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Development of an algorithm for detecting slow peak-wave activity in non-convulsive forms of epilepsy*

A. S. Belokopytov[1✉], *M. M. Makarova*[1], *M. I. Salamatin*[1], *O. M. Redkozubova*[2]

[1]National Research University Higher School of Economics, Moscow, Russia
[2]National Research University of Electronic Technology, Moscow, Russia
E-mail: ✉a.belokopytov@neurobotics.ru, m.makarova@hse.ru, mihail.salamatin@gmail.com, redkozubova@gmail.com

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Abstract. The *purpose* of this study is to develop a classifier capable of detecting typical absence seizures in real-time using electroencephalogram (EEG) data and a Support Vector Machine (SVM) model. *Methods.* Sections of the EEG, previously identified by a specialist as containing typical absences, were used to train the SVM model. Key features for classification include the number of zero crossings, cross-correlation between two consecutive windows, spectral power across various frequency bands, and the standard deviation of instantaneous signal power. *Results.* Training and testing datasets were established, consisting of EEG windows with various types of artifacts. The SVM model was successfully trained and tested, achieving high performance metrics. The developed algorithm can be integrated into a mobile application and used in conjunction with a wearable EEG device with dry electrodes for real-time detection of typical absences. *Conclusion.* The study results affirm the potential for using machine learning techniques for the automatic detection and logging of epileptic activity. However, additional testing on a larger dataset is needed for more conclusive results, including data acquired through a wireless EEG device using dry electrodes. Future work will involve selecting a suitable EEG device and developing a mobile application for real-time data collection and analysis.

Keywords: absence epilepsy, support vector machine, dynamic classifier, electroencephalography, real-time detection, machine learning.

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Introduction

Problems of seizure detection. Slow spike-wave activity in non-convulsive forms of epilepsy is attributed to the EEG picture of one of the types of epileptic seizures (absences). Absence is a type of generalized epileptic seizure (fit), characterized by a sudden short-term

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(seconds to tens of seconds) loss of consciousness, blockade of motor activity and amnesia. They are most often observed in childhood (however, there is evidence of seizures occurring at a later age [1]) and are associated with specific electroencephalographic (EEG) patterns [2], including bilateral, frontal-dominated spike-wave discharges with a frequency of 3–4 Hz. Studies in both humans and animals suggest that these seizures are caused by oscillations in the corticothalamic network [3, 4].

When prescribing antiepileptic therapy, neurologists rely on the seizure diary that patients keep themselves. Based on these reports, conclusions are made about further treatment. However, as practice shows, self-monitoring by patients is unreliable. According to [5], they notice less than 50% of seizures, and according to a study [6], 26% of epilepsy patients note that they never noticed seizures during the day, 47% claim to have noticed less than half of the seizures that occurred. At the same time, 64% of patients have never noticed night seizures and 79% believe that they have missed most of the night seizures.

The study [7] found that self-reports were inaccurate in more than two-thirds of patients suffering from absence seizures. It was found that 37.5% of seizure reports were significantly overreported, while 29.2% were significantly underreported.

The study authors also noted that patients are instructed to record any seizure-like symptoms in a diary. This leads to false reports and patients being overtreated in cases where antiepileptic therapy is needed in lesser amounts or not at all.

Comparison of patients' reports with real EEG recordings confirmed the unreliability of self-monitoring by epilepsy patients. In a study involving 552 people, long EEG recording sessions were conducted. At the same time, patients had to note any manifestations of epilepsy in a diary, indicating the time of the seizure. As a result, out of 47 cases of focal seizures, the participants noticed only 29 (61.7

In the article [9] the authors found the following pattern: in some cases, tonic-clonic seizures were preceded by spike-wave activity. Therefore, sometimes absence epilepsy can act as a predictor of generalized seizures, which only emphasizes the relevance of developing a device for detecting spike-wave activity.

Patients who cannot reliably document the number of seizures are at risk. Among the possible negative consequences of absences in humans are the following: decreased academic performance at school [10], increased risk of accidents for oneself and others [11], increased incidence of anxiety-depressive disorders [12], attention deficit disorder [13], neurodegenerative processes in the brain [2], as well as the risk of transition of absence epilepsy to other convulsive forms [14, 15].

Thus, there is a need for an objective assessment of seizure frequency. However, the use of video recording of the patient in parallel with EEG recording (the gold standard for seizure detection) requires large resources that not every hospital has [7]. The option of recording video-EEG in an outpatient setting is not yet available to all those in need. In addition, this approach leads to the accumulation of huge arrays of visual data, the analysis of which takes a lot of time [14]. This could be avoided by using wearable devices for automatic detection of absences.

The authors of the study [16] conducted a survey among patients (a total of 92 people were surveyed) suffering from epilepsy, their relatives, and treating physicians. The results showed that interest in the detection device correlates with anxiety about undetected seizures. Interest and anxiety were assessed on a scale from 1 to 7, where a lower value means less interest and anxiety (Spearman correlation coefficient $r = 0.489$, significance coefficient $p < 0.001$). This means that there is a moderate statistically significant correlation between the level of anxiety about undetected seizures and interest in using a seizure detection device.

The use of a wearable device for automatic detection of absences could solve the above-mentioned problems. Such devices do not require the use of gel, they are comfortable and easy to use. Special software would significantly simplify and speed up the work of a neurologist, and its use together with a device that could be used as a Holter would simplify the task of assessing the effectiveness of the treatment, and it would be based on objective data. With the help of a hardware and software complex, it would also be possible to warn the patient, his relatives or others about the high probability of an absence seizure at a particular point in time. Such diagnostic methods would allow collecting more data and conducting their online analysis, eliminating the need for constant visits to the clinic. The implementation of this idea would open up new opportunities for studying epilepsy in natural conditions (outside the laboratory), allowing us to analyze the causes (triggers) of seizures.

The creation of a device and software designed to record absence seizures could replace the practice of keeping diaries. In addition, the hardware and software complex could potentially perform the following functions:

- call for help (warning others, relatives, doctors about a seizure),
- warning about the need to take medications,
- activation of an antiepileptic stimulating device,
- recording an EEG for further consultation with a specialist.

The issue of detecting spike-wave activity has been raised for several years. Research groups have put forward their own solutions to the problem of detecting absence patterns. Russian research groups tested detection systems on WAG/Rij rats using intracranial electrodes [17]. After it was shown that the sensitivity and accuracy of the developed algorithms were high enough, a smooth transition to recording EEG of epilepsy patients was started. The initial detection algorithm was quite simple: a convolution of the mother wavelet (usually Morlet) with the EEG signal was performed, and if the signal energy in a certain range was high enough relative to other frequencies, then the algorithm recognized the studied segment as "spike-wave activity". The work was carried out very consistently, as a result of which a special mathematical apparatus was developed that takes into account the features of various oscillatory patterns on the EEG [17–21]. The question for further research with this approach remained the selection of the best parameters of the EEG window under study and the parameters of the wavelet transform and evaluation (EEG window width, detection delay time, threshold value of the frequency band energy, etc.). Moreover, the gradual development of the theoretical base made it possible to approach the issue of predicting spike-wave activity in the EEG, as well as complicating the analysis of the EEG by adding new methods, for example, the empirical mode method [22, 23].

In the field of seizure detection, there is a significant diversity of methodologies developed by researchers from different countries. For example, these developments included neural networks using the backpropagation method [24]; analysis of signal velocity changes over short intervals using the first derivative [25]; convolution of a mother wavelet (mostly Morlet type) with the EEG signal [18, 26]; application of a model based on radial basis functions [27]; and a deep learning approach [28]. The latter involved line length feature analysis based on multi-bit wavelet transform decomposition, combined with an artificial neural network to classify EEG signals as to the presence or absence of a seizure.

In [29], wavelet transform was also applied to EEG analysis with an emphasis on line length analysis. However, this approach was successfully integrated with artificial neural networks. Of particular note is a computationally efficient algorithm for real-time absence seizure detection in wearable EEG hardware [30], where special attention was paid to creating an algorithm optimized for execution on microcontrollers with minimal memory and computational power. A dataset of eight patients with juvenile absence epilepsy was used to test the effectiveness of the method. The results showed high efficiency of the new method with relatively low computational costs.

The development of a hardware and software complex designed for detection and visualization of slow spike-wave activity is a pressing task, the implementation of which could find wide application among people suffering from epilepsy. However, the project requires the development of a classifier, which is discussed in more detail later in the article.

Spike-wave activity in absence epilepsy. Absence epilepsy is manifested on the EEG in the form of absences (Fig. 1) — spike-waves [2, 31, 32].

Absences can be classified by their manifestation in electroencephalography recording as typical and atypical absence. The change in potential difference in typical absence has the following character: generalization, synchronicity, symmetry, the form of oscillations — spike-waves with a frequency of about 3 Hz. Atypical absence can be characterized as follows: less pronounced synchronicity and symmetry, the form of oscillations — spike-waves with a frequency of more or less than 3 Hz. Thus, absence epilepsy has a pathognomonic electroencephalographic correlate [33] (for typical absences, which are more common), which allows diagnosing the disease according to the analysis of the EEG recording.

The spike-wave complex consists of a sharp jump (peak) and a subsequent slow wave. The spike and wave correlate in amplitude, which stands out sharply against the background of the rest of the EEG.

The amplitude of the potential difference during a seizure varies from electrode to electrode and at different points varies from white noise values of ±15 μV to ±600 μV [34].

Numerous methods for automatic spike-wave detection are presented in the scientific literature, but only two products are available on the market: Sensor Dot [35] and Epyhunter [36]. Sensor Dot uses the support vector machine. Epyhunter is based on the principles of neural learning. The detection model used in both systems is built according to the following algorithm.

1. Neurologists analyze the EEG and identify areas of spike-wave activity.
2. The properties of the EEG time windows marked by specialists with a duration of 0.4 seconds (the maximum period of a typical absence) are assessed with a shift of 0.2 seconds. At this stage, the process of machine learning or neural network training takes place.
3. The trained models are then used to subsequently detect spike-wave activity.

1. Methodology

The aim of this paper is to develop a mechanism for identifying a typical absence. This is a specific mathematical problem. First, it is necessary to identify and highlight the key characteristics of an absence.

1. Number of zero crossings.

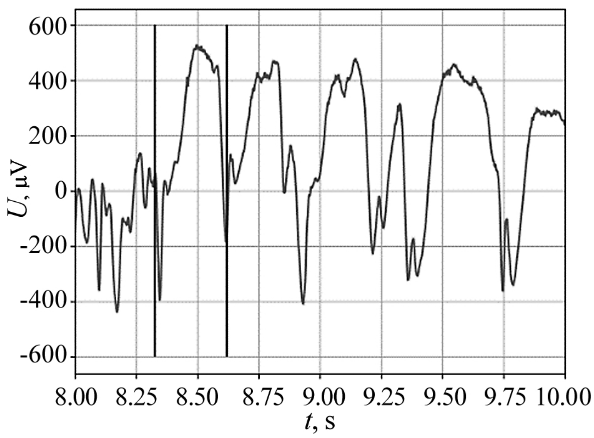

Fig 1. Spike-wave activity (absence) in a patient with tonic-clonic seizures (spike-wave complex marked by vertical lines)

2. Cross-correlation between two consecutive 0.4 s windows.
3. Spectral power 32...64 Hz.
4. Spectral power 16...32 Hz.
5. Spectral power 8...16 Hz.
6. Spectral power 2...4 Hz.
7. Standard deviation of instantaneous signal power.

Then, based on this data, machine learning must be applied to create a classifier using the support vector machine.

The most proven simple and effective methods for determining the spectral power are the windowed Fourier transform (WFT) and the continuous wavelet transform (CWT). However, the WFT has a drawback in the form of spectral leakage and the following uncertainty: the narrower the window, the better the time resolution and worse the frequency resolution; the wider the window, the better the frequency resolution and worse the time resolution [37]. Thus, it is more convenient to use the CWT, since it allows you to keep the frequency resolution constant over the entire spectrum and avoids the phenomenon of spectral leakage.

The procedure of continuous CWT is similar to the WFT. First, we select the analyzing function (mother wavelet) $\psi(t)$ and perform a convolution of its wavelet family with our signal. According to the works [17, 20, 28], the Morlet wavelet is suitable as a mother wavelet

$$\psi(t) = e^{-\frac{t^2}{2}} \cos(2\pi f_{\max} t), \tag{1}$$

where $f_{\max}$ — initial (maximum) analyzed frequency from the range of frequencies of interest to us, t — time. The family of wavelets is obtained by the formula

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

where a — scale factor, τ — wavelet shift coefficient along the time axis. The scale factor is related to the analyzed frequency f by the following formula:

$$f = \frac{f_{\max}}{a}, \quad a = \frac{f_{\max}}{f}, \tag{3}$$

where f — the analyzed frequency (studied during convolution according to formula (4))

$$W(a,\tau) = \frac{1}{\sqrt{a}} \int\limits_{T_1}^{T_2} Q(t)\psi^*\left(\frac{t-\tau}{a}\right) dt, \tag{4}$$

where $1/\sqrt{a}$ is a multiplier that ensures the independence of the function norm from the scaling number a. Taking into account formula (3), we obtain a frequency-time representation of the obtained values of the signal convolution

$$W(f,\tau) = \sqrt{\frac{f}{f_{\max}}} \int\limits_{T_1}^{T_2} Q(t)\psi^*\left(f\frac{t-\tau}{f_{\max}}\right) dt, \tag{5}$$

where ψ^* — complex conjugate wavelet ψ. Convolution is a measure of similarity between the original signal $Q(t)$ and the wavelet ψ^* at time τ. The greater the value of $W(f,\tau)$ in absolute value, the greater the prevalence of the frequency component f at that moment.

After converting the signal into a frequency-time representation $W(f, \tau)$ we calculate the instantaneous energy values $\omega(\tau)$ for the frequency range under study $[F_1, F_2]$

$$\omega(\tau) = \int_{F_1}^{F_2} |W(f, \tau)|\, df. \tag{6}$$

In formula (6), the modulus is taken so that later, when calculating the average power using formula (7), a situation of "zeroing" of values does not arise, but the entire energy of the signal at a point is calculated regardless of the sign of the instantaneous power.

Since EEG is a complex signal, in which individual bursts of activity in different frequency ranges may appear, a sharp short-term increase in instantaneous energy (convolution value) may occur, and this will lead to an incorrect interpretation of the signal. Thus, it would be more convenient to take for analysis the values averaged over the time interval T_{int} (on a window equal to one period of spike-waves). This will smooth out the energy values at each point, reducing the influence of short-term energy bursts

$$\omega(\tau) = \langle \omega(\tau) \rangle = \frac{1}{T} \int_{T} \omega(\tau)\, dt. \tag{7}$$

To estimate the variability of the instantaneous signal power, we calculate its standard deviation sd on the window of incoming values $\omega(\tau)$ (the window is equal to one period of the studied spike-waves). However, we will slightly modify formula (6) for calculating sd, removing the module

$$\omega_{sd}(\tau) = \int_{F_1}^{F_2} W(f, \tau)\, df, \tag{8}$$

$$\text{sd} = \sqrt{D[\omega_{sd}]}, \tag{9}$$

where $D[\omega_s d]$ — dispersion of instantaneous power values.

In the process of developing the detection algorithm, we used formulas (1)–(7) to calculate the spectral power values of various frequency components of the signal using the continuous wavelet transform (CWT), where the instantaneous power values were averaged over a time interval equal to one period of spike-wave activity. Formulas (1)–(5) and formulas (8) and (9) were used to determine the root-mean-square deviation of the instantaneous power. The cross-correlation between two consecutive signal windows was calculated using the Pearson coefficient. To determine the number of zero crossings inside the EEG window under study, we counted the number of sign changes of the values inside the window.

2. Results

The purpose of this section is to analyze the performance of the detection algorithm. The main statistical characteristics that were taken for evaluation are: specificity SPE, sensitivity SEN and accuracy ACC.

$$SPE = \frac{TN}{TN + FP}, \tag{10}$$

$$SEN = \frac{TP}{TP + FN}, \tag{11}$$

$$ACC = \frac{TP + TN}{TP + FP + TN + FN}. \tag{12}$$

Table 1. The effectiveness of the support vector machines (N — is the number of analyzed records of 5–10 seconds in size)

pattern	N	TP	TN	FP	FN	ACC	SEN	SPE
relaxed state	30	-	30	0	-	-	-	1
blinking	30	-	30	0	-	-	-	1
chewing movements	30	-	30	0	-	-	-	1
head movements (nodding)	30	-	20	10	-	-	-	0.67
facial muscle tension	30	-	30	0	-	-	-	1
squatting	30	-	30	0	-	-	-	1
walking around the room	30	-	30	0	-	-	-	1
spike-wave activity	30	30	-	-	0	-	1	-
final results	420	178	186	24	32	0.94	0.94	0.96

Here TP denotes true positives, TN denotes true negatives, FP denotes false positives, and FN denotes false negatives.

The algorithm was tested on EEG recordings provided by the authors of the studies [39,40]. These authors also provided data on the time intervals with recorded spike-wave activity in the participants.

The algorithm was implemented in Python using the PyCharm development environment. The Python MNE library was used to process EEG files in the .edf format. Before analysis, the data were filtered with a frequency range of 1 to 64 Hz.

EEG records contain various patterns reflecting various external influences. Therefore, it was decided to conduct testing on data containing various artifacts. A list of high-amplitude EEG patterns was formed: relaxed state (sitting), blinking, chewing movements, head movements (nodding), facial muscle tension, squatting, walking around the room, spike-wave activity.

To create a training set, EEG records with various artifacts were used, obtained using a wireless electroencephalograph NeuroPlay-6C [41]. This device with amplifiers allows obtaining high-quality records comparable to those made in clinical conditions.

Table 1 presents the results of classification of various EEG patterns. For some patterns, there are missing values in certain columns. This is due to the specificity of these patterns and the peculiarity of the analysis performed.

For example, for the patterns "blinkin", "relaxed stat", "chewing movements" the main emphasis was on identifying false positives. These patterns serve as controls and should not be interpreted as spike-wave activity under ideal conditions. Therefore, for such patterns the key indicators are true negatives TN and false positives FP. It is because of this that the indicators of true positives TP and false negatives FN are meaningless and are absent from the table.

For the pattern "spike-wave activity" the main thing is to determine the sensitivity (SEN) of the system. Here, the main focus is on the correct recognition of this abnormal activity. Therefore, for this pattern, the values TP and FN are of greatest interest.

Thus, the missing values in the table are not an error or omission, but are due to the research methodology and the specific features of the analyzed patterns.

We analyzed 30 3-second most significant EEG patterns to assess specificity and 30 5-10 second segments of spike-wave activity to determine the sensitivity of the algorithm.

The largest number of false positives were registered with head nodding. A possible solution to this problem could be to install an accelerometer and a gyroscope in the amplifier, which would register sudden movements. In this case, it would be possible to modify the algorithm so that it would discard all intervals in which certain movements (for example, nodding) were registered.

Best parameters for support vector model. During the hyperparameter tuning for the support vector model, various parameter combinations were explored. The best results, presented in Table 2, were achieved using the following parameters.

Table 2. Optimal parameters for the support vector machines

Parameter	Meaning
Kernel type	Radial-basic (RBF)
Regularization coefficient C	1.0
Parameter "gamma"	0.01
Degree for polynomial kernel	3 (was not used for RBF)

The choice of the radial basis kernel is explained by its ability to handle complex spatial transformations. This can be especially useful for analyzing EEG data, where different patterns can be quite complex and nonlinear. A regularization coefficient C of 1.0 provides an optimal balance between maximizing separation between classes and preventing overfitting. A small value of "gamma" (a factor that determines the degree of influence of a single training example) allows the model to capture complex but global patterns in the data, which also helps improve performance.

Cross-validation. To evaluate the performance and robustness of the model, k-fold cross-validation was used with $k = 5$. This means that the original data was divided into 5 equal blocks and the model was trained and tested 5 times. Each time, a different block was used as the test dataset and the remaining blocks as the training set. Cross-validation allowed us to estimate how well the model would perform on new, previously unseen data.

30 records for each EEG pattern may seem like a small data set. However, for this task, this data size turned out to be optimal. Our experiments showed that increasing the sample size only slightly improves the quality of the model. This is probably due to the fact that the signal characteristics for different patterns are quite stable and distinguishable even with a small amount of data. Given time and resource constraints, the current sample size represents a reasonable compromise between the need for a large amount of data and the ability to conduct a high-quality study.

Conclusion

The evaluation of the effectiveness showed the potential of using the machine learning model for further development of the idea of creating a system for automatic detection and recording of various types of epileptic activity. However, the model needs to be tested on a larger volume of data. And since the ultimate goal is to use the algorithm together with a wireless electroencephalograph on dry electrodes, the training data must be recorded on it. Therefore, the next task will be to select such a device and create an Android application designed to collect and analyze EEG in real time.

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