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TOWARDS AN ON-DEMAND INTERSECTION ASSISTANT

-INITIAL USER ACCEPTANCE AND SYSTEM DEVELOPMENT-

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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 differences between drivers in the left-turn behaviour. The results of this driving simulator study show that there are large inter-individual differences. Based on these results we performed another driving simulator study where participants compared manual driving to driving with a default and a personalized AOD system. The results of this 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 first steps towards the implementation of the AOD system into a prototype car.

KEY WORDS: advanced driver assistance system (ADAS), speech-based system, on-demand, user study, critical gap, personalization

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 also can lead to distraction and annoyance of the driver due to undesired 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 following section we will first give more details on our AOD concept and the concrete scenario we currently apply it to. Next we will report results of a user study, which evaluated the AOD concept in comparison to driving without assistance and a visual assistance system in Section 3. Section 4 presents results of a user study regarding the individual left-turn behaviour of drivers. We used these results in a subsequent user study, presented in Section 5, to investigate if a personalization of the AOD system taking the individual left-turn behaviour into account will lead to higher user acceptance. We report on the status of the first steps we made towards the implementation of the system in a prototype car in Section 6. Section 7 presents a conclusion and an outlook.

2. The Assistance on Demand Concept

Driving in dense urban traffic is 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. [3], [4]). Currently available assistance systems for urban intersections mainly 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 [5] 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 more risky driving.

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 support while managing a difficult intersection. In particular when turning left they transfer the task of monitoring the right side traffic to the passenger and request feedback on suitable time gaps to enter the intersection[1]. These considerations led to the development of the system as an assistance system for urban intersections, which acts like a co-pilot with which the driver can interact via speech communication [1, 2]. The system helps to find suitable time gaps to cross the intersection 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 an "assistance on demand" (AOD) concept. With this on-demand concept we aim to increase the driver acceptance and reduce the annoyance from the system. In [6] 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. 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.

2.2. Intersection assistant scenario

In a first step we have implemented our AOD concept in a speech-controlled intersection assistant. After the driver has activated the system via a speech command, it monitors the right side traffic and informs 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: "Car is approaching."
- …
- System: "Gap after next car."

The system does not provide 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]. The user study was performed in a static driving simulator.

[1] Throughout the paper we only consider right-hand traffic. Yet the results can easily be transferred to 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, the other in the centre console to display optional additional information.

Fig. 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 right-side traffic, 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 to the intersection falls below the assumed suitable time gap for entering the intersection, while simultaneously another vehicle is following with a time gap lower than the suitable time gap, the system interprets this as a sequence of vehicles, which does not allow entering the intersection for turning. The linked speech output is “vehicle from the right.” If a vehicle from the right is expected to reach the intersection within 3 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 previous 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 6.5s 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 Figure 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 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 now also traffic from the left was included. The speech output “vehicle from right” in the AOD system was replaced by a red arrow either from the right or left or both. 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 [5]) for the same reasons that led to the AOD system not announcing “right is free.” Instead, the red or yellow arrow simply disappears, if the respective condition is valid.

3.1.4. Scenario

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 should assure that all drivers 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.

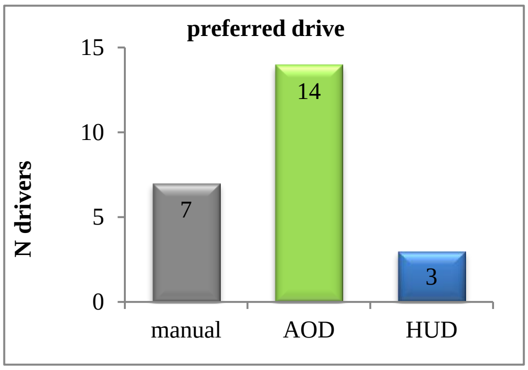

Fig. 3: Preferred drive of the 24 participants of the first user study. Without assistance (manual), with speech-based Assistance On Demand (AOD) or visual assistance via a head-up display (HUD).

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 a parameter, which 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 [7]. In our case, however, we use it as a criterion to quantify 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 [8]. 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 [9], 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 [9], [10]. 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 driver at intersection i and a_i the logarithm of the gap accepted by the driver at intersection i. The hidden parameters μ and σ of the distribution of the logarithm of the critical gap μ_c can then be found by maximizing the log-likelihood:

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

for all observations N. Following the argumentation in [9] 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 [11]. 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 [12].

4.2. Methodology of the user 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.

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 user 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 an 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 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 had to drive 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 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 a short break took place. 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.

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 variances of the critical gaps, since we don't possess any observations of the latter.

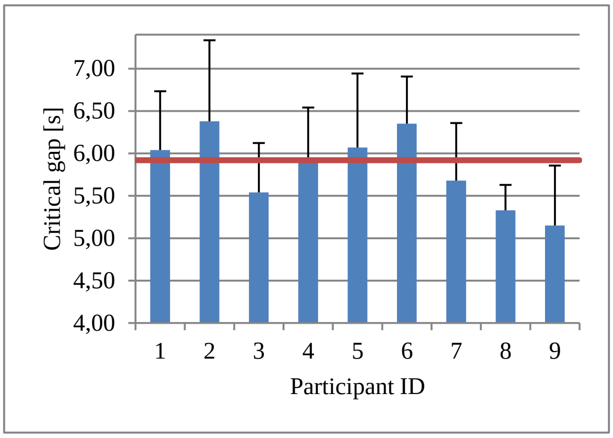

Fig. 4: Critical gap for each participant (blue bars), standard deviation of critical gap (black lines) and critical gap using data of all participants for estimation (red line).

5. User Acceptance of Personalized AOD

We saw in the previous section that different drivers chose different gaps in traffic. This motivated us to investigate in another user study if a personalization of the gap suggestions of the AOD system to the individual driver will further increase its acceptance [13].

5.1. Methodology

This user study was similar to the one described 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 travelled kilometres in the previous year was 18660 km (SD=12375 km).

5.1.2. Study environment

This study took also 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, the critical gaps, 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, a 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 in large parts identical to the one described in Section 3.1.5. 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. From this we conclude that the personalization of the gap suggestions to the individual driver very notably improves the acceptance of the AOD system.

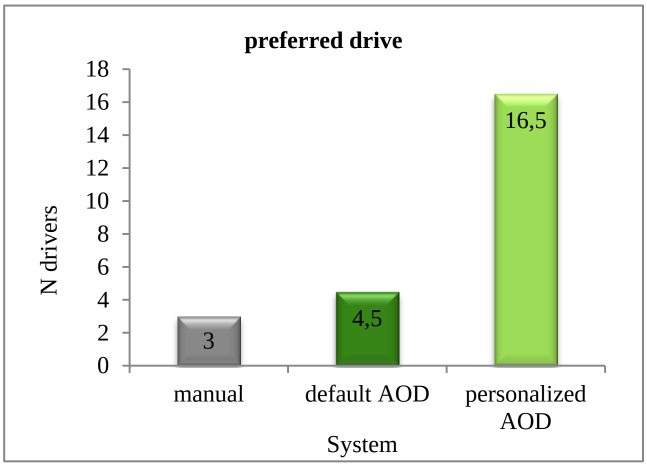

Fig. 3: Preferred drive of the 25 participants of the user study[2]. Without assistance (manual), with speech-based Assistance On Demand using a default gap (default AOD) or a personalized, driver-dependent gap (personalized AOD). The reason for the occurrence of the non-integer values is that some participants rated both the personalized AOD and the default AOD as equally good. These votes were split between the two alternatives.

6. Real-car Implementation

We currently work on the implementation of the AOD system in a prototype vehicle to test it in real traffic. A key part of this is the acquisition and evaluation of data recorded from different urban intersections.

6.1. Prototype system

As the prototype vehicle, we are using a modified 2012 model year Honda CR-V. 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.

For speech acquisition, we use a Plantronics Bluetooth headset and for speech feedback the standard audio equipment of the vehicle. Speech recognition and synthesis are accomplished via the VoCon™ and Vocalizer™ software respectively, both from Nuance.

6.2. Evaluation of urban intersections

With our prototype vehicle, we have made recordings at different unsignalized urban intersections in the Frankfurt Rhine-Main area. Based on these recordings we are currently evaluating if our laser-based sensor setup is capable of perceiving the relevant traffic participants. We assume traffic with a speed of 50 km h^{-1}, the maximum allowed speed for many German urban streets. Based on an upper limit of 6.5 s for the critical gap and another 2.5 s in which the driver is informed and is able to apprehend the information, the system has to make its decision 8.5s before the relevant vehicle arrives at the intersection. This means that we have to detect vehicles at least in a distance of 125m. Our recordings show that this target can be achieved for intersections with good to medium visibility. From this, we conclude that our current sensor setup is capable of supporting the AOD system under development. Consequently, we are currently implementing the necessary scene understanding and human-machine interface components of the AOD system. After finishing this, we will be able to evaluate the system in real traffic.

[2] Only 24 of the 25 participants answered this question. Consequently the numbers only add up to 24.

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 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 gap setting or personalized gaps adjusted to the individual driver. The results have shown 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 discussed our current efforts towards the implementation of the AOD system in our prototype vehicle. Here we saw that based on the laser sensors deployed in our prototype vehicle we will be able to perceive the traffic environment with sufficient fidelity to support the implementation of the AOD. This enables us to continue the implementation of the complete AOD system in the prototype car.

8. Acknowledgments

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