Detecting Fatigue from Steering Behaviour Applying Continuous Wavelet Transform

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ABSTRACT

The aim of this paper is to develop signal processing based method to measure fatigue from motor behaviour. The advantages of this steering wheel movement approach are that obtaining steering data within driving is robust, non obtrusive, free from sensor application and calibration efforts. Applying methods of continuous wavelet transform (CWT) provides additional information regarding the dynamics and structure of steering behavior comparing to the commonly applied spectral Fourier transform features.

Author Keywords

Motor behavior, fatigue detection, wavelet transformation, pattern recognition.

ACM Classification Keywords

H.5.m Human-Computer-Interaction

INTRODUCTION

Some biosignals contain more information about fatigue than others. Among them, EEG (reflecting cortical activity) and EOG (reflecting eye and eyelid movement dynamics) have the potential to be used as a laboratory reference standard and have been utilized e.g. in evaluating fatigue monitoring technologies. Even so, the requirements for these electrode based instruments are not conducive for being used out in the field. Developing fatigue monitoring devices, which are cheap, non-intrusive, and robust even under extreme demanding environmental conditions (e.g. high background noise, temperature, or humidity) still remains a challenging task [1]. In contrast to these electrode-based instruments, using steering wheel movement as an indicator for fatigue is more robust under these same operating conditions. Collecting this data is favourable for fatigue detection since it is non-obtrusive and uses cheap, durable, and maintenance free sensors that are already integrated into the steering wheel system [2-3]. However, little empirical research has been done to examine thoroughly the benefits of more recently feature extraction methods as e.g. the wavelet analysis [4].

The traditional technique in signal analysis for tracking frequencies as they change over time is the Short-time Fourier Transform (STFT). Using sliding frame segmentation and a subsequently windowing of the signal can provide an acceptable time-frequency representation (Weighted Overlapped Segment Averaging; WOSA). In contrast to the Fourier transform (FT), the continuous wavelet transform (CWT) possesses the ability to construct a time-frequency representation of a signal that offers very good time and frequency localization. A CWT is used to divide a continuous-time function into wavelets. Since CWT is very resistant to noisy signals and has the ability to decompose complex information and patterns into elementary forms, it is commonly used in acoustics processing, biosignal analysis, and business information analysis. Hence, the aim of this study is to compare multiple state-of-the-art pattern recognition methods [5-7] on CWT vs FT based steering features to detect fatigue.

METHOD

Twelve healthy young adults completed 7 overnight driving sessions (1 - 8 a.m.) in our real car driving simulation lab. The combinations of observed and self-rated fatigue (Karolinska Sleepiness Scale; KSS) measured verbally every 2 minutes were considered as ground truth of fatigue. The fixed-based driving simulator consisted of a normal passenger city car (GM Opel Corsa) with original controls. The driving task involved a 40-minute night drive on a monotonous two-lane motorway course with simulated effects of headlights, i.e. involving a restricted range of sight. One round on the course with a speed of about 100

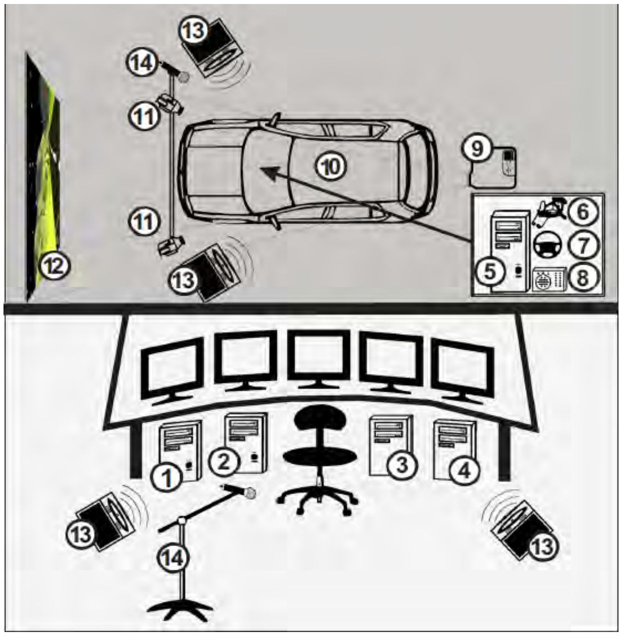

Figure 1. Monitoring and control units of the fixed-based driving simulator consisting of a passenger city car (GM Opel Corsa) with original controls.

km/h took about 15 minutes. The course was mainly straight with sustained long curves. There were no obstacles or oncoming traffic.
Steering angle as well as other driving performance signal and biosignals were recorded. Here we analyzed only the raw steering angle time series, i.e. without any further event specific selection as e.g. steering away from obstacles or steering back to a suggested driving path.

Feature Extraction. To extract relevant features from the steering behavior data we split the data into 714 non-overlapping 4 min segments (4800 measurement points). We computed two spectral feature sets using Fourier-transform (FT) and continuous wavelet transform (CWT) to capture fatigue impaired steering patterns. To measure fine temporal changes of spectral descriptors we performed a signal segmentation (sampling rate = 20 Hz, segment length = 25.6 s (512 data points), segment shift = 12.3 s (256 data points), hanning window), and computed the power spectral density per segment (Welch-Method; Weighted Overlapped Segment Averaging; WOSA). This procedure results in 975 frequency domain features as relative and absolute power spectral densities (PSD) of raw and first derivate contours in 30 spectral bands (e.g. minimum of relative PSD of first derivate in the 0.6-0.7Hz spectral band), band energy ratios, (e.g. $PSD_{1\text{-}5Hz}$ / $PSD_{0\text{-}1Hz}$), spectral flux (e.g. max of spectral flux = Euclidean distance of PSD between consecutive segments), and long term average spectrum descriptors (e.g. skewness of PSD distribution). Within the wavelet domain we computed the equivalent of these features applying the continuous wavelet transform (CWT; 'db4' wavelet, scaling factor a = [1:1:512]) resulting again in 975 features.

Classifier	Specification	FT	CWT	Δ
SVM	'JmySVM', linear kernel, C=0	1.06	0.99	-0.07
	'JmySVM', polyn. kernel, d=2, C=0	1.40	1.25	-0.15
	'JmySVM', radial kernel, C=0	1.19	0.90	-0.29
	'SMO-Reg', linear kernel, C=0	1.10	0.95	-0.15
NN	k=1	1.37	1.15	-0.22
	k=3	1.13	0.97	-0.16
	k=5	1.10	0.94	-0.16
	k=7	1.09	0.93	-0.16
	k=9	1.08	0.90	-0.18
	k=11	1.09	0.90	-0.19
MLP	'NeuralNetImproved', 2 x 5 nodes	1.65	0.99	-0.66
	'W-RBF-Network'	1.15	1.05	-0.1
LR	'W-LinearRegression'	1.12	0.99	-0.13
	'IsotonicRegression'	1.07	0.83	-0.24
GPL	'GaussianProcess'	1.16	0.98	-0.18
Average Learner		*1.18*	*0.98*	*-0.20*

Table 1. Mean absolute prediction error (in KSS units) of several learning methods on the test set using driver-dependent validation schemes. FT: Fourier Transform feature set; CWT: Continous Wavelet Transform feature set.

Machine Learning. We investigated validation of the classification algorithms to examine which automatically trained model can be used to recognize the fatigue of participants best. We applied the following static classifiers - known to be successful within many biosignal based classification tasks - of the popular 4.5 RapidMiner [8] software using standard parameter settings: Support Vector Machines ('JMySVM', linear, radial, or dot kernel function; 'SMO-Reg', Sequential Minimal Optimization), Multilayer Perceptrons ('NeuralNetImproved', 2 hidden sigmoid layer, 5 nodes each), k-Nearest Neighbors ('NearestNeighbors'; k = 1,3,5), Logistic Base ('W-LogisticBase'), Linear Regression ('LinRegression', 'W-LinRegression'), Polynomial Regression ('PolynomialRegression'), and Gaussian Process Learner ('GPLeaner'). In a driver-dependent validation protocol, we applied 10-fold cross validation. The final prediction errors were calculated averaging over all 10 validations.

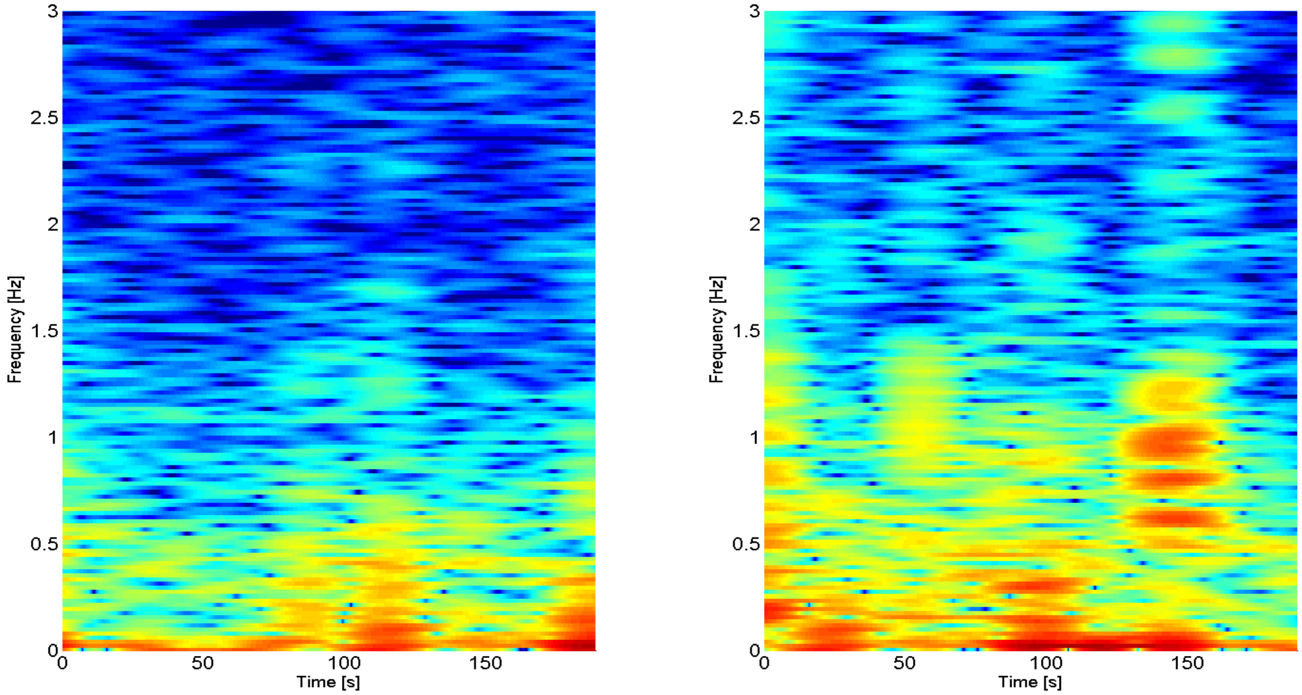

Figure 2. Spectrogram of alert (left) vs. fatigue (right) steering sample based on FT. High Power spectral densities are indicated by the red colour.

RESULTS

The mean absolute prediction error (MAP) of the KSS fatigue value was computed (see Table 1). Within the applied learning algorithms the Isotonic Regression using the CWT feature set reached the lowest MAP of 0.83. For the FT feature set, the Isotonic Regression learner achieved the second best prediction. A Support Vector Machine (linear kernel) reached the lowest prediction error of MAP = 1.06. Averaging all applied learning schemes the CWT feature set achieved 0.98, the FT feature set 1.18 MAP, which document a noteable and statistically significant benefit of 0.20 MAP (-16.9% error reduction) when using the CWT vs. FT feauture set.

DISCUSSION

The aim of this paper is to the test the added value of a wavelet based feature set for (automatic) fatigue detection. Wavelet based features have not been used before for driver fatigue detection. Using the CWT based steering behavior features we achieved over all applied regression learner an mean MAP of 0.98 in terms of the KSS clearly outperforming the FT feature set (MAP = 1.18), which corresponds to an error reduction of 16.9%.

A secondary aim of this study was to compare the performance of different pattern recognition methods for learning task with nearly the same amount of instances and features. Within the FT feature set the best learner yielded a MAP of 1.06 (Support Vector Machine, linear kernel), which was again clearly outperformed by the best learner within the CWT feature set (MAP = 0.83; Isotonic Regression). Nevertheless, the question whether this size of error is acceptable for real life application still remains open.

Our results are limited by several facts. We did not primarily aim at finding the best single regression learner and thus relinquish to optimize the performance of SVM by a fine grained hyperparameter optimization. Therefore, the performance has to be recognized as lower border of the SVM capabilities. Moreover, the present results should be replicated using laboratory gold-standard fatigue measures [9], and enlarged simulator and real-life databases. A further performance gain might be realized by advanced preprocessing steps as the decomposition of the steering signal using Independent Component Analysis (ICA) [10], Empirical Mode Decomposition (EMD) [11] or wavelet-based decomposition in approximation and detail signals [4]. Referring to the fatigue reference KSS, it has to be mentioned that up to now a gold standard measure of fatigue is lacking. But approximating fatigue by concordance of self and observer ratings might act as an intermediate solution. Furthermore, it would seem advisable that future studies address the main topics of enriching the steering feature set. Figure 2 provides a first insight in further possible fatigue sensitive spectral features. Finally, easy accessible driving related informations as e.g pedal movement behaviour should be considered as source for fatigue monitoring.

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