



# Recognizing of stereotypic patterns in epileptic EEG using empirical modes and wavelets

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## HIGHLIGHTS

- An automatic method for detection of stereotypic patterns in EEG is proposed.
- The method is based on combination of wavelets and empirical mode decomposition.
- Such combination increases the quality of patterns detection in rodents EEG.
- The detection of sleep spindles can be done with high sensitivity and specificity.

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## ABSTRACT

Epileptic activity in the form of spike–wave discharges (SWD) appears in the electroencephalogram (EEG) during absence seizures. This paper evaluates two approaches for detecting stereotypic rhythmic activities in EEG, i.e., the continuous wavelet transform (CWT) and the empirical mode decomposition (EMD). The CWT is a well-known method of time–frequency analysis of EEG, whereas EMD is a relatively novel approach for extracting signal's waveforms. A new method for pattern recognition based on combination of CWT and EMD is proposed. It was found that this combined approach resulted to the sensitivity of 86.5% and specificity of 92.9% for sleep spindles and 97.6% and 93.2% for SWD, correspondingly. Considering strong within- and between-subjects variability of sleep spindles, the obtained efficiency in their detection was high in comparison with other methods based on CWT. It is concluded that the combination of a wavelet-based approach and empirical modes increases the quality of automatic detection of stereotypic patterns in rat's EEG.

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## 1. Introduction

Electroencephalographic methods are widely used for monitoring of electrical brain activity in normal and pathological conditions, e.g., in the case of epilepsy [1–3]. The electroencephalogram has a complex time–frequency structure and consists of various rhythmic components, specific oscillatory patterns, background activity, artifacts, etc. [3–7]. The key problem of algorithms for automatic detection of EEG patterns is their strong variability including both, within- and between-subjects variations. An automatic system for on-line detection of SWD, i.e. hallmarks of absence epilepsy in WAG/Rij rat

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genetic model, was earlier proposed in [8,9]. In general, the automatic detection methods should be appropriately selected in order to precisely recognize specific patterns in the long lasting EEG records and to control for individual variations in a group. This can be achieved by improving approaches for time–frequency analysis of EEG and by developing advanced recognition techniques.

The present study is focused on two types of EEG activity. The first type appears in EEG in the form of sleep spindles during non-rapid eye movement sleep in humans and animals [10]. The second type is paroxysmal SWD that accompany absence seizures in patients [1,11] and in WAG/Rij rat genetic model [12,13]. Absence epilepsy in patients manifests with brief periods (about 10 s) of impaired consciousness, i.e., cloudiness or slight confusion, so-called “absence” and may be confused with daydreaming. Inasmuch as absence seizures do not manifest convulsions or other visible motor attacks and characterized by mild behavioral changes, they often go unnoticed. The presence of SWD in EEG is the only diagnostic test for absence epilepsy. In rat models of absence epilepsy, the waveform of SWD drastically changes with age [14–17], and its waveform is influenced by antiepileptic drugs [18,19], furthermore, changes in the waveform of spike–wave activity in EEG yield important diagnostic and prognostic information [11].

Sleep spindles and SWD can be detected in EEG visually; however, the quality of such detections is influenced by individual variations in the waveforms and by the presence of noise in EEG. Moreover, visual analysis of long-term EEG records (i.e., 24 h length and more) is a hard routine procedure that should be optimized by methods of automatic recognizing. Recently, several reports demonstrated that wavelet-based approaches for EEG pattern recognition resulted in accurate and precise detections [20–28]. In these studies, sleep spindles and SWD patterns were extracted based on information about the time–frequency content of EEG. For the successful application of wavelet-based automatic detection methods, it is important to choose an appropriate basis, i.e., the “mother” wavelet function. In some applications, “adaptive” wavelet bases (adapted from EEG signal) were effectively used in automatic EEG detection systems [25,27].

Empirical mode decomposition (EMD) is an alternative to the abovementioned procedure [29–31]. An advantage of EMD is that, unlike wavelets, it does not require adjustment of parameters or selection of basic functions. EMD has already showed its potential in spectral analysis of nonstationary data [31–34]. The general aim of this paper is to propose a combined recognition method based on both, CWT and EMD. We show that such a combined approach allows improving the quality of automatic recognition of EEG patterns.

## 2. Materials and methods

### 2.1. Experiments

The current study was performed in WAG/Rij rats with a genetic predisposition to the absence epilepsy [12] at Institute of Higher Nervous Activity and Neurophysiology RAS, Moscow, Russia in accordance with the Guide for the Care and Use of Laboratory Animals (NIH Publication No. 85–23, revised 1996). In our experiments, EEG was recorded in six male WAG/Rij rats (1 year old, body weight 320–350 g) during 24 h. Experimental protocols were approved by the animal ethics committee of this institution.

EEG signals were recorded with epidural screw electrodes placed over the frontal cortex (AP + 2 mm and L 2.5 mm relatively to the bregma), band–pass filtered between 0.5–200 Hz, digitized with 400 samples/second/per channel and stored in a hard disk.

SWD in EEG represented a sequence of high-voltage repetitive 7–10 Hz spikes and waves with minimal duration of 1 s [12,35]. Sleep spindles were recognized in EEG as oscillations with waxing and waning amplitude, frequency in spindle range (10–14 Hz) and duration >300 ms [3,10,36]. These patterns were first visually determined in 0.5–1 h EEG epochs by an expert, and then used to test the quality of the newly developed detection algorithm (see below).

### 2.2. Continuous wavelet transform

The continuous wavelet transform (CWT) is widely accepted method for time–frequency analysis of multimodal nonstationary processes [28,37–39]. During the last decades, this method has been effectively used for analyses of experimental biological data providing essential information about complex dynamics of physiological systems [26,40–47]. The CWT-based spectral analysis is usually performed with the aid of the Morlet-wavelet as the “mother” function [42], because this function provides good resolution both in time and frequency domains:

$$\psi(\tau) = \pi^{-0.25} \exp(j\omega_0 t) \exp\left(-\frac{t^2}{2}\right). \quad (1)$$

The Morlet wavelet represents the complex harmonic oscillating function,  $\exp(j\omega_0 t)$ , modulated by the Gaussian function,  $\exp(-t^2/2)$ . The parameter  $\omega_0$  (called usually as the central frequency) adjusts the time–frequency resolution in the resultant CWT. In the current study, we also used the function (1) as the “mother” wavelet in the CWT. It allows analyzing short fragments of data series (e.g., 3–5 oscillations) and, therefore, can be used for analysis of different types of EEG patterns. Wavelet basis  $\psi_{s,\tau}(t)$  was constructed as

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t-\tau}{s}\right) \quad (2)$$

with  $s$  and  $\tau$  representing the time scale and the translation parameters, respectively. The CWT of a signal  $x(t)$  was computed as

$$W(s, \tau) = \int_{-\infty}^{\infty} x(t) \psi_{s,\tau}^*(t) dt \quad (3)$$

where the asterisk denotes the complex conjugation. In order to interpret results of the CWT, we converted wavelet scales  $s$  into the Fourier frequencies  $f$  using the formulae (4) for the Morlet wavelet [38]

$$f = \frac{\omega_0 + \sqrt{\omega_0^2 + 2}}{4\pi s}. \quad (4)$$

Here we used the value  $\omega_0 = 2\pi$ . Such value of the central frequency leads to a simple relation between the wavelet scale  $s$  and the Fourier frequency  $f$ , namely,  $f = 1/s$ . This relation allows a clearer representation of the results along with the possibility to compare estimations performed using the wavelet analysis and by means of other numerical techniques.

Finally, we computed the wavelet energy

$$E(f, \tau) = |W(f, \tau)|^2, \quad (5)$$

characterizing distribution of spectral power in time and in frequency domains.

Scalograms (analogue to the classical power spectrum) were obtained by averaging the wavelet energy  $E(f, \tau)$  over time. Previously we used the value of wavelet energy as the basic criterion for identifying sleep spindles and SWD in EEG [8,27,43]. However, an approach based on the thresholding of the wavelet-energy averaged within a selected frequency band can result in incorrect detections or missing of patterns. Here, we aimed to improve the quality of EEG pattern recognition using the EMD (see below).

### 2.3. Empirical mode decomposition

The EMD is used within the Hilbert-Huang transform, which has been recently proposed for time–frequency analysis of nonlinear and nonstationary data [29]. It has several important advantages. Thus, the EMD is simple, appears naturally, does not assume an a priori knowledge about the signal and can be applied a wide class of processes. Considering benefits of the EMD, some authors concluded that the EMD outperforms wavelet-based techniques from the viewpoint of its time–frequency resolution [29,30]. Application of the EMD is beneficial for automatic signal processing and recognition of EEG patterns, because the EMD does not require selection of basic functions or appropriate parameters, in opposite to the CWT, which is sensitive to the choice of the “mother” wavelet. Besides, the CWT in its standard form can be inappropriate in several cases such as, e.g., the frequency modulation when the modulated and the modulating frequencies are nearly close in contrast to the EMD that detects this regime [31]. However, the EMD is not often applied in physiological studies and this circumstance can be explained by several disadvantages of this tool. Thus, the theory of the EMD is still under developing leading to difficulties in appropriate interpretation of the intrinsic modes. This is especially the case when the modes are related to interleaved frequency areas.

The EMD decomposes the original signal  $x(t)$  into a set of hierarchically ranged relatively simple components  $c_j(t)$

$$x(t) = \sum_{j=1}^n c_j(t) + r_n \quad (6)$$

where  $r_n$  is a non-oscillatory residual component with slow nonstationarity (a trend). The set of  $c_j(t)$  is ordered from high-frequency to low-frequency empirical modes as determined with repeated procedures [29].

More specifically, EMD is based on the idea that any signal  $x(t)$  consists of simple oscillatory components (intrinsic modes) characterized by zero local mean value  $m(t)$  that have the same (or different at most by one) number of minima (maxima) and zero-crossings. The local mean value  $m(t)$  was computed by averaging the upper and the lower envelopes of the signal  $x(t)$  and then extracted from the original signal  $x(t)$ . This procedure did not necessary provide zero local mean value of the remaining signal, and a sifting process was needed to return  $m(t) = 0$  for all local fragments of the signal. Such process is stopped when deviations of the local mean value become extremely small compared with the amplitude of oscillations. The latter yielded the first mode  $c_1(t)$  that is further extracted from  $x(t)$ . Sifting process repeated several times ( $n$ ) and resulted in several empirical modes  $c_j(t)$ . The decomposition was finished when the remaining signal became monotonical and did not contain oscillatory components. Aiming to improve the quality of estimating the envelopes, an additional interpolation of data points by smooth functions such as, e.g., the cubic spline can be provided that may be important if the sampling rate is low.

Although  $c_j(t)$  had a simpler structure than the original signal  $x(t)$ , they showed a broad power spectrum, and this fact is difficult to interpret, considering the presence of rhythmic activity in these components. As far as EEG is concerned,  $c_j(t)$  could not easily be associated with frequency-specific rhythmic components, such as theta, alpha, and beta activities. Nevertheless, EMD-based approach is a promising tool for data processing, since it is adjustable to time–frequency features of experimental signal (because it uses adaptive bases) and it is not limited by the uncertainty principle [31].

Considering the fact that EEG sums up independent rhythmic contributions (according to general assumptions, no nonlinear interactions between EEG-rhythms is expected), the EMD may facilitate processing of EEG by determining basic EEG features. By using the EMD in the current automatic detection system, we relied upon energies of intrinsic modes  $E_j(t) = c_j^2(t)$  and determined the threshold level for energies averaged within a temporal window  $\langle E_j(t) \rangle$ . This level was selected based on visual (expert) detection of patterns performed for an initial part of EEG used for the development of the recognizing method. Oscillatory activity in EEG was detected under the condition that its energy exceeded the threshold value.

#### 2.4. Combination of EMD and CWT

Both, EMD and CWT represent effective tools to study EEG-signals. These two methods were applied together and compared in some studies of physiological signals [48,49]. In the given paper we consider a new method that combines elements of EMD and CWT.

EEG has a complex multi-component structure; therefore, decomposing EEG into a set of simpler components may facilitate detection of specific patterns. This may either be achieved by the band-pass filtering of EEG or by EMD. EMD seems to be preferable than the band-pass filtering, because it removes not only lower and higher frequencies relative to the frequencies of the recognized pattern, but also reduces signal's complexity in the remaining band of frequencies (i.e., extracts independent oscillatory components) [29]. Unlike the band-pass filtering, EMD separates between the intrinsic modes with interleaving frequency ranges that is important for simplifying the structure of patterns and, therefore, for their better recognition. The CWT of the remaining (processed) signal leads to wavelet spectrum with clearer and sharper time–frequency structure as compared with the original signal  $x(t)$ . In EMD-processed signals, independent rhythmic contributions do not influence the wavelet-energy, and this minimizes the risk of false positive detections with threshold-based techniques.

Based on this, we suggest a combined approach that includes the following steps:

- EMD-based processing. Decomposition of EEG into a set of empirical modes  $c_j(t)$ ;
- Determining the mode that contains main information about the oscillatory pattern to be recognized (usually  $c_1(t)$  or  $c_2(t)$ );
- The CWT analysis of the selected empirical mode, computing the wavelet energy  $E(f, \tau)$ ;
- Averaging of  $E(f, \tau)$  within the frequency band  $F$  that comprises the oscillatory pattern

$$w(t) = \int_F E(f, t) df. \quad (7)$$

- Time averaging of  $w(t)$  within a sliding window in order to reduce error recognition caused by the presence of short-time artifacts

$$\langle w(t) \rangle = \frac{1}{T} \int_T |w(t)| dt. \quad (8)$$

The value of  $T$  should be comparable with the mean duration of the considered pattern type (i.e., it is chosen to be different for SS and SWD patterns that are recognized separately).

- Comparing the averaged energy  $\langle w(t) \rangle$  with the *a priori* chosen threshold value  $w_{cr}$  and determining time intervals during which  $\langle w(t) \rangle$  exceeds the threshold. The threshold value  $w_{cr}$  is chosen to maximize the number of detections of patterns (SS and SWD) with the lowest possible number of missed patterns. It is chosen according to visual (expert) detection of the patterns performed for an initial part of EEG used for the adjustment of the automatic recognizing method. Different values of  $w_{cr}$  were empirically tested in order to find optimal threshold. With too low value of  $w_{cr}$ , some high-energy patterns of EEG could be falsely detected as SS or SWD, while too high  $w_{cr}$  leads to the increased number of missed patterns. It was empirically found, that optimal value of  $w_{cr}$  is related with the maximal level of the averaged wavelet energy of EEG signal. Thus, it can be estimated as about 40% of the maximal wavelet energy.

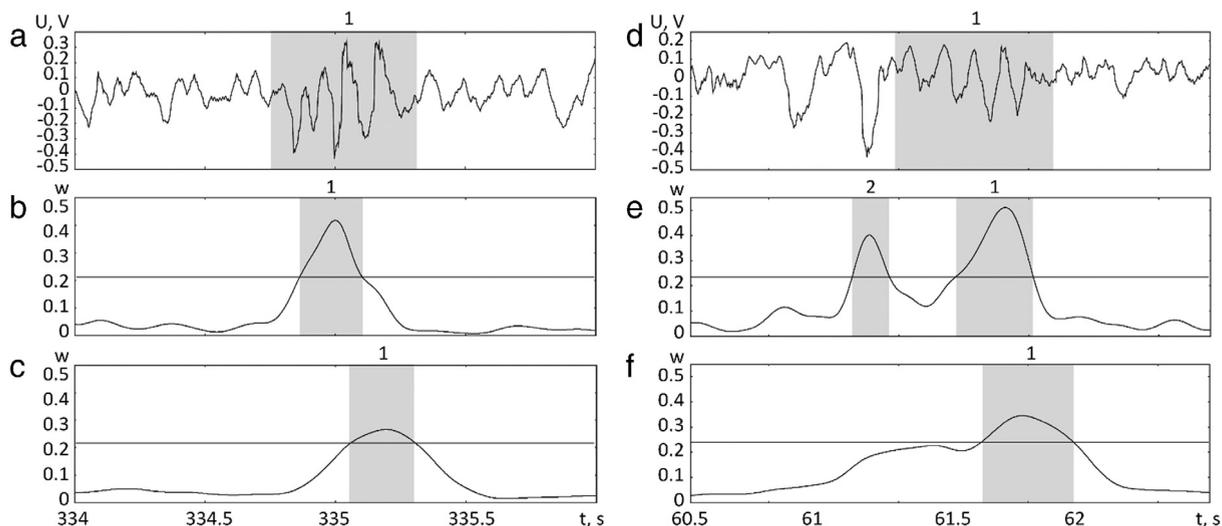
#### 2.5. Statistical evaluation

In order to statistically evaluate the quality of pattern recognition with the combined EMD–CWT approach, we computed the sensitivity ( $\delta$ ) and the specificity ( $\beta$ )

$$\delta = \frac{N_{TP}}{N_{TP} + N_{FN}} \cdot 100\%, \quad (9)$$

$$\beta = \frac{N_{TP}}{N_{TP} + N_{FP}} \cdot 100\%. \quad (10)$$

Here  $N_{TP}$  is the number of true positive detections (correctly recognized events). The onset and offset moments in each sleep spindle were determined automatically and compared with visual expert's detection. The borders of the automatically and visually detected sleep spindles rarely matched. Sleep spindles were considered to be detected properly when the



**Fig. 1.** Examples of normal and false detections of sleep spindle pattern obtained with the CWT-based approach for EEG pattern recognition: (a, d) original EEG tracks with sleep spindles; (b, e) distributions of the wavelet energy  $w(t)$ ; (c, f) distributions of the averaged wavelet energy  $\langle w(t) \rangle$ . Detected patterns are marked by 1 (sleep spindles) and 2 (non-spindle component).

overlap between the automatic and visual expert's detection exceeded 60%.  $N_{FP}$  is the number of false detections (i.e., events recognized by the method, but not recognized by an expert), and  $N_{FN}$  is the number of false negative detections (i.e., events missed by the method). The value of  $\delta$  characterizes sensitivity of the method, i.e. the percentage of correctly recognized patterns from all existing patterns of this type. The specificity  $\beta$  quantifies the percentage of correctly recognized patterns from all recognized patterns of this type.

### 3. Results

#### 3.1. CWT-based method of EEG pattern detection

As it was mentioned above (Section 2.2), this approach occasionally resulted to false positive detections. Fig. 1a demonstrates experimental EEG records with a typical sleep spindle (marked by gray area "1"). By introducing the threshold value  $w_{cr}$  for the wavelet energy (Fig. 1b), we obtained one time interval where  $w(t)$  exceeded the threshold (marked by gray area "1" in Fig. 1b); this interval was a part of the recognized sleep spindle. Fig. 1d demonstrates another situation with two time intervals where  $w(t)$  exceeded the threshold: the first (marked by gray area "1" in Fig. 1e) was a part of the recognized sleep spindle, and the second (marked by gray area "2" in Fig. 1e) was a non-spindle component. Artifact that caused false detection is a high-energy but short burst of oscillations. Such components on EEG can produce abrupt escalation on wavelet energy in short time interval so their influence can be countered by time averaging of wavelet energy.

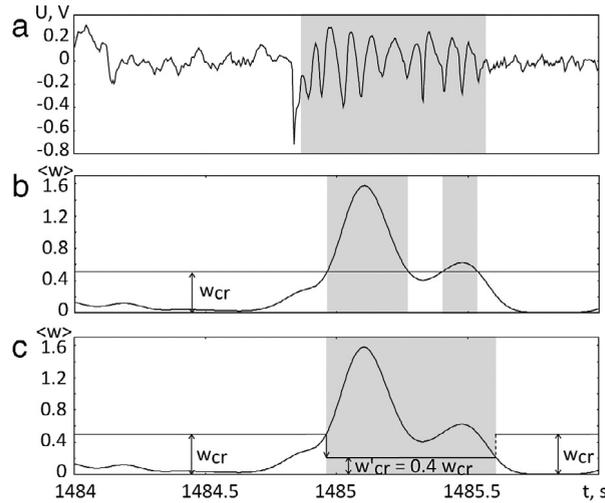
Time averaging within a sliding window improved the quality of pattern detection (Fig. 1f, gray area "1"): the function  $\langle w(t) \rangle$  became more flat, and false detection of non-spindle episode was prevented, yet timing of sleep spindle was not exactly recognized. At the same time the procedure of averaging did not prevent detection of normal sleep spindle without any artifacts before it (Fig. 1c, gray area "1").

Thresholding of the wavelet energy could be sufficient for recognizing relatively simple waveforms in EEG, but it was not always suitable for recognizing EEG patterns with complex time–frequency structure. Some patterns could be recognized with a "floating" threshold, as shown in Fig. 2. This example illustrates EEG with sleep spindle activity (shown by gray region in Fig. 2a).

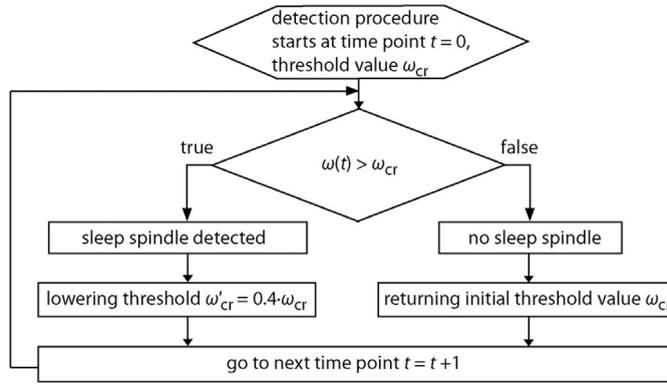
Algorithm of detection with "floating" threshold is illustrated in Fig. 3. Detection procedure started with the initial threshold level  $w_{cr}$ . When criteria  $w > w_{cr}$  was fulfilled the threshold  $w_{cr}$  was reduced to the value  $w'_{cr}$  (e.g.,  $w'_{cr} = 0.4w_{cr}$ ), and the wavelet energy on next steps was compared with this new threshold (criteria changed to  $w_{cr} > w'_{cr}$ ). When wavelet energy did not exceed the lowered threshold value  $w'_{cr}$  the threshold level was returned to the initial value  $w_{cr}$ . Reduced threshold value  $w'_{cr}$  was determined empirically as in case of the initial threshold value  $w_{cr}$ . Testing was performed for different reduction of  $w_{cr}$  in order to find optimal ratio  $w_{cr}/w'_{cr}$  with the highest number of detected patterns. It was found that good results are provided when  $w'_{cr}$  is selected as 40% of the initial threshold  $w_{cr}$  (i.e.,  $w'_{cr} = 0.4 w_{cr}$ ).

This "floating" threshold may help to avoid detection errors, as shown in Fig. 2b (two filled region), when a part of the recognized pattern was undetected due to fast changes of frequency in time.

The abovementioned approach with use of time averaging and "floating" threshold was applied to several different EEG data sets. It was found that new approach increased the quality of automatic recognition of sleep spindles. While there were



**Fig. 2.** Application of a “floating” threshold in the CWT-based algorithm for EEG pattern recognition: (a) original EEG track with sleep spindle marked by gray area; (b) results of false detections with a constant threshold (filled in gray); (c) results of detection with a “floating” threshold (filled in gray).



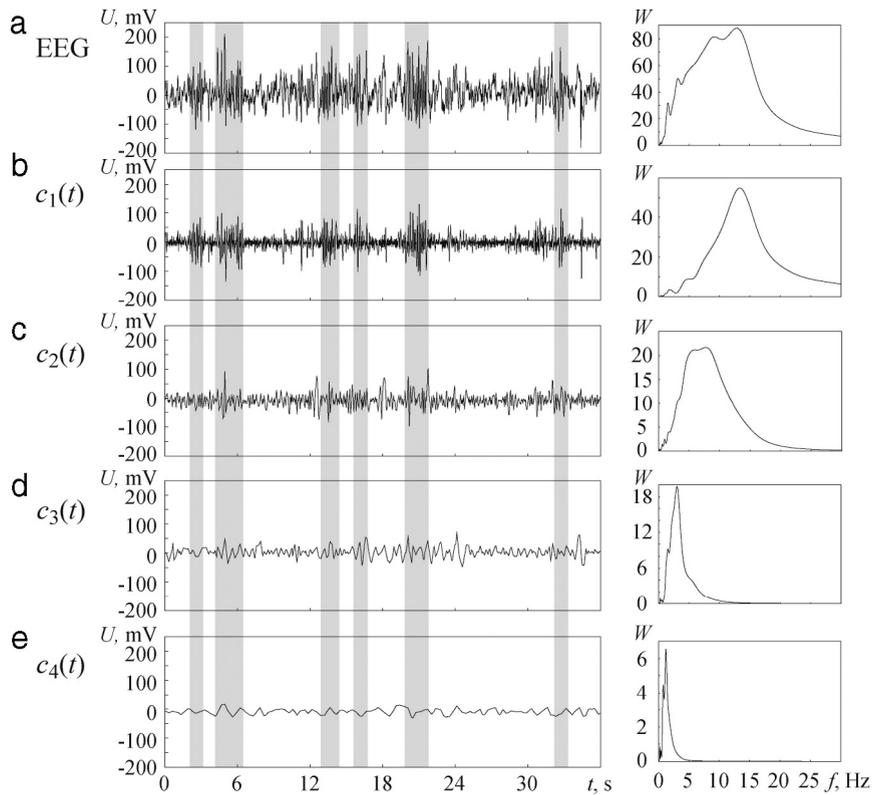
**Fig. 3.** Algorithm of EEG pattern recognition with a “floating” threshold.

almost no increase in sensitivity (78% for original method and 80% for new method) the main benefit lies in considerable increase of specificity (from 70% to 82%). The new approach was mostly aimed on decreasing the number of false detections which explains the growth of specificity.

### 3.2. Empirical mode decomposition of EEG patterns

Figs. 4 and 5 show examples of EEG records with sleep spindles and SWD and results of their decomposition in empirical modes  $c_j(t)$ . In sleep spindles, the first empirical mode  $c_1(t)$  conveyed the most important information about sleep spindles (Fig. 4b), including frequency component between 10 and 14 Hz. Our previous results displayed that majority of spindles in WAG/Rij rats showed amplitude maximum in the frequencies 10–14 Hz [15–18; 24–27], therefore, we selected 10–14 Hz frequency band as informative for the automatic detecting sleep spindles. The second mode (Fig. 4c) also contained oscillatory components in this frequency range, however, their power was significantly lower. In general,  $c_2(t)$  mainly contained spindle-like oscillations of non-spindle frequencies 5–9 Hz, and these oscillations were often recognized as sleep spindles (false positive detections); the latter decreased the quality of automatic recognition. Thus, by removing  $c_2(t)$  from the original EEG with EMD, we reduced complexity of EEG signal and improved the quality of recognition. The remaining empirical modes (Fig. 4d,e) described slow wave oscillations with the frequency  $< 5$  Hz that did not impede the process of automatic recognition.

The EMD of SWD (Fig. 5) also displayed the most important information in the first two empirical modes. The first mode  $c_1(t)$  (Fig. 5b) comprised peak components in SWD and frequencies 14–30 Hz corresponding to the first and second harmonics (14–20 and 21–30 Hz correspondingly) of the main frequency of SWD (7–10 Hz). The second empirical mode  $c_2(t)$  (Fig. 5c) included frequencies 5–15 Hz comprising the main frequency of SWD. Similar to what was found in sleep



**Fig. 4.** Results of EMD of the original EEG with sleep spindles and four empirical modes  $c_j(t), j = 1, \dots, 4$  (b–e) and their wavelet power spectra.

spindles, the higher modes in SWD,  $c_3(t)$  and  $c_4(t)$  (Fig. 5d,e), carried information about low frequencies  $<5$  Hz. The third mode,  $c_3(t)$ , reflects low activity during SWD, and the fourth mode  $c_4(t)$  – low frequency modulation. The latter two modes demonstrate a high variability between SWD and are not used for pattern recognition purposes.

In both sleep spindle and SWD, the first two modes contained information about the specific oscillatory patterns. Therefore, these two modes solely can be used for effective EEG pattern recognition, and the other modes could be eliminated in order to improve the quality of EEG pattern recognition. In general, each empirical mode contained certain waveforms extracted from the original EEG signal, therefore, decomposition of EEG into a set of empirical modes may be considered as a new approach to waveform analysis of EEG. Moreover, in majority of SWD only the first high-frequency empirical mode is enough for pattern recognition, which contains basic information about its structure.

Fig. 6 illustrates the procedure of detecting sleep spindles in EEG by measuring the averaged energy  $\langle E_1(t) \rangle$  of the first empirical mode ( $c_1(t)$ , Fig. 6b). Inasmuch as  $c_1(t)$  contained information about the waveform of sleep spindles, maximum values of  $\langle E_1(t) \rangle$  were associated with the presence of sleep spindles in EEG (Fig. 5c). An example in Fig. 6d indicates that sleep spindles (filled in gray) are mainly detected in EEG by thresholding the dependence  $\langle E_1(t) \rangle$ . However, this approach often resulted in numerous negative and positive false detections. Thus, two visually detected patterns (Fig. 6e) were missed by the EMD-based method.

### 3.3. Combined application of EMD and CWT for EEG pattern recognition

Details of the combined approach are illustrated in Fig. 7 for the same fragment of EEG recorded during sleep with sleep spindles as in Fig. 6a. As it was described in Section 2.4, the first empirical mode  $c_1(t)$  was extracted and used as the input signal in the CWT. Instantaneous wavelet energy  $\langle w(t) \rangle$  (7) of the CWT was averaged (see Eq. (8) for  $\langle w(t) \rangle$  value) (Fig. 7c), and sleep spindles were detected in EEG with the threshold  $w_{cr}$  for  $\langle w(t) \rangle$  (Fig. 7d). Timing of sleep spindles (i.e., the moments of onset and offset) are close to the expert's decision (Fig. 7e). In comparison to the energy assessed with solely EMD technique ( $\langle E_j(t) \rangle$ , Section 2.3), the wavelet energy  $\langle w(t) \rangle$  demonstrated a smoother time dependence, and the difference between wavelet energy of sleep spindles and the background EEG was more pronounced. This is an important issue for the accurate detection of oscillatory patterns. In contrast to the method illustrated in the Fig. 6d, the combined EMD–CWT method capable of recognizing all sleep spindles (Fig. 7d).

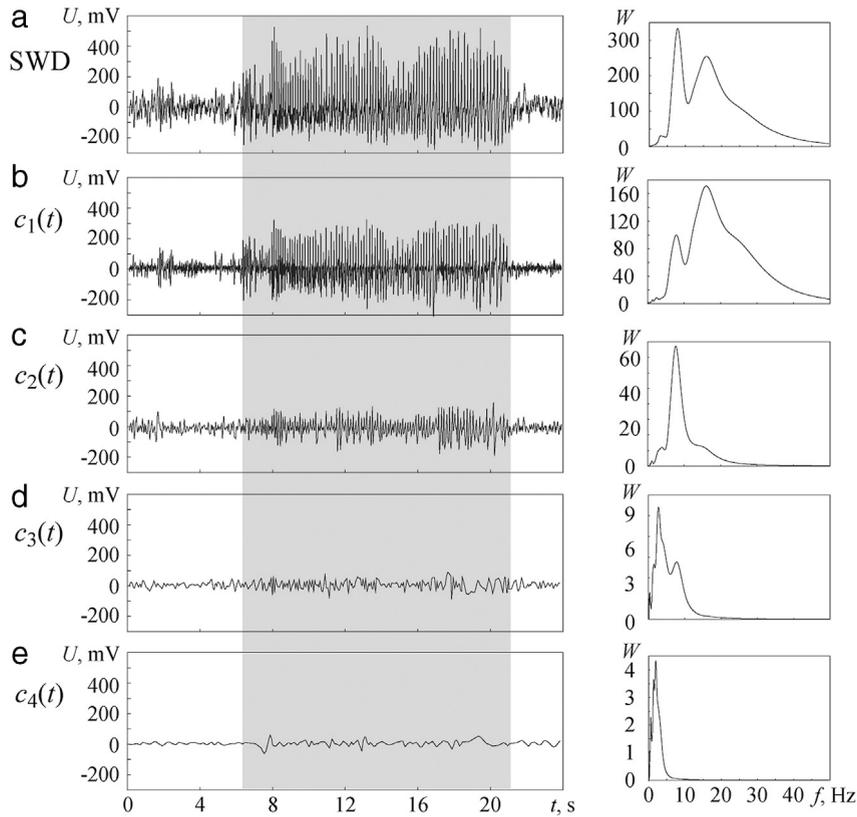


Fig. 5. Results of EMD of EEG with spike-wave discharges (a) and four empirical modes  $c_j(t), j = 1, \dots, 4$  (b–e) and their wavelet power spectra.

Automatic recognition of sleep spindles was performed in the full-length EEG recorded in six WAG/Rij rats. The first empirical mode  $c_1(t)$  underwent the CWT, and the instantaneous wavelet energy (7) was averaged in accordance with Eq. (8), and sleep spindles were detected in EEG with the thresholding of the wavelet energy.

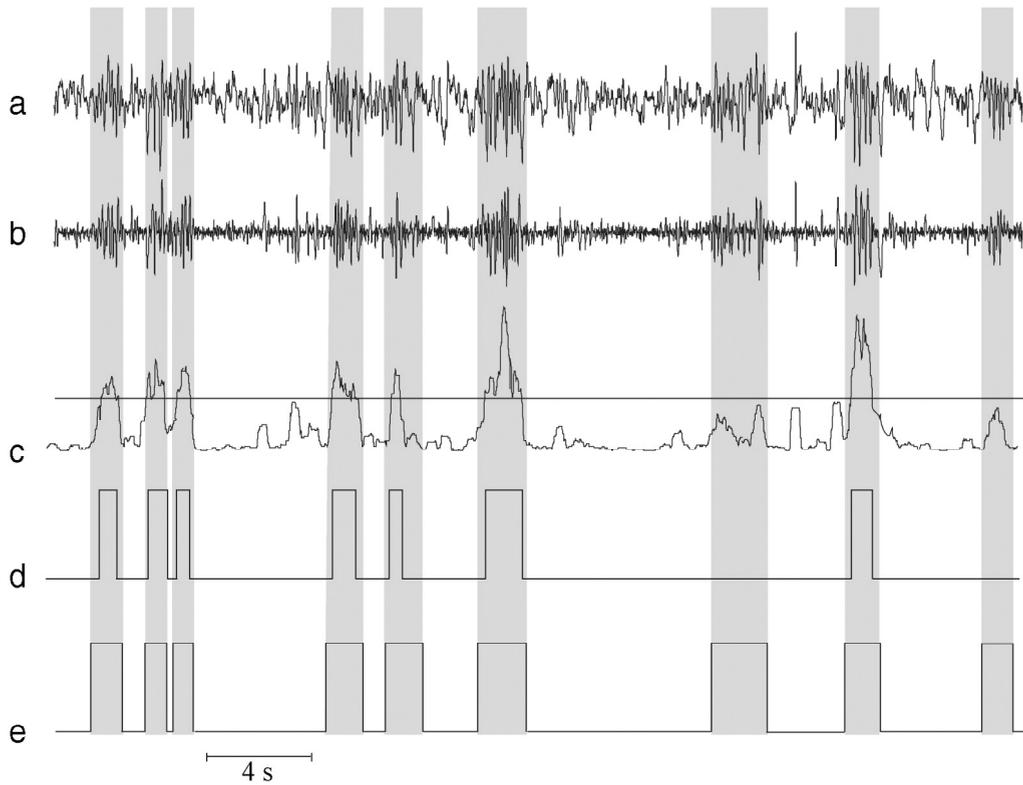
Table 1 shows the outcomes of the three methods (EMD, CWT and combined EMD–CWT methods) used for detection of sleep spindles in 23 h EEG records (all full-length EEG excluding 0.5–1 h epochs used for the development of the detection algorithms). Table 2 presents statistical parameters characterizing the quality of automatic detection of SWD in 23 h EEG. The combined EMD and CWT approach resulted to the sensitivity  $\delta$  of 86.5% and specificity  $\beta$  of 92.9% (Table 1) for sleep spindles and 97.6% and 93.2% for SWD, correspondingly. Considering the strong variability of sleep spindles (within- and between-subjects variability), the values of  $\delta$  and  $\beta$  were high, suggesting that the proposed approach was effective for automatizing the process of pattern recognition in EEG.

However some sleep spindles were still missed by the combined CWT and EMD detection methods. The main reason of misdetection could be the low amplitude of these sleep spindles. It could led to the low energy on wavelet spectrum that could not exceed the threshold level.

#### 4. Discussion

This paper evaluates different approaches for automatic detections of rhythmic activity in EEG. We introduce the EMD as a part of a combined recognition method. By means of the EMD, the original signal was translated to 1–2 empirical modes that embraced EEG waveforms and reduced complexity of EEG [44]. In general, the EMD could act as an adjustable filter that removes redundant information (noise, background activity, artifacts, etc.), however, it is different from the classical band-pass filtering. The estimated empirical modes showed a broad power spectrum and they are not necessary related to distinct frequency ranges, so spectra of two consequent modes were superposed. This means that each mode reduced complexity of the original EEG in the frequency range of the recognized pattern by removing other independent contributions. In the EMD, information about oscillatory patterns could be obtained by measuring the amplitude or energy of empirical modes: an increased energy corresponded to the detected patterns.

Typically, CWT and EMD are considered as independent approaches, and several studies discussed advantages and restrictions of each of the given techniques [26,31,50]. Combination of these methods for EEG pattern recognition appeared

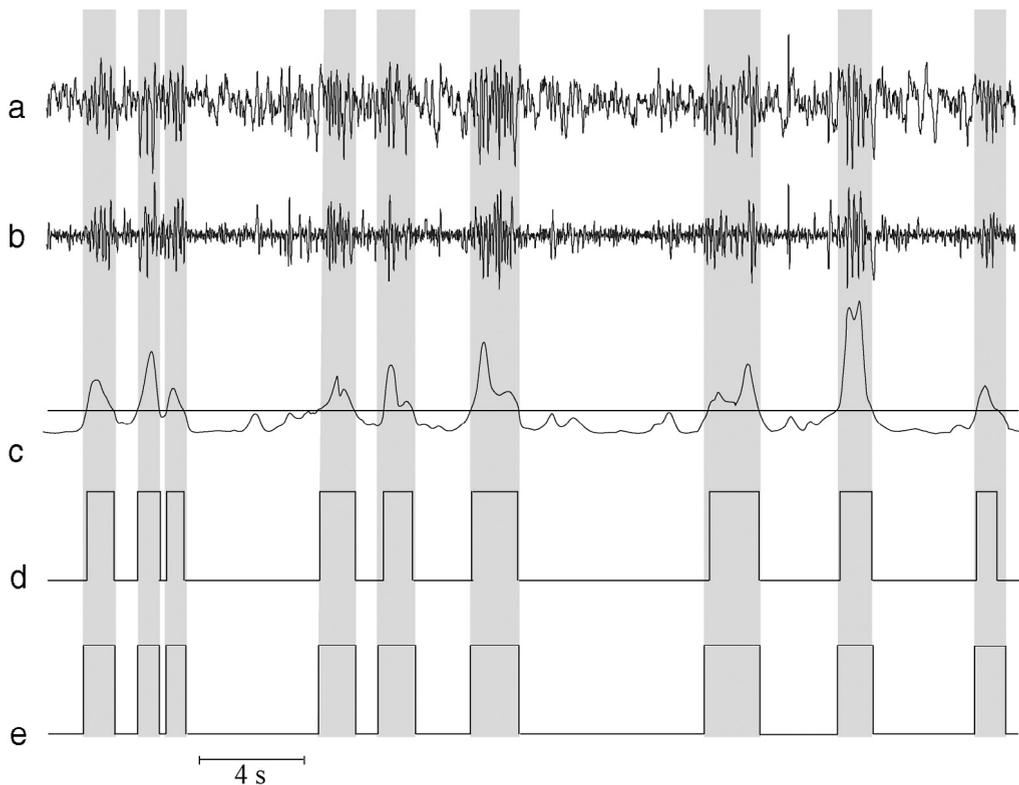


**Fig. 6.** Automatic detection of sleep spindles in EEG (a) using the EMD approach. (b) The first empirical mode  $c_1(t)$ ; (c) the time averaged energy  $\langle E_1(t) \rangle$  of this mode; (d) results of detection (filled in gray), and (e) visual (expert) detection.

**Table 1**

Statistical characteristics of the three methods used for automatic detection of sleep spindles in 23 h EEG in six WAG/Rij rats.

| Rat ID                             | $N_{TP}$ | $N_{FP}$ | $N_{FN}$ | $\delta, \%$   | $\beta, \%$     |
|------------------------------------|----------|----------|----------|----------------|-----------------|
| <b>EMD method</b>                  |          |          |          |                |                 |
| 1                                  | 3708     | 1319     | 733      | 83.5           | 73.8            |
| 2                                  | 2463     | 1728     | 1446     | 63.0           | 58.6            |
| 3                                  | 2603     | 289      | 868      | 75.0           | 90.0            |
| 4                                  | 2449     | 286      | 866      | 73.9           | 89.5            |
| 5                                  | 3327     | 434      | 1013     | 76.7           | 88.5            |
| 6                                  | 3473     | 581      | 1303     | 72.7           | 85.7            |
| Mean $\pm$ S.D.                    |          |          |          | 74.1 $\pm$ 6.7 | 81.0 $\pm$ 12.5 |
| <b>CWT method</b>                  |          |          |          |                |                 |
| 1                                  | 3512     | 1315     | 881      | 80.0           | 72.7            |
| 2                                  | 2801     | 781      | 1029     | 73.1           | 79.2            |
| 3                                  | 3617     | 1012     | 583      | 86.1           | 78.1            |
| 4                                  | 2603     | 434      | 1014     | 72.0           | 85.7            |
| 5                                  | 4045     | 701      | 436      | 90.3           | 85.2            |
| 6                                  | 3806     | 439      | 1026     | 78.8           | 89.7            |
| Mean $\pm$ S.D.                    |          |          |          | 80.0 $\pm$ 7.2 | 81.8 $\pm$ 6.2  |
| <b>Combined EMD and CWT method</b> |          |          |          |                |                 |
| 1                                  | 2912     | 813      | 587      | 83.2           | 78.2            |
| 2                                  | 3649     | 712      | 439      | 89.3           | 83.7            |
| 3                                  | 3623     | 2        | 582      | 86.2           | 100.0           |
| 4                                  | 2908     | 143      | 868      | 77.0           | 95.3            |
| 5                                  | 3896     | 0        | 436      | 89.9           | 100.0           |
| 6                                  | 4028     | 1        | 290      | 93.3           | 100.0           |
| Mean $\pm$ S.D.                    |          |          |          | 86.5 $\pm$ 5.8 | 92.9 $\pm$ 9.6  |



**Fig. 7.** Combined EMD–CWT approach for detecting sleep spindles in EEG. (a) Original EEG track; (b) the first empirical mode  $c_1(t)$  and (c) its averaged wavelet energy  $\langle w(t) \rangle$ . (d) Results of pattern recognition with the proposed approach, and (e) visual (expert) detection.

**Table 2**

Averaged parameters of the three methods characterizing the quality of automatic detection of SWD in 23 h EEG in six WAG/Rij rats.

| Method               | $\langle N_{TP} \rangle$ | $\langle N_{FP} \rangle$ | $\langle N_{FN} \rangle$ | $\langle \delta \rangle, \%$ | $\langle \beta \rangle, \%$ |
|----------------------|--------------------------|--------------------------|--------------------------|------------------------------|-----------------------------|
| EMD                  | 181                      | 55                       | 30                       | $85.7 \pm 5.3$               | $76.6 \pm 11.6$             |
| CWT                  | 212                      | 37                       | 8                        | $95.2 \pm 7.1$               | $83.3 \pm 8.5$              |
| Combined EMD and CWT | 218                      | 15                       | 1                        | $97.6 \pm 6.9$               | $93.2 \pm 12.1$             |

to be more effective than independent application of each method alone. EMD has advantages over the CWT in respect to the spectral resolution, and, therefore, it is appropriate for spectral analysis of rhythmic activity characterizing by a small frequency shift, when the resolution of CWT was insufficient and resulted to interferences [26,29,30,34]. Here, with the EMD, we initially decomposed EEG into a set of independent contributors (empirical modes) and then selected contributors containing the most relevant information about the recognized patterns. It is important to note that empirical modes of nonstationary EEG signal do not have obvious physical interpretation, and the latter circumstance is the main shortcoming of the EMD-technique. Due to this time–frequency content of each mode could be studied with the wavelet transform.

The proposed method was applied to long lasting EEG (24 h) recorded in six rats. Sleep spindles were first visually detected in EEG epochs, and these detections were used to estimate the quality of automatic detection algorithm, i.e., to measure false positive and false negative errors. The sensitivity ( $\delta = 85\%–95\%$ ) and the specificity ( $\beta = 90\%–100\%$ ) were high, suggesting that the proposed approach is effective for EEG pattern recognition. Moreover, the efficiency of patterns recognition was higher as compared with other CWT-based approaches. Thus, the combination of CWT and EMD increases the quality of automatic detection of stereotypic patterns in rat's EEG. While automatic detection of SWD-patterns is related to the task of finding or even predicting epileptic seizures, this problem draws attention of many researches. There are various methods and approaches to the problem of SWD detection [51–53]. The combined EMD–CWT method proposed in the given paper provides the detection that is comparable or even better from the viewpoint of sensitivity and specificity. Main advantage of this technique is the automated procedure for selection of optimal parameters for each EEG signal. Besides, it provides a real-time SWD-detection.

## 5. Conclusion

This paper provides several clues for automatic EEG pattern recognition. First, application of the CWT with a “floating” threshold helped to minimize false detections caused by complex time-varying dynamics of EEG. Second, with the EMD, the original EEG signal could be decomposed into several empirical modes, where the first two modes (time dependences) contained the most important information about the waveform of detected patterns, i.e., sleep spindles and SWD. Each empirical mode of EEG signal is characterized by a lower complexity in comparison to original EEG. Application of empirical modes could increase sensitivity and specificity of the automatic pattern recognition. We demonstrated that a combined application of EMD and CWT was beneficial for automatic detection of sleep spindles in rat’s EEG.

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