Steering wheel motion analysis for detection of the driver’s drowsiness

DANIEL HAUPT, PETR HONZIK, PETER RASO, ONDREJ HYNCICA
Department of Control and Instrumentation
Brno University of Technology
Kolejni 2906/4, 612 00 Brno
CZECH REPUBLIC
haupt@feec.vutbr.cz, honzikip@feec.vutbr.cz, xrasop00@stud.feec.vutbr.cz, hyncica@feec.vutbr.cz
http://www.feec.vutbr.cz

Abstract: Reliable system for driver’s drowsiness recognition is the aim of many studies. Unfortunately, majority of researchers work with data acquired in laboratory with ideal or simulated conditions. Therefore it is difficult to implement their results to real car and prove its reliability and accuracy. The analyzed data in this paper is acquired from real traffic and therefore it contains all disadvantages partially modeled in laboratory. For data acquisition has been chosen in-direct measurement from car CAN bus in order to not affect the driver. All data are preprocessed according to assumptions about driver’s behavior and transformed to frequency domain by means of orthogonal transform (STFT, CWT and DWT). Subsequently, data is analyzed by data mining methods including features extraction and filter feature selection. The performance of the features is measured by the area under the receiver operating characteristic.

Key-Words: drowsiness, driver, wavelet transform, fourier transform, fatigue, data, feature extraction, AUC

1 Introduction

From the international as well as national statistics it follows that the primary cause of the car accidents is the inattention (including distraction and sleepiness). Inattention accounts for over 25% of the crashes in Europe [1] and over 28% crashes in the Czech Republic [2]. In the last decade a big effort was made to develop reliable systems for detection of the oncoming sleepiness. Many approaches to detect driver’s drowsiness has been proposed and developed. Systems which use driver’s biosignals (EEG – reflecting cortical activity, EOG – reflecting eye and eyelid movement dynamic) contain more information about fatigue than others [3]. Thus they are used as a laboratory standard reference but practical usage is difficult due to influencing of driver. Other approaches take advantages of information accessible in car busses i.e. steering wheel motion, longitudinal and lateral acceleration etc. They are measured by car, hence their values are easy to get and process. Unfortunately until now the sufficiently precise detection of the driver’s drowsiness was not achieved. Especially in noninvasive or unobtrusive systems the accuracy of driver’s drowsiness detection is not sufficient.

2 Driver’s drowsiness detection

The methodology for driver’s detection can be divided into 3 parts. The first part deals with the monitoring of the driver. The second part involves data preprocessing and transformations. And the last part analyzes the processed data in order to recognize the vigilance state of the driver.

2.1 Monitoring systems

Monitoring systems are sensors or devices that measure quantities, which are considered to be important, for driver’s drowsiness recognition. Currently two different approaches are used to monitor the driver [9]: direct systems (physiological signals, driver’s behavior) and indirect systems (driver’s performance, vehicle performance).

2.1.1 Direct Monitoring Systems

Majority of researchers who deal with driver’s drowsiness detection use this system to monitor the driver. The most observed physiological signals and features are the head motion, facial expressions, yawning, eye tracking and blinking, EEG (electroencephalogram), ECG (electrocardiogram) and heart-rate variability, pulse-monitoring, galvanic skin resistance and body temperature [4,5,6,7,8] etc. The main advantages of these methods are:

- high accuracy – many measurements are very similar to medical noninvasive investigations; in general the results prove the best performance;
• universality – the findings are valid in general and may be directly used in other scientific or commercial domains;
• research in laboratory – the experiments can be carried out in laboratories because the point of interest is the human and not the vehicle.

The basic disadvantages of these methods are:
• privacy invasion – direct measurements are intrusive to the driver;
• sensitivity to external conditions – different light and weather conditions, dress and fashion accessories (winter clothes, gloves, dark glasses), actual health conditions of the driver and others may decrease the precision of the measurement or even disable it.

2.1.2 Indirect Monitoring Systems
The indirect monitoring of the driver is less common. The most typical features to be analyzed are the steering wheel movements [11] and the lateral acceleration [12,13]. Among others belong e.g. the pedals acceleration (gas, break) [8]. The short time inattention is usually expected when using cell phone, tuning the radio or setting up the air condition etc. [1,14]. The main advantages of the indirect methods are:
• high robustness – the influence caused by the changes in driver’s or vehicle’s accessories, weather etc. are low and cannot disable the measurement;
• privacy – these methods are nonintrusive to the driver.

On the other hand the basic disadvantages are:
• experimental conditions – to achieve significant results, the test rides should be done using a real vehicle in the real traffic conditions, what is possible only to some degree of the driver’s fatigue; to overcome this limitation the experiments are carried out on the simulators; their influence on the credibility of the results will be discussed further;
• industrial applicability – even the promising results usually cannot be reused in other research domains and without any serious relation to some car manufacturer the results have not any practical impact.

Especially in case of the indirect measurements the quality of a simulator is crucial for the meaningfulness of the results. If ever, only the ergonomic and lighting conditions are being simulated [3] but not the dynamics of the drive (forces influencing the vehicle and the driver – rain, wind etc.). But these forces influence e.g. the movements of the steering wheel, which is the most popular indirect feature being analyzed.

2.2 Data preprocessing and transformations
In indirect monitoring systems is crucial to determine suitable features or their combinations for driver’s drowsiness recognition. As it is mentioned above, the steering wheel movements and lateral acceleration are the most typical observed quantities during drive. In this paper are only analyzed steering wheel movements in real car and in real traffic.

Measurement in real environment is more difficult than measurement in a laboratory because of changing conditions (weather, driver is under stress etc.) and also driver is influenced by environment. Unfortunately, for proper analysis of driver’s behavior is necessary to ensure at least approximate conditions. It is accomplished by addition of further assumptions about drive and filter data according to these assumptions. This filter data is processed as independent samples of driver’s behavior with relevant drowsiness level.

Data measurement is linked with drowsiness measurement. Many techniques exist for drowsiness detection as it is mentioned in previous subchapter. But for indirect monitoring systems analysis is required to determine the time when the drowsiness is measured and choose appropriate unobtrusive methods. Among exact methods belong some psycho-diagnostic devices or psychological tests. Subjective feeling should be recorded as well. These techniques can be used prior to or/and during (pauses) or/and after drive depending on desired result e.g. actual drowsiness state, drowsiness degradation etc. It is evident that these methods affect driver’s drowsiness because they are psychological strenuous and they also take appreciable amount of time.

The measured data can be analyzed in terms of signal analysis, time series analysis, statistical analysis or data mining analysis. Those techniques require different data preparation such as features extraction, data filtering etc. In this contribution the aim is to create large amount of features by means of three orthogonal transforms i.e. Continuous and Discrete Wavelet transform (CWT, DWT), Short-time Fourier transform (STFT). CWT, DWT and...
STFT are typically used to determine the level of driver’s sleepiness from the steering wheel movements [3]. Obtained frequency bands are related to the driving pattern. Fast and short movements refer to a normal driving pattern, whereas slow movements indicate drowsiness [15]. The continuous analyses are usually more readable than the discrete, but DWT saves more space and significantly shortens evaluation time what is important in embedded applications. Those are reasons for using both types of Wavelet Transformations.

2.3 Processed data analysis
Processed data has to be analyzed with respect to the driver’s drowsiness level. There are many ways to analyze the data but proposed approach is based on feature extraction from CWT, DWT and STFT. All of these methods were already successfully used in similar experiments carried out under the laboratory conditions [3]. The feature selection process is equivalent to the microarray data analysis, where the number of features strongly overwhelms the number of measurements and the interdependences among features must be treated [16]. In our presented experiments the number of series to be analyzed is in dozens and the extracted features are in hundreds (and are planned to be in tens of thousands). The multiclass area under receiver operating characteristic (AUC) [17] is used as a performance measure for the selection of the potentially interesting features.

3 Data analysis and results
The analyzed data is acquired from the CAN bus of the Skoda Octavia II car. All rides were carried out in real traffic situations – one ride lasted approx. 30 min. Each ride corresponds with some level of drowsiness and the level is considered as output argument for classification. Driver’s drowsiness level is ranked from 1 (alertness: excellent) to 4 (alertness: poor) and it is fusion of flicker test (calibrated at EEG in laboratory) and subjective feeling [9].

The frequency of steering wheel motion samples is 100Hz. For reduce amount of data it has been under-sampled to 50Hz. It is considered that driver’s reaction cannot change faster than 50Hz (sample period is 0.02s) and thus sample frequency is sufficient.

![Fig. 1 - The angle of steering wheel selected according to speed limit assumption; the blue line corresponds to the steering wheel angle, the red lines are selected parts of steering wheel angle, the green line is car speed in km/h and the black lines are borders of speed interval i.e. <60;120>](image-url)
In order to compare all rides correctly is necessary to preserve approximately the same conditions for every ride. Unfortunately, due to traffic influence, changing conditions on the road or drive various ways, it is almost impossible. To approximate the same conditions it is assumed that slow car speed is not good descriptor of drowsiness because of driver is more concentrated – gear shifting, city traffic restrictions etc. In opposite fast driving implies more monotonous ways and thus the drowsiness is more dangerous and likelier (usual driver is considered, exceptions breaking these assumptions exist). Therefore each ride is split into sections with respect to the car speed. The interval between 60 and 120 kilometers per hour is assumed as substantial for data analysis. Fig. 1 shows data selection according to the actual speed. Subsequently, sections shorter than 30s are disregarded and sections longer than 50s are split into smaller ones i.e. each section is long from 30 to 50 second and it is recorded within 60 to 120 kmph speed interval. Moreover, each section is considered as independent with corresponding level of drowsiness.

3.1 Features extraction methods description and evaluation of its performance

STFT, CWT and DWT are used for transformation each section from time domain to frequency domain. In frequency domain, there have been extracted various features of the transformed section such as band energy ratios, mean and standard deviation of spectrum bands, local maximums and long term spectrum descriptors such as skewness and kurtosis of the distributions and their combinations etc. Different spectral bands ratios and spectral ranges were tested and evaluated by their AUC. Based on it the frequency band with the highest informative value has been determined as the interval between 0.2 and 3.5 Hz. The highest decomposition level of DWT was determined to 8. Higher or lower values than these thresholds has not brought any profitable improvement.

By means of STFT the power spectral density (PSD) is computed and used for features extraction instead of usual STFT in order to manipulate with spectrogram. The elements of the PSD matrix are given by (1) in dB.

\[ P(i, j) = k |S(i, j)|^2 \]  

where \( k \) is real valued scalar defined as follows (2) (consider only real values of input signal – segment)

\[ k = \frac{2}{F_s \sum_{n=1}^{N} |w(n)|^2} \]  

where \( w(n) \) denotes the window function and \( F_s \) is the sampling frequency. Matrix \( S \) contains elements of section STFT created with relevant window function, window length and number of overlap samples. Window length must not exceed the length of shortest section i.e. 30s. In experiment was used Hamming window to eliminate Gibbs phenomenon. The length of the window was set to 3 seconds with the 1 second overlap. Twelve frequency bands were processed into the features extraction mechanism. CWT was used in its pure form (3)

\[ X_w(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t) \psi^* \left( \frac{t-b}{a} \right) dt \]  

where \( a > 0 \) is the scale and \( b \) (real number) is the translation of the wavelet \( \psi \). Scale values determine the degree to which wavelet is compressed or stretched. Because angle of steering wheel contains mostly higher frequencies therefore lower scales in CWT were used. It means that higher scale value was set to 32.

Fig. 2 – A three level filter banks for wavelet decomposition; \( x[n] \) is input series, \( g[n] \) is low-pass filter and \( h[n] \) is high pass filter (quadrature mirror filter), \( \downarrow 2 \) symbol means subsampling by 2; (downloaded from http://en.wikipedia.org/wiki/Discrete_wavelet_transform)
DWT is carried out as multilevel 1-D wavelet decomposition. It returns the decomposition structure by means of low and high pass decomposition filters as is shown in Fig.2. Its detail coefficients are used for extracting features as in CWT. Maximum decomposition level was set to 5. It corresponds to scales 2, 4, 8, 16 and 32. In case of CWT and DWT different more wavelets were applied e.g. Symlet 2, Daubechies etc. More than 1000 features were extracted by these methods and evaluated by the AUC [17] which is measure of separability.

3.2 Results of experiment
Kurtosis and standard deviation of DWT distribution around the 4th decomposition level belong to the most promising features according to their AUC values. In the Fig. 3 can be viewed dissimilarity between graph for drowsy driver and graph for alert driver. Especially for DWT levels higher than 4 differences are observable even in graph. Similar results are visible in CWT evaluation around the frequency correspond to 4th decomposition level in DWT. The parameters kurtosis and standard deviation are in CWT the most significant features as well. Other significant feature is standard deviation of the wavelet spectrum around the 6th scale factor. By using STFT frequency bands between 0.5Hz to 1.5Hz are most readable to distinguish between drowsy and alert driver. These results and assumptions need to be testified on more rides with different drivers to be experimentally proven.

4 Conclusion
The experiment is designed to test acquisition system for recording data from the engine bus in real-time fashion. Acquired data are publicly available at the site: “http://project-bay.eu/vehicle-dataset”. Data has been preprocessed according to assumptions about driver’s behavior in real traffic and in order to be eliminated differences in different rides. The first attempt to recognition of the driver’s drowsiness has aimed to use orthogonal transforms (STFT, CWT and DWT) for feature extraction. Many features were created and evaluated by AUC. Their performances were compared and the first promising results were introduced, meeting with the theoretical expectations. For further research is also assumed to use other methods for extracting features e.g. Hilbert transformation, Cepstral analysis etc. In addition, more rides is necessary to statistically prove significance of obtained results.

Fig. 3 - The DWT of the angle of steering wheel; the graph on the left corresponds to the drowsy driver (alertness: poor), the graph on the right corresponds to the alert driver (alertness: excellent).
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References:


