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THEORY AND METHODS OF SIGNAL PROCESSING

Adaptive Wavelet Transform–Based Method for Recognizing Characteristic Oscillatory Patterns

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Abstract—The problem concerning the automatic recognition of characteristic oscillatory patterns in multicomponent signals is investigated using the brain's electric activity records, electroencephalograms (EEGs), as an example. It has been ascertained that recognition errors can be decreased by optimally selecting continuous wavelet transform (CWT) parameters to obtain characteristics describing the most important information on analyzed patterns. The adaptive CWT-based method for identifying the characteristic types of EEG rhythmic activity is proposed.

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INTRODUCTION

The development of tools for digital processing of multichannel records of the brain's electric activity is the topical direction of modern neurodynamics. Special methods for analyzing electroencephalogram (EEG) structures makes it possible to diagnose basic interactions between different brain regions and the mechanisms underlying the formation of different types of rhythmic activity [1, 2]. Investigation of these issues has not only a fundamental scientific meaning concerned, e.g., with the study of cognitive brain functions but also practical significance, in particular, to create the monitoring systems of pathologic activity and specific brain–computer interfaces [3, 4].

A large number of various rhythmic components, the frequencies of which are important characteristics of the functional activity of nervous structures, can be extracted from EEG signals [1]. The characteristic oscillatory patterns of EEGs, such as sleep spindles (SSs) and spike-wave discharges (SWDs), can be visually identified in experimental EEG records. However, the visual examination of long multichannel EEG signals is an intricate procedure. When the amount of analyzed and decoded data is large, even a skilled expert will commit errors. For example, according to the estimates presented in [5], solving the similar problem (the identification and recognition of long neural spike sequences), expert can take erroneous decisions in 50% of cases even when a single-channel record is analyzed. During the identification of, e.g., SS patterns, the number of errors will be substantially lower. At the same time, they always occur if an expert must estimate a large experimental sample. Automatic recognition of EEG oscillatory patterns completely eliminates a human factor. This increases the reliability of results and ensures their repeatability and reproducibility, which are especially important for independent expert estimation. Thus, the creation of efficient algorithms capable of automating EEG signal analysis is the problem of vital importance. It should be emphasized that the automatic recognition of the features of an EEG signal can be the first stage in solving more complicated problems at which the type of a cognitive human activity is recognized using an EEG signal shape in the real time mode (the brain–computer interface) or the technical problems of hardware control.

In the last few years, wavelet analysis is successfully employed to investigate the normal and pathological EEGs of animals and people [6–8]. This is due to the fact that wavelet analysis is applicable to research of nonstationary signals, the spectral composition and statistical characteristics of which vary with time, and enables us to localize their peculiarities in time and frequency domains. In complex multichannel processes, the oscillatory pattern recognition problem is efficiently solved via wavelet analysis because this mathematical tool exhibits a number of properties [9, 10]. First, the application of soliton-like functions (wavelets) localized in the time domain makes it possible to implement efficient signal "scanning" in time, revealing the typical features of rhythmic dynamics and comparing them with the assigned template. Since the used basis is localized, the time interval within which signals are analyzed can be narrowed to several oscillations. As a result, digital processing of experimental data is performed rather rapidly. Second, in contrast to simple correlation methods that estimate the degree of the linear dependence (correlations) between the chosen fragment of experimental data and the previously chosen template, wavelet analysis makes it possible to carry out much more detailed investigations of the structure of an analyzed signal.

In our previous studies [8, 11–14], the various types of EEG oscillatory patterns were recognized by means of wavelet analysis. In this study, we propose the updated algorithm for automatic EEG pattern recognition [11] to increase the reliability of EEG automatic marking, which relies on the stricter approach using optimization theory methods to the selection of continuous wavelet transform (CWT) parameters.

1. METHOD FOR IDENTIFYING THE CHARACTERISTIC SHAPES OF RHYTHMIC ACTIVITY IN ELECTROENCEPHALOGRAMS VIA THE CONTINUOUS WAVELET TRANSFORM

A distinction between wavelet analysis and classical spectral analysis involving the expansion of signal $x(t)$ in the harmonic function basis is a diversity in the selection of functions $\psi(t) \in L^2(R)$ underlying the basis formation. In this case, the necessary requirement is that a basis function and its Fourier transform must be localized in time and frequency domains. Drawing the known analogy between wavelet analysis and a "mathematical microscope" [15], it is possible to assume that quantity $\psi(t)$ is selected in the same way as it is done by a microscope lens enabling the observation of either separate details or a general view of the object under examination. Hence, the selection of appropriate basis (or "mother") function $\psi(t)$ strongly affects the efficiency of solution to the problem concerning the identification of oscillatory patterns in EEGs.

After quantity $\psi(t)$ is chosen, the CWT is applied to signal $x(t)$:

$$W(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt. \qquad (1)$$

As a result, wavelet coefficients $W(a, b)$ are calculated at the fixed values of scale parameter a corresponding to an oscillation period (in the case of rhythmic dynamics) and parameter b characterizing the shift in basis function along the time axis. During scale transformations of a basis function, its norm is retained due to the multiplier before the integral sign in formula (1). Wavelet coefficients are often used together with the energy spectrum $E(a, b) = |W(a,b)|^2$, which contains no information on the oscillation phase (with the use of complex bases) but is more convenient when the amplitude characteristics of signals are compared.

As basis functions $\psi(t)$, the derivatives of the Gaussian function (WAVE, MHAT, DOG, and other wavelets) can be chosen [6, 7, 9, 10]. In particular, they were used to solve the electric activity recognition problem in neuron systems [16–19]. In the identification of EEG oscillatory patterns, it is reasonable to employ complex basis functions [8, 11, 14, 20], e.g., the Morlet wavelet:

$$\psi(t) = \pi^{-0.25}\exp\left(j2\pi f_0 t\right)\exp\left(-t^2/2\right). \qquad (2)$$

The number of oscillations of function (2) varies with parameter f_0 called the central frequency. In the frequency–time representation of rhythmic processes, it is suitable to pass from scale a to the corresponding values of frequency f [7]. In particular, in the case of function (2), the approximate equality $f \approx f_0/a$ can be used.

As is known from [8, 11–14], the SWD patterns of EEGs is conveniently identified by means of the integral instantaneous energy

$$E(b) = \int_{\Delta f} E(f,b)df \qquad (3)$$

in the frequency range $\Delta f \in [30, 50]$ Hz because the SWD is characterized by the increased energy of the corresponding range. The given amplitude criterion enabled us to identify SWD patterns to within 98–100% [12]. The more complicated situation was observed during SS recognition. As opposed to SWDs, spindles exhibited an appreciable variability in shape and frequency composition, which extremely impeded their identification and automatic recognition [11]. When the Morlet wavelet and the amplitude criterion (by analogy with SWD patterns) were used, the SSs of an EEG signal were recognized with the lower accuracy (about 60%). An additional complexity of identification consists in overlapping the frequency ranges of different EEG patterns. Hence, they cannot be separated from each other with the help of simple principles of digital filtering. Wavelet analysis also serves as a filter, and wavelet transform parameters are selected according to the optimal frequency range within which the desired pattern exhibits the maximum distinction from other EEG patterns. In [11, 13], the authors have proposed the special adaptive wavelet transform–based method whereby EEG fragments most similar to the shape of sought SS patterns were selected as basis functions. The advantage of the given method is that oscillatory patterns are recognized with a high quality, and its disadvantage is a significant amount of precalculations caused by the necessity of testing a large number of EEG fragments with SSs used as adaptive wavelets.

Another variant for improving the SS identification quality, which is discussed below, is to modify the algorithm for recognizing EEG oscillatory patterns. In this

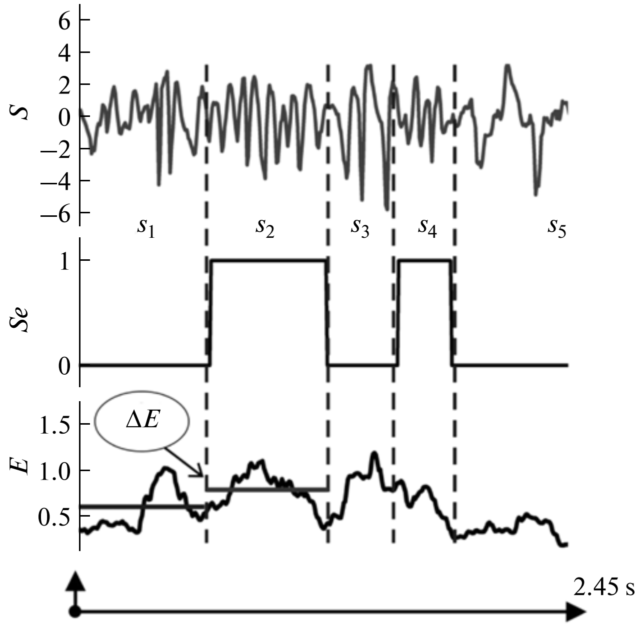

Fig. 1. Calculated values of instantaneous oscillation energy $E(t)$ in the fragment of EEG signal $S(t)$ with expert mark $Se(t)$. Regions s_2 and s_4 correspond to SS patterns and the higher instantaneous energies. Regions s_1, s_3, and s_5 designate the EEG fragments without SS patterns.

case, CWT parameters are optimally chosen to obtain specific characteristics by means of which these patterns can be distinguished from other oscillatory structures. The given approach was evolved in [14, 21]. However, the CWT and wavelet basis parameters were selected empirically without the use of numerical optimization methods. In this study, we propose the adaptive EEG pattern recognition technique based on the CWT, which formalizes the automatic recognition method and demonstrates the stricter approach to selection of the wavelet basis and CWT parameters.

Let us consider the essence of the proposed method. It is assumed that the analyzed EEG signal is function $S(t)$. SS patterns can be identified with the help of the characteristic templates thereof. They can be existing data bases containing the most typical types of rhythmic activity or patterns marked by an expert in the short (as a rule, initial) fragment of an experimental record. Let us consider the second variant and select a comparatively short fragment of initial signal $S(t)$, where characteristic oscillatory structures were marked by a neurophysiologist. Expert estimate $Se(t)$ was represented as a telegraph signal: $Se(t) = 1$ or 0 at instants when the desired patterns under examination were or were not observed in the system. Using the given estimate, we can adjust (adapt) the CWT-based recognition algorithm. Duration T of the marked fragment (the adaptation period) is determined experimentally according to the frequency at which desired patterns appear.

The given method is based on CWT (1) combined with Morlet basis function (2). With the help of expression (1), initial signal $S(t)$ is converted to the space of wavelet coefficients. Quantity $W(a, b)$ is traditionally regarded as the function of two variables (scale and shift), actually representing a surface in the 3D space. However, using the Morlet wavelet, we obtain an additional parameter, central frequency f_0, which specifies a tradeoff between resolutions in the time and spectral domains, defining the number of oscillations of the basis function. The given wavelet in formula (2) can be simplified by introducing the parameter $\omega_0 = 2\pi f_0$. Since basis function shift b defines the "focusing" point of the wavelet (the selection of a definite instant), this quantity does not affect the spectral resolution in the neighborhood of the chosen instant. Thus, to increase the EEG pattern recognition quality, two other parameters (a and ω_0) must be optimally adjusted. For this purpose, the wavelet transform results is assumed to be interpreted as three-variable function $W(a, \omega_0, b)$, two of which can be used to perform optimization. Let us introduce objective function R_1, which characterizes distinctions between the energy characteristics of desired patterns and other oscillatory structures in the marked region of the EEG, i.e., a change in the average oscillation energy (Fig. 1). In this study, function R_1 is specified as follows [22]. According to formula (3), oscillation energies E averaged over all regions with SS patterns (Fig. 1, regions s_2, s_4) and other EEG fragments without SS patterns (Fig. 1, regions s_1, s_3, s_5) are calculated in chosen frequency range Δf. Note that the given energies depend on parameter ω_0 and frequency range Δf (or parameter a that determine the center of the given frequency range). Let us designate the average energies of regions with SS patterns and EEG fragments without SS patterns as $G_1(a, \omega_0)$ and $G_2(a, \omega_0)$, respectively. The optimal set of parameters a and ω_0 enabling us to distinguish between required patterns and other EEG fragments is found by maximizing the function

$$R_1(a, \omega_0) = \frac{(G_1(a, \omega_0) - G_2(a, \omega_0))}{\max(G_1(a, \omega_0), G_2(a, \omega_0))}, \qquad (4)$$

i.e., by searching for parameters that satisfy the condition

$$\frac{\partial R_1(a, \omega_0)}{\partial a} = 0, \quad \frac{\partial R_1(a, \omega_0)}{\partial \omega_0} = 0. \qquad (5)$$

Since the value of instantaneous oscillation energy (3) can exhibit strong fluctuations within the characteristic pattern under consideration, which can lead to the erroneous interpretation of the results (in the case of fluctuations $E(t)$, two adjacent patterns can be identified instead of a single one), additional filtering of the given time dependence must be performed by means of a low-pass filter. For this purpose, filtering operator F is introduced. In this case, any of the standard approaches to digital filtering, including direct and inverse Fourier transforms, wavelet filtering, averaging over the sliding

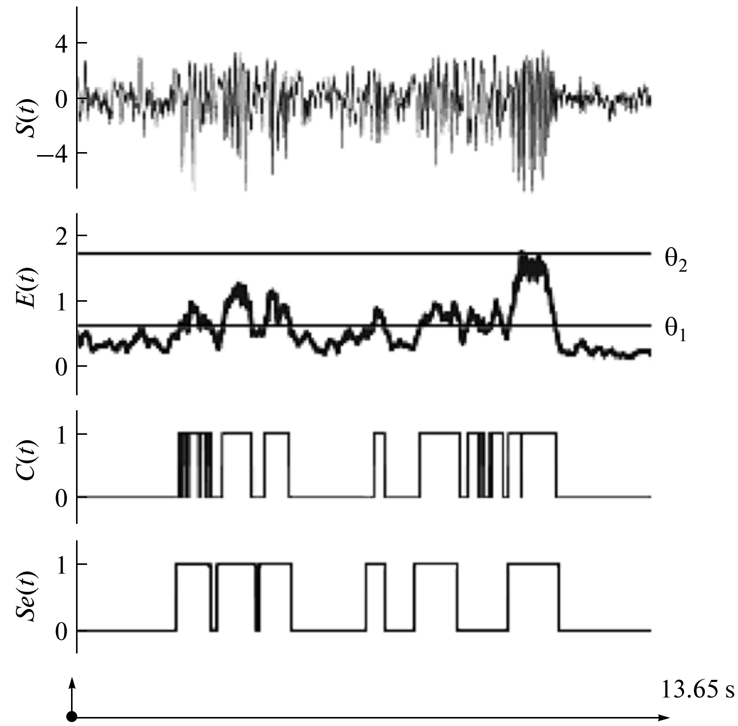

Fig. 2. EEG signal $S(t)$ fragment estimated according to the proposed adaptive method. The values of instantaneous oscillation energy $E(t)$, threshold function C, and expert estimate $Se(t)$ are presented.

time window, and so forth, can be implemented. This study deals with the last method, which is the simplest variant of function smoothing enabling the elimination of high-frequency fluctuations.

Let chosen filter F be specified by vector $\vec{\upsilon}$ of parameters that characterizes the adjustment of its spectral properties. In particular, the parameters of the moving-average method are the time window duration (averaging is carried out within this window) and the number of average values. After filtering implemented with the help of operator F, output signal $F[E(t),\vec{\upsilon}]$ is analyzed by means of threshold function C with thresholds θ_1 and θ_2. Function C serves as a comparator used to compare an input signal with the assigned thresholds. If the signal takes the value belonging to the interval $[\theta_1, \theta_2]$, the given function is equal to unity. Otherwise, its value is zero. When an expert visually mark signal $Se(t)$, he usually adheres an analogous approach (zero or unity is chosen if there is no or is the sought pattern). Hence, to compare the result of automatic marking with an expert signal in an opportune manner, objective function R_2 is commonly defined as

$$R_2 = \frac{1}{T}\int_0^T [C(F[E(t),\vec{\upsilon}],\theta_1,\theta_2) - Se(t)]\,dt. \qquad (6)$$

At the stage of adaptation, the thresholds θ_1 and θ_2 of function C are selected by minimizing objective function R_2. The given algorithm can be generalized in terms of the set of mathematical operations, which makes it possible to improve the quality of solution to the EEG oscillatory pattern identification problem. This set involves the following operations:

(i) EEG signal $S(t)$, in which the fragment of duration T is selected, is recorded to obtain expert estimate $Se(t)$.

(ii) CWT $W(a,\omega_0,b)$ is calculated, and an optimal set of parameters a and ω_0 is determined according to objective function R_1 (4). The instantaneous energy E is calculated from formula (3).

(iii) The thresholds θ_1 and θ_2 of function C are selected under the condition of minimum of objective function R_2 (6).

(iv) EEG signal $S(t)$ is marked with the help of the built-in algorithm.

2. RESULTS

The theoretical justification of the applicability of CWT-based adaptive algorithm was confirmed by investigating the 25-min record of an EEG signal containing about 200 SS patterns. To analyze the accuracy of the proposed method, the expert estimate $Se(t)$ of the entire signal was used. However, in this case, the duration of the fragment used to adjust the algorithm was approximately 15%. During an adaptation process, the algorithm was adjusted so as to identify only SS patterns. For a relatively short fragment of the analyzed EEG, an example of operation of the proposed adaptive algorithm is presented in Fig. 2.This example illustrates the main principles of the proposed method and does not correspond to the case of the minimum error of SS pattern recognition. In particular, as is seen in Fig. 2, the selection of thresholds θ_1 and θ_2 strongly affects the quality of automatic marking of an EEG signal. Threshold θ_2 makes it possible to remove large-amplitude signal fluctuations associated, e.g., with more powerful SWD patterns or various artifacts. In particular, when quantity θ_2 diminishes, two closely spaced patterns can appear instead of a single one identified by an expert (Fig. 2). Changes in threshold θ_1 also vary the number of automatically recognized patterns. As a consequence, the marking obtained by means of the algorithm under consideration will differ from the expert estimate. Calculations performed to optimize the selection of algorithm parameters enable us to diminish the number of erroneously identified patterns, thereby increasing the automatic marking accuracy.

The accuracy of detection of sought patterns also depends on the variant of objective function R_1. According to the principles of optimization theory [22], different variants of selection can be offered, e.g., with allowance for both average oscillation energies $G_1(a,\omega_0)$ and $G_2(a,\omega_0)$, and the spread of oscillation energy $E(t)$ with respect to the average level in the regions with desired SS patterns and the other fragments of an EEG signal. In our studies, four variants of function R_1 were tested. Comparison of test results enabled us to choose the variant defined by formula (4), which is relatively simple and provides a high accuracy.

Further investigations were performed with the help of the data base containing multichannel EEGs of six rats. At the very beginning, an expert marked the initial fragment of each experimental record. During processing, the accuracy of automatic recognition of SS patterns reached approximately 90%. An advantage of the proposed adaptive method is that an EEG is automatically marked without the influence of human factors, e.g., an expert experience needed to select CWT parameters. The difference between the results of the given approach and expert estimates is about 10%. This can be related to the fact that the given signal contains several oscillatory patterns with almost identical shapes (SSs, five- and nine-Hz oscillations, and SWDs), which can be erroneously interpreted by means of the algorithm, impeding estimation of functions C at the stage of algorithm adjustment (adaptation) and during its application to unestimated EEG regions. Moreover, the quality of expert estimates depends on the human factor: an expert can make mistakes when an EEG record is analyzed. Hence, expert estimate $Se(t)$ cannot be considered an absolute standard.

The advantage of the developed adaptive method is that the algorithm adjustment enables us to obtain the definite accuracies of identification. As was demonstrated with the help of the numerical experiment, these accuracies remain almost unchanged at the stage of analysis of an unestimated EEG region. In particular, this circumstance can be employed to simplify an empirical search for adaptation period T.

CONCLUSIONS

The proposed adaptive method for identifying oscillatory patterns is capable of eliminating the main drawback of approaches based on the wavelet transform, namely, the problem of empirical selection of parameters affecting the solution quality. It is this problem that restricts the efficiency of the wavelet methods for sorting neural spikes in the automatic mode [16–19] because parameters (and respective wavelet coefficients) selected from general recommendations [23] often make it impossible to achieve an acceptable accuracy of recognition of similar oscillatory structures in the analyzed signal. In the proposed approach, wavelet transform parameters are adjusted using the optimization theory. As a result, the desired oscillatory patterns in electroencephalogram signals are recognized with minimum errors. The error arising when sleep spindle patterns of EEGs are determined is four times lower in the performed investigations than in previous studies based on the empirically chosen continuous wavelet transform parameters. Although the given method has been developed to perform automatic processing of EEG records, the field of its potential applications is rather wide because the algorithm can be used to solve various problems of image recognition with the help of wavelet analysis tools, including the problems of radio physics, radar, and so forth.

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