Clustering Methods Analysis for Terrain Colors Characteristics Determination

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Abstract

This paper considers one of the stages of designing camouflage concealment means - the identification of characteristic colors of the terrain. Color is an integral part of the visual characteristic of camouflage means intended to conceal personnel, material resources, weapons and military equipment from enemy reconnaissance and destruction means. It is proposed to identify characteristic colors using cluster analysis, which refers to unsupervised machine learning methods. The number of clusters obtained determines the number of colors that will be displayed on the camouflage coating. As a result of the research, mathematical clustering algorithms were analyzed to determine the characteristic colors of the terrain. The need to conduct these studies is due to the lack of a universal way to determine the number of clusters, and is based on the research of other scientists who have determined that for each subject terrain only a certain clustering algorithm works most effectively, which must be determined experimentally. According to the results of the research, it was determined that the optimal algorithm for determining the characteristic colors of the terrain was the k-means++ clustering algorithm.

Keywords

Cluster analysis, k-means, fuzzy c-means, Kohonen self-organizing maps, elbow method, characteristic color, camouflage properties of the terrain, camouflage, camouflage pattern.

1. Introduction

The experience of combat operations in the East of Ukraine shows that the enemy widely uses modern optoelectronic devices and mobile platforms for their deployment in the course of reconnaissance and adjustment of fire of destruction means. At present, the most effective way to preserve the lives of personnel, material resources, weapons and military equipment is to use camouflage means to conceal these military objects and to take measures to mislead the enemy. This is also confirmed by the analysis of recent local conflicts in the territory of the Republic of Azerbaijan, the Syrian Arab Republic, the State of Libya, etc. [1].

Therefore, despite the continuous improvement of thermal, laser and multispectral surveillance equipment, means of reducing visibility in the visible range remain an important element of ensuring the safety of troops. World arms manufacturers continue to develop and improve the structures of camouflage patterns (patterns and coloring) of camouflage means for their effective operation in the visible range of the electromagnetic spectrum of waves [2, 3]. In 2022, the American company Digital

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Concealment Systems announced the start of production of equipment and clothing in the new universal camouflage A-TACS U|CON (Universal Camouflage), the pattern of which was created almost from scratch using mathematical modeling. The company has ambitious plans to adopt this camouflage pattern as the main one for the military uniforms of the US Armed Forces.

2. Related works

Currently, the issue of providing and adopting modern camouflage means, including concealment means, for the Armed Forces of Ukraine is an urgent one. Concealment camouflage means are means designed to eliminate the characteristic demasking features of military equipment, facilities and troops' activities (individual camouflage means, camouflage kits, masks, coverings, etc.). The means of concealment from optical reconnaissance means should ensure the achievement of the required masking effect within the near ultraviolet, visible and near infrared spectral ranges, and reduce the possibility of detecting objects in the optical range [29].

The fighting in Ukraine is taking place on a wide front in different natural zones, each of which has its own vegetation, which has certain colors in different periods of the year. In spring, it is bright green; in summer, the plants fade and have dark green, light green, green-yellow colors; in autumn, yellow, brown, brown, dark colors of tree trunks and bushes. The results of research by Timothy O'Neill, a well-known developer of the MARPAT camouflage pattern for the US Marine Corps, show that such camouflage components as the pattern and color palette should be developed for the specific environment where combat missions will be performed [4, 6]. That is, for each theater of operations, a camouflage pattern of military uniforms should be used, which is more effective in that particular territory [5]. This is especially true for the Armed Forces of Ukraine; whose personnel wear the camouflage uniforms of the armies of all countries that help us fight the enemy. However, this uniform and its camouflage pattern were designed for other theaters of war and are not always suitable for the territory of Ukraine.

Given that the color palette is one of the main elements of a camouflage device, it is necessary to conduct research to determine the color palette that is effective for the territory of Ukraine.

When designing camouflage means, both a single color and a wide color palette can be used in its camouflage pattern. If you use only one color for camouflage coloring, the product will have a monotonous appearance and will stand out as a spot on the ground. To ensure the effectiveness of concealment, the camouflage agent must be painted in the optimal number of colors [28].

The palette of characteristic colors of any object consists of dominant, supporting and accent colors. The technology of their selection is an important stage in the development of camouflage means [7].

To determine the characteristic colors of the terrain, it is necessary to group colors into groups, according to certain characteristics, the group that will have the largest size will be the dominant color in the color gamut of the image, the second largest group will be the supporting color, and the remaining color groups will be accent colors [30, 33-35].

The dominant color gives an idea of the color of an object at a glance. In multi-color painting, the dominant color maintains the integrity of the composition and its semantic unity. The supporting color complements the dominant one. Their combination, in fact, creates a color composition. If the percentage of two colors in an image is the same, they start to compete for attention, and the color space looks contradictory and fragmented. Accent colors create accents - spots of color that enliven the space. Using four, five, or more colors further enriches the color palette of an object. However, increasing the number of colors complicates the task of creating a harmonious composition and determining their proportions.

To work with terrain images, at present, images obtained by digital optoelectronic equipment are mainly used and stored on electronic media in certain data formats. In the process of analysis, the task of dividing the entire set of colored pixels (pixel, from the English PICture'S ELement - the smallest unit of a digital image in raster graphics) of a given terrain image into subsets called clusters, so that each cluster consists of similar colors, and the colors of different clusters differ significantly, is solved [8].

In machine learning, solving such problems is considered unsupervised machine learning and is referred to as data clustering [12, 36].

The purpose of cluster analysis is to divide objects in a sample into relatively homogeneous (homogeneous) groups of similar objects. Objects in a group are relatively similar in terms of their characteristics and differ from objects in other groups.

Cluster analysis itself is not a specific algorithm, but a general task that needs to be solved using different algorithms. There is no objectively "correct" clustering algorithm. The most appropriate clustering algorithm should be chosen experimentally, depending on the data set, or if there is no mathematical reason to prefer a particular algorithm.

Clustering methods can be divided: by the way data is processed, by the way data is analyzed, by scaling, by execution time, etc. Different clustering methods can produce different cluster solutions for the same data [8].

Currently, when clustering an image, pixels are usually taken as cluster samples. Therefore, as the size of the image increases, the number of cluster samples inevitably increases dramatically, which leads to a significant increase in computational overhead.

Methods, according to the way they analyze data, are divided into clear (traditional) and fuzzy. Clear algorithms include those that assign each data object to one specific cluster. Fuzzy clustering algorithms include those in which each data object belongs to several clusters or does not belong to any.

In general, the existing methods for building cluster models are divided into two main types according to the data processing methods: hierarchical and iterative. Hierarchical algorithms are characterized by a visual analysis of the dendrogram (a schematic representation of relationships in the form of a tree) and determination of the most predictable number of clusters based on it [13]. However, this approach is not formalized and is therefore used only as a preliminary analysis of the partitioning result. In addition, visual analysis of the dendrogram is extremely difficult when the number of objects under consideration is large and the data structure is not explicit.

For iterative algorithms, the number of clusters is usually not known in advance and is selected according to subjective criteria, and serves as one of the input parameters of the algorithm [15].

Research conducted in [14] shows that there is no universal way to determine the number of clusters. Each criterion that is used and shows good performance in terms of the number of clusters works only within certain limits determined by the subject area and clustering algorithm. The specifics of the subject area are expressed in the specific parameters of the clustering process and the properties of the clusters, such as shape, cluster size, distance between adjacent clusters, and distances within a cluster.

According to Kleinberg's theorem: for a data set consisting of two or more objects, there is no clustering algorithm that is simultaneously scale-invariant, consistent, and complete. That is, it is fundamentally impossible to find a solution to the clustering problem, because there are many criteria for assessing the quality of partitioning, and the number of clusters is usually unknown in advance [17].

This suggests that it is impossible to build a universal clustering algorithm that suits all tasks - algorithms need to be selected and customized for each data sample separately.

All of this indicates that research conducted abroad on the creation of camouflage means is not suitable for the Armed Forces of Ukraine, as it does not take into account the peculiarities of the Ukrainian terrain.

In recent decades, the advancement of digital technology has led to an unprecedented development of algorithms for working with digital images [37-41]. Color, texture, and shape in recent decades, the advancement of digital technology has led to an unprecedented development of algorithms for working with digital images [42-46]. Color, texture, and shape are the most common visual characteristics of these objects [47-54].

Foreign researchers and developers of camouflage devices use a variety of mathematical algorithms to detect these features. The following clustering algorithms have been widely used: K-means clustering [9], fuzzy C-means clustering [10], fast fuzzy C-means clustering [11], etc.

One of the disadvantages of the above clustering algorithms is the need to specify the number of clusters into which the input data should be divided before starting the calculation. The problem of determining the number of clusters is one of the most difficult tasks of cluster analysis [13].

The algorithm for color clustering using Kohonen's self-organizing maps is worthy of attention, which is a further development of the Kohonen neural network with unsupervised learning [16]. The main disadvantage of this approach is the increase in computational time with the increase in the size of the image to be processed, and it is also necessary to specify a fixed map size (number of clusters) as input parameters.

The analysis of scientific papers shows that a significant number of authors of works in the field of masking are scientists from China. Their success in this field is also confirmed by the interesting fact that during the competition for the selection of camouflage patterns for the uniforms of the US Armed Forces, the uniform with the pattern of the Chinese Armed Forces was noted as one of the best, but given the antagonism between these countries, the US Armed Forces could not adopt it..

The purpose of the article is to study mathematical methods for determining the characteristic colors of the terrain as a component of the camouflage pattern of camouflage means for concealing personnel, objects, weapons and military equipment in the optical range of the electromagnetic spectrum of waves.

3. Methods

The fighting in eastern Ukraine is currently taking place on a wide front in different natural zones. For example, the contact line, which runs through the territory of Donetsk and Luhansk regions, is located in the zone of grass and fescue steppes. Forests and shrubs cover about 7% of the territory of Luhansk region and 5.6% of Donetsk region [22]. Forests of the gully type prevail, located along rivers, on the slopes of valleys, gullies (ravines) and ravines and are characterized by significant diversity. The following species predominate: pine forests in the Siverskyi Donets valley, oak, birch, ash, etc. on the Donetsk ridge. Therefore, for example, let's define the character colors for the grass and fescue steppe, pine forest, and oak forest (Fig. 1).

As mentioned above, to work with terrain images, images stored on electronic media in certain data formats are used. The main image storage formats are JPEG, TIFF and RAW [18].

The most common is the JPEG format (abbreviated as Joint Photographic Expert Group), which is represented in both professional and amateur digital cameras. JPEG technology allows you to store images, depending on the required image quality, with a significant reduction in file size. Another feature of this format is the ability to save information about camera settings and scene programs. The main difference between TIFF (Tagged Image File Format) and JPEG is that it does not compress the image and does not introduce distortions in the final result, but as a result, the files take up much more space.

Figure 1: Photo of the Ukrainian countryside from the Internet (from top to bottom: oak forest, pine forest, grass steppe)

The RAW file format is a data format that contains raw (or minimally processed) data from the optical sensor of the equipment, which avoids information loss. However, in addition to large file sizes, this format does not have a single specification and differs for each equipment, which leads to difficulties in processing it.

Color models are used to represent information about the color of each pixel of an image. These are abstract mathematical models that determine exactly how color data is encoded. Typically, colors are represented as three or four values called color coordinates.

More understandable for humans is the HSV color model (also called HSB), which is based on three color characteristics: hue, saturation, and value, also called brightness [19]. Another common color model is the LAB color model (CIE 1976 L*a*b*), which uses the following parameters: lightness, the ratio of green to red (a), and the ratio of blue to yellow (b). These three parameters form a three-dimensional space whose points correspond to certain colors.

Some researchers use the HSV color model to analyze terrain color [20, 21], but given that the JPEG format, with the YCbCr encoding method, stores information in the additive RGB color model (abbreviated as Red, Green, Blue), and the conversion from one color model to another is possible using a nonlinear transformation, it is advisable to analyze images in the RGB color model. The color image of the terrain is stored in a three-dimensional matrix, where each layer corresponds to one color according to the RGB color model.

Given that the numerical values of the RGB color model are in the constant range of 0-255 for each color, it is impractical to scale and standardize the input data. This was confirmed by the identical results of clustering the input data that were scaled using the MinMaxScaler (the range of scaled data will be from 0 to 1) and StandardScaler functions (the mean value is 0, the variance is 1) and were not pre-processed.

During the research, the images were analyzed using cluster analysis methods implemented in the Python programming language using the NumPy, Pandas, SciPy, Scikit-learn, and fuzzy-c-means libraries. The Pillow, Yellowbrick, and Matplotlib libraries were used to display the calculation results.

The Scikit-learn library (version 1.2.1) provides functionality for clustering using a variety of methods:

- hierarchical (agglomerative);
- spectral biclustering;
- centroid partitioning (k-means, MeanShift);
- based on density (DBSCAN, OPTICS);
- based on affinity propagation.

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The mathematical description of the k-means algorithm [23] is as follows: the input data set $X = \{x_1, x_2, \dots, x_n\}, x_i \in R^d, i = 1, \dots, n$ must be divided into the required number $k, k \in N, k \leq n$ clusters $S_1, S_2, \dots, S_k$, where $S_i \cap S_j = 0, i \neq j$ та $\bigcup_{j=1}^{k} S_j = X$ in such a way as to minimize the sum of the squared distances from each cluster element to its center. This is how the k-means algorithm performs the search:

$$\arg\min_{S} \sum_{j=1}^{k} \sum_{x \in S_j} p(x, \mu_x)^2,$$

where μ_j is cluster centers (centroids), $j = 1, \dots, k$, $p(x, \mu_j)$ is a function of the distance between x та μ_j.

The step-by-step operation of the algorithm is as follows:

Step 1. Determine the number of clusters k, into which the input objects should be divided.

Step 2. Select the initial centers of the clusters.

The set of points is determined $\mu_j, j = 1, \dots, k$, considered as initial cluster centers$\mu_j^{(0)}, j = 1, \dots, k$.

*S*tep 3. The objects are distributed among the clusters - the distance to the center of which is the closest (the distance is measured in Euclidean metric).

At each t ste$p$, $\forall_{x_i} \in X, i = 1, \dots, n; x_i \in S_j \Leftrightarrow j = \arg\min_{k} p(x_i, \mu_j^{(t-1)})^2$

Step 4. The new centers of each cluster are determined in the form of an element whose features are calculated as the arithmetic mean of the features of the objects included in this cluster.

$$\forall_j = 1, \dots, k: \mu_j^{(t)} = \frac{1}{|S_j|} \sum_{x \in S_j} x.$$

Step 5. The condition that the cluster centers have become stable (i.e., the same objects will be in each cluster at each iteration) is checked. Otherwise, steps 3 and 4 (t=t+1) are repeated until the variance within a cluster is minimal and between clusters is maximal

$$\exists i \in \overline{1, k}: \mu_j^{(t)} \neq \mu_j^{(t-1)}.$$

The disadvantages of the k-means algorithm are:

- it is necessary to predict the number of clusters in advance, in our case, the number of colors of the camouflage agent;
- the algorithm is very sensitive to the choice of initial cluster centers. The classic version uses a random selection of cluster centers, which leads to instability of the results.

For the calculations, we used an improved version of the k-means++ clustering algorithm [24]. The essence of the improvement is to find more optimal initial values of the cluster centers.

Paper [26] provides a taxonomy of approaches to estimating the required number of clusters and notes that their number reaches several dozen. There are various formal approaches that facilitate the procedures for determining the "best" number of clusters. Most of them involve repeated cyclical execution of the clustering algorithm with an increase in the number of clusters and plotting the calculated values of certain metrics on the graph.

4. Experiments, results and discussion

The elbow method involves plotting the intra-cluster variance (the distance from the cluster elements to its center), which decreases to 0 when the number of clusters is equal to the number of all objects in the sample. At an intermediate stage, you can see that the decrease in this variance slows down - in the graph, this happens at a point called the "elbow." In Figure 2, you can see that the graph is bent at cluster #4, which in our case means that there are 4 characteristic colors of the terrain. It is possible to increase the number of colors, but it is necessary to check for expediency.

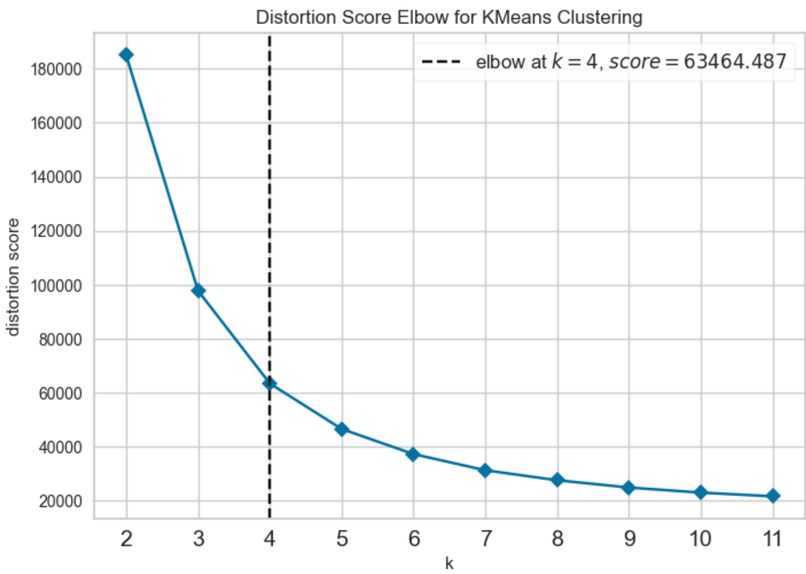

Figure 2: Determination of individual clusters by the elbow method

Calinski and Harabasz proposed the following criterion [13, 27]:

$$F = \frac{trace(B)/(k-1)}{trace(W)/(n-k)},$$

where B, W are the matrix of intercluster and intracluster sums of squared distances;

k is number of clusters;

n is number of clustering objects.

The maximum value will indicate the most likely number of clusters (Fig. 3).

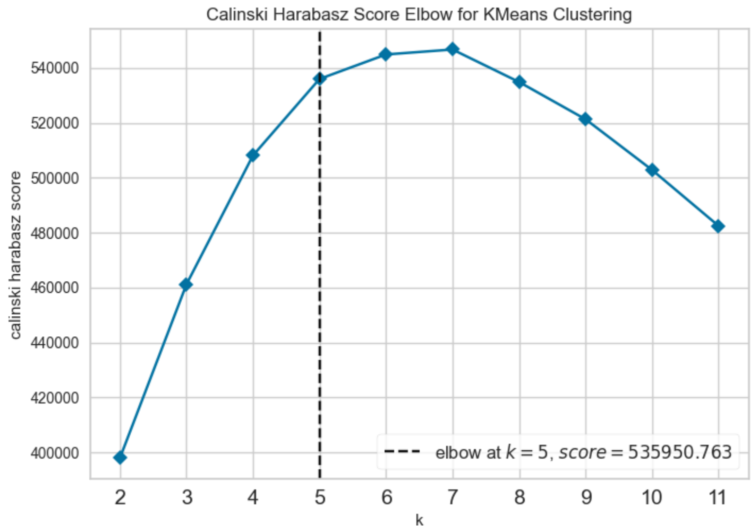

Figure 3: Determination of the number of clusters by the method of Calinski and Harabasz

The calculations performed by the following methods: silhouette coefficient (Fig. 4); Davies-Bouldin score; Gaussian mixture models with Bayesian information criterion (BIC) and Gap Statistics (Fig. 5) did not reveal any signs that could explicitly determine the number of clusters.

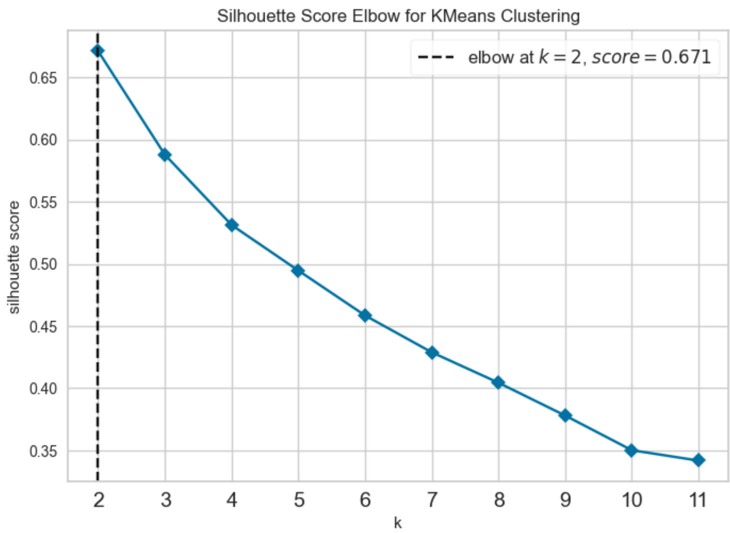

Figure 4: Determining the number of clusters by the silhouette coefficient method

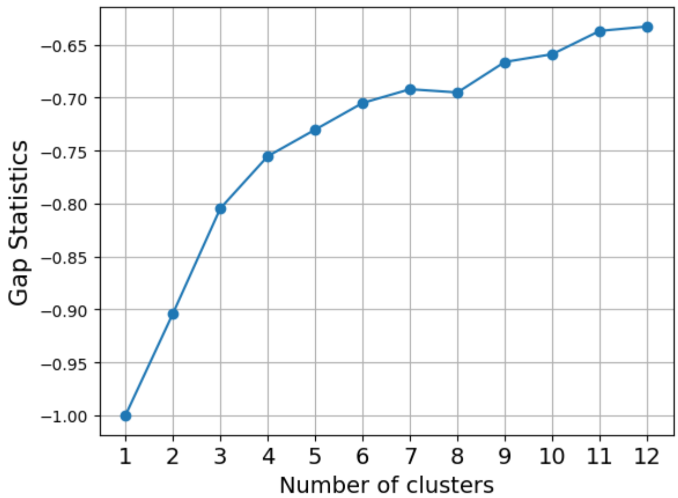

Figure 5: Determining the number of clusters by the Gap Statistics method

Figure 6 shows the values determined by the k-means++ clustering algorithm of 4 characteristic colors for the following terrain types: oak forest, pine forest, and herbaceous steppe.

The assumption that fuzzy clustering can be used to analyze image colors arises from the presence of possible color outliers in images that are not included in any of the clusters. Such outliers include: bright colors of flowers, the color of the sky and clouds in the gaps between trees, etc. The fuzzy-c-means library (version 1.7.0) was used to implement the c-means fuzzy clustering algorithm. The results of determining the characteristic colors for each type of terrain are shown in Figure 7.

The similarity of the colors obtained by the k-means and c-means algorithms was compared using the color difference formula proposed by the International Commission on Illumination (CIE - Commission Internationale de l'Eclairage). An indicator of the difference between two colors is Delta E (from the German empfindung), which, according to the CIEDE2000 standard [32], is determined by the formula:

$$\Delta E_{00} = \sqrt{\left(\frac{\Delta L'}{S_L}\right)^2 + \left(\frac{\Delta C'}{S_C}\right)^2 + \left(\frac{\Delta H'}{S_H}\right)^2 + R_T \frac{\Delta C'}{S_C}\frac{\Delta H'}{S_H}},$$

where R_T is the color tone angle rotation;

S_L is compensation for light;

S_C is compensation for color saturation;

S_H is compensation for hue (SH).

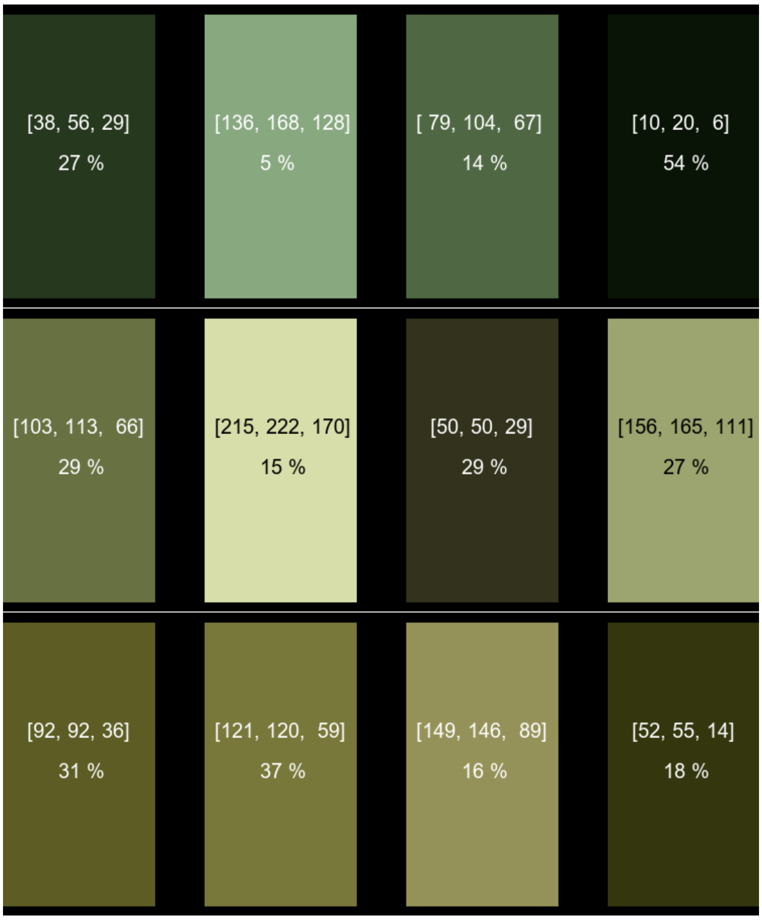

Figure 6: Characteristic colors with their values in RGB format and percentage in the image, determined using the k-means++ clustering algorithm (from top to bottom: oak forest, pine forest, grass steppe)

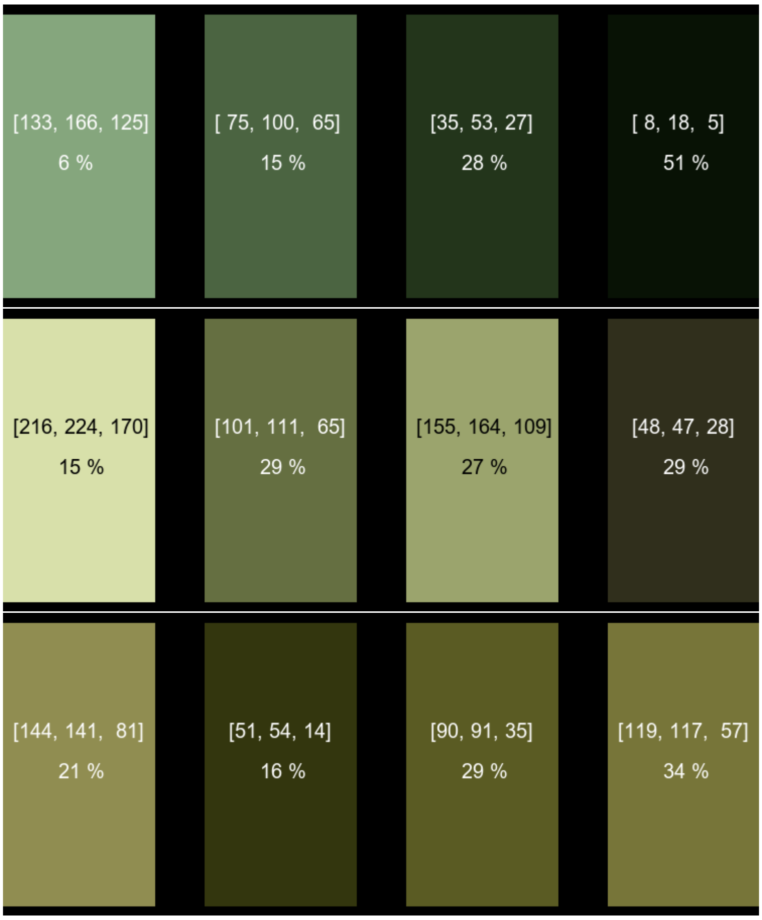

Figure 7: Characteristic colors with their values in RGB format and percentage in the image, determined using the fuzzy c-means clustering algorithm (from top to bottom: oak forest, pine forest, grass steppe)

Delta E is measured on a scale from 0 to 100, where 0 means no difference in color and 100 means complete color difference. The standard ranges of Delta E perception are as follows:

- <= 1.0 - no difference is perceived by the human eye;
- 1-3 - noticeable on close observation;
- 3-10 - noticeable at a glance;
- 11-49 - colors are more similar than opposite;
- 100 - colors are completely opposite.

The above formula shows that the color comparison is performed in the CIE LAB color model, so it is necessary to convert the image in the RGB color model to the CIE LAB color model. The software implementation was performed using the Colour science library (version 0.4.2). The output data, which are the color values from Figures 6-7 sorted by the percentage of their presence in the images, are shown in Tables 1-2. The results of calculating the Delta E color difference are shown in Table 3.

Table 1
Color values determined using the k-means++ clustering algorithm

	Color №1	Color №2	Color №3	Color №4
Pine forest	(136, 168, 128)	(79, 104, 67)	(38, 56, 29)	(10, 20, 6)
Pine trees	(215, 222, 170)	(156, 165, 111)	(103, 113, 66)	(50, 50, 29)
Grass steppe	(149, 146, 89)	(121, 120, 59)	(92, 92, 36)	(52, 55, 14)

Table 2
Color values determined using the fuzzy c-means clustering algorithm

	Color №1	Color №2	Color №3	Color №4
Pine forest	(133, 166, 125)	(75, 100, 65)	(35, 53, 27)	(8, 18, 5)
Pine trees	(216, 224, 170)	(155, 164, 109)	(101, 111, 65)	(48, 47, 28)
Grass steppe	(144, 141, 81)	(119, 117, 57)	(90, 91, 35)	(51, 54, 14)

Table 3
Color difference values determined using the k-means++ and fuzzy c-means algorithms

	Color №1	Color №2	Color №3	Color №4
Pine forest	0.75	1.28	1.45	2.96
Pine trees	0.72	0.51	0.46	2.22
Grass steppe	1.89	0.81	0.69	0.52

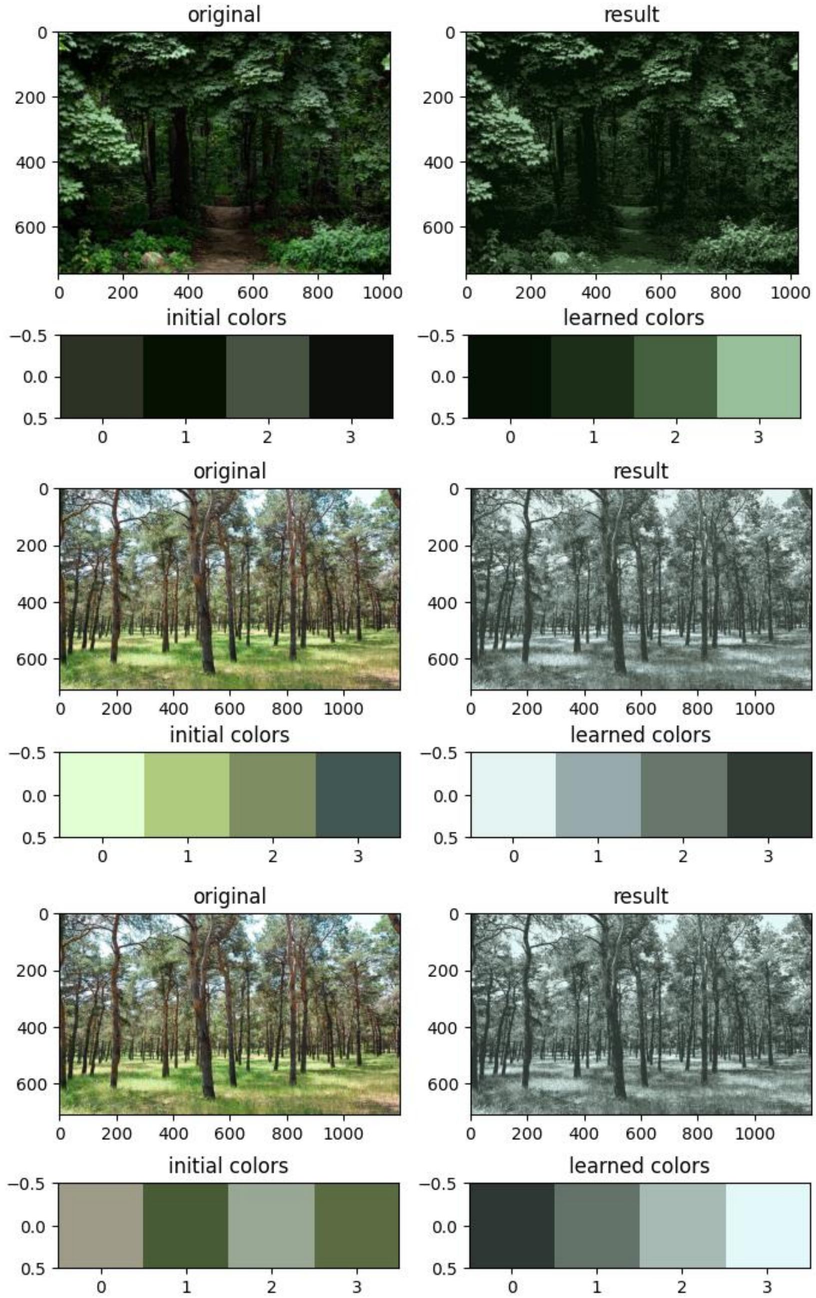

Figure 8: Colors obtained using the Kohonen self-organizing map algorithm

Calculations and comparisons of the k-means and c-means algorithms showed almost identical results: the difference in the distribution of the number of elements in the clusters (the proportion of colors per image) was observed within 3%, in most colors the difference is not perceived by the human eye, only in some it is noticeable upon close observation, but with the increase in clusters, the Delta E values for all colors are less than 1. These calculations indicate that when choosing k-means or c-means algorithms for clustering image colors, it is advisable to choose the one whose algorithm implementation will be simpler.

To highlight the characteristic colors of an image, image quantization algorithms are also used, the essence of which is to reduce the number of colors used in the image to the required number. One of these algorithms is Kohonen's neural networks [31]. In this work, one of the varieties of these networks, self-organizing Kohonen maps, was used to determine colors. The software model of the Kohonen network was implemented on the basis of the MiniSom library (version 2.3.0). The network structure has only two layers: input and output. The number of input neurons is equal to the number of pixels in the image, the number of output neurons is determined by the required number of colors of the masking coating.

The modeling results are shown in Figure 8 (original - original image, result - image based on the obtained colors, initial colors - colors selected as initial coefficients for training the neural network, learned colors - colors obtained as a result of training the neural network). As you can see visually from the results, the detected colors do not match the color palette of the original image. Probably, to obtain more reliable results, it is necessary to pre-process the image by removing colors that do not match the terrain palette. Therefore, we can conclude that the Kohonen's self-organizing map algorithm is not suitable for solving our problem.

5. Conclusions

As a result of the research, mathematical clustering algorithms were analyzed to determine the characteristic colors of the terrain.

The need to conduct these studies is due to the lack of a universal way to determine the number of clusters, and was based on the research of other scientists [14, 17], who determined that for each subject area only a certain clustering algorithm works most effectively, which must be determined experimentally. According to the results of the research, it was determined that the optimal algorithm for determining the characteristic colors of the terrain was the k-means++ clustering algorithm.

6. References

[1] S. A. Tsybulia, V. M. Aborin, Yu. A. Nastishin, Means of imitation of objects and military equipment as an important component of improving the survival of the troops. The Second Karabakh War as a new generation warfare, in Proceedings on the International scientific-practical conference. October 21-22, War College of the Armed Forces of the Republic of Azerbaijan, 2021, pp. 74-76.

[2] HyperStealth Camouflage Patterns. URL: htps://www.hyperstealth.com/camouflagepatterns.html.

[3] Saab provides camouflage systems to France, 2022. URL: https://www.saab.com/newsroom/press-releases/2022/saab-provides-camouflage-systems-to-france.

[4] T. O’Neill (camoufleur), 2022. URL: https://en.wikipedia.org/wiki/Timothy_O’Neill.

[5] Pentagon Accused of Wasting Up to $28M on ‘Inappropriate’ Afghan Soldier Uniforms. URL: https://www.nbcnews.com/news/world/pentagon-accused-wasting-28m-inappropriate-afghan-soldier-uniforms-n775081.

[6] T. O’Neill, Innovative camouflage measures for the United States Marine Corps. MARCORSYSCOM under Sverdrup technology agreement number 0965-36-01-C1.

[7] X. Yang, W.D. Xu, Q. Jia, L. Li, W.N. Zhu, Research on extraction and reproduction of deformation camouflage spot based on generative adversarial network model, Defence Technology, 2020. DOI: 10.1016/j.dt.2019.06.021.

[8] N. V. Karaeva, I. A. Varava, Ecological and economic optimization of production: methods and means of cluster analysis: methodical instructions for performing laboratory work [Ekoloho-

ekonomichna optymizatsiya vyrobnytstva: metody ta zasoby klasternoho analizu: metodychni vkazivky do vykonannya laboratornykh robit]. Kyiv: NTUU "KPI", 2016.
[9] Feng Xuen, Shan Xu, Yue-Tong Luo, Wei Jia, Design of digital camouflage by recursive overlapping of pattern templates. Neurocomputing 172 (2015) 262–270. DOI: 10.1016/j.neucom.2014.12.108.
[10] W. Xiao, Y. Zhao, X. Gao, C. Liao, S. Huang, L. Deng, Implementation of Fuzzy C-Means (FCM) Clustering Based Camouflage Image Generation Algorithm, *IEEE Access* 9 (2021) 120203-120209. DOI: 10.1109/ACCESS.2021.3108803.
[11] Zun-yang Liu, Feng Ding, Ying Xu, Xu Han, Background dominant colors extraction method based on color image quick fuzzy c-means clustering algorithm, Defence Technology 17(5) (2021) 1782-1790. DOI: 10.1016/j.dt.2020.10.002.
[12] A. A. Patel, Hands-on unsupervised learning using Python: how to build applied machine learning solutions from unlabeled data. O'Reilly Media, 2019.
[13] I. Yatskiv, I. Gusarova, Methods for determining the number of clusters in classification without training, Transport and Telecommunication Journal 4 (1) (2003) 23-28.
[14] V. Frolov, S. Slipchenko, O. Prikhodko, Method for calculating the number of clusters for the k-means algorithm. Economy. Computer science 47(1) (2020) 213–225. DOI: 10.18413/2687-0932-2020-47-1-213-225.
[15] Arbelaitz Olatz, Gurrutxaga Ibai, Muguerza Javier, Pérez Jesús M., Perona Iñigo, An extensive comparative study of cluster validity indices, Pattern Recognition 46(1) (2013) 243-256. DOI: 10.1016/j.patcog.2012.07.021.
[16] P. Sarlin, S. Rönnqvist, Cluster Coloring of the Self-Organizing Map: An Information Visualization Perspective, in Proceedings on the 17th International Conference on Information Visualisation, London, 2013, pp. 532-538. DOI: 10.1109/IV.2013.72.
[17] J. Kleinberg, E. Tardos, Algorithm Design, 2006. Livros de autores brasileiros importantes também estão disponíveis, 2019.
[18] V. Volkov., Digital camera. Sova, 2005.
[19] S. A. Douglas, A. E. Kirkpatrick, Model and representation: the effect of visual feedback on human performance in a color picker interface. ACM Transactions on Graphics 18(2) (1999) 96–127. DOI: 10.1145/318009.318011.
[20] P. Bian, Y. Jin, N. Zhang, Fuzzy c-means clustering based digital camouflage pattern design and its evaluation, in Proceedings on the 10th International conference on signal processing proceedings, Beijing, China. 2010, pp. 1017-1020. DOI: 10.1109/ICOSP.2010.5655856.
[21] Q. Jia, H., Xue S. Wang, C. Ma, Design and Camouflage Effect of Facial Camouflage Pattern, in Proceedings on the International Conference on Advances in Electrical Engineering and Computer Applications, Dalian, China. 2020, pp. 768-772. DOI: 10.1109/AEECA49918.2020.9213453.
[22] S. A. Tsybulia, I.V. Chernykh, Problematic issues of the development of camouflage nets for the needs of the Joint Forces Operation [Problemni pytannya rozroblennya maskuvalʹnykh sitok dlya potreb provedennya Operatsiyi Obʺyednanykh syl]. Creation and modernization of OVT in modern conditions: materials of the 20th scientific and technical conference, Chernihiv, September 03-04, 2020 / DNDIVSOVT. Chernihiv, 2020, pp. 269-270.
[23] J. MacQueen, Some methods for classification and analysis of multivariate observations, Proc. of in Proceedings on the fifth Berkeley Symp. on Mathematical Statistics and Probability, 1(14) (1967) 281–297.
[24] D. Arthur, S. Vassilvitskii, k-means++: the advantages of careful seeding. Society for Industrial and Applied Mathematics Philadelphia, in Proceedings on the eighteenth annual ACM-SIAM symposium on Discrete algorithms., PA, USA, 2007, pp. 1027–1035. DOI: 10.5555/1283383.1283494.
[25] D. Selukov, V. Shilov, Finding the optimal number of clusters by the "elbow method". Innovative technologies: theory, tools, practice 1 (2016) 107–111.
[26] B.G. Mirkin, Cluster analysis methods for decision support: a review. Ed. home of the National Research University Higher School of Economics. 2011.
[27] R.B. Calinski, J. Harabasz, A dendrite method for cluster analysis. Comm. in Statistics 3 (1974) 127.

[28] M.A. Hogervorst, A. Toet, P. Jacobs, Design and evaluation of (urban) camouflage. SPIE Proceedings. 2010. DOI: 10.1117/12.850423.
[29] Military standard VST 01.106.001 – 2018 (01). Engineering support. System of general tactical and technical requirements for engineering weapons. Technical requirements for camouflage means [Viysʹkovyy standart VST 01.106.001 – 2018 (01). Inzhenerne zabezpechennya. Systema zahalʹnykh taktyko-tekhnichnykh vymoh do inzhenernoho ozbroyennya. Tekhnichni vymohy do maskuvalʹnykh zasobiv]. Kyiv: Ministry of Defense of Ukraine, 2018.
[30] Chijiiwa Hideaki, Color harmony: a guide to creative color combinations. Vol. 1. Rockport Pub, 1987.
[31] T. Kohonen, Self-organizing maps: Ophmization approaches. Artificial neural networks, North-Holland, 1991, pp. 981-990).
[32] ISO/CIE 11664-6:2022 | EN ISO/CIE 11664-6:2022 Colorimetry – Part 6: CIEDE2000 colour-difference formula.
[33] Z. Al-Ameen, Contrast Enhancement for Color Images Using an Adjustable Contrast Stretching Technique. International Journal of Computing 17(2) (2018) 74-80.
[34] I. Paliy, A. Sachenko, V. Koval and Y. Kurylyak, Approach to Face Recognition Using Neural Networks, in Proceedings on the Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, Sofia, Bulgaria, 2005, pp. 112-115, doi: 10.1109/IDAACS.2005.282951.
[35] B.P. Rusyn, V.H. Ivanyuk, H. Lau, V.M. Dovhunyk, V.V. Kornii, Computer analysis of the phase composition of the material based on color images of sections. Materials Science 40(5) (2004) 662–667.
[36] L. Khrissi, N. El Akkad, H. Satori, K. Satori, A Performant Clustering Approach Based on An Improved Sine Cosine Algorithm. International Journal of Computing 21(2) (2022) 159-168. DOI: 10.47839/ijc.21.2.2584.
[37] O. Tymochko, V. Larin, M. Kolmykov, O. Timochko, V. Pavlenko, Research of images filtration methods in computer systems. Advanced Information Systems 5(1) (2021) 93–99. DOI: 10.20998/2522-9052.2021.1.13.
[38] O. Yakovleva, K. Nikolaieva, Research of descriptor based image normalization and comparative analysis of SURF, SIFT, BRISK, ORB, KAZE, AKAZE descriptors. Advanced Information Systems 4(4) (2020) 89–101. DOI: 10.20998/2522-9052.2020.4.13.
[39] I. Ruban, N. Bolohova, V. Martovytskyi, O. Koptsev, Digital image authentication model. Advanced Information Systems 5(1) (2021) 113–117. DOI:10.20998/2522-9052.2021.1.16
[40] E. Sabziev, Determining the location of an unmanned aerial vehicle based on video camera images. Advanced Information Systems 5(1) (2021) 136–139. DOI: 10.20998/2522-9052.2021.1.20.
[41] S. Tyshko, O. Lavrut, V. Vysotska, O. Markiv, O. Zabula, Y. Chernichenko, T. Lavrut. Compensatory Method for Measuring Phase Shift Using Signals Bisemiperiodic Conversion in Diagnostic Intelligence Systems. CEUR-WS Proceedings 3312 (2022) 144-154.
[42] D. Mozgovoy, V. Hnatushenko, V. Vasyliev, Automated recognition of vegetation and water bodies on theterritory of megacities in satellite images of visible and IR bands, ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. IV-3 (2018)167–172. DOI: 10.5194/isprs-annals-IV-3-167-2018.
[43] Y. Shedlovska, V. Hnatushenko, Shadow detection and removal using a shadow formation model, in Proceedings on the First International Conference on Data Stream Mining & Processing (DSMP), 2016. DOI: 10.1109/dsmp.2016.7583537.
[44] V. Kashtan, V. Hnatushenko, Y. Shedlovska, Processing technology of multispectral remote sensing images, in Proceedings on the IEEE International Young Scientists Forum on Applied Physics and Engineering (YSF), 2017. DOI: 10.1109/ysf.2017.8126647.
[45] V. Gnatushenko, The use of geometrical methods in multispectral image processing. Journal of Automation and Information Sciences 35(12) (2003) 1-8. DOI: 10.1615/JAutomatInfScien.v35.i12.10.
[46] V. Gnatushenko, Usage of geometrical methods at multispectral images analysis. Problemy Upravleniya I Informatiki (Avtomatika) 6 (2003) 72-81.

[47] D. Mozgovoy, V. Hnatushenko, V. Vasyliev, Accuracy evaluation of automated object recognition using multispectral aerial images and neural network, in Proceedings on the SPIE 10806, Tenth International Conference on Digital Image Processing (ICDIP 2018), 9 August 2018, 108060H. DOI: 10.1117/12.2502905.
[48] D. Hordiiuk, V. Hnatushenko, Neural network and local laplace filter methods applied to very high resolution remote sensing imagery in urban damage detection, in Proceedings on the IEEE International Young Scientists Forum on Applied Physics and Engineering (YSF), 2017. DOI:10.1109/ysf.2017.8126648.
[49] Y. Shedlovska, V. Hnatushenko, V. Kashtan, Satellite imagery features for the image similarity estimation, in Proceedings on the IEEE International Young Scientists Forum on Applied Physics and Engineering (YSF), 2017. DOI: 10.1109/ysf.2017.8126673.
[50] B. Rusyn, V. Ostap, O. Ostap, A correlation method for fingerprint image recognition using spectral features, in Proceedings on the International Conference on Modern Problems of Radio Engineering, Telecommunications and Computer Science, TCSET 2002, pp. 219–220.
[51] B. Rusyn, V. Korniy, O. Lutsyk, R. Kosarevych, Deep Learning for Atmospheric Cloud Image Segmentation, in Proceedings on the 11th International Scientific and Practical Conference on Electronics and Information Technologies, ELIT, 2019, pp. 188–191.
[52] B. Rusyn, A. Lutsyk, R. Kosarevych, Modified architecture of lossless image compression based on FPGA for on - Board devices with linear CCD. Journal of Automation and Information Sciences 51(2) (2019) 41–49.
[53] R. Kosarevych, O. Lutsyk, O. Kapshii, B. Rusyn, Random point patterns and bags of visual words for remote sensing imagery. Journal of Applied Remote Sensing 13(3) (2019), 034521.
[54] B. Rusyn, Ya. Varets'kyi, Yu. Lysak, A. Pokhmurs'kyi, Reconstruction and quantitative analysis of metallic surfaces with pits based on improved stereo image matching method. Materials Science 47(2) (2011) 255–263.