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USE OF BACKSCATTERING ULTRASOUND PARAMETERS FOR IRON ORE VARIETIES RECOGNITION

Purpose. Development of the method for recognizing the main mineral-technological varieties of iron ore in the deposits being developed by selecting an analytical model for the spectral characteristics of the received ultrasonic echo signals and quantitative assessment of their parameters.

Methodology. The work uses methods for modeling the processes of propagation of ultrasonic waves in a randomly heterogeneous medium. The process of backscattering of ultrasound in mineral structures formed by inclusions of iron ore of various varieties and associated rock was considered. The estimated parameters of the spectral characteristics of the inversely scattered probing ultrasound pulse were studied.

Findings. A method for recognizing the main mineral and technological varieties of iron ore of the deposit being developed, based on the parameters of the propagation of ultrasonic waves in the studied samples, was proposed. This is achieved by selecting an analytical model for the spectral characteristics of the received echo signals and quantifying their parameters. The amplitude of the echo signal and its spectral properties depends on the size and concentration of the scatterers, i.e., the structural and textural features of the iron ore sample under study. Taking into account these factors, the extracted parameters of the model were used to identify the main mineralogical and technological varieties of iron ore of the studied deposit.

Originality. The proposed method for recognizing mineral-technological varieties of iron ore differs from the known ones in that the amplitude, central frequency, and bandwidth of the amplitude spectrum of the Gaussian parametric model of the measured echo signals are used as evaluation parameters.

Practical value. The proposed scientific and technical solution allows for operational non-destructive control of the main mineralogical and technological types of iron ore in the process of its extraction and processing.

Keywords: *ultrasonic analysis, backscattering, iron, mineral varieties*

Introduction. Iron-containing ores are an important raw material for the mining and metallurgical industries. They are a complex combination of mineral formations and associated rock. Mineralogical analysis of iron ore is necessary at all stages of its extraction and preparation for metallurgical processing, for example, for operational control and effective control of beneficiation processes [1]. Modern control systems of mining production processes work in conditions of incomplete and unclear information about processed raw materials [2]. Therefore, the development of methods for operational assessment of mineralogical characteristics of iron ore that is mined and processed is an important scientific and technical task [3].

Ultrasonic methods are a powerful tool for solving this task, since ultrasonic waves are absorbed and scattered by mineral formations, and the measurement and further analysis of these and other interrelated parameters allow evaluating the physical-mechanical and chemical-mineralogical characteristics of the ore. The intensity of scattered ultrasonic waves largely depends on the frequency. This can be used to characterize the studied ore by spectral analysis of reflected waves (measurement of acoustic echo parameters) or waves (measurement of transmission parameters) that passed through the studied volume [4].

Literature review. In the practice of ultrasonic measurements, the inhomogeneity of the acoustic impedances of the structural formations of the sample under study leads to the scattering of the sounding ultrasonic pulse [5]. The spatial position of the scatterer causes a phase difference due to the superimposition of waves. Such regularities are determined and described by first- and second-order statistics.

Scattering occurs during the propagation of elastic waves in an inhomogeneous medium, which is determined by random spatial fluctuations of its elastic properties. While classical analytical studies are based on lower-order scattering assumptions, numerical methods, in contrast, do not have such limitations because they inherently involve multiple scattering. However, most studies have generally been limited to two or one dimension due to computational limitations [6].

Quantitative methods of ultrasound analysis have been developed and evaluated based on the envelope of backscattered ultrasound. The envelope of scattered ultrasound can be modeled as a superposition of signals scattered from individual scatterers in the environment being studied [7]. Thus, the envelope signal is statistical in nature. By applying the model to the amplitude distribution of the envelope, it is possible to obtain information about the scatterer number density and the organizational structure.

Investigation of the statistics of envelope harmonic signals in order to relate the parameters of the distribution to the nonlinear coefficients provided in [8]. The main results show that the distributions show different behavior for fundamental and harmonic signals and that environments with different nonlinearities can be distinguished when using the Nakagami statistic for the harmonic signal.

Attenuation is one of the main analyzed parameters of the ultrasound propagation process, as its value is closely related to the characteristics of the studied environment. Attenuation estimates are characterized by high variance due to the stochastic nature of the scattered ultrasound signal, and some special preprocessing methods are used to improve the quality of the obtained estimates. The paper [9] presents the application of spatial compounding (SC), frequency compounding (FC) and their combination. The obtained parametric results are compared by root mean square errors. The analysis shows that the combined SC and FC methods significantly improve the quality and accuracy of parametric attenuation distribution estimation results.

Time-of-flight (TOF) is widely used in ultrasonic nondestructive examination (NDE). In [10], a model-based method for estimating the parameters of the ultrasonic echo is proposed. It is assumed that the ultrasound signal consists of an unknown number of Gaussian echoes distorted by Gaussian white noise. The Hilbert transform is used to extract the envelope of the signal. The quasi-maximum likelihood method is used to estimate the parameters of the signal envelope. The number of echo signals is estimated using the agreed information criterion of Akaika [11]. Two measures are used to evaluate the effectiveness of the proposed method: the probability of detecting reflected echo signals and the error of the estimated flight time. The proposed approach is compared with the methods of cross-correlation and maximum likelihood, in which the output signal is used. Simulated and experimental signals are used to evaluate the performance of each method. Both experimental and simulated results show that the proposed method can improve parameter estimation, which ultimately improves damage detection and assessment.

Ultrasonic control of heterogeneous media largely depends on the quality of simulation of the expected signals for detection and correct interpretation of the structure of the sample under study. In work [12], disturbing factors affecting the parameters of ultrasonic waves in polycrystalline media are studied. One of them is scattering due to the granular microstructure of the polycrystal. The resulting microstructural noise varies depending on the granulometric composition and the frequency of the ultrasonic waves used in [13]. A method for simulating this noise by means of geometrical modeling of the granular microstructure to determine its influence on the scattered ultrasonic signal is presented. For this purpose, Laguerre mosaics are used, generated by random packing of spheres that divide the space into convex polyhedral cells.

Data acquisition time and storage requirements become increasingly important in signal processing applications as data sets grow in size. Compressive Sensing (CS) has emerged as an alternative processing method because the original signals can be reconstructed using fewer data samples collected at frequencies below the Nyquist sampling rate. However, further analysis of CS data in both the time and frequency domains requires the reconstruction of the original data form in the time domain, since traditional signal processing techniques are designed for compressed data. In paper [14], a signal processing framework is proposed that extracts spectral properties for frequency domain analysis directly from undersampled CS ultrasound data.

Thus, the theoretical and practical results of the analysis of the process of ultrasound propagation in heterogeneous media allow us to draw a conclusion about the feasibility of using the scattering parameters of probing signals to assess their structural and textural properties.

Purpose. The purpose of the presented work is to develop a method for recognizing the main mineral and technological varieties of iron ore of the deposit being developed. This is achieved by selecting an analytical model for the spectra of the received echo signals and quantifying their parameters.

Methods. Iron ore is a randomly heterogeneous medium containing mineral formations with densities and compressibility that vary relative to the host rock and other inclusions. Currently, the methods for evaluating the characteristics of iron ore based on measurements of the propagation parameters of ultrasonic waves have become widespread. The speed of propagation and the amount of attenuation of ultrasound are most often used. Thus, according to the results of research conducted on samples of various mineral varieties of iron ore of the Kryvyi Rih iron ore basin, the propagation speed of longitudinal ultrasonic waves was 4100–5800 m/s, transverse – 2300–2900 m/s, and the attenuation was 23–44 dB/m. These dependencies are an estimate of the physical and mechanical characteristics of the ore. At the same time, it should be noted that for the successful recognition of at least the main mineralogical and technological types of ore of the studied deposit, the specified parameters and their interrelationships are not enough. Thus, according to the results obtained for the studied deposit, the correlation coefficient between the velocities of longitudinal (C_L) and transverse (C_T) waves and the density ρ of rocks is 0.53–0.72, between C_L, C_T and elastic characteristics (Young's modulus, coefficient Poisson, shear modulus) – 0.55–0.94 and the correlation coefficient between the attenuation coefficient with the same characteristics does not exceed 0.71 [15].

To improve the quality of operational mineralogical analysis of iron ore, it is proposed to use the parameters of the process of propagation of backscattered ultrasonic waves formed in the studied environment.

In the works by Lazarenko O. K., Pirogov B. I. and other authors, a description of the mineral composition, as well as the size of individuals and aggregates in the layers of hornblendes and jespilites of the magnetite deposits of the Kryvyi Rih iron ore basin is given. Magnetite is one of the most common minerals of the Kryvyi Rih Basin. It is part of iron ores and ferrous rocks as an important ore-forming mineral. The distribution of types of magnetite aggregates in some ore formations is given in Table 1.

In mineral varieties, individual types of magnetite aggregates are unevenly distributed (Table 2).

Magnetite aggregates contain a significant number of individuals characterized by a multifaceted structure (polyhedral). Aggregates and individuals with tortuous and irregular contours are also present, differing in the morphology of aggregate types: solid, ribbon, polyhedral, branched, granular interspersed (Fig. 2). Moreover, 50–80 % of magnetite in corneas is represented by aggregates and grains of various degrees of idiomorphism. Magnetite grains often acquire an elongated lenticular, rectangular shape and uneven winding intergrain boundaries.

The given information indicates that the texture and structure of mineral formations in iron ore can be used to identify its mineralogical and technological varieties.

The influence of absorption and scattering on the propagation process of the echo signal received by the ultrasonic sensor manifests itself in the aggregate as a decrease in its amplitude. The process of ultrasound scattering in rock depends on many geometric factors, such as the size, shape and spatial distribution of the scattering objects, as well as on physical fac-

Table 1

Characteristic of the mineral composition and size of individuals and aggregates by layers of magnetite hornblende and jespilites of the Skelevatsky magnetite deposit

Corneals and jespilites	Types of layers	Magnetite			Quartz	
		Size, mm		Con-tent, %	Grain size, mm	Con-tent, %
		grain	unit			
Magnetite	Rudney	0.15	0.35	90	0.04	8.5
	mixed	0.11	0.18	37.5	0.04	59.5
	Non-ore	0.06	0.00	3	0.07	95

Table 2

Distribution of types of magnetite aggregates in ore layers of hornblendes and jespilites

Corneals and jespilites	Unit type			
	Polyhedral	Branched	Ribbon	Solid and interspersed
Magnetite	50	40	5	5
Carbonate-chlorite-magnetite	50	35	15	0
Hematite-magnetite	80	10	5	5

tors, such as the elastic characteristics and density of the material from which these objects are composed. Fig. 1 schematically presents the process of ultrasonic wave scattering on structural formations in a heterogeneous environment [16].

An ultrasonic wave $\hat{\imath}$ falls on a representative scattering site with density ρ and compressibility κ. The scattering location of the inclusion is surrounded by a medium with density ρ_0 and compressibility κ_0. In real conditions, both separate formations (mineral inclusions) and fragments of the environment (for example, accompanying rock) can have their own properties. Any point in space within the scattering is denoted by the position vector *r*. The scattered ultrasonic wave is observed at a spatial point denoted by the position vector r_0. It propagates in the ô direction and is characterized by the distance *R* from the scattering point. The scattering angle between the direction of the incident and scattered waves is denoted by θ. Falling it propagates in the direction $\theta = 0°$.

Depending on the ratio of the ultrasound wavelength and the size of the scatterers in the studied sample, three types of scattering are distinguished. Specular scattering occurs when the size of the scatterers is much larger than the wavelength of the ultrasound. At the same time, the ultrasonic wave can be reflected or transmitted through the boundary between the diffuser and the environment. Diffuse scattering occurs when structural entities are much smaller than the wavelength of the ultrasound. And, finally, with diffraction scattering, the wavelength of ultrasound and the size of the scattering formations are commensurate. In this case, the incident wave is equally dispersed in all directions.

Existing models of ultrasound scattering allow obtaining numerical parameters describing the number of scatterers and their spatial distribution from the information contained in the characteristics of the enveloping echo signal. The work [17] describes the characteristics of the most commonly used models of ultrasound scattering. The simplest scattering model is a discrete model, in which a wave propagates in a homogeneous medium with inclusions whose properties depend on the properties of this medium. The ability of a point object to scatter a wave is described by one parameter – the scattering cross section. Also used is the backscattering coefficient, which is a measure of the power scattered by the object in the direction opposite to the direction of the incident wave.

The point model of the signal $s(t)$ assumes separate sources located in the resolution cell as scatterers

$$s(t) = \sum_{n=1}^{N} a_n \cos(w_0 t + \varnothing_n),$$

where w_0 is the average frequency of the excitation pulse; *N* is the number of scatterers.

Phases are modeled as uniformly distributed [0; 2], and the amplitude is usually assumed to be normally distributed. The fully diffuse scattering model assumes the presence of a large number of scatterers, so the diffuse echo signal can be expressed as $\varnothing_n \pi$

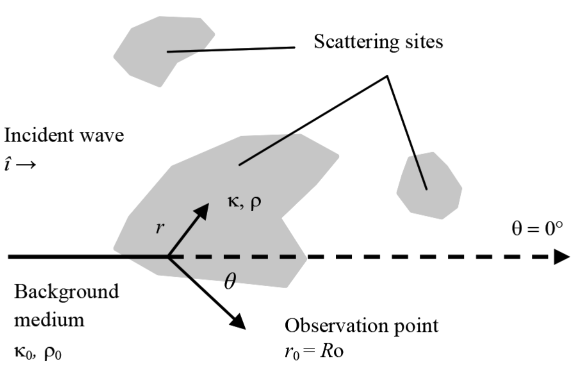


Fig. 1. Scheme of ultrasound scattering on structural formations in a heterogeneous environment

$$s(i) = X\cos(w_0 t) + Y\sin(w_0 t),$$

where *X* and *Y* are identical Gaussian distributions with zero mean.

In the event that the backscattered echo signal has a fair expression, we have the Rayleigh distribution [18], the probability density of which has the following expression $R = \sqrt{X^2 + Y^2}$

$$f_R(r) = \frac{r}{\sigma^2} e^{-\frac{r^2}{2\sigma^2}} u(r),$$

where $u(\cdot)$ is the Heaviside step function defined as

$$u(x) = \left\{ \begin{matrix} 0, \ x < 0 \\ 1, \ x \le 0 \end{matrix} \right\}.$$

With the previously made assumption about a large number of effective scatterers, but in the presence of resolvable structures in the resolution cell (mirror component), *X* and *Y* become nonzero Gaussian distributions. In this case, the shell no longer follows the Rayleigh distribution, but corresponds to the Rice distribution [19].

$$f_{Rician}(r) = \frac{r}{\sigma^2} e^{-\frac{r^2 + C^2}{2\sigma^2}} I_0\left(\frac{rC}{\sigma^2}\right) u(r),$$

where $I_0(\cdot)$ is a modified Bessel function of the first kind.

The Rice distribution transforms into a Gaussian distribution and into a Rayleigh distribution in the extreme cases of very large and very small signal-to-noise ratios.

The K-distribution models the case when the number of scatterers is itself a random variable, which is modeled as a Poisson distribution, the local mean of which is a gamma distribution [20]. The K-distribution is formed by joining two separate probability distributions [17]. The model used to represent the observed intensity X involves the union of two gamma distributions. The probability density function of the gamma distribution has the form

$$f(x; a, b) = x^{a-1} \frac{1}{b^a \Gamma(a)} e^{-\frac{x}{b}},$$

where $\Gamma(x)$ is the material Gamma function

$$\Gamma(x) = \int_0^{-\infty} t^{x-1} e^{-t} dt, \quad x > 0.$$

Parameter *a* can be considered as a shape parameter and *b* as a scale parameter.

Unlike the previously discussed models, Nakagami's model is not based on physical arguments. However, empirically it has shown better performance than the Rayleigh and Rice distributions. The probability density of the Nakagami distribution has the form [21]

$$f_{Nak}(x; \mu, w) = \frac{2\mu^\mu}{\Gamma(\mu) w^\mu} x^{2\mu - 1} e^{\frac{\mu}{w} x^2},$$

where $w = E(X^2)$ is a positive parameter controlling the spread, $\mu = \frac{E^2(X^2)}{D(X^2)}$ is a shape parameter, $\mu > \frac{1}{2}$.

The shape parameters of the K-distribution and the Nakagami distribution are directly related to the effective number of scatterers. The shape parameter of the gamma distribution also depends on the density of scatterers, but not linearly [17].

The given mathematical expressions of ultrasound scattering models can be used to analyze and evaluate real distributions obtained from experimental data and, in particular, to determine envelope parameters.

The envelope of the signal in the time domain is its instantaneous amplitude, which changes in time [22]. In the time domain, the real part of the analytical signal x_a(t), is just the output signal $x(t)$, and the new imaginary part $x_h(t)$ is calculated using the Hilbert transform $x_h(t) = HT\{x(t)\}$, which suppresses negative frequency components, i. e.

$$x_a(t) = x(t) + jx_h(t).$$

The mathematical definition of the Hilbert transformation $x(t)$ is carried out according to the expression

$$x_h = pv\int_{-\infty}^{\infty}\frac{x(t)}{\pi(t-\tau)}d\tau,$$

where pv is the principal value of the Cauchy integral.

Then the envelope of the signal E is defined as the amplitude of the analytical signal

$$E = \sqrt{x(t)^2 + x_h(t)^2}.$$

An alternative approach is presented in the works by Marple S.L. It is based on the calculation of parameters of analytical signals of the discrete time domain based on spectral properties. In this procedure, $X[m]$ are the coefficients of the N-point discrete Fourier transform (DFT) of the output signal $x[n]$ and is defined as

$$X[m] = T\sum_{n}^{N-1}x[n]\exp(-j2\pi fnT),$$

where $x[n] = x(nT)$.

Thus, the DFT coefficients of the analytical signal $Z[m]$ can be obtained from $X[m]$ as follows [22].

$$Z[m] = \begin{cases} X[0], & \text{for} \quad m = 0 \\ 2X[m], & \text{for} \quad 1 \le m \le \frac{N}{2}-1 \\ X\left[\frac{N}{2}\right], & \text{for} \quad m = \frac{N}{2} \\ 0, & \text{for} \quad \frac{N}{2}+1 \le m \le N-1 \end{cases}.$$

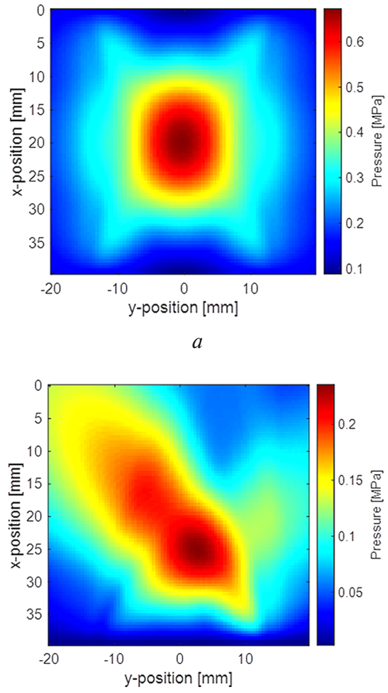
The envelope is calculated directly from the real and imaginary parts of the complex analytical signal with discrete time $x[n]$ and $x_h[n]$, respectively, as follows

$$E = \sqrt{x[n]^2 + x_h[n]^2}.$$

Results. Simulation of the ultrasonic field in iron ore samples was carried out using the k-Wave software package for MATLAB. A direct model of the propagation of acoustic waves in the time domain for acoustically heterogeneous media with a static absorption law was used. Fig. 2 shows the visualization of the ultrasonic field in the studied iron ore sample.

When conducting experimental studies, the methodology given in works [23] was used. Measurements were carried out using an ultrasonic transducer with a nominal central frequency f_0 = 1 MHz and an aperture diameter D = 16 mm. A converter with a large bandwidth of 6 dB was used, which made it possible to perform high-quality time gating and analyze echo signals over a relatively wide frequency range. A generator/receiver combined in one unit was used to generate and receive ultrasonic probing pulses. The received signals were digitized using an analog-to-digital converter (ADC) with a resolution of 14 bits and a frequency of 10 MHz. Digitized data were transferred to a personal computer (PC) for further digital processing and analysis.

Each digitized echo signal was synchronized before spectral analysis to analyze only the backscatter of the ultrasound probe pulse in the iron ore. For this purpose, the Hamming window function was applied in the range of axial distances from 75 to 125 mm. First, the amplitude spectrum of each individual temporal echo signal was calculated using the short-time Fourier transform (STFT). The obtained amplitude spectra of echo signals were averaged in order to suppress their random fluctuations. Then the parametric model was fitted to the average amplitude spectrum. An important advantage of using the Gaussian model is that there is an analytical and unambiguous mathematical solution for the calculation of the least squares method for any given spectral data measurements [24]. At the last stage of the selected model, quantitative parameters are derived: amplitude A, central frequency w_0, bandwidth Δw at the level of –6 dB. The amplitude spectra of the Gaussian parametric model of the measured echo signals are completely described by these three parameters.



b

Fig. 2. Visualization of the ultrasonic field in the studied iron ore sample:

a — transverse projection; b — longitudinal projection

It was shown in [25] that the propagation of the pulse through the attenuating medium results in a shift of its average frequency towards lower frequencies. This allows you to calculate the attenuation coefficient of ultrasound using the following expression

$$\alpha_1 = -\frac{1}{\sigma_0^2}\frac{\Delta f_m}{\Delta x}\underset{\Delta x\to 0}{\rightarrow} -\frac{1}{\sigma_0^2}\frac{df_m}{dx},$$

where $\Delta f_m = f_m - f_0$ is the change in the average (central) frequency when the pulse travels the distance Δx; σ_0^2 is spectral dispersion of the signal.

As it was shown above, the parameter of the process of ultrasound propagation in iron ore – attenuation, carries information about its physical and mechanical characteristics. On the other hand, the amplitude of the echo signal, and even its spectral properties, depends on the size and concentration of scatterers, i. e. structural and textural features of the studied iron ore sample. Taking into account these factors, the ex-

Table 3

Results of analysis of different types of ores

Type	Content, %					density, kg/m^3
	Quartz	Magnetite	Martyt	Hematite	Siderite	
1	63.7	30.9	0	1.4	3.8	3431
2	68.4	21.7	0	0.4	9.1	3248
3	64.5	30.2	0	1.5	3.8	3414
4	65.4	24.4	3.3	3.7	3.2	3412
5	60.8	31.4	0	5.4	2.5	3530

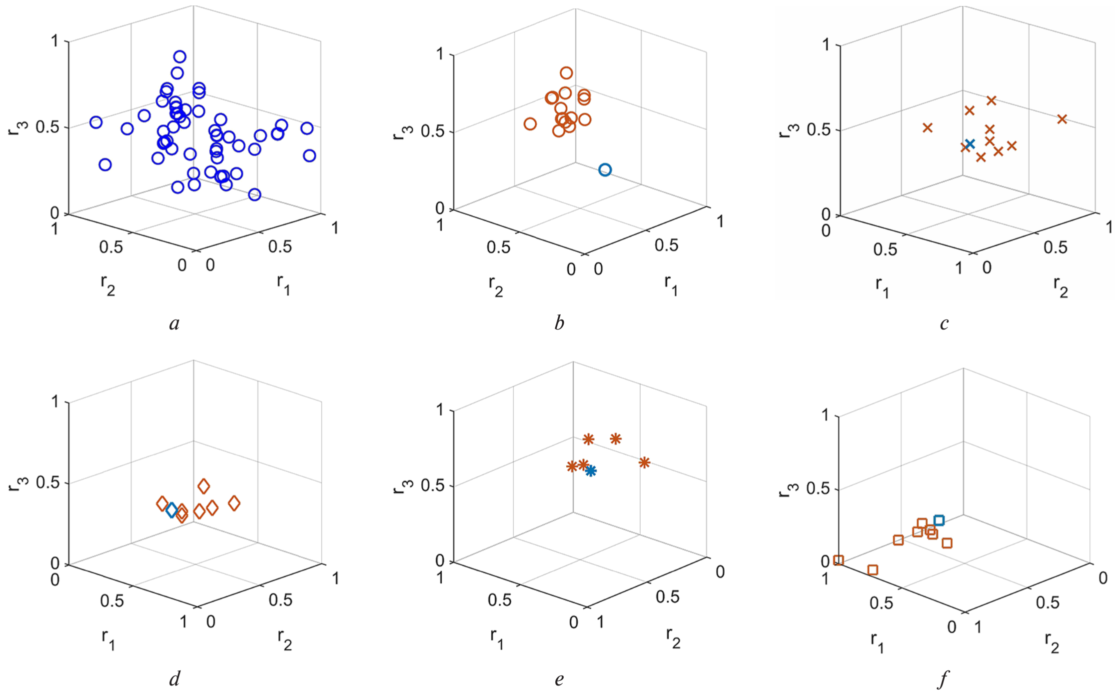


Fig. 3. Characteristics of iron ore samples of the studied varieties:
a – and the results of their clustering; b – 1st cluster; c – 2nd cluster; d – 3rd cluster; e – 4th cluster; f – 5th cluster

tracted parameters of the model were used to identify the main mineralogical and technological varieties of iron ore of the studied deposit. Reference measurements of ore samples with known properties were used to calibrate the system.

In the process of experimental research, five main types of iron ore were identified. Table 3 shows their main characteristics. The following designations of ore types are used: 3 – red-striped magnetite and hematite-magnetite hornblende; 4 – semi-oxidized and oxidized corneas; 5 – hematite-magnetite hornblende.

Recognition of mineralogical and technological varieties of ore is carried out by means of fuzzy clustering of ore material parameters, which are determined on the basis of ultrasonic measurements: amplitude A, (r_1), central frequency w_0, (r_2), bandwidth at the level of -6 dB, (r_3). Clustering of input data was performed using the C-means algorithm in the MATLAB package. A three-dimensional representation of the characteristics of iron ore samples of the above mineralogical and technological varieties is shown in Fig. 3 Δw.

Fig. 4 shows the dependence of the change in the values of the target function (C-means functional) J on the number of iterative calculation procedures n.

Partition Index (SC) and Xie and Beni's Index (XB) were used to quantify the clustering results. SC – the ratio of the sum of compactness and separation of clusters, 0.2283. XB determines the ratio of total variation within clusters and separation of clusters, respectively $XB = 4.3145$. The average recognition accuracy was 90.8 %.

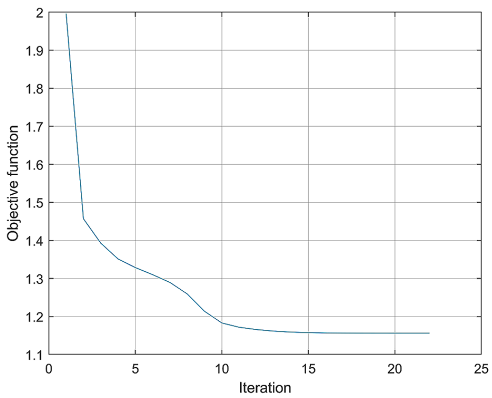


Fig. 4. The graph of changes in the objective function J values

Thus, the proposed method for recognizing the main mineralogical-technological varieties of iron ore with a sufficiently high accuracy for practical purposes allows for operational non-destructive control of ore in the process of its extraction and processing.

Conclusions. Iron ore is a randomly heterogeneous medium that contains multiple mineral formations with densities and compressibility that vary relative to the host rock and other inclusions. To improve the quality of operational mineralogical analysis of iron ore, the parameters of the propagation process of backscattered ultrasonic waves formed in the studied environment were used.

The attenuation of ultrasound, which is determined by the shift of the average (central) frequency, carries information about its physical and mechanical characteristics. The amplitude of the echo signal and its spectral parameters depends on the volume and concentration of scatterers, i.e. structural and textural features of the studied iron ore sample.

A method for recognizing the main mineral-technological varieties of iron ore of the deposit being developed is proposed, based on the parameters of propagation of ultrasonic waves in the studied samples. This is achieved by selecting an analytical model for the spectral characteristics of the received echo signals and quantifying their parameters. Fuzzy clustering of the output data (amplitude, central frequency, bandwidth) was performed using the C-means algorithm in the MATLAB package. The average accuracy of recognition of the main mineralogical and technological varieties of iron ore of the studied deposit was 90.8 %.

The direction of further research should be considered to be the use of additional parameters characterizing the nonlinear properties of the studied environment and non-Gaussian models in the analysis of the process of propagation of ultrasonic waves in rock.

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Використання параметрів зворотного розсіювання ультразвуку для розпізнавання різновидів залізної руди

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Мета. Розробка методу розпізнавання основних мінералого-технологічних різновидів залізної руди у родовищі, що розробляється, шляхом підбору аналітичної моделі до спектральних характеристик отриманих ультразвукових ехо-сигналів і кількісної оцінки їх параметрів.

Методика. У роботі використані методи моделювання процесів поширення ультразвукових хвиль у випадково-неоднорідному середовищі. Розглянуто процес зворотного розсіювання ультразвуку в мінеральних структурах, утворених включеннями залізної руди різних різновидів і супутньої породи. Досліджені оціночні параметри спектральної характеристики обернено розсіяного зондувального ультразвукового імпульсу.

Результати. Запропоновано метод розпізнавання основних мінерально-технологічних різновидів залізної руди родовища, що розробляється, на основі параметрів поширення ультразвукових хвиль у досліджуваних зразках. Це досягається підбором аналітичної моделі до спектральних характеристик отриманих ехо-сигналів і кількісної оцінки їх параметрів. Амплітуда ехо-сигналу та його спектральні властивості залежать від розміру й концентрації розсіювачів, тобто, структурних і текстурних особливостей досліджуваного зразка залізної руди. З урахуванням цих факторів зазначені параметри моделі застосовувалися для ідентифікації основних мінералого-технологічних різновидів залізної руди досліджуваного родовища. Середня точність розпізнавання основних мінералого-технологічних різновидів залізної руди досліджуваного родовища склала 90,8 %.

Наукова новизна. Пропонований метод розпізнавання мінералого-технологічних різновидів залізної руди відрізняється від відомих тим, що в якості оціночних параметрів використовуються амплітуда, центральна частота та ширина смуги пропускання амплітудного спектру параметричної моделі Гауса виміряних ехо-сигналів.

Практична значимість. Запропоноване науково-технічне рішення дозволяє здійснювати оперативний неруйнівний контроль основних мінералого-технологічних різновидів залізної руди у процесі її видобутку й переробки.

Ключові слова: *ультразвуковий аналіз, зворотне розсіювання, залізна руда, мінеральні різновиди*

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