Detection of Strong Fatigue During Overnight Driving

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Abstract

Overnight driving is associated with increased accident risk due to impaired alertness and reduced performance. As a consequence of monotony and factors like time-of-day, time-since-sleep and time-on-task, fatigue is generally increasing during driving. This increase is not always monotonically, but often shows slow waxing and waning patterns, which can be recognized in measures of driving performance and repeatedly self-reported sleepiness. The presented study shows that simultaneous changes in EEG can be found by pattern recognition methods.

1 Introduction

Overnight driving is associated with increased risk of accidents due to impaired alertness and reduced performance. The importance of fatigue as a risk factor is exceeding the impact of drugs and alcohol [1]. Main causal factors are considered as [1]:

a) time-of-day, i.e. influences of circadian rhythm,
b) long durating wakefulness (time-since-sleep),
c) inadequate sleep and accumulated lack of sleep,
d) pathological sleepiness caused by diseases, e.g. sleep apnea or narcolepsy,
e) prolonged work hours which are not necessarily behind the wheel (time-on-task).

There are also psychological variables influencing the actual level of fatigue, e.g. motivation, stress, and monotony. Monotony is believed to play an important role because driving is, in most situations, a low-event, simple lane-tracking task. Fatigue is not always increasing monotonically during driving, but often shows slow waxing and waning patterns, which can be recognized in measures of driving performance and repeatedly self-reported sleepiness [2].

There are many biosignals which are more or less coupled to fatigue. Among them, the EEG is a relatively direct functional reflection of mainly cortical activities and to some low degree also subcortical activities. Therefore, it should be the most promising signal to find a good measure. Akerstedt et al. [3] showed that with increasing working time subjectively rated sleepiness strongly increases and EEG shows a significant but moderate increase of hourly mean spectral power density only in the alpha band but not in the theta band. In contrast, Makeig & Jung 1995 [4] concluded from their study that the EEG typically loses its prominent alpha and beta frequencies as lower frequency theta activity appears when performance is deteriorating due to strong fatigue. Subjects performing an auditory detection task [5] show performance lapses accompanied by counterbalanced changes in vertex EEG power spectral densities; there is an increase around 4 Hz and a decrease around 40 Hz. Also in continuous visuomotor compensatory tracking task sleep deprived subjects [6] show increasing EEG power densities in the lower theta range (3-4 Hz) during periods of poor performance. Many authors reported of very high inter-individual variances sometimes showing counteracting EEG. The presented study shows that simultaneous changes in EEG can be found by pattern recognition methods.

2 Material and Methods

Twelve healthy volunteers (3 female, 9 male, 21.4 ± 2.1 years) participated in an overnight study from 1 a.m. to 8 a.m. Wakefulness after normal daytime and evening activities was continued of at least 16 hours prior to first driving simulation, which was verified by wrist actometry. During each of seven sessions (duration: 40 min.) in our real car interactive driving simulator subjects were asked every 2 min to report orally their subjectively perceived sleepiness using Karolinska Sleepiness Scale (KSS) [7]. KSS values were divided in two groups: moderate fatigue (KSS<8) and strong fatigue (KSS≥8).

Driving tasks were chosen intentionally monotonous to provoke drowsiness and microsleep events (MSE). The latter are defined as short intrusions of sleep into wakefulness under demands of attention. They were detected online by the experimenter who observed subjects left eye region, her/his face, and driving scene utilizing three infrared video cameras. If MSE were observed and values of KSS<8 were actually reported, then this example was reassigned to “strong fatigue”.

EEG was recorded from occipital, central and frontopolar locations (O1, O2, C3, C4, Cz, Fp1, Fp2). Additionally, submental EMG and EOG (vertical, horizontal) were recorded. Unfortunately, EOG had to be excluded from further analysis because of technical problems. Entropies of the output signals of a 7-stage-wavelet decomposition tree and Power spectral densities were used as input vectors of several machine learning algorithms [8]. Here we report only on the results of Learning Vector Quantization.

3 Results

For each single EEG channel the segment length was varied in the range of 10 to 300 sec to find an empirical optimum utilizing multiple hold-out cross validation. Training errors (**Fig.1**) showed a monotonically decrease which is roughly proportional to the number of segments (dashed plotted). Small segment lengths lead to a high number of input vectors following to higher complexity presented to the classification algorithms and therefore to higher error rates. Test errors showed no significant optimum; values between 60 and 240 sec seem to be good choices. Classification of single channel EMG (diamonds) resulted in relatively high errors, while the combinations of O1, O2 (stars), of C3, Cz, C4 (squares) and Fp1, Fp2 (circles) performed much better. Best results were obtained by combining all EEG channels (bold dots) on the feature level.

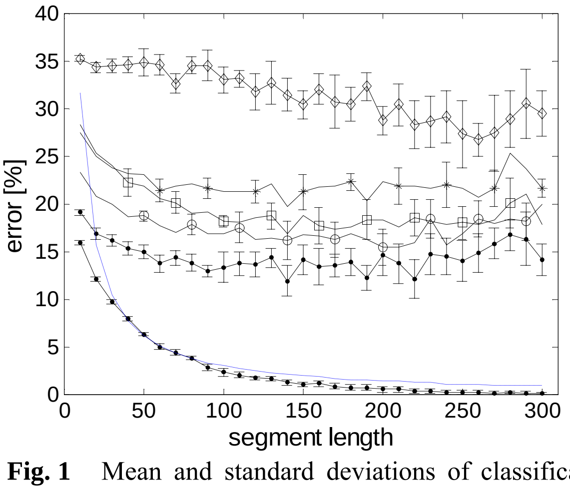

Fig. 1 Mean and standard deviations of classification errors on training sets (lowest graph) and on test sets (upper five graphs) of different signals.

The question arises if machine learning algorithms have found some generally valid properties of fatigue in EEG. This was checked out by cross validation on the subject level. Learning algorithms were tested on all data of only one subject after they were trained on all data of all other subjects. This was repeated for every subject. Results show high inter-individual variability (**Fig. 2**) indicating that common characteristics were rarely found. EEG characteristics of e.g. subject 10 can not be explained by the data of all other subjects, because mean errors of 50% are as high as them of completely random classifications. In contrast, it was possible to explain the EEG characteristics of subject 8 by relatively low mean errors of 15%.

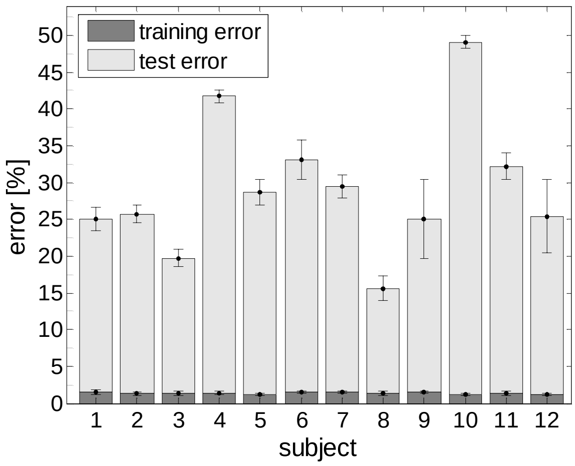

Fig. 2 Mean and standard deviations of errors of one subject tested against all other.

Training errors indicate that the learning algorithm had in all cases no problems to adapt to the given data sets. Future work has to validate the stability to intra-subject variations and has to show if groups of subjects can be established with similar EEG characteristics concerning strong fatigue.

4 Literature

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