ANALYSIS OF THE ROBUSTNESS OF STEERING PATTERN BASED DROWSINESS DETECTION

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ABSTRACT

Several studies show that up to one in four severe traffic accidents can be attributed to drowsiness. Drivers often over-estimate their fitness level or are not aware of the danger that always accompanies drowsy driving.
Since associations like the NHTSA pointed to the relevance of this topic, more and more research has been conducted and in the meantime there is also a variety of commercial systems on the market to address this risk.
In this paper, we do not aim to find new methods of detecting drowsiness of a driver. Our approach is rather to choose an established method and enhance it in a way that it not only performs well in a driving simulator but also in real world drives.
The chosen drowsiness detection method is the observation of the steering wheel angle signal. It has been shown that the frequency of occurrence of a typical steering pattern, which can roughly be described as a deadband followed by a rather fast correction, is an indicator for the state of drowsiness of a driver. The advantage over other techniques like camera-based detection is that it can run in standard equipped cars. Thus it is available for the largest number of drivers and can thereby achieve the greatest effect on accident avoidance.
We investigate the chosen detection method in real world drives and discuss which other effects not related to drowsiness can evoke the described steering pattern. We focus on environmental effects like crosswind and can show that those events may lead to an increase of the amount of steering patterns. Finally, we quantify the influence on drowsiness measures. The underlying database comprises more than two million kilometers of more than one thousand drivers, all real-world drives.
Our evaluation shows that particularly on routes or in situations where those environmental influences accumulate, the drowsiness measure can be affected to an extent that leads to false triggering of the system. Therefore, we suggest measures that can be taken to reduce the influence of steering patterns that are not related to the driver's drowsiness state.
The aim of most drowsiness detection systems is to inform a driver when his state has reached a critical level and to motivate him to take appropriate measures. This presupposes confidence in the system. False warnings will negatively affect the credibility of the system.
Our purpose is to show the importance of enabling this kind of system to recognize external influences, thus making detection more robust. We consider it very important to make such systems as reliable and credible as possible, as otherwise the driver will not take the advice the system will give him. Limiting the influence of external factors is a key to achieving this goal.

INTRODUCTION

Numerous reports name drowsiness and distraction as the cause of alarming numbers of accidents. The National Highway Traffic Safety Administration (2010) reports that in 2009 16% of all fatal crashes in the United States involved distracted driving. As regards drowsiness, Horne and Reyner (1995) found that 20% of all accidents on motorways in Southwest England to which the police was present were sleep-related. According to Langwieder et al. (1994), 24% of all fatal crashes in Bavaria, Germany, in 1991 happened because the driver fell asleep. NHTSA (Royal, 2002) reports 56,000 crashes annually to be related to drowsiness as mentioned by the police, resulting in 1,550 fatalities. In the same report, NHTSA lists reasons why these numbers are presumed to be conservative. Furthermore, crashes due to drowsiness tend to have a severe outcome (Wang et al., 1996).
The focus on the topic is still increasing. NHTSA names distracted and drowsy driving as one of the traffic safety problem areas (Goodwin et al., 2013) and the Euro NCAP 2020 Roadmap aims to reward manufacturers in the area of driver state monitoring in order to bring down the numbers of vehicles departing the road (European Car Assessment Programme, 2014).

A lot of research has been conducted in the field of drowsiness recognition and in the last years several commercial systems have become available on the market, using different methods. Dong et al. (2011) and Platho et al. (2013) give an overview of driver monitoring systems and also mention the commercial products of Ford, Mercedes-Benz, Volvo and VW. All those systems aim to suggest the driver to take a rest when he has reached a critical level. Many different algorithms were developed that analyze the driving performance, e.g. based on steering behaviour or lane keeping ability. These algorithms normally detect drowsiness if the driver shows an unusal driving behaviour (e.g. leaving the lane too often) or if the driving behaviour changes significantly from the beginning (e.g. lane keeping ability decreases).

A problem of methods that use driving performance as criteria for drowsiness detection is that only the reaction of the driver can be analyzed, not the reason for certain driving manoeuvers. Attwood (2014) mentions that systems, though they work in driving simulators, may fail on real roads, as they are not able to detect what the driver is responding to, considering environmental characteristics related to road, traffic and weather.

In the present paper we discuss which environmental characteristics may have an impact on driver monitoring systems. In detail, the influence of crosswind and road disturbances is analyzed and it is estimated to what extent those events have an impact on drowsiness recognition. Finally it is shown how these external factors are taken into account in the system under consideration.

The following evaluation is based on the steering wheel angle signal as the main information source. The main advantage of this method is that no special sensor, e.g. lane detection or driver monitoring camera, is needed. The steering wheel angle signal is part of the standard equipment of present-day cars. By this means, it is possible to integrate the drowsiness detection as a standard feature and thus reach a high number of drivers.

APPROACH

Steering wheel angle based drowsiness detection

Several studies investigating the use of the steering wheel angle signal for drowsiness detection have been carried out. Dingus et al. (1987) found that the number of steering wheel velocities over 150deg/s is an indicator for drowsiness. Bouchner et al. (2006) show a positive correlation of the ratio of fast and slow steering corrections with drowsiness.

A combination of slow and fast steering velocities is also used in this study. It is based on the Mercedes-Benz Attention Assist, which is a system that detects drowsiness and long-term distraction. Both kinds of driving impairment affect the steering behavior in a similar way. The steering pattern we evaluate consists of a deadband (phase without or with very slow steering) and a subsequent fast steering correction. Friedrichs and Yang (2010) show that this pattern correlates with drowsiness.
In our experience, steering velocities differ widely between drivers. Therefore, several thresholds in the algorithm are adapted continuously during the drive and according to the behavior in the first minutes of a drive, when the driver is presumed to be rather awake.
The accumulated steering pattern is the basis for the drowsiness measure. Figure 1 shows other factors that are taken into account to make the system more robust and useable in real road environment.

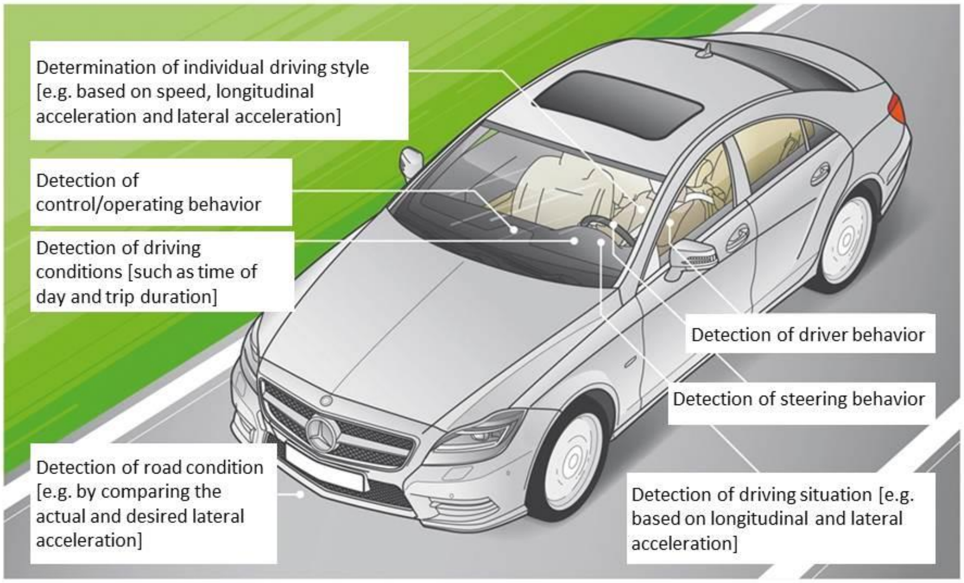

Figure1. Features of the Mercedes-Benz Attention Assist.

Situations potentially provoking steering patterns

Friedrichs et al. (2011) identified external influences on the driving behavior. We refer to the factors listed in that study and cluster them as shown below.

Gaze direction, distraction, vehicle operation. Factors describing different kinds of driver action. These include for example eating or drinking, which can lead to abnormal steering behavior as the driver does not operate the vehicle with both hands. It may also be the driver not keeping his eyes on the road because he is attending to his children on the back seat or reading messages on his smartphone. The steering patterns arising from these actions can be classified as indicators of distraction and are thus treated by the system in the same way as steering patterns evoked by drowsiness. Vehicle operations on the other hand are part of the driving task. They can be detected by the system and the related steering patterns can be filtered out.

Vehicle type/motorization, posture. Influences that can be summarized as characteristics of the vehicle and the driver. A key issue of these factors is that they normally do not change during a drive. Hence, adaptive systems are able to minimize the influence.

Rain/fog/snow, traffic density, lane width/-number, speed, curvature. Description of the driving situation. An impact on the driving behavior is probable. Those situations are usually of longer duration. Some of these situations can easily be detected with standard sensors, e.g. speed or curvature. Others are more complicated to be analyzed online, e.g. traffic density. Nevertheless, as the factors are usually of longer duration, adaptive algorithms can react on the change in an adequate time.

Road condition, road bumps, crosswind, warping. Single, strong events with sudden occurrence that may have immediate impact on the driving behavior. Crosswind often occurs unexpectedly, laterally displaces the vehicle and thus requires a fast counter-steering. Road bumps, warping or potholes can also lead to unintentional steering corrections. Steering corrections that potentially arise from these environmental influences are neither related to drowsiness nor to distraction and should therefore not be considered for driver state monitoring.

In this study, we concentrate on the environmental events and investigate the influence of crosswind and road irregularities (road bumps, potholes) in detail. Friedrichs et al. (2011) conducted special drives for their evaluation in order to keep the dimension of the influences as small as possible. In the following evaluation real road data from naturalistic driving is used. Some restrictions were made on speed range and rated drowsiness. Therefore, a much larger number of drives are part of the evaluation and the study of Friedrichs et al. (2011) is extended towards real driving situations.

Recognition of environmental influences

A prerequisite for all further evaluation is the ability to detect the presence of environmental influences. The detection of potholes and road bumps is based on an algorithm that looks for characteristics in the rotational speed of the wheels. The occurrence of crosswind is detected by comparing the steering angle, which provides information regarding the driver's intention, to the lateral acceleration, which supplies the actual lateral vehicle movement. This approach of crosswind detection also includes the recognition of road warping. Often a mixture of road bumps and warping occurs, which means that the detection of crosswind, warping and road bumps is not always separable. Hence, some events are recognized by both algorithms. All signals mentioned are available in standard equipped cars.

The algorithms described have been extensively proven in real world drives. For the following evaluations, the results of those algorithms have been used as labels for the presence of environmental influences.

EVALUATION

Underlying Database

All data used comes from naturalistic drives. Driving simulator data is not included. The database comprises more than two million kilometers conducted by more than one thousand drivers. Self-rating of driver drowsiness is available for each drive. This rating has been conducted according to the Karolinska Sleepiness Scale (KSS) (Âkerstedt & Gillberg, 1990). Every single drive has undergone a validation process to make sure quality standards like consistent values of the KSS-rating are fulfilled. All drives come from Mercedes-Benz cars, but have been conducted in different models from the A-Class (compact car) to the S-Class (luxury large car).

Evaluation of steering behavior

Prior to the investigation of the occurrence of steering patterns, a more general look at the steering behavior was taken. Steering velocities were explored regarding the influence of crosswind or road bumps.

As there are significant differences in steering behavior between individuals the analysis was conducted separately for single drivers. From the entire database, the ten drivers with the largest amount of recorded data were selected. Since Friedrichs et al. (2011) have shown that speed has a strong impact on the steering velocities, distributions of this signal in different speed ranges were compared for single drivers. Afterwards, the speed range under consideration was limited to velocities between 100km/h and 200km/h, as the signal values vary more at lower speeds. In addition, only parts of the drives were considered in which the driver was awake and alert.

For each drive of the ten selected drivers the ratio of the presence of crosswind to the duration of the whole drive in the considered speed range was calculated. The lower quartile Q_1 and the upper quartile Q_3 of this ratio were then used for each driver to group his measurements into rather smooth drives (*group 1*) and drives under windy conditions (*group 2*). The same was done for proportions of the presence of road bumps and warping. Accordingly, *group 1* comprises smooth drives and *group 2* drives on roads with frequent disturbances.

Subsequently, mean (*mean*) and variance (*var*) of the steering wheel velocity (*swv*) of each group of drives was calculated.

Table 1 shows the results for the crosswind comparison. The calculated ratios are defined according to Eqs. (1-2).

$$ratio\ mean = \frac{mean(swv)_{group2}}{mean(swv)_{group1}} \tag{1}$$

$$ratio\ var = \frac{var(swv)_{group2}}{var(swv)_{group1}} \quad (2)$$

From the values in Q_1 and Q_3 it can be seen how much crosswind was present in *group 1* and *group 2*. The interquartile range IQR shows how strong the two groups differ in their amount of crosswind.

It can be seen from the table that driver A sticks out, having the highest *ratio mean* and *ratio var*, which means that the mean value of his steering velocity is higher for drives under windy conditions while also the distribution is spread more widely. In comparison, for driver E both ratios are still greater than one but with much smaller values. Hence, this driver also has higher steering velocities with a higher variance for his drives of *group 2*, but the effect is less marked than for driver A. A look at the quartiles gives an explanation for this difference. The value of Q_3, which is the threshold for drives under windy conditions, is much higher for driver A than for driver E, while Q_1 is the same for both drivers. Thus, data from more windy conditions is existent for driver A than it is for driver E, which results in a higher effect on the steering velocities.

In summary, for all drivers the mean value and the variance of *swv* is higher for drives of *group 2* than *group 1*. A look at the individual thresholds Q_1 and Q_3 and the IQR shows that this effect is stronger for individuals for which a greater difference in the ratio of crosswind occurrence is present. Taken together, these results reinforce the expectation that higher steering velocities occur with environmental disturbances.

Table1.
Comparison of steering velocity mean and variance for drives with different ratios of crosswind occurrence.

Driver	**data selection**	**number of drives**	**evaluated time [min]**	***mean(swv)* [°/s]**	***var(swv)* [°/s]**	***ratio mean***	***ratio var***	Q_1	Q_3	***IQR***
A	Group 1	79	6369	1.00	2.17	2.84	10.06	0.03	0.13	0.10
	Group 2	79	4420	2.84	21.79					
B	Group 1	44	3608	1.44	4.04	1.41	1.92	0.03	0.10	0.07
	Group 2	44	2751	2.04	7.75					
C	Group 1	43	3879	1.38	3.18	2.01	3.18	0.03	0.18	0.15
	Group 2	43	2234	2.78	10.12					
D	Group 1	87	7276	1.72	4.12	1.93	4.51	0.03	0.11	0.08
	Group 2	87	4668	3.33	18.56					
E	Group 1	37	2942	1.27	2.86	1.18	1.22	0.03	0.07	0.04
	Group 2	37	2923	1.51	3.48					
F	Group 1	39	2766	1.68	4.37	1.19	1.46	0.02	0.04	0.02
	Group 2	39	2832	2.01	6.38					
G	Group 1	44	4110	1.09	1.94	1.19	1.48	0.02	0.06	0.04
	Group 2	44	2636	1.29	2.88					
H	Group 1	47	3203	1.22	2.72	1.27	1.53	0.03	0.09	0.06
	Group 2	47	3017	1.54	4.14					
I	Group 1	29	1768	1.28	2.64	1.22	1.42	0.02	0.06	0.04
	Group 2	29	2335	1.57	3.75					
J	Group 1	36	3872	1.04	1.81	1.27	1.63	0.02	0.07	0.05
	Group 2	36	2346	1.32	2.95					

The same procedure was applied for the presence of road disturbances. The result is presented in Table 2. Though not as definitive as for crosswind, the findings are the same. For all drivers, both mean and variance of the steering velocity are higher for data of *group 2*, which are the drives with a high amount of road disturbances. The tendency of a higher portion of road irregularities leading to higher mean values and higher variance of the steering wheel velocity can also be observed: driver I has the smallest IQR, which means the difference of the ratio of road disturbance occurrence between his drives in *group 1* and *group 2* is smaller than for the other drivers. This explains why the mean steering velocity differs less between *group 1* and *group 2* than it does for example for driver D, whose drives in *group 2* feature a larger ratio of road irregularities.

Table2.
Comparison of steering velocity mean and variance for drives with different ratios of road bumps occurrence.

Driver	**data selection**	**number of drives**	**evaluated time [min]**	***mean(swv)* [°/s]**	***var(swv)* [°/s]**	***ratio mean***	***ratio var***	Q_1	Q_3	***IQR***
A	Group 1	79	6701	1.01	2.15	2.47	8.46	0.03	0.18	0.15
	Group 2	79	5487	2.51	18.22					
B	Group 1	44	3040	1.53	4.20	1.43	2.06	0.03	0.13	0.10
	Group 2	44	2464	2.19	8.66					
C	Group 1	43	3849	1.62	3.98	1.50	2.14	0.04	0.23	0.19
	Group 2	43	2504	2.42	8.54					
D	Group 1	87	6853	1.82	4.47	1.65	3.59	0.03	0.14	0.11
	Group 2	87	5824	3.00	16.04					
E	Group 1	37	2991	1.27	2.89	1.18	1.24	0.07	0.18	0.11
	Group 2	37	2875	1.50	3.60					
F	Group 1	39	3068	1.76	5.01	1.01	1.07	0.04	0.10	0.06
	Group 2	39	2315	1.78	5.35					
G	Group 1	44	3762	1.05	1.94	1.22	1.40	0.02	0.10	0.08
	Group 2	44	2160	1.28	2.71					
H	Group 1	47	3542	1.33	3.28	1.10	1.05	0.02	0.10	0.08
	Group 2	47	3155	1.47	3.45					
I	Group 1	29	2163	1.37	3.04	1.06	1.14	0.02	0.08	0.06
	Group 2	29	1859	1.46	3.45					
J	Group 1	36	3647	1.05	1.92	1.11	1.19	0.03	0.09	0.06
	Group 2	36	3382	1.17	2.28					

Evaluation of the occurrence of steering patterns

To find out whether there are peculiarities in the number of steering patterns with the presence of crosswind, all time instances of onsets of crosswind in the speed range 60-200km/h were identified for 11,604 drives. Afterwards a time range of ten seconds before and ten seconds after those time instances was investigated for steering patterns.

Figure 2 provides the cumulated result for all time instances in which crosswind was detected. Zero on the time axis marks the beginning of crosswind. As the duration differs, the red vertical line marks the median of the end of the detected crosswind. The number of steering patterns have been counted and plotted at their instant of occurrence, relative to the beginning of crosswind and normalized with the number of crosswind events. As can be seen, in general the number of steering patterns moves around a certain level. After the onset of crosswind, a very strong rise can be observed. The subsequent lower amount is attributable to the violation of the deadband criteria caused by the counter-steering. It is apparent from this data that more steering corrections are produced under the influence of crosswind.

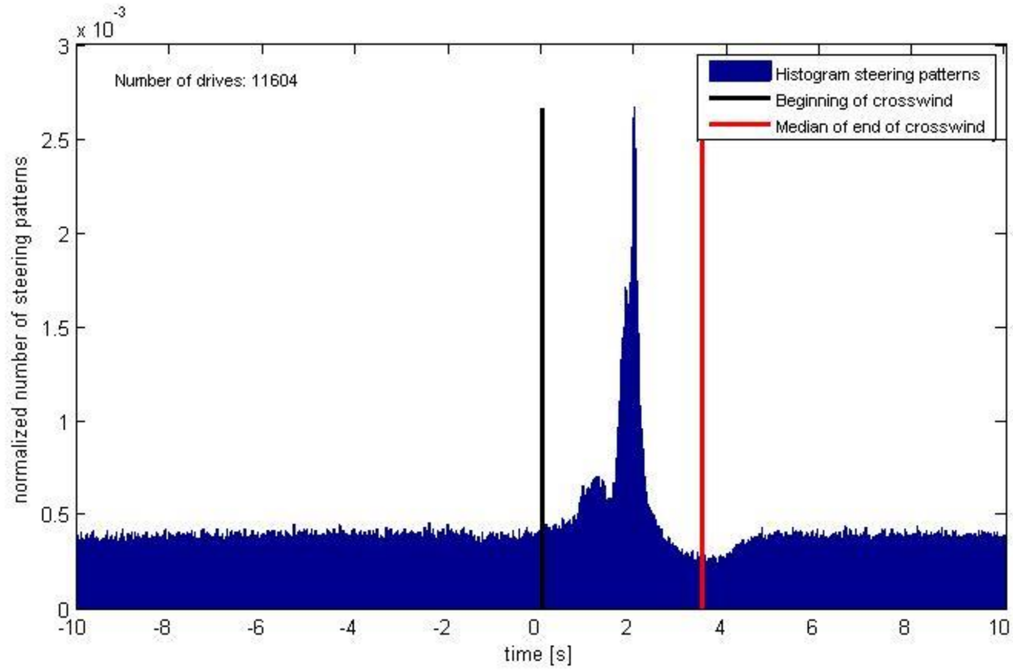

Figure2. Histogram of steering patterns around crosswind events.

The same procedure was applied for road surface irregularities. The results obtained from 11,638 drives are shown in Figure 3. The observation is the same as for crosswind. The number of steering patterns varies little around a certain level and increases strongly when road bumps occur. It is thus confirmed that road disturbances can lead to steering corrections.

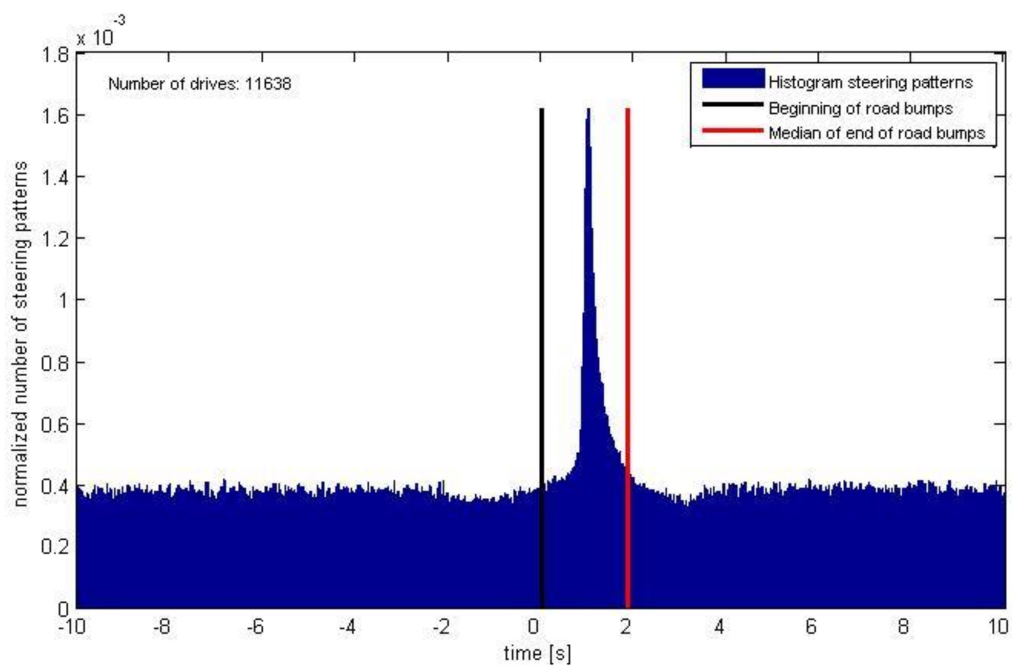

Figure3. Histogram of steering patterns around road disturbances.

Quantification of influence on drowsiness detection

The previous evaluation proofed that environmental characteristics can evoke steering patterns. In the next step the dimension of the influence on a possible drowsiness measure was estimated. Based on this final evaluation it could be determined whether environmental influences present a severe problem or if effects are minor and can be neglected.

This estimation was performed by calculating the factor by which the number of steering corrections increases if environmentally influenced ones are taken into account. Only data was used, in which the driven speed lay for at least 30min in the range of 60 to 200km/h. This led to 6075 evaluable drives. For each drive, the ratio of the amount of steering corrections that were detected during the presence of crosswind to the amount of steering patterns that occurred when no environmental disturbances were present was calculated. The result shows by which factor the number of steering patterns would increase if those evoked by crosswind were ignored. It also represents an estimation of how much a drowsiness measure, based only on a summation of steering patterns, would be affected.

The same principle was applied for the computation of the increase of steering patterns as a result of road disturbances. Figure 4 presents the distributions of the results for both kinds of environmental influences in a boxplot. A factor of increase of one means that the number of steering patterns would double by taking into account the environmental disturbance-evoked ones. For a better readability, only values up to 1.5 are shown. This was done due to some striking outliers, which may occur for special driving conditions, e.g. extraordinary windy conditions.

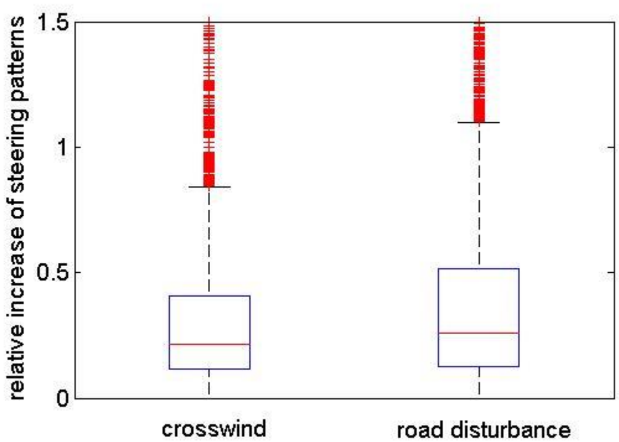

Figure4. Increase of number of steering patterns with environmental disturbances.

The median for the factor of increase on account of crosswind lies at a value of 0.215, due to road irregularities at 0.258. As explained before, the crosswind recognition and the detection of road bumps may sometimes be effective for the same events, thus it has not to be assumed that both factors of increase would add up. But, for half of the drives in the existing database, a possible drowsiness measure increases by more than 20% even regarding only one of the influences, which may indeed lead to false warnings. The problem is less severe for drives under smooth conditions and more severe if more disturbances occur. Figure 5 shows that the rise of steering patterns and the relative amount of crosswind is highly correlated, as can be expected. The same observation can be made for road irregularities, as shown in Figure 6. Especially for drives under more extreme conditions, measures have to be taken to increase the robustness of the drowsiness recognition system to prevent false alarms.

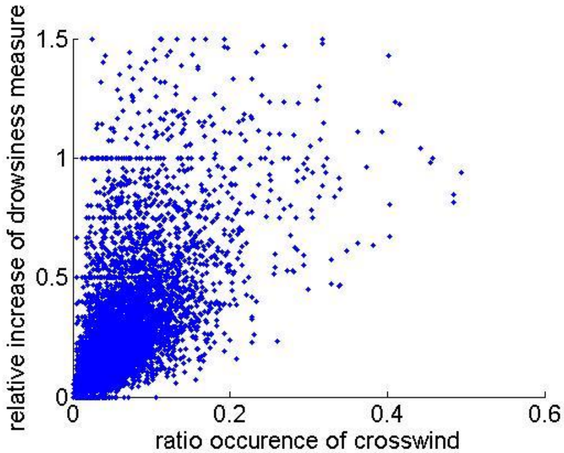

Figure5. Relation between amount of crosswind and increase of steering patterns.

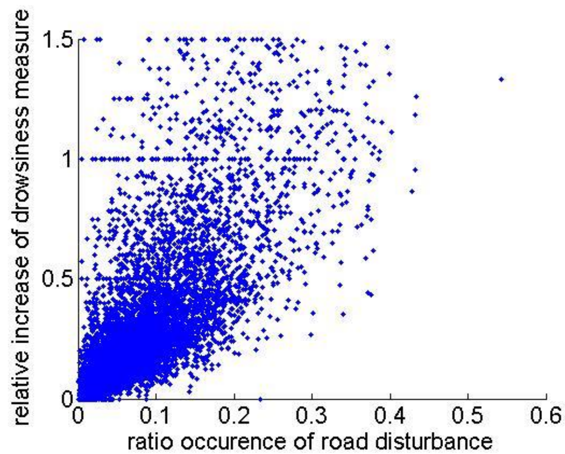

Figure6. Relation between amount of road disturbances and increase of steering patterns.

PROPOSAL OF MEASURES

The evaluations show that the impact of environmental influences on steering pattern based drowsiness detection systems is too strong to be neglected. In the following we propose measures that increase the robustness as they are implemented in the Mercedes-Benz Attention Assist system.

Masking

In the first step, steering corrections evoked from events like crosswind or road bumps are left out of the estimation of drowsiness. A prerequisite for this is the possibility of recognizing such disturbing influences. Not to consider those steering patterns means that the system cannot evaluate the driver's steering behavior during the presence of the environmental disturbance. This leads to some kind of system inactivity. Inactivity due to environmental influences is of short duration. Figure 2 and Figure 3 depict the median of the duration of disturbing environmental events, about 3.5s and 2s respectively. In our database, crosswind led to 4.3% of overall system inactivity, while masking due to road disturbances concerned 6.2% of all data. Both values were obtained from data in the speed range 60-200km/h. Hence, the inactive periods have only minor influence on the overall system performance.

If the system is inactive for a long time, we recommend letting the driver know that he cannot expect it to work without restrictions. This is for example the case if the system works only in a certain speed range. Transparency, such as displaying inactivity, can lead to better understanding and thus more trust in the system.

Adaption

While masking is effective for determined events, another measure is needed for all non-specific influences that cannot be detected as single environmental events can be. Increased robustness can also be achieved by making algorithms adaptive, not only to the driver but also to changes in the driving situation that cannot be attributed to special events. For example thresholds for the recognition of steering patterns should adapt during the whole drive.

CONCLUSIONS

The purpose of the current study was to determine the necessity of making driving-performance based driver state monitoring systems, especially those that rely on steering patterns, robust against environmental influences. The results of the investigations have shown that environmental influences have a significant impact on the steering behavior and can lead to steering patterns that are not related to drowsiness or distraction.

It has also been found that the number of unwanted steering patterns cannot be disregarded. The influence on the drowsiness measure is significant, especially with higher presence of disturbances. The implementation of possibilities to detect environmental events and ignore the consequent steering corrections helps to achieve better performance of such systems in real road scenarios. The performance can be further improved by designing adaptive algorithms, e.g. by fitting certain parameters to the special driving situation.

The effectiveness of drowsiness detection systems that are limited to give advice depends on the driver's confidence. An increase in the drowsiness measure because of environmental influences can lead to false triggering of the system and thus to the driver not taking it seriously.

The presented method of evaluating influence of certain events on drowsiness detection algorithms can also be used to study the effect of other events, e.g. certain vehicle operations. It allows estimating the scale of the effect and helps deriving measures to decrease the negative consequences on the system performance. The method shows especially an efficient way to extract this information in a huge amount of existing real road data.

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