Advanced EEG Processing for the Detection of Drowsiness in Drivers

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Abstract: Drowsiness is a serious problem for drivers which causes many accidents every day. It is estimated that drowsiness is the cause of four deaths and 100 injuries per day in the United States. In this paper two methods have been developed to detect drowsiness based on features of ocular artifacts in EEG signals. The ocular artifacts are derived from the EEG signals by using Canonical Correlation Analysis (BSS-CCA). Wavelet transforms are used to automatically select components containing eye blinks. Sixteen features are then calculated from the eye blink and used for drowsiness detection. The first method is based on linear regression, the second on fuzzy detection. For the first method, the drowsiness level is correctly detected in 72% of the epochs. The second method uses fuzzy detection and detects the drowsiness correctly in 65% of the epochs. The best results are obtained when using one single eye blink feature.

1 INTRODUCTION

Drowsiness is the strong desire to sleep felt before actually falling asleep (Geetha and Geethalakshmi, 2011). When someone is drowsy, he is less alert and will perform less efficiently tasks that require a lot of concentration (Borghini et al., 2012). It is a natural process which normally causes no extraordinary problems but it can be dangerous while performing a task that requires mental attention such as driving. Drowsy drivers are estimated to be the cause of 7% of all traffic accidents. Additionally, 16% of all accidents with at least one casualty involve a tired driver (A.A.A. Foundation, 2010), causing more than four deaths and 100 injuries per day in the United States (Borghini et al., 2012). Interviews with drivers indicate that, while they are not aware of the moment they fall asleep, they are aware of the fact that they are becoming drowsy (Reyner and Horne, 1998). Detecting the level of drowsiness and giving an alarm signal when this level becomes too high would thus be a way to decrease the number of accidents and dangerous situations caused by drowsy driving.

Drowsiness has an effect on many physiological parameters, such as EEG rhythms, heart rate variability and EOG signals (Borghini et al., 2012). For drowsiness detection in drivers, the best base for detection is the use of EOG signals. (Borghini et al., 2012) indicate that characteristics of EOG signals significantly change while performing a task that requires visual attention such as driving. Often, features such as velocity, duration and amplitude are derived from the EOG signal and variations in those features are used to detect drowsiness (Yue, 2011) (Svensson, 2004) (Picot et al., 2011). Different detection approaches have been used, using for example Support Vector Machines (Hu and Zheng, 2009), multiple regression (Verwey and Zaidel, 2000) and artificial neural networks (Vuckovic et al., 2002). In this paper a simpler approach using linear regression and fuzzy detection is explored. The validation of drowsiness detection is done by comparing the detected drowsiness level with a subjective rating given by the subject himself. The rating can be given on the Karolinska sleepiness scale (KSS) (Kaida et al., 2006) which has values from one to nine. Often, a scale with less gradations is used to make detection easier.

In this paper, drowsiness is detected using the ocular artifacts present in the EEG signal. The brain signal is first separated from the artifact signal using a blind source separation method. Out of all BSS methods, Canonical Correlation Analysis is chosen (BSS-

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CCA), since (Vergult et al., 2007) and (Borga and Knutsson, 2001) show that CCA performs better in separating brain and muscle signals and equally well for brain and ocular signals than alternatives such as ICA. Furthermore, it performs an order of a magnitude faster than ICA (Borga and Knutsson, 2001).

2 DATA COLLECTION

The data used in this project are obtained from an experiment that was conducted by Philips Research in collaboration with the Dutch Organization for Applied Scientific Research (TNO) in February 2011.

20 male experienced drivers and 7 back-up subjects between 25 and 45 years old were selected and had to be present in the testing center for one full day. During this day they finished three different drives in a driving simulator and filled in a number of questionnaires about their sleep quality. In the morning, the participant drove for one hour in the simulator. During this time, the baseline measurement was performed: a measurement of the participant's biosignals when he is alert. In the afternoon session, two more drives of 3.5 hours had to be finished where the participant was driving in monotonous traffic conditions. Every 5 minutes a questionnaire appeared on the screen where the subject had to indicate his state of alertness at that moment.

Different types of signals are recorded throughout the experiment. The first type are biosignals. They include EEG, EOG, heart rate and respiration measurements. The sampling rate of all biosignals is 1024 Hz. The EEG signals were measured with 32 electrodes using the International 10-20 system (Homan et al., 1987). In addition, the user perception questionnaires assess how tired the subject feels. The Karolinska sleepiness scale is used, a 9-graded scale with 1 being extremely alert and 9 extremely sleepy (Kaida et al., 2006). A digital version of KSS is shown on a screen every 5 minutes, and the participant has to indicate his state of alertness.

Not every participant managed to finish all three drives, and for two participants the KSS-rating was not recorded. Therefore, the final dataset consists of the (bio)signals of 19 subjects.

3 METHODOLOGY

The complete drowsiness detection consists of five steps. First, the EEG signal is decomposed in different components to separate brain signal and EOG signal. The EOG components are selected and EOG

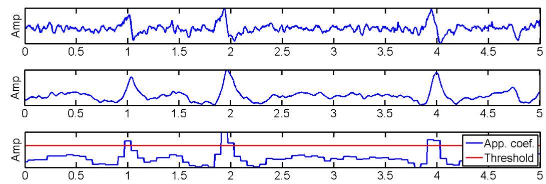

Figure 1: Illustration of method for component selection.

features are extracted from these components. Then, the drowsiness detection is performed. Two methods have been developed: one based on linear regression and one on fuzzy detection. Finally, both methods are validated by comparing the results with the KSS-rating.

3.1 Component Decomposition

A Blind Source Separation method (BSS), BSS-CCA, is used to decompose the signal in different components arising from different sources:

$$X(t) = A \cdot s(t) \tag{1}$$

$X(t)$ is the measured EEG signal, $s(t)$ are the different sources and A is a mixing matrix that represents the distribution of the different sources over all channels. BSS-CCA will generate components that are mutually uncorrelated but with maximal temporal correlation within each component. The complete algorithm is described by De Clercq et al. (De Clercq et al., 2006).

The signal is first divided in subsequent epochs of 1 second. One second is experimentally determined to be the optimal window length for this dataset. BSS-CCA decomposes this epoch in components. If the EEG signal has n channels, the result will be n components.

3.2 Component Selection

The identification of the EOG components is done using a wavelet-based method, based on Krishnaveni et al. (Krishnaveni et al., 2006). Figure 1 illustrates the different steps.

First, each component is scaled with a coefficient c:

$$c_i = A(1,i) \tag{2}$$

A is the mixing matrix from Equation (1), i is the index of the components. The first row of the mixing matrix corresponds to electrode Fp1. Since eye blinks are best visible on the signal of this electrode, the amplitude of the artifact-components will enlarge, leading to easier detection. This can be seen on Figure 1: the first row is an epoch containing three eye blinks and the second row is one of the scaled components, where the actual eye blinks are more clearly visible. Each component is then decomposed with the Haar wavelet up to 4 levels. The Haar wavelet is used since Salwani and Jasny show that it gives the best results in detecting ocular artefacts compared to other mother wavelets (Salwani and Jasmy, 2005) . The reconstruction of the approximation coefficients results in a step function with a rising edge when the eye closes and a falling edge when the eye opens, as is shown on the third row of Figure 1. When there is no ocular artifact present in the component, the approximation coefficients will have low values. The artifact components are then identified by comparing the maximal approximation coefficient with a threshold of 80. If the maximum is larger than 80, the component is identified as an EOG component. The value of 80 has been determined experimentally. When the epoch contains no artifacts, the component with the highest approximation coefficient is selected. This way, for each epoch j, a new signal $X_{EOG}(t)$ is constructed:

$$X_{EOG,j}(t) = \sum_{i=1}^{k} A_j(1,i) \cdot s_{i,j}(t) \qquad \forall j \tag{3}$$

In this equation, j is the index of the epoch, A_j and s_j are respectively the mixing matrix and components found in epoch j, i is the index of the component and k are the number of components identified as EOG.

When the signals for all epochs are concatenated, they form a signal with the same length as the original EEG signal but with only one row. The newly formed signal, from now on referred to as 'artifact signal', contains all artifacts found by BSS-CCA and only minimal EEG information. It is thus ideal for the derivation of different eye blink features.

3.3 Feature Calculation

First, the time instance when the artifact is at peak amplitude is detected using the wavelet-based method described in Section 3.2. The approximation coefficients are now compared with a threshold to detect the individual eye blinks. Now, the threshold is determined for each subject individually to make detection more accurate. The actual moment of the peak amplitude is then found by looking for a local maximum in the artifact signal 0.15 s around the detected blink.

Four points are detected for each eye blink, which are indicated on Figure 2: the onset (red) and end (blue) of the eye blink, the half-rise time (green) and the half-fall time (orange). First, a moving average filter with length ten samples smooths the artifact signal. The first derivative of the smoothed signal consists of a part larger than zero followed by a part smaller than

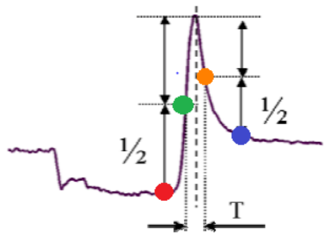

Figure 2: Eye blink with detected points (Svensson, 2004).

zero, corresponding to the rising and falling flank of the eye blink. The onset and end are then found by looking for zero-crossings in the derivative.

For each eyeblink, 16 features are now derived from these values that can be grouped in three groups: amplitude features, time features and velocity features. The different features and their calculation are listed in Table 1. During the experiment, the subject only had to score his drowsiness on the KSS-scale once every five minutes. Therefore, all eyeblinks in each five minute interval are grouped together and two values for each feature are calculated: the mean value and standard deviation over a five minute interval.

This means that in the end there are 32 features.

3.4 Drowsiness Detection

Training data are used to determine which features are affected by drowsiness and to set the different parameters needed for the prediction. A sufficient amount of training data is needed since the training data need to contain enough variation in drowsiness levels. In this case, the data of the second drive are used as training data, the data of the third drive as test data.

The calculation of all 32 features is done for the training data and Pearson's product-moment correlation coefficient between the KSS-rating and each feature is then computed (Fenton and Neil, 2012). The significance of the correlation coefficient is measured by its p-value. When p is close to zero, there is significant correlation. The p-values of all correlation coefficients are calculated and sorted in increasing order. Both methods use maximally the m features with a p-value smaller than 0.2. Typically, p-values of 0.01 or 0.05 are used, but this value was increased to assure that at least one feature is chosen so drowsiness can be predicted. It is also possible to use less features, in that case the n features with the lowest p-values are selected.

3.4.1 Detection based on Linear Regression

Hargutt and Kruger show that there is a linear relationship between various EOG parameters and

Table 1: EOG features and their calculation.

Group	Feature	Calculation
Amplitude	Peak amplitude	Peak amplitude
	Rise value	Peak amplitude – onset amplitude
	Fall value	Peak amplitude – end amplitude
	Onset difference	Onset amplitude – end amplitude
Time	Total length	End time – onset time
	Rise length	Peak time – onset time
	Half-rise length	Peak time – half-rise time
	Half-fall length	Half-fall time – peak time
	Fall length	End time – peak time
	Half length	Half-fall time – half-rise time
	Time between two blinks	$\frac{\Delta(peaktime)}{\Delta t}$
Velocity	Rise velocity	$\frac{Rise\,value}{Rise\,length}$
	Half-rise velocity	$\frac{0.5*Rise\,value}{Half-rise\,length}$
	Fall velocity	$\frac{Fall\,value}{Fall\,length}$
	Half-fall velocity	$\frac{0.5*Fall\,value}{Half-fall\,length}$
	Total velocity	$\frac{Rise\,value}{Total\,length}$

drowsiness stages (Hargutt and Kruger, 2001). For each of the selected features, this linear relationship between the feature and the KSS rating is modeled by fitting them with a polynomial of degree 1:

$$KSS = a_i \cdot feature + b_i \tag{4}$$

The process of detecting the eye blinks and calculating the features is now repeated for the test data. Only the features that had significant correlation in the training data are calculated. The drowsiness is then predicted by using linear regression to predict the drowsiness based on each feature and taking the average over all predictions:

$$KSS = \frac{1}{n}\sum_{i=1}^{n} KSS_i \tag{5}$$

$$= \frac{1}{n}\sum_{i=1}^{n} a_i \cdot feature_i + b_i \tag{6}$$

i is the feature's index and n is the number of features that are used to predict the drowsiness, which can range from 1 to m. Increasing n will increase the number of features used, but each extra feature will have a less strong correlation with the KSS rating than the previous features.

3.4.2 Fuzzy Detection

The second method is based on a paper by Picot et al. (Picot et al., 2011). For each feature that is used, two parameters a and b are calculated:

$$a = \mu_i + 0.25\mu_i \tag{7}$$

$$b = \mu_i - 0.25\mu_i \tag{8}$$

where i is the index of the feature and μ_i the mean value of feature i in the training data. The feature calculation is repeated for the test data, and the calculated features are converted to fuzzy indicators: a number between 0 and 1 that indicates the drowsy state. When this number is closer to one, the drowsiness level will be higher. When the correlation between the feature and the KSS rating is positive, the fuzzy drowsiness indicator is calculated by:

$$D(f_i) = \begin{cases} 0, & \text{if} f_i \leq \text{a} \\ \frac{f_i - a}{b-a}, & \text{if } a \leq f_i \leq b \\ 1 & \text{if } f_i \geq b \end{cases} \tag{9}$$

When the correlation is negative, Equation (9) becomes

$$D(f_i) = \begin{cases} 1, & \text{if} f_i \leq \text{a} \\ \frac{f_i - b}{b-a}, & \text{if } a \leq f_i \leq b \\ 0 & \text{if } f_i \geq b \end{cases} \tag{10}$$

In both equations (9) and (10), D is the drowsiness indicator, i the index of the feature and f_i the value of feature i. Finally, the mean of the drowsiness indicators is taken and converted to a number between one and nine:

$$KSS = 8 \cdot (\frac{1}{n}\sum_{i=1}^{n} D_i) + 1 \tag{11}$$

n is again the number of features used to predict the drowsiness, which can be varied to include more or less features.

3.5 Validation

Finally, the prediction results are compared with the KSS rating given by the subjects to examine the quality of the prediction. The comparison can be presented by constructing a confusion matrix. The values on the diagonal are the most important values, since they represent a perfect prediction. However, since KSS is a scale with nine gradations, results where the prediction differs one value from the true rating can also be considered good results. Therefore, from now on the distinction will be made between perfect results (e.g. the predicted value is equal to the real value) and good results (e.g. the difference between the predicted and true value is one).

4 RESULTS

The eye blinks present in the signal are first counted manually and the result is compared with the number of eye blinks detected by the methods described in Section 3. The developed methods detect in total $85.7 \pm 8.1\%$ of all eye blinks. The different features and their correlation with the KSS rating are then calculated. Features for which the correlation coefficient is small enough are used for drowsiness detection. The ten features that are most often used to detect drowsiness are listed in Table 2.

Table 2: Features included in most subsets.

Feature	%
Mean half-rise speed	89.4
Mean rise speed	84.22
Mean fall value	78.9
Std half-fall length	78.9
Mean half-fall speed	78.9
Mean rise value	73.6
Mean half-rise length	73.6
Mean rise-length	73.6
Mean peak amplitude	73.6
Std total length	73.6

The first column is the name of the feature and the second column the percentage of subsets that includes the feature. When a feature is included in a lot of subsets, it means that the correlation between the feature and the KSS rating is significant for a lot of subjects. The majority of the most frequently included features are calculated as the mean value over a five-minute interval. Only two features are the standard deviation over a five-minute interval.

4.1 Method 1: Linear Regression

Figure 3 (a) shows the results for the drowsiness detection using the first method for one subject. The predicted values are shown in red, the true values in blue. One thing is immediately clear: the predicted values and true values have the same trend over time, but there appears to be a constant difference of four between the red and blue values. This difference, or bias, is observed in almost all results. If the bias is added to the predicted values, the results improve tremendously: in the example from Figure 3 originally only 12% of the results were predicted well (meaning a difference of one between the predicted and the true value) and none of the values were predicted perfectly. If a bias of four is added, 75% of the results are good and 54% of the results are perfect. For each subject, the bias is determined visually and added to the predicted values.

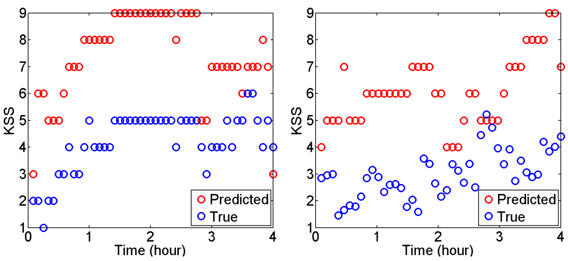

Figure 3: Results for drowsiness detection using method 1 (left) and method 2 (right).

In Equation (6), n, the number of features used to predict drowsiness can be varied. In Table 3 (a) the average percentage of good results is shown for different numbers of features used.

Table 3: Effect of number of features of results of (a) linear regression and (b) fuzzy detection for one subject.

(a) Linear regression

Number	% good
1	75.4
2	37.9
3	25.6
4	14.7
5	9.13

(b) Fuzzy detection

Number	% good
1	71.4
2	68.1
3	63.4
4	61.8
5	60

The best results are obtained using only one feature. The accuracy decreases consistently with rising n. Therefore, the number of features is fixed at one and the complete dataset is processed likewise. The confusion matrix is shown in Table 4, the sum of the good and perfect results is shown at the end of each row.

The drowsiness prediction works well for large KSS values. When the true value is one or two however, the majority of the predictions are wrong.

The results for individual subjects are good as well. On average, $72 \pm 18\%$ of the predictions are good. The percentage of perfect results is a lot lower: $29 \pm 11\%$

Table 4: Confusion matrix for linear regression expressed in percentages.

Predicted value

		1	2	3	4	5	6	7	8	9	
	1	0	1.85	22.22	25.92	25.92	14.81	7.40	1.85	0	**1.85**
	2	0	8.33	8.33	58.33	25	0	0	0	0	**16.66**
	3	0	3.22	35.48	45.16	0	3.22	6.45	3.22	3.22	**83.86**
	4	0	0	24.50	32.35	19.60	8.82	2.94	5.88	5.88	**76.45**
True	**5**	0	0.76	6.87	22.13	22.13	26.71	14.50	2.29	4.58	**70.97**
value	**6**	1.76	1.76	4.42	7.07	13.27	26.54	38.05	6.19	0.88	**77.86**
	7	2.87	2.15	0.71	1.43	7.19	12.94	33.09	30.93	8.63	**76.96**
	8	0.69	1.38	1.38	1.38	3.47	4.86	25	29.86	31.94	**86.8**
	9	3.33	1.11	1.11	2.22	6.66	14.44	10	11.11	50	**61.11**

4.2 Method 2: Fuzzy Detection

The second method again has a bias, as can be seen on Figure 3(b), although the bias is smaller. Table 3(b) shows that using one feature also gives the best result in this case.

Table 5 shows the confusion matrix.

The predictions for a KSS rating of one are not good: only 6.45% is predicted well. the results for the other values are a lot better, the majority of predictions differ maximum one value from the true rating. After examining the results of all subjects, $34 \pm 12\%$ of all predictions are perfect and $65 \pm 12.2\%$ are good.

5 DISCUSSION

In this paper, drowsiness is detected based on the artifacts in the EEG signal. Equation 3 constructs a new signal containing all artifacts and a minimum of EEG signal. The signal will be similar to the EOG signal, measured by placing electrodes around the eye, since the EOG signal also contains all EOG artifacts and minimal EEG signal. It would therefore be possible to use the described methods with electrodes placed around the eye. The advantage would be a reduction in the number of electrodes which would benefit the user friendliness. However, an advantage of using the complete EEG signal is that it contains a lot more information than merely EOG artifacts. This information can be either be used for other purposes (such as stress or concentration monitoring) or can be incorporated in the drowsiness detection to make the results more accurate. Since CCA can effectively remove both ocular and muscle artifacts, further calculations can immediately be done on the clean EEG signal. This makes the detection of other drowsiness indications in the EEG signal easier, since they are often missed when the signal quality is bad (Simon et al., 2011). It would be very interesting to repeat the calculations using less electrodes, to see if similar results can be obtained. This would increase the practical usability, while still recording EEG signals that can be used for further drowsiness detection.

The optimal number of features to detect drowsiness is shown to be one. In one way, this could be expected since the features are sorted based on the significance of their correlation. The feature with the strongest correlation gives the best results. Adding next important features didn't increase the detection performance, even in the case when the first prediction was incorrect. This indicates that the correlation of the first feature is a lot more significant than the other features.

Table 2 shows "the most popular" features for each set of training data. Mean speed and mean half-rise speed are clearly two key features; they are included in the majority of the subsets. First it has to be noted that it is very probable that the rise speed and half-rise speed are very correlated with each other. If the speed of the total eye opening increases, it is expected that the speed at which half the eye opens increases as well. Therefore it might be useful to first reduce the number of features using principal component analysis. PCA can be used to convert a set of possibly correlated variables to a set of linearly uncorrelated variables (Abdi and Williams, 2010). Second, it is curious that the correlation of the rise speed decreases most with increasing drowsiness. (Yue, 2011), (Svensson, 2004) and (Borghini et al., 2012) all state that eye parameters such as blink duration and frequency are influenced most by drowsiness, but no one of them names velocity as an important parameter. The reason for this difference might lie in the nature of the experiment. During the experiment, the participants had to look at a screen for longer than three hours. (Rosenfield, 2011) demonstrates that this may reduce the blink rate and cause Computer Vision Syndrome, leading to dry and irritated eyes, which may again influence eye blink behaviour. It is thus

Table 5: Confusion matrix for fuzzy detection expressed in percentages.

		Predicted value									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	
	1	0	6.45	9.67	25.8	12.9	16.12	19.35	3.22	6.45	**6.45**
	2	0	6.25	25	50	6.25	6.25	6.25	0	0	**31.25**
	3	0	1.47	29.41	32.35	23.52	7.35	2.94	1.47	1.47	**63.23**
	4	0 .99	0.99	16.83	31.68	23.76	14.85	3.96	2.97	3.96	**72.27**
True	**5**	0	2.06	3.09	19.58	21.64	18.55	14.43	11.34	9.27	**59.77**
value	**6**	2.43	1.62	9.75	7.31	12.19	30.89	22.76	10.56	2.43	**65.84**
	7	3.61	1.2	1.8	4.81	8.43	13.85	41.56	16.26	8.43	**71.76**
	8	0.84	0.84	1.68	2.52	4.2	6.72	22.68	42.01	18.48	**83.17**
	9	5.26	0	3.15	2.10	1.05	7.36	10.52	8.42	62.10	**70.52**

probable that in a natural environment (e.g. while driving a real car instead of a driving simulator) other features will be more important. Since using one feature gives the best prediction results and mean speed and mean half-rise speed are clearly features that often have significant correlation with the drowsiness level, it would be possible to only calculate one of both features.

Figure 3 shows that there is a difference between the drowsiness level predicted and the true drowsiness level. The bias is different for each subject. There could be two reasons why there is a bias present. First, the subjects do not rate their drowsiness consistently. They for example think they are less tired than they actually are. Since the subjects rate their drowsiness after a questionnaire is shown on a screen, it is possible that the appearance of this questionnaire influences the perceived drowsiness. If that is the case, the questionnaire arouses the subject for a short time, effectively decreasing the drowsiness rating. Therefore, it would be interesting to obtain a more objective drowsiness rating by analyzing video recordings or the driving behaviour of the subjects. Second, the coefficients of the polynomial that is fitted to the training data might not be entirely correct. This may be explained by the fact that there are not many data available for low KSS values.

The second reason is obviously not relevant for explaining the offset in the second method since no linear fit is used. However, there is also a bias noticed in the results of the second method, although the bias is smaller than in the results of the first method. Therefore, it is suspected that both reasons apply in this case.

Finally, the results of both methods can be considered good, also when compared with other similar methods. Svensson (Svensson, 2004) detects drowsiness based on changes in blink behaviour and uses a four graded scale. There, a correspondence with KSS values of 70% is obtained. Picot et al. (Picot et al., 2011) obtain an accuracy of 82% when distinguishing between drowsy and not-drowsy, making the classification significantly easier.

It is not easy to choose the best method among the two tested here, since they both have their strengths and weaknesses. If the two confusion matrices are compared, it is clear that the method based on fuzzy detection gives more perfect results and the linear regression-based method gives more good results. The differences are however small. They also show that the fuzzy detection performs better for small KSS values (although the result for KSS = 1 is still not good). However, since the aim is detecting drowsiness, large values are more important. Even more, since drowsiness varies gradually, a small difference in the true and predicted values is not very important. Therefore, in most applications the linear-regression based method would be preferred. However, when perfect classifications need to be obtained, one would probably start with fuzzy detection. In that case, the method would have to be adjusted to improve the accuracy.

6 CONCLUSIONS

The methods described in this paper are ways of detecting drowsiness based on EOG artifacts present in the EEG signal. They work semi-automatic: both the threshold to detect eyeblinks and the bias are determined individually. The results of the methods are good when perfect accuracy is not required. On average 70% of the predictions differ at most one value from the KSS rating given by the subject. In applications when perfect accuracy is required however, the methods should be improved or combined to give better results. The results of the drowsiness detection could be improved by extending the developed methods. It is possible to incorporate more information extracted from the EEG in the methods. This way, the accuracy and more specifically the number of perfect results would be increased.

If the methods were to be used in real-life applications, they need to be used in real-time. Therefore, the methods would have to be adapted. It would for example be possible to calculate the features in a sliding window, hereby giving a continuous prediction. The thresholds for eye blink detection, which are now defined manually, can be fixed during a test drive. To increase the practical usability, the number of electrodes should be decreased, since it is virtually impossible to equip drivers with a full EEG cap. Finally, to reduce the computational load, it can be researched if the method gives good results when only calculating one or two features, instead of calculating 32 features and selecting one of them.

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