Comparing Contribution of Algorithm Based Physiological Indicators for Characterisation of Driver Drowsiness

Manuel Rost[1,2], Eugene Zilberg[1], Zheng Ming Xu[1], Yue Feng[1,2], David Burton[1], and Sara Lal[2]
[1]Compumedics Medical Innovation Pty Ltd, 30-40 Flockhart St Abbotsford 3067 Australia
[2] Neuroscience Research Unit, School of Medical and Molecular Biosciences, University of Technology Sydney (UTS), Broadway NSW 2007 Australia
Email: manuel.rost@student.uts.edu.au

Abstract—**The algorithm based physiological characteristics of driver drowsiness – ocular parameters (derived from the frontal electroencephalogram (EEG)), EEG alpha bursts and spectral power (derived from the central and occipital sites) as well as heart rate variability (HRV) were estimated from data derived during a driving simulator experiment (30 non-professional drivers). The statistical associations of these parameters with the "gold standards" of driver drowsiness were investigated using linear regression and linear mixed models. The statistical models were also examined for a number of hybrid algorithms, which combined multiple characteristics of driver drowsiness. A combination of ocular parameters showed the strongest association (R^2=0.48) with the applied trained observer rating (TOR) method; followed by EEG alpha bursts indicators (R^2=0.30) and EEG spectrum data (R^2=0.21). The HRV parameters showed a weak association (R^2=0.04) A joint model including the eye parameters and the EEG alpha bursts resulted in the highest R^2=0.54 to TOR. The results indicate that a hybrid automatic algorithm, based on multiple characteristics of the eye blinks and EEG patterns, but not necessarily including the HRV measures, is likely to achieve a level of accuracy in characterising driver drowsiness similar to that of a trained observer.**

Index Terms—**driver, drowsiness, fatigue, physiological, EEG, alpha bursts, eye behaviour, automatic, hybrid**

I. Introduction

Driver drowsiness and fatigue are universally recognized risk factors for road safety [1]-[3]. A sleep deprived driver (17 hours without sleep) shows similar effects as having a blood alcohol concentration of about 0.05% [4]. Subsequently, a number of road accidents can be avoided by installing an adequate automatic drowsiness counter measure system in a vehicle.

Over the last decades several methodologies have emerged to detect driver drowsiness. Ocular parameters have been shown to have a strong correlation with the states of drowsiness [5], [6]. PERCLOS (percentage of eye closure over the pupil over time) is a broadly accepted marker of drowsiness [7]. It was validated using EEG data and expert rating of drowsiness [8]. In addition to PERCLOS the other promising ocular correlates of driver drowsiness include average eye closure speed, amplitude/velocity ratio as well as blink duration [9], [10].

EEG signals are currently widely used to measure drowsiness [11], [12]. The EEG alpha activity (8-13Hz), manifesting itself as short bursts particularly in the occipital or central areas, is known to be associated with drowsiness [13]. Our previous research have also demonstrated that EEG alpha burst as well as spectral analysis in the alpha band are useful practical indicators of drowsiness [14], [15].

The heart rate and the heart rate variability (HRV) have also been used to identify drowsiness due to their links with changes in autonomic nervous system activity during transition from an alert to a drowsy state. It has been observed that drowsy drivers show a lower heart rate [16], [17]. The HRV can be analysed by frequency-domain techniques; mainly into three bands: high frequency (HF, 0.15 to 0.4 Hz) band, low frequency (LF, 0.04 to 0.15 Hz) band as well as very low frequency band (VLF, 0.0033 to 0.04 Hz). The reduction in the LF/HF ratio as well as increase in the HF power are hereby relevant prospective indicators of drowsiness and sleep onset [18]-[20].

This paper presents the first, novel attempt to extract fully automatic, physiological pattern based indicators of driver drowsiness utilising eye parameters, EEG waveforms and patterns as well as HRV measures, and subsequently statistically evaluate the associations between the above indicators and non-physiological 'gold standards' of drowsiness. The objective of the presented research is to identify individual contributions of the ocular, EEG and HRV parameters for characterisation of driver drowsiness and quantify potential accuracy of a hybrid drowsiness detection algorithm by using multiple regression models.

II. Methods

A. Driving Simulator Study and Data Acquisition

Driving simulator data were collected by Karrar [21] during an earlier study conducted by Compumedics Ltd,

Manuscript received July 25, 2014; revised October 25, 2014.

doi: 10.12720/jomb.4.5.391-398

Australia in association with the University of Technology, Sydney. The study took place after a regular night of sleep commencing at 2:46 pm ± 33min with data obtained for up to 2.5 hours per driver. The following recordings were obtained: EEG (Fp1 (frontal-polar), Fp2, T7 (temporal), T8, P7 (parietal), P8, C4 (central) and O2 (occipital); reference A1 and A2 (auricular)) & EOG (electro-oculogram) (as per the standard international 10-20 system introduced by [22]), electrocardiogram (ECG), breathing (using a thoracic band) lateral lane position and video images of the driver's face, steering wheel and driving scenery. The study included 30 non-professional drivers (age 20-60 years, healthy) and was conducted at the Monash University Accident Research Centre (MUARC), Melbourne. The physiological data were recorded using the Siesta Physiological Monitoring System (Compumedics, Australia).

The video images of the participants were used as a reference to evaluate driver drowsiness. The applied Trained Observer Rating (TOR) was based on the scale by Wierwille and Ellsworth [23] and contains five drowsiness levels: Alert, Slightly Drowsy, Moderately Drowsy, Significantly Drowsy and Extremely Drowsy (see Table I). The state of drowsiness was visually assessed within a 10s interval.

TABLE I. TRAINED OBSERVER RATING (TOR) BASED ON A SCALE BY WIERWILLE AND ELLSWORTH [23]

Level	Drowsiness State	Video image indicators
0	not drowsy	Normal fast eye blinks, often reasonably regular; Apparent focus on driving with occasional fast sideways glances; Normal facial tone; Occasional head, arm and body movements.
1	slightly drowsy	Increase in duration of eye blinks; Possible increase in rate of eye blinks; Increase in duration and frequency of sideway glances; Appearance of "glazed eye" look; Appearance of abrupt irregular movements – rubbing face/eyes, moving restlessly on the chair; Abnormally large body movements following drowsiness episodes; Occasional yawning.
2	moderately drowsy	Occasional disruption of eye focus; Significant increase in eye blink duration; Disappearance of eye blink patterns observed during alert state; Reduction on degree of eye opening; Occasional disappearance of facial tone; Episodes without any body movements.
3	very drowsy	Discernable episodes of almost complete eye closure, eyes never fully open; Significant disruption of eye focus; Periods without body movements (longer than for level 2) and facial tone followed by abrupt large body movements.
4	extremely drowsy	Significant increase in duration of eye closure; Longer duration of episodes of no body movement followed by large isolated "correction" movements.

B. Spectral EEG Analysis

After applying a band-pass filter (0.3-35Hz) the spectrum of the recorded EEG channels was computed using the short-time Fourier transform (hamming window=1s, overlap=0.75s). Four different band-power spectra (delta: 0.5-4Hz, theta: 4-8Hz, alpha: 8-13Hz, beta: 13-35Hz) were then extracted and the relative contribution of the frequency bands, in particular the alpha band, to the total power ($P_{delta}+P_{theta}+P_{alpha}+P_{beta}$) was calculated. The next step included the determination of the following input parameters for the regression model:

- Average alpha power spectrum ratio (APSR) from the C4 and O2 channels over a 30s period
- Maximum alpha power spectrum ratio (MPSR) from the C4 and O2 channel over a 30s period

The parameters were adjusted by subtracting the average of the initial 15min drive from the subsequent values.

C. Alpha Burst Detection

The applied C4 and O2 channels are filtered (0.3-35Hz) and then analysed by a proprietary pattern matching algorithm written in Matlab (R2011a) to determine the following characteristics of alpha bursts (AB) for a minimum of four waves:

- Total duration;
- Number of individual EEG waves within an alpha burst;
- Amplitude similarity parameter (measure of similarity of the amplitudes of individual EEG waves within an alpha burst);
- Duration similarity parameter (measure of similarity of the durations of individual EEG waves within an alpha burst);
- Noise index (measure of "cleanness" of the alpha burst from contribution of background noise to the signal)
- Mean amplitude (average of peak to peak amplitude)
- Relative amplitude (ratio of mean amplitude of alpha burst to mean amplitude signal 2 s prior to the onset of alpha burst)

The parameters were normalised by subtracting the average data of the initial 15min drive from the subsequent values. The alpha-burst parameters were then averaged within a 30s segment.

D. Eye Parameter Detection (Algorithm Based)

The proprietary Matlab (R2011a) based algorithm determined automatically short eye blinks as well as long eye blinks/movements (see Fig. 1) using the Fp1/A2 channel. The algorithm detects blinks shorter than 0.5 s accurately but does not distinguish between blinks and eye movements longer than 0.5 s, which cannot be always differentiated using visual analysis of frontal EEG (Fp1-A2). However, the majority of longer blink/eye movement patterns were long blinks rather than eye movements. The following eye parameters were obtained:

- Blink duration for the short blinks (<0.5 s) as well as long blinks/eye movements;
- Blink rate for the short blinks and long blinks/eye movements;

- Blink amplitude for the short blinks and average blink amplitude for long blink/ eye movement;
- Eye closure duration (ECD) for the short blinks and long blinks/eye movements;
- Eye opening duration (EOD) for the short blinks and long blinks/eye movements;
- Average Eye Closure Speed (AECS) for the short blinks and long blinks/eye movements

The eye parameters were then averaged within a 30s time interval.

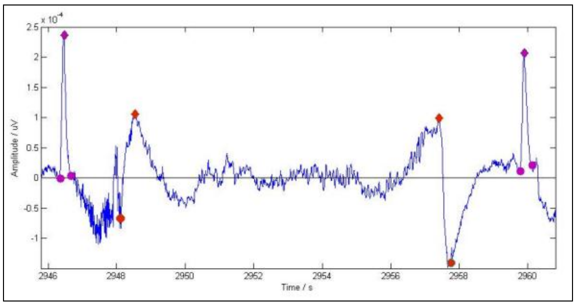

Figure 1. Automatically detected short blinks and long blink

E. Manual Scoring of Eye Parameters

The channel Fp1/A2 was visually inspected and the duration of eye blinks were marked (as shown in Fig. 1).

F. Determination of Heart Rate Variability

The polysomnographic software ProFusion 4.0 (Compumedics Ltd, Australia) determined the R-R intervals from the ECG. The HRV measures were subsequently calculated by an algorithm programmed in Matlab within a 5min window. The following parameters, which are considered to be the most relevant indicators of drowsiness and sleep stages [20], were obtained:

- High frequency (HF)
- LF/HF ratio

However, despite selecting a window of 5min, the spectral analysis produced a lot of invalid data due to the small number of R-R intervals within the respective window. The HRV data were generated every 30s for a window of 5min.

G. Statistical Analysis

The statistical analysis was computed by the statistical software package Stata (StataCorp, USA). A linear regression model [24] was applied and the R^2 coefficient (interpreted as relative measure of variation in the outcome variable attributable to the explanatory variables) was computed using the mentioned parameters above as independent variables. The references TOR as well as standard deviation of lane position (SDLP) were the outcome variables to explore associations between the parameters of interest and driver drowsiness. The Stata function *regress* was used.

To take into account potential correlation between multiple observations for the same subject linear mixed model was also fitted to the same observations (Stata function xtmixed) [24], Subsequently the findings of linear regression and linear mixed models were compared to verify if the identified associations between the physiological indicators of drowsiness the "gold standard of drowsiness", and the respective R^2 values were still valid after potential correlation was considered.

III. Results

A. Single Parameter Predictors of Drowsiness

Table II provides an overview of the investigated drowsiness predictors. The strongest R^2 can be seen in the eye parameters, followed by the alpha bursts indicators. The spectral EEG parameters appear weaker than the alpha bursts. The weakest association can be found in the HRV data, where in addition the linear mixed model is not significant in relation to the reference TOR.

The channel O2 in both spectral and alpha burst parameters showed a stronger R^2 than C4. The EEG indicator MPSR in both channels had a higher R^2 value compared to APSR. The alpha burst relative amplitude appears to have a slightly stronger association with TOR than the duration of alpha bursts. The blink durations, especially the eye closing duration, showed the best goodness of fit out of all eye parameters.

On the basis of these results important and significant drowsiness predictors were selected for further analysis, in particular to use as inputs for multiple regression models.

B. Parameters Based on Spectral EEG Analysis

The parameters MPSR in the EEG alpha band for the channels C4 and O2 were used in a regression model and showed a contribution of R^2=0.21 (Table III). The variables APSR as mentioned in section II B. were excluded from the model because the p-values were > 0.05. In addition, MPSR showed a significantly stronger association than APSR in both channels. MPSR C4 alone had a significant association of R^2=0.15 and MPSR O2 of R^2=0.2.

C. Combined Alpha Burst Parameters as Dowsiness Indicators

A linear regression model was used to show associations between characteristics of alpha bursts extracted from C4 & O2 and certain levels of drowsiness using the TOR scale as a reference. The model consists of only significant covariates (duration, mean amplitude and relative amplitude) and reached a goodness of fit R^2=0.30 (see Table II). The estimated values of the regression coefficients were all positive except for the mean amplitude (for C4 & O2).

D. Spectral EEG Analysis and Alpha Bursts Combined

The addition of the parameters from the EEG alpha band to the alpha bursts variables did not increase the overall R^2.

E. Computer Generated Eye Parameters as Drowsiness Indicators

The significant eye parameters: average duration blink (<0.5s), total duration blink / eye movement, ECD blink/eye movement, AECS blink/eye movement and amplitude blink/eye movement contributed to the linear regression model with R^2=0.48 (see Table III). As expected, the characteristic duration increased whereas AECS as well as amplitude decreased with the level of drowsiness.

TABLE II. SINGLE DROWSINESS PREDICTORS AND STRENGTH OF ASSOCIATION WITH TOR AND SDLP. THE SIGNIFICANCE VALUES ARE GIVEN FOR BOTH: LINEAR REGRESSION MODEL AND LINEAR MIXED MODEL.

Drowsiness Predictor	TOR					SDLP				
	LRM			LMM		LRM			LMM	
	p-value	t	R^2	p-value	z	p-value	t	R^2	p-value	z
TOR	N/A					<0.001	31.07	0.17	<0.001	25.83
EEG APSR C4	<0.001	23.58	0.11	<0.001	26.37	<0.001	10.94	0.03	<0.001	8.78
EEG MPSR C4	<0.001	27.63	0.15	<0.001	31.88	<0.001	11.32	0.03	<0.001	10.21
EEG APSR O2	<0.001	26.96	0.14	<0.001	30.73	<0.001	10.40	0.03	<0.001	10.38
EEG MPSR O2	<0.001	32.86	0.20	<0.001	35.99	<0.001	11.92	0.03	<0.001	11.74
AB Duration C4	<0.001	25.51	0.13	<0.001	24.03	<0.001	12.15	0.04	<0.001	7.88
AB Duration O2	<0.001	35.70	0.22	<0.001	35.42	<0.001	13.47	0.04	<0.001	13.48
AB Mean amplitude C4	<0.001	26.31	0.14	<0.001	26.07	<0.001	10.81	0.03	<0.001	8.37
AB Mean amplitude O2	<0.001	28.72	0.16	<0.001	29.54	<0.001	8.93	0.02	<0.001	9.09
AB Relative amplitude C4	<0.001	30.08	0.17	<0.001	27.84	<0.001	11.61	0.03	<0.001	8.61
AB Relative amplitude O2	<0.001	35.94	0.23	<0.001	34.72	<0.001	10.23	0.03	<0.001	9.92
Blink average duration <0.5s	<0.001	47.39	0.30	<0.001	37.44	<0.001	19.64	0.07	<0.001	10.65
Blink/eye movement total duration ≥0.5s	<0.001	39.61	0.23	<0.001	37.92	<0.001	21.43	0.09	<0.001	17.22
Blink/eye movement duration combined: Blink average duration <0.5s	<0.001	37.48	0.39	<0.001	31.01	<0.001	13.60	0.12	<0.001	6.88
Blink/eye movement duration combined: Blink/eye movement total duration ≥0.5s	<0.001	28.36		<0.001	31.62	<0.001	15.99		<0.001	15.11
Blink rate for Blinks <0.5s	<0.001	-16.78	0.05	<0.001	-14.73	<0.001	-17.77	0.06	<0.001	-13.43
Blink rate for Blinks/eye movements >0.5s	<0.001	22.33	0.22	<0.001	19.38	<0.001	11.88	0.09	<0.001	9.17
Blink/ eye movement ECD	<0.001	48.73	0.31	<0.001	43.58	<0.001	21.96	0.09	<0.001	16.96
Blink/ eye movement EOD	<0.001	37.18	0.21	<0.001	31.80	<0.001	15.59	0.05	<0.001	9.70
Blink/eye movement AECS	<0.001	-32.72	0.17	<0.001	-46.16	<0.05	-17.69	0.06	<0.001	-17.57
Blink/eye movement amplitude normalized	<0.001	-19.46	0.08	<0.001	-21.42	<0.001	-6.28	0.01	<0.001	-9.20
HRV HF adjusted	<0.001	-3.52	0.02	<0.001	-1.97	0.83	-0.22	0.00	<0.001	-0.06
HRV LF/HF ratio adjusted	<0.001	-3.26	0.01	<0.001	1.22	<0.001	-7.52	0.08	<0.001	-4.98

F. Visually scored Eye Parametrers as Drowsiness Indicators

The strength of association for the logarithm transform of duration of eye blinks/movement reached R^2=0.46 and was therefore larger than the association based on automatically detected equivalent eye parameters (R^2=0.39). However, only the blink duration was derived from visual scoring and could therefore serve as a single drowsiness predictor.

G. HRV Drowsiness Indicators

A linear regression model was applied using the normalized HRV data HF and LF/HF ratio, which reached a goodness of fit R^2=0.04 (see Table III). Both covariates for the linear regression model were significant. However, the number of observations dropped by a factor of 6 in comparison with the analysis of alpha bursts and eye parameter due to many invalid data. In addition, the linear mixed models for HF as well as LF/HF ratio, in relation to TOR, were not significant (see Table II). Based on these findings, HRV data were not included in the overall regression model, described in the next section.

TABLE III. COMBINATION OF PARAMETERS AND THEIR STRENGTH OF ASSOCIATION TO TOR AS WELL AS SIGNIFICANCE BASED ON LINEAR REGRESSION MODEL

Drowsiness Predictor	Reg. Coefficient	t	p	R^2
EEG Alpha Band Normalized				
MPSR C4	1.179 [0.928; 1.430]	9.21	<0.001	0.21
MPSR O2	2.034 [1.824; 2.244]	18.97	<0.001	
Alpha Bursts Normalized (minimum four waves)				
Duration C4	0.102 [0.052; 0.151]	3.09	<0.001	0.30
Duration O2	0.304 [0.229; 0.379]	7.70	<0.001	
Mean amplitude C4	-0.017 [-.022; -0.011]	-5.36	<0.001	
Mean amplitude O2	-0.016 [-0.022; -0.010]	-5.48	<0.001	
Relative amplitude C4	0.649 [0.521; 0.778]	9.77	<0.001	
Relative amplitude O2	0.587 [0.477; 0.696]	10.38	<0.001	
Spectral EEG Analysis and Alpha Bursts combined				
Parameters EEG alpha band and alpha bursts (as above)				0.30
Eye Parameter (algorithm based)				
Average duration blink<0.5s	4.398 [4.030; 4.766]	23.42	<0.001	0.48
Total duration blink/eye movement ≥0.5s	0.056 [0.047; 0.064]	13.17	<0.001	
ECD blink/eye movement	1.946 [1.572; 2.321]	10.19	<0.001	
AECS blink/eye movement	-73.20 [-95.82; -50.61]	-6.37	<0.001	
Amplitude blink/eye movement normalized	-3727 [-4103; -3351]	-19.34	<0.001	
HRV Data Normalized				
HF	-5e-5 [-7e-5; -3e-5]	-4.72	<0.001	0.04
LF/HF ratio	-0.054 [-0.079; -0.031]	-4.53	<0.001	
Eye Parameter (manual scoring)				
Average eye blink/movement duration	0.851 [0.809; 0.892]	40.55	<0.001	0.27
Log of average eye blink/movement duration	0.573 [0.555; 0.592	65.54	<0.001	0.46

H. Alpha Burst and Eye Parameter combined

A linear regression model based on alpha bursts and eye parameter characteristics was created using only significant covariates. Table IV illustrates the strength of associations between the drowsiness predictors and TOR as well as SDLP and provides an overview of the respective p-values from the linear regression model and the linear mixed model. The combination of eye and alpha burst parameters resulted in an increase of R^2 to 0.54. R^2 of eye and alpha burst parameter with SDLP (0.15) approached that of TOR (0.17).

TABLE IV. ALPHA BURSTS NORMALIZED (MINIMUM FOUR WAVES) & EYE PARAMETERS (ALGORITHM BASED)

Drowsiness Predictor	TOR				SDLP			
	LRM	LMM			LRM	LMM		
Alpha Burst and Eye Parameter combined	R^2= 0.54				R^2= 0.15			
	t	z	p>|t|	p>|z|	t	z	p>|t|	p>|z|
Duration C4	3.24	2.93	<0.001	<0.001	3.89	0.05	< 0.001	0.960
Duration O2	4.06	5.07	<0.001	<0.001	4.16	5.63	< 0.001	< 0.001
Relative amplitude C4	5.02	7.15	<0.001	<0.001	-0.43	1.37	0.668	0.170
Relative amplitude O2	7.55	7.05	<0.001	<0.001	-3.27	-2.13	< 0.001	0.033
Average duration blink<0.5s	19.9	11	<0.001	<0.001	6.30	0.59	< 0.001	0.553
Total duration blink/eye movement ≥0.5s	7.00	8.04	<0.001	<0.001	6.36	4.23	< 0.001	< 0.001
ECD blink/eye movement	11.24	6.73	<0.001	<0.001	3.03	3.46	< 0.001	0.001
AECS blink/eye movement	-6.9	-8.75	<0.001	<0.001	-5.14	-1.24	< 0.001	0.216
Amplitude blink/eye movement normalized	-14.43	-2.43	<0.001	<0.001	-2.71	-2.48	< 0.001	0.013
Error SD estimates		constant=0.265 residual=0.367				constant=0.098 residual=0.162		

All p-values in the linear regression model as well as the linear mixed model are < 0.05; hence there is a significant relationship between TOR and drowsiness predictors. However, a significant association can also be seen between the covariates and SDLP in the linear regression model but not in the linear mixed model. When LMM was used, the standard deviation (SD) of constant subject error was markedly smaller than the SD of the residual error, confirming appropriateness of using R^2 from LRM for comparing contributions of different covariates.

The strengths of association with the ocular and alpha burst parameters were subsequently individually analysed for each subject to explore the relative roles of these groups of parameters. Table V illustrates several groups of subjects depending on their individual R^2 as well as the overall drowsiness (TOR scale) of the subject within the study. The subjects were allocated into "TOR low" group if the subject's drowsiness score stayed <3 during the whole experiment and into "TOR high" group if the video based score reached ≥ 3 (very drowsy subjects) during the study. Subjects with a high TOR were then further divided depending on their respective association of the eye parameters as well as the alpha burst parameter with TOR. The first group in this context, which consists of five subjects, showed a strong association for the eye parameters and a low relation for the alpha bursts indicators. In contrast, only one subject with a high TOR was identified having a weak eye and a strong alpha burst association with TOR.

TABLE V. SEVERAL GROUPS OF SUBJECTS DEPENDING ON THEIR STRENGTH OF ASSOCIATION

Group of subjects	Number Subjects	R^2 Eye	R^2 Alpha Burst	R^2 combined
TOR low	11	0.20	0.04	0.22
TOR high	19	0.51	0.33	0.57
R^2 Eye high R^2 Alpha Burst low TOR high	5	0.62	0.03 (spectral EEG: R^2=0.005)	0.62
R^2 Eye low R^2 Alpha Burst high TOR high	1	0.14	0.25	0.32

It can be seen from Table V that in approximately 15% of the subjects who reached high levels of drowsiness, the EEG alpha bursts are not present and cannot be used as an indicator of drowsiness. However, these subjects have a strong association of the ocular parameters with TOR and the combined association resulted in R^2=0.62, which is higher than the overall R^2=0.54 (see Table IV). Such compensation occurred also in one drowsy subject (TOR high), where the association of the eye parameter with TOR was low and that of the alpha burst indicators was high. However, in that case, R^2 combined = 0.32 was significantly smaller than the overall R^2=0.54. In addition, subjects with a low TOR had a significantly smaller R^2 combined compared with those showing a high TOR.

IV. DISCUSSION

The objective of this paper was to estimate contributions of the algorithm based physiological indicators, derived from EEG and ocular patterns and HRV measures, into potential automatic characterisation of driver drowsiness. The associations for these parameters were established with the references TOR as well as SDLP. As linear regression requires an assumption of independent observations, linear mixed models were also investigated to take into account potential correlation between multiple observations for the same subject (although the majority of analysed characteristics were derived over non-overlapped time intervals). Similar values of regression coefficients between LMM and LRM justifies interpretation of the linear regression R^2 as a measure of the association strength. The data were recorded from 30 subjects during a driving simulator experiment.

It has been shown in previous studies that the most prominent EEG spectral range is the alpha band [25], [26], in particular the duration and other parameters of the alpha bursts have the strongest association with driver drowsiness [14]. As observed from Table II the strength of association for the spectral power of EEG Alpha Band is lower than that of the duration of alpha bursts, when they are detected using a morphological rather than a spectral method. In this study, the multiple regression model based on C4 and O2 sites using a combination of alpha bursts parameters (duration, amplitude, relative amplitude and others) showed a significant goodness of fit R^2=0.3, whereas the EEG spectral parameters MPSR O2 & C4 reached R^2=0.21. Combing the spectral and morphological parameters did not improve the model's goodness of fit due to an obvious substantial collinearity between these characteristics. Therefore, the duration and amplitude parameters of the alpha bursts are the most promising indicators for drowsiness using EEG. In addition, the channel O2 showed in both EEG spectrum and EEG alpha bursts a stronger relation than C4. This can be explained by the fact that alpha bursts in the occipital areas are related to eye closures [13], which have been demonstrated to have a very strong association with driver drowsiness [5], [6].

The eye parameters in this study, which were automatically detected by an algorithm written in Matlab, have shown the strongest relation to driver drowsiness. A multiple regression model based on blink duration, eye closure duration, average eye closure speed as well as amplitude reached an association to TOR of R^2=0.48. The eye parameter, eye blink/movement duration, which was scored manually, resulted (by using log of average eye blink/movement duration) in R^2=0.46 and was therewith slightly weaker than the automatically based one (although a smaller set of additional parameters was derived for the manually detected eye blinks). Out of a number of the automatically detected eye parameters those related to the eye blink duration performed the best. The two prominent drowsiness indicators such as PERCLOS as well as amplitude/velocity ratio according to [9], [10] have not been implemented into our algorithm yet. The parameter eye closure duration has been reported to be stronger than the duration of eye blinks [9], [10], which could not be demonstrated for the algorithm derived indicator eye closure duration. An explanation is that the precise beginning/end for the slow eye closures/openings could be ambiguous. The eye blink amplitude showed the weakest correlation with drowsiness, which is in line with previous studies [9], [10].

The HRV data HF power and LF/HF ratio have been investigated and showed in contrast to other publications [18]-[20] a weak association with the average drowsiness rating. In addition, both HRV parameters had no significant association with the reference TOR by using the linear mixed model. Due to these findings the HRV data were not included in the following described hybrid model.

A hybrid solution was investigated using a multiple regression model based on eye and alpha bursts parameters. The overall strength of association reached $R^2=0.54$ and the association with SDLP was similar to that between SDLP and TOR ("gold standard"). The associations using both LRM and LMM were both significant. A further investigation, where subjects and their respective influence were assessed, revealed that in about 15% of the subjects alpha bursts were not observed, when the driver reached ≥ 3 of the drowsiness scale (i.e. significant level of drowsiness). This result is consistent with the fact that in about 20% of the subjects little or no alpha activity occurs during eye closure [13]. In contrast, for one subject, when TOR reached ≥ 3, the linear regression model based solely on eye parameters, showed a weak association, whereas the alpha burst based model reached a relative high correlation. These observations support the feasibility of potential benefits for the hybrid drowsiness algorithm. Finally, the overall association of the combination of ocular and EEG measures with TOR was significantly weaker ($R^2=0.22$), when TOR was <3 and stronger ($R^2=0.57$) when TOR was ≥ 3. This finding highlights the possibility of false positives in a prospective automatic drowsiness detection algorithm.

V. Conclusion

Using the driving simulation data, this paper reported the statistical associations between several automatically detected characteristics of physiological drowsiness indicators with the "gold standards" of drowsiness – trained observer rating and deviation from the middle of the lane. From the ocular, EEG pattern and HRV parameters, the ocular measures were demonstrated to be the strongest markers of drowsiness. For the EEG measures, the morphological detection of alpha bursts was confirmed to be superior to the characteristics derived from spectral analysis. The conventional HRV parameters – HF power and LF/HF ratio showed the weakest association with drowsiness. A combination of EEG alpha bursts and eye parameters resulted in a marked strengthening of drowsiness predictive ability. The results imply that a hybrid automatic algorithm, based on multiple characteristics of the eye blinks and alpha bursts, potentially derived from a single EEG electrode, but not necessarily including the HRV measures, is likely to achieve a level of accuracy in characterising driver drowsiness similar to that of a trained observer.

Acknowledgements

The research was supported by the Australian Research Council Linkage grants: LP0989708 and LP100200842.

References

[1] World Health Organization, *World Report on Road Traffic Injury Prevention*, 2004.

[2] S. Vitabile, A. De Paola, and F. Sorbello, "Bright pupil detection in an embedded, real-time drowsiness monitoring system," in *Proc. 24th IEEE International Conference on Advanced Information Networking and Applications*, 2010.

[3] European Academy of Sleep Medicine, *The International Classification of Sleep Disorders: Diagnostic and Coding Manual*, American Academy of Sleep Medicine, 2001.

[4] Transport Accident Commission, *Reducing Fatigue - a Case Study*: Victoria.

[5] W. W. Wierwille, M. G. Lewin, and R. J. I. Fairbanks, "Final Report: Research on Vehicle-Based Driver Status/Performance Monitoring; Part 1," V.A.a.S. Laboratory, Editor, Virginia Polytechnic Institute and State University: Virginia, 1996.

[6] D. Liu, *et al*, "Drowsiness detection based on eyelid movement," in *Proc. 2nd International Workshop on Education Technology and Computer Science*, Wuhan, Hubei, China, 2010.

[7] N. Wright, *et al.*, *A Review of In-vehicle Sleepiness Detection Devices*, TRL Limited QinetiQ, 2007.

[8] D. F. Dinges and R. Grace, "PERCLOS: A valid psychophysiological measure of alertness as assessed by psychomotor vigilance," Federal Highway Administration, Office of motor carriers, Tech. Rep. MCRT-98-006, 1998.

[9] I. Damousis, *et al*., "Physiological indicators based sleep onset prediction for the avoidance of driving accidents," in *Proc. Engineering in Medicine and Biology Society, 29th Annual International Conference of the IEEE*, 2007.

[10] F. Friedrichs and Y. Bin, "Camera-based drowsiness reference for driver state classification under real driving conditions," in *Proc. Intelligent Vehicles Symposium (IV)*, 2010.

[11] M. Akin, *et al*., "Estimating vigilance level by using EEG and EMG signals," *Neural Computing and Applications*, vol. 17, no. 3, pp. 227-236, 2008.

[12] Y. Tran, *et al*., "Improving classification rates for use in fatigue countermeasure devices using brain activity," in *Proc. Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2010.

[13] J. Santamaria and K. H. Chiappa, *The EEG of Drowsiness*, New York: Demos Publications, 1987.

[14] M. Karrar, *et al*., "Detection of driver drowsiness using EEG alpha wave bursts - comparing accuracy of morphological and spectral algorithms," in *Proc. International Conference on Fatigue Management in Transportation Operations: A Framework for Progress*, Boston, USA, 2009.

[15] S. Pritchett, *et al*., "Comparing accuracy of two algorithms for detecting driver drowsiness — Single source (EEG) and hybrid (EEG and body movement)," in *Proc. 6th International Conference on Broadband and Biomedical Communications*, 2011.

[16] S. K. L. Lal and A. Craig, "Driver fatigue: Electroencephalography and psychological assessment," *Psychophysiology*, vol. 39, no. 3, pp. 313-321, 2002.

[17] J. Riemersma, *et al.*, *Performance Decrement During Prolonged Night Driving*, 1976.

[18] S. Elsenbruch, M. J. Harnish, and W. C. Orr, "Heart rate variability during waking and sleep in healthy males and females," *Sleep*, vol. 22, no. 8, pp. 1067, 1999.

[19] S. K. L. Lal and A. Craig, "A critical review of the psychophysiology of driver fatigue," *Biological Psychology*, vol. 55, no. 3, pp. 173-194, 2001.

[20] P. K. Stein and Y. Pu, "Heart rate variability, sleep and sleep disorders," *Sleep Medicine Reviews*, vol. 16, no. 1, pp. 47-66, 2012.

[21] M. Karrar, "Developing vehicle-based advanced warning system for driver drowsiness based on a hybrid algorithm," University of Technology, Sydney: Sydney, 2010, p. 212.

[22] H. H. Jasper, "Report of the committee on methods of clinical examination in electroencephalography: 1957,"

Electroencephalography and Clinical Neurophysiology, vol. 10, no. 2, pp. 370-375, 1958.

[23] W. W. Wierwille and L. A. Ellsworth, "Evaluation of driver drowsiness by trained raters," *Accident Analysis & Prevention*, vol. 26, no. 5, pp. 571-581, 1994.

[24] B. S. Everitt and S. Rabe-Hesketh, *Handbook of Statistical Analyses Using Stata*, CRC Press, 2006

[25] S. Otmani, *et al.*, "Effect of driving duration and partial sleep deprivation on subsequent alertness and performance of car drivers," *Physiology & Behavior*, vol. 84, no. 5, pp. 715-724, 2005.

[26] M. Simon, *et al*., "EEG alpha spindle measures as indicators of driver fatigue under real traffic conditions," *Clinical Neurophysiology*, vol. 122, no. 6, pp. 1168-1178, 2011.

Manuel Rost received his Diplom-Ingenieur degree from the Technical University Ilmenau, Germany in the area Computer Science for Medical Applications. He is currently a PhD student in the faculty of science at the University of Technology, Sydney. His main research activities are in drowsiness & sleep, sleep disorders, analysis of bio-signals and development of a fatigue detection system.