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APPROACH TO PROCESSING RADIO SIGNALS WITH AMPLITUDE MODULATION OF MANY COMPONENTS USING ONE-DIMENSIONAL CONVOLUTIONAL NEURAL NETWORK

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The object of research is the methods of using one-dimensional convolutional neural networks in radio receiving systems in order to increase their interference resistance.

The task of the research is to test the hypothesis about the likely higher efficiency of radio signal recognition under conditions of high noise (or weak signals) by neural network models of radio signal reception in comparison with trivial reception systems.

With the use of one-dimensional convolutional neural networks, a higher efficiency of extracting useful information from a signal-noise mixture at sufficiently high noise levels and, accordingly, a higher accuracy of radio signal recognition accuracy has been achieved. This result was achieved due to the specific architecture of convolutional neural networks, the ability to automatically detect important patterns in the data and analyze radio signals more deeply and informatively. Hierarchical representation of data with the selection of more complex and abstract features of the signal as the convolutional neural models become more complicated is one of the main advantages of using the proposed methods and algorithms under complex conditions of radio signal transmission.

The comparison with trivial methods of radio signal processing is performed on the basis of the symbol error probability parameter at different signal-to-noise ratios of the investigated signals and demonstrates a stable decrease in the symbol error probability at signal-to-noise ratios of less than 4 dB.

The results could be used in real radio communication systems, especially under conditions where it is necessary to quickly and reliably recognize radio signals among noise, under conditions of interference or with weak signals. They could also be useful in military applications, Earth remote sensing systems, mobile communication networks, etc.

Keywords: signal processing, artificial neural network (ANN), convolutional neural network (CNN)

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1. Introduction

Artificial neural networks open up new opportunities for signal processing with their ability to learn complex patterns directly from data without the need for manual feature generation. They are used for a variety of tasks such as speech recognition, signal anomaly detection, audio processing, and many others. Artificial neural networks are able to adapt to different signal sources and learn features that may not be obvious or unattainable by traditional methods.

In today's world, the number and volume of transmitted radio signals is growing rapidly due to the development of mobile communications, Internet of Things devices, and unmanned vehicles. At the same time, the complexity of the transmission conditions also increases – the amount of noise, interference and other disturbances increases. This requires new and efficient methods for processing and analyzing radio signals that can automatically adapt to changing transmission conditions.

Convolutional neural networks are a class of artificial neural networks that are most often used in the analysis of spatial data, in particular images and videos. Their effectiveness can be explained by the ability to detect patterns in the data structure, regardless of the placement of these patterns in the general context of the data being processed. Such regularities are called local features. Two-dimensional and three-dimensional convolutional networks are the most popular, but in the context of processing signals as one-dimensional sequences, one-dimensional convolutional neural networks may be of particular interest. Previous studies of the use of one-dimensional convolutional neural networks have already demonstrated the high efficiency of their use in performing signal processing tasks. The advantages of one-dimensional convolutional neural networks can include increased accuracy of radio signal recognition, reduced analysis time, and the ability to work with large amounts of data and high levels of noise. This, in turn, makes it possible to improve the quality of communication services, reduce the number of errors in data transmission and optimize the use of the radio frequency spectrum.

The relevance of radio signal processing research using one-dimensional convolutional neural networks is due to the need to find effective solutions for modern radio communications challenges. Taking into account the constant development of technologies, the increase in the amount of transmitted data and the complexity of the radio environment, the need for new methods of processing and analyzing radio signals is becoming more and more urgent. Such studies open new horizons for improving the quality of radio communication systems and respond to modern challenges in this field.

2. Literature review and problem statement

The idea of using artificial neural networks for signal processing is not new. However, the introduction of new means and methods of forming models of artificial neural networks made it possible to conduct new research aimed at finding new ways of effective use of artificial neural networks in signal processing.

Study [1] proposed a model with parallel recurrent parts, each of which defines different local features of the signal. The determined local features are combined in the matrix of features and with the help of vector compression, the result of the classification of the signal with which the proposed model works is obtained. This approach is proposed to be used for signal analysis when there are a large number of local features per period and thus different recurrent parts are responsible for different local features. However, the question of the stability of the operation of such a model with an unbalanced sample of training data remains unresolved. The solution to this issue is proposed in [2], where knowledge about local features is built into the developed convolutional model. Using a model with built-in knowledge of local features has the advantage of greater control over the learning process of an artificial neural network, but complicates the calculation process and, accordingly, requires a significant amount of time to train the model.

The models in works [1, 2] are proposed to be used for signals of very low frequencies, such as electrocardiograms. For higher-frequency audio signals, work [3] suggests combining a discrete sinusoidal transformation network and a recurrent neural network for the classification of the type of audio signal. This approach demonstrates effectiveness when the information to be obtained from the signal is contained in the nature of changes in its frequency and amplitude parameters. A limitation of such a model is that it primarily determines the global or long-term features of the signal.

In the case of radio frequencies, a number of works consider determining the secondary characteristics of the signal. Secondary refers to the characteristics of signal distortion, which was formed in the process of signal formation and transmission. Such distortions can be caused by weather conditions, interference or internal noise of transmitter and receiver components.

Work [4] proposes a one-dimensional convolutional neural model for the identification of inconspicuous radars in an environment with added Gaussian noise and demonstrates the advantages of this approach compared to traditional automatic classification methods. The limitation of such a model is that although one-dimensional convolutional networks have a good ability to detect both local and global features, the uncertainty of noise can significantly impair the effectiveness of the model. In [5], a cascade model is proposed, in which, for greater efficiency of the analysis of radar pulses, noise parameters are also analyzed, which makes it possible to determine the operating modes of radars under more unstable transmission conditions. Work [6] proposes a model that also estimates the data transmission channel but is able to detect signals in non-orthogonal OFDM multiple access systems. Although such systems demonstrate high efficiency in environments with interference, they have a limitation, which is the determinism of the signals with which they work. This is due to the fact that in the case of radars, the structure of the signal to be received is usually known in advance, which facilitates the process of searching and further analyzing the signal in an environment with a high level of added noise.

In [7], a method of forming signal processing algorithms using an artificial neural network with LSTM layers (long short-term memory) is proposed. Such a system analyzes the features of the signal and offers an effective processing algorithm. Although meaningful analysis of the signal is carried out in such a system, nevertheless, the main task performed is to help form the transmission algorithm, and to accompany the process itself.

In [8], a technique of secure analysis of signals and detection of data types using deep learning is proposed. This approach has a closer relationship to the transmitted data and analyzes the data based on the probability distributions of byte sequences, spectral density and byte sequence redundancy in the signal. The limitation of this approach is working with signals that have undergone demodulation and decoding a priori.

In cases where the signal can be represented as a graph, the principles of graph theory can be applied in the processing process. Works [9–11] tackle the problem of denoising graphic signals. The graph-like signal processing approach demonstrates high efficiency, but such networks require a more complex learning process compared to traditional recurrent and convolutional networks.

Paper [12] proposes the use of a one-dimensional convolutional network for signal processing with binary phase manipulation. The proposed system is coordinated with a symbol synchronization algorithm to perform better under conditions of unwanted frequency shifts of the modulated signal and sampling rate errors.

Study [13] proposes the use of a one-dimensional convolutional network with recurrent elements of long short-term memory for signal processing with Gaussian two-position frequency manipulation under conditions of strong disturbances caused by the solar wind.

Works [12, 13] show a certain potential of using one-dimensional convolutional networks for digital signal processing. However, in these works, only the operation of the proposed models with such types of modulation, where there are only two symbols, is demonstrated.

In general, the review of works by other authors shows the active use of recurrent neural networks and one-dimensional convolutional networks in signal processing tasks. These models are used in a wide range of tasks, from medical applications to decoding sequential data. However, although numerous sources confirm the effectiveness and potential of these approaches, it is still clear that there are problems that have not yet been fully resolved. Some of these issues may include the limited ability of the models to work with high levels of added noise or require the signals to conform to certain conditions. Such conditions may include the need for preliminary demodulation of the signal or the possibility of representing the signal in the form of a graph.

Local problems encountered in the examined sources can be reduced to one main issue: the difficulty of adapting the reported models to changing transmission conditions, as well as to work with more complex signals. Despite extensive research in the field, the lack of a comprehensive approach that would integrate various techniques and algorithms into one capable system leaves this problem not fully resolved.

3. The aim and objectives of the study

The goal of our research is to devise such an approach to radio signal processing that would make it possible to work with signals with a modulation scheme containing more than two symbols, as well as with high levels of added noise. This could make it possible to improve the efficiency of radio communication systems and expand the possibilities of their use under various conditions.

To achieve the goal, the following tasks were set:

– to build an artificial neural network model that combines the advantages of recurrent and one-dimensional convolutional networks for effective processing of radio signals;

– to develop an algorithm for validation and evaluation of the effectiveness of the constructed model.

4. The study materials and methods

The object of this study is the application of one-dimensional convolutional neural networks in radio receiving systems with the aim of increasing their immunity to interference and the accuracy of radio signal processing, in particular, reducing the probability of error when recognizing discrete signals.

The need for this research is based on the assumption that one-dimensional convolutional neural networks, due to their ability to automatically extract characteristic features in one-dimensional sequences, can more effectively distinguish usable radio signals from interference. Thus, the use of these networks in radio receiving systems can serve as a key to improving their performance under difficult conditions.

This study assumes the possibility of forming such a model of a convolutional neural network, the functionality of which would approximately correspond to the functionality of an optimal filter. The main difference is that if an optimal filter separates a signal from an additive mixture with noise due to the determinism of its spectral characteristic, then a convolutional neural network does this due to the detection of local features. According to the accepted assumption, in the developed model, the convolutional layers will isolate local features of the signal from the additive mixture with noise. Recurrent layers, in turn, will analyze selected local features in a wider context, as a result classifying the sequence of symbols contained in the input signal.

The use of a one-dimensional convolutional neural network for the given task may have the following advantages:

1. Invariance with respect to shifts when local features are detected. That is, signal fragments or more abstract changes in signal parameters are detected regardless of their location in the entire time sequence being analyzed.

2. Analysis of information in signal fragments based on the general context. That is, based on the detected local features, a general context is formed, which makes it possible to process signals more efficiently.

To form a sample of training data, fragments of signals with amplitude modulation of many components (AMMC) were chosen – a type of amplitude-phase manipulation, which is characterized by greater energy efficiency than signals with quadrature amplitude modulation [14].

AMMC signal $U_{AMMC}(t)$ is defined as the sum of its N components with the difference in their initial phases, which is $\varphi_0+\varphi_n$ (rad):

$$U_{AMMC}(t)=U_n a_n U_{m_n}(t)\cos(\omega_0+\varphi_0+\varphi_n), \quad (1)$$

where a_n is the proportionality coefficient of the n-th subchannel, and $U_{m_n}(t)$ are the modulation signals of the n-th input of the modulators.

The Euclidean distance between the nearest points of the AMMC signal constellation is determined by the following ratio:

$$d_{sign}=U(M_U-1), \quad (2)$$

where U is the maximum possible signal amplitude and M_U is the number of equidistant amplitude levels of modulating signals.

The further procedure for calculating the AMMC constellation is based on observations of the structure of the constellation. The essence of the observation is that if you draw conventional lines between all the nearest points of the constellation, the resulting image will look like a grid of equilateral triangles (Fig. 1). Based on this property, it is possible to simplify and streamline the process of calculating the AMMC constellation using trigonometric transformations and properties of right triangles with angles of 60° and 30° [14].

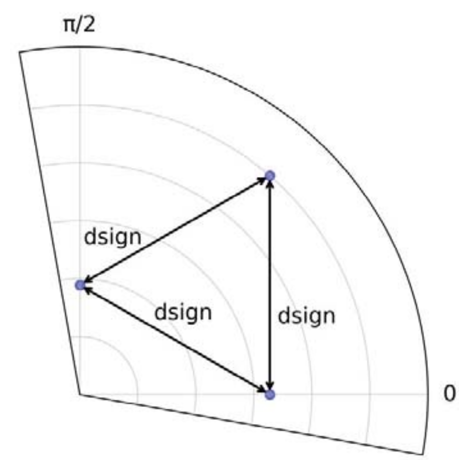

Fig. 1. A fragment of the signal constellation of a three-component multicomponent amplitude modulated signal

As input data, it was decided to use the Euclidean distance between the horizontal levels of the constellation – d_m, which is also the length of the median of an equilateral triangle with sides d_{sign} – this length is found in the first place:

$$d_{sign} = 2\frac{d_m}{\sqrt{3}}.$$

The number of horizontal levels of the constellation is found using the following ratio:

$$N_y = \frac{1}{d_m} + 1.$$

The number of points on each horizontal level (without taking into account the condition of the distance from the center of the constellation) is determined by the following expression:

$$N_x = \frac{\sqrt{3}}{d_m}.$$

Next, the horizontal levels are divided into even and odd, to form between adjacent levels shifts along the *X* axis necessary for an equilateral triangular structure.

Accordingly, on even horizontal levels, the *X*-coordinates are determined by the following expression:

$$X_i = i \cdot \frac{d_{sign}}{2},$$

where $i \in (-N_x; N_x+1)$.

And at odd horizontal levels, the X-coordinates are defined by the following expression:

$$X_i = \frac{d_m}{2} + i \cdot \frac{d_{sign}}{2},$$

where $i \in (-N_x; N_x+1)$.

At each horizontal level, all points obviously have the same Y-coordinates, which are defined as follows:

$$Y_i = j \cdot d_m,$$

where $j \in (-N_y; N_y)$.

The points in the obtained set are additionally checked for compliance with the condition $\sqrt{(x_i + y_j)} < U$, the points that meet this condition actually form the AMMC signal constellation (Fig. 2).

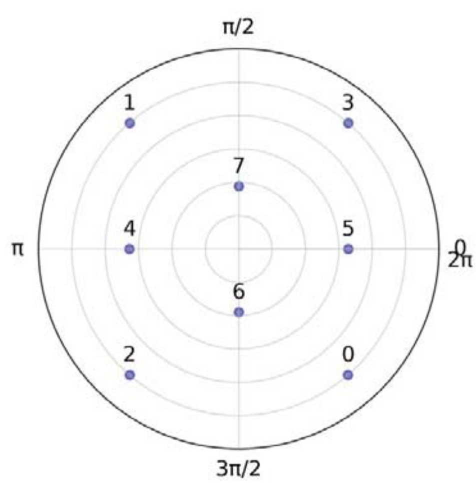

Fig. 2. A signal constellation of a signal with amplitude modulation of many components

After obtaining the coordinates of the points of the AMMC signal constellation, it is possible to start forming signal fragments with added noise, which will be used in the future to train the proposed artificial neural network model.

The proposed method of forming an array of radio signals for training artificial neural networks [15] is based on the hypothesis that the Voronoi diagram is the most effective way of dividing space into parts. The points of the signal constellation become Voronoi vertices, and Voronoi cells are formed around them. Each cell is formed from those points that are closer to the vertex of this cell than to the vertices of other points – hence it follows that the borders of the cells are straight lines equidistant from the vertices of the cells they separate (Fig. 3).

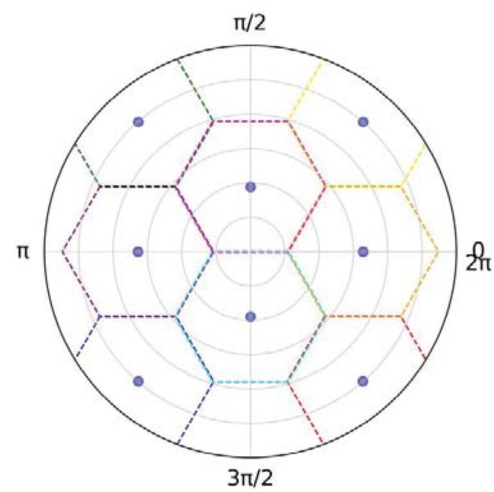

Fig. 3. Boundaries of Voronoi cells in a signal with amplitude modulation of many components

To simplify the calculation, one may not form variations of signal fragments separately for each cell, but only once for a cell with a vertex at zero coordinates and extrapolate the resulting set to all other cells. First, it is necessary to calculate the distances from the zero coordinates to the neighboring points (Table 1) – this calculation is based on the properties of right triangles with sides of 30° and 60°, into which the equilateral triangles of the AMMC grid are divided by the median.

Table 1

Coordinates closest to zero points

No.	1	2	3	4	5	6
x	$d_m/\sqrt{3}$	$2d_m/\sqrt{3}$	$d_m/\sqrt{3}$	$-d_m/\sqrt{3}$	$-2d_m/\sqrt{3}$	$-d_m/\sqrt{3}$
y	d_m	0	$-d_m$	$-d_m$	0	d_m

From the set of coordinates of neighboring points, using the same previously mentioned properties of right triangles, the coordinates of the corners of individual cells are obtained, in turn (Table 2).

Table 2

Coordinates of angles of the Voronoi cell

No.	1	2	3	4	5	6
x	0	$d_m/\sqrt{3}$	$d_m/\sqrt{3}$	0	$-d_m/\sqrt{3}$	$-d_m/\sqrt{3}$
y	$2/3\ d_m$	$1/3\ d_m$	$-1/3\ d_m$	$-2/3\ d_m$	$-1/3\ d_m$	$1/3\ d_m$

The received coordinates of the corners of the cell make it possible to determine the limits in which it is necessary to form a set of points that will represent different variations of the signal with added noise. Further, these boundaries can be filled with variations of points – the simplest method from the point of view of calculations to do it uniformly is to divide the hexagon into 6 triangles and already add the points from all triangles into one resulting array (Fig. 4).

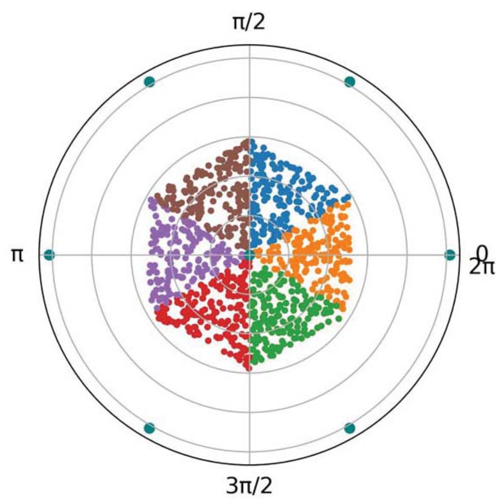

Fig. 4. Voronoi's cell with filling points

By taking the coordinates of the obtained set of points and adding to them the coordinates of any signal point of the AMMC constellation, it is possible to obtain an extrapolated cell for this particular point.

The time representation of the signal corresponding to a certain point of the constellation is calculated according to the following formula:

$$S(t)=\sqrt{x^2+y^2}\cdot\sin\left(t+\tan^{-1}\left(\frac{y}{x}\right)\right),$$

where x and y are the coordinates of the point of the constellation (or the coordinates of a random "noisy" point from the cell).

In the time plane, 3 points (π/4, π, 5π/4) are chosen, which is the minimum number of discretization points according to some refinements of the Nyquist-Kotelnikov-Shannon theorem. Choosing the minimum number of discretization points makes it possible to evaluate the effectiveness of the proposed artificial neural network model at the limit of the capabilities of the receiving and transmitting systems.

TensorFlow was chosen to build the artificial neural network model, which provides a convenient and flexible interface for designing, training, and deploying machine learning models on various platforms, from mobile devices to high-power clusters. TensorFlow supports a wide range of algorithms and architectures and provides tools for visualizing the processes of learning and evaluating models.

TensorFlow is a low-level library, and one can significantly simplify the process of working with it by using a higher-level Python library – Keras, which works on top of TensorFlow (as well as other frameworks, such as Theano). Keras simplifies and accelerates the process of creating and training artificial neural network models by providing simple abstractions and more intuitive interfaces.

Conv1D elements will be used to form an artificial neural network model – this is a type of convolutional layer in the architecture of artificial neural networks designed to work with one-dimensional sequences. It is well suited for detecting local patterns in sequences and can reveal important features in data that are usable for classification and other tasks.

5. Results of research on the development and validation of an artificial neural network for processing radio signals

5. 1. Construction of an artificial neural network model

The designed artificial neural network model (Fig. 5) is a combination of recurrent and one-dimensional convolutional elements of artificial neural networks. That has made it possible to combine the advantages of both types of networks, which made it possible to obtain high efficiency of the resulting model.

The input layer (Input) has a dimensionality determined by the number of sampling points in one signal period (2π) and the number of symbols determined in one cycle of the system. That is, with 3 sampling points and 16 symbols defined simultaneously, the dimensionality of the input layer will be 48.

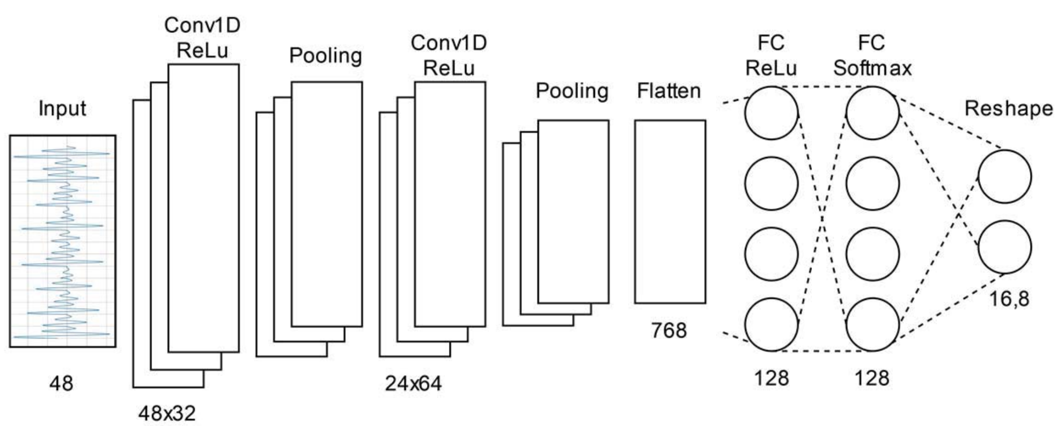

Fig. 5. Structure of the formed model

Convolutional layers (Conv1D) perform the function of determining local features of the signal. Increasing the number of convolutional layers increases the abstractness of the detected features but can also lead to overtraining. In the developed model, taking into account the dimensionality of the input data, it was decided to use 2 convolutional layers. It is also worth considering that the dimensionality of the output data of each prepared layer corresponds to the dimensionality of the input data. In the context of the problem of signal processing, it is especially important to store data dimensions when performing convolution, therefore, zero first and last elements are added to data arrays processed in convolutional layers.

Due to the low sampling rate of the input signal, it is difficult to accurately describe which local features are determined by the system, but some assumptions can be made. In particular, it can be assumed that the artificial neural network is able to detect such regularities as the change in amplitude over the entire duration of the symbol and transient processes when the symbol changes (Fig. 6).

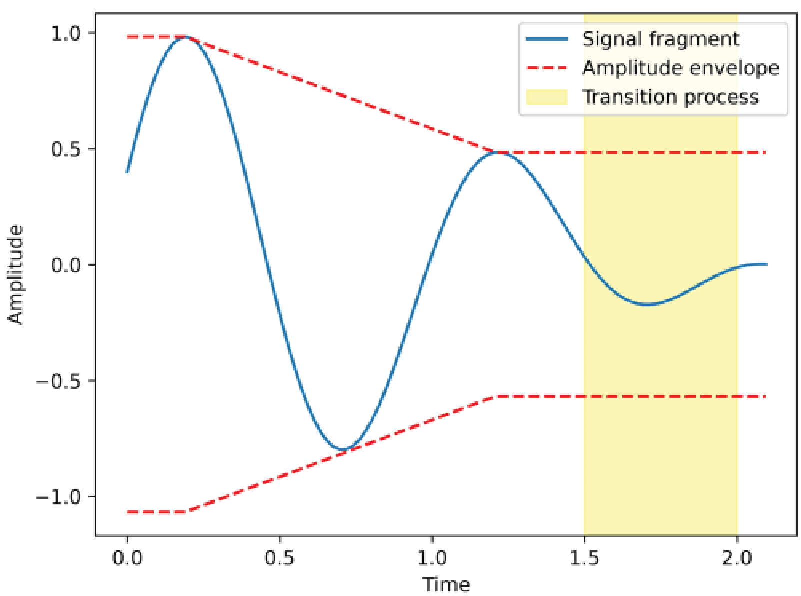

Fig. 6. Probable features of the signal determined by the formed model

Pooling layers perform the function of generalizing features. This is necessary in order to reduce the dimensionality of the output data from previous convolutional layers and highlight the most important features.

The leveling layer (Flatten) is an intermediate layer between the convolutional and recurrent parts of the formed artificial neural network model. This layer performs the function of converting multidimensional features into a one-dimensional array so that further.

Fully connected layers (FC) are used to analyze the entire array of local features and form a certain parameter function based on it.

The activation function of the intermediate layers of the developed model is a straightened linear node (ReLu). Choosing such a function avoids the vanishing gradient problem but may require finer tuning of the regularization parameters to avoid a condition where the output of a layer with such an activation function no longer depends on the input.

The activation function of the output layer is a normalized exponential function (Softmax). The use of this function is appropriate in the case of using cross-categorical entropy as a loss function.

Also, considering that the input sequence contains more than one character, it will be logical to reduce the output data to the appropriate form. For this, the model has a Reshape layer. When setting the parameters of this layer, it is taken into account that there are 16 symbols in the input sequence and the signal modulation type has 8 different symbols.

5. 2. Development of a validation algorithm and evaluation of the effectiveness of the constructed model

To validate the effectiveness of the improved mathematical model of the artificial neural network, it will be advisable to conduct testing on a large set of signal fragments. The same set of fragments was also preprocessed with a reference model, which is equivalent to a real receiving device working with AMMC [12, 13]. The main evaluation criterion is the number of false identifications of symbols during signal processing. To perform this task, a special validation algorithm was developed (Fig. 7).

The test samples did not participate in the training, so it can be assumed that the test results are objective and make it possible to assess the real ability of the model to correctly process new, previously unknown data. The key indicator that was analyzed was the probability of an error in character recognition. This metric represents the percentage of falsely identified characters to the total number of characters in the sample. It should be noted that the testing of the models was carried out at different levels of noise on the input signals, which made it possible to evaluate the stability of the models to different conditions of reception of radio signals and their ability to adapt to various interferences.

The input data set contains several arrays of amplitude values of AMMC signal fragments and arrays of their corresponding symbols. Arrays contain variations of signal fragments with different levels of added interference (Fig. 8). In the context of this work, it will be appropriate to evaluate the effectiveness of the developed model in the range of signal-to-noise ratio −12..4 dB from the entire data set.

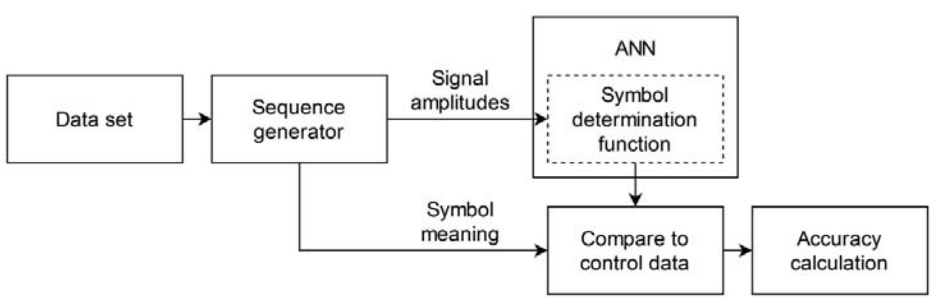

Fig. 7. Validation algorithm architecture diagram

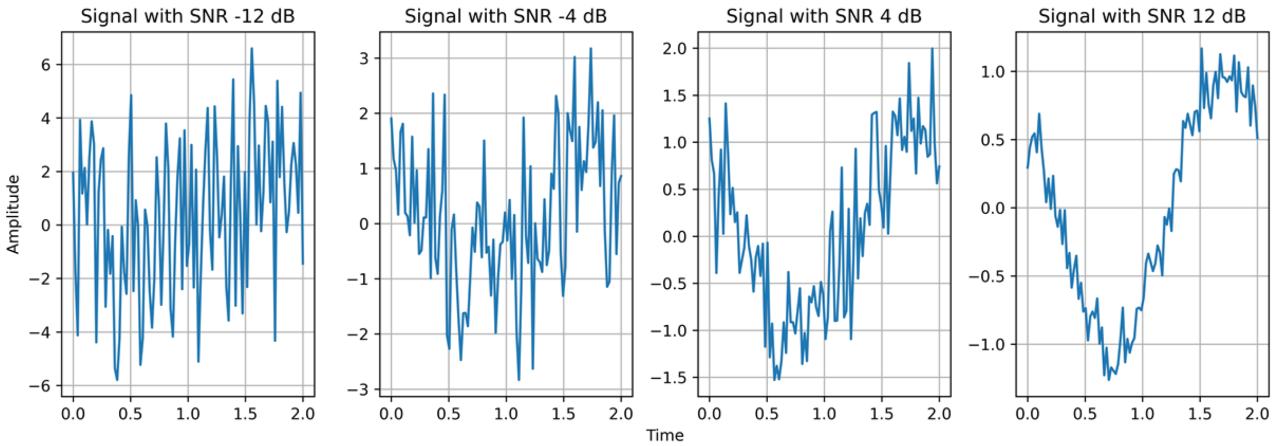

Fig. 8. Variations of the first signal symbol at signal-to-noise ratios of −12, −4, 4, 12 dB

The sequence generator forms time sequences with a larger number of symbols from signal fragments in the data set. This makes it possible to evaluate the effectiveness of the proposed model not only in the context of individual symbols but also in the context of their sequences.

Further, by means of the constructed model, based on the formed input time sequence, a conclusion is drawn regarding the sequence of symbols corresponding to this time sequence. This finding is compared with control data.

The number of inspection cycles is set taking into account the desired accuracy. If we assume that for an adequate assessment of accuracy, it will be sufficient to check the correctness of the assessment of 10,000 characters per level of the signal/noise ratio, then it will be necessary to form 625 sequences with a length of 16 characters. When evaluating signals with 5 different signal/noise ratios, the number of different sequences will be 3125. After the system processes all sequences, one can compare the efficiency with the reference model (Table 3)

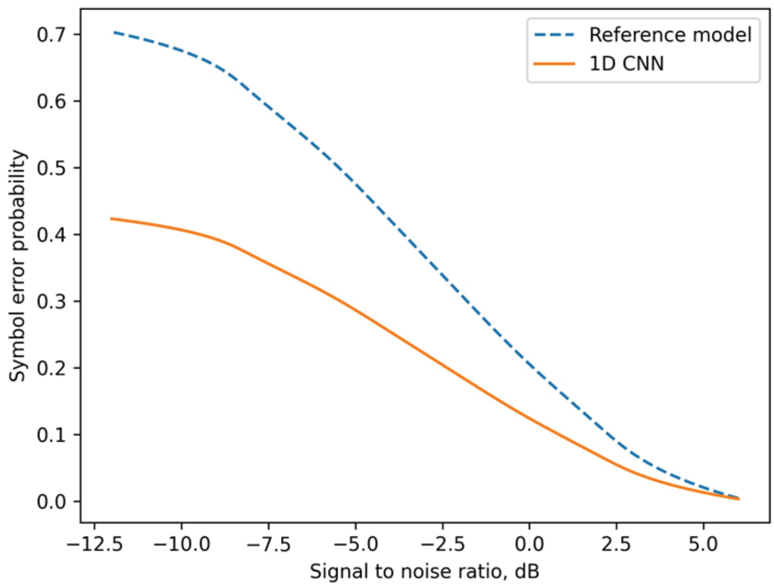

Fig. 9. Comparison of the effectiveness of the reference and proposed models

Table 3

Comparison of the effectiveness of the reference and proposed models

Model	SNR, dB	−12	−8	−4	0	4
Reference	Error probability δ	0.703	0.613	0.421	0.205	0.041
1D CNN		0.423	0.378	0.269	0.141	0.036

From the data in Table 3, it will also be appropriate to build a plot (Fig. 9). In addition, it is worth noting that in the process of determining the efficiency of both the reference and the proposed models, no coding methods were used that would detect or correct errors.

The resulting dependence of the probability of error on the signal-to-noise ratio demonstrates an increase in the relative efficiency of symbol detection as the noise level increases.

6. Discussion of results of the construction of an artificial neural network model for radio signal processing and its validation algorithm

The built model demonstrates some increase in efficiency compared to the reference model (Table 3, Fig. 6), which can be explained by the chosen structure of the model (Fig. 5). Such a structure makes it possible to form a system whose transfer function approximately corresponds to the transfer function of the optimal filter of a real receiver. But in the case of our model, instead of an a priori determined signal shape, a priori determined features of the signal are used, which the model selects from a mixture of signal and noise. Such a result is achieved by selecting such transfer functions of individual layers, their weighting factors and optimization functions, which form the overall transfer characteristic of the system, which approximately corresponds to the optimal filter.

In comparison with the models described in [4, 5], the constructed model demonstrates the ability to work with pseudorandom signals. Compared to models in [8, 10], it does not require the representation of the signal in the form of a graph and uses a simpler neural model learning algorithm.

The main difference between our model and similar examined models is in the specifics of the performed task – performing a process similar to signal demodulation and decoding, using an artificial neural network, and not determining the secondary characteristics of the signal.

It is the task similar to signal demodulation and decoding that is performed by models [12, 13]. However, these models work with such types of digital modulation that have only 2 symbols. The model in this paper is distinguished by its ability to classify signal fragments with a larger number of symbols.

The developed model validation algorithm together with the previously proposed algorithm for the formation of training samples [15] and, in fact, the model itself, together form a complete structure. In such a structure, the validation process takes place immediately after the training process and makes it possible to more easily evaluate the system's performance and quickly make the necessary changes. When forming the training data, the parameters of the signal constellation structure, noise range parameters, and the number of fragments for each symbol are specified. The specified parameters of the noise range are then used for validation, thus enabling the most efficient evaluation of the system's performance. The integration of all modules into one more monolithic structure makes it possible to increase control over the learning process, which is the most important component of the formation of neural models with one-dimensional convolutional layers.

The developed model validation algorithm made it possible to effectively evaluate it and compare our model of an artificial neural network with the closest mathematical model to the real receiving device [15, 16].

A limitation of the constructed model and additional data generation and validation algorithms is the difficulty of adapting third-party datasets (such as RadioML) for the model training process, as this will reduce the controllability of the training process.

The lack of means of preliminary evaluation of the final and intermediate transfer functions of the model can be defined as a drawback of the developed system. Such tools would make it possible to evaluate the characteristics of the model before the process of compilation and training.

The potential of future research is the creation of means of preliminary assessment of the transfer functions of the model. The difficulties of such studies may relate to the need for extensive statistical evaluation of model characteristics. Extensive evaluation means that the characteristics of all possible variations of individual layers and their weighting factors will be evaluated. Representing the collected data in a comprehensible form can also present a certain complexity due to the large number of different parameters.

7. Conclusions

1. An artificial neural network model was built, which performs the task of demodulating signals with high noise levels. Our model skips all intermediate stages of signal processing and immediately forms symbol sequences from the received radio signal, which in turn can be converted into bit sequences and considered the final result of demodulation. The main difference between the model constructed and the previously proposed ones is the specificity of the performed task – demodulation of signals with complex modulation schemes. That is, instead of performing an auxiliary function in the process of receiving radio signals – determining secondary characteristics or demodulating signals with binary modulation schemes, the proposed model performs the function of demodulating a signal with 8 symbols.

The relative effectiveness of our model can be explained by the selection of specific layers and the setting of such weighting factors, which makes the function performed by the model similar to the function of an optimal filter. By similarity with the function of the optimal filter, we mean the selection of a signal from an additive mixture with noise according to its shape. In the case of an optimal filter, the shape refers to the shape of the spectral characteristic of the signal, while in the case of a convolutional neural network, the shape is determined by local features and the general context of the signal. But in this case, the constructed model is purely a software element and does not require complex circuit-technical decisions, which are made when creating optimal receivers.

2. The developed validation algorithm made it possible to evaluate the effectiveness of the model at different noise levels, compare it with the reference model, and easily systematize the results. The results showed that the developed artificial neural network model demonstrated a certain increase in efficiency compared to reference methods, showing a high ability to classify radio signals even in difficult conditions. The most pronounced increase in efficiency was obtained at high noise levels – a reduction in the number of symbol errors by ≈40 % at a signal-to-noise ratio of −12 dB. At higher signal-to-noise ratios, the increase in efficiency is noticeably reduced – ≈13 % at a signal-to-noise ratio of 4 dB.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study and the results reported in this paper.

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Data availability

All data are available in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the presented work.

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