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THE APPLICATION OF SPECTRAL ANALYSIS OF EEG DATA FOR THE IDENTIFICATION OF OPEN AND CLOSED EYE STATES

Annotation. The article examines the analysis of electroencephalogram (EEG) data for the classification of open and closed eye states using the Fast Fourier Transform (FFT). It is shown that this method demonstrates stable recognition accuracy at the level of 70-80% in distinguishing between open- and closed-eye states, demonstrating its effectiveness in classifying biomedical signals. General information about EEG is described, points for their reading, in particular about the "10-10 system", information about the main types of brain rhythms is given. Modern methods for analyzing EEG data were also reviewed, highlighting three main approaches: spectral analysis, recurrence analysis, and machine learning methods. Software was developed for classification of information presented in the form of EEG time series obtained in the state of open and closed eyes. The software was developed in Python utilizing the PyRQA library.
Key words: spectral analysis, electroencephalography, time series, Fast Fourier Transform, brain rhythms, frequency artifacts, PyRQA.

Introduction and purpose. The analysis of electroencephalographic (EEG) signals is one of the leading methods of researching brain activity. Among the current tasks in this field is the classification of states of consciousness, in particular, the recognition of the states of open and closed eyes, which is important for understanding cognitive processes. Identifying distinct differences in brain activity during these states enables a deeper investigation into the dynamics of brain rhythms and their relationship to cognitive functions such as perception, concentration, and relaxation.

Today, several basic approaches are used to analyze EEG signals, including spectral analysis, recurrent analysis, and machine learning methods. Spectral analysis, in particular the Fast Fourier Transform (FFT), allows us to distinguish the main rhythms of the brain, such as alpha, beta and theta rhythms, which are associated with different states of consciousness. Recurrent analysis provides a deeper exploration of the nonlinear and chaotic characteristics of EEG signals, while machine learning techniques open up possibilities for building accurate classification models based on large data sets. In this study, spectral analysis was chosen as one of the most effective and affordable approaches for recognizing eye conditions.

The purpose of the article is, firstly, to review approaches to the analysis of EEG signals and to justify the choice of spectral analysis for further classification of open and closed eyes. The frequency characteristics of the signals, in particular the activity of the alpha rhythm, which increases when the eyes are closed, are estimated on the basis of the FFT. Additionally, noise and artifacts are filtered to ensure signal purity. The study was performed on data from the “EEG Motor Movement/Imagery Dataset”, which includes 109 participants and allows obtaining statistically significant results for further application in neuroscience and cognitive research.

Reference Analysis. The article by Farzad et al. (2023) [1] is a systematic review investigating the presence of chaos in electroencephalogram (EEG) signals associated with human activity. The authors emphasize the importance of chaos theory for understanding the complex dynamics of brain activity and analyze the various methods used to study these phenomena. The review presents the results of many studies focusing on cognitive functions, and also found that the most common methods of chaos analysis are correlation dimension, fractal analysis and various entropy algorithms. The authors conclude that further study of the chaotic dynamics of the brain can improve our understanding of cognitive activity and contribute to the development of neuroscience.

The article by Wang et al. (2010) [2] investigates the relationship between the chaotic characteristics of EEG signals and high-level intellectual brain activity. Using phase space reconstruction to analyze one-dimensional and multidimensional time series, the authors study EEG signals during five types of conscious activity: relaxation, verbal multiplication, writing a letter, visualization of an object in three-dimensional space, and number representation. The results of the analysis of chaotic characteristics, including determinism, phase graphs and power spectra, indicate the presence of chaos in consciousness.

Statistical data confirm that the central tendencies are similar to the phase graphs, and the spectra indicate small differences between the frequency channels of conscious activities. Differences in the approximated entropy indicate a higher level of innovativeness among the subjects. The correlation dimension and the Lyapunov exponent indicate brain activity in attractors with fractional dimensions. A non-linear quantitative criterion using neural networks shows positive results in the classification of different types of activity, with arithmetic-related tasks standing out more clearly compared to other types of activity.

A paper by Gallego-Rudolf et al. (2022) [3] investigates the effect of ballistocardiography artifact (BCG) on EEG spectral characteristics during functional magnetic resonance (MR) scanning (fMRI). The authors evaluate the effectiveness of seven BCG correction methods to preserve the spectral properties of the EEG and examine the reactivity of the posterior alpha band during the eye-closing-opening (EC-EO) task.

The study included EEG recordings from 20 healthy young adults outside the MR environment and during fMRI data acquisition. The average artifact subtraction (AAS) method was found to be effective in removing the gradient artifact, while BCG correction was performed using AAS, independent component analysis (ICA), and their combinations. The authors compare the spectral power of traditional frequency bands with corrected EEG-fMRI data and off-scanner recordings.

They found that the BCG artifact significantly distorts the data in all frequency ranges, with residual artifacts remaining even after all correction methods. The results showed that

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EEG reactivity to the EC-EO task is better preserved with ICA-based correction methods, especially when extracting alpha power fluctuations. The authors emphasize that current solutions to eliminate BCG artifacts have limited effectiveness, recommending the improvement of existing approaches and combining them with hardware solutions to improve the quality of the EEG signal during simultaneous recording.

The article by Makeig et al. (1996) [4] is devoted to the application of the independent component analysis (ICA) algorithm for source separation of electroencephalographic (EEG) data. Due to the distance between the skull and the brain and the different electrical conductivity, EEG data collected from the surface of the head contains activity generated in a large area of the brain, resulting in spatial blurring. However, it is not accompanied by significant time delays, making ICA appropriate for blind source separation in EEG data.

The authors demonstrate that ICA separates source identification from source localization. Early results show that ICA training is independent of random initial values and can be used to segregate artifactual components such as electromagnetic noise and eye movements. In addition, ICA is able to isolate superimposed EEG phenomena, including alpha and theta bursts.

Instabilities in EEG and behavioral state can be monitored with ICA through changes in residual correlation between output channels. The paper highlights the posibilities of ICA to improve EEG analysis and understanding of brain processes related to perception and attention.

An article by Noor et al. (2022) [5] discusses the importance of electroencephalography (EEG) data analysis and processing in brain activity studies. The researchers emphasize that there are many standard procedures for obtaining informative results in EEG analysis, but the methods used in these procedures can vary significantly depending on the preferences of the researchers and the specifics of the experiments.

One of the main challenges is that traditional manual analysis methods are resource-intensive, and researchers often focus only on the small subset of brain signals that are most relevant to the study. In response to these challenges, the authors propose an automated method for classifying eight different EEG bands (very low, delta, theta, alpha-1, alpha-2, beta-1, beta-2, and gamma) by crossing the FFT with three by machine learning methods: KNN, SVM and ANN.

Research results show that the FFT+SVM method achieves an impressive 100% accuracy, successfully classifying signals into all eight EEG bands. This approach not only improves the efficiency of EEG analysis, but also opens up new possibilities for automating data processing in neuroscience, which can greatly simplify the work of researchers in this field.

Spectral characteristics of time series. Spectral analysis is a method that facilitates the investigation of signal frequency components, particularly in the context of EEG. FFT is one of the main tools of spectral analysis, which allows you to move from the time domain to the frequency domain. This transformation helps reveal the brain’s rhythms, which are essential for understanding neural functionality and states.

FFT [6] allows you to efficiently calculate the discrete Fourier transform (DFT), which is defined by the following formula:

$$X_k = \sum_{n=0}^{N-1} x_n \, e^{-i\frac{2\pi}{N}kn}, \quad k = 0,1, \dots, \frac{N}{2},$$

where:

• X_k is the complex frequency for the k-th component,

• x_n is an input signal in the time domain with N discrete points,

• N is the number of points in the analyzed signal.

FFT implements an algorithm that reduces the computational complexity of DFT from $O(N^2)$ to $O(N\log N)$, making it particularly useful for processing large data sets such as EEG signals. When using FFT to analyze EEG signals, a frequency spectrum is obtained that shows which rhythms dominate brain activity at the time of recording. From the obtained spectrum, you can calculate:

- **Signal strength** in each frequency band, which helps to identify dominant rhythms.
- **Power spectral density**, which allows you to determine how much energy is in each frequency, which is important for analyzing changes in brain activity in different states.

The relationship between the index k and the frequency in Hz following the discrete Fourier transform is governed by the sampling frequency f_s and the number of points N in the signal:

$$f_k = \frac{k \cdot f_s}{N},$$

where f_k is the frequency in Hz corresponding to the index k, f_s is the sampling frequency in Hz. Thus, each index k in the spectrum corresponds to the frequency f_k, which increases linearly from 0 to $f_s/2$ Hz.

EEG signals reflect the brain's electrical activity, which consists of different frequency components, forming brain rhythms classified based on their frequency ranges. In particular, **delta rhythms (0.5–4 Hz)** are observed during deep sleep and indicate the body's restoration and regeneration; **theta rhythms (4–8 Hz)** are associated with light sleep, meditation and creative states; **alpha rhythms (8–12 Hz)** occur during quiet activity and are often associated with relaxation and rest; **beta rhythms (12–30 Hz)** are observed during active thinking, attention, and mental effort. And **gamma rhythms (greater than 30 Hz)** are associated with cognitive functions such as attention, memory and awareness.

However, when analyzing EEG signals, it is important to take into account not only brain rhythms, but also various factors that can distort them. Among such factors is frequency artifacts, which means the presence of unwanted frequency components or random frequency changes in the signal. frequency artifacts can come from a variety of sources and significantly affect signal quality and data analysis accuracy.

Among the main sources of frequency artifacts can be distinguished:

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1. **Electromagnetic interference**. Electronic devices, wires or other electrical devices can emit electromagnetic fields that enter the signal reading system and change its frequency characteristics.

2. **Artifacts from muscles and movements**. Muscle movements or physical activity can create noise in the measured signal, especially if the probe is sensitive to mechanical vibrations or movements.

3. **Electrical network**. frequency artifacts can originate from the electrical network, especially from interference at frequencies of 50 or 60 Hz used in various countries to power electrical devices.

In this article, it is worth considering alpha rhythms in more detail, since the state of open and closed eyes refers to the calm activity that is inherent in the alpha rhythms of the brain.

The influence of the condition of the eyes on the activity of alpha rhythms in the brain is an important aspect for understanding the psychophysiological processes of a person. With closed eyes, the brain generally shifts towards a relaxed state. In this state, the alpha rhythm becomes more noticeable, in particular in the region of the back of the brain. It promotes deep relaxation and improves the ability to concentrate. Conversely, with the eyes open, the brain is active and focused on processing visual information and interacting with the environment. In this case, alpha rhythms usually decrease or may disappear, as the brain is busy performing various tasks and perceiving external stimuli. This contrast between states with individual eyes helps in understanding how the human brain reacts to different conditions and affects our perception and psychophysiological state.

Features of alpha waves:

1. **Frequency and location**. Alpha waves are most often found in the back of the brain (occipital region), although they can be present in other parts of the brain as well.

2. **Psychophysiological conditions**. Alpha waves become more prominent during rest and mindless contemplation, with the eyes closed, and during mild relaxation without active mental or physical activity.

3. **Association with relaxation**. A high amplitude of alpha rhythms in the back of the brain may indicate a state of relaxation. This may be useful for research into stress, anxiety, and sleep disorders, as changes in alpha activity may reflect changes in a person's psychophysiological state.

Points for reading EEG. EEG uses special points to place electrodes on the surface of the scalp, which enables precise measurements of cerebral electrical activity. These points are determined according to the international system of electrode placement, which is known as the "10-10" system.

A continuation of this approach is the "10-10" system (fig. 1), which is the standard for placing electrodes in EEG studies. This system got its name from the percentage distances between the electrodes, which are measured as a percentage of the size of the head. It ensures standardized and reproducible electrode positioning, which is critical for comparing results between different studies and patients.

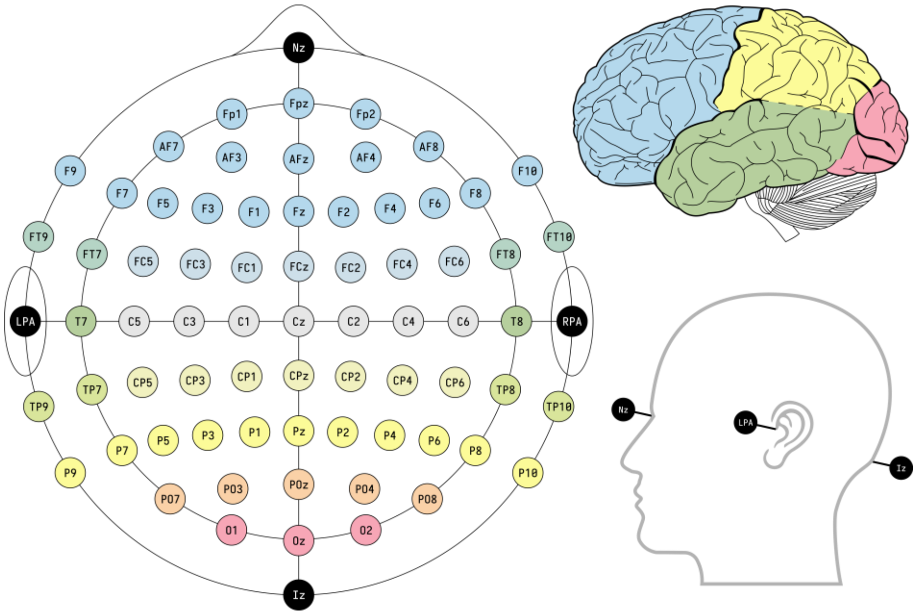

Figure 1 - “10-10” system

Within the framework of the “10-10” system, there are several main points on which electrodes are placed for reading EEG signals. These points include:

1. **Fp (frontal polar)**:
   – Fp1: frontal polar point on the left.
   – Fp2: frontal polar point on the right.
2. **F (frontal)**:
   – F3, F4: left and right frontal points.
   – F7, F8: lower forehead points left and right.
   – Fz: middle frontal point.
3. **C (central)**:
   – C3, C4: left and right center points.
   – Cz: middle center point.
4. **P (parietal)**:
   – P3, P4: parietal points on the left and right.
   – Pz: middle parietal point.
5. **O (occipital)**:
   – O1, O2: occipital points on the left and right.
6. **T (temporal)**:
   – T3, T4: left and right temporal points.
   – T5, T6: lower temporal points on the left and right.
7. **A (auricular)**:
   – A1, A2: points on the left and right ears, often used as reference electrodes.
8. **Nasion**: Point on bridge of nose.
9. **Inion**: A point on the back of the head, where the occipital bone protrudes.

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These points play an important role in ensuring the accuracy and reliability of the obtained data, which is critical for successful analysis of the electrical activity of the brain.

Investigation of the state of human eyes according to known spectral characteristics. When analyzing the frequency spectrum, we face the problem of discretization of frequencies, which affects the accuracy of determining frequency ranges. Because of this, the frequencies cannot be analyzed in a continuous physical sense, as the frequency limits change depending on the chosen sampling step. Since our task is to select certain frequency ranges and eliminate noise at other frequencies, it is necessary to apply filters with increased accuracy of limiting frequency components. For this, during the research, the Hann window function [7] was chosen for a limitation of frequency ranges, which avoids sharp transitions and provides a smoother smoothing of the spectrum.

Let's build from the well-known Hann window function, which looks like this:

$$w[n] = 0.5\left[1-\cos\left(\frac{2\pi n}{N}\right)\right] = \sin^2\left(\frac{\pi n}{N}\right), \quad 0 \le n \le N,$$

modified function $w(n,\Delta f)$, which will smooth the required range $[0,\Delta f]$:

$$w(f) = 0.5\cdot\left[1-\cos\left(\frac{2\pi f}{2\Delta f}\right)\right].$$

Let's build functions for the low-frequency H_{low} and high-frequency filters H_{high} that will allow us to process the signal within the specified range of the frequencies f_{low} Hz and f_{high} Hz. For this, we use gradual sinusoidal frequency limiting, which allows to reduce the impact of artifacts arising from sharp transitions in the frequency spectrum.

$$H_{low}(f_k, f_{low}) = \begin{cases} 0, & f_k < f_{low} - \Delta f \\ w(f_k - f_{low} + \Delta f), & f_{low} - \Delta f < f_k < f_{low} \\ 1, & f_{low} < f_k \end{cases}$$

$$H_{high}(f_k, f_{high}) = \begin{cases} 1, & f_k < f_{high} \\ 1 - w(f_k - f_{high}), & f_{high} < f_k < f_{high} + \Delta f \\ 0, & f_{high} + \Delta f < f_k \end{cases}$$

By combining both filters, we get the general filter function:

$$H(f_k, f_{low}, f_{high}) = H_{low} * H_{high}$$

Thus, it is possible to construct a filter that provides a smooth sinusoidal transition of values at the boundaries of the given range $[f_{low}, f_{high}]$. In further experiments, the value $\Delta f = 2$ will be used, which allows us to achieve sufficient accuracy in signal processing, reducing the influence of noise and artifacts. This provides more stable results and better data processing quality in the frequency domain. As noise, we will consider frequencies from 59 to 61 Hz, and those close to 0 Hz, that is, according to the increasing filter from 0 to 2 Hz:

$$H_f(f_k) = 1 - H_{low}(f_k, 2) - H(f_k, 59, 61)$$

Then, let's assume that the noise-free value of the DFT is defined by the formula:

$$Z_k = X_k * H_f(f_k) \tag{1}$$

The EEG Motor Movement/Imagery Dataset [8] was used for analysis, which contains more than 1,500 one- and two-minute EEG recordings from 109 participants. As part of the experiment, participants performed various motor and imagination tasks, during which 64-channel EEG signals were recorded using the BCI2000 system [9]. Each participant completed 14 experimental trials, including two one-minute baseline trials (one with eyes open and one with eyes closed) and three two-minute trials for each of the four tasks.

The task consisted of the following: participants opened and closed their fist according to the appearance of a target on the left or right side of the screen, or imagined performing this movement. Additionally, participants opened and closed both fists or both feet depending on the position of the target.

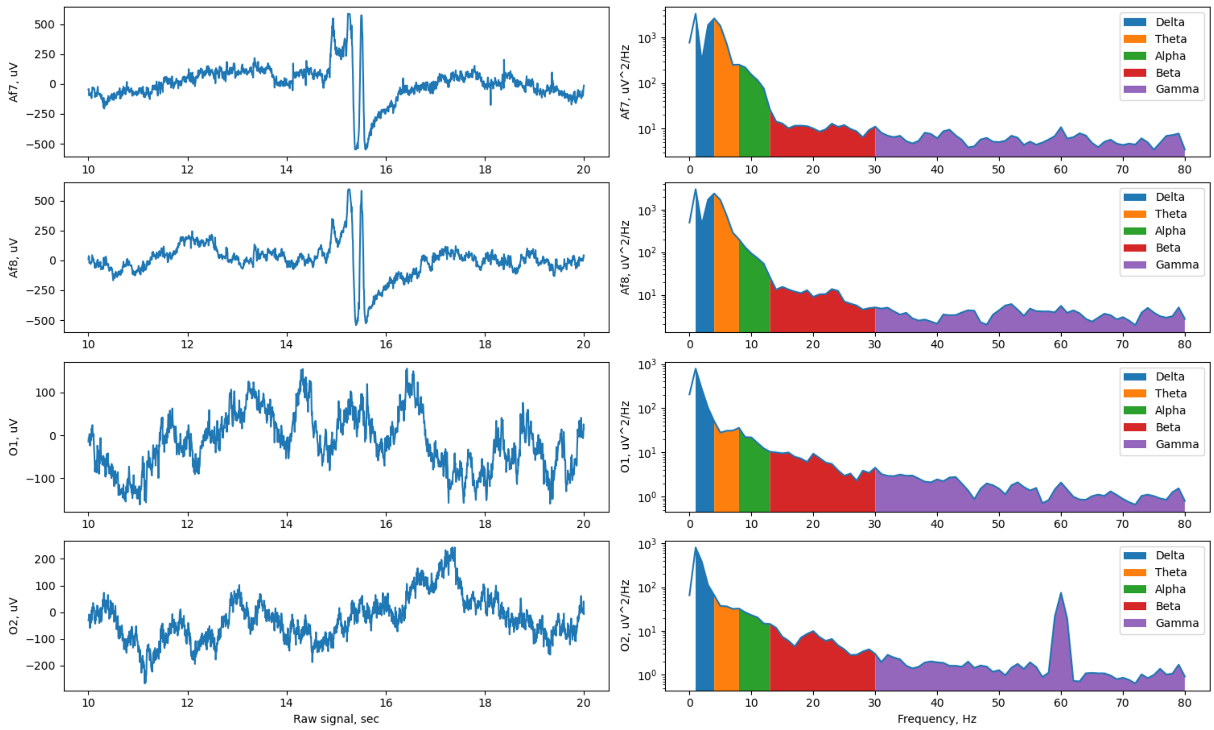

Figure 2 - Brain rhythms (opened eyes, S043R01.edf)

The recordings are in EDF+ format, containing 64 EEG signals recorded at 160 Hz, as well as an annotation channel. Annotations include codes denoting different states: T0 for rest, T1 for initiation of movement (real or imagined) of the left fist or both fists, and T2 for movement of the right fist or both legs. Recordings are made using electrodes according to the international 10-10 system, that excludes some specific electrodes. The EDF+ format is adapted for use with the PhysioToolkit software [10].

Each participant is labeled S001 to S109, and each participant has 14 files labeled R01-R14 in which the corresponding EEG data is recorded. Thus, for each write iteration, there are SsssRrr.edf format files. In the future, we will denote as s the number of the participant, and r the number of the stage. For our study, we used the following stages: 1 - no task, eyes open, 2 - no task, eyes closed.

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The PyRQA library [11] was used for the analysis, which provides efficient execution of recurrence analysis on long time series thanks to the use of the OpenCL framework.

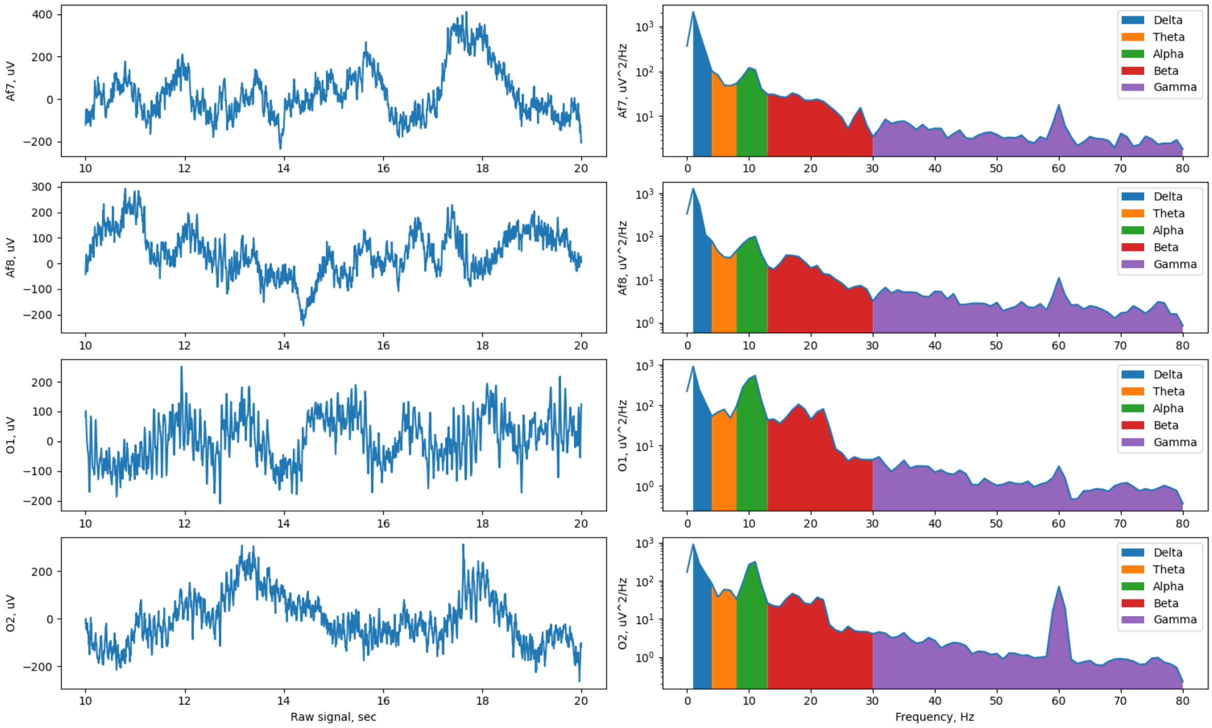

Figure 3 - Brain rhythms (closed eyes, S043R02.edf)

Figures 2 and 3 present the EEG signals of participant S043 from the studied data set, as well as the power of each frequency calculated using the Welch method [12] of spectral density calculation. These graphs clearly illustrate the differences between open and closed eyes. In particular, increased activity in the alpha rhythm is noticeable during eyes closed, where a peak frequency of about 10 Hz is observed, which is typical for this rhythm. In some cases, similar phenomena can be observed in beta rhythm. In addition, the signals from the electrodes located in the frontal area (points Af7 and Af8) show sharp fluctuations associated with the participant's blinking when the eyes are open. These artifacts originate from ocular muscle activity rather than cerebral signals. In the back regions of the head, in particular in the occipital region, blinking does not occur, since these points are located at a considerable distance from the eyes. In addition, the spectra clearly show a peak at a frequency of 60 Hz, which corresponds to the noise of the power grid.

During the construction and analysis of spectral diagrams, it was found that when the eyes are closed, there is a decrease in the activity of delta and theta rhythms, while the activity of alpha and beta rhythms increases. To solve the problem of recognizing the state of the eyes, the power in the range from 8 Hz to 21 Hz, which corresponds to the alpha rhythm and part of the beta rhythms, as well as the total signal power, was calculated. The ratio of these powers can serve as a marker to distinguish open from closed eye states.

Using the noise-free signal (1), we construct a filter for the required frequency range $H_e(f_k) = H(f_k, 7{,}22)$ and a power function for the given range P_e and of the entire possible frequency range P:

$$P = \sum_{k=0}^{N/2} |Z_k|^2$$

$$P_e = \sum_{k=0}^{N/2} |Z_k * H_e(f_k)|^2$$

$$R_e = \frac{P_e}{P}$$

In our case, we work with data relative to time, so it is advisable to divide the time series into several segments of the minimum length without losing information. It was established that the optimal length of segments for calculations is 5-10 seconds. At shorter time intervals, significant fluctuations of values between segments are observed relative to time. This is clearly visible in figures 4 and 5, where spectrograms of the participant are shown using STFT. In the figure 4, where the segments are 1 second each, the values are very varied, and mathematically it is difficult to determine a clear pattern. Instead, the 10-second segments show the most powerful frequencies that remain stable over time.

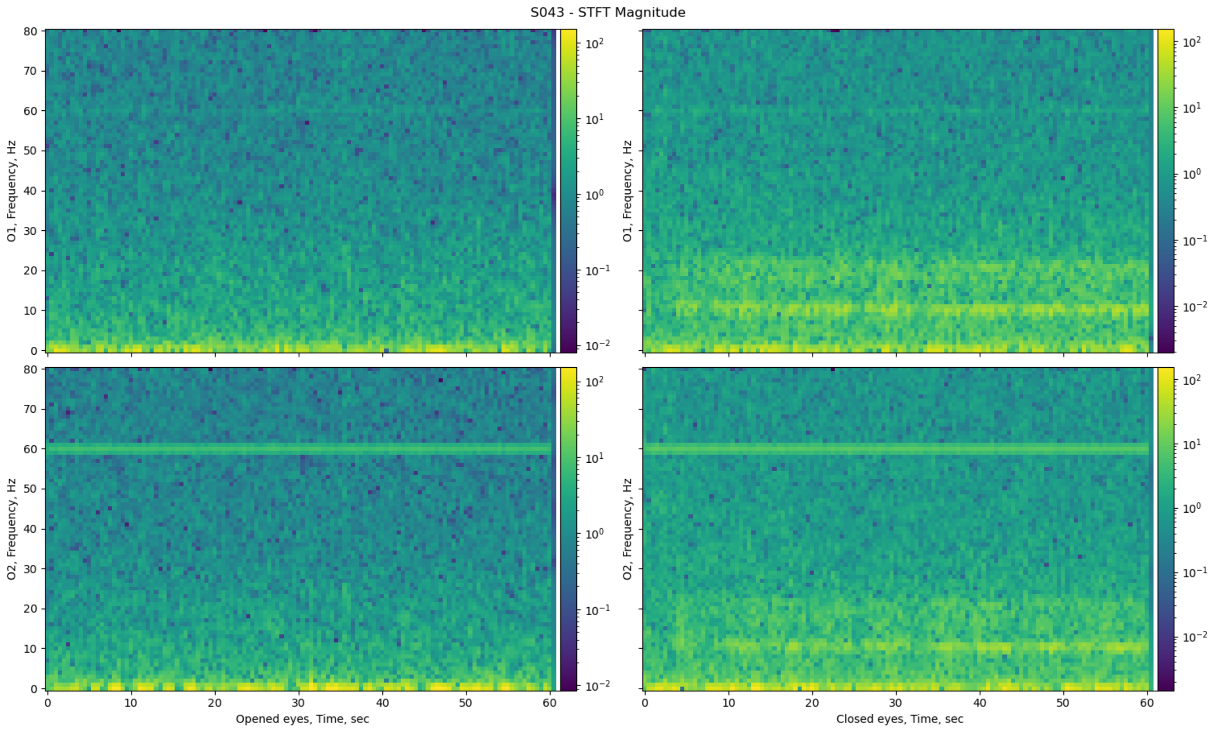

Figure 4 - Spectrograms of participant S043 with 1 second segments

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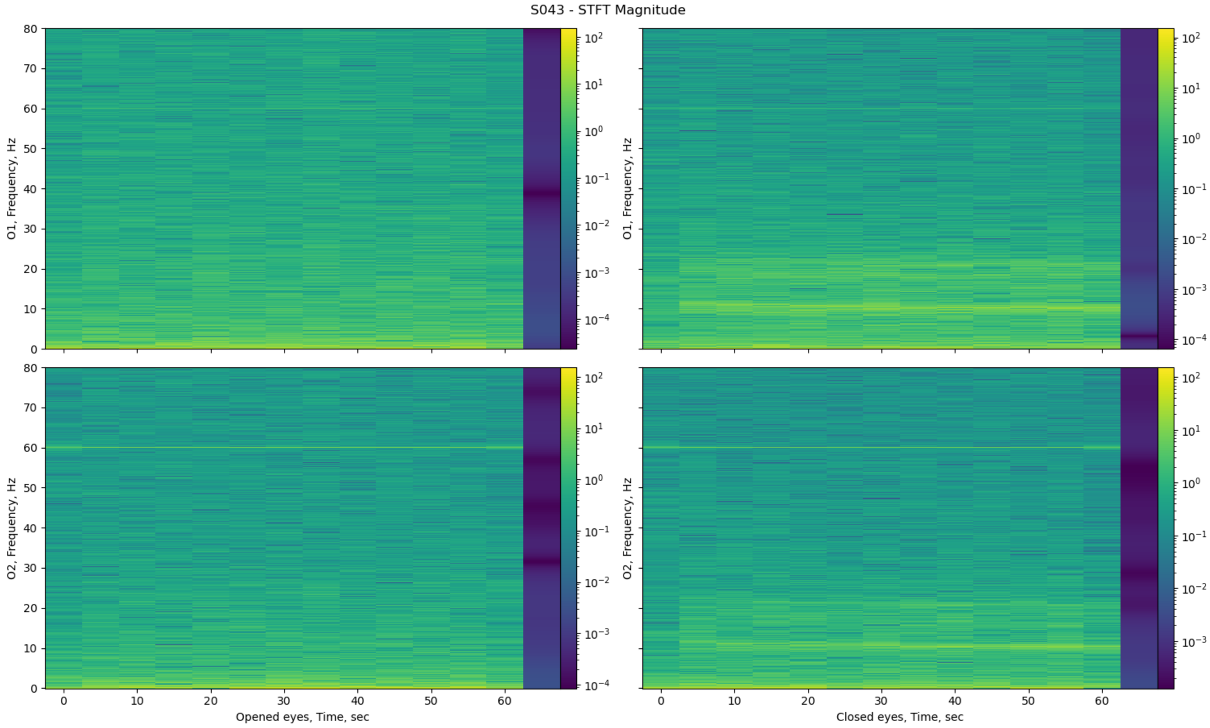

Figure 5 - Spectrograms of participant S043 with 10 second segments

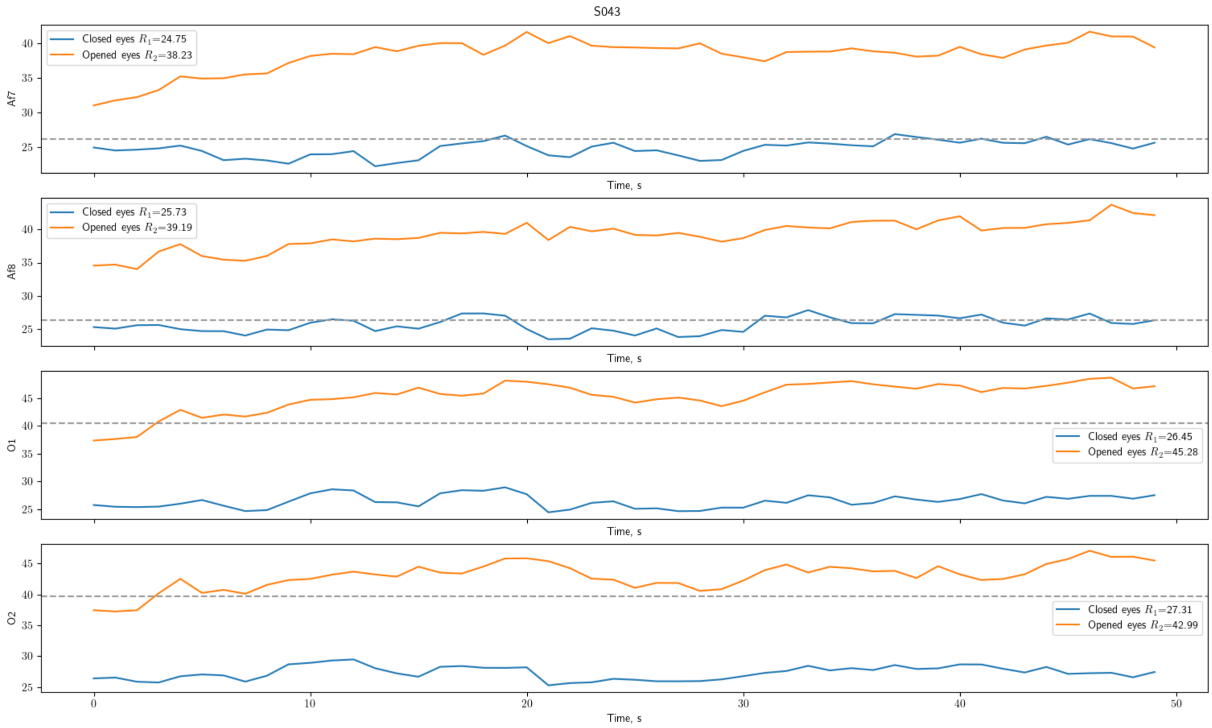

Figure 6 - Percentage of 8-21 Hz band power relative to total power

Figure 6 presents graphs converted to percentages, where the dashed line represents the average value of this ratio over the entire dataset. As can be seen, for participant S043, the alpha rhythm shows a clear trend over the entire time interval: with eyes closed the power is above average, while with eyes open it is lower.

In order for identifying open- and closed-eye states, let's calculate for each point of the brain some threshold value among all participants of the dataset R_{avg}, above which it can be considered that the participant has closed eyes, and below which the eyes are open. And for each participant, we will calculate R_{sr}, where s is the participant's number, and r is the stage number, that is, $r = 1$ for open eyes and $r = 2$ for closed eyes. In this way, we can build the simplest classifier. Let's calculate the classification accuracy for open-eye A_o and closed-eye A_c states, and take the general one as a minimum of these values $A = min(A_o, A_c)$. We will also calculate the average absolute difference between R_{avg} and R_{sr} for each participant:

$$D_{avg} = \frac{1}{n}\sum_{s=0}^{n} |R_{avg} - R_{sr}|$$

This formula shows how close participants' classification values are to the common threshold value, and lower values may indicate better classification accuracy. Here is a table 1 containing the classification results of the eye state (open or closed) for different points in the brain, including the classification accuracy, the mean threshold value, and the mean absolute difference between the participants' values and the total threshold.

Table 1

Open and closed eyes classification results

Point	A	A_o	A_c	R_{avg}	D_{avg}
Fc3	75.45%	79.09%	75.45%	33.94%	7.60%
Fc1	75.45%	76.36%	75.45%	34.23%	7.51%
Fcz	75.45%	75.45%	75.45%	34.67%	7.65%
Fc2	75.45%	78.18%	75.45%	34.39%	7.84%
Fc4	75.45%	76.36%	75.45%	32.99%	7.91%
Fc6	73.64%	80.00%	73.64%	30.14%	7.83%
Cz	73.64%	73.64%	74.55%	35.72%	7.07%
C6	73.64%	78.18%	73.64%	31.53%	6.65%
Cp4	73.64%	73.64%	73.64%	36.61%	7.09%
Fp1	77.27%	83.64%	77.27%	27.10%	10.42%
Fpz	79.09%	86.36%	79.09%	28.00%	10.75%
Fp2	79.09%	87.27%	79.09%	26.93%	10.69%
Af7	78.18%	84.55%	78.18%	26.16%	9.87%
Af3	76.36%	84.55%	76.36%	29.28%	10.29%
Afz	80.00%	84.55%	80.00%	31.53%	10.41%
Af4	79.09%	84.55%	79.09%	29.01%	10.95%
Af8	80.00%	87.27%	80.00%	26.47%	10.27%
F5	73.64%	74.55%	73.64%	29.28%	8.67%
F3	78.18%	82.73%	78.18%	32.04%	9.07%

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Point	A	A_o	A_c	R_{avg}	D_{avg}
F1	79.09%	80.91%	79.09%	33.09%	9.02%
Fz	79.09%	80.91%	79.09%	33.45%	9.11%
F2	80.00%	81.82%	80.00%	32.66%	9.61%
F4	80.91%	82.73%	80.91%	32.11%	9.96%
F6	78.18%	80.91%	78.18%	29.01%	10.06%
F8	74.55%	83.64%	74.55%	27.40%	8.99%
Ft8	74.55%	75.45%	74.55%	28.39%	7.43%
Po3	74.55%	77.27%	74.55%	39.52%	8.85%
Po4	74.55%	79.09%	74.55%	39.27%	9.57%
Po8	74.55%	81.82%	74.55%	38.71%	10.41%
O1	73.64%	73.64%	73.64%	40.51%	9.29%
Oz	74.55%	79.09%	74.55%	40.19%	9.02%
O2	76.36%	76.36%	76.36%	39.81%	9.73%

Thus, we can conclude that with careful selection of the dataset and the application of appropriate data processing methods, spectral analysis allows for the effective classification of states of brain activity, such as open and closed eyes. The use of correct filters and window functions to select the necessary frequency components allows you to minimize the impact of noise and ensures stable recognition accuracy. Therefore, proper processing of EEG data and adaptation of spectral analysis to specific tasks increase the possibilities of using this method for reliable analysis of brain states.

Conclusions. In the results of the conducted research, spectral analysis was used to classify the states of open and closed eyes based on data from the "EEG Motor Movement/Imagery Dataset". Hann's window function was used for the analysis, which ensured a smooth limitation of frequency components and minimized frequency fluctuations between frequency segments. Time segments with a duration of 5-10 seconds turned out to be optimal for calculations, since shorter intervals showed significant fluctuations in spectral characteristics.

The most accurate results were obtained for points in the frontal area, in particular **Fp2**, **Af7** and **Af8**, where the classification accuracy reached **79.09%-80.00%** for closed eyes and **87.27%** for open. In addition, significant results were obtained for points in the occipital region, particularly **O1** and **O2**, where accuracy reached **73.64%** for closed eyes and **76.36%** for open eyes. To eliminate artifacts, filters for frequency artifacts in the range of 59-61 Hz (mains noise) and low-pass filters for frequencies around 0 Hz were used.

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The application of spectral analysis of EEG data for the identification of open and closed eye states

The article examines the analysis of electroencephalogram (EEG) data for the classification of open and closed eye states using the Fast Fourier Transform (FFT). It is shown that this method demonstrates stable recognition accuracy at the level of 70-80% in distinguishing between open- and closed-eye states, demonstrating its effectiveness in classifying biomedical signals. General information about EEG is described, points for their reading, in particular about the "10-10 system", information about the main types of brain rhythms is given. Modern methods for analyzing EEG data were also reviewed, highlighting three main approaches: spectral analysis, recurrence analysis, and machine learning methods. Software was developed for classification of information presented in the form of EEG time series obtained in the state of open and closed eyes. The software was developed in Python utilizing the PyRQA library.

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