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TECHNICAL PAPER

Drowsiness detection during different times of day using multiple features

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Abstract Driver drowsiness has been one of the major causes of road accidents that lead to severe trauma, such as physical injury, death, and economic loss, which highlights the need to develop a system that can alert drivers of their drowsy state prior to accidents. Researchers have therefore attempted to develop systems that can determine driver drowsiness using the following four measures: (1) subjective ratings from drivers, (2) vehicle-based measures, (3) behavioral measures and (4) physiological measures. In this study, we analyzed the various factors that contribute towards drowsiness. A total of 15 male subjects were asked to drive for 2 h at three different times of the day (00:00–02:00, 03:00–05:00 and 15:00–17:00 h) when the circadian rhythm is low. The less intrusive physiological signal measurements, ECG and EMG, are analyzed during this driving task. Statistically significant differences in the features of ECG and sEMG signals were observed between the alert and drowsy states of the drivers during different times of day. In the future, these physiological measures can be fused with vision-based measures for the development of an efficient drowsiness detection system.

Keywords Driver drowsiness · ECG · EMG · Physiological measures · Subjective measures

Introduction

According to the statistics released by the World Health Organisation more than 1.2 million people die each year on the world's roads, and between 20 and 50 million suffer non-fatal injuries due to road accidents [1]. The US National Highway Traffic Safety Administration (NHTSA) conservatively estimated that 100,000 vehicle crashes each year were the direct results of driver drowsiness. These accidents also result in approximately 1,550 deaths, 71,000 injuries and $12.5 billion in monetary losses [2]. In the year 2009, the National Sleep Foundation (NSF) reported that 54 % of adult drivers had driven a vehicle while feeling drowsy and 28 % had actually fallen asleep [3]. These statistics convey that driver drowsiness is a contributing factor in a significant number of road accidents which may be avoided if the drowsy driver is alerted on time. However, this requires the development of an efficient drowsiness detection system that can detect drowsiness.

The term "drowsy" is synonymous with sleepy, which simply means an inclination to fall asleep. The stages of sleep can be categorized as awake, non-rapid eye movement sleep (NREM), and rapid eye movement sleep (REM). The second stage, NREM, can be subdivided into the following three stages: [4].

Stage I	Transition from awake to asleep (drowsy)
Stage II	Light sleep
Stages III	Deep sleep

In order to analyze driver drowsiness, researchers have mostly studied Stage I, which is the drowsiness phase.

Driver drowsiness mainly depends on (i) time of day, (ii) the quality of the last sleep and (iii) the duration of the driving task [5–7]. The time since the last sleep and sleep deprivation also influence drowsiness [8]. Recent statistics from countries, such as the United Kingdom, the United States, Israel, Finland, and France, indicate that an increased number of vehicle accidents caused by driver drowsiness occur during the peak sleeping hours of 02:00–06:00 and

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14:00–16:00 h. During these time frames, the drivers are 3 times more likely to fall asleep than at 10:00 h or at 19:00 h [9].

Researchers have attempted to determine driver drowsiness using the following four measures: (1) subjective ratings from the driver [10–12], (2) vehicle-based measures [13, 14] (3) vision-based measures [15–17] and (4) physiological measures [6, 18].

Subjective measures that evaluate the level of drowsiness are based on the driver's personal estimation and many tools have been used to translate this rating to a measure of driver drowsiness. The most commonly used drowsiness scale is the Karolinska sleepiness scale (KSS), a nine-point scale that has verbal anchors for each step, as shown in Table 1 [19, 20]. Researchers have determined that major lane departures, high eye blink duration and drowsiness-related physiological signals are prevalent in drivers with KSS ratings between 5 and 9 [5].

Vehicle-based measures are useful to measure hypovigilance when the driver's lack of vigilance has an effect in vehicle control. Some researchers found that drowsiness can result in a larger variability in the driving speed [21, 22]. The deviation from lane position is also a consistent vehicle-based measure associated with drowsiness [5, 10, 21]. However, in some cases, there is no impact on vehicle-based parameters even if the driver is drowsy [5]. Thus, a vehicle-based drowsiness detection system alone cannot be used as a viable tool to measure drowsiness.

Most of the published studies on using vision-based approaches to determine drowsiness focus on blinking [15, 17, 23, 24]. However, the background and lighting make it difficult to accurately measure blinking and these remain issues to be addressed.

Although intrusive, the physiological signal-based measures are "reliable & accurate" because they provide information on the true internal state of the driver. The electrooculogram (EOG) signal measures the electric potential difference between the cornea and the retina, thus generating an electrical field dependent on the orientation of the eyes [25–28]. Researchers have used EOG to track eye movement, which is then used to determine drowsiness. The electroencephalogram (EEG) signal has various frequency bands, such as the delta band (0.5–4 Hz), which corresponds to sleep activity, the theta band (4–8 Hz), which is related to drowsiness, the alpha band (8–13 Hz), which corresponds to relaxation and creativity, and the beta band (13–25 Hz), which corresponds to activity and alertness [4, 18, 29]. Many researchers have extracted features from the beta band and have used them to classify drowsiness [18, 29–32]. Akin et al. [18], observed that the success rate of using a combination of EEG and EMG signals to detect drowsiness is higher than using either signal alone.

Table 1 Karolinska sleepiness scale (KSS)

Rating	Verbal descriptions
1	Extremely alert
2	Very alert
3	Alert
4	Fairly alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, but no effort to keep alert
8	Sleepy, some effort to keep alert
9	Very sleepy, great effort to keep alert, fighting sleep

The surface EMG (sEMG) is a non-invasive index of the level of muscle activation [33]. The muscle activity during simulated driving showed significant difference between 1st and 15th min of driving [34]. Surface EMG was captured from trapezius and deltoid muscles during monotonous car driving and muscle fatigue was analyzed by [35]. Though sEMG has not been studied in the context of drowsiness, it would be of significance if the pattern of muscle fatigue during drowsiness is analyzed. Researchers have observed that the heart rate (HR) derived from ECG signals varies significantly during the drowsy state [6, 36]. Heart rate variability (HRV) signals that are derived from Electrocardiogram (ECG) signals are also found to vary significantly during the alertness and drowsiness states of the driver [6, 37] and it is a passive means to quantify drowsiness [38]. In relation to driver drowsiness, HRV can provide useful information [39]. The frequency domain spectral analysis of HRV shows that a typical HRV in human has four frequency bands: high frequency band (HF) that lies in 0.15–0.4 Hz, low frequency band (LF) in 0.04–0.15 Hz, very low frequency (VLF) in 0.0033–0.04 Hz and ultra-low frequency in 0.0–0.0033 Hz [40, 41]. A number of HRV analyses during sleep suggest that the sleep frequency of HRV lies in the region of 0.05–0.15 Hz. As the HRV is analyzed over a range of 5 min, the lower bands of the HRV spectrum (ULF and VLF) does not have any importance. Hence the analysis of these frequencies should be avoided in short term recordings [40]. A more detailed review on driver drowsiness detection can be found in our previous work [42].

One of the challenges in developing an efficient drowsiness detection system is the acquisition of proper drowsy data. Drowsiness should be simulated in a controlled environment to avoid fatal accidents that are prone to occur in real time. Hence, in this work data were collected in a simulated environment during different the times of day when physiological activity diminishes. Researchers have observed behavioral [43], vehicle based [44] and physiological [45] similarity between simulated and on road experiments.

Fig. 1 Our experimental setup

In our experiment, drowsiness is identified using the video recordings and then compared with the subjective measures (obtained through questionnaire) to find if there is any correlation between them. The statistical analysis of ECG signals, LF/HF ratio of the HRV spectrum and higher order statistical (HOS) analysis of sEMG signals showed significant difference between the normal and drowsy states.

Materials and methods

Protocol

The experimental protocol was designed to obtain data during three different times of the day (00:00–02:00, 03:00–05:00 and 15:00–17:00 h) with the corresponding lighting conditions. A simulator game, TORCS, was used to enable driving. To create a monotonous environment, the speed was set to a maximum of 70 km/hr [46]. The subjects were asked to drive in this environment for 2 h.

Subjects and experimental setup

The experimental set up is shown in Fig. 1. A fixed table top driving simulator was used to enable driving. ECG was recorded using disposable Ag–AgCl electrodes placed on both arms. The reference electrode was placed on the left leg. The Power Lab Data Acquisition System (ML856 AD Instruments, Australia) was used to collect the ECG data at a sampling frequency of 1,000 Hz. The EMG data was collected using three Ag–AgCl electrodes placed on the upper fibers of the trapezius muscle (descending part) and PHYWE COBRA 3 (Germany) with a gain factor of 1,000 was used for the EMG data collection. The sampling frequency was set to 256 Hz. The video of the subject's face while driving was also recorded for the entire 2 h session using an IR camera (30 fps). Fifteen healthy university male students (mean age ± SD = 25.6 ± 2.5 years, range 23–32) with valid driving license participated in the experiment after providing written consent. All the experiments were conducted during the times of the day when drowsiness commonly occur (00:00–02:00, 03:00–05:00 and 15:00–17:00 h). All the fifteen subjects returned on different days to participate in all the three sessions and some of the subjects were partially deprived of sleep.

Subjective analysis

The video recorded during the experiment was used to assess the level of drowsiness in each of the 15 subjects during all the three times of day. After completion of the experiment, the subjects were asked to rate their performance using KSS. These ratings were used to analyze the effect of driving at various times of day, the time since the last sleep and the task duration. The correlation between the KSS rating and the driving performance was then examined and validated. The vehicle-based measures, such as the speed of the vehicle and the change in lane position, were also analyzed.

ECG analysis

The raw ECG signal is prone to muscle noise, 60 Hz interference, baseline wander, T-wave interference. To reduce the effects of these, the signal must be filtered properly. The ideal band pass frequency to maximize the QRS energy is approximately 5–15 Hz [47]. Therefore, the raw ECG signal was filtered using Chebyshev 6th order band pass filter, which attenuated frequencies below 5 Hz and above 15 Hz. Then the R–R peaks of the electrocardiogram (ECG) data are extracted using the technique specified by [48]. The mean of the ECG signal is subtracted from the processed ECG signal to effectively remove all baseline wander. After that the driving simulator performance was assessed using the following six statistical measurements for the ECG signals. The statistical features measure the central tendency of the normal and drowsy physiological signals and are easy to compute. The feature energy, a reliable parameter to detect drowsiness was computed from the ECG signal. In addition LF/HF power ratio of the HRV was also computed.

Consider the signal, x_n, n = 0, 1, 2,…N, where N is the length of the signal.

Standard Deviation:

$$\sigma_X = \frac{1}{N-1}\sum_{n=1}^{N}(x_n - \mu_x)^2 \tag{1}$$

Mean:

Table 2 KSS ratings and subjective measures collected from the 15 subjects during different times of day

Subject no.	Age (yrs)	00:00–02:00 h					03:00–05:00 h					15:00–17:00 h				
		Not slept for (h)	KSS	Change in speed of vehicle	Deviation from Lane position	Got drowsy	Not slept for (h)	KSS	Change in speed of vehicle	Deviation from Lane position	Got drowsy	Not slept for (h)	KSS	Change in speed of vehicle	Deviation from Lane position	Got drowsy
1	25	10	9	Yes	Yes	Yes	10	7	No	Yes	Yes	3	7	No	Yes	Yes
2	25	10	7	No	No	No	15	8	No	Yes	Yes	2	5	No	No	No
3	23	14	9	No	Yes	Yes	18	9	No	No	Yes	9	8	No	No	No
4	26	12	8	No	Yes	Yes	2	4	No	No	No	4	9	No	Yes	Yes
5	24	13	9	No	No	Yes	17	9	No	Yes	Yes	8	9	No	No	Yes
6	23	16	9	No	Yes	Yes	14	9	No	Yes	Yes	8	9	No	No	No
7	25	14	9	No	No	Yes	16	8	No	Yes	No	5	8	No	No	No
8	28	11	9	Yes	Yes	Yes	20	8	Yes	Yes	Yes	6	8	Yes	Yes	Yes
9	24	1	7	No	No	No	14	9	No	No	Yes	5	7	No	No	No
10	32	11	9	No	Yes	Yes	15	9	No	Yes	Yes	2	9	No	No	No
11	26	18	9	No	Yes	Yes	19	7	No	Yes	Yes	7	9	No	Yes	Yes
12	24	7	6	No	No	No	17	9	No	Yes	Yes	15	9	No	Yes	Yes
13	25	7	9	Yes	Yes	Yes	16	9	Yes	Yes	Yes	14	9	Yes	Yes	Yes
14	25	9	6	No	No	No	13	9	Yes	Yes	Yes	1	8	No	No	No
15	30	14	9	No	Yes	Yes	16	9	No	Yes	Yes	5	9	No	Yes	Yes

$$\mu_x = \frac{1}{N}\sum_{n=1}^{N} x_n \quad (2)$$

Median:

$$\text{median} = (N + 1)/2 \quad (3)$$

Maximum:

$$\max = \max(x_n) \quad (4)$$

Minimum:

$$\min = \min(x_n) \quad (5)$$

Energy:

$$\text{energy} = \sum_{n=1}^{N} x_n^2 \quad (6)$$

These features were then used to find the statistically significant differences between normal and drowsy data.

EMG Analysis

The noise in sEMG signals were removed by using a 4th order Chebyshev low pass filter with a cutoff frequency of 100 Hz [49]. The spectral energy and spectral higher order statistical (HOS) features were obtained by applying fast fourier transform (FFT) on the filtered signals. FFT decomposes signal into its component frequencies and their amplitudes. Higher order statistical parameters namely skewness and kurtosis can be used to analyze the muscle activity [50].

For univariate data $Y_1, Y_2,\ldots,Y_N$, skewness and kurtosis can be computed as:

$$\text{skewness} = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^3}{(N-1)s^3} \quad (7)$$

$$\text{kurtosis} = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^4}{(N-1)s^4} \quad (8)$$

where $\bar{Y}$ is the mean, s is the standard deviation, and N is the number of data points.

The standard deviation, mean, median, maximum, minimum and energy of sEMG signals were computed using Eqs (1)–(6) respectively.

Results

Subjective measures

The ratings collected from the 15 subjects during the different times of day are shown in Table 2.

A total of 13, 8, and 11 drivers showed drowsiness at least once when driving between the hours of 00:00–02:00, 03:00–05:00 and 15:00–17:00, respectively. While driving between midnight and 02:00 h, and, between 03:00 and 05:00 h, all the subjects who were deprived of sleep for more than 10 h experienced at least a short period of drowsiness. This was not observed in the period between 15:00 and 17:00 h. Even those drivers that woke up only 3 h before the experiment, experienced drowsiness during the 2 h of driving. This result is in agreement with the finding published by Otamani et al. [19], who observed that sleep deprivation alone does not directly influence drowsiness, but that the duration of the task has a strong influence.

The ratings on the change in vehicle speed and change in lane position showed that the vehicle speed did not change even when the drivers were drowsy, which is consistent with the experimental results obtained by Ingre et al. [5]. Between 03:00 and 05:00 h, thirteen drivers were drowsy at least once during the two hour driving task and eleven of them mentioned that, there was deviation in their lane position. Similarly, eight and eleven drivers got drowsy at least once between 00:00–02:00 h and between 15:00–17:00 h respectively, and out of them eight and nine drivers, respectively, reported a change in lane position. These observations indicate that ‘deviation of lane position’ is a reliable tool in the measurement of drowsiness. However, the video analysis revealed that

Table 3 Statistical analysis of the ECG signals of normal and drowsy subjects during different times of day

Parameter	Normal			Drowsy		
	00:00–02:00 h	03:00–05:00 h	15:00–17:00 h	00:00–02:00 h	03:00–05:00 h	15:00–17:00 h
Std Dev	0.122	0.156	0.127	0.157	0.147	0.155
Mean	0.000	0.000	0.000	0.000	0.000	0.000
Median	−0.019	−0.035	−0.027	−0.026	−0.028	−0.034
Max	0.488	0.660	0.635	0.716	0.733	0.861
Min	−0.288	−0.316	−0.274	−0.455	−0.435	−0.406
Energy	5.699	5.824	5.582	8.246	7.517	8.170
LF/HF	1.008	1.006	1.008	0.994	0.979	1.003

Table 4 Statistical analysis of the EMG signals of normal and drowsy subjects during different times of day

Parameter	Normal			Drowsy		
	00:00–02:00 h	03:00–05:00 h	15:00–17:00 h	00:00–02:00 h	03:00–05:00 h	15:00–17:00 h
Std Dev	0.018	0.074	0.200	0.023	0.142	0.065
Mean	0.046	0.048	0.054	0.046	0.046	0.046
Median	0.047	0.049	0.083	0.043	0.018	0.045
Max	0.105	0.173	0.283	0.115	0.258	0.179
Min	−0.005	−0.076	−0.185	−0.014	−0.156	−0.083
Energy	0.397	0.395	0.398	0.432	0.431	0.431
Spectral power	9.241	9.2495	9.2706	7.8645	8.1571	8.3143
Spectral skewness	49.989	45.414	49.462	35.334	35.190	38.995
Spectral kurtosis	2499.626	2337.870	2467.899	1276.279	1394.286	1549.550

some subjects changed their lane position when they were not drowsy.

Those drivers that reported a KSS rating between 7 and 9, got drowsy at least once during the driving task. However, even when the rating indicated by the driver was 9, there was no sign of drowsiness in their facial actions. This is in line with observations made by other researchers, which state that the subjective rating does not fully coincide with vehicle-based, physiological and vision-based measures [5, 51].

Physiological measures

The ECG and EMG signals over the 2 h drive were analyzed using the different features specified earlier and is tabulated in Table 3 and Table 4 respectively. The energy (power) of ECG signals showed a significant difference ($p < 0.01$) between normal and drowsy during all the three different times of day. The power spectral analysis of HRV provides the ability to distinguish between parasympathetic (HF) and sympathetic (LF) activity with LF/HF ratio being the sympathovagal balance [40]. Table 3 shows LF/HF ratio of the normal and drowsy state. ANOVA results indicate statistically significant difference ($p < 0.01$) between normal and drowsy state during 00:00–02:00 and 03:00–05:00 h. There was no statistically significant difference ($p > 0.05$) during 15:00–17:00 h which falls during day time.

Mean values of the spectral power, skewness and kurtosis extracted from the sEMG signals when the subjects were normal and drowsy are shown in Table 4. ANOVA was performed on the extracted features during different times of the day and the results indicate statistical difference ($p < 0.001$) between normal and drowsy data at all times of the day.

Discussion and conclusions

Because driver drowsiness is one of the major reasons for road accidents, the development of a method to accurately monitor the behavior of a driver would prove helpful in ensuring safe driving.

Although sleep deprivation had a significant effect during certain times of day, this measure alone cannot be a reliable tool to predict drowsiness. In fact, the combination of sleep deprivation and an increase in the duration of the driving task had a significant effect on the drowsiness of the driver. Although the KSS ratings showed significant changes in the performance, these ratings differed between subjects. Our assessment of vehicle-based measures showed that there was no significant change in the speed of the vehicle. There was, however, a change in the lane position but this was observed in some cases even when the driver was not drowsy. Therefore, vehicle-based measures alone cannot be used as a viable tool to measure drowsiness. Thus, the correlation between physiological signals and the state of driver needs to be studied.

The different features computed from ECG, HRV and sEMG signals show significant difference between normal and drowsy states. In the case of HRV, the physiological correlates of VLF and ULF components are largely unknown [40]. Hence, it is better not to analyze them especially for short term recordings. The distribution of the power and the central frequency of LF and HF are not fixed but may vary in relation to changes in autonomic modulations of heart period [40]. Decrease in LF/HF was observed when subjects were sleeping [52, 53]. In specific experiments conducted on driver drowsiness, the LF/HF decreased when the driver was drowsy [39, 54]. A similar observation can be found in Table 3 during times of day (00:00–02:00 and 03:00–05:00 h). The subjects were very drowsy and there was significant decrease in LF/HF ratio whereas during afternoon (15:00–17:00 h) significant difference could not be found. During afternoon though drowsy, the subject returns to normal within a few seconds whereas that was not the case during 12 a.m. and especially during 3 a.m. where they could not avoid falling asleep for a longer duration. This impact of alertness is prevalent during afternoon as the data were segregated for 5 min, during which the subjects wavered between normal and drowsy. Segregating the data into smaller segments may help to identify minute drowsy changes. So it would be of interest if drowsy HRV data of 2 min duration or lesser is studied. The energy features of the ECG signals are also a reliable measure of drowsiness showing significant difference between normal and drowsy state during all three times of day.

The sEMG muscle force studied using higher order statistical features: skewness and kurtosis also conveys significance [50]. In experiments conducted on sleep deprived subjects, it was observed that genioglossal EMG activity decreases selectively [55]. In this study, there was significant difference in the trapezius muscle activity between the normal and drowsy state of the subject ($p < 0.001$) during all three different times of the day. So in future, sEMG can also be used as a measure for detecting driver fatigue.

Currently this work was done only on male subjects. The experiment can be extended to female subjects in the future. Among all physiological parameters investigated, ECG and sEMG can be measured in a less intrusive manner. EEG signals require a large number of electrodes to be placed on the scalp and the electrodes used for measuring EOG signals are placed near the eye which can hinder driving. Non-obtrusive physiological sensors to estimate the drowsiness of drivers are expected to become feasible in the near future [37, 56]. Thus the advantage of physiological measures and the increasing availability of non-intrusive measurement equipment make it beneficial to combine physiological signals with behavioral and vehicle-based measures to obtain a more accurate drowsiness detection system.

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