Classification of Pre-Stimulus EEG of K-complexes using Competitive Learning Networks

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Abstract

The spectral powers of the pre-stimulus EEG are used as input feature vectors to Learning Vector Quantization and to Self-Organizing Map networks to classify these vectors into four classes. The four classes were observed in the EEG as eliciting patterns of K-complexes due to double-tone pip stimulations during sleep. A modified Learning Vector Quantization algorithm was applied resulting to higher classification rates and lower sensitivity to network initialization. With both algorithms classification rates over 90% are achievable.

Introduction

K-complexes are conspicuous patterns in the human EEG and arise only in the sleepy and in the conscicuous state. They are an important factor for the classification of sleep stages, by definition they separate stage S1 and stage S2. Their functional importance, however, is discussed controversal. Their morphology and their probability of occurence are varying over night, but until now this information is not used in scoring and analysis of sleep.

There are two groups of K-complexes, spontaneous and induced. In this study we only investigated K-complexes induced by loud short tone pips. First components of the potential complex arise around 350 ms and the latest clearly components arise between 900 and 1500 ms after stimulus. In contrast to evoked potentials, however, K-complexes are relativ seldomly elicitable over night. The elicitability is varying inter- and intraindividual and was observed in stage S2 at low stimulus rate by $p_E = 0.2 ... 0.65$ [Bastien 1992].
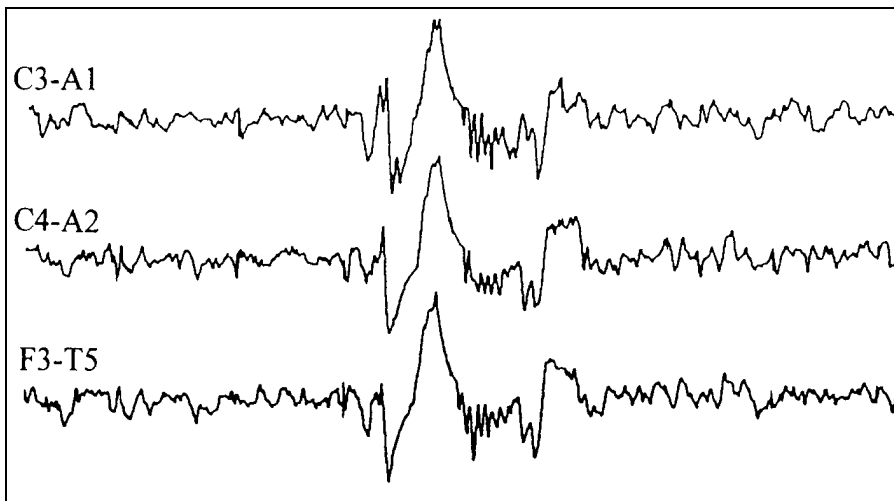

Fig. 1
Typical K-complex patterns in the human EEG.

In this study we investigated the pre-stimulus EEG of K-complexes. We supposed that there should be characteristic short-time-stationary feature sets in the EEG, so-called microstates, indicating the functional behaviour of sleep rela-ted brain structures. These microstates should also be related with the elicitability of K-complexes. Another author [Halasz 1993] found some hints that there are no significant spectral features in the pre-stimulus EEG of K-complexes detectable, but a significant long lasting spectral change in the post-stimulus EEG leading to a sustained inhibition of the

sleep spindle activity. The pre-stimulus EEG in our investigations, however, show clear differences between the two events K-complex response and no K-complex response.

Experiment

10 healthy subjects in the age between 20 and 45 years were sleeping one night in the sleep lab. We recorded two bipolar (Fz-Cz, Cz-Pz) and two unipolar (C3-A2, C4-A1) EEG-signals, EOG on both eyes and a submental EMG. The signals were low-pass filtered at 35 Hz and sampled at a rate of 128 per sec.

Instead of stimulating the subject with single tone pips we applied over the whole night in all sleep stages a double-tone-stimulus (60 dB, 1 KHz, 50 ms) with an interstimulus interval of 3 sec. The intertrial interval was randomly distributed between 20 and 30 sec.

During off-line visual sleep scoring all artefact-free pre-stimulus EEG-segments in stage 2 were selected and stored together with the information on occurence of K-complexes:

K00 - no K-complexes occured after both tone pips,

K10 - a K-complex occured after the first tone pip but not after the second,

K01 - a K-complex occured after the second tone pip but not after the first,

K11 - K-complexes occured after both tone pips.

This information will later serve as grouping information to the statistical analysis and to the LVQ networks. The length of the EEG segments was 2000 msec. The occurence of K-complexes was recognized by experienced scorers with the following criterions: bi- or triphasic waves, minimal length of 0.5 sec, occurence within 1 sec post stimulus and amplitudes higher than 1.5 of the basis EEG process. K-complexes on the first stimulus followed by a delta group [Halasz 1993] were disregarded to obtain a clear separation to the group K11.

Statistical Analysis

The calculated probabilities for each occurence class is shown in fig.2. The probability of eliciting no K-complexes is according to expectations high. The probability of eliciting K-complexes on the first tone is in sum higher (K10+K11). Seldomly one can observe no K-complex after the first but after the second stimulus (K01). Further considerations on the elicitability in relation to motoric reaction were published elsewhere [Golz 1996].
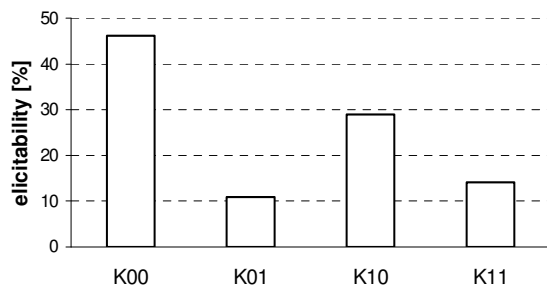

Fig.2   Probabilities of eliciting K-complexes for each occurence class

Over all subjects and over all sleep stages S2 we collected 3581 artefact-free pre-stimulus EEG-segments. For further analysis we only used signal Cz-Pz, where the amplitudes of K-complexes are relative high and the disturbing influ-ence of the EOG-potentials are relative low. For all EEG-segments the spectral power in the deltaband (1.0 ... 3.5 Hz), in the thetaband (4.0 ... 7.5 Hz), in the alphaband (8.0 ... 13.5 Hz) and in the betaband (14 ... 20 Hz) was calculated using Fast Fourier Transform. Fig.3 shows a box and whisker plot [MATLAB 1997] of the calculated band power data of all EEG-segments grouped into the four classes K00, K01, K10 and K11. Each box has lines at the lower quartile, at the median and at the upper quartile. The whiskers show the extend of the rest of the data. Outliers are not shown. As it can be seen from fig.3 the classes K00 and K01 and the classes K10 and K11 are similar in all features.

With these spectral power data statistical tests were performed. The test of normality failed on a significance level of 5 %. That's why we used the Mann-Whitney rank sum test, a nonparametric procedure which does not require that you assume normality or equal variance. A rank sum test ranks all the observations from smallest to largest without regard to which group each observation comes from. The ranks for each group are summed and the rank sums compared. The null hypothesis states that two samples were not drawn from populations with different medians. Putting group K10 and K11

together to group K1x and putting group K01 and K00 together to group K0x results in significant differences between K0x / K1x for every feature.
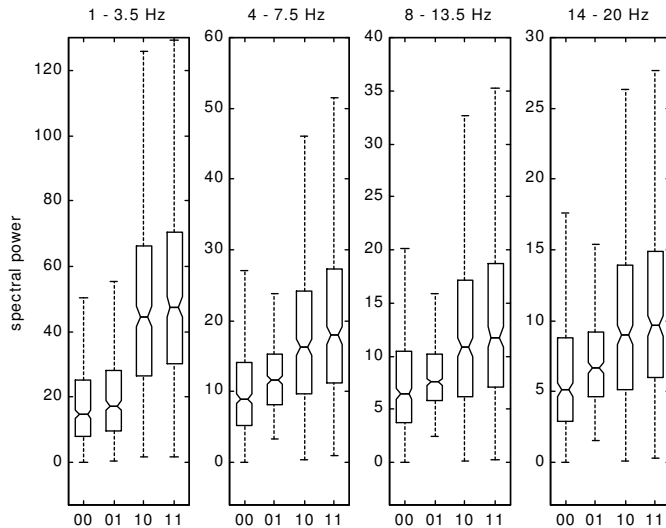

Fig.3   Box plot of the spectral power summed in four EEG frequency bands and grouped in four elicitability classes

In further investigations we applied artificial neural networks as a tool for multivariate nonlinear and distribution-free clustering of data. Another goal was the establishment of a discriminant function set.

Classification by Learning Vector Quantization

In a first step we applied a LVQ network [Kohonen 1995] for classification. As mentioned above the feature vectors are four-dimensional, they contain the relative spectral power in the four EEG bands.

To obtain equal size for all classes (K00, K10, K01, K11) we randomly selected 380 feature vectors for each class. Every network application started with a randomly partitition into training data (80%) and test data (20%). For the training we used the LVQ1-algorithm with 200 epochs and an initial learning rate of 0.1. The training converged in all cases but with different succes: both the reclassification rate of the learning set and the classification rate of the test set depend on initialization of the weight vectors.

Fig.4 shows the classification rate versus the number of simulated neurons. Each network configuration was simulated 50 times with another 80/20 partitition mentioned above. The weight vectors were initialized with the mean feature vector of the class belonging to the neuron. We obtained classification rates of about 85% in the mean and about 94% in the maximum. These results are already available with 30 neurons. Further numerical investigations not shown in this paper result in slight poorer classification rates after noise was added during initialization and in much poorer classification rates in the case of initializing the LVQ network uniform randomly in the input data range.
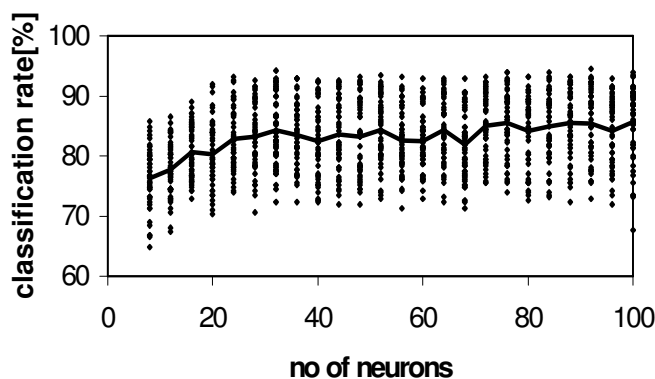

Fig.4   Classification results with the LVQ-algorithm versus the number of simulated neurons for several 80/20 partititions between training and test set. The solid line shows the mean classification rate.

Modifications to the LVQ-Algorithm
With two-dimensional example data sets we investigated the numerical behaviour of the LVQ-Algorithm. In the case of several compact regions for each class distributed in the feature space we observed an oscillating update of some weight

vectors. They won the competition in several regions of their class, but the learning rate was yet to small and the number of neurons allocated to this class was to low. On the other hand they won the competition in regions not allocated to their class and were in some cases unable to come over the barrier of other classes. Therefore we made the following modifications to LVQ:

1. We introduced a SOM-like first training phase, let us call phase 1, where no class information were taken into account. The winner of the competition always moved to the input vector. Phase 1 was started with a high number of neurons, e.g. 200.

2. At the end of phase 1 the winning frequencies of the neurons were calculated over all training vectors and stored for each neuron and each class. Afterwards dead neurons were eliminated and the neurons were reallocated to the class where their winning frequency was the highest.

After phase 1 the calculations were continued with the LVQ1-algorithm.

In our application these modifications resulted in a better classification rates of about 93% in the mean and about 97.5% in the maximum (fig. 5). These results are already available with 40 neurons.
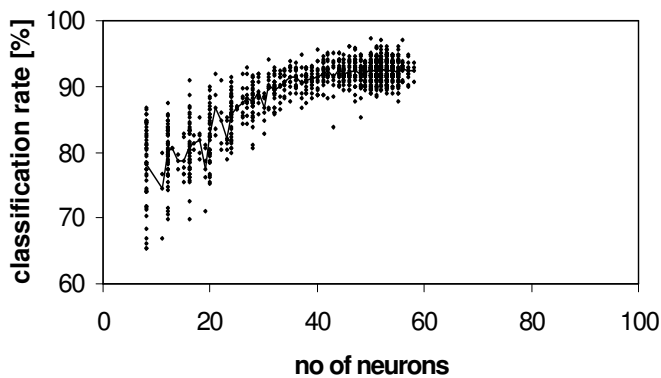

Fig.5 Classification results with the modified LVQ-algorithm versus the number of simulated neurons for several 80/20 partitions between training and test set. The solid line shows the mean classification rate.

As ist can be seen from fig.5 the variance of the classification rates obtained for several 80/20 partitions under modi-fied LVQ training is lower than under unmodified LVQ training.

Classification by Self –Organizing Maps

In a further step we applied a SOM network [Kohonen 1995] for classification using the same four-dimensional feature vector set as in LVQ. Again we used a randomly 80/20 partitition of training and test data for each network simulation run.

In our application the learning rate was not a critical parameter. According to the recommendations in [Kohonen 1995] the initial radius of the neighbourhood function was choosen by 60% of the diagonal of the map. The training was in all cases successfull within 200 epochs (about 250,000 iterations). 10% of the training were choosen for the ordering phase. After finishing the ordering phase the radius of neighbourhood reached zero and the learning rate reached the final value of 0.01maintained in the convergence phase.

After training we calibrated the map using the winning frequencies of each neuron in each class and allocating the neurons th the class where their winning frequency was the highest.
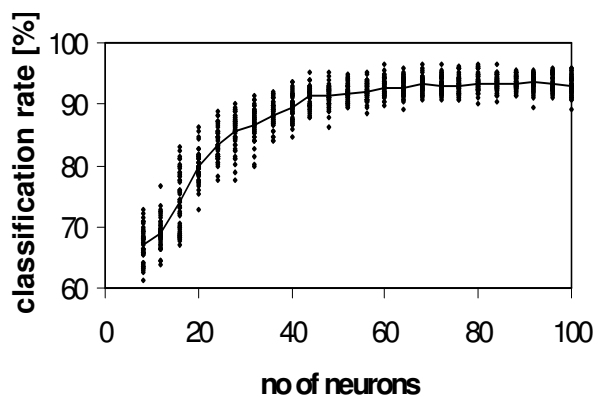

Fig.6 Classification results with the SOM algorithm versus the number of simulated neurons for several 80/20 partititions between training and test set. The solid line shows the mean classification rate.

In contrast to LVQ the success of the SOM algorithm was nearly unindependent from weight initialization. The variance of the classification rates obtained for several 80/20 partitions is, too, lower (fig.6). The classification rates are about 93.5% in the mean and about 96.5% in the maximum. These results are available with 45 neurons.

In the topographic map we fixed the number of neurons in one direction and only incremented the number on the other side. In fig. 6 the results for 4 * X maps (X = 2...25) are presented. Simulations of the SOM with other two-dimensional maps and with a one-dimensional neighbourhood relation map yields nearly the same results as in the 4 * X maps.

Leaving the in electrophysiology commonly accepted summation of spectral powers in bands and operating with the single spectral power for every frequency bin, leading in our case to feature vectores with 39 dimensions, results in a better classification rate with a maximum over 99%. The computational expense was nor remarkable. Therefore a summation in EEG bands is not necessary in analysis with artificial neural networks.

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