Neural net classification of REM sleep based on spectral measures as compared to nonlinear measures

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Abstract. In various studies the implementation of nonlinear and nonconventional measures has significantly improved EEG (electroencephalogram) analyses as compared to using conventional parameters alone. A neural network algorithm well approved in our laboratory for the automatic recognition of rapid eye movement (REM) sleep was investigated in this regard. Originally based on a broad range of spectral power inputs, we additionally supplied the nonlinear measures of the largest Lyapunov exponent and correlation dimension as well as the nonconventional stochastic measures of spectral entropy and entropy of amplitudes. No improvement in the detection of REM sleep could be achieved by the inclusion of the new measures. The accuracy of the classification was significantly worse, however, when supplied with these variables alone. In view of results demonstrating the efficiency of nonconventional measures in EEG analysis, the benefit appears to depend on the nature of the problem.

1 Introduction

Many facts point to the view that brain dynamics are essentially of a nonlinear nature. Nonlinear phenomena were experimentally proven at the neuronal level, and multiple feedback loops are known on each of the hierarchic levels of the CNS (Lopes da Silva 1991). Harmonics and subharmonics, for example, can be easily observed in the so-called steady-state response to periodic visual or auditory stimuli, which is a clear sign of the nonlinear character of the EEG. It was also shown by surrogate data tests that EEG signals exhibit nonlinear elements and thus cannot be described completely by linear stochastic models (Pritchard et al. 1995; Rombouts et al. 1995; Fell et al. 1996b; Palus 1996; Ehlers et al. 1998). Moreover, nonlinear EEG measures enhanced the classification accuracy of Alzheimer’s disease versus controls (Pritchard et al. 1994), yielded a differentiation between high-IQ and low-IQ groups (Lutzenberger et al. 1992), improved the overall discrimination of sleep stages (Fell et al. 1996a), enabled the localization of the primary epileptogenic area (Lehnertz and Elger 1995), and allowed the distinction between different mental tasks (Fell et al. 2000b).

On the other hand, there are several theoretical and practical difficulties associated with the use of nonlinear measures. Because the requirements of stationarity and long-enough observation periods need to be met at the same time, only the nonlinear analysis of low-dimensional deterministic real world systems stands on a solid theoretical basis. For a complete characterization of EEG signals, however, a high-dimensional nonlinear deterministic or a nonlinear stochastic model might be required (Fell et al. 2000a). Moreover, in the majority of experimental situations the question remains as to whether the application of nonlinear methods indeed yields information which cannot be obtained by an extended application of conventional EEG measures (Röschke and Aldenhoff 1991, 1992; Röschke et al. 1993, 1994).

An algorithm for the automatic recognition of rapid eye movement (REM) sleep has been developed in our laboratory for releasing alarms in selective REM sleep deprivation and has been continuously improved. For this system the spectral power values of a single EEG recording were calculated in six frequency bands by means of the RMS (root mean square) values and served as input to a backpropagation neural network (Grözinger et al. 1995, 1997; Grözinger and Röschke 1996). In the present study, we addressed the question of whether the inclusion of nonlinear and nonconventional stochastic input variables could improve the recognition accuracy of the algorithm. We selected the two nonlinear measures of the largest Lyapunov exponent L1 and correlation dimension D2, and, moreover, spectral entropy and entropy of amplitudes. These measures had previously been shown to be efficient in the
discrimination of sleep stages (Fell et al. 1996a). In short, the correlation dimension \( D_2 \) yields a lower boundary for the degrees of freedom or in other words the complexity of a system, whereas the largest Lyapunov exponent \( L_1 \) quantifies the so-called sensitive dependence on initial conditions or ‘chaoticity’ (Grassberger et al. 1991). Spectral entropy and entropy of amplitudes estimate the degree of disorder incorporated in the frequency and amplitude distribution of a signal, respectively. We compared the accuracy of a backpropagation network processing spectral amplitudes from six different frequency bands as input, with a network utilizing information from the four additional measures and a combined network using information from all ten EEG measures together.

2 Materials and methods

2.1 Sleep EEG data

Thirteen male volunteers between 23 and 33 years of age (average 25 years), who were in self-reported good health with regular sleep–wake patterns, participated in the investigation. In order to become acquainted with the conditions of the sleep laboratory, the data of the adaptation night of all subjects were disregarded. Afterwards polysomnographic recordings were performed in five subjects during two separate nights each (group 1: night 1 and night 2) and in eight additional subjects (group 2) during one night each. Sleep EEG was recorded from 11.00 p.m. until 7.00 a.m. the next day.

Surface electrodes were placed on the skull (\( P_z, C_z, C_3, \) and \( C_4 \); international 10-20 system) and mastoid to record electroencephalographic activity, at the outer canthi of the left and right eye to record eye movements, and on the chin to record submental electromyographic activity. The analog EEG signal from position \( C_z \) was filtered with a 0.53 Hz high-pass filter and a 45 Hz low-pass filter (48 dB/octave), and was digitized by a 12-bit analog-to-digital converter with a sampling frequency of \( f_s = 100 \) Hz. The total night-time EEG was divided into 1440 consecutive segments of 20.5 s, each consisting of 2048 data points.

Visual sleep-stage classification of the 1440 EEG epochs was performed according to Rechtschaffen and Kales (1968) criteria by two independent raters. Deviant judgements were settled by agreement. Afterwards, all time periods were assigned a corresponding output \( t'_i = 1 \) in the case of REM sleep and \( t'_i = 0 \) in the case of non-REM sleep.

2.2 Network implementation

The following network architectures were implemented: network 1 serving the spectral measures consisted of six input, four hidden, and one output neuron; network 2 serving only the additional measures consisted of four input, three hidden, and one output neuron; and network 3 serving the combined measures consisted of 10 input, six hidden, and one output neuron. In all cases the number of hidden neurons included one threshold neuron. All networks were organized as strictly feedforward, and adjacent layers were totally interconnected. For all three networks the input neurons were linear, whereas hidden and output neurons had a sigmoid output function and were connected to a threshold neuron.

2.3 Training and evaluation

The five EEG recordings of group 1/night 1 served to train the three networks. The 7200 input–output data-points were pooled and a subset of 1440 was randomly selected as the training dataset. A generalized backpropagation algorithm was used as a learning rule for computer simulation minimizing the QME (quadratic mean error) between the network output and the desired output during the training period. The software program was provided by the Neural Networks Research Group at the University of Kassel (Klöppel 1990). Starting from randomly chosen synaptic weights, training was stopped when the error improved less than \( 10^{-4} \) within 50 training loops, which occurred in a maximum of 2500 loops. Each learning cycle was repeated from at least three different starting points to avoid local minima.

In working mode, the three networks were applied to all time periods \( 1 \leq i \leq 1440 \) of the EEGs of group 1/night 2 and group 2. According to the training process, the level \( t_i \) of the output neuron indicated a tendency of the network to decide in favor of REM sleep. For every EEG, the accuracy of the neural net classification with respect to the visual scoring was quantified by the QME:

\[
QME = (1/2880) \times \sum (t_i - t'_i)^2 \quad 1 \leq i \leq 1440
\]

A time period was assigned as REM, according to the network, if \( t_i > 0.5 \).

2.4 Input measures

2.4.1 Spectral amplitude measures. The signal in each time period was digitally filtered into six different frequency bands by FFT, rectangular windowing, and backtransforming. The bands were chosen as: 0.5–3.5 Hz, 3.5–7.5 Hz, 7.5–15 Hz, 15–25 Hz, 35–45 Hz, and 0.5–45 Hz. Afterwards the RMS values were calculated for the filtered signals, revealing the spectral measures for the six different frequency bands.

2.4.2 Spectral entropy. The evaluation of the spectral entropy (SEN) was suggested by Inouye et al. (1991). The spectral entropy is given by

\[
SEN = - \sum_{\omega_i} S(\omega_i) \times \log S(\omega_i) \quad \text{with normalized spectral power}
\]

\( S(\omega_i), 0.5 \text{Hz} < \omega_i < 45 \text{Hz} \)
If the power is concentrated on a single frequency, spectral entropy reaches a minimum, whereas for a broad frequency distribution high values are obtained for the spectral entropy.

2.4.3 Entropy of amplitudes. The entropy of amplitudes (ENA) resulted from the normalized amplitude distribution $P_i$ of the time series:

$$\text{ENA} = -\sum_i P_i \times \log P_i$$

For the calculation of amplitude distributions, the amplitude domain was partitioned into 100 equidistant boxes covering the interval between maximum and minimum amplitude of the respective EEG segment.

2.4.4 Nonlinear measures. The behavior of dynamical systems can be studied by investigating the properties of their state distribution in phase space. A time continuous $n$th order system is defined by a set of $n$ first-order differential equations. Its states can be represented by points in a $n$-dimensional space, where the coordinates are just the values of the state variables $x_1, \ldots, x_n$. The phase space is the set of all possible states that can be reached by a certain class of systems. Every single point of the phase space represents a defined state. As time increases the sequence of such states defines a curve in phase space, called a trajectory. If the trajectories converge to a lower dimensional indecomposable subset, this subset is called an attractor. Takens (1981) has shown that from the measurement of a single component $x_i$ of a $n$th order system, the system states $y$ can be reconstructed by the so-called time-delay procedure:

$$y(t) = (x_i(t), x_i(t+\tau), \ldots, x_i(t+2n\tau))$$

He proved that original and reconstructed attractor possess the same topological properties and that embedding into $\mathbb{R}^{2n+1}$ is generally sufficient.

Attractors of dynamical systems are often characterized by their correlation dimension D2 (Parker and Chua 1989; Grassberger et al. 1991). The correlation dimension is a special case of the generalized Renyi dimensions, which in contrast to the topological dimension of manifolds allow noninteger values. D2 is a metric property of the attractor that yields a lower boundary for the number of degrees of freedom, meaning the number of independent variables of a system. The correlation dimension is often called complexity of a system, although complexity is not a uniquely defined term. Lyapunov exponents measure the mean exponential contraction or expansion of the axes of a sphere describing a set of different initial conditions. In other words, Lyapunov exponents quantify the sensitivity to initial conditions. Mathematically, they are defined by the logarithm of the eigenvalues of a matrix which determines the development of trajectories starting in an infinitesimal neighborhood of a reference trajectory. Lyapunov exponents are usually arranged in descending order from $L_1$ (highest value) to $L_n$ (lowest value). For dissipative dynamical systems, the sum of all Lyapunov exponents is less than zero. A nonlinear system possessing a positive largest Lyapunov exponent $L_1$ is by definition chaotic. This makes the largest Lyapunov exponent an important classification measure.

For the estimation of nonlinear measures we applied the reconstruction procedure proposed by Takens (1981) to each EEG segment by embedding the signal into a 20-dimensional (correlation dimension) or 10-dimensional (Lyapunov exponent) phase space. For the time increment $\tau$ we used the first zero crossing of the autocorrelation function. If no zero crossing of the autocorrelation function was found within the first 300 samples, the first minimum of the autocorrelation function was taken for the time increment.

The correlation dimension $D_2$ was estimated according to the proposal of Grassberger and Procaccia (1983):

$$D_2 = \lim_{R \to 0} (\log C(R, 20) / \log R)$$

where $C(R, 20) := \sum_{i,j=1, i \neq j}^{N} \Theta(R - \|y_i - y_j\|); \Theta(x) = 1$

$$\text{for } x > 0, \Theta(x) = 0 \text{ otherwise;}$$

where $y_i$ are state vectors in the embedding space, $C(R)$ are correlation sums, and $R$ is the Euclidian distance. Fifty reference points and a R-axis domain of five decades were implemented. We applied a Theiler correction of plus or minus the delay time (Theiler 1986). The value of $D_2$ was automatically extracted from the averaged slopes of the curves $[\log C(R) \text{ vs } \log R]$ within the stationarity region $\log C(R) \in [2.0, \log C_{\text{max}} - 1.0]$ in embedding dimension 20.

The largest Lyapunov exponent $L_1$ was calculated by applying a modified version of the Wolf algorithm (Wolf et al. 1985). Essentially, the Wolf algorithm computes the vector distance $X$ of two nearby points and evolves its length for a certain propagation time. If the vector length $X'$ between the two points becomes too large, a new reference point is chosen with the properties to minimize the replacement length and the orientation change. Now the two points are evolved again, and so on. After $m$ propagation steps the first positive Lyapunov exponent results from

$$L_1 = (1/(t_m - t_0)) \sum_{k=1}^{m} \log_2(X'(t_k)/X(t_k-1))$$

We implemented a modified replacement procedure (Frank et al. 1990) and a randomized choice of propagation steps (Fell and Beckmann 1994). For theoretical background and further information on algorithms, we refer to Fell et al. (1996a).

3 Results

The diagrams on the left-hand side of Fig. 1 demonstrate typical 10-s samples of sleep EEG recordings
During stages I, II, slow-wave sleep, and REM. In each of the four cases the corresponding frequency spectrum on the right-hand side shows a decay in signal power proportional to the inverse of the frequency. Nevertheless, there are characteristic features contained in the spectra that allow for a discrimination based on the spectral parameters.

Concerning the training behavior of the networks, the data structure turned out rather benign. Whenever changing the initial synaptic weights for invariant training data sets, the QME approximated the same limits provided that the initial values were chosen to be not too far from zero. Problems with local minima did not occur. The synaptic weights themselves however were mostly not identical at the end of the training process, indicating that the optimization problem did not completely determine the neural network architecture.

The final averaged QME values are demonstrated in the upper diagram of Fig. 2 for the different groups of EEGs and the various sets of input variables. Because the training data were chosen as a 20% subset of group 1/night 1, the corresponding error rate is lower or equal in comparison to the other groups independently of the choice of input variables. For all three groups of EEGs, the averaged QMEs reached their minimum for network 1 (spectral measures) and network 3 (combined measures), whereas the QMEs for network 2 (additional measures) were markedly increased.

A characterization of the errors in terms of the percentage of misclassified epochs is provided in the lower diagram of Fig. 2. As compared to the QMEs, no major discrepancies were found concerning the qualitative relationship between the error rates of the different networks and groups.

For the QMEs, Table 1 below provides the matched pairs t-test statistic concerning the effect of the four additional variables. Because group 1 was involved in the training process of the neural networks, any statistical judgement should be based on the results of group 2. The values for group 1 were added for descriptive purposes. No significant differences were found between quadratic mean errors of network 1 and network 3. Thus, no improvement of neural-net-based REM classification could be obtained by inclusion of the additional measures spectral entropy, entropy of amplitudes, correlation dimension D2, and largest Lyapunov exponent L1.
On the other hand, the QMEs of group 2 were significantly enhanced for network 2 as compared to network 1 and network 3 (significance level set to 0.05/3 for the three tests). Therefore, the spectral variables or the combination of inputs allow a better classification than the new parameters alone.

In visual scoring, the most difficult subproblem is the discrimination between sleep stage 1 and REM sleep. The ability of nonlinear measures to separate these two states is therefore an important issue. To address this question an additional network was trained for each of the three sets of variables by exclusively presenting stage 1 and REM sleep of group 1/night 1. The evaluation was again based on the three subject groups using all epochs classified as REM or stage 1. These two categories together represented 26%, 27% and 25% of the nights in group 1/night 1, group 1/night 2, and group 2, respectively. The resulting QMEs are presented in Fig. 3. According to the more difficult problem, all error rates were found to be increased as compared to Fig. 2. Again the additional input of nonlinear measures did not improve the classification.

4 Discussion

During recent years considerable theoretical and clinical efforts have been combined to develop algorithms for the automatic classification of sleep stages (Mamelak et al. 1991; Roberts and Tarassenko 1992; Schaltenbrand et al. 1993; Jobert et al. 1994; Kubat et al. 1994; Grözing et al. 1995, 1997). Grözing and coworkers demonstrated that a reliable online recognition of REM sleep in humans can be realized by a backpropagation network based on one channel of EEG information only, without using EOG or EMG data. Eighty-nine percent of all time periods could be classified correctly as compared to manual evaluation. This result proved to be robust for depressive patients under the influence of antidepressive medication (Grözing and Röschke 1996).

In the present investigation the inclusion of nonlinear and nonconventional stochastic EEG measures could not improve this spectral-power-based algorithm. The same was true for the subproblem to classify REM versus stage 1 sleep. The almost identical averaged QMEs of network 1 and network 3 as well as the significantly higher error rates of network 2 suggest that the information of the additional variables spectral entropy, entropy of amplitudes, correlation dimension D2, and largest Lyapunov exponent L1 is not relevant to the discrimination of the sleep stages REM and nonREM. Nevertheless, these parameters have some ability to discriminate between different sleep stages (Fell et al. 1996a). On the other hand, the neural network algorithm can obviously substitute the information of the nonconventional inputs by comprehensively evaluating the spectral power in a broad range of frequency bands.

Table 1. The quadratic mean errors belonging to the three sets of input variables – six spectral (spect), four nonconventional (nonconv), and ten combined (comb) – were compared pairwise for all three groups of EEGs. The matched pairs t-test statistic is indicated in the first, the degrees of freedom in the second, and the P value for the two-tailed test in the third place for each set

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Spect–nonconv</th>
<th>Nonconv–comb</th>
<th>Comb–spect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group 1/night 1</td>
<td>4.86/4.008</td>
<td>5.01/4.007</td>
<td>0.17/4.087</td>
</tr>
<tr>
<td>Group 1/night 2</td>
<td>3.96/4.017</td>
<td>3.59/4.023</td>
<td>0.90/4.049</td>
</tr>
<tr>
<td>Group 2</td>
<td>3.69/7.008</td>
<td>3.63/7.008</td>
<td>0.48/7.064</td>
</tr>
</tbody>
</table>

Fig. 2. Means and standard deviations of the quadratic mean errors (QME) are shown in the upper diagram for the three networks and the datasets of group 1/night 1, group 1/night 2, and group 2. The lower diagram demonstrates the same analysis in terms of the percentage of misclassified epochs.

Fig. 3. Means and standard deviations of the QMEs for three networks trained to discriminate REM sleep and stage 1, for the three subject groups.
The example presented here might be an exception in the sense that nonlinear behavior is generally relevant for EEG analysis but might not be important for the classification of REM and non-REM sleep. The opposite interpretation assumes that the EEG signal might be treated in the first order by a linear approach and that most of the applications do not require nonlinear methods. In view of results demonstrating the efficiency of nonconventional measures in EEG analysis, the benefit appears to depend on the nature of the problem. As far as the classification REM or non-REM is concerned, the rules according to Rechtschaffen and Kales (1968) are – except for stage I – based on the visual inspection of the background EEG and of phasic events. Spectral measures seem to correspond well to these criteria and might therefore be best suited for the purpose. The problem of stage I has to be considered separately because it is still unknown if the physiological differences in REM sleep are reliably reflected in the EEG signal.

The results shown here could induce the conclusion that due to high intra- and intersubject EEG variability, it might not be possible to improve the separation of the two sleep stages REM and non-REM. This is certainly not the case. Based on spectral measures, the averaged error rate could be reduced significantly in more recent studies by the simultaneous evaluation of shorter time periods (Grözinger et al. 1997).

We conclude that nonlinear and also nonconventional stochastic EEG measures do not yield additional information per se when differentiating REM and non-REM sleep. Different kinds of experimental situations and hence classes of EEG data may demand different strategies for analysis. For some kinds of EEG data conventional measures will suffice, whereas in other cases the application of nonlinear and nonconventional stochastic measures may be appropriate.

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References