DROWSINESS MONITORING BY STEERING AND LANE DATA BASED FEATURES UNDER REAL DRIVING CONDITIONS

Fabian Friedrichs, Bin Yang

Chair of System Theory and Signal Processing, University of Stuttgart
Pfaffenwaldring 47, 70550 Stuttgart, Germany, {fabian.friedrichs, bin.yang}@lss.uni-stuttgart.de

ABSTRACT

Experts state that driver drowsiness is responsible for about 30% of severe traffic accidents. Driver monitoring systems, such as the Mercedes-Benz *Attention Assist* aim to reduce these road-crashes caused by fatigued drivers using standard equipment sensors. In this article, new measures (*features*) for detecting drowsiness are proposed in addition to promising features in literature. Most studies in literature are based on driving simulator data, whereas this article focuses on real world driving. External influences such as road condition, road bumps and cross-wind are furthermore taken into account. The presented results are based on a large selection of the Mercedes-Benz drowsiness database which covers over 1.2 million kilometers of measurements. Features are analyzed for their correlation with the subjective Karolinska Sleepiness Scale (KSS). The performance of a combination of features is assessed by sophisticated classifiers and dimension reduction techniques. Even after these improvements, the classification results do not reach the results obtained in a driving simulator.

1. INTRODUCTION

The vast majority of road accidents are primarily related to mistakes by the driver. According to the 100-Car Study, performed in 2006 by the National Highway Traffic Safety Administration (NHTSA, VTTI) [20] drowsiness increases the driver's risk of a crash or near-crash by at least a factor of four. The NHTSA recognizes driver drowsiness as one of the major causes of single and multiple car accidents in the US. Drowsy driving is assumed to be significantly under-reported in police crash investigations (1-3% in [17]) as it can not be measured as easily as alcohol consumption for instance (breathalyzer). Experts assume that about 24-33% of the severe accidents are related to drowsiness, especially when the driver falls asleep and does not attempt to avoid the crash [5, 6, 15]. Truck driver fatigue is more prevalent than either alcohol or drugs in fatal accidents [12]. Young people under 30 are four times more endangered than elder groups [13]. Especially young males are involved in drowsy-driving crashes five times more likely than females [28]. Cold air, loud music and energy-drinks have not been demonstrated to reliably help against fatigue. Two cups of coffee have been shown to initially increase alertness after a break [19, 23]. The most effective countermeasure against sleepiness is sleeping, for instance by taking a 15-20 minutes break or letting a passenger drive [19].

1.1 Literature review

There were many studies about driver monitoring over the last decades. Most studies were based on data from driving simulator data since in-vehicle drowsiness experiments require a tremendous amount of efforts. Wierwille [8, 14] proposed a set of features based on driving simulator data. Schmitz [27] proposed improvements to suppress intended lane departures. Altmüller [2] analyzes the deadband rate in the steering velocity, based on 44 simulator drives. Berglund [4, 11, 21] used multiple regression on in-vehicle steering and lane data variables to accurately (87%) classify drowsiness, based on 22 truck simulator drives. Eskandarian *et. al.* [7, 25] found the steering activity and lane data, among other variables to be a good candidate to correlate with drowsiness using simulator data and artificial neural networks (ANN). They achieve an accuracy of 89% for the class *awake* and 85% for *drowsy*.

1.2 Objectives of the current study

- In addition to known variables in literature, introduce further drowsiness related features based on CAN-data.
- Propose more efficient feature extraction methods.
- A thorough investigation of their performance in a large number of realistic road drives.
- Adaption to varying driving styles and environment conditions.
- Propose a feature similar to *Degree-of-Interaction* but without the need of the steering moment and an alternative method for detecting zig-zag events [21].

1.3 Database

The database used within this study covers over 10 300 real drives with a total number of 1.23 Mio km (courtesy of Merceds-Benz). After filtering this database for drives over 30km, with valid and plausible self-rating (KSS), valid lane-tracking data and without measurement errors, 52 768km of real drives remained:

- 204 drives (45 by women; 36 night experiment drives)
- 10 vehicles (Six E- and four S-Class)
- 54 drivers

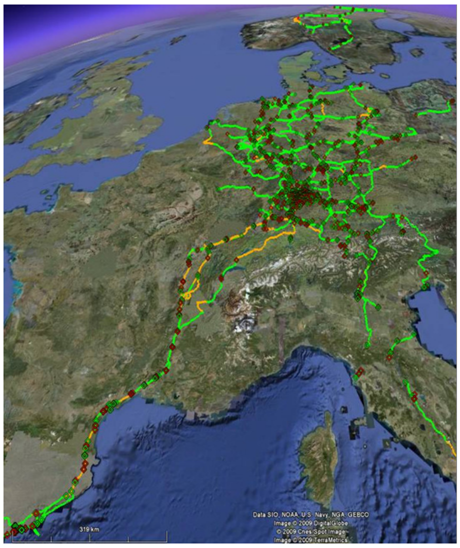

Figure 1: Map of drives: Green lines indicate *awake* driving sections, orange indicate *questionable* and red *drowsy* drives (see 2).

Fig. 1 shows a map with the drives in Europe. A typical night experiment is conducted on a low-traffic, monotonous motorway with limited speed from about 120 to 140 km/h. Drivers were monitored by specially trained supervisors, capable to drive the vehicle from the passenger seat with a second set of pedals [26]. The participant's self-rating (KSS), blinking behavior and EEG were constantly recorded and monitored. The drives were aborted with the onset of severe drowsiness according to the driver's responsibility or by the supervisor, based on fixed criteria. The rest of the drives were regular road drives with drivers well trained to estimate their KSS drowsiness level. There are big differences between free drives and simulator or night drives. The behavior in the simulator, un-

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der restricted conditions and under supervision is more strained and calmer than in free drives. A lot of variation is introduced by different routes, road types, lane markings, curvature, traffic density, driving styles and vehicles. As drives on public roads must be interrupted in an early phase of sleepiness for safety reasons, the drowsiness related patterns are rare and not as significant as in a simulator where drivers often become very sleepy.

1.4 Drowsiness Reference

Different measures were recorded as drowsiness reference:

- The subjective self-estimation using the Karolinska Sleepiness Scale (KSS) [1] for all drives (Tab. 1).

Table 1: Karolinska Sleepiness Scale (KSS)

KSS	Description
1	Extremely alert
2	Very alert
3	Alert
4	Rather alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, no effort to stay awake
8	Sleepy, some effort to stay awake
9	Very sleepy, great effort to keep awake, fighting sleep

- Eye-tracker cameras to record blinking behavior and gaze.
- Electroencephalogram (EEG), to measure electric brain activity and Electrooculogram (EOG) to monitor eye blinking behavior.

EEG, EOG and eye-tracker are not considered in the present paper, because they were not available for all drives. The KSS was interrogated every 15 minutes as a trade-off between high temporal resolution and avoiding intrusive feedback. As a consequence, it was not capable to record sudden drowsiness variations caused from different situations. The KSS was used anyway for several reasons:

- The technical KSS recording is very reliable and relatively accurate, whereas EEG and eye-tracking did not work for everybody.
- Recording EEG and blinking signals is laborious, which made them unsuitable for the large number of free drives.
- The system is desired to provide plausible warnings to the driver concerning his self-estimation.

2. DROWSINESS-RELATED FEATURE ACQUISITION

The basic principle of feature extraction is to detect drowsiness-related patterns in the data and reduce the input signals (101) to a few variables that strongly correlate with drowsiness and, if possible, nothing else. Drowsiness can result in different patterns for different drivers or situations. The task of classification is to combine these different patterns to a single continuous-valued drowsiness measure or the discrete classes *awake* (KSS < 6), *questionable* ($6 \leq$ KSS < 8) and *drowsy* ($8 \leq$ KSS). In practice, the extracted features still depend on the road conditions, the driver and other factors. The simplest approach to cope with this problem is to use a sophisticated classifier that automatically adapts to these conditions. The present work investigates to understand these relationships and consider them already during the feature extraction. A selection of 48 important features is listed in Tab. 2. Features with superscript ^{1} are baselined and superscript ^{2} are newly introduced. Features are grouped into classes LANE if they require camera-based lane information, STW for steering wheel angle and CAN if they are based on other CAN-bus signals such as lateral or longitudinal acceleration, wheel rotation etc. We further propose to distinguish between *causal* and *a-priori* features. Causal features result from specific patterns that the driver causes *because* he is drowsy. A-priori features (e.g. DAYTIME) simply say that it is probable for the driver to become drowsy in certain situations. Causal features are the most selective, and thus important ones. However, a-priori features are also important as they can provide a significant contribution to the system performance. For instance, road exits are very probable to result from sleepiness in a monotonous driving situation. Another grouping of features can be made by classifying them into *event-based* and *continuous*. The latter can be calculated permanently (e.g. LANEDEV), whereas zig-zags or road exits occur seldom.

Table 2: Selection of Features

ID	CLASS	Feature Name	Description
15	LANE	LANEDEV^{1}	Lane deviation
17	LANE	ZIGZAGS^{1}	Num of zig-zag events
19	LANE	LATMEAN^{1}	Lateral mean
29	LANE	LNMNSQ^{1}	Lane mean squared
32	LANE	LANEX^{1}	Lane exceeding
33	LANE	LNERRSQ^{1}	LANEX squared
34	LANE	ORA^{1}	Overrun area
35	LANE	TLC1MIN^{1}	Time-to-lane crossing
36	LANE	VIBPROP^{1}	Warnings
16	LANE	LATPOSZCR^{1,2}	Lateral pos. ZCR
30	LANE	LNIQR^{1,2}	IRQ of lateral position
31	LANE	LNCHGVEL^{1,2}	Lane change velocity
37	LANE	DELTADUR^{1,2}	Duration between infl. points
38	LANE	DELTALATPOS^{1,2}	Lateral displacement
39	LANE	DELTALATVELMAX^{1,2}	Max lateral velocity
14	LANE	LANEAPPROX^{1,2}	Approximation to lane
40	LANE	LANEAPPROXADP^{1,2}	Adaptive LANEAPPROX
42	STW	ELLIPSE^{1}	Steering angle and velocity abs.
50	STW	NMWRONG^{1}	Num. of times stw. is corrected
69	STW	NMRHOLD^{1}	Num. of times stw. is hold
48	STW	AmpD2Theta^{1}	Amp_D2_Theta
72	STW	VHAL^{1}	Ratio high/low stw. corrections
71	STW	MICROSTEERINGS^{1}	Small steering adjustment rate
18	STW	STWZCR^{1,2}	Steering ZCR
25	STW	STWVELZCR^{1,2}	Steering vel. ZCR
52	STW	STV25^{1,2}	Steering vel. 1st Quartile
53	STW	STV50^{1,2}	Steering vel. 2nd Quartile
54	STW	STV75^{1,2}	Steering vel. 3rd Quartile
44	CAN	ACTIVE	System active
24	CAN	LNACTIVE	Lane signals active
41	CAN	VEHSPEED	Vehicle speed [km/h]
47	CAN	DAYTIME	Seconds since midnight
66	CAN	TOT	Time-on-task
22	CAN	DEGOINT^{1}	Degree of interaction
23	CAN	REACTIM^{1}	Reaction time
45	CAN	CIRCADIAN^{1,2}	Circadian weighting
51	CAN	STWEVNT^{1,2}	Steering event rate
55	CAN	CROSSWIND^{1,2}	Cross-wind / warping intensity
58	CAN	DYNDRIVINGSTYLE^{1,2}	Dynamic driving style
59	CAN	MONOTONY^{1,2}	Monotonous driving
61	CAN	OPERATION^{2}	Vehicle operation
63	CAN	ROADBUMPS^{2}	Road bump detection
67	CAN	TOTMONO^{2}	Monotonous TOT
68	CAN	TOTSPEED^{2}	TOT around 130km/h
70	CAN	LIGHT^{2}	Light intensity (day/night)
26	CAN	TRFCDENS^{2}	Traffic density
27	CAN	TURNINDADVANCE^{1,2}	Blinking time before ln change
28	CAN	TURNINDDUR^{1,2}	Turn indicator duration
...	...	...	...

In the following, the features are described according to the basis features, they are based on. In general, for event-based features, the presence of a single pattern does not directly indicate a drowsy driver. The increased rate and intensity of these events is of relevance. For this reason, further processing steps are generally applied to the basis features, such as:

- Moving average, median or exponentially weighted moving average (EWMA) (c.f. 3.3)
- Standard deviation, interquartile-range or exponentially weighted moving variance (EWVAR) (c.f. 3.3)

2.1 Steering Wheel Angle-based Features

In contrast to the lateral lane position, the steering wheel angle is directly related to the driver's control action. The steering signal contains higher frequencies and higher resolution of the desired vehicle track. In order not to flatten steering peaks, the steering velocity is calculated with a Digital Polynomial Smoothing- and Differentiation Filter, described in [24]. The STWZCR (zero-crossing rate) is the number of steering direction changes per second. In a broader sense, the ZCR can also be related to the frequencies in the steering signal. It provides several advantages in comparison to the Fourier-transform of the steering signal as the frequencies are very low. A classification of different driving styles has also shown that the STWZCR is very characteristic for different drivers. STV50 is the median and STV25 and STV75 are the 1st and 3rd quartiles of the EWMA windowed steering velocity. The ELLIPSE feature is calculated as the magnitude of steering wheel angle and velocity against their means [4]. According to Wierwille [14], NMWRONG is defined as the number of times the steering angle is quickly corrected. NMRHOLD is the rate that the steering wheel angle is hold below 0.5° for longer than a given time. The STWEVNT is a quite sophisticated combination of a deadband phase without steering, followed by a sudden steering correction [2]. Thresholds are adaptive to the driving situation and other criteria, such as correction intensity, vehicle speed and monotony. Events are suppressed for cross-wind, rough road sections, sporty driving style, lane changes and other disturbing influences. VHAL is the ratio of high against low steering corrections and increases with reduced vigilance. The idea of MICROCORRECTIONS is that an alert driver permanently makes small steering corrections whereas a drowsy driver has a more sloppy steering behavior without small steering corrections.

2.2 Lane-based Features

The lateral lane position is rather a result of the low-passed reaction of the vehicle to the steering signal and road condition. The major information about the lateral lane data is the knowledge of the *absolute* position in the lane. One other benefit is that lane changes can be detected even if the driver doesn't use the turn indicator. Data of a calibrated serial lane tracker (LDW) were used which provided over 35 signals with high accuracy. The availability of LDW signals is lower than other sensor signals as good lane markings are needed.

2.2.1 Lane Position

There is a large number of features associated to the vehicle's deviation in the lane. LATMEAN is the average lateral position within the last minutes, calculated with the EWMA proposed in 3.3. It was observed that sleepy drivers tend to drive closer to the right lane boundary as they are afraid of drifting into the left lanes and crash with an overtaking vehicle. LANEDEV, LNIQR are the standard deviation (EWVAR) and interquartile range of the lateral position against the driver-dependent lateral mean. Using the lane middle was less performant. In the parameter optimization, an exponential weighting of the lateral position has shown to be beneficial. The overrun area (ORA) is the average overridden surface and an alternative to LANEDEV. DELTADUR is the duration, DELTALATPOS the amplitude and DELTAVELMAX the maximum velocity between lateral inflection points. These are also used as criteria for detecting ZIGZAG events, which are oscillations within the lane with an amplitude of 0.7 - 1.2 meters and a duration between 2.5 - 17.5 seconds. LNCHGVEL is the velocity of lane changes and TURNINDADVANCE is the duration between turn indicator utilization and lane change. Both features are very driver dependent.

2.2.2 Unintended Lane Approximation and Exceeding

LANEAPPROX and -ADP are features that describe the number of times any part of the vehicle is entering in a proximity-zone of the lane bounds. The latter is using a driver adaptive zone size. This can be interpreted as an 'almost' lane departure. The advantage is that these occur much more often than real lane departures and thus allow a higher temporal resolution. LANEX, LNERRSQ and VIBPROP [21, 30] are based on the intensity and frequency of lane departures (dashed road markings) and road exits (solid road markings). Unintended lane departures are suppressed if the driver was steering towards the lane or acc-/decelerated [27]. Different weightings for curves and lane types have shown to be practical. It was observed that some drivers almost never exit the lane boundaries whereas others have over 50 lane exits per hour. For some drivers, lane departure warnings LANEX and VIBPROP have been observed to be very helpful during the onset of drowsiness. Thus, it is proposed to adapt the LDW warning sensibility to the driver state.

2.2.3 Time-to-Lane-Crossing (TLC)

TLC is the estimated time remaining until any part of the vehicle crosses the lane boundary if no other steering correction is made [9, 18]. TLC model 1 is the simplest method calculated from the lateral position y and velocity $\dot{y}$ as $TLC = \frac{y}{\dot{y}}$. Model 2a and 2b takes the road curvature and vehicle track into account. The inclusion of the second clothoid parameter c_o has not shown any improvement. Due to calibration problems, model 1 was used as it has shown better and more robust results. TLC1MIN is the number of TLC values below a threshold.

2.2.4 Driver-Vehicle Interaction

DEGOINT and REACTIM are originally defined as the degree-of-interaction and the reaction time to lateral acceleration peaks [11]. The idea behind these features is that the driver has to continuously react to lateral displacements caused by the road. As there was no steering *moment* sensor available, this paper proposes a similar method to obtain DEGOINT based on the steering wheel *angle* only. Therefore, the measured *lateral acceleration* a_y is compared to the *lateral acceleration* $\breve{a}_y$ calculated from the *steering wheel angle* δ_s using the single track model in Eqn. (1).

$$\breve{a}_y = \frac{v^2 \cdot \delta_a}{l + SG \cdot v^2} \tag{1}$$

$\breve{a}_y$ is obtained by the *velocity* v, the *steering ratio* SR, the *steering angle* $\delta_a = \delta_s \cdot SR$ and the *self-steering gradient* $SG = 1/v_{ch}^2$ with the vehicle's *characteristic velocity* v_{ch} and the *wheel base* l. a_y and $\breve{a}_y$ were smoothed by a 2nd order Butterworth low-pass filter with corner frequencies 1 and 2 Hz. In order to compensate road incline, the difference of $\Delta_{ay} = a_{y,LP} - \breve{a}_{y,LP}$ has been subtracted from $\hat{a}_{y,LP} = \breve{a}_{y,LP} - \Delta_{ay}$. The feature is then obtained by DEGOINT $= \text{EWMA}(a_{y,LP} - \hat{a}_{y,LP})$.

2.3 Road Condition

CROSSWIND measures the cross-wind and road-warping intensity also from the measured and calculated lateral acceleration. ROADBUMP continuously estimates the road condition from the wheel rotation sensors and others.

2.4 Drowsiness Supporting Situations

Known factors that are related to reduced alertness are the time-on-task (TOT), the time driving monotonously TOTMONO, DAYTIME and vehicle speed VEHSPEED. Also the LIGHT condition was included as the daylight suppresses fatigue (melatonin). TRFCDENS measures the traffic density calculated from the lane change rate, the vehicle operation and acc-/deceleration events. The driver activity DRACTIVITY measures how dynamic or monotonous a situation is. It was observed that the lower the activation (e.g. by traffic) the higher the probability of becoming sleepy.

3. IMPLEMENTATION DETAILS

A number of pre-processing steps were done before extracting the drowsiness-related features from the raw signals. The presented methods have several advantages in performance and computation time when compared to the common implementation in literature.

3.1 System Active State

There is a large number of driving states or events that decide if the system is active or not. It is active between 80 and 180km/h which selects most highways and country roads. Strong external influences such as road-bumps, cross-wind and road-warping are suppressed. Special driving situations such as lane changes, curves, sporty driving, acc-/deceleration are suppressed as well. In order to blind out short-term distraction, most vehicle operations (levers and other buttons) are blinded out.

3.2 Driver Adaption (Baselining)

The variance between drivers has a severe impact on the features and overlays the drowsiness-related patterns. For this reason *baselining* provides an essential contribution to the feature performance. It is assumed that the drivers are usually awake during the first minutes. Hence, every baselined feature ([2] in Tab. 2) is normalized by the *maximum* of the first minutes active time. Using parameter-optimization algorithms has shown the best results for using the *maximum* and window sizes of up to 40 minutes.

3.3 Exponentially Weighted Moving Average and Variance

In literature, simple moving average filters are commonly used to calculate event rates. A simple, but very powerful improvement is the introduction of a recursive *Exponentially Weighted Moving*

Average (EWMA) filter. It has the property to take present values more into account while storing only one value instead of an entire window. Similarly, the sliding variance can be approximated by the *Exponentially Weighted Moving Variance* (EWVAR) for a given *input signal* x_n as described in the following. The *forgetting factors* λ_μ and λ_{σ^2} are used from the adjusted window sizes N_μ and N_{σ^2}:

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

EWMA is obtained by $\text{EWMA}_n = \lambda_\mu \cdot \text{EWMA}_{n-1} + (1 - \lambda_\mu) \cdot x_n$ with the initial value EWMA_0. The EWVAR is approximated by $\text{EWVAR}_n = \lambda_{\sigma^2} \cdot \text{EWVAR}_{n-1} + (1 - \lambda_{\sigma^2}) \cdot (x_n - \text{EWMA}_n)^2$ with the initial value EWVAR_0. A second improvement is the use of adaptive window sizes. For instance starting with $N_\mu = 5$ and increasing by 1 for every sample or event, depending on the feature. The window size is again reduced if the driving condition quickly changes, e.g. for a changed vehicle speed. Furthermore, the initial values $EWMA_0$ and $EWVAR_0$ are set to the mean of each feature.

4. FEATURE EVALUATION

Features were assessed and optimized in multiple ways. Beside statistical tests (ANOVA, F-Test), the *Bravais-Pearson correlation coefficient* ρ_p, *Spearman correlation coefficient* ρ_s and the *Fisher-metric* MDA [29] were used as metrics. ρ_p is calculated to estimate the linear correlation between the feature F_i and the interpolated, smoothed KSS:

$$\rho_p(F_i, \text{KSS}) = \frac{cov(F_i, \text{KSS})}{\sqrt{var(F_i) \cdot var(\text{KSS})}}, \tag{3}$$

where *cov* is the *covariance* and *var* the *variance*. High positive/negative values mean strong positive/negative correlation, whereas a value near zero indicates a random relationship. The correlation coefficients of often selected features from Tab. 2 are listed in Tab. 3. Scatter plots, class histograms and boxplots [16] were also used to get a visual impression of the features. As only a few plots can be listed here, the STV50 class histogram can be found in Fig. 2 as an example. It can be seen that the steering velocities decrease with increasing vigilance. In Fig. 3, the histogram of the Spearman correlation coefficients of all drives are shown for the feature NMWRONG. It can be seen that there is a tendency towards the right, that indicates that most drives are positively correlated with drowsiness. It's correlation coefficient is $\rho_s = 0.25$, which is relatively good for a causal feature. The boxplots in Fig. 4(a) to 4(c) show the relationship between different features and the KSS. All plots show that the classes are severely overlapping which pose a lot of difficulties for the drowsiness classification.

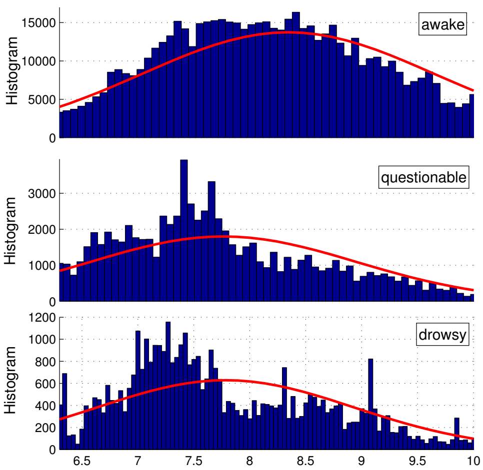


Figure 2: Class Histogram of feature STV50 (ID: 53)
$\rho_p = -0.30$ $(p = 0.0)$; $\rho\_s = -0.33$ $(p = 0.0)$; MDA $= 16.9$

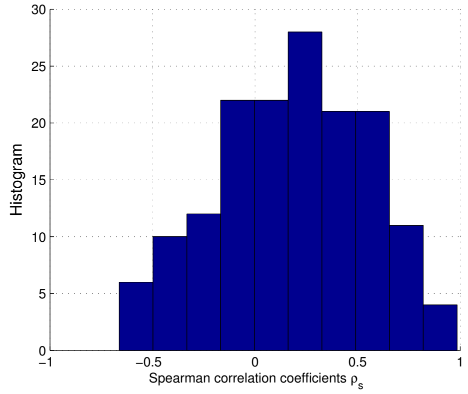


Figure 3: Histogram of ρ_s coefficient for all drives (NMWRONG)

5. CLASSIFICATION

For classification, all features were downsampled to a step width of 5 seconds. As we could assume that the driver state change is much slower than that, a lot of computation time could be saved. Different classifiers such as *k*-nearest neighbours, linear discriminant analysis, Bayes classifier, Gaussian mixture models and artificial neural networks (ANN) were compared. Results were obtained by cross-validation with a training to test set ratio of 80 to 20 percent. It is important to split the data by entire drives so that the drives in the test set are completely unknown to the classifier. The results were averaged over ten permutations of the training/test set to obtain a more stable result.

5.1 Feature Selection

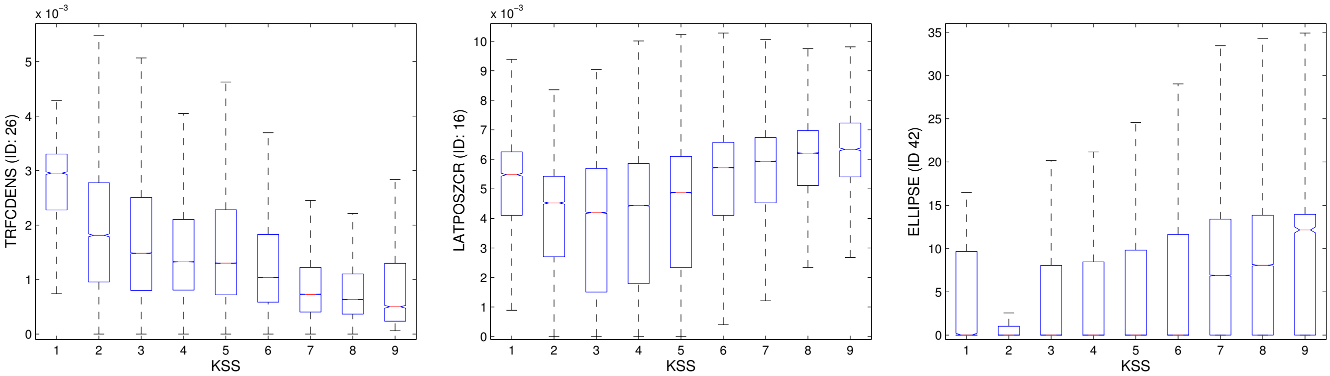
In theory, using more features is better as more information is incorporated. But, if the number of features gets too high, the need of more training data can't be fulfilled any more (*curse of dimensionality*). For this reason, dimension reduction techniques were applied. Principle Component Analysis (PCA) and Fisher transform (LDA) are methods to transform a given feature space to a lower dimensional one. The *sequential floating forward selection* (SFFS) algorithm, introduced by [22], was applied to select the most promising features for a classifier. The advantage of SFFS over feature transform techniques is its high transparency as the selected features remain without any change. PCA and LDA have shown poor results in comparison to the SFFS, so that only SFFS was used here. Tab. 3 lists a statistic of the most often selected features after thirty SFFS repetitions in combination with the Bayes classifier. It can be seen that correlation coefficients of individual features are not necessarily related to the performance of the features in combination.

Table 3: Correlation Coefficients of often Selected Features

ID	Feature Name	Selections	ρ_p	ρ_s
45	CIRCADIAN	30	0.49	0.51
43	TOT	30	0.16	0.22
22	DEGOINT	30	-0.19	-0.22
29	LNMNSQ	30	-0.00	-0.00
51	STWEVNT	29	0.16	0.17
52	STV25	29	-0.30	-0.34
54	STV75	29	-0.32	-0.36
38	DELTALATPOS	19	0.01	0.01
39	DELTALATVELMAX	18	-0.02	-0.01
17	ZIGZAGS	17	0.02	0.00
34	ORA	14	-0.03	-0.04
40	LANEAPPROXADP	14	-0.05	-0.06
53	STV50	14	-0.27	-0.32
33	LNERRSQ	13	-0.01	-0.08
35	TLC1MIN	11	0.06	0.07
30	LNIQR	9	0.06	0.06
14	LANEAPPROX	6	-0.00	-0.01
19	LATMEAN	5	-0.10	-0.11
36	VIBPROP	5	0.00	0.02
26	TRFCDENS	4	-0.33	-0.40
31	LNCHGVEL	3	-0.04	-0.11

5.2 Classification Results

A comparison of test errors for different classifiers is given in Tab. 4. The results are based on the best 11 features that were selected by SFFS in combination with the Bayes classifier. The detailed confusion matrix of the neural networks classification results is given in Tab. 5 (feed-forward backpropagation algorithm with 30 neurons in three hidden layers).



(a) TRFCDENS (ID: 26)

(b) LATPOSZCR (ID: 16)

(c) ELLIPSE (ID: 42)

Figure 4: Boxplot of Three Feature

Table 4: Classification Error for three Classes

Classifier	**Test Error**
***k*-NN (*k*=5)**	44.0%
GMM (3. Modes)	43.3%
Linear discriminant	32.4%
Bayes classifier + SFFS	36.6%
ANN	16.6%

Table 5: Confusion Matrix for ANN

		correct		
		Awake	Questionable	Drowsy
	Awake	76.0 %	24.0 %	0.0 %
estimated	Questionable	8.4 %	89.9 %	1.7 %
	Drowsy	0.0 %	45.4 %	54.6 %

6. CONCLUSIONS AND FUTURE WORK

It was observed that there are different types of drivers, those who accurately keep the lane by lots of steering corrections and those who do not hastily correct the lateral position and rather have a loose lane keeping. Numerous features were analyzed for their correlation with the KSS drowsiness reference. Many of them correlate relatively well, especially a-priori features, such as time of day, time-on-task, monotony and traffic density. However, a-priori features need to be treated with care as they are not sensitive to the real driver condition. In general, lane based features were often selected in combination with steering based features as they provide complementary information. Neural networks, LDA and the Bayes classifier, in combination with SFFS feature selection, performed best for the difficult features. Especially under real world conditions, the suppression of external influences and adaption to the driver is very important. But even with a large set of new and improved steering and lane based features, the classification performance is not as good as the results reported in literature using a smaller amount of data from a simulator or drives under testing conditions. Still, we must expect that a certain percentage of the performance is due to overfitting to this larger, but still limited number of drivers, vehicles, driving conditions etc. Driving in a driving simulator and under supervised conditions has a big influence on the driver's behavior. It was observed that many awake drivers also drive sloppy when the motorway is empty or if they are distracted by talking or other actions. The driving behavior in these situations is the same as for drowsiness and thus cannot be distinguished. For this reason, a good strategy is to combine the detection of drowsiness with giving the driver feedback about his objective driving performance (e.g. by a bargraph). Usually, drivers tend to drive more aware if they have a feedback of their driving performance.

6.1 Future Works

- EEG, eye-signals (such as PERCLOS [3, 10]) and a distraction measure in addition to the KSS for a better temporal resolution
- Hidden Markov-models and Bayes networks to model temporal aspects and expert knowledge
- Multi-level classification to adapt varying driving styles and road conditions

REFERENCES

[1] T. Âkerstedt and M. Gillberg. Subjective and objective sleepiness in the active individual. *International Journal of Neuroscience*, 52:2937, 1980.

[2] T. Altmüller. *Driver Monitoring and Drowsiness Detection by Steering Signal Analysis*. PhD thesis, Universitaet der Bundeswehr München, 2007.

[3] J. Batista. A drowsiness and point of attention monitoring system for driver vigilance. *Proc. of the IEEE Intelligent Transp. Systems Conf.*, 4,no.4:702–708, 2007.

[4] J. Berglund. In-vehicle prediction of truck driver sleepiness - steering related variables. Master's thesis, Lulea University of Technology, 2007.

[5] Daimler. Hightech report 2/2008 - feature attention assist. 2008.

[6] G. I. W. Duncker. Jeder vierte autofahrer sitzt übermüdet am steuer. Technical report, Deutsche Ophthalmologische Gesellschaft e.V., 2007.

[7] A. Eskandarian and A. Mortazavi. Evaluation of a smart algorithm for commercial vehicle driver drowsiness detection. In *Proceedings of the IEEE Intelligent Vehicles Symposium, Istanbul, Turkey*, 2007.

[8] R. J. Fairbanks, S. E. Fahey, and W. W. Wierwille. Research on vehicle-based driver status/performance monitoring: Seventh semi-annual research report. Technical report, National Highway Traffic Safety Administration, 1995.

[9] S. Glaser and S. Mammar. Experimental time to line crossing validation. *IEEE Conference on Intelligent Transportation Systems*, 8:791–796, 2005.

[10] V. Hargutt. *Das Liedschlussverhalten als Indikator für Aufmerksamkeits- und Müdigkeitsprozesse bei Arbeitshandlungen*. PhD thesis, Univ. Würzburg, 2001.

[11] L. Kanstrup. Method for detection of sleepiness - measurement of interaction between driver and vehicle. Master's thesis, University of Linköping, 2006.

[12] R. R. Knipling and J.-S. Wang. Crashes and fatalities related to driver drowsiness/fatigue. Technical report, Nat. Highway Traffic Safety Administration, 1994.

[13] R. R. Knipling and J. S. Wang. Revised estimates of the u.s. drowsy driver crash problem size based on general estimates system case reviews. *39th Annual Proc., Association for the Adv. of Automotive Medicine, Chicago*, October, 1995.

[14] R. R. Knipling and W. W. Wierwille. Vehicle-based drowsy driver detection: Current status and future prospects. 1994.

[15] D. Künzel. *Die Rolle von Ablenkung und Müdigkeit bei Verkehrsunfällen: Nationale und internationale Statistiken*. Kuratorium für Verkehrssicherheit, 2008.

[16] P. Löfgren. Identification of driver unawareness based on user interaction. Master's thesis, Institutionen för systemteknik Dept. of Electrical Engineering, 2007.

[17] J. M. Lyznicki, T. C. Doege, R. M. Davis, and M. A. Williams. Sleepiness, driving, and motor vehicle crashes. *JAMA: Journal of the American Medical Association*, 279 (23):1908–1913, 1998.

[18] S. Mammarand, S. Glaser, and M. Netto. Time to line crossing for lane departure avoidance: A theoretical study and an experimental setting. *IEEE Transactions on Intelligent Transportation Systems*, 7 No. 2, June:226–241, 2006.

[19] J. Mara. Drowsy driving and automobile crashes. *NHTSC*.

[20] E. Martin. Breakthrough research on real-world driver behavior released. *National Highway Traffic Safety Administration*, 2006.

[21] K. Mattsson. In-vehicle prediction of truck driver sleepiness: lane position variables. Master's thesis, Lulea University of Technology, 2007.

[22] P. Pudil and F. J. Ferrii. Floating search methods for feature selection with non-monotonic criterion functions. In *In Proceedings of the Twelveth International Conference on Pattern Recognition, IAPR*, pages 279–283, 1994.

[23] L. A. Reyner and J. A. Horne. Early morning driver sleepiness effectiveness of 200 mg caffeine. *Psychophysiology*, 37:251256, 2000.

[24] A. Savitzky and M. J. E. Golay. Smoothing and differentiation of data by simplified least squares procedure. *Anal. Chem. (1964)*, 36:1627, 1964.

[25] R. Sayed. Unobtrusive drowsiness detection by neural network learning of driver steering. *Proc. Institution of Mech. Engineers*, 215 D:969–975, 2001.

[26] E. Schmidt. Drivers misjudgement of vigilance state during prolonged monotonous daytime driving. *Accident Anal. & Prevent.*, 41:1087–1093, 2009.

[27] C. H. Schmitz. *Adaptiver Spurverlassenswarner mit Fahrerabsichts- und fahrerzustandsabhngiger Warnstrategie*. PhD thesis, University Karlsruhe, 2004.

[28] J. S. Wang and R. R. Knipling. The role of driver inattention in crashes: New statistics from the 1995 crashworthiness data system. *40th An. Proc. Assoc. for the Adv. of Automotive Med.*, IA:377–392, 1996.

[29] M. Welling. Fisher linear discriminant analysis. Technical report, University of Toronto, Department of Computer Science, 2005.

[30] W. W. Wierwille. Research of vehicle-based driver status/performance monitoring - part iii. Technical report, 1996.