Visualizing Detection Algorithms of Highly Automated Vehicles: Creating Transparency to Support Remote Assistant's Understanding and Predictability?

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ABSTRACT

The scalable implementation of highly automated driving systems (ADS, SAE L4) on German roads depends on the availability of a remote assistant. Although ADS are highly sophisticated, they still need support to overcome technical limitations. Reaching these limitations will lead to minimal risk manoeuvres (MRM), causing the vehicle to safely stop in traffic. Remote assistants (RA) provide high level support for these situations. However, the effectiveness of a RA's intervention depends on the RA's understanding of the system state. The understanding of these RAs can be improved with transparent system design that provides information about the ADS. However, the most efficient design to communicate the information is yet to be determined. This study investigates the effect on a RA's understanding by providing information about an ADS's visual detection. Different types of visualizations were used to highlight detected objects in the ADS's video stream to the RA. In an experimental online study, the influence of the visualizations on the understanding, predictability, and complacency of RAs was investigated. Participants experienced different situations where they saw one of three types of different visualizations in the vehicle's video streams (boxing vs. saliency mapping vs. combined). Results indicated no influence on understanding and predictability. However, results on complacency provide insights into future research possibilities. This may shed light on adequate design solutions to improve trust and complacency towards the ADS.

Keywords: Automated Driving Systems, Remote Assistance, Human-Computer Interaction, Object Detection Algorithm, Transparency, Complacency.

1 INTRODUCTION

While vehicle automation progresses more towards highly automated driving systems (ADS, SAE L4), some situations remain that cannot be handled by the ADS. In part these limitations originate from the algorithms used in ADS. For example, there are many situations that remain new to algorithms demanding nevertheless appropriate solutions from them (Koopman & Wagner, 2017). One solution to this so-called unknowable-unknowns problem are remote assistants (RA) (Koopman & Wagner, 2017). In situations in which ADS reach their operational design domain (ODD) limits, they perform minimal risk manoeuvres and come to a safe stop (Karakaya et al., 2020). RA can interact with the ADS and resolve the situation, increasing the system's resilience (Aramrattana et al., 2024; Haupt, 2022; Kettwich et al., 2022). The implementation of RA into ADS requires new workplaces, as RA are confronted with new tasks in a new context (Schrank, Merat, et al., 2024; Schrank, Walocha, et al., 2024). RA must understand the ADS, its limitations and capabilities. Also, they must gain awareness of the situation that caused the ADS to perform an MRM.

Understanding and predictability require information that has to be provided to the RA in a human-machine interface (HMI, Páez, 2019). This may include information about sensors, vehicle status, infrastructure, and the system. For example very detailed information about the entire RA-ADS system would overwhelm RA (Dahl, 2018). Information about the ADS status, and ADS' interaction with its surrounding, status of infrastructure, and other road traffic users appear necessary (Lombrozo & Gwynne, 2014). More specifically, visualizing the information that is necessary for RA to understand the ADS' situation is important (Kettwich et al., 2021). Partially, this can be achieved by visualizations about the vehicle's object detection in the vehicle's video streams that provide system transparency of the ADS. Highlighting where other traffic participants and objects are appears promising as the perception of other road users and objects is a central aspect for vehicle control. Still, a misleading depiction can also cause confusion about system's capabilities and result in complacent behaviour (Ehsan & Riedl, 2021). To date, it is an open question how object detection should be presented to RA. Therefore, this paper addresses the following research question: How can transparency information be visualized in an HMI to support RAs understanding and predictability of the situation without causing complacency?

1.1 Theoretical Background

Different types of visualizations may help to provide the information that is necessary for system transparency that helps the RA's understanding, and predict an ADS without overwhelming them. System transparency separates into seeing-through (no transparency) and seeing-into systems (transparency) (Eschenbach, 2021; Selkowitz et al., 2017; Skraaning et al., 2020; van de Merwe et al., 2024). Systems without transparency or seeing-through system are systems, where users are unaware of the system's presence or activity; they see through the system. Automation systems that act without user knowledge completely prevent them from observing or interacting with these systems (Skraaning et al., 2020). Here, transparency can be provided on a superficial level by making the system and its actions observable (Ponn et al., 2020). More information is necessary explaining the parts of the system relevant for a specific behaviour to support the understanding of an automated system (Vorm & Combs, 2022; Zhang et al., 2021).

An important part of an automated system is the object detection system. It determines which objects are identified by the ADS. Providing information concerning the ADS' object detection provides transparency about the systems' status. Visualizing the ADS' object detection may therefore support a RA's understanding about the status of the ADS. While system transparency generally helps in understanding and predicting a system's actions (Chen et al., 2014), it can also lead to a false sense about the system's capabilities (Ehsan & Riedl, 2021). Fake transparency or ill-chosen explanations about a system can cause overtrust and complacency (Ehsan & Riedl, 2021; Liu, 2023). Therefore, visualizations of object detection may help understanding ADS status, but the type of visualization may affect this understanding and the RA's overall evaluation of the system.

In previous research, different approaches to depict an ADS's object detection have been investigated.

Most prominent research was performed on box detected objects (Ponn et al., 2020). Another recurring approach is saliency mapping, which means colouring of individual pixel according to their belonging to a specific object and its classification (Colley et al., 2021; Mukhopadhyay et al., 2020). The latter approach may provide a more transparent visualization, as it is closer to the functioning of the ADS object detection algorithms. Most object detection algorithms (e.g., convolutional neural networks) identify objects by evaluating individual pixels and merging them, based on that evaluation, into a conjugated object (Elngar et al., 2021). This provides more evidence to the RA as to why an object was identified by highlighting each pixel that was used to identify the object. Boxing itself is more abstract, because the object itself is not highlighted but surrounded by a marker to indicate its detection. It provides less information about the visual cues used by the algorithm to identify the object. This means that RA must interpret every box provided by the ADS to understand what was highlighted. In cases with several objects in a box, e.g., multiple pedestrians, RAs might not be able to distinguish if one or all the pedestrians in the box have been identified as relevant objects for the vehicle's behaviour.

The way in which objects are highlighted, could become especially important when different objects, like pedestrians and cyclists are highlighted by the same box or when boxes overlap in a way that makes them indistinguishable. Since pedestrians and cyclists move with different speeds, highlighting them with the same box could result in challenging situations for the RA to understand the situation quickly. Therefore, both types of visualization of objects have a different explanatory value and provide different levels of transparency. These levels of transparency may influence RA understanding and their subjective predictability for the ADS's behaviour. Generally, understanding results from explanations leads to updates in peoples' mental models (Beggiato & Krems, 2013). Therefore, the more transparent the explanation is, the more profound the understanding should be.

Also, with increasing transparency, trust towards the ADS should be influenced as well. Trust can be regarded as the attitude towards an agent's ability to reach a goal (Hoff & Bashir, 2015). Accordingly, RA knowledge about the ADS's capabilities should lead to calibrated trust towards the system. Following the assistant's trust, complacency should be influenced as well. Complacency is a user's attitude towards their responsibility to supervise an automated system they cooperate or work with (Parasuraman & Manzey, 2010). When trust can describe the attitude towards the capabilities of an automated system, complacency is the attitude about the appropriate behaviour towards the system. With explanations about the system's capabilities, both should be influenced accordingly (Desai et al., 2012; Glick et al., 2022).

1.2 **Hypotheses**

Following the theoretical considerations, using visualizations with more transparency of the ADS object detection should improve the RA's understanding and predictability of the ADS. The type of presentation affects the RA' ability to observe and interpret the behaviour of the ADS on a given situation. Thus, we derived the following hypothesis:

Hypothesis 1: "*Increasing transparency using visualizations of the object detection of an ADS increases*

RA's understanding and predictability of the ADS."

Because the visualizations provide information about ADS object detection, objects in the surrounding of the vehicle are visible more prominently. This should support the remote assistant's ability to detect highlighted objects, resulting in an increased situation awareness.

Hypothesis 2: "*Increasing transparency using visualizations of the object detection of an ADS increases the remote assistant's situation awareness*."

With increasing transparency RAs knowledge about possible system limitations should improve. With knowledge of possible limitations to detect objects, trust and subjective complacency should decrease.

Hypothesis 3.1: "*Increasing transparency in the visualizations of the object detection of an ADS decreases remote assistant's trust*."

Hypothesis 3.2: "*Increasing transparency in the visualizations of the object detection of an ADS decrease remote assistant's subjective complacency*."

2 METHOD

The study was conducted as an experimental online study using the SoSci-Survey platform (Leiner, 2024). Participants were recruited using a research panel consisting of Brunswick (German) locals, and via advertising on LinkedIn and circles of acquaintances.

2.1 Study Sample

Participants' (*n* = 114, 45 female) ages ranged between 18 and 47 years (M = *41.5, SD = 14.9*). Participants reported higher than medium technical affinity (M = 4.53, SD = 0.93; [1="completely wrong", 6="completely right"]) in the Affinity for Technology Interaction (ATI) by Franke et al. (2019).

2.2 Study Design

The study utilized a between-factors design were videos concerning three types of visualization and a control group (saliency mapping vs. boxing vs. saliency mapping and boxing vs. no visualization) of the ADS' object detection were shown. Each group experienced one of these visualization types in seven scenarios, in which an MRM was performed by the ADS.

2.3 Study Materials

The three types of visualization were created using the Unreal Engine 5 (Epic Games, Inc., 2022). For each visualization type, seven videos with varying scenarios (see section 2.3.2) were created to present them in realistic scenarios involving visually challenging situations, resulting in 28 videos total.

2.3.1 Types of Visualization

In the first type of visualization, boxes are used to highlight vehicles and pedestrians using different colours (red and yellow, Fig. 1). In the second type, vehicles and pedestrians are highlighted as Saliency Maps by colouring them completely in red or yellow (Fig. 2). In the third types, both visualizations used in the first and second types were combined, resulting in colouring and boxing of vehicles and pedestrians (Fig. 3).

The Boxing (Fig. 1) provides a first level of transparency by highlighting objects relevant for the ADS in an abstract way. The boxes provide an explanation about what the algorithm has detected and how it classified the object, i.e., pedestrian or vehicle, but it does not provide an explanation what information in the images specifically lead to the detection and classification.

Figure 1. Interface visualization with Boxing.

The Saliency Mapping (Fig. 2) provides additional information about the detected object since it provides information about the exact pixels that have been used by the algorithm to identify and classify the object. It therefore provides an explanation about the why, not just what the algorithm has seen.

Figure 2. Interface visualization with Saliency Mapping.

The combination of both the Boxing and the Saliency Mapping (Fig. 3) provides the most information in terms of what, where and why objects have been classified. This interface provides all available information at the same time, resulting in the highest level of transparency.

Figure 3. Interface visualization with a combination of Boxing and Saliency Mapping.

2.3.2 Scenarios

The different interfaces were shown as between factor to participants in seven scenarios serving as within factor. In the first scenario, a construction site with a truck parking next to it blocked the road. Here, pedestrians crossed the street in front of the blockage. In the second scenario a parked car blocked the road with pedestrians crossing around it, both causing the MRM. In the third scenario, an accident on an intersection blocked the road with pedestrians next to the car. In the fourth scenario an intersection with a construction site blocked the sides of the road and the intended route of the vehicle in front. In the fifth scenario the ADS approached a left turn with oncoming traffic making a right turn, blocking the vehicle as a result. A cyclist approaches the same turn as the oncoming traffic while being partially hidden behind it. In the sixth scenario the ADS approached a right turn where it was blocked by numerous pedestrians. In the seventh scenario the ADS approached oncoming traffic on a one-way street with cyclists hidden behind the oncoming traffic.

2.3.3 Questionnaires

To investigate the participant's trust, the trust in automation questionnaire from Körber and Gleissl (2022) was used. This questionnaire has 19 items which participants answer using a 5-point Likert-type scale (1="strongly disagree", 5="strongly agree") with a "no response" option. The questionnaire has 6 subscales assessing different aspects of trust. The "understanding and predictability" subscale was used to investigate each participant's understanding and subjective predictability regarding the system based on the experienced visualization type. Complacency was measured using the automation induced complacency monitoring scale (Merritt et al., 2019). It measures subjective automation induced complacency with 10 items in two subscales, "monitoring" and "alleviated workload" on a 5-point Likert-type scale. Situation awareness was measured using the SART questionnaire by Taylor (2016). It measures subjective situation awareness with 10 items on a 7-point rating scale. The items can be attributed into "understanding", "demand" and "supply" and are then used to calculate situation awareness (SA = Understanding – (Demand – Supply)).

2.4 Study Procedure

Firstly, participants were instructed about the study's purpose and setting. They were given information about the ADS and the role of the RA, and what they were going to see in the process of the study. They were also instructed about the nature of the remote assistance task and how the visualizations were supposed to support remote assistants. They were also told that the study was conducted under the declaration of Helsinki (The World Medical Association, Inc., 2008) and that they could quit the study at any time without repercussions and their rights regarding the collected data.

3 RESULTS

Results were evaluated using Excel calculating descriptive statistics, and IBM's SPSS calculating ANOVA, t-test, post hoc tests and effect sizes. Omega square (ω^2) served as effect size, as it is less biased (Okada, 2013). Cohen (1988) defines effect sizes as: small >= .01, medium >= .06, and large >= .14.

3.1 Understanding and Predictability

Table 1. Results of Trust in Automation Subscale "Understanding and Predictability".

Understanding and Predictability				*95%-CI*	
	N	*M*	*SD*	*Lower*	*Upper*
No Augmentation	25	3.13	0.45	2.50	4.00
Saliency Mapping	30	3.17	0.49	2.99	3.35
Boxing	29	3.18	0.54	2.97	3.38
Combined	25	3.08	0.44	2.89	3.26

M = Mean, *SD* = Standard Deviation, *SE* = Standard Error, *95 % - CI* = Confidence Interval

An ANOVA for repeated measures with a Greenhouse-Geisser correction revealed no significant differences concerning understanding and predictability between the types of visualization, $F(3,110) = 0.973$, $p = .408$, $\omega^2 = 0.001$. When applying Bonferroni-adjusted post-hoc analysis, also no significant effects on understanding and predictability in any of the conditions were found. As a result, hypothesis 1 is not supported by the results and cannot be confirmed.

3.2 Situation Awareness

ANOVAs with a Greenhouse-Geisser correction revealed no significant differences regarding situation awareness between the types of visualization in any of the scenarios (Table 4). Bonferroni-adjusted post-hoc tests support these results. Hypothesis 2 is, therefore, not supported by the results and rejected.

Table 2. Results of ANOVAs for Situation Awareness for each scenario.

Situation Awareness	*QS*	*df*	*MdQ*	*F*	*Sig.*
Scenario 1	50.482	3, 110	16.827	0.386	.763
Scenario 2	21.568	3, 110	7.189	0.212	.888

Scenario 3	41.347	3, 110	13.782	0.299	.826
Scenario 4	130.455	3, 110	43.485	0.857	.466
Scenario 5	40.021	3, 110	13.340	0.318	.813
Scenario 6	36.232	3, 110	12.077	0.273	.844
Scenario 7	97.043	3, 110	32.348	0.767	.515

M = Mean, *SD* = Standard Deviation, *SE* = Standard Error, *95 % - CI* = Confidence Interval

3.3 Complacency

Table 3. Results of Complacency Monitoring Scale.

Subjective Complacency				*95%-CI*	
	N	*M*	*SD*	*Lower*	*Upper*
No Augmentation	25	2.82	0.67	2.54	3.09
Saliency Mapping	30	3.14	0.69	2.88	3.39
Boxing	29	2.75	0.58	2.53	2.97
Combined	25	3.03	0.58	2.79	3.27

M = Mean, *SD* = Standard Deviation, *SE* = Standard Error, *95%-CI* = Confidence Interval

An ANOVA for repeated measures with a Greenhouse-Geisser correction revealed significant differences with a low effect size regarding complacency between the types of visualization, $F(3, 110)$ = 3, 110, $p = .042$, $\omega^2 = 0.046$ (Fig. 4). When applying Bonferroni-adjusted post-hoc analysis, no significant effects on complacency in any of the conditions were found. Hypothesis 3.1 regarding complacency is not supported by the results.

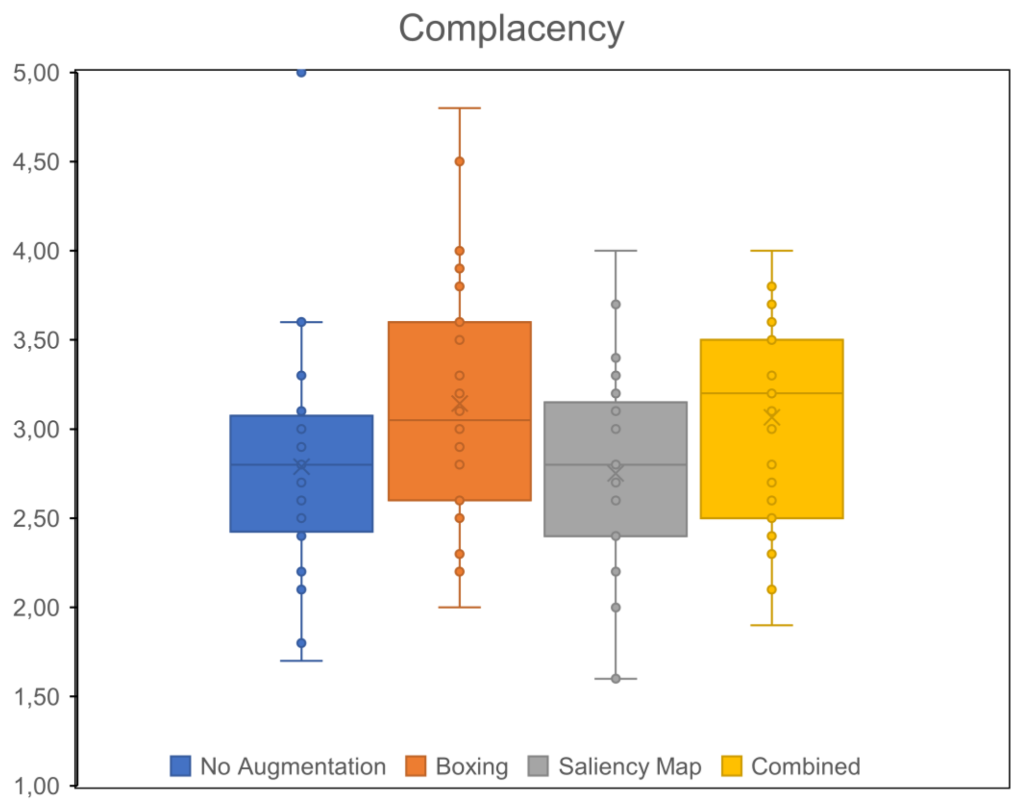

Figure 4. Boxplot diagram for results of the Complacency Monitoring Scale.

3.4 Trust

Table 4. Results of Trust in Automation Questionnaire.

Trust				*95%-CI*	
	N	*M*	*SD*	*Lower*	*Upper*
No Augmentation	25	3.23	0.50	3.03	3.44
Saliency Mapping	30	3.20	0.36	3.07	3.34
Boxing	29	3.14	0.37	3.00	3.28
Combined	25	3.16	0.36	3.01	3.31

M = Mean, *SD* = Standard Deviation, *SE* = Standard Error, *95%-CI* = Confidence Interval

An ANOVA for repeated measures with a Greenhouse-Geisser correction revealed no significant differences regarding trust between the types of visualization, $F(3, 110) = 0.407$, $p = .748$, $\omega^2 = 0.016$. When applying Bonferroni-adjusted post-hoc analysis, also no significant effects on understanding and predictability in any of the conditions were found. Hypothesis 3.2 regarding trust is not supported by the results.

4 DISCUSSION

The study aimed at providing insights into possible visualizations that could provide system transparency and result in a better understanding, predictability, trust, complacency and SA of RA's. Results provided no evidence towards hypotheses 1, 2 and 3.2. There was no effect of the visualizations on understanding and predictability (H1). A possible explanation for this might be that the visualizations did not provide additional transparency. We assumed that more transparency through visualizations would improve RA's understanding and predictability (Skraaning et al., 2020). But though the saliency mapping should provide more transparency, it might not have been perceived by users as a significant increase that significantly supported understanding and predictability. Also, participants might have been insecure about the actual ability of the system based on the visualizations (Oliveira et al., 2020). Since the technical details of the visualizations were not instructed, they might have been insecure about how to interpret them and the respective increase in transparency, thus not affecting understanding and predictability.

Additionally, only one perspective of the vehicle (the front camera) was shown to them in the videos, further introducing insecurity and mitigating the transparency of the system throughout the visualizations as they were limited to this perspective. Though participants, taking the perspective of a RA, were presented a perfect system, they were unable to properly assess the entire situation and might therefore have been insecure about the evaluation of the system. This might have resulted in a tendency towards neutral answers. This may have been increased further by the scenario depiction, which stopped at the end of the MRM. Participants may have felt insecure about assessing the vehicle's behaviour based on a static image. Since the visualizations mainly supported the RA's ability to monitor the vehicle's object detection, they might have continuously wanted to do so. The ability to continuously monitor the situation and execute a concrete task (e.g. manual confirmation of the continuation of the journey), could have led to less insecurity of the participants in their ability to evaluate the system and the situation based on the visualizations.

Results also did not provide evidence to an influence of visualizations on SA (H2), which did not significantly improve in any of the different scenarios. What might have limited the effects in this study are the scenarios in which the visualization types were shown. The aim of the situations was presenting visually challenging situations to the participants. Yet, the depictions of the situations might have been perceived as relatively unchallenging, since they depicted fairly common situations, were trust in the abilities of the system might have been high in general (Kenesei et al., 2022). As the context of the situations was uncritical as well, there might have been no need for additional information about the object detection. In order to improve SA, the visualizations would have to provide a sense of usefulness. However, if participants did not perceive the situations as challenging despite their complex character, the visualizations might not have provided any use to them. For example, visualizations have shown to improve situation awareness in adverse conditions like fog or rain (Schrank et al., 2025). This may indicate that visualizations primarily provide their use only in adverse conditions, and thus differences in visualizations should be investigated in such scenarios as well.

Results in trust (H3.2) ratings indicate no influence of the different visualization types on the RA's trust as well. This was also true for the subscales of the questionnaire. As mentioned, if the visualizations would not have been perceived as useful in showcasing the ability of the system better, they would not have influenced trust as well (Hoff & Bashir, 2015). Only the results regarding complacency showed evidence of an influence on complacency (H3.1), which provides some evidence that complacency was influenced by the type of visualization. It was lowest in conditions that showed no boxing, i.e., the control condition and the saliency mapping. Though post-hoc tests did not confirm an effect, it indicates a possible influence with a small effect. Since complacency was lowest in the saliency mapping condition, this could mean that transparent visualizations affect RA's subjective complacency but this effect is not based on a better understanding and predictability. In the conditions including boxing, complacency was higher albeit not significantly. This could be due to the boxing not providing any indication of occluded objects or partly visible objects. Taking the results of all variables into account, we assume that in order to support RA in their task execution, saliency mapping as a theoretically more transparent way, might show advantages. But with the limitations of the results and the used method, we cannot provide a clear testimony. We rather propose a more holistic approach to investigate the effects further that incorporates transparency and informational design, operationalized in a simulator with more complex scenarios in adverse conditions and a more challenging task. More technical instructions about the visualizations and their informational value about the system may benefit the perceived usefulness of them and the participants' understanding and predictability. This way, immersion and an interactive task design may provide better evidence to the transparent interface design approach.

5 CONCLUSION

Since the results of this research are limited, more research is needed to shed light onto the best visualizations for object detection algorithms in ADS for remote assistance. Especially with increasing use of AI driven automation technology, it becomes more and more important to find practical solutions that make these systems more understandable. Theoretic considerations regarding system design for ADS are only the first step in making the systems more reliable, efficient and safe. Though this research did not provide results towards a clearer understanding of HMI design for remote assistance, it may provide an indication towards an adaptive visualization. In unchallenging conditions, they might not be needed by RA to assess the situation. In adverse conditions however, visualizations may very well prove useful. Future research can investigate ideal types of visualization that facilitate this use. Thus, it remains an open question, how the object detection should be presented to RA in order to be most beneficial for the RAs' tasks. We still believe that complacency is a promising factor to determine the ideal way to do so and transparency as a viable approach to understandable system design.

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