AUTOMATIC RECOGNITION OF MICROSLEEP EVENTS

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Abstract—*Short segments of EEG, EOG and pupil diameter signals recorded in overnight driving simulation sessions of 21 young subjects were extracted during microsleep events and during fatigue states, where driving is still possible. Both classes were found by video based subjective scoring of experts. Estimated spectral power densities were used as input vectors of several classification methods. Results of multiple hold-out method of cross validation are compared. Support-Vector Machines show lowest mean and standard deviation of estimated test errors of (9.7±0.8) % by processing 6 channels of EEG and EOG. With same methods but with only one pupillometric channel errors are about 10 % higher. Shifting signal segments in time leads to rapidly increasing test errors; pure prognosis of ongoing events is possible, but with mean errors higher than 27.5 %.*

Keywords— *EEG, Pupil, Microsleep, Neural Networks*

Introduction

Sleepiness is estimated as the most significant identifiable and avoidable cause of accidents in transport. Their portion among all accidents is estimated as 15 to 20 % and is exceeding in this respect the importance of alcohol and drugs [1]. Among several technological concepts the recognition of driver states based on electrophysiological measures, mostly EEG and EOG [2-4], and based on oculomotoric measures, especially eye movements, pupil diameters and eye lid movements, are considered [5-7]. Dangerous states are microsleep events (mse), which appear as short intrusions of sleep into wakefulness and happen in monotonic situations which require continuing attentiveness.

Material and Methods

Here we present results of overnight driving simulation sessions of 21 young subjects (18 - 32 years). Points of time were marked when mse are ongoing and when fatigue states (non-mse) are observable. During non-mse driving is still possible. Both events were found subjectively by experts by off-line scoring of two video recordings of driver's portrait and right eye region. Recorded EEG (C3-A2,C4-A1,C3-O1,C4-O2), EOG (vertical, horizontal) and pupillogram were segmented with variable length and offset. The last parameter is defined as the difference in time between mse or non-mse and first sample in segment.

Estimated spectral power densities were used as inputs of the following classification methods, with which we have experiences and tested implementations:

1.) Learning Vector Quantization, with variants LVQ1, LVQ2.1, LVQ3 and OLVQ1 [8]
2.) Support-Vector Machines (SVM) with Gaussian kernel function [9]
3.) Self-Organizing Maps (SOM), calibrated, with modification supervised [10]
4.) Growing Cell Structures (GCS), calibrated, with modification supervised [11]
5.) k-Means (kM), calibrated, with modification supervised [12]

Classification errors are estimated by multiple hold-out. This method of cross validation repeats random partitioning of all data into test and training set and uses descriptive statistics to assess capability for generalization and adaptivity, respectively.

Results

As expected, supervised methods (LVQ, SVM) result in lower classification errors than calibrated unsupervised methods (GCS, SOM, k-Means). SVM performs best and achieves test errors below 10 % and achieves lower standard deviations (Tab.1). Though a series of parameter optimizations were done, the results of pupillometric measures are unsatisfactory. This is not surprising because in contrast to EEG / EOG, where up to six signals were processed, here only one signal was analyzed. On the other hand, loss of data due to eye lid closures leads to interpolated parts of the signal, which contain only dependent information and are therefore not beneficially. Results of eye gaze signals (eyetracking) were more badly and should be therefore not presented.

Table 1: Mean and standard deviation of test errors for different classification methods

Classification Method	EEG / EOG E_{TEST} [%]	Pupil Diameter E_{TEST} [%]
LVQ1	14,9 ± 1,3	28,7 ± 1,7
LVQ2.1	14,8 ± 1,4	28,7 ± 1,7
LVQ3	14,9 ± 1,4	28,7 ± 1,7
OLVQ1	14,0 ± 1,2	28,2 ± 1,6
SVM	9,7 ± 0,8	19,2 ± 1,7
kM	16,6 ± 1,5	29,8 ± 1,8
kM, sv	15,0 ± 1,4	29,0 ± 1,7
SOM	17,7 ± 1,6	32,8 ± 1,8
SOM, sv	14,4 ± 1,3	28,3 ± 1,6
GCS	16,1 ± 2,1	30,1 ± 1,9
GCS, sv	14,7 ± 1,9	28,0 ± 1,8

By varying offset between events and signal segments the ability to predict ongoing events is judgeable. A sensitive dependence of errors from offset was found (Fig. 1). Optimal segment length were found in empirical investigations, not mentioned here, to be about 8 sec. Optimal offsets are at -3 sec. In this case 3 sec of signal are immediately before

an event and 5 sec of signal are during an event. Decreasing offsets below -8 sec would lead to segments completely before an event. Mean classification errors for such cases of pure prognosis are above 27.5 % (Fig.1). Validation of SVM was performed by leave-one-out method, which is effectively calculable in case of SVM and leads to comparable estimations [13].

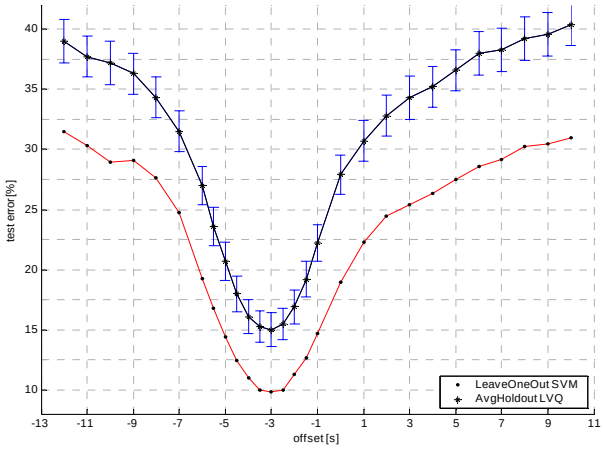

Figure 1: Mean test errors versus segmentation offset; a comparison of OLVQ1 and SVM on EEG and EOG

Discussion

We observed large behavioural differences between subjects during drowsiness. Two subjects showed no visible sign of clear mse; other showed many extended episodes of mse. Furthermore, all results were obtained in a laboratory situation; the extent of degradation in case of real on-the-road measurements is not predictable. Our results were based on electrophysiological measures in six different channels. Based on a contact-less measured signal degradations in test errors of about 10% occur. For all this reasons we summarize that practicable applications in microsleep warning devices are not inferable.

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