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VECTOR-DIFFERENCE TEXTURE SEGMENTATION METHOD IN TECHNICAL AND MEDICAL EXPRESS DIAGNOSTIC SYSTEMS

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ABSTRACT

The study shows the need for express systems, in which it is necessary to perform the analysis of texture images in various areas of diagnosis, for example, in medical express diagnostics of dermatologic disorders. Since the reliability of decision-making in such systems depends on the quality of image segmentation, which, as a rule, have the nature of spectral-statistical textures, it is advisable to develop methods for segmentation of such images and models for their presentation. A model of spectral-statistical texture is proposed, which takes into account the random nature of changes in the field variations and quasi-harmonics. On its basis, a vector-difference method of texture segmentation has been developed, which is based on the vector transformation of images of spectral and statistical textures based on vector algebra. The stages of the vector-difference method are the following: an evaluation of the spectral texture feature; an evaluation of the statistical texture feature; vector-difference transformation of texture images; a boundary detection of the homogeneous regions. For each pixel of the image in the processing aperture, the features of the spectral and statistical texture are evaluated. Statistical texture evaluation was performed by the quadratic-amplitude transformation. At the stage of vector-difference transformation of texture images, a vector of features of each pixel of an image is constructed, the elements of which are estimates of features of a spectral and statistical texture, and the modulus of the difference of two vectors is calculated. At the stage of boundary detection of homogeneous regions, Canny method was applied. The developed vector-difference texture segmentation method was applied both to model images of spectral-statistical texture and to texture images obtained in technical and medical diagnostics systems, namely, for images of psoriasis disease and wear zones of cutting tools. To compare the segmentation results, frequency-detector and amplitude-detector methods of texture segmentation were applied to these images. The quality of segmentation of homogeneous textured regions was evaluated by the Pratt's criterion and by constructing a confusion matrix. The research results showed that the developed vector-difference texture segmentation method has increased noise tolerance at a sufficient processing speed.

Keywords: texture segmentation; texture features; spectral-statistical texture; detector methods; classification methods; confusion matrix; vector-difference method

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INTRODUCTION

Today, systems of computer visual patterns recognition (SCVPR) are extensively used in a wide class of intelligent diagnostic systems, among which some can be distinguished as ones making a diagnostic decision by analyzing the texture regions of images. It should be noted that there is a great need for express systems using image understanding for the analysis of texture images in various areas of diagnostics, for example, in medical express diagnostics of dermatological disorders (psoriasis, eczema, atopic dermatitis) [1-4] and in technical express diagnostics of the quality of cutting tools [5-6]. Such systems are characterized by the necessity of peripheral computing, i.e. calculations must be performed without using server processing characterized by high efficiency and low resource consumption alongside with high reliability of diagnostic solutions. However, despite the need to apply these systems in practice, their implementation is very slow, insofar as the existing express diagnostic systems do not provide the efficiency for practical needs, which is determined by the reliability of diagnostic solutions and/or efficiency.

Systems of computer visual patterns recognition for express diagnostic contain a number of traditional procedures such as image acquisition, preprocessing, segmentation, identification, classification [7]. It is noteworthy that the segmentation procedure is one of the most important in SCVPR and affects the efficiency and responsiveness of the process. The purpose of texture segmentation when detecting texture-homogeneous regions of images is to reduce the amount of processed data. The matter of this procedure is to combine similar group of pixels into segments based on one or more segmentation features. The choice of a particular segmentation method depends on the texture model. In this paper, we consider two main types of textures - statistical and spectral. The statistical texture is modeled as a random field, at the boundaries of which its numerical characteristics change. The spectral texture is a linear combination of quasi-harmonic oscillations. However, in practice, some images have features that are inherent in statistical, spectral and combined spectral-statistical models of textures. These include, for example, images of dermatological disorders (psoriasis), which are analyzed in medical diagnostic systems, and images of wear zones of cutting tools (CT), which are analyzed in technical diagnostic systems. Textural features of combined spectral-statistical textures have both statistical and spectral character. In this case, the methods of texture segmentation of spectral and statistical textures do not provide the segmentation quality necessary in practice, which reduces effectiveness and efficiency of SCVPR in general.

The literature analysis has shown that, depending on the texture model, the main approaches to texture segmentation are the classification and detector ones. With the detector approach, a certain feature of the texture image is converted into intensity, which, in the future, is taken into account when identifying the boundaries of homogeneous texture regions using the methods of contour segmentation. The classification approach uses pattern recognition techniques which include identification and supervised or unsupervised classification when assigning an image to a specific type of texture. Analysis of the existing methods of texture segmentation suggests that the detector methods are not noise-tolerant, but they provide high-speed image processing, whilst the classification methods are characterized by low efficiency, but provide high noise tolerance and allow segmentation in a wider class of images and textures. It should be noted that account of the features of both statistical and spectral textures leads to a decrease in the quality of segmentation and/or an increase in processing time during texture image segmentation with known methods.

Thus, an important and urgent task is to develop a model and a method for segmentation of spectral-statistical textures to improve their quality in SCVPR for medical and technical express diagnostics

ANALYSIS OF TEXTURE SEGMENTATION METHODS

The authors analyzed typical images that are processed in medical and technical diagnostics systems (Table 1): dermatologic disorders (psoriasis) analyzed in medical diagnostics systems and images of wear zones of cutting tools, which are analyzed in technical diagnostics systems. Images analyzed by the authors (Table 1, columns 4-5): (were obtained from https://www.dermentnz.org (images of psoriasis disease) and from the stand of DSc. O. Dereviianchenko (Odessa National Polytechnic University) (for images of wear zones of cutting tools were obtained).

Analysis of the images given in the table showed that both medical images and images of wear zones of cutting tools have features of statistical, spectral and combined texture models.

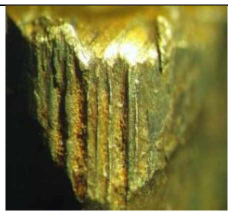
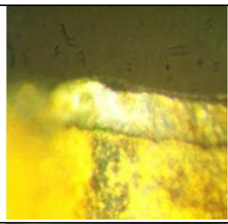
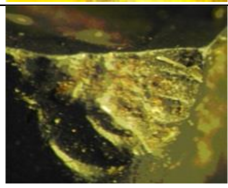
Thus, the CT wear zones, which appear due to processes of different, speed when cutting materials, can be described by the spectral model of the texture (the fragile destruction) (line 1) [8]. If, as a result of the operation of the tool, roughness and raveling appear on its surface, then such cases can be reflected in the image by the statistical model of the texture (line 2). In the case of both factors conjoined a combined spectral-statistical model of the texture is observed (line 3).

Similar features are inherent in medical images of psoriasis. The identification of the textures of these images by the method, based on multifractal indicators [9], showed that they contain regions of statistical (line 2), spectral (line 1) and combined spectral-statistical texture (line No. 3).

As noted above, at the stage of texture segmentation, the image definition region Ω is represented as a union of non-intersecting regions (segments) Ω_i ($i = \overline{1,k}$), in each of which the vector of texture features slowly changes, that is $\Omega = \bigcup_{i=1}^{k} \Omega_i$ [10]. The result of the image segmentation procedure is a set of segments of homogeneous regions or a set of contours of homogeneous textured regions.

There are various approaches to the classification of texture image segmentation methods [11-16]. But within this work, the subject of interest is the classification of methods which are based on determining the features of segmentation. As such ones, the statistical and spectral texture features can be used. Statistical features are calculated using statistical central moments of various orders. The second-order statistical features take into account interactions between pixels. Calculations of such characteristics are performed using the Co-occurrence Matrices [17] and the Local Binary Pattern [18]. The first-order statistical features do not take into account the interaction between image pixels, but estimate one of the statistical parameters (mean, standard deviation, smoothness, homogeneity, entropy) and consider the value of this parameter as a new value of the intensity (amplitude) of the image [19].

Table 1. **Classification of texture models**

No.	Texture model	Texture estimation characteristics	Methods	Examples of texture images	
				Of wear zones of cutting tools	Of psoriasis disease
	1	2	3	4	5
1	Spectral	Changes in spatial frequency [21]	Spectral methods; Wavelet transform; Fourier transform; Detector methods; Classification methods		
2	Statistical	Changes of field variations (eg, variance of pixel intensity) [24]	Histogram analysis; Correlation analysis; Statistical methods; Detector methods; Classification methods		
3	Combined spectral-statistical	Random variati-on in spatial frequency and field variation	Spectral and/or statistical methods		

***Source*: compiled by the author**

The spectral characteristics of a texture are characteristics of a texture in terms of spatial frequency. To determine the spectral characteristics of the texture, Fourier spectrum are used, the amplitude spectrum of which is different for textures with different frequency characteristics. Also, to determine the characteristics of the spectral texture, an autocorrelation function is used, which is calculated in the processing aperture of each pixel of the image. The size of texture primitives is proportional to the width of the autocorrelation function [20].

In the case of determining statistical features, we speak of statistical methods of texture segmentation, in the case of spectral – of spectral ones (Table 1).

In addition, segmentation can be carried out according to one or several features. In the first case, the segmentation methods are related to the detector ones, in the second – to the classification [21] ones. The methods of the first group provide the transition from the values of the segmentation feature to the values of the image intensity and include procedures for evaluating the segmentation feature; emphasizing the boundary between homogeneous image regions by thresholding and morphological processing of potential boundaries of homogeneous texture regions. According to the second group of methods of texture image segmentation [10], the segmentation features are evaluated, the feature vector is classified, the boundary pixels of homogeneous regions are identified and the boundaries are processed [22]. Analysis of literature sources showed that detector methods are used for the segmentation of textures that differ in the amplitudes of spectral components (amplitude-detector methods) or frequency characteristics (frequency-detector methods).

The procedures that make up the content of the methods of the first group of texture image segmentation (detector one) allow achieving high performance and are easy to implement. However, they are not noise-tolerant and give a high inaccuracy in determining the coordinates of the pixels of the boundaries of texture regions. The texture segmentation methods that use the classification [23] of the feature vector are complex and do not have high performance. But these methods are noise-tolerant and allow you to obtain a low inaccuracy in determining the coordinates of the pixels of the texture regions boundaries.

Therefore, the analysis of texture segmentation methods showed the peculiarities of existing methods: for detector methods – low-quality segmentation at high speed; for classification methods – high noise-tolerance at low speed.

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Since in the tasks of medical and technical diagnostics, images related to combine spectral and statistical textures are analyzed, the use of detector and classification methods for their segmentation does not provide the segmentation quality necessary for practice with sufficient efficiency. Therefore, it is necessary to develop segmentation methods for combined spectral-statistical types of textures that would provide high-quality segmentation while maintaining efficiency for practical needs. The authors propose to carry out a parallel estimation of the texture in the neighborhood of each pixel by both types of texture features: statistical and spectral and to perform vector transformation of texture images based on vector algebra for improving the quality of segmentation of spectral-statistical types of textures.

THE AIM AND OBJECTIVES OF THE RESEARCH

The aim of this work is to improve the quality of segmentation of combined spectral-statistical textures for practical efficiency.

To achieve this, the following tasks have been set:

– developing a model of spectral-statistical texture;

– developing a vector-difference segmentation method for combined spectral-statistical textures, which is based on vector transformation of texture images using the vector algebra;

– conducting an experimental research of the vector-difference segmentation method on model images of combined spectral-statistical textures;

– conducting an experimental research of the vector-difference segmentation method on images of psoriasis disease and wear zones of cutting tools.

DEVELOPMENT OF A MODEL OF SPECTRAL-STATISTICAL TEXTURE

Generally, the selection of the appropriate segmentation methods occurs at the modeling stage, considering the model of the texture type. If the type of texture is determined correctly, the use of appropriate methods of texture segmentation gives high indicators of the segmentation quality. For texture modeling, there are models of statistical [21] and spectral texture [10], but there are no models of combined spectral-statistical one, which are in demand in express systems of technical and medical diagnostics. Therefore, it becomes necessary to develop a model of a combined spectral-statistical texture and a segmentation method that could provide a segmentation quality sufficient for the needs of practice.

Since the spectral models of textures are characterized by the value of the background component and a change in the spatial frequency, the value of the intensity of the *m*-th raw of the spectral texture image (Table 2, line 1, column 3) is represented as a union of non-intersecting segments:

$$I(x, y_m) = \bigcup_{i=1}^{k} \{c_i(x, y_m) + \sum_{j=1}^{n} A_j(x, y_m) \sin(\omega_m^{ij} x)\},\ x \in [q_{i-1}, q_i], \quad (1)$$

where: $A_j(x, y_m)$ is the amplitude of the modulated *j*-th oscillation of the *m*-th image raw; ω_m^{ij} is the frequency of the *j*-th oscillation on the *i*-th segment of the *m*-th image raw; $c_i(x, y_m)$ is the notation of the background in the *i*-th segment of the *m*-th image raw; $q = (q_0, ..., q_{k+1})$ is the vector of boundaries texture regions of the *m*-th image raw, where $q_0=1$, $q_{k+1}=N+1$, N is the number of pixels in the image raw.

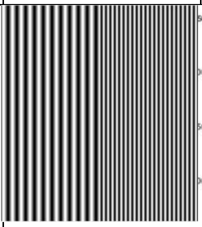
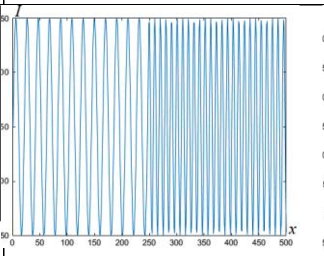
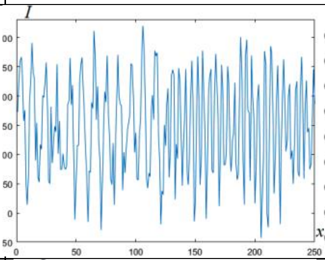
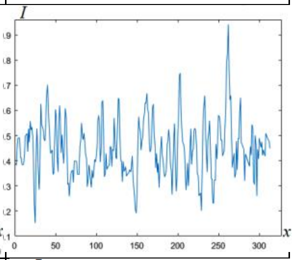
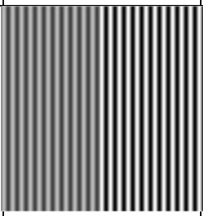
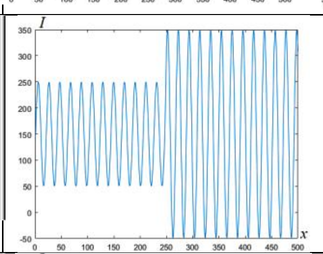
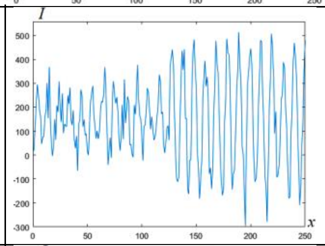
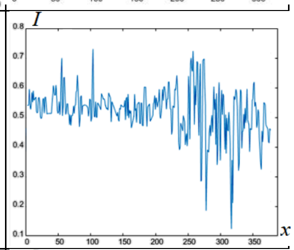
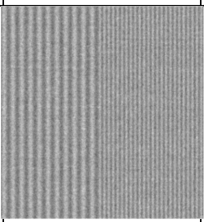
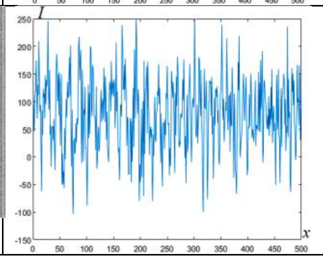
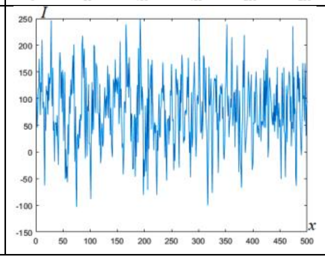
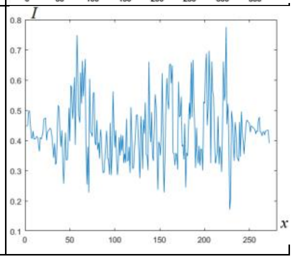
An example of a model image of a spectral texture (1) (Table 2, line 1, column 2), a raw of a model image of a spectral texture with noise (Table 2, line 1, column 4), and a raw of an image of a psoriasis disease, which is described by a spectral texture model (Table 2, line 1, column 5), are presented in Table 2, line 1. The model image has a dimension of 512×512, the intensity of the image pixels varies from 0 to 256, the texture image is represented by two regions with different frequencies $\omega_1 = 25$ per/m, $\omega_2 = 50$ per/m.

Statistical models of textures, in turn, are characterized by the value of the background component and the change in field variations, and then the value of the intensity of the *m*-th raw of the image of the statistical texture (Table 2, line 2, column 3) is represented as a union of non-intersecting segments:

$$I(x, y_m) = \bigcup_{i=1}^{k} \{c_i(x, y_m) + \sum_{j=1}^{n} A_{ij}(x, y_m) \sin(\omega_m^{j} x)\},\ x \in [q_{i-1}, q_i], \quad (2)$$

where $A_{ij}(x, y_m)$ is the amplitude of the modulated *j*-oscillation of the *m*-th image raw on the *i*-th segment of the *m*-th image raw; ω_m^j is the frequency of the *j*-oscillation of the *m*-th image raw.

Table 2. **Model texture images**

No.	Texture type	Model texture image	Raw of model texture image	Raw of model texture image with noise	Raw of psoriasis disease image
	1	2	3	4	5
1	Spectral				
2	Statistical				
3	Combined spectral-statistical				

***Source*: compiled by the author**

An example of a model image of a statistical texture (2) (Table 2, line 2, column 2), a raw of a model image of a statistical texture with noise (Table 2, line 2, column 4) and a raw of an image of a psoriasis disease, which is described by a statistical texture model (Table 2, line 2, column 5), are presented in Table 2, line 2. The image has a dimension of 512×512, the intensity of the image pixels varies from 0 to 256, the texture image is represented by two regions with different amplitudes $A_1 = 1$, $A_2 = 3$.

The combined spectral-statistical model of the texture is characterized by the value of the background component and a random changes in the spatial frequency and field variations.

Then the value of the intensity of the *m*-th raw of the image of the spectral-statistical model of the texture in Table 2, raw No. 3, column No. 3 is represented as follows:

$$I(x, y_m) = \bigcup_{i=1}^{k} \{c_i(x, y_m) +$$

$$\sum_{j=1}^{n} \xi_{ij} A_{ij}(x, y_m) \sin(\eta_{ij} \omega_m^{ij} x)\}, \ x \in [q_{i-1}, q_i], \quad (3)$$

where ξ_{ij}, ω_m^{ij} are, respectively, a random change in the amplitude of the modulated *j*-oscillation of the *m*-th raw of the image and a random change in the frequency of the *j*-oscillation on the *i*-th segment of the *m*-th raw of the image.

An example of a model image of a spectral-statistical texture (3) (Table 2, line 3, column 2), a raw of an image of a psoriasis disease, which is described by a spectral-statistical model of textures (Table 2, line 3, column 5), is presented in Table 2, line 3. The image has a dimension of 512×512, the intensity of the image pixels varies from 0 to 256, the texture image is represented by two regions with different frequencies $\omega_1 = 25$ per/m, $\omega_2 = 50$ per/m and amplitude $A = 1$, a random change in amplitude and frequency occurs due to the superposition of a Gaussian noise with zero mean and different variance of the Gaussian noise for different segments of the image.

Concerning the graphs in Table 2, the abscissa represents the value of the spatial coordinate x, which corresponds to the image pixel index, and the ordinate represents the pixel intensity values of the *m*-th raw of the texture image.

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For the segmentation of statistical textures, the amplitude-detector method [8; 21] is used, for the segmentation of spectral textures, the frequency-detector method [25]. For the spectral-statistical texture, taking into account changes in the frequency components of the texture and variations in the spatial field, a vector-difference method is proposed.

VECTOR-DIFFERENCE METHOD for SPECTRAL-STATISTICAL TEXTURE SEGMENTATION

The proposed scheme for the implementation of the vector-difference spectral-statistical texture segmentation method contains the following stages:

1) evaluation of the numerical dispersion characteristics c_1 and spectral texture c_2 for i-th pixel of the image in the processing aperture;

2) formation of a vector $\vec{c}_i\,(c_{1,i}, c_{2,i})$ in the space of features;

3) evaluation of the feature vector for the $(i+1)$-th pixel of the image in the processing aperture; $\vec{c}_{i+1}\,(c_{1,i+1}, c_{2,i+1})$;

4) calculation of the difference of vectors $\vec{c}_{i+1}\,(c_{1,i+1}, c_{2,i+1})$ і $\vec{c}_i\,(c_{1,i}, c_{2,i})$;

5) calculation of the modulus of the difference of two vectors $\vec{c}_{i+1}\,(c_{1,i+1}, c_{2,i+1})$ і $\vec{c}_i\,(c_{1,i}, c_{2,i})$ (4) using the methods of vector algebra (Fig. 1):

$$\vec{c} = \left|\vec{c}_{i+1}\,(c_{1,i+1}, c_{2,i+1}) - \vec{c}_i\,(c_{1,i}, c_{2,i})\right| = \overrightarrow{(c_{1,i+1} - c_{1,i}, c_{2,i+1} - c_{1,i})}\ ; \qquad (4)$$

6) detection of the boundaries of a homogeneous textured region.

Thus, the vector $\vec{c}$ can be considered as the result of spatial differentiation in the feature space. It can be used to define the contours of objects, for example, using a threshold transformation (Table 3, No.1). Based on the foregoing, the proposed vector-difference method combines the advantages of detector – and classification methods. The authors considered the development of the method for 3 or more feature vectors for the case of multidimensional vector transformation of images based on vector algebra.

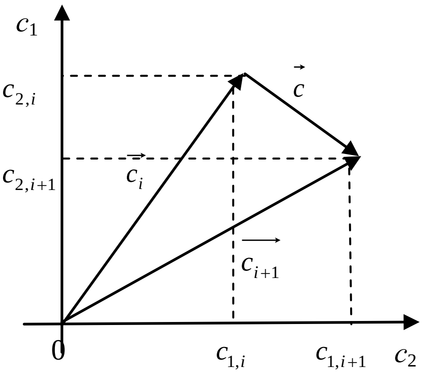


Fig. 1. **For illustration of the vector-difference method in the feature space**
***Source*: compiled by the author**

The following functional diagram of the implementation of the vector-difference spectral-statistical texture segmentation method (Fig. 2) is proposed, which contains the following blocks: evaluation of the spectral texture feature; evaluation of the statistical texture feature; vector-difference block; block of boundary detection of the homogeneous regions.

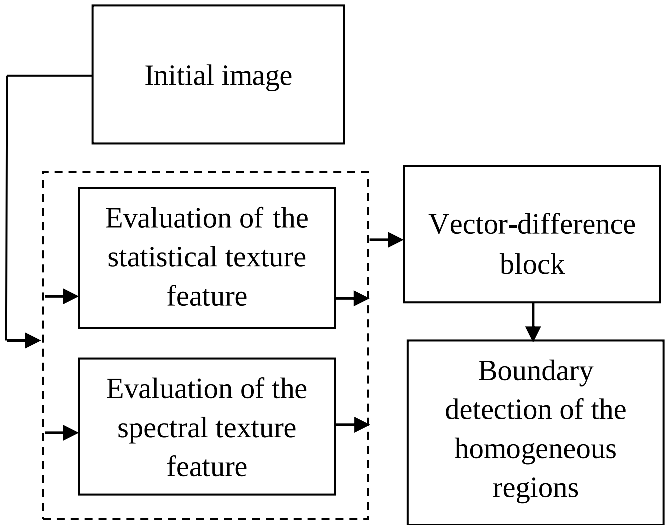


Fig. 2. **Functional diagram of the vector-difference spectral-statistical texture method segmentation**
***Source*: compiled by the author**

Within the block of evaluation of the statistical texture feature, a vector of statistical texture features is formed, each element of which is defined as follows:

1) the processing aperture is formed for each pixel of an image of size *M*. The size of the processing aperture is selected depending on the purpose of processing;

2) the average intensity of pixels $\bar{I} = \frac{\sum_{i=1}^{M} I_i}{M}$ in each row of the image matrix in the processing aperture of each pixel is calculated;

3) the statistical evaluation of the variance $\bar{\sigma}$ in each processing aperture of each pixel is calculated.

It should be noted that the calculation of the statistical estimate of the variance $\bar{\sigma}$, depending on the purpose of processing, can be carried out by the following means (Table 3): a square-amplitude transformation (expression 5, line 1, column 2), a full-wave amplitude transformation (expression 6, line 2, column 2) or a half-wave amplitude transformation (expression 7, line 3, column 2). The analysis of the results of detection the boundaries of homogeneous regions of model images (2) for various types of statistical evaluation of variance (5) - (7) is carried out by the authors. The table shows an example of such processing (Table 3, lines 1-3, column 3). Detection the boundaries of homogeneous regions was carried out by the Canny edge detector [19] (Table 3, lines 1-3, column 4). Evaluation of the quality of detection of the boundaries of homogeneous regions, which was carried out using the Pratt's criterion [26], showed that the value of the Pratt's criterion in the case of applying the square-amplitude transformation is 1.1 – 1.5 times higher than in the case of using the full-wave amplitude transformation and 1.5-2.5 times higher in the case of a half-wave amplitude transformation with a signal-to-noise ratio of 2 or more in power. Thus, in this work, to calculate the statistical evaluation of the variance, it was advisable to use the square-amplitude transformation.

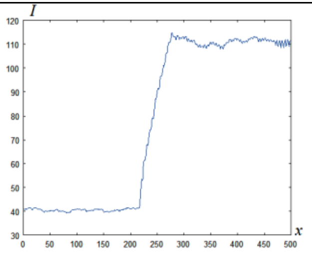
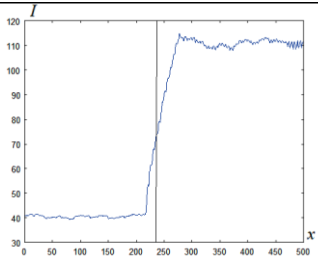
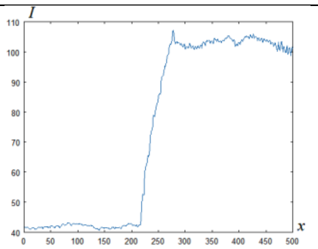
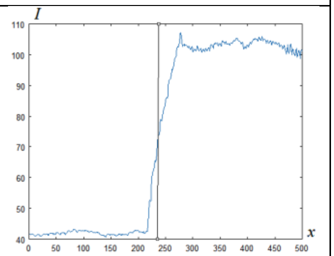
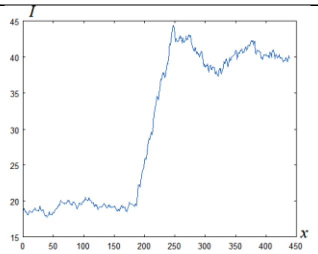
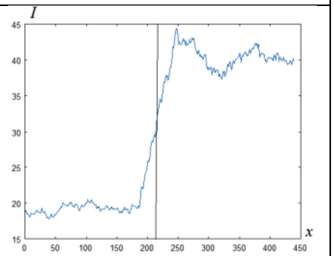
Within the block for evaluation of a spectral texture feature, a vector of features of a spectral texture is formed according to the following algorithm:

1) the processing aperture of size M is formed for each pixel of the image. The size of the processing aperture is selected depending on the purpose of processing;

2) the direct Fourier transform is performed in each raw of the image matrix in the processing aperture of each pixel:

$$\hat{I}(\omega) = \frac{1}{M} \sum_{x_i=1}^{M-1} I(x_i, y_m) e^{-j2\pi\omega x_i / M}, \quad \omega = \overline{0, M-1};$$

Table 3. **Applying different types of amplitude transformation**

No.	Amplitude transformation types	The equation for calculating the statistical estimate of variance	The result of applying the amplitude transformation	The boundaries of homogeneous regions
	1	2	3	4
1	The square-amplitude transformation	$\bar{\sigma} = \frac{\sum_{i=1}^{M} (I_i - \bar{I})^2}{M}$, (5) где $I_i > \bar{I}$, $i = \overline{1, M}$		
2	The full-wave amplitude transformation	$\bar{\sigma} = \frac{\sum_{i=1}^{M} \lvert I_i - \bar{I} \rvert}{M}$, (6) где $I_i > \bar{I}$, $i = \overline{1, M}$		
3	The half-wave amplitude transformation	$\bar{\sigma} = \frac{\sum_{i=1}^{M} (I_i - \bar{I})}{M}$, (7) где $I_i > \bar{I}$, $i = \overline{1, M}$		

***Source*: compiled by the author**

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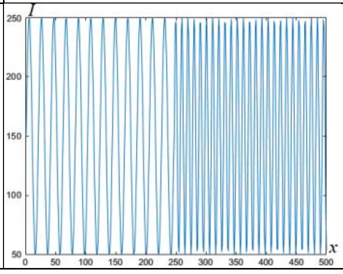
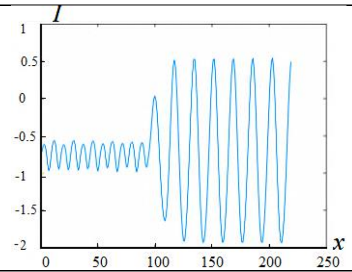
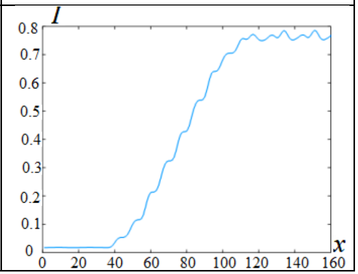
Table 4. **The results of the stages in determining the feature of the spectral texture**

No.	Model image raw	Frequency transformation	Square-Amplitude transformation
	1	2	3
1			

***Source*: compiled by the author**

3) the linear transformation of frequency is performed in the processing aperture of each pixel: $z(\omega) = k \cdot \hat{I}(\omega)$, as a result of which the spectral composition of the texture is converted into spread;

4) the inverse Fourier transform is performed $I(x_i, y_m) = \sum_{\omega=1}^{M-1} z(\omega) e^{j2\pi\omega x_i / M}$, $x_i = \overline{0, M-1}$;

5) the statistical evaluation of the numerical variance characteristics (5) is calculated for each pixel of the image in the processing aperture.

The results of applying the stages of algorithm determining spectral texture feature for model image texture (1) are shown in the table 4 (Table 4, line 1, columns 1-3).

In the tasks of segmentation of real images of spectral textures, the signal spectrum is normalized to equalize the amplitudes of the signal harmonics which are close in frequency [27]. In this work, the normalization of the signal spectrum was performed as pre-processing to the stage of determining the vector of spectral texture features.

As a result of the execution of the blocks for evaluation of the features of the statistical and spectral texture, the authors obtained two feature vectors: a vector of features of a statistical texture $\overline{\sigma_1}$ and a vector of features of a spectral texture $\overline{\sigma_2}$, which are sent for processing to a vector-difference block, where the vector of features of a spectral-statistical texture $\overline{\sigma_r}$ is calculated as the difference of two vectors (4).

In the block of the boundary detection for homogeneous regions, contour segmentation is performed. The work used the noise-tolerant Canny method of contour segmentation. The Canny method identifies two types of contours (strong and weak) and applies a morphological dilation operation that connects these types of contours [28].

EXPERIMENTAL RESEARCH OF THE VECTOR-DIFFERENCE SEGMENTATION METHOD ON MODEL IMAGES

Testing of the vector-difference method was carried out on a model image of a spectral-statistical texture (Table 2, No. 2), (3) at various signal-to-noise power ratios. To determine the boundaries of the spectral-statistical texture region, frequency-detector, amplitude-detector, and the proposed vector-difference segmentation methods were applied. To determine the quality of segment boundaries identification, a comparative analysis of ideally and really segmented images was carried out according to the Pratt's criterion, which is defined as:

$$R = (1/I) \sum_{i=1}^{I_A} 1/(1 + \alpha d_i^2), \qquad (8)$$

where: I=max(I_i, I_p); I_i, I_p are the numbers of pixels on the border of segments of ideally and really segmented images, respectively; α is scale factor; *di* is the distance between the pixels of the border of the really segmented image and the line consisting of the pixels of the ideal border of the segment.

The graphs of the dependence of the Pratt's criterion on the signal-to-noise power ratio had been obtained (Fig. 3).

The results of the experimental research showed that the proposed vector-difference texture segmentation method is better than the frequency-detector texture segmentation method by 1.5-1.8 times and the amplitude-detector method by 13-50 times with a signal-to-noise ratio of 5 or more in power.

The quality of segmentation of homogeneous regions of spectral-statistical texture was assessed based on the confusion matrix [29] (Table 5) using vector-difference, frequency-detector, and amplitude-detector methods.

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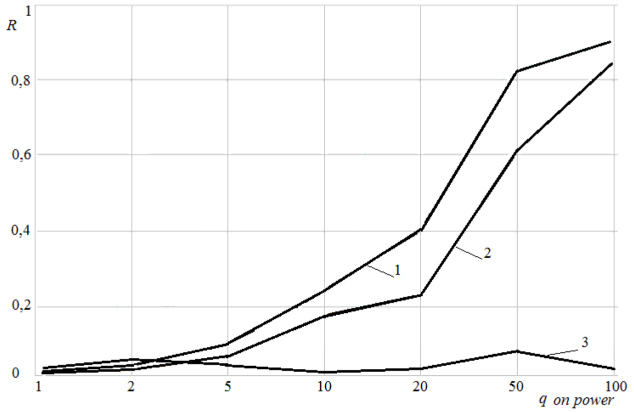

Fig. 3. **Dependence of the Pratt's criterion on the signal-to-noise power ratio:**
1 – for the vector-difference method;
2 – for frequency-detection method;
3 – for amplitude-detection method of texture segmentation
***Source*: compiled by the author**

Table 5. **General view of the confusion matrix**

Ideally mapped image, %	Image mapping obtained as a result of the experiment, %	
	Region 1	Region 2
Region 1	TP (true positive)	FN (false negative)
Region 2	FP (false positive)	TN (true negative)

***Source*: compiled by the author**

The elements of the confusion matrix are used to calculate the following segmentation quality scores: $Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$, Precision $P = \frac{TP}{TP + FP}$, Recall $R = \frac{TP}{TP + FN}$, Specificity $S = \frac{TN}{(TN + FP)}$, F-measure (also called F_1-score) $F_1 = \frac{2 \cdot PR}{P + R}$ [30]. The Accuracy score measures the proportion of all data predicted correctly. The Precision score is the fraction of pixels that actually belong to a given class relative to all ones that have been assigned to this class by the system. The Recall score is responsible for the accuracy of assigning pixels to the 1st class if they really belong to it. The Specificity score measures the reliability of assigning pixels to the 2nd class if they really belong to it. The F-measure is the harmonica mean between Precision and Recall scores.

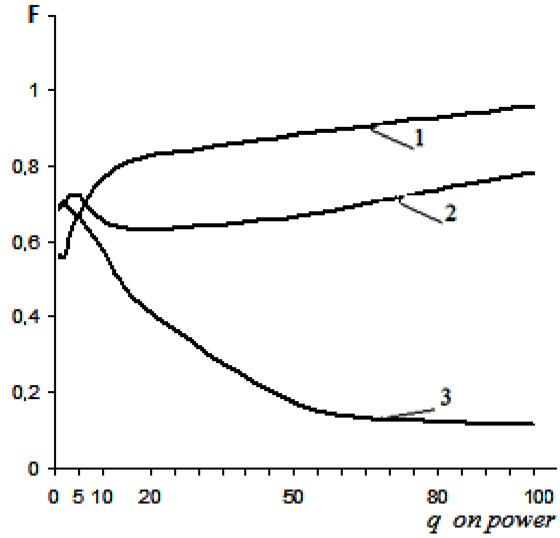

Fig. 4. **Dependence of the F-measure on the signal-to-noise ratio by power:**
1 – for the vector-difference method;
2 – for the frequency-detector method;
3 – for the amplitude-detector method of texture segmentation
***Source*: compiled by the author**

Comparative analysis of the quality assessment of the texture segmentation on the model image depending on the signal-to-noise power ratio (Fig. 4) when using vector-difference, frequency-detector and amplitude-detector methods showed that the proposed vector-difference method of texture segmentation is better than the frequency-detector the method of texture segmentation by 1.2-1.6 times and the amplitude-detector method by 1.1-8.4 times with a signal-to-noise ratio of 5 or more in power.

APPROBATION OF THE VECTOR-DIFFERENCE TEXTURE SEGMENTATION METHOD IN THE SYSTEMS OF MEDICAL AND TECHNICAL DIAGNOSTICS

To test the vector-difference method and the possibility of its operation in diagnostic systems, this method was tested on test images in two applications: when determining the wear zone of cutting tools and psoriasis skin disorders (Table 1, No. 3). The test sample contained 50 images of psoriasis skin disorders (https://www.dermentnz.org) and 30 images of the wear zone of cutting tools (from the stand of DSc. O. Derevianchenko (Odessa National Polytechnic University). A comparison was made of the work of the proposed vector-difference method (Fig. 5a and Fig. 6a) and the frequency-detector method (Fig.5b and Fig.6b). Testing the operation of the amplitude-detector segmentation method on a model image (3) showed that the amplitude-detector method does not give a satisfactory result, so its use is not advisable.

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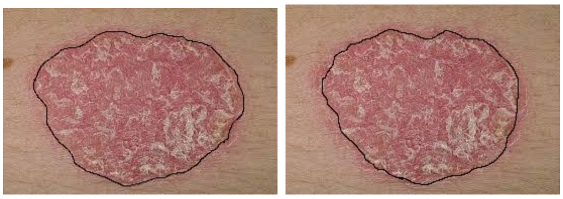
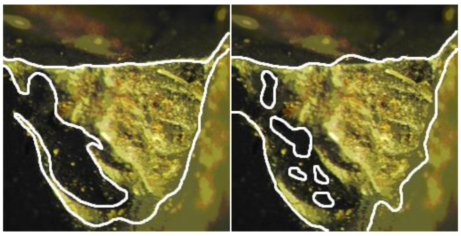


a b

Fig. 5. **Image of the spectral-statistical texture of the psoriasis disease with the border determined as a result of segmentation:**
a – by vector-difference method;
b – by frequency-detector method
***Source*: compiled by the author**



a b

Fig. 6. **Image of the spectral-statistical texture of the wear zones of cutting tools with the boundary determined as a result of segmentation:**
a – by vector-difference method;
b – by frequency-detector method
***Source*: compiled by the author**

The authors compared the results of image segmentation of psoriasis disease and wear zones of cutting tools using vector-difference and frequency-detector methods with image mapping by an expert with constructing a confusion matrix. Table 6 presents confusion matrices for vector-difference and frequency-detector methods when processing test images of psoriasis disease, Table 7 - test images of wear zones of cutting tools. The presented confusion matrices (Table 6 and Table 7) contain the average comparison results for all test images of psoriasis disease and cutting tools wear zones, respectively.

The proposed vector-difference method made it possible to improve the quality of segmentation of images of psoriasis disease and images of wear zones of cutting tools. Assessment of the quality of texture segmentation was evaluated by Accuracy and *F*-measure. The experimental results showed that the segmentation accuracy by the vector-difference method is higher than the same parameter obtained by the frequency-detector method by 10 % for images of psoriasis disease and by 5 % for images of wear zones of cutting tools.

Table 6. **Confusion matrix for vector-difference and frequency-detector methods in image processing of psoriasis disease**

Results of mapping images by an expert, %	Results of image segmentation by vector-difference method, %	
	Psoriasis plaque	Healthy skin
Psoriasis plaque	94,87042	5,129578
Healthy skin	4,506589	90,49341
Results of image segmentation by frequency-detector method, %		
Psoriasis plaque	88,0474	12,9526
Healthy skin	9,771256	91,22878

***Source*: compiled by the author**

Table 8 presents the average assessments of the quality of texture segmentation for images of psoriasis disease and wear zones of cutting tools using vector-difference and frequency-detector methods.

Table 7. **Confusion matrix for vector-difference and frequency methods when processing images of wear zones for cutting tools**

Results of mapping images by an expert, %	Results of image segmentation by vector-difference method, %	
	Cutting tools	Background
Cutting tools	94,8447	5,4553
Background	8,2072	88,7928
Results of image segmentation by frequency-detection method, %		
	Cutting tools	Background
Cutting tools	92,13525	6,86475
Background	16,74653	83,75348

***Source*: compiled by the author**

Table 8. **Assessment of the quality of texture segmentation for images of psoriasis disease and wear zones of cutting tools**

Quality- rate	Image			
	Of psoriasis disease		Of wear zones of cutting tools	
Method	Vector-difference	Frequency-detector	Vector-difference	Frequency-detector
Accuracy	0,951	0,888	0,931	0,882
F-measure	0,952	0,886	0,933	0,886

***Source*: compiled by the author**

CONCLUSIONS

The study solves the applied problem of improving the quality of segmentation of combined spectral-statistical textures with sufficient efficiency for practice.

A model of spectral-statistical texture has been developed, which takes into account the random nature of changes in field variations and quasi-harmonics.

A vector-difference texture segmentation method of spectral-statistical textures has been developed. The comparison of the developed vector-difference method with the frequency-detector and amplitude-detector segmentation methods is carried out by calculating the Pratt's criterion to determine the quality of the detection for the texture segments boundaries. Comparative analysis showed that the developed vector-difference method exceeds the frequency-detector method of texture segmentation by 1.5-1.8 times and the amplitude-detector method by 13-50 times at a signal-to-noise ratio of 5 or more in power.

An experimental research of the proposed vector-difference method was carried out on images of psoriasis disease and wear zones of cutting tools, which can be described by spectral-statistical texture models. Comparison of the segmentation results by the proposed method and the frequency-detector method showed that the quality of segmentation by the developed method exceeds the quality of segmentation by the frequency-detector method by an average of 5-10 %.

The developed model of spectral-statistical texture and vector-difference texture segmentation method can be recommended for use in systems of computer visual patterns recognition for express diagnostics requiring high reliability of diagnostic solutions, for example, in medical express diagnostics of dermatological disorders (psoriasis) and in technical express diagnostics of the quality of cutting tools.

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ВЕКТОРНО-РІЗНИЦЕВИЙ МЕТОД СЕГМЕНТАЦІЇ ЗОБРАЖЕНЬ ТЕКСТУР В СИСТЕМАХ ТЕХНІЧНОЇ І МЕДИЧНОЇ ЕКСПРЕС ДІАГНОСТИКИ

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АНОТАЦІЯ

Показана потреба в експрес системах, в яких необхідно виконувати аналіз текстурних зображень в різних областях діагностики, наприклад, при медичній експрес діагностиці дерматологічних захворювань. Оскільки достовірність прийняття рішень в таких системах залежить від якості сегментації зображень, що мають, як правило, характер спектрально-статистичних текстур, то доцільно розроблять методи сегментації таких зображень ті моделей для їх представлення. Запропоновано модель спектрально-статистичної текстури, яка враховує випадковий характер зміни варіацій поля та квазігармонік. На її основі розроблено векторно-різницевий метод текстурної сегментації в основі якого лежить векторне перетворення образів спектральної і статистичної текстур на основі векторної алгебри. Етапами векторно-різницевого методу є: оцінка ознаки спектральної текстури; оцінка ознаки статистичної текстури; векторно-різницеве перетворення образів текстур; виділення границь однорідних областей. Оцінка ознак спектральної і статистичної текстури виконується для кожного пікселя зображення в апертурі обробки. На етапі оцінки статистичної текстури виконувалася шляхом квадратично-амплітудного перетворення. На етапі векторно-різницевого перетворення образів текстур будується вектор ознак кожного пікселя зображення, елементами якого є оцінки ознак спектральної і статистичної текстури, і виконується розрахунок модуля різниці двох векторів. На етапі виділення границь однорідних областей застосовано метод Канні. Розроблений векторно-різницевий метод текстурної сегментації було застосовано як до модельних зображень спектрально-статистичної текстури, так і до зображень текстур, які отримані в системах технічної і медичної діагностики, а саме для зображень захворювання псоріаз і зон зносу ріжучих інструментів. Для порівняння результатів сегментації до даних зображень були застосовані частотно-детекторний і амплітудно-детекторний методи текстурної сегментації. Проведено оцінку якості сегментації однорідних текстурних областей на основі критерію Прета і шляхом побудови матриці неточностей. Результати дослідження показали, що розроблений векторно-різницевий метод текстурної сегментації має підвищену завадостійкістю при достатній швидкості обробки.

Ключові слова: текстурна сегментація; текстурні ознаки; спектрально-статистична текстура; детекторні методи; класифікаційні методи; матриця неточностей; векторно-різницевий метод

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ВЕКТОРНО-РАЗНОСТНЫЙ МЕТОД СЕГМЕНТАЦИИ ИЗОБРАЖЕНИЙ ТЕКСТУР В СИСТЕМАХ ТЕХНИЧНОЙ И МЕДИЦИНСКОЙ ЭКСПРЕСС ДИАГНОСТИКИ

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АННОТАЦИЯ

Показана необходимость в экспресс системах, в которых необходимо выполнять анализ текстурных изображений в различных областях диагностики, например, при медицинской экспресс диагностике дерматологических заболеваний. Поскольку достоверность принятия решений в таких системах зависит от качества сегментации изображений, имеющих, как правило, характер спектрально-статистических текстур, то целесообразно разрабатывать методы сегментации таких изображений и моделей для их представления. Предложена модель спектрально-статистической текстуры, учитывающая случайный характер изменения вариаций поля и квазигармоник. На ее основе разработан векторно-разностный метод текстурной сегментации, в основе которого лежит векторное преобразование образов спектральной и статистической текстур на основе векторной алгебры. Этапами векторно-разностного метода являются: оценка признака спектральной текстуры; оценка признака статистической текстуры; векторно-разностное преобразование образов текстур; выделение границ однородных областей. Для каждого пикселя изображения в апертуре обработки выполняется оценка признаков спектральной и статистической текстуры. Оценка статистической текстуры выполнялась путем квадратично-амплитудного преобразования. На этапе векторно-разностного преобразования образов текстур строится вектор признаков каждого пикселя изображения, элементами которого являются оценки признаков спектральной и статистической текстуры, и выполняется расчет модуля разности двух векторов. На этапе выделения границ однородных областей применен метод Канни. Разработан векторно-разностный метод текстурной сегментации был применен как к модельным изображениям спектрально-статистической текстуры, так и к изображениям текстур, полученных в системах технической и медицинской диагностики, а именно для изображений заболевания псориаз и зон износа режущих инструментов. Для сравнения результатов сегментации к данным изображениям были применены частотно-детекторный и амплитудно-детекторный методы текстурной сегментации. Проведена оценка качества сегментации однородных текстурных областей на основе критерия Прэтта и путем построения матрицы неточностей. Результаты исследования показали, что разработанный векторно-разностный метод текстурной сегментации обладает повышенной помехоустойчивостью при достаточной скорости обработки.

Ключевые слова: текстурная сегментация; текстурные признаки; спектрально-статистическая текстура; детекторные методы; классификационные методы; матрица неточностей; векторно-разностный метод

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