	0.21	0.33

Table 1 - Means and standard deviations of Break Reaction Time and Steering Reaction Time

Perceived direction of alert appeared to be related to reaction times. Both auditory and tactile alerts directed towards participants resulted in faster reaction times than alerts directed away from participants (see table 1). This was true for both BRT and SRT, though SRT [F(1,17)=0.18, p=.678] was not significantly influenced by the warnings while BRT [F(1,19)=87.75, p=.000] was. This is likely because not all participants chose to steer out of danger's way, but all hit the brakes during warning conditions.

Both BRT [F(1,19)=35.19] and SRT [F(1,17)=47.26] were significantly influenced by the mode of alert (p=.000). The T-tests were all significant when compared with the null condition, meaning any signal is better than no signal, or at least the manipulation of the various conditions was effective. It appears, however, that auditory alerts seem to be somewhat more effective than tactile alerts at inspiring faster reaction times (see table 1).

DISCUSSION

As predicted, direction of the alert influenced reaction times. Specifically, alerts perceived as approaching participants inspired faster reaction times than alerts perceived as moving away in all conditions. Direction of the alert seemed to be more important in vibrotactile alerts than in auditory alerts. The difference in reactions for these apparent warnings may be due to a perceived urgency, with a warning that approaches a driver being perceived as more urgent than one that moves away.

Against predicted outcomes, auditory alerts produced faster reaction times than tactile alerts. Perhaps this due to conditioning, such that vibrations are more associated with less urgent warnings compared to sounds, though more research in this area would be required to arrive at any conclusions.

One interesting finding came from the differences between breaking and steering. Not all participants chose to steer in any given direction during critical events, but all participants opted to hit the brakes. Hitting the brakes may simply be a stronger habitual reaction to such critical events, but it is possible that those participants failed to recognize the lane opening available to them. Further investigation should be conducted to determine methods for aiding drivers in quickly identifying safe passage. Perhaps having multiple directional points rather than just a single point such that the directional warnings are more specific would be helpful in enabling drivers to quickly reorient themselves to approaching danger and take appropriate action.

The single-point of direction is one limitation for this study. The direction of the warnings was fairly low-fidelity, and increasing the quality of the directional warnings may produce different results. As in the previous example, perhaps having the directional warnings indicate specifically where the danger is would produce better reactions.

Another area that could be improved upon is the sample. College-age drivers, while a good sample, are not necessarily representative of current drivers of highly-automated vehicles. Identifying that population and using a sample more representative of it may influence the study outcome.

Even with this study’s limitations, the results support dynamic warnings as an effective means of alerting drivers. Highly automated vehicles should apply dynamic warnings to provide their drivers with better tools to enable quick reactions during critical events. Future research should examine how multiple-modalities in concert influence reaction times to identify the best combination of alerts, and examine whether increased fidelity of perceived direction can further improve reaction times.

Automated driving is rising in popularity, but automation in its current state is imperfect. Drivers are encouraged by system design to remove themselves from the loop, yet they are an essential part of system integrity. By understanding how different modes of alert can influence driver reaction times, systems can be designed to more effectively recover driver attention and situation awareness during times of need. This will lead to greater system success and safety for the driver and passengers of automated vehicles.

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