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DEVELOPMENT OF A CLUSTERING ALGORITHM FOR PARAMETERS OF EXPLOSIVE OBJECTS BASED ON A COMPREHENSIVE INDICATOR

Purpose. To enhance the efficiency of clustering parameters of explosive objects through the development of hybrid clustering elements.

Methodology. A classifier for explosive objects based on a comprehensive indicator, serving as the main principle for classifier improvement, was developed using mathematical modeling. Data processing was carried out using the Python programming language and scikit-learn libraries. The research methodology involves grouping explosive objects into two clusters with the aim of improving the existing algorithms for detecting explosive objects.

Findings. The proposed comprehensive indicator demonstrates a standard deviation 8.2 % less than the existing one. The improved clustering algorithm exhibits Davis-Bouldin index values of 0.517 and 0.525, while the existing ones show 0.572 and 0.572, respectively. This indicates that the output estimations of the new algorithm are less susceptible to noise, which enhances clustering quality and reduces the number of errors during practical application.

Originality. A parameter clusterer for explosive objects is proposed which, unlike the existing ones, incorporates complex estimates built on the basis of a linear model with combined parameters as input data.

Practical value. The practical significance of the proposed solution lies in the fact that improving existing algorithms for detecting explosive objects will increase the efficiency of computer vision in solving reconnaissance and demining tasks. The proposed solutions can be used as an addition to existing approaches for monitoring and managing national security to prevent emergencies.

Keywords: *linear model, parameter clusterer, explosive object, computer vision, artificial intelligence*

Introduction. The ongoing war in Ukraine is a process that demands various types of resources and necessitates the development of technologies to ensure the state's security [1]. Addressing terrorism and protecting territories lacks a singular algorithmic solution, as evidenced by the existing research [2].

Currently, the determination of cluster centroids often relies on an intelligent approach [3]. This is corroborated by leading global search engines, such as Google Trends, which showed sustained interest levels exceeding 70 % in this topic during the period from March 5, 2023, to March 5, 2024.

The existing studies highlight diverse strategies for detecting dangerous objects, including fluorescent sensing technology [4]. These technologies not only enable the detection of such objects but also facilitate the prediction of potential consequences and strategies for handling them. Differentiating parameters of explosive objects into groups allows for the study of their neutralization mechanisms and an analysis of their environmental impact [5]. Clustering algorithms serve as essential tools for grouping these objects.

However, the problem of object grouping has not been fully addressed, particularly concerning the improvement in the accuracy of input evaluations for clusterers. This deficiency leads to computational errors, impacting the fault tolerance [6], stability, and reliability of computer systems [7]. Consequently, there is a clear need to develop new and enhance the existing tools for clustering object parameters, specifically by focusing on improving the precision of input data.

Literature review. The photoluminescence signal from explosive objects represents a viable method for their detection in space [8]. The numerical parameters of this signal form the basis for future research, involving analysis, processing, and the creation of clusterer models. These object parameters can serve as primary inputs for artificial intelligence models directly, without being combined into complex indicators. Alternatively, they can be aggregated into complex indicators for use in clustering tasks. While the applied aspects of utilizing complex indicators were explored in [9], their specific application in object clustering tasks has not been sufficiently investigated.

Existing object clusterers are conventionally categorized into two groups. The first group encompasses approaches aimed at improving the clustering algorithm itself, while the second focuses on enhancing the accuracy of the algorithm's input data. Both research avenues are founded on the principles of ensembling. This principle is detailed in [10], which outlines its theoretical aspects and proposes a model for parallel clustering ensembles.

The work in [11] examines the process of creating indicators for a comprehensive assessment of resource reduction in damaged buildings. Unlike [10], this research specifically considers evaluation indicators that are consolidated into a single, unified assessment.

The detection of concealed prohibited objects in X-ray images, leveraging a global Multi-Scale function with context awareness, was studied in [12]. The core idea of this research is the development of a module for combining features at different scales, which enhances the effectiveness of object detection in images.

A prominent example of the second subgroup, focusing on improving the accuracy of clusterer input data, is the work by [13]. This study proposes a scaled representation of a dummy variable as an element of the input data function. Essentially, it advocates for improving the accuracy and objectivity of input data based on the ensembling principle, rather than enhancing the clustering algorithm directly.

Beyond techniques for improving input data through the creation of combined indicators, significantly more robust methodologies exist that incorporate a preliminary data restoration process [14]. This approach effectively eliminates noise, preserves the necessary data quality, and complements earlier solutions such as those in [13]. However, a notable drawback of the proposed solutions is their limited real-time operational capability.

For real-time object detection and the prevention of video data falsification, [14] proposes the use of You Only Look At Once (YOLO) deep learning technologies. This approach helps prevent information forgery in videos, which is a crucial element for object recognition. A logical continuation of the research in [14] is the work presented in [15], which also discusses techniques for creating complex indicators, specifically for quality diagnostics.

An alternative approach to clustering under conditions of insufficient information about the input parameters of sought objects involves the use of fuzzy systems. The mathematical apparatus of fuzzy logic is widely applied to solve a diverse range of scientific and practical problems, including the creation of automated decision-making systems [16]. For instance, when it is partially or completely impossible to define the set of parameters for an explosive device (e.g., due to intentional masking or poor visibility conditions), fuzzy inference systems can serve as auxiliary tools for computer vision. This can involve considering additional parameters, such as typical deployment schemes or other characteristics. Crucially, the specific set of parameters accounted for by such a fuzzy system significantly influences the solution of the clustering task. A limitation of this approach is the prerequisite for having correct training data beforehand, which is not always feasible to collect.

It should be noted that object grouping also depends on the research environment. For example, in [17], explosive objects on the seabed are analyzed. This necessitates the use of marine vessels and specialized equipment for object detection, along with the development of specialized research technology and the implementation of information systems and decision-making systems. A decision support system itself allows for the realization of single-criterion and multi-criterion tasks [18] and can be utilized as an element of a robotic complex and a reconnaissance tool [19].

The aforementioned research ideas collectively indicate that the process of clustering explosive objects requires not only novel proposals regarding clustering task research tactics but also the careful selection of appropriate clustering algorithms. The proposed solutions can serve as elements of a relevant methodology. A substantiated methodology for selecting and utilizing clustering algorithms is provided in [20], where research results demonstrate how the input data set influences algorithm effectiveness.

However, the fundamental basis for increasing the accuracy of clusterer results lies in the development of more precise methods. One of the main principles for constructing a complex indicator is the sum of products of values, specifically the criterion and the weight coefficient [21]. This proposed approach is currently in use. The calculated sum of products is then employed as an input evaluation for artificial intelligence methods. Undoubtedly, artificial intelligence methods are continuously evolving, as highlighted in [22], yet a classical method for constructing the clusterer is utilized.

Unsolved aspects of the problem. In the existing works [7–22], hybrid methods for object clustering were utilized, which entail the use of more complex research tools, particularly mathematical apparatus, thereby increasing the research duration. Furthermore, the combination of complex indicators with clustering algorithms has not been sufficiently explored, which highlights the relevance of the subject under investigation.

Purpose and tasks statement. The purpose of this study is to enhance the efficiency of clustering parameters of explosive objects through the development of hybrid clusterer elements.

To achieve this goal, the following objectives have been set:

1. To analyze the parameters of explosive objects, determined by the magnetic anomaly method, in order to create a model that unifies these parameters into a single complex indicator.
2. To develop a clusterer based on a comprehensive method for combining parameters of explosive objects.
3. To conduct experimental verification of the proposed results.

Description of the research methodology. Given a set of environmental parameters $S = \{s_1, s_2\}$, where s_1 and s_2 are specific environmental parameters. The set of mine parameters is $M = \{m_1, m_2\}$, where m_1 and m_2 are specific mine parameters. The set of evaluations is $E = \{e_1, e_2, e_3, \ldots, e_m\}$, where e_i is a specific evaluation from the total number of evaluations m $(i = \overline{1, m})$. There exists an interaction between the environmental evaluation parameters and the mine evaluation parameters: $E_{environment} \in E_{mine}$. The set of clusters is $C = \{c_1, c_2\}$, where c_l is a cluster for a given number $l = \overline{1, 2}$.

The task is to find a model that optimally describes the interaction between the parameters of an explosive object and the parameters of the external environment. We define the model K_i under the condition

$$K_{opt} = \arg\ \min\ _{K_i \in} SD(K_i),$$

where $SD(K_i)$ represents the standard deviation for the K_i model.

The logical culmination of the research is the construction of a clustering model using all evaluations from set E. The study considered environmental parameters where landmines are laid: c_1 type of soil, with $c_1 \in [1, 6]$, and c_2 type of shaft, with $c_2 \in [1, 5]$. Mine parameters included: c_3 voltage, with $c_3 \in [0, 1]$, and c_4 sensor height from the ground, with $c_4 \in [0, 1]$. All investigated parameters were obtained using a known passive method. Since the initial research parameters had different scales, they were normalized.

The volume of the theoretical sample n_1 was determined by calculating the number of placements with repetitions. In addition to the basic theoretical sample, three additional bootstrap samples n_2, n_3, n_4 were used. These bootstrap samples were generated using the numpy library's function np.random.normal(mean, std_dev, size = n_rows), supporting the hypothesis of a normal distribution. Each bootstrap sample consisted of four variables belonging to [0, 1], and each sample volume comprised 1,000 evaluations.

For the experimental sample, the "Land Mines Detection" dataset [23] was utilized, which initially contained $N_0 = 338$ object parameters. As some parameters yielded zero results, they were cleaned, resulting in a final experimental sample of $N_1 = 316$ object parameters.

The research methodology involved employing several mathematical operations to construct the complex indicator, including exponentiation and root extraction for linear, nonlinear, and combined approaches to parameter representation.

Furthermore, other methods for combining sets of evaluations into a single indicator were investigated, specifically multiplier methods that incorporate weight coefficients. Their determination was carried out using unsupervised learning methods. The theoretical premise for the complex indicator to approximate a normal distribution lies in the specific construction of variables, which allows for a distribution close to normal. To avoid asymmetry in the distribution of evaluations determined by the aforementioned operations, logarithmization and exponentiation were applied. Subsequently, the hypothesis of normal distribution was tested using the Jarque-Bera test at a significance level of *p-value* > 0.05, as implemented in the scipy.stats package. Here, *p-value* is a known measure of the fit between the examined data and the hypothesis of a normal distribution. Hypotheses regarding normally distributed data (at a significance level of *p-value* > 0.05) and the absence of normally distributed data (at a significance level of *p-value* < 0.05) were considered. The distribution of evaluations was determined by constructing a histogram and a cumulative probability distribution function. The complex indicator for evaluating explosive objects was built based on a linear combination of various variables, specifically those related to explosive objects, shaft type, voltage, and sensor height from the ground.

The clustering model was constructed using a well-known algorithm [24], and its quality was assessed using the Davies-Bouldin index [25] and silhouette score [26]. The optimal number of clusters was selected using the elbow method. A comparative analysis of the proposed clusterer with the existing ones was also performed under the condition of using a single sample, consistent with the approach for the complex indicator. The software implementation of the proposed solutions was carried out using the Python programming language and the Scikit-learn, Pandas, and NumPy libraries. Additionally, the TensorFlow library was employed for building the clustering models.

Results. In accordance with the research methodology, the initial input data for the study consists of two parameters each, related to the environment and the characteristics of explosive objects. Each investigated parameter possesses a specific scale, which complicates subsequent analysis and necessitates normalization. Several normalization techniques for evaluations were examined, including the method of linear transformation. Under the condition $a_1 = [(1 - 0) \cdot (c - 1)]/(6 - 1)$, we obtain an array of values ranging from 0 to 1.0. The limitation of condition a_1 is an inadequate transformation of the input set of evaluations to the output. For example, if an input value of 1 is provided, the output will be 0.

For nonlinear transformation, $a_2 = (c_2^2 - 1^2)/(6^2 - 1^2)$ yields an array of values from 0 to 1.0, but this expression has certain limitations where zero values are obtained. Therefore, we normalize the environmental parameters, specifically soil type and shaft type, to the range [0, 1] using the formula

$$Normalv = actual/k, \tag{1}$$

where *actual* refers to the actual value of the variable c_1 or c_2; k is the scaling coefficient, which is 6 for c_1 and 5 for c_2.

Utilizing this approach represents one of the simplest forms of variable normalization, yielding minimal standard deviation values. Thus, the variables c_{1norm}, c_{2norm}, c_3 and c_4 serve as input data for creating the complex indicator used to evaluate explosive objects. This complex indicator for evaluating explosive objects is defined based on the model

$$A = \sum_{i=1}^{b}\sum_{j=1}^{d}\left[\begin{matrix}(c_{1norm} \cdot c_{2norm} + c_{1norm} \cdot x_{11} + c_{2norm} \cdot x_{12}) + \\ +(c_3 \cdot c_4 + c_3 \cdot x_{21} + c_4 \cdot x_{22})\end{matrix}\right], \tag{2}$$

where b and d denote the summation limits; c_{inorm} and c_i represent the parameters under investigation; x_i are the weight coefficients, determined by an artificial intelligence method.

The evaluations determined by formula (2) must adhere to a normal distribution or closely approximate it. The theoretical justification for utilizing a normal distribution is based on the characteristics of explosive object evaluations.

The complex indicator is integrated into the explosive object clusterer and can be algorithmically represented using a block diagram.

Block 1. The input evaluations of explosive objects are determined using a passive method.

Block 2. The input evaluations of explosive objects, specifically soil type and shaft type, are normalized to the range [0, 1] using formula (1). The normalized research evaluations are recorded in Table 1.

The evaluations from Block 2 are used in Block 3 for determining the complex indicator.

Block 3. The complex indicator for explosive objects is determined using formula (2).

Block 4. The adequacy of the complex indicator for explosive objects is verified, specifically using the Jarque-Bera test, graphical methods, and by comparing standard deviations. If the obtained result is satisfactory

Table 1

Input evaluations of explosive object parameters

No.	c_{1norm}	c_{2norm}	c_3	c_4
1	c_{11norm}	c_{12norm}	c_{13}	c_{14}
....	....	....	....	....
k	c_{k1norm}	c_{k1norm}	c_{k3}	c_{k4}
Sum	$\sum c_{k1norm}$	$\sum c_{k2norm}$	$\sum c_{k3}$	$\sum c_{k4}$

to the decision-maker, the process proceeds to Block 5; otherwise, it returns to Block 3.

Block 5. The clusterer for explosive object parameters is constructed using the technology from [24].

Block 6. The quality of clustering is determined using metrics from [25] and [26].

Block 7. Decisions are made, and the clusterer is put into practical use. A dataset update is envisioned.

For the purpose of experimentally verifying the proposed solutions, theoretical samples will be formed. If four variables, each belonging to [0, 1] with a step of 0.1, are considered, the number of possible permutations will reach $11^4 = 14{,}641$. However, under this condition, the complex indicator would yield zero values. If we consider four variables, each belonging to [0.1, 1] with a step of 0.1, the number of possible permutations will be 10,000, as shown in Table 2.

Let us consider the procedure for creating three additional bootstrap samples n_2, n_3, n_4 to verify the proposed solution. As in the previous case, these bootstrap samples each comprised four variables belonging to the range [0.1, 1], as shown in Table 3.

Table 2

The input primary evaluations, utilized for determining the complex indicator for assessing explosive objects, were generated using combinatorial methods (specifically, the number of permutations with repetitions)

No.	c_1	c_2	c_3	c_4
1	0.1	0.1	0.1	0.1
...	...	...	...	...
10,000	1.0	1.0	1.0	1.0
Sum	5,500	5,500	5,500	5,500

These three bootstrap samples n_i were used for additional verification of the proposed assumptions. Table 4 presents the resulting evaluations of the complex indicators.

For all four variants of the theoretical samples n_i, on which the complex indicator was determined, the *p-value* > 0.05. Concurrently, the standard deviation of the complex indicator varied: for sample n_1 it was 0.1642, and for n_2, n_3, n_4 it was 0.1325, 0.1364, and 0.1323, respectively. These results lead to an interim conclusion regarding the satisfactory adequacy of the proposed linear combination, which is further supported graphically in Fig. 1.

As can be seen in Fig. 1, the distribution diagrams exhibit no asymmetry. This confirms the validity of using solely a normal distribution. The final decision regarding the proposed approach was based on the experimental sample, where the complex indicator values were determined as $A_{i1} = 0.061$; $A_{i2} = 0.119$; $A_{i3} = 0.153$; ...; $A_{i316} = 1.0$.

Bootstrap samples were not employed in the experimental test. A comparative analysis of the proposed method was conducted against the method presented in [27]. The results of this comparative analysis, based on the standard deviation criterion for both the proposed and existing approaches, are shown in Table 5.

Based on the comparative analysis of evaluations derived from the proposed (determined by formula (2)) and existing complex indicators, their standard deviations are 0.195 and 0.212, respectively, indicating the superiority of the proposed method. This is precisely

Table 3

The output primary evaluations, utilized for determining the complex indicator for assessing explosive objects, were generated using bootstrap samples n_2, n_3, n_4

No.	Sample 1, n_2				Sample 2, n_3				Sample 3, n_4			
	c_1	c_2	c_3	c_4	c_1	c_2	c_3	c_4	c_1	c_2	c_3	c_4
1	0.6	0.44	0.59	0.37	0.53	0.58	0.57	0.62	0.6	0.66	0.64	0.64
...	...	...	...	...	...	...	...	...	...	...	...	...
10,000	0.62	0.34	0.51	0.62	0.76	0.57	0.37	0.47	0.5	0.56	0.61	0.57
Sum	5,495.3	5,178.4	5,462.3	5,896.8	5,943.5	5,736.7	5,631.8	5,883.1	5,256.6	5,457.0	5,276.3	5,466.6

Table 4

Results of calculating the complex indicator for evaluating explosive objects based on theoretical samples generated using different approaches (combinatorial methods and the bootstrap method)

No.	Complex indicator based on the sample created using combinatorial methods (number of permutations with repetitions)	Complex indicator based on the bootstrap sample		
	n_1	n_2	n_3	n_4
1	0.018	0.295	0.463	0.702
....	....	....	....	....
10,000	0.069	0.356	0.38	0.526
Standard deviation	0.1642	0.1325	0.1364	0.1323
p-value significance level	*p-value* < 0.05	*p-value* < 0.05	*p-value* < 0.05	*p-value* < 0.05

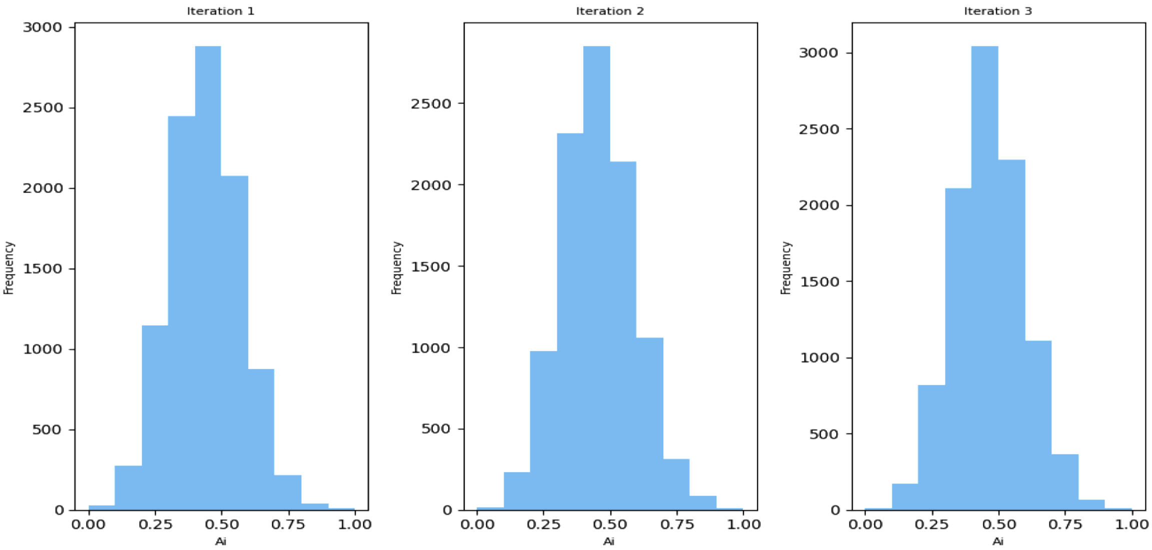

Fig. 1. Example of the distribution diagram of evaluations for three bootstrap samples

Table 5

Comparative analysis of the proposed and existing complex indicators for evaluating explosive objects based on an experimental sample

Comparison criterion	Standard deviation
Proposed complex indicator, which determined by formula (2)	0.195
Existing complex indicator [21]	0.212

why the chosen linear combination was put forward. The advantages of the proposed complex indicator are explained by its construction characteristics. The adherence of the indicator to a normal distribution is not its primary advantage.

To determine the percentage difference between the standard deviations, we use the well-known formula

$$Efficiency = (1 - SDp/SDex) \cdot 100\ \%, \qquad (3)$$

where *SDex* is the standard deviation of evaluations determined by the existing complex indicator; *SDp* is the standard deviation of evaluations determined by the proposed complex indicator.

Thus, the proposed complex indicator demonstrates a standard deviation 8.2 % lower than the existing one, as determined by formula (3).

The experimental sample of complex indicators showed support for the hypothesis of a normal distribution via the Jarque-Bera test, yielding a Jacques-Ber statistic is 3.371 at a significance level of $p\text{-}value = 0.185$. The results of the distribution type verification were also confirmed by graphical methods, specifically the probability distribution function, as shown in Fig. 2.

Since the theoretical and experimental lines on the graph almost coincide, we conclude that the complex indicator's distribution is normal. The evaluations determined by the complex indicator are then fed into the clusterer.

Among the clustering algorithms used were K-Means and Agglomerative Clustering, which optimally group the investigated objects. Within the clustering methodology, K-Means and Agglomerative Clustering algorithms were selected due to their proven ability to optimally group objects. While the elbow method suggested an optimal number of clusters for the investigated dataset to be 3 or 4, the current study focused on analyzing two clusters, as detailed in Table 6.

From the perspective of the investigated clusterer quality criteria, namely the Davies-Bouldin and Silhouette indices, clustering algorithms based on the proposed complex indicator are more effective. Specifically, the Davies-Bouldin index for K-Means and Agglomerative Clustering built on evaluations from the proposed complex indicator are 0.517 and 0.525, respectively, while for those based on the existing indicator, they are both 0.572.

The Silhouette index for K-Means and Agglomerative Clustering built on evaluations from the proposed complex indicator are 0.618 and 0.616, respectively, compared to 0.575 and 0.575 for the existing one. This demonstrates superior cluster differentiation due to more precisely determined complex indicator evaluations. The proposed indicator indeed enhances diagnostic efficiency, as these specific characteristics influence the grouping of evaluations and subsequent decision-making, as shown in Table 7.

Table 7 presents the top four ranked positions for the complex indicator values and the clustering re-

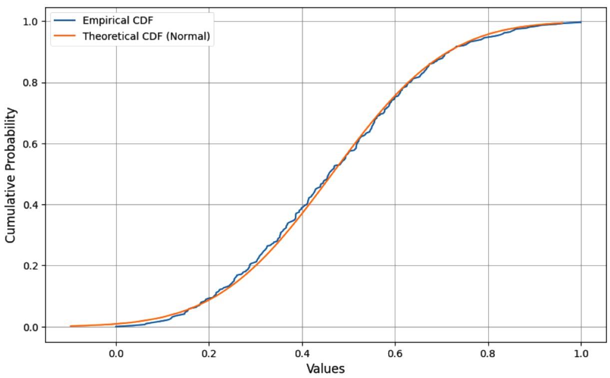

Fig. 2. Graphical interpretation of the support for the normal distribution condition, set of evaluations determined by the proposed method, probability distribution function of the complex indicator

Table 6

Comparative analysis of clusterers for explosive object parameters based on the complex indicator (proposed and existing)

Investigated algorithm	Based on the proposed indicator		Based on the existing indicator [21]	
	Davies-Bouldin index	Silhouette index	Davies-Bouldin index	Silhouette index
K-Means	0.517	0.618	0.572	0.575
Agglomerative Clustering	0.525	0.616	0.572	0.575

Table 7

Results of constructing the clusterer based on input data from the existing and proposed complex indicators, as determined by formula (2)

Rank position	Results of constructing the clusterer based on input data from the existing complex indicator			Results of constructing the clusterer based on input data from the proposed complex indicator, as determined by formula (2)		
	Existing complex indicator [21]	Cluster by K-Means	Cluster by Agglomerative Clustering	Complex indicator determined by formula (2)	Cluster by K-Means	Cluster by Agglomerative Clustering
1	0.0908	0	1	0.061	0	0
2	0.1244	0	1	0.119	0	0
3	0.1472	0	1	0.153	0	0
4	0.1782	0	1	0.21	0	0

sults for both existing and proposed approaches. As evident from Table 7, the cluster numbers from Agglomerative Clustering differ between the compared approaches. For instance, the first rank shows a complex indicator of 0.0908 for the existing method and 0.061 for the proposed method. For Agglomerative Clustering, these correspond to the first and zero clusters, respectively.

This indicates that the more precisely the complex indicator is determined, the better the evaluations will be clustered. This conclusion highlights the effectiveness of the diagnosis, specifically the difference between measurements using the proposed and existing methods, which leads to different grouping outcomes for the evaluations. To confirm these results, we will additionally use classical clusterer construction ideas from [22] and compare the results, taking input data from the experimental sample.

In this context, K-Means demonstrates a Davies-Bouldin index of 1.73, while Agglomerative Clustering shows a Davies-Bouldin index of 2.064. The silhouette scores are 0.221 and 0.175 for K-Means and Agglomerative Clustering, respectively. This signifies that the resulting grouping of evaluations is less accurate than what was observed in Table 6.

The proposed ideas are suitable for practical application as an addition to existing approaches [27]. Thus, the complex indicator, unlike existing ones, is built upon a linear model. The obtained research results are a logical continuation of the work in [9, 28]. A practical aspect of using the clusterer is the integration of solutions into the national security system of a state or its elements. This will allow for improved monitoring and national security management processes to prevent emergencies. Furthermore, the developed model can be practically implemented using hardware, specifically a Raspberry Pi single-board computer, for studying aspects of computer vision in solving tasks such as reconnaissance, demining, and so on. Among the limitations, it is important to consider the use of only four variables, especially when explosive objects may not be located on the soil surface.

Conclusions. In this study, the problem of enhancing the efficiency of clustering parameters of explosive objects was addressed. The task of creating a model for combining explosive object parameters was resolved by employing a linear combination of parameters with weighted coefficients, which accounts for combinations between various variables. The application of the proposed solutions to theoretical samples, generated through different methods, including combinatorics and bootstrap, indicates a positive trend. This is evident in the results of quality and model adequacy measurements.

The task of developing a clusterer was tackled by utilizing hybridization concepts, where the clusterer receives evaluations determined by a more precise method than the existing ones. Consequently, the K-Means and Agglomerative Clustering algorithms demonstrate more effective index values, specifically Davies-Bouldin indices of 0.517 and 0.525, respectively, whereas the existing ones show 0.572 and 0.572. This directly addresses the problem of improving clustering accuracy.

Experimental verification of the proposed solutions showed that using the evaluations from the proposed complex indicator in the clustering method improves clustering quality. The accuracy of the complex indicator is directly proportional to the increase in clustering quality, as measured by the Davies-Bouldin index and the silhouette score.

The practical application of the proposed solutions lies in improving existing algorithms for detecting explosive objects for studying aspects of computer vision in solving reconnaissance and demining tasks. The proposed solutions can be used as an addition to existing approaches for monitoring and managing national security to prevent emergency situations.

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Розробка кластеризатора параметрів вибухонебезпечних об'єктів на основі комплексного показника

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Мета. Підвищення ефективності кластеризації параметрів вибухонебезпечних об'єктів за рахунок розробки елементів гібридного кластеризатора.

Методика. Методом математичного моделювання розроблено класифікатор вибухонебезпечних об'єктів на основі комплексного показника, що є основним принципом удосконалення класифікатора. Обробка даних здійснювалася із використанням мови програмування Python і бібліотек scikit-learn. Методологія дослідження передбачає групування вибухонебезпечних об'єктів на два кластери з метою удосконалення існуючих алгоритмів виявлення вибухонебезпечних об'єктів.

Результати. Комплексний показник демонструє стандартне відхилення на 8,2 % менше від існуючого. Удосконалений алгоритм кластеризації демонструє значення Девіса-Болдіна 0,517; 0,525; у той час як існуючі – 0,572 і 0,572 відповідно. Це вказує на те, що вихідні оцінки нового алгоритму є менш залежні від шумів, що покращує якість кластеризації та зменшує кількість помилок під час практичного використання.

Наукова новизна. Запропоновано кластеризатор параметрів вибухонебезпечних об'єктів, котрий, на відміну від існуючих, ураховує в якості вхідних даних комплексні оцінки, побудовані на основі лінійної моделі з комбінованими параметрами.

Практична значимість. Полягає в тому, що удосконалення існуючих алгоритмів виявлення вибухонебезпечних об'єктів дозволить підвищити ефективність комп'ютерного зору при вирішенні задач розвідки, розмінування. Запропоновані рішення можуть бути використані як додаток до існуючих підходів із моніторингу, керування національною безпекою для запобігання надзвичайним ситуаціям.

Ключові слова: *лінійна модель, кластеризатор параметрів, вибухонебезпечний об'єкт, комп'ютерний зір, штучний інтелект*

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