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# Texture segmentation method for computer-assisted dermatologic diagnostic system

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## ABSTRACT

The wide spread of dermatological diseases is an important medical and social problem. Doctors note the constant growth of psoriasis among people of all ages. The psoriasis disease symptoms are similar to the symptoms of such diseases as eczema, atopic dermatitis and medicinal disease. Therefore, there is a high probability of an error in the disease diagnosis, which prevents the full treatment and prevention of the disease. Dermatological diagnostic systems are decision-making support systems for dermatologists when establishing a diagnosis and assessing the severity of the disease course. The development of new image processing methods for dermatological diagnostic systems is an important task, which allow to increase the accuracy of the diagnostic decision. In this work, the segmentation method of psoriasis images for systems of medical dermatological diagnostics based on a vector-difference approach to improve the quality of segmentation was developed. The vector-difference approach allows to calculate a certain texture feature of the image as a vector transformation of various texture features by linear algebra methods. Psoriasis disease images can be described by texture (spectral, statistical, spectral-statistical) and color, so it is proposed to take into account textural and color characteristics of images for image segmentation. The color models that are most often used in segmentation methods of psoriasis disease images were analyzed. Based on the analysis, the Hue-Saturation-Intensity color model was chosen. It is proposed to use spectral, statistical and spectral-statistical texture models and color characteristics of image pixels to represent psoriasis disease images. The developed segmentation method includes the following stages: image pre-processing; identification; vector-difference transformation; threshold processing. At the pre-processing stage, homomorphic filtering was applied to psoriasis disease images. The result of the identification stage is a set of features calculated by the textural and color characteristics for image objects. The vector-difference transformation converts the texture image into intensity. Threshold processing is performed with a global threshold. Experimental research of the proposed segmentation method of psoriasis disease images was performed. As a result of the experimental research, it was found that the probability of correct identification of psoriasis disease area on average is 0.97, the probability of a false alarm is about 0.05.

**Keywords:** Texture segmentation; segmentation accuracy; texture models; detector methods of texture segmentation; classification methods of texture segmentation; vector-difference segmentation method

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## INTRODUCTION

Recently, in various fields of medicine, doctors have been using medical computer-assisted diagnostic (CAD) systems to more accurately establish a diagnosis. Medical CAD systems are actively used in dermatology. Most of the dermatological diseases with the correct diagnosis and treatment are treated. However, a complete cure for psoriasis which affects about 125 million people worldwide is currently not possible. Psoriasis is a chronic disease and it is characterized by an undulating course with periods of remissions and exacerbations. In addition, people with psoriasis develop comorbidities such as psoriatic arthritis and myocardial infarction. However, timely diagnosis of the disease allows to prescribe maintenance therapy and achieve stable remission. Diagnosing psoriasis is complicated by the fact that the symptoms are very similar to the symptoms of the other diseases. That's why a new algorithm is constantly being developed for the computer-aided image recognition (CAIR) system, which is a part of medical CAD systems.

The reliability of the diagnostic solution directly depends on the quality of image processing in the CAIR. In addition, it is very important to ensure a high speed of image processing in CAIR, as this affects the timely diagnosis of the disease and the appointment of the correct treatment. The segmentation procedure is one of the CAIR procedures that affects the speed of image processing. As a result of the image segmentation procedure, the volume of processed data is reduced by combining data into segments according to certain features. The segmentation method depends on the content of the processed images. It is developed taking into account the features by which data can be combined into separate segments. Most often, segmentation uses geometric, color and texture features.

There are different types of psoriasis: plaque psoriasis (psoriasis vulgaris, plaque psoriasis), pustular psoriasis (pustular psoriasis), guttate or pit psoriasis (guttate psoriasis), erythrodermic psoriasis (flexural psoriasis). These types of psoriasis differ in texture. So, they can be represented by different texture models (statistical, spectral or combined (spectral-statistical)). When the psoriatic plaque looks like a red spot raised above the skin surface and covered with a set of paraffin lakes, it can be represented by a spectral texture model (plaque psoriasis). If the psoriatic plaque looks like a red spot covered with small silver-white scales, then we have a statistical type of texture (pustular psoriasis). If the spot is covered with large silvery-white scales and paraffin lakes, then it can be described by a combined spectral-statistical texture (flexural psoriasis).

Depending on the number of features by which segmentation occurs, segmentation methods are divided into two types: detector segmentation method (segmentation by one feature) and classification segmentation method (segmentation by several features). The advantage of detector segmentation methods is high efficiency in image processing. Detector segmentation methods are developed based on the texture model and provide high quality segmentation, if the texture model is defined correctly. The advantage of classification segmentation methods is that they allow segmenting texture images which described by different texture models. The disadvantage of classification segmentation methods is the low efficiency of image processing.

In [1], a vector-difference approach is proposed, which has the features of both a classification and a detector approach. As a result, the segmentation of texture images by the vector-difference method can be carried out according to several features with high efficiency. Based on this approach, a feature of a texture image is calculated as a vector transformation of texture features using linear algebra methods. On the basis of this approach, a vector-difference segmentation method was developed for textures that can be described by spectral, statistical, and spectral-statistical texture models [1].

However, the image of psoriasis disease can be described by both textural and color features. To take into account texture and color features in the segmentation of psoriasis images, classification methods are used [2, 3], [4, 5], [6, 7], which provide high quality segmentation with low efficiency. The use of mobile CAD systems for express diagnostics requires the development of segmentation methods that would improve the quality of segmentation with sufficient efficiency for the needs of practice. The use of such methods will increase the reliability of the diagnostic solution.

This article proposes the development of the segmentation method based on a vector-difference approach taking into account texture and color features to improve the quality of psoriasis images segmentation.

## ANALYSIS OF TEXTURE IMAGE SEGMENTATION METHODS IN DERMATOLOGICAL DIAGNOSTIC SYSTEMS

The analyses of the works with the purpose of developing the methods for the treatment of psoriasis disease images in CAIR CAD systems were performed. The analyzed works can be conditionally divided into the following groups: development of the classification methods of psoriasis disease images [2, 3], [4, 5], [6, 7]; development of segmentation methods of psoriasis disease images [8, 9], [10, 11]; development of the automatic classification methods of psoriasis disease images and evaluation of psoriasis disease images parameters [12, 13], [14].

The analysis of the works of the first group showed that the authors use classification methods with and without Supervised Learning for the object classification in images.

In [2, 3], [4, 5] the authors use deep learning algorithms. Thus, in [2], the authors classify five types of psoriasis using the following algorithms: convolutional neural network (CNN) and long short-term memory (LSTM). The stages of processing input images were: pre-processing, segmentation, feature extraction of color, texture and shape. The classification accuracy using the CNN method was 84.2% and using the LSTM method was 72.3%.

The aim of the work [3] was to classify the following types of psoriasis: erythrodermic, guttate, inverse, plaque, pustular and nail. The authors used the MobileNet machine learning architecture. At the pre-processing stage, images are reduced to a size of 224 x 224 pixels, after which they are fed as input to 28 layers. The Adam optimizer algorithm is used to train the network. The network uses the rectified linear activation function. The accuracy of classification by the proposed method was 86%. The authors noted that this method is applicable to use in low powered hand-held devices.

In [4], the authors use one of the CNN algorithms – Alex Net for learning. Texture features are extracted from the trained data. The co-occurrence matrix (GLCM) method is used to extract texture features. The authors use the Support Vector Machine (SVM) for classification of psoriasis disease images.

In [5], the authors proposed an automated system for classifying six different dermatological diseases. The method developed in the work consists of the following stages: data collection; pre-processing for filtering and resizing of images; pretraining of CNN models using CNN algorithms: DenseNet121, ResNet50, Inceptionv3 and ResNeXt101; image classification. The accuracy of classification by the proposed method was 94%.

Images of objects are constructing for classification using the methods proposed in [6, 7] taking into account the features of the images. The method developed in [6] consists of the following steps: image acquisition; pre-processing using median filtering; segmentation; identification; classification. At the identification stage, texture features are obtained using Gabor and Sobel filters and Entropy calculation. Further, the textures are classified according to the obtained features using known methods: Support Vector Machine (SVM), Random Forest (RF) and KNearest Neighbor (K-NN). The accuracy of classification by the proposed methods was compared for the following dermatological diseases: acne, cherry angioma, melanoma and psoriasis. The best result was obtained using the SVM method, the classification accuracy was 90.7%.

In [7], the authors proposed a classification method based on texture features. To obtain texture features, the authors use the gray-level co-occurrence matrix (GLCM) method with reduction of features to six. The classification was carried out using a multilayer neural network. The authors built a confusion matrix to estimate the classification accuracy. The resulting classification accuracy was 92%.

In the works of the second group, the authors develop segmentation methods for CAIR of medical CAD systems. The proposed methods, as well as the methods of the first group, use CNN algorithms [8, 9], [10], in which images are fed to the network input and then the feature map is extracted from the input images by convolution operation [11].

In [8, 9], the authors apply the method using convolutional neural networks (CNN). In [9], neural networks are used (You Only Look At CoefficienTs – YOLACT), which composed of backbone, feature pyramid network (FPN), Protonet, and prediction head is used to deal with psoriasis images. When developing the method, the authors aimed to process the unconstrained psoriasis images. The method developed by the authors turned out to be better than the Mask R-CNN method in terms of quality and execution speed.

In [10], the authors proposed automatic segmentation of psoriasis images using the U-Net network, which does not require a large training set. The quality of segmentation was assessed using the Jaccard Index and Dice Similarity Index, which averaged 0.9102 and 0.8371, respectively.

In [11], the authors use the Scaling Technique for 2-D skin pore images and the SVM method. The scaling technique is used with the help of the following features: color, contrast and image texture.

Based on the results of the image segmentation procedure in CAIR, it is possible to calculate indicators for assessing the severity of psoriasis: Body Surface Area (BSA), Psoriasis Area Severity Index (PASI) and Severity Score (SS).

In [12], segmentation is performed based on texture, color, and shape descriptors using a genetic algorithm. The accuracy of the proposed segmentation method is, on average, 95.7%. Using segmented regions of the psoriasis disease, the authors proposed a method for calculating PASI scores.

In [13], the authors proposed a methodology for automatic calculation of the psoriasis disease characteristics. The stages of the proposed methodology are: image preparation; pre-processing (hair removal); obtaining features (color, texture); classification of disease regions; obtaining disease parameters.

In [14], the authors propose the automatic segmentation method of psoriasis images using the U-Net network, followed by the calculation of the BSA index based on the segmentation results, which was compared with the BCA index calculated by a dermatologist. The calculation accuracy was 95%.

The analysis of the works showed that the automatic segmentation methods of psoriasis images with subsequent calculation of indicators of the degree of the disease use methods using convolutional neural networks that require a large training set. These methods provide high quality segmentation, but they have low image processing speed. Segmentation methods based on image features extraction are classification methods and require a representative sample. The considered methods provide high quality segmentation by taking into account a large number of features. But as the number of features increases, the image processing speed decreases.

There is a need in methods development for medical CAD systems for express diagnostics of psoriasis disease that will provide high quality segmentation with sufficient efficiency for practice. As mentioned above, such methods are detector segmentation methods. Detector segmentation methods depend on the texture model and perform segmentation according to a certain feature, but images of psoriasis disease are characterized by the texture and by the color.

Therefore, there is a need to develop a psoriasis image model taking into account texture and color features and a segmentation method that will provide high quality segmentation.

## THE SEGMENTATION METHOD OF PSORIASIS IMAGES IN SYSTEMS OF DERMATOLOGICAL DIAGNOSTICS

The main idea of the vector-difference approach is that a certain feature of a texture image is calculated as a vector difference of the texture images. Thus, the calculation of certain texture features of images depends on models of textures. As mentioned above, different types of psoriasis are different in color and texture, so they can be represented by different models of texture (statistical, spectral and combined (spectral-statistical)) taking the color into account. The models of spectral, statistical, and spectral-statistical textures were proposed in [15]. Let $\xi(x, y_m)$ be the color characteristic of the image, then models of texture (spectral, statistical, and spectral- statistical) with taking into account color are represented as (1)-(3).

Then, the value of the intensity of the $m$-th row of the image of the spectral texture with taking into account the color is represented as follows:

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

where $A_{ij}(x, y_m)$, $\omega_m^{ij}$ is the amplitude and frequency of the modulated $j$ -th oscillation on the $i$ -th segment of the $m$ -th image row respectively; $c_i(x, y_m)$ is representation of the background on the $i$- th segment for the $m$ -th row of the image; $\xi(x, y_m)$ is the color characteristic on the $i$- th segment for the $m$ -th row of the image $(x, y_m)$; $q = (q_0, \ldots, q_{k+1})$ is the vector of boundaries of texture areas for the $m$ -th row of the image, when $q_0 = 1$, $q_{k+1} = N + 1$, $N$ is the number of pixels in the image line; $x$ = 1, ..., $N$ ; $y$ = 1, ..., $M$ –spatial coordinates.

The value of the intensity of the $m$-th row of the image of the statistical texture with taking into account the color is represented as follows:

$$I(x, y_m) = \bigcup_{i=1}^{k} \{c_i(x, y_m) + N_i(x, y_m) + \xi(x, y_m)\}, \quad x \in [q_{i-1}, q_i], \tag{2}$$

where $N_i(x, y_m)$ is Gaussian noise with zero mean and variance $\sigma_i^2$ on the $i$ -th segment of the image.

The value of the intensity of the $m$ -th row of the image of the spectral-statistical texture with taking into account the color is represented as follows:

$$I(x, y_m) = \bigcup_{i=1}^{k} \{c_i(x, y_m) + N_i(x, y_m) + \sum_{j=1}^{n} A_{ij}(x, y_m) \sin(\omega_m^{ij} x) + \xi(x, y_m)\}, \quad x \in [q_{i-1}, q_i], \tag{3}$$

where $N_i(x, y_m)$ is Gaussian noise with zero mean and variance $\sigma_i^2$ on the $i$ -th segment of the image.

From the analysis of the literature, the following color models are most often used for image segmentation of psoriasis disease: RGB, CMY, Lab, YCbCr [16, 17], [18, 19].

Color models are divided into separate classes according to the principle of actions on the color components included in the corresponding model:

additive – based on the addition of colors (RGB);

subtractive – based on the color subtraction operation (CMY, CMYK);

perceptual – based on color perception (HSI, Lab, Luv, YCbCr).

The RGB color model [16] (red, green, blue) represents an image as a set of halftone images, the brightness of which corresponds to the intensity of red, green, and blue colors. The RGB color model is uneven in visual perception and does not accurately reflect the true color of the image. In addition, there is dependence between the color channels: when the brightness of one channel increases the other's brightness is decreasing. Therefore, this model cannot be effectively used to calculate color distances.

The CMY color model [16] (cyan, magenta, yellow) will be used to obtain hard copies (printing) of images.

The conversion from the RGB color model to the CMY color model is performing in a such way:

$$\begin{cases} C = 1 - R \\ M = 1 - G \\ Y = 1 - B \end{cases}.$$

In practice, the CMY model is extended to the CMYK model by adding black to the three colors.

The RGB and CMY (K) color models are very simple in hardware implementation, but they have one significant disadvantage: it is very difficult for a person to operate with the colors specified in these models.

In the Lab color model [17] color is determined by lightness ($L$) and two chromatic components: channel $a$ is colors from dark green through gray to magenta; channel $b$ is colors from blue through gray to yellow.

The YCbCr color model (Y is the luminance component, Cb and Cr are the blue and red color difference components) is used to transmit color images in video and digital photography. The transition from the RGB color model to the YCbCr model allows transmitting full brightness information. This color model is used to delete the background of the image [18, 19].

The HSI color model takes into account the fact, that a person most often operates with such concepts as: color tone (Hue), saturation (Saturation) and lightness (Intensity). With some assumptions, brightness is understood as the intensity (brightness) of light. In the HSI model, information about brightness is separated from information about color (hue and saturation). At the same time, the color tone is responsible for the color. Saturation shows how much the described color is diluted with white.

The color tone H (4), saturation S (6) and intensity I (7) for each pixel specified in RGB image format is determined by the formula:

$$H = \begin{cases} \theta, \text{when B} \le \text{G}, \\ 360 - \theta, \text{when B} > \text{G}, \end{cases} \quad (4)$$

where

$$\theta = \arccos\left\{ \frac{\frac{1}{2}\left[(R-G)^2 + (R-B)(G-B)\right]^{1/2}}{\left[(R-G)+(R-B)\right]} \right\}, \quad (5)$$

$$S = 1 - \frac{3}{(R+G+B)}\left[\min(R,G,B)\right], \quad (6)$$

$$I = \frac{1}{3}(R+G+B) \quad (7).$$

From the analysis of color models it follows that for taking into account color in the segmentation method it is expedient to use color models, which belong to perceptual classes, as they are based on human perception of color.

For the segmentation of spectral – statistical textures in [1] a vector – difference texture segmentation method was developed, which includes the following stages:

– image scanning by the processing window;

– identification – a texture image is built for each pixel of the image in the processing window;

– vector-difference transformation – transformation of the texture image into intensity using vector algebra methods;

– threshold processing is homogeneous texture regions selection, taking into account changes in intensity at the boundaries of homogeneous regions.

The segmentation method of psoriasis images was developed based on the vector-difference texture segmentation methods for spectral-statistical texture.

The stages of the developed segmentation method are follows:

1) pre-processing with the psoriasis image filtering by a homomorphic filter to remove multiplicative noise that occurs due to uneven illumination of the object when receiving its image;

2) identification – evaluation of the image features for each image pixel of the image in the processing window:

2.1) texture features;

2.2) color features;

3) vector – differential transformation – calculation a certain texture feature of the image as a vector transformation of texture and color features based by vector algebra methods;

4) threshold processing;

5) morphological processing with the morphological methods to remove uninformative objects, filling holes, smoothing boundaries which appeared as a result image binarization.

At the identification stage, for an $m \times n$ image ($m$, $n$ – the number of rows and columns of the image, respectively), the texture features vectors $\vec{\sigma}_1$ and $\vec{\sigma}_2$, the color features vector $\vec{\sigma}_3$ are formed with the length $m \cdot n$:

1. At formation of the texture features vector $\vec{\sigma}_1$, the frequency-amplitude transformation is used. The texture feature $\sigma_1$ is evaluation of the statistical texture which obtained with the quadratic-amplitude transformation.

2. At formation of the texture features vector $\vec{\sigma}_2$, the amplitude transformation is used. The texture feature $\sigma_2$ is evaluation of the statistical texture which obtained with the frequency-amplitude transformation.

3. The formation of the color features vector $\vec{\sigma}_3$ includes the following stages:

3.1. Loading an RGB image;

3.2. Conversion from the RGB color model to the corresponding color model;

3.3. Selection and normalization of the color feature $\sigma_3$.

The result of the identification stage is features vector of three features for each $i$-th pixel of the image in the processing window $\vec{c}_i(\sigma_{1,i}, \sigma_{2,i}, \sigma_{3,i})$.

The texture image feature is calculated as a vector transformation of texture and color features using vector algebra methods (Fig. 1):

1) Calculation of the difference of vectors in the $(i+1)$-th and $i$-th pixels of the image, that is, the calculation of the difference of vectors $\vec{c}_{i+1}(\sigma_{1,i+1}, \sigma_{2,i+1}, \sigma_{3,i+1})$ and $\vec{c}_i(\sigma_{1,i}, \sigma_{2,i}, \sigma_{3,i})$.

2) Calculation of the modulus of the difference of two vectors $\vec{c}_{i+1}(\sigma_{1,i+1}, \sigma_{2,i+1}, \sigma_{3,i+1})$ and $\vec{c}_i(\sigma_{1,i}, \sigma_{2,i}, \sigma_{3,i})$ using methods of vector algebra:

$$\vec{c} = \left| \vec{c}_{i+1}(\sigma_{1,i+1}, \sigma_{2,i+1}, \sigma_{3,i+1}) - \vec{c}_i(\sigma_{1,i}, \sigma_{2,i}, \sigma_{3,i}) \right| = \\ = \overrightarrow{(\sigma_{1,i+1} - \sigma_{1,i}, \sigma_{2,i+1} - \sigma_{2,i}, \sigma_{3,i+1} - \sigma_{3,i})}. \quad (8)$$

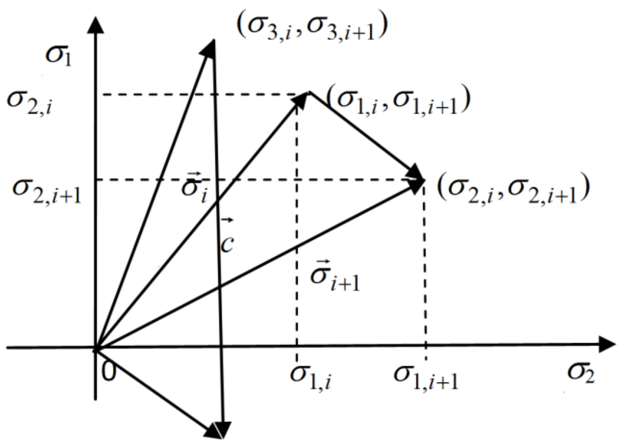


*Fig. 1.* **For illustration of the vector-difference method in the feature space**
***Source:*** **compiled by the authors**

Thus, as a result of the vector difference transformation, the texture image is converted into intensity. The images obtained as a result of applying the vector-difference transformation contain intensity drops at the boundaries of homogeneous regions. Next, thresholding is used to selection homogeneous texture regions.

## EXPERIMENTAL RESEARCH OF THE DEVELOPED TEXTURE SEGMENTATION METHOD IN DERMATOLOGIC DIAGNOSTIC SYSTEM

An experimental research of the developed segmentation method, based on the vector-difference approach, taking into account textural and color features has been carried out on the images of psoriasis disease. In the course of the research, the vector-difference method of texture segmentation was applied to images of psoriasis disease to compare results of the image segmentation. The test sample consisted of 50 *mxn* pixel images of psoriasis disease (https://www.dermnetnz.org/).

A confusion matrix was used to assess the quality of image segmentation by the considered methods (Table 1, line 2 and 3) in comparison with the image marking by an expert (Table 1, line 1) [20].

*Table 1.* **Segmentation results**

| No. | Texture model | Spectral | Statistical | Spectral-statistical |
|---|---|---|---|---|
| 1 | Initial image marking by an expert |  |  |  |
| 2 | The result of segmentation by the developed method |  |  |  |
| 3 | The result of segmentation by the vector-difference method |  |  |  |

***Source:*** **compiled by the authors**

Table 2 is a confusion matrix which contains comparing results of segmentation of psoriasis disease images by the method developed in the work, the vector-difference method and image marking by an expert.

Based on the confusion matrix, the values of the TPR (true positive rate) and FPR (false positive rate) metrics were calculated. True positive rate metric is used to measure the probability for the correct detection of the psoriasis disease region (9) and FPR metric is used to measure the false alarm probability (10) [21]:

$$TPR = \frac{TP}{TP + FN}, \tag{9}$$

$$FPR = \frac{FP}{FP + TN}. \tag{10}$$

*Table 2.* **Confusion matrices for the proposed method and vector-difference method**

| Results of image marking by an expert, % | Results of image segmentation by the method developed in the work, % | |
|---|---|---|
| | Psoriasis plaque | Healthy skin |
| Psoriasis plaque | 95.37 ( TP – true positive) | 4.63 ( FP – false positive) |
| Healthy skin | 3.37 ( FN – false negative ) | 96.62 ( TN – true negative) |
| | Results of image segmentation by the vector-difference method, % | |
| Psoriasis plaque | 94.66 ( TP – true positive) | 5.34 ( FP – false positive) |
| Healthy skin | 4.71 ( FN – false negative ) | 95.29 ( TN – true negative) |

***Source:*** **compiled by the authors**

According to the results of the experiment, we found that at segmentation psoriasis images by the developed method the probability for the correct detection of the psoriasis disease region on average is 0.97 with a false alarm probability of 0.05. The probability for the correct detection of the psoriasis disease region by the vector-difference segmentation method on average is 0.95 with a false alarm probability of 0.05.

Thus, the results of the experiment showed that the use of the developed texture segmentation method based on the vector-difference approach taking into account textural and color features made it possible to increase the determination reliability of the psoriasis disease region. The probability for the correct detection of the psoriasis disease region by the developed method is higher than the probability for the correct detection of the psoriasis disease region by the vector-difference method by 2%. The error of false detection of the psoriasis disease region by the developed method is less than 4%. The error of not detection of the psoriasis disease region is less than 5%.

The error of false detection of the psoriasis disease region by the developed method is less than 4%, and the error of not detection of the psoriasis disease region less than 5 %.

## CONCLUSIONS

1. The segmentation method for psoriasis disease images has been developed based on the vector-difference approach and texture models (statistical, spectral, spectral-statistical) taking into account color features.

**2.** An experimental research of the proposed segmentation method on images of various types of psoriasis was carried out. The results of segmentation by the proposed method were compared with the results of segmentation by the vector-difference method. It was established, that the probability for the correct detection of the psoriasis disease region is on average 0.97 with a false alarm probability of 0.05. With segmentation by the vector-difference method, the probability for the correct detection of the psoriasis disease region is on average 0.95 with a false alarm probability of 0.05.

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# Сегментація зображень текстур в системах дерматологічної діагностики

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## АНОТАЦІЯ

Широка поширеність дерматологічних захворювань є важливою медико-соціальною проблемою. Лікарі відзначають постійний зріст хвороби псоріаз серед людей різного віку. Симптоми хвороби псоріаз схожі з симптомами таких захворювань як екзема, атопічний дерматит та лікарська хвороба. Тому існує велика ймовірність помилки при діагностиці захворювання, що перешкоджає повноцінному лікуванню та профілактиці хвороби. Системи дерматологічної діагностики є системами підтримки прийняття рішень лікарів-дерматологів під час встановлення діагнозу і оцінки важкості перебігу хвороби. Розробка нових методів обробки зображень для систем дерматологічної діагностики, які дозволяють підвищити точність діагностичного рішення є важливою задачею. В даній роботі розроблено метод сегментації зображень хвороби псоріаз для систем медичної дерматологічної діагностики на основі векторно-різницевого підходу для підвищення якості сегментації. Векторно-різницевий підхід дозволяє розрахувати певну ознаку текстурного зображення як векторне перетворення образів текстур побудованих на основі різних ознак методами лінійної алгебри. Зображення хвороби псоріаз можна описати текстурою (спектральною, статистичною, спектрально-статистичною) та кольором, тому для сегментації зображень запропоновано враховувати текстурні і кольорові ознаки зображень. Було проаналізовано колірні моделі, які найбільш часто застосовуються в методах сегментації зображень хвороби псоріаз. На основі аналізу було обрано колірну модель Hue-Saturation-Intensity. Для представлення зображень хвороби псоріаз запропоновано використати моделі спектральної, статистичної та спектрально-статистичної текстури і колірну характеристику пікселів зображення. Розроблений метод сегментації містить наступні етапи: попередня обробка зображення; ідентифікація; векторно-різницеве перетворення; порогова обробка. На етапі попередньої обробки до зображень хвороби псоріаз було застосовано гомоморфна фільтрація. Результатом етапу ідентифікації є побудовані образи об'єктів зображення на основі текстурних та колірних ознак. Векторно-різницеве перетворення виконує перетворення образа текстури в інтенсивність. На етапі порогової обробки виконується порогова обробка з глобальним порогом. Було проведено експериментальне дослідження запропонованого методу сегментації зображень хвороби псоріаз. В результаті експериментального дослідження було встановлено, що ймовірність вірного виявлення області хвороби псоріаз в середньому дорівнює 0.97 при ймовірності помилкової тривоги 0.05.

**Ключові слова:** текстурна сегментація; точність сегментації; моделі текстури; детекторні методи текстурної сегментації; класифікаційні методи текстурної сегментації; векторно-різницевий метод сегментації

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