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MATHEMATICAL MODEL FOR AUTOMATED SYSTEMS OF SEISMOACOUSTIC MONITORING OF A MORTAR EXPLOSION CLASSIFICATION FOR CONDUCTING REMOTE RECONNAISSANCE

Abstract. Reconnaissance is the most important type of ensuring military operations; it is a set of measures taken by all commanders and staff to timely obtain information about the enemy, the terrain, climatic and weather conditions in the area of future hostilities to most effectively use their forces and means to defeat the enemy. The paper presents mathematical models for flavored seismo-acoustic monitoring systems for evaluating classes of mortars that fire to conduct remote reconnaissance. When evaluating the parameters of the mathematical model for seismoacoustic monitoring systems of the mortar explosion signal in the general case, we are faced with such a presentation of the seismoacoustic field model, which is observed when observations are complicated by additive interference. The model depends on the temporal and spatial coordinates and the vector of informative parameters of the model characterizing the research object. The model of the field formation process is defined by two vectors of free parameters of the model, and the model itself is the researcher's hypothesis about the process being modeled. We divide the parameter vectors according to how they enter the model, linearly and non-linearly. Object classification processes aim to investigate the differences between signals from different mortars to conduct remote reconnaissance for the classification of the object under study. The paper presents mathematical models of automated seismo-acoustic monitoring systems for conducting remote reconnaissance for mortar classification based on seismo-acoustic records of artillery fire. In this work, detection processes operating on one recording channel are considered. With the help of the proposed model, the object under investigation is mapped into the vector of informative parameters of the model, which characterizes this type of object. Having collected statistics on a set of different types of objects in various conditions, we can build a procedure for classifying the objects under investigation based on the classification of the vector of informative parameters of the model. The paper considers the generalization of the mathematical model of a single explosion in the case of overlapping signals in the process of recording the wave seismic field. Mathematical models of automated seismo-acoustic monitoring systems are used to model fields of mechanical elastic waves. This work presents such a model for identifying mortar weapons for remote reconnaissance. It can be concluded that this parametric model reflects the process in the feature space and characterizes the object that fires shots. Thus, the presented model maps each type of mortar fire into its n -dimensional vector of informative parameters, which enables the classification of small arms. Therefore, an effective analysis method for estimating the parameters of mortar explosion signals and an unconventional model of the natural background on which mortar explosion signals are recorded is proposed.

Keywords: seismoacoustic monitoring; mortar explosion; seismic signal; mathematical model; vector of informative model parameters.



INTRODUCTION

Nowadays, when hostilities are taking place on the territory of our country, the use of remote intelligence becomes an urgent task. Reconnaissance is the most critical type of ensuring military operations; it is a set of measures taken by all commanders and staff to timely obtain information about the enemy, the terrain, and climatic and weather conditions in the area of future hostilities to most effectively use their forces and means to defeat the enemy. Numerous examples testify that those units and units with well-organized intelligence performed the assigned combat tasks with minimal losses. Nowadays, the volume of tasks solved by intelligence has grown significantly. At the same time, the terms of their implementation have shortened considerably. The requirements for the time of data transmission and the accuracy of determining the coordinates of enemy objects (targets) have increased. The enemy's use of new long-range, high-precision, all-weather means of destruction, the high mobility of troops, and their mobile and decisive actions during the battle increased demands on intelligence, expanding the phase of active intelligence action to 24-hour. Nowadays, it is not enough to identify the enemy. The time factor, the extreme shortening of the "detection-report" cycle, is increasingly coming to the fore.

The conducted analysis of various reconnaissance systems allows us to single out seismoacoustic systems as the most effective for detecting and pointing the positions of firing artillery and determining the fact of a border violation with subsequent identification under the condition of conducting military intelligence. This statement is based on the fact that seismoacoustic systems have the following advantages: They provide stable automatic functioning in difficult weather conditions (rain, snow, fog); in conditions of poor optical visibility (night); in the direction of bright light sources (the sun); in conditions of heavy, smoky, and dusty conditions; in conditions of rugged terrain (hills, mountain passes, gorges, riverbeds, etc.). Seismoacoustic systems have complete stealth since they do not generate sounding signals; this excludes their early detection. The essential quality of these systems is the preservation of performance in modern radio-electronic suppression conditions. Such systems have small dimensions, low energy consumption, and are better than other systems (radio-location, optical-electronic, etc.) and meet the criteria of "efficiency—cost". Thus, to solve the intelligence tasks, it is proposed to create an integrated passive system for monitoring the surrounding space with a set of jointly functioning seismic-acoustic and optical-electronic sensors, means of communication, computing and software, control and indication means designed to obtain information about various types of objects, combining the incoming data from the sensors and displaying the resulting information. The use of three heterogeneous information streams significantly reduces the error when determining the coordinates of the target. The functioning of such a system will increase survivability and, therefore, the effectiveness of its means. In this case, the situation will not look like a duel (the attacker will need to neutralize a certain number of intelligence objects to exclude possible influence on him, which is not always feasible). In particular, the use of the resources of such a system provides an essential basis for the development of new ways of using both weapons and units. Thus, the development of modern technologies and means of information processing make it possible to take another step in improving the practice of using weapons systems, particularly to develop new conceptual approaches to creating a unified information intelligence system. Dynamic analysis of various systems in the monitoring mode has the following feature: the mode of processing the observed data and deciding to detect the monitoring object must be performed in a mode close to real-time. At the same time, systems are often described by rather complex models with a significant dimension of the vector of free parameters of such models. Moreover,



only some of these parameters are included in the model linearly, and most are included nonlinearly. In such cases, a priori knowledge of the processes of the system's response to disturbances plays a significant role in simplifying the process of estimating free parameters. In such cases, it is natural to build a procedure for estimating these parameters based on Bayesian estimates and, thus, consider the a priori information available to researchers. As a result, monitoring and analyzing changes in time of a set of free parameters allows us to draw conclusions about the classification of the research object and predict its detection in the future in real time.

METHODS

It is necessary to construct a mathematical model of the classification of a mortar gun, which would reflect the essential moments of the monitoring process, including the process itself, the interference accompanying this process, and the natural noise background superimposed on the experiment. 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 useful signal. This weakening is achieved by optimizing the processing procedures and considering the a priori statistics of the random interference process. The spectral parameters of the explosion's impact for each mortar type have their characteristics. The method of classification of mortar weapons to conduct remote reconnaissance consists of evaluating the spectral characteristics of the seismo-acoustic recording of the wave field of artillery shelling. For the accurate classification of mortar weapons during seismo-acoustic monitoring, it is necessary to collect statistics of mortar shelling wave field reserves, considering the transfer function that characterizes a specific type of terrain. In this work, mathematical models for the classification of mortar weapons are proposed. These models have been tested at one of the testing grounds in Ukraine. The processing results are presented below.

A new mathematical model for identifying a single mortar explosion is proposed, which reflects the most significant aspects of the monitoring process, which includes both the process itself and the interference and background noise accompanying this process imposed on a natural research. The proposed model is a nonlinear regression problem. To find an approximate solution to such a problem, the author uses non-convex optimization methods, for example, to find local minima—Livenberg-Marquardt gradient methods [1], [2], and to find a global minimum, the Monte Carlo method [3] using specific sequences is effective.

As a signal model, a superposition of solutions of a second-order differential equation was chosen, which describes a superposition of oscillators that entered at different times, having their eigenfrequency and corresponding amplitudes.

The optimal estimation of the signal parameters consists in determining the vector of free parameters that minimize the value of the criterion of agreement between the model and the observed data. Such a model is supported by the fact that it gives good agreement in the case of modeling a linear system of oscillating objects and, thus, takes into account the oscillating nature of the observed data and its simplicity. Thus, the presented model displays each type of mortar firing shots into its n-dimensional vector of informative parameters, making classifying small arms possible. To evaluate the informative parameters of the proposed model of the automated seismo-acoustic monitoring system, the article solves the problem of nonlinear regression, considering them as the point of the criterion optimum in the n-dimensional space.



Mathematical model. Physical ideas about the nature of mortar explosion signals, taking into account the multimodality of its spectrum, allow us to put forward a hypothesis about the possibility of modeling it as follows:

$$y_m(t) = \sum_{l=1}^L S_{ml} \exp\{-\mu_{ml}t\} \sin(\omega_{ml}t + \varphi_{ml}) + n_m(t) \quad (1)$$

In the last expression, m is the number of registered signal. Optimal estimation of the parameters of the mathematical model of seismoacoustic monitoring of the flow of permitted signals of mortar explosions in the seismoacoustic frequency range.

$$\mathbf{y} = \{y_m(t)\}; \quad m = \overline{1, M} \quad (2)$$

Here, M is the number of mortar explosion signals. $S_{ml}, \mu_{ml}, \omega_{ml}, \varphi_{ml}$ — free parameters of the model, n — additive noise in measurements of the m -th explosion. \mathbf{L} is a set of analyzed submodels of the same type, the superposition of which models the process $y_m(t), l \in \Lambda$.

The problem is to determine the free parameters of the model optimally. The optimality criterion is the degree of closeness of the model to the observed data in the selected metric. Based on the physical conditions of setting the task, it is advisable to choose the metric L_2 . In the metric L_2 , the criterion is the functional of each of the components of the form:

$$F_m(\mathbf{P}_m) = \left\| \left(\sum_{l=1}^L S_{ml} \exp\{-\mu_{ml}t\} \sin(\omega_{ml}(t - \varphi_{ml})) \right) - y_k(t) \right\|_{L_2}; \quad k = \overline{1, K} \quad (3)$$

Here, the free parameters of the model describing the mortar explosion signal with the number k are summarized in the \mathbf{P}_k matrix. The s th column in this matrix is a vector of free parameters $\mathbf{P}_k^{(s)}$ of the same submodel with the number s .

$$\mathbf{P}_m^{(l)} = \begin{Bmatrix} S_{ml} \\ \mu_{ml} \\ \omega_{ml} \\ \varphi_{ml} \end{Bmatrix}, \quad l = \overline{1, L} \quad (4)$$

As a result of the analysis, we conclude that the model at $L=3$ gives an entirely satisfactory agreement of the observed data with the model. The model at $L=4$ increases agreement by only 5% in metric L_2 , but at the same time the dimensionality of the problem increases significantly: the space of estimated parameters changes from 12 dimensional to 16 dimensional. We see that the further increase in the dimensionality of the model in this particular case makes no sense. If we take into account that each parameter of the model should be considered as the noise it brings to the model (this phenomenon in statistics is called the “curse of dimensionality”), then for this case the model with 12 free parameters is the limit in complexity for models of the selected type for data obtained in this experiment.

In the calculations, we used the notation for the 12th parametric model. For the convenience of calculating the free parameters of the model (2), we present this model in the form:

$$M(t, \mathbf{P}_m) = \sum_{l=1}^L P_{m,1+4(l-1)} \left\{ \exp[-P_{m,2+4(l-1)}t] \times \sin[P_{m,3+4(l-1)}(t - P_{m,4+4(l-1)})] \right\} \quad (5)$$

Here parameters $P_{m,1+4(l-1)}, P_{m,2+4(l-1)}, P_{m,3+4(l-1)}, P_{m,4+4(l-1)}$ are amplitudes, logarithmic decrements, corner frequencies, and phase shifts for each of the submodels $l = \overline{1, L}$, respectively.



To determine the extremum points of our criterion $F_m(\mathbf{P}_m)$, we look for a $\min\{F_m(\mathbf{P}_m)\}$; $m = \overline{1, M}$; $\mathbf{P}_m \in A_m$ on a set A_m of possible values \mathbf{P}_k of a vector function consisting of partial derivatives of the model $\partial M(t, \mathbf{P}_m) / \partial P_{m,j} = 0$; $j = \overline{0, 11}$ for each parameter $\partial P_{m,j}$.

$$\begin{aligned} \frac{\partial M(t, \mathbf{P}_m)}{\partial P_{m,1+4(l-1)}} &= \exp[-P_{m,2+4(l-1)}t] \times \sin[P_{m,3+4(l-1)}(t - P_{m,4+4(l-1)})], \quad l = \overline{1, L} \\ \frac{\partial M(t, \mathbf{P}_m)}{\partial P_{m,2+4(l-1)}} &= -tP_{m,1+4(l-1)} \exp[-P_{m,2+4(l-1)}t] \times \sin[P_{m,3+4(l-1)}(t - P_{m,4+4(l-1)})], \quad l = \overline{1, L} \\ \frac{\partial M(t, \mathbf{P}_m)}{\partial P_{m,3+4(l-1)}} &= P_{m,1+4(l-1)}(t - P_{m,4+4(l-1)}) \exp[-P_{m,2+4(l-1)}t] \times \cos[P_{m,3+4(l-1)}(t - P_{m,4+4(l-1)})], \quad l = \overline{1, L} \\ \frac{\partial M(t, \mathbf{P}_m)}{\partial P_{m,4+4(l-1)}} &= -P_{m,1+4(l-1)}(t - P_{m,4+4(l-1)}) \exp[-P_{m,2+4(l-1)}t] \times \cos[P_{m,3+4(l-1)}(t - P_{m,4+4(l-1)})], \quad l = \overline{1, L} \end{aligned} \quad (6)$$

Using the Monte Carlo method, according to a priori distributions, a point in the n-dimensional space is thrown out; in the neighborhood with a local extremum, we find the global one, which gives the minimum of the criterion (3).

The values of frequencies and logarithmic decrement of the object of study have physically meaningful values. The latter are especially important, since they give an idea of the quality factor of the system, its ability to accumulate and retain for a time the energy of external disturbances. A high-quality factor (low decrement) at some frequencies in the model characterizes the special sensitivity of the object to external disturbances at these frequencies. For example, dynamic changes in the decrement towards a decrease indicate an object's readiness for destruction from a weak external influence. Unfortunately, the Monte Carlo method in the article converges to a solution only by probability. The number of calculation cycles must be large enough to be confident in the correctness of the result, which becomes complicated when the model dimension is large. Or you need to have good a priori ideas about the expected result. The following are the optimal parameters for the signal.

Using the Monte Carlo method, according to a priori distributions, a point in the n-dimensional space is thrown out; in the neighborhood with a local extremum, we find the global one, which gives the minimum of the criterion (3).

So, we find the global minimum of the functional $F_m(\mathbf{P}_m)$ on the set A_m of admissible vectors \mathbf{P}_m with a known a priori distribution.

$$\min\{F_m(\mathbf{P}_m)\}, \quad m = \overline{1, M}; \quad \mathbf{P}_m \in A_m.$$

Calculation results for a model with n damped harmonics are summed vectors of dimension n, combining one-dimensional parameters, i.e., a parametric model of dimension $n \times 4$ is considered.

THE RESULTS

Let's analyze the quality of the optimal model. Model with free parameters is presented. The evaluation of the model's quality is the criterion's value at the point of the global minimum. Fig. 1 presents a fragment of a recording of a mortar explosion and a mathematical model of this fragment.

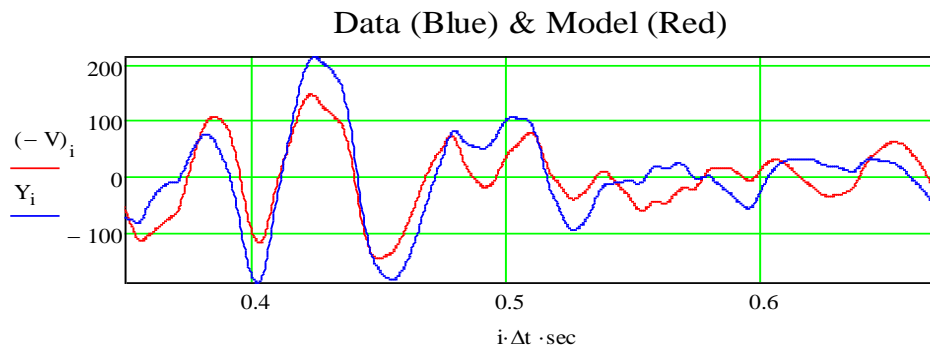


Fig. 1. A fragment of the mortar explosion signal recording against background noise (blue line). A model approximating this signal, the free parameters of which are obtained as a result of evaluating the optimal parameters of criterion (3) (red line). The abscissa represents time in seconds; the ordinate represents the amplitude of the oscillation speed in relative units

The above calculations illustrate their role in computerized technology, which estimates free parameters in models and data. These calculations pertain to only one of the components of recording oscillating acceleration, but the process for the other component follows a similar technological cycle.

Transposed vector of amplitudes of natural frequencies:

$$\mathbf{S}^T = \{1,102 \ 0,638 \ 0,324\}$$

Transposed vector of decrements at natural frequencies:

$$\boldsymbol{\mu}^T = \{0,076 \ 0,068 \ 0,938\}$$

Transposed natural frequency vector:

$$\boldsymbol{\omega}^T = \{0,291 \ 2,436 \ 15,831\} \Gamma_{\Pi}$$

The discrepancy between the resulting model and the observed data is 7% in metric. L_2 .

GENERALIZATION OF THE MODEL

A new model of passive monitoring has been created. The model considers physical concepts of the nature and character of the object's oscillations. The multimodality of its spectrum allows us to put forward a hypothesis about the possibility of modeling it by a superposition of oscillators with damping. Physically, the local value is looming ahead of the frequency values that are logarithmic to the monitored object's decrement. It is essential to indicate the system's quality factor and ability to accumulate and manage the energy of current storms at any time. Unfortunately, the Monte Carlo method, shown in statistics, allows saving up to the decision made solely for fairness. The number of cycles to calculate may be significant for the accuracy of the result, which becomes complicated with the large model size. Otherwise, it is necessary to have good priori statements about the recovery results. Next, the optimal parameters for the first signal are given. At this point, the detection and mortar fire model at low signal-transformation is improved. This leads to problems with signal detection and the presence of seismic noise. Seismic background noise establishes a natural boundary that can be detected by seismic equipment. The culprits of instrumental seismology and seismic noise are given great respect. It has been noted that the nature of seismic noise is complex. Warehouses of noise have a different nature, and today, there is no longer any way to feed the physical



nature of noise. In this section there is an emphasis on the statistical power of seismic noise, as information is essential to increase the intensity of the signal

The model can be generalized to a more complex case: the flow of illegal signals, i.e., when signal carriers cross. Then the signal model for each sensor is:

$$y(t) = \sum_{k=1}^K \sum_{l=1}^L \eta(t - \tau_{k,l}) S_{k,l} \exp\{-\mu_{k,l}t\} \sin(\omega_{k,l}t + \varphi_{k,l}) + n(t) \quad (7)$$

Here $\eta(t - \tau_{kl})$ is the Heaviside function of each submodel of each signal, K is the number of intersecting signals in the group, i.e., the group consists of unresolved signals. In general, K is a random value. In the matrix of free parameters $\{S_{kl}, \tau_{kl}, \mu_{kl}, \omega_{kl}, \varphi_{kl}\}$ of the model (7). Parameter τ_{kl} is the signal time of arrival of each submodel of each signal.

For the convenience of calculating the free parameters of the model (7), we present this model in the form:

$$M(t, \lambda) = \prod_{k=1}^K \prod_{i=0}^L h(t - l_{0+i,k}) l_{1+i,k} \exp^{-l_{2+i,k}(t - l_{0+i,k})} \sin[l_{3+i,k}(t - l_{0+i,k})] \prod_{i=0}^L \quad (8)$$

where K is the number of intersecting signals in the group, i.e., the group consists of unresolved signals. In general K is a random value. In the matrix of free parameters of the model (8). $\Lambda = \{l_{k,l}\}; k = \overline{0, K}; l = \overline{1, L}; L = 4I;$

A column with a number k is a vector of parameters of the k -th signal. In this parameter vector, the $\text{mod}(k, 4)$ is the number $\lambda_0, \lambda_1, \lambda_2,$ or λ_3 of the corresponding decaying harmonic parameter. This harmonica has a number $\text{ant}(k, 4)$. We adopt the following symbols: $\text{mod}(k, 4)$ —this is the remainder from dividing the number k by 4, and $\text{ant}(k, 4)$ —this is the whole part from dividing k by 4.

The example of a model (2) considered above can be considered a special case of this more general model (6) when $l_{0+i,k}$ it does not depend on i . Then each harmonic, one of the oscillators, is one of the components of the optimal signal.) is a separate signal from a group of unresolved signals, each with its own onset time.

The optimal estimate of the matrix of free parameters in the model (6) Λ is obtained as an estimate of the free parameters that gives the minimum value of criterion (3) at a set of local minima of this criterion. Each local minimum is calculated as in the case of model (1). The procedure for obtaining an optimal estimate is that for a set of M pseudo-random matrices Λ , the points of local extremes closest to each are determined. Then, a global one is selected for a set of local minima. The point that gives this criterion minimum in the $(K + 1) \cdot S$ dimensional space and is chosen as optimal for the free parameters of the signal model. As before for model (1), in this procedure, we are provided with convergence to the optimal solution in terms of probability with an increase in the number M of pseudo-random matrices Λ .

In this case, we can consider that as a result of the solution, we obtained a superposition of three signals that entered at different times (in our example, in the interval from the moment of entry of the first oscillator to the moment of entry of the last one.



CONCLUSIONS

A mathematical model for identifying a mortar explosion is considered, reflecting the most significant aspects of the monitoring process, including the process itself and the interference and noise background accompanying this process imposed on the investigation. The model is a nonlinear regression problem for which nonlinear optimization solution approaches are used.

Mathematical models of automated systems of seismoacoustic monitoring are used to model fields of mechanical elastic waves [4] – [8]. This paper presents such a model for identifying mortar weapons for remote reconnaissance. We can see that the informative parameters of the signal model characterize the above-described process with a high degree of sufficiency. We can conclude that this parametric model maps the process into the feature space and characterizes the object that fires the shots. Thus, the presented model (1) displays each type of mortar firing shots into its n-dimensional vector of informative parameters, making classifying small arms possible. Thus an effective analysis method is proposed for estimating the parameters of mortar explosion signals, and non-traditional model of the natural background against which signals of mortar explosions are recorded is proposed.

REFERENCES (TRANSLATED AND TRANSLITERATED)

1. K. Levenberg. (1944). A method for the solution of certain non-linear problems in least squares. *Quart. Appl. Math.*, 2, 164–168.
2. D. Marquardt. (1963). An algorithm for least-squares estimation of nonlinear parameters. *J. Soc. Indust. Appl. Math.*, 11, 431–441.
3. Kroese, D. P., Brereton, T., Taimre, T., & Botev, Z. I. (2014). Why the Monte Carlo method is so important today. *WIREs Comput Stat.* 6(6), 386–392. <https://doi.org/10.1002/wics.1314>
4. Mostovyy, S., Mostovyy, V., & Osadchuk, A. (1996). A mathematical model of prediction of seismic events. *Proceedings of the second workshop "Application of artificial intelligence techniques in seismologic and engineering seismology" Consel de l'Europe Cahiers Europeen de Geodinamiqueet de seismologie*, 12, 163–164.
5. Mostovyy, S., Mostovyy, V., Osadchuk, A. (1996). Processing of seismic signals under coastal background noise. *Application of artificial intelligence techniques in seismologic and engineering seismology Consel de l'Europe Cahiers Europeen de Geodinamiqueet de seismologie*, 12, 297–299.
6. Mostovyy, V., Mostovyy, S., Osadchuk, A., & Gay, A. (1997). On-line systems of monitoring of ecologically hazardous objects. *Transactions of KDS-97*, 1, 456–465.
7. Mostovyy, V., & Mostovyy, S. (2014). Estimation of parameters of seismic waves. *Transactions of NAS of Ukraine*, 2, 118–123.
8. Mostovoy, V. S., Mostovyi, S. V. (2016). Mathematical model of seismic signal, as a flow of physically non realizable single seismic waves. *Geophysical Journal*, 38(5), 166–169.

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СЕЙСМОАКУСТИЧНОГО МОНІТОРИНГУ КЛАСИФІКАЦІЇ МІНОМЕТНОГО
ВИБУХУ ДЛЯ ВЕДЕННЯ ДИСТАНЦІЙНОЇ РОЗВІДКИ**

Анотація. Розвідка є найважливішим видом забезпечення бойових дій військ, вона є сукупністю заходів усіх командирів і штабів із метою своєчасного отримання інформації про противника, місцевість, кліматичні і погодні умови в районі майбутніх бойових дій з метою найбільш ефективного застосування своїх сил і засобів щодо ураження противника. В роботі представлено математичні моделі для автоматизованих систем сейсмоакустичного моніторингу для оцінки класів мінометів, які проводять обстріл з метою ведення дистанційної розвідки. При оцінці параметрів математичної моделі для систем сейсмоакустичного моніторингу сигналу мінометного вибуху в загальному випадку, ми стикаємося з таким поданням моделі сейсмоакустичних полів, що спостерігаються, коли спостереження ускладнені адитивною завадою. Власне модель залежить від часової, просторової координати, та вектору інформативних параметрів моделі, що характеризують об'єкт дослідження. модель процесу формування поля визначається двома векторами вільних параметрів моделі, а сама модель є гіпотезою дослідника про процес, що моделюється. причому ми поділяємо вектори параметрів тому, як вони входять у модель, лінійно, та — не лінійно. Мета процесів класифікації об'єктів полягає в тому, щоб дослідити відмінності між сигналами від різних мінометів, з метою ведення дистанційної розвідки для класифікації досліджуваного об'єкта. В роботі представлені математичні моделі автоматизованих систем сейсмоакустичного моніторингу ведення дистанційної розвідки з метою класифікації мінометної по сейсмоакустичним записам артилерійських обстрілів. В даній роботі розглядаються процеси виявлення, що працюють на одному каналі запису. За допомогою запропонованої моделі об'єкт, що досліджується, відображається у вектор інформативних параметрів моделі, який характеризує даний тип об'єкта. Набравши статистику на множині різних типів об'єктів у різних умовах ми можемо побудувати процедуру класифікації об'єктів, що досліджуються, за класифікацією вектору інформативних параметрів моделі. В роботі розглянуто узагальнення математичної моделі одиночного вибуху на випадок накладання сигналів в процесі запису хвильового сейсмічного поля. Математичні моделі автоматизованих систем сейсмоакустичного моніторингу використовуються для моделювання полів механічних пружних хвиль. У даній роботі представлена така модель для ідентифікації мінометного озброєння для дистанційної розвідки. Можна зробити висновок, що дана параметрична модель відображає процес у простір ознак і характеризує об'єкт, що робить постріли. Таким чином, представлена модель відображає кожен тип пострілів мінометної стрільби у свій n -мірний вектор інформативних параметрів, що уможливило класифікацію стрілецької зброї. Таким чином, запропоновано ефективний метод аналізу для оцінки параметрів сигналів вибухів мінометів, а також запропоновано нетрадиційну модель природного фону, на якому реєструються сигнали вибухів мінометів.

Ключові слова: сейсмоакустичний моніторинг; мінометний вибух; сейсмічний сигнал; математична модель; вектор інформативних параметрів моделі.



СПИСОК ВИКОРИСТАНИХ ДЖЕРЕЛ

1. K. Levenberg. (1944). A method for the solution of certain non-linear problems in least squares. *Quart. Appl. Math.*, 2, 164–168.
2. D. Marquardt. (1963). An algorithm for least-squares estimation of nonlinear parameters. *J. Soc. Indust. Appl. Math.*, 11, 431–441.
3. Kroese, D. P., Brereton, T., Taimre, T., & Botev, Z. I. (2014). Why the Monte Carlo method is so important today. *WIREs Comput Stat.* 6(6), 386–392. <https://doi.org/10.1002/wics.1314>
4. Mostovyy, S., Mostovyy, V., & Osadchuk, A. (1996). A mathematical model of prediction of seismic events. *Proceedings of the second workshop "Application of artificial intelligence techniques in seismologic and engineering seismology" Consel de l'Europe Cahiers Europeen de Geodinamiqueet de seismologie*, 12, 163–164.
5. Mostovyy, S., Mostovyy, V., Osadchuk, A. (1996). Processing of seismic signals under coastal background noise. *Application of artificial intelligence techniques in seismologic and engineering seismology Consel de l'Europe Cahiers Europeen de Geodinamiqueet de seismologie*, 12, 297–299.
6. Mostovyy, V., Mostovyy, S., Osadchuk, A., & Gay, A. (1997). On-line systems of monitoring of ecologically hazardous objects. *Transactions of KDS-97*, 1, 456–465.
7. Mostovyy, V., & Mostovyy, S. (2014). Estimation of parameters of seismic waves. *Transactions of NAS of Ukraine*, 2, 118–123.
8. Mostovoy, V. S., Mostovyi, S. V. (2016). Mathematical model of seismic signal, as a flow of physically non realizable single seismic waves. *Geophysical Journal*, 38(5), 166–169.

