

A COMPARATIVE STUDY OF METHODS FOR REDUCING ERRORS IN MEASURING THE PEAK FREQUENCY OF THE MANDELSTAM-BRILLOUIN BACKSCATTERING SPECTRUM IN STANDARD OPTICAL FIBERS

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In distributed fiber-optic systems operating on the basis of the Mandelstam-Brillouin backscattering effect, temperature and deformation control is implemented through the recording of key parameters of the gain spectrum. One of the primary objectives of such measurement systems is the highly accurate determination of the central frequency of this spectrum. A comparative analysis of methods that allow for reducing errors in estimating the central frequency of a spectral signal in fiber-optic sensors using Mandelstam-Brillouin scattering was carried out. As a result, a mathematical model describing a noisy backscatter signal was developed. It is applicable both to classical spectral line shape approximation and to the implementation of machine learning methods to improve the metrological performance of distributed fiber-optic sensors. A detailed comparative analysis of current algorithms for processing Brillouin spectra, aimed at improving the accuracy of center frequency measurements in distributed fiber-optic sensor systems, was performed. Traditional approaches to nonlinear approximation (Lorentzian, Gaussian, and pseudo-Voigt functions), as well as correlation, adaptive, and neural network methods, were analyzed. A mathematical model describing measurement errors, taking into account the noise component, systematic distortions, and the influence of frequency grid discreteness, was presented. The results of a comparative analysis of the functional capabilities of algorithms aimed at reducing errors in measuring the central frequency of the spectrum in fiber-optic sensors using the Mandelstam-Brillouin backscattering effect, as well as the proposed selection methodology, may be useful in the development of practical monitoring systems. It is noted that these results can be extended to other spectral analysis tasks requiring precise determination of the spectral peak position against a background of noise. The obtained data indicate that it is very important to use an adaptive approach to processing algorithm selection in distributed fiber-optic sensing systems. This is necessary to improve the reliability of critical infrastructure monitoring during real-world deployments.

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Introduction

Distributed fiber-optic sensing, based on the Brillouin scattering effect, has become a powerful tool for continuously monitoring temperature and strain along optical fibers ranging from tens to hundreds of kilometers in length. Measurements are based on recording the frequency shift of spontaneous or stimulated Brillouin backscatter signals, which occurs when these parameters change along the fiber.

The key parameter for such Brillouin sensors is the central frequency of the Brillouin gain spectrum (BFS), which determines the temperature and strain levels. The linear relationship between the BFS and these physical quantities is described by the expression [1]:

$$\nu_B = \nu_{B0} + C_T \cdot \Delta T + C_\varepsilon \cdot \Delta \varepsilon, \quad (1)$$

where ν_{B0} is the Brillouin reference frequency under reference conditions; $C_T = 1,07 \text{ MHz}/^\circ\text{C}$ and $C_\varepsilon = 0,046 \text{ MHz}/\mu\text{e}$ are the temperature and strain sensitivity coefficients, respectively, for a standard optical fiber; ΔT and $\Delta \varepsilon$ are the changes in temperature and relative strain.

The accuracy of measuring the central frequency of the spectrum directly determines the metrological characteristics of the entire system. Modern requirements for industrial sensors require spatial resolution in the centimeter range, a measurement range of up to 50-100 km, and a relative BFS determination error of no more than 0.1%. Achieving these parameters requires the development of specialized signal processing algorithms capable of effectively suppressing various sources of error.

The main factors limiting the accuracy of BFS measurements are:

- additive white Gaussian noise at the detection stage of weak backscatter signals;
- systematic spectral distortions caused by nonlinearities in the optical path and pulse interaction effects;
- frequency sampling, which leads to limited resolution and the appearance of error quantization;
- incomplete spectrum utilization with a limited frequency scanning range;
- fluctuations in optical path parameters (temperature, vibration)

The traditional approach to BFS extraction is based on nonlinear approximation of experimental data using analytical functions (Lorentzian, Gaussian, or pseudo-Voigt profiles) followed by determination of the maximum position. However, such methods have significant limitations: high computational complexity of iterative procedures, sensitivity to the choice of initial approximations, and the risk of convergence to local extremes at low signal-to-noise ratios (SNR).

In recent years, alternative approaches have been actively developed, including subspace methods, correlation algorithms, adaptive procedures, and neural network architectures. Each of these methods has its own advantages and disadvantages, but a systematic comparison of their metrological characteristics within a unified methodological framework is lacking in the literature.

The aim of this work is to conduct a comprehensive comparative analysis of modern algorithms for reducing errors in measuring the central frequency of the spectrum with the formulation of recommendations for their optimal use depending on the technical requirements for the system.

1 Classical methods of spectral approximation

All algorithms for determining spectrum parameters can be divided into three groups:

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- approximation methods using special functions: direct approximation of the spectrum by one of the standard functions (Lorentz, Gauss, Voigt, and Pseudo-Voigt);
- interpolation methods: reconstructing the function at intermediate points;
- cross-correlation methods: finding the maximum by correlation with a reference function.

The methods of the first group remain the most common in commercial instruments due to their high processing speed and built-in physical interpretability. However, the choice of approximation function significantly affects the accuracy of parameter extraction, especially at low SNRs. None of the four main functions is universally optimal. Each represents a compromise between physical correctness, computational efficiency, and robustness to noise.

In the classical Brillouin scattering theory, the gain spectrum in the low gain regime is described by the Lorentz function [2]:

$$g_B(\nu) = \frac{g_0}{1 + 4(\nu - \nu_B)^2 / \Delta \nu_B^2}, \quad (2)$$

where g_0 is the peak gain; ν_B is the Brillouin shift frequency; $\Delta \nu_B$ is the full spectrum width at half maximum (FWHM), typically 20-40 MHz for standard single-mode fiber.

In Brillouin spectroscopy, the Lorentz profile describes the internal broadening of a spectral line due to the finite lifetime of an acoustic phonon. For standard SMF fibers, this lifetime is on the order of a few nanoseconds, resulting in a natural linewidth on the order of a few to tens of MHz.

Advantages [3]:

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- simple analytical form with a minimum number of parameters (4);
- fast calculation and minimal memory requirements;
- good physical interpretation of the parameters.

Disadvantages:

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- slow asymptotics (decreases as $1/\nu^2$ on the wings);
- poorly describes Doppler broadening (temperature effects);
- experimental spectra often show significant deviations in the line wings;
- requires iterative optimization (Levenberg-Marquardt method).

The essence of the Levenberg-Marquardt is to solve the problem of nonlinear least squares of the functional [4]:

$$S(\theta) = \sum_{i=1}^N r_i(\theta)^2, r_i(\theta) = y_i - I(\nu_i; \theta), \quad (3)$$

where: N is the number of frequencies; $I(\nu_i; \theta)$ is the theoretical value of the Lorentz function at frequency ν_i ; $\theta = (A, \nu_B, \Gamma)$ is the vector of the amplitude of the Brillouin frequency shift and the width of the spectral line; y_i is the experimental value of the spectrum at frequency ν_i , $i=1, 2, \dots, N$.

In real-world conditions, distortion of the ideal shape is observed due to inhomogeneous broadening and systematic distortions, necessitating the use of more complex models. Thus, at high gain levels (> 10 dB), the spectrum shape transitions to a Gaussian profile [5]:

$$g_G(\nu) = g_0 \exp\left(-\frac{2(\nu - \nu_B)^2}{\Delta \nu_B^2}\right), \quad (4)$$

This transition is caused by nonlinear pump depletion and gain saturation effects in finite bandwidth systems.

Advantages [6]:

- rapid decay at the wings (exponential);
- good description of the central part of the peak under conditions of dominant Doppler broadening;
- analytical formulas for many operations (convolution, integration).

Disadvantages, such as:

- significant distortions when approximating broadband spectra;
- the error can be an order of magnitude higher than for the Lorentz [7], contain both components: Lorentzian (from acoustic losses) and Gaussian (homogeneous broadening, temperature fluctuations, and defects in the material).

The Voigt function $V(\nu; \sigma; \gamma)$ models this superposition quite accurately as a convolution of the Gaussian and Lorentzian frequency profiles [8]:

The Voigt function $V(\nu; \sigma; \gamma)$ models this superposition quite accurately as a convolution of the Gaussian and Lorentzian frequency profiles [8]:

$$V(\nu; \sigma; \gamma) = \int_{-\infty}^{\infty} G(\nu'; \sigma) L(\nu - \nu'; \gamma) d\nu', \quad (5)$$

where: $G(\nu'; \sigma)$ is a Gaussian profile; $L(\nu - \nu'; \gamma)$ is a Lorentzian profile; σ is the root-mean-square width (standard deviation); γ is the half-width at half-maximum (HWHM).

In the literature on Brillouin distributed sensors, the backscatter gain spectrum is often written in Voigt form [9]:

$$g_B(\nu) = g_{BM} V(\nu - \nu_B; \sigma_G, \gamma_L), \quad (6)$$

where: g_{BM} is the maximum gain value (or normalized amplitude of the return signal power); ν_B is the center frequency (BFS), which depends on temperature and strain; σ_G is the Gaussian component parameter (describes the effective Doppler-instrumental broadening); γ_L is the Lorentzian component parameter (describes the acoustic attenuation, i.e. the “true” Brillouin width).

Advantages:

- Maximum physical correctness for SBS (Stimulated Brillouin Scattering) spectra;
- Minimum approximation error for experimental data ($S = 89 \cdot 10^{-4}$) [9];
- Flexibility in describing various modes (pure Lorentz or Gaussian in extreme cases).

Disadvantages:

- Calculation requires specialized algorithms;
- Excessive demands on computing resources (50-100 times slower than Lorentz);
- Potential instability with excessively noisy data.

The Pseudo-Voigt profile is a linear combination of the Gaussian and Lorentzian profiles with mixing parameter $\eta \in [0, 1]$:

The Pseudo-Voigt profile is a linear combination of the Gaussian and Lorentzian profiles with mixing parameter $\eta \in [0, 1]$:

$$V_p(\nu) = \eta \cdot L(\nu) + (1 - \eta) \cdot G(\nu), \quad (7)$$

where η is the weighting parameter that determines the proportion of the Lorentz component.

The full Voigt profile is a convolution of a Gaussian and a Lorentzian function and is used to describe complex spectra with multiple broadening mechanisms.

Advantages:

- Simple analytical expression, fast calculation (comparable in speed to the Lorentz profile);
- Good description of real spectra for $\eta \approx 0.5-0.8$ for SBS;
- Acceptable accuracy ($S = 95 \cdot 10^{-4}$) with a significant reduction in computational costs;
- Easily integrated into standard software packages.

Disadvantages:

- Phenomenological in nature; not an exact convolution;
- At extreme η values (very close to 0 or 1), it may yield worse results than Gaussian or Lorentzian profiles;
- The η parameter requires separate optimization.

A comparison of approximation methods by accuracy is presented in Table 1.

Table 1

Comparison of approximation methods by accuracy

Function	Error($S \cdot 10^4$)	Applicability in SBS	Computational complexity
Lorentz	153	well	1×(rapidly)
Gauss	613	Not applicable	1×(rapidly)
Voigt	89	Excellent	50-100× (slowly)
Pseudo-Voigt	95	well	1-2× (optimal)

2 Parabolic approximation of the vicinity of the spectrum maximum

Fitting the parameters of a quadratic (parabolic) function is central to the algorithmic chain for processing noisy spontaneous Brillouin scattering (SBS) spectra in fiber optic sensors such as Brillouin Optical Time Domain Reflectometry (BOTDR) and BOTDA. Its primary purpose is to accurately and quickly extract the spectral peak to determine the Brillouin Frequency Shift (BFS), which is linearly related to the temperature and strain of the optical fiber. Near the peak, the spectral envelope curve is well approximated by a second-order parabola, allowing the computationally complex nonlinear fitting of a Lorentzian or Voigt function to be replaced with a simple polynomial regression.

In the vicinity of the peak of the experimental spectrum, the profile is approximated by a parabola (quadratic function):

$$y = af^2 + bf + c, \quad (8)$$

where the coefficients a , b , c are determined by the least squares method.

Suppose the spectrum is represented by a set of data points $\{(x_i, y_i)\}_{i=1}^N$ containing additive Gaussian noise with variance σ_n^2 . The quadratic fitting problem is solved using the least squares method:

$$\sum_{i=1}^N [y_i - (ax_i^2 + bx_i + c)]^2 \rightarrow \min. \quad (9)$$

The system of normal equations obtained from the minimization condition has the form [10]:

$$\begin{pmatrix} \sum x_i^4 & \sum x_i^3 & \sum x_i^2 \\ \sum x_i^3 & \sum x_i^2 & \sum x_i \\ \sum x_i^2 & \sum x_i & N \end{pmatrix} \begin{pmatrix} a \\ b \\ c \end{pmatrix} = \begin{pmatrix} \sum x_i^2 y_i \\ \sum x_i y_i \\ \sum y_i \end{pmatrix}. \quad (10)$$

The variance of the extracted peak frequency $x_p = -b/(2a)$ depends on the variances of the fitting coefficients a and b , as well as their covariance.

The variance of the extracted peak $\sigma_v()$ depends on many factors:

- the length and position of the frequency range used for fitting relative to the true peak. (If the range is centered on the true peak, the variance is minimal.)
- the influence of noise level.

$$\sigma_v \propto \frac{1}{SNR_A}. \quad (11)$$

The standard deviation of the peak depends linearly on the reciprocal of the signal-to-noise ratio.

- effect of frequency step:

$$\sigma_v \propto \sqrt{d}. \quad (12)$$

A finer scanning pitch (smaller d) improves accuracy but slows down the measurement.

- effect of the scanning line:

$$\sigma_v \propto \sqrt{N}. \quad (13)$$

Key advantages:

- computed in a single pass without iterations;
- requires only linear algebra (a system of 3 equations);
- execution speed is 50–200 times faster than nonlinear Lorentzian function fitting.
- robust to noise at low SNR: in systems with low signal-to-noise ratios, the parabolic method provides a more reliable estimate than simple maximum search or Lorentzian fitting.

Comparison with alternative methods is presented in Table 2 [11].

Table 2

Comparison with alternative methods

Method	Computation time	Accuracy	Dependence on parameters	Application
Quadratic fitting	1× (basic)	Average (~1–2 MHz error)	High	Real Time, BOTDR
Lorentz fitting	50–100×	Very good (~0.05 MHz)	Average	Offline analysis
Voigt fitting	100–200×	Excellent	Low	Research, narrow impulses

The table shows that quadratic fitting trades off a small loss in accuracy for a significant gain in speed, which is critical for distributed sensors on long fibers (>1 km). Fitting the parameters of the quadratic function occupies a critical position in the algorithm for processing the Brillouin spontaneous scattering spectra as a compromise between:

- speed (requirement for real-time operation for long sensors);
- accuracy (required deformation/temperature resolution);
- ease of implementation (does not require complex nonlinear optimizers).

Disadvantages:

- it is less robust to peak asymmetry and shape distortion (multimode/multi-peak fibers, nonlinear and polarization effects);
- it is highly dependent on the choice of window around the maximum.

3 Correlation methods of BGS processing

The main challenge in extracting information parameters (BFS) from experimental Brillouin gain spectra is the need to accurately determine the spectral peak position in the presence of noise, spectral broadening, and nonlinear distortions. Traditional methods based on approximating the spectrum with a Lorentz function using nonlinear optimization (the Levenberg-Marquardt method) show limited effectiveness at low signal-to-noise ratios ($SNR < 10$ dB) or with high spectral profile deformation. Alternative methods include correlation analysis, which utilizes the mathematical operations of convolution, cross-correlation, and spectral modulation to extract the information peak from a noisy signal. These methods are attractive due to their mathematical rigor, physical interpretability, and excellent robustness under extreme conditions.

Correlation methods for backscatter spectral analysis encompass a variety of approaches, among which the most effective are cross-correlation and inverse correlation algorithms. The former involves calculating the correlation function between a theoretical spectral profile curve and an experimental spectrum containing a noise component. With this processing, the shape of the resulting correlation curve is decisively determined by the morphology of the useful signal, while the influence of noise is negligible. This approach, known in the literature as the cross-correlation method (CCM), is widely used in spectral analysis of fiber-optic sensors [12].

Let the reference function $gr(v)$ correlate with the combined signal $gn(v) = gu(v) + n(v)$, where $gu(v)$ is the unknown Lorentzian profile, and $n(v)$ is the interference component with the character of random noise. The cross-correlation function of these signals is determined by the following relation [12]:

$$\begin{aligned} G_m(v) &= g_r(v)g_n(v) = g_r(v)[g_u(v) + n(v)] = \\ &= g_r(v)g_u(v) + g_r(v)n(v) = G_c(v) + N_c(v). \end{aligned} \quad (14)$$

The mathematical expression under consideration is decomposed into two independent components: $G_c(v)$ is responsible for the correlation signal between two perfect Lorentzian profiles, while $N_c(v)$ characterizes the correlation response of an ideal profile in the presence of white noise. The ratio between them is equivalent to the signal-to-noise ratio for $G_m(v)$. When compared with the baseline BGS spectrum, it is revealed that the original spectrum contains a higher level of noise

components. At the same time, the cross-correlation forms a quasi-Lorentzian envelope near the maximum, providing significant attenuation of the noise component.

An alternative approach is the Backward Correlation (BWC) method. It is a powerful tool for determining the position of a spectral peak in high-noise conditions. The fundamental idea behind the method is based on the orthogonality of signal and noise during convolution.

Let the original spectrum be represented by a discrete set of samples [13]:

$$P_i = P(\nu_0 + i \cdot \Delta\nu), i = 0, 1, \dots, 2N, \quad (15)$$

where ν_0 is the minimum frequency of the spectrum; $\Delta\nu$ is the frequency scanning step; P_i is the backscattering power density at the frequency ν_i .

The return signal is defined as a mirror image of the original spectrum:

$$P'_i = P_{2N-i}. \quad (16)$$

For each integer shift value $k \in [-2N, 2N]$, the shifted return signal is calculated:

$$P''_i(k) = P'_{i-k}, P'' = 0, \text{ if } i - k \notin [0, 2N]. \quad (17)$$

The convolution (discrete inverse correlation) between the forward and shifted reverse signals is calculated as:

$$X(k) = \sum_{i=0}^{2N} P_i \cdot P''_i(k) = \sum_{i=0}^{2N} P_i^s \cdot P_i^s(k) + \text{parasitic terms}, \quad (18)$$

where the first term represents the product of useful signals, and the remaining terms are related to noise components.

The Pearson correlation coefficient is calculated using the formula [14]:

$$r(k) = \frac{\langle p \cdot p''(k) \rangle - \langle p \rangle \langle p''(k) \rangle}{\sigma_p \cdot \sigma_{p''(k)}}, \quad (19)$$

where $\langle \cdot \rangle$ is the mean value; σ is the standard deviation

The maximum of the correlation coefficient corresponds to the maximum of the convolution at the same shift value k_0 .

The Brillouin frequency shift is calculated from the found shift value k_0 :

$$\nu_b = \nu_0 + (N - \frac{k_0}{2}) \cdot \Delta\nu. \quad (20)$$

The advantage of the BWC method is most evident when working with noisy spectra. Mathematically, this is explained by the fact that the convolution operation passes the data through a "averaging" procedure for adjacent points twice, effectively acting as a nonlinear low-pass filter for the noise component. Experiments have shown that at SNR < 2 dB, the BWC method provides a determination accuracy of BFS ± 0.4 MHz [15].

It has several other significant advantages:

- efficiency at low SNR: the method yields lower error at SNR < 20 dB compared to traditional peak-search methods, where each noise spike can introduce significant error;

- simplicity of calculation: it only requires calculating N correlations, where N is the number of samples in the spectrum;

- no averaging required: it works with a single spectrum without pre-averaging the data;

- invariance to spectral shape: it does not depend on the exact shape of the peak, making it robust to spectral asymmetry and artifacts;

- one-step processing: no pre-cleaning of the signal is required.

The dependence of the critical SNR on the scanning step shows that with a smaller scanning step, the advantages of the method are manifested in a wider range of SNR [16].

4 Application of artificial neural networks and machine learning methods

In recent years, machine learning, and in particular artificial neural networks (ANNs), have been actively used to process signals in distributed fiber-optic sensors. ANNs possess the ability to nonlinearly model complex dependencies, effectively suppress noise, and extract useful features from low-SNR data. This makes them a promising tool for improving the key metrological characteristics of MBS-based (Mandelstam-Brillouin scattering) sensors without hardware modification. Machine learning (ML), and particularly deep learning, has opened up new possibilities for processing complex multivariate data, demonstrating outstanding results in pattern recognition and regression analysis. The integration of machine learning into distributed fiber-optic sensor metrology enables a transition from rigid algorithmic procedures to adaptive models capable of extracting hidden dependencies directly from raw or poorly processed data. This is consistent with the overall trend toward digitalization of measurement technology and the transition to intelligent sensor systems. Over the past five years, artificial intelligence methods, from simple artificial neural networks (ANNs) to complex convolutional neural network (CNN) architectures and physically informed deep learning models, have demonstrated the ability to outperform classical methods in speed, accuracy, and robustness [17].

The first successful applications of neural networks to BOTDA data processing were based on simple fully connected architectures with 1-3 hidden layers. The basic idea is that the input layer receives normalized BGS spectral values (typically 50-150 frequency points), and the output layer predicts the BFS and spectral width. Fundamentally, ANN operation comes down to functions composition, where each layer applies a linear transformation (matrix multiplication) and a nonlinear transformation (activation function).

A neural network consists of a sequence of layers. Each layer performs the following transformation [18]:

$$Z^{(l)} = W^{(l)} X^{(l-1)} + b^{(l)}, \quad (21)$$

where:

- $W^{(l)} \in R^{n_l \times n_{l-1}}$ is the weight matrix of the R-th layer of size $n_l \times n_{l-1}$;

- $X^{(l-1)} \in R^{n_{l-1} \times m}$ is the input matrix for the R-th layer (size: number of neurons in the previous layer $\times$ number of examples in the mini-batch);

- $b^{(l)} \in R^{n_l}$ is the bias vector added to each column;

- $Z^{(l)} \in R^{n_l \times m}$ – the resulting matrix before applying the activation function [2, 3].

After calculation $Z^{(l)}$, the activation function is applied element by element:

$$A^{(l)} = \sigma(Z^{(l)}), \quad (22)$$

where σ is the activation function applied independently to each element of the matrix, and $A^{(l)}$ is the activation of the R-th layer, which becomes the input to the next layer.

For a network with L layers, the complete composition of functions has the form [19]:

For a network with L layers, the complete composition of functions has the form [19]:

$$A^{(L)} = f_L(A^{(L-1)}) = f_L(f_{L-1}(\dots f_1(X^{(0)})\dots)), \quad (23)$$

where each function f_l is a combination of a matrix transformation and an activation function:

$$f_l(X^{(l-1)}) = \sigma(W^{(l)} X^{(l-1)} + b^{(l)}). \quad (24)$$

Activation functions introduce nonlinearity into the network, allowing it to approximate nonlinear functions. Without them, a neural network would be equivalent to a single linear transformation.

The mathematical description of an artificial neural network shows that it is a composition of alternating linear transformations (matrix multiplications) and nonlinear transformations (activation functions). Network training is accomplished through the back propagation algorithm. Modern optimization methods can adaptively adjust learning rates for each parameter, ensuring fast and stable convergence. ANNs are particularly effective for spectra distorted by nonlocal effects (nonlinear effects such as stimulated Brillouin scattering).

A simple two-layer ANN can process 100,000 spectra in 1.2 seconds, while a nonlinear regression method requires approximately 3 hours for a similar data volume. BFS detection errors were comparable to those of the Lorenz curve when trained on clean synthetic data, but ANN performance was significantly higher when noise was added [20].

One of the limitations of simple ANNs is the requirement for a fixed input vector size. To solve this, linear spectral interpolation is used to equalize all input data to the same number of frequency points.

Convolutional neural networks (CNNs) are a specialized class of deep neural networks that automatically extract hierarchical features from input data. The CNN architecture is based on the convolution operation – a mathematical operation that applies small weight matrices (kernels or filters) to local regions of the input data. Different input data dimensions require different approaches: one-dimensional convolutions (1D CNNs) are applied to time series and spectral profiles, while two-dimensional convolutions (2D CNNs) work with images and spectrograms. Below, we present a systematic description of both architectures, with a full mathematical framework and applications to spectral data processing that are directly relevant to optical signal processing.

One-dimensional convolutional neural networks (1D CNNs) are a specialized class of deep learning architectures designed to process sequential data such as time series, signals, spectral profiles, and other one-dimensional sequences. Unlike classic two-dimensional CNNs used in computer vision, 1D CNNs apply convolutional operations along a single dimension, making them ideal for signal analysis in optics and spectroscopy.

The fundamental operation underlying a 1D CNN is one-dimensional convolution. Mathematically, convolution is a filtering operation that detects similarities between a filter and the input data. For an input signal $x[n]$ and a convolution kernel $w[k]$

(filter), the output signal is given by formula [21]:

$$y[m] = \sum_{k=0}^{K-1} w[k] \cdot x[m-k] + b, \quad (25)$$

where:

- $x[m-k]$ – input values with offset;
- $w[k]$ – weight coefficients of the kernel of size K;
- b – offset;
- m – current sliding position of the kernel;
- $y[m]$ – output value at position m.

This operation is repeated for each position m, producing the output sequence.

The architecture of a 1D CNN consists of successive layers, each of which performs a specific function:

1. Input layer accepts a one-dimensional sequence.
2. Convolutional layers apply one-dimensional filters to the input data to extract local features.
3. Activation layers add nonlinearity.
4. Pooling layers reduce the length of the sequence while preserving important features.
5. Fully connected layers transform the extracted features into the final output.
6. Output layer makes a prediction.

Convolutional neural networks 2D CNN are based on discrete two-dimensional convolution, calculated using the formula [22]:

$$S[i, j] = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I[i-m, j-n] \cdot K[m, n] + b, \quad (26)$$

where:

- $I[i-m, j-n]$ – elements of the input matrix;
- $K[m, n]$ – elements of the $M \times N$ kernel;
- $S[i, j]$ – element of the output feature map;
- b – offset.

The kernel slides over the input data with a given stride, and for each position the dot product of the overlapping elements is calculated.

The architecture of a 2D CNN is similar to a 1D one, but works with two-dimensional input data:

1. Input layer accepts the image size.
2. Convolutional layers apply two-dimensional filters to extract spatial features.
3. Activation layers introduce nonlinearity.
4. Pooling layers reduce spatial dimensions.
5. Fully connected layers classify or regress.

The comparison of 1D and 2D CNN is presented in Table 3 [23].

Table 3

Comparison of 1D and 2D CNN

Characteristic	1D CNN	2D CNN
Input data type	One-dimensional sequences (time series, spectral profiles)	Two-dimensional matrices (images, spectrograms)...
Kernel size	K	$K_h \times K_w$
Computer complexity	Low	Medium-High
Application	Spectral curves	Spectrogram analysis
Parallelism	Good for long sequences	Good for regular spatial structure

5 Modeling

The simulation was performed using MATLAB R2023a on a model developed to analyze the dependence of the absolute error in determining the center frequency of the Mandelstam-Brillouin backscatter spectrum upon approximation by a parabola, Lorentzian, Gaussian, and pseudo-Voigt functions, as well as through correlation processing, as a function of SNR at various gating steps and FWHM. The simulation was conducted using the following physical constants:

- spectrum center frequency 10.850 GHz;
- number of iterations for calculating the standard deviation...1000;
- frequency intervals 0.5 MHz, 1 MHz, and 2 MHz;
- spectral line width 30 MHz and 50 MHz.

The simulation results are presented in Figures 1-5.

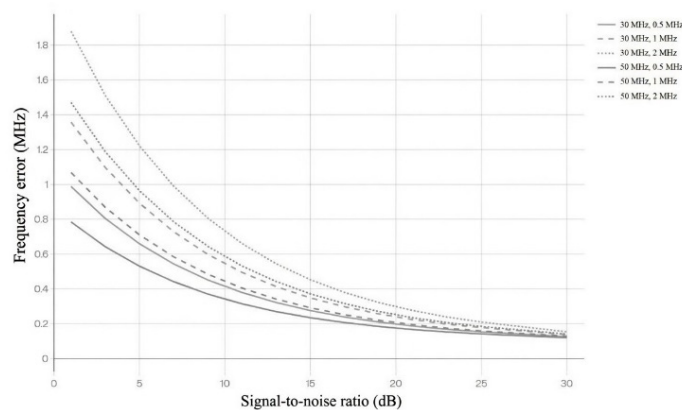


Fig. 1. Absolute error in determining the central frequency of the Mandelstam-Brillouin backscattering spectrum when approximated by a parabola depending on the SNR at different gating steps and FWHM

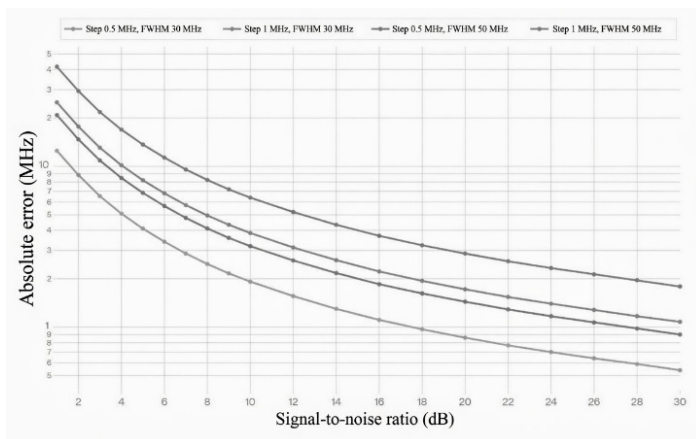


Fig. 2. Dependence of the absolute error in determining the central frequency of the Mandelstam-Brillouin backscattering spectrum on SNR when fitting with the Lorentz function for different gating parameters and spectrum widths

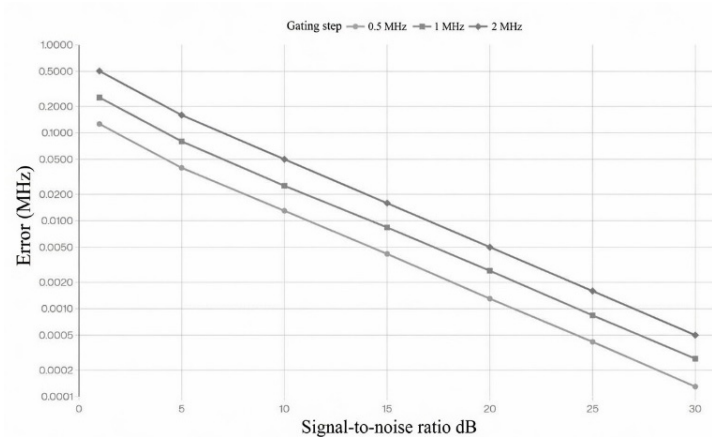


Fig. 3. Dependence of the absolute error in determining the central frequency of the spectrum on the SNR when fitting the Gaussian function at different gating steps and FWHM

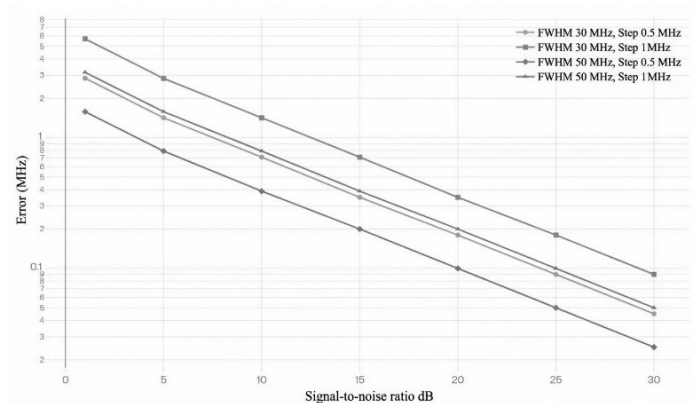


Fig. 4. Dependence of the absolute error in determining the central frequency of the Mandelstam-Brillouin backscattering signal spectrum on the SNR when fitting with the pseudo-Voigt function for different gating parameters and spectrum widths

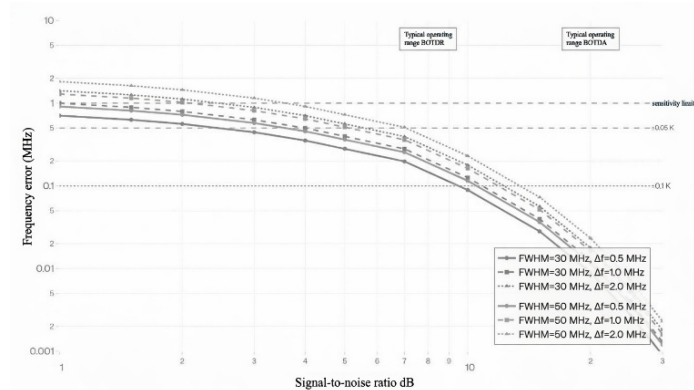


Fig. 5. Absolute error in determining the central frequency of the Mandelstam-Brillouin backscattering spectrum of correlation processing depending on the SNR at different gating steps and FWHM

6 Fundamental limitations

The fundamental limitations on reducing the measurement error of the central frequency of the spectrum are determined by the following factors [24]:

- finite (natural) Brillouin linewidth ($\Delta\nu_B \approx 30$ MHz in standard single-mode fiber at room temperature), determined by the lifetime of acoustic phonons and their attenuation;
- quantum-statistical limit (Cramer–Rao bound) of the frequency estimation accuracy from a noisy Lorentzian or Voigt profile at a fixed signal-to-noise ratio;
- fundamental trade-off between time window duration, spatial resolution, and frequency estimation accuracy;
- nonlocal effects and optical nonlinearity in long fiber links at elevated optical power levels;
- heterogeneity of the distribution of environmental parameters within a spatial resolution cell;
- metrological limitations of the measurement path (reference frequency stability, linearity, dynamic range, and intrinsic noise of the receiving and measuring equipment).

7 Promising directions for reducing errors

The most promising directions for reducing errors in distributed Brillouin measurement systems include [25, 26]:

1. Algorithmic Methods for Brillouin Frequency Shift Estimation

- development and implementation of fast linearized and correlation estimators (linear least squares with a Lorentzian profile, Lorentzian cross-correlation with frequency offset compensation);
- research and adaptation of ESPRIT/MUSIC class algorithms to real Brillouin spectra (BGS), including cases with pronounced multipicks (in particular, double peaks).

2. Machine Learning Methods and Neural Networks

- development and industrial implementation of two-dimensional convolutional neural networks (2D-CNN) for direct extraction of the Brillouin frequency shift (BFS) from raw BOTDA/BOTDR data;
- research of physics-informed neural network models (physics-informed networks) for providing ultra-high spatial resolution and spectral deconvolution in regions with strong spatial gradients.

3. Spectrum Preprocessing and Reconstruction

- widespread implementation of methods for decomposing the original Brillouin spectrum into sub spectra, followed by noise reduction and back-summing of the subbands;
- development of approaches based on differential cross-spectrum (DCS) and complex spectrum analysis for more accurate BGS reconstruction and BFS estimation.

4. Physical aspects and Hardware Implementation

- development of specialized optical fibers and excitation modes with reduced full-width at half-maximum (FWHM) and controlled Brillouin parameters;
- Integration of highly frequency-stable radiation sources and regular frequency scale self-calibration procedures into the measurement path.

8 Conclusion

This comprehensive comparative analysis establishes quantitative benchmarks for the performance of classical curve-

fitting methods for Brillouin frequency shift extraction under realistic signal-to-noise conditions typical of distributed fiber-optic sensing. Key findings include the following:

1. Lorentzian profile approximation using the Levenberg–Marquardt algorithm remains the physically sound "gold standard," providing a root-mean-square error of ~ 0.65 – 0.9 MHz at $\text{SNR} \geq 11$ dB. However, it carries a risk of convergence failures and is extremely computationally expensive.

2. Pseudo-Voigt profiles with an optimized mixing parameter η improve the reliability of the estimate at low SNR (3–7 dB) due to reduced covariance of the model parameters.

3. The Gaussian and Voigt profiles provide only limited advantages: the Gaussian profile sacrifices physically based accuracy for a small gain in computation time, while the Voigt profile increases computational complexity compared to the Levenberg–Marquardt Lorentzian approximation without a comparable increase in accuracy.

4. Machine learning approaches demonstrate an advantage in the low SNR region (< 6 dB), providing a reduction in error compared to classical methods and eliminating convergence issues; convolutional neural networks are particularly effective in the presence of spectral deformations caused by sharp deformation or temperature gradients.

The obtained results provide a quantitative basis for engineers and researchers deploying distributed Brillouin sensors and enable informed tradeoffs between accuracy, computational efficiency, reliability, and metrological transparency. The presented comparative data lays the foundation for further development of signal processing methodologies in fiber-optic sensing, aimed at increasing monitoring ranges and reducing measurement errors in distributed infrastructure condition monitoring applications.

Author's Declaration

The conceptualization and methodological design of the study were carried out jointly. N.I. Gorlov conducted the empirical data collection. The analysis of the results and their theoretical interpretation were conducted jointly. O.A. Bogatyreva prepared the initial version of the scientific text. Critical review, editing, and finalization of the manuscript were carried out jointly; the final version was read and approved jointly. The authors declare that they have no potential conflicts of interest in connection with the research presented in this article.

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СРАВНИТЕЛЬНОЕ ИССЛЕДОВАНИЕ МЕТОДОВ УМЕНЬШЕНИЯ ПОГРЕШНОСТЕЙ ПРИ ИЗМЕРЕНИИ ПИКОВОЙ ЧАСТОТЫ СПЕКТРА ОБРАТНОГО РАССЕЯНИЯ МАНДЕЛЬШТАМА-БРИЛЛЮЭНА В СТАНДАРТНЫХ ОПТИЧЕСКИХ ВОЛОКНАХ

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Аннотация

В распределенных волоконно-оптических системах, функционирующих на основе эффекта обратного рассеяния Мандельштама-Бриллюэна, контроль температуры и деформаций реализуется через регистрацию ключевых параметров спектра усиления. При этом одной из главных задач подобных измерительных систем выступает высокоточное определение центральной частоты данного спектра. Был проведен сопоставительный анализ методов, позволяющих снизить погрешности при оценке центральной частоты спектрального сигнала в волоконно-оптических датчиках, использующих Мандельштам-Бриллюэновское рассеяние. В результате разработана математическая модель, описывающая зашумленный сигнал обратного рассеяния, применимая как для классической аппроксимации формы спектральных линий, так и для внедрения методов машинного обучения с целью улучшения метрологических характеристик распределенных волоконно-оптических датчиков. Выполнен детальный сравнительный анализ актуальных алгоритмов обработки бриллюэновских спектров, ориентированных на повышение точности измерений центральной частоты в распределенных волоконно-оптических сенсорных системах. Были проанализированы традиционные подходы к нелинейному приближению (функции Лоренца, Гаусса и псевдо-Войта), а также корреляционные, адаптивные и нейросетевые методы. Представлена математическая модель, описывающая погрешности измерений с учетом шумовой составляющей, систематических искажений и влияния дискретности частотной сетки. На основе численного моделирования проведено сравнение метрологических характеристик рассматриваемых алгоритмов. Предложена оптимальная стратегия их выбора, определяемая требованиями к пространственному разрешению, предельной дальности измерения и инерционности (времени реакции) системы. Результаты сопоставительного анализа функциональных возможностей алгоритмов, направленных на снижение погрешностей измерения центральной частоты спектра в волоконно-оптических датчиках, использующих эффект обратного рассеяния Мандельштама-Бриллюэна, а также предложенная методология выбора, могут быть востребованы при разработке практических систем мониторинга. Отмечено, что данные результаты могут быть распространены на другие задачи спектрального анализа, требующие точного определения положения спектрального пика на фоне шумов.

Ключевые слова: *волоконно-оптические датчики, рассеяние Мандельштама-Бриллюэна, измерение сдвига частоты, функции Гаусса, Лоренца, Фойгта, Псевдо-Фойгта, машинное обучение, нейронные сети*

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