Application of Learning Vector Quantization to detect drivers dozing-off

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Abstract

EEG-signals and EOG-signals of eleven subjects were recorded during an overnight driving simulation task. By scoring the recorded videos clear microsleep events and clear non-microsleep events were picked out and small segments of the measured EEG- and EOG-signals before and during the events were analyzed. The spectral densities of these segments were classified using three methods of Learning Vector Quantization. Best classification results, up to 91%, were obtained with inclusion of all used EEG and EOG channels.

Keywords: EEG, EOG, Microsleep, Learning Vector Quantization

1. Introduction

Reliable methods to discriminate dozing-off events from continuously measured signals of a driver will be an important milestone in the development of drowsiness warning systems. Dozing-off periods are characterized by sudden intrusions of sleep into wakefulness, lasting for 2 to 30 sec [1], and often called as microsleep events (MSE). As pointed out by several authors, it is very difficult to get a drowsiness measure; for review see [2]. On the other hand, drowsiness measures are often calculated on a minute-scale, while signal processing to discriminate MSE has to be on a scale of seconds. As stated in [2], the only method that measures continuous fluctuations of sleepiness should be polysomnography, mainly by analyzing the electroencephalogram (EEG) and the electrooculogram (EOG). Later on, some success was made by pupillography [3-5]. By processing the pupil diameter signal, only, a discrimination performance of over 80% is achievable, as recently reported by us [6].

In this paper we are regarding the following questions:

1) Do small segments of EEG and of EOG immediately before and during a MSE contain enough information to discriminate them from segments during non-microsleep episodes (NMSE), when the driver is drowsy but still attentive?
2) Is it possible to detect MSE without a noticeable decrement by analyzing only one channel of the multi-channel EEG- /EOG- recordings?
3) Which segment length and which time offset related to the MSE starting time are optimal?

2. Experiment

Our experimental setup is comparable to [7]. Four EEG-signals and two EOG-signals were recorded of eleven young subjects during driving simulation sessions lasting 25 min and repeated every hour between 1 a.m. and 7 a.m. Two video cameras were utilized to record drivers portrait and right eye region for visual off-line scoring of MSE, typically recognizable by closed eyes or by drop of the head. Scoring was performed by two experienced persons under the guideline to take only undoubtable cases into account. Disadvantageously, attention losses with open eyes and with stare gaze are not detectable by this scoring method. The number of MSE was very different between subjects and was increasing with time of day for all subjects. All in all 1,675 MSE and 1,286 NMSE were scored.

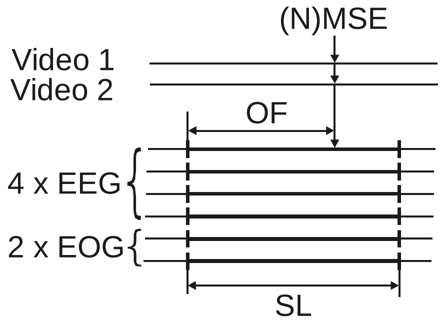

Figure 1: Segmentation of EEG- / EOG- signals with relation to visually scored microsleep- (MSE) or nonmicrosleep- (NMSE) events by two parameters offset (OF) and segment length (SL).

3. Analysis

EEG and EOG were lowpass filtered with 40 Hz cut-off frequency and sampled at 64 Hz. After synchronization between both video recordings and EEG- / EOG- recordings, segments were stored for further processing using variable time offsets (OF) and variable segment length (SL) (Fig. 1).
After linear trend removal and applying Hanning window, spectral estimation was done by discrete Fourier transform. Spectral power densities were averaged by summing up in frequency bands of width of 0.5 Hz, 1 Hz and 2Hz and in conventional bands of EEG research: delta (0.5 … 3.9 Hz), theta (4.0 … 7.9 Hz), alpha (8.0 ... 11.9 Hz), sigma (12.0 … 13.9 Hz) and beta (14.0 … 29.9 Hz).

4. Discrimination analysis

For each feature vector consisting of averaged absolute spectral power densities of all six signals a label “MSE” or “NMSE” was scored, thus we have a two-class classification problem. Analysis was done by Learning Vector Quantization (LVQ) [8]. All three methods OLVQ 1, LVQ 2.1 and LVQ 3 were processed sequentially preceded by an initialization phase [9]. The learning set was partitioned into 80% training set and 20% test set. Partitioning was repeated 50 times for each parameter setting of the LVQ network. The classification rate was estimated as the ratio between the number of correct classifications to the number of all classifications using the test set. This kind of discrimination analysis is comparable to that in [10].

Elimination of dead neurons after training, slightly improves classification rates, therefore it is recommended.

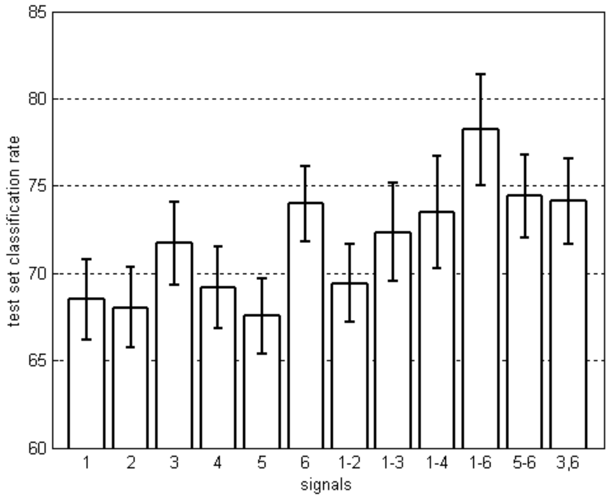

Figure 2: mean values and standard deviations of classification rates for different selected signals. Label “1-4” e.g. means inclusion of signal 1, …, 4 (all EEG-signals) and label “3,6” means inclusion of signal 3 and 6.

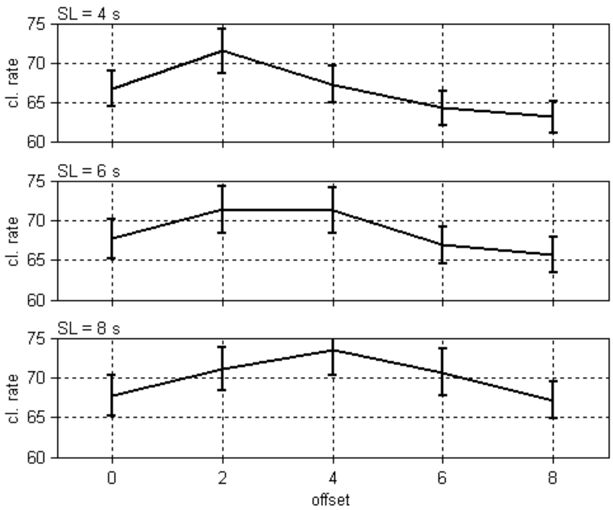

Figure 3: mean values and standard deviations of classification rates for different offsets (OF) and three different segment lengths (SL). Best results are obtained with SL = 8 sec and OF = 4 sec.

At first, we come to question 2, concerning the number of signals necessary for optimal classification. The LVQ network was trained and tested by different selections of signals (Fig. 2). Every signal was selected alone for training and testing. Signal 3, an EEG signal, and signal 6, an EOG signal, were much more suitably than the others. Both EOG signals (5-6) were more suitably

than all EEG signals (1-4). But most success was gained by inclusion of all six signals (1-6).
Best classification results were obtained for averaging the spectral power densities in frequency bands. In general, a compromise has to be found between the number of features, because of curse of dimensionality, and the lack of refinement in spectral domain, i.e. extend of information loss. For band width of 1Hz results were slightly better than for 0.5 Hz and for 2 Hz. Surprisingly, decrease of classification rates were only about 3% when using the five frequency bands of EEG research mentioned above.
At second, we varied two preprocessing parameters (question 3), segment length (SL) and temporal offset (OF), mentioned above (Fig. 3). Larger segment lengths were better than shorter. The optimal offset was 4 sec. That means segments of all EEG- and EOG-signals beginning 4 sec before MSE- or NMSE-starting points and 4 sec after starting of an event were optimal.

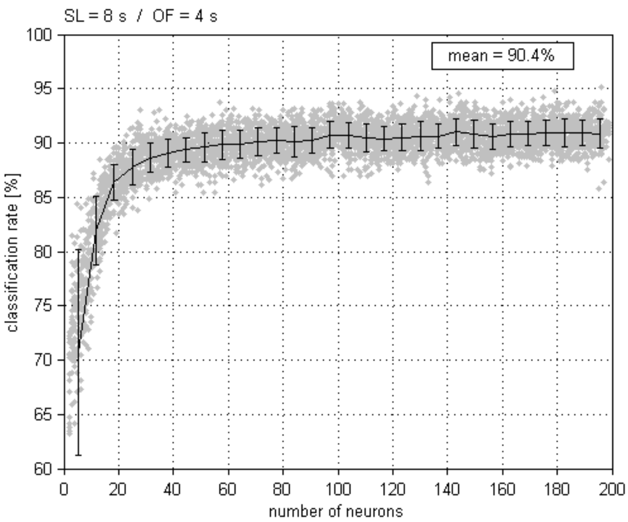

Figure 4: Classification rates versus number of neurons. 5,000 LVQ networks were trained and tested with different training set / test set partitions and different initializations. Mean classification rate was computed between 30 and 200 neurons.

Further improvements in classification were reached by transformation log(x) of spectral power density as proposed in [14] and by choosing the number of neurons. Fig. 4 shows a typical plot of classification rate versus number of neurons. Classification success is increasing up to 90% in the mean if more than 50 neurons were used, and up to 91% with more than 140 neurons. With more neurons no significant changes are gained. Standard deviations are nearly constant.

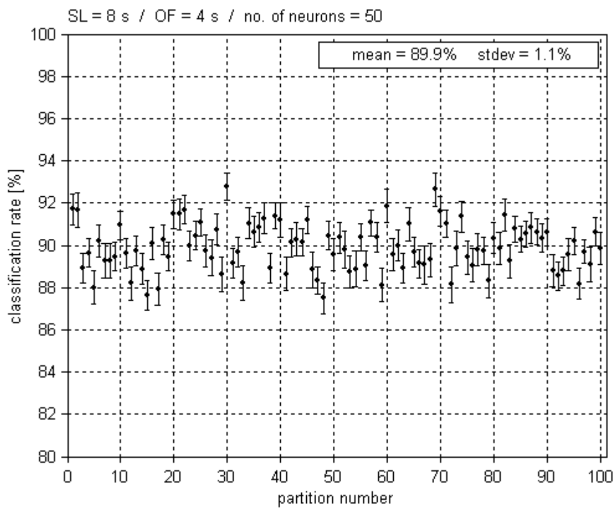

Figure 5: Classification rates of 100 fixed training set / test set partitions and different initializations. Grand mean and standard deviation of mean classification rates was computed.

One might assume, that these results were obtained for a picked out test set. Therefore, we repeated partitioning many times. Classification results for 100 random partitions are shown in Fig. 5. For each partition, training and testing was repeated 500 times with different weight matrix initializations. The standard deviation caused by different initializations of the LVQ network and caused by training progress due to randomly applied input vectors is shown by error bars in Fig. 5. The deviations of the mean values are caused by different partitions and also caused by training progress and are slightly higher than the deviations caused by initialization.

5. Discussion

Some authors pronounced that a combination of EEG and EOG measures should be most successful in predicting MSE [7,12,15]. Our results give further support for this statement. Classification rates of 90.4% in the mean were unexpectedly high and standard deviations of 1.4% were moderate. The high discrimination ability is also important in a general sense, because sudden behavioral transitions might be detectable by analyzing cortical potentials with modern signal analysis methods.
Estimation of spectral densities as a simple feature extraction method was applied because of a lack of prior knowledge for special patterns. Many authors reported an occurrence of alpha bursts, an increased EEG activity in the alpha frequency band, preceding MSE or during MSE [2,7]. But some subjects do not produce such an activity. Another characteristic

pattern during wake / sleep transitions are slow eye movements [12,13], detectable in the EOG. Slow eye movements as well as alpha bursts don't occur during every MSE and their temporal relationship to the moment of starting MSE seems to be loose [2,11,16]. Therefore, we refrained from enforcing pattern specific analysis.

Further investigations are necessary to validate these results on additionally subjects. Many authors reported of large inter-individual differences of the EEG- and EOG- characteristic [2,11,15-17]. It is conceivable that the LVQ networks are representing individual characteristics of each of the eleven subjects under investigation. Furthermore, it should be investigated if the combination of EEG- / EOG-features and features of pupillography [4-6] might improve the discrimination of MSE.

Another topic of interest on the way to drowsiness warning systems must be investigation on discrimination of MSE from continuously measured and analyzed signals. Besides of robust artifact elimination techniques additional driver status estimation techniques, like sleepiness estimation, are strongly requested.

6. References

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