The use of deep neural networks to detect alarms in mines

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Abstract. The article discusses the problem of detecting signals against a background of noise for alarms for miners in underground mine workings in case of emergency. The theoretical aspects of linear and non-linear filtering of alarms are given, the solution to the problem of constructing a non-linear filter based on deep neural network (DNN) is described. The simulation results are presented and a comparative analysis of the performance of an individual miner receiver using the methods of linear coherent reception and a DNN filter is made. Neural network training was carried out on model and experimental data obtained at an existing underground mine.

1. Introduction
Starting from 2012, deep learning algorithms for neural networks allowed us to obtain breakthrough results in problems of computer vision, speech recognition and synthesis, and many others [1-3]. Nevertheless, the use of deep learning in more general tasks of digital signal processing remains little studied at the moment. The work of deep learning models is based on the idea that a deep neural network performs non-linear transformation on input data, the parameters of which are selected during the training procedure. Recently, in connection with the rapid development of equipment for parallel computing (graphics cards), it has become possible to use a deep neural network apparatus for processing low-frequency radio signals in real time [4]. Known, for example, work on the selection of signals with frequency manipulation based on machine learning, which shows the fundamental possibility and effectiveness of the application of nonlinear digital signal processing methods based on deep neural networks under normal white as well as Rayleigh noise [5, 6]. The paper investigates and proposes an option to search for an optimal nonlinear filter for the transmission of emergency or telemetric signals with low bit rates through highly conductive media. Another important task for confirming the effectiveness of the selected methods is to compare the selected approach with the methods of linear filtering and the classical construction of the receiving detector.

This article is aimed at studying the optimal signal processing algorithms for constructing a complex Through-the-Earth TTE channel for low-speed information messaging in emergency mines based on EM penetrating signals of the microwave range [7].

2. Theoretical background
The TTE system should cover the entire mine in the direction from the dispatcher to the miners, providing a personal call to each miner who has his own miniature radio receiver integrated into the miner's lamp.
The propagation of the electromagnetic field and energy loss in a real medium is determined by the attenuation index $\alpha$, which depends on the conductivity, dielectric and magnetic permeabilities, and the frequency of EM waves [8]:

$$\alpha = \omega \sqrt{\frac{\mu' \varepsilon'}{2} \left(\sqrt{1 + \frac{1}{\mu' \varepsilon'} - 1}\right)},$$

(1)

where $\omega = 2\pi f$ – electromagnetic frequency; $\mu' = \frac{\mu}{\mu_0}$ – relative magnetic permeability; $\varepsilon' = \frac{\varepsilon}{\varepsilon_0}$ – relative permittivity; $\mu, \varepsilon$ – absolute magnetic and dielectric constant; $\mu_0, \varepsilon_0$ – vacuum magnetic and dielectric constant; $\tan\delta$ – dielectric loss tangent.

From (1), and also taking into account the fact that the range of the rock conductivity parameter $\sigma$ is in the range from 0.001 S/m to 0.1 S/m, the ULF or VLF frequency ranges are used. In this case, the requirements for the TTE system are limited by the communication range - 1000 m, Bit Error Rate $= 10^{-3}$, Bit Rate $= 2$ bit/s.

Due to the specifics of the technological process of mining enterprises conducting mining in a closed way (a large number of power energy and technological equipment giving broadband powerful pulsed as well as concentrated interference, the duration of which is often commensurate with the duration of the transmission of an information message), the interference can have a pronounced non-Gaussian character (figure 1).

![Figure 1. Temporary implementation of interference observed in a working mine.](image)

This leads to a non-Gaussian interference distribution and, consequently, errors in the transmission of messages. Pulsed noise can be time-dependent, which leads to the evolution of the parameters of the posterior density of the probability distribution in the Stratonovich equation [9].

Typically, a signal is not linearly dependent on messages. It is assumed that the signal in a known manner depends on several time-varying parameters - processes belonging to the Markov class. The statistical properties of these parameters are considered a priori known and given in the form of corresponding stochastic differential or difference equations. The signal is received against a background of uncorrelated and Markov (not necessarily additive) interference. The filtering task in this case is to select one or more information parameters of the signal according to the criterion of maximum posterior probability.

For most signals, the maximum posterior probability criterion leads to very complex modeling devices. To simplify the result, they resort to the Gaussian approximation of the signal parameters (the density of the posterior probability is accepted as normal), and the additive is Gaussian additive white noise (GAWN). Filtering quality is characterized by a posteriori dispersion of the filtered message. In this case, the optimal filtering device must be nonlinear. To date, there are no general methods for the synthesis of nonlinear filters with the required characteristics - their analytical representation is possible only in some special cases.
3. Methods and approaches

At the heart of the basic approach to solving the problem lies the idea of working deep learning models. The training procedure is an optimization of some loss function, depending on the task. If, as a function of the loss, we propose the probability of a bit error when decoding the portion of the input signal, the resulting deep neural network will perform non-linear filtering of the signal with subsequent demodulation. From the point of view of machine learning, this task is a simple binary classification, where the classes correspond to the bit values “0” and “1”. At the same time, an important trend in the development of deep learning was the rejection of data preprocessing and the manual design of attributes. In this regard, it is interesting to solve the demodulation problem with minimal appeal to DSP methods.

Figure 2 shows the block diagram of the experiment. Experimental work was carried out in underground mining. Records of signals at various depths were obtained. Measurements were taken at 300 observation points. The signal was transmitted from the surface by exciting the ultra-long-wavelength EM field by means of a long dipole earthed antenna in Frequency Shift Keying (FSK) mode.

In this case, the distribution of the EM field by power under the cable is described in detail in [10]. Logical "0" corresponded to a frequency of \( f_2=966 \) (or 975) Hz, the log "1" - respectively, \( f_1=984 \) Hz. The signal sequences were recorded at different points in the underground mine with a range of rock conductivity from 0.001 Sm/m to 0.1 Sm/m, at various depths. The recording was performed on a miniature magnetic ferrite antenna with a number of turns from 4000 to 6000 turns, loaded on a 24-bit ADC with a sampling frequency of 14.468 kHz. Figures 3a and 3b show the spectrogram and amplitude spectrum of the transmitted bit sequence 10101010, recorded at a depth of 400 m under the cable.

![Figure 2](image2.png)

Figure 2. Underground mining signal recording scheme.

![Figure 3a](image3.png)

Figure 3a. Spectrogram of FSK bit sequence.
In the framework of the approach described below, the raw amplitude spectrum of the final subsequence of the signal (frame) corresponding to the transmission of 1 bit is fed to the input of the neural network. Due to the limited amount of training data, as a result, we still had to resort to preprocessing the amplitude spectrum, but in fact, preprocessing was reduced to discarding obviously uninformative spectral samples. DNN was trained to predict the probability $p$ that the analyzed frame corresponds to the bit value “0”. The demodulation algorithm in this case is to return “0” if the estimate is $p > 0.5$ and “1” otherwise.

To compare the filtering efficiency based on DNN and matched filtering, a linear FSK signal detector circuit is implemented (figures 4a – 4g). After preliminary amplification, the input signal (figure 4a) is filtered in the PF0 input bandpass filter with a central frequency $f_0=975$ Hz and Q factor $Q = 10$ (figure 4b). It is then filtered by two parallel narrow-band filters PF1, $f_1=984$ Hz (figure 4c) and PF2, $f_2=966$ Hz.
Hz or 975 Hz (figure 4d). After quadratic rectification of the output signals PF1 and PF2 (figure 4e), several integration steps are carried out with the reset of the difference of the rectified signals by the integrators (figure 4f). The decision on the received binary signal is carried out in the resolver RU1, which forms a binary information sequence of zeros and ones (figure 4g).

4. Results
Initially trained on DNN model data, where the bit sequences “1” and “0” were used as an input signal at frequencies $f_1=984$, $f_2=966$ Hz in the frequency telegraphy mode without phase discontinuity when the noise model is in the form of GAWN, with the SNR ratio = 10 dB, provided the probability of a bit error BER $<10^{-3}$. The results of this computational experiment showed the fundamental possibility of using DNN for filtering FSK signals. However, from the point of view of practical value, they were not of interest, because for signals with GAWN the optimal solution is known and is based on well-known linear filtering methods, for example, using correlation processing and consistent filtering.

A DNN based receiver was implemented as follows. To train the neural network, data was prepared. The signal sequence was divided into frames - signal segments corresponding to one bit. In the case described below, its duration is $0.5 \text{ s} = 2 \text{ bits/s}$ (on model data it reached $0.1 \text{ s} = 10 \text{ bits/s}$). In the case of real signals, frame borders are manually selected. The result of the DNN receiver in demodulating real FSK signals is shown in Fig. 5 using an example of a real recording of a bit sequence of duration $T = 30 \text{ s}$. In this case, the entire bit sequence was correctly received. The result of processing all 37 sequences using an NF-based DNN receiver allowed us to achieve the result BER$=5\cdot10^{-3}$ averaged over all sequences.

![Figure 5. The result of the DNN receiver.](image)

In the case of a linear detector, the main accumulation was carried out in the integrator with a reset. The reset of this integrator is carried out after a time interval equal to a quarter of the period of the sequence of bit information $- T/4$. The signal is completely integrated over the interval $T$ using a matched filter (MF), matched with a rectangular pulse of duration $T$. The role of such a filter is performed by the adder of 4 neighboring samples of the main integrator with a reset, which forms a bipolar signal of the full (over time $T$) integrator. The maximum positive level of this signal corresponds to the maximum stored energy of the output signal PF1 (which corresponds to the moment of adoption of bit 1), the minimum negative level of this signal corresponds to the maximum stored energy of the output signal PF1 (which corresponds to the moment of adoption of bit 0). As an additional condition for decision making in RU1, the receiver additionally measures the average energy $<E>$ of the last two received bits (including the noise energy at the integrator output) and sets the decision threshold separately for “1” and separately for “0”. Figure 6 shows the results of processing the same bit sequence as for a DNN receiver.

In contrast to the results obtained using a non-linear DNN filter, in the case of linear processing using a matched filter, an erroneous reception of 2 bits is observed in the bit sequence. The result of processing all 37 records of signal sequences using an FSK receiver based on a matched filter made it possible to achieve a result of BER$=1.7\cdot10^{-2}$ averaged over all sequences.
5. Conclusions
In the article, it was theoretically and experimentally shown that the approach to constructing NFs based on machine learning methods, in particular, using GNS, allowed to achieve a better result for problems of transmitting messages at low bit rates through high conductivity media in comparison with linear filtering methods, in particular, in the conditions of industrial impulse noise present in the industrial mining of minerals in a closed way.

An obvious drawback of the construction of a receiving path based on a linear FSK example is that the use of narrow-band filters to extract an information message leads to a loss of information present in the subharmonics of the useful signal.

The simulation results are presented and a comparative analysis of the performance of an individual miner receiver using the methods of linear coherent reception and a DNN filter is made. NS training was conducted on model and experimental data obtained at a real underground mine.

Acknowledgements
The reported study was funded by Russian Foundation for Basic Research, Government of Krasnoyarsk Territory, Krasnoyarsk Regional Fund of Science to the research project № 18-47-243004 “Investigation of nonlinear filtering methods based on deep neural networks to enhance data transmission bitrate for wireless channels through a medium with high conductivity” and was funded and by RFBR, the Government of Krasnoyarsk Krai and enterprise of Krasnoyarsk Krai according to the research project № 18-47-242017.

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