Detecting Sleepy Drivers by Pattern Recognition based Analysis of Steering Wheel Behaviour

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Abstract

Using steering wheel behaviour based approaches for sleepiness monitoring might have the advantage of being cheap, non-intrusive, and robust even under extreme demanding environmental conditions (e.g. high background noise, temperature, or humidity). 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 sleepiness (Karolinska Sleepiness Scale; KSS) were considered as ground truth of sleepiness. Steering angle, lane deviation and pedal movement were recorded. In order to investigate sleepiness-induced changes in steering wheel behaviour, spectral and state space domain features are computed. Using advanced signal processing procedures for feature extraction, we computed 3 feature sets in the time, frequency and state space domain (a total number of 1251 features) to capture fatigue impaired steering patterns. Within the time domain we extracted class distribution measures, peak amplitudes and distances, and zero crossing distances (e.g. maximum of peak amplitude, mean distance between consecutive zero crossings). Each feature set was separately fed into 5 pattern recognition methods (e.g. SVM, KNN, MLP). We yielded a recognition rate of 86.1% in classifying slight from strong fatigue.

Sleepiness and Steering

Drivers are constantly judging the situation ahead and applying small, smooth, steering adjustments to correct for small road bumps and crosswinds by turning the steering wheel in small increments. This steering behavior can be impaired when drivers are becoming fatigued. A wide variety of steering wheel metrics have been suggested to measure steering behavior, from standard deviation of steering wheel angle, steering wheel velocity (Peters, Kloeppel, & Alicandri, 1999), steering wheel action rate (Verwey, 2000), to more advanced metrics such as high frequency component of steering wheel angle (Östlund, Nilsson, Carsten et al., 2004) and steering entropy (e.g. Nakayama, Futami, Nakamura, & Boer, 1999).

Until recently, the analysis of steering wheel movement was based on finding single features correlating with fatigue. The detection task was reduced to a simple thresholding of these features, but large inter- and intra-individual differences in fatigued driving patterns are an issue. Due to this overwhelming complexity, a sufficient and accurate classification of individual steering samples was not achieved. Thus, we propose a multivariate, data fusion, and machine learning based approach including the computation of a large, highly redundant feature set modelling fine grained temporal steering behavior structures (cf. Sayed & Eskandarian, 2001). This approach showed its superiority in many pattern recognition tasks (e.g. Ruvolo & Movellan, 2008).

Feature Extraction for Steering Behavior. Features of steering wheel movement can be divided into time, frequency and state space domains. This assignment follows the first processing step of computing frame level descriptors, independent of feature characteristics of the second, contour describing, functional based processing step:

(a) time domain features. Within the time domain the following features can be extracted: regression descriptors (e.g. regression slope, intercept, maximum of regression error), class

distribution measures (e.g. number of values within steering angle bin 0.0-0.1), peak amplitudes and distances (e.g. mean distance of peaks; maximum of peak amplitude), entropy, zero crossing distances and slope (e.g. maximum of distance between consecutive zero crossings; mean velocity of steering angle in zero crossings)

(b) frequency domain features. To capture fine temporal changes of spectral descriptors we performed a framing and windowing of the signal (frame size = 512, frame shift = 256, hanning window), and computed the power spectral density per frame. This procedure results in 803 frequency domain features as e.g.: relative and absolute power spectral density (PSD) of raw and first derivate contours in 30 spectral bands (e.g. minimum of relative PSD of first derivate of 0.6-0.7Hz spectral band contour), band energy ratios (PSD 1-5hz/ PSD 0-1hz), spectral flux (e.g. max of spectral flux = Euclidean distance of PSD between consecutive frames), and long term average spectrum descriptors (e.g. skewness of PSD distribution).

(c) state space features. To extract the nonlinear properties of the steering angle signal, we computed a three-dimensional state space (steering wheel position, steering wheel velocity, steering wheel acceleration), and a reconstructed phase space ($d = 3,4$; $\tau = 1$; steering angle t_0, steering angle t_1, steering angle t_2). The geometrical properties of the resulting attractor figures were described by trajectory based descriptor contours (angle between consecutive trajectory parts, distance to centroid of attractor, length of trajectory leg). The temporal information of the contours was captured by computing functionals.

Method

Subjects, Instruments, and Experimental Procedure. Twelve participants took part in this study voluntarily. Initial screening excluded those having severe sleep disorders or sleep difficulties. The participants were instructed to maintain their normal sleep pattern and behavior. We conducted a within-subject sleep deprivation design (01.00 - 08.00 a.m). During the driving sessions a well established, standardized self-report fatigue measure, the Karolinska Fatigue Scale (KSS), was used orally by the subjects and 2 experimental assistants every 4 min. In the version used in the present study, scores range from 'extremely alert' to 'extremely sleepy, can't stay awake'. Given the verbal descriptions, scores of 8 and higher appear to be most relevant from a practical perspective as they describe a state in which the subject feels unable to keep stay awake.

During the night, the subjects were confined to the laboratory, conducting a driving simulator task and were supervised throughout the whole period. The driving simulation software system has been developed by the Department of Computer Science, Univ. of Applied Sciences Schmalkalden, Germany. 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 km/h took about 15 minutes. The course was mainly straight with sustained long curves. There were no obstacles or oncoming traffic.

Driving data and Feature Extraction. We conducted a validation experiment to examine whether automatically trained models can be used to recognise the fatigue of subjects. Our approach can be summarized in four steps: 1. Collect individual steering data and the associated fatigue ratings for each participant; 2. Extract relevant features from the steering data; 3. Build statistical models of the fatigue ratings based on the features; 4. Test the learned models on unseen steering data. The collection of data took place in a nearly dark laboratory room (sampling rate: 20 Hz). Furthermore the subjects were given sufficient prior practice so that they were not uncomfortable with this procedure. After elimination of values in the threshold region (7.5 ± 0.5 KSS) the binarization of the fatigue values leads to two classes: non-strong fatigue (KSS ≤ 7; Non-SF) and strong fatigue (KSS ≥ 8; SF). The total number of 714 steering samples

was split into 390 samples of Non-SF and 324 samples of SF (KSS:= mean of one self-report and two observer report KSS-ratings; M= 7.06; SD= 1.99). To extract relevant features from the steering behavior data the data was split into segments 240 seconds in duration each for a total of 4800 data points per segment. As explained above, we estimated 88 time domain features, 803 frequency domain features, and 360 state space domain features. In sum, we computed a total amount of 1251 features per driving segment including also the standard steering behavior features as variance of steering angle, high frequency component, steering reversal rate, steering wheel action rate, peak steering deflection, number of steering holds. The potential advantage of the brute-force feature extraction approach proposed here (large collection of simple, light weighted features) is that it could cover a broad range of possible steering phenomena related to fatigue.

Pattern Recognition. To enhance robustness of the classification we feed these features separately into 5 sophisticated, but standard machine learning methods (support vector machine linear kernel (SVM_l) and radial kernel (SVM_r), 5- nearest neighbour (5-NN), decision tree (DT), and logistic regression (LR). By averaging the classification outputs, an ensemble classifier was created per each feature subset. In a last step the ensemble-classificator outputs from the feature subsets (time, frequency and state space) were combined (averaged and dichotomized) to a final fatigue prediction value.

Results

In the fatigued driver the raw steering wheel position and velocity signal show the following correlations to KSS measured fatigue: (a) time domain features: $r_{\text{mean peak amplitude}} = .59$, $r_{\text{90th percentile}} = .57$, $r_{\text{mean absolute deviation of steering velocity}} = .52$, (b) frequency domain features: $r_{\text{median spectral flux}} = .59$, $r_{\text{median spectral flux of steering velocity}} = .59$, $r_{\text{interquartile range of PSD in frequency band 1-3 Hz}} = .55$ (cf. Fig. 1), and (c) state spece domain: $r_{\text{95th percentile of distance to centroid of attractor (time lag = 1, embedded dimension = 4)}} = .55$, $r_{\text{95th percentile of distance to centroid of attractor (time lag = 1, embedded dimension = 3)}} = .54$, $r_{\text{mean distance to centroid of attractor (time lag = 1, embedded dimension = 3)}} = .50$. Applying the above described ensemble classification method, this feature set achieved 86.1% recognition rate (RR; ratio correctly classified samples divided by all samples) and 85.4% class-wise averaged classification rate (CL; average of sensitivity and specificity) in the classification of sleepy driver (sensitivity =77.4%; specificity 93.3%).
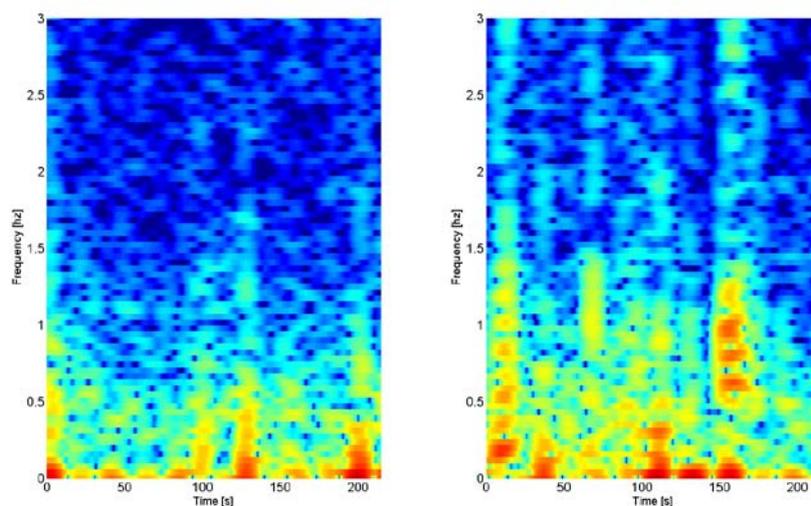

Figure 1. Steering angle spectrogram of non-strong fatigue (Non-SF, left) and strong fatigue (SF, right) driver. High power spectral densities (PSD) are coded red, low PSD are coloured blue within the spectrogram.

Discussion

Assessing driver fatigue using the steering wheel behavior analysis presented here yielded a recognition rate of 86.1%, which is among the highest values ever reached for a totally non-obtrusive system. The main findings referring to construction principles of this system may be summarized as following. The time, frequency and state space domain features extracted from the driving simulator contains a substantial amount of information about the driver's fatigue state. Furthermore, the final meta-ensemble classifier combining fatigue prediction of 3 feature subsets (time, frequency and state space domain) on unseen data but known driver enhanced robustness of the classification.

Future research should address the topic of improving the fatigue monitoring by enriching the feature sets with information of lane deviation, time to lane crossing, and pedal movements. Furthermore, implementing separate fatigue prediction models for different driving tasks, geometrical road characteristics and environmental conditions (as e.g. speed, crosswind, street-granularity, curvature, or lane width) might improve the general fatigue prediction accuracy. Another promising improvement could be realized by using driver state data as e.g. personal driving performance baselines for the personalization of the prediction models. Moreover considering various driver states could be useful, because it is likely that especially combinations of activation and arousal states might be responsible for intra-individual variance in fatigue steering patterns. When combining a low energetic activation state such as fatigue with high self-induced (e.g. fighting against sleepiness) or external stressor-induced arousal (e.g. inner tension within high mental workload situations), the typical fatigue driving pattern might be masked. To handle this fact, explicit (for each internal state combination separately) or implicit (based on classifier immanent clustering) modelling is necessary. In both cases it is essential to feed the classifiers with sufficient learning data including these combinations of fatigue and arousal states.

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