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Identification of mineralogical ore varieties using ultrasonic measurement results

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Abstract

Purpose. To improve the measurement and information base of ultrasonic measurements rock characteristics to assess their mineralogical varieties. It is proposed to use a combination of measurement results of the acoustic quality factor of the test sample in relation to longitudinal and transverse ultrasonic waves, as well as the characteristic coefficient based on the dispersion and the average amplitude value of the received signal, for fuzzy identification of mineralogical and technological varieties of iron ore.

Methods. As elastic waves propagate through the rock mass, they undergo attenuation due to absorption and dissipation of ultrasonic signal energy. The degree of attenuation, as well as the wave propagation velocity, is dependent on the physical-mechanical and chemical-mineralogical properties of the medium through which they travel. In this paper, we analyze a rock characterized by a complex structure comprising ore inclusions and surrounding matrix, each of which differs in its physical-mechanical and chemical-mineralogical properties. In particular, in iron ore samples, the distribution of mineral grains and aggregates exhibits significant heterogeneity in terms of both amount and size.

Findings. An iterative method of fuzzy identification of mineralogical-technological iron ore varieties, based on the analysis of their properties in vector space of features, allows, by minimizing the sums of weighted distances between the analyzed and reference values of ultrasonic measurement results, to attribute them with a certain degree of belonging to the main technological types of ores mined at the deposit, and define them as magnetite quartzite with a confidence probability of 0.93.

Originality. As an information base for identification of mineralogical iron ore varieties, the results of measuring the velocity and attenuation of longitudinal and transverse ultrasonic waves of appropriate frequency are used, on the basis of which the acoustic quality factor of the rock sample is calculated, as well as the characteristic parameter *S*, which is determined by the dispersion and average values of the received ultrasonic signal intensity, which has traveled a certain distance in the studied environment.

Practical implications. The results of tests and practical approbation of the method for identifying mineralogical iron ore varieties based on the data of ultrasonic well logging testify to its high efficiency, which allows recommending the developed scientific-technical solutions for wide industrial application at mining enterprises.

Keywords: *iron ore, identification, ultrasound, fuzzy clustering*

1. Introduction

Ultrasonic technology has found wide application in the mining industry at all stages of mining and processing of minerals [1], [2]. There are two main applications of ultrasonic waves in the mining industry: one is to assess the mechanical properties and condition of the rock mass [3], [4], and the other – to determine its geological and mineralogical structure [5], [6]. Ultrasonic measurements and technological ultrasound are also widely used in the practice of ore beneficiation and preparation for metallurgical processing [7].

Mineral identification is an important part of geological exploration and evaluation of mineral deposits [8], [9]. Non-destructive measurements of ultrasonic wave propagation parameters make it quite easy to obtain indirect data for classifying mineralogical rock mass analysis, which favorably distinguishes them from classical methods that are expensive and time-consuming. However, the results of the analysis and the quality of the estimates obtained are directly dependent on the data set used and their ability to fully characterize the features of the samples under study. To solve the above problems, research is being carried out using various measurement technologies and intelligent algorithms for identifying mineral varieties of rocks [9]-[12]. In order to increase the number of determined minerals and the accuracy of their identification, artificial neural networks are used in a number of works [13]-[15].

Ultrasonic measurements of rock characteristics can be effectively used both in laboratory conditions in relation to

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their samples and directly in the rock mass using acoustic well logging methods.

The results of experimental studies of the relationship between ultimate strength and acoustic quality factor on rock samples are described in [15]. Two methods for determining the tensile strength by direct and interpolation methods are compared. The advantage of the acoustic quality factor compared to elastic wave velocity measurement results in assessing the disturbance and residual strength of rocks is shown. The resulting dependences can be used to assess the residual strength and service life of the structural elements of mining systems - pillars and roofs of underground workings.

The nature of the change in the amplitude peak, ultrasonic wave velocity, as well as the frequency dependence of the probing pulse travel time for different structures of rock samples was studied in [16]. This study was carried out on blocks of artificially prepared rock samples filled with gypsum mortar, with the introduction of artificial joints at different angles. The dependence of the ultrasonic wave velocity change on the structure and presence of damage in the test sample has been determined.

Logging is an effective method for determining geophysical rock properties based on the results of magnetometric, nuclear, acoustic, electrical and other measurements [17]. In the last decade, new logging technologies for exploration and mining of deposits have been developed, such as image analysis and nuclear magnetic resonance.

Acoustic technology is widely used to measure the elastic properties of rocks surrounding a drilled well. An additional advantage of the technology is the ability to quantify elastic properties with minimal penetration effects. The research [18] highlights the main aspects of acoustic logging modeling that should be considered to obtain reliable and accurate results. It is noted that mathematical methods of finite elements allow solving complex problems in accordance with the specifics of each problem. The used and similar methods of mathematical modeling of technological processes in mining provide a reliable and flexible unified environment for solving multiphysical problems.

Acoustic logging data is the basis for creating initial geological models and their subsequent use [19]. However, the quality of the information obtained directly depends on the state of the wellbore. And before creating the initial wave impedance model, it is necessary to make a correction for the environment [20]. Acoustic environment correction makes it possible to take into account the impact of wellbore collapse, interpret missing and anomalous sections of the acoustic curve, eliminate unreasonable spikes, dips, etc.

The full elastic wave parameters are usually stored in memory for subsequent analysis and assessment in stationary conditions, but the measurement results of the probe pulse passage time can be transmitted directly during drilling for real-time use. This information is useful for the assessment of lithology, porosity, pore pressure and drill bit position correlation with seismic maps [21], [22]. Rapid assessment of the mechanical rock properties is also useful for determining wellbore stability during drilling. Acoustic logging during and after drilling allows monitoring changes in the state of the rock during the period of open hole operation. This can form an early warning of possible deterioration in rock integrity, ultimately leading to wellbore stability problems.

For effective mineralogical analysis, it is fundamentally important to choose the information about wave propagation characteristics that are used for this purpose. Studies [23], [24] have found that unlike the elastic wave propagation velocity, the physical dispersion of which is practically absent in most rocks, the attenuation coefficient is determined by the elastic oscillation frequency. In the wide frequency range – from 1 Hz to 10 MHz, the attenuation coefficient of elastic waves in different rocks varies from $1 \cdot 10^{-8}$ to $2 \cdot 10^{2}$ m^{-1}. The attenuation decrement over the same frequency range varies from $1 \cdot 10^{-2}$ to 1.0 on average. It is claimed that the attenuation decrement in each type of igneous and sedimentary rock is not frequency dependent. The influence of intergrain boundaries on the attenuation coefficient is manifested by the fact that the attenuation coefficient in a single crystal is at least an order of magnitude lower than in a rock consisting of a given mineral. At the same time, the finer the rock grains, the stronger the scattering factor is. Rock studies show that the attenuation coefficient of elastic waves decreases with increasing pressure. This is due to the strengthening of bonds between minerals. The grain size in the rock (d) determines the cutoff frequency at which a quadratic scattering law is observed. In granite (d = 2.5 mm), the limit frequency according to experimental data is 2 MHz; in gabbro-diabase (d = 1 mm) – 6 MHz; in sandstone (d = 1.2 mm) – 3.5 MHz [23], [24].

Thus, the dependence of ultrasonic wave propagation parameters on the studied medium characteristics is widely used in practice. However, given the complex structure and variety of physical-mechanical and chemical-mineralogical properties of ore formations, the solution to the problem of mineralogical analysis of ore deposits should be sought in the direction of using new informative parameters, methods for analyzing the information obtained and improving measurement technologies.

2. Methods

Consider a rock, the characteristics of which are defined as a structure consisting of ore inclusions and associated rocks that differ in their physical-mechanical and chemical-mineralogical properties. In the iron ore varieties, grains and mineral aggregates that form them are distributed unevenly both in quantity and size. Table 1 shows the mineral composition characteristics, as well as the size of individual elements and aggregates in the layers of hornfelses and jaspilites of the Skelevatsky magnetite deposit ("Pivdennyi GZK" Mining and Processing Plant, Kryvyi Rih, Ukraine). Figure 1 shows the structural peculiarities of the main iron-bearing minerals [25]. A variety of sizes and shapes of sections of individual elements and aggregates of iron-bearing minerals allow us to conclude that it is expedient to use these peculiarities in their identification by acoustic logging methods.

The theoretical basis of acoustic logging is mainly based on the Lame equation describing the elastic wave propagation in a continuum. In the frequency domain ($e^{-i\omega t}$), for isotropic media it looks as follows:

$$\mu \nabla \cdot \nabla \cdot u - (\lambda + 2\mu) \nabla (\nabla u) - \omega^2 u = 0 , \tag{1}$$

where:

u – the displacement vector;

$\lambda = K - 2/3\,\mu$ and μ – the Lamé parameters (μ – the shear modulus);

K – volumetric module.

Table 1. Mineral composition characteristics, as well as the size of individual elements and aggregates in the layers of hornfelses and jaspilites of the Skelevatsky magnetite deposit

Hornfels and Jaspilites	Layer types	Magnetite			Hematite			Quartz	
		Size, mm		Content, %	Size, mm		Content, %	Grain size, mm	Content, %
		grain	unit		grain	unit			
Magnetite	Ore	0.15	0.35	90.5	–	–	–	0.04	8.5
	Mixed	0.11	0.18	37.5	–	–	–	0.04	59.5
	Nonmetallic	0.06	0.00	3.0	–	–	–	0.07	95.0
Chlorite-carbonate-magnetite	Ore	0.18	0.45	85.0	–	–	–	0.05	8.0
	Mixed	0.12	0.20	22.0	–	–	–	0.06	53.5
	Nonmetallic	0.05	–	2.5	–	–	–	0.075	73.0
Hematite-magnetite	Ore	0.15	0.60	87.0	0.06	0.10	7.5	0.03	5.5
	Mixed	0.12	0.33	38.0	0.03	0.05	6.0	0.05	55.6
	Nonmetallic	0.08	0.10	1.8	0.01	–	5.0	0.06	92.0
Magnetite-cummingtonite-chlorite-siderite	Ore	0.15	0.20	76.0	–	–	–	0.08	4.0
	Mixed	0.07	0.12	10.7	–	–	–	0.06	49.6
	Nonmetallic	0.04	–	5.0	–	–	–	0.10	52.0

Figure 1. Structural peculiarities of iron-containing minerals: (a) lancetonide hematite; (b) martite with relics of magnetite; (c) euhedral-grained magnetite segregations in the hornfels; (d) the relationship of hematite (white) and magnetite (gray)

The solution of this equation in a homogeneous medium is the sum of two elastic waves: longitudinal compression (potential) and transverse (shear) waves [26].

When ultrasonic waves propagate in the rock, they are absorbed and scattered by ore (mineral) inclusions (formations) – individual elements and aggregates. The parameters of these processes are characterized by their effective extinction (attenuation) cross sections σ_p, absorption σ_c and scattering σ_s. Under effective extinction cross section σ_p, the area of the section perpendicular to the direction of ultrasonic wave incidence, for which the incoming sound energy is equal to the sum of the energies absorbed and scattered by ore formations, is meant. In this case, the linear absorption $\sum_c(\lambda)$ and scattering $\sum_s(\lambda)$ coefficients can be determined by Formulas (2):

$$\Sigma_c(\lambda) = n\sigma_c(\lambda), \quad \Sigma_s(\lambda) = n\sigma_s(\lambda), \tag{2}$$

where:

n – the concentration of inclusions (the number of inclusions per unit volume V);

$\sigma_c(\lambda)$ and $\sigma_s(\lambda)$ – the total cross sections of absorption and scattering of ultrasonic waves on the ore formation.

The total absorption and scattering cross sections depend not only on the wavelength of ultrasonic vibrations, but also on the sizes of inclusions r. The linear absorption and scattering coefficients should be understood as the values determining the average energy fraction absorbed and scattered by the medium per unit path length per unit time.

Denote the ultrasonic signal intensity when it passes through a fixed distance Z in the rock:

$$\xi = I_\circ \exp\left\{-\frac{1}{V}\sum_{i=1}^{k}\sigma(r_i)Z\right\}, \tag{3}$$

where:

$\sigma(r_i)$ – the extinction cross-section of particles of ore formations with a size of r_i.

The dispersion of this value is determined by the Expression:

$$D_\xi = M\xi^2 - <\xi>^2, \tag{4}$$

where:

$$M\xi^2 = \sum_{k=0}^{\infty} M\left(\frac{\xi^2}{k}\right)F(k). \tag{5}$$

Here $M\xi$ means the mathematical expectation of a random variable ξ; $M\left(\frac{\xi}{k}\right)$ is conditional mathematical expectation for a fixed number of ore inclusions k, and the symbol < > is an averaging of fluctuations in their size and number.

According to the methodology given in the works [27], [28], the average value of the signal passing through the controlled rock volume V is determined by the Expression:

$$<\xi> = I_\circ \exp\left\{-nV\left(1-\int_\circ^\infty e^{-\frac{1}{V}\sigma(r)Z}F(r)dr\right)\right\}, \tag{6}$$

where:

$F(r)$ – the size distribution function of mineral inclusions.

Then Expression (5) can be written in the following form:

$$M\left(\xi^2\right) = I_\circ^2 \exp\left\{-nV\left(1-\int_\circ^\infty e^{-\frac{2}{V}\sigma(r)Z}F(r)dr\right)\right\}. \tag{7}$$

Substitute the found values into Expression (4) and obtain:

$$D\xi = I_{\circ}^{2} \exp\left\{-nV\left(1-\int_{\circ}^{\infty} e^{-\frac{2}{V}\sigma(r)Z} F(r)dr\right)\right\}- \\ -I_{\circ}^{2} \exp\left\{2nV\left[1-\int_{\circ}^{\infty} e^{-\frac{1}{V}\sigma(r)Z} F(r)dr\right]\right\}. \quad (8)$$

Denote:

$$\psi = \exp\left\{\frac{nZ^2}{V}\int_{\circ}^{\infty}\sigma^2(r)F(r)dr\right\}. \quad (9)$$

Then:

$$D\xi = I_{\circ}^{2} \exp\left\{2nZ\int_{\circ}^{\infty}\sigma(r)F(r)dr\right\}\left[\psi^2-\psi\right]. \quad (10)$$

Define the relative value:

$$\frac{\sqrt{D\xi}}{<\xi>} = \frac{I_0 \exp\left\{-nZ\int_{0}^{\infty}\sigma(r)F(r)dr\right\}\sqrt{\psi^2-\psi}}{I_0 \exp\left\{-nZ\int_{0}^{\infty}\sigma(r)F(r)dr\right\}\sqrt{\psi}} = \sqrt{\psi-1}. \quad (11)$$

Taking into account (9) and (11), define the characteristic function S [28]:

$$S = \frac{\ln\psi}{\ln I_0/<\xi>} = \frac{Z}{V}\frac{\int_{\circ}^{\infty}\sigma^2(r)F(r)dr}{\int_{\circ}^{\infty}\sigma(r)F(r)dr}. \quad (12)$$

From this it follows that the value S is a function of the size of mineral inclusions in a controlled rock mass volume and thus characterizes its structural and textural features.

3. Results and discussion

The measurement results of the characteristics of 5 types of ores mined and supplied for processing from one of the deposits of the Kryvyi Rih iron-ore basin are given in Table 2. At the same time, the following designations of ore types are adopted [5]: 1 – magnetite corneas; 2 – silicate-carbonate-magnetite hornblende; 3 – red banded magnetite and hematite-magnetite hornblende; 4 – semi-oxidized and oxidized corneas; 5 – silicate slates, ore-free hornblende and quartz.

Table 2. Results of the analysis of different varieties of ores

Ore variety	Content in %				Density, kg/m^3
	Quartz	Magnetite	Hematite	Siderite	
1	63.7	30.9	1.4	3.8	3431
2	68.4	21.7	0.4	9.1	3248
3	64.5	30.2	1.5	3.8	3414
4	74.6	4.5	0.7	20.2	2989
5	60.8	31.4	5.4	2.5	3530

Distribution of mineral components in the specified ore varieties is presented in Figure 2. The speed of longitudinal ultrasonic wave propagation in these samples is 4100-5800 m/s, transverse – 2300-2900 m/s, and the attenuation is 23-44 dB/m. These dependences are an assessment of the physical-mechanical rock mass characteristics. The dependence of the speed of longitudinal CL ultra-sonic waves on density ρ and elastic characteristics of the studied rock (E – Young's modulus, μ – Poisson's ratio, σ – shear modulus) is exemplified in Figure 3.

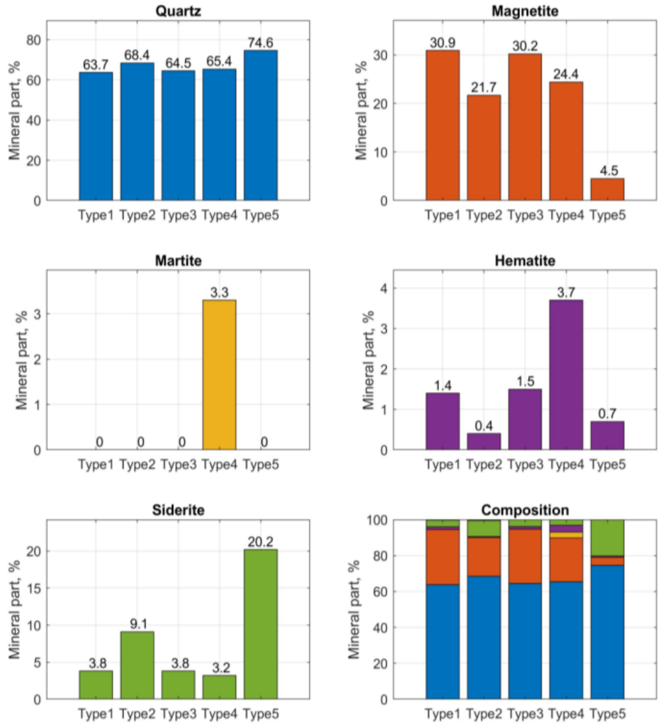

Figure 2. Mineral composition of the studied ore varieties

For further analysis of the studied rock based on the obtained measurement results, it is convenient to use its acoustic quality factor Q according to longitudinal and transverse waves, since it is determined simultaneously with attenuation coefficients and propagation velocity of ultrasonic signals of a certain frequency [29].

The acoustic quality factor of a rock sample is determined as follows:

$$Q = \frac{\pi}{\theta} = \frac{\pi f_0}{\alpha C}, \quad (13)$$

where:

θ – the attenuation decrement;

f_0 – is the ultrasonic oscillation frequency;

C – the elastic wave propagation velocity.

At the same time, the spatial attenuation coefficient of elastic waves is determined by the Formula (14):

$$\alpha = \frac{1}{l_2 - l_1}\ln\left[\frac{A(l_1)}{A(l_2)}\right], \quad (14)$$

where:

l_1, l_2, $A(l_1)$, $A(l_2)$ – the measurement bases and the corresponding signal amplitudes.

However, it should be noted that for the successful identification of at least the main mineralogical-technological types of ore of the studied deposit, the specified parameters and their interrelationships are not sufficient.

Thus, according to the results obtained for the studied deposit, the correlation coefficient between the longitudinal C_L and transverse C_T wave velocities and density ρ of rocks is 0.53-0.72, between C_L, C_T and elastic characteristics (Young's modulus, Poisson's ratio, shear modulus) – 0.55-0.94, and the correlation coefficient between the attenuation coefficient and the same characteristics does not exceed 0.71.

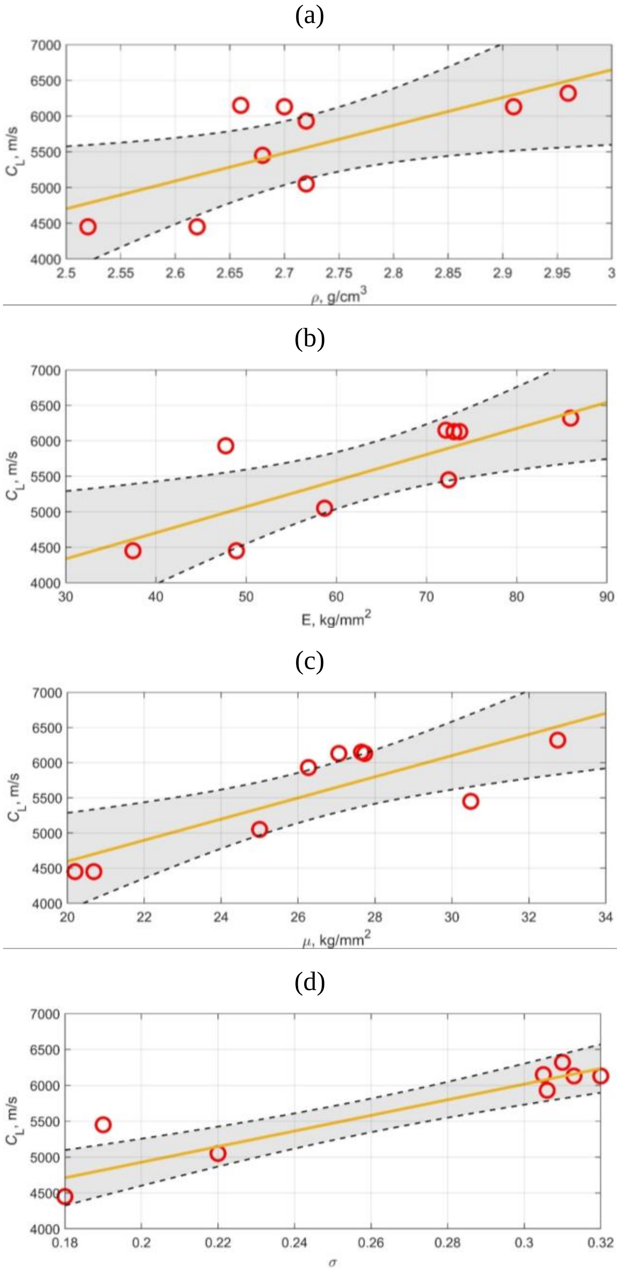

Figure 3. Dependence of the velocity of longitudinal ultrasonic waves, C_L, on rock characteristics (the shaded bands are the Working-Hotelling uncertainty intervals of the regression lines at the 95% confidence level): (a) density; (b) Young's modulus; (c) Poisson's ratio; (d) shear modulus

Since the rock is a complex conglomerate consisting of crystalline and amorphous mineral formations with different strength properties, structural texture and particle size distribution, which are of a stochastic nature, the characteristics of a particular medium under study, by definition cannot be unambiguous (which is confirmed for the same samples from different deposits). To improve the adequacy of mineralogical analysis of ore, it is advisable to consider its physical-mechanical characteristics and the results of their indirect estimates in the form of fuzzy sets, and to classify them in the vector space of features, use the appropriate mathematical apparatus [30].

To implement this approach, the Fuzzy C-means (FCM) fuzzy clustering method was chosen [31], [32]. In this case, the set of informative attributes X is divided into c fuzzy subsets, and the structure of the fuzzy distribution matrix $U = [\mu_{ik}]$ has the following form:

$$U = \begin{bmatrix} \mu_{1,1} & \mu_{1,2} & \cdots & \mu_{1,c} \\ \mu_{2,1} & \mu_{2,2} & \cdots & \mu_{2,c} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{N,1} & \mu_{N,2} & \cdots & \mu_{N,c} \end{bmatrix}. \tag{15}$$

Clustering algorithm FCM is based on the minimization of the objective function:

$$J(X;U,V) = \sum_{i=1}^{c} \sum_{k=1}^{N} (\mu_{ik})^m \|x_k - v_i\|_A^2, \tag{16}$$

where:

$$V = [v_1, v_2, \dots, v_c],\ v_i \in R^n, \tag{17}$$

is a vector of cluster prototypes (centers) to be determined, and:

$$D_{ikA}^2 = \|x_k - v_i\|_A^2 = (x_k - v_i)^T A (x_k - v_i), \tag{18}$$

is the square of the scalar product of the distance norm.

Minimization of the objective Function (16) is possible only if:

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c} \left(D_{ikA} / D_{jkA} \right)^{2/(m-1)}}, 1 \le i \le c, 1 \le k \le N, \tag{19}$$

and

$$v_i = \sum_{k=1}^{N} \mu_{ik}^m x_k \Big/ \sum_{k=1}^{N} \mu_{ik}^m,\ 1 \le i \le c. \tag{20}$$

Equation (20) gives vi as a weighted average of the data elements belonging to the cluster, where weights are the degree of membership.

Figure 4 shows the stages in the execution of the FCM algorithm [33].

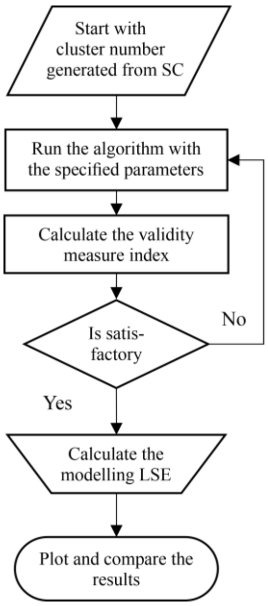

Figure 4. Stages of the FCM algorithm execution

In accordance with the above, the results of measuring the velocity, as well as longitudinal and transverse ultrasonic wave attenuation with the corresponding frequency are used as an information base for the identification of mineralogical varieties of iron ore. Based on these results, the acoustic quality factor of the rock sample is calculated, and the characteristic parameter *S*, determined by the variance and average values of the intensity of the received ultrasonic signal that has traveled a certain distance in the studied medium.

It has been found that when identifying 5 mineralogical iron ore varieties, which is characteristic for the studied deposit, and, accordingly, dividing the obtained array of measured data into 5 clusters using the Fuzzy C-means algorithm, it is necessary to perform on the average 22 iterations. The change in the objective function during the operation of the algorithm is presented in Figure 5.

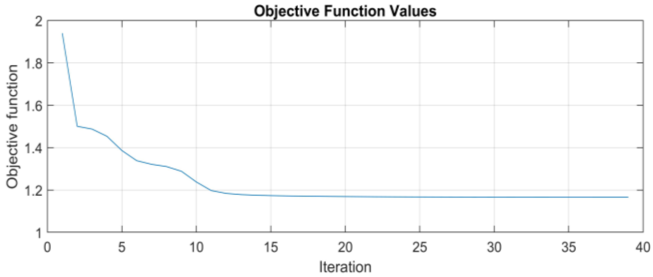

Figure 5. Dependence of the objective function value on the number of clustering algorithm iterations

The analysis of the scale diagrams for the membership functions of the points – the measurement results of iron ore characteristics for each cluster is shown in Figure 6.

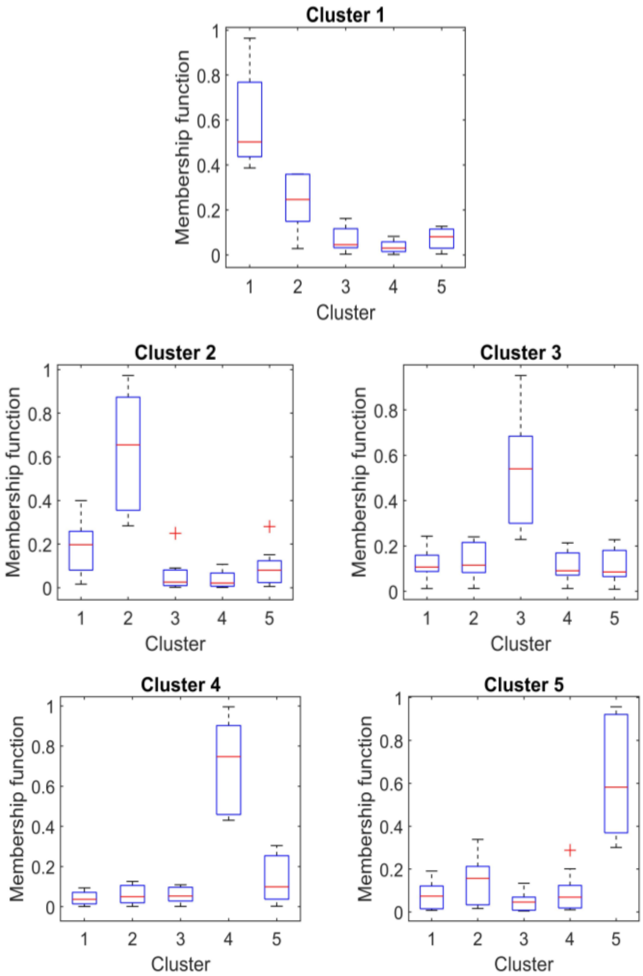

Figure 6. Diagrams of the membership function range values

The following indicators are used to assess the quality of clustering [32]-[35]: Partition Coefficient (PC), Classification Entropy (CE), Partition Index (SC), Separation Index (S), Xie and Beni's Index (XB), Dunn's Index (DI), Alternative Dunn Index (DII). The values of these indicators based on the results of experimental studies are given in Table 3.

Table 3. Assessments of clustering quality

PC	CE	SC	S	XB	DI	ADI
0.6965	0.7013	0.5410	0.0046	3.9887	0.2032	0.0003

The value of the membership function of belonging to its cluster for each studied sample point significantly exceeds the value of the function of belonging to other clusters (number of parallel experiments in a series conducted under the same conditions $k = 9$, number of series $n = 24$). The experimental data processing results for each of the three informative data features are shown in Table 4.

Table 4. Experimental data processing results

Sign	Cochrane criterion	
	G calculated	G tabular
C1	0.4417	0.4748
C2	0.4326	0.4748
C3	0.4225	0.4748

For all experimental data obtained, the estimated value of the Cochran criterion is less than the tabulated values. Therefore, the analysis performed confirms the reproducibility of the results obtained. The results of tests and practical approbation of the method for identifying mineralogical iron ore varieties based on the ultrasonic well logging data testify to its high efficiency, which allows recommending the developed scientific-technical solutions for wide industrial application at mining enterprises.

4. Conclusions

As an information base for identification of mineralogical iron ore varieties, the results of measuring the velocity and attenuation of longitudinal and transverse ultrasonic waves of appropriate frequency are used, on the basis of which the acoustic quality factor of the rock sample is calculated, as well as the characteristic parameter *S*, which is determined by the dispersion and average values of the received ultrasonic signal intensity, which has traveled a certain distance in the studied environment.

An iterative method of fuzzy identification of mineralogical-technological iron ore varieties, based on the analysis of their properties in vector space of features, allows, by minimizing the sums of weighted distances between the analyzed and reference values of ultrasonic measurement results, to attribute them with a certain degree of belonging to the main technological types of ores mined at the deposit, and define them as magnetite quartzite with a confidence probability of 0.93.

Author contributions

Conceptualization: VM, NM, GF; Data curation: NM, GF, VT; Formal analysis: NM, VT; Funding acquisition: VM, NM, GF; Investigation: VM, NM, GF, VT, AH, YB; Methodology: NM, VT; Project administration: NM; Resources: NM, GF; Software: VT; Supervision: VM; Validation: AH, YB; Visualization: VT, AH, YB; Writing – origi-

nal draft: VM, NM, GF, VT, AH, YB; Writing – review & editing: VM, NM, VT. All authors have read and agreed to the published version of the manuscript.

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Conflicts of interests

The authors declare no conflict of interest.

Data availability statement

The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

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Розпізнавання мінералогічних різновидів руди з використанням результатів ультразвукових вимірювань

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Мета. Вдосконалення вимірювальної та інформаційної бази ультразвукових вимірювань характеристик порід для оцінки їх мінералогічних різновидів. Пропонується використання комбінації результатів вимірювань акустичного якісного показника тестового зразка стосовно подовжніх і поперечних ультразвукових хвиль, а також характерного коефіцієнту, що базується на дисперсії та середньому значенні амплітуди отриманого сигналу для нечіткої ідентифікації мінералогічних і технологічних різновидів залізної руди.

Методика. Під час проникнення еластичних хвиль крізь масив породи вони піддаються затуханню через поглинання та розсіювання енергії ультразвукового сигналу. Ступінь затухання, а також швидкість поширення хвиль, залежить від фізико-механічних та хіміко-мінералогічних властивостей середовища, через яке вони проходять. У роботі аналізується порода, що характеризується складною структурою, яка складається з включень руди та оточуючої речовини, з відмінними фізико-механічними та хіміко-мінералогічними властивостями.

Результати. Ітеративний метод нечіткої ідентифікації мінералогічних і технологічних різновидів залізної руди, заснований на аналізі їхніх властивостей у векторному просторі ознак, дозволяє, мінімізуючи суми зважених відстаней між аналізованими та довідковими значеннями результатів ультразвукових вимірювань, присвоїти їм певний ступінь належності до основних технологічних різновидів руди, що видобуваються на родовищі, та визначити їх як магнетитові кварцити з вірогідністю 0.93.

Наукова новизна. Як інформаційна база для ідентифікації мінералогічних різновидів залізної руди використовуються результати вимірювання швидкості та затухання подовжніх і поперечних ультразвукових хвиль відповідної частоти, на основі яких розраховується акустичний якісний показник породи та характерний параметр, що визначається дисперсією і середніми значеннями інтенсивності отриманого ультразвукового сигналу, який пройшов певну відстань у вивченому середовищі.

Практична значимість. Результати тестувань та практичної апробації методу ідентифікації мінералогічних різновидів залізної руди на основі даних ультразвукового каротажу свердловин свідчать про його високу ефективність, що дозволяє рекомендувати розроблені науково-технічні рішення для широкого промислового застосування на гірничодобувних підприємствах.

Ключові слова: *залізна руда, ідентифікація, ультразвук, нечітка кластеризація*

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