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Development of a Cooperative On-Demand Intersection Assistant

-Concept Evaluation, Personalization and Prototype Implementation-

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ABSTRACT: In this paper, we present our recently introduced "assistance on demand (AOD)" concept, which allows the driver to request assistance via speech whenever he or she deems it appropriate. The target scenario we currently investigate is turning left from a subordinate road in dense urban traffic. We first compare our system in a driving simulator study to driving without assistance or with visual assistance. The results show that drivers clearly prefer our speech-based AOD approach. Next, we investigate the differences between drivers' left-turn behaviour in a driving simulator. The results of this investigation show that there are large inter-individual differences. Based on these results, we present another driving simulator study, where participants can compare manual driving to driving with a default and a personalized AOD system. The results of this second study show that the personalization very notably improves the acceptance of the system. Given the choice between driving with any of the AOD variants and manual driving, 87.5% of the participants preferred driving with the AOD. Finally, we present an evaluation of the AOD system in a prototype vehicle in real urban traffic.

KEY WORDS: **electronics and control,** advanced driver assistance system (ADAS), speech-based system, on-demand, user study, critical gap, personalization [E1]

1. Introduction

In recent years, many new advanced driver assistance systems (ADAS) have been presented. These systems aim to support the driver in the driving task and to reduce her cognitive load. However, as these systems usually do not work flawlessly, they can also lead to distractions and may even annoy the driver with undesired and unnecessary warnings. In an attempt to overcome these limitations, we recently developed the concept of "assistance on demand (AOD)" [(1), (2)]. This describes an ADAS which supports a driver only if she asks for assistance. The two key elements of this concept are, on one hand, the control of the ADAS via speech, and on the other hand, the personalization of the system to the individual driver. The speech-based control allows the driver to flexibly formulate her requests for assistance while the situation develops. The personalization will help to adapt the interaction of the system to the driver's individual preferences and skills. In the context of ADAS, personalization has not yet been investigated thoroughly but the number of studies has been increasing quickly in recent years [(3)].

In this paper we will give an overview of the AOD concept and its implementations. We will present the results of two user studies, in which we investigated the AOD concept and also show results of an evaluation of the AOD concept in a prototype vehicle in urban traffic.

2. The Assistance On Demand Concept

Driving in urban traffic can be highly demanding. In particular, turning left at an unsignalized intersection from a subordinate road into a superordinate road with high traffic density is one of the most challenging tasks for drivers (e.g. (4), (5)). Therefore significant effort is invested in the research of assistance systems which support the driver in such left-turn scenarios with crossing traffic[(6)] and also for the less challenging task of only oncoming traffic [(7), (8)]. To further improve these systems, in particular the participants' manoeuver and intention prediction is investigated [(9), (10), (11)]. These systems provide collision avoidance functionality, which prevents safety-critical situations. Yet, in many cases the driver might also benefit from support in the monitoring and decision making process before entering an intersection. In (12) information on safe gaps was presented via a HUD in a driving simulator. However, the system rather led to a focus of the driver's attention to the centre instead of to the left and right and to a more risky driving behaviour.

From observing drivers' natural behaviour we derived an alternative approach for assistance. When driving with a front-seat passenger, they often use the opportunity to ask her for

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support while managing a difficult intersection. In particular, when turning left, they transfer the task of monitoring the traffic on the right-hand side to the passenger and request feedback on suitable time gaps to enter the intersection[1]. These considerations led to the development of our system as an assistant for urban intersections, that acts like a co-pilot, with which the driver can interact via speech (1), (2). The system helps to find suitable time gaps to turn left comfortably and safely. The system is not always active, but the driver activates the system in situations where she wants to have support. Hence it is based on our "assistance on demand" (AOD) concept. With this on-demand concept, we aim to increase the driver acceptance and reduce any possible annoyance due to the system. In (13) a very similar approach for the use case "turning left at a rural intersection with oncoming traffic" was applied with positive results for the system. In contrast to his approach, the presented AOD approach strongly pronounces the collaborative sharing of tasks between the driver and the system in a more demanding use case. The system is intended as a comfort system, which should support the driver while waiting at an intersection and monitoring the traffic. It takes over only the monitoring of one direction, namely the traffic from the right-hand side. Furthermore, it assists in manoeuvre decisions by announcing suitable gaps in traffic for turning or crossing the intersection. The driver is still responsible for the final decision and manoeuvre execution. We have chosen speech as the modality for interaction between the driver and the system as speech is thought to be the most flexible, natural, and interactive way of communication between the two agents.

2.1. Intersection Assistant Scenario

In a first step we have implemented our AOD concept in a speech-based intersection assistant. After the driver has activated the system via a speech command, it monitors the traffic on the right-hand side and informs the driver about suitable gaps to enter the intersection, just like a co-driver would do. A typical interaction with the system might look like this:

- Driver: "Please watch right!"
- System: "Okay, I'm watching."
- …
- System: "Vehicle from the right."
- …
- System: "Gap after next vehicle."

The system does not provide direct action recommendations and we expect that the driver uses the system information only as support and does not fully rely on it for making the turn.

3. Initial User Acceptance

In a first user study, we have evaluated the user acceptance of the AOD concept in comparison to driving without any assistance and to a system that gives visual information in a virtual head-up display (HUD) (1), (2)

[1] Throughout the paper we only consider right-hand traffic. Yet, the results can easily be transferred to turning right in left-hand traffic.

3.1. Methodology

3.1.1. Participants

N=24 drivers took part in the study; half of them were female. They all had participated at least in a 2.5 h training session in the simulator prior to this particular experiment. Their mean age was 49.1 years (SD = 19.3 years), with ages ranging from 25 to 77 years. Their mean mileage driven in the last 12 months was 15408 km (SD= 9851 km).

3.1.2. Study Environment

The study took place in the static driving simulator of the Würzburg Institute for Traffic Sciences (WIVW; see Fig. 1). The simulator is based on a full-car mock-up of an Opel Insignia, for which outside rear-view mirrors are replaced with LCD displays. The scenery is projected onto five screens. The steering wheel has an integrated steering force simulator. The mock-up interior includes two integrated LCD-displays, one replacing the speedometer, while the other, in the centre console, can display optional additional information.



Figure 1: Static driving simulator at the Würzburg Institute for Traffic Sciences (WIVW), used for the user study.

3.1.3. System Specification

The functionality of the AOD system was restricted to the monitoring of traffic arriving from the right. Therefore, all system outputs only refer to traffic from the right-hand side, so that traffic from the left still has to be monitored by the drivers themselves. While the driver is approaching the intersection, the driver's request (e.g. "Please watch right") activates the system. In the simulator study, the final activation of the system was triggered by a button pressed by the experimenter (this was the only manual action of the experimenter). The system confirms the successful activation by answering "Okay - I will watch." When the driver reaches the intersection, the AOD system starts giving recommendations. If the time distance of the closest vehicle from the right to the centre of the intersection is above 10s, the system will interpret this as no vehicle being present and it triggers the output "no vehicle from the right." It was deliberately decided not to announce "right is free," as this could be interpreted as a permission to drive without further monitoring the actual traffic. This could lead to hazardous situations. If a vehicle is approaching from the right and the time distance of this vehicle to

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the intersection falls below the assumed suitable time distance for entering the intersection the linked speech output is “vehicle from the right.” If a vehicle from the right is expected to reach the intersection within 2.5 s and if the time gap to the next oncoming vehicle is larger than or equal to the suitable time gap, the system will inform the driver of this suitable gap. The system output is given before the first vehicle has passed the intersection, in order to create a certain preparation time. Hence, the speech output is “gap after approaching vehicle.” If the time gap has elapsed and the next vehicle is approaching under the same conditions, the output is replaced by: “Gap after next vehicle.” In this user study we assumed a time gap of 6.5 s as suitable for entering the intersection.

To evaluate the AOD system and in lack of a suitable intersection assistant system, we also created a reference system. To contrast it with the AOD system, the reference system is always active and uses the visual modality to give feedback on oncoming traffic at the intersection. We implemented it via coloured arrows displayed in a virtual head-up display HUD (compare Fig. 2).



Figure 2: Simulated HUD display in the driving simulator with the coloured arrows visualizing traffic information from the left and right direction at an urban intersection

This system is able to monitor traffic from both directions (i.e. left and right). Comparable system states, comparable conditions and identical parameter specifications as in the AOD system were used with the exception that traffic from the left was also included. The speech output “vehicle from right” in the AOD system was replaced by a red arrow either from the right or the left or both directions, depending on the approaching vehicles. The system state connected with the speech output “gap after approaching vehicle” was replaced by a yellow arrow either from the right or left or both. The decision for entering the intersection has to be made by the driver by combining the information from both directions (e.g. a yellow and a red arrow means it is not possible to enter the intersection). It was deliberately decided not to display a green arrow in the system state when no vehicles are in the sensor range of the system (in contrast to the system described in (13)), for the same reasons that led to the decision against announcing “right is free.” Instead, the red or yellow arrow simply disappears, if the respective condition is valid.

3.1.4. Scenarios

Each experimental drive consisted of a set of several scenarios, all containing an urban intersection. As the basic layout for this scenario, a four-way intersection was chosen with the ego vehicle approaching from the subordinate road. For one drive, 13 different scenarios were put together into one driving course, meaning that the driver drove from one intersection to the next by always turning left. Yield signs were placed at the roadside. A stop line nudged all drivers to stop at a comparable distance from the entrance of the intersection. The surroundings at the intersection were created in such a way that the drivers could not see the arriving vehicles on the superordinate road when they approached the intersection. Having stopped at the intersection, the line-of-sight was about 8 s to the right and 10 s to the left (taking 50 km h^{-1} as a basis). The instruction asked the driver to turn left at the intersection. The participants were asked to drive under three conditions: a “manual drive” where no system was activated, an AOD system drive where the communication with the driver was realized via speech and a head-up display (HUD) system drive where arrows were presented to the driver.

3.1.5. Experimental Plan

All 24 participants had an introductory drive to familiarize themselves with the driving simulation and the simulation environment. Then, the manual drive without any assistance was performed. Before conducting the drives with the activated AOD system, the participants had an introduction into the AOD functionality following a practice drive with the activated AOD system. After this, they performed the AOD drive. We proceeded in the same way for the HUD drive. The sequence of the AOD system drive and the HUD system drive was permuted and counterbalanced and drivers were assigned at random to one of the two sequence orders. The participants filled different questionnaires after the individual drives and once they had finished all drives.

3.1.6 Measures

Here we will only report the results of the questionnaire administered after all three drives, where participants were asked to rank the different drives.

3.2. Results

Figure 3 displays which of these three drives the drivers preferred. The results show that most drivers prefer our speech-based AOD system (14 out of 24). Only 3 drivers favoured the HUD system. Our speech-based system allowed the drivers to focus visually on that part of the environment which they currently considered the most relevant, while still receiving input from the system via the unoccupied acoustic channel. The HUD system, on the other hand, required them to divert their gaze to see the system response. We assume that this difference is at the heart of the clear preference for the AOD system. The remaining 7 drivers preferred to drive without any assistance.

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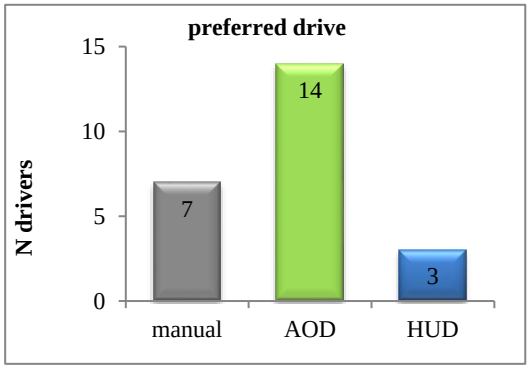

Figure 3: Preferred drive of the 24 participants of the first user study. Without assistance (manual), with speech-based ”assistance on demand” (AOD) or visual assistance via a head-up display (HUD).

This high acceptance of the AOD system by the drivers might be due to different unique aspects of the system. In a questionnaire they stated that they considered the interaction as natural and the use of speech as meaningful and specific enough [1], [2]. In particular, they highly appreciated the on-demand concept. Furthermore, they considered the system the more useful the more difficult the scenario was.

4. Personalized Left-turn Prediction

One result of the first user study described above was that drivers mentioned that the gaps recommended by the system did not suit their driving behaviour: for some drivers the gaps were too short and for others they were too long. Based on this outcome, we have performed a new user study, in which we investigated the variation between different drivers with respect to what constitutes a suitable gap in traffic to make the turn.

4.1. Critical Gap Estimation

The so-called critical gap is often used to calculate the capacity and delay of a minor road, especially for unsignalized T-intersections. It signifies how large a gap minimally has to be for the driver to accept it and take the turn, thus vacating the minor road. Previously, this value was primarily used to measure the capacity of a specific intersection and hence was calculated from a large pool of drivers all passing this intersection [14]. In our case, however, we use it as a criterion to predict the behaviour of one individual driver. To facilitate this, for the moment, we assume that the layout of the intersections and the traffic density at the intersections are all identical.

A method often used to estimate critical gaps was proposed by Troutbeck [15]. Troutbeck assumes that a driver's critical gap lies somewhere between the largest rejected gap and the gap accepted by the driver. To model the behaviour of the drivers, he uses a log-normal distribution for the critical gaps. The transformation of the observed gaps in the logarithmic domain allows using the normal distribution for the core computations. In (16), Brilon recently motivated the approach of Troutbeck by analogies to a classical problem in survival theory. More concretely, he argues that it corresponds to the failure time estimation of interval censored data [16], [17]. The critical gap, i. e. the failure event, cannot be observed directly. It can only be observed that it lies in the semi-closed interval $(r_i,\ a_i]$ when r_i indicates the logarithm of the largest gap rejected by the i-th driver at the intersection and a_i the logarithm of the gap accepted by this driver. The hidden parameters μ and σ of the distribution of the critical gap μ_c can then be found by maximizing the log-likelihood:

$$\sum_{i=1}^{N} \ln p(r_i < \mu \leq a_i | \mu, \sigma) ,$$

for all observations N. Following the argumentation in (16) we can rewrite this as:

$$\sum_{i=1}^{N} \ln[F_c(a_i) - F_c(r_i)] ,$$

where $F_c(\,)$ denotes the cumulative distribution function of the normal distribution with parameters μ and σ. Hence the parameters can be determined via:

$$(\mu_c, \sigma_c) = \arg\max_{\mu,\sigma} \sum_{i=1}^{N} \ln[F_c(a_i) - F_c(r_i)] .$$

As a final step, we go back from the logarithm domain and the critical gap t_c and variance s^2 in linear scale are computed according to

$$t_c = e^{\mu_c + 0.5\sigma_c^2}, \quad s^2 = t_c^2\left(e^{\sigma_c^2} - 1\right).$$

In contrast to [8], in our case, the index i in the equations above is not used to indicate a tuple $(r_i,\ a_i)$ of the i-th driver but of the i-th intersection.

The failure time estimation of interval censored data requires that $r_i < a_i$. Consequently, the method of Troutbeck assumes a consistent and homogeneous driver. This means that the largest rejected gap r_i recorded at intersection pass i must always be smaller than the corresponding accepted gap a_i. This is, however, often not fulfilled. To overcome this limitation, we have recently introduced a novel maximum likelihood approach to critical gap estimation [18]. By extending it to a maximum-a-posteriori approach via the introduction of a prior on the expected critical gap, we were also able to significantly increase the estimation accuracy when only few observations from a given driver are available [19].

4.2. Methodology of the Initial Personalization Study

4.2.1. Participants

N=9 participants (two female) with a mean age of 32 years and a standard deviation of 4 years took part in this study. Their driving experience ranged from 3 to 18 years, while their travelled distance per year lay between 7.000 km and 40.000 km.

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4.2.2. Study Environment

As simulation software, we have used IPG CarMaker 4.5, which is a simulation environment mainly intended for the physical simulation of cars. We used three displays to render the traffic environment. The drivers interacted with the simulation via a Logitech G27 steering wheel and corresponding pedals, but there was no force-feedback support for this software in conjunction with the Linux operating system.

4.2.3. System Specification

With this initial personalization study, we wanted to investigate the participants' normal left-turn behaviour. Hence they were driving without any system support.

4.2.4. Scenario

To test the hypothesis that there are differences in the critical gaps different drivers accept, we have built an inner-city intersection scenario in our driving simulator. We have set up a road layout with four consecutive T-intersections, which allows the participants to drive through a potentially infinite number of successive intersections. The buildings have been placed in such a way that the participants are forced to stop at the intersection, in order to see if there are cars approaching from the left or right. The layout of all intersections was identical, as the goal was to observe the behaviour of an individual driver in many identical situations. The only difference between the intersections is the arrangement of the buildings. Nevertheless, the visibility of the driver onto the crossing traffic is identical for the different intersections.

4.2.5. Experimental Plan

After some initial simulator training, each participant drove 3 scenarios with 16 intersections each. The distribution of the presented gaps was different for each intersection and simulated medium to high traffic density from the left and right. The gap sizes presented to the participants were between two and eight seconds. All traffic cars were driving at 50 km h^{-1}. Hence the scenario simulated typical urban traffic. Each participant drove the same scenario, i.e. the traffic was controlled in a fully deterministic way. Variations occurred as participants approached the intersections at different speeds, stopped at different points in front of the intersections and decided to take different gaps. After each of the 3 scenarios, there was a short break. With this setting we have obtained up to 48 (largest rejected gap, accepted gap) tuples per participant from the recordings. To ensure that no habituation effects to the observed gap sizes could occur, different gap sizes were used in the three scenarios. After the experiment, the critical gap μ_c and the corresponding variance σ_c were calculated. Due to violations of the assumption in Troutbeck's algorithm of a consistently behaving driver, it was not possible to use the gap recordings from all 48 intersections of each participant. The average number of used intersections for a participant was 44.9 with a standard deviation of 2.9.

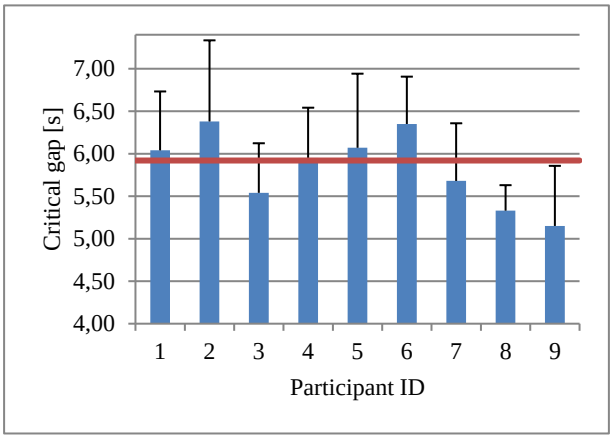

Figure 4: Critical gap for each participant (blue bars), standard deviation of critical gap (black lines) and critical gap using data of all participants for estimation (red line).

4.3. Results

In this section, we analyse the inter-individual differences of the estimated critical gap. Figure 3 shows the estimated critical gap t_c and the corresponding standard deviation s for every participant. The red line shows the estimated critical gap when jointly using the recordings of all participants. One can see that there are clear differences between the critical gaps of the nine participants. A one-way ANOVA of the results of both methods has also confirmed that there is a significant inter-individual difference in the critical gaps of the different participants. Note that the explanatory power of the ANOVA result is reduced due to the fact that we are forced to use the estimated means and corresponding variances of the critical gaps, since we don't possess any observations of the latter.

5. User Acceptance of Personalized AOD

We saw in the previous section that different drivers chose different gaps in traffic. This motivated us to carry out a third study, investigating whether a personalization of the gap suggestions of the AOD system to the individual driver will further increase its acceptance [20], [21].

5.1. Methodology

This personalization study was similar to the first AOD study in Section 3 in many aspects. In particular, it was also performed in the same static driving simulator using a very similar scenario. In the following we will only highlight the differences.

5.1.1. Participants

A total of N=25 participants took part in this study, 12 of them were male. The mean age was 42 years (SD=13.1 years) with driver ages ranging from 22 to 64 years. The mean number of years of driving experience was 22.8 with a standard deviation of 12.0. The mean number of kilometres driven in the previous year was 18660 km (SD=12375 km).

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5.1.2. Study Environment

This study also took place in the static driving simulator of the Würzburg Institute for Traffic Sciences described in Section 3.1.2.

5.1.3. System Specification

The AOD system was implemented as described in Section 3.1.3. The only difference was that the gaps suggested to the drivers were different. Details on how these gaps were modified will be given below. Furthermore, there was no visual system variant in this study.

5.1.4. Scenario

The layout of the scenarios was identical to the one described in Section 3.1.4. The participants were asked to drive under three conditions: a "manual drive" where the AOD system was not activated, a "default AOD" system drive and the "personalized AOD" drive. In the default AOD system drive, a fixed critical gap of 5.5 s was set in the system. For the personalized AOD system drive, an individual critical gap was calculated from the recorded data of the manual drive, according to the algorithm detailed in Section 4.1, and then used in the system.

5.1.5. Experimental Plan

The experimental plan was identical to the one described in Section 3.1.5 in large parts. The main differences were that now, in addition to the manual drive, the participants performed a "default AOD" and a "personalized AOD" system drive. The sequence of the default AOD system drive and personalized AOD system drive was also permuted and counterbalanced and drivers were assigned at random to one of the two sequence orders. The participants were not informed on the differences between them. The participants again filled in different questionnaires, once after each individual drive, and once more after they had finished all drives.

5.1.6 Measures

For this experiment, we again only report the results of the final questionnaire, in which participants ranked the different drives.

5.2. Results

Figure 3 displays which of these three drives the drivers preferred. Most drivers preferred the personalized AOD system. Some preferred the default AOD system and only a few preferred driving without AOD support. More precisely, 87.5% preferred driving with any of the two AOD variants compared to 12.5% who preferred driving manually. This clear preference for the personalized AOD system remained, when we split the drivers into two groups according to their individual critical gap. Both groups, with an individual critical gap smaller or larger than the 5.5 s default, clearly preferred the personalized system variant. From this we conclude that the personalization of the gap

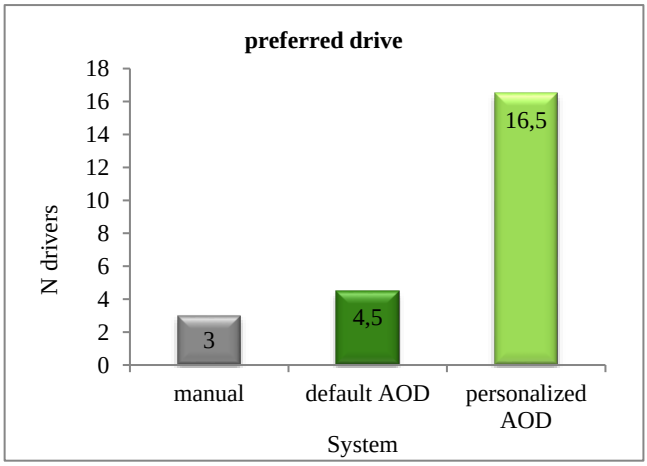

Figure 5: Preferred drive of the 25 participants of the user study. Without assistance (manual), with speech-based Assistance On Demand using a default gap (default AOD) or a personalized, driver-dependent gap (personalized AOD). The reason for the occurrence of the non-integer values is that some participants rated both the personalized AOD and the default AOD as equally good. These votes were split between the two alternatives.

suggestions to the individual driver very notably improves the acceptance of the AOD system.

Out of the 25 drivers, 16 considered the gap recommendations of the personalized system as more appropriate for them [20), 21)]. Only 3 preferred the default gaps and 6 considered both as comparable. They also felt that the personalized system was more reliable and facilitated the decision of entering the intersection further.

6. AOD Prototype System

After the very positive results from the user studies, we implemented an AOD prototype system and evaluated it in real urban traffic [22), 23)].

6.1. Prototype system layout

The prototype system consists of the following main building blocks: sensor data acquisition, scene understanding, dialog manager and system output (compare Fig. 6). The sensor data acquisition block receives the data from the vehicle's IBEO laser scanners, CAN bus and microphone array. The laser data is pre-processed, i.e. it yields objects with their position and speed. The scene understanding component processes and analyses this data for the dialog manager, the component controlling the behaviour of the system. In particular it extends the IBEO tracking such that it can also cope with occlusions of vehicles arriving from the right by vehicles from the left [22)]. Based on this data it then calculates the lengths of the gaps between the vehicles arriving from the right. Furthermore, based on the CAN data it determines if the ego vehicle is arriving at the intersection, standing at the intersection or leaving the intersection [22)]. It also analyses the microphone input to infer the driver's commands. The dialog manager then uses this information to decide on the appropriate

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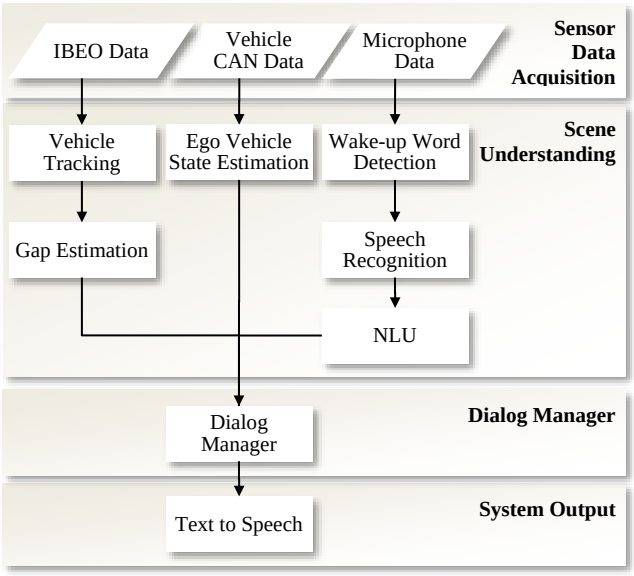

Figure 6: AOD system layout.

Table 1: Examples of system announcements.

Vehicle in the distance
Vehicle from the right
Gap after the next vehicle
No vehicle after the next two vehicles

speech feedback which is then generated by the Text to Speech module (compare Table 1 for some exemplary system announcements). After the driver activates the system via a wake-up word and the corresponding speech command, the system gives feedback on the traffic from the right while the ego vehicle is standing at the intersection and until the driver starts leaving the intersection [15].

6.2. Prototype System Hardware

To implement the AOD prototype we used a modified 2012 model year Honda CR-V (compare Fig. 7). In addition to the standard equipment, it features 360° sensing via an Ibeo Automotive Systems laser sensor and cameras. Furthermore, the trunk hosts computing hardware to store and process the sensor data. We acquire the speech commands from the driver via an XCore 7-channel microphone array and use the standard audio equipment of the vehicle for speech feedback. Wake-up word detection, speech recognition and synthesis are accomplished via



Figure 7: The prototype vehicle.

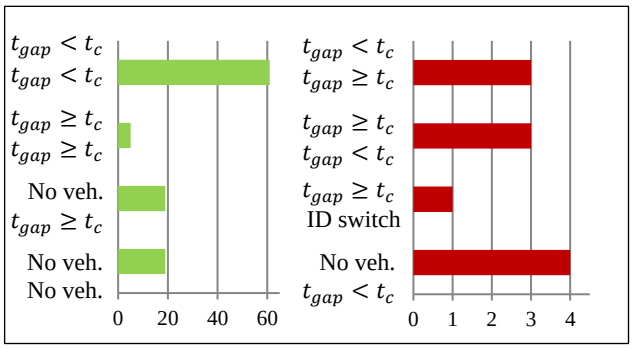

Figure 8: Comparison of the correct (left) and incorrect (right) announcements of the system (in absolute numbers). t_{gap} is the gap measured by the system and t_c the critical gap needed by the driver to make the turn. In each pairs the top condition refers to the condition which was present when the system made the announcement and the bottom one when the corresponding vehicle passed in front of the ego vehicle. "No veh." indicates that the system did announce no vehicle, "ID switch" indicates that the object ID had changed between the announcement and the passing of the vehicle, i.e. a new vehicle appeared or one was lost.

the VoCon™ and Vocalizer™ software respectively, both from Nuance.

6.3. Evaluation in Urban Traffic

Using our prototype vehicle, we have made recordings at an unsignalized urban intersection in the Frankfurt Rhine-Main area [23]. These recordings contain 115 vehicles arriving from the right side, which we could use to evaluate the performance of our AOD prototype. We assume traffic with a speed of 50 km h^{-1}, the maximum allowed speed for many German urban streets. Based on a critical gap $t_c = 6$ s and another 2.5 s preparation time (in which the driver is informed and is able to process the information), the system has to make its decision 8.5s before the relevant vehicle arrives at the intersection. This means that the system has to detect vehicles at least at a distance of 125 m to be able to decide if a gap is suitable for the driver to make the turn. For the evaluation of the system, we consider all announcements of the system as equivalent if they lead to the identical behaviour of the driver. E.g. if the system announces "no vehicle after the next vehicle" the driver will assume that there might be an option to make the turn after the next vehicle. If in the meantime a new vehicle will enter the perception range of the system the announcement will no longer be correct at the time the system has finished it but the distance to this vehicle will still be large enough for the driver to make the turn, we count this announcement as valid. In Fig. 8 we depict the results of our evaluation broken down into the different conditions present when the system made the announcement and when the corresponding vehicle passed in front of the ego vehicle. Overall, the evaluation shows that the system has a high performance and, despite the challenging setting, it made correct announcements in 103 out of the 115 cases (89.6%) [23].

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7. Conclusion

In this paper, we have first presented our recently introduced Assistance On Demand (AOD) concept. It allows the driver to request assistance via speech whenever she deems it appropriate. We have investigated the benefits of this approach in different driving simulator studies. As the scenario, we have chosen turning left from a subordinate road in dense urban traffic. In the first study, we were able to show that drivers clearly prefer our proposed speech-based interaction to a visual assistance system or to not having an assistance system at all. One further result was that participants mentioned that they felt that the gaps, announced by the system, did not always fit to their driving behaviour. Hence, in a follow-up study we have investigated the left-turn behaviour of different drivers. The results have shown that there is a large variation in the gaps that individual drivers prefer to take. This confirms our hypothesis that a personalization of the intersection assistant has a high potential to further improve usability and driver acceptance. We have tested this in a third user study. Here drivers compared manual driving to driving with the assistance of AOD, either with a system using a default critical gap setting or personalized critical gaps adjusted to the individual driver. The results show that the personalization very significantly improves the acceptance of the system. Given the choice between driving with any of the AOD variants and manual driving, 87.5% of the participants preferred driving with an AOD. Finally, we have presented our AOD prototype and its evaluation in urban traffic. The results show that the system is able to make correct announcements in 90% of the cases. This is a very promising outcome and shows that the system can provide valuable support to the driver despite the strong limitations of the LIDAR sensing of our prototype vehicle and the fact that it has to predict the traffic situation more than 8 s into the future in highly dynamic urban traffic. Nevertheless, in its current form, the system is not able to provide correct announcements in all cases. Yet, this is also not required for the system to be safe and useful. The following usage pattern is ideal in our view: when the system announces an approaching vehicle from the right, the driver relies on it. When the system announces a gap in traffic, the driver only considers this as a potential gap. She then looks to the right and assesses the situation for herself. Hence, the driver is relieved from regularly confirming that it is still not possible for her to enter the intersection while at the same time maintaining adequate situation awareness before starting the manoeuvre. When a driver follows this usage pattern, she will look to the right less frequently but still perform a control glance to the right before entering the intersection. In our user studies we observed that drivers naturally and without instruction to do so, adapt to such a usage pattern [(2), (21)].

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