Describing the sleep EEG with an Adaptive Autoregressive Model.

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Introduction

The spectral information of the sleep EEG is an important indicator for the sleep stage[1]. Adaptive autoregressive parameters can describe the time-varying spectrum. The AR spectrum is a maximum entropy spectral estimator, which is optimal with respect to the number of parameters. No selection of frequency bands is required if the AR parameters are combined by a classifier. Adaptive estimation algorithms are useful for the on-line and real-time sleep analysis[2].

Method

EEG processing

The EEG of polygraphic recordings (SIESTA database)[3] from eight European sleep labs was analysed; ECG artefacts and line interference were minimised with regression analysis and 50Hz notch filtering. The data were downsampled to 100Hz. Next, the AAR parameters were estimated with Kalman filtering assuming a multivariate random walk of AAR parameters[2,4].

Classification

Linear discriminant analysis (LDA) was used to learn a classifier from 52 all-night recordings. Epochs for learning must confirm on all following criteria:

- 3 scorers must agree on the sleep stage according to R&K[5]
- no saturation of the input and no flat line must be detected in any EEG channel
- the variance of the residual process must be between the 10 and 90 percentile for each recording and each channel.

Results

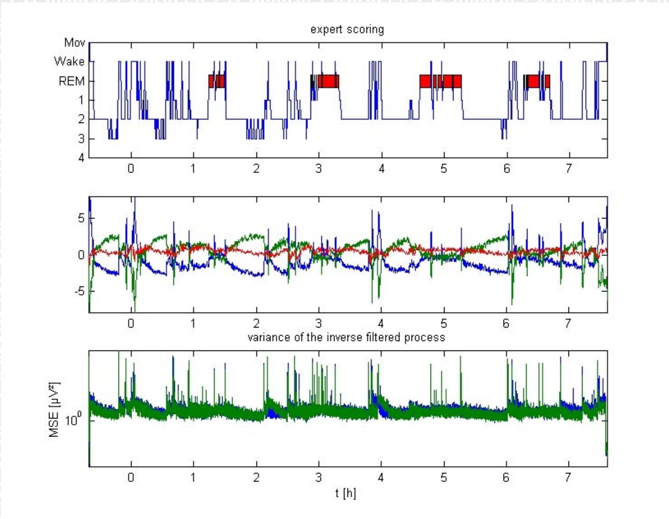

Figure 1: Sleep analysis using AAR parameters (healthy subject). On top, the hypnogram scored by an expert is shown. Below, the classification with AAR parameters using channels C3-M2 and C4-M1 is given for deep sleep (green line), REM (red line) and awake (blue line) – the highest curve indicates the appropriate sleep stage. The bottom plot shows the variance of the inverse filtered process (logarithmic scale). Spikes indicate artefacts and transient events.

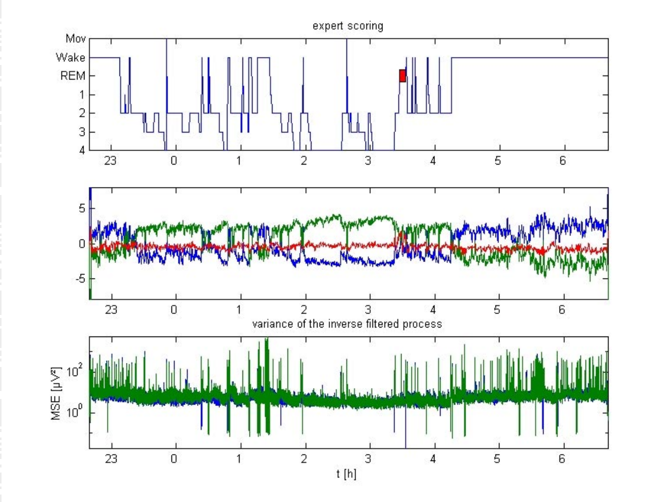

Figure 2: Sleep analysis using AAR parameters (Parkinson patient). The description of the curves is the same as in Figure 1.

Fig.1 and 2 show the results of classification (linear combination of the AAR parameters) of two all-night recordings, which were not part of the learning set. The deep sleep periods occur when S34:S2 (green line) is highest; also the REM-periods (R:W1234) can be identified easily (red line is highest). In this examples, also W-R (W:R234) can be clearly distinguished (blue line tops the other lines).

Summary

It is shown that AAR parameters can be used to describe the time course of the sleep (including wake and REM) process. The advantages are:

- classifiers are easy to learn
- any combination of channels (single, multiple, all) can be applied.
- the classification output is continuous, it overcomes the problem of discrete states

Possible improvements:

- considering the time delay of the AAR estimates when training the classifier
- improved artefact processing
- careful selection of training set (only normal subjects)

References

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