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STRUCTURAL METHOD OF DESCRIBING THE TEXTURE IMAGES

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Abstract. This article describes the histograms and polarograms obtained from the different types of textures using BRVAL filters. Comparative analysis of the polarograms and histograms showed that BRVAL filters description for textures in a wide range of distances and the light does not depend by the researched factors, and the level of detail segments on polarograms are inversely proportional to the increasing the number of absolute zero tending picture elements.

Key words: texture, polarogram, histogram, filter, pattern recognition, the two-dimensional convolution.

INTRODUCTION AND OBJECTIVE

Pattern recognition problems [15, 19] are very diverse as to their belonging to a particular domain [2, 11, 14] and the approach used to analyze them, for simplifying a partial or complete solution [13, 19], so and in features used mathematical methods [12, 17, 20], software and hardware tools.

An important role in successfully solving any problems related to the pattern recognition [2, 3, 11] are knowledge about features used (analyzed) the initial information, the preparation conditions and the presentation formats.

The complex structure of space observations cannot effectively solve the data analysis problem directly by the spectral features. Spectral objects portraits of the earth's surface are transient, because they depend on many factors, such as topography, soil type, climate, geographical position of the area. To increase the reliability of the accepted decisions we need to use a priori information about the shooting geometry, on one side, and context information from images - on another.

Observation context information is expressed in the spatial organization of objects elements and their boundaries. Comprehension of the task context, that is, the limitations that imposed on the mutual relationship between the components of the image and increases the efficiency of decision rules. The simplest form of contextual information for a pixel on the image is the neighborhood of the pixel. In [14] proved the assertion that the object decision rule when the fragment is taken, as a whole is effectively then pixel decision rule.

Another form of contextual information is the concept of texture. An **image texture** is a set of metrics calculated in image processing designed to quantify the perceived texture of an image. Image Texture gives us information about the spatial arrangement of color or intensities in an image or selected image region.

There are two ways to analyze an image texture in computer graphics: Structured Approach and Statistical Approach [4].

A structured approach analyzes an image texture as a set of primitive texels in some regular or repeated pattern.

A statistical approach analyzes an image texture as a quantitative measure of the arrangement intensities in a region. In general, this approach is easier to compute and is more widely used, since natural textures are made of irregular patterns sub elements [18].

The preference textural features are potential opportunities to aggregate context information of this type with certain invariance properties for a specific task of pattern recognition [1, 6 - 10].

One of the tasks in texture analysis is precise texture definition. To do this, need to determine the dependence of the textures description on the following factors:

1) distance (the distance to the analyzed object),

2) direction (the angle of observation of the object),

3) lighting (relative to the time of shooting information, namely, day, evening, etc.),

4) nature (species) texture.

There are three main types of texture:

a) texture with regular repetition of elements (masonry, mosaic),

b) texture with a random distribution of elements (gravel, hay),

c) image texture of polygonal objects (aerial photos of forests, fields).

In this article we focused on the structural description of the images and the experimental study of the texture characteristics, depending on these factors.

DESCRIPTION OF TEXTURE IN THE IMAGE

As the original textures pictures, in order to compare with the results which described in article [18], were selected (bricks, mosaic, hay, slate, etc.) and added new ones. All of these pictures (Fig. 1) were made with different distances (10m, 20m), with different angles of fixing the image (45°, 90°, 135°), with different lighting (morning, evening, afternoon, sunny, cloudy). The size of the texture is the same - 640×354 pixels.

For the experiment were selected large values filters (BRVAL - The big range of values) [3], which mask size is $N \times N$ pixels. The set of characteristic masks forms a kind of alphabet. The choice of the alphabet was determined by the following considerations: separate point of the image cannot held significant information, the information contains in the distribution of light location fragment relative to its central element. Filter is a square matrix with size $(3\times 3,\ 5\times 5,\ \ldots n\times n)$, consisting of zeros and ones elements, each letter of the alphabet can be obtained through the use of logic operation "or" to the other two letters (filters) of the same alphabet. The choice of the values "0" and "1" due to necessity of limiting the number of filters and process calculations optimization. The choice of filters and sequences of their use caused by possible changes for the scanned image at a predetermined pitch.

An example of possible mask filters (the alphabet) in the case of 3*3 matrix shown in Fig. 2. There are the basic concepts that will be used in the future. The letter - a simple indivisible character (some non-derivative element), that presents as an element of selected alphabet. The only limitation is a finite number of symbols of the alphabet.

The set of all words over the alphabet A is called the closure and is denoted by A^* [16].

$$A_i^* = ((((a_{i,j}^0 \cup a_{i,j+1}^{k_{z1}}) \cup a_{i,j+2}^{k_{z2}}) \cup a_{i,j+3}^{k_{z3}}) \cup \ldots \cup a_{i,j+n-1}^{k_{zn-1}}) \cup a_{i,j+n}^{k_{zn}} = \bigcup_{k_{zn=0}}^{zn=\infty} a_i^n$$

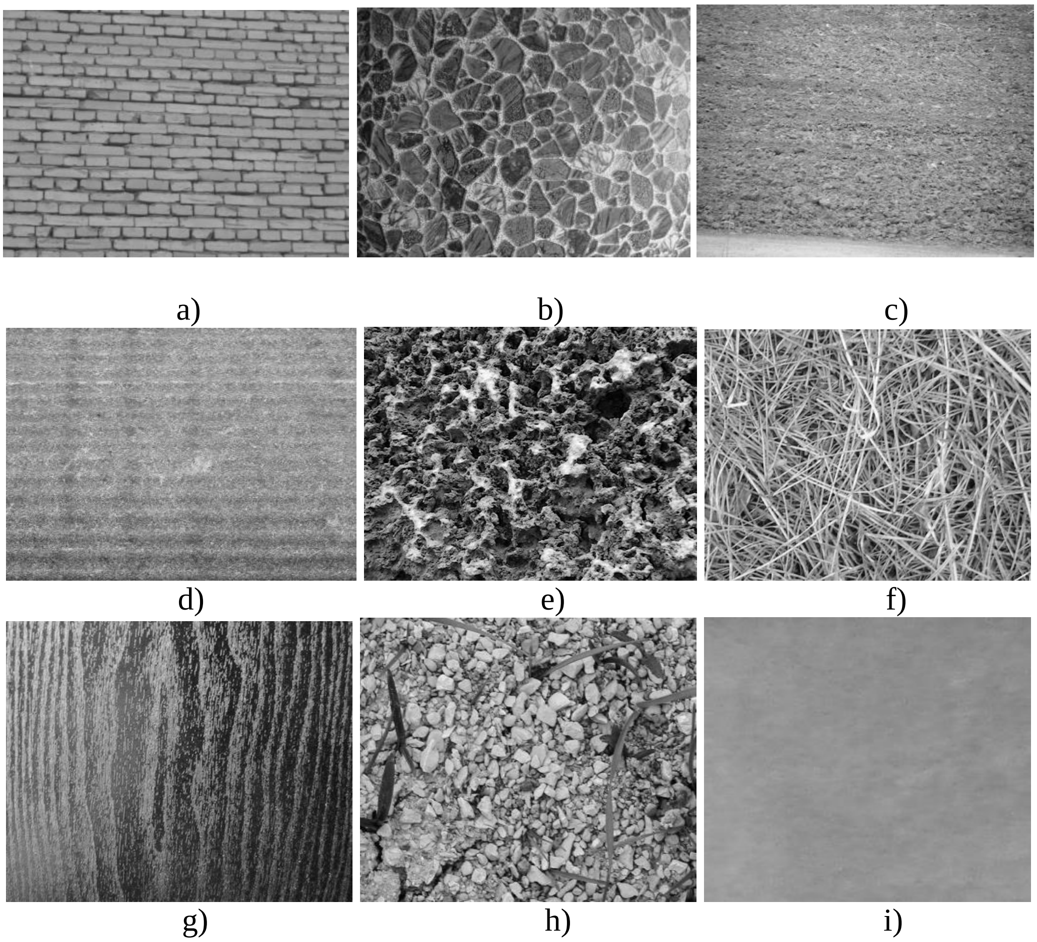


Fig. 1. Photos of different textures: a) a brick wall, b) mosaic,a) arable land, g) slate, d) coquina, e) hay, g) slice of wood, h) gravel, i) walls – plaster

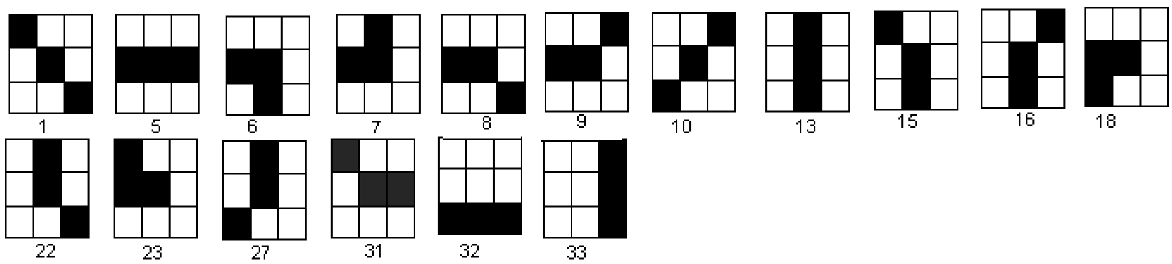


Fig. 2. Example of possible mask filters (the alphabet)

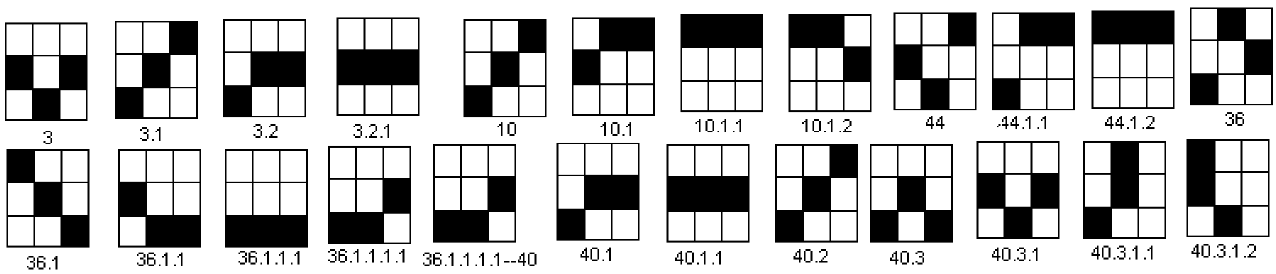


Fig. 3. Example of possible sequences of transformations

As in ordinary languages, the basic operations over words (strings) is a concatenation. Formally, it can be defined as a binary operation Θ on the set of elements of words as follows:

$$\Theta:(a^{k_{z1}},a^{k_{zi}})\xrightarrow{p_i}a^{k_{z1}}a^{k_{zi}},$$

where: p_i the probability of transition k_{z1} into k_{zi}.

The result of the merger of alphabet letters (words) in the following procedure: the letter $a^{k_{z2}}$ imposed on off-center letter $a^{k_{z1}}$ with some step. Fig. 3 shows a graphic illustration of the obtained results.

It should be noted that the procedure described above assumes the linear independence of the rows that for the image is not true (Fig. 4 illustrates this).

$$A^*_{ij}=\bigcup_j \bigcup_{k_{zn}=0\ j}^{k_{zn}=\infty} a_i^n$$

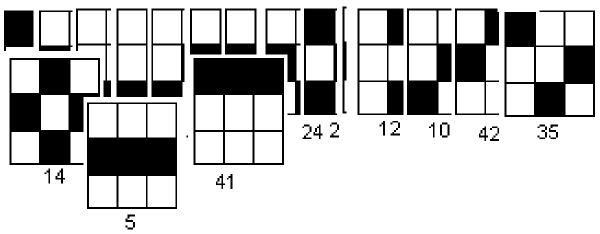


Fig. 4 - Example of a possible transformation of the alphabet letters

The processed image is discretized monochrome images that digitally describes the matrix

$$B=\lfloor b_{ij}\rfloor,\ i\in I,\ j\in J.$$

The value of the image b_{ij} (i - row number, j - column number) is quantized at the K level of the brightness value represented by the nodes of the sensor or display device and additive noise superimposed on it. Image processing can be represented as a transformation of one set of strings consisting of symbols - the brightness values in the other set.

The initial matrix B being transformed and as a result of which we obtain a new matrix $G=\lfloor g_{ij}\rfloor$ with sizes $(I-1)\times(J-1)$, each element of which is the result of a convolution of a local fragment with sizes $L\times K$ with a set of masks - alphabet BRVAL.

DIGITAL TWO-DIMENSIONAL CONVOLUTION OPERATION

Mathematically, the two-dimensional convolution can be described as follows:

$$g_{i,j}^{a_z}=\sum_{m=-M}^{M}\sum_{n=-N}^{N}b_{i-m,j-n}\omega_{m,n}^{a_z} \qquad (1)$$

where: $B=[b_{i,j}]$ - the original image, wherein the brightness values is representted in the sensor nodes or the forming device (display) images and additive noise imposed on it, $G=[g_{i,j}^{a}]$ - code representtation of the image dimension $(I-1)\times(J-1)$, the dimension of weights matrix $W=[\omega_{m,n}^{a_z}]$, is $(m,n)\in(2*M+1)(2*N+1)$, a - the set of filters masks, z- filter number (letter).

The process of classifying and identifying objects in the image, based on the above described approach which is consist of finding a statistically significant chains of alphabet letters (words).

In the simplest case, identification can be obtained by analyzing the histogram of features derived from the filters BRVAL.

Histogram features fragment image with size $I\times J$ - $H_{IJ}=\{h_{ij}(a)\}$- we will be called the empirical probability distribution of the filter response:

$$h_{ij}(a)=P\{g_{ij}=a\mid g_{ij}\in W_{mn}\};\quad \sum_{a=0}^{A}h_{ij}=1.$$

TEXTURE COMPARISON ON THE IMAGE

Often textures are present in the images of natural scenes, containing both natural and man-made objects. Bricks, tiles, pebbles and many other objects form the texture image content [18].

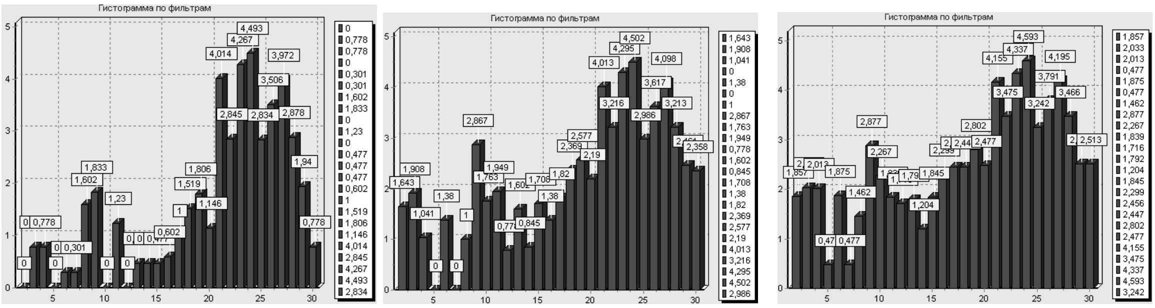
Consider a brick wall photos, taken from different angles in the evening and at a distance of 10 meters. The results of research we will be displayed in the form of histograms and polarograms. Under the polarograms we will understand the histogram constructed in the polar coordinate system on which the data are divided into groups and form a local coordinate system for each group.

After the experiment we obtained the histograms (Fig. 6) and polarograms (Fig. 7) which showing the distribution of the values features for different textures. From this examples we can see changes on polarograms, depending on the direction of image registration, but these differences are not essential to the assigned in this article task of identification texture. In addition, we observe amplitude change, but not the whole histogram generally (Fig. 8 - comparison textural features on the polarograms with the help of the brick wall photos which were made from the left and right side in the evening and on the different distance).

Similar results were obtained for different textures, such as pebbles, mosaics, hay, slate that are presented below (Fig. 9-17). They show the constancy of the global distribution of the filter values response in researched textures.

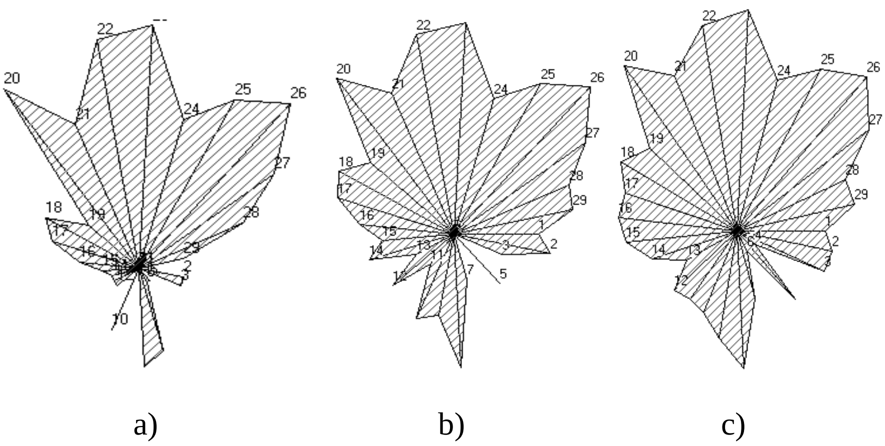
a) b) c)

Fig. 5. Photo of a brick wall in the evening at distance of 10 meters from different directions: a) from the left side, b) from the right side, c) straight



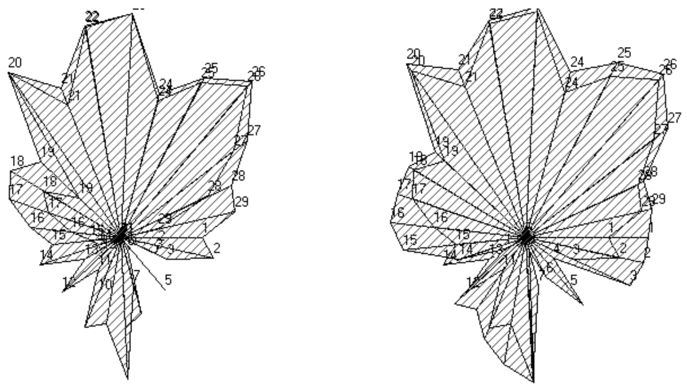
a) b) c)

Fig. 6. Histograms of a brick wall in the evening at distance of 10 meters from different directions: a) from the left side, b) from the right side, c) straight



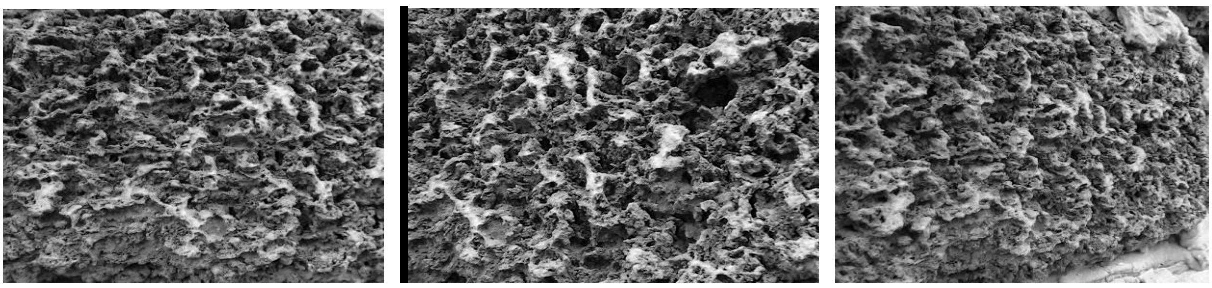
a) b) c)

Fig. 7. Polarograms of a brick wall in the evening at distance of 10 meters from different directions: a) from the left side, b) from the right side, c) straight



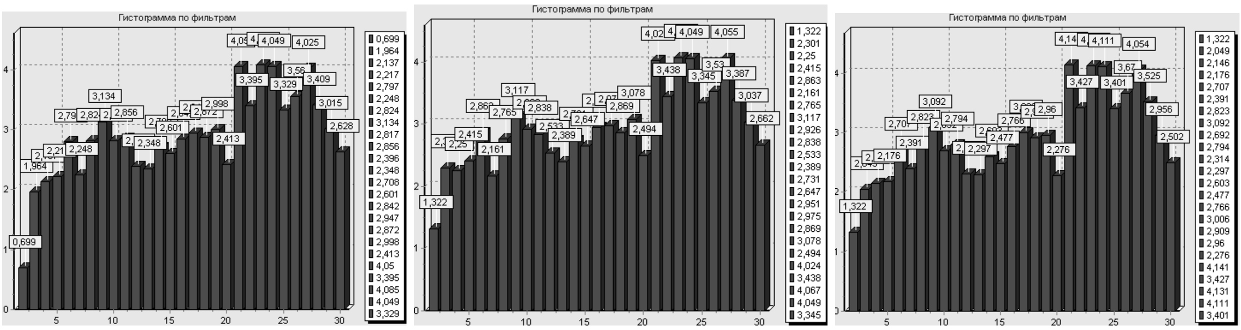
a) b)

Fig. 8. Comparison textural features on the polarograms wall photos from the left and right side on the different distance: a) 10 meters, b) 20 meters



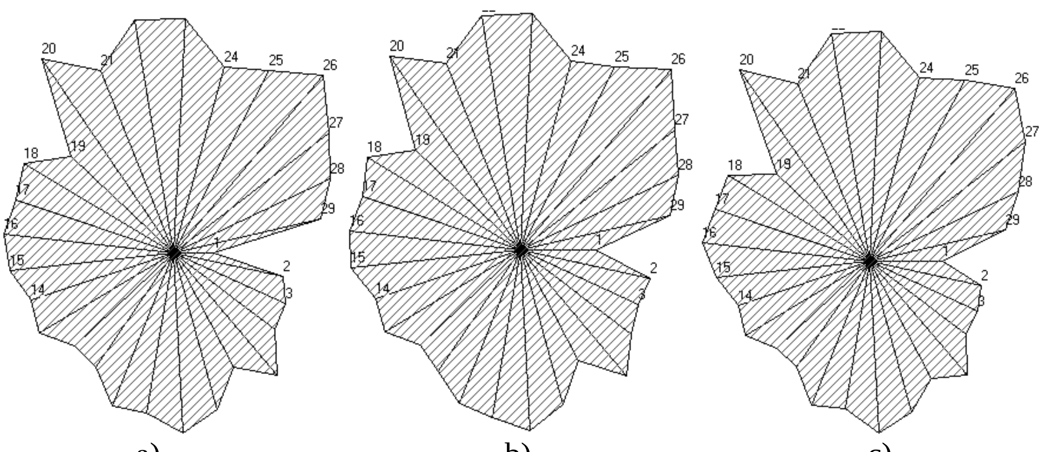
a) b) c)

Fig. 9. Photo of the shell rock: a) straight, b) from the right side, c) from the left side



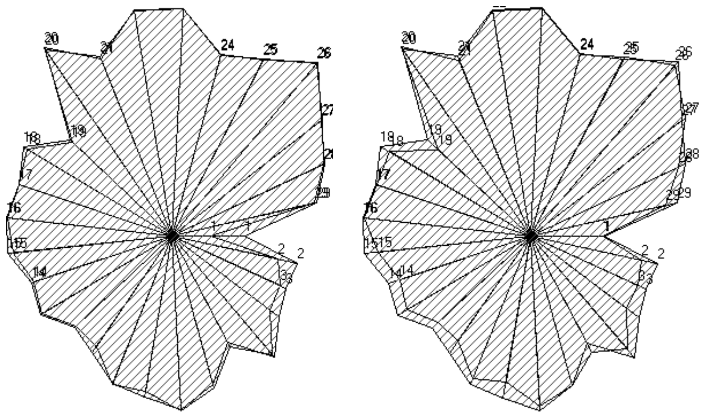
a) b) c)

Fig. 10. Histograms of the shell rock: a) straight, b) from the right side, c) from the left side



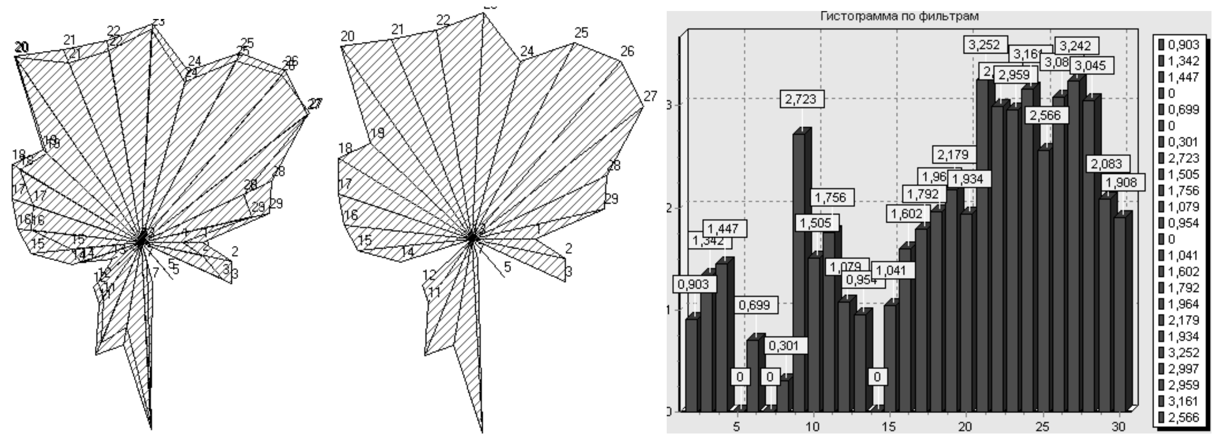
a) b) c)

Fig. 11. Polarograms of the shell rock: a) straight, b) from the right side, c) from the left side



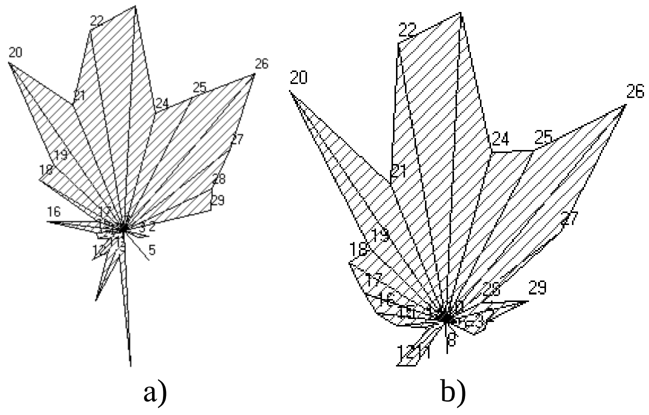
a) b)

Fig. 12. Comparison the textural features on the polarograms with the help of the shell rock photos, which were made from the different sides: a) straight and left, b) left and right



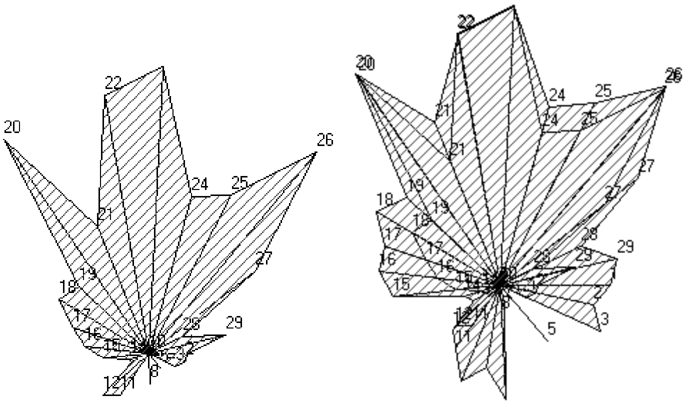
a) b) c)

Fig. 13. Comparison the textural features on the polarograms with the help of the brick wall photos: a) the straight wall and the wall at a distance of 20 meters and at an angle of 45 °, b) wall at a distance of 20 meters and at an angle of 45 °, a) histogram of the brick wall texture



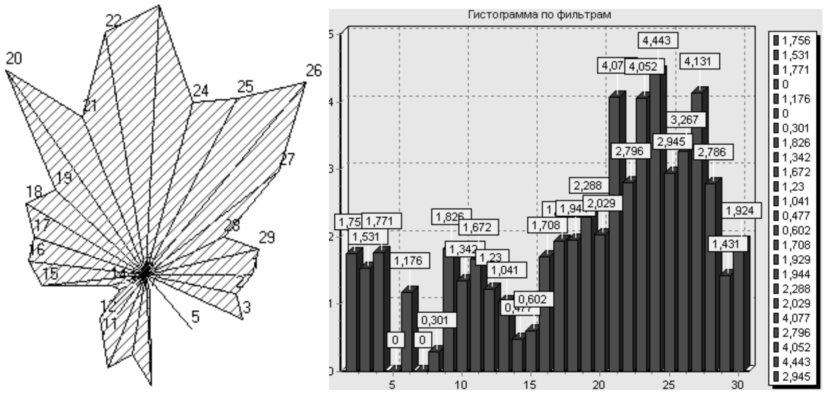
a) b)

Fig. 14. Polarograms of the wall and smooth concrete textures at a distance of 10 meters and at an angle of 45 °: a) wall, b) smooth concrete



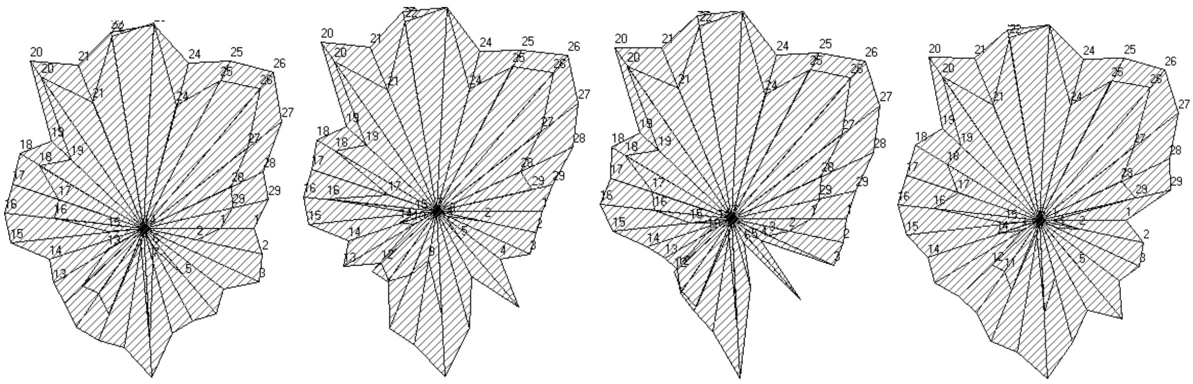
а) б)

Fig. 15. Comparison of the textural features on polarograms wall and smooth concrete textures: a) wall at a distance of 10 meters and at an angle of 45°; the concrete at a distance of 10 meters and at the angle of 90 °, b) smooth concrete and wall at a distance of 10 meters and at the angle of 90°



а) б)

Fig. 16. Comparison of the textural features with the help of the wall and smooth concrete textures at a distance of 10 meters and at an angle of 135 °: a) on the polarogram, b) on the histogram



a) b) c) d)

Fig. 17. Comparison the textural features of the brick wall texture on the polarograms with: a) the slate, b) shell rock, c) mosaics, d) plowed land

The analysis of the experiments shows that for the BRVAL filters describe texture in a wide range of distances and lighting independent of researched factors. Thus, we can say that under a texture image we will understand the set of points (distribution of a random process) image, between which there is a statistically significant association.

Of course, at distances when information structural elements of the image are merged, distribution statistics will be violated. It concerns also the field angle, but such experiments are not the purpose of this work.

The most important in this experiment is the mutual comparison of the research textures. Various textures, as seen from the results of experiments, are essentially differ from each other, which is the indication of their recognizability.

As can be seen from the experimental results observed the following trend: the more fine detail, the less visible changes on the polarographic curves.

CONCLUSION

There were investigated different types of textures and analyzed a number of texture images using polarograms and histograms. The algorithm description of texture images using textural elements presented in the form of the alphabet distribution filters that allow us to describe the texture images in a wide range of invariant factors: distance, viewing angle and lighting conditions. It was given the definition of texture based on the proposed algorithm.

The results obtained in this paper provide a basis for further research in identifying texture of the images, including analysis of the position, direction and speed of objects in time.

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