Camera-based Drowsiness Reference for Driver State Classification under Real Driving Conditions

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***Abstract*— Experts assume that accidents caused by drowsiness are significantly under-reported in police crash investigations (1-3%). They estimate that about 24-33% of the severe accidents are related to drowsiness. In order to develop warning systems that detect reduced vigilance based on the driving behavior, a reliable and accurate drowsiness reference is needed. Studies have shown that measures of the driver's eyes are capable to detect drowsiness under simulator or experiment conditions. In this study, the performance of the latest eye tracking based in-vehicle fatigue prediction measures are evaluated. These measures are assessed statistically and by a classification method based on a large dataset of 90 hours of real road drives. The results show that eye-tracking drowsiness detection works well for some drivers as long as the blinks detection works properly. Even with some proposed improvements, however, there are still problems with bad light conditions and for persons wearing glasses. As a summary, the camera based sleepiness measures provide a valuable contribution for a drowsiness reference, but are not reliable enough to be the only reference.**

Keywords: *drowsiness detection, blinking behavior, eye-tracking, driver monitoring, classification, KSS.*

I. Introduction

A. Motivation

According to the National Highway Traffic Safety Administration (NHTSA), annually, about 100,000 crashes in the USA are the result of driver sleepiness. The 100-Car Study, performed in 2006 by the NHTSA [1] and Virginia Tech Transportation Institute (VTTI), states that drowsiness increases the driver's risk of a crash or near-crash by at least a factor of four. Drowsy driving is assumed to be significantly under-reported in police crash investigations (1-3% in [2]) as it can't be measured as easily as alcohol consumption for instance. Experts assume that about 24-33% of the severe accidents are related to drowsiness [3]–[6]. Reyner and Horne [7] found that cold air and radio as "in-car" countermeasures have not shown to significantly reduce the number of lane departures during sleepiness. They are at best temporary expedients to reduce driver drowsiness, enabling drivers to find a suitable place to take a break and avail themselves of caffeine and a brief nap, which had been shown to be more effective [8], [9]. Emerging driver monitoring systems, such as the Mercedes Benz *Attention Assist* or the Volvo *Driver Alert Control* are systems that aim to reduce sleepiness-related road crashes caused by fatigued and distracted drivers by using series production sensors. In order to develop and optimize such systems, a reliable and accurate sleepiness reference is needed. There are several common ways to "measure" the driver's vigilance state:

- The most common reference measure for drowsiness is the driver's subjective self-estimation according to the Karolinska Sleepiness Scale (KSS) [10] in Tab. I.

TABLE I
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

  Several thousand real road drives have been recorded with over 900 briefly instructed drivers. The KSS was interrogated every 15 minutes as a trade-off between high temporal resolution and avoiding intrusive feedback. As a consequence, the KSS was not capable to record sudden drowsiness variations caused from different situations. A large number of drives were invalid due to implausible KSS entries by the drivers. The reasons range from unmotivated drivers to missunderstanding of the KSS. Schmidt *et. al.* [11] demonstrated that drivers have difficulties in judging their fitness, especially after about three hours of continuous monotonous daytime driving and with increasing drowsiness. For these reasons, it is not sufficient to record solely the KSS.
- The Electroencephalogram (EEG) is another common way to predict driver fatigue by measuring the electric brain activity in the alpha and gamma band. The Electrooculogram (EOG) monitors eye blinking and movement. However, the recording of the EEG and EOG is too laborious for such a large number of drives.
- Additionally to these methods, this paper studies the performance of an eye-tracking camera for in-vehicle fatigue detection, since no wiring of drivers or repeated interrogation is required.

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Another major benefit of an eye-tracking system is the detection of short- and mid-term distraction by the gaze direction (eyes of road). The 100-Car Study by NHTSA [1] found that about 80% of crashes involve driver distraction, at least as a second reason.

B. Literature review

Within the last years, a lot of effort has been made to investigate driver monitoring based on blinking behavior. In [12], the measure referred to as PERCLOS [13] (cf. III-C) was found to be the most reliable and valid determination of a driver's alertness level. Batista [14] presents a framework for face localization and eyelid movement parameters. While focusing on facial detection algorithms, he also calculates the measures PERCLOS and AECS (cf. III-H) without further investigating them. Hargutt [15], [16] attached electric spindles to the eyes in order to analyze vigilance and attention within a driving context. He stated that a combination of blinking related parameters is necessary for estimating every vigilance stage. He found the blink duration to be related to sleepiness and verified his results by conducting a driving simulator study with 12 participants. The baselining he applied made the effects more stable. Picot [17] recently proposed a fuzzy logic algorithm for drowsiness detection in high frame rate videos. In 60 h of driving with 20 drivers, it detects 80% of the drowsiness states. Thorslund and Svensson [18], [19] use EOG to estimate the driver's alertness in regard to the subjective self-rating and EEG. Using simulator drives, Svensson reaches a 70% correspondence towards the self-rating and 56% for the EEG.

C. Objectives of the current study

Starting from the output signals of a recent camera-based eye-tracker, we study their potential as a reference for drowsiness detection under real road driving conditions. We review some popular features extracted from the eye signals and propose new ones. We investigate their properties and relationship to the KSS measure. We also use these features, trying to predict the current KSS value. Further contributions of this paper are:

- Propose improved algorithms for feature extraction, such as the EWMA explained in App. A
- Cope with deficites [11] of self-ratings (KSS) such as low temporal resolution and subjectivity
- Assess the signal quality for drivers with glasses
- Suppress looks to the dashboard that are often accompanied with eye blinks
- Include vehicle signals to suppress low speed, lane changes and vehicle operation

D. Database

The database used within this project covers over 10 300 real drives with a total number of 1.23 Mio km (courtesy of Mercedes-Benz). Thereof, three night experiments and some free drives were performed with the latest camera algorithms. In total, 30 real road drives with valid self-rating (KSS) and without measurement problems are available:

- 23 real road night experiment drives (7,054 km)
- 7 normal free daytime drives (2,607 km)
- 23 drivers (8 with glasses)

The conduction of night experiments and regular drives is explained in [11], [20].

E. Driver State Sensor

The latest *Driver State Sensor 3.0* algorithm from *Seeing Machines* [21] was used for the recording of the eye- and head signals. The system covers an IR-Camera unit (640×480 pixels) and two IR-pods for illumination. The camera was installed in the instrument cluster and both IR-pods were mounted such that reflections on the glasses were minimized. The essential pre-processed signals (Tab. II) are recorded over an USB-drive by a portable computer unit. GPS signals were obtained from an external USB device. The obtained signals were relatively good, especially for drivers without glasses.

TABLE II
USED SIGNALS FROM THE DRIVER STATE SENSOR

Description	Signal	DSS Signal Name
Eye closure l/r	$e_{l,r}$	LEFT_ / RIGHT_EYE_CLOSE
Eye confidence l/r	$c_{l,r}$	LEFT_ / RIGHT_CLOS_CONF
3D head position	x,y,z	HPOS_FILT_X / Y / Z
3D head rotation	φ,ψ,γ	HROT_PITCH / _YAW / _ROLL
3D head confidence	c_h	HPOS_CONF
GPS time	τ	GPS_GMT_TIME
GPS longitude	λ	GPS_Longitude
GPS latitude	θ	GPS_Latitude
GPS veh. speed	v	GPS_SPEED_KM_H

II. Processing of the Eye Signals

This section presents several pre-processing steps that are involved in extracting individual drowsiness-related patterns from the raw signals.

A. Pre-processing

The recorded camera data are converted, synchronized and time offset is compensated with the vehicle CAN data using the extrapolated GPS GMT-time and velocity signal which is sufficiently accurate. The data obtained from the camera have a frame rate of 60Hz. The detection of eye blinks works well for this frame rate but the calculation of the blinking velocity becomes more inaccurate. Svensson [19] stated that the sampling frequency should be high (at least 500Hz) when blinking related characteristics like blink duration are measured. The camera frame rate often dropped and introduced measurement gaps of up to half a second. These gaps were lineary interpolated in order to keep the timestamp synchronized. Next, both eye signals e_l and e_r are combined to a single eye signal e_c by weighting and normalization with the confidence values c_l and c_r of both eyes. The system is defined to be active for head yaw angle $|\psi| \leq 15^\circ$ to suppress lane changes (5-20%) and for a high enough combined confidence $(c_l + c_r)/2 \geq 55\%$. Furthermore, vehicle speed $v \leq 30$ km/h and lane changes are suppressed. An average active time of about 70-90% remained for most drives. For some drivers with glasses it was lower ($\approx 60\%$).

B. Detection of Blinks

Another important pre-processing step for most features is the detection of blinks. At first, blinking candidates are searched by applying an adaptive threshold to the eye signal e_c. Then the system active signal was applied. It is also important to suppress the blink during a head rotation or at the same moment as the confidence signal dropped below a threshold. A major problem is vertical looks to the dashboard, instrument cluster or head-unit. Such eye movements often occur with short blinks. For this reason, a minimum blink duration of 130 ms was defined to neglect these looks. Then, each blinking candidate that fulfilled several other criteria (min/max duration, shape and minimum amplitude) was labeled as a valid eye blink.

C. Driver Adaption (Baselining)

An essential contribution to the feature performance is the *baselining*. The variation between drivers has a severe impact on the features and overlays the drowsiness-related patterns. We assume that the drivers are usually awake during the first 15 minutes of a drive. The *mean* or *maximum* of features during this time is then used for normalization of features.

D. Feature Extraction

For many drowsiness measures, the increased rate and intensity of patterns is of relevance. Processing steps as described in App. A and [20] can often be applied to the signals, such as:

- Moving average, median or exponentially weighted moving average (EWMA)
- Standard deviation, interquartile-range or exponentially weighted moving variance (EWVAR)
- Digital polynomial smoothing- and differentiation [22]

These methods, have several advantages in regards to performance and computation time towards the common implementation in literature.

III. Feature Extraction

From the eye signals returned by the camera system, we now extracted 18 features for drowsiness detection as listed in Tab. III. They will be briefly explained in this section.

TABLE III

Eye Features

ID	CLASS	Feature Name	Description
74	EYE	AECS	Average eye closure speed
75	EYE	APCV	Amplitude/velocity ratio
92	EYE	APCVBL	APCV with regression
76	EYE	BLINKAMP	Blink amplitude
77	EYE	BLINKDUR	Blink duration
95	EYE	BLINKDURBL	BLINKDUR baselined
78	EYE	BLINKFREQ	Blinking frequency
80	EYE	EC	Energy of blinking
98	EYE	ECBL	EC baselined
85	EYE	MICROSLEEP	Microsleep event 0.5 s rate
94	EYE	MICROSLEEP1S	Microsleep event 1.0 s rate
81	EYE	EYEMEAS	Mean square eye closure
84	EYE	MEANCLOS	Mean eye closure
88	EYE	PERCLOS70	Percentage eyes >70% closed
89	EYE	PERCLOS80	Percentage eyes >80% closed
99	EYE	PERCLOS70BL	PERCLOS70 baselined
100	EYE	PERCLOSEWBL	PERCLOS80 EWMA baselined
90	EYE	HEADNOD	Head nodding

A. Blink Duration

Different methods to estimate the blink duration (BLINKDUR) have been evaluated as illustrated in Fig. 1. In this article, the blink duration is calculated in the same

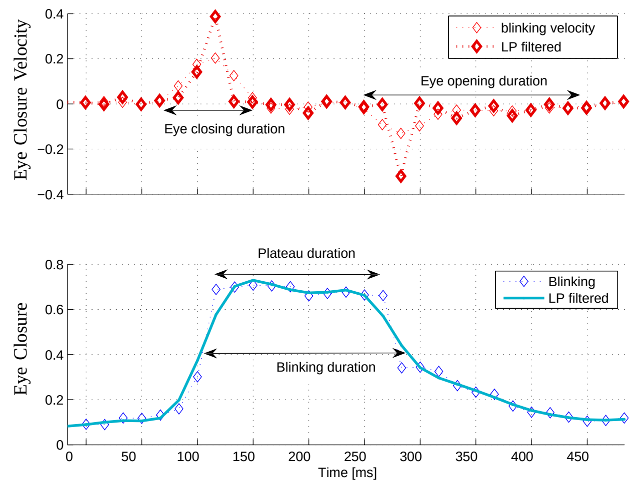


Fig. 1. Eye blink and related parameters

way as for EOG. In EOG, the blink duration is defined as the time difference between the beginning and the end of a blink, each at the point where half the amplitude is reached. A better definition is the sum of half the raise time and the fall time [18], [19], [23]. Also the *plateau* duration (Fig. 1) of an eye blink was calculated.

B. Eye Closure

One of the simplest measures for drowsiness is the MICROSLEEP event rate. Events are defined as eye closures longer than 0.5s (1s for MICROSLEEP1S). The opening duration is calculated in the same way as for BLINKDUR. MICROSLEEP events occur in an advanced phase of drowsiness.

C. PERCLOS and EYEMEAS

PERCLOS is the most common blinking based measure for drowsiness, first defined by Wierwille et al. [24]. It is the proportion of time in three minutes that the eyes are at least 80% closed. Of the drowsiness-detection measures, it was found to be the most reliable and valid determination of a drivers alertness level [12]–[14]. Today, there are also other PERCLOS measures: PERCLOS70, which is the same but with a threshold of 70%; EYEMEAS, which is the mean square percentage of the eyelid closure rating. EC is the averaged energy of blinks and is closely related to PERCLOS. PERCLOSEWBL is the same as PERCLOS80 but using EWMA for averaging (App. A).

Fig. 2 shows PERCLOS for a night drive. The driver (ID=340) has entered the KSS more frequently and with more care than usual. Thus, it can be seen how well PERCLOS correlates with the KSS ($\rho_p = 0.74$) and EEG ($\rho_p = 0.67$) measures [11]. As the KSS entry is retrospective and EEG / PERCLOS are filtered with a three minute moving average filter, all signals are delayed. This is one of the major weaknesses that PERCLOS detects fatigue too late and fails to detect participants that are drowsy with eyes wide open.

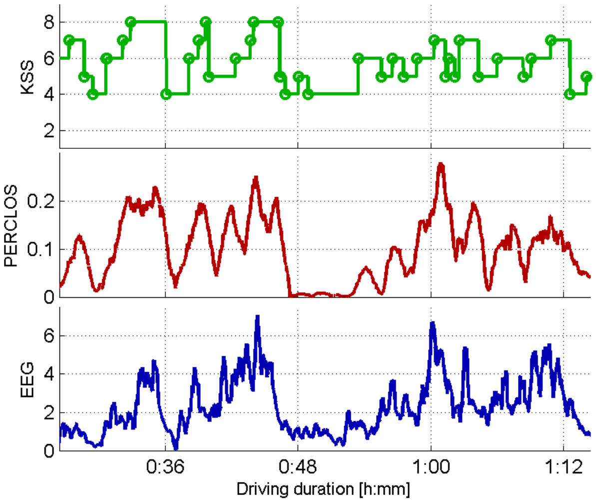


Fig. 2. Drive (ID=14 589) with KSS, PERCLOS and EEG

D. Amplitude-Velocity Ratio

Hargutt and Krüger [25] found that the ratio of amplitude and maximum blinking velocity (APCV) can be used well for drowsiness detection.

E. Blinking Rate

BLINKFREQ is the blinking frequency. According to Andreassi [23], a relaxed person blinks about 15-20 times per minute, which drops to 3 blinks per minute when performing cognitive tasks [19]. According to Hargutt and Krüger [25], an increased blinking rate indicates reduced vigilance. It also increases with driving duration (time-on-task) [15]. It was observed that it varies severely for different drivers and is also related to the air humidity in the vehicle.

F. Mean Eye Opening

MEANCLOS measures the mean eye opening between blinks. We observed that drivers often do not completely open their eyes any more when they become sleepy.

G. Head Nodding Frequency

An often observed sign of drowsiness is head nodding (HEADNOD). It is calculated from the head pitch angle φ with the EWVAR as described in App. A. The estimation of φ was quite accurate. Drivers often start moving in the seat and move their head to fight sleep. A second reason for head nodding is related to microsleep events when a driver lets his head fall and hastily pulls it up when he realizes his absence.

H. AECS

AECS is the average eye closure speed [14], [17], which was estimated by the maximum eye opening speed.

IV. Feature Evaluation

The above features were analyzed in different ways. Besides statistical tests (ANOVA, F-Test), the *Bravais-Pearson correlation coefficient* ρ_p, *Spearman correlation coefficient* ρ_s and the *Fisher-metric* MDA [26] were used as metrics. ρ_p is calculated to estimate the linear correlation between the feature F and the interpolated, smoothed KSS:

$$\rho_p(F, \mathrm{KSS}) = \frac{cov(F, \mathrm{KSS})}{\sqrt{var(F) \cdot var(\mathrm{KSS})}}, \qquad (1)$$

where *cov* is the *covariance* and *var* the *variance*. ρ_s describe how well the relationship between two measures can be described by a *monotonic* function. High positive/negative values mean strong positive/negative correlation, whereas a value near zero indicates a random relationship. The correlation coefficients of good features are listed in Tab. IV. Scatter plots, class histograms and boxplots [27] were also used to get a visual impression of the features. In Fig. 3, the Spearman correlation coefficients of all drives for the feature EC are shown in a histogram. It can be seen that there is a

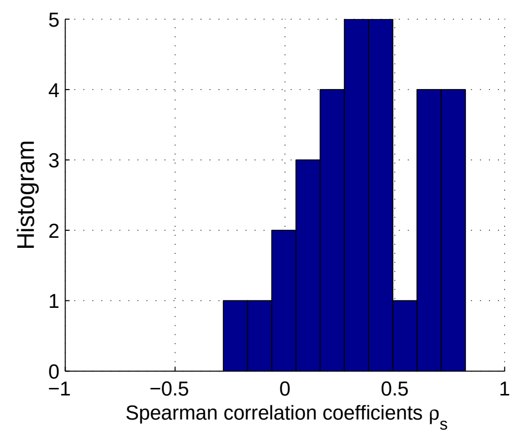
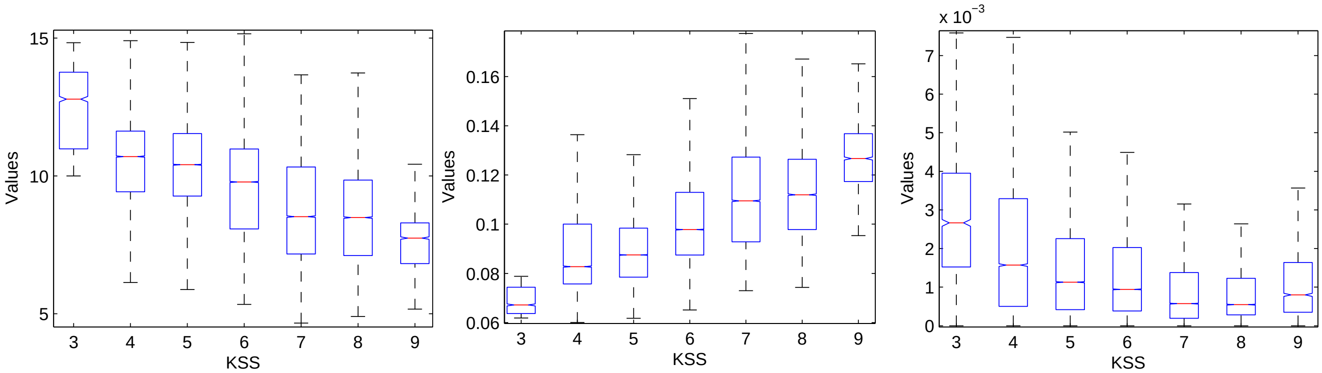


Fig. 3. Histogram of ρ_s coefficient for all drives (EC ID=80)

tendency towards the right, that indicates that most drives are positively correlated with drowsiness. The feature's correlation coefficient is $\rho_s = 0.22$, which is relatively good for a causal feature [20]. 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. There are no drives with KSS below 3, so these were neglected.

V. Classification

The task of drowsiness classification is to combine these different features to a single continuous-valued drowsiness measure or the discrete classes *awake* (KSS $\leq$ 6), *questionable* (6 $<$ KSS $<$ 8) and *drowsy* (8 $\leq$ KSS). All features were downsampled to a samling frequency of 0.5 Hz, as we assume that the blinking behavior change is much slower than that. An artificial neural network (ANN) was used for classification (V-B).



(a) AECS (ID: 74) (b) APCV (ID: 75) (c) HEADNOD (ID: 90)

Fig. 4. Boxplot of three features

A. Feature Selection

In theory, using more features incorporates more information is incorporated. But, if the number of features gets too high, the need for 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 in [28], 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. In our study, PCA and LDA have shown poor results in comparison to SFFS. Hence we only report results achieved by SFFS. Tab. IV shows the most often selected features.

TABLE IV
CORRELATION COEFFICIENTS OF OFTEN SELECTED FEATURES

ID	Feature Name	ρ_p	ρ_s
74	AECS	-0.46 (0.000)	-0.48 (0.000)
75	APCV	0.50 (0.000)	0.53 (0.000)
76	BLINKAMP	0.18 (0.000)	0.14 (0.000)
77	BLINKDUR	0.16 (0.000)	0.27 (0.000)
78	BLINKFREQ	-0.11 (0.000)	-0.04 (0.000)
98	ECBL	0.21 (0.000)	0.19 (0.000)
81	EYEMEAS	0.07 (0.000)	0.08 (0.000)
90	HEADNOD	-0.25 (0.000)	-0.32 (0.000)
84	MEANCLOS	0.09 (0.000)	0.07 (0.000)
94	MICROSLEEP1S	0.01 (0.000)	0.07 (0.000)
99	PERCLOS70BL	0.27 (0.000)	0.40 (0.000)

B. Classification Results

The confusion matrix of the neural network classification is given in Tab. V. The classification 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 several permutations of the training/test set to obtain a more stable result. A feed-forward backpropagation algorithm with 25 neurons in one hidden layer was used. The total recognition rate is 82.5%.

TABLE V
CONFUSION MATRIX FOR ANN

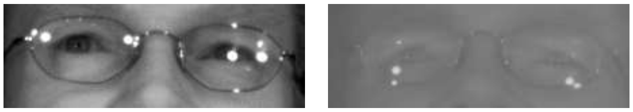
		given		
		Awake	Questionable	Drowsy
	Awake	88.0 %	11.8 %	0.2 %
estimated	Questionable	13.6 %	81.2 %	5.3 %
	Drowsy	0.9 %	36.5 %	62.6 %

VI. DISCUSSION AND CONCLUSIONS

The presented results show that camera based drowsiness detection works very well for some drivers, but is ill-posed for others. Several of the analyzed features show good potential for fatigue detection. Features related to the eye opening speed and PERCLOS perform best. Head movements also seem to be early indicators for sleepiness. The blink duration is also well related to the driver's advanced drowsiness level, but many of the vertical looks to the dashboard are still recognized as blinks. One reason for the moderate classification rate of the class *drowsy* is certainly that only 1.6% of the data contain sleepiness at KSS 9 in which video based approaches work best. Furthermore, the results can't be better than the self-rated KSS reference which also contains inaccuracy. One of its main deficites is the low temporal resolution. It is well known, that the vigilance level varies more quickly depending on the current situation and visual "novelty". During the night experiments, the blinking based parameters were mostly observed to correspond well to the actual driver state. The mean eye opening degree between blinking intervals was also observed to be a good indicator as the drivers often do not completely open their eyes any more during sleepiness. Baselining was needed, as it was observed that there are huge variations between different drivers, especially regarding to blink duration and frequency.

As long as the blinking signals were correctly detected (high confidence), the drowsiness could be estimated well from the degrading of the blinking parameters for most drivers. But even after many improvements, there are still open issues regarding camera based drowsiness detection:

- Reflections on glasses lead to bad signal quality, see Fig. 5(a)
- Varying light conditions during daytime driving pose problems for the eye signal tracking, see Fig. 5(b)



(a) Reflections on glasses (b) Bad light due to sun backlight

Fig. 5. Image processing problems

Therefore, it is very important to know if the obtained signals are valid. All confidence signals $c_{l,r,h}$ were well related to the data quality.

A. Future Work

Current work investigates the mentioned problems by:

- Improvement and validation of the algorithms based on the large real road study that is currently conducted
- Improve camera, mounting and image processing algorithms to be more robust with drivers wearing glasses and under varying light conditions
- Use higher sampling frequency for a better estimation of the blinking velocity

APPENDIX

A. 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 *Exponently Weighted Moving Average* (EWMA) filter. It has the property to take present values greater into account while storing only one value from the past instead of values of an entire window. Similary, 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}:

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

The EWMA is obtained by

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

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

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

with the initial value $EWVAR_0$.

A second improvement is using adaptive window sizes starting with e.g. $\lambda_\mu = 5$ and increasing by one 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 average of each feature.

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