Detection of quasi-harmonic signals with a priori unknown parameters in strong additive noise by machine learning methods

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Abstract. Signals with a priori unknown parameters in strong noise are used in various fields of science and technology. This paper is devoted to features and limits deep neural networks for signal detection. We study quasi-harmonic signals with a priori unknown parameters. Neural network method was compared with classical methods for detecting signals in terms of accuracy and speed. We use realistic models of hexogen nuclear quadruple resonance (NQR) signals with parameters dependence by temperature. Experiments show that proposed method is more accurate and one hundred times faster than alternative ones. We achieve a probability of NQR signal detection about 95%, when signal-to-noise ratio is -15 dB and the signal parameters are unknown. When the signal-to-noise ratio is -20 dB, probability of NQR signal detection is 80%.

1. Introduction
Detection of signals with strong noise is a task that appears in different areas of science for example: in communications, radar, seismology and spectrometry of chemical compounds. Usually, optimal reception methods are used if all parameters of the received signals are known [1]. These methods are based on matched filtering. In the case when the signal parameters are unknown the most common methods of detection are energy detection (ED) [2], set of matched filters (SMF) [3], adaptive narrowband filtering [4], and various methods of quasi-likelihood estimates [5]. Let's say few words about enumerated methods. The optimal method of signal detection use maximum likelihood estimates of signal parameters. For signals mixture in strong additive noise this method is practically not applicable in real conditions due to huge computational cost. Therefore, this method of detecting signals can be used only in post-processing. Set of matched filters is a much less computational cost solution. However, the accuracy of this method is greatly reduced when the signal parameters uncertainty increases. Energy detection in combination with narrowband filtering is a classic and most often applicable method. It does not require a high computational cost although, but its efficiency is very low, especially in situations where the signal energy is a priori unknown. In additional, this
detection method works poor if there is external interference in the frequency range of the signal, which often happens in practice.

Recently, the popularity of machine learning methods in various fields of science is growing. This is especially noticeable in image recognition [6–7]. Authors show that machine learning methods can increase efficiency and speed of the system for recognizing signals in detection [8–9] and classification of signals in additive noise [10–11]. Neural network does not require solving the optimization problems and many computations after learning [12].

In this article, we propose and investigate neural networks as the universal method for detecting signals with amplitude modulation and priori unknown parameters. In particular, we apply machine learning methods for the task of rapid explosive detection in systems using NQR signals. Such systems are used to detect mines or explosives in bags or suitcases at airports or other public places. The main problem of NQR explosives detectors is the very low signal-to-noise ratio (SNR). A neural network can successfully solve these problems.

2. Signal’s model

We study various quasi-harmonic decaying signals, which contain one or more harmonics with additive noise:

\[ y[n] = x_k[n] + \xi[n] = \sum_{k=0}^{K-1} A_k \sin \left( \frac{2\pi \omega_k n}{\omega_d} + \varphi_k \right) \exp(-\gamma_k n) + \xi[n]. \] (1)

Here \( n = 0, 1, 2, \ldots, N - 1 \), \( N \) is number of signal’s point, \( K \) is signal multiplicity, \( \omega_k \) is \( k \) harmonic frequency, \( \omega_d \) is signal sampling rate, \( \gamma_k > 0 \) is attenuation constant, \( \varphi_k \) is initial phase, \( A_k \) is signal component amplitude, \( \xi[n] \) is normal white noise. The signal-to-noise ratio (SNR) is determined by the formula:

\[ \text{SNR} = 10 \lg \left( \frac{E_s}{E_n} \right), \]

where \( E_s \) is the energy of \( x_k \), and \( E_n \) is the energy of noise.

3. The structure of the neural network and the training set

Full connected and convolutional neural network layers are used most often in tasks of signal detection and classification [10]. Experiments show that mixed architecture is the optimal for detecting signals (1) with any parameters in terms of accuracy and computation cost. This architecture consists of two convolutional and one full connected layers. The optimal parameters of neural network layers for detecting signals with \( N = 2000 \) listed in Table 1. This neural network is used for all experiments described below.

| Layer | 1 | 2 | 3 |
|-------|---|---|---|
| Type  | Convolution | Convolution | Full |
| Neurons | 20 | 40 | 1 |
| Kernel, size×stride | 100×1 | 100×1 | – |
| Max pooling, size×stride | 10×10 | 10×10 | – |
| Activation | ReLU | ReLU | Sigmoid |

Training set consists of three thousand model signals. Signals of training set are created in accordance with the model (1). Their parameters are evenly distributed in the ranges determined by the conditions of the detection task. The training set is divided into two parts: 2000 signals are used for training and 1000 are used as a test set. The test set is used to calculate the probability of the correct answer after neural network learning. We use the Adam method for network training. It is a variation
of the gradient descent method. Moreover, we use cross-entropy function for learning error calculating.

It should be noted that neural network method is applicable even if exact signal model is unknown. Dataset can be created with real NQR scanner and sample of aim substance by measuring signals with and without sample.

4. Experiments

4.1. Experiments with the singlet signals

We investigate the neural network (NN) for detecting singlet signals (1). The parameters of the signals are \( N = 2000 \), \( K = 1 \) and \( \omega_d = 10 \) MHz. Parameter uncertainty ranges are \( \omega_k : 1 \ldots (1 + \Delta \omega) \) MHz, \( \Delta \omega : 0 \ldots 200 \) Hz, \( \varphi : 0 \ldots 2\pi \), and \( \gamma : 0 \ldots 0.0008 \). We compared the neural network method with alternative methods of receiving signals. This approach allows to determine the limits of applicability of machine learning methods for detecting signals with uncertain parameters. The effectiveness of correlation methods is significantly reduced with large uncertainty ranges of signal parameters. Therefore, for comparison, in a large range of uncertainties, we used the most commonly used method for the described task, the energy detection method with filtering. Correlation technique cannot be used if the signal parameters are slowly varying according to an unknown law. In practice the varying could be caused by non-linear distortion, fading or unsteady interference.

The main ED method idea is comparing the signal energy \( E_s \) with the detection threshold. The signal \( y[n] \) is filtered by the band-pass filter in signal band. The signal energy \( E_s \) is calculated from filtered signal samples \( y'[n] \) by the formula:

\[
E_s = \sum_{n=0}^{N-1} y'^2[n].
\]

If \( E_s > \delta \), then the signal is detected, otherwise not. The detection threshold \( \delta \) is defined as:

\[
\delta = \sum_{n=0}^{N-1} \left( \frac{1}{2} x_{\text{min}}^2[n] + \frac{1}{2} x_{\text{min}}^2[n] \right),
\]

where \( x_{\text{min}} \) is a signal with arbitrary non-energy parameters \((\omega, \varphi)\) and minimal energy parameters \( (A_1, \gamma) \).

For comparison, we used different \( \Delta \omega \), when SNR was –20 dB. For the ED method, the signal was previously processed by a digital bandpass filter with a band from 1 MHz to 1 MHz + \( \Delta \omega \).

![Figure 1. Comparison of signal detection methods with different frequency uncertainty for an SNR of –20 dB.](image-url)
Let us call the quantity \( W = \Delta \omega / \omega \) is the relative frequency uncertainty range. Figure 1 shows that the neural network works much better than the energy detector with filtering when \( 0.01 < W < 0.1 \).

Also, we compared the efficiency of energy detector with filtering and neural network for detecting signals (1) with unknown and slowly varying frequency and amplitude. The frequency \( \omega \) varies according to the law \( \omega = 1000 + \delta n \), where \( \delta \) is a random value for each signal not exceeding 0.01. The amplitude is described by the formula \( A_1 = 1 + \beta n \), where \( \beta \) is a random value for each signal not exceeding 3. The results of the comparison of methods are shown in Figure 2.

![Figure 2](image)

**Figure 2.** Comparison of signal detection methods with a priori unknown and slowly varying parameters according to unknown law.

How we can see from figure 2, the neural network is much more efficient in detecting a signal with slowly varying parameters than the energy detector.

### 4.2. Experiments with the NQR RDX signals

Main problem of real signal detection is the uncertainty of the spectral composition. This is typical for nuclear magnetic resonance (NMR) signals, nuclear quadruple resonance (NQR), radio signals, or bitwise data transmission signals. This problem does not allow to use correlation reception methods and greatly complicates signal filtering. There are many real signals described by model (1) with the condition \( 0 < W < 0.1 \) and unknown initial phase and amplitude. Typical example is the NQR signal of nitrogen-containing substances, such as RDX explosive. The spectral method is the classical one for studying NQR signals. This method is practically not applicable in the strong noises. An example of the NQR signal of the RDX and its spectrum is shown in Figure 3.

Priori uncertainty of the parameters of the NQR signals is related to the fact that in real experiments the sample temperature, its volume and temperature history are often unknown. It is known that the RDX NQR signal has a strong dependence on all these factors [13 – 14]. To study the detection of NQR signals, we used realistic models of NQR signal RDX explosives. These models satisfy formula (1) and it take into account dependence parameters versus sample temperature. The range of parameters uncertainties of the RDX NQR signals under realistic temperature conditions is given in Table 2. The temperature uncertainty here is approximately 50 K.

| Signal parameter | \( \omega_1 \), kHz | \( \omega_2 \), kHz | \( \omega_3 \), kHz | \( A_1, A_2, A_3 \) | \( \varphi_1, \varphi_2, \varphi_3 \) | \( \gamma_1, \gamma_2, \gamma_3, s_1 \) | SNR, dB |
|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| Range of uncertainty | 5020 – 5050 | 5190 – 5220 | 5240 – 5270 | 0.25 – 1 | 0 – 2\( \pi \) | (0 – 4) \( \cdot 10^4 \) | 0 – 25 |
Figure 3. The RDX NQR signal and its spectrum with an SNR of -20 dB.

Since the RDX NQR signals have several sinusoidal components, hence the band-pass filter have a wide band. It makes energy detection ineffective in such conditions. SMF method is effective when the parameters of the signals have a small uncertainty. We used $m = 100$ filters to implement this method. The impulse responses of these filters $h_m$ are NQR $x_k(1)$ signals with parameters randomly selected from known uncertainty ranges. The analyzed signal $y[n]$ is processed by each of the created filters. If at least one of them indicates the presence of a signal, then the signal is detected, otherwise there is no signal. Figure 4 show a comparison of various methods.

Figure 4. Comparison of various methods for detecting NQR signals of RDX explosives.
As can be seen from the figure 4, the efficiency of the neural network exceeds the efficiency of alternative methods if SNR $<-15$ dB. This result suggests that the neural network implements a complex hybrid method of detection. It not just using a set of convolution filters matched with the signals. Spectral analysis is not effective when SNR $<-10$ dB.

ROC-curves are used for estimate efficiency of detection methods. ROC-curve is dependence probability of detection versus probability of false alarm. Detection method with larger area under curve is more effective. The ROC-curves for the studied methods for SNR $-15$ dB are shown on Figure 5.

![Figure 5. The ROC-curves for SNR $-15$ dB.](image)

NN probability of detection is 90 \% for 2 \% probability of false alarm. SMF probability of detection is 30 \% for the same conditions. Area under the ROC-curve for NN is larger than others. The ROC-curves for the studied methods for SNR $-20$ dB are shown on Figure 6.

![Figure 6. The ROC-curves for SNR $-20$ dB.](image)

All of these methods are not efficient for SNR $<-20$ dB. But the neural network is still the most efficient. Computational cost is an important criterion for evaluating a detection method. We estimate the criterion by measuring of computation time. Methods are implemented by Python 3.6 scripts and test it on i5 8600 processor: MSF – 0.35 sec and NS – 0.003 sec, ED – 0.02 sec.
5. Conclusion
Thus, the neural network is more effective than alternative methods in almost examples of RDX NQR and singlet signals. The proposed method is faster than others for multiplet signals. At the same time, the detection accuracy of neural network method for NQR signal exceeds others with realistic temperature uncertainty and SNR < –15 dB. The neural network method can be generalized to complex signals of any nature, for example, in radar or communication systems. However, the proposed method can be used as the most versatile and fast detector only if it is possible to receive many training signals in advance.

6. References
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