ORIAS: On-The-Fly Object Identification and Action Selection for Highly Automated Vehicles

Mark Colley
mark.colley@uni-ulm.de
Institute of Media Informatics, Ulm University
Ulm, Germany

Ali Askari
ali.askari@uni-ulm.de
Institute of Media Informatics, Ulm University
Ulm, Germany

Marcel Walch
marcel.walch@uni-ulm.de
Institute of Media Informatics, Ulm University
Ulm, Germany

Marcel Woide
marcel.woide@uni-ulm.de
Institute of Psychology and Education, Dept. Human Factors, Ulm University
Ulm, Germany

Enrico Rukzio
enrico.rukzio@uni-ulm.de
Institute of Media Informatics, Ulm University
Ulm, Germany

ABSTRACT

Automated vehicles are about to enter the mass market. However, such systems regularly meet limitations of varying criticality. Even basic tasks such as *Object Identification* can be challenging, for example, under bad weather or lighting conditions or for (partially) occluded objects. One common approach is to shift control to manual driving in such circumstances, however, post-automation effects can occur in these control transitions. Therefore, we present *ORIAS*, a system capable of asking the driver to (1) identify/label unrecognized objects or to (2) select an appropriate action to be automatically executed. *ORIAS* extends the automation capabilities, prevents unnecessary takeovers, and thus reduces post-automation effects. This work defines the capabilities and limitations of *ORIAS* and presents the results of a study in a driving simulator (*N*=20). Results indicate high usability and input correctness.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; *Interaction techniques.*

KEYWORDS

Automated driving; human-machine cooperation; interface design.

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1 INTRODUCTION

Operating under all circumstances is still not possible for AVs (AVs) [55]. A prerequisite for AVs to perform the driving task is the perception and recognition of one's surroundings. This includes static objects such as infrastructure and vegetation, but also dynamic items such as other road users. Especially dynamically changing objects such as signalized intersections, or electronic announcements, which are not part of the vehicle‘s a priori high-resolution environment map, are challenging. Also, to be independent of such data, manufacturers strive to develop vehicles that do not rely on high fidelity a priori maps [63]. Therefore, real-time *Object Identification* (*Obj. Ident.*) is vital but still challenging, for example, under bad weather conditions [63]. Factors such as occlusion, bent signs, or graffiti complicate this recognition. In cases where the AV fails to recognize objects, a human would have to take over this task. Such a preliminary cooperative approach called "CooperationCaptcha" to solve this issue has been proposed by Walch et al. [65]. They propose to incorporate the human user to classify unrecognized objects via speech or touch input. This should avoid handovers and, therefore, post-automation effects such as unstable lateral control [45] or reduced distance between vehicles after platooning [5]. The ability of humans to classify objects was used in different contexts, such as distinguishing bots from human website visitors [12], to recognize street names on signs [22] or to identify audio sources [77]. Walch et al. [65] name several benefits of such a system: labeling data for machine learning (ML), consensus on ambiguously labeled objects, updated map material, transparency of system capabilities, and avoiding handovers [65]. However, in their preliminary work, the authors do not present a concise description of this disruptive idea: (1) In which situations is the system useful? (2) What are the limitations of it? (3) How exactly should an AV equipped with the system behave? (4) What is an appropriate design? (5) Are there other possibilities besides *Obj. Ident.* to use the system? (6) How is such a system used and (7) how do people rate such a system? Therefore, a thorough description and extension of CooperationCaptcha called *ORIAS* (Cooperative Object Recognition and Identification and Action Selection) addressing the aforementioned aspects is presented. Two different possible concepts are described: (1) *ORIAS* as *Obj. Ident.* (as proposed by Walch et al. [65]) and (2) *ORIAS* as

Action Selection (*Act. Sel.*) where the human user directly decides what is to be done. Results of a study (*N*=20) comparing these two implementations show high usability and high input correctness.

2 RELATED WORK

This work presents a novel cooperative approach to overcome difficulties in traffic sign and, more generally, *Obj. Ident.*. Therefore, we present related work on the driving task and how this can be subdivided, cooperation in highly AVs with special focus on *Obj. Ident.* ands on work in the domain of automatic traffic sign detection and recognition (TSDR).

2.1 Driving Task Actions

ORIAS is described as an *Obj. Ident.* or an *Act. Sel.* system. To define relevant actions the automation has to perform, the driving task has to be broken down into its atomic operations. However, research has mostly described the driving task high-level. In his work, Donges describes three actions to fulfill the stabilization of the vehicle: Steering, accelerating, and braking [13]. Hollnagel et al. [30] distinguish four levels of tasks: Targeting, monitoring, regulating, and tracking. On every level, the driver has to constantly assess the situation and decide on measures to take. Fastenmaier and Gstalter [21] define the "basic driving task" for the navigational level ("find and reach a defined destination" [21, p. 963]) and the control level ("steering and speed control" [21, p. 963]). The authors divide these tasks into "tasks in longitudinal direction", "tasks in intersections", and "other driving tasks" [21] which are situation dependent.

For AVs, Kaß et al. [35] collected "all possible driving maneuvers". They divide these into lateral and longitudinal maneuvers. With partially or highly AVs, the driving task changes [20, 23]. While some work proposes to shift control entirely between human and AV (i.e., handovers and takeovers [44]), shared control was proposed as a novel input paradigm [48, 50]. Walch et al. [66] see three disjoint interaction paradigms for driving task-related interaction with AVs: control shifts, shared control, and cooperation without tasks on the control level.

For the *Act. Sel.* system of *ORIAS*, actions for the human user to select, therefore, are steering (i.e., select a lane or route), accelerating, and braking. Additionally, the human user can aid the AV to determine the relevance of an object (also see [65]).

2.2 Traffic Sign Detection and Recognition

Stallkamp et al. [58] report superhuman vision performance for the detection of road signs. However, they note that the "images in the dataset vary strongly in terms of quality and readability" [58, p. 7], i.e., resolution, contrast, motion blur, or reflection. 18 teams took part in the *International Joint Conference on Neural Networks* and evaluated their networks on the *German Traffic Sign Detection Benchmark* [31]. One team achieved 99.97%. Still, there is ongoing work on the detection and recognition of road signs with challenges to overcome [78]. Multiple challenges are named [2, 61, 63, 74]: lighting conditions, motion artifacts, damaged or obscured signs as well as real-time capability and unavailability of public databases. Recent approaches achieve a precision of 91.1% [2] even under challenging weather conditions. These algorithms likely become near perfect in the not so distant future.

2.3 Cooperation in (Highly) Automated Driving and On-The-Fly Object Labeling

While switching to manual driving is a common approach to deal with shortcomings of AVs [3, 46], concerns regarding this approach have also been mentioned: situational circumstances that cannot be handled by an automated system are likely also very challenging for a driver. Therefore, switching off the automated system entirely, even when some supporting functionality would be available, is questionable [69]. Moreover, switching from automated driving to manual driving can have negative effects on the driving performance of the human user [5, 45, 56].

Consequently, driver-vehicle cooperation has been suggested as a driving-task related interaction concept for AVs with the assumption that the system and driver act as team players and help each other to overcome weaknesses [69]. Humans can help AVs to recognize unforeseen situations and decide how to deal with them [71], predict how pedestrians will behave (i.e., will they cross the road) [68], and to approve the execution of maneuvers [72].

Today, in situations when an AV can not recognize objects with sufficient confidence, handing over control to the human driver would be the default protocol. However, the human passenger of an AV could take responsibility and classify the objects. Walch et al. [65] implemented two interaction techniques. In the *free text* system, the driver can define the unrecognized object via voice. In the *choice* system, a more sophisticated system was assumed. The AV would be able to suggest touch-selectable potential correct objects without being able to definitively choose the right one. This could happen for very similar-looking or slightly changed objects (e.g., [75]). Walch et al. [65] report low mental workload, high usability, and high system aptitude for both systems. Input duration was significantly longer in the *free text* system and varied strongly from one word to long sentences. Participants were also asked for their strategies when labeling the objects. 25 of 28 participants stated that they never looked at the scene in both systems, only at the screen. This seems to be the reason for poor classification in situations when high SA is needed (e.g., for traffic lights). The authors themselves partly address several concerns: due to the statically displayed image of the unrecognized object, context information is missing. *Irrelevant* and *Other* represent two distinct input choices, as these have to be treated differently: While an *irrelevant* object can be ignored, an *other* object potentially has to be accounted for [65, guideline (2)]. Additionally, we argue that the display of a recognition (un-)certainty (in the form of a percentage) carries the potential to confuse the user as humans have difficulties understanding probabilities [34]. The procedure in the case of wrong or no selection is not described. As they used video in their experiment, the system would slow down to increase the time budget and, without input, "the system would eventually simulate to have recognized the object and continue the automated journey" [65, p. 4]. It seems reasonable to argue that this will, in reality, not always be possible. We argue that a more realistic AV response would be to drive to the curb of the road and come to a halt.

3 *ORIAS* DESIGN

We present *ORIAS*, a system based on the preliminary findings addressing the expressed lessons learned [65]. As Walch et. al show [65, 72], human users can be included temporarily in the driving task by acting as an additional sensor. In the case of problematic *Obj. Ident.* due to limited sensor capability or unaccounted object variation (bent signposts with graffiti, reflecting surfaces, weather conditions [63]), an AV equipped with *ORIAS* can ask the human user for aid. The user can interact with the AV in two ways: On the one hand, the user can define the unrecognized object (e.g., "This is a 30km/h sign"). The AV then has to use this information to decide on appropriate measures on the navigation, guidance, and stabilization level, thus, reducing the user to a sensor. This concept is called *Obj. Ident.*. On the other hand, the user can already derive the required measure by defining the missing information and context. For example, if the vehicle is travelling faster than 30km/h, the driver can respond with a command such as "slow down". In this case, the user takes more responsibility and has more control. Thus, the user defines an instruction at guidance level that the AV has to follow. In this case, the user has a higher influence on the driving task and can, if wanted, define parts of the driving style, for example, whether the unrecognized sign indicates the need to slow down or not. This concept is called *Act. Sel.*. The two concepts vary in the *level of control* the user holds and in the situation awareness needed to input the proper information: The user has a higher level of control in the *Act. Sel.* concept but also needs higher situation awareness as the context is relevant to determine the appropriate action.

ORIAS is intended for conditionally, highly, and fully AVs (SAE Level 3, 4, and 5 [53], e.g., to enhance the operational driving domain). These (partly) AVs can operate in situations of varying difficulty. While recognition algorithms already work well (see Section 2.2), we doubt that all kinds of objects **under all conditions imaginable** can be classified. Humans, however, are very proficient in classifying objects and could even classify objects such as hand-drawn signposts. While it is not mandatory to follow these messages (e.g., "Please slow down - children playing"), it is highly expected by the residents. Also, for assessing signposts only applying if other criteria are met (e.g., when raining) could be difficult for AVs. In the following, we describe the process that led to and the final design of *ORIAS*. Additionally, behavior with incorrect or insufficient input and system limitations are discussed.

3.1 Process

We developed prototypes in an iterative design process involving people with various backgrounds such as Design, Computer Science, and Human-Computer Interaction (see Figure 1). The *Live-Preview* and option selection via click or speech remained unchanged. A key difference was to differentiate between a system that asks the driver for an action to execute (Figure 1c) or for help identifying the object to be able to execute proper actions on its own (Figure 1b). This is based on the difficulties some participants had in naming the relevant objects and, thus, named the required action [65].

3.2 User Interface Concept

The user interface (UI) contains an always-on *Live-Preview* [65] (Figure 1b A) enabling a constant mapping between the real world and the *Live-Preview* to prevent cognitive overload when the main functionality of *ORIAS* is triggered.

When the AV could not identify an object, the *ORIAS* feature will be triggered (Figure 2 step (2)). The causing object will be roughly visually highlighted (Figure 1b A), an information message and corresponding selection fields will be displayed. As no other relevant textual information is presented above the *Live-Preview*, the order of processed information follows the order of priority: Directive text box first (i.e., the instruction "Please select the correct object (action) or apply the brakes to take control over the vehicle"; Figure 1b B). Then Input options (Figure 1b C), followed by an indicator for the activated microphone (Figure 1b D).

As numerous traffic signs in Germany contain blue (183 of 715), Yellow (100 of 715), and Red (208 of 715), we chose different shades of gray (e.g., HEX #4b4b53 and HEX #646469) and orange (HEX #f06831) as the color scheme (see Figure 1). For other countries, *ORIAS* should adapt these colors to the traffic system and the local cultural color interpretation [11, 47, 59]. As a label for the UI in the *Obj. Ident.* system, the official wording of the according Ministry of Traffic could be used, however, these are mostly legal terms or numbers which we assume are barely known (see [65]). In the instrument cluster, we show the upcoming maneuver of the AV as guidance for the human user.

3.3 Automation Behavior

When the AV encounters an un-identifiable object, it shows the *ORIAS* UI in the center touchscreen. A sound alerts the operator (as this decreases reaction time [41]). The AV initially continues to drive at a constant pace to avoid interrupting traffic flow when the user can identify the object quickly or when the AV itself can identify it based on novel information (e.g., better angle, better lighting conditions). After a specified time driving with the same velocity, the vehicle will slow down and finally stop at the unknown object if the user fails to interact with *ORIAS* (see Figure 2 (4)) and ask the driver to take over. This approach does pose risks in a real scenario as other road users could be surprised by an unforeseen standstill. However, this is a proposed exit strategy and will, for example, be implemented in the new Mercedes S-Class in 2021 [27]. The vehicle should, therefore, try to minimize this risk by coming to a halt at the curb. With a take over or a standstill, a handover screen (see Figure 2 (3)) to continue the automated journey is shown. To hand over control to the automation again, *ORIAS* will again ask the user for the unknown objects (see Figure 2 (5)). This provides data for ML [65] and prevents the user to ignore an unknown object. Asking for the object can be avoided if all relevant information is available, for example, via a priori maps.

Waymo claims to "identify [...] stop signs greater than 500 meters away" [32]. However, we assume a sensor range of ≈ 100m as in non-linear settings such as historical inner cities, this range will not be usable. For a deceleration from 50km/h (≈ 30 mph, a typical allowed velocity in European and US cities [1, 10]) to 0km/h with a continuous deceleration of -2.5m/s^2 (for petrol cars; full brake with -8.9m/s^2 [4]), ≈ 39m and ≈ 5.6s are needed. Therefore, for the

(a) First paper prototype. (b) Final prototype for *Obj. Ident.* (c) Final prototype for *Act. Sel.*

Figure 1: The user interface of *ORIAS* at different stages of the design process.

remaining 61m of the 100m drive to the unrecognized object with a constant velocity of 50km/h, ≈ 4.4s are needed. This time budget could be enhanced via earlier deceleration. This would also provide a physical notification to the user. Consequently, after ≈ 4.4s of continuing driving at a constant speed, the AV decelerates linearly. This combined time budget of 4.4s + 5.6s = 10.0s could allow even for a safe take over [26].

3.4 Selection, Approval, and Cancellation

Multimodal (*touch* and *speech*) input [49] is possible simultaneously. For the selection of an option, the appropriate button has to be held. When holding a suggestion, the button fills up with green color, indicating a status bar. For touch input, we propose to employ the HOLD technique as it was shown to be faster for cancellations compared to clicking [73]. The user would, therefore, click the option until the vehicle drove past the object. While clicking was rated as more usable in Walch et al.'s use case of overtaking slower vehicles [73], we prioritize the cancellation aspect to increase safety. This interaction is not possible for speech input. For speech, switching the chosen option is possible until the object is reached as *ORIAS* will continue to show and highlight the object until the vehicle drove by.

Depending on the concept, "Irrelevant" or "Ignore" can be chosen. In both concepts, it is possible to choose "Other". In this case, the user has to use speech to define the object. This would be communicated to the user via text displayed (e.g.,"Please define the object"). The microphone is automatically activated as suggested by Walch et al. [65]. This is visualized via a highlighted microphone symbol (see Figure 1b D). The user can choose a suggestion by (1) naming the displayed option, (2) the name of the object or sign (e.g., "Tempo 50") (3) or by saying "Irrelevant" or "Ignore".

3.5 Incorrect or Insufficient Input Behavior

To act appropriately, *ORIAS* requires the specific object, signpost, or action. Naming the object class (see [65]), while being semantically correct, does not help the AV in planning appropriate measures. Thus,*ORIAS* would tell the user "Please be more accurate". In cases when the user would classify an object wrongly, the AV would act possibly wrong while keeping distances to other road users and doing sanity checks of the input (e.g., in a city, entering that a signpost says that 100km/h are allowed is inconclusive), thus, preventing abusive usage of *ORIAS*. This does pose some legal (e.g., driving too fast) as well as safety risk (e.g., for ignoring the right of way) to the human operator of the vehicle. Still, the overriding of user's input poses other questions [42, 43], including legal ones.

3.6 *ORIAS* Limitations

ORIAS is only usable with a sophisticated version of an AV capable of realizing that *it is not able to classify an object*. (Un-)Certainty of object classification algorithms, however, is already common [64]. Challenges of the *ORIAS* are evident in scenarios when multiple objects have to be classified. Here, the *Act. Sel.* system could provide benefits as the decision can be condensed into one appropriate action. Another problematic application is in critical situations with small time budget. While the AV decelerates to enhance the available time budget, this could be too small in high-velocity scenarios (e.g., on highways). A small time budget could also be a problem in winding roads or when objects are blocked, for example, through houses or trees. In Germany, the "[the road authorities] [...] have to take particular care to ensure that road signs and traffic installations are clearly visible and in good condition, even in the dark" [7, number IV 1 to § 45 (3)], however, it is not clearly defined what "clearly visible" means. *ORIAS* is currently not intended to input information the automation can not perceive but only for objects it can not classify.

4 EXPERIMENT

To evaluate *ORIAS*, we conducted an experiment in a driving simulator guided by the research question: What effect does the *type of interaction request* for *ORIAS* have on (1) number of takeovers, (2) input accuracy, (3) input duration, (4) cognitive load, (5) usability, (6) intuitiveness, (7) trust, (8) control, and (9) perceived safety?

Participants were recruited by e-mail and via social media. They received € 12 for participation. All subjects needed to hold a driver's license and speak German and English fluently. The final sample (5 female, 15 male) consisted of N=20 participants with an average age of M=25.20 (SD=2.46; range: 21 to 29 years).

4.1 Materials

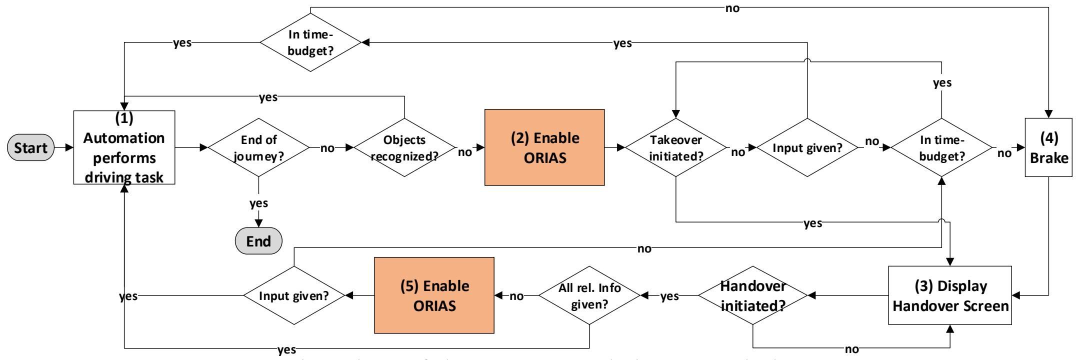

Figure 2: Flow chart of the automation behavior including *ORIAS*.

Figure 3: Driving simulator as used in the study. Situation 1 is currently displayed.

4.1.1 Driving Simulator. The study was conducted in a driving simulator (see Figure 3). The driving simulator mockup contains three driving simulation related screens (FullHD, 42 inches), a steering wheel, pedals and simulates a vehicle with an automatic gearbox. The touchscreen (1280 x 1024,17 inches) was used in portrait mode for *ORIAS*. A fifth screen (10 inches, FullHD) behind the steering wheel simulated an instrument cluster. The hygiene concept regarding COVID-19 for studies (ventilation, disinfection, wearing masks) involving human subjects of our university was applied.

The track simulated an existing small city in Germany. During the course, participants passed a school, a construction site, and an avenue. We simulated eight roughly equidistantly distributed engagement situations (see Figure 4). The track was simulated with the *SILAB* [24] simulation software.

4.1.2 Measurements. The system recorded the number of takeovers, the input, and the input duration as objective dependent variables. After each condition, participants were asked to rate the subjectively needed cognitive load with the raw NASA-TLX [29] on 20-point scales, usability using Brooke et al.'s System Usability Score (SUS) [6], intuitiveness using the INTUI [62] questionnaire, SA using the situation awareness rating technique (SART) [60], trust using the German version of the Trust in Automation scale [33] by Kraus et al. [39], perceived safety using four 7-point semantic differentials [19], and control with the subscales power and mutual dependence using the Human-Machine-Interaction-Interdependence-Questionnaire (HMIIQ) [76]. Finally, participants were asked open questions regarding feedback and improvement proposals as well as their spontaneous command for all eight situations.

4.2 Study Design

The experiment was conducted as a two conditional (*Obj. Ident.* and *Act. Sel.*) within-subject design with the same eight measurement points (unidentified signposts) in each condition. In the condition *Obj. Ident.*, the participants need to recognize the object asked by the system and select a sign within the UI (see Figure 4 "a" subfigures). In the condition *Act. Sel.*, the participants select a proper command (see Figure 4 "b" subfigures).
The participants were also able to select the requested traffic sign or command by voice instead of using the touch screen. Voice input was resolved via the experimenter as a Wizard-of-Oz. This method allows the experimenter to manipulate the system with the participant believing the system to be autonomous. The proposed cancellation options as described in Section 3.4 were not implemented as we were interested in the raw input duration and correctness. To avoid confounding factors, we also did not simulate traffic or pedestrians. As subjective dependent variables, the questionnaires described in Section 4.1.2 were used. Additionally, the system recorded the number of takeovers, the selected sign or command, and the input duration as objective dependent variables.

4.3 Procedure

After giving informed consent and a brief overview of the study, participants filled out a demographic questionnaire. Afterward, participants were introduced to the setup and were able to adjust the seat to their needs. Next, the brief overview of the study's content was repeated by the experimenter and it was highlighted that if the AV were not able to recognize an object, it would ask the participant for help. The various options were explained. Then, the participants were randomly assigned to one of the conditions as the start condition. After completing the eight situations in the starting condition, the participants filled in the questionnaires (see Section 4.1.2), and begin with the other condition. At the end of the second run, participants filled in the questionnaires again and were asked open questions regarding feedback and improvement proposals, their spontaneous command for all 8 situations, and they were asked to rate which alternative (*Obj. Ident.*, *Act. Sel.* or manually driving) they like the most. Subsequently, the test persons were informed about the study objectives and compensated with € 12. This marked the end of the experiment. Each session lasted approximately 70 min. The study was conducted in German. Quotes were translated.

Figure 4: The eight interaction scenarios with the first two options for *Obj. Ident.* (a) and *Act. Sel.* (b). Ticks show the correct option(s). In all situations, the first or second option was regarded correct, this was inverse for the other condition. For some signs, multiple options were appropriate, for example, the correct classification or choosing "irrelevant". Also, some signs do not enforce to drive slower but it is a common reaction, see the "Attention children" sign.

5 RESULTS

Dependent on the nature of the data, we employed t-tests (Cohen's d for effect size) or Wilcoxon Signed Rank tests (effect sizes calculated using the formula proposed by Rosenthal [52]). We used Version 4.0.5 of R with all packages up-to-date as of May 2021. RStudio Version 1.4.1103 was used.

5.1 Cognitive Load & Situation Awareness

The overall score of the NASA TLX was M=5.73 (SD=2.97) for the *Obj. Ident.* and M=7.45 (SD=3.13) for the *Act. Sel.* system. Significance between these systems was almost reached with a t-test ($t(19)$ = -2.06, p=0.055, r=-0.46). We found no significant differences on any of the subscales except the mental workload subscale (*Obj. Ident.*: M=7.25, SD=4.45; *Act. Sel.*: M=10.35, SD=5.00; $t(19)$ = -2.12, p=0.048, r=-0.47).For SA, no significant differences were found (*Obj. Ident.*: M=21.15, SD=4.28; *Act. Sel.*: M=21.15, SD=6.08). Additionally, no significant differences were found for the subscales Supply, Demand, and Understanding.

5.2 System Usability & Intuitiveness

System usability was rated excellent (above 80.3 [54]) for the *Obj. Ident.* (M=82.50, SD=12.93) and very good for the *Act. Sel.* system (M=72.88, SD=16.61). A t-test revealed a significant difference ($t(19)$ = 2.51, p=0.02, r=0.56).

No significant differences in any of the subscales effortlessness, gut feeling, magical experience, or verbalizability of the INTUI were found. In the single item measuring overall intuitiveness, however, a Wilcoxon Signed Rank test revealed an almost significant difference between the *Obj. Ident.* (M=5.95, SD=1.28) and the *Act. Sel.* system (M=5.25, SD=1.29; Z = -1.78, p=0.075, r=-0.28).

5.3 Trust, Perceived Safety, Power, and Mutual Dependence

A t-test revealed that trust was significantly ($t(19)$ = 2.55, p=0.02, r=0.57) higher in the *Obj. Ident.* (M=4.36, SD=0.81) than in the *Act. Sel.* system (M=3.75, SD=1.02).The *Obj. Ident.* system caused a little higher feeling of perceived safety (M=1.54, SD=1.25) compared to the *Act. Sel.* system (M=1.29, SD=1.17. No significance was reached and one participant in the *Obj. Ident.* system did not feel safe at all (value = -2.25 compared to 2.00 in the *Act. Sel.* system).

A t-test revealed that subjective power was significantly ($t(19)$ = -3.09, p=0.006, r=-0.69) higher in the *Act. Sel.* system (M=3.04, SD=0.96) than in the *Obj. Ident.* system (M=2.41, SD=0.87).For the mutual dependence subscale of the HMIIQ [76], no significant difference was detected (*Obj. Ident.*: M=3.53, SD=0.78; *Act. Sel.*: M=3.42, SD=0.80).

5.4 Input and Cancellations

We found no significant effect on the input duration (*Obj. Ident.*: M=5857 ms, SD=2063; *Act. Sel.*: M=6447 ms, SD=1807).

A Wilcoxon Signed Rank test revealed that the *Obj. Ident.* system performed significantly (Z = -3.31, p<0.001) better in the correctness of classification.In the *Obj. Ident.* system, M=6.75 (SD=1.45) signposts were classified correctly, in the *Act. Sel.* system M=4.5

(*SD*=1.57). This changed, however, if taking "irrelevant"/"ignore" into account.While, at least in the *Obj. Ident.* system, a correct option was always selectable, "irrelevant", for example, in the second situation was also a valid input as the sign is not intended for cars. A Wilcoxon Signed Rank test still revealed a significant difference (Z = -2.02, p=0.04, r=-0.32), the difference, however, became smaller (*Obj. Ident.*: M=7.30, SD=0.66; *Act. Sel.*: M=6.80, SD=0.83). The usage of these buttons did not significantly differ between the systems.

33 / 320 (10.31%) of the interactions with *ORIAS* were via speech input. No significant differences in the usage of voice input were found between the systems. Only three participants took over when *ORIAS* was active and two of them only aborted once, the other twice (4 / 320 = 1.25%). One takeover occurred during the first encounter with the *Act. Sel.* system and was explained by the participant with the unfamiliarity.

We also evaluated differences for input duration and correctness for each situation. (for situations, see Figure 4). In the situation 1 (Z = -3.60, p<0.001, r=-0.57), situation 2 (Z = -2.38, p=0.02, r=-0.38), situation 3 (Z = -4.35, p<0.001, r=-0.69), and situation 6 (Z = -2.52, p=0.01, r=-0.40) a significant difference in input duration was found. Input duration was only lower for *Act. Sel.* in situation 2. For the analysis of the correctness of the input, we used the values including "irrelevant"/"ignore" as correct input. Comparisons were done using the Chi Square test as categorical data (correct vs. incorrect) was used. We found no significant differences in correctness scores for any of the eight situations.

5.5 Preference, Open Feedback, and Command Suggestions

Participants ranked the two systems and driving yourself after both conditions. The *Obj. Ident.* system received rankings indicating the highest preference, i.e., the lowest mean (M=1.70, SD=0.73). Both, the *Act. Sel.* system (M=2.25, SD=0.91) and driving yourself (M=2.05, SD=0.76) received almost the same rankings. Therefore, no significant differences between the ratings were found by a Friedman's ANOVA. Participants could provide a rationale for their ratings. Opinions were rather strong and diverse and no clear consensus was found.

Several participants highlighted the ease of the *Obj. Ident.* ([P16]: "A great thing here was that you only had to support the car during recognition and not additionally during the decision making [...] This made driving much more pleasant"). The *Act. Sel.* and the deceleration of the vehicle seemed to induce more stress ([P11]: "I felt like the system decreased speed until the decision. Pressure was built up to make a decision to continue the journey normally"). Two participants argued to include the *Live-Preview* into the instrument cluster and to use zoom functionality.

After the conditions, we asked participants to provide a command for each of the eight situations (see Table 1). Of the 160 provided commands, 51 were a description of the signpost. 4 of them were wrong. The other commands were distributed between "Ignore" (44 times) and speed adjustments (31). Especially interesting is the "Ignore" command for the "Attention children" sign, as the participant explicitly mentioned that ignore is only valid "as no children are visible", showing that the participant took the surroundings into account. In some cases participants actually gave two commands, therefore, some columns sum up to have more than 20 commands.

6 DISCUSSION

Two implementations of *ORIAS* were described and evaluated: *Obj. Ident.* and *Act. Sel.*. The study revealed high to excellent usability, high input correctness, higher trust in the *Obj. Ident.* system, and revealed how participants would spontaneously command such a system. Additionally, the automation behavior was described. In the following, we want to discuss the advantages and disadvantages of the concept, the implementations, and its applications.

6.1 Object Identification vs. Action Determination

Participants reported significantly higher ratings in the perceived power for the *Act. Sel.* system (M=3.04, SD=0.96). This confirms our expectations as the person clearly defines the next action of the AV compared to only classifying data. Trust in the *Obj. Ident.* system (M=4.36, SD=0.81) was rated significantly higher (*Act. Sel.*: M=3.75, SD=1.02). System transparency was shown to increase trust in AVs [8, 14, 38]. The *Obj. Ident.* system is more transparent as the internal classification results are clearly shown as input options one and two (see Figure 4 "a"). In the *Act. Sel.* system, the more abstract resulting action is displayed. The process resulting in these options is, however, unclear as these could also originate from various other signposts (e.g., "Drive 20" can originate from an attention sign or a sign enforcing this velocity), therefore, transparency and trust are lower in the *Act. Sel.* system. We also believe this to be one reason for a significantly higher mental workload in the *Act. Sel.* system.An additional reason can be be derived by the concept of SA. As stated by Endsley [16], SA consists of three levels: Perception (Level 1), Comprehension (Level 2), and Projection (Level 3). Level 3 allows for "timely and effective decision making" [16]. Level 1 is achieved much quicker, and with less cognitive load. Therefore, *Obj. Ident.* should result in lower cognitive load and faster input duration. Our experiment validated this (*Obj. Ident.*: M=7.25, SD=4.45; *Act. Sel.*: M=10.35, SD=5.00).However, *Obj. Ident.* can be difficult if numerous objects that only differ in details are presented as alternatives. Objects (e.g., signposts) can vary in detail, for example, in number or position of arrows. Therefore, there is a risk of confusion for the human user. While a human user could quickly identify, for example, that this object can be ignored, identifying the correct version of such an object could be cumbersome.Here *Act. Sel.* seems to be more appropriate. Despite feeling more in power in the *Act. Sel.* system and trusting the *Obj. Ident.* system more, perceived safety was almost equal. The dependency between these variables are unclear. Both systems were rated highly usable, the *Obj. Ident.* system even significantly more usable. This is attributed to the higher system transparency and the lower mental workload.

Walch et al. summarized four requirements for cooperation between an AV and a human: mutual predictability, directability, shared situation representation, and calibrated trust [69]. In the two implementations, shared situation representation is not equal: for the *Obj. Ident.*, the AV and the human user both know the position and the actual signpost. In the *Act. Sel.* system, the AV does not know about all relevant objects. For example, when the user orders

Command class	Children	Bicycle	Right of way	30 km/h	Tank rules	Cab spot	Trucks prohibited	Construction site
Ignore	1 ([P3]: "as no children are visible")	9 (one: "continue ride")			14	10	10	
Speed adjustment	8	0	1	14				8 (incl. "attention" and "caution")
Give right of way			20					
Identification	12	11		5	4	10	9	12
Misjudgment				1 ([P2]: "oncoming traffic")	2 ([P2]: "watch [...] oncoming traffic", [P12]: no answer)		1 ([P9]: "do it yourself")	

Table 1: Proposed commands for the eight situations including 3 wrong commands and 51 *Obj. Ident.* proposals.

the AV to slow down to 20 km/h, this could be because a signpost enforces this speed limit or due to a children warning sign. While this decreases shared situation representation, the relevant information (driving speed) is still distributed, should not negatively impact driving performance, and could make use of the specific strengths of the actors.

In the presented study, the focus was on a variety of driving-task relevant signpost recognition. While the *Obj. Ident.* system performed better in terms of input duration in most situations, participants were able to provide input more quickly in situation 2 with the *Act. Sel.* system (see Figure 4). No significant differences in correctness were found for any of the situations. Therefore, we argue that there will be situations in which the *Act. Sel.* system is more appropriate. We believe the better performance of the *Act. Sel.* system in situation 2 to be dependent on the signpost. As it is yellow, it is quickly clear that it is not relevant for one's own driving. However, determining the exact version of it is difficult as there are several similar-looking signposts. While *Obj. Ident.* with a single signpost was under investigation, *ORIAS* in the variant *Act. Sel.* could also be employed for more complex tasks such as pedestrian intention recognition (e.g., [8, 25]). The variant *Obj. Ident.* seems unfeasible for such scenarios as the input for this is difficult: the user would have to provide a direction of movement or whether the person will stop. In scenarios in which context information is relevant, even a *Live-Preview* could fail in providing sufficient information. For example, when a traffic sign is dependent on another sign defining prerequisites such as "only relevant when raining" or Variable Message Signs [15], a stationary sign might be irrelevant. In such cases, *Obj. Ident.* could be beneficial as the AV will have recognized the other traffic sign. *Act. Sel.* might fail or would have to provide the relevant prior information. Therefore, we conclude that the proposed implementations are highly situation-dependent. Additionally, the preference of the study participants was not clear. Looking into technical advantages, only the *Obj. Ident.* has the advantage that human users would aid future ML systems by providing classifications (i.e., labels) for objects.

6.2 Appropriate Use Cases

Numerous fields of application seem feasible. Instead of simple signpost recognition, which is likely to become better over time, other objects can be also classified by the human user. This includes a broad range of objects such as variable traffic signs, handwritten signs, but also advertisement, or traffic-relevant shaped objects. There are no limitations regarding this object classification, therefore, *ORIAS* enables the collection and labeling of massive data for ML. Another use case without a link to signposts and *Obj. Ident.* was already shown by Walch et al. [67, 70]. A broken down car is standing at the side of the road. The vehicle or the driver has to assess whether it is possible to drive past or stop, for example, because there is a traffic jam or the vehicle is standing there to form a rescue alley. *ORIAS* in the *Act. Sel.* variant could be used to provide relevant input. Additionally, more complex use cases in which the surroundings have to be taken into account can be addressed. This can include legal, weather, or other aspects. One example are "residents only" signs. Here, the human user can take responsibility and allow the vehicle to enter this street. In some cases, the signposts' relevance is also dependent on the circumstances (e.g., "slow down in case of snow"). While the vehicle will have to be able to detect snow (accuracy today around 90% [36]) or fog (also around 90% [37]), a threshold for when applying this limited velocity has to be defined. As perceived safety is an essential factor for the acceptance of AVs and people are likely to perceive the objectively same scenario differently, being able to define a personal threshold will likely function as a positive factor regarding acceptance of AVs. We also argue that because of this, it should always be possible to enter the desired velocity without having to take over control. This would then enable a personalization of driving styles for the AV which, we believe, would increase acceptance.

6.3 Takeover vs. *ORIAS*

Taking over an AV in poses numerous challenges such as post-automation effects [5, 17, 18, 45, 51]. Walch et al. [67, 70], therefore, investigated cooperation between human users and the automation. The benefit is that only a small part of the actual driving task has to be performed by the human user potentially limiting the negative post-automation effects. The same holds for our implementation: instead of having to take over full control (including steering, braking or accelerating, setting turning lights, look for other vehicles, ...), the human user can focus on the relatively simple task of identifying an object or determining an appropriate action which can be performed by the automation safely. Therefore, a takeover can be prevented and less negative effects of post-automation seem likely. Also, *ORIAS* can be used for the handover process (see Figure 2). In case of unclear or missing information, the AV can ask the human user. This can, for example, include the definition of an occluded signpost the vehicle drove past earlier. While the AV does not need this information during manual mode, it is necessary for activating the automation. Providing this retrospective information again can help to push the current boundaries of AVs.

6.4 Design Implications

One participant highlighted that showing the *Live-Preview* in the instrument cluster or a head-up display during *ORIAS* would improve usability as glancing would be minimized. This could even be enhanced by providing zoom functionality. Going even further in the future, Augmented Reality systems have already shown to improve situation awareness and trust in automated systems [8, 9, 57]. With windshield displays [28], *ORIAS* could be even more usable. Still, the *Obj. Ident.* system already received excellent SUS ratings of *M*=82.50. Thus, we argue that our current implementation is ready to use. No participant mentioned concerns about the automatic microphone activation, still, privacy concerns remain. We propose to use an opt-in policy if such a system were to be implemented.

7 LIMITATIONS

Participants were relatively young (*M*=25.20 years old). As driving experience is expected to have a significant impact on the approval and adoption of *ORIAS*, future studies should account for the differences between age and especially driving experience groups. Based on the experiment setup, learning effects could not be avoided as the same route with the same signposts was used in both conditions. We targeted this by alternating the correct answer differently per condition: if the first answer was correct in condition 1, then the second answer was correct in condition 2. Additionally, we did not simulate other road users such as vehicles, pedestrians, or cyclists to avoid confounding factors. As one participant stated, having a vehicle approaching you from the rear when one is trying to determine the correct sign will lead to higher stress. Therefore, *ORIAS* has to be evaluated under more realistic settings. Additionally, the effect of other irrelevant objects such as advertisement has to be investigated. This may also include varying the time of day or inducing cognitive load, for example, via a secondary task. We are also aware that this study presents only cases in which *ORIAS* is able to present the correct information or action. It is important to study the effects of erroneous options, however, we focused on general usability in this first study.

8 CONCLUSION & FUTURE WORK

Overall, this work provides detailed considerations of *ORIAS* highlighting the usefulness but also limitations [40]. *ORIAS* pushes the boundaries of current automation technology by involving the human user in the *Obj. Ident.* and *Act. Sel.* process. Additionally, the *Obj. Ident.* results can be used for training of ML algorithms. We implemented the two interaction possibilities *Obj. Ident.* and *Act. Sel.* and conducted an experiment assessing usability, cognitive load, intuitiveness, situation awareness, perceived safety, human-machine-interaction-interdependence, input duration, and correctness.Participants (*N*=20) rated the implementations as highly usable, intuitive, and were able to correctly assess most of the signposts. In line with previous work [72], *ORIAS* shows that cooperation between an AV and the human user is feasible and often preferred to taking over in case of reaching automation limits.

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