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DEVELOPMENT OF A HYBRID NEURAL NETWORK MODEL FOR MINE DETECTION BY USING ULTRAWIDEBAND RADAR DATA

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The object of the study is the architecture of a hybrid neural network for mine recognition using ultra-wideband radar data. The work solves the problem of filtering reflected signals with interference and recognizing mines detected by ultra-wideband (UWB) radar. A hybrid neural network model in combination with the Adam learning algorithm is proposed. Filtering of reflected signals from mines is carried out using an MLP (multilayer perceptron) filter, which selects low-amplitude parts of signals that carry information about a hidden mine from the entire reflected signal. Mine recognition is carried out by a Hilbert block and an oscillatory neural network, which are included in the structure of a hybrid neural network. The peculiarity of the obtained results, which allowed to solve the investigated problem, is the transformation of the signal frequency by the Hilbert block and the recognition of mines by the oscillatory neural network in the resonant mode. The three-layer MLP filter effectively filters out the unwanted component in the total signal reflected from the subsurface object, as the MSE (Mean Squared Error) of the MLP filter is $1\bullet10^{-5}$. If the frequency of the Hilbert signal is equal to the natural frequency of oscillations of neurons then the recognition of signals with a small amplitude from subsurface objects is carried out by an oscillatory neural network based on the resonant amplitude, which is indicated by a small value of cross-entropy. The proposed model of a hybrid neural network provides amplification of useful signals due to resonance and has higher performance compared to existing models of artificial neural networks. The practical significance of the obtained results lies in their application in the field of automated neural network technologies for detection and recognition of subsurface objects of various nature based on reflected radar signals with an amplitude at the noise level

Keywords: multilayer perceptron-filter, Hilbert block, oscillatory neural network, resonance

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1. Introduction

The task of detecting underground objects and their automatic recognition is relevant and necessary for many areas of human activity. In particular, for a quick inspection of the territory for the presence of mines, unexploded ammunition, finding the location of grounding structures, cable breakage or short circuit, for identifying and mapping archaeological sites.

The technology used to detect hidden objects includes ultra-wideband (UWB) radar.

UWB (Ultra-Wide-Band) is a wireless ultra-wideband (bandwidth over 500 MHz) low-power data transmission technology. In particular, UWB makes it possible to determine the location of objects with an accuracy of 2 centimeters. This technology makes it possible to maintain a high data transfer rate of up to 480 Mbps at a distance of up to 3 meters, and at a distance of 10 meters – 110 Mbps. The main disadvantage of this technology is a drop in bandwidth to 40 Mbps with an increase in distance to 100 meters. This is due to the fact that the dispersion of electromagnetic radiation in the air leads to significant distortion of the broadband signal compared to the narrowband signal.

The results of such studies are needed in practice because the detection of mines is a constant and growing problem that affects millions of people around the world because of the enormous danger that mines pose to humans. In particular, to overcome the consequences of the temporary occupation of the territories of Ukraine. However, during the construction of automated systems for detecting and recognizing mines, there is a problem of automating mine recognition based on reflected radar signals of small amplitude commensurate with the amplitude of noise. At the same time, classical methods of detecting and recognizing mines no longer provide the required level of reliability and efficiency of solving these tasks. Given the decrease in bandwidth, real-time object recognition becomes long-term but, by using an oscillatory neural network based on the resonant effect, it is possible to increase the speed of recognition of hidden objects. In particular, the oscillator neural network under the resonant mode could improve the signal-to-noise ratio during recognition.

2. Literature review and problem statement

To obtain information about an object (mines, unexploded ammunition, cluster bombs), which is located below the ground, ultra-wideband (UWB) radar is used [1]. The main advantages of this radar are the accuracy of determining the location of objects up to 2 centimeters; short-distance data rate. The disadvantage of this technology is the drop in data transmission capacity to 40 Mbps with an increase in distance to 100 meters. Also, automation of detection and recognition of subsurface objects that are in soils with different structural inhomogeneities remains an unsolved problem. Owing to the use of ultrashort nanosecond pulses, the radar has a high scanning resolution, i.e., high accuracy of detecting the position of the object and sufficiently deep penetration of the electromagnetic pulse with losses due to the powerful low-frequency component of the wave [2]. This type of survey allows detecting low-level non-metallic objects of small size [3] and remote sensing of road conditions. To ensure high resolution scanning of underground objects, in work [3] an ultra-wideband georadar with ultrashort nanosecond pulses was proposed. The key advantages of [3] are the proposed methods for detecting weak signals and the described effects of backscatter of a large target.

In particular, for the case of a point underground object, the electromagnetic field scattered by it along the sounding path has a hyperbolic shape of field maxima, containing information about the size, depth of occurrence of the object, heterogeneity and electrical characteristics of the soil. These parameters take into account the maximum amount of information, including the object's response to irradiation by waves of various polarizations [4, 5]. The authors of [4] reported an effective approach to determining the location of an object due to the fitted geometry of hyperbola in radargrams. In [5], a complete polarimetric scattering matrix is extracted from a two-channel georadar reflection signal to estimate the target azimuthal angle. The authors of work [5] concluded that radar polarimetry can provide more useful information than a single-polarization georadar. One of the approaches to obtaining information from reflected pulses generated with interference and overlapping is the method of deconvolution [6]. The method of extended common midpoint in [6] is used on a multichannel three-dimensional georadar to estimate the thickness of the asphalt pavement. However, the main disadvantage is that for a thin asphalt pavement, the resolution of a three-dimensional georadar signal is insufficient to determine the blocked pulses of asphalt concrete. Also, the problem of filtering interference of the signal reflected from the subsurface object and amplification of the useful signal remains unsolved.

Detecting objects based on real radargrams is difficult due to high noise and interference values. Therefore, to simulate the forms of the received signal, the method of finite differences in the time domain (FDTD) is used [7]. This method makes it possible to obtain from the object under study samples of time forms of the reflected electromagnetic signal. After that, it is possible to train an artificial neural network for automatic recognition of objects of various shapes in heterogeneous soils with different electrical parameters at different depths [8]. The FDTD method forms the basis for obtaining information about the location of subsurface objects by wave inversion [9]. This method can be used to obtain samples of time forms of the reflected electromagnetic signal, taking into account the features of the antenna system and the electrophysical parameters of the soil.

Paper [10] investigated the use of ultra-wideband (200–800 MHz) ground-based double polarization radar (GPR) as a tool for detecting buried metal mines. This paper does not solve the problems of automation of mine recognition and signal interference filtering.

Pulse ground penetrating radars have a wide range of applications, including the UWB Through-The-Wall radar with 3D images used as a radar demonstrator «through the wall» in terms of identification [11]. Medium-frequency and low-frequency ground-based radars are used for geological stratification, and high-frequency ground-based radar, given its high detection accuracy, makes it possible to distinguish layers and objects at the centimeter level [12]. Ultra-wideband radar with a metal detector touch head with an accuracy of a subcentimeter to detect dangerous metal targets [13]. The authors of work [13] showed that the accuracy of the UWB system can be improved using the calibration procedure and more marks on the sensor head to maintain a high refresh rate.

When constructing automated data processing systems obtained using ultra-wideband radar, there is a problem of automated classification and recognition of underground objects. In [14], the detector semi-analytically analyzes the scattered signal from the entire target, and not from each spatial pixel, as in the SAR image. The generalized Hough transform [15] is implemented by a neural network in order to establish a nonlinear relationship between the location of targets and the inversion of their parameters. In [16], an intercorrelation approach between an artificial neural network and a cross-correlation method is used in the classification of mines in the presence of white noise. This approach does not require time synchronization between the emitter and receiver as opposed to an artificial neural network but requires considerable computation time. Works [14–16] do not specify the metric of mine classification.

The authors of work [17] proposed a method for detecting subsurface objects with low dielectric constant under variable soil conditions. However, the proposed method for detecting mines has a low signal-to-noise ratio compared to methods using information resonance.

1To solve the problem of recognition of subsurface objects, convolutional neural networks were used in [19]. One known limitation of convolutional neural networks is that they require large amounts of data to learn (i. e., parameter determination). This poses a serious challenge for target detection with ground penetrating radar due to the relatively small number of marked target examples.

The authors of work [20] proposed a method for recognizing subsurface objects based on convolutional neural networks that recognize B-scan images. The disadvantage of the results of study [20] is that signal interference is not taken into account.

To solve the problems of automated classification and location recognition of underground objects, artificial neural networks are used [17–20]. However, the problem of filtering signal interference and signal amplification remains an unsolved issue.

The proposed procedures for detecting and recognizing mines using ultra-wideband radar and artificial neural networks [10–20] require further development of a methodology for localizing landmines for demining. Since the construction of automated systems for detecting and recognizing mines raises the problem of accuracy in determining the location of underground objects and registering part of the reflected signal, which is the carrier of information about the underground object. This is due to the fact that the amplitude of the reflected signal from the underground object is much less than the amplitude of the part of the reflected signal from the elements of the receiving antenna system (UWB georadar) with different orientation of the polarization plane and from the earth's surface. This problem is partially solved in [18] as a result of addition and subtraction operations of four received reflected signals.

However, the task of suppression filtering of a part of the signal reflected from the elements of the receiving antenna system and from the earth's surface and amplification of a part of the signal reflected from a hidden object remains unsolved. This problem needs to be addressed.

3. The aim and objectives of the study

The aim of this study is to build a model of a hybrid neural network for recognition of subsurface objects (mine PMN-1, PMN-4) in the presence of interference in the reflected signal. This network consists of an MLP filter, a Hilbert unit, and an oscillator neural network. This will make it possible to apply the model of a hybrid neural network in the field of automated neural network technologies for detecting and recognizing mines based on radar signals with amplitude at the noise level.

To accomplish the aim, the following tasks have been set:

– to build an architecture of a hybrid neural network consisting of an MLP filter, a Hilbert unit, and an oscillator neural network;

– to form a complex of informative signs of mines by reflected electromagnetic pulses in the time domain. To solve this problem, a three-layer neural network MLP filter is proposed in the current work, which will pass only usable information about an explosive object received from the UWB of the radar. The reflection signal from the receiving antennas and from the ground surface will be filtered from the total reflected signal;

– to convert a usable variable frequency signal into a constant average Hilbert frequency signal Ω_k^H;

– to conduct a computer experiment on recognition of subsurface objects by a hybrid neural network.

4. The study materials and methods

Research object: architecture of a hybrid neural network for mine recognition using ultra-wideband radar data.

The main hypothesis of the study. The three-layer MLP filter is able to effectively filter out an unusable component in the signal reflected from a subsurface object, and the Hilbert unit is able to transform the signal frequency to recognize mines by an oscillatory neural network under resonant mode.

To obtain information about underground objects, the ultra-wideband radars with antenna systems «1Tx+4Rx» (USA) are used [21]. These radars irradiate the surface of the earth with a soil dielectric constant of ε=9 and a conductivity of σ=0.005 cm/m with electromagnetic nanosecond pulses [22], which penetrate to a depth of several meters. For our task, the subsurface objects considered are the mines PMN-1 (USSR) (Fig. 1), PMN-4 (USSR) (Fig. 2). Mine PMN-4 is shown in Fig. 2. It has a height of 42 mm, and a diameter of 95 mm. PMN-4 has a similar internal structure as PMN-1 (Fig. 1), but its metal detonation mechanism is more massive. This gives a greater reflection of the electromagnetic pulse, and as a result, more stable detection is possible. The body materials and electrical characteristics of the explosive in PMN-4 are the same as those of PMN-1.

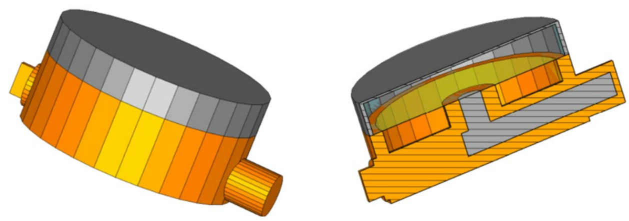


Fig. 1. PMN-1 mine model [18]

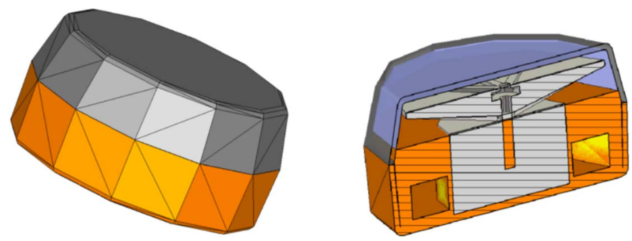


Fig. 2. PMN-4 mine model [18]

The process of propagation of nanosecuded electromagnetic pulses taking into account the features of the antenna system, electrophysical parameters of the soil is modeled by the method of finite differences in time domain (FDTD) [8]. The reflected wave from explosive objects and from the components of the receiving system is received by four antennas with different polarization orientation (Fig. 3).

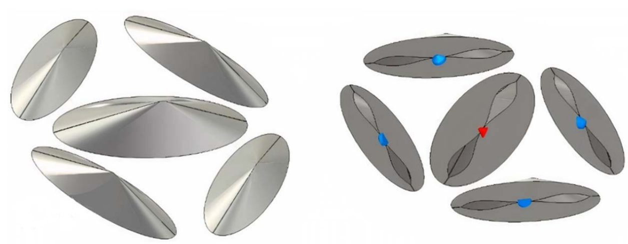


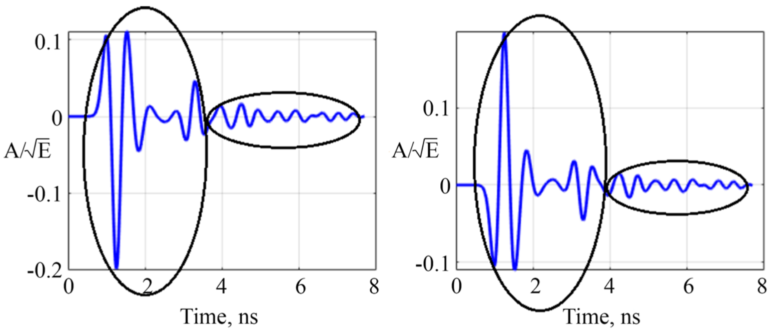
Fig. 3. Ultra-wideband radar, where the central antenna is the emitter; antennas at the edges – receivers with different polarization [18]

This arrangement of antennas with different planes of polarization (Fig. 3) makes it possible to record the reflection of the wave at different points in time and indicate the direction from which the reflected wave came.

However, the reflected incoming signals need to be preprocessed before being fed to the neural network classifier. These signals should be divided into two parts, where the first part of the reflected signal is a noise carrier (reflection between all receiving elements of the UWB of the radar), and the second part of the reflected signal transmits information about an explosive object.

Fig. 4 shows the time dependence of the normalized amplitudes of the two reflected signals received by the UWB antenna system [18]. These signals are signs of PMN-1 and

PMN-4 mines. Analysis of the reflected signals (Fig. 4) reveals that each of the signals can be divided into two parts.



a *b*

Fig. 4. Examples of signals received by an ultra-wideband antenna system: 1 – mutual reflections from the antenna system and the ground; 2 – usable part of the signal containing information about the hidden object: *a* – signal received from the PMN-1 mine; *b* – signal received from the PMN-4 mine [18]

The first part displays the reflected signals between the elements of the antenna system and from the earth's surface. The second part of the reflected signal carries usable information about the hidden object. The amplitude of the usable reflected signal from the hidden object is much less than the amplitude of interference in the first part of the signal due to the absorption of the electromagnetic signal by a layer of heterogeneous soil. To recognize hidden images, the method of artificial neural networks is used. In this work, the morphology of artificial neural is based on a hybrid neural network that represents a synthesized structure from an MLP filter, a Hilbert unit, and an oscillatory neural network.

5. Results of the study on the construction of a hybrid oscillatory neural network and the process of recognition of subsurface objects

5. 1. Building a hybrid oscillatory neural network architecture

To recognize hidden objects detected by ultra-wideband subsurface radar, a hybrid neural network is proposed (Fig. 5).

This network consists of an MLP filter, a Hilbert unit (converts a usable variable frequency signal into a signal with a constant average frequency), and an oscillatory neural network [23, 24].

5. 2. Building a set of informative signs of mines by reflected electromagnetic pulses in the time domain

Before giving four reflected signals to the input of a three-layer MLP filter (Fig. 5, *a*), they were sampled with a constant time step of 0.25 ns. Then we normalize them into square roots of their energy and form a single array of input data in the form of a matrix of size 4×31, $S^T_{k,31\times1}$, $k=\overline{1,4}$, which refers to the neurons of the input layer of the MLP filter. From the input layer, the signals go to the hidden layer of MLP, at the output of which we receive signals $Y^{[h]}_{k,63\times1}=\mathrm{ReLU}\left[W^{[h]}_{63\times31}\cdot S^T_{k,31\times1}+B^{[h]}_{63\times1}\right]$, coming to the output layer, and after the output layer we get filtered signals $S^{[f]}_{k,13\times1}=W^{[o]}_{13\times63}\cdot Y^{[h]}_{k,63\times1}+B^{[o]}_{13\times1}$. $W^{[h]}_{63\times31}$ – weighting coefficients of synaptic connections between the input and hidden layer; $B^{[h]}_{63\times1}$ – offset in a hidden layer; – weights of synaptic connections between hidden and output layer in MLP; $B^{[o]}_{13\times1}$ – offset in the source layer.

5. 3. Converting a usable signal with a variable frequency into a signal with a constant average Hilbert frequency

Hilbert's unit is needed for the condition of information resonance (when the frequency of the external usable signal is equal to the natural frequency of oscillations of neurons $\Omega^H_i=\omega_{ij}$), at which there is an increase in the signal-to-noise ratio at the output of the oscillator neural network.

Subsequently, the filtered signals $S^{[f]}_{k,13\times1}$ are fed to the Hilbert unit to convert a usable signal with a variable frequency into a signal with a constant average frequency Ω^H_k. To find the amplitude A^H_k and average Hilbert frequency Ω^H_k, the usable signal $S^{[f]}_{k,13\times1}$ is written in a complex half-plane, that is:

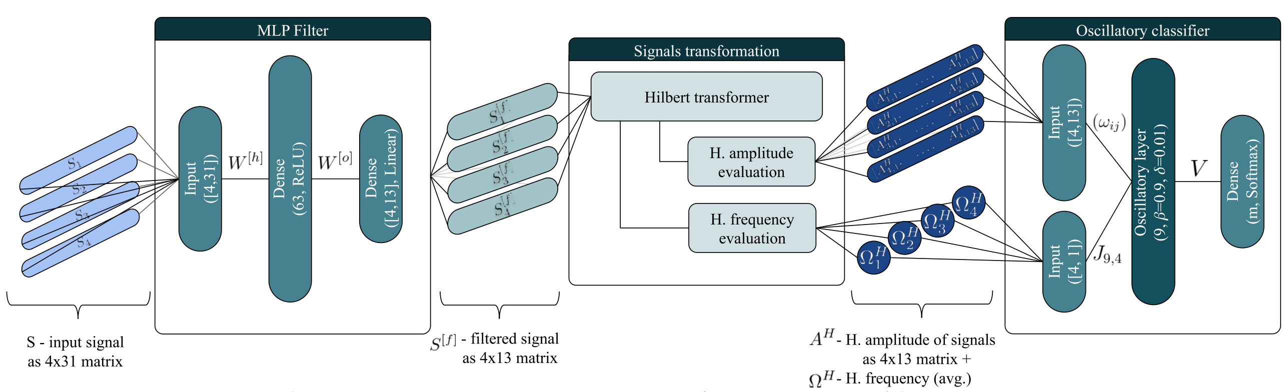
$$H\left(S^{[f]}_k\right)=S^{[f]}_k+iS^{[f]^H}_k, \tag{1}$$

where $S^{[f]^H}_k$ is the imaginary part of the complex signal [25];

$$S^{[f]^H}_k(t)=P\int_{-\infty}^{\infty}\frac{S^{[f]}_k}{\pi(t-\tau)}\mathrm{d}\tau, \tag{2}$$

$$A^H_k=\sqrt{\left(S^{[f]}_k\right)^2+\left(S^{[f]^H}_k\right)^2}, \tag{3}$$

$$\varphi^H_k=\arctan\frac{S^{[f]^H}_k}{S^{[f]}_k}. \tag{4}$$



a b c

Fig. 5. Hybrid neural network classifier: *a* – three-layer neural network MLP filter; *b* – Hilbert unit; *c* – oscillatory neural network

$$\omega_k^H = \left|\varphi_k^H\right| = \frac{\Delta\varphi_k^H}{\Delta t}, \quad (5)$$

$$\Omega_k^H = \left|\frac{1}{T}\int_{t_0}^{t_n}\omega_k^H dt\right| = \frac{1}{T}\sum_{j=1}^{12}\omega_{kj}^H \Delta t, \quad (6)$$

where ω_{kj}^H is the frequency between the i-th and k-th time samples in the external signal $S_{k,13\times1}^{[f]}$.

The equation of an oscillatory neural network is represented as (7) [23]:

$$\theta_i = \frac{1}{1+\exp\left(-\beta\sum_{k=1}^{4}\Omega_k^H\sum_{i=1}^{13}\frac{A_{ki}^H}{\sqrt{\left(\omega_{ij}^2-4\left(\Omega_k^H\right)^2\right)^2+16\delta^2\left(\Omega_k^H\right)^2}}\right)}, \quad (7)$$

$$\Theta = \left[\theta_i \mid j=\overline{1,9}\right]^T, \quad (8)$$

$$O = softmax\left[V_{2\times9}\cdot\Theta_{9\times1}+b_{2\times1}^{[\omega]}\right]. \quad (9)$$

As can be seen from formulas (7) to (9), signals transformed by Hilbert's unit are fed to an oscillator neural network, which classifies signals under resonant mode and determines the type of mine.

5. 4. Conducting a computer experiment

The implementation of the structure of the hybrid neural network (Fig. 5) and its learning algorithm is carried out in the Python language using the TensorFlow library. As for the hardware, a computer with a processor I7-6700K 4.00 GHz and 16 Gb RAM was used for the experiment.

To train the hybrid neural network, the adam algorithm [26–28] was used for gradient optimization of first-order stochastic objective functions. In particular, the following hyperparameter values were used to train the MLP filter: the size of the data batch – 12; learning pace – 0.001; β_1=0.9; β 2=0.999 – parameters that describe the rate of decline of the stochastic gradient; number of epochs – 15, and for oscillator network: learning rate – 0.0001; β_1=0.9; β_2=0.999; number of epochs – 40.

Based on the array of input data, 1200 signals were generated within a uniform distribution, among them 200 signals were noisy. This input data array is used to train the neural network.

All these signals were randomly divided into 2 parts: 80 % training kit, 20 % test kit.

Fig. 6 shows the numerical calculations of the root mean square error (MSE) of signal deviation at the output of the MLP filter $S_{k,13\times1}^{[f]}$ from the reference signal $S_{k,13\times1}^{[f](e)}$ depending on the number of epochs. Fig. 7, 8 show the numerical calculations of cross-entropy for an oscillatory neural network and for a hybrid neural network depending on the number of epochs. Fig. 9 shows the process of filtering using MLP filter.

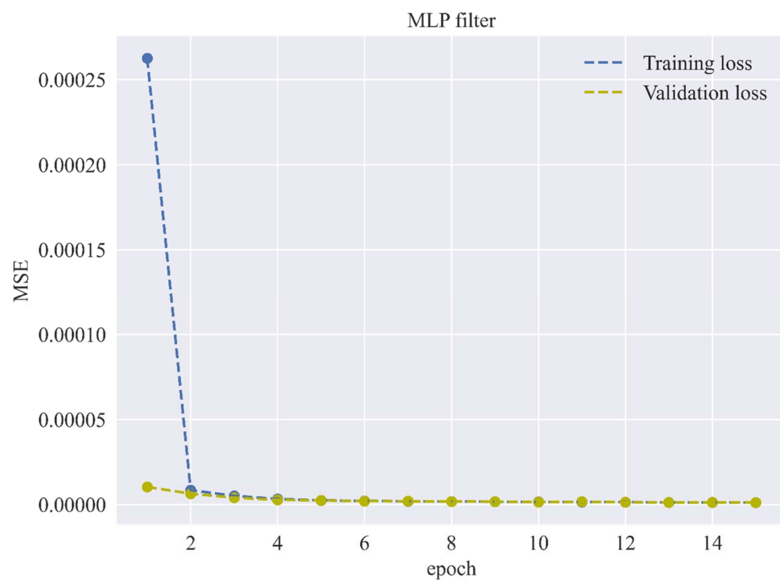


Fig. 6. Numerical calculations of the root mean square error (MSE) of signal deviation at the output of the MLP filter $S_{k,13\times1}^{[f]}$ from the reference signal $S_{k,13\times1}^{[f](e)}$

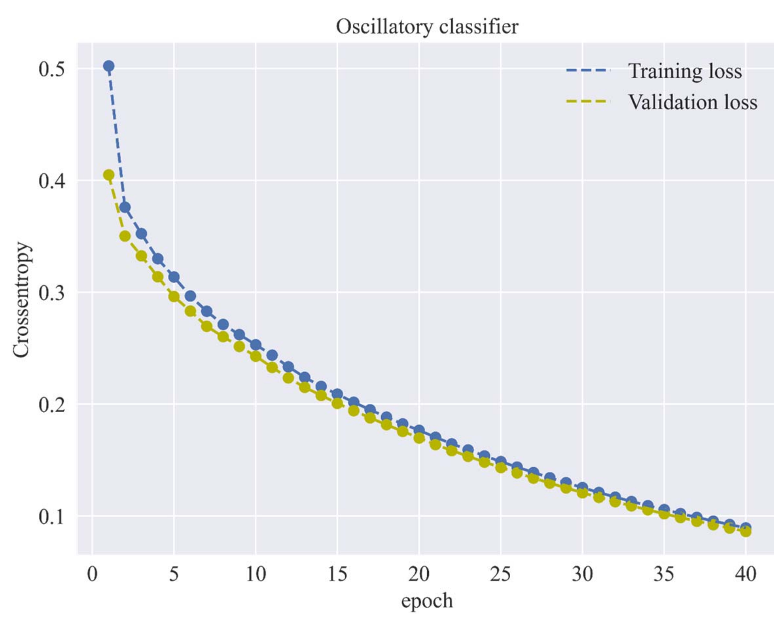


Fig. 7. Numerical calculations of cross-entropy for an oscillatory neural network depending on the number of epochs

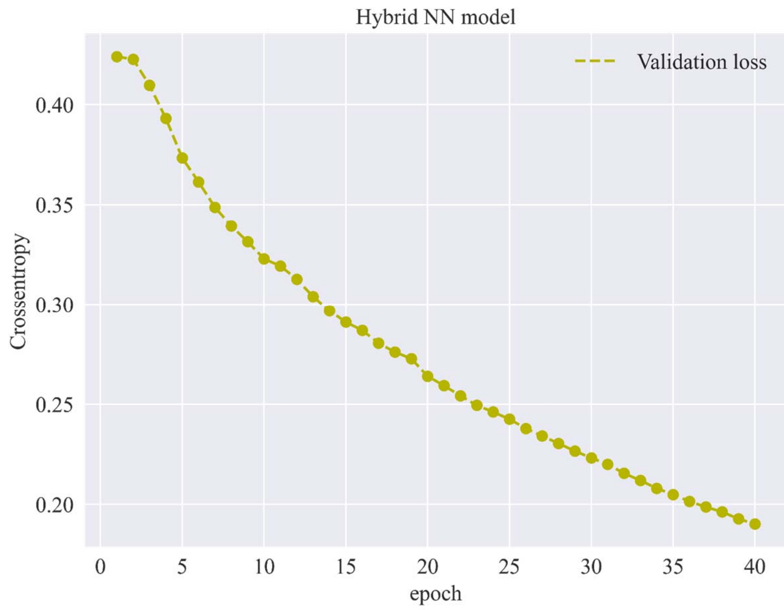
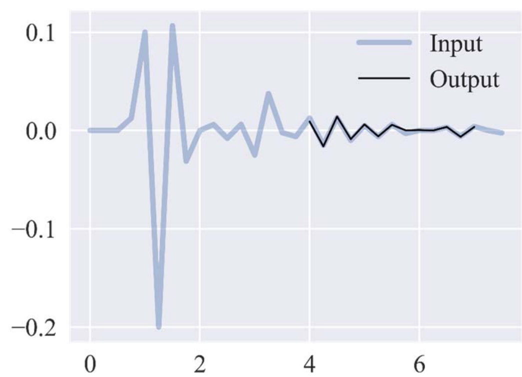
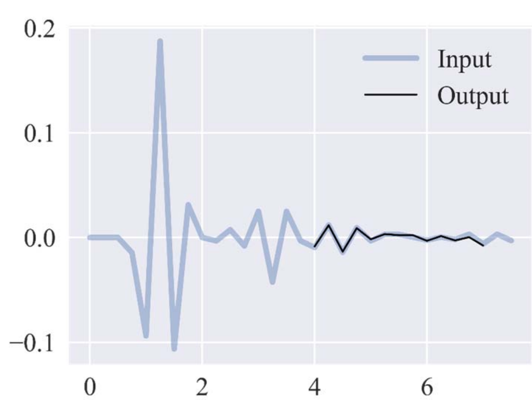


Fig. 8. Numerical calculations of cross-entropy for a hybrid neural network depending on the number of epochs



a



b

Fig. 9. Visualization of the filtration process with an MLP filter: *a* — signal from the PMN-1 mine that was filtered; *b* — signal from the PMN-4 mine that was filtered

Dark oscillation curves indicate the usable signal at the MLP filter's output, and light curves represent reflected signals that have been filtered out.

6. Discussion of results on the construction of a hybrid oscillatory neural network and the process of recognition of subsurface objects

The proposed model of hybrid oscillatory neural network provides amplification of usable signals with amplitude commensurate with noise amplitude and demonstrates higher performance compared to existing models of artificial neural networks. The amplification of usable signals is carried out under the condition of resonance as a consequence of the coincidence of the frequency of the reflected filtered signal at the output of the Hilbert unit with the natural frequency of the neurons of the oscillatory neural network. In contrast to [17–20], the proposed mathematical model of a hybrid neural network recognizes signals with a small amplitude from subsurface objects based on resonant amplitude, as indicated by a small value of cross-entropy.

Signals reflected from mines are processed using an MLP filter. To train the MLP filter, we use as an input vector the full reflected signal from a subsurface object. As marks of signs at the output of the MLP filter, we use the second part of the usable reflected signal. That is, the MLP filter selects low-amplitude parts of it from the entire reflected signal, carrying information about the hidden object.

The filtered signals $S^{[f]}_{k,13\times1}$ are fed to the Hilbert unit to convert a usable signal with a variable frequency into a signal with a constant average frequency Ω^H_k. To find the amplitude A^H_k and average Hilbert frequency Ω^H_k, the usable signal $S^{[f]}_{k,13\times1}$ is recorded in a complex half-plane. The result obtained is the transformation of variable frequency signals into a signal with an average frequency Ω^H_i, fed to the input of an oscillatory neural network.

As can be seen from Fig. 6, with an increase in the number of epochs for both training and validation of the MLP filter and hybrid neural network, the root mean square error (MSE) and cross-entropy, respectively, decrease monotonically. Moreover, the MLP filter is trained in almost 6 epochs and MSE is $1{\cdot}10^{-5}$, while 40 epochs are needed to match cross-entropy during training and validation of oscillatory and hybrid neural networks.

Small values of MSE ($1{\cdot}10^{-5}$) for MLP filter (Fig. 6) and cross-entropy for hybrid neural network (Fig. 8) indicate effective filtering of the reflected signal from the subsurface object (Fig. 9) and high accuracy of its recognition. At 40 epochs, cross-entropy is the smallest, which means that the probability of the result obtained using the neural network model is closest to the probability of the expected result.

Regarding the limitations of this study, two points can be distinguished:

– conditions of application – the results obtained may depend on the size of the dataset, weather conditions, types of terrain and soils;

– robustness of solutions to changing factors – the proposed solutions may be unstable to changes in the size of the dataset or the number of model parameters.

The main disadvantage of this study is that the research was conducted on artificial data (the process of propagation of nanosecuded electromagnetic pulses taking into account the features of the antenna system and the electrophysical parameters of the soil is modeled by the method of finite differences in time domain (FDTD)), which may be different from real conditions. In further studies, it is necessary to conduct experiments under actual conditions and compare the results with other methods.

This study may be advanced thru the following steps:

– improvement of experimental methodology. In the study, difficulties may arise related to the experimental procedure, such as data collection and analysis, parameter control, etc.;

– taking into account meteorological parameters, terrain type and soil structure in the mathematical model;

– the use of real data. In this study, model data (FDTD) were used, so there is a need to conduct experiments under actual conditions to verify the theoretical results;

– extending research to other areas of technology. The proposed method could be applied not only in the recognition of mines but also to find the location of grounding structures, cable breakage or short circuit, to detect and map archaeological sites.

7. Conclusions

1. The morphology of a hybrid neural network for automated recognition of subsurface objects detected by ultra-wideband radar has been devised. The peculiarity of this hybrid neural network is that it operates under the mode of information resonance, which provides amplification of usable signals with an amplitude commensurate with the noise level.

2. It is shown that a three-layer MLP filter effectively filters out an unusable component in the signal reflected from a subsurface object since the MSE of the MLP filter is $1{\cdot}10^{-5}$.

3. It was established that if the frequency of the Hilbert signal is equal to the natural frequency of oscillations of neurons $\Omega_i^H = \omega_{ij}$, then the recognition of signals with a small amplitude from subsurface objects by an oscillatory neural network occurs on the basis of the resonant amplitude.

4. It is shown that high accuracy of recognition of subsurface objects is ensured since MSE is $1{\cdot}10^{-5}$. This is due to the use of Adam's optimization algorithm, oscillator neural network resonance effect, and ReLU activation function, which ensures the absence of explosion and attenuation of the gradient during neural network training.

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

The data will be provided upon reasonable request.

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