ONLINE ESTIMATION OF THE DRIVER'S STATE
ENHANCEMENT OF LANE-KEEPING ASSISTANCE

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ABSTRACT

Lane-departure warning and lane-keeping assistance systems may be more acceptable to users if the assistance was adaptive to the driver's state. Techniques to detect the driver as being distracted while driving are discussed. Eye- and head-tracking devices seem to be most promising today. Nonetheless, other methods such as detection of the use of in-vehicle information systems or tracking of drivers' activities bear potential. While adaptations of lane departure warning systems to the driver's state were not found to increase user acceptance, the use of an adaptive lane-keeping assistance system yielded higher acceptance as well as superior lane-keeping performance.

KEYWORDS

Driver's state, lane-keeping assistance, driver monitoring, driver activity

INTRODUCTION

Driver inattention is one of the major factors in traffic accidents. The National Highway Traffic Safety Administration estimates that in 25 % of all crashes some form of inattention is involved [1]. Distraction (besides drowsiness) as one form of driver inattention may be characterized as: "any activity that takes a driver's attention away from the task of driving" [2]. Naturalistic driving studies, such as the "100-Car Naturalistic Driving Study" [3], show in detail what kind of activities drivers engage in and what the likelihood of accidents for each kind of secondary task is. In almost 80 % of crashes and 65% of near-crashes the driver was inattentive. In the majority of these cases the driver was preoccupied with a non-driving related task. The use of wireless devices, as well as passenger-related and in-car distractions are the most frequent forms of driver inattention. Although, in the last few years, many European countries have prohibited the use of wireless devices without hands-free kit while driving, it should not be expected that the amount of distraction in driving will necessarily decrease. Even without the distractions caused by mobile devices, the amount of distraction due to in-car information systems is likely to increase.

Multimedia devices, which allow the driver to select their favorite song out of thousands or the connection of the navigation system to Google search functions, provide plenty of opportunities to reduce the attention paid to the roadway. Even if new laws restrict the use of such in-car devices in the future, distraction will still be a problem in other forms, e.g. from roadside events or passengers in the car. Thus, OEMs and automotive suppliers will need to find a way to deal with this problem.

At present there are three main approaches handling distraction: prevention, mitigation and minimizing negative outcomes of distraction.

One example for *distraction prevention* methods are workload-managers. Based on driving-data, road conditions and traffic driving demand is estimated. If the demand is high, possible distracting events like incoming phone calls will be postponed or functions of the in-vehicle information system will be locked out. For more information on workload-managers see [4-6].

To *mitigate distraction*, distraction-warning-systems are in development. If a driver is detected as being distracted, he will be given a warning, which will hopefully guide his attention back to the roadway. More information about distraction mitigation can be found in [5-7].

This paper focuses on the third approach: The idea of *minimizing negative outcomes of driver distraction* by driver assistant systems, especially lane keeping assistance systems.

LANE KEEPING ASSISTANCE AND ITS PROBLEMS

With the evolution of adequate lane tracking, lane departure warning as well as lane keeping assistance systems which attract drivers' attention when lane departures occur were introduced into the market recently. These systems track the lane markings in front of the vehicle and compute the time until the vehicle will cross the marking. If the driver does not show an intention of leaving the lane by using the indicator, the systems will initiate a warning or start assistance. Lane departure warning systems generate acoustic or haptic warnings. More sophisticated lane keeping assistance systems use directed steering torques on the steering wheel to guide the car to the middle of the lane.

Authors of several studies [8,9] reported overall effects of lane departure warning systems on lane keeping performance. Subjective evaluations are rare. In [10] the different warnings were rated as helpful, while participants in [9] judged the lane departure warning system as annoying but effective. The reason why those systems are annoying for some drivers is easy to explain. That is, lane keeping assistance aims at preventing the driver from making unintended lane departures. However, these systems do not yet respond to the driver's state or his intent. The control is mainly based on the car's speed and its position in the lane. An estimation which does not suit the driver's needs every time. [11] analyzed data of a field operational test. Only in 24 % of lane departure warnings did the drivers respond to the warning. In all other cases, the warnings were due to unsignaled lane changes (33%), an overly sensitive algorithm (17 %) or other factors. If it was possible to recognize a driver's state reliably, the system would give just as much assistance as the driver needs. This would allow for a greater safety margin without annoying the driver with false alarms or unwanted assistance in normal driving situations.

In the following sections, different studies about and approaches to driver state detection are discussed, with a focus on main stream research. It concludes with a discussion regarding the usefulness of these techniques for lane keeping assistance systems.

The focus lies on detection of short distracting events, which take a driver's attention away from the driving task. Only those events are of interest, where the distraction is of a visual and maybe additional cognitive nature. A meta-analysis [12] shows that a cognitively distracting conversation without visual distraction does not impair lane keeping performance. Consequently, due to our focus on lane-keeping assistance, events where the driver is only cognitively distracted are of no interest here. This also applies to long-term effects like fatigue and vigilance problems.

METHODS TO MONITOR DRIVER DISTRACTION

There are different approaches to estimating the driver's state online. Interpreting the driving task as a control loop as shown in Figure 1 provides several possibilities for such estimations.

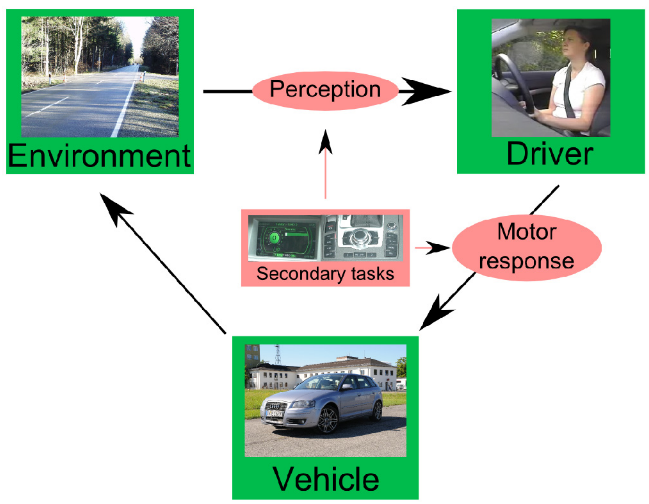

Figure 1 - Driving task as a control loop

According to Figure 1 one possibility to detect driver distraction is to monitor the driver's perception. The chapter 'Monitoring driver perception' discusses studies concerning acceptable eyes-off-road times and eye-tracking devices to detect inappropriate visual distraction. Furthermore, the usefulness of head-tracking, which is from a technical point of view more feasible than eye-tracking, is debated. Concerning this topic, results from an own study are presented.

Another possibility might be to take a look at the use of steering wheel and pedals (motor response). If the driver divides his attention to driving and the secondary task, limits in attentional capacity may lead to unusual driving behavior. The chapter 'Monitoring driving data' discusses studies on distraction detection via driving data such as steering wheel movements, use of pedals and lane keeping performance. Although some studies refute the usefulness of these signals, an own study shows more promising results.

As a third possibility, not the driver's input (perception) or output (motor response) but a detection of the driver's driving-unrelated activities may be possible. In the chapter 'Monitoring driver activity', concerns regarding a global driver-tracking and the use of in-vehicle information systems (IVIS) as an indicator of driver distraction are discussed.

The chapter 'Driver distraction detection for lane-keeping assistance' closes this report with a discussion about the use of those distraction related information for an adjustment of a lane keeping assistance system.

Monitoring driver perception

Past research

Being aware of and looking to the road ahead is a crucial factor for driving a car safely. A lot of research in the last two decades focused on eye-movements, attentional demands and visual distraction of drivers. [13] shows off-road-glances due to radio adjustments with a mean length of approximately 1.4 seconds and a standard deviation of app. 0.45 seconds. Other studies (e.g. [14]) confirm the finding that most off-road glances are nearly one second long while driving 'normally'. The engagement of the driver in a more complex secondary task does not affect the mean length of the glances; instead the absolute number of off-road-glances will increase. For a discussion of this and other influencing factors such as the driver's age, driving task demand, etc. see [15].

The link between a driver's visual distraction and lane keeping performance is obvious. In [16] drivers in a driving simulator were told to read words presented in different locations whilst following a vehicle. The on-road area was defined as a 24 x 24 degree window around the driver's normal gaze direction. The proportion of gazes in- and outside of the 'attention window' was computed over a time window of 4.3 seconds. The results show a correlation between standard deviation of lane position and eyes-off-road-proportion of $r = .84$. This strong relationship argues for the estimation of the driver's distraction based on gaze behavior. Exactly this was done in the SAVE-IT Project ('SAfety VEhicles using adaptive Interface Technology'), which [16] was part of. One task within SAVE-IT was to estimate the distraction level of the driver. It was concluded that if eyes-off-road proportion (within the 4.3 second time window) is bigger than 0.5, drivers should be labeled as 'visually distracted'. Within the SAVE-IT project, [17] conducted another study in which 10 participants were distracted by IVIS-use in a simulator. Using 'support vector machines' to learn patterns in drivers' eye movement data they achieved an accuracy of 81.4 percent in distraction detection.

Within the European AIDE project ('Adaptive Integrated Driver-vehicle InterfacE') [18,19] built 'support vector machines'-classifiers which should not only be able to detect visual distraction but also – much more challenging - cognitive distraction. Twelve professional truck drivers were distracted by visual (e.g. looking to speedometer or radio) and non-visual secondary tasks (e.g. mental arithmetic). Due to studies [20,21], which show a decrease in visual scanning and a decrease in lane position variance during cognitive tasks, different indicators were chosen within a time window of fifteen seconds length. Depending on road type, cognitive tasks were recognized with an accuracy of between 40-80 %, while 80 % of non-distracted driving was classified correctly. For the classification of visual distraction different areas like "road ahead", "speedometer" and "radio" were defined. While classification of "road ahead" seems rather good with an accuracy of 84%, the gazes to other areas could not be classified with similar accuracy.

Eye-tracking devices are able to produce data in real-time and show the diagnostic ability to differentiate between on-road and off-road glances. The accuracy of the above mentioned algorithms is quite good by now. So it seems likely that more sophisticated systems will be more precise in the near future. But as beneficial as eye-tracking systems seem, they are still not applicable in a standard vehicle today. In order to reach high accuracy, most systems have to be calibrated precisely to each driver. This procedure takes at least a few minutes and would have to be performed each time before starting on a journey, which would likely be regarded as impractical by most drivers. Furthermore, eye-tracking requires a lot of processing power, because in order to estimate gazes the head has to be tracked as well.

Even though such systems are not yet feasible for automobile serial production, these problems are likely to be solved within the next few years. Until then, an alternative might be to track only the head and not the eyes of the driver. Lexus [22] was able to build a small and applicable system, which can track head-pose. At present this ‘driver-monitoring system’ can be purchased in the ‘LS’ series. The information about drivers’ visual focus is used for an adjustment of pre-crash warnings. Nonetheless, there is no published study which shows the usefulness of such an approach. [23] report of a close relation between eye- and head-movements. However, that does not imply that the driver’s focus can be estimated by the orientation of his head. How strong is this relation? And how much information about the driver’s focus and his visual distraction can be gained by tracking his head?

The role of head-pose in driver distraction detection

To answer if head-pose is sensitive enough to detect the driver as visually distracted we conducted a separate study. This study was part of the German AKTIV-project (‘Adaptive und kooperative Technologien für den intelligenten Verkehr’), which was founded by the ‘Bundesministerium für Wirtschaft und Technologie’.

Twenty-eight participants (12 female and 16 male) with a mean age of 35.8 years were recruited.

An Audi A6 was equipped with an eye and head-tracking system (faceLAB) and a personal computer to measure CAN-Bus data and to record a video of the driver’s face. Both computers were synchronized and controlled by an instructor seated on the backseat of the car. This instructor was present during the whole trip and gave the participants information regarding where they need to go and when to start secondary tasks. He also marked driving maneuvers (overtaking, lane change, turning) and different road types during the trip in the data stream. The route was 70 kilometers long and can be classified into rural areas (1 lane per direction, speed limit between 70 km/h and 100 km/h), city areas (2 lanes per direction, speed limit of 50 km/h), highways (2-3 lanes per direction, no speed limit) and small towns (1 lane per direction, speed limit of 50 km/h). The participants were told to pay full attention to the road, even when secondary tasks needed to be performed.

Two realistic secondary tasks were chosen. The first one was dialing a phone number on the car’s in-vehicle information system (IVIS). The control button of the IVIS was located between the driver’s and the co-driver’s seat. The display was positioned in the middle console just under the dashboard. The second task simulated a typical situation of everyday driving. The subjects were told – as if they were searching for a specific street - to read out aloud all names of the streets they cross while driving through two towns.

faceLAB and CAN-Bus data were collected during the whole trip. Afterwards the data streams were filtered using the integrated markers. In order to be able to compare “distracted”- to “baseline”-scenes some parts had to be removed. First of all, scenes were deleted where the vehicle was slower than 3 km/h. In the next step driving maneuvers such as lane change, overtaking, etc. were excluded. Then the scenes “IVIS-use” and “Street names” were taken apart. Aiming to exclude data which might be out of context due to the filtering, only those remaining scenes were taken which were at least 20 seconds long. These were then categorized into the four road types “rural areas”, “city areas”, “highways” and “small towns”.

The algorithm for distraction detection was built based on the above-mentioned studies. Following [16] an “attention window” with a width of 24 degrees – 12 to the left and 12 to the right hand side of the driver’s head - was used. However, unlike [16], this window was based on head- and not on eye-rotation. A preliminary test showed considerably more false alarms (algorithm labels “distracted” but driver is “attentive”) when the “attention window” was also limited vertically to 24 degrees. So there was no vertical limit for the attention window set. A limit of 1.5 seconds head-off-road was chosen. The algorithm was used with the remaining scenes. Each time the driver’s head-pose was longer than 1.5 seconds outside the attention window a warning was logged. In order to categorize these warnings as “true-” or “false-classification” a video analysis was made. If it was clear that the driver was looking at the road, the warning was classified as “false-classification”. If not, a “true-classification” was counted. To get an overview of the usefulness of the algorithm, the classifications were grouped to road and distraction type. In the end, the classifications were relativized by exposition time for each group.

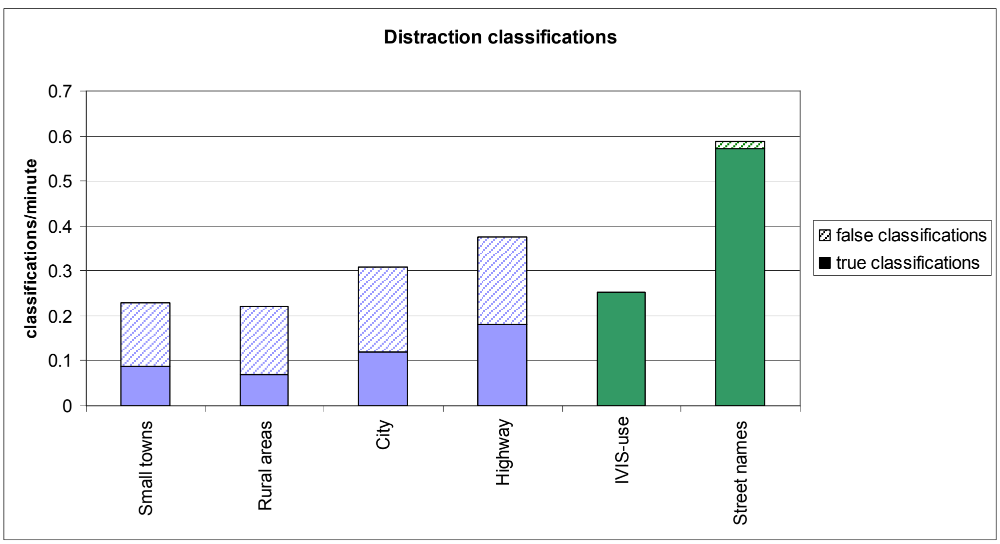

Figure 2 - True and false classifications per minute for road types and distraction conditions

Figure 2 shows true and false classifications per minute for the four road types and the two distraction conditions. Table 1 shows the corresponding calculations. The four blue bars on the left hand side in Figure 2 show distraction classifications for “normal” driving on different road types. In these situations the drivers were not given any task by the instructor, but were told to drive ‘attentively’. However, as the analysis shows, drivers did not only look to the road ahead in these scenes. That is, between 0.09 and 0.18 times a minute they have a head-pose of more than 12 degrees to the left or right for longer than 1.5 seconds. True distraction classifications can also be found during the two secondary tasks (two blue bars on the right hand side). While the drivers were using the IVIS, 0.25 right classifications were counted, whilst during the "street name" task, 0.57 right classifications per minute were produced by the algorithm. Apparently the used algorithm is capable of detecting drivers' visual distraction. Looking at the "street name"-task, the results seem quite good. This analysis cannot take into account the real number of times the driver looked away from the roadway. Nevertheless 0.57 true classifications per minute based on head-pose seem to be realistic for this task.

Table 1: Classifications overall, true and false classifications and exposition time

	Classifications per minute	True classifications per minute	False classifications per minute	Exposition (in minutes)
Small towns	0,23	0,09	0,14	184,3
Rural areas	0,22	0,07	0,15	440,9
City areas	0,31	0,12	0,19	58,4
Highway	0,37	0,18	0,19	77,4
IVIS-use	0,25	0,25	0,00	15,9
Street names	0,59	0,57	0,02	290,6

Nevertheless, other results and the comparison of true classifications per minute between the groups are not as good as was originally hoped. During IVIS-use approximately one classification per four minutes was given. Due to the fact that drivers needed no more than one minute – in most cases less – to accomplish the IVIS-task, only few drivers would be detected as distracted by the algorithm. Obviously, the algorithm is not capable of detecting visual-distraction due to IVIS-use. One simple solution to increase the sensitivity might be to use an "attention window" smaller than 24 degrees in width. However, looking at the false classifications in "baseline" scenes (towns, rural areas, city areas and highways) this might not work out. The drivers were driving mostly attentively in these scenes, but there are a lot of false classifications by now. Looking at the highway data there are nearly as many false classifications as there are correct ones. If the algorithm is more sensitive, for example by focusing on a smaller "attention window", more false classifications have to be expected.

The results show a classification of the driver's visual focus based on the head-pose as measured by an actual head-tracking system. It is obvious that the used algorithm is not sensitive enough to detect gazes to an IVIS-display, but to detect bigger head-movements to street signs on the left and right hand side of the road. Compared to eye-tracking devices, the sensitivity is much smaller and is not sufficient for a clear distinction between on- or off-road glances.
For the detection of the driver's visual focus eye-tracking devices are needed. A system like faceLAB, which is used for research today, has an accuracy which is high enough to distinguish whether it is an on-road gaze or a gaze to the IVIS-display. It is just a matter of time until such systems are feasible to build into standard cars.

Monitoring driving data

Past research
The possibility of recognizing the driver's state based on steering wheel movements, throttle position and other driving data offers a big advantage. In modern cars there are already sensors

for steering wheel, throttle and – in case the car is equipped with a lane departure warning system - car position on the lane. Following this, systems could be upgraded just by making software changes.
The idea of measuring distraction by steering wheel movements, throttle use and lane keeping behavior is already accepted and used. Many studies prove the fact that visually distracted drivers steer their car in a different way than do attentive drivers ([24] give an overview). In all of these studies the distraction or the workload are estimated post hoc after the test drive and not online in the car. For an online estimation the data available is limited to the last few seconds, because a decision has to be quick. It will be too late if the system can only predict a driver to be distracted after as much as 20 seconds. Furthermore, an online estimation is considerably different, because you have to deal with factors like different road types, random traffic, influence of weather and much more, which are held constant in an experiment.
Only a few approaches can be found in the literature, which try to estimate the driver to be distracted online using steering wheel, throttle and other already accessible information on CAN-Bus. Promising results can be found in [25]. The authors tried to build a driver's state predictor (attentive vs. distracted) based on sensor data already available in-vehicle. Ten participants drove in a driving simulator and were instructed to look for pictures in the blind spots of the car. The measured variables were steering wheel angle, throttle position, distance to lane markings, the car's lateral velocity as well as acceleration in the lane, steering error (difference to an optimal steering wheel angle to keep the vehicle in the middle of the lane) and the curviness of the road. They used 'multiple adaptive regression trees' to find patterns in the data and report an accuracy of 78 % for a distraction condition and one of 98.4 % for attentive driving, which would be more than satisfactory. These results have one caveat. That is, it is not clear, whether the reported accuracies stem from a cross-validation. If the classifier was tested on the same data as it was built on, the result may simply be overfitted and cannot be generalized to other data.
There were also concerns to estimate the driver's state online based on driving data within the SAVE-IT Project. In [17] 'support vector machines' were used to detect patterns not only in driver's eye movement data, but also in lane deviation, steering wheel position and steering error. The authors were able to show an increase in prediction accuracy, when the driving data was used in addition to eye movement data, however, the driving data itself showed poor accuracy.
These results may be explained by the limited number of driving data signals, which were used for prediction. As such, they do not indicate that an online estimation of the driver's state would be necessarily inaccurate.

Using driving data to predict IVIS-use

In order to overcome difficulties of the above mentioned studies and to gain more insight in the potential of estimating a driver's state based on driving data, a separate study was conducted. More precisely, the handling of throttle, steering wheel and information regarding the car's position in the lane were used to predict a driver to be distracted or to drive with full attention.
The results of the previously mentioned studies show the relationship between visual distraction and this kind of behavioral data to be very complex. As no psychological model is detailed enough to make the desired prediction, a machine learning algorithm was used as well. A decision tree or C4.5 algorithm (for more information see [26]) was chosen.
Underlying data of the here depicted analysis derive from the test drives in real traffic. 25 drivers (10 female, 15 male) with a mean age of 37.9 years drove on the same country road two times.

One time they were instructed to drive with full attention and one time they were told to drive while entering a city name into the IVIS.
Before constructing the decision tree the data was prepared. Potentially useful CAN-Bus signals from the test vehicle were extracted. Each signal was broken down into time windows of five seconds length. Within each of these windows different metrics were computed for the whole five seconds and for the last second within the window. These metrics were chosen because of known metrics used in the previously mentioned studies and own theoretical thoughts (e.g. mean, standard deviation, gradient of linear regression, steering error, etc.).
To compensate for interindividual differences, data of each participant were standardized. Lastly, the entire sample was split into two parts (Set 1: Drivers 1-12 vs. Set 2: Drivers 13-25).
To construct a decision tree classifier the open-source software Weka ('Waikato Environment for Knowledge Analysis') was used. The C4.5 algorithm in Weka (named: J48) was chosen with default settings. For both samples a decision tree was built. In a cross-validation experiment each tree was then tested on the other sample. This procedure allows an estimation of the classification accuracy on an unknown dataset without using only a small subset of data. The results of both tests were averaged and are shown in Table 2.

Table 2 - Results of cross-validation

	Averaged results
Correctly Classified Instances	77.4
Attentive	84.4
Distracted	64.3
Incorrectly Classified Instances	22.6
False Positives Attentive	35.7
False Positives Distracted	15.6
Kappa statistic	0.4952

A classification if the driver is attentive or not based on data from steering wheel, throttle position and lane keeping data does not seem to be impossible. The cross-validation in this analysis revealed a correct classification of 84.4 % of attentive and 64.3 % of inattentive samples. The false positives rate of 'attentive' ('inattentive' samples which were classified as 'attentive' to the number of all 'inattentive' samples) is with 35.7 % higher than the false positives rate of 'inattentive' classifications ('attentive' samples which were classified as 'inattentive' to the number of all 'attentive' samples) with 15.6 %.
The accuracy of the depicted decision trees is probably not high enough to support the conclusion that CAN-Bus data gain enough information to predict a driver's state reliably and accurately. Furthermore, it is conceivable that the found predictability might be a result of the 'simple' test scenario. More complex traffic scenarios and other speeds might lead to different error rates and may make an accurate prediction even more difficult.
However, this analysis was conducted as a first attempt. Contrary to previous studies a bigger sample of test data taken under real traffic conditions was used. Based on theoretical thoughts metrics of CAN-Bus signals were computed and used to construct decision trees, and their prediction capabilities were cross-validated. The found accuracies demonstrate the potential of CAN-Bus data for detecting the driver's state. Most likely, other machine learning tools like 'Support Vector Machines' or 'Random Forrest'-approaches may be more efficient in this regard.

Furthermore, the chosen attribute set was limited. More sophisticated variables (e.g. spectral analysis of the steering behavior) might help to reduce prediction errors even further. To this end, further studies will have to be conducted.

Monitoring driver activity

A third alternative to recognize the driver as being distracted may be to detect him directly as being involved in a secondary task. [27] identified a driver's activity by video tracking of different areas in the cockpit. He tracked the area in front of the car's radio. A change of the video image in this area was interpreted as use of radio and driver distraction. [28,29] generalized this idea. They used up to four color and thermal infrared cameras to track different parts of the driver's body (head, torso, arms and hands) and their movements. Although they used this information to detect driver intentions such as turning left or right, it may also be used for the detection of distraction. Many secondary tasks described in the 100-car-naturalistic-driving study [3] might be detected. Reaching for objects in the car, looking to passengers, eating and drinking or adjustments on climate control or IVIS may be detectable via movements of body parts. To our knowledge there has been no study to try such detection, but it is obvious that at least extensive movements would compromise a driver's ability to drive the car safely or to react appropriately in a critical situation. On the other hand, it is debatable if such a "black or white" decision is worth the technical effort. The grey area between bodies' normal position and extensive movements bears a lot of questions. Is it possible to distinguish whether the driver is resting his arm on the adjacent seat or whether he is searching for his mobile in a bag? Is it possible to judge the driver's ability to drive safely, based on whether or not one arm is stretched? Future research may further investigate this issue.

A more widespread idea is to estimate the driver's state based on IVIS-use. IVIS-use might only be one of many secondary tasks that drivers engage in. Nevertheless, little information about the driver's activities is better than none; furthermore, IVIS-use is easily detectable by tracking the car's infotainment data stream. In addition, more and more nomadic devices like cell phones and mp3-player are connectable to IVIS (e.g. using Bluetooth), which also allows for the detection of their use.

A plethora of studies show the influence of IVIS-use on lane keeping (e.g. [24]). In order to estimate the driver's state during IVIS-use, it is essential to differentiate between IVIS-tasks according to different kinds of distraction. Using the voice control to dial a number does not require as much visual capacity as manual dialing would need. The question is how detailed such a categorization has to be. There are several approaches which are more or less detailed. [2] differentiated between visual, cognitive, biomechanical and auditory distractions. A more complex method is described in [30]. He modeled four different tasks by breaking down each task into basic "production rules" within the ACT-R architecture ('Adaptive Control of Thought-Rational') and was able predict their influence on driving performance.

As promising as this approach is, it is questionable if it is useful for online estimation of distraction rather than as guidelines for designing less distracting IVIS. In real traffic, drivers do not execute secondary tasks from beginning to end, but pause when the driving situation demands more attention. Furthermore, IVIS-experience and strategies the drivers use are likely to mediate cognitive and visual demand, which makes an online estimation much more challenging.

In an own approach [31], eight visually demanding tasks of the Audi IVIS were examined. The results show the duration of tasks to be more important than is the task type. Hence, our recommendation is not to distinguish different visually demanding tasks, but to label the driver as "visually distracted" each time the IVIS is used.

The same seems to be appropriate for "verbal" or cognitive IVIS-tasks. A meta-analysis [12] shows that a cognitively distracting conversation increases reaction time to unforeseen events, but does not diminish lane keeping performance. From a technical point of view it is extremely difficult to estimate the cognitive demand when voice control is used or when the driver is talking on the IVIS-integrated phone. Thus an online categorization into the two categories 'cognitively distracted' or 'non-cognitively distracted' would be the only possibility.

On first thought, this classification might seem to be oversimplified. But it is debatable whether or not we really need more than the categories "attentive" and "distracted" for the adaptation of driver assistance systems.

DRIVER DISTRACTION DETECTION FOR LANE-KEEPING ASSISTANCE

There are two ways to adapt a lane keeping assistance system to a driver's state: Suppress warnings and adjust the warnings' timing.

If it is possible to detect reliably the driver as being distracted, warning or assistance will only be given in that instant. If the driver is not detected as being distracted, the warning will be suppressed.

The other alternative is not to suppress warnings, but to adjust their timing. If it is certain that the driver is distracted, the warning will be given earlier. This increases the safety margin respectively the time for the driver to react. If the driver cannot be detected definitively as being attentive, the warning will be given with a "standard" timing.

The discussed techniques of driver distraction detection have different advantages for the use in a lane keeping assistance system.

Eye-tracking systems are able to acquire data about the driver's point of view in real-time, which should match the driver's visual distraction with high accuracy. As long as those systems turn out to be unfeasible for the use in commercial cars, head-tracking systems may be a viable alternative. Our own study showed a lot of false classifications, if distraction detection was based on head-pose only. Thus, a distraction mitigation system, which warns the driver in moments of inattention, would produce a lot of nuisance alarms. However, since lane-keeping assistance is of particular interest here, lane deviation can also be taken into account. Three studies should be mentioned which used head-pose for adjusting a lane-departure warning system.

Two of these studies were accomplished in the SAVE-IT project. [32] examined the usefulness of a lane departure warning system which adapts the timing of the warning to the driver's head-pose in a driving simulator. They did not find any significant differences between the adaptive and the non-adaptive version based on the driver's reaction times. Neither did they find a higher acceptance of the adaptive system. Whether or not this was due to the short time period(30 minutes) the drivers were able to familiarize themselves with the system cannot be answered. [33] used head-pose information to suppress warnings. If the driver was detected as looking to the road ahead no warning was given. They were able to show a reduction of lane departure warnings of 88% in a real-traffic test drive. Furthermore, they did not find any false negative alarms (i.e. drivers are distracted, but the system does not recognize them as such). Contrary to these positive findings, however, the acceptance of the adaptive system was not higher than it

was of the non-adaptive version. [34] used head-pose differently than [33]. They did not suppress warnings when the driver was detected as attentive, but they initialized warnings only when the driver was detected as “distracted” and crossed a lane marking the same time. Because of no false positive interventions and a good true positive performance the authors concluded head-tracking to be beneficial for lane keeping assistance.
The results seem promising. Based on head-pose a suppression of lane keeping assistance decreases the number of nuisance alarms considerably. Whether or not an adaptation of the warnings’ timing is useful could not be clarified here. Neither was it possible to show an increase in acceptance due to driver state adaptive systems.

It would be very useful to estimate a driver’s state based on driving data due to the fact that the sensors are already installed in most cars. As promising as this idea might seem, the research is only at the beginning. There is still no final evidence on how good such recognition might be. Our approach shows potential, but if its prediction power is high enough to be considered useful, it should be further explored. Future work has to focus on variables, metrics and algorithms which take into account different road types, traffic, influence of weather and all other things, which influence one’s driving style. At this point it can only be speculated if driving data is useful for enhancement of driver assistance systems. It seems unlikely that the driver can be detected as being involved in a secondary task from the start, if only driving data is monitored. Furthermore, the adjustment of driver assistance systems leads to a change in the driver’s behavior. Therefore, continuous monitoring of the driver’s state is interfered with by the assistance itself. Even if these facts argue against an adaptation of driver assistance based on a driver’s steering behavior, there are other possible uses for this approach, such as distraction mitigation or prevention. However, research has to prove the basic premise of detecting driver’s distraction based on driving data first, before further work regarding its application is warranted.

Detecting IVIS-use is simple and can be realized in real-time. But an estimation of driver’s actual cognitive and visual distraction based on IVIS-use is imprecise. The arising question is whether or not an adjustment of lateral assistance based on this imprecision will be accepted by the driver. In [31] drivers were confronted with different timings of a lane keeping assistant while using the IVIS. The results show that all lateral support algorithms increased lane-keeping performance with the algorithms providing an early assistance proving the most useful. All assistance systems were rated as helpful and were considered to increase driver safety, both by the drivers who did and those who did not have problems in lane-keeping without assistance.
Based on these results it seems very practical to adjust the timing of lateral assistance if the IVIS is used neither nor the estimation of driver’s visual distraction is imprecise.
It is obvious that the detection of IVIS-use is only one small piece in the puzzle of distraction detection, but it might increase the efficiency of lane keeping assistance systems a little bit more.
How much information about the driver’s state body-tracking systems can acquire, cannot be answered yet. Those systems are able to ascertain information about the driver not being in his normal driving position, but further research has to compare the gain of this information with the costs for such tracking devices.

CONCLUSION

At the moment eye- and head-tracking devices are the most promising techniques to recognize the driver as being distracted. These systems allow firsthand and real-time insight into one of the

most important tasks while driving: perception. Most distractions caused by secondary tasks include visual components, which may be recognized. Although eye-tracking devices are not feasible for car serial production, head-tracking seems to be useful for some types of assistance. Other techniques might have the advantage that they are based on already accessible sensors, but they cover only a small area of distraction (IVIS-use) or are not technologically mature (driving data and body tracking). Future research has to prove their potential in detecting distraction.
The idea of adjusting lane keeping assistance systems if the driver is distracted seems to be beneficial. [33] have clearly shown a high decrease in lane departure warnings. The adjustment of the timing of assistance has not proved to be useful in a lane departure warning system. But [31] showed a gain in terms of safer lane keeping and high user acceptance when a more sophisticated lane keeping assistance system is adapted.
We are just at the beginning to detect and use information about the driver's state for control of in-vehicle systems. But before vehicles drive fully autonomously, the driver's state and intentions will be important in increasing safety and comfort in the control loop of driver, vehicle and environment.

LITERATURE

[1] Wang, J., Knipling, R.R. & Goodman, M.J. (1996). The role of driver inattention in crashes; new statistics from the 1995 crashworthiness data system (CDS). *40th Annual Proceedings: Association for the Advancement of Automotive Medicine,* pp. 377-392.

[2] Ranney, T.A., Mazzae, E., Garrott, R. & Goodman, M.J. (2000). *NHTSA driver distraction research: past, present and future.* Available at: www-nrd.nhtsa.dot.gov/departments/nrd-13/driver-distraction/PDF/233.pdf

[3] Dingus, T.A., Klauer, S.G., Neale, V.L., Petersen, A., Lee, S.E., Sudweeks, J., Perez, M.A., Hankey, J., Ramsey, D., Gupta, S., Bucher, C., Doerzaph, Z.R., Jermeland, J. & Knipling, R.R. (2006). *The 100-Car Naturalistic Driving Study, Phase II - Results of the 100-Car Field Experiment.* Available at: http://www-nrd.nhtsa.dot.gov/departments/nrd-13/driver-distraction/PDF/100CarMain.pdf

[4] Green, P. (2004). *Driver distraction, telematics design, and workload managers: Safety issues and solutions*, SAE paper No. 2004-21-0022, 2004.

[5] Engström, J. & Victor, T.W. (2008). Real-time distraction countermeasures. In: Regan, M.A., Lee, J.D. & Young, K.L. (eds.), *Driver distraction – Theory, effects and mitigation.* Boca Raton: CRC Press.

[6] Zhang, H., Smith, M.R.H. & Witt, G.J. (2008). Driving task demand-based distraction mitigation. In: Regan, M.A., Lee, J.D. & Young, K.L. (eds.), *Driver distraction – Theory, effects and mitigation.* Boca Raton: CRC Press.

[7] Donmez, B., Boyle, L. & Lee, J.D. (2008). Designing feedback to mitigate distraction. In: Regan, M.A., Lee, J.D. & Young, K.L. (eds.), *Driver distraction – Theory, effects and mitigation.* Boca Raton: CRC Press.

[8] Rimini-Döring, M., Altmüller, T., Ladstätter, U. & Rossmeier, M. (2005). Effects of Lane Departure Warning on Drowsy Drivers' Performance and State in a Simulator. *Proceedings*

of the Third International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design, 2005, Rockport, Maine, USA.

[9] Alkim, T.P., Bootsma, G. & Hoogendoorn, S.P., Field Operational Test "The Assisted Driver", *Intelligent Vehicles Symposium*, 13-15 June 2007, Istanbul, Turkey, pp.1198-1203.

[10] Kozak, K., Pohl, J., Birk, W., Greenberg, J., Artz, B., Blommer, M., Cathey, L. & Curry, R. (2006). Evaluation of lane departure warnings for drowsy drivers. *Proceedings of the Human Factors and Ergonomics Society 50th Annual Meeting.* 16-20 October 2006, San Francisco, California, USA.

[11] LeBlanc, D., Sayer, J., Winkler, C., Ervin, R., Bogard, S., Devonshire, J., Mefford, M., Hagan, M., Bareket, Z., Goodsell, R., Gordon, T. (2006). *Road departure crash warning system field operational test: Methodology and results.* The University of Michigan, Transportation Research Institute.

[12] Horrey, J.H. & Wickens, C.D. (2006). Examining the impact of cell phone conversations on driving using meta-analysis techniques. *Human Factors,* 48 (1), pp 196-205.

[13] Rockwell, T. H. (1988). Spare Visual Capacity in Driving – Revisited: New Empirical Results for an Old Idea. In: Gale, A.G., Freeman, M.H., Haslegrave, C.M., Smith, P. & Taylor, S.P. (eds). *Vision in Vehicles II.* Amsterdam : North Holland Press, 1988, pp. 317-324.

[14] Wierwille, W.W., Antin, J.F., Dingus, T.A. & Hulse, M.C. (1988). Visual attentional demand of an in-car navigation display system. In: Gale, A.G., Freeman, M.H., Haslegrave, C.M., Smith, P. & Taylor, S.P. (eds). *Vision in Vehicles II.* Amsterdam : North Holland Press, 1988, pp. 307-316.

[15] Zhang, H. & Smith, M. (2004). SAfety VEhicles using adaptive Interface Technology (Task 7) - *A Literature Review of Visual Distraction Research*. Available at: http://www.volpe.dot.gov/hf/roadway/saveit/docs/dec04/litrev_7a.pdf

[16] Zhang, H., Smith, M. & Dufour, R. (2008). *A Final Report of SAfety VEhicles using adaptive Interface Technology (Phase II: Task 7C): Visual Distraction*. Available at: http://www.volpe.dot.gov/hf/roadway/saveit/docs/visdistract.doc

[17] Lee, J., Reyes, M., Liang, Y. & Lee, Y-C. (2007). *Algorithms to Assess Cognitive Distraction.* Final Report: Phase 2, Task 5, Safety Vehicles using adaptive Interface Technology. Available at: http://www.volpe.dot.gov/hf/roadway/saveit/docs/phase2/allgorithms-cognitive-distraction.doc

[18] Kutila (2006). *Methods for machine vision based driver monitoring applications.* Dissertation theses at Tampere University.

[19] Kutila, M., Jokela, M., Markkula, G. & Rue, M.R.(2007). Driver Distraction Detection with a Camera Vision System. Paper presented at *2007 IEEE International Conference on Image Processing*.

[20] Recarte, M.A. & Nunes, L.M. (2003). Mental workload while driving: Effects on visual search, discrimination, and decision making. *Journal of experimental psychology: Applied*, 2003, 9 (2), pp. 119-137.

[21] Victor, T.W., Harbluk, J.L. & Engström, J.A. (2005). Sensitivity of eye-movement measures to in-vehicle task difficulty. *Transportation Research Part F: Traffic Psychology and Behaviour*, 8 (2), pp. 167-190.

[22] Lexus (2009). Lexus LS – Driver monitoring system. http://www.lexus.eu/range/ls/key-features/safety/safety-driver-monitoring-system.aspx

[23] Land, M. & Horwood, J. (1996). The relations between head and eye movements during driving. In: Gale, A.G., Brown, I.D., Haslegrave, C.M. & Taylor, S.P. (eds.). *Vision in vehicles V.* Amsterdam: North Holland Press, pp. 153-160.

[24] Young, K., Regan, M. & Hammer, M. (2003). *Driver Distraction: A review of literature,* Monash University Accident Research Center, Report No. 206.

[25] Torkkola, K., Massey, N. & Wood, C. (2004). Detecting Driver Inattention in the Absence of Driver Monitoring Sensors. *Proceedings of International Conference on Machine Learning and Applications*, 16-18 December 2004, Louisville, Kentucky, USA.

[26] Quinlan, J. R. (1993). *C4.5: Programs for Machine Learning*. San Francisco: Morgan Kaufmann Publishers.

[27] Wahlstrom, E., Masoud, O. & Papanikolopoulos, N. (2004). *Monitoring driver activities*. Technical Report No. CTS 04-05. Artificial Intelligence, Robotics and Vision Laboratory, Department of Computer Science, University of Minnesota.

[28] Park, S. & Trivedi, M. (2005). Driver activity analysis for intelligent vehicles: Issues and development framework. *Proceedings of IEEE Intelligent Vehicle Symposium*, 6-8 June 2005, Las Vegas, USA, pp. 644-649.

[29] Cheng, S.Y., Park, S. & Trivedi, M.M. (2006). Multi-spectral and multi-perspective video arrays for driver body tracking and activity analysis. *Computer Vision and Image Understanding,* No. 106, pp. 245-257.

[30] Salvucci, D. D. & Macuga, K. L. (2002). Predicting the effects of cellular-phone dialing on driver performance. *Cognitive Systems Research*, 3, pp. 95–102.

[31] Blaschke, Breyer, Färber, Freyer und Limbacher (in press). Driver Distraction Based Lane-Keeping Assistance. *Transportation Research Board Part F: Traffic Psychology and Behaviour.*

[32] Brown, T., Marshall, D., Moeckli, J. & Smyser, T. (2007). *A final report of Safety Vehicle(s) using adaptive Interface Technology (SAVE-IT) Program: Task 14a Evaluation*. Available at: http://www.volpe.dot.gov/hf/roadway/saveit/docs/task14a.pdf

[33] LeBlanc, D., Eby, D.W., Bareket, Z. & Vivoda, J.M. (2008). *On-Road Evaluation of the SAVE-IT Vehicle Prototype* – Task 14c Final Report for the SAfety VEhicles using adaptive Interface Technology (SAVE-IT) Project. Available at: http://www.volpe.dot.gov/hf/roadway/saveit/docs/saveiteval14c.doc

[34] Pohl, J., Birk, W. & Westervall, L. (2007). A driver-distraction-based lane-keeping assistance system. *Proceedings of the Institute of Mechanical Engineers Part I: Journal of Systems & Control Engineering*, 221 (4), pp. 541-552.