Consideration of Influences on Driver State Classification

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Abstract

Objective: This article aims on finding all influences that impair the driving performance in a similar way as drowsiness or distraction. The goal is to consider these influences such that driver state classification systems become robust against these factors. Such factors are for instance road condition, road curvature, cross-wind, vehicle speed and construction sites. **Background:** Driver warning systems aim to reduce drowsiness-induced road-crashes as a major cause of severe accidents by analyzing the driving performance using standard equipment sensors. These systems inform fatigued or inattentive drivers about their driving performance by an online bargraph or by issuing a warning that proposes to have a pause. **Method:** Special driving experiments have been conducted in order to isolate single disturbing factors. Methods to extract measures for these factors from the recorded data are presented. The measures are analyzed for their correlation with the driving behavior. **Results:** The relationships between measures for influencing factors and the driving performance are presented and discussed. **Conclusion:** Compensating influences from real driving conditions is an even more challenging task than the detection of sleepiness patterns. This topic is crucial to optimize the performance of driver state classification systems. The presented work shows the relevance of considering such factors. We show the potential to further investigate this topic and validate the results with a larger set of experiments.

INTRODUCTION

According to the National Highway Traffic Safety Administration (NHTSA, VTTI), nearly 80% of the crashes and 65% of near-crashes within three seconds before the event involve some form of driver inattention (Martin, 2006). Distracting activities, such as cell phone use, and drowsiness are beneath the primary causes. Experts assume that about up to one third of the severe accidents are related to drowsiness (Duncker, 2007; Künzel, 2008; Daimler, 2008; Fertner, 2009).

Driver warning systems, such as the Mercedes-Benz ATTENTION ASSIST or Volvo Driver Alert Control aim to reduce fatigue related road-crashes by monitoring the driving performance using today's standard equipment sensors. These systems issue a warning to fatigued drivers and/or

display an online bargraph of the estimated driver performance. The current work aims to improve the accuracy of such a system by reducing the sensitivity of disturbing factors that falsely induce reduced driving performance. The database used within this project (courtesy of Mercedes Benz) covers over 1.4 million kilometers of testdrives under real driving conditions with several thousand recorded vehicle signals.

As reference, the drivers rated their own fitness according to the Karolinska Sleepiness Scale (KSS) (Åkerstedt & Gillberg, 1990). The blinking behavior and the Electroencephalogram (EEG) are also recorded for a large number of drives.

This article refers to measures (*features*) for detecting driver attention that we proposed in Friedrichs & Yang (2010b). About 200 features have been derived from the vehicle signals originating from the steering wheel angle sensor, yaw rate sensor, vehicle speed sensors, acceleration sensors and the lane tracking camera. Over 100 vehicle signals are taken into account. Individual driving styles are learned and adapted within the first minutes of the drive.

Whereas most studies in literature are based on a small set of driving simulator data and test drives under restricted conditions, this work focuses on a large number of drives under real traffic driving conditions.

Motivation

The left picture in Figure 1 shows a driver in a modern driving simulator. The right picture shows a test drive with a real vehicle. In both cases, the patterns caused by a drowsy driver are sim-
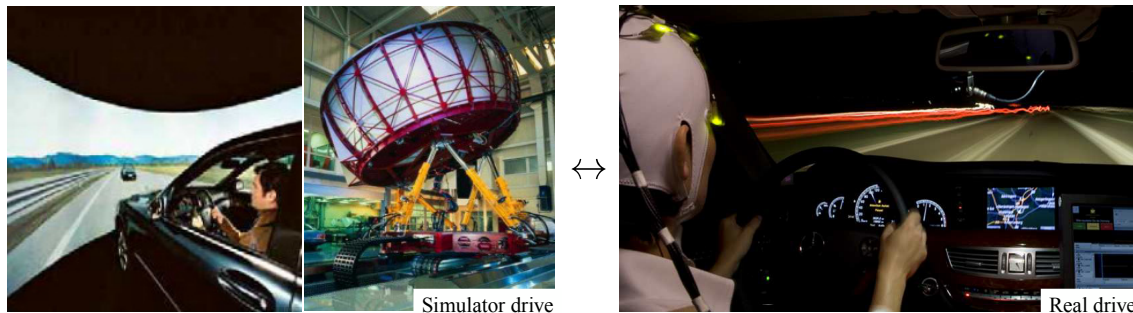

Figure 1. The difference between driving in a simulator (left) and under real conditions (right).

ilar and the basic idea behind approaches to detect them are the same. However, if the approaches from the simulator are directly transfered to the real driving environment, the classification performance is inferior. The reason for this is that influences from road condition, cross-wind etc. have a similar impact on the driving performance as sleepiness. Even the most advanced simulators cannot model such realistic driving conditions comparably to real world driving. Moreover, not only measures used for driver state estimation are affected by real-world influences, but also signals used in the drowsiness reference generation (like EEG or blinking based measures).

Finding a measure that is only sensitive to sleepiness while being completely independent of other factors still is an unsolved research topic of paramount importance. Eye-tracking devices that are monitoring sleepiness by a subject's blinking behavior (as described in Friedrichs & Yang (2010a)) are quite independent of such driving influences. However, eye-tracking requires an expensive camera setup and suffers from other problems, like varying lighting conditions, head movements or subjects wearing glasses. If we consider the lane deviation to measure the driver's level of

fatigue, the measure also varies if there is cross-wind, curves, road warping and so on. In practice, many of the drowsiness-related patterns vanish in the sum of all these other driving effects.

The idea behind this article is to find a measure for each of these driving factors in order to analyze and understand the relationship between these factors and the drowsiness measures. In order to facilitate the analysis and to be able to conduct controlled experiments, we are making the assumption that these factors can be taken into account independently of each other in order to compensate or suppress them. Thereby, the measures become less sensitive from these influences. This is one of the most important keys for a high performance and robustness of a drowsiness detection system under a broad scope of real driving conditions.

External influences

Figure 2 illustrates the most important factors that affect the driving style within every-day driving situations. The influence of individual driving styles is also not discussed here and was
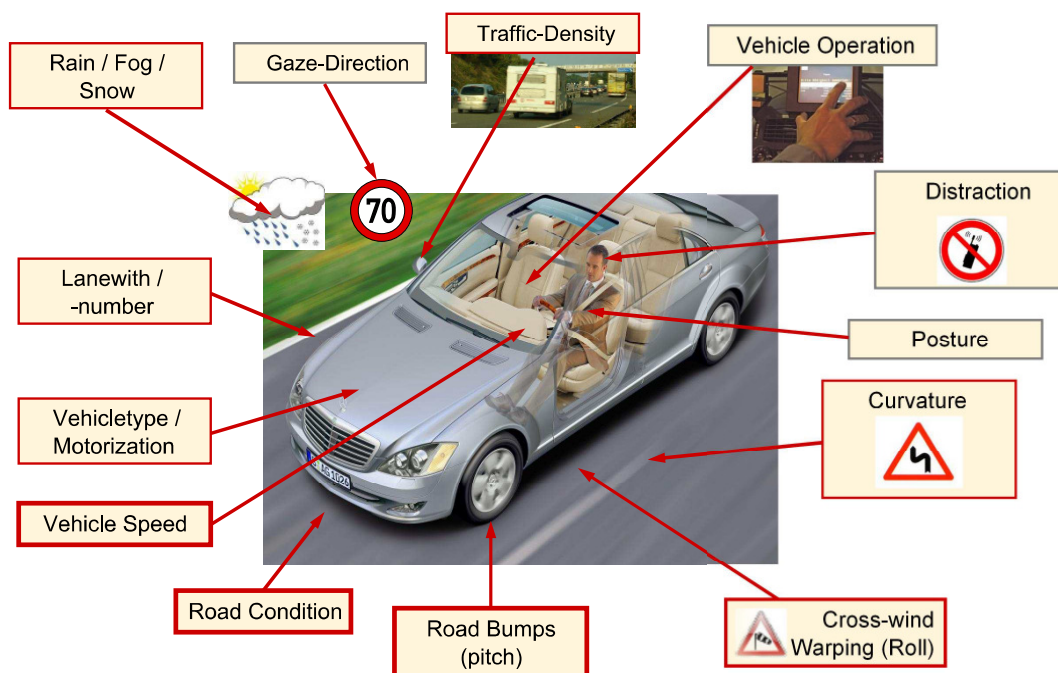

Figure 2. External influences on the driving behavior

studied in Gärtner (2009). The driver's daily mood (e.g. if he is driving calm/sporty) is another factor which is difficult to classify and discussed in works, like Kuhn & Heidinger (1997). The way that drivers hold the steering wheel (e.g. with one or two hands) was also observed to have an influence on the steering behavior. However, additional sensors would be required for the detection and therefore this is not considered here.

In this article, new methods are presented to detect road bumps, traffic density and cross-wind. Specific test drives have been conducted at night to vary only one isolated factor while keeping the others constant. Such constant factors were for instance the driver condition, traffic density, overtaking maneuvers, vehicle speed, road curvature, road bumps, vehicle parameters, cross-wind as well as precipitation and light conditions. The detection methods have also been implemented in

real-time to evaluate the performance while driving in different situations. In the offline analysis, the correlation between the varied factors and sleepiness features extracted for this road section were evaluated. This paper emphasizes the importance to consider driving influences in driver monitoring. For many factors we present methods to detect them and take them into account to achieve better classification performance.

Methodology

The goal of this work is to find a single measure for most of the thirteen factors from Figure 2. Hereby, the simplest factor is the vehicle velocity, which is already represented by its speedometer signal. However, measuring the curvature or road condition is not as simple. If we consider these thirteen dimensions, it's obvious that it's impossible to record drives for every combination of these factors. This means that we can only analyze each measure isolated from others. Thereby we assume that superposition applies, i.e. that factors overlay and the combination can be approximated linearly. Fortunately, it is quite rare that multiple factors occur at the same time. For instance it is not very probable that a driver is driving on a construction site that is curvy, with cross-wind etc.

The next step is to analyze the relationship of the measures for the factors with the features that are supposed to correlate with sleepiness. In general, it is easier to compensate the measured input signals rather than every feature individually.

INFLUENCES OF EXTERNAL FACTORS ON THE DRIVING BEHAVIOR

This section will provide an overview of the most relevant external factors. Details about the detection are proposed and illustrations are given for important examples. Due to the number of influences, providing details for all measures would exceed the scope of this article.

Distraction and Vehicle Operation

In general, drivers accept distraction in situations which they consider as safe enough to perform other tasks beside driving. Drivers can interrupt their side-activities if a traffic situation requires them to. However, they cannot easily "switch off" their sleepiness. Thus, it is helpful to distinguish drowsiness from acceptable short term distraction (e.g. by vehicle operation) or long-term distraction such as phone calls or discussions with the co-driver. Also the operation of the levers close to the steering wheel or the manual shifting can result in steering errors. Distraction by vehicle control can easily be detected from the vehicle signals of buttons and levers. Discussions on the phone can only be detected if they are performed over the hands-free head-unit. The intensity of the distraction can be estimated using an low-pass filter as presented in Friedrichs & Yang (2010b). For simplicity, steering operations or lane exceedings during intensive short-term distractions can then be suppressed from drowsiness detection.

Rain, Snow, Fog, Light Conditions and Tunnels

It was observed that the driving behavior changes severely during heavy rain or snow fall. Usually the steering becomes more hectic and the driver has to concentrate more. This influence is refreshing in the beginning but can become even more exhausting after a while. Rainfall and foggy weather usually require the driver to slow down. As illustrated in Figure 3, rain can be detected well by the rain sensor and the windshield wiper lever position. It was observed that reduced

Figure 3.   Windshield wiper lever position on the route for rain and snow detection

vision due to dark lighting conditions also affects the steering and lane keeping performance for several persons even if they are awake. These drivers need to concentrate more than during the day. This can be quite exhausting after a while. The light level can again be detected well through the light sensor. Illuminated tunnels or other road sections provide a certain degree of *novelty* to the driver and usually improve his level of attention. Tunnels can be detected well by looking for fast changes in the light sensor signal. For simplicity, sections with intensive rain, fog or snow are simply suppressed here and treated as system inactivity.

Vehicle Speed

The vehicle velocity has a big influence on the steering velocities and the necessary reaction times to vehicle displacements. The time remaining to react, when heading towards the lane markings at high speeds is of course shorter than for lower speeds. Thus, it is mandatory to consider the vehicle speed during the generation of features.

Database. In order to evaluate the speed dependency, drives have been recorded where all factors were held constant except the vehicle speed. A 20 km section on a German autobahn was driven multiple times by the same driver with a Mercedes-Benz S-Class at different speeds. The speed was varied sequentially from 90, 110, 140 to 180km/h. The drives took place between 2 and 5 a.m. such that lane changes and interferences by traffic and trucks could be kept at a minimum. With the low traffic, the speed could be kept very constant without the use of a cruise control. The drivers rested well for two days before the experiment, so that they were driving fully awake (KSS $\leq$ 5) at night. Furthermore, a specially trained co-pilot supervised the drives. The acceleration pedal, the turn indicator lever signal and the steering wheel angle have been used to detect the bounds of the drive. Overtaking maneuvers were suppressed in the same way.

Analysis. After extracting the features as described in Friedrichs & Yang (2010b) for the relevant road sections, some of the effects were very clear to see:
- The steering velocities increase almost proportional to the vehicle speed
- Also the steering amplitudes increased with increasing velocity

    ○ The number of overtaking increased from $2/h$ at 90 km/h to over $84/h$ at 180 km/h, even with the low traffic

    ○ The lane deviation remained approximately the same, just the lane oscillation frequency increased

    ○ The variance of the accelerator pedal increased as more gas is required at higher speeds to obtain the same acceleration

    ○ When driving with different speeds on the same road section, the frequency of curvature increases with higher velocity.

    ○ Similarly, on similar road sections, the lateral acceleration increases with higher speeds.

Figure 4 shows the steering velocities at different vehicle speeds. It can be seen that the signal values are much higher for higher speeds.
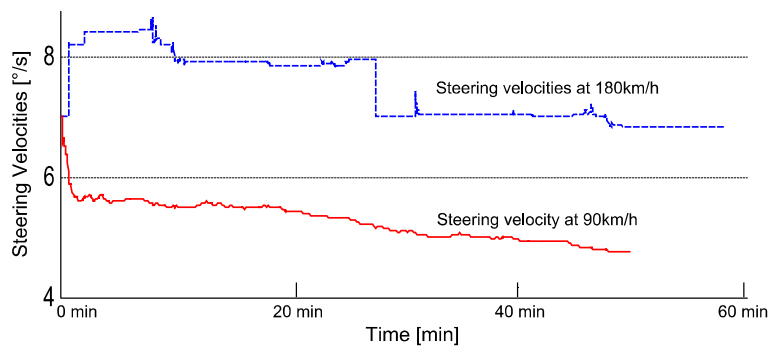

Figure 4. Steering velocities for difference vehicle speeds

    In the left, Figure 5 depicts the maximum steering velocity between inflection points. In the right, it shows the increasing lane deviation with increasing speed.
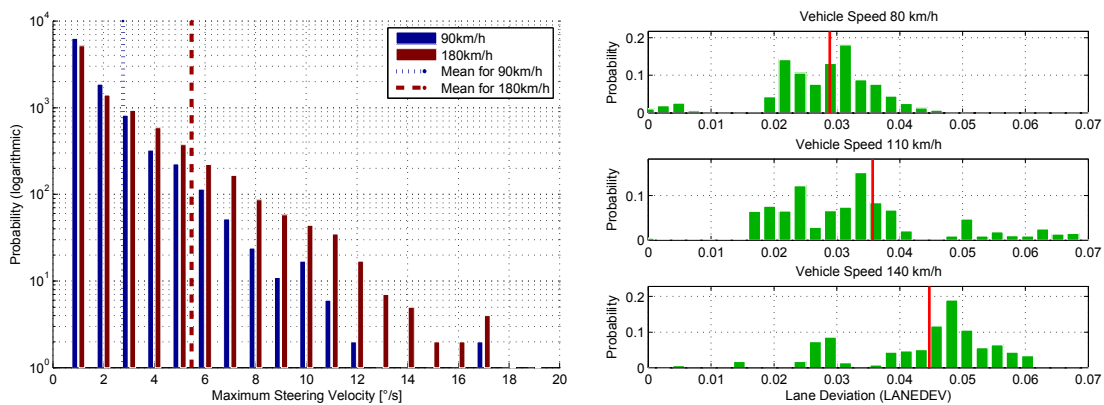

Figure 5. Vehicle speed dependency of the maximum steering velocity between inflection points

    Figure 6 shows the same principle for the steering jerk rate that severely increases with higher speed. One approach to compensate this signal derived from the steering wheel velocity is to divide the actual signal by the current vehicle speed $v(n)$.
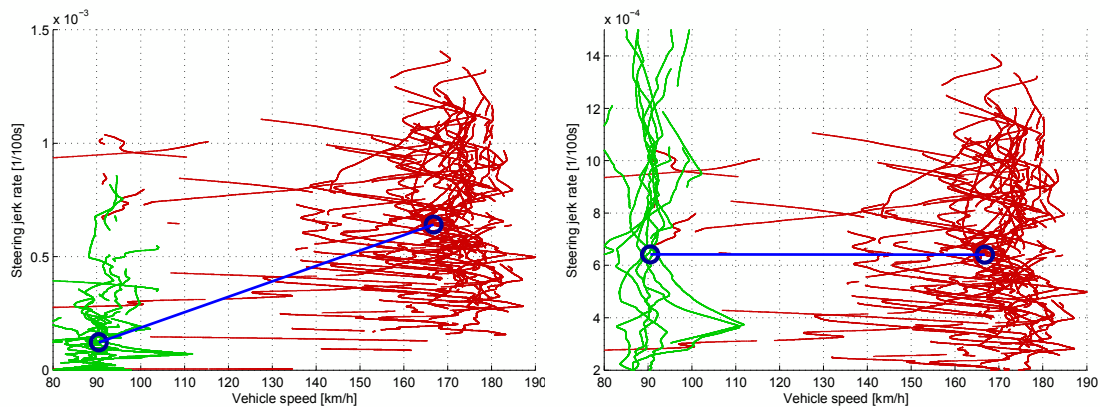
Figure 6. Vehicle speed dependency of the maximum steering velocity between inflection points

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Construction Sites and Narrow Lanes

Road construction sites are usually characterized by more narrow lanes and thus accompanied by more hectic steering. Lane exceedings are often not avoidable. Even if the speed limit is reasonably low, people in many countries tend to drive faster. For this reason, the following combination of criteria is used in the decision for the detection of construction site passages:

- Narrow roads: lane width $<$ threshold t_1
- Vehicle speed below 85km/h
- Bad lane quality signal from the lane tracking unit
- Specific lane colors (in Germany: white lane markings for regular roads and yellow for construction sites)

An implementation using fuzzy thresholds can make the detection more robust. For the evaluation, the same drives have been used as for road bumps explained on page 10. The classification of road construction sites was performed for the available drives and then projected to the coordinates where they occurred. The match was in average very good (over $\approx 90\%$). For simplicity, construction sites were suppressed and treated as system inactivity.

Curvature

In order to evaluate the influence of the road curvature, drives from a straight, softly and strongly curved road section have been selected. 27 drives were taken from a night experiment with an average speed of 130 km/h. All drives were conducted at night with awake drivers (KSS ≤ 5). In general, it was observed, that the transition from a straight road into a curve is often followed by steering adjustments that is more intensive than necessary. Figure 7 shows in the left how the lateral lane deviation increases for all drivers with increasing curvature. When comparing the results in Friedrichs & Yang (2010b), the correlation between the lateral lane deviation and the curvature appears stronger than the correlation between the lane deviation and drowsiness. On the right hand side of Figure 7, it can be seen how the fast steering velocities increase with raising curvature. The vertical line indicates the mean in each class.
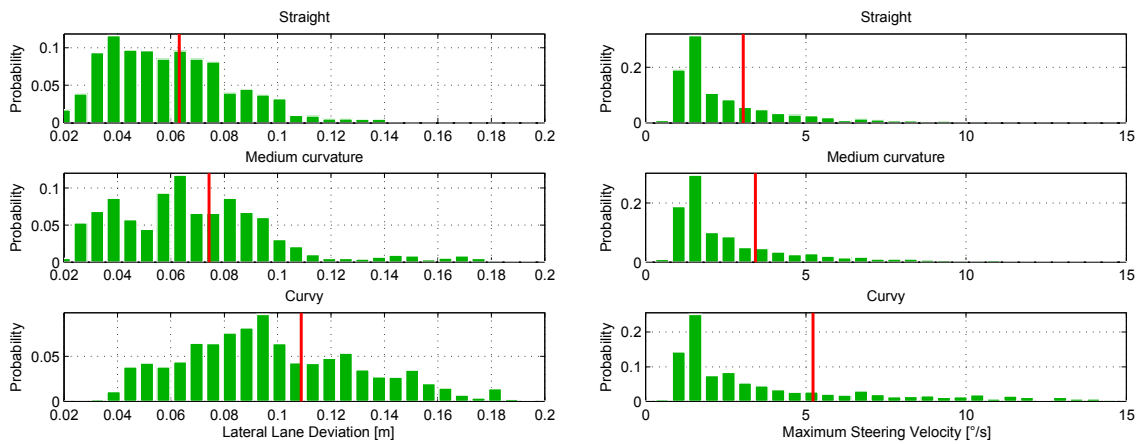
Figure 7. Curvature dependency of the maximum steering velocity between inflection points (Left: lane deviation; right: maximum steering velocities)

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Road Condition

The evaluation of the impact of the road condition covers different aspects:

- An average rate of road surface irregularities that lead to permanent disturbances
- Short road bumps that usually affect both wheels
- Road warping where the road changes its lateral inclination causing the vehicle to roll around the longitudinal axis

Database. In addition to the existing database with over 1.3 Mio km of real-world test drives, more specific drives had to be recorded in order to reliably set all but one factor to constant. After a validation process, 18 drives remained from two night experiments on a motorway. The average speed was 130km/h and the drivers were awake (KSS ≤ 5). As usual, there was a well trained co-pilot supervising the drives.

Regional Position Evaluation. Classification of road bumps and the road surface would be a straight forward task, if there was a good reference to assess the sensitivity and accuracy of these signals. One approach to evaluate the results is mapping road bumps to the world position where they occur. This is not solving the lack of a good reference, but shows at least the reproducibility of the measures. In order to plot a signal not over time but over a place or distance, Figure 8 shows different line segmentations as abscissas with their pros and cons. The solution used here as *x*-axis is a combination of odometric data corrected by an accurate GPS reference mapped to a 2D representation. The GPS reference was created as the average of all GPS tracks on this route.

Road pavement condition. The vehicle travels in general calmer on a new pavement than on an old, very dammaged road surface. These irregularities are usually not immediately realized by the driver but still result in small lateral displacements which the driver has to correct after a while. Roughly speaking, when a driver holds the steering wheel still, the vehicle stays longer within the lane, if the road surface is better. Estimation of a measure for the road condition can be done by detecting a simultaneous vibration in the inertial sensory from a shock through a road unevenness. In order to calculate the vibration from the shock on the sensor, the *exponentially weighted moving*
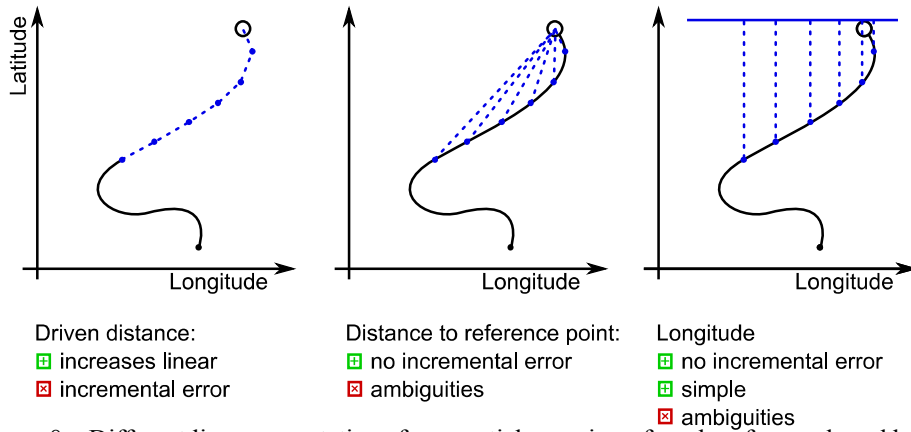
Driven distance:
⊞ increases linear
⊠ incremental error

Distance to reference point:
⊞ no incremental error
⊠ ambiguities

Longitude
⊞ no incremental error
⊞ simple
⊠ ambiguities

Figure 8.   Different line segmentations for a spatial mapping of road surface and road bumps

variance (EWVAR) can be calculated efficiently for sensors as explained in Equation (1) and (2):

$$\text{EWMA}_n = \lambda_\mu \cdot \text{EWMA}_{n-1} + (1 - \lambda_\mu) \cdot x_n \; , \tag{1}$$

with the initial value EWMA_0. The EWVAR is then approximated by

$$\text{EWVAR}_n = \lambda_{\sigma^2} \cdot \text{EWVAR}_{n-1} + (1 - \lambda_{\sigma^2}) \cdot (x_n - \text{EWMA}_n)^2 \; . \tag{2}$$

with the initial value EWVAR_0 and forgetting factors:

$$\lambda_\mu = \frac{N_\mu - 1}{N_\mu}, \qquad \lambda_{\sigma^2} = \frac{N_{\sigma^2} - 1}{N_{\sigma^2}} \; .$$

Figure 9 shows a general example of the EWVAR. The variance of all sensors can then be combined
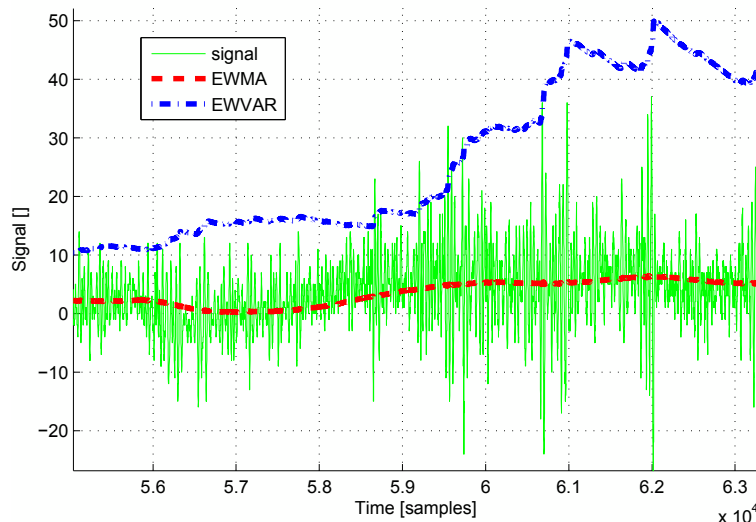

Figure 9.   General example of exponentially weighted moving variance

by multiplication to favor a simultaneous vibration. This makes it less sensible to other motion based signal variations and noise. An EWMA filter was then used to obtain the ratio signal over the last three minutes.
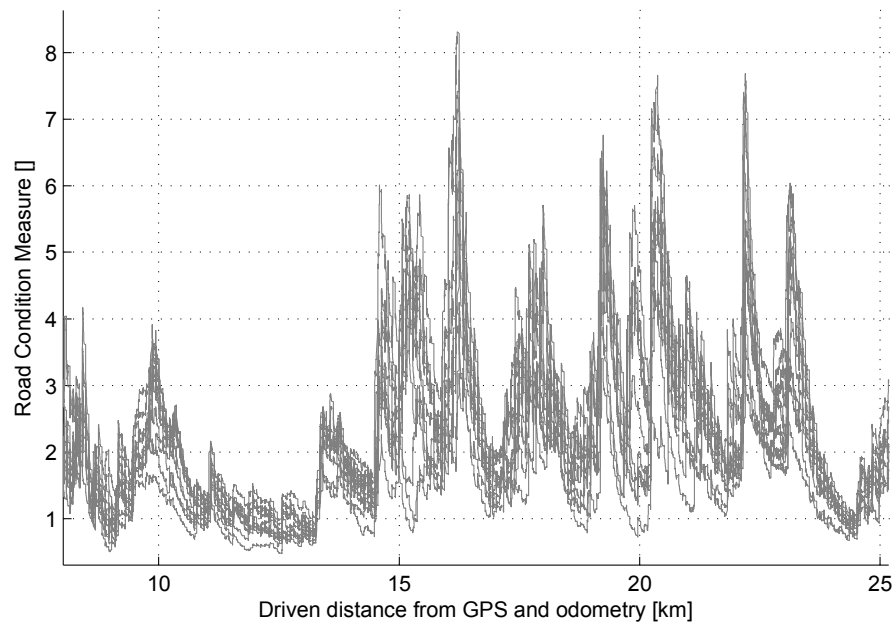
Figure 10. The road surface condition measure over driven distance for all selected drives

Figure 10 shows an overlay of the road surface condition signals over the driven distance for all selected drives. It is very clear to see, that all vehicles detect the road condition in the same way. However, Figure 11 shows that there is no immediate correlation between this road condition signal and the steering velocities. If we look deeper into this, we come to the detection of road bumps and the driving behavior, which leads us to the next section.
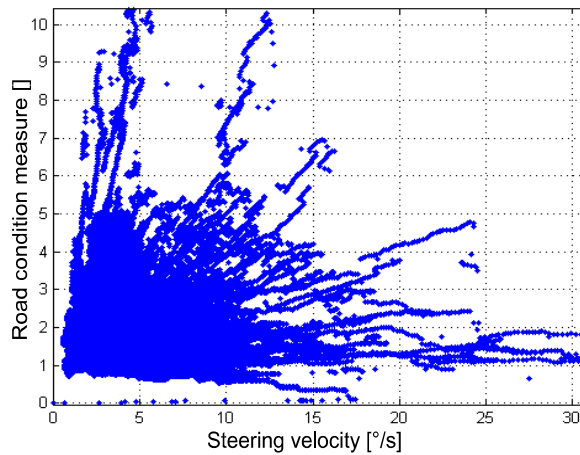

Figure 11. Weak correlation of road condition measure with steering velocity

Road Bumps. The signals used to detect road bumps are the same as for the road pavement detection. Road bumps are detected as peaks in the road surface condition signal without smoothing. Figure 12 shows a histogram of the delay between steering jerks and road bumps ($t = 0$). This proves that road bumps have an influence on the driving behavior since the distribution in the surrounding of road bumps would be uniform otherwise. The time delay obtained from this histogram was used for the compensation of road bumps in the extraction of features.
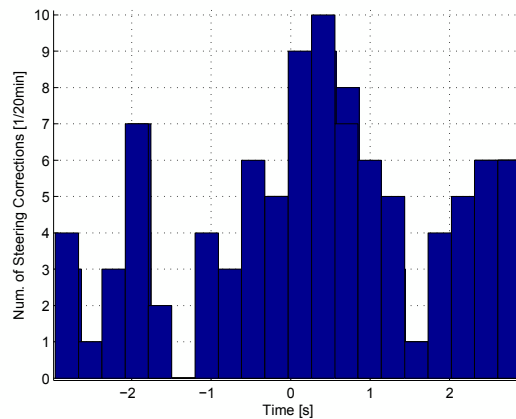
Figure 12. Delay between steering jerks and road bumps

CONCLUSION AND FUTURE WORK

We have shown that there are many influencing factors that have a strong impact on the driving behavior and thus impair sleepiness features. We proposed means to normalize features according to these influences. For instance the steering velocity highly depends on the vehicle speed and can be compensated quite well. As other examples, road bumps or overtaking maneuvers need to be suppressed individually for different features. There are many more effects that we could not discuss within the scope of this paper. This paper should also provide an impression of the large effort that is required for the recording of appropriate test data. Primarily, the examples made clear that the relationship between external influences and computed features is in many situations more severe than the impact of the sleepiness patterns. It would not make sense to compare the classification performance with and without consideration of such factors. Driver monitoring simply doesn't work without taking them into account. The latest classification results presented in Friedrichs & Yang (2010b) consider these factors as described here in more detail.

Future Work

More measurements need to be recorded in order to obtain more accurate models and parameterizations of external factors. Also the assumptions that the superposition principle holds for all factors needs to be validated on a larger dataset. The continued investigation of external influences to online driver state estimation is the key to good classification performance.

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BIOGRAPHIES

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Peter Hermannstädter received his diploma (Dipl.-Ing.) in Engineering Cybernetics in 2010 from the Department of Mechanical Engineering of the University of Stuttgart, Germany. Since 2010, he is a PhD fellow with the Institute of Signal Processing and System Theory at the University of Stuttgart. His present research is within the field of driver state monitoring for active vehicle safety.

Keywords

Distraction, driver attention, driver monitoring, road condition, driving influences, feature extraction, classification.

Precis

When performing driver attention classification under real driving conditions, the factors such as road condition, cross-wind, curvature, vehicle speed play a major role. Detecting these factors and considering them in feature extraction is a key to improve the classification accuracy.
(41 words)