Date of publication DEC-31, 2025, date of current version DEC-21, 2025.
www.computingonline.net / computing@computingonline.net

Print ISSN 1727-6209
Online ISSN 2312-5381
DOI 10.47839/ijc.24.4.4332

Machine Learning Based Method for Acoustic Recognition of Anthropogenic Underground Voids

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ABSTRACT Underground tunnel identification remains difficult in spite of the development of recognition methods. There is often no direct access to the Earth's surface above bunkers; above-ground structures may be located there; the soil structure may contain dense layers opaque to radio waves. Therefore, it is promising to use geophysics acoustic recognition methods. The study aims to develop an information system schematic diagram for identifying man-made underground cavities using machine learning methods based on acoustic reconnaissance data. In contrast to known methods for monitoring vibration waves during earthquakes, the initiation of vibration waves can be carried out by delivering precise strikes of known power to specified surface points. However, solving the inverse problem for the propagation of acoustic waves is problematic due to the small relative sizes of these structures. The scientific novelty lies in the fact that we find a solution to this problem using machine learning methods based on model calculations for a known geological structure of the soil. Combining it with satellite observation data on the above-ground structures makes it possible to build a neural network for analyzing the vibrations of sensors located in controlled territory.

KEYWORDS underground voids, acoustic waves, inverse problems, neural networks, machine learning.

I. INTRODUCTION

Defensive underground fortifications have been one of the oldest means of protection for more than a millennium. These structures have been under intense development starting from the period of the WWI, where they demonstrated their reliability in preserving manpower. Underground storage and tunnels take a form of man-made cavities and their identification by existing methods poses a significant challenge, despite the almost two-thousand-year history of the development of recognition methods and the use of satellite mapping systems. For example, even though the war in Gaza has been going on for more than 500 days, Israel has managed to destroy only 20-40% of the extensive network of tunnels created by Hamas [1, 2]. It is clear that scouts do not have direct access to the earth's surface above bunkers and crossings. The task is complicated by the fact that above-ground structures may be located there, as is the case in the Gaza Strip. In addition, the soil structure can be heterogeneous and contain dense layers and inclusions that reflect radio waves [3, 4]. Therefore, it is promising to use acoustic recognition methods, which are already used in geophysics [5-7].

The purpose of the study is to develop a schematic diagram of an information system for the identification of man-made underground cavities using machine learning methods based on acoustic reconnaissance data. The scientific novelty lies in the fact that we find a solution to this problem by the use of machine learning methods based on model calculations for the known geological structure of the soil.

The structure of this work is as follows: Section II presents an overview of existing models for voids recognition and technique of computer vision; Section III describes the basic local and FEM problems statements; Section IV presents examples of the scheme application to determine the state of underground voids, the obtained results and discusses them.

II. INVESTIGATION METHODS REVIEW

A. EXISTING MODELS FOR VOIDS RECOGNITION

Seismic exploration is a suit of acoustic methods for studying the geological structure of the earth's crust, which are based on the study of the propagation of artificially generated elastic waves (by explosions, shocks) or by an earthquake. Elastic waves, which arise from an explosion or impact, propagate in rocks at different speeds [4, 8, 9]. At the boundary that separates rocks of different compositions, elastic waves are reflected, refracted, and partially returned to the Earth's surface. By studying the time and velocity of wave propagation, their amplitude, signal shape, and the nature of ground vibrations on which vibrating receivers (seismic receivers or geophones) are installed, it is possible to determine the depth and shape of boundaries in the surrounding environment, their angle of incidence, the direction of propagation, and many other characteristics of the geological environment. The wave propagation and detection diagram is shown in Figure 1. Pulsed excitation generates an acoustic wave that propagates within the layer and is reflected from its boundary. The reflected and refracted waves are recorded by a system of acoustic sensors.

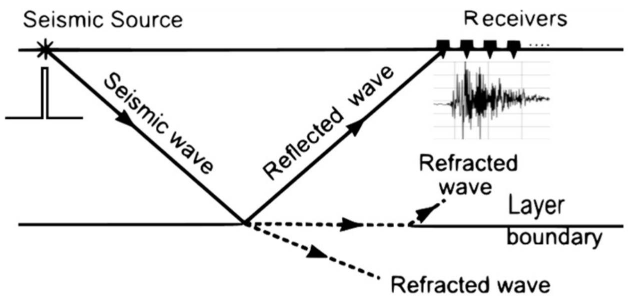


Figure 1. Part of an algorithm of acoustic wave processing

Longitudinal waves, less often transverse and mixed waves, are used in seismic exploration. The reflected wave method has become the most widely used, which makes it possible to map boundaries with an accuracy of up to 1-2% at depths of up to 7-10 km [10]. A greater depth of investigation characterizes the method of refracted waves [5]. Still, it has lower accuracy and resolution, which makes it possible to study only layers with an increased speed of seismic waves. For the detection of minerals, modifications of the method are used by adding signals reflected from the common depth point, three-dimensional seismic, multi-wave seismic, etc. [5, 17].

Hydrogeological seismic surveying is used in engineering seismic surveys [6, 10]. It is used to study the depth of rock deposits, dismemberment of sedimentary strata, determine the strength of the weathering crust, map permafrost, study discontinuous faults, fractured, karstified zones, study landslides, determine the level of underground water Engineering-hydrogeological seismic exploration deals with small depths, therefore the excitation of elastic waves is carried out with the help of small explosions. Profiles and measurement points are located at a short distance from the sources of wave excitation. Therefore, high-frequency waves (150 - 200 Hz) are recorded, increasing the method's resolution.

In seismic exploration, the complete formulation of the problem consists of solving the equations of propagation of elastic oscillations with piecewise continuous coefficients under the condition that they are excited by a point explosion [5, 17]. The solution of this task is currently carried out only for the simplest models of the structure of the environment. The main measured value in seismic exploration is the arrival time of reflected signals. The signal delay time is measured at various points on the earth's surface [7, 10].

A significant number of seismic systems operate in conditions where the intensity of the useful seismic signal exceeds the interference level, mainly due to the use of explosive sources of elastic wave formation [11]. However, when studying small structures relative to the plan, special methods should be used to recognize their influence on acoustic waves, among which automatic processing of geoinformation data using a combination of computer vision and machine learning methods can be considered the most promising [12, 16, 18, 19]. When using ML, fuzzy logic is used to increase the sensitivity and accuracy of conventional neural networks, for example [14, 15, 43], and also the Radon transform, which effectively detects hidden objects [44].

B. APPLICATION OF COMPUTER VISION AND ML

Computer vision is the theory and technology of creating machines that can detect, track, and identify objects [4, 16]. Acoustic object recognition is also a field of computer vision [6, 27]. Depending on the software, it can analyze objects at a higher speed and perform its task more efficiently and cheaply than a human [16]. Military applications are currently the largest area of computer vision used for tasks such as detecting enemy soldiers, vehicles, and fortifications, as well as controlling drones and missiles. Control systems send drones or missiles to a given area instead of a specific target, and target identification occurs based on incoming video data when the controlled object reaches the given area. The modern military term "combat awareness" is based on various sensors, including acoustic and optical, providing information about the battlefield, which is used to make tactical decisions.

To reduce labor intensity and increase the reliability of the information obtained, automatic data processing is carried out based on machine learning (ML) [6, 7, 12, 18]. The inverse problems of geophysics under consideration belong to the class of computationally complex ones. Traditional methods of solving them are often unstable and require additional regularization [10]. Machine learning studies methods for constructing algorithms that can improve the performance of calculations based on experience. The main method of machine learning is the use of multi-level neural networks for the tasks of identifying and separating objects. Machine learning algorithms can process huge amounts of data in a reasonable time, identify hidden patterns in them, and provide the necessary information for decision-making.

III. SEISMIC EXPLORATION OF ANTHROPOGENIC VOIDS

A. BASIC LOCAL PROBLEM STATEMENT

Based on the statement, we intend to solve the local oscillation problem of an infinite elastic body with a thin inhomogeneity [8]. The material properties of the thin-walled interphase inclusion W_0, matrix W_1, and scatterer W_2 are given by densities ρ_j and Lamé moduli λ_j, μ_j, respectively. In the process of obtaining models of the dynamic interaction of fine heterogeneity with the surrounding environment it is convenient to use a set of Cauchy equations of motion and the relationship of Hooke's law:

$$\begin{gathered}\frac{1}{H_1 H_2 H_3}\sum_{i=1}^{3}\sum_{m=1}^{3}\frac{\partial}{\partial\alpha_m}\frac{H_1 H_2 H_3}{H_m}\sigma_{jmi}\mathbf{e}_i+\omega^2\rho_j\mathbf{u}_j=0,\\ \sigma_{jmi}=\lambda_j\delta_{mi}\sum_{l=1}^{3}\frac{\mathbf{e}_l}{H_l}\frac{\partial\mathbf{u}_j}{\partial\alpha_l}+\mu_j\left(\frac{\mathbf{e}_m}{H_l}\frac{\partial\mathbf{u}_j}{\partial\alpha_l}+\frac{\mathbf{e}_i}{H_m}\frac{\partial\mathbf{u}_j}{\partial\alpha_l}\right),\end{gathered}\tag{1}$$

$$\mathbf{u}_j(\mathbf{x},\omega)=\int_{-\infty}^{\infty}\mathbf{u}_j(\mathbf{x},t)\exp(i\omega t)\,dt\,,\boldsymbol{u}_j(\boldsymbol{x},t)=\frac{1}{2\pi}\int_{-\infty}^{\infty}\boldsymbol{u}_j(\boldsymbol{x},\omega)exp(-i\omega t)\,dt,$$

where $\mathbf{u}_j$ – movement in interphase inclusion, matrix, and scatterer, respectively, t – time, σ_{jmi} – stress tensor components in regions W_i, $\boldsymbol{x}$ – Cartesian coordinates of points, $\boldsymbol{\alpha}$ – coordinates of the local tri-orthogonal system with basis $(\mathbf{e}_1,\mathbf{e}_2,\mathbf{e}_3)$, H_l – Lamé coefficients of curvilinear orthogonal coordinate system $\boldsymbol{\alpha}$:

$$\mathbf{x}=(x_1,x_2,x_3),\ \boldsymbol{\alpha}=(\alpha_1,\alpha_2,\alpha_3),\quad H_l(\alpha_1,\alpha_2,\alpha_3)=\left|\frac{\partial\mathbf{x}}{\partial\alpha_l}\right|. \tag{2}$$

Conditions of the perfect mechanical contact are met on the surfaces of the connection of components of the form $g_+(\alpha_1,\alpha_2)$ and $g_-(\alpha_1,\alpha_2)$ determined in the local basis as it can be seen in figure 2. We obtain an analytical approximation of these functions, which provide sufficient accuracy and smoothness, by applying our developed method of approximating wireframe inclusion points by fifth-order Bezier surfaces [20, 21] or multiply Fourier series [22, 23].

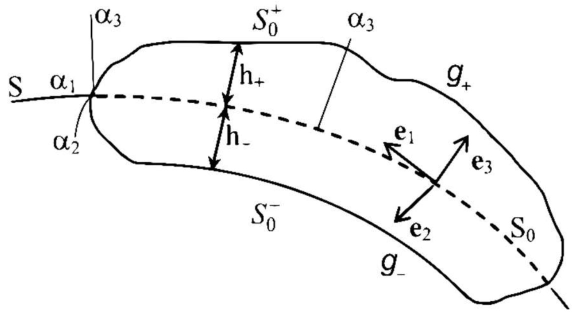


Figure 2. Scheme of thin-walled interphase inclusion

The wave field in the matrix is formed by the superposition of the field of given incident $\mathbf{u}_{in}(\mathbf{x},t)$ and scattered $\mathbf{u}_{sc}(\mathbf{x},t)$ waves:

$$\mathbf{u_1}(\mathbf{x},t)=\mathbf{u}_{in}(\mathbf{x},t)+\mathbf{u}_{sc}(\boldsymbol{x},t). \tag{3}$$

Zero initial conditions should also be taken into account:

$$\mathbf{u}_{sc}(\boldsymbol{x},0)=0. \tag{4}$$

According to the scheme of the asymptotic approach [37, 38], we introduce an artificial small parameter ε and an internal variable $\bar{\alpha}_3$ into the domain W_0 as follows

$$\bar{\alpha}_3=\varepsilon\alpha_3. \tag{5}$$

The displacement and components of the stress tensors are presented in the form of asymptotic expansions in a series with a small parameter

$$\boldsymbol{\sigma}_{kij}(\mathbf{x})=\sum_{n=0}^{\infty}\varepsilon^n\boldsymbol{\sigma}_{kij}^{(n)}(\alpha_1,\alpha_2,\bar{\alpha}_3)+\delta_k^0\varepsilon^{-1}\boldsymbol{\sigma}_{kij}^{(-1)}(\alpha_1,\alpha_2,\bar{\alpha}_3), \tag{6}$$

$$\mathbf{u}_k(\mathbf{x})=\sum_{n=0}^{\infty}\varepsilon^n\mathbf{u}_k^{(n)}(\alpha_1,\alpha_2,\bar{\alpha}_3),\quad k\in\{0,1,2,in,sc\},$$

where δ_k^0 – δ-function.

Then we substitute the series into the Cauchy equation and the boundary conditions. Having equated the coefficients with the same powers of ε, we obtain a recurrent sequence of ordinary differential equations in the variable $\bar{\alpha}_3$ with respect to the sought terms of the expansions. When the contact conditions are satisfied, the asymptotic terms in the equations are represented by Taylor series in vicinity of α_3 equals zero, which are convergent under the conditions of applying a generalized summation to them by using the previously developed Padé transformation [25, 26]. In this way, the restriction [8, 24] on the length of waves propagating in a composite body is eliminated, which requires them to be much longer than the thickness of the interphase inhomogeneity for the convergence of the obtained asymptotic solution,

Let us present the Cauchy equation of motion, the relationship of Hooke's law, as well as the conditions of contact of inhomogeneity with the matrix and inclusion in the variables $(\alpha_1,\alpha_2,\bar{\alpha}_3)$. Considering the solutions of the obtained ordinary differential equations and equating the terms with the same powers of the parameter ε from the boundary conditions, we determine the effective contact conditions of the bodies adjacent to the fine inhomogeneity. The type of effective contact conditions of the bodies adjacent to the thin inhomogeneity is determined by the order of smallness of the parameters of the mechanical contrast γ_k of the thin-walled interphase inclusion:

$$\gamma_k=\frac{\max(\lambda_0,\mu_0)}{\max(\lambda_k,\mu_k)}. \tag{7}$$

B. BASIC FEM PROBLEM STATEMENT

The resulting local analytical model is used to construct a full-size model based on FEM [11]. This makes it possible to avoid significant mesh thickening in the tunnel zone and significantly speed up the calculation, which is important for multiple calculations. FEM allows one to consider soil heterogeneous in a specific area where underground structures are located.

Usually, we can use the ANSYS package, or PyFEM framework, or any other FEM package which allows for the calculation of the propagation of vibrations under pulsed and explosive loads [27, 35]. The mesh of three-dimensional 16-point nonlinear elements was refined until the stability of the results was achieved.

The effect of voids was defined as the difference between the calculated parameters and the oscillations of the region without voids in phase and amplitude, which increases the accuracy of determining the influence of voids. When calculating the vibrations of a soil massif with a void, we must consider the massif's geological structure and the presence of capital buildings, canals, and other man-made objects on the surface. For this purpose, we use the data accumulated at Dnipro University of Technology over many years on the geological structure of our country and satellite mapping data [41]. This is possible due to the digital databases in the RAPID and CONTOUR systems [28, 29] created in our department. We have specialized information systems for collecting, storing, and processing satellite, geological, and seismic survey data containing long-term observation data.

GIS RAPID [29] is a geo-information system for forecasting and supporting decision-making in nature management, ecology, mineral exploration, and emergency forecasting. It contains the following data

- Materials of geological, geophysical and geochemical studies.
- Results of testing and description of wells, pits, ditches, etc.
- Cartographic sources.
- Materials of aerospace survey.
- Data of environmental studies.
- Attributive information (tables, codifiers, etc.).

GIS RAPID allows Input, storage, conversion, filtering, and visualization of grid, raster, and vector data (spatial images, geophysical fields, geological and environmental data, maps, images, etc.), and forecasts of natural and man-made objects on the earth's surface.

The main purpose of technology based on GIS CONTOUR [28] is to allow the specialist to build three-dimensional models of geological objects (GO). Since before creating three-dimensional models, users operate with two-dimensional representations of the GO, the system also allows obtaining geological sections, horizon plans and creating their printed copies (Figure 3). The developed GIS solves the following set of problems:

- Automated creation of 3D models and visualization of geological observation data.
- Vector and raster representation of data, management of data layers.
- Visual analysis of borehole sample data.
- Data display filtering.

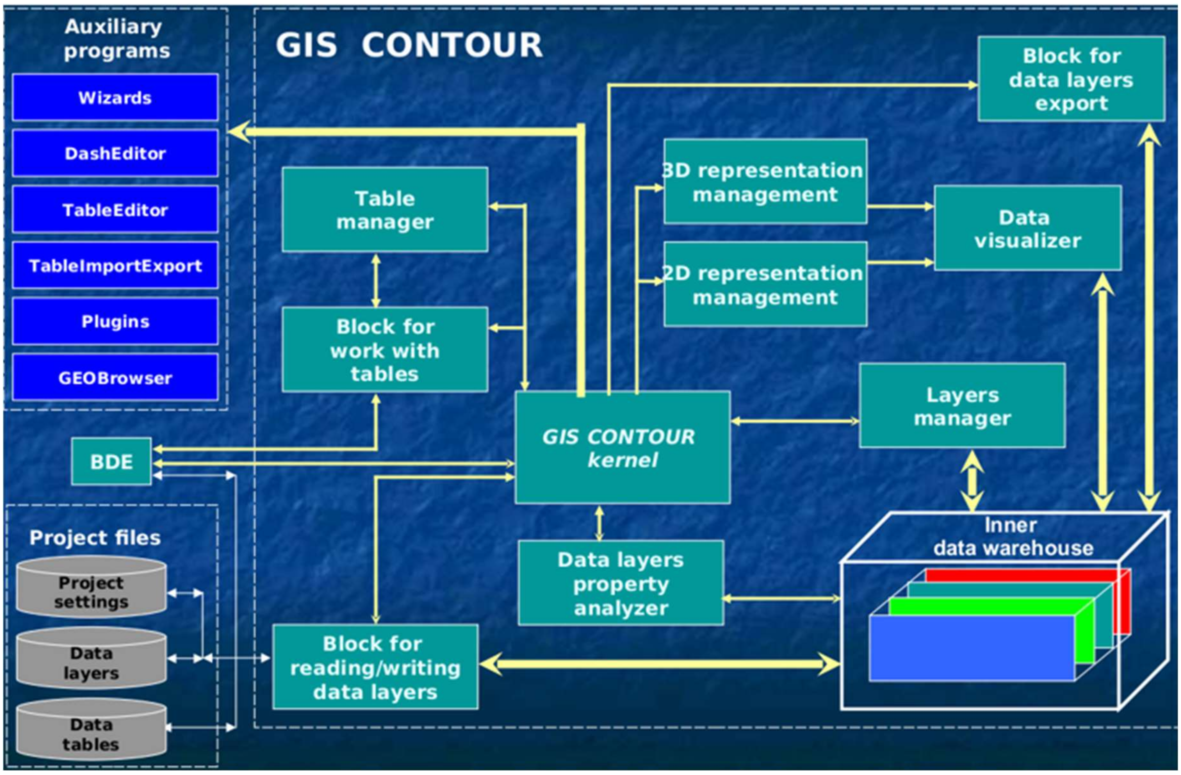


Figure 3. GIS CONTOUR structure diagram

Thus, the recognition task comes down to constructing a neural network specific to a given area and the location of troops. The input parameters of the network are the coordinates of the location of seismic sensors and their readings, the output parameters are the location of the ends and nodes of linear underground voids. Due to the specifics of the task, training such neural networks cannot use full-scale training data sets, but only the results of simulation calculations [8, 30].

The Dnipro University of Technology has a huge knowledge base about the geological structure of Ukraine, which can now be used to build the described neural networks. We have specialized information systems for collecting, storing and processing satellite, geological and seismic survey data containing long-term observation data.

C. SECOND LEVEL INVERSE PROBLEM STATEMENT

To effectively and quickly identify enemy protective underground structures in combat conditions, it is necessary to rationally select the number and location of seismic sensors, as well as the location, power and number of explosions [5, 31, 32]. We solve this problem as the inverse problem [34, 35, 42] to the previous one by constructing a second-level neural network [33, 36, 37].

Thus, after receiving information about the specific location of the enemy and one's own troops on the ground, geological information about the soil structure in the area is extracted. Next, several neural networks are trained on simulated data, representing the geological structure and for a different number of sensors and locations of explosion points. After this, the inverse problem of optimizing the number and location of sensors and explosion coordinates is solved. Seismic sensors are located at suitable points and explosions are applied with a given power and location.

As a result of the research, an information system was created to form the architecture and parameters of a rational neural network for identifying linear man-made voids based on active seismic exploration data in combat conditions.

IV. EXAMPLES OF METHOD APPLICATION

A. APPLICATION OF THE SCHEME TO DETERMINE THE STATE OF UNDERGROUND VOIDS

Let us consider the application of the described calculation scheme to determine the state of underground voids of two types – adjacent to the soil surface and located deep in the soil (Figure 4). In both cases, the void is considered a soft heterogeneity, but in the first case, W_2 is air, and in the second, W_1 and W_2 are soil with possibly different mechanical characteristics. By equating the material characteristics of the matrix and bulk inclusion, we obtain separate models of thin-walled inclusion in a homogeneous elastic medium.

B. EXAMPLES OF DIRECT FEM SOLUTION

As an example of calculating the reaction of underground voids, an experiment was considered for a 100 m × 100 m×100 m, the scheme of which can be seen in Figure 5a. Figures 5b-5d represent a transparent grid diagram for the calculated area, a view of finite element mesh on the vertical section near the void, and a view of finite element greed on the soil surface near a phased array of acoustic sensors.

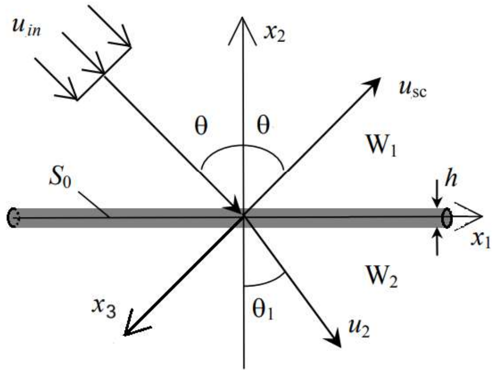


Figure 4. Scheme for calculating underground voids using the proposed method

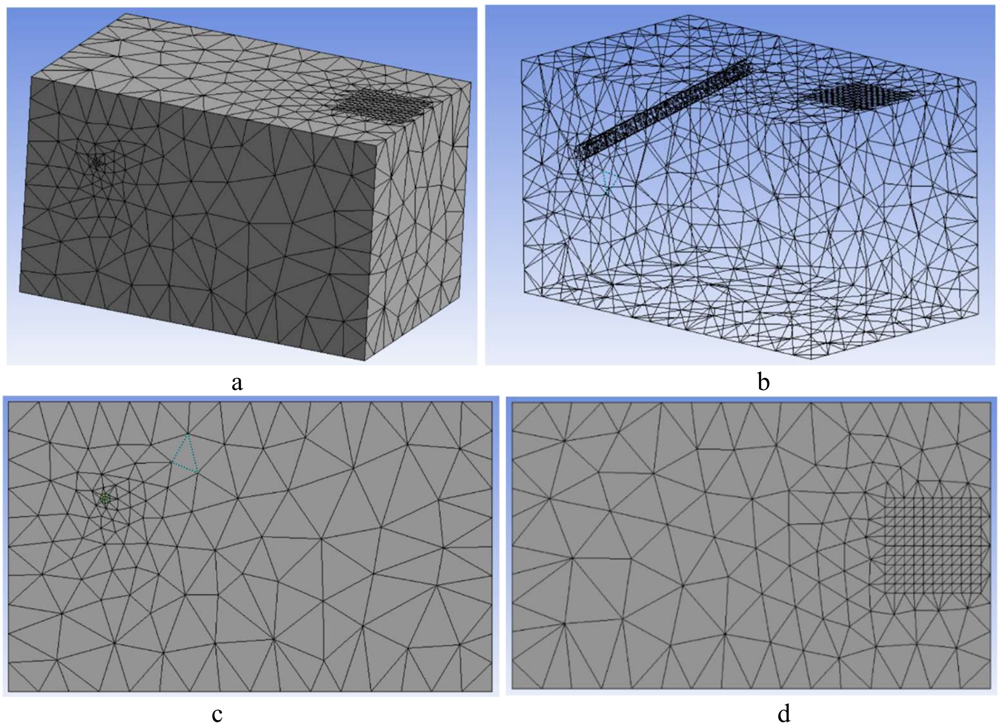


Figure 5. Scheme of FEM grid near a void and phased array of acoustic sensors: a – opaque diagram of the relative position of the soil mass, void, a phased array of acoustic sensors and finite element mesh; b – transparent diagram of the same objects; c – view of finite element mesh on the vertical section near void; d – view of a finite element mesh on the soil surface near a phased array of acoustic sensors

During the theoretical considerations, it has been decided that modeling the system in the discrete-time domain directly would be ineffective in terms of precision and use of computational resources. As an alternative, the research was conducted in the frequency domain, with the resulting frequency responses then used to obtain the result for an explosion model via linear filtering techniques.

The source was placed close to the soil model and the frequency response for the acoustic pressure was calculated for a grid of virtual microphones, similar to the classic planar phased antenna array [4, 31]. The obtained frequency responses were then used as a linear filter transfer function in order to allow for the easy and less computer-intensive modeling of responses to arbitrary input signals by multiplying their frequency representation by the filter transfer function and using the inverse DFT, or by directly convolving the filter's impulse response with the signal in the time domain.

The resulting signals are classically then fed into direction-finding algorithms, which can be facilitated by using the MUSIC method, the ESPRIT method, Prony's method, or the matrix pencil method [38, 41].

In the current paper, instead of standard approaches, an artificial neural network is applied. In this case the resulting output can then be either directly fed into a neural network or pretreated via such techniques as matched filtering in order to compress the signal and thus reduce the number of needed input nodes. For the initial research, the explosion was modeled via a delta-function, which yields the impulse response as the output of the filter. This impulse response can be calculated using the inverse fast Fourier transform.

During research, the depth D and distance L to the tunnel were chosen from the ranges of 50 to 100 m and 200 to 400 m, respectively. The slope angle α of the tunnel was chosen from the values between 0 and 30 degrees. The radius of the tunnel R is between 10 and 25 m for this initial testing stage.

An example of the frequency response H obtained during the experiment can be seen in Figure 6. The resulting impulse response h, taking into account the reflected wave, which can be used to model the explosion, can be seen in Figure 7.

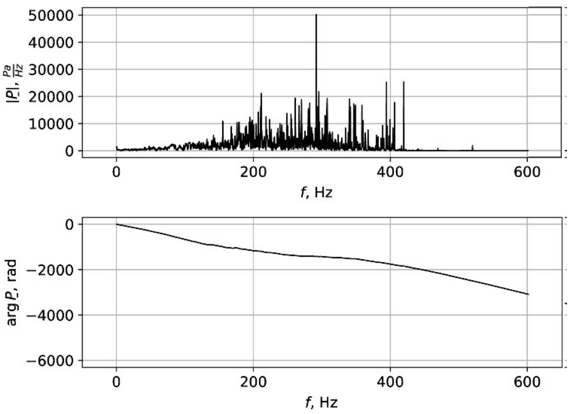


Figure 6. Frequency response for the middle sensor

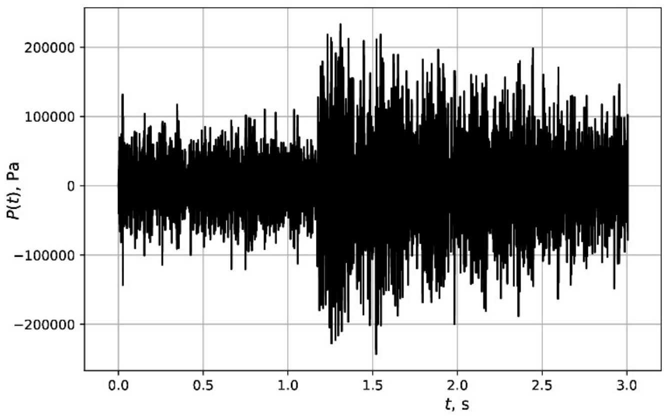


Figure 7. Impulse response for the central sensor

C. EXAMPLE OF INVERSE SOLUTION

To solve the inverse problem, a special neural network was built based on the TensorFlow 2.0 framework [39, 40]. This task is essentially a pattern recognition task, for which it is convenient to use a stacked neural network [12]. Each layer can learn features at a different level of abstraction. However, training neural networks with multiple hidden layers can be difficult. One can effectively train a neural network by training a special type of network known as an autoencoder for each hidden layer (Figure 8). First, we train the hidden layers individually in an unsupervised fashion using autoencoders. Then, we train a final layer and join the layers together to form a stacked network (SAE), which we train once in a supervised neural network training.

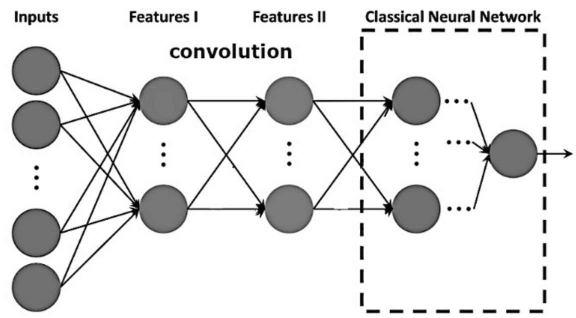
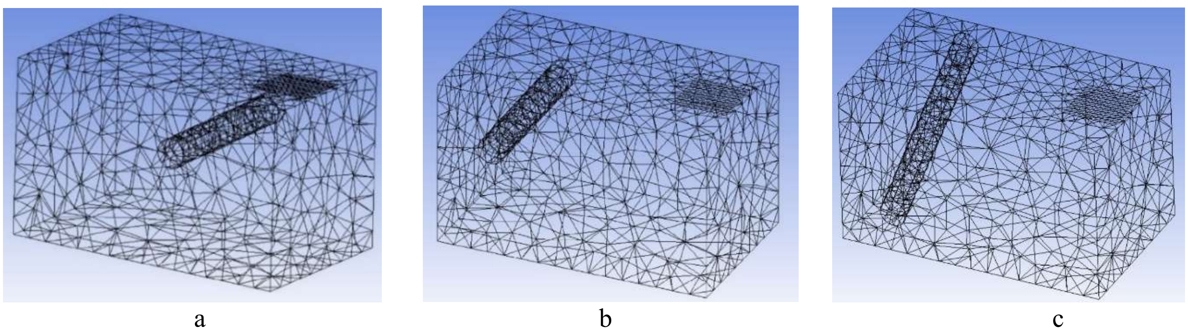


Figure 8. Scheme of a deep stacked neural network with 2 layers of autoencoders (SAE)

In order to simulate the response of the microphone array to any disturbance without the need to use computationally heavy finite element simulations, it has been decided to employ linear filtering techniques. This is possible due to linear laws governing the propagation of acoustic waves in a solid medium. During the initial investigation it was found that most of the energy of the initial disturbance is concentrated in the frequency band between 0 and 1000 Hz. It is important to note that due to the average speed of sound in the soil being equal to $1900\ m/s$, the minimum frequency of the wave needed for the tunnel width, which is assumed to be around 5 meters, to pass the diffraction limit is 380 Hz, which is included in the obtained range.

Some examples of variants of the training set calculations' frequency response and impulse response are represented in Figure 9 and 10.

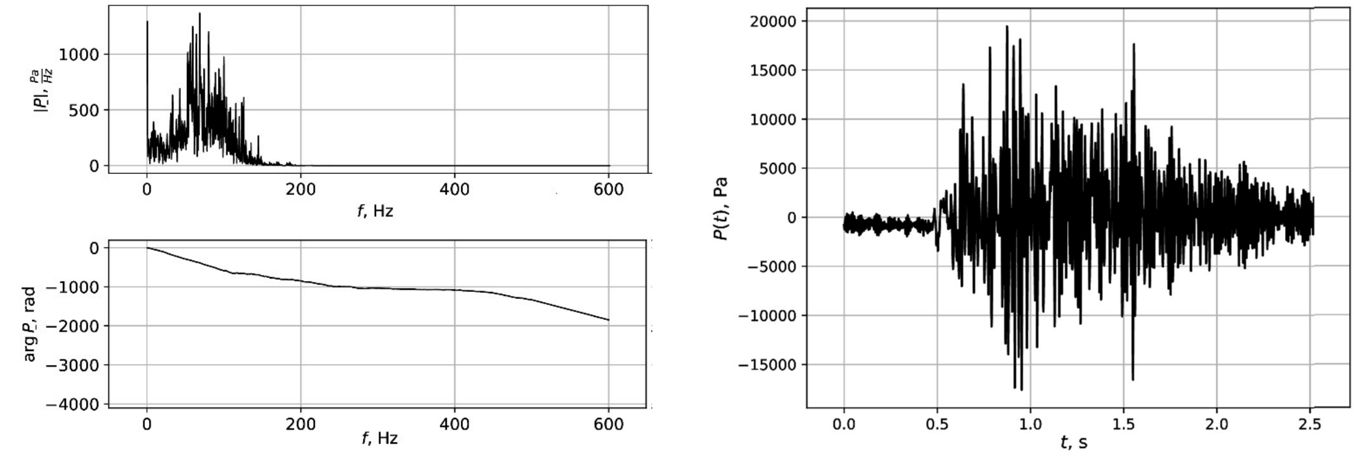


a b c

Figure 9. Elements of the training set (R=25 m): a – D=100 m, L= m, $\alpha=0^0$; b – D=100 m, $\alpha=0^0$; c – D=50 m, $\alpha=30^0$

In order to suppress the time-domain aliasing effects, the number of points for the spectral analysis was set to 4000, thus leading to the maximum length of the allowable impulse response of 4 s. Due to the impulse response being real, only the 4000 points over 1000 Hz included only the part containing the positive frequencies with the other being restored as a conjugate reverse signal. In order to separate the response of the tunnel from the background response of the signal traveling through air and propagating inside the soil, the frequency response of a model with the tunnel filled with soil was subtracted from the response of the air-filled tunnel. This approach was chosen instead of using a model of a solid block of soil in order to preserve the mesh geometry and exclude the errors arising from the calculation inaccuracies.

Autoencoders extract useful features of their input data unsupervised by separating the factors of variation [12]. For the first autoencoder hidden representation size was set to 100, which means that 100 features were selected for each sensor. The input of the second autoencoder was fed by the training set passed through the first one. The second autoencoder hidden layer size was reduced to 50 to form an even smaller feature set.



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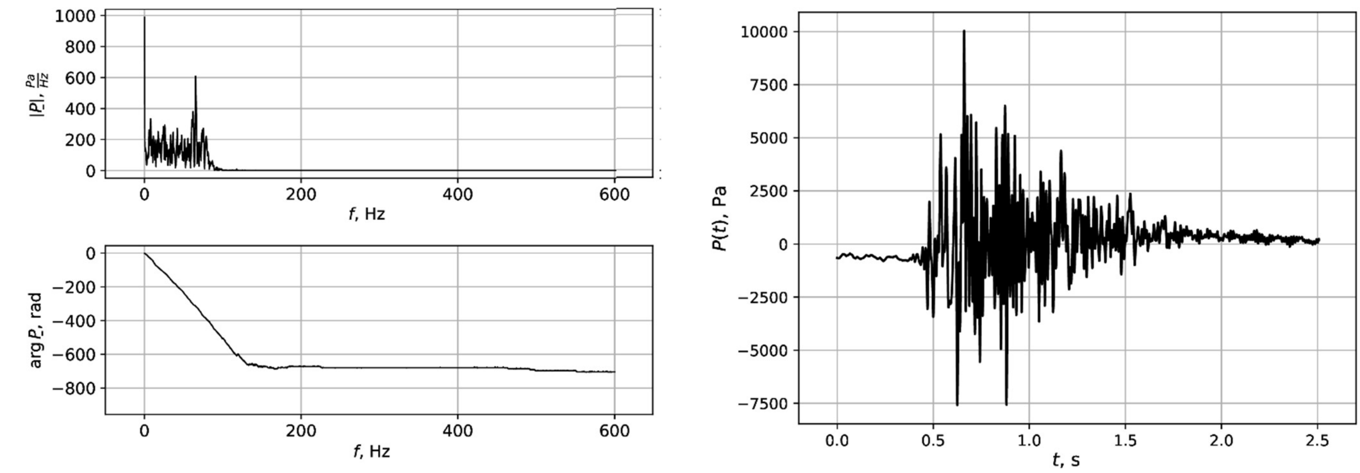

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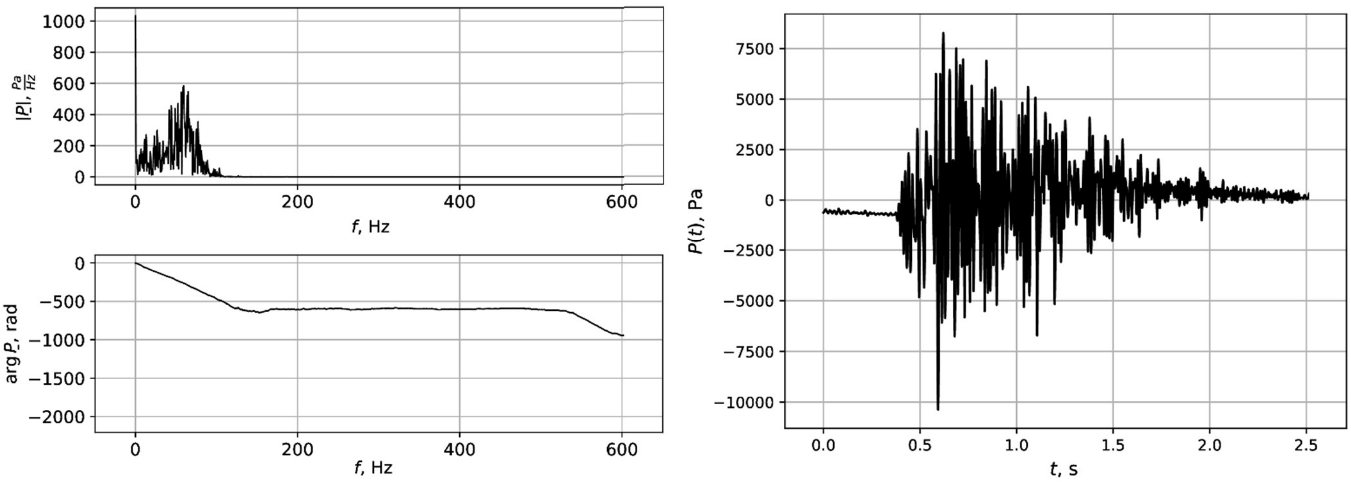

c

Figure 10. A frequency and an impulse response for the middle sensor for corresponding variants of the training set in Figure 9

The maximum number of epochs was set to 400 for the first autoencoder and then reduced to 100 for the second one. Both autoencoders were trained with the scaled conjugate gradient algorithm. The last layer is applied to the 50-dimensional feature vectors from its input and represents the 10-dimensional feature vectors of the detected void.

Testing the obtained neural network on a set of 100 experiments to identify voids when localizing an explosion at a distance of 10 m behind the projection of the void onto the surface of the massif and at a height of 5 m above the surface showed that it identifies the presence of a void with an accuracy of 72% and determines the parameters of its location with an accuracy of 70%. In this case, the orientation and location of the void in the vertical plane perpendicular to the direction of wavefront propagation are determined more accurately. Thus, determining the location of the void requires solving the second inverse problem on the optimal location of the pulse source and sensors. In addition, it is apparently necessary to consider the adaptive architecture of the neural network, which allows it to be further trained.

A comparative quantitative evaluation of our model with known models for detecting underground cavities shows its effectiveness for cases of small cavities and large distance to sensors [2, 4, 9]. One of the related works is [44], which considers the identification of underground artificial cavities based on a Bayesian convolutional neural network and the frequency-domain SAEM method. The interior of this model is divided into two parts: the upper part is the atmosphere with a size of 6000 m × 4000 m × 1000 m (length × width × height), and the lower part is a large stratum with a size of 6000 m × 4000 m × 1000 m. The dimensions of the cavity in question are 50-30 m wide and 150-250 m long. The classification accuracy of the neural network achieved in this way as a result of training is 75.05%. Considering that the cavity being sought in our studies is smaller and the size of the analyzed soil is significantly larger, the achieved recognition result of 70-75% is sufficient.

V. CONCLUSIONS

Thus, we have developed an information system, method, and schematic diagram for identifying artificial underground cavities using machine learning techniques based on acoustic exploration data. It identifies the presence of a void with 72% accuracy and determines its location parameters with 70% accuracy. We solved this problem based on model calculations for a known geological soil structure. The developed method for identifying artificial underground cavities is significantly innovative, as it allows us to determine the parameters of relatively small underground cavities at significant distances from the sensor locations. It can be used to create practical seismic exploration systems in conditions where the ground surface above the voids is inaccessible. Future research directions include studying the influence of noise, structure sizes and overhead structures on the efficiency of subsurface void recognition.

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