Micro- and macrostructure of sleep EEG

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Electroencephalogram (EEG) provides an important and unique information about the sleeping brain. For the past sixty years, polysomnography was the major method of sleep analysis and main diagnostic tool in sleep medicine. The standard interpretation of polysomnographic recordings describes their macrostructure in terms of sleep stages, delineated according to the criteria summarized by Rechtschaffen and Kales (R&K, [1]). From 1960s onwards, R&K scoring criteria are a golden standard, allowing to compare the results between laboratories.

This description of sleep macrostructure relies on division of the time axis into fixed time epochs (20 or 30 s) - this naturally implies some limitations. Therefore, several descriptors of sleep microstructure have been proposed. They rely e.g. on quantification of sleep spindles and slow wave activities, detection of arousals, etc. However, these descriptors are usually assessed by means of substantially different signal processing (or visual) methods. This hinders possibilities of combining their results into a coherent description of the sleep process. The most needed extensions to the R&K system, enumerated e.g. in [2], are:

a) a finer time scale than the arbitrary division into 20-30 s epochs,
b) a measure of spindle intensity,
c) the differentiation of single, randomly evoked K-complexes in response to stimuli from spontaneous periodic ones.

This study proposes a solution to these problems in terms of a framework based upon adaptive time-frequency approximations—a recent, advanced method of signal processing. Proposed approach provides compatibility with the visual EEG analysis and standard definitions of EEG structures, and describes both the macro- and microstructure of sleep EEG.

Adaptive time-frequency approximations of signals, calculated by means of the matching pursuit (MP) algorithm, were introduced by Mallat and Zhang in 1993 [3]. Unbiased version of the algorithm, needed for biomedical applications, was presented in [4]. MP provides a detailed description of transients, present in the EEG time series. Signal structures are described not only in terms of their frequency and amplitude (energy), but also, contrary to the previously applied methods, their exact time positions and durations are determined.

Almost decade of MP applications in the analysis of EEG provides results, which suggest that adaptive time-frequency approximations of signals can unify most of the univariate computational approaches to EEG analysis, and offer compatibility with its visual analysis, used in clinical applications [5], [6]. In the context of this study, some of these results are of special importance:

- High accuracy of MP identification and parameterization of sleep spindles, and its concordance with their visual detection was presented in [7].

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- Spectral integrals, used traditionally in pharmaco-EEG to estimate power of sleep spindles and SWA, were replaced by selective MP-based estimators in [8]. It significantly improved the sensitivity of the procedure, giving results fully concordant with the physiological expectations and the traditional approach (spectral analysis), which statistically proves correctness of the parameterization of sleep spindles and SWA, achieved via MP-based procedure.
- Finally, [9] presented the applicability of MP parameterization to non-oscillating structures like the epileptic EEG spikes.

In this paper we combine these achievements into a unified description of sleep EEG, including:

- detection of deep sleep stages (3 and 4) based directly upon the classical R&K criteria,
- continuous description of slow wave sleep, fully compatible with the R&K criteria,
- a measure of spindling activity,
- detection of arousals.

Finally, we show that properties of the MP algorithm investigated in [9] allow for discrimination between series of unrelated structures (like e.g. randomly evoked K-complexes) and oscillatory activity. Detection, parametrization and description of all these features of sleep EEG is based upon the same unifying approach.

1. METHODS

A. Matching pursuit

Matching pursuit is an algorithm introduced in [3] as a sub-optimal solution to the intractable problem of an optimal approximation of a signal *(f)* in a redundant dictionary of functions *(D)*. In the first step of MP, the waveform g_{go} which best matches the signal f is chosen from the dictionary *D*. In each of the consecutive steps, the waveform g_{g_n} is matched to the signal $R^n f$, which is the residual left after subtracting results of previous iterations:

$$\begin{cases} R^0 f = f \\ R^n f = \left\langle R^n f, g_{g_n} \right\rangle g_{g_n} + R^{n+1} f \\ g_{g_n} = \arg\max_{g_{g_n} \in D} \left| \left\langle R^n f, g_{g_i} \right\rangle \right| \end{cases} \quad (1)$$

For a complete dictionary the procedure converges to *f* in theoretically infinite number of iteration, but in practice relatively few waveforms provide very good approximation:

$$f = \sum_{n=0}^{M} \left\langle R^n f, g_{g_n} \right\rangle g_{g_n} = \sum_{n=0}^{M} a_n g_{g_n} \quad (2)$$

Functions g_q are chosen from dictionaries composed—apart from the complete Dirac and Fourier bases—from the Gabor functions, since these functions provide optimal joint time-frequency localization [10]. Real valued Gabor can be expressed as:

$$g_g(t) = K(g) e^{-p\left(\frac{t-u}{s}\right)^2} \cos(w(t-u)+j) \quad (3)$$

where $K(\gamma)$ is such that $\left\| g_g \right\| = 1$. Parameters $\gamma = \{u, \omega, s\}$ of the possible Gabor functions constitute a 3-dimensional continuous space (phase φ is optimized separately in practical implementations), from which a finite dictionary must be chosen for an implementation of the procedure given by Eq. (1). In the implementation described in [3], dictionary's atoms were chosen from predefined dyadic sequences. However, any fixed scheme of subsampling the space of possible dictionary's functions leads to a statistical bias of the resulting decompositions. A solution proposed in [4] relies on stochastic dictionaries, in which parameters $\{u,\omega,s\}$ are drawn from uniform distributions across ranges defined by sizes of the signal and the dictionary.

Parameters of Gabor functions, fitted to the signal by the MP algorithm, can be used directly in further analysis, as will be presented in the next sections. Apart of that, advantages of such a detailed description of the signal can be explored to construct a high resolution and free of cross-terms estimate of signals energy density. Wigner distribution of the whole signal's expansion (2) is

$$Wf \approx W\left(\sum_{i=1}^{M} a_i g_{g_i}\right) = \sum_{i=1}^{M} a_i^2 W g_{g_i} + \sum_{i=1}^{M}\sum_{j\neq i} a_i \overline{a_j} W\left(g_{g_i}, g_{g_j}\right) \tag{4}$$

where $W(g_{g_i}, g_{g_{ji}})$ is a cross-Wigner transform of g_{g_i} and g_{g_j} given by

$$W(g_{g_i}, g_{g_{ji}}) = \int g_{g_i}(t+\frac{t}{2})\overline{g_{g_j}(t-\frac{t}{2})} e^{-iwt}\, dt \tag{5}$$

Double sum in (4) contains all the cross-terms. Owing to the representation (2), we can omit them explicitly and construct the time-frequency representation of signal's energy density from the first sum, containing auto-terms:

$$Ef = \sum_{i=1}^{M} a_i^2 W g_{g_i} \tag{6}$$

Energy conservation of this distribution is easily demonstrated (c.f. [3]). Complete software implementation of a bias-free MP decomposition, used in this study, is freely available at http://eeg.pl/mp.

B. From MP decomposition to sleep EEG structures and stages

Previous section presented the nonlinear MP algorithm, which offers approximation of the analyzed signal in terms of a linear weighted sum (Eq. 2) of known waveforms (Eq. 3). Depending on their parameters, Gabor functions can represent a wide variety of EEG structures (called sometimes *graphoelements),* as exemplified in Figure 1.

Gabor functions are characterized, apart from the energy (or amplitude) related to $\left\langle R^n f, g_{g_n} \right\rangle$ by the set of parameters $\gamma = \{u, \omega, s\}$: time position, frequency and duration. Working in the space of parameters of the functions fitted to the EEG epochs, we construct filters to choose the relevant structures. In some cases, like e.g. sleep spindles and slow waves, these filters can be almost directly based upon the classical definitions of these structures. However, some modifications are necessary, e.g.:

- Taking into account the inter-subject difference in EEG amplitudes, which influence the minimum SWA amplitude, we applied an empirical relation between the optimal SWA cutoff amplitude and the standard deviation of the whole EEG channel.
- Frequency range of sleep spindles was set slightly wider than classical 12-14 Hz, as suggested by our experience and [11]—[13].

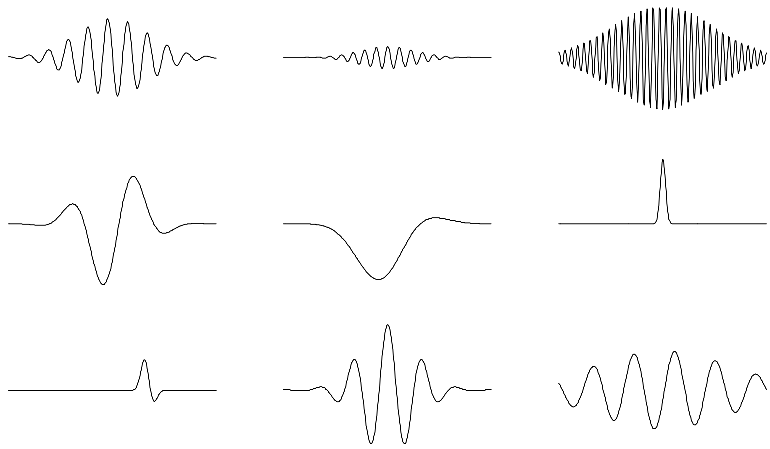

Figure 1. Examples of different shapes of Gabor functions, which can be included in the dictionary used for MP decomposition.

By applying criteria from Table 1 to the MP decomposition of sleep EEG, we can achieve an automatic detection and exact parameterization of sleep spindles and SWA in any EEG channel—in this study we used derivation C3-A2. Contrary to the previous approaches, this parameterization includes also explicitly the length of each of these structures. Owing to this feature we can *directly* apply the R&K [1] criteria to detect stages 3 and 4: an epoch occupied by SWA from 20% to 50% of time corresponds to stage 3, and above 50%—to stage 4.

	frequency	time duration	min. amplitude
SWA	0.5-4 Hz	0.5-∞ s.	$0.99\times V_{EEG}$ + 28.18μV
sleep spindles	11-15 Hz	0.5-2.5 s.	15 μV

Table 1: Criteria defining sleep spindles and SWA, applied in this study. Minimum amplitude of SWA was found for each channel separately from an empirical relation $A_{SWA} = 0.99 \times V_{EEG} + 28.18 mV$, where V_{EEG} is the standard deviation of the whole EEG chanell.

The first approach to the automatic detection of arousals was based upon the MP decomposition of one EEG channel (C3-A2) and the standard deviation of EMG, implementing the ASDA rules [14]. Arousal was scored in case of a shift in EEG frequency lasting 3 seconds or longer, which may include theta, alpha and/or frequencies above 16 Hz—with the exception of sleep spindles. In this study, these shifts were tentatively related to the presence of corresponding structures in the MP representation of EEG (Eq. 2). At least 10 seconds of continuous sleep had to precede the EEG arousal, and a minimum of 10 seconds of intervening sleep was necessary to score a second arousal. Arousals in REM sleep were scored only when accompanied by concurrent increase in submental EMG amplitude.

C. Experimental data

In total 19 healthy subjects (10 males and 9 females, age 22–51 years, mean 35 years) were included in the study. Polysomnograms were recorded during two consecutive nights, only the data from the second night were analyzed. Recordings were acquired from standard polysomnographic channels (EOG and EMG) and from 21 EEG derivations, according to the 10-20 system. Silver electrodes were applied with collodion. Maximal resistance was 5 kΩ. The signal was filtered with an analog bandpass filter (0.15-30 Hz) and then sampled with frequency 128 Hz. Analog-digital 12-bit converter was used.

The visual analysis of the sleep EEG, based on 20 sec. epochs, was performed according to R&K [1] rules by experienced sleep researchers. The automatic EEG analysis presented in this paper refers to derivation C3-A2, from sleep onset to final awakening.

An informed consent was obtained from all the subjects. The study was approved by the University Ethics Committee.

2. RESULTS

A. Parametrization of EEG rhythms an transients

Using the algorithm described in Section 1-A, 20-sec epochs of sleep EEG from derivation C3-A2 were decomposed into a weighted sum (Eq. 2) of basic waveforms g_γ (Eq. 3). Detection of EEG structures, sleep stages and arousals was obtained from these decompositions by applying criteria described in Section 1-B.

Figure 2 illustrates the MP representation of transients and rhythms present in the EEG time series. Each blob on a time-frequency map of energy (Eq. 6) corresponds to one Gabor function (Eq. 3) fitted to the signal by the MP procedure (Eq. 2). On the upper plot we observe several structures between 8 and 12 Hz, corresponding to the alpha waves. Next plot presents structures reflecting sleep spindles and one K-complex. Comparison of MP parametrization of sleep spindles with visual detection is presented in [9]; the issue of K-complexes is much more complicated, due to lack of a strict definition and resulting low inter-expert repeatability of their detection (c.f. [18]). Parametrization of similar structures (epileptic spikes) was presented in [9]. The lower two plots present slow wave activity; a discussion of MP parametrization of SWA in the context of pharmaco-EEG can be found in[8].

B. Continuous description of sleep EEG features

Detailed parameterization of all the relevant structures allows the construction of a wide variety of descriptors of the sleep process, in both micro- and macroscale, within the same framework. As an example, Fig. 3 presents, together with a visually constructed hypnogram:

- Percentage of epoch's time occupied by the waveforms classified as SWA. Lines denoting the 20% and 50% of epoch's time occupied by SWA correspond to the classical R&K [1] criteria for stages 3 and 4.
- Number of sleep spindles per 3 minutes.
- Number of arousals per 10 minutes.

We observe continuous and gradual changes of SWA, which correspond to the rough description offered by visual scoring of stages 3 and 4. The identification of stages 3 and 4 according to R&K rules was given in [15]. The concordance was on the level of inter-expert agreement.

Sleep spindles, detected automatically within the same framework, exhibit the inverse relation to the SWA, documented previously in literature [16]. Finally, automatically detected arousals (Fig. 3d) decrease in relation to SWA and increase in relation to the amount light non-Rapid Eye Movement (NREM) sleep, with particular concentration before the Rapid Eye Movement (REM) episodes, as observed previously in [17].

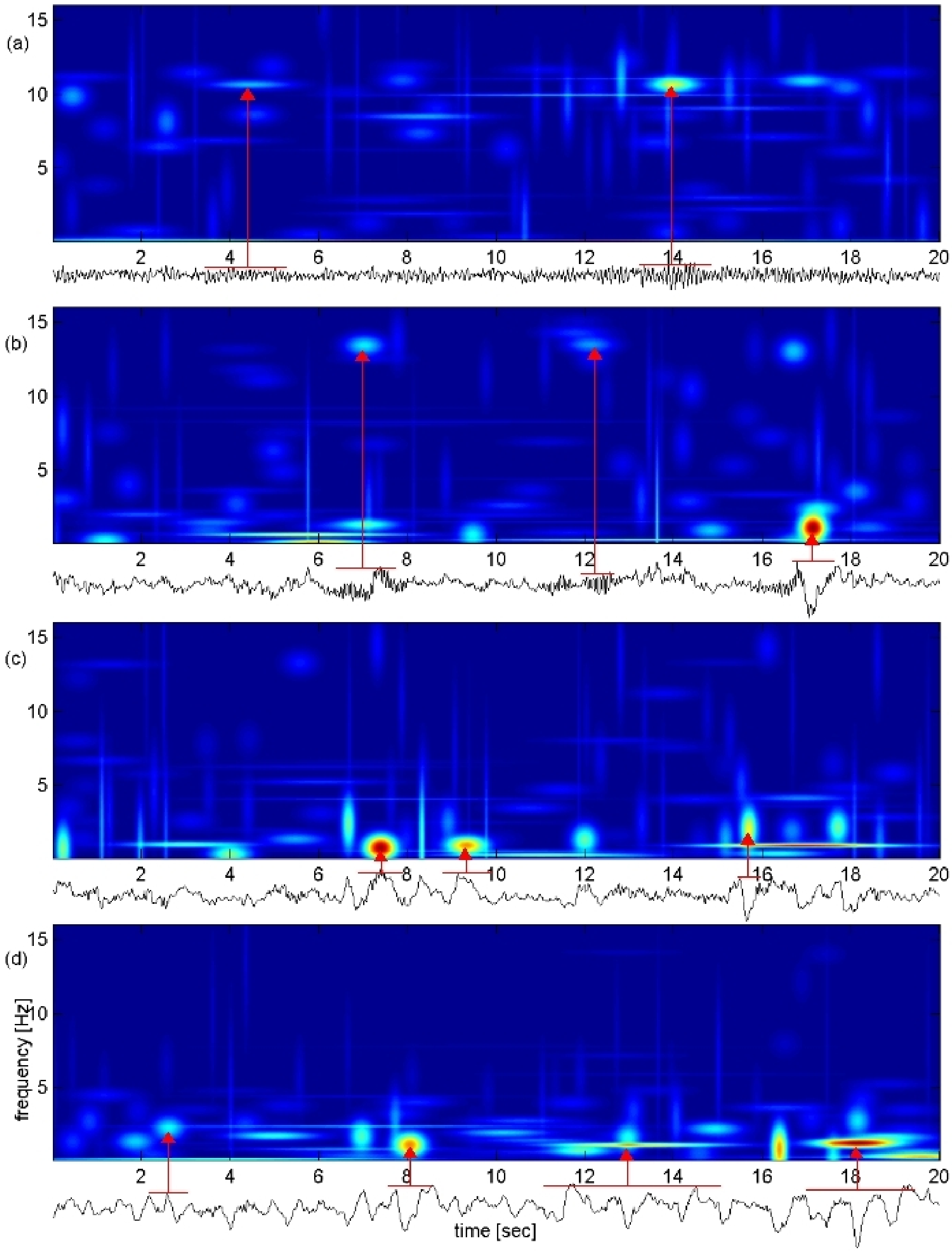

Figure 2. Time-frequency maps of energy (Eq. 6) of 20-s epochs of sleep EEG in different stages, energy scale from blue (zero) to red (max). Relevant EEG structures are connected with the corresponding blobs in the time-frequency plane by red arrows: (a) wake, marked alpha; (b) Stage 2, two spindles and K-complex; (c) and (d) Stages 3 and 4, marked SWA.

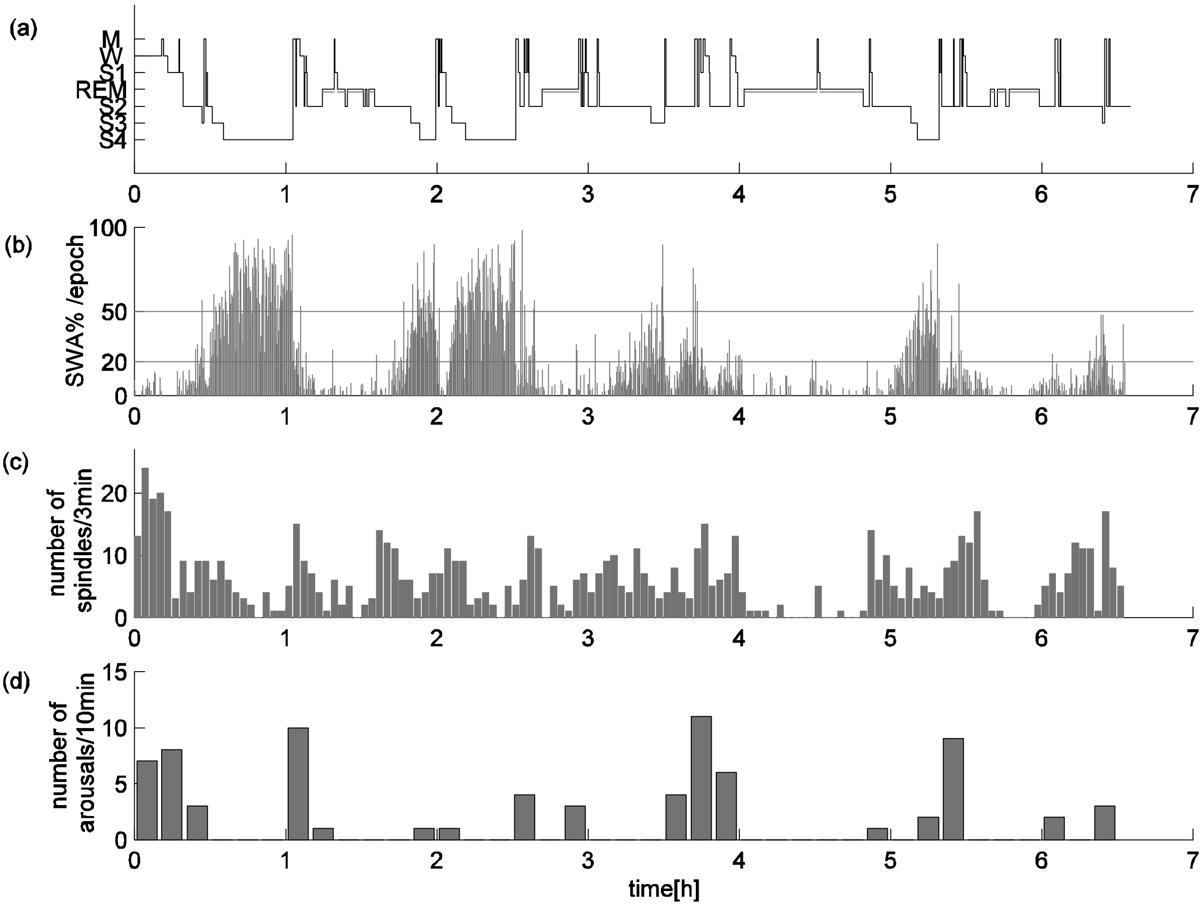

Figure 3. (a) Hypnogram (by human expert); (b): The SWA % denotes the percentage of epoch occupied by waveforms classified as SWA. This continuous description of the slow wave sleep is fully compatible with the delineation of stages 3 and 4 proposed in R&K [1], as indicated by the 20% an 50% lines. (c) The number of sleep spindles per 3 minutes, (d) the number of arousals per 10 min. Profiles (b)-(d) were obtained automatically from the MP decomposition of sleep EEG in derivation C3-A2, according to the criteria from section 1-B. Artifacts were not removed from analysis.

C. Differentiation of phase-locked and randomly occurring activity

According to [2], one of the unsolved problems in automatic analysis of sleep EEG is *differentiation of single, randomly evoked K-complexes in response to stimuli from spontaneous periodic ones.* Owing to the high sensitivity of the matching pursuit algorithm to the phase of oscillatory structures, widely discussed in [9], such a differentiation is possible within the framework of the proposed paradigm. Figure 4 gives an example of a K-complex, which is hard to distinguish a priori from the on-going SWA activity. However, due to subtle differences in phase, it is parameterized by the MP algorithm as a separate structure. Such a difference in phase indicates also that this structure is not a part of synchronized activity produced by the same generator.

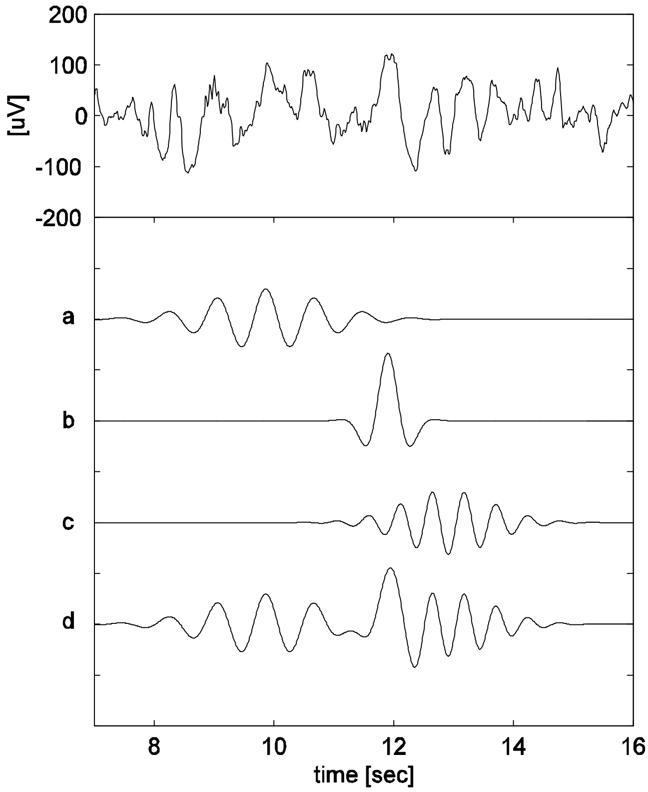

Figure 4. An example of a slow wave activity, containing a single K-complex, which is not phase-locked to the SWA. Therefore, in the MP parameterization, it appears as a separate structure, giving a reliable distinction between the synchronized slow waves and a separate, non-synchronized structure. At the top is the original signal. The middle—waveforms from Gabor dictionary represent some components of decreasing energy: (a), (c) slow wave activity, (b) most likely a single K-complex. Bottom trace (d) presents superposition of waveforms (a) - (c).

3. Discussion

Detection of EEG sleep spindles and SWA amount to a significant percentage of the tedious work, involved in scoring sleep stages. Presented results suggest the possibility of a reliable detection of most of the structures, relevant in the process of sleep analysis and staging. As ones of the results, this feature may be a valuable aid in and extinction of sleep scoring, based ***directly*** on the classical criteria of Rechtschaffen and Kales[3]. On the other hand the proposed approach makes possible construction of diagnostic methods aimed at detection of specific features of polysomnogram connected with sleep disorders. For example the methods devised for identification of arousals can be applied for diagnosis of apneas or other sleep disturbances leading to arousals.

Owing to the high resolution selective parameterization of relevant EEG structures, proposed approach allows to construct different continuous descriptors of the sleep process (e.g. energy or amplitudes of selected structures) in almost any desired time resolution—

[3] Unlike the other systems designed to reproduce/mimic the visual staging, this approach should result in a more or less *a priori* correct procedure. Some non-critical problems remain still open, like e.g. the issue of detecting K-complexes, problematic because of the lack of their strict definition and low inter-expert agreement in visual detection (e.g. [18] report 50% agreement between two experts)

not only 20-sec. epochs presented in this paper[4]. Contrary to the multitude of completely new descriptors, proposed in this field, the approach presented in this paper for the first time exhibits the major advantage, which can be called a backward compatibility. It relates to the fact that previous, well established and widely used descriptions (e.g. visual detection of transients or estimation of power in frequency bands) can be efficiently derived as special cases of this universal, adaptive time-frequency parameterization.

Presented framework enhances the methodology of electroencephalography by a reliable automatic detection and parametrization of EEG transients and rhythms. Apart from possibilities of processing larger amounts of data, this approach offers repeatability, required by the scientific paradigm. Within this framework we may also describe new effects, such as the previously undetectable phase differences, exemplified in Figure 4 and discussed in [9]. Still, previous approaches can be derived as approximations of this approach: e.g. hypnogram (stages 3/4) can be approximated as a discretization of the exact SWA content per epoch, presented in Figure 3b, using the "20-50%" rules from [1].

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REFERENCES

[1] A. Rechtschaffen and A. Kales, Eds., *A manual of standardized terminology, techniques and scoring system for sleep stages in human subjects*, ser. National Institutes of Health Publications. Washington DC: US Government Printing Office, 1968, no. 204.
[2] M. Billiard, "The standardized sleep manual, love it or leave it (guest editorial)", *Sleep Medicine Reviews*, vol. 4, no. 2, pp. 129–130, 2000.
[3] S. Mallat and Z. Zhang, "Matching pursuit with time-frequency dictionaries", *IEEE Transactions on Signal Processing*, vol. 41, pp. 3397–3415, Dec 1993.
[4] P. J. Durka, D. Ircha, and K. J. Blinowska, "Stochastic time-frequency dictionaries for matching pursuit", *IEEE Transactions on Signal Processing*, vol. 49, no. 3, pp. 507–510, March 2001.
[5] P. J. Durka and K. J. Blinowska, "A unified time-frequency parametrization of EEG", *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 5, pp. 47–53, Sept/Oct 2001.
[6] P. J. Durka, "From wavelets to adaptive approximations: time-frequency parametrization of EEG", *BioMedical Engineering OnLine*, vol. 2, no. 1, January 2003. (http://www.biomedical-engineering-online.com/content/2/1/1)
[7] J. Żygierewicz, K. J. Blinowska, P. J. Durka, W. Szelenberger, S. Niemcewicz, and W. Androsiuk, "High resolution study of sleep spindles", *Clinical Neurophysiology*, vol. 110, no.12, pp. 2136–2147, 1999.
[8] P. J. Durka, W. Szelenberger, K. Blinowska, W. Androsiuk, and M. Myszka, "Adaptive time-frequency parametrization in pharmaco EEG", *Journal of Neuroscience Methods*, vol.117, no.1, pp. 65–71, 2002.
[9] P. J. Durka, "Adaptive time-frequency parametrization of epileptic EEG spikes", *Physical Review E,* vol. 69, no. 051914, p.1-5, 2004.
[10] S. Mallat, *A wavelet tour of signal processing*, 2nd ed. New York: Academic Press, 1999.
[11] P. Hae-Jeong, O. Jung-Su, J. Do-Un, and P. Kwang-Suk, "Automated sleep stage scoring

[4] We detect the time position of each structure (e.g. sleep spindle or slow wave) with the accuracy limited only by the sampling interval

using hybrid rule- and case-based reasoning", *Computers and Biomedical Research*, vol. 33, no.5, pp. 330–349, 2000.
[12] F. Amzica and M. Steriade, "Electrophysiological correlation of sleep delta waves", *Electroencephalography and clinical Neurophysiology*, vol. 107, no.2, pp. 69–83, 1998.
[13] P. Schimicek, J. Zeitlhofer, P. Anderer, and B. Saletu, "Automatic sleep-spindle detection procedure: aspects of reliability and validity", *Clinical Neurophysiology*, vol. 25, no. 1, pp. 26–29, 1994.
[14] American Sleep Disordes Association, "EEG arousals: scoring rules and examples. a preliminary report from the Sleep Disorders Task Force of the American Sleep Disordes Association", *Sleep*, vol. 15, no.2, pp. 174–184, 1992.
[15] P. J. Durka, U. Malinowska, W. Szelenberger, A. Wakarow and K. J. Klinowska, „High resolution parametric description of slow wave sleep", *Journal of Neuroscience Methods,* vol.147, no.1, pp.15-21, 2005.
[16] D. Aeschbach and A.A. Borbely, "All-night dynamics of the human sleep EEG", *Journal of Sleep Research*, vol. 2, no.2, pp. 70–81, 1993.
[17] M. G. Terzano, L. Parrino, A. Rosa, V. Palomba, and A. Smerieri, "CAP and arousals in the structural development of sleep: an integrative perspective", *Sleep Medicine*, vol. 3, no.3, pp. 221–229, 2002.
[18] G. Bremer, J. Smith, and I. Karacan, "Automatic detection of the K-Complex in sleep electroencephalograms", *IEEE Transaction on Biomedical Engineering*, vol. 17, no.4, pp. 314–323, 1970.