Adaptive wavelet-based recognition of oscillatory patterns on electroencephalograms

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ABSTRACT

The problem of automatic recognition of specific oscillatory patterns on electroencephalograms (EEG) is addressed using the continuous wavelet-transform (CWT). A possibility of improving the quality of recognition by optimizing the choice of CWT parameters is discussed. An adaptive approach is proposed to identify sleep spindles (SS) and spike wave discharges (SWD) that assumes automatic selection of CWT-parameters reflecting the most informative features of the analyzed time-frequency structures. Advantages of the proposed technique over the standard wavelet-based approaches are considered.

Keywords: Recognition, wavelet analysis, electroencephalogram, oscillatory patterns

1. INTRODUCTION

Automatic recognition of specific oscillatory patterns on EEG represents an important problem in neurophysiology. The structure of EEG-signals is characterized by a variety of rhythmic components whose frequencies represent important quantities of the functional activity of neural structures.[1] Specific oscillatory patterns such as, e.g., sleep spindles or spike wave discharges can be visually identified in the course of data processing. However, complex time-frequency organization of EEG-signals and the existence of many rhythmic components being close enough in the frequency domain lead to a hard procedure of experimental data analysis by human operators. The development of advanced tools for EEG processing and patterns recognition provides a way to diagnose basic interactions between different areas of the brain and to reveal features of the formation of different types of rhythmic activity.[1,2] Besides new fundamental knowledges associated with cognitive functions of the brain, the latter has clear practical significance (monitoring of pathological activities, creation of specific brain-computer interfaces, etc.).[3,4]

At present, there are different techniques that are able to solve the recognition problem with a required level of accuracy. Among them, wavelet-based methods are related to the most powerful tools.[6–9] In order to provide recognition procedure with wavelets, one needs: 1) to select an appropriate basis constructed from a single soliton-like function; 2) to select appropriate scale and translation parameters associated with the most informative wavelet-coefficients.

In our previous studies wavelets were successfully applied for detection of different types of oscillatory patterns.[10–12] Here, we discuss a modified algorithm proposed to improve the reliability of automatic recognition of patterns that provides a more rigorous approach for selection of CWT-parameters based on the optimization theory. This approach allowed us identify SS- and SWD-patterns using the standard Morlet-function. The feature of this approach is that optimal parameters of the CWT are automatically selected and, therefore, this

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procedure does not depends on the experience of a researcher. We show that the proposed technique improves the quality of recognition of specific oscillatory patterns on EEG compared with the standard recognition procedures used, e.g., in solving the problem of classification of neuronal activity from extracellularly recorded action potentials.[5] The precision of recognition of specific EEG-patterns with the proposed approach exceeds 90% and can be improved by providing additional modifications of the optimization procedure.

2. METHOD

2.1. Continuous wavelet-transform

The continuous wavelet-transform can be written as

$$W(\rho, q) = \sqrt{\rho} \int_{-\infty}^{\infty} S(t) \psi^*(\rho[t-q]) dt, \tag{1}$$

where $W(\rho, q)$ are the wavelet-coefficients, $S(t)$ is the analyzed signal, ψ is the wavelet-function being localized in both, time and frequency domains, ρ and q are the scale and the translation parameters, respectively. A more detailed description is given, e.g., in the books.[6,7]

In the analysis of rhythmic components the Morlet-function is mainly used

$$\psi(t) = \pi^{-1/4} \exp(j2\pi f t) \exp\left(-\frac{t^2}{2}\right). \tag{2}$$

The instantaneous energy $E(t)$ of the signal $S(t)$ in the selected frequency band $\Delta\rho$ is estimated as

$$E(t) = \frac{1}{\Delta\rho} \int_{\Delta\rho} |W(\rho, t)|^2 d\rho. \tag{3}$$

2.2. Patterns recognition

Patterns recognition by a human operator is performed in the course of visual inspection of the acquired EEG-signal $S(t)$ (Figure 1A). Fragments associated with the patterns are coded by "1" while other parts of the data are coded by "0". As a result, a binary signal $Se(t)$ is obtained (Figure 1B).

According to earlier studies, the instantaneous energy $E(t)$ can be used for patterns identification in the case of appropriately chosen $\Delta\rho$ (the latter varies for different types of oscillatory patterns) and a threshold (Figure 1C).[8,10,11] The disadvantage of this approach is that the threshold is set up arbitrarily and, therefore, its selection depends on the researcher's experience.

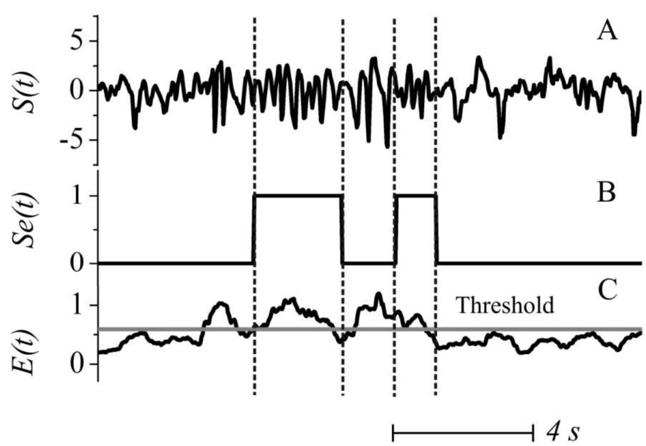

Figure 1. Acquired EEG-data (A), the expert's signal (B), and a time dependence of the instantaneous energy (C)

2.3. Adaptive algorithm

Introducing of a threshold can lead to spurious identifications of oscillatory patterns. This situation is illustrated in Figure 1C. Aiming to improve recognition abilities of this approach, the following adaptive algorithm is proposed based on the optimization theory.

At the first stage, the continuous wavelet-transform of a signal $S(t)$ with the Morlet-function is performed, and the wavelet-coefficients are averaged over the selected range of scales

$$F(q) = \frac{1}{N}\sum_{j=1}^{N} \mid \sqrt{\rho_j}\int_0^T S(t)\sin(2\pi f_j\rho_j(t-q))\exp\left(-\frac{1}{2}(\rho_j(t-q))^2\right)dt \mid . \tag{4}$$

Let us consider the vector of parameters $\vec{w} = \{\rho_j, f_j\}, j = 1, 2, \ldots N$, where ρ_j is the scale parameter and f_j is the central frequency of the Morlet-function. The translation parameter q takes all values from the selected fragment of EEG $[0, T]$.

At the second stage, a filtration of the signal $F(t)$ with the filter Φ is performed (this filter will be described below). Let us introduce the vector of parameters $\vec{v}$ that characterizes adjustment of the filter Φ. As the result of this filtering, the signal $F'(t)$ is obtained

$$F'(t) = \Phi(F(t), \vec{v}). \tag{5}$$

At the last stage, two thresholds th_1 and th_2 are introduced and a binary signal $Sp(t)$ is computed according to the following expression

$$Sp(t) = C(F'(t), th_1, th_2) = \begin{cases} 1, F'(t) \geq th_1 \cap F'(t) \leq th_2 \\ 0, F'(t) < th_1 \cup F'(t) > th_2 \end{cases} . \tag{6}$$

Within the proposed adaptive technique, some fragment of EEG-data should be analyzed by an expert in order to establish searching rules that can further be used to adjust all parameters including those of CWT (4) and the functions (5) and (6). This adaptation allows us to eliminate ambiguity of the standard wavelet-based recognition approaches.

2.4. Φ-filter

The Φ-filter introduced in Sec. 2.3 is characterized by the parameter vector $\vec{v}$ that defines its spectral properties. In the simplest case, such filter can be realized within the procedure of a running average

$$F^{(n)}(j\Delta t + v_1\Delta t) = \frac{1}{2v_1+1}\sum_{i=j}^{i=j+2v_1+1} F^{(n-1)}(i\Delta t), \quad n = 1, 2, \ldots, v_2, \tag{7}$$

where n denotes the iteration number. Another parameter is the "window" length $2v_1 + 1$.

Let us note, that other filtering approaches can also be useful. As we shall further show, however, simple variant of the Φ-filter given by Eq. (7) is well suited for the purpose of patterns recognition.

2.5. Optimization of CWT-parameters

Adjustment of the parameter vector $\vec{w}$ is the first stage of the proposed adaptive algorithm. An appropriate selection of the scale parameters $\rho_j, j = 1, \ldots, N$ is a quite typical approach in the wavelet-analysis. Besides, we consider an adjustment of the central frequency of the Morlet-function $f_j, j = 1, \ldots, N$ aiming to optimize the time-frequency resolution of the wavelet-transform.

This adjustment is supposed to be realized within the optimization theory as described below.

2.6. R-functional: Estimation from experimental data

Let us rewrite the Morlet-function in the following form

$$\psi_{\rho f q}(t) = \sqrt{\rho}\sin(2\pi f \rho(t-q))\exp\left(-\frac{1}{2}(\rho(t-q))^2\right). \tag{8}$$

In the course of signal processing (Figure 2A), an expert introduces a binary signal $Se(t)$ (Figure 2B) where the value “1 corresponds to a recognized pattern. Fragments of the original EEG-data associated with the presence of patterns are extracted from $S(t)$ to get a signal $s_p(t)$ that is fully constructed from patterns of some specific type (e.g., SS or SWD). Remaining parts of EEG-data form a signal $s_n(t)$ (Figure 2C and 2D).

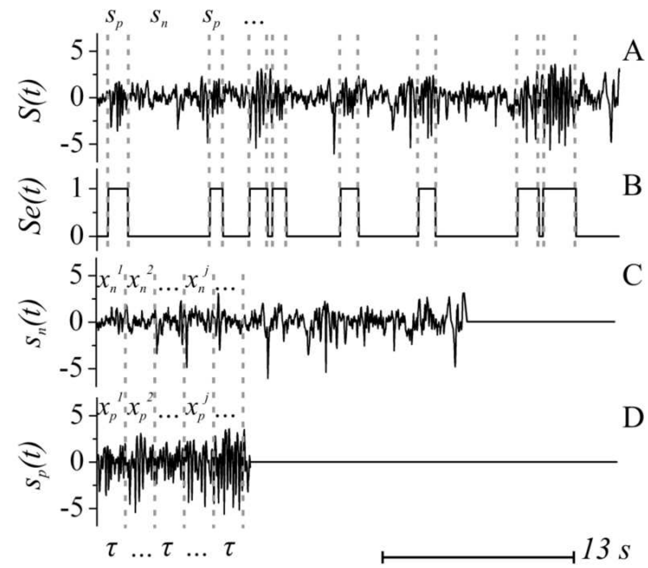

Figure 2. EEG-signal (A), the expert’s signal (B), and the extracted signals $s_n(t)$ (C) and $s_p(t)$ (D)

Aiming to compute a functional R_I of the integral type, we need to estimate the wavelet coefficients according to Eq. (9)

$$\begin{aligned} W^{s_n}(\rho, f, q) &= \int_0^T s_n(t)\psi_{\rho f q}(t)dt, \\ W^{s_p}(\rho, f, q) &= \int_0^T s_p(t)\psi_{\rho f q}(t)dt. \end{aligned} \tag{9}$$

At the next stage, the R_I-functional is computed as follows

$$r_I(\rho, f, q) = \frac{W^{s_p}(\rho, f, q) - W^{s_n}(\rho, f, q)}{max(W^{s_p}(\rho, f, q), W^{s_n}(\rho, f, q))} \tag{10}$$

$$R_I(\rho, f) = \frac{1}{T}\int_0^T r_I(\rho, f, q)dq \tag{11}$$

Maximum of R_I is associated with the best selection of the parameters ρ and f of the Morlet-function (8).

Another type of the functional can be introduced for adaptation procedure by separating the signals $s_p(t)$ and $s_n(t)$ into intervals of a duration τ. The obtained fragments are analyzed using Eq. (12)

$$\begin{aligned} W^{x_n^j}(\rho, f) &= \frac{1}{\tau}\int_0^\tau \mid \int_0^\tau x_n^j(t)\psi_{\rho f q}(t)dt \mid dq \\ W^{x_p^j}(\rho, f) &= \frac{1}{\tau}\int_0^\tau \mid \int_0^\tau x_p^j(t)\psi_{\rho f q}(t)dt \mid dq \end{aligned} \tag{12}$$

Further, the mean values a and the standard deviations σ of the coefficients $W^{x_n^j}(\rho, f)$ and $W^{x_p^j}(\rho, f)$ are estimated, and a R_D-functional is computed according to Eq. (13)

$$R_D(\rho, f) = \frac{a^{s_p}(\rho, f) - a^{s_n}(\rho, f)}{\sigma^{s_p}(\rho, f) + \sigma^{s_n}(\rho, f)}. \tag{13}$$

Maximization of R_D provides a selection of CWT-parameters being optimal for patterns recognition.

2.7. R-functional: Estimation from surrogate date

The presence of additional patterns in the signal $s_n(t)$ (Figure 2C and 2D) creates additional difficulties when solving the recognition problem that is why the procedure of parameter optimization using Eq. (11) or Eq. (13) becomes significantly more complicated. Aiming to eliminate the impact of these additional patterns (they may have similar energy, etc.) we propose to construct surrogate date at the adaptation stage. The signal $s_n(t)$ is changed by color noise with similar spectral properties and similar energy (the latter can be controlled within the adaptation process).

When performing such changes, the whole EEG-data is separated into fragments following the signal $Se(t)$. As a result, the signals $x_n^j(t)$ and $x_p^j(t)$ with the durations τ_n^j and τ_p^j are obtained from the processes $s_n(t)$ and $s_p(t)$ (Figure 3).

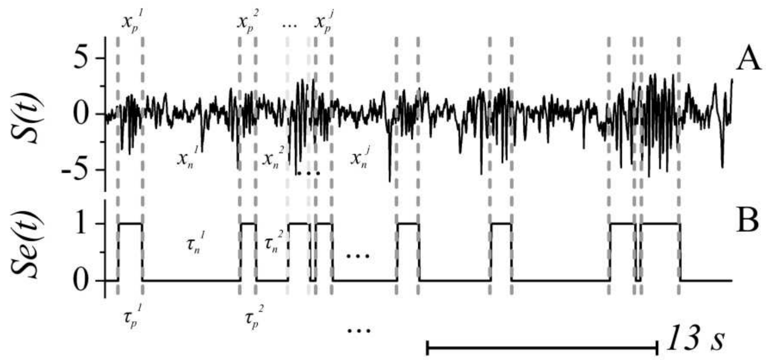

Figure 3. EEG-signal (A) and the signal $Se(t)$ with indicated intervals (B)

At the next stage, the CWT-coefficients are estimated

$$\begin{aligned} W^{x_n^j}(\rho, f) &= \frac{1}{\tau_n^j}\int_0^{\tau_n^j} \mid \int_0^{\tau_n^j} x_n^j(t)\psi_{\rho f q}(t)dt \mid dq \\ W^{x_p^j}(\rho, f) &= \frac{1}{\tau_p^j}\int_0^{\tau_p^j} \mid \int_0^{\tau_p^j} x_p^j(t)\psi_{\rho f q}(t)dt \mid dq \end{aligned} \tag{14}$$

and two functionals R_{CA} and R_{CD} are introduced by analogy with R_D*

$$R_{CA}(\rho, f) = \frac{a^{x_p}(\rho, f) - a^{x_n}(\rho, f)}{max(a^{x_p}(\rho, f), a^{x_n}(\rho, f)}, \quad R_{CD}(\rho, f) = \frac{a^{x_p}(\rho, f) - a^{x_n}(\rho, f)}{\sigma^{x_p}(\rho, f) + \sigma^{x_n}(\rho, f)}. \tag{15}$$

2.8. Optimization of the remaining parameters

The proposed algorithm includes procedures of additional filtering using Eq. (5) and a comparison with two thresholds th_1 and th_2. Therefore, optimal values of the parameter vector $\vec{v}$ and the thresholds should also be selected. In order to realize such selection, two quantities are introduced according to Eqs. (16) and (17)

$$Er = \frac{1}{T}\int_0^T \mid C(F'(t), th_1, th_2) - Se(t) \mid dt, \tag{16}$$

*R_{CA} is now estimated relative to mean values.

$$Ac = \frac{N_I}{N_D}, \tag{17}$$

where Er is an error obtained as the difference between $Sp(t)$ estimated using Eq. (6) and $Se(t)$, Ac is an accuracy estimated as the ratio of correctly identified patterns N_I to the whole number of analyzed patterns N_D.

Aiming to realize the optimization, a procedure of error minimizing with the maximizing of Ac should be provided.

3. RESULTS

Experimental verification of the proposed adaptive algorithm was performed using a 25-minute EEG-signal containing 277 SS-patterns. In order to estimate the accuracy of patterns recognition, the whole signal was previously analyzed by an expert, however, only the beginning fragment of the process $Se(t)$ (about 14%) was used for adjustment of all parameters. An example of recognition of SS-patterns is given in Figure 4.

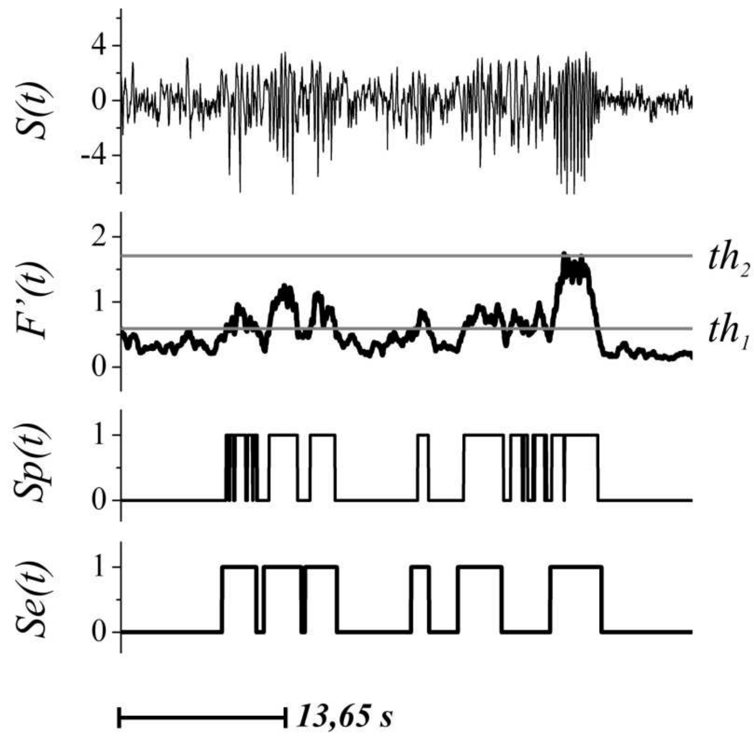

Figure 4. An example of recognition of SS-patterns by the proposed algorithm

This Figure illustrates how the choice of the thresholds th_1 and th_2 affects the quality of patterns identification. The threshold th_2 eliminates high-amplitude fluctuations in the signal associated, e.g., with SWD-patterns or different artifacts. When th_2 decreases, two neighboring patterns instead of a single pattern can be recognized (Figure 4). Variations of th_1 also influence the number of patterns and, therefore, the result of automatic recognition differs from the experts signal $Se(t)$ (Figure 4). Optimization of parameters that are used in the proposed algorithm allows us to improve the quality of EEG-analysis by reducing the number of spurious identifications.

An additional circumstance affecting the accuracy of patterns detection is the choice of the functional. All four versions given by Eqs. (11), (13) and (15) have been tested in our study. The results are given in Figure 5. The highest accuracy was reached for R_{CA} and R_{CD} introduced for a surrogate signal. They provided an essential improvement of the accuracy as compared with R_I. The error Er did not exceed 12% for all these functionals. Moreover, the value Er was insensitive to the choice of R.

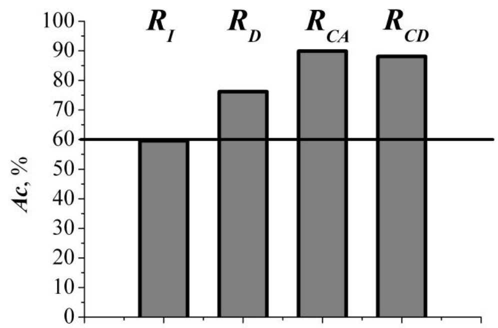

Figure 5. Accuracy of the proposed technique

4. CONCLUSIONS

The proposed adaptive method for patterns recognition enables us to eliminate one of the main shortcomings of the wavelet-based approaches namely the problem of optimal tuning of CWT-parameters. Wavelet-analysis is called as a "mathematical microscope" that can reveal a detailed structure of the analyzed signal only at the condition of appropriate adjustment of its "optical properties". The latter problem limits effectiveness of wavelets when solving recognition problems and it was widely discussed, e.g., for spike sorting techniques.[5] Inappropriate selection of the CWT-parameters often fails to achieve acceptable recognition accuracy at the presence of different types of patterns with similar shapes. The proposed technique is based on rigorous approaches of the optimization theory. It allows us to perform an optimal tuning of the algorithm parameter in an automatic regime. As a result, the quality of patterns recognition does not depend on the experience of a researcher that performs data processing. Despite the fact that this technique is developed for EEG-analysis it can be used in solving a broad range of pattern recognition problems in physics, medicine, biology, etc.

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