Oscillatory events in the human sleep EEG - detection and properties

E. Olbrich [a], P. Achermann [b]

[a] *Physics Institute, University of Zürich CH-8057 Zürich, Switzerland*

[b] *Institute of Pharmacology and Toxicology, University of Zürich, CH-8057 Zürich, Switzerland*

Abstract

A new algorithm for the detection of oscillatory events in the EEG is presented. By estimating autoregressive (AR) models on short segments the EEG is described as a superposition of harmonic oscillators with damping and frequencies varying in time. Oscillatory events are detected, whenever the damping of one or more frequencies falls below a predefined threshold. The algorithm works well for the detection of sleep spindles and in addition identifies delta and alpha waves. The distribution of the occurrence of oscillatory events shows a similar pattern with maxima around 3-4 s for most classes of events except for slow delta waves (< 2 Hz).

Key words: AR model, human sleep EEG, sleep spindles, delta waves

1 Introduction

Linear modeling has a long-lasting history in EEG analysis (see e.g. [1]). The models were mainly considered as mathematical description of the signal and less as a biophysical model of the underlying neuronal mechanisms. In 1985 Franaszczuk et al. [2] proposed to interprete linear models as damped harmonic oscillators generating EEG activity based on the equivalence between stochastically driven harmonic oscillators and autoregressive (AR) models. There is a unique transformation between the AR-coefficients and the frequencies and damping coefficients of the corresponding oscillators. Wright et al. [3] criticized such an interpretation. First, the model order determined by criteria such as Akaikes information criterion AIC (statistically most efficient for prediction) might not correspond to the order of the underlying system, especially not in the case of a high dimensional system such as the EEG. Second, they emphasized that the nonstationary character of the EEG has to be taken into account. While the first argument is valid in general, it does not

exclude the possibility that some of the detected oscillators might have neurophysiological meaning. In particular at times when the EEG is dominated by a certain rhythmic activity, e.g. in the case of sleep spindles or alpha activity, one might expect, that this activity will be reflected by a pole with a corresponding frequency and low damping. This idea was the starting point of our analysis. The sleep EEG is nonstationary. However, we demonstrated that the effects of nonstationarity become relevant only with scales longer than 1 s [4]. Therefore, short segments with a duration of around 1 s are sufficiently described by linear models. The nonstationarity on longer time scales might be reflected by the variation of the AR-coefficients and thus by the corresponding frequencies and damping coefficients.
Based on the above considerations we propose an easy way to define oscillatory events. They are detected, whenever the damping of one of the poles of a 1-s AR-model is below a predefined threshold.

2 Materials and Methods

Our detection algorithm is based on modeling 1-s segments of the EEG time series using autoregressive(AR) models of order p. From the AR(p)-model

$$x_n = \sum_{i=1}^{p} a_i x_{n-i} + \epsilon_n \qquad \epsilon_n \ldots \text{normal distributed white noise} \tag{1}$$

the frequencies $f_k = \phi_k/(2\pi\Delta)$ and damping coefficients $\gamma_k = -\Delta^{-1} \ln r_k$ (Δ denotes the sampling interval) are estimated (for details see e.g. [2]) using

$$z^p - \sum_{k=1}^{p} a_k z^{p-k} = \prod_{k=1}^{p} (z - z_k) \qquad z_k = r_k e^{i\phi_k} \ . \tag{2}$$

The poles z_k are related to the power spectrum by

$$P(f) = \sigma_\epsilon^2 \left| \frac{z^p}{\prod_{k=1}^{p}(z - z_k)} \right|^2 \qquad z = e^{2\pi i f \Delta} \ , \tag{3}$$

σ_ϵ denotes the standard deviation of the residuals ϵ_n.
Oscillatory events are detected, if the damping coefficient γ_k falls below a predefined threshold and, hence, r_k exceeds the corresponding threshold.
In practice we use two thresholds, a lower one, r_a, to detect candidate events scanning the EEG with non-overlapping 1-s segments. When r_a is crossed we go back to the previous segment and use a smaller step size of 1/16 s (overlapping 1-s segments). If r_k exceeds a second threshold $r_b > r_a$ the beginning

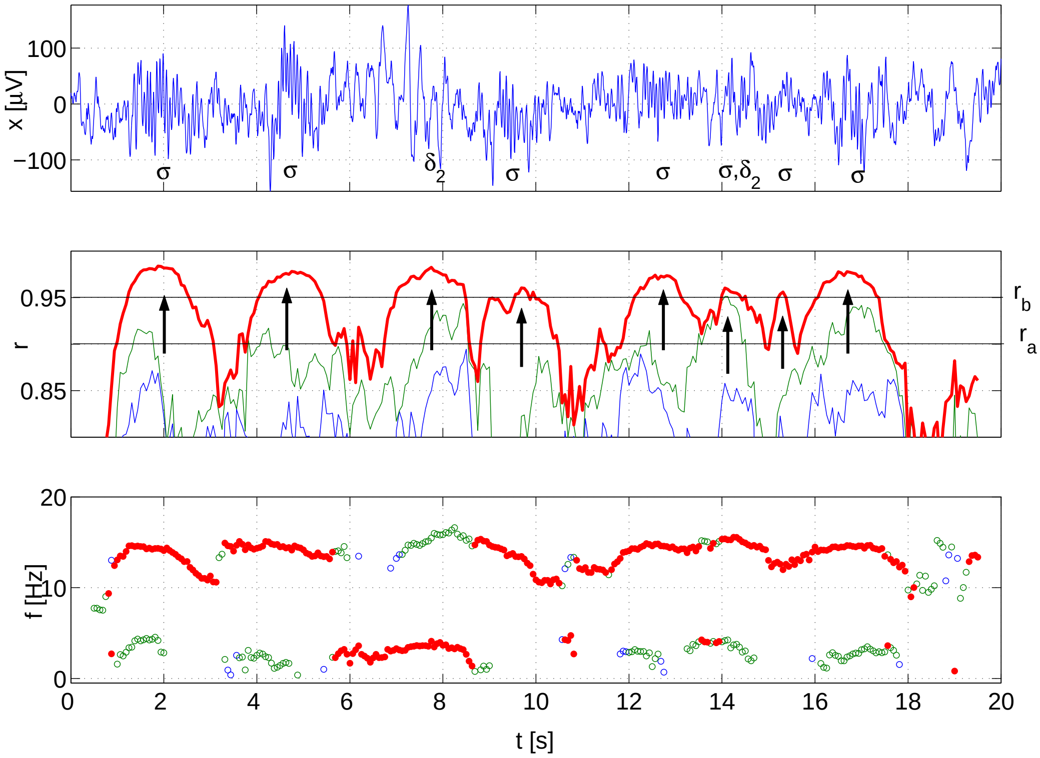

Fig. 1. EEG data (upper panel) with oscillatory events marked by arrows, σ -spindles and δ_2 - fast delta waves. The time course of r_k and the corresponding frequencies f_k are shown in the lower panels. The pole with lowest damping is indicated by the bold red line and filled circles, the poles with the second and third lowest damping by the green and blue lines and circles, respectively.

of an oscillatory events is detected. The oscillatory event is terminated by the time when r_k is lower than r_b for the last time before it falls below r_a. The frequency and time at the position of the maximal value r_{max} are considered as the frequency and occurrence of the event, respectively. In the present analysis the order of the AR-model was set to $p = 8$ and the threshold values were set to $r_a = 0.9$ and $r_b = 0.95$. These parameters were chosen in such a way, that clearly visible sleep spindles were reliably detected by the algorithm. Fig. 1 shows a 20-s EEG segment with several oscillatory events. It illustrates, how the occurrence of events corresponds to r_k crossing the threshold.
The algorithm was applied to 8-h sleep EEG data of six healthy male subjects, each contributing with two consecutive nights. The data were baseline recordings (23:00 to 7:00 h, including sleep latency) of a previous study [5]. The EEG derivation C_3-A_2 was analyzed (sampling rate 128 Hz). Sleep stages were visually scored according to standard criteria.

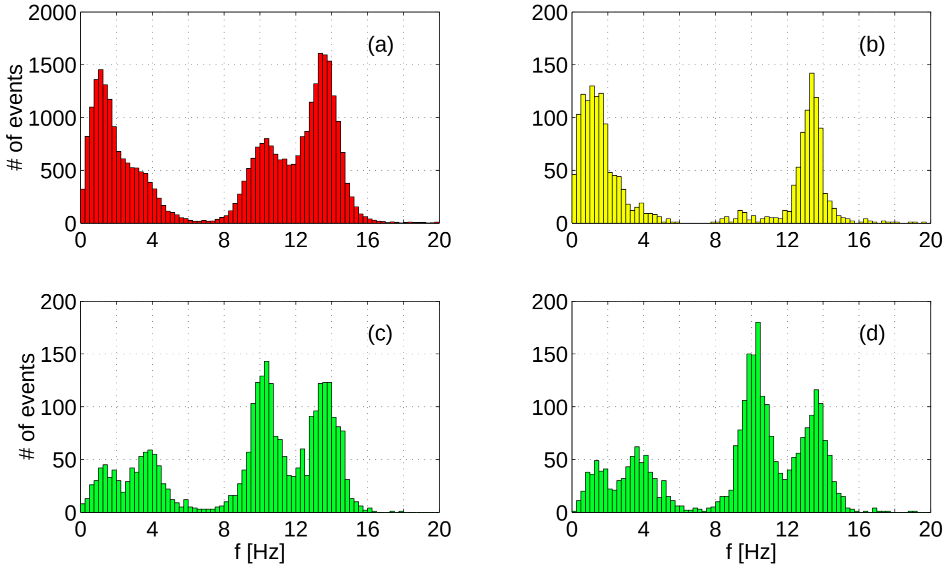

Fig. 2. Distributions of the detected oscillatory events. (a) Cumulated distribution from all 6 subjects (12 nights). (b) One night of a single subject. (c) and (d): Two consecutive nights of another subject.

3 Results

The algorithm worked not only for the detection of sleep spindles but also for the detection of oscillatory events in other frequency bands. Fig. 2 shows the cumulated distribution of the detected events from all 12 recordings and from single nights - two from the same subject and one from another one. It is evident that the inter-individual variability is much larger than the intra-individual one.

The distributions show modes in four frequency bands: in the slow delta (δ_1: 0-2 Hz), in the fast delta (δ_2: 2-5 Hz), in the alpha (α: 8-11.5 Hz) and sigma (spindles,σ: 11.5-16 Hz) bands.

These modes are also evident in the distribution of the events in the different sleep stages (Fig. 3). Alpha waves predominate in waking, spindles in stage 2 while the occurrence of slow delta waves increases from stage 2 to stage 4 (deepening of sleep). Fast delta waves are the prevalent events in REM sleep and stage 1. Note that they also occur in stage 2 with almost the same incidence.

For a chosen sample of events we evaluated the original data also visually. Events in the sigma band were unambiguously related to sleep spindles. They were accompanied with a pole in the spindle frequency range and a maximum in r_k. However, a few spindles are not detected by the algorithm with the chosen parameters, i.e. the maximum of r_k remains smaller than the threshold r_b. Therefore, the algorithm needs to be further optimized for a more sensitive spindle detection.

Events in the alpha frequency range correspond to continuous alpha activ-

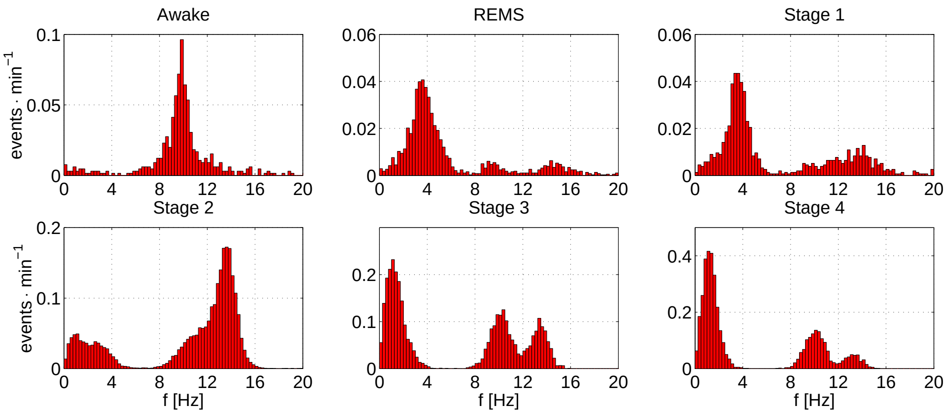

Fig. 3. Relative cumulated distribution (number of events per time in stage; 12 nights) of the occurrence of the oscillatory events in the different vigilance states. Note the different scaling of the y-axis.

ity during waking and to small amplitude, sometimes spindle-like activity in NREM sleep.

K-complexes are related to oscillatory events in the delta band (0.5-3 Hz). Examples for fast delta waves (3 Hz) can be seen in Fig. 1 marked with δ_2. Most events in the fast delta range were not single slow waves or K-complexes, but short lasting oscillations with amplitudes ranging from $< 50\ \mu V$ (mostly in REM sleep) up to $> 100\ \mu V$.

Events in the slow delta band are either K-complexes or single slow waves. However, in particular during NREM sleep stages 3 and 4, slow waves are often not detected as oscillatory events because they yield a relaxatory pole (frequency zero) in the AR-model.

The analysis of the time intervals between the occurrence of consecutive events yields distributions with a maximum below 4 s and an exponential decay for larger intervals (Fig. 4). In the case of sleep spindles this result is in accordance with earlier findings based on visual spindle detection [6] or quantitative analysis [7].

For the events in the alpha and fast delta band, the maxima of the distribution became broader and were shifted towards shorter intervals. For the slow delta waves intervals of 0-1 s occured most frequently. This finding is related to a behavior of the corresponding r_k different from the one observed for the other classes of events. During slow wave oscillations the corresponding maximal r_k sometimes drops suddenly below r_a for a short time interval (< 0.5 s), because the low frequency oscillatory pole is replaced by a relaxatory pole at this instant.

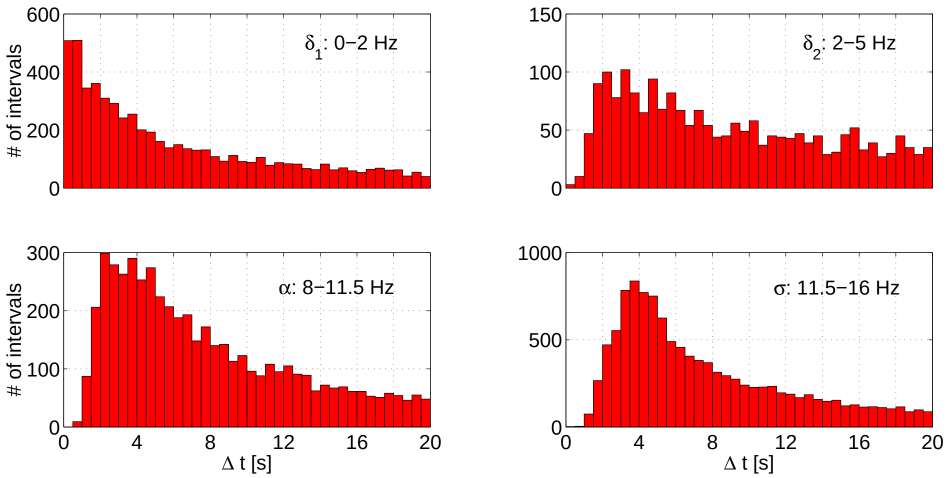

Fig. 4. Distribution of the time intervals between consecutive oscillatory events in different frequency bands.

4 Discussion

The algorithm is rather a model based approach than a pattern recognition algorithm. Thus, it might help to identify the dynamical processes leading to the occurrence of spindles or other oscillatory events in the sleep EEG. The detected oscillatory events in the different frequency bands revealed a strong similarity in their periodicity of occurrence. The modes of the distributions of the recurrence intervals (2-4 s) may correspond to the slow frequency peak observed in the power spectra [7] and relate to the slow oscillations of the thalamocortical system [8]. The present approach is a promising tool for the investigation of rhythmic EEG activity and may contribute to a better understanding of oscillatory phenomena.

Acknowledgments

This work was supported by the Swiss National Science Foundation and the University of Zurich. We thank H.P. Landolt for comments on the manuscript.

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