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V. I. SLYUSAR, *Doctor of Technical Sciences, Professor*
https://orcid.org/0000-0002-2912-3149

V. G. KOZLOV, *PhD*
https://orcid.org/0000-0002-7708-6143

D. V. KOZLOV
https://orcid.org/0009-0001-3909-0504

NEURAL NETWORK METHOD FOR INVESTIGATION SPECTRAL CHARACTERISTICS

This article considers the problem of radio signal classification based on spectral features formed from complex low-frequency signal samples (in-phase and quadrature components). The main goal of the research is to build a single machine learning model capable of effectively identifying the type of signal by its spectral characteristics. The signal is represented using the power spectral density (PSD), calculated by the Welch method, as well as additional statistical and frequency-energy features that reflect the amplitude-phase structure of the signal. The model structure is proposed and the processes of its training, validation and testing are implemented. An analysis of the influence of spectral decomposition parameters on classification quality is conducted. The experimental results demonstrate that the combined use of spectral and statistical features allows achieving high accuracy in recognizing various types of radio signals. The proposed approach can be applied in practical systems for automatic radio frequency spectrum analysis and signal detection in complex electromagnetic environments.

Keywords: *power, approach, validation, testing, model, system, feature, classification, radio signals, amplitude, phase.*

INTRODUCTION

With the increasing complexity and density of the modern radio frequency spectrum, there is a significantly growing demand for automated radio signal classification systems capable of identifying the type of transmission source or the functional purpose of the signal. Such systems are employed by leading countries in the fields of wireless communications, radio monitoring, electronic intelligence and autonomous control of devices based on Software-Defined Radio (SDR) [1]. With the advancement of software-defined radio technologies and the increasing availability of high-frequency data in the form of complex low-frequency samples (IQ data), there arises a necessity to implement modern machine learning methods for automated signal processing and analysis [1–3].

A key stage in building a recognition system is the formation of a feature vector that fully and accurately reflects the signal properties in both the time and frequency domains. This work considers an approach based on the combination of spectral, statistical and phase characteristics of the signal [1–8]. The spectral representation is primarily based on the power spectral density (PSD), which is estimated using Peter Welch's method. Additionally, generalized statistical parameters such as mean, standard deviation, skewness and kurtosis are taken into account, along with derived features describing the structure of the amplitude and phase components, entropy, center frequency and spectral bandwidth [1–8].

The **objective of this article** is to develop an approach for constructing feature vectors of radio signals based on complex signal samples represented by in-phase and quadrature components, followed by the creation of a dataset suitable for training machine learning models. Within the scope of the study, a complete signal preprocessing pipeline is implemented, which includes reading and transforming complex samples, extracting statistical and spectral features, normalizing them, as well as structuring the results into consistent datasets for classification. The proposed approach enables the formation of informative feature vectors even under conditions of limited input data volume, which is critically important for the application of machine learning methods in automated radio signal type recognition tasks.

REVIEW OF KEY RESEARCHES AND PUBLICATIONS

In the process of studying the spectral features of radio signals based on complex signal samples (IQ data), it is important to examine both the theoretical foundations of signal processing and modern practical approaches, which are predominantly implemented using the Python programming language. A review of the literature has shown that a solid knowledge base has been established in this field, covering both fundamental digital signal processing (DSP) and intelligent classification methods.

The review article [1] systematizes existing deep learning frameworks applied in cognitive radio networks. It discusses main approaches to automatic modulation classification, spectral window recognition, unauthorized transmission detection and spectrum access optimization. The authors also outline a range of open research challenges, including performance limitations under constrained computational resources, the need for real-time signal processing, as well as reliability and power consumption issues in mobile devices.

Reference [2] describes a lightweight deep learning model (i.e., a model with a small number of parameters and low computational requirements) designed for automatic modulation classification in cognitive radio environments. Instead of large CNN or RNN architectures, the authors use a compact model optimized for deployment on resource-limited devices. Experiments demonstrate acceptable accuracy even under low SNR conditions.

A CNN architecture with enhanced noise robustness for the task of automatic modulation classification is presented in [3]. The model is trained on spectral and temporal representations of signals, including IQ samples. The main goal is to provide high classification accuracy under low signal-to-noise ratio (SNR) conditions, which is critical for electronic warfare and operation in complex electromagnetic environments.

In «PySDR: A Guide to SDR and DSP using Python» [9], the fundamental principles of complex signal processing, particularly IQ data, as well as the concepts of spectral analysis and modulation, are described in detail. This is an interactive guide tailored for the practical implementation of tasks using Python and SDR tools. The SciPy documentation [10] complements the toolbox for digital signal processing in Python, including filtering, spectral analysis, Fourier transforms and window functions. This tool is a standard for scientific computing in Python.

The PEOSAT web resource [11] explains IQ data principles in the context of satellite radio communications and SDR, focusing on storage formats and practical examples of signal analysis. The IQ Signal Master software developed by Anritsu [12, 13] implements an engineering approach to signal analysis at the hardware level, with a focus on IQ data processing. The accompanying documentation provides tools for detailed spectral analysis, including functionality for working with vector signals.

An MIT lecture [14] presents the basic mathematical foundation of modulation/demodulation of in-phase and quadrature components. The material clearly explains how sinusoids with a 90° phase shift form the basis of the complex signal representation, which is key in digital processing. West and O'Shea [15] presented an approach to wireless signal classification using deep learning. A convolutional neural network (CNN)-based model demonstrates the capability to recognize modulation types directly from raw IQ data.

O'Shea et al. [16] extend this topic by presenting a model for classification of high-frequency (HF) transmission signals based on the same data. Dozens of signal classes were tested under various SNR conditions, showing the potential of machine learning methods in radio spectrum analysis. «Data Analysis in Python» [17] examines data handling structures in Python, including processing numerical and complex data types necessary for analyzing IQ files.

The article [18] by R. Lyons, «Quadrature Signals: Complex, But Not Complicated», describes the principles of formation and use of quadrature signals, which are represented in the form of IQ data.

READING IQ FILES AND GENERATING COMPLEX NUMBERS

Files containing complex signal data are the primary source of information for Software-Defined Radio (SDR) systems, as they store instantaneous values of the in-phase (I) and quadrature (Q) components. For further processing, these data are read from the file and formed as complex numbers, which enables the application of spectral analysis methods and extraction of physically meaningful signal characteristics. This approach provides accurate representation of amplitude-frequency and phase properties necessary for classification, detection or identification of emission sources.

Such files are typically stored in a format where IQ data values are interleaved and encoded as 16-bit integers, sometimes taking byte order into account. A common approach involves converting each pair of IQ values into a complex number using the formula [9]:

$$s[n]=I[n]+jQ[n], \quad (1)$$

where I[n] and Q[n] are the in-phase and quadrature components of the signal at time index n, respectively, and j is the imaginary unit for which $j^2 = -1$. This representation allows the signal to be expressed as a complex envelope, which is convenient for further analysis in the frequency domain.

During the study, a function was implemented to read complex radio signals from a binary file with subsequent conversion of the data into an array of complex numbers. The developed algorithm includes a check for an even number of samples, which prevents the loss of one of the signal components (real or imaginary), and, if necessary, performs amplitude normalization.

The resulting array of complex numbers is used in subsequent stages of digital signal processing, including spectral analysis, extraction of informative features and further application in machine learning models. Fig. 1 presents a block diagram of the function that takes the path

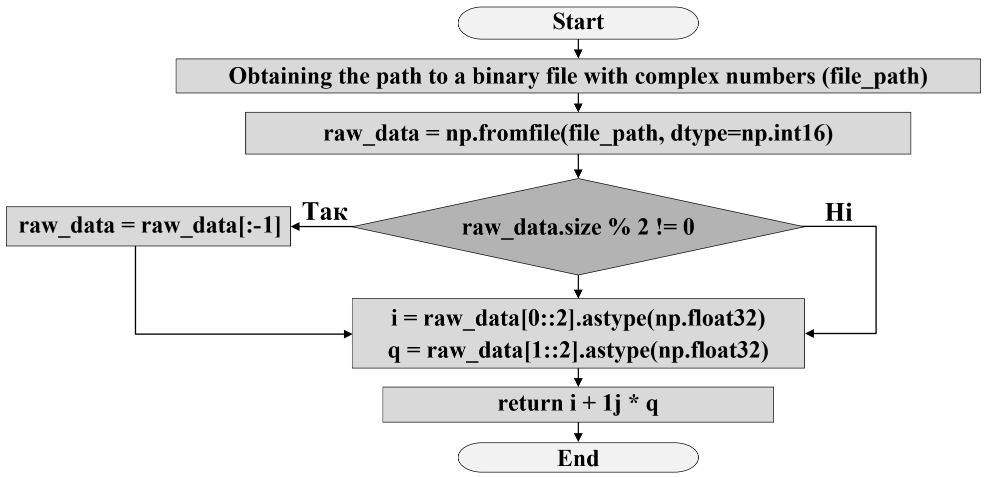


Fig. 1. Algorithm for forming complex numbers

to the binary signal file as input and returns the formed array of complex samples.

This approach ensures accurate and consistent signal representation, which is critical for the reliability of the classification process.

CALCULATION OF SPECTRAL FEATURES

For effective recognition of the radio signal type or source of emission, it is necessary to form an informative feature vector that reflects key characteristics of the signal in the time, frequency, and phase-amplitude domains. The signal formed from IQ data as complex samples undergoes preprocessing aimed at extracting its statistical, energy and spectral characteristics.

The obtained features allow describing the signal structure both as aggregated metrics (e.g., mean value, variance, entropy) and in a more detailed form, including an expanded spectrum or amplitude distribution. This approach provides the machine learning model with a comprehensive representation of the signal characteristics, significantly improving classification accuracy even in the presence of noise, interference or frequency overlap.

The process of building spectral features is based on the estimation of the power spectral density (PSD), which reflects how the signal energy is distributed across frequencies.

This not only preserves the key frequency characteristics of the signal but also represents them as numerical statistical indicators suitable for use as input features in classification algorithms.

In particular, the mean value of the signal spectrum is calculated using the formula [8, 17]

$$\mu=\frac{1}{N}\sum_{i=1}^{N}\left|X(f_i)\right|^2, \qquad (2)$$

where N is the number of frequency bins in the spectrum, corresponding to the division of the frequency range into equal intervals during the PSD computation and $X(f_i)$ is the FFT component of the signal at frequency f_i.

The standard deviation of the spectrum [16, 13] is defined as

$$\sigma=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\left|X(f_i)\right|^2-\mu\right)^2}, \qquad (3)$$

where «μ» is the mean value of the power spectral density.

The coefficient of spectrum asymmetry [11] is calculated as follows

$$\mathrm{Kurt}=\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\left|X(f_i)\right|^2-\mu}{\sigma}\right)^4-3, \qquad (5)$$

which allows assessing the deviation of the distribution from normality and indicates the presence or absence of sharply expressed peaks in the spectrum, which is critical for detecting tonal or impulsive components in the signal.

In addition to aggregated metrics, a complete vector of spectral characteristics is formed in the form of $\left\{\left|X(f_i)\right|^2, \left|X(f_1)\right|^2, \ldots, \left|X(f_{N-1})\right|^2\right\}$, where each spectral power value is recorded individually and associated with a specific discrete frequency bin. Such a feature structure allows the model to account for both global and local frequency characteristics of the signal.

Unlike the traditional approach, which involves only an aggregated estimation of the power spectral density, this study performs an analysis of the full spectral shape.

This enables the extraction of a number of informative characteristics related to the energy distribution across the frequency domain, its concentration, symmetry of the distribution and the overall shape of the spectrum.

These features are particularly useful for tasks of signal recognition, classification, or clustering based on their frequency properties, as they allow for an accurate description of the signal structure. The amplitude spectrum [9, 10] is formed by calculating the magnitude of the Fourier transform of the signal x(t), which is defined as:

$$S(f_i)=\left|F\{x(t)\}_i\right|, \qquad (6)$$

where $S(f_i)$ is the amplitude at the i-th frequency and $F\{x(t)\}_i$ is the value of the Discrete Fourier Transform (DFT) of the signal x(t) at the frequency f_i.

The spectral centroid [10, 11], that is, the weighted average frequency, is calculated using the formula:

$$f_c=\frac{\sum_{i=1}^{N}f_i\cdot S(f_i)}{\sum_{i=1}^{N}S(f_i)}, \qquad (7)$$

where f_i is the frequency of the i-th bin, $S(f_i)$ is the amplitude value of the spectrum at frequency f_i, f_c is the frequency center of the spectrum.

The spectral width [10, 11] (spectral dispersion) is defined as the standard deviation of frequencies relative to the centroid:

$$\sigma_f=\sqrt{\frac{\sum_{i=1}^{N}(f_i-f_c)^2\cdot S(f_i)}{\sum_{i=1}^{N}S(f_i)}}, \qquad (8)$$

which makes it possible to estimate the degree of spread of energy components in the frequency domain.

Spectral flatness [10, 11] is an indicator of how much the signal spectrum resembles a flat (i.e., noise-like) shape or has pronounced peak frequencies. It is calculated as

$$F=\frac{\exp\left(\frac{1}{N}\sum_{i=1}^{N}\ln\left(S(f_i)+\varepsilon\right)\right)}{\frac{1}{N}\sum_{i=1}^{N}S(f_i)+\varepsilon}, \qquad (9)$$

where $\varepsilon=10^{-12}$ – a small positive value to avoid logarithm of zero. A value of $F\approx 1$ indicates a noise-like signal, while $F\ll 1$ indicates the presence of pronounced peaks.

The roll-off frequency [9, 11] $f_{rolloff}$ is the frequency below which 85 % of the signal energy is concentrated. It is determined by finding the frequency threshold f_k, such that

$$\sum_{I=1}^{k}S(f_i)\geq 0.85\cdot\sum_{i=1}^{N}S(f_i). \qquad (10)$$

This feature is useful for evaluating the effective bandwidth of the signal spectrum.

The peak frequency of the spectrum [10, 11] f_{peak} is the frequency at which the amplitude of the spectrum reaches its maximum:

$$f_{peak}=f_j,\ \text{де}\ j=\arg\max\left(S(f_i)\right). \qquad (11)$$

This parameter allows identification of the dominant frequency component in the signal. Thus, the calculated frequency features not only capture the position and structure of the energy spectrum but also retain a high degree of informativeness for subsequent application in signal analysis algorithms based on machine learning.

Unlike features based on the spectral representation of the signal, amplitude-phase analysis allows the examination of the IQ data structure directly in the time domain. This approach takes into account variations in instantaneous amplitude and phase, as well as their statistical and informational characteristics. It is especially relevant for signals with phase or pulse modulation, where spatial or spectral representations may lose critical temporal details. It is particularly relevant for signals with phase or pulse modulation, where the spatial or spectral representation may lose critical temporal details.

As a result of the analysis, a compact feature vector is formed, which generalizes the key characteristics of the signal without the need to transform into the frequency domain. One of the basic quantities is the mean amplitude [10, 11], calculated by the formula

$$\mu_a = \frac{1}{N}\sum_{i=1}^{N}|x_i|, \qquad (12)$$

where x_i is the i-th complex sample of the in-phase and quadrature components of the signal, and N is the total number of points in the signal.

The amplitude variance [9, 10] is defined as

$$a_a^2 = \frac{1}{N}\sum_{i=1}^{N}(|x_i| - \mu_a)^2, \qquad (13)$$

which allows estimating the variability of amplitudes in the signal.

The total signal power [4, 6] is calculated as

$$P = \frac{1}{N}\sum_{i=1}^{N}|x_i|^2, \qquad (14)$$

i.e., the mean value of the squared amplitude.

To assess the informational content of the signal, the amplitude entropy [4, 5] is used:

$$H_a = -\sum p(|x_i|) \cdot \leq \log(p(|x_i|)), \qquad (15)$$

where $p(|x_i|)$ is the estimated probability of observing a certain amplitude value, usually determined by a histogram.

Phase characteristics of the signal are also analyzed separately. The mean phase value [4, 5] is calculated as

$$\mu_\varphi = \frac{1}{N}\sum_{i=1}^{N}\angle x_i, \qquad (16)$$

where $\angle x_i$ is the phase of the i-th sample.

The phase variance [10, 12] is defined by the formula

$$\sigma_\varphi^2 = \frac{1}{N}\sum_{i=1}^{N}(\angle x_i - \mu_\varphi)^2, \qquad (17)$$

and the phase entropy [8]

$$H_\varphi = -\sum p(\angle x_i) \cdot \log(p(\angle x_i)), \qquad (18)$$

where $p(\angle x_i)$ is the estimated probability density of phase values.

For analyzing the skewness and kurtosis of the distribution, the statistics of skewness and excess are used. The skewness of the real part [7] of the signal is defined as

$$\text{Skew} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{R(x_i) - \mu}{\sigma}\right)^3, \qquad (19)$$

where $R(x_i)$ is the real part of the signal, μ and σ are the mean and standard deviation, respectively.

The excess kurtosis of the real part of the signal [10] is calculated as

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{R(x_i) - \mu}{\sigma}\right)^4, \qquad (20)$$

which allows estimating the degree of peakedness of the distribution.

Additionally, the zero crossing rate (ZCR) [6, 7] is introduced, which estimates the frequency of sign changes in the real part of the signal. It is defined by the formula

$$ZCR = \frac{1}{N}\sum_{i=1}^{N-1}\left[\text{sign}(R(x_i)) \cdot \text{sign}(R(x_{i+1}))\right] < 0 \qquad (21)$$

and serves as a useful indicator of the impulsive or noisy structure of the signal.

Overall, the amplitude-phase feature vector provides a high degree of descriptiveness for subsequent analysis and classification of radio signals while preserving the temporal structure without distortion associated with transformation into the frequency domain.

As a result, feature extraction from complex signals includes the calculation of spectral, amplitude-phase and statistical characteristics, which together form an informative representation of the signal. Spectral features (mean, variance, skewness, kurtosis, centroid, roll-off, flatness) characterize the distribution of energy in the frequency domain. Amplitude-phase analysis accounts for instantaneous values of amplitude and phase (mean, variance, entropy), as well as temporal indicators, specifically the zero crossing rate (ZCR). Additionally, statistics of the real part of the signal (skewness, kurtosis) reflect its shape.

This set of features provides a flexible and comprehensive description of the signal, suitable for classification in machine learning systems.

IMPLEMENTATION OF SPECTRAL FEATURE CALCULATIONS

The calculation of signal features is a critically important stage in building a classification system, since the feature vector determines the degree of informativeness of the signal representation for the machine learning model. Within the scope of this work, a comprehensive function extract_features has been implemented, which processes the complex radio signal and forms a set of features combining spectral, statistical, amplitude-phase and frequency information. This function consists of three main submodules: extract_psd_features, extract_spectrum_features and extract_amplitude_phase_features.

The first module, extract_psd_features, is responsible for calculating the power spectral density (PSD) using Peter Welch's method. In this approach, the signal is transformed into the frequency domain with windowing, where the parameter nperseg defines the segment length, affecting frequency resolution. The resulting PSD vector describes the distribution of signal energy across the entire frequency range.

In addition to this vector, which is stored fully and used as a set of detailed frequency features, generalized statistical characteristics of the spectrum are also calculated. In particular, the mean value of the PSD (psd_mean) characterizes the overall level of signal energy saturation; the standard deviation (psd_std) reflects the variability of power within the spectrum; skewness (psd_skew) allows assessment of whether the energy is shifted towards lower or higher frequencies; kurtosis (psd_kurt) indicates the peakedness of the distribution, i.e., the presence of narrow localized maxima.

Thus, the formed feature set enables the model to consider both general characteristics of the spectrum and the detailed energetic structure of the signal, significantly improving classification performance. Fig. 2 illustrates the algorithm of the extract_psd_features method.

The second module, extract_spectrum_features, is responsible for calculating generalized characteristics of the signal's amplitude spectrum based on its Fast Fourier Transform (FFT). Unlike Peter Welch’s method, which performs averaging of the spectra of individual segments, this approach applies the Fourier transform to the entire array of complex samples at once. This approach provides a complete spectral representation of the signal at the time of analysis without smoothing. As a result, the amplitude spectrum (spectrum) and the corresponding frequency scale (freqs) are computed, after which key statistical and energetic characteristics of the spectrum are calculated.

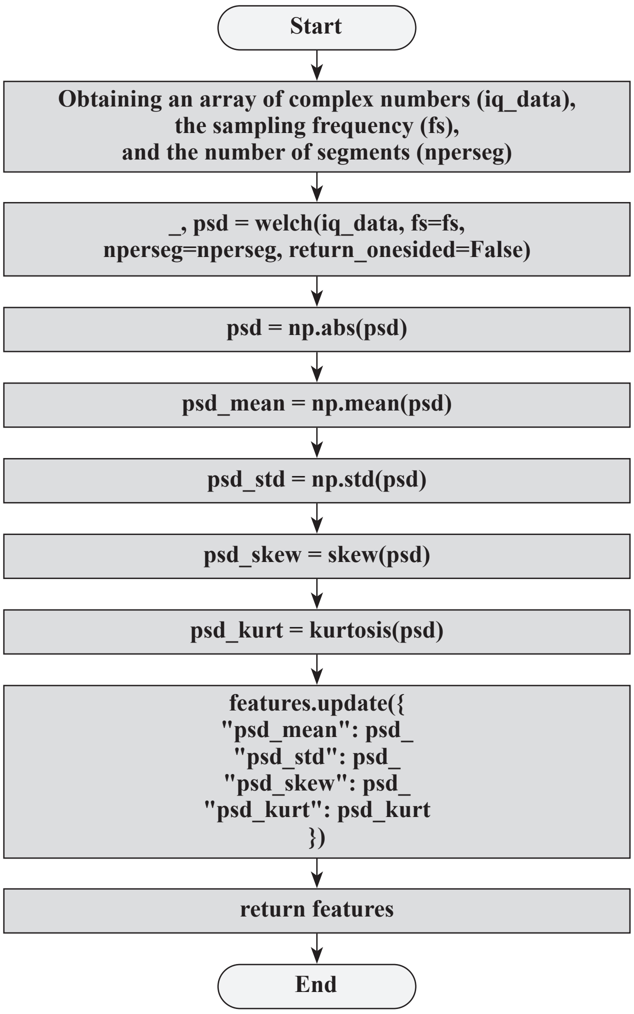


Fig. 2. Algorithm of the extract_psd_features method

Among them is the spectral centroid (spec_centroid), which reflects the center of mass of the spectrum considering the amplitude at each frequency. This parameter indicates around which frequency the main energy of the signal is concentrated. Next, the spectral bandwidth (spec_bandwidth) is calculated, which characterizes the degree of energy distribution around the centroid; the larger this value, the wider the signal spectrum. Another feature is the spectral flatness (spec_flatness), which evaluates the ratio of the geometric to arithmetic mean of the amplitudes, allowing differentiation between peaked (tonal) and flat (noisy) signals.

Additionally, the spectral roll-off (spec_rolloff) is computed, i.e., the frequency below which 85 % of the total signal energy is concentrated. This characteristic allows determining the boundary of the main spectral content of the signal, which is useful when analyzing bandwidth or filtering noise.

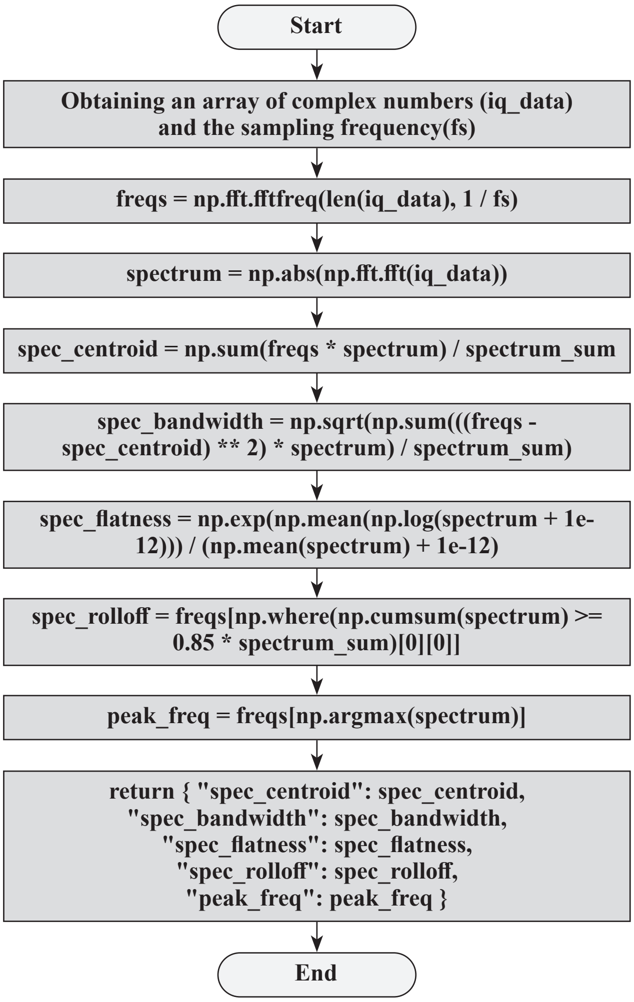
The last feature is the peak frequency (peak_freq), which corresponds to the frequency at which the amplitude spectrum reaches its maximum. It reflects the strongest component of the signal and allows determining the frequency region where the main energy is concentrated. This is especially important for signal type recognition or radiation source detection.

Together, these spectral features form a compact yet deep representation of the signal in the frequency domain. Unlike the detailed PSD vector obtained in the first module, here the focus is on integral spectral characteristics that preserve key information about the position (spec_centroid, peak_freq), distribution (spec_bandwidth, spec_rolloff) and shape (spec_flatness) of the signal’s spectral content. This enables their effective use in classification or clustering tasks. Fig. 3 depicts the algorithm of the extract_spectrum_features method.

The extract_amplitude_phase_features module is responsible for calculating the statistical and informational characteristics of the signal in the amplitude-phase domain. Unlike frequency analysis based on spectral features, this approach utilizes instantaneous signal parameters in the time domain obtained by decomposing complex radio signal samples into amplitude and phase. At the first stage, the amplitude and phase of each signal sample are calculated. Then features are formed that describe both the energy structure and the distributions of amplitude and phase components.

Initially, the signal power is determined as the sum of squared amplitudes. The mean and variance of the amplitude allow assessing the intensity and variability of the signal in the time domain. To better describe the complexity of the distribution, amplitude entropy and phase entropy are used, which define the degree of disorder or informational richness of each component.

In addition, phase characteristics are analyzed: mean value and variance of the signal phase, which can reflect



F i g . 3. Algorithm of the extract_spectrum_features method

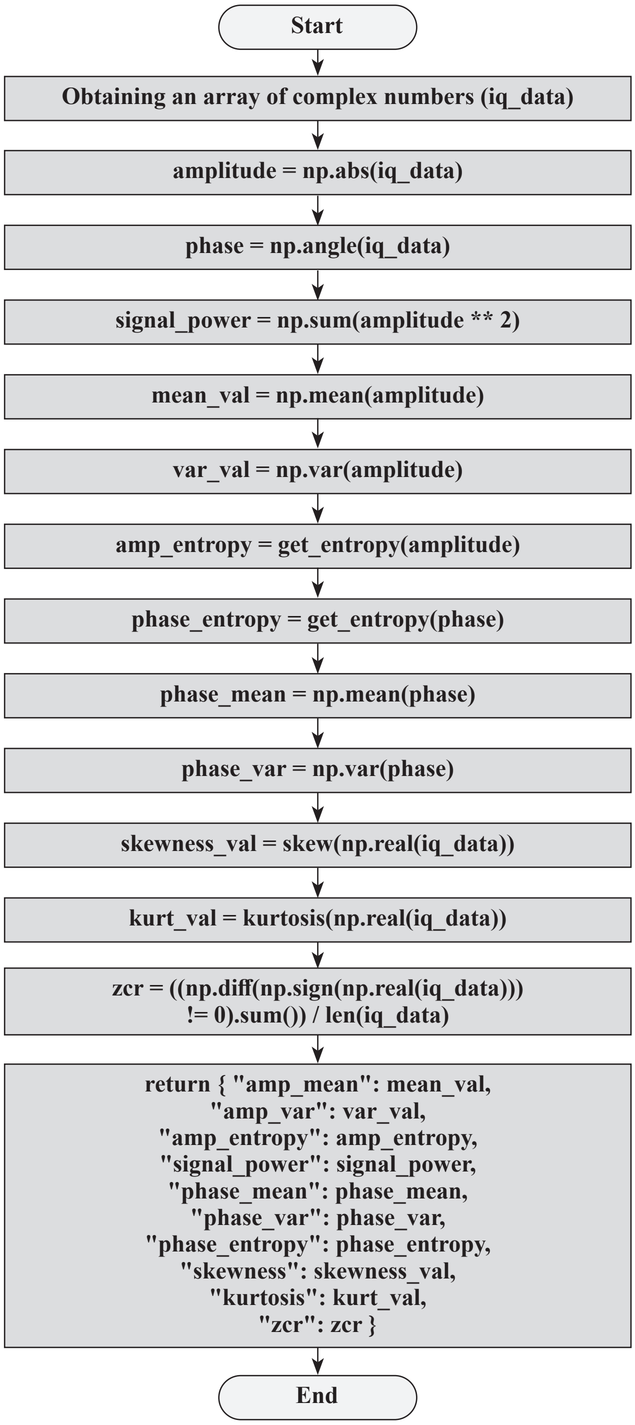
symmetry or asymmetry of the phase inherent to certain types of modulation. Additionally, features calculated based on the real part of the signal – skewness and kurtosis – indicate asymmetry and peakedness of the distribution, respectively. Finally, an important characteristic is the zero crossing rate (ZCR), which reflects how often the signal changes sign and can be informative in vibration analysis or detection of impulsive components.

Thus, extract_amplitude_phase_features forms a feature set that encompasses both energetic (for example, signal_power) and statistical and informational properties of the signal, providing its full representation in the time domain. These characteristics can effectively complement spectral features in classification or signal type recognition tasks.

Fig. 5 shows the overall logic of feature vector calculation, where each function computing a specific signal feature (for example, skewness, flatness, or peak frequency) is called sequentially and the results are collected into a single array for further use.

IMPLEMENTATION OF SAVING RESULTS IN COMMA-SEPARATED VALUES (CSV) FORMAT FOR FURTHER PROCESSING

After calculating spectral features for each segment of the complex radio signal, it is advisable to save the results in a convenient format for further analysis, visualization or use

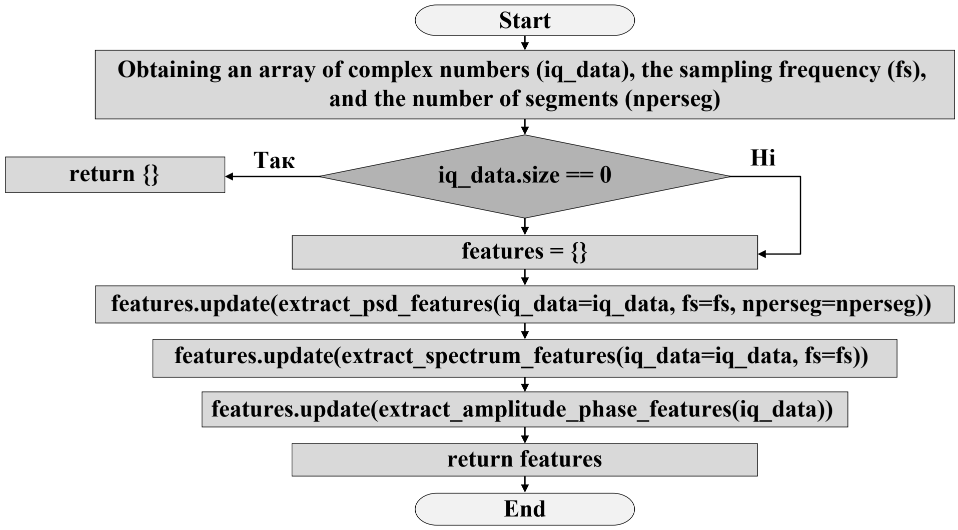


F i g . 4. Algorithm of the extract_amplitude_phase_features method

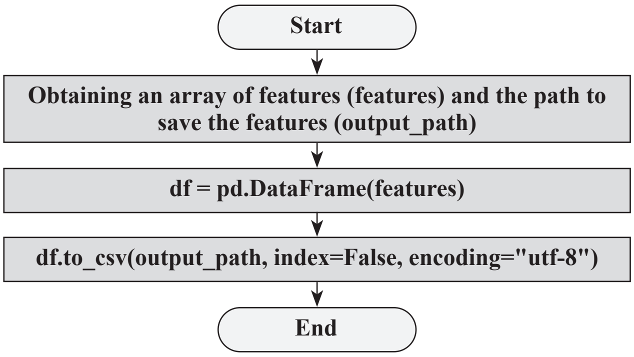
in classification tasks. The most common and convenient format for storing structured data is CSV, which is supported by most Python libraries, machine learning systems and spreadsheet editors.

To form a table with features, the pandas DataFrame structure is used, where each row corresponds to one segment of the signal and columns represent individual spectral features. Fig. 6 illustrates the algorithm for saving the formed feature dataset.

Fig. 7. Algorithm for initializing all features by saving the path to the IQ file and the name of each directory containing these files into an array.



F i g . 5. Algorithm for calculating all features

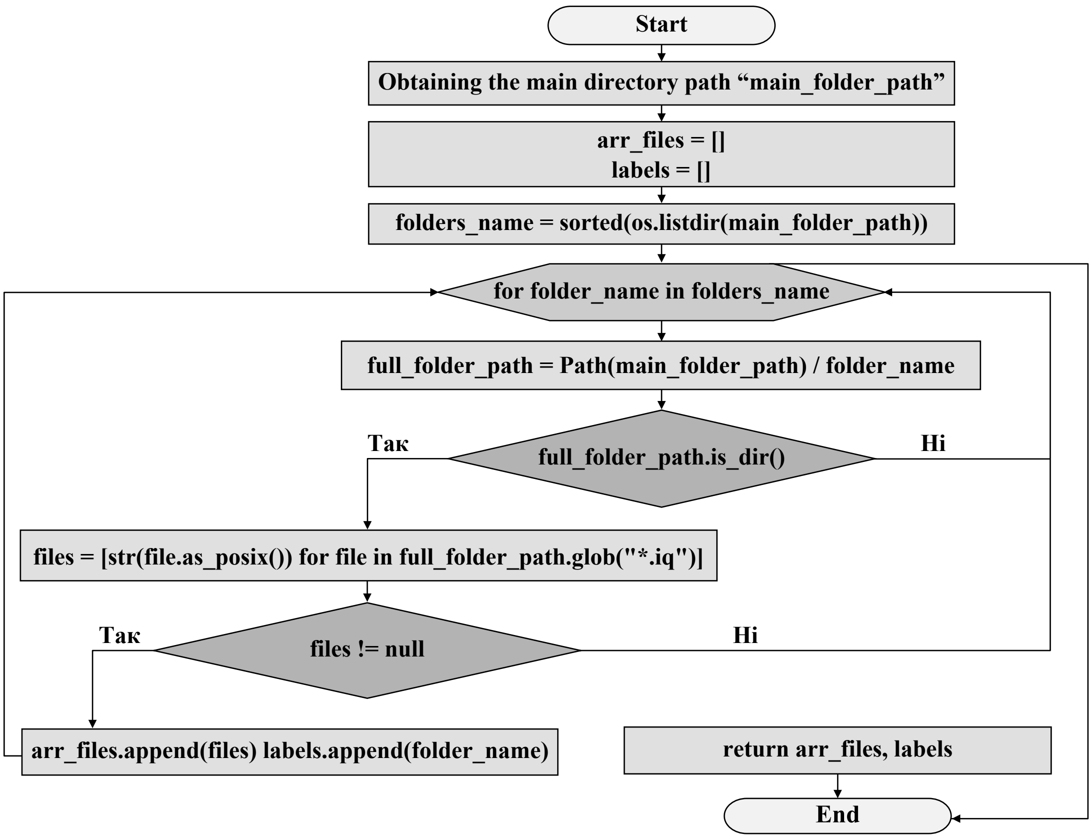


F i g . 6. Algorithm for saving the formed feature dataset

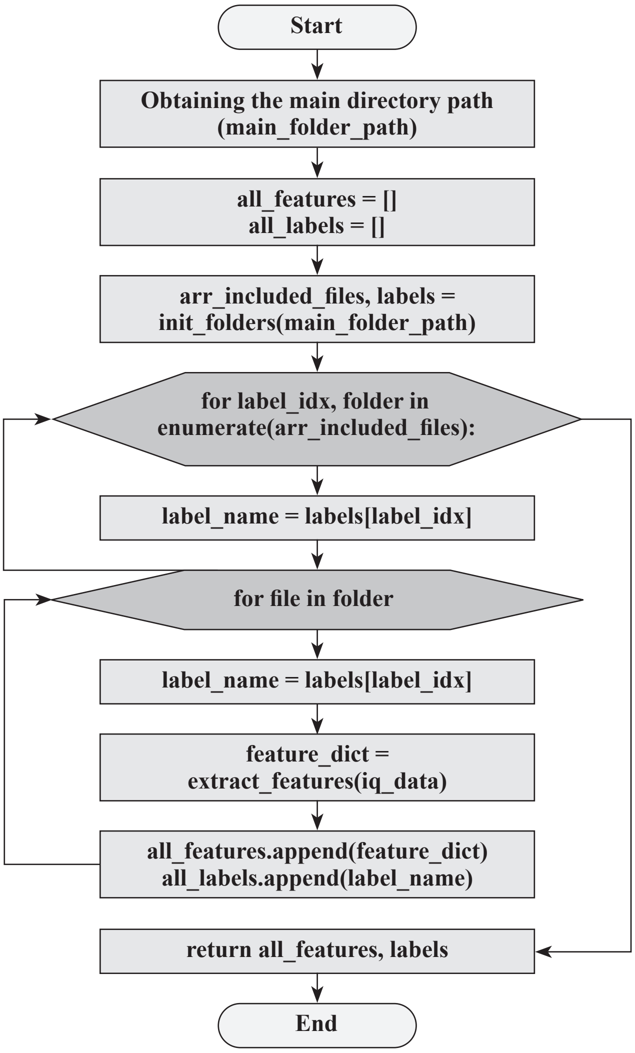
After determining the access paths and directory names, it is necessary to perform feature extraction for each individual signal record. Fig. 8 shows the algorithm for calculating features for each signal read from a separate element of the input dataset.

After executing each of the algorithms listed in this section, we obtain as a result a feature dataset. Fig. 9 shows a fragment of the dataset.

The presented functional blocks, depicted as structured diagrams, reflect the complete logic of signal processing from reading input data to forming a feature vector suitable for subsequent analysis or classification.



F i g . 7. Algorithm for generating directory names and determining access paths to signals in IQ data



F i g . 8. Algorithm for computing features for each signal read from an individual element of the input IQ data

Each diagram illustrates the key stages of the corresponding method: calculation of the PSD, formation of generalized spectral characteristics (centroid, bandwidth, flatness, roll-off, peak frequency), as well as the computation of statistical metrics based on the amplitude and phase of the signal. This approach has allowed not only to document the implementation of algorithms in code but also to visualize their internal structure, which is important for verifying the correctness of the logic and for further integration into larger systems.

The implemented functions are universal, modular, and can be used to build a flexible and extensible system for automated processing and classification of radio signals. This creates prerequisites for further system optimization, addition of new features describing the structure and properties of signals with new informative metrics and adaptation of algorithms to specific tasks in the fields of radio monitoring, intelligence or spectral analysis.

CONCLUSIONS

1. A multi-level approach to the analysis of complex radio signals has been implemented with the purpose of extracting informative features suitable for automated recognition and classification.
2. Processing of spectral, temporal and amplitude-phase domains allowed for a comprehensive assessment of the signal structure.
3. Individual features were distinguished: power spectral density indicators, integral spectral characteristics (centroid, bandwidth, flatness, roll-off, peak frequency) and statistical metrics of the amplitude-phase structure.
4. Generalized parameters such as mean, variance, entropy and zero-crossing rate enabled coverage of both global and local signal characteristics.
5. The obtained results confirmed that the combination of these methods forms a reliable feature space for machine learning tasks, improving classification accuracy even in the presence of noise or low signal-to-noise ratio.
6. Further research should focus on comparing the effectiveness of various machine learning models based on the formed features, as well as on optimizing computational costs for real-time applications.
7. A promising direction is the expansion of the feature set considering phase transitions, detection of cluster structures in the spectrum and adaptation of the methodology for wideband signals.

	amp_mean	amp_std	amp_max	amp_skew	amp_kurtosis	phase_mean	phase_std
1	1831.4536	3090.094	14095.227	1.8800377930256893	2.0640965379771163	142210.48	115346.57
2	1961.2703	3112.7825	13989.333	1.850015392126522	1.9391086488080722	479807.4	190763.4
3	1936.0365	3026.7715	13891.269	1.8334691132352061	1.8702793554594797	332630.28	187822.08
4	1952.7899	3093.8662	13971.309	1.8380752665013838	1.9002891915314812	-191299.36	201104.72
5	2048.4841	3137.9043	14023.131	1.735830801610125	1.49087493602255	101091.34	147802.03
6	1969.9705	3067.1128	13975.484	1.8153502103089052	1.7883250320399275	-88395.93	190996.28
7	1960.5115	3052.6484	14001.762	1.8840210067106582	2.115819903417929	-238490.14	159384.23
8	1980.843	3093.8518	14184.329	1.7883332991710894	1.7251331339340972	3127.8557	193228.36
9	1940.5796	3062.8003	14031.621	1.8928292159579956	2.1005278943149355	349798.16	158373.47
10	2021.5847	3056.6514	13977.065	1.8256337331530905	1.886251349512154	-58503.508	153974.3
11	2014.6664	3064.01	13979.331	1.8213433572430322	1.8683486970416023	165537.48	175737.33
12	1900.2875	3152.198	14333.477	1.840660139245009	1.8526934814467584	94310.11	184806.55
13	1990.9191	3048.5088	14008.874	1.8482019762288397	1.9735842624733486	154248.02	192181.3

F i g . 9. A fragment of the dataset with features extracted from complex signals represented as IQ data

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Слюсар В.І., Козлов В.Г., Козлов Д.В.

НЕЙРОМЕРЕЖЕВИЙ МЕТОД ДОСЛІДЖЕННЯ СПЕКТРАЛЬНИХ ХАРАКТЕРИСТИК

У статті розглядається задача класифікації радіосигналів на основі спектральних ознак, сформованих із комплексних низькочастотних вибірок сигналу, що включають інфазну та квадратурну компоненти. Основною метою дослідження є розроблення моделі машинного навчання, здатної ефективно ідентифікувати тип сигналу за спектральними характеристиками. Для представлення вхідних даних використано спектральну щільність потужності (PSD), обчислену методом Petera Welcha, а також сукупність статистичних та частотно-енергетичних ознак, що відображають амплітудно-фазову структуру сигналу.

Порівняльний аналіз з класичними методами класифікації сигналів, заснованими на узагальнених статистиках, продемонстрував перевагу запропонованого підходу як за точністю, так і за швидкодією при обробці великих обсягів даних.

У межах дослідження запропоновано архітектуру моделі, описано процес її навчання, валідації та тестування. Додатково проаналізовано вплив параметрів спектрального розкладу на якість класифікації. Результати експериментального моделювання засвідчують, що поєднання спектральних та статистичних дескрипторів дозволяє досягти високої точності при розпізнаванні різних типів радіосигналів. Запропонований підхід може бути ефективно застосований у практичних системах автоматизованого аналізу радіочастотного спектра та виявлення сигналів в умовах складної електромагнітної обстановки.

Ключові слова: *потужність, підхід, валідація, тестування, модель, система, ознака, класифікація, радіосигнали, амплітуда, фаза.*