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O. IVANCHUK[1], O. TUMSKA[2]

[1] *Department of Photogrammetry and Geoinformatics of National University «Lviv Polytechnic», 12, S. Bandery Str., Lviv, 79013, Ukraine, tel. +38(096)4143409, e-mail: ivanchuk_oleh@ukr.net
[2] Department of «Photogrammetry and Geoinformatics» of National University «Lviv Polytechnic», 12, S. Bandery Str., Lviv, 79013, Ukraine, tel. +38(050)7455711, e-mail: ol.tums@gmail.com

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A STUDY OF METHODS FOR TEXTURE CLASSIFICATION OF SEM IMAGES OF MICRO-SURFACES OF OBJECTS AND THEIR SEGMENTATION

Purpose. The goal of this work was to develop and study the methods of texture classification of SEM images of micro surfaces of objects based on the statistical and spectral characteristics of texture fragments, as well as a comparative analysis of segmentation methods of SEM images. **Methods.** The determination of the texture characteristics was based on statistical moments computed by the brightness histogram of a SEM- image or its region. The spectral measures of texture of SEM image were based on properties of the Fourier spectrum. To determine the spectral texture characteristics, the parameters of the amplitude and axial functions were chosen. SEM images were segmented using four methods, namely: the global thresholding; the region growing; the region splitting and merging; and the watershed using markers. **Results.** The experiments on texture classification of the SEM series of soils and metals images showed the best result of texture classification by the feature of homogeneity compared to other statistical characteristics. Calculation of the spectral characteristics was used to detect the directionality of periodic or almost periodic texture elements in the SEM images of metals. Classification results using spectral properties and homogeneity values made it possible to obtain generalized texture characteristics of SEM images of metals. A comparative analysis of the four segmentation methods showed that the best result of finding the boundaries of objects in the SEM image was obtained by the watershed method using markers. Software implementation of texture classification and image segmentation methods were performed in the MatLab system. **Scientific novelty.** The authors proposed a method for classifying SEM-images based on spectral texture characteristics using the parameters of the amplitude and axial functions. It is shown that the segmentation by the splitting and merging method allows you to set the conditions for selecting regions with certain texture characteristics in the SEM-image. **The practical significance.** A generalized characteristic of SEM-image texture, determined by statistical and spectral measurements, is that it would be useful for automatic texture recognition and SEM-images analysis. The selection of regions with certain texture characteristics is the preprocessing step for finding points of interest suitable for the SEM-image matching and objects recognition.

Key words: scanning electron microscope (SEM), statistical and spectral texture features of the SEM image, classification, segmentation.

Introduction

Texture is an important source of image information. Automatic texture analysis is widely used in the study of metallographic and fractographic SEM images, micro images of biological structures, and soil samples. Texture features play an important role in the analysis of medical images [Rangayyan, 2005; Melnik, 2012], images of semiconductor heterostructures [Noman, et al., 2014], to detect surface defects (steel, textile, tile, wood, etc.) [Tsapaev, et al., 2012; Neogi et al., 2014], and for assessing food quality [Gonzales-Barron et al., 2006; Przybyl et al., 2019]. Texture is the basis for creating digital textured microrelief models [Khokhlov, et al., 2012].

By texture we mean a region of an image that has uniform statistical characteristics which can be described using some features. Characteristic features are usually understood as characteristic properties common to all textures of a given class [Haralick, 1979]. Features of textures are used for their classification and when subdividing the image into its constituent parts it is termed texture segmentation [Zavalishin, 1975; Polyakova et al., 2008]. Statistical, structural, spectral and fractal approaches are used to describe textures [Haralick, 1979; Potapov, 2003; Rangayyan, 2005; Fisenko, et al., 2008; Melnik & Shostak, 2009; Hu, 2017]. Among the statistical characteristics (moments) of texture fragments, and more informative, are considered the measures of entropy, homogeneity, and brightness [Shapiro, et al., 2001; Forsyth, et al., 2004].

A brief review of related studies

A review of image texture analysis methods from 2001 to 2014 was given by Bagalkote & Vibhute, 2015. Various aspects and methods of texture analysis have also been proposed [Bavrina, et al., 2002; Gray, et al., 2006; Gulakov, et al., 2011; Visilter, et al., 2011; Bogucharsky, et al., 2014;]. Over the past years, approaches to the analysis of image textures can be found in the reviews [Tuceryan, M., 1998] for 1962–1993, [Materka, et al., 1998] for 1965–1998.

Reviews of classification methods were presented in [Lu, 2007; Jing, et al., 2009; Cord, et al., 2010; Asatryan, et al., 2014; Cavalin, et al., 2017]. The texture features for image classification were described in a review [Kolodnikova, 2004].

Methods of image analysis based on segmentation were given in [Manjunath, et al. 2005; Liu, et al., 2006; Szumilas, et al., 2006; Madasu, et al., 2007; Kupriyanov, 2008; Sizov, et al., 2011; Bhosle, et al., 2013; Goldueva, et al., 2015; Sparavigna, 2016].

Other related studies included an influence of various types of noise on the process of images segmentation [Lee, et al., 2008; Al-Janabi Akil Bahr Tarkhan, et al., 2014] and an analysis of the types noise arising in SEM images [Ivanchuk, Tumska, 2017]. In [Haindl, et al., 2016], an adaptive strategy is proposed for selecting more interest points in textured areas to find the corresponding points in a pair of images.

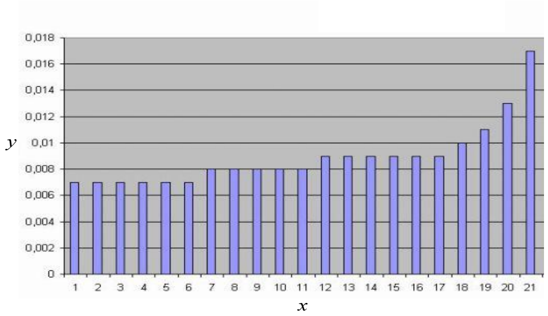
The theoretical basis of all aspects of image processing was considered in the works of scientists: Shapiro and Stockman, 2001, Forsyth and Pons, 2004, Gonzalez and Woods, 2005. The theory and examples of solving specific image processing problems using the MatLab and Image Processing Toolbox (IPT) functions can be found in [Gonzalez, Woods and Eddins, 2006].

This study will propose the methods of classification of SEM-images based on statistical and spectral texture characteristics and the comparison of the various methods segmentation.

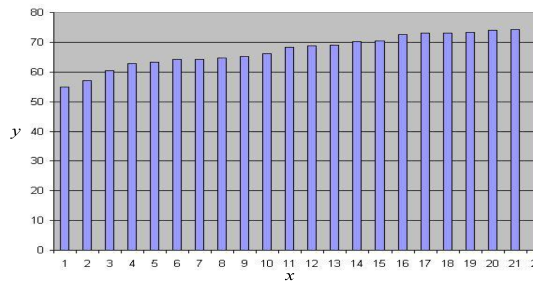
Classification of SEM-images of soil samples by statistical texture measures

The studies were based on the processing of a series of SEM-images of the samples soils, metals, and erythrocytes obtained from SEM “Hitachi S-800”, SEM JCM (JEOL, Japan) and SEM “Stereoscan S4-10” in the range of magnifications from 1,000x to 3,000x; the frame sizes were 47×49 mm (metal), 55×60 mm (erythrocytes) and 54.6×62.4 mm (soil). The images (film) were scanned at the resolution of 300 dpi and stored in JPEG format with image sizes on the order of 554×576 pixels (metal), 650×710 pixels (erythrocytes) and 645×737 mm (soil).

The determination of the statistical characteristics of the texture of SEM images was based on statistical moments calculated from histograms of texture measures: brightness, homogeneity, and entropy [Gonzalez, 2005]. Image soils belong to a mixed type of texture, consisting of fragments of various types. In this case, it is not possible to separate objects from the background. To classify and recognize such a type of image, we selected fragments of textures of different types in the image (see Figures in Table 1) [Smelyakov, 2008]. To improve the original images the histogram-equalization technique was applied. The classification of image fragments by soil type is based on histograms of distributions of statistical characteristics of textures before and after equalization of histograms. Compared to the original image, the average values of brightness, contrast, and homogeneity properties have changed significantly in the equalized image. However, after the equalization procedure, these characteristics became more similar for different SEM images of the same soil type. Figure 1 shows histograms of the distribution of texture measures by the values homogeneity and contrast. The homogeneity distribution histogram shows a smooth change in function for values 0.007 to 0.010 and a sharper change for values 0.011 and greater (Fig. 1a).The histogram of the contrast distribution shows a smooth growth of the function, which makes it difficult to select the boundaries of the classes (Fig. 1b). Table 1 shows the results of the classification of fragments of SEM images soil based on the histogram of homogeneity. In addition, Table 1 shows ranges of contrast and entropy values, which correspond to classes homogeneity. As you can see, fragments with visually similar texture characteristics belong to the same class.



a

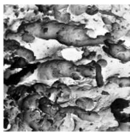
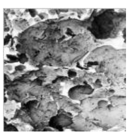
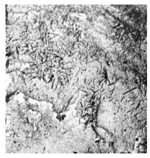


b

Fig. 1. Histograms of the distribution of texture measures of fragments SEM images of soil samples (x-number of fragment): a – as average homogeneity (y); b – as average contrast (y)

Table 1

Classification of SEM-images of soil samples by homogeneity texture measures

Statistical measures	Class 1	Class 2	Class 3	Class 4
	 			 
	Rough 1	Rough 2	Rough 3	Smooth
Homogeneity	0.75–0.87	0.88–0.99	1.00–1.19	1.20–1.66
Contrast	60.53–74.32	64.15–70.21	70.21–72.99	54.83–57.03
Entropy	7.28–6.99	7.01–6.71	6.67–6.59	6.59–6.13

From an analysis of Table 1, it follows that when classifying according to contrast, Class 1 contains Class 2. The ranges of the classes of entropy correspond to the ranges of the classes of homogeneity in descending order. Note that the measure of entropy characterizes the uneven distribution of the brightness properties of image elements. Note: for convenience of perception, in Tables 1 and 2, the values of the homogeneity measure are increased 100 times.

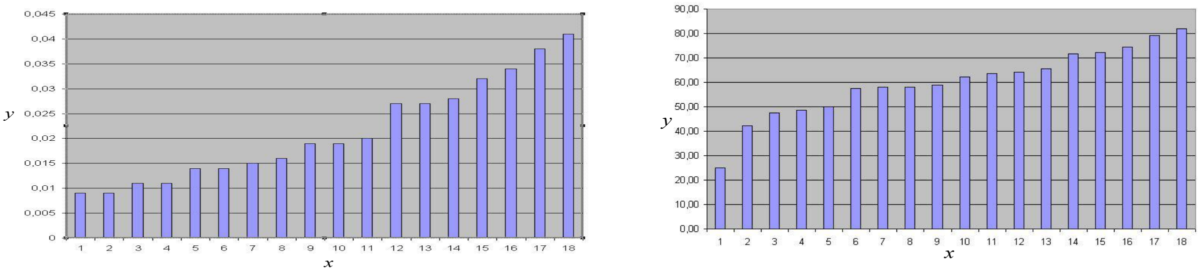
Classification of SEM images of samples of the micro surfaces of metals by statistical texture measures

As in the previous case, the classification is performed for fragments of the SEM images of metals samples with different types of textures. Figure 2*a* shows the histogram of the distribution of texture measures by homogeneity values for images fragments of various types of metals samples. The nature of the distribution of homogeneity values (Fig, 2*a*) shows the presence of five classes (Table 2).

The histogram of the distribution of contrast values, as in the case of soils, shows a smooth growth of the function, which complicates the choice of class boundaries.

Classification of SEM-images of samples micro surfaces of metals by spectral texture measures

The spectral measures of the texture were calculated from the Fourier spectrum for the same images of metals samples as the statistical measures. Spectral measures of texture make it possible to identify the directivity of periodic and quasiperiodic structures in the image [Hu, 2017]. The parameters of the amplitude and axial functions, such as maximum value, maximum location, average value, standard deviation and the difference between maximum and average values, were chosen as the spectral texture features of the SEM images [Gonzalez, 2006]. To determine the spectral measures of the textures of SEM images of metals, graphs of spectral functions were constructed. The experiment showed that the parameters of the amplitude and axial functions differ for images of various types of metals and, thus, are applicable for their classification. The amplitude function characterizes the behavior of the spectrum (the presence of peaks) in the direction of the radius from the origin. The axial function gives a picture of the behavior of the spectrum in a circle with the center at the origin. Classification was carried out taking into account the location of the maximum of the axial function and visually according to the graphs of the amplitude and axial function (sees Figures in Table 3).

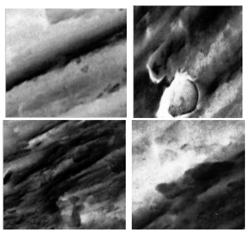
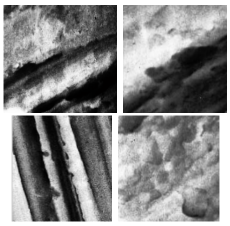
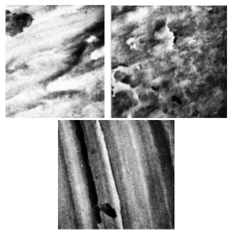
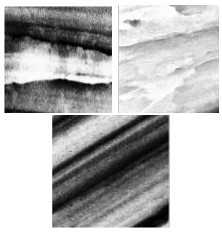
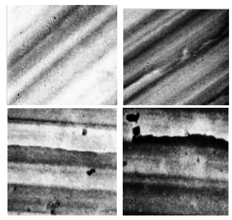


a *b*

Fig. 2. Histograms of the distribution of texture measures of SEM images of metals samples (x-number of fragment): a – as average homogeneity (y); b – as average contrast (y)

Table 2

Classification of SEM-images of samples micro surfaces of metals by homogeneity texture measures

Class 1	Class 2	Class 3	Class 4	Class 5
				
Rough 1	Rough 2	Rough 3	Smooth 1	Smooth 2
0.70–1.19	1.20–1.59	1.60–2.29	2.302–2.79	2.80–4.10

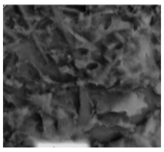
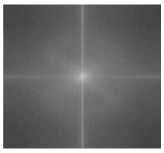
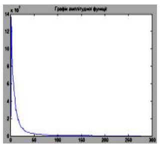
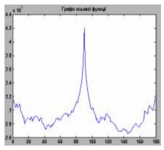
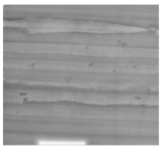
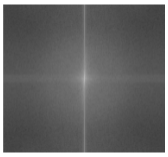
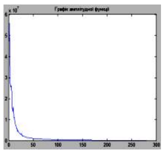
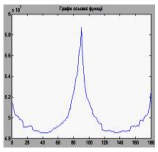
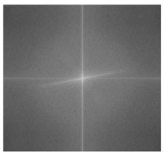
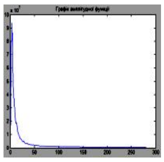
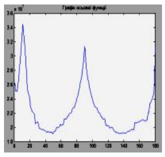
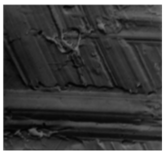
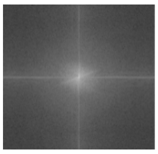
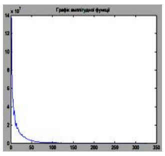
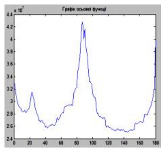
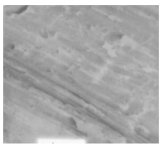
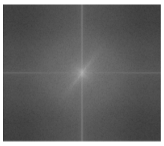
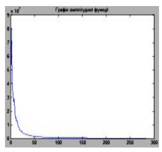
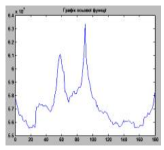
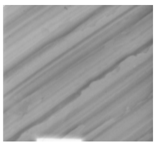
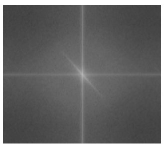
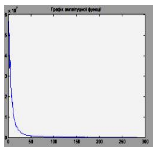
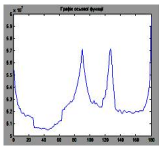
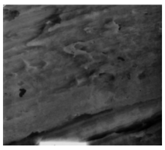
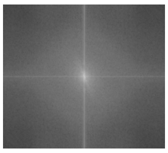
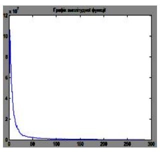
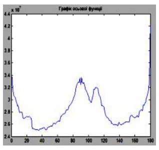
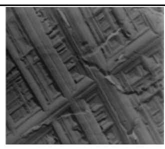
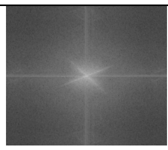
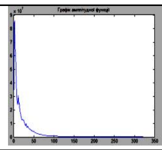
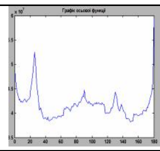
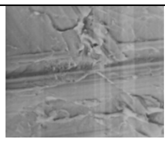
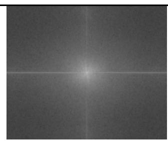
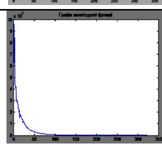
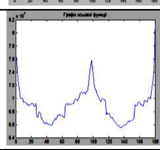
The last row of the Table shows the ranges of classes by values of homogeneity.

The location of the maximum values of the axial function is from 0º to 180º.

The 1st class is intended for chaotic textures of a rough surface. In this case, in the vicinity of the coordinate origin of the amplitude function, there is only one peak corresponding to the constant component of the transformation. At the same time, the graph of the axial function is characterized by the variability of the spectrum curve in the ranges from 0º to 90º and from 90º to 180º, which corresponds to a frequent change in the orientation of texture elements. The 2nd class is intended for samples with periodic (quasiperiodic) horizontal or vertical texture. Such an amplitude function has another peak in the vicinity of the origin. The axial function graph is characterized by an almost smooth spectrum curve in the ranges from 0º to 90º and from 90º to 180º. The 3rd class includes quasiperiodic textures in which the axial function of the spectrum has significant peaks in the range from 0º to 90º and is almost smooth from 90º to 180º. Such a texture is characterized by periodicity and the preferred orientation of the texture in the direction northwest → southeast.

Table 3

The distribution of the texture classes of SEM images of micro surfaces of metals for spectral measures

Class	Sample No.	Original image	Fourier spectrum	Graph of amplitude function, $S(r)$	Graph of axial function $S(\theta)$	Location maximum function	
						$S(r)$	$S(\theta)$
I	220					2	90º
II	214					1	90º
III	325					4	11º
	172					2	87º
	223					2	90º
IV	330					2	180º
	332					2	180º
V	170					3	180º
	171					2	180º

Texture elements have a direction perpendicular to the direction of the spectrum lines. The 4th class contains a quasiperiodic texture, in which, in contrast to the 3rd class, the preferred orientation of the texture in the direction southwest → northeast. The 5th class contains a more complex texture, the elements of which can be oriented in both directions (Table. 3).

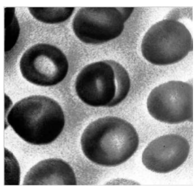
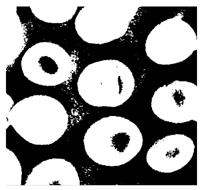
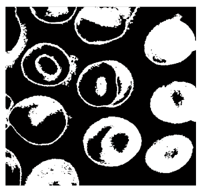
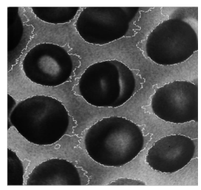
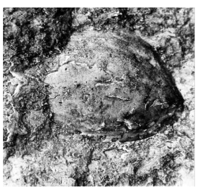
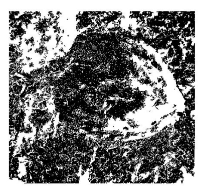
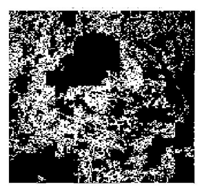
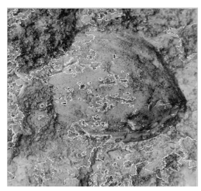
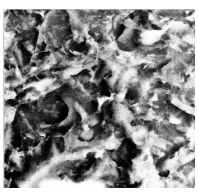
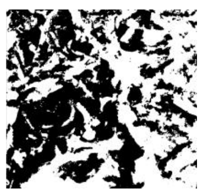
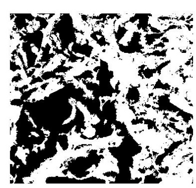
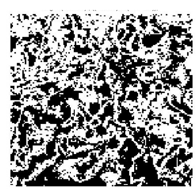
So, the graphs of the spectral functions of SEM images of metal surfaces allow us to identify the periodicity and direction of texture elements present in the image, and together with the results of classification by homogeneity measures give a generalized characteristic of the texture image.

Segmentation of SEM images of micro surfaces of objects

SEM images of the samples were segmented by four methods, namely: the global thresholding (selecting a threshold using the Otsu method), the region growing by pixel aggregation, the region splitting and merging and the watershed with a selection of markers [Gonzalez, 2005]. To compare the segmentation methods, SEM images of samples of each type were selected, namely, erythrocytes soil and metal (Table 4). Segmentation with automatic threshold selection by the Otsu method [Otsu, 1979] is most effective in the case of a bimodal histogram (Table 4, image erythrocytes). Automatic technique to determine the threshold of unimodal distributions led to the selection of an excessive amount of small fragments in the SEM images of samples of the soil and metal surface (Table 4). The result of the segmentation by the method of growing regions depends on the selection of starting point that properly represent regions of interest and the selection of the similarity criterion for including points in the various regions during the growing process [Sizov, 2011]. Selecting a starting point and the similarity criterion for a region growing method were based on the analysis a brightness histogram and texture properties of the SEM-image. To include a pixel in either region is that the absolute difference between the brightness value of that pixel and the brightness value of the starting pixel be less than a threshold T. The results of images segmentation by the region growing obtained using S = 45, T = 25 for image erythrocytes; S = 175, T = 50 for image soil; S = 170, T = 50 for image metal are shown in Table 4. Here S is the value of the brightness of the starting point; T — a given threshold. For the given parameters S and T, the results of soil and metal images in region growing segmentation are similar to the results of thresholding by the Otsu method (see Table 4).

Table 4

SEM-images segmentation results

Sample / Image size (pixels)	Original SEM-image	Otsu thresholding	Region growing	Split and merge	Watershed
Erythro-cytes 650x710					
Soil 645x737					
Metal 554x576					

A comparison of Table 4 columns 3 and 4 for image of erythrocytes shows that by changing the parameters S and T, additional details can be obtained as a result of segmentation by the region growing method.

In table 4, columns 3–5 show binary masks, where white regions correspond to the objects and black regions correspond to the background. Column 6 shows the boundaries of the watersheds plotted on the original image.

A split and merge procedure is initially intended to subdivide an image into a set of arbitrary, disjointed regions and then merge the adjacent regions that satisfy the given conditions. [Gonzalez, 2005, Haindl, 2016]. To define conditions splitting and merging regions were used statistical texture measures, namely: average brightness, average contrast, uniformity, entropy, and combinations thereof. The experiment confirmed that the split and merge procedure is suitable for the selection of image regions with the specified texture characteristics. Table 4, column 5 shows the results of image segmentation by the region splitting and merging method with the conditions

(t_2 >50) *or* (t_1>15) and (t_1<130) for image of erythrocytes;

(t_2>34) ***and*** (t_1>0) and (t_1<175) for image of soil;

(t_2>13) *or* (t_1>70) and (t_1<140) for image of metal,

where t_1 is the mean brightness value, t_2 is the average contrast value. The minimum block size was 4x4 pixels after which the subdivision of the image ended.

The experiment confirmed that the split and merge procedure is suitable for the selection of image regions with the specified texture characteristics.

The application of the watershed method with markers makes it possible to most clearly detect on SEM images the boundaries of erythrocytes and dark fragments of the metal surface (Table 4, column 6**,** top and bottom rows). As a result of applying the above method to an SEM-image of a soil sample with a complex surface structure, excessive segmentation has occurred (Table 4, column 6, middle row).

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Conclusions

The possibility of classifying SEM images of micro surfaces of objects by their texture characteristics using statistical and spectral measures has been established. The calculation of the spectral characteristics of SEM images of metals revealed the periodicity and directionality of texture elements present in the image.

Classification results according to homogeneity measure and spectral measures allow obtaining a generalized characteristic of the image texture, which contributes to solving problems of recognition and automation of image analysis.

A comparative analysis of four segmentation methods showed that the best result of determining the boundaries of objects in a SEM image was obtained by the watershed method using markers. It is shown that the segmentation of SEM images using splitting and merging method allows you to select regions with specified texture characteristics.

Selection of interest points in areas with specified texture characteristics is a promising area of study for recognizing identical points in paired SEM images.

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О. ІВАНЧУК[1], О. ТУМСЬКА[2]

[1] Кафедра фотограмметрії та геоінформатики, Національний університет «Львівська політехніка», вул. С. Бандери, 12, Львів, 79013, Україна, тел. +38(068)0720575, ел. пошта: ivanchuk_oleh@ukr.net

[2] Кафедра фотограмметрії та геоінформатики, Національний університет «Львівська політехніка», вул. С. Бандери, 12, Львів, 79013, Україна, тел. +38(050)7455711, ел. пошта: ol.tums@gmail.com

ДОСЛІДЖЕННЯ МЕТОДІВ КЛАСИФІКАЦІЇ ТЕКСТУР РЕМ-ЗОБРАЖЕНЬ МІКРОПОВЕРХОНЬ ОБ'ЄКТІВ ТА ЇХ СЕГМЕНТАЦІЯ

Мета. Метою даної роботи було розроблення і дослідження методів класифікації текстур РЕМ-зображень мікроповерхонь об'єктів на основі статистичних та спектральних характеристик текстурних фрагментів, а також порівняльного аналізу методів сегментації РЕМ-зображень. **Методи.** Визначення характеристик текстури РЕМ-зображень ґрунтувалось на статистичних моментах, розрахованих за гістограмою яскравості. Спектральні міри текстури обчислювались за спектром Фур'є. Для визначення спектральних текстурних характеристик було вибрано параметри амплітудної та осьової функцій. Сегментація РЕМ-зображень мікроповерхонь об'єктів виконувалася чотирма способами, а саме: методом глобальної порогової сегментації, методом нарощування області, методом поділу та злиття і методом вододілу з використанням маркерів. **Результати.** Опрацювання серії РЕМ-зображень ґрунтів показало найкращий результат класифікації текстур за мірою однорідності, ніж за іншими статистичними характеристиками. Обчислення спектральних характеристик РЕМ-зображень металів виявило періодичність або майже періодичність і спрямованість присутніх у зображенні елементів текстур і разом з результатами класифікації за мірою однорідності дозволяє отримати узагальнену характеристику текстури зображення. Порівняльний аналіз чотирьох методів сегментації показав, що найкращий результат визначення меж об'єктів на РЕМ-зображенні отримано методом вододілу з використанням маркерів. Програмна реалізація методів класифікації текстур та їх сегментація виконувалась в системі MatLab. **Наукова новизна.** Авторами запропоновано метод класифікації РЕМ-зображень на основі спектральних текстурних характеристик за параметрами амплітудної та осьової функцій. Показано, що сегментація РЕМ-зображень методом поділу і злиття дозволяє задати умови для виділення на зображенні областей з певними характеристиками текстури. **Практичне значення.** Узагальнена характеристика текстури РЕМ-зображення, що визначається за статистичними і спектральними мірами, корисна для автоматизованого розпізнавання текстур і аналізу РЕМ-зображень. Вибір ділянок з певними характеристиками текстури є важливим етапом попередньої обробки зображень під час знаходження точок інтересу, що придатні для зіставлення РЕМ-зображень і розпізнавання об'єктів.

Ключові слова: растровий електронний мікроскоп (РЕМ), статистичні та спектральні характеристики текстури РЕМ зображення, класифікація, сегментація.

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