КІБЕРБЕЗПЕКА: освіта, наука, техніка № 2 (30), 2025
CYBERSECURITY: EDUCATION, SCIENCE, TECHNIQUE
Спеціальний випуск ISSN 2663 – 4023
Special issue

DOI 10.28925/2663-4023.2025.30.981
УДК 550.348

Igor Yarmolai
postgraduate student
Military Institute of Taras Shevchenko National University of Kyiv, Kyiv, Ukraine
ORCID: 0009-0001-7013-5790
mazay0607@gmail.com

METHOD OF SEISMOACOUSTIC MONITORING OF SEPARATE SIGNALS OF EXPLOSIVE FIELDS FOR REMOTE RECONNAISSANCE

Abstract. The article is devoted to the development and justification of an effective method of remote reconnaissance and monitoring that uses the unique physical characteristics of explosive fields. The need for such a method is driven by the requirement for reliable, all-weather, and covert identification and localization of explosion sources, which is critical for security, military, and engineering reconnaissance. The method considers an explosion as a complex source that simultaneously generates seismic (elastic) and acoustic (infrasonic) signals. The main objective of the work is to present a method of seismoacoustic monitoring of explosive fields, which allows not only to register but also to classify individual signals, generating highly informative data for remote reconnaissance. The methodology is based on the stages of mathematical modeling of seismoacoustic processes. These stages include: determining the physical conditions for signal generation: a detailed analysis of the conversion of explosion energy into seismic waves propagating in the ground and acoustic (shock/infrasonic) waves propagating in the atmosphere; mathematical principles of modeling physical processes: development of a formalized approach to describe the propagation and registration of these waves, taking into account the characteristics of the environment. The main scientific result is the creation and justification of a parametric mathematical model of seismoacoustic monitoring. This model is presented as a superposition of oscillators, where each oscillator is responsible for modeling a specific informative component of the explosion signal. The proposed model allows the informative parameters that directly characterize the explosion field signal (e.g., energy, frequency composition, arrival time, amplitude) to be isolated and quantitatively evaluated. The use of oscillator superposition ensures high model flexibility and its ability to adapt to different types of explosive signals and environmental conditions. The proposed method provides a solid theoretical basis for the construction of automated remote reconnaissance systems. The use of a parametric model in the form of a superposition of oscillators allows for the effective classification and localization of explosive events, distinguishing them from natural and man-made noise. This significantly increases the reliability and informativeness of seismoacoustic complexes, making the method a valuable tool for operational control and strategic monitoring.

Keywords: seismoacoustic monitoring, remote reconnaissance, explosive fields, signal classification, mathematical modeling, parametric model, superposition of oscillators, seismic signals, acoustic signals.

INTRODUCTION

The method of seismoacoustic monitoring of individual signals from explosive fields for remote reconnaissance is an integrative scientific and technical field at the intersection of geophysics, acoustics, signal processing, and military/engineering reconnaissance. In the context of modern challenges related to critical infrastructure control, military activity monitoring, natural resource exploration, and security, remote detection and localization of explosion sources is of strategic importance.

The relevance of researching this method is due to the need to improve the accuracy, speed, and reliability of intelligence information about events related to explosions (both controlled and unauthorized). Traditional methods often face limitations in terms of range, environmental noise, and the complexity of identifying the nature of the source. The seismoacoustic approach, which combines the analysis of seismic (elastic) waves propagating in the ground and acoustic (infrasonic and sound) waves propagating in the air, allows the creation of comprehensive spatial and temporal “portraits” of explosive events.

The method of seismoacoustic monitoring of individual signals from explosive fields is a highly effective tool for remote reconnaissance. It is based on the synergy of seismic and acoustic data, which allows obtaining a complete “wave portrait” of an explosive event. The key elements for its successful implementation are precise time synchronization, complex sensor systems (antenna arrays), and adaptive processing algorithms that take into account real physical models of wave propagation in a heterogeneous environment. Further development of the method, especially in terms of AI/ML integration and new sensor technologies, will ensure its leading position in early warning and strategic monitoring systems.

Seismic monitoring is distinguished by its unique coverage of seismic phenomena, specifically infrasound and the lower part of the sound frequency range.

First of all, it is necessary to build a mathematical model of the object of study, which would reflect the most significant moments of the monitoring process, including both the process itself and the interference accompanying this process and the natural noise background superimposed on the experiment [1, 2].

A priori knowledge of the random interference process will significantly weaken its influence on obtaining estimates of the parameters of the process perceived as a helpful signal. This weakening is achieved by optimizing the processing procedures that take into account the a priori statistics of the random interference process. In this work, optimization of the processing procedures for the observed data is made, according to criteria that take into account the characteristics of the natural interference background, the instability of the parameters of the probing signal in active monitoring, and the consequences associated with this instability [3].

Monitoring the state of an object involves observing the parameters that characterize its state, with significant changes indicating a departure from its stationary behavior.

This definition is the closest to the definition of deformation monitoring [4] among many existing ones.

By seismoacoustic monitoring, we mean routine observations of seismic and acoustic fields and their analysis to study the dynamics of the object under study to predict its condition.

The observation process is reduced to assessing events associated with the object under monitoring, directly at the moment when they occur or immediately after. This involves analyzing the results of measuring the object's parameters, detecting changes in these parameters, and responding to these changes.

By an automated monitoring system, we mean the following:

An automated monitoring system is a group of mutually influencing, interacting, or interdependent elements of software and equipment that form a complex whole for monitoring the condition of the parameters of the object under study, which does not require human intervention after installation. This definition is close to that given in [5].

By passive monitoring, we mean a definition close to [6]: passive monitoring is monitoring the emission of signals from the object itself or signals from the object's response to random external disturbances. Such monitoring is necessary for the analysis of seismoacoustic emission, which is used to monitor and control both natural and anthropogenic structures.

Passive monitoring is based on the ability to build physically meaningful conclusions about the state of the object of study, based on the analysis of emission signals of this object or signals of its response to external stochastic disturbances. This type of monitoring has been carried out since ancient times in seismically dangerous zones in attempts to predict earthquakes.

The stages of development and formation of modern passive seismic monitoring systems, up to the creation of a worldwide observation network, fit into the last half-century period [7].

Analysis of recent studies and publications. Currently, issues related to seismic acoustic monitoring and the impact of shock waves on objects are described in the works of domestic and foreign researchers, namely: Mostovoy V.S., Vyzhva S.A., Shcherbina S.V., Kendzera O.V., Gabriel Albert (a French scientist who studied shock waves and worked on their mathematical description), Gaizim Walzman (Garry J. Walzmann - American physicist specializing in shock physics and explosive phenomena), John Solomon (John Solomon - scientist working in the field of shock wave physics and materials mechanics), Kevin Truscott (Kevin M. Truscott - engineer and scientist who studies the interaction of shock waves with structures), Leonardo Bassani (Leonardo Bassani - Italian scientist who studied the physics of explosions and shock waves), James R. Melville (James R. Melville – physicist specializing in the study of shock phenomena and materials mechanics).

Method of seismoacoustic monitoring of separate signals of explosive fields for remote reconnaissance. When estimating the parameters of a mathematical model for systems of seismoacoustic monitoring of an explosive field in the general case, we encounter such a representation of the seismoacoustic field model based on observation data $y(t,x)$ complicated by additive noise $n(t,x)$ (t – time, x – spatial coordinates). Two vectors of free parameters determine the model $M(l,\eta,t,x)$ of the field formation process, l and η the model itself is the researcher's hypothesis about the process being modeled. The vector enters the model l linearly and η nonlinearly. This difference is significant in the estimation of free parameters, since they require different complex procedures for their determination.

In the general case, the mathematical model for seismoacoustic montoring systems of the explosive field signal can be represented in the following form:

$$y(t,x) = M(l,\eta,t,x) + n(t,x), \tag{1}$$

here $M(l,\eta,t,x)$ - mathematical model of the explosive field signal;
l – vector of parameters entering the model linearly;
η – vector of parameters that nonlinearly enters the model;
$n(t,x)$ - additive nose;
x - spatial coordinate (in the general case, a three-dimensional vector);
t – time ccordinate.

In the general case, the dimension of vectors is a parameter of the model. The model $M(l,\eta,t,x)$ can be represented as a linear combination of models $M(l,\eta,t,x)$, where n is the dimension of the vector l. Then model (1) takes the form:

$$M(l,\eta,t,x) = \sum_{i=1}^{n} M_i l_i(\eta,t,x). \tag{2}$$

Solving problem (2) means determining for the selected model $M(l,\eta,t,x)$ two vectors of free model parameters l and η. The calculated value l and η the standard deviation $n(t,x)$ are estimated. In the general case, the dimensions of these vectors of free model parameters are also subject to determination. In the following, we will consider the separate procedure for estimating the vectors l and η, assuming they belong l only to the linearly set Λ, and η to nonlinearly, set N.

To solve model (1), we propose a selection method [8]. This involves searching for parameter vector values that minimize the deviation of the model $M(l,\eta,t,x)$ from the observed data $r(t,x)$, given the selected scalar product in the Hilbert space. The Hilbert space is chosen taking into account the stochastic characteristics of the process $n(t,x)$. Therefore, we need to find the minimum of the model (1) for all its free parameters. The definition of the scalar product is the square of the noise norm at the point $x - n(t,x), r(t,x)$

$$\min_{l\in\Lambda,\eta\in N}\left[(n(t,x)-M(l,\eta,t,x), r(t,x)-M(l,\eta,t,x\right] < \varepsilon . \tag{3}$$

here ε the restriction threshold, i.e., a compromise between the acceptable level of errors of the first and second kind..

The value of ε is determined subjectively as the researcher's attitude to the quality of the model, taking into account errors of two kinds [9, 10]. If (3) is fulfilled, that is, the deviation of the model from the observation data does not exceed the threshold limit set by the researcher. A decision is made on the adequacy of the hypothetical model $M(l,\eta,t,x)$ of the process $y(t,x)$.

In (3), the optimal parameter estimates of model (1) are defined as the point in the parameter space at which the selected criterion reaches its global minimum.

Since the minimum of criterion (3) is the square of the norm of the noise component at the point x, it is natural to choose the scalar product. It must be selected in such a way that the noise norm is minimal. The square of this norm is the variance of the random process at the point t.

$$\left(n(t,x_1), n(t,x_2)\right) = E\left(n(t,x_1), n(t,x_2)\right) \tag{4}$$

here E the expectation operator of a random process with zero expectation at a point t;
x_1 and x_2 − coordinates of a spatial vector x

For the chosen scalar product (4), with a fixed value of the vector η, the minimum of criterion (3) is achieved at a point in the space of linear parameters l which satisfies the equation:

$$\frac{\partial\left[(n(t,x)-M(l,\eta,t,x), r(t,x)-M(l,\eta,t,x\right]}{\partial l} = 0 \tag{5}$$

$$\left(\frac{\partial M(l,\eta,t,x)}{\partial l}, M(l,\eta,t,x)\right) - \left(\frac{\partial M(l,\eta,t,x)}{\partial l}, r(t,x)\right) = 0 \tag{6}$$

In (5) the expression $\frac{\partial M(l,\eta,t,x)}{\partial l}$ means the column vector:

$$\frac{\partial M(l,\eta,t,x)}{\partial l} = \begin{Bmatrix} \frac{\partial M(l,\eta,t,x)}{\partial l_1} \\ \dots\dots\dots \\ \frac{\partial M(l,\eta,t,x)}{\partial l_n} \end{Bmatrix} \tag{7}$$

The system of linear equations (5) concerning the parameter vector l at a fixed value of the vector η can be represented as a system of linear equations:

$$\begin{Bmatrix} \frac{\partial M(l,\eta,t,x)}{\partial l_1}, M(l,\eta,t,x) \\ \dots\dots\dots \\ \frac{\partial M(l,\eta,t,x)}{\partial l_n}, M(l,\eta,t,x) \end{Bmatrix} = \begin{Bmatrix} \frac{\partial M(l,\eta,t,x)}{\partial l_1}, r(t,x) \\ \dots\dots\dots \\ \frac{\partial M(l,\eta,t,x)}{\partial l_n}, r(t,x) \end{Bmatrix}. \tag{8}$$

Let represent the system of linear equations (7) in vector form:

$$\left(\frac{\partial M(l,\eta,t,x)}{\partial l_1}, M(l,\eta,t,x)\right) = \left(\frac{\partial M(l,\eta,t,x)}{\partial l_1}, r(t,x)\right), s = \overline{1,n}. \tag{9}$$

In the special case, when the model has the form (2), this system of equations takes the form of a system of linear equations concerning the vector l:

$$\sum_{i=1}^{n} l_1 \left(M_i(\eta,t,x) \cdot M_s(\eta,t,x)\right) = \left(r(t,x) \cdot M_s(\eta,t,x)\right), s = \overline{1,n}. \tag{10}$$

The vector of parameters l calculated in this way will be optimal (in the sense of the chosen criterion) for a fixed vector of nonlinear parameters. To obtain optimal estimates l and η, it is necessary to minimize criterion (3) by η searching for local minima. In this case, other methods can be applied, for example, gradient methods or the Monte Carlo method using special sequences [11].

In choosing the scalar product of criterion (3), it is necessary to take into account heuristics based on experience. In this regard, the question arises whether heuristics can be formalized related to the expected nature of the background In choosing the scalar product of criterion (3), it is necessary to take into account heuristics based on experience. In this regard, the question arises whether heuristics can be formalized related to the expected nature of the background n(t,x), for example, high-frequency, low-frequency, etc. From this point of view, it is natural to use models of existing stochastic processes in the first approximation., for example, high-frequency, low-frequency, etc. From this point of view, it is natural to use models of existing stochastic processes in the first approximation [12.

The optimized procedure for estimating the parameters of explosion field signals with characteristics in the seismoacoustic frequency range in model (1) for monitoring studies of separate explosion signals will be considered based on field research data. Input data in the continuous model (1) during field research are observation data presented in the form of a discrete function represented by a matrix.

Thus, it is possible to formulate the stages of the method of seismoacoustic monitoring of an explosive field for conducting remote reconnaissance:

Stage I – The selection of a parametric mathematical model for seismoacoustic monitoring of explosive fields to conduct remote reconnaissance is carried out by (2). In this case, the conditions of monitoring, the specifics of the environment, and the physical feasibility are taken into account; the researcher must choose the type of parametric mathematical model of seismoacoustic monitoring of explosive fields.

Stage II – The selection of the criterion for determining the informative parameters of the mathematical model of seismoacoustic monitoring of explosive fields for conducting remote reconnaissance is carried out by clause 3. The selection of the criterion for determining the informative parameters of the mathematical model is carried out by the selected parametric model of seismoacoustic monitoring of explosive fields for conducting remote reconnaissance (stage I) and the transfer function of the explosive signal propagation environment.

Stage III – The determination of the vector of informative parameters of the mathematical model of seismoacoustic monitoring of explosive fields for conducting remote reconnaissance is carried out by clauses 5-7. To determine the informative parameters of the mathematical model of seismoacoustic monitoring of explosive fields for conducting remote reconnaissance, the problem of nonlinear regression of the mathematical model with observation data is solved, using the criterion selected at stage II.

Stage IV – Selection of the criterion for assessing the deviation of the mathematical model of seismoacoustic monitoring of explosive fields for conducting remote reconnaissance from observation data and the threshold for maximum deviation of observation data is carried out by clause 8. The criterion for assessing the deviation of the mathematical model of seismoacoustic monitoring of explosive fields for conducting remote reconnaissance from observation data is carried out by an expert, taking into account the results of the preliminary research statistics [13].

Stage V – Assessment of the adequacy of the developed mathematical model of seismoacoustic monitoring of an explosive field for conducting remote reconnaissance. By the criterion for assessing the deviation of the mathematical model of seismoacoustic monitoring of an explosive field for conducting remote reconnaissance and the threshold for maximum deviation of observation data selected at stage IV (stage IV), a decision is made on the adequacy of the model. Suppose the deviation of the model in (8) does not exceed the threshold selected at stage IV. In that case, a decision is made on the adequacy of the model, i.e., it is used for signal classification, for seismoacoustic monitoring of the blast field, for remote sensing. Otherwise, a new mathematical model of the blast field signal is selected, by stage I

Parametric mathematical model of seismoacoustic monitoring of explosive fields for conducting remote reconnaissance.

$$y_m(t) = \sum_{l=1}^{L} S_{ml} \exp\left\{-\mu_{ml} t\right\} \sin(\varpi_{ml} t + \varphi_{ml}) + n_m(t) \quad . \tag{11}$$

Here m - sensor number that reconstructs the explosion signal, $m=\overline{1,M}, M$, is the number of explosion signals;

$S_{ml}, \mu_{ml}, \varpi_{ml}, \varphi_{ml}$ - free parameters of the model (11):

S_{ml} - the amplitude of the l - th harmonic;

μ_{ml} - sinusoid damping coefficient of the l - th harmonic;

ϖ_{ml} - is the frequency of the l - th harmonic;

φ_{ml} - is the phase shift of the l - th harmonic;

$n_m(t)$ - additive noise in measurements m –th blast;

L – a set of analytical submodels of the same type, the superposition of which models the process $y_m(t), \quad l \in \Lambda$.

$$y=\{y_m(t)\}; m=\overline{1,M}, \qquad (12)$$

here y is the vector function whose components are the observation data of each of the M sensors.

The solution of the parametric mathematical model of seismoacoustic monitoring of explosive fields for remote sensing consists in the optimal determination of the free parameters of the model. The optimality criterion is the degree of proximity of the model to the observed data in the selected metric L_2. From the physical conditions of the problem statement, it is advisable to choose a metric L_2. In the metric, the criterion is the functionality of each of the components of the form:

$$F_m(P_m)=\left\|\sum_{l=1}^{L} S_{ml}\exp\{-\mu_{ml}t\}\sin(\varpi_{ml}t+\varphi_{ml})+n_m(t)\right\|_{L_2}, m=\overline{1,M}. \qquad (13)$$

Here P_m is the matrix of free parameters of the model, which consists of vectors of models describing each explosion signal with the number $m=\overline{1,M}$

Let us denote the vector of free parameters of the same type of submodel with the number l, as $P_m^{(l)}$ thus l is the column number in this matrix. M is the number of observation points:

$$P_m^{(l)}=\begin{Bmatrix} S_{ml} \\ \mu_{ml} \\ \varpi_{ml} \\ \varphi_{ml} \end{Bmatrix}, l=\overline{1,L}.$$

here L is the number of parameters of each oscillator in the model (13).

Fixed L, we reduce the matrix P_m by dimension $4\times L$ to a vector.

$$P_m=\{P_{m,j}\}, j=\overline{1,4L},$$

here P_m – these are the free parameters of the model; the dimension of this vector is equal $4\times L$, so that the first 4 elements of the vector are the parameters of the first submodel, the following four are the parameters of the second submodel, and so on

$$F\left(P^*\right)=\min_{P\in\Im}F(P). \tag{14}$$

$y(t)$ - is the one dimensional vector y in the model (11) this means $y(t)=\left\{y_m(t)\right\}; m=\overline{1,M,M=1}$. $y(t)$ is an analytical approximation of the vector of values of the processed observation data. $\Im$ is the set of possible values of a vector P. From a theoretical and practical point of view, for a qualitative estimate of the vector of free parameters P, it should be chosen so that the point P^* is inside the set $\Im$ [14].

The optimization problem of finding the optimal vector of free parameters can be solved in different ways. Problem (13) was solved numerically using the Levenberg-Marquardt algorithm [15]. This method is repeated for different stochastically obtained points in the set $\Im$ of which the local extremum is sought. Then, on the finite set of all local extrema, the global extremum is found. To select the points in the vicinity of which the local extremum is sought, the method presented in the work is used [14]. The convergence of the algorithm was investigated in the work [16].

To solve model (11), it is necessary to find the global extremum on the set of all found local extrema. The convergence of the algorithm is investigated in the vicinity of points selected by the Monte Carlo method according to prior distributions.

Below, we consider problem (11) for $L=3$. If we take into account that each parameter of the model should be considered as the noise that it brings to the model (this phenomenon in statistics is called the "curse of dimensionality"), then for this case, a model with 12 free parameters is the limiting complexity for models of the selected type for the data obtained in this experiment. The notation for the 12th parametric model is used in the calculations [17]. To integrate model (11) into automatic processing algorithms, we will represent this model in the following form:

$$M\left(t,P_m\right),\ M\left(t,P_m\right)=\sum_{l=1}^{L}P_{m,1+4(l-1)}\left\{\exp\left[-P_{m,2+4(l-1)}t\right]\times\sin\left[P_{m,3+4(l-1)}\left(t-P_{m,4+4(l-1)}\right)\right]\right., \tag{15}$$

here $P_{m,1+4(l-1)}, P_{m,2+4(l-1)}, P_{m,3+4(l-1)}, P_{m,4+4(l-1)}$ is the free parameters of the model (15) for each of the submodels $l=\overline{1,L}$:

$P_{m,1+4(l-1)}$ is the amplitude for each of the submodel $l=\overline{1,L}$;

$P_{m,2+4(l-1)}$ is the logarithmic decrements for each of the submodel $l=\overline{1,L}$.;

$P_{m,3+4(l-1)}$ is the angular frequencies for each of the submodel $l=\overline{1,L}$.;

$P_{m,4+4(l-1)}$ is the phase shifts for each of the submodel $l=\overline{1,L}$.

To determine the extremum points of the criterion $F_m(P_m)$, we search $\min F_m(P_m)$; $m=\overline{1,M}$; $P_m\in\Im_m$ for on the set $\Im_m$ of possible values. P_m is the vector function consisting of partial derivatives of the model $\partial M(t,P_m)/\partial P_{m,j}=0; j=0,11$, for each of the parameters $P_{m,j}$:

КІБЕРБЕЗПЕКА: освіта, наука, техніка № 2 (30), 2025
CYBERSECURITY: EDUCATION, SCIENCE, TECHNIQUE
Спеціальний випуск ISSN 2663 – 4023
Special issue

$$\frac{\partial M(t,P_m)}{\partial P_{m,1+4(l-1)}} = \exp\left[-P_{m,2+4(l-1)}t\right]\times\sin\left[P_{m,3+4(l-1)}\left(t-P_{m,4+4(l-1)}\right)\right], l=\overline{1,L}$$

$$\frac{\partial M(t,P_m)}{\partial P_{m,2+4(l-1)}} = -tP_{m,1+4(l-1)}\exp\left[-P_{m,2+4(l-1)}t\right]\times\sin\left[P_{m,3+4(l-1)}\left(t-P_{m,4+4(l-1)}\right)\right], l=\overline{1,L} \quad (16)$$

$$\frac{\partial M(t,P_m)}{\partial P_{m,3+4(l-1)}} = P_{m,1+4(l-1)}\left(t-P_{m,4+4(l-1)}\right)\exp\left[-P_{m,2+4(l-1)}t\right]\times\cos\left[P_{m,3+4(l-1)}\left(t-P_{m,4+4(l-1)}\right)\right], \ l=\overline{1,L}$$

$$\frac{\partial M(t,P_m)}{\partial P_{m,4+4(l-1)}} = -P_{m,1+4(l-1)}\left(t-P_{m,4+4(l-1)}\right)\exp\left[-P_{m,2+4(l-1)}t\right]\times\cos\left[P_{m,3+4(l-1)}\left(t-P_{m,4+4(l-1)}\right)\right], \ l=\overline{1,L}$$

Using the Monte Carlo method, according to a priori distributions, a point in -dimensional space is taken, in the neighborhood of which there is a local extremum, and we find the value of the vector of free parameters of the model (11), which gives the minimum of criterion (14), namely the deviation of the model (15) from the observation data in the metric. L_2.

So, we find the global minimum of the functional $F_m(P_m)$ on the set of admissible vectors with a known a priori distribution P_m from the set $\Im_m$. Here $\Im_m$ is the set of all possible values of the vector of free model parameters (15) $\min\limits_{P_m}\{F_m(P_m)\}; m=\overline{1,M};\ P_m\in\Im_m$.

The calculation results for the model with n fading harmonics are reduced to vectors of dimension n, combining one-dimensional parameters, i.e. a parametric model of dimension is considered $n\times 4$.

CONCLUSIONS

The article presents a method of seismoacoustic monitoring of explosive fields for remote reconnaissance. The method makes it possible to classify separate signals. Within the framework of the method, the stages of mathematical modeling of seismoacoustic monitoring of explosive fields for remote reconnaissance are presented. In which the physical conditions of generation of explosive field signals and the mathematical principles of modeling physical processes are provided, namely, the following are considered:

The conditions for choosing a parametric mathematical model of seismoacoustic monitoring of explosive fields for remote reconnaissance are carried out by the stages mentioned above. In this case, the conditions of monitoring, the specifics of the environment, and the physical feasibility of the model are taken into account.

Within the framework of the proposed method, a parametric mathematical model of seismoacoustic monitoring of explosive field signals for remote reconnaissance is presented in the form of a superposition of oscillators, the informative parameters of which characterize the explosive field signal.

REFERENCES (TRANSLATED AND TRANSLITERATED)

1. Allaby, A., & Allaby, M. (2003). *Oxford dictionary of earth sciences* (2nd ed., reissued with corrections and new covers). Oxford University Press.
2. Dunnicliff, J. (1993). *Geotechnical instrumentation for monitoring field performance.* Wiley.
3. Lay, T. (Ed.). (2009). *Seismological grand challenges in understanding Earth's dynamic systems: Long-range science plan for seismology workshop.* Report to the National Science Foundation, IRIS Consortium.

4. Marquardt, D. (1963). An algorithm for least-squares estimation of nonlinear parameters. *SIAM Journal on Applied Mathematics, 11*(2), 431–441.
5. Mostovoy, S. V., Mostovoy, V. S., & Osadchuk, A. E. (1998). Non-identified detection of signals against a microseismic background. *Geophysical Journal, 18*, 265–271.
6. Mostovoy, V. S. (2011). Optimal estimates of nonlinear parameters in seismic acoustic monitoring models. *Proceedings of the National Academy of Sciences of Ukraine, (8)*, 103–106.
7. Mostovoy, V. S., & Mostovoy, S. V. (2012). On the correctness of nonlinear regression tasks in monitoring natural and man-made objects. *Geophysical Journal, 34*(2), 140–143.
8. Mostovoy, V., & Mostovyy, S. (2014). Estimation of parameters of seismic waves. *Transactions of the National Academy of Sciences of Ukraine, 2*, 118–123.
9. Mostovoy, V., & Mostovyi, S. (2016). Mathematical model of seismic signal as a flow of physically non-realizable single seismic waves. *Geophysical Journal, 38*(5), 166–169.
10. Mostovoy, V. S., Toliupa, S. V., & Shevchenko, A. M. (2023). Optimization of the dynamic parameters of an object in a mathematical model of seismo-acoustic monitoring of natural and engineering objects. *Science-Intensive Technologies, 2*(58), 412–422. https://doi.org/10.18372/2310-5461.58.17647
11. Plessix, R.-E. (2006). A review of the adjoint-state method for computing the gradient of a functional with geophysical applications. *Geophysical Journal International, 167*(2), 495–509.
12. Robinson, M., & Houghtalen, R. (2011). Dangerous dams. *Rhode Island Canoe/Kayak Association (Rhode Island).* Retrieved from https://www.ricka.org/
13. Shevchenko, A. (2024). Methodology for seismoacoustic monitoring of the impact of shock waves on critical infrastructure facilities. *Cybersecurity: Education, Science, Technology, 4*(24), 351–362.
14. Shevchenko, A. M., & Yarmolai, I. O. (2024). Parametric mathematical model of seismoacoustic monitoring of a single mortar explosion. *Telecommunications and Information Technologies, 1*(82), 122–129.
15. Shevchenko, A. M., & Yarmolai, I. O. (2024). Optimization of informative parameters of a mathematical model for seismoacoustic monitoring of natural and engineering objects. *Zv'iazok, 5*, 83–89.
16. Shevchenko, A. M. (2024). A mathematical representation of an automated system designed to monitor critical infrastructure objects using seismic and acoustic signals. *Scientific Notes of the State University of Telecommunications, 1*(5), 85–93.

Ярмолай Ігор Олександрович
аспірант
Військовий інститут Київського національного університету імені Тараса Шевченка, Київ, Україна
ORCID: 0009-0001-7013-5790
mazay0607@gmail.com

МЕТОД СЕЙСМОАКУСТИЧНОГО МОНІТОРИНГУ ОКРЕМИХ СИГНАЛІВ ВИБУХОВИХ ПОЛІВ ДЛЯ ДИСТАНЦІЙНОЇ РОЗВІДКИ

Анотація. Стаття присвячена розробці та обґрунтуванню ефективного методу дистанційної розвідки та моніторингу, що використовує унікальні фізичні характеристики вибухових полів. Необхідність такого методу зумовлена потребою у надійній, всепогодній та прихованій ідентифікації та локалізації джерел вибухів, що є критично важливим для безпеки, військової та інженерної розвідки. Метод розглядає вибух як складне джерело, що одночасно генерує сейсмічні (пружні) та акустичні (інфразвукові) сигнали. Основна мета роботи – представити метод сейсмоакустичного моніторингу вибухових полів, який дозволяє не тільки реєструвати, але й класифікувати окремі сигнали, генеруючи високоінформативні дані для дистанційної розвідки. Метод базується на етапах математичного моделювання сейсмоакустичних процесів. Ці етапи включають: визначення фізичних умов генерації сигналів: детальний аналіз перетворення енергії вибуху в сейсмічні хвилі, що поширюються в землі, та акустичні (ударні/інфразвукові) хвилі, що поширюються в атмосфері; математичні принципи моделювання фізичних процесів: розробка формалізованого підходу до опису поширення та реєстрації цих хвиль з урахуванням характеристик навколишнього середовища. Основним науковим результатом є створення та обґрунтування параметричної математичної моделі сейсмоакустичного моніторингу. Ця модель представлена як суперпозиція осциляторів, де кожен осцилятор відповідає за моделювання конкретного інформативного компонента сигналу вибуху. Запропонована модель дозволяє виділити та кількісно оцінити інформативні параметри, що безпосередньо характеризують сигнал вибухового поля (наприклад, енергію, частотний склад, час приходу, амплітуду). Використання суперпозиції осциляторів забезпечує високу гнучкість моделі та її здатність адаптуватися до різних типів вибухових сигналів і умов навколишнього середовища. Запропонований метод забезпечує міцну теоретичну основу для побудови автоматизованих систем дистанційної розвідки. Використання параметричної моделі у вигляді суперпозиції осциляторів дозволяє ефективно класифікувати та локалізувати вибухові події, відокремлюючи їх від природних і штучних шумів. Це значно підвищує надійність та інформативність сейсмоакустичних комплексів, роблячи метод цінним інструментом оперативного контролю та стратегічного моніторингу.

Ключові слова: сейсмоакустичний моніторинг, дистанційна розвідка, вибухові поля, класифікація сигналів, математичне моделювання, параметрична модель, суперпозиція осциляторів, сейсмічні сигнали, акустичні сигнали.

СПИСОК ВИКОРИСТАНИХ ДЖЕРЕЛ

1. Allaby, A., & Allaby, M. (2003). *Oxford dictionary of earth sciences* (2nd ed., reissued with corrections and new covers). Oxford University Press.
2. Dunnicliff, J. (1993). *Geotechnical instrumentation for monitoring field performance.* Wiley.
3. Lay, T. (Ed.). (2009). *Seismological grand challenges in understanding Earth's dynamic systems: Long-range science plan for seismology workshop.* Report to the National Science Foundation, IRIS Consortium.
4. Marquardt, D. (1963). An algorithm for least-squares estimation of nonlinear parameters. *SIAM Journal on Applied Mathematics, 11*(2), 431–441.
5. Mostovoy, S. V., Mostovoy, V. S., & Osadchuk, A. E. (1998). Non-identified detection of signals against a microseismic background. *Geophysical Journal, 18*, 265–271.
6. Mostovoy, V. S. (2011). Optimal estimates of nonlinear parameters in seismic acoustic monitoring models. *Proceedings of the National Academy of Sciences of Ukraine, (8),* 103–106.

7. Mostovoy, V. S., & Mostovoy, S. V. (2012). On the correctness of nonlinear regression tasks in monitoring natural and man-made objects. *Geophysical Journal*, *34*(2), 140–143.
8. Mostovoy, V., & Mostovyy, S. (2014). Estimation of parameters of seismic waves. *Transactions of the National Academy of Sciences of Ukraine*, *2*, 118–123.
9. Mostovoy, V., & Mostovyi, S. (2016). Mathematical model of seismic signal as a flow of physically non-realizable single seismic waves. *Geophysical Journal*, *38*(5), 166–169.
10. Mostovoy, V. S., Toliupa, S. V., & Shevchenko, A. M. (2023). Optimization of the dynamic parameters of an object in a mathematical model of seismo-acoustic monitoring of natural and engineering objects. *Science-Intensive Technologies*, *2*(58), 412–422. https://doi.org/10.18372/2310-5461.58.17647
11. Plessix, R.-E. (2006). A review of the adjoint-state method for computing the gradient of a functional with geophysical applications. *Geophysical Journal International*, *167*(2), 495–509.
12. Robinson, M., & Houghtalen, R. (2011). Dangerous dams. *Rhode Island Canoe/Kayak Association (Rhode Island).* Retrieved from https://www.ricka.org/
13. Shevchenko, A. (2024). Methodology for seismoacoustic monitoring of the impact of shock waves on critical infrastructure facilities. *Cybersecurity: Education, Science, Technology*, *4*(24), 351–362.
14. Shevchenko, A. M., & Yarmolai, I. O. (2024). Parametric mathematical model of seismoacoustic monitoring of a single mortar explosion. *Telecommunications and Information Technologies*, *1*(82), 122–129.
15. Shevchenko, A. M., & Yarmolai, I. O. (2024). Optimization of informative parameters of a mathematical model for seismoacoustic monitoring of natural and engineering objects. *Zv'iazok, 5*, 83–89.
16. Shevchenko, A. M. (2024). A mathematical representation of an automated system designed to monitor critical infrastructure objects using seismic and acoustic signals. *Scientific Notes of the State University of Telecommunications, 1*(5), 85–93.