УДК 621.391

СПОСІБ ФОРМУВАННЯ ОЗНАК ЗОБРАЖЕНЬ ДИСТАНЦІЙНОГО ЗОНДУВАННЯ НА ОСНОВІ ХАРАКТЕРИСТИК ВИПАДКОВИХ ТОЧКОВИХ ПОЛІВ

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Запропоновано спосіб формування ознак зображень дистанційного зондування Землі за допомогою характеристик випадкових точкових полів та їх узагальнень. Вхідне зображення поділяється на фрагменти, для елементів яких будується гістограма, визначаються її локальні максимуми, формується випадкове точкове поле, як множина геометричних центрів фрагментів для кожної яскравості. За утвореною конфігурацією кожне поле класифікується як кластерне, регулярне або випадкове. Формуються розподіли кількості елементів точкового поля у фрагменті зображення для кожної яскравості та розподіли кількості елементів точкового поля для діапазону яскравостей. Проведені дослідження точності класифікації зображень за сформованими ознаками.

Ключові слова: *випадкові точкові поля, дистанційне зондування, сегментація зображень, текстурні ознаки.*

METHOD OF FEATURES CONSTRUCTION FOR REMOTE SENSING IMAGES BASED ON THE CHARACTERISTICS OF RANDOM POINT FIELDS

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Texture features are widely used in remote sensing image classification. In most cases they are extracted from grayscale images without taking color information into consideration. The texture descriptors, which consist of characteristics of random point fields formed for pixels of distinct intensity of grayscale and color band images are presented. The input image is divided into fragments for the elements of each of which the histogram is constructed and their local maxima are determined. Size of fragments are chosen depending on image resolution. For each of the intensity of the dynamic range of the image, a random point field, as a set of geometric centers of fragments, is formed. By the formed configuration, each field is classified as cluster, regular or random. To form a description of image elements a distribution of the number of field elements for each intensity and fragment is constructed. Separately, the vectors of the point field element for each intensity in the image fragment and the point field element for the selected intensity are formed. Experimental results demonstrate that proposed descriptors yield performance compared to other state-of-the-art texture features.

Keywords: *random point fields, remote sensing, image segmentation, texture descriptors.*

Results of the Earth's remote sensing by aviation or spacecraft equipped with various types of recording technique have become widely used in studies of numerous natural phenomena and objects. In most cases, such observations are reduced to images that display the Earth's surface in a certain range of reflected radiation. Further, their quantitative analysis is required, which is based on the allocation of particular areas of interest in the image or assignment of the whole image to one particular class. Different methods of image segmentation are used to solve such problems, which, in most cases, analyze the texture represented on the image. To do this, numerous statistical descriptions of the texture are formed that reflect the relationship between the pixels in some local area. Most often, the descriptions are formed on the basis of matrices gray level co-occurrence matrix [1], Gabor filter [2], wavelet transform [3], local binary pattern [4], neural network [5]. When analyzing of the remote sensing data it is not enough to have only grayscale image that cannot display all the variety of colors represented in the image and their shades, and the above-mentioned approaches are mainly designed for grayscale images. Therefore, recently, the methods that describe the texture of the image with its grayscale and color channels, have been actively developed [6]. However, the use of a larger amount of information often leads to a disproportional increase in the processing time of such a class of images, which, due to the formation have a fairly large linear dimensions. This requires the development of new approaches for forming a texture description that would solve the problem of image segmentation or classification without significant increase of computations. Thus the use of random point processes as a model for image information representing is proposed.

Random field points. Many technical and social tasks often require a statistical description of the sequence of events occurring at separate points of space or at individual moments of time. In the simplest one-dimensional case, the sequence of random events occurring in time moments can be characterized by random points of their appearance, on the time axis. This sequence of events is often referred to as a random point process [7], as the implementation of such a process is a random sequence of points, although the main attention is paid to the moment of the event occurrence. For a two-dimensional case, the occurrence of an event with respect to other events has already a greater significance, provided the events occur almost simultaneously. In this case, random point processes are called random point fields (RPF). The analysis of the RPF can determine the patterns of the random events location and thereby identify the type of their effects: either mutual or asymmetric, or its absence. By setting the properties of the process, which describes the object of research, more information about the object itself will be obtained. Historically, the possibility of analyzing various objects with the help of RPF began to be used in the areas with the location of events – objects can be seen in the map: forestry, seismology, biology, economics, astronomy, sociology [8, 9], but recently all of these methods more often find their application in the analysis of images, when the model of image formation acts as a random process [10]. One of the main characteristics of the RPF is its appearance (cluster, regular or random) which means the nature of the elements location and the type of interaction between them. For cluster RPF it is assumed that there exists the interaction, which leads to the attraction of elements to each other; for the regular – the existence of interaction, which leads to repulsion of elements; and for random RPFs, there is a lack of interaction between elements. Such a feature allows it to be used in the analysis of remote sensing images, since, as a rule, the images depicted, namely the textures that represent them, can be matched to one or another type of RPF or a combination of them [11].

The Poisson homogeneous point process is a fundamental model for the RPF, and serves as the basis for constructing more complex models. This process formalizes the concept of “absolute” randomness, which is expressed by the absence of a definite structure of the set of points that correspond to the given point process. Perhaps more importantly, the Poisson process can be used as a reference model for distinguishing point patterns that are random or prone to formation of aggregates (or, conversely, to repulsion), that is, a regular arrangement in which the distance between the points cannot be less than a certain threshold. A series of tests have been developed to test the hypothesis of a complete spatial randomness (CSR). In particular, the most commonly used is the Clarke-Evans test [12], which is based on verifying a compliance with the normal distribution of the standardized mean distance to the nearest neighbor for the RPF elements, which is determined from the expression:

$$Z_m = \frac{\bar{D}_m - E\left(\bar{D}_m\right)}{\sigma\left(\bar{D}_m\right)}, \quad (1)$$

where $\bar{D}_m = \frac{1}{m}\sum_{i=1}^{m} D_i$ and D_i – the distance to the nearest neighbor for the *i*-th element of the RPF. Since, as is known, in accordance with the central limit theorem $\bar{D}_m \approx N\left[\frac{1}{2\sqrt{\lambda}}, \frac{4-\pi}{m(4\lambda\pi)}\right]$ for a RPF with a CSR, where λ is the intensity of the RPF, then $Z_m \approx N[0,1]$ for such RPF. So the test is to determine (1) and compare it with the limit values Z_α, where α is the level of significance, namely $\Pr\left(|Z_m| \geq z_\alpha\right) = \alpha$. There is no the "best" value of α for such a test. Typical values that are presented in most statistical texts are given in Table 1.

Thus, in order to assert that the investigated point configuration is the implementation of a cluster RPF one needs to make sure that the condition $z_m < -z_\alpha$ is fulfilled, and $z_m > z_\alpha$ in the case of a regular RPF. For random RPF necessary condition is $-z_\alpha \leq z_m \leq z_\alpha$.

Table 1. Limit values of significance level

Significance	α	z_α
Strong	0.01	2.58
Standard	0.05	1.96
Weak	0.10	1.69

Classification of remote sensing images. As with any task for the classification of images, it requires the construction of a special system, which, in general, can consist of a team of trained specialists and a set of technical means for receiving and processing information intended to be solved on the basis of specially constructed algorithms of objects recognition tasks [13].

The type of the features selected for the description of the object of classification actually determine the entire structure of the classification system. The features of the same object are chosen on the basis of one or another model of its representation. Therefore, the classification of images, and in particular, remote sensing, can be based on the pixel formation of features when analyzing the spectral characteristics of a single point of the image; their formation for the local areas of the image, which requires analysis of the texture in the vicinity of the image point, as well as their object-oriented formation, which is based on the previous segmentation of objects in the image. Due to the specifics of remote sensing images, the most widely used approaches for their classification are based on textural features.

The proposed approach to the formation of the features of remote sensing images consists in the definition of the RPF's type, formed for each intensity from the dynamic range of the grayscale and the RGB channels of image and a number of discrete distributions of the quantity of RPF points, formed for each one of the image intensity. The image is divided into fragments of the same size for each of which the local maxima of its histogram are determined. For each intensity from the dynamic range of the grayscale image and the RGB channels the RPF is formed as a set of geometric centers of the fragments whose histogram has a maximum for this intensity (Fig. 1*a*). The relative location of the RPF elements can be described quantitatively by means of their intensity distributions separately in the section of intensity and in the section of fragments. In the first case, the number of RPF elements for each intensity is calculated and the distribution of their values is constructed, in the second case the number of RPF elements for each of the image fragments is calculated and the distribution of their values is built. Also, the distribution of vector values obtained as a product of the intensity range and the matrix of indicators of availability of the corresponding intensity maximum in the image fragments is constructed (Fig. 1*b*). Thus, the set of features for the classification of the image will be formed from four vectors that contain the values of the above discrete distributions and a vector of values z_m for each RPF of the image intensity. Thereby the chosen features allow to describe the classes of images and to divide the area of features in the areas that correspond to each class, and also impose restrictions on the choice of the form of the deciding rule. When the space of features formed the areas that correspond to each of the specified classes, assigning the objects is naturally performed by using the distance function. In the proposed method the image refers to a class based on the minimum distance to an element of this class.

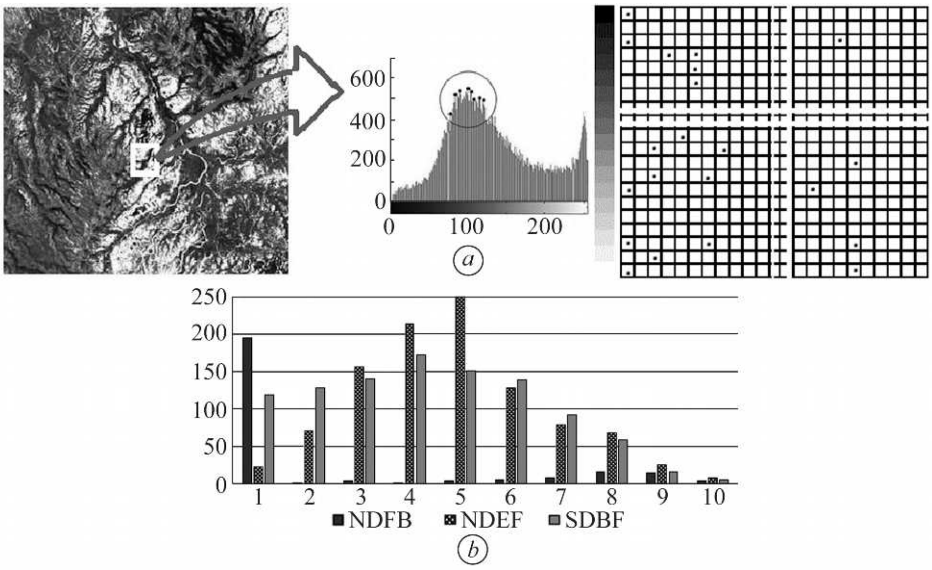

Fig. 1. Formation of image features: *a* – RPF forming; *b* – vectors of features.

Implementation of the proposed approach. The application of the proposed method for the features construction for the task of remote sensing images classification was considered. We used the image base described in [14], which contained 21 classes of images of treated and untreated Earth sites. Each class contained one hundred images of 256×256 pixels. For each image a system of attributes was formed based on the proposed method. In the process of testing, the image was randomly selected from the set of all images and the degree of proximity to the rest of the images was determined. The selected image was classified as a specific class image based on its closeness to the reference image of this class. A comparison of classification based on only a grayscale image and using additional RGB channels was also carried out. Examples of the first eight of the most similar images are shown in Fig. 2. From the examples below, it can be noted that the applying, in addition to the gray-scale image, RGB channels improves the quality of the classification. On the one hand, we can see that the set of similar images resemble each other rather in content, but on the other hand, when using a larger amount of information, the closest in the sense of the chosen measure is the image of the same class. It should also be noted that if additional information from RGB image channels is used, the overall time of the construction of the features increased almost linearly from 1.91 s, in the case of using only a grayscale image up to 7.8 s with the additional use of RGB channels. The proposed system of features was compared with that proposed in [6] which is based on the convolution of a grayscale image and RGB channels with the Gabor filter. The results are presented in the form of a diagram in Fig. 3 where for a number of images classes the precision of the classification of the image is indicated by the proposed features [6].

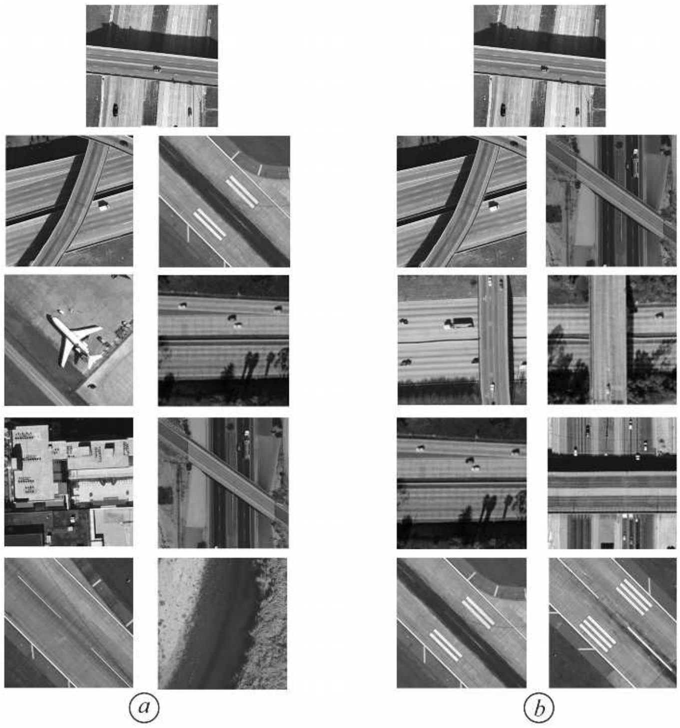

Fig. 2. Classification of grayscale (*a*) and color (*b*) images.

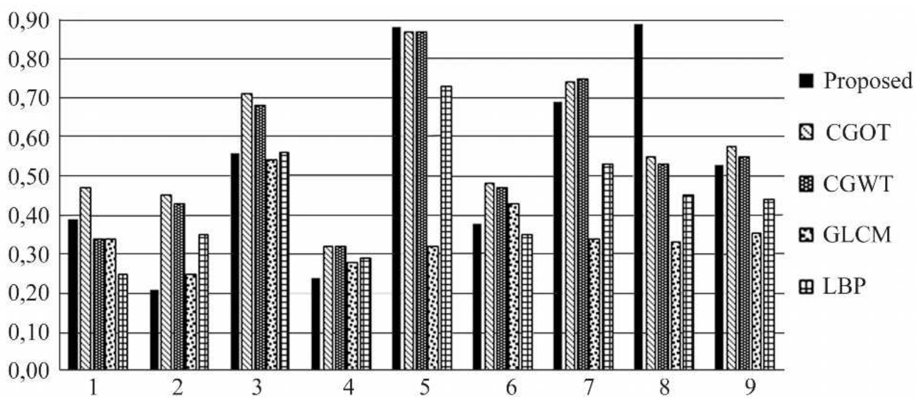

Fig. 3. Accuracy of image classification: 1 – agricultural; 2 – airplane; 3 – beach; 4 – buildings; 5 – chaparral; 6 – residential; 7 – forest; 8 – harbor; 9 – average.

It may be noted that the proposed system of features has a higher accuracy of classification for the vast majority of these classes of images compared with the features that are formed using classical approaches – co-occurrences matrices (GLCM) and LBP (local binary pattern) histograms. In addition, in some cases, the proposed system of attributes has a higher accuracy than the features formed on the basis of the Gabor filter (CGOT, CGWT) which are known to require additional research to select optimal parameters.

CONCLUSIONS

For the classification of remote sensing images a system of features is proposed. It is based on the local extremes of the image fragments histograms. Analyzing the mutual arrangement of fragments with extremes of same intensity, the type of correspondent RPF, formed by this intensity, is determined. The system of features is also supplemented by vectors describing the distribution of the number of RPF elements for image intensity and the distribution of the number of local extremes for image fragments. The research of accuracy of classification of remote sensing images and comparison with known methods of formation of texture features are carried out. On the basis of the conducted research it can be concluded that the proposed system of features, despite a rather simple method of formation, has classification properties that are comparable with known systems formed on the basis of analysis of the image texture.

Present research was supported by the grant of the fund of fundamental researches of the Ministry of Education and Science of Ukraine #1698: "System of monitoring and classification of regions of Ukraine according to the distribution of mass of clouds in the seasons of the year on the basis of images of satellite maps of the weather".

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Received 12.10.2017