THE APPLICABILITY OF INFORMATIVE TEXTURAL FEATURES FOR THE DETECTION OF FACTORS NEGATIVELY INFLUENCING THE GROWTH OF WHEAT ON AERIAL IMAGES

Automated processing of aerospace information makes it possible to effectively solve scientific and applied problems in cartography, ecology, oceanology, exploration and development of minerals, agriculture and forestry, and many other areas. At the same time, the main way to extract information is to decipher images, which are the main carrier of information about the area.

Aerospace images are a combination of natural texture regions and man-made objects. This article discusses methods for analyzing texture images. The main tasks of the analysis of texture areas include the selection and formation of features that describe texture differences, the selection and segmentation of texture areas, the classification of texture areas, and the identification of an object by texture. Depending on the features of the texture areas of the images used, segmentation methods based on area analysis can be divided into statistical, structural, fractal, spectral, and combined methods.

The article discusses textural features for the analysis of texture images, and defines informative textural features to identify negative factors for crop growth. To solve the tasks, textural features are used. Much attention is paid to the development of software tools that allow to highlight the features that describe the differences in textures for the segmentation of texture areas. This approach is universal and has great potential on the studied aerospace image to identify objects and boundaries of regions with different properties using clustering based on images of the same surface area taken in different vegetation periods. That is, the question of the applicability of sets of texture features and other parameters for the analysis of experimental data is being investigated

Keywords: textural features, agricultural crops, image processing, space images

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1. Introduction

Recently, a lot of work has been done on texture analysis of color images. When analyzing the texture of color images, additional features of their characteristics are introduced, based on the measurement of the intensity levels of each color and their distribution over the field of the image. The modern state of the problem of texture analysis is explained by a large

number of proposed methods, as well as a wide range of texture objects and the different nature of the tasks to be solved.

Texture is one of the important characteristics used to describe desired areas or properties on the earth's surface in aerospace grayscale images [1].

Unfortunately, there is no theory of the synthesis of textural features, which provides, for example, a minimum of average recognition errors. In this regard, textural features are still being invented, and their quality is tested empirically for a specific classification task. Therefore, the following approach is justified: synthesize a large number of textural features and examine all subsets of the extended system of textural features for informativeness.

The texture can be divided into several classes as follows:

1) by origin: both artificial – for example, graphic patterns, and natural – for example, grass, forest, earth;

2) by surface structure: structural, consisting of geometrically regular repeating elements, and stochastic, formed by a sequence of random elements; the texture of elements in relative sizes: fine-grained and coarse-grained;

3) the texture of elements in the form: wavy, spotty, irregular, linear, and so on [2]. It follows from the above definitions and characteristics that the texture is a certain part of the image, which has uniform statistical characteristics. This means that each texture of this class can be described using a characteristic property common to all textures of this class [3]. Such properties are called texture features [4]. Texture features play an important role in dividing the image into separate areas. For example, on aerial images, it is possible to distinguish fields on which cereal or leguminous plants grow, to distinguish deciduous or coniferous forests, to reveal foci of weeds on agricultural crops, etc.

The results obtained can be applied in automated image analysis systems, which are used in scientific research and in industry. Their use in industry makes it possible to reduce the cost of fertilizers for the destruction of weeds, and in some cases improve the quality of agriculture. Therefore, a study to develop an improvement in identifying negative factors on crop growth is relevant.

In the scientific literature, signs based on statistical characteristics (energy, entropy, variation, etc.) are considered. Namely, as such signs, it is possible to use statistical characteristics of spatial distributions, calculated as measures of homogeneity based on a one-dimensional histogram of signal values (characteristics of the 1st order) and two-dimensional histograms of signal values (characteristics of the 2nd order).

The second class is features that take into account mutual location. An approach based on the use of the adjacency matrix (another name is the gradient distribution matrix [5]) is used to form textural features that take into account the mutual location of pixels within the sliding window.

Therefore, research that determines the applicability of texture features for processing aerospace images, in particular images of the earth's surface, scientific relevance.

2. Literature review and problem statement

In the article [6], the authors determined the focus of flax and its weeds by textural features on aerospace images. Based on the scientific literature, there is no exact informative texture feature vector for each problem statement. And this article does not consider, in particular, wheat and the factor negatively affecting its growth have not been identified.

In this [7] article, the author's considered methods for analyzing aerospace images and showed the state of crops in different growing seasons. In particular, methods of orthogonal transformations were applied to aerospace images. The authors did not determine the effectiveness of other methods other than those indicated in the article.

In article [8] the authors consider the maximum of the posterior probability principle and the formalism of Markov random fields for describing the neighborhood of pixels for related classes of objects, with an emphasis on forests of different species and ages. Some results of the applicability of the Bayesian classifier for the recognition of hyperspectral aerial photographs with the use of appropriate improvements are presented. The authors of this article do not consider classification according to textural features.

In [9], the indicators of tests for the collective use of spectral and textural features for the systematization of vegetation cover on aviation hyperspectral images are considered. The images obtained with the experimental sensor can improve the quality of classification of textural features only when using a small number of channels. But in order to increase the information content, it is necessary to deal with a set of textural features individual for each scene.

In [10], the authors developed a theoretical and methodological framework for applying systems of Vilenkin-Krestenson functions in the smallest possible non-trigonometric form. Based on the rules and conclusions following from the theory of discrete signals on finite intervals, the most appropriate variant of constructing a system of basic functions from all types of Vilenkin-Chrestenson functions is shown. The resulting theoretical and methodological rules were used to filter aerospace images. This work improved the quality of aerospace images and did not single out specific objects, i. e., areas with crops.

In [11], a new automatic, hierarchical, multidimensional, histogram-based clusterization algorithm is considered. A method for choosing the clusterization detailedness in different regions of the vector space of spectral features depending on the average reparability of clusters is proposed. The algorithm is applied to automatically classify multispectral satellite data in recognizing the land cover. This article does not compare methods based on orthogonal bases.

The work [12] presents an automatic algorithm for clustering statistical textural features of an image based on histograms, which includes an assessment of the quality of the obtained distribution of feature vectors over clusters. Algorithms were used to classify forest aerospace images, but the article does not consider the classification of crops.

Despite the presence of textures in images, there is no single and formal approach to the description of textures and their strict definition. Texture analysis methods are usually developed individually for each case. All this allows to assert that it is expedient to conduct a study on of the applicability of sets of texture features for the analysis of experimental data in order to identify characteristic areas in aerospace images is being investigated.

3. The aim and objectives of the study

The aim of the study is the selection and formation of traits that determine the negative factors affecting the growth of wheat.

To achieve this aim, the following objectives are solved:

– to study the textural features for the analysis of texture images, and the selection of the most informative of them;

– apply informative textural features, which allows to identify factors that negatively affect the growth of wheat.

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4. Materials and methods

The statistics of the spatial interdependence of the brightness values are calculated from the transition matrices of the brightness values between the nearest neighboring points. One aspect of the texture is related to the spatial distribution and spatial interdependence of the brightness values of the local area of the image with increasing distance between the estimated points. According to the matrix of joint occurrence, about twenty features are calculated, the most commonly used of them are the following. Below are the mathematical characteristics of texture symbols where $p(i,j)$ is the frequency of occurrence of two pixels with brightnesses i and j, N – window size:

1. Energy determines the degree of image homogeneity:

$$T_1 = \sum_{i=1}^{N}\sum_{j=1}^{N}\left[p(i,j)\right]^2.$$

2. Entropy is an uneven distribution of the brightness properties of image elements:

$$T_2 = -\sum_{i=1}^{N}\sum_{i=1}^{N} p(i,j)\cdot\log_2\left(p(i,j)\right).$$

3. Homogeneity (homogeneity) is understood as a measure of homogeneity:

$$T_3 = \sum_{i=1}^{N}\sum_{j=1}^{N}\frac{p(i,j)}{1+|i-j|}.$$

4. Contrast is a measure of the distribution of brightness levels. Local variation is determined by magnitude. As the number of local variations increases, the contrast increases:

$$T_4 = (i-j)^2\cdot p(i,j).$$

5. The differential entropy is similar to the common matrix entropy and adjacency matrix entropy, but is calculated for the histogram of brightness differences:

$$T_5 = -\sum_{i=2}^{N} p_{x+y}(i)\log\left(p_{x+y}(i)\right),$$

here

$$p_{x+y}(k) = \sum_{i=1}^{N}\sum_{j=1}^{N}\delta_{i+j,k}\, p(i,j),$$

$$k = 2,3,...,2N, \quad \delta_{m,n} = \begin{cases}1,\text{ if } m=n \\ 0,\text{ if } m\neq n.\end{cases}$$

6. The sum of the variance is the variation in the change in brightness about the sum of the average value:

$$T_6 = \sum_{i=2}^{2N}(i-T_5)^2\, p_{x+y}(i).$$

7. Correlation is a measure of video brightness versus linear regression:

$$T_7 = \sum_{i=1}^{N}\sum_{j=1}^{N}\frac{(i-\mu_i)(j-\mu_j)\cdot p(i,j)}{\sigma_i\sigma_j},$$

mean values and standard deviations for $\mu_i, \mu_j, \sigma_i, \sigma_j - p(i,j)$.

8. The overall average value is determined from the histogram of the sum of brightness values for pairs of video elements closely related to the adjacency matrix:

$$T_8 = \sum_{i=2}^{2N}i\cdot p_{x+y}(i),$$

here

$$p_{x+y}(k) = \sum_{i=1}^{N}\sum_{j=1}^{N}_{i+j=k} p(i,j),$$

$k=2, 3, ..., 2N$ – distribution along the tangent diagonal.

9. The inverse difference moment is closely related to contrast and shows the degree of scattering of elements around the main diagonal of the gradient matrix. This function is an alternative to contrast in the presence of edge structures, since relatively large differences in brightness values have minimal effect on the final result:

$$T_9 = \sum_{i=1}^{N}\sum_{j=1}^{N}\left[1+(i-j)^2\right]^{-1} p(i,j).$$

10. The total (total) entropy is determined by the classical value of the statistical theory of information and represents an uneven distribution of the brightness properties of video elements:

$$T_{10} = -\sum_{i=0}^{N-1} p_{x-y}(i)\log\left(p_{x-y}(i)\right);$$

here $p_{x-y}(k) = \sum_{i=1}^{N}\sum_{j=1}^{N}_{|i-j|=k} p(i,j)$ $k=0, 1, 2, 3,..., N-1$ distribution along the main diagonal.

11. 1 – informative measure of correlation:

$$T_{11} = \frac{T_2 - HXY_1}{\max(HX,HY)},$$

here

$$HX = -\sum_{i} p_x(i)\log\left(p_x(i)\right),$$

$$HY = -\sum_{j} p_y(i)\log\left(p_y(i)\right),$$

$$HXY_1 = -\sum_{i}\sum_{j} p(i,j)\log\left(p_x(i)p_y(j)\right),$$

$$p_x(i) = \sum_{j=1}^{N} p(i,j); \quad p_y(i) = \sum_{i=1}^{N} p(i,j).$$

Information measures are determined by the relationship of statistical information theory for the elements of the adja-

cency matrix, the histogram of the sum of brightness values and the histogram of the difference of brightness values.

A series is a maximum set of pixels of the same brightness, recorded along a straight line [8, 9]. The series is characterized by brightness, length and direction. In coarse-grained textures, these series are longer than in fine-grained textures.

Series statistics. N_g – the existence of values that brightness takes, N_r – of the possible lengths of the series, $p(i, j)$ – brightness, i – number of series, j – number of series lengths. The following statistical values exist for texture analysis.

12. Inverse torque is a measure of local similarity that determines the clarity of short series:

$$T_{12} = \frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} \frac{p(i,j)}{j^2}}{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} p(i,j)};$$

13. Moments – the weight of a line with constant optical density. This feature is characterized by the magnitude of each line weight multiplied by the length weight for any gray level:

$$T_{13} = \frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} j^2 p(i,j)}{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} p(i,j)}.$$

14. Variation of brightness – gray level distribution. This sign assumes a minimum value in cases where the number of optical density lines is uniformly distributed over the gray level:

$$T_{14} = \frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} \left(p(i,j)\right)^2}{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} p(i,j)}.$$

15. Run length heterogeneity is the distribution of line length with constant optical density. With a uniform distribution, the minimum value is:

$$T_{15} = \frac{\sum_{i=1}^{N_g} \left(\sum_{j=1}^{N_r} p(i,j)\right)^2}{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} p(i,j)}.$$

16. Share of the image in the series:

$$T_{16} = \frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} p(i,j)}{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} jp(i,j)}.$$

The above textural features are considered in the scientific literature, and informative textural features were selected based on these features.

5. Results of applying informative texture features to aerospace images

5. 1. The study of textural features for the analysis of texture images, and the selection of the most informative of them

The main tasks of the analysis of texture areas include: selection and formation of features that describe textural differences; selection and segmentation of texture areas; classification of texture zones; object detection by texture. To select texture regions, the problem of texture segmentation is solved, which consists in dividing the image into regions with a constant texture, i. e., identification of areas where the values of certain textural features are relatively stable. Segmentation methods based on territorial analysis can be divided into statistical, structural, fractal, spectral, and mixed methods, depending on the features of the texture areas of the images used. Automated processing of aerospace information makes it possible to effectively solve scientific and applied problems of cartography, natural science, oceanology, exploration and development of minerals, agriculture and forestry, and many other areas (Fig. 1).
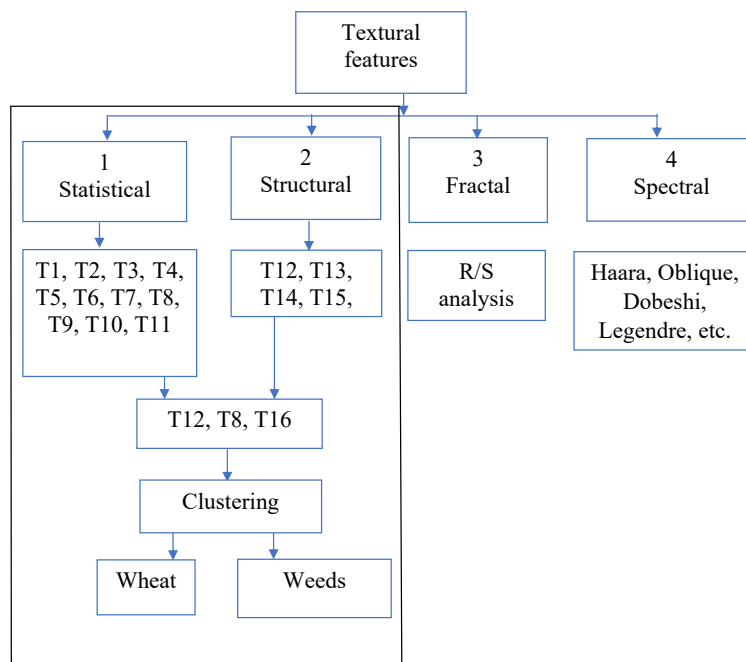

Fig. 1. Conceptual model of weed isolation on wheat during the growing season

The program is implemented in the MatLab environment. Aerospace images were taken as input data. To solve this problem, many approaches and algorithms have been proposed. The main attention was paid to the creation of efficient algorithms for calculating texture features. The selected areas were chosen randomly (Fig. 2). Textural features are calculated for each region. According to the scheme, each feature was checked for informativeness, and out of 16 features, 3 textural features were selected: T12, T8, and T16.

The most important result of branch clustering is a hierarchical tree. Ward's method differs from all other methods in that it uses analysis of variance methods to estimate the distance between clusters. The method minimizes the value of

the sum of squared distances. In particular, the sum of squared distances between objects and the cluster center is taken as the distance between clusters. In general, the method seems to be very efficient, but it tends to create small clusters (Fig. 3).

Fig. 2. Regions for analysis from a given image

Table 1 shows the values of the selected informative textural features, which are shown between groups (between SS) and within groups (within SS). The label more clearly describes the belonging of an object to a cluster, since the variance of values within a group is small, while the variance of values between groups is large. When analyzing the variance of 16 considered textural features, informative textural features were selected taking into account the large distance between classes and the small distance between features within a class. In addition, the quality of clustering can be expressed by the value of the F-test (the more, the better) and the level of significance (the smaller, the better). The results of the analysis of variance for the three classes show a good classification quality: the level significance value is less than 5 % everywhere.

Table 1

Analysis of variance of textural features

Variable	Analysis of Variance (data_textura_1)					
	Between (SS)	df	Within (SS)	df	F	signif. (p)
Opt (T12)	474,345.4	4	41,581.50	28	79.85324	0.000000
sum_avg (T8)	961.3	4	156.01	28	43.13366	0.000000
Dolya (T16)	0.0	4	0.00	28	34.61647	0.000000

The number of clusters and the distance between the selected regions are shown in the table below (Table 2).

As shown in Table 2, Ward's Euclidean distance was performed in StatistaSoft.
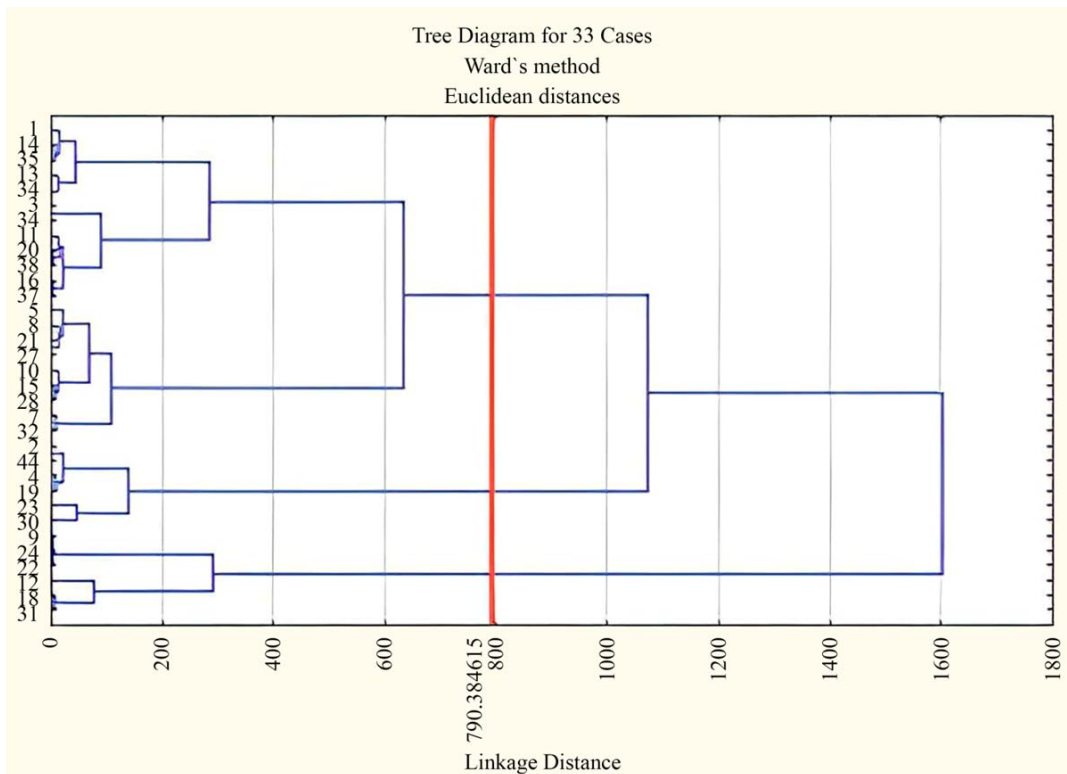

Fig. 3. Dendogram of clusters obtained with 16 textural features: Ward's method, Euclidean distance

Table 2

Cluster number, distance results

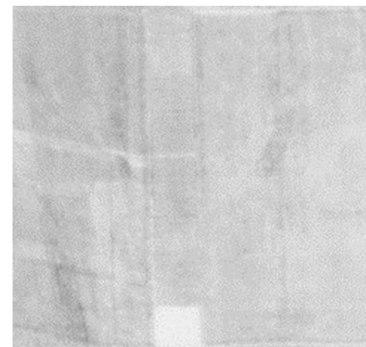| fragment numm bers on images	data_textura_1		
	CASE_NO	CLUSTER	DISTANCE
1	1	1	3.77
3	3	1	16.54
13	12	1	18.14
14	13	1	3.85
34	28	1	11.95
35	29	1	3.97
36	30	1	16.74
2	2	2	4.25
4	4	2	6.73
19	17	2	1.62
44	33	2	3.84
5	5	3	20.09
7	6	3	35.57
8	7	3	6.92
10	9	3	6.57
11	10	3	14.82
15	14	3	0.80
16	15	3	26.69
20	18	3	19.59
21	19	3	12.29
27	23	3	11.76
28	24	3	2.62
32	27	3	29.37
37	31	3	25.04
38	32	3	21.52
23	21	4	13.14
30	25	4	13.14
9	8	5	32.53
12	11	5	9.73
18	16	5	41.78
22	20	5	30.97
24	22	5	33.77
31	26	5	45.76

5. 2. The use of informative textural features, makes it possible to identify negative factors affecting the growth of wheat

The satellite images were requested from the Planet.com server and were taken from Sentinel-2, the European Space Agency's family of Earth remote sensing satellites, created as part of the Copernicus Global Environmental and Security Monitoring Project. Image data consists of 4 layers Red, Green, Blue, Near InfraRed. The default image size is 3.57 meters per pixel at the current scale and center latitude. Or when downloading the 1st image 684×639, 96 dpi, 64 bit, also the 2nd image 2415×2864, 96 dpi, 64 bit image.

In this work, let's examine the areas where agricultural crops are grown at the Scientific and Production Center of Grain Farming named after A.I. Barayev in the North Kazakhstan region. Research work was carried out on aerospace images obtained from the Planet.com site about cultures belonging to this research center (Fig. 4).

a

b

Fig. 4. Original image: *a* — selection of the considered area on images; *b* — original image of wheat

In this work, out of 16 statistical and structural textural features, 3 informative textural features, i. e., T12, T8, T16, identifying wheat and its weeds, are identified. In Fig. 5, clustering is carried out in a standard way, that is, the size of the current window is 3×3.

According to agronomists A.I. Barayev wheat was sown in the period from 05/12/2021 to 05/25/2021. Weeds have been poisoned since 06/17/2021. The table below shows the dynamics of weed plants in different growing seasons as a result of the use of textural traits (Table 3).

Table 3

Results of the value of clustering by textural features

data methods	9.06.2021	01.07.2021	21.07.2021	06.08.2021	14.09.2021
Textural features (T12, T8, T16)	37 %	7 %	3 %	2 %	1 %

After determining the information content of textural features, an information system was created to help farmers monitor the condition of their large fields. The figures below show the focus of weed growth in different periods of vegetation of the land plot of the Research Institute A. I. Baraev (Fig. 6).
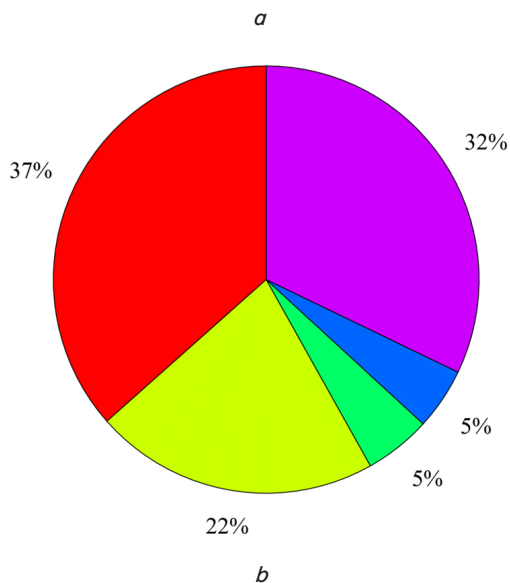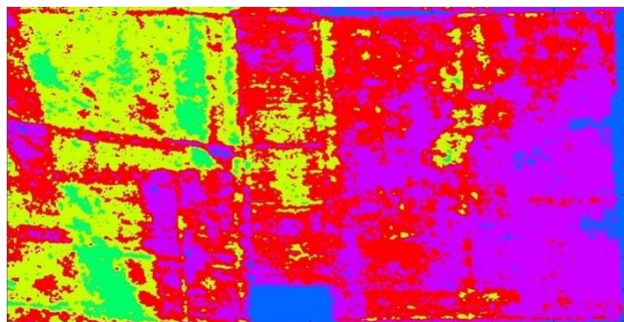
a

b

Fig. 5. The result of clustering: *a* — clustering by textural features T12, T8, T1; *b* — result of clustering in percent

As a result of the research work, the possibility of using informative textural features on aerospace images was determined.
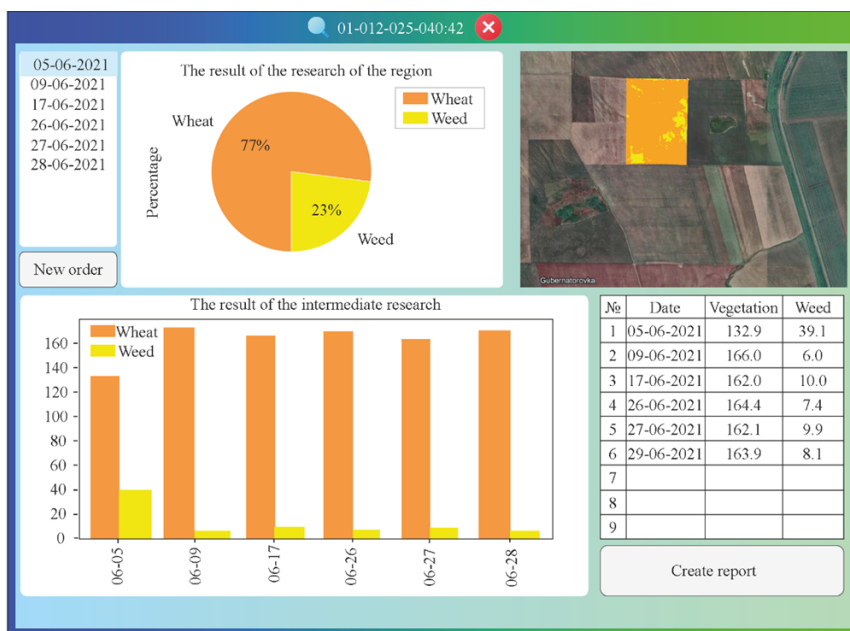

Fig. 6. Dynamics of growth of wheat and weeds

6. Discussion of the experimental results of informative textural features

After multispectral image processing, a grayscale image (NDVI) is identified using informative textural features. Studying aerospace images obtained by the spectral brightness coefficient, research work was carried out in different periods of the growing season. The applicability of textural traits is shown in Table 3 with changes for each growing season.

After the application of informative textural features on aerospace images, areas of inhomogeneity were revealed, i. e. the presence of weeds in crops of grain crops. In the course of research, according to the actual data given by agronomists of the A. I. Baraev Agricultural Research Center, the percentage of weeds corresponded.

The disadvantage of this method is the impossibility of identifying plant pests and diseases in aerospace images. And also, the main problem when choosing informative features is to determine which and how many features should be extracted in order to reliably segment texture areas with similar color and texture values in the image. It is known that an excessive increase in features in the primary system does not give positive results, since a given set of features with the same size is inversely proportional to the size of the functional space [13]. The most important requirements for the features used to solve the problem of segmenting image areas can be the following [14]: the feature must be informative, i. e., contain important information within the framework of the problem being solved for this image and be able to provide accurate segmentation of objects; the attribute must allow the processing of the image segmentation algorithm, that is, it must have a special format for the selected segmentation algorithm.

Thus, solving the problem of creating a minimum set of informative features is one of the main factors in the development of algorithms and information technologies for segmenting textured image areas. Textural features can be divided into four main classes (Fig. 1).

The main problem in feature selection is to determine which and how many features should be extracted in order to reliably segment texture regions with similar color and texture values in an image. It is known that an excessive increase in features in the primary system does not give positive results, since a given set of features with the same size is inversely proportional to the size of the functional space.

The result of applying informative texture features to aerospace images, weed foci were found in the resulting images, which corresponded to their data.

The results obtained can be applied in automated image analysis systems, which are used in scientific research and in industry. Their use in industry makes it possible to reduce the cost of fertilizers for the destruction of weeds, and in some cases improve the quality of agriculture.

7 Conclusions

1. When analyzing a large set of texture symbols using standard windows 3×3, 5×5, 7×7, etc. clustering takes a long time. Therefore, to determine informative textural features, we chose a non-standard method, i. e. informative textural features were obtained as a result of calculations carried out in the Statistica Soft environment, taking a vector of texture features in 150×200 windows. As a result, informative 3 features (T12, T8, T16) were identified, which very well identified homogeneous areas in the image.

2. For the selected area of aerospace images, the applicability of informative textural features was experimented. A factor has been identified that negatively affects the growth of crops, namely wheat, weeds, and their growth centers. In each growing season, the percentage of weeds corresponds to the given data and we observe a dynamic change. Based on the data obtained, after the poisoning since 06/17/2021, the percentage of weeds has decreased, that is, the applicability of the signs has been determined.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Acknowledgments

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