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Reconstruction of Object Inhomogeneity Parameters by Near-Field Measurements in Microwave Tomography Using Neural Networks

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Abstract

The article proposes a method for reconstruction inhomogeneity parameters based on the results of near-field measurements in medical diagnostics. This is a classical inverse problem arising in various fields of science and technology. At the first stage, the problem of wave propagation inside an object is considered. A rigorous description of the problem is given both as a boundary value problem and as a volume integral equation. Next, using the numerical solution of this equation, the field values outside the body in the near zone are determined. At the second stage, using the obtained near-field values using a two-step algorithm, a search for inhomogeneities occurs. A specially trained neural network filters the values obtained before and after the two-step algorithm, thereby improving the quality of images visualizing inhomogeneities. Graphic illustrations of the original and restored values of inhomogeneities for the objects under consideration are presented. An experiment was conducted demonstrating the features of restoring object parameters using neural networks. The results show the effectiveness of filtering the calculated data by the autoencoder. A software package for determining the parameters of inhomogeneities inside the object is proposed and implemented.

Keywords: numerical methods, integral equation, Helmholtz equation, inverse problem, neural network.

1. Introduction

Let us consider the problem of determining the structure of objects. Similar problems often arise when solving various technical problems of object control. Of particular interest are the tasks of medical diagnostics and non-destructive testing methods. When researching, it is necessary to rely on one principle, such as non-invasiveness. This means that the object under consideration must maintain integrity during the research; it is impossible to penetrate and destroy the object under consideration. In cases where it comes to medical diagnostics, additional restrictions are imposed on the measurement methods used. These problems are often solved using electrodynamic or acoustic methods by exposing the object of measurement to a radiation source. Such approaches are well studied and are essentially classical in acoustics and electrodynamics and are called “inverse problems of acoustics and electrodynamics”.

In acoustics or electrodynamics, the term “inverse problem” usually refers to problems related to the search for and identification of inhomogeneities in objects. Two main classes of these problems can be distinguished: time-dependent and time-independent problems. The first class of problems is effectively solved by using finite-difference methods. The second class is the most difficult, so it is usually solved by reducing the boundary value problem to integral equations. In this paper, the emphasis is on problems that are not related to time. It is worth noting that most inverse problems are ill-posed and nonlinear, which makes the process of solving them extremely difficult. Even small changes in the input data can significantly affect the results. Nonlinearity, in turn, adds difficulties to the solution.

Initial attempts to solve inverse problems were tied to the development of simple iterative methods, which have their pros and cons. Among the advantages is the ability to work with incomplete data, while a crucial drawback is the necessity of finding a high-quality initial approximation.

This paper proposes a numerical method for solving acoustic problems using neural networks, which is due to the need to find effective methods for filtering data. The importance of developing new methods can be demonstrated using the example of medical diagnostics, where, despite the existing modern diagnostic equipment, the issues of detection accuracy and procedure safety remain relevant. Effective mathematical algorithms can help solve these problems not only in medicine, but also in flaw detection.

Multiple attempts to solve inverse diffraction problems on screens have been well studied in the works of domestic and foreign researchers [1-16].

2. Statement of the problem

The propagation of sound waves in free space R^2 and their interaction with objects is a complex problem that is actively studied in acoustics. Imagine a two-dimensional object, such as an airplane wing or part of a building, located in free space. A sound wave U^0, approaches this object, for example, a loudspeaker, an airplane engine, or even a person. Our goal is to determine the complete sound field U that occurs around and on the surface of this object, taking into account both the incident sound wave from the source and the reflected and scattered waves from the object itself. This problem, determining the complete field from a known incident field, is called the forward problem of acoustics. Solving this problem is critical in many fields. In aeroacoustics, for example, understanding the interaction of sound waves with an airplane wing allows us to design quieter aircraft. In architectural acoustics, modeling sound propagation in a room helps optimize the acoustic performance of concert halls or recording studios by minimizing echo and reverberation. In medicine, acoustic modeling is used to design and optimize ultrasound diagnostic devices. Even in the field of underwater sonar, understanding how sound waves interact with underwater objects is key to detecting and identifying targets. Methods for solving direct acoustic problems vary and depend on the complexity of the object and the frequency range of the sound waves. For simple geometric objects such as spheres or cylinders, analytical solutions based on diffraction and scattering theory can be used. However, for objects of complex shape, there are no analytical solutions, and numerical methods must be used. The choice of an appropriate method depends on many factors, and the constant development of numerical methods and computing technology allows us to solve increasingly complex problems.

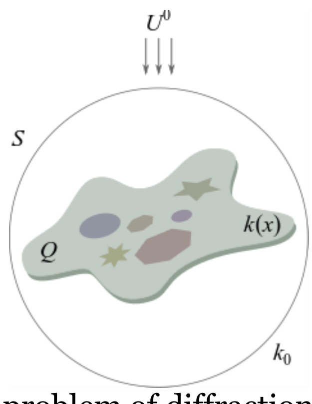


Fig. 1. The problem of diffraction on a body.

The behavior of the scattered field U can be determined by solving the inhomogeneous Helmholtz equation:

$$\Delta u + k^2 u = f(x) \tag{1}$$

The function is piecewise continuous and is determined by the relation $k^2 = \begin{cases} k^2(x) \\ k_0^2 \end{cases}$.

Here $k(x)$ -defines the wave parameters inside the object, Q, k_0 -is the wave parameter of free space. The right-hand side of equation (1) is given by a known function $f(x)$ with a compact support. We require that the conjugation conditions be met at the interface between the two media.

$$[u]_{\partial Q} = 0, \left[\frac{\partial u}{\partial n} \right]_{\partial Q} = 0 \tag{2}$$

where $[\cdot]$ denotes a field jump.

To ensure the uniqueness of the problem, we write the Sommerfeld radiation conditions:

$$\frac{\partial u}{\partial r} = ik_0 u + o\left(\frac{1}{\sqrt{r}} \right), r := |x| \to \infty \tag{3}$$

Problem (1)-(3) is reduced to a linear inhomogeneous Lippmann-Schwinger integral equation using the second Green formula [3,8]:

$$u(x) = f^0(x) + \int_Q G(x,y)\left(k^2(y) - k_0^2\right)u(y), \tag{4}$$

where $G(x,y) = H_0^{(1)}\left(k_0 |x-y|\right)$ are the Hankel functions.

The Lippmann–Schwinger integral equation is a powerful mathematical tool widely used to solve wave scattering problems in a variety of fields of physics. Its fundamental importance lies in the ability to reformulate the problem of wave interaction with an obstacle (or potential) from a differential equation, often difficult to solve analytically, into an integral equation. This integral equation takes into account the influence of the scattering object on the incident wave by means of an integral covering the entire interaction domain. This approach is especially useful when the geometry of the scattering object is complex or when the interaction potential is not a smooth function. In acoustics, for example, the Lippmann–Schwinger equation allows one to calculate the sound field scattered by an object of arbitrary shape under the influence of a sound wave. Here, the integral describes the sum of elementary spherical waves emitted by each point on the surface of the object in response to the incident wave. The amplitude and phase of these secondary sources are determined by both the incident field and the properties of the object's material, which affect the reflection and transmission coefficients. The resulting solution provides a complete description of the scattered field, including the amplitude, phase, and direction of propagation of scattered waves. A similar approach is applicable in electrodynamics, where the Lippmann-Schwinger equation is used to describe the scattering of electromagnetic waves by various objects, from microscopic particles to large antenna systems. In this case, the integral takes into account the contribution of each element of the scattering object to the resulting electromagnetic field. The solution allows one to predict the characteristics of the scattered radiation, such as the effective scattering cross-section (ESR), an important characteristic for radar and remote sensing technologies.

The operator form of equation (4) is obtained after introducing the following notation

$$Au := \int_Q G(x,y)\left(k^2(y) - k_0^2\right)u(y), \tag{5}$$

$u := u(x), F := f^0(x)$ then the equation takes the form:

$$Lu := u - Au := F, \tag{6}$$

where $u \in L_2(Q), F \in L_2(Q), L : L_2(Q) \to L_2(Q)$.

We will search for solutions to equation (4) using the space $L_2(Q)$.

Statement 1.

The operator $Au := \int_Q G(x,y)\left(k^2(y)-k_0^2\right)u(y)$ s Fredholm with zero index..

Lemma 1.

[3] The solution to problem (1)-(3) is unique.

Statement 2.

The operator $L := I - A : L_2(Q)$ is continuously invertible..

In works [2-7] numerical studies of the integral equation (4) were carried out.

The use of identification approaches in diffraction problems in medical diagnostics is possible only with the use of non-invasive methods. Let us consider the issue of choosing observation points when examining an object. It should be noted that a poor choice of points can have a significant impact on the diagnostic results. Observation points should be located close enough to the object under study and, if possible, cover the body evenly from all sides. However, personal experience in studying the problem has shown that the radiation source should be slightly removed from the observation points to avoid the so-called sensor overexposure. We recommend removing the observation points by one or two integration step lengths. We will place these points evenly along the boundaries of the object under study at a small distance from each other in several layers. A wave propagating from a point source is used as incident radiation. In such a formulation of the problem, it is possible to use a two-step algorithm for identifying inhomogeneities.

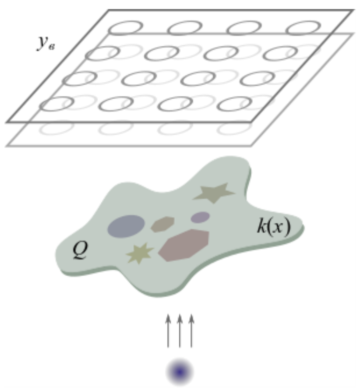


Fig. 2. Object, radiation source and observation points.

Let's divide a flat object into cells Π_i, $i=(i_1,i_2)$. Let's introduce the assumption that the inhomogeneity parameters inside each cell do not change $k(x)=k_i$. Let's apply a two-step algorithm.

1) In the first step, using the field values $u\ (y_в)$ measured at the observation points $y_в$, we calculate the current value $J(y)$ by solving the following equation.

$$u\ (y_в)-f(y_в)=\int_Q G(x,y_в)J(x)\,dx \tag{7}$$

It should be noted that equation (7) is the most complex part of the two-step method, since it is an equation of the first kind. The system of linear algebraic equations obtained as a result of solving the integral equation (7) is ill-conditioned, which leads to highly noisy reconstructed data.

2) In the second step, we recalculate the value of the inhomogeneity parameters $k(y)$ using the value

$$k^2(y)-k_0^2=\frac{J(y)}{f(y)+\int_Q G(x,y_в)J(x)\,dx} \tag{8}$$

The use of various regularization methods and matrix preconditioning algorithms in some cases reduces the condition number. These approaches work effectively until the matrix condition number exceeds 1014. Therefore, these approaches are not universal. The paper also uses an approach based on the use of neural networks.

3. Application of neural network approach to the filtering problem

Consider the noise reduction problem for the two-step algorithm using neural networks. Noise reduction will be performed at the stage of restoration of values $J(x)$. The problem can be defined:

$$z = x + y \tag{9}$$

z - noisy data represented the sum of true signal x and some noise y. The essence of the basic methods is to approximate the x using z.

We choose a convolutional autoencoder as a model for solving the filtering problem and introduce the function of recovery error (loss function) from the true and processed by the model data:

$$L\left(x, g\left(f\left(\tilde{\ } \quad \tilde{\ } \right.\right.\right. \tag{10}$$

Autoencoder is a neural network, which designed to encode the input into a compressed representation and then decode it back such that the reconstructed input is similar as possible to the original data. During the dimensionality change, the data x is compressed into some latent-space.

$$h = f(x) = \phi(Wx + b),\ h \in [0,1]^d \tag{11}$$

where ϕ - is the activation function.

The result of network computations is a multiple application of (11) with different parameters. The first part of transformations changing the dimensionality of the input tensor to the dimensionality of the latent space is called encoder.

Then a transformation is applied to it bringing it to its original dimensionality.

$$g = \phi(W'h + b') \tag{12}$$

Noisy autoencoder is a stochastic extension of the classical autoencoder designed to recover raw data from their noisy variants. Such models can be combined into complex architectures, creating deep neural networks to solve more complex problems.

Convolutional autoencoders utilize the described idea of autoencoders by replacing transformations (11) with convolutional layers.

The convolution operation is understood as the following matrix transformation:

$$y_{ij} = \sum_m \sum_n w_{mn} \cdot x_{(i+m)(j+n)} + b \tag{13}$$

y_{ij} - output data (feature map),

w_{mn} - layer filter (trainable parameter)

$x_{(i+m)(j+n)}$ - input data,

b - bias.

From a mathematical perspective, the convolution operation involves the sliding application of a filter (kernel) to input data. At each step, the sum of the products of the kernel elements and the corresponding values of the local region of the input matrix is computed. The key parameters defining the nature of this process are the kernel size and the stride. The former specifies the processing window (e.g., 3×3 or 5×5), while the latter regulates the distance between adjacent filter positions, influencing the size and overlap of the extracted submatrices.

An important complement to convolutions in neural networks is the pooling operation. Its goal is to progressively reduce the spatial dimensionality of the data while preserving the most significant features. Unlike convolution, pooling does not use trainable parameters but instead aggregates information within local regions (e.g., selecting the maximum value in max-pooling). This enhances the model’s robustness to minor distortions in the input data.

$$\delta_i^l = \begin{cases} \delta_j^{l+1} & if\, i = \arg\max_i (z_i^l) \\ 0 & otherwise \end{cases} \tag{14}$$

In this case, the dimensions of the output matrix can be found as:

$$H_{out} = \left\lfloor 1 + \frac{H - \text{pool\_height}}{\text{stride}} \right\rfloor \tag{15}$$

$$W_{out} = 1 + \frac{W - \text{pool\_width}}{\text{stride}} \tag{16}$$

$(pool\_height, pool\_width)$ - pooling submatrix size

Convolutional autoencoders demonstrate a significant advantage over classical autoencoders when working with images due to their specialized architecture based on convolutional neural networks (CNNs). Unlike the fully connected layers of traditional autoencoders, convolutional layers operate on local regions of data, preserving the spatial structure of the image and uncovering hierarchical patterns (e.g., edges, textures, objects). This enables the model to efficiently capture the topological features of the input data matrix, minimize the number of trainable parameters through shared weights, and reduce the risk of overfitting.

Thus, convolutional autoencoders are not only adapted for handling multidimensional structured data but also provide more meaningful compression of information, which is critically important for tasks such as image reconstruction and generation.

An example of such a model is shown in Figure 3.

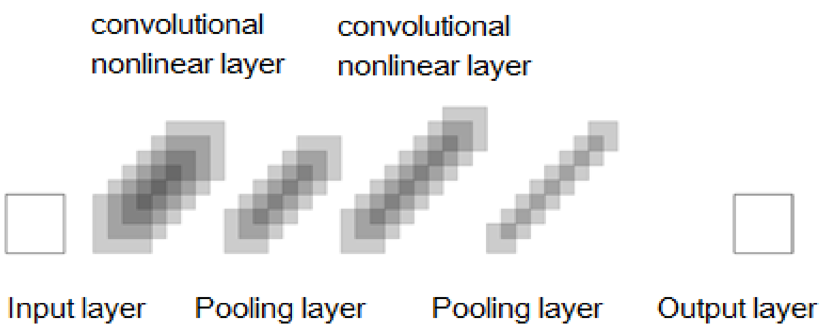


Figure 3. Example of convolutional autoencoder architecture.

In formulas $\{W, B, W', B'\}$ are the model parameters that are optimal in terms of minimizing the recovery error, which can be achieved using different loss functions such as RMS error or cross-entropy.

Thus, the model accumulates information about the distribution of the reconstructed data $p_{rec}(x|\tilde{.}$ from the pair estimates of the training sample. $(x,\tilde{.}$.

Generating an example x from the training dataset.

Noising of the generated example $\tilde{.}$ from $C(\tilde{.}$.

Estimation of the probability distribution $p_{rec}(x|\tilde{.}$ $_r(x|h)$

For the experiment, training and test datasets were created, containing 6,000 and 2,000 examples, respectively. Each data instance was generated according to the following algorithm:

Structure Generation: The number, geometric shape, size, and physical parameters of inhomogeneities were assigned stochastically based on the problem conditions.

Noise Addition: Artificial noise with a uniform distribution was applied to the resulting matrix at three intensity levels—15%, 30%, and 50% of the original signal’s amplitude.

The original and noise-modified data were saved in a format suitable for neural network processing and used during its training and validation stages. Visualizations of typical examples from the dataset (including variations with different noise levels) are shown in Figure 4.

As an example, consider a problem with the following initial data (Figure 4). We solve the forward problem and calculate the field values at special observation points (Figure 5).

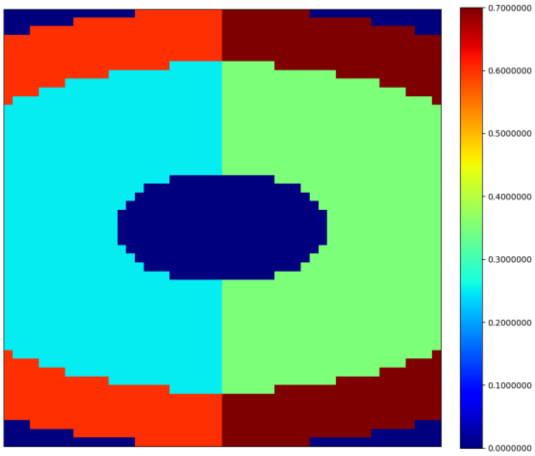


Fig. 4 Wave value function of initial object.

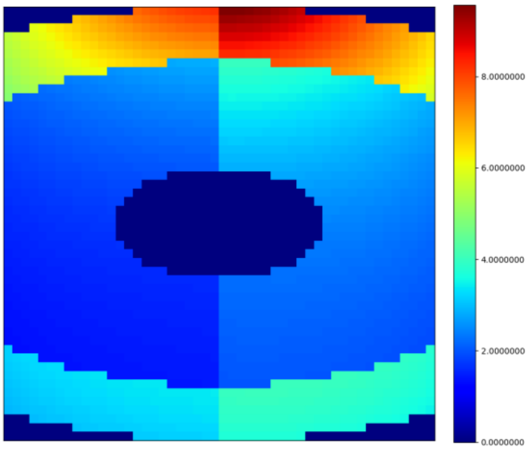


Fig. 5 Module of the solution of the integral equation (4).

We add 40% white noise into the J (рис. 6) and filter it using the autoencoder model (Fig. 7).

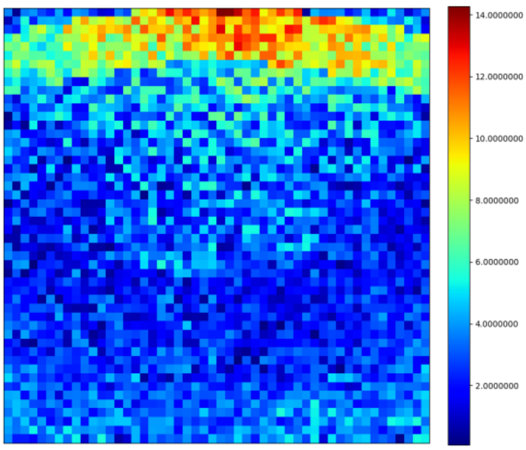


Fig. 6 Module of the solution of integral equation equation (4) without filtration.

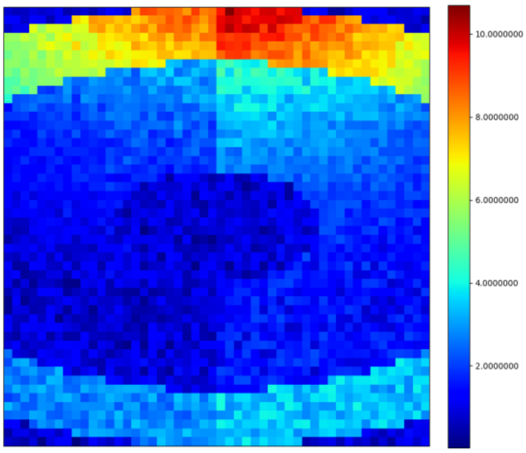
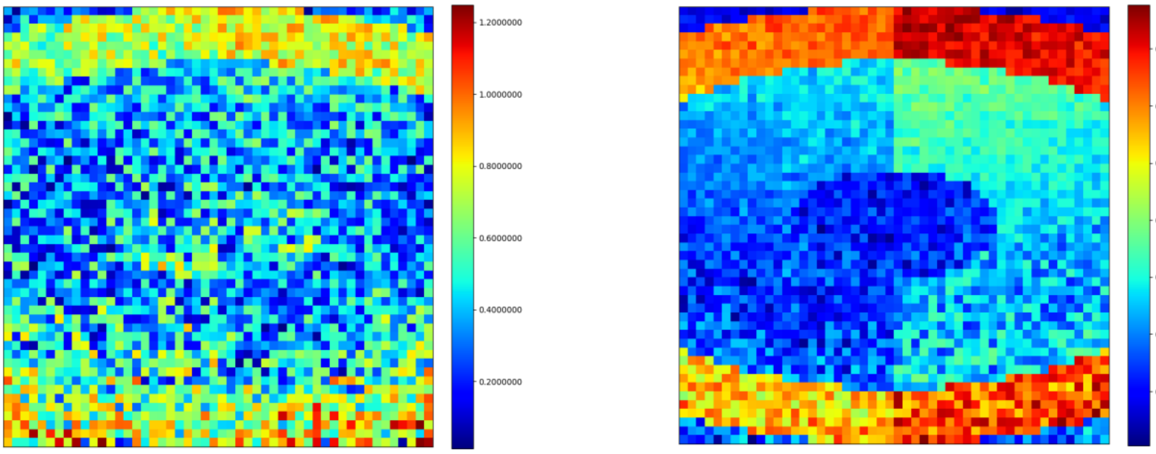


Fig. 7 Module of the solution of the integral equation equation (4) after the filtering procedure.

Next, the problem of restoring the body structure is solved by substituting the calculated J into formula (8). As a result, the value of the wave function $k^2(y)-k_0^2$ is restored.



(a) (b)

Figure 8. Modulus of the reconstructed values of the wave function: a - without filtering, b - with filtering.

Figure 8 shows the solution of the inverse problem for the considered figure (Fig. 4). From Fig. 8 we can conclude that the recovery is significantly improved when using the neural network model to filter the noisy data in the solution. The effectiveness of the model is especially noticeable when it is applied to high noise levels.

4. Using different signal filtering methods

In the previous experiment, the modulus of the difference between the original and noisy data is a large value. As the noise level decreases, the efficiency of gradient methods decreases. To solve this problem, we will convert the input data to the frequency range using a two-dimensional Fourier transform, where we will perform filtering. We will introduce a small error of about 0.1% into the measured data and apply the Fourier transform. The training process of the neural network model is similar to that described above. We will approximate the noise level by the model after preprocessing using a two-dimensional Fourier transform.

The direct two-dimensional Fourier transform is the function:

$$g(\lambda_1,\lambda_2)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f\left(x_1,x_2\right)e^{-i\left(x_1\lambda_1+x_2\lambda_2\right)}dx_1dx_2 \tag{17}$$

Inverse two-dimensional transformation:

$$f(x_1, x_2) = \frac{1}{(2\pi)^2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\lambda_1, \lambda_2) e^{i(x_1\lambda_1 + x_2\lambda_2)} d\lambda_1 d\lambda_2 \tag{18}$$

After applying the transformation (17), the data values in the frequency range are not small, which makes it possible to effectively use gradient methods to filter the data. The following order of transformations for the input data is defined: the original vector is divided into a real and imaginary part. For each of the parts, the model is trained on the training sample.

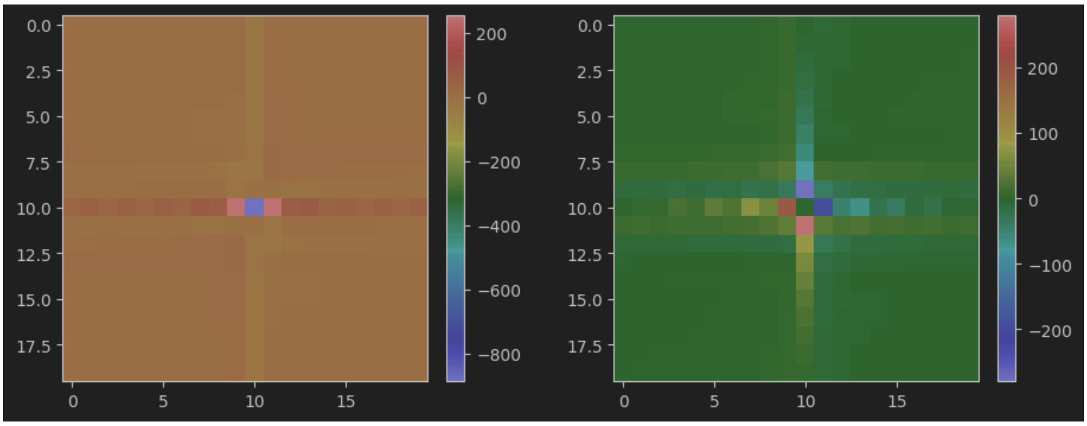


Fig. 9 Fourier transform of the real part

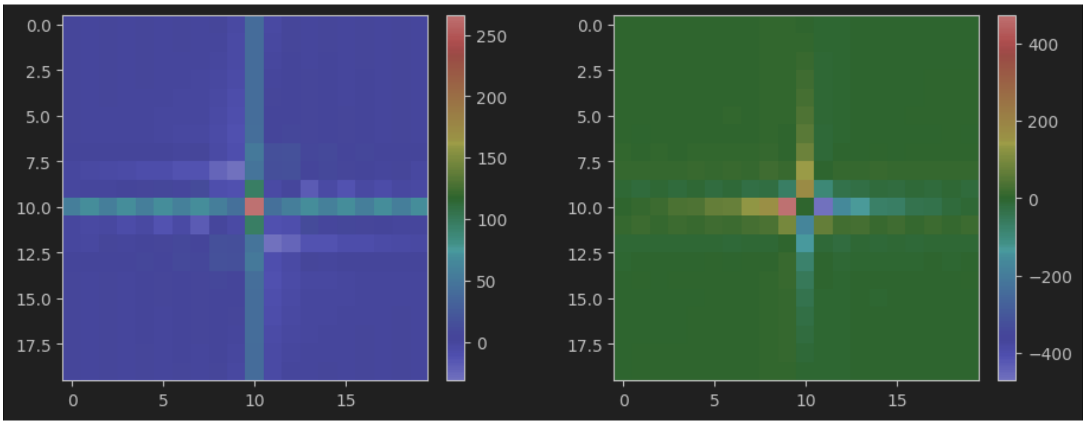


Fig. 10 Fourier transform of the imaginary part

At the stage of using the trained model, the inverse transformation (18) is applied. As a result of filtering, the noise level can be reduced by one order of magnitude.

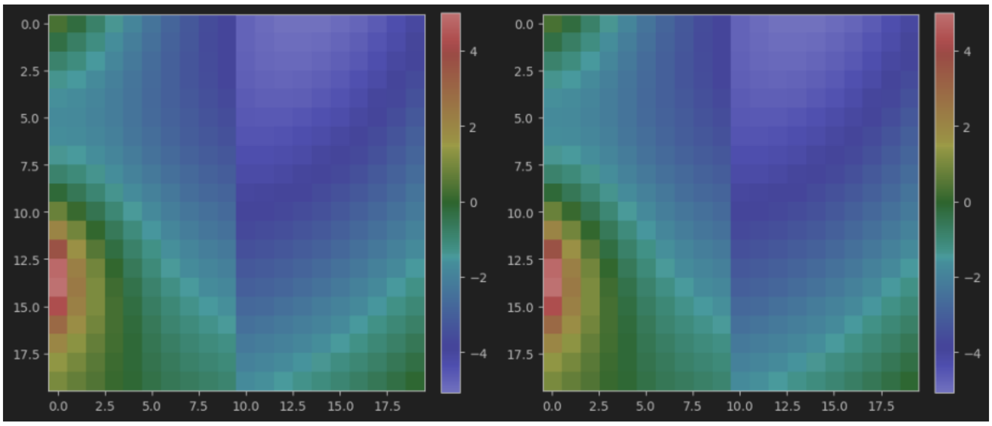


Fig. 11 Original (left), reconstructed (right) values of the real part.

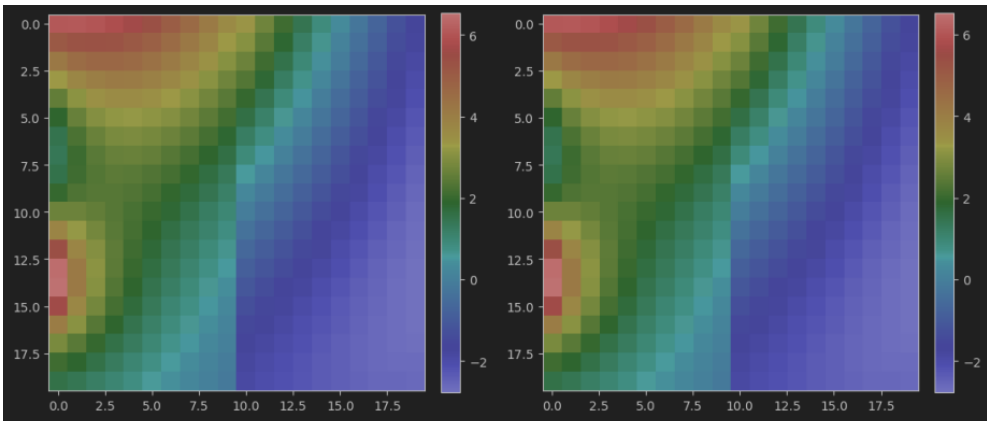


Fig. 12 Original (left), reconstructed (right) values of the imaginary part.

Based on the Fourier transform, other methods not related to machine learning can be used. There are various algorithms, such as the recursive average algorithm, the exponentially weighted average algorithm, the five-point moving average algorithm. However, these algorithms do not provide a sufficient result for the task. Filtering methods using the Fourier transform, based on the introduction of weight functions (Hanna, Hamming, Kaiser, ...) work more efficiently.

An example of the restoration of a sinusoidal signal using the Fourier transform is shown in the graphs below (Fig. 13 – 14).

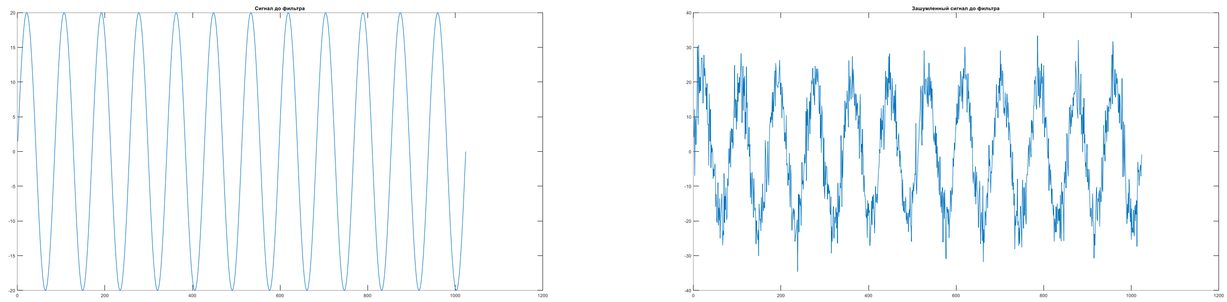


Fig. 13 Original (left), noisy (right) signal.

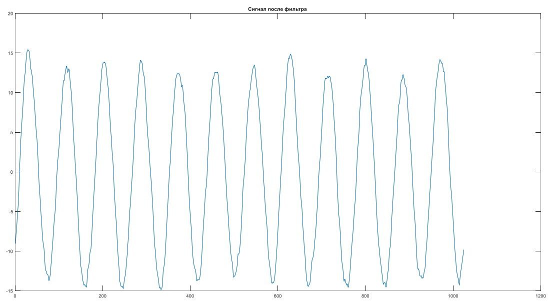


Fig. 14 Recovered signal.

However, these methods are not effective for the problem under consideration. Therefore, it is proposed to use averaging algorithms based on the impact of two types of error. The first is white noise, the second is a system error and models the background impact on the input data. When working with a sample of 100 values, it is possible to effectively restore inhomogeneities at a system error level of about 1% and a white noise error of 0.01%.

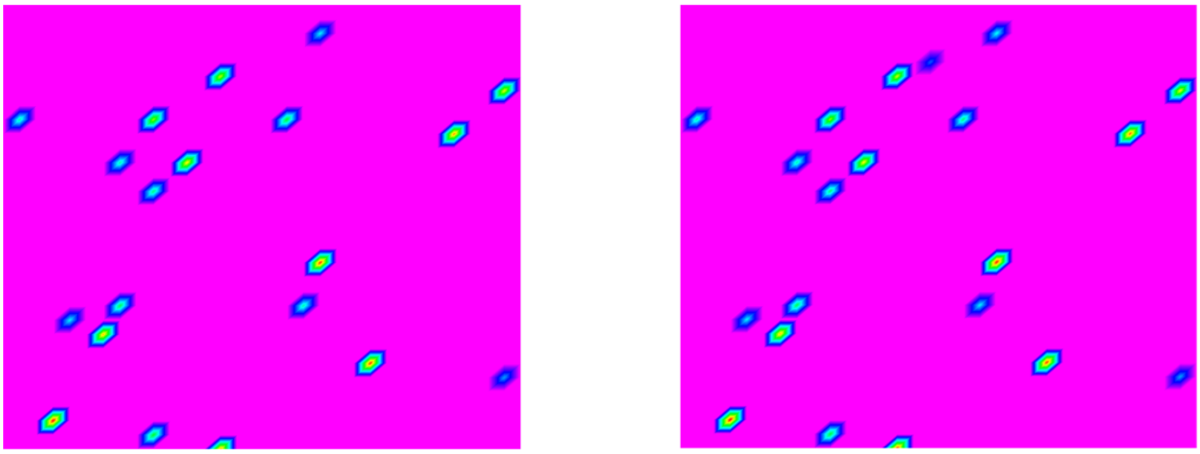


Fig. 15. Recovered values of the modulus of the solution of the integral equation (4).

Figure 15 demonstrates good quality of restoration of the value of the solution module of equation (4). However, a minor deviation in the form of new non-existent inhomogeneities appears in the restored data. These inhomogeneities are called artifacts. They are easily removed by conducting additional measurements at other frequencies. When developing medical diagnostic methods, the task is often to suspect a disease at an early stage, when the tumor does not exceed a certain size. The obtained results show that the algorithm copes with this problem.

5. Conclusion

The paper considers the problem of restoring the structure of an object. The problem under consideration is of great interest in medical diagnostics. The paper proposes algorithms that allow restoring the structure of an object. The problem under consideration is ill-posed, so it is proposed to use various data filtering methods. The filtering algorithms are based on the use of neural networks. Convolutional autoencoder models were used for training. Visualization of the obtained data helps to separate important information about the structure of objects from irrelevant information, including various artifacts. Graphical representation of the data allows us to assert that the algorithms proposed in the paper effectively restore the structure of an object at different levels of noise in the data. To obtain numerical results, a set of programs was implemented in C++. Data filtering and visualization were implemented in Python using the Pytorch and Matplotlib libraries.

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