Recognition of images of wavelet spectra of Chirp signals using a neural network

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Abstract

The article developed an algorithm for recognizing images of wavelet spectra of Chirp-type radar signals. Known augmentation methods cannot be used to expand the data set for training and improving the convolutional neural network. Generation of images of signal spectra is carried out with the addition of additive noise to the Chirp signal. The frequency modulation coefficient changes regardless of the presence of amplitude modulation by a half-sine wave. When preparing the data, the limitation of the power range of the Gaussian noise additively added to the signal was applied. Limitation is carried out in the frequency domain by comparing the wavelet coherence of the noise and the noisy signal using the example of the most common signal with linear frequency modulation of the Chirp type. It is shown that the wavelet autocoherence of Gaussian white noise has a constant value over the entire range of noise power variation. At the same time, the numerical value of autocoherence depends exclusively on the choice of wavelet. The wavelet autocoherence of the noisy signal when the noise power changes intersects with the noise autocoherence at the power value, which, in addition to the wavelet, depends on the frequency modulation coefficient. The described procedure for preparing spectrum images for processing in a neural network increases the probability of recognizing a given type of signal due to the exclusion of signals that cannot be recognized due to the lack of distinction from noise. For each continuous wavelet, such a level of non-stationarity is determined, at which a noisy signal can be recognized. This allows you to expand the database. Perform augmentation by changing the wavelet, as well as amplitude modulation of the signal. The effectiveness of the developed model was evaluated and the results were compared with known analogues. The trained neural network model for image recognition of continuous wavelet spectra using the example of the Chirp signal provides up to 100% accuracy of image detection and classification (the best result of the analogue is up to 95.7%).

Keywords

augmentation, wavelet-spectrum, convolutional neural networks, wavelet-autocoherence

1. Introduction

Since the appearance of radar with pulse compression, the Chirp (Compressed High-Intensity Radiated Pulse, LFM) signal has become one of the most common forms of radar signal [1].
The radar signal is modulated by phase or frequency, and this makes it possible to separate targets in space when receiving signals using special methods, the echoes of which intersect [2]. It should also be noted that pulse compression technology was developed for conditions where

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noise in the receiver always has a wide frequency band and random distribution [3]. It was believed that the spectral density of the noise is quite small compared to the echo signal. Since the noise intensity in the signal after the compression filter is significantly reduced, it makes it possible to identify the target in cases where the amplitude of the echo signal is less than the noise level [3, 4].

By changing the signal modulation to nonlinear frequency modulation (NLFM), better performance values in terms of peak voltage to side lobe ratio (PSLR) can be achieved. Changing the modulation of the signal provides a mitigating effect of masking nearby targets and can generally increase the useful dynamic range [5]. When adding appropriate amplitude modulation, PSLR can reach very low values (about -60 dB) [6].

Noise Radar Technology (NRT) is a viable alternative to deterministic waveforms. It uses pseudo-random waveforms to implement the noise process [6]. Common to NRT and deterministic radar technology is the use of a matched filter or an approximation thereof to maximize the signal-to-noise ratio (SNR). However, a noisy radar is capable of transmitting an almost unlimited set of realizations ("sampling functions") of a random process with an appropriate matched filter adjusted in real time to implement the well-known "correlation receiver" [7]. Thus, the main advantage of noise radar technology is the ability to work with highly noisy signals, in conditions of interference, since interference is perceived by the radar as a kind of noise [6].

The greatest contribution to the development of the theory of radar signal processing was made by K. Shanon, D. Flynn, S. Kay, A. Widoms, and R. L. Kriplin. Numerous publications in recent years by A. Gayvel, E. Liu, E. Monge, J. Delinget and many others confirm that the development and improvement of devices for the formation and processing of radar signals is an urgent task, especially for our country during a full-scale war. LFM signals can rightly be considered today as one of the elements of ensuring information security in telecommunication systems [8].

2. Analysis of literary data and statement of the problem

Recognition of images of noisy signals is an urgent task for many fields of technology. The rapid development of unmanned aerial vehicle technologies also requires solving the problems of image recognition in real time. The task is further complicated by the fact that in real conditions more complex forms of radar signals are used than those that have been well studied by researchers [9, 10]. Accordingly, there is a need to improve signal processing algorithms and image preparation for analysis and classification.

The development of machine learning made it possible to implement neural networks for processing signals of various types: data from sensors [11], audio signals [12] and images [13]. In recent years, various architectures of neural networks have been developed, which are designed to solve different types of problems. Neural network training methods are constantly self-improving and developing, retraining is reduced, and learning speed is increased. The latest models are characterized by increased resistance to noise and changes in input data, which increases their efficiency. The scaling of neural networks allows processing large data sets and solving complex tasks, including the processing of radar signals [14].

One of the most common tools for image classification and recognition today is a convolutional neural network (CNN) [15]. As a classification method, the convolutional neural network was developed and became the most widely used in computer vision technology [16].

The restraining factor in the development of CNN models is the presence of an output analog signal. A promising approach is the transition to time-frequency images using signal classification in convolutional neural networks. A difficult issue is the analysis of non-stationary signals. The use of wavelet transformation in time-frequency image research shows good results [17].

The accuracy of classification of wavelet spectrum images depends on the ability to learn the similarity of the neural network. The authors have already investigated the problem of not having enough data set for model training [18]. To increase the representativeness of the data set and improve the performance of neural networks, in particular, in the areas of computer vision and image processing, various augmentation methods are used [19].

Geometric transformations such as rotations, shifts, mirroring, scaling change the spatial position of the object and the model is able to learn at different positions of the objects. Changing the brightness, contrast and color allows you to increase the variety in the training set and improve the model's robustness to changes in lighting and color. Adding noise corresponding to different distributions helps train the model to effectively recognize objects in environments where different levels of noise are present. But in the given task, the known methods of augmentation do not allow to obtain the desired result, since the number of classification groups is unknown in advance during object recognition.

The second factor affecting classification accuracy is the influence of conversion parameters, frequency modulation coefficient, and noise added to the signal additively. The authors do not provide data on the effect of changes in noise power on Chirp-type signals. There is also no information on the effect of noise autocoherence on the wavelet autocoherence of a noisy signal, the use of additional signal modulation, and the visualization of these changes in the image of wavelet spectra.

The purpose of this article is to develop an algorithm for recognizing images of wavelet spectra of Chirp-type radar signals based on the numerical value of the frequency modulation coefficient while limiting the power of additively added noise by comparing the autocoherence of the signal and noise in the frequency domain using a convolutional neural network model. As an algorithm for the image augmentation procedure in the neural network, the method of changing continuous wavelets is investigated, and the division of wavelet spectrum images into classes is performed by checking the homogeneity of the class according to the Shannon entropy value.

3. Algorithm for image recognition of continuous wavelet spectra of Chirp-type signals

3.1. Mathematical model of the Chirp signal in the time domain, taking into account the variable coefficient of linear frequency and amplitude modulation

We will use the ratio for the Chirp signal with linear frequency modulation:

$$x(t_i) = \mathrm{anp}\cos\left(2\pi f_0 t_i + \pi\beta t_i^2\right) + \eta_i, \quad (1)$$

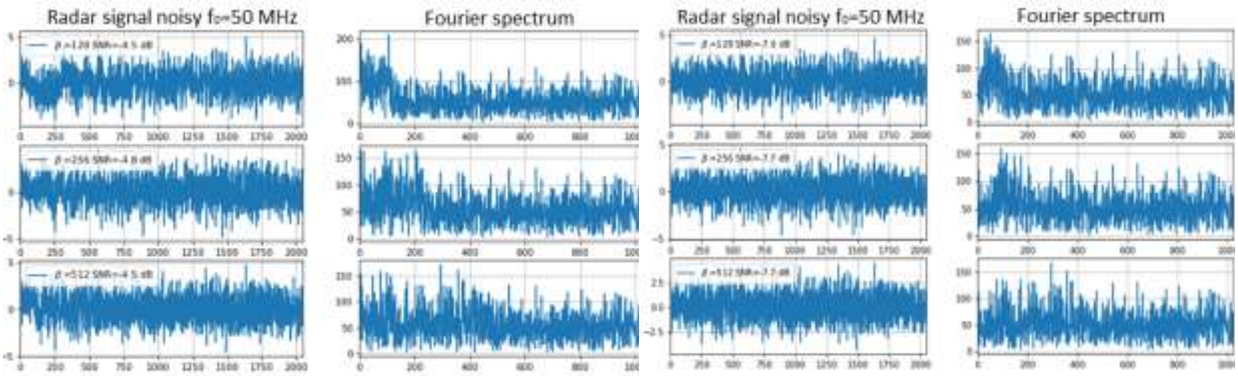
where anp –signal amplitude; f_0 –initial value of the frequency; β –coefficient of linear frequency modulation; η uncorrelated Gaussian noise, mathematical expectation is zero..

To take into account the amplitude modulation, we add a multiplier in the form of half-sine waves (anp sin(πt)):

$$x(t_i) = \mathrm{anp}\sin\left(\pi t\right)\cos(2\pi f_0 t_i + \pi\beta t_i^2\right) + \eta_i. \quad (2)$$

The modulation band to use the ratios must satisfy the inequality β<0.5N, where N – length of the signal, for our case N=2048, that is, the condition for β_{max}=512<1024 is fulfilled.

Let's examine the Fourier spectra of the Chirp signal by changing the coefficient of linear frequency modulation using linear frequency modulation and adding amplitude modulation by a half-sine wave (Fig. 1).



a) b)

Figure 1: Fourier spectra of the Chirp signal with parameters f_0=50 MHz, β=128; 256; 512 for signals: a) according to ratio (1); b) by relation (2)

The results obtained in the graphs of Fig. 1 show that for the same root mean square deviation of the additive noise with additional amplitude modulation by a half-sine according to the ratio (2), the relative noise level in decibels is higher.

3.2. Mathematical model of image generation of continuous wavelet spectra for Chirp-type signals in the frequency domain

Wavelet coefficients will be determined by the formula for a continuous wavelet spectrum [9, 20]:

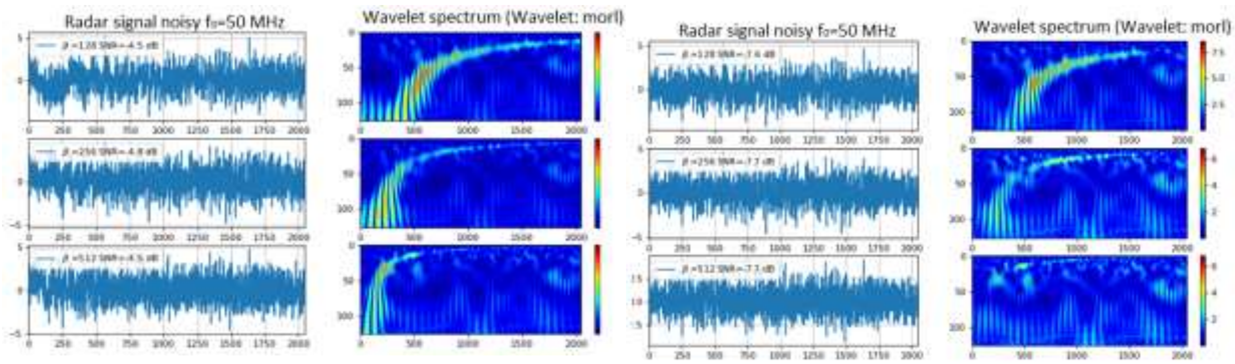
$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi\left(\frac{t-b}{a}\right) dt, \qquad (3)$$

f(t) – signal with a random component; $\psi(\frac{t-b}{a})$– the basic wavelet can be chosen from the list cgau1, cgau2, cgau3, cgau4, cgau5, cgau6, cgau7, cgau8, cmor, fbsp, gaus1, gaus2, gaus3, gaus4, gaus5, gaus6, gaus7, gaus8, mexh, morl, shan; a≠0 scale parameter; b≥0 – shift parameter [20]. The studied data are discrete, therefore formula (1) will be presented in the form, by selecting two arrays for the scales of *coeffs* for shifts *fred*:

$$coeffs, fred = \frac{\Delta t}{\sqrt{a}} \sum_{i=0}^{N-2} x(t_i) \psi\left(\frac{t_i - b}{a}\right). \qquad (4)$$

To exclude the dependence on the displacement b, we obtain a representative amplitude of the inhomogeneity of the scale *coeffs* for the displacements *fred*. The formation of an experimental data set (Dataset) for training a convolutional neural network will be carried out by generating images of signal spectra with the addition of additive noise to the Chirp signal. We will change the frequency modulation coefficient regardless of the presence of amplitude modulation by a half-sine wave (Fig. 2).

The results obtained in the graphs of Fig. 2 for images of wavelet spectra, as well as for Fourier spectra, confirm the preliminary conclusion to Fig. 1 that for the same root mean square deviation of additive noise with additional amplitude modulation by a half-sine according to the ratio (2), the relative noise level in decibels higher.



a) b)

Figure 2: Wavelet-spectra of the Chirp signal for the wavelet morl, f_0=50 MHz, β=128; 256; 512 for signals a) according to ratio (1); b) by relation (2)

3.3. The method of detecting the noise threshold in the frequency domain

Consider the cross wavelet spectrum to check the level of influence of various interferences on the signal: white Gaussian noise and additively added noise. To assess the impact, we use autocoherence, which was already used in previous works to solve a similar problem [21]:

$$\left.\begin{aligned} S_x &= \frac{\Delta t}{\sqrt{a}} \sum_{i=0}^{N-2} x(t_i)\psi\left(\frac{t_i - b}{a}\right), \\ S_y &= \frac{\Delta t}{\sqrt{a}} \sum_{i=0}^{N-2} \frac{dx(t_i)}{dt_i}\psi\left(\frac{t_i - b}{a}\right), \\ \kappa^2 &= \frac{\left|S_{xy}\right|^2}{|S_x|^2\left|S_y\right|^2}. \end{aligned}\right\}. \qquad (5)$$

where $\psi(\frac{t-b}{a})$– the wavelet function; S_x– scale-time spectrum of the signal x(t); S_y– scale-time spectrum of the derivative signal $\frac{dx(t_i)}{dt_i}$; a– scale factor; b– elimination of the signal along the time axis; k^2– the square of the coherence coefficient, which varies from zero to one, characterizes the level of stationarity of signal observation in the presence of noise.

It was established that for Gaussian noise, autocoherence according to relation (5) does not depend on the power of the noise. It is shown that the self-coherence depends only on the wavelet with the help of which a number of large-scale wavelet noise coefficients are formed (Fig. 3). The results of studies of the influence of a wider list of wavelet types will be given in future publications.

For the case under consideration, the mexh wavelet provides the minimum self-coherence and, accordingly, the maximum non-stationarity. Let's determine the noise threshold for the Chirp signal for this wavelet according to ratios (1), (2) with the noise measured in decibels. Autocoherence according to relation (5) is used twice: first for noise, and then for a signal with the addition of noise (Fig. 4).

Based on the obtained results (Fig. 4), when preparing the DataSet for the convolutional neural network model, we will have to limit the noise levels depending on the value of the modulation coefficients and the type of wavelet.

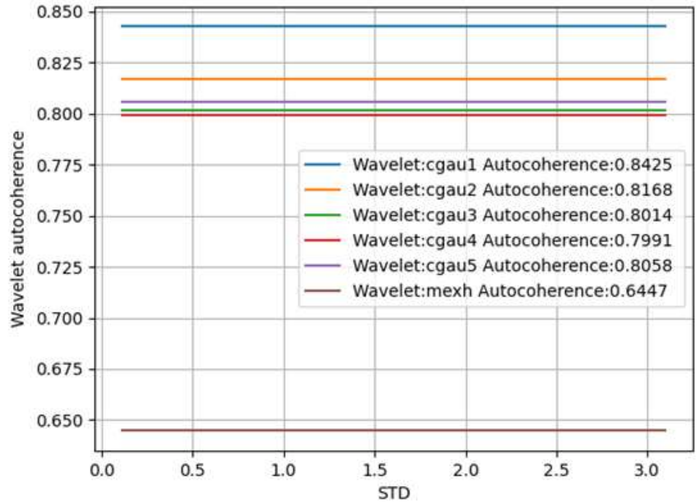
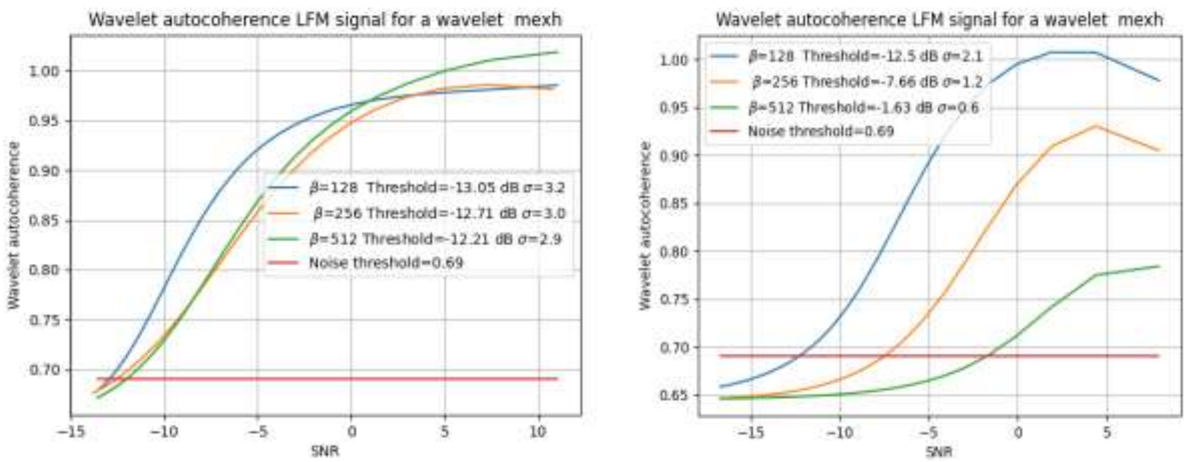


Figure 3: Dependence of the autocoherence of Gaussian noise on a continuous wavelet



a) b)

Figure 4: Graphs for determining the noise threshold based on the equality of non-stationarity of the signal and noise for the signal: a) for relation (1); b) for relation (2)

3.4. Peculiarities of the algorithm for preparation of the experimental data set CNN

Convolutional neural networks use images as input data. In this way, special procedures for recognizing specific elements or symbols can be introduced into the CNN architecture [22]. Changing the architecture of multilayer models such as ResNet50, VGG16, VGG19 by using an additional layer does not provide a solution to the problem, complicates fine-tuning of the model and increases the training period.

By analogy with previous works, the TensorFlow framework was used to build a neural network model - a computing library for building neural networks of various architectures with the Keras deep learning library, which provides full access to the scalability and cross-platform capabilities of TensorFlow [23]. Due to the lack of a dataset required for research in the Keras library, it is necessary to create your own experimental dataset. The block diagram of the developed algorithm for preparing wavelet spectrum images for the built high-precision neural network is shown in Fig. 5.

The accuracy of the deep learning model depends on the procedure for extracting data features, which is built on a large number of various experimental data [24]. In the absence of such data, the augmentation procedure is used - a method of artificial generation of a "training" data set, which is used to train the model. Usually, augmentation is implemented by the Tensorflow image generator, with the help of which each "training" image is modified randomly: it is rotated to a certain angle, changes its size or contrast, is mirrored [25]. Thanks to this approach, an artificial increase in the representativeness of the data set for neural network training is achieved [26].

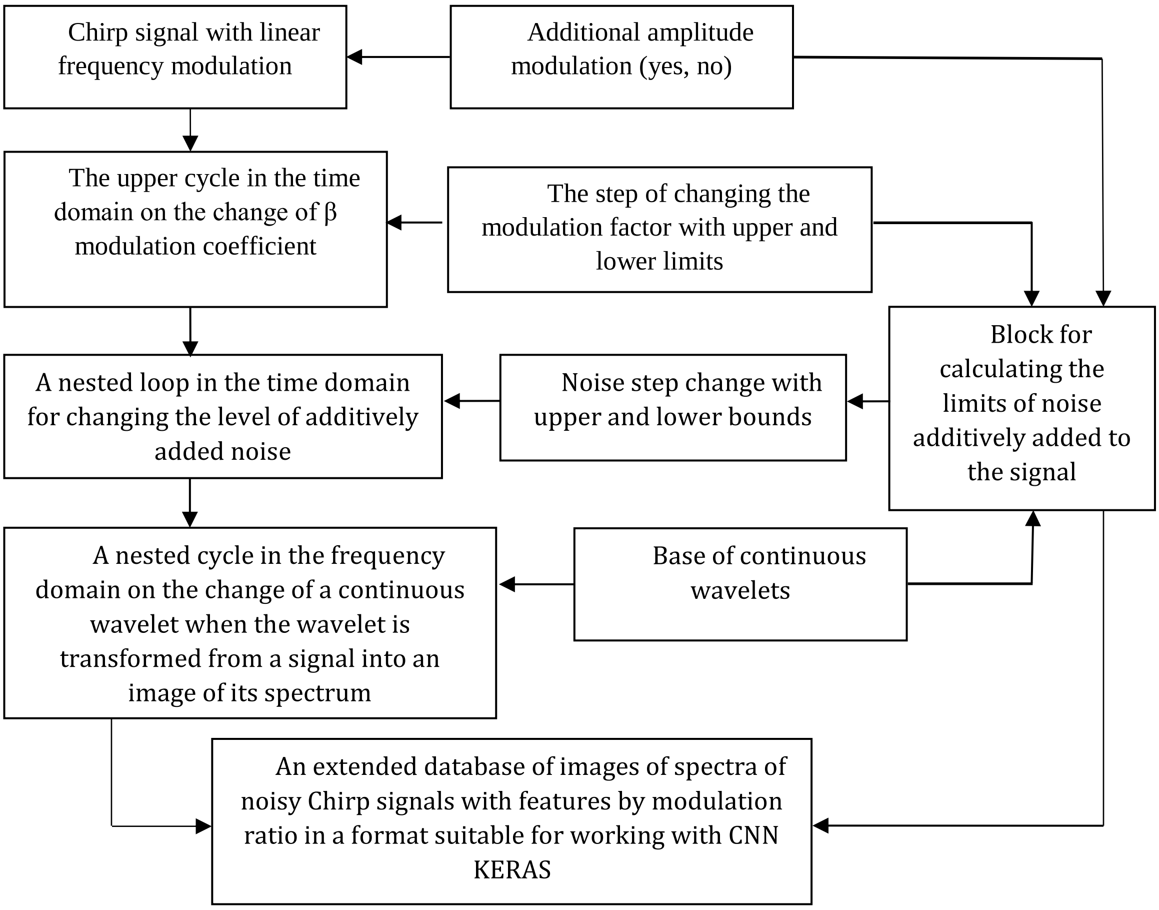


Figure 5: Block diagram of the DataSet preparation algorithm for image recognition of Chirp-type radar signal spectra taking into account the modulation coefficient

The obtained set of experimental images is formed into three subsets: training (7056 samples), validation (2520 samples) and test (504 samples) samples. The training sample is used to train the network; the validation sample in the learning process serves to select the hyper parameters of the network; a test sample is a set of images used to evaluate the performance of the network after training.

A convolutional neural network is a stack of two-dimensional convolutional layers with the activation function of the Rectified Linear Unit (ReLU), which alternate with MaxPooling 2D layers. In addition, the depth value of the hidden layers gradually increases from 32 to 64, while the size of the feature maps decreases from 248×248 to 29×29.

The CNN architecture for the detection model is parameterized to train and predict images with a size of 250×250 pixels and three RGB channels, and the size of the output images is 640×480 pixels. The model has a binary output, so the detection task is focused on six classes of signals. Each class is configured to detect the signal spectrum belonging to the corresponding signal type as listed 128ChirpN, 256ChirpN, 512ChirpN, 128ChirpM, 256ChirpM, 512ChirpM.

The training schedule of the developed neural network model is shown in Fig. 6 - Fig. 7. The calculation was performed for 50 training epochs. The results show that the accuracy of the developed model is higher at the validation stage, this is explained by the fact that the generalization of the model training is higher than the training data. Already at the tenth epoch, a plateau is noticeable. At the training stage, model losses decrease sharply, which is explained by a decrease in the complexity of recognizing signals when they are distorted by the addition of noise, changes in the wavelet function, and changes in frequency and amplitude modulation coefficients.

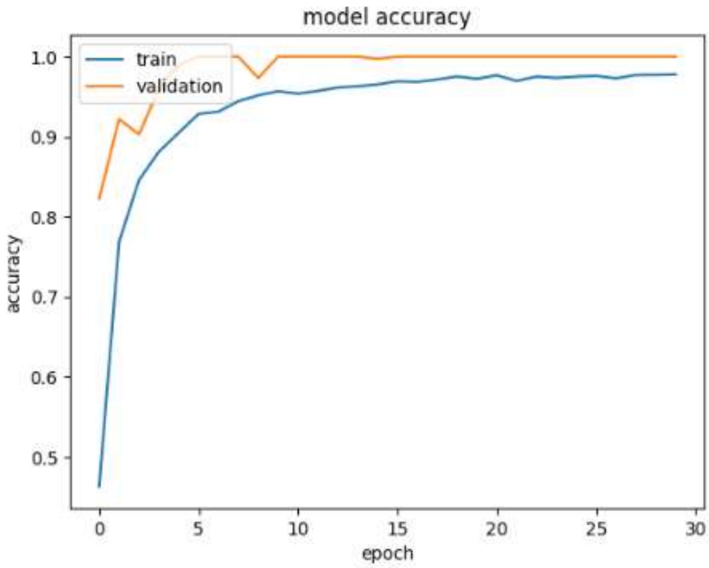


Figure 6: Accuracy of training and validation when using Wavelet Dataset

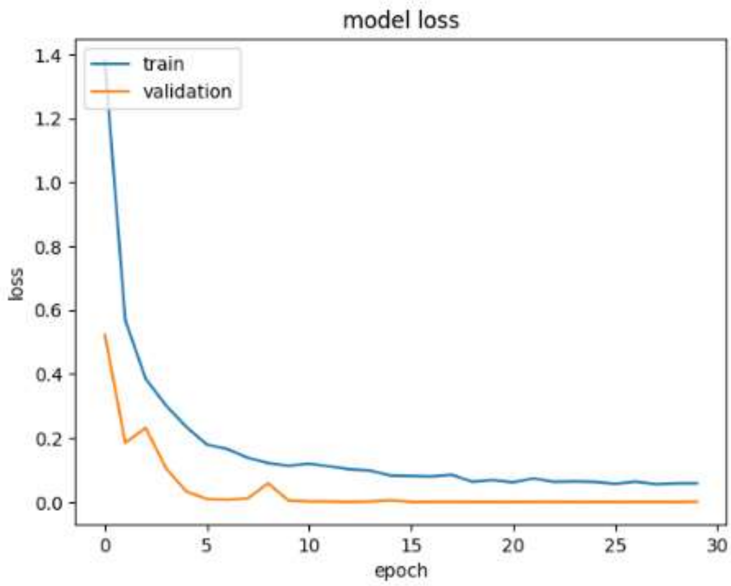


Figure 7: Training and validation losses when using Dataset wavelets

The loss reduction is associated with the limitation of the upper threshold of additively added noise, according to the proposed algorithm for its determination in the frequency domain. This excluded from the analysis the images of spectra that have already turned into solid noise and their further recognition is not possible at all.

It should be noted that it is the changes in the frequency and amplitude modulation coefficients that cause oscillation, which is particularly noticeable on the validation curve (Fig.6– Fig. 7). Accuracy increases rapidly thanks to the proposed algorithm (Fig. 5). According to the algorithm, the upper limit of additive noise, which is determined under the conditions of the ability to recognize the image of the spectrum, is created using the technology of continuous wavelet transformation. At the same time, the limit corresponds to the moment when recognition is still possible.

For the convenience of managing the model, an interface was developed that simplifies the visualization of the results of recognizing the component spectra of a complex signal after digitization by generating an image from a digital matrix (Fig. 8).

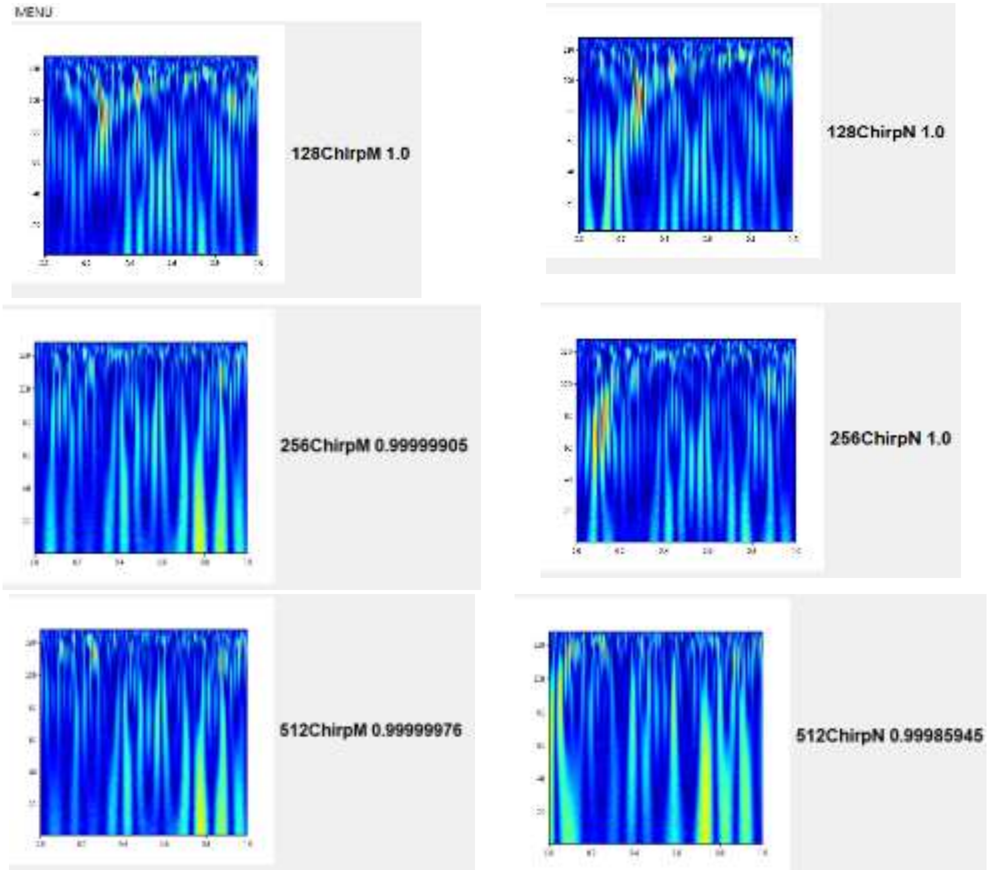


Figure 8: The operation of a simple interface for recognizing the components of the signal spectrum: 128ChirpN, 256ChirpN, 512ChirpN, 128ChirpM, 256ChirpM, 512ChirpM

Checking the accuracy on the test set shows the effectiveness of recognition:

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Found 504 images belonging to 6 classes.
4/4 [==============================] - 4s 877ms/step - loss: 0.0023 - accuracy: 1.0000
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To evaluate the effectiveness of the developed algorithm for preparing images of wavelet spectra for a high-precision neural network with augmentation using a continuous wavelet transformation and limiting the upper limit of noise in the frequency domain during wavelet image generation, we will perform a comparison with a known model [26].

The authors of the study [25] investigated the image recognition model of thermal imagers. The convolutional neural network model presented in [26] with an artificial increase in representativeness provides image classification with an accuracy of up to 99.37% on the test sample, but cannot be used for the classification of wavelet spectra, as it analyzes a monochrome image.

The trained neural network model using the Tensorflow library ensures the reliability of image detection and classification at the level of up to 95.7% [26]. A neural network with augmentation using primitive wavelet spectra and limiting the upper limit of noise in the frequency domain for wavelet image generation has an accuracy of up to 100% (Table 1).

The proposed spectrum recognition system takes into account signal digitization on an analog local oscillator. The presence of many signals distorts the shape of the spectrum, which is analogous to the use of different wavelets.

Table 1
Comparative analysis of model training efficiency using continuous wavelet-spectrale

A set of experimental data (Dataset)	Classification accuracy on the training sample, %	Classification accuracy on the validation sample, %	Classification accuracy on the test sample, %
Without using augmentation and limiting the upper limit of the noise	84,3	88,1	93,1
Augmentation using Tensorflow tools, which consist of reducing, enlarging and rotating images, changing the palette	86,3	89,8	95,7
Augmentation using continuous wavelet spectra and limiting the upper limit of noise in the frequency domain for wavelet image generation	90,1	92,9	100

Discussion

In the work, when forming the data, the limitation of the range of the power change of the Gaussian noise additively added to the signal was applied. The limitation is carried out in the frequency domain by comparing the wavelet coherence of the noise and the noisy signal using the example of the most common signal with linear frequency modulation of the Chirp type.

It was established that the wavelet autocoherence of Gaussian white noise has a constant value in the entire range of noise power change. At the same time, the numerical value of autocoherence depends exclusively on the choice of wavelet. The wavelet autocoherence of the noisy signal when the noise power changes intersects with the noise autocoherence at the power value, which, in addition to the wavelet, depends on the frequency modulation coefficient. A variable Chirp waveform with additional amplitude modulation by a half-sine wave was also investigated.

The accuracy of recognition of a given type of signal in the developed model was increased due to the exclusion from the analysis of signals that cannot be recognized due to lack of distinction from noise. For each continuous wavelet, such a level of non-stationarity is determined, at which a noisy signal can be recognized. This allows you to expand the database, implement augmentation by changing the wavelet, as well as amplitude modulation of the signal.

Conclusions

An effective algorithm for image recognition of continuous wavelet spectra of noisy Chirp-type radar signals under conditions of change in the coefficient of linear frequency modulation has been developed. Formation of an experimental data set for training a convolutional neural network is carried out by generating images of signal spectra with the addition of additive noise to the Chirp signal. The frequency modulation coefficient changes regardless of the presence of amplitude modulation by a half-sine wave

The developed neural network model for image recognition of continuous wavelet spectra using the Chirp signal as an example has an accuracy of up to 100% (the best analog result is up to 95.7%).

The prospect of research is a detailed study of the potential of various wavelets or their influence on signal recognition.

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