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METHOD FOR ANALYSING COLOR IMAGES BASED ON DIGITAL SIGNAL PROCESSING AND MACHINE LEARNING

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ABSTRACT

Context. In recent decades, rapid advances in digital signal processing and artificial intelligence have greatly expanded capabilities in visual information analysis. A color image, as a complex multidimensional signal, carries geometric, spectral, and textural data about objects. Efficient processing of such data requires integrating filtering, segmentation, and transformation methods with machine learning algorithms to extract hidden patterns and meaningful features.

Objective. The purpose of this work is to develop a method for analyzing color images based on quantization, binarization, clustering, and selection of priority clusters.

Method. The proposed approach combines digital signal processing and machine learning to improve the accuracy and speed of extracting informative elements. It includes several interrelated techniques: Quantization of three-color components in the training template to reduce color diversity and accelerate binary image formation; selection of priority template colors based on occurrence probability with a normalized threshold, enhancing feature detection accuracy; quantization of the original image's color components to optimize segmentation and avoid excessive clustering; construction of a binary image using quantized template colors to eliminate false clusters and improve clustering precision; extraction of binary elements via clustering, verifying only white-point surroundings to suppress noise and automatically identify elements of various shapes; selection of priority binary elements using probabilistic assessment to enhance reliability.

Results. The method was implemented in Matlab and tested on a specialized database. Compared with traditional approaches, it demonstrated higher accuracy and stability in element extraction while reducing processing time through color optimization and removal of redundant clusters.

Conclusions. The comprehensive application of quantization, binarization, clustering, and priority element selection ensures accurate, fast, and adaptive analysis of color images. The method expands the functionality of visual information processing systems and can be used for statistical analysis, intelligent image processing, segmentation, and classification of complex visual structures.

KEYWORDS: image analysis, training template, quantization, binarization, clustering, machine learning, digital signal processing.

ABBREVIATIONS

EM is an expectation-maximization algorithm;

PAM is a partitioning around medoids algorithm;

ISODATA is an iterative self-organizing data analysis technique algorithm;

FCM is a fuzzy classifier means algorithm;

DISMEA is a divisive hierarchical clustering algorithm that uses the *k*-means algorithm to subdivide a cluster into two;

DIANA is a divisive analysis algorithm;

DBSCAN is a density-based spatial clustering of applications with noise algorithm;

OPTICS is an ordering points to identify the clustering structure algorithm.

NOMENCLATURE

$A = \{A_1, ..., A_c\}$ is a correct set of image elements;

T is a time;

c is a counter of the number of clusters;

$RP(n_1, n_2)$ is a red color component;

$GP(n_1, n_2)$ is a green color component;

$BP(n_1, n_2)$ is a blue color component;

n_1 is a line number of the training template;

n_2 is a column number of the training template;

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M_1 is an end of the current row of the training template;

M_2 is an end of the current column of the training template;

Δ is a quantization step;

k is a color number;

$rp(n_1, n_2)$ is a quantized red color component;

$gp(n_1, n_2)$ is a quantized red color component;

$bp(n_1, n_2)$ is a quantized red color component;

$(rp0, gp0, bp0)$ is a background color;

E is a set of quantized colors of the training template;

$d(m)$ is a counter of the number of appearances of colors;

m is a counter of the number of quantized colors;

M is a number of quantized colors;

q_m is a vector of color appearance probabilities;

ε is a normalized threshold.

$R(n_1, n_2)$ is a red color component;

$G(n_1, n_2)$ is a green color component;

$B(n_1, n_2)$ is a blue color component;

n_1 is a row number of the image;

n_2 is a column number of the image;

N_1 is an end of the current row of the image;

N_2 is an end of the current column of the image;

$Q_k(n_1, n_2)$ is a k-th binary image;

D is a size of Moore neighborhood of point;

$M(n_1, n_2)$ is a point label matrix;

i is a current point of the image;

$U_{i,\varepsilon}$ is a neighborhood of the i-th point;

v is a first element from the set of neighborhood of the i-th point S;

m_1, m_2 are coordinates of the v-th point in the image;

mod is a modulo division;

[ ] is an integer part of the number;

$z(n)$ is a power vector of clusters;

p_n is a probability of appearance of clusters in a binary image;

γ is a normalized threshold.

INTRODUCTION

The rapid development of information technology and computing has led to qualitative changes in the ways visual information is processed, analyzed, and interpreted. Modern methods of digital signal processing and machine learning have enabled the transition from manual and semi-automatic image processing to fully automated analysis systems capable of extracting informative elements, interpreting scenes, and making decisions in real time.

Today, there are many areas of application where color image analysis systems are widely used.

One such area is computer graphic design, where fragments of existing images are often used to synthesize new images. In this regard, the importance of developing methods for accurate and rapid extraction of the required elements from the source images is increasing [1–3].

Another area of application for visual data analysis is the system for recognizing and understanding sign language, used in human-machine interaction interfaces, robotics, and communication tools for people with hearing impairments.

Image analysis methods also play an important role in biometric identification, which is aimed at solving the problems of user authentication and access control to software and hardware systems. Among the various biometric approaches, facial recognition occupies a special place as one of the most technologically accessible and widespread forms [4–6].

In addition, considerable attention is paid to the application of visual information analysis in military-technical systems, in particular in the tasks of automatic detection and recognition of ground targets for unmanned aerial vehicles. In such systems, it is critically important to ensure high accuracy and speed of decision-making when analyzing complex visual scenes.

Methods of automatic and automated image analysis based on the integration of digital signal processing algorithms and machine learning technologies have undergone particular development. These approaches not only allow for the effective identification and classification of visual objects, but also enable adaptation to changing observation conditions, noise, and variations in lighting.

The object of study is the process of analyzing color images.

The subject of study is methods of analyzing color images based on digital signal processing and machine learning algorithms.

The purpose of the work to develop the method of forming a set of quantized colors of the training template and method for analyzing color images based on quantization, binarization, clustering, and selection of the most priority clusters, ensuring increased accuracy and efficiency in the selection of image elements.

To achieve this goal, the following tasks were set and solved in the work:

1) to develop a technique for quantizing the three-color components of the training template to reduce the number of colors represented in the image and, accordingly, reduce the computational complexity of subsequent operations.

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2) to develop a technique for selecting the most important colors in the training template based on a probabilistic assessment of their occurrence, aimed at improving the reliability of color feature extraction.

3) to develop a technique for quantizing the three-color components of the original color image to reduce the number of color clusters, which optimizes the process of image element extraction and prevents the appearance of redundant segments, as well as contributes to more accurate segmentation and subsequent classification of objects.

4) to create a technique for generating a binary image based on a set of quantized colors from a training template, which will allow the extraction of elements belonging exclusively to specified color regions and prevent the formation of false clusters associated with unspecified colors.

5) to develop a technique for extracting binary image elements based on binary image clustering, which is aimed at improving the accuracy of object selection of various shapes and sizes.

6) to develop a technique for selecting the most important elements of a binary image based on a probabilistic assessment of cluster occurrence in order to identify the most informative elements of the binary image and improve the accuracy of the final analysis.

7) to conduct a numerical study of the effectiveness of the proposed method and perform a comparative analysis with traditional approaches.

1 PROBLEM STATEMENT

The problem of improving the efficiency of image analysis based on clustering is represented as the problem of finding such an ordered set of image elements $A^* = \{A_1^*, ..., A_c^*\}$ in time T, at which $F = \sum_{k=1}^{c} \left\| A_i - A_i^* \right\| \to \min$ and $T \to \min$.

The problem of improving the efficiency of color image analysis based on digital signal processing and machine learning lies in the need to ensure accurate and rapid extraction of informative image elements with limited computing resources.

Thus, the task is formulated as a search for an ordered set of image elements $A^* = \{A_1^*, ..., A_c^*\}$ extracted in time T, for which the conditions $F = \sum_{k=1}^{c} \left\| A_i - A_i^* \right\| \to \min$, $T \to \min$ and $c \to \min$ are satisfied.

That is, it is necessary to develop a method of analysis that minimizes the error of image element extraction while limiting the execution time and the number of clusters in order to further reduce the volume of computational operations.

2 REVIEW OF THE LITERATURE

Modern methods of automatic and automated image analysis and synthesis are largely determined by the efficiency of the stage of extracting informative image elements. Various digital processing methods are used to solve this problem, including quantization, binarization, clustering, and algorithms for selecting priority colors and clusters, which significantly reduce the computational complexity of subsequent operations and improve the accuracy of analysis.

Image binarization methods. Binarization is one of the key stages of image preprocessing, ensuring the separation of the background and objects of interest. The most common approaches to binarization are [7]:

– methods for automatically selecting a single-level global threshold, such as the Otsu method [8];

– methods for automatically selecting a single-level local threshold, including the approaches of Eikwall, Bernsen, Sauvola, Niblack, and Christian [9].

Despite their widespread use, these methods have a number of limitations:

– insufficient binarization accuracy under uneven lighting;

– high computational complexity when determining the threshold value;

– the need to select additional parameters.

In this regard, an urgent scientific and practical task is to develop a binarization method that improves accuracy while reducing computational costs and eliminating the need for manual parameter adjustment.

Image segmentation methods. Image segmentation is a central stage in the analysis of visual information and is aimed at dividing an image into regions that are homogeneous in terms of certain characteristics. The following approaches are used in practice [7]:

– use of Markov random fields [10];

– regional methods (growth, division and merging of regions, watershed) [11];

– methods for extracting boundaries based on intensity gradients or color differences [12];

– clustering methods [13];

– methods based on solving partial differential equations [14];

– histogram approaches [15];

– graph methods [16];

– variational methods [17].

Among the approaches listed, clustering methods have found the widest application, providing a balance between versatility, accuracy, and computational complexity.

Clustering methods. Classical approaches to clustering can be divided into several groups:

1. Model-based methods (model mixture), based on probabilistic data distribution models, such as the EM algorithm [18].

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2. Partitioning/center-based methods, including *k*-means [19], PAM (*k*-medoids) [19], ISODATA [20], and FCM [21] algorithms.

3. Hierarchical methods, which are divided into:

– divisive (top-down) – DISMEA, DIANA [22];

– agglomerative (bottom-up) – Vard, centroid, complete, single linkage, and group average methods [23].

4. Density-based methods, such as DBSCAN [24] and OPTICS [25].

5. Methods based on artificial neural networks [26] and genetic algorithms [27].

Despite the variety of approaches, most of them have a number of limitations:

– high computational complexity;

– the need to predefine the number of clusters and algorithm parameters;

– low resistance to noise and outliers;

– limitations on the shape and size of the extracted clusters.

These shortcomings necessitate the development of new clustering methods capable of automatically adapting to the data structure, identifying noise elements, and forming clusters of arbitrary shape without specifying their number in advance.

Methods for improving clustering efficiency. One way to improve computational efficiency is to pre-quantize the color components of an image and then binarize it, which significantly reduces the dimension of the color space and the number of pixels analyzed [28–30]. These operations form the basis for the next stage of clustering, ensuring increased speed and stability of algorithms while preserving the informativeness of the data.

3 MATERIALS AND METHODS

The method proposed by the authors in their previous work [31] is effective for images with a small number of sharply contrasting colors.

This paper proposes an approach for more complex images, which may produce inaccurate segmentation when converted to grayscale. Before analyzing an image, this work requires the operator to specify a training template. Since this template may contain small unwanted artifacts and be large in size with a small number of informative colors, this work proposes to first create a set of quantized colors for the training template.

1 The method of forming a set of quantized colors of the training template includes four stages:

– the first stage corresponds to the technique of reducing the colors of the training template;

– the second stage corresponds to the technique of creating the initial set of quantized colors of the training template;

– the third stage corresponds to the technique of calculating the probabilities of colors appearing in the quantized color training template;

– fourth stage corresponds to the technique of selecting the most priority colors in the quantized training template.

Stage 1.1 The technique of quantization of a color training template based on three color components

1. Set the color training template $RP(n_1,n_2)$, $GP(n_1,n_2)$, $BP(n_1,n_2)$, $n_1 \in \overline{1,M_1}$, $n_2 \in \overline{1,M_2}$. Set the quantization step Δ.

2. Set the row number of the training template $n_1 = 1$.

3. Set the column number of the training template $n_2 = 1$.

4. Set the color number $k = 1$.

5. If $k\Delta - \Delta \le RP(n_1,n_2) \wedge RP(n_1,n_2) < k\Delta$, then $rp(n_1,n_2) = k\Delta - \Delta/2$.

6. If not the last color, i.e. $k < 256/\Delta$, then increase the color number, i.e. $k = k+1$, then go to step 5.

7. If $RP(n_1,n_2) = 255$, then $rp(n_1,n_2) = 256 - \Delta/2$.

8. Set the color number $k = 1$.

9. If $k\Delta - \Delta \le GP(n_1,n_2) \wedge GP(n_1,n_2) < k\Delta$, then $gp(n_1,n_2) = k\Delta - \Delta/2$.

10. If not the last color, i.e. $k < 256/\Delta$, then increase the color number, i.e. $k = k+1$, then go to step 9.

11. If $GP(n_1,n_2) = 255$, then $gp(n_1,n_2) = 256 - \Delta/2$.

12. Set the color number $k = 1$.

13. If $k\Delta - \Delta \le BP(n_1,n_2) \wedge BP(n_1,n_2) < k\Delta$, then $bp(n_1,n_2) = k\Delta - \Delta/2$.

14. If not the last color, i.e. $k < 256/\Delta$, then increase the color number, i.e. $k = k+1$, then go to step 13.

15. If $BP(n_1,n_2) = 255$, then $bp(n_1,n_2) = 256 - \Delta/2$.

16. If not the end of the current row of the training template, i.e. $n_2 < M_2$, then increase the column number of the current row, i.e. $n_2 = n_2 + 1$, then go to step 4.

17. If not the last row of the training template, i.e. $n_1 < M_1$, then increase the row number of the current row, i.e. $n_1 = n_1 + 1$, then go to step 3.

Stage 1.2 The technique of formation of the initial set of quantized colors of the training template

1. Set the quantized color training template $rp(n_1,n_2)$, $gp(n_1,n_2)$, $bp(n_1,n_2)$, $n_1 \in \overline{1,M_1}$, $n_2 \in \overline{1,M_2}$. Set the background color $(rp0, gp0, bp0)$.

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Define the set of quantized colors of the training template $E = \varnothing$.

2. Set the row number of the training template $n_1 = 1$.

3. Set the column number of the training template $n_2 = 1$.

4. If the color of the training template dot does not match the background color, i.e. $rp(n_1, n_2) \neq rp0 \vee gp(n_1, n_2) \neq gp0 \vee bp(n_1, n_2) \neq bp0$, then include the dot color in the set of quantized colors of the training template $E = E \cup \{(RP(n_1, n_2), GP(n_1, n_2), BP(n_1, n_2))\}$.

5. If not the end of the current row of the training template, i.e. $n_2 < M_2$, then increase the column number of the current row, i.e. $n_2 = n_2 + 1$, then go to step 4.

6. If not the last row of the training template, i.e. $n_1 < M_1$, then increase the row number of the current row, i.e. $n_1 = n_1 + 1$, then go to step 3.

Stage 1.3 The technique of calculating the probabilities of colors appearing in a quantized color training template

1. Set the quantized color training template $rp(n_1, n_2), gp(n_1, n_2), bp(n_1, n_2)$, $n_1 \in \overline{1, M_1}$, $n_2 \in \overline{1, M_2}$. Define the set of quantized colors of the training template $E = \{(er_m, eg_m, eb_m)\}$, $m \in \overline{1, M}$. Set the vector of the number of colors $d(m) = 0$, $m \in \overline{1, M}$.

2. Set the number of the element of the set of quantized colors of the training template $m = 1$.

3. Set the row number of the training template $n_1 = 1$.

4. Set the column number of the training template $n_2 = 1$.

5. If the color of the training template dot does not match the color of the set of quantized colors of the training template, i.e. $rp(n_1, n_2) = er_m \vee gp(n_1, n_2) = eg_m \vee bp(n_1, n_2) = eb_m$, then increase the counter of the number of appearances of colors, i.e. $d(m) = d(m) + 1$.

6. If not the end of the current row of the training template, i.e. $n_2 < M_2$, then increase the column number of the current row, i.e. $n_2 = n_2 + 1$, then go to step 5.

7. If not the last row of the training template, i.e. $n_1 < M_1$, then increase the row number of the current row, i.e. $n_1 = n_1 + 1$, then go to step 4.

8. If not the last element of the set of quantized colors of the training template, i.e. $m < M_2$, then increase the element number, i.e. $m = m + 1$, and proceed to step 3.

9. Calculate the probabilities of colors appearing in the training template

$$q_m = \frac{d(m)}{M_1 M_2}, m \in \overline{1, M}.$$

Stage 1.4 The technique of selecting the most prioritized colors in a quantized training template

1. Set the quantized color of the training template $rp(n_1, n_2)$, $gp(n_1, n_2)$, $bp(n_1, n_2)$, $n_1 \in \overline{1, M_1}$, $n_2 \in \overline{1, M_2}$. Define the set of quantized colors of the training template $E = \{(er_m, eg_m, eb_m)\}$, $m \in \overline{1, M}$. Set the vector of color appearance probabilities q_m, $m \in \overline{1, M}$. Set the normalized threshold ε.

2. Sort the set of quantized colors of the training template in descending order of color appearance probabilities.

3. Select colors whose probability of occurrence is less than the threshold ε, i.e. reduce the set of quantized colors of the training template.

2 The method of analyzing a color image based on clustering includes five stages:

– the first stage corresponds to the technique of reducing image colors;

– the second corresponds to the technique of creating a binary image;

– the third stage corresponds to the technique of clustering a binary image;

– the fourth stage corresponds to the technique calculating the probabilities of cluster points appearing in a binary image;

– the fifth stage corresponds to the technique of selecting the most priority clusters in a binary image.

Stage 2.1 The technique of quantization of a color image according to three color components

1. Set the color image $R(n_1, n_2)$, $G(n_1, n_2)$, $B(n_1, n_2)$, $n_1 \in \overline{1, N_1}$, $n_2 \in \overline{1, N_2}$. Set the quantization step Δ.

2. Set the image row number $n_1 = 1$.

3. Set the image column number $n_2 = 1$.

4. Set the color number $k = 1$.

5. If $k\Delta - \Delta \leq R(n_1, n_2) \wedge R(n_1, n_2) < k\Delta$, then $r(n_1, n_2) = k\Delta - \Delta / 2$.

6. If not the last color, i.e. $k < 256/\Delta$, then increase the color number, i.e. $k = k + 1$, go to step 5.

7. If $R(n_1, n_2) = 255$, then $r(n_1, n_2) = 256 - \Delta / 2$.

8. Set the color number $k = 1$.

9. If $k\Delta - \Delta \leq G(n_1, n_2) \wedge G(n_1, n_2) < k\Delta$, then $g(n_1, n_2) = k\Delta - \Delta / 2$.

10. If not the last color, i.e. $k < 256/\Delta$, then increase the color number, i.e. $k = k + 1$, go to step 9.

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11. If $G(n_1,n_2)=255$, then $g(n_1,n_2)=256-\Delta/2$.

12. Set the color number $k=1$.

13. If $k\Delta-\Delta \le B(n_1,n_2) \wedge B(n_1,n_2) < k\Delta$, then $b(n_1,n_2)=k\Delta-\Delta/2$.

14. If not the last color, i.e. $k<256/\Delta$, then increase the color number, i.e. $k=k+1$, go to step 13.

15. If $B(n_1,n_2)=255$, then $b(n_1,n_2)=256-\Delta/2$.

16. If not the end of the current image row, i.e. $n_2<N_2$, then increase the column number of the current row, i.e. $n_2=n_2+1$, go to step 4.

17. If not the last image row, i.e. $n_1<N_1$, then increase the row number, i.e. $n_1=n_1+1$, go to step 3.

Stage 2.2 The technique of creating a binary image

1. Define the set of quantized colors of the training template E.

2. Binary image $Q(n_1,n_2)=0$, $n_1\in\overline{1,N_1}$, $n_2\in\overline{1,N_2}$.

3. Set the image row number $n_1=1$.

4. Set the image column number $n_2=1$.

5. If $(r(n_1,n_2), g(n_1,n_2), b(n_1,n_2))\in E$, then $Q(n_1,n_2)=1$.

6. If not the end of the current image row, i.e. $n_2<N_2$, then increase the column number of the current row, i.e. $n_2=n_2+1$, go to step 5.

7. If not the last image row, i.e. $n_1<N_1$, then increase the row number, i.e. $n_1=n_1+1$, go to step 4.

Stage 2.3 The technique of clustering of a binary image

1. Set the binary image $Q(n_1,n_2)$, $n_1\in\overline{1,N_1}$, $n_2\in\overline{1,N_2}$. Set the size of the Moore neighborhood of point D. Set the point label matrix $M(n_1,n_2)=0$, $n_1\in\overline{1,N_1}$, $n_2\in\overline{1,N_2}$. Set the cluster count counter $c=0$.

2. Set the image row number $n_1=1$.

3. Set the image column number $n_2=1$.

4. Determine the current image point number $i=(n_1-1)N_2+n_2$.

5. If the i-th point is already labeled, i.e. $M(n_1,n_2)\ne 0$, then go to step 20.

6. Determine the neighborhood of the i-th point

$$U_{i,\varepsilon}=\{e \mid Q(l_1+n_1, l_2+n_2)=1\},$$
$$e=(l_1+n_1-1)N_2+l_2+n_2,\ l_1,l_2\in\{-1,0,1\}.$$

7. If not all neighbors of the i-th point fall within its neighborhood, i.e. $\left|U_{i,\varepsilon}\right|<D$, then mark the i-th point as a random outlier or noise, i.e. $M(n_1,n_2)=-1$, go to step 20.

8. Increment the number counter of connected regions, i.e. $c=c+1$.

9. Mark the i-th point as the c-th cluster, i.e. $M(n_1,n_2)=c$.

10. Create the set $S=U_{i,\varepsilon}$.

11. Extract the first element from the set S, i.e. $v=s_1$, and remove it from the set S, i.e. $S=S\setminus\{v\}$.

12. Determine the coordinates of the v-th point in the image

$$m_2=v \bmod N_2,\ m_1=\left[(v-m_2)/N_2\right].$$

13. If the v-th point was marked as a random outlier or noise, i.e. $M(m_1,m_2)\ne -1$, then mark it as the c-th cluster, i.e. $M(m_1,m_2)\ne c$.

14. If the v-th point is already marked, i.e. $M(m_1,m_2)\ne 0$, then proceed to step 19.

15. Mark the v-th point, i.e. $M(m_1,m_2)\ne c$.

16. Determine the neighborhood of the v-th point

$$U_{v,\varepsilon}=\{e \mid Q(l_1+m_1, l_2+m_2)=1\},$$
$$e=(l_1+m_1-1)N_2+l_2+m_2,\ l_1,l_2\in\{-1,0,1\}.$$

17. If not all neighbors of the v-th point fall within its neighborhood, i.e. $\left|U_{v,\varepsilon}\right|<D$, then proceed to step 19.

18. Combine the set S with the neighborhood of the v-th point, i.e. $S=S\bigcup U_{v,\varepsilon}$.

19. If the set S is not empty, i.e. $|S|>0$, then proceed to step 11.

20. If not the end of the current image row, i.e. $n_2<N_2$, then increase the column number of the current row, i.e. $n_2=n_2+1$, go to step 4.

21. If not the last image row, i.e. $n_1<N_1$, then increase the row number, i.e. $n_1=n_1+1$, and proceed to step 3.

Stage 2.4 The technique of calculating the probabilities of clusters appearing in a binary image

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1. Set the point label matrix $M(n_1, n_2)$, $n_1 \in \overline{1, N_1}$, $n_2 \in \overline{1, N_2}$. Set the cluster power vector $z(n) = 0$, $n \in \overline{1, c}$.

2. Set the image row number $n_1 = 1$.

3. Set the image column number $n_2 = 1$.

4. If a point belongs to a cluster, i.e. $M_k(n_1, n_2) > 0$, then increase the cluster power, i.e. $z(M(n_1, n_2)) = z(M(n_1, n_2)) + 1$.

5. If not the end of the current image row, i.e. $n_2 < N_2$, then increase the column number of the current row, i.e. $n_2 = n_2 + 1$, go to step 4.

6. If not the last image row, i.e. $n_1 < N_1$, then increase the row number, i.e. $n_1 = n_1 + 1$, and proceed to step 3.

7. Calculate the probabilities of clusters appearing in the binary image

$$p_n = \frac{z(n)}{\sum_{n_1=1}^{N_1} \sum_{n_2=1}^{N_2} Q(n_1, n_2)}, \quad n \in \overline{1, c}.$$

Stage 2.5 The technique of selecting the highest priority clusters in a binary image

1. Set the point label matrix $M(n_1, n_2)$, $n_1 \in \overline{1, N_1}$, $n_2 \in \overline{1, N_2}$. Set the vector of probabilities of cluster occurrence in the binary image p_n, $n \in \overline{1, c}$. Set the normalized threshold γ.

2. Sort the set of cluster numbers in descending order of the probabilities of cluster point occurrence, i.e., by their power.

3. Select clusters whose probability of occurrence is less than the threshold γ.

4 EXPERIMENTS

A numerical study of the proposed method for analyzing color images was conducted using the Matlab package based on a sign language database.

In this work, the image sizes are $N_1 = 637$ and $N_2 = 423$, the quantization step is $\Delta = 16$, and a Moore neighborhood of size $1 \le D \le 9$ is used for white points. The normalized thresholds are $\varepsilon = 0.001$ and $\gamma = 0.01$.

5 RESULTS

In Fig. 1, the original color image is shown. The stages of color image analysis based on clustering are illustrated below.

In accordance with the first stage, Fig. 2 shows the original image quantized with quantization step $\Delta = 16$, i.e., the possible colors are 8, 24, 40, 56, 72, 88, 104, 120, 136, 152, 168, 184, 200, 216, 232, 248 for each of the three color components R, G, B.

Figure 1 – Original image

Figure 2 – The quantized color image with $\Delta = 16$

For comparison, Fig. 3 shows a quantized grayscale image. As can be seen in Fig. 3, the colors of the hands and the T-shirt pattern are barely distinguishable, which can create problems for subsequent segmentation. Therefore, grayscale image quantization is not used in this work.

In accordance with the second stage, a binary image is created using the following set of quantized colors from the training template E = {(184, 120, 88), (184, 120, 104), (184, 120, 120), (184, 136, 104), (184, 136, 120), (184, 136, 136), (184, 152, 136 (200, 120, 88), (200, 120, 104), (200, 120, 120), (200, 136, 88), (200, 136, 104), (200, 136, 120), (200, 136, 136), (200, 152, 120), (200, 152, 136), (200, 168, 136), (200, 168, 152), (216, 136, 88), (216, 136, 104), (216, 136, 120), (216, 136, 136), (216, 152, 88), (216, 152, 104), (216, 152, 120), (216,

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152, 136), (216, 168, 136), (216, 168, 152), (216, 184, 168), (232, 152, 88), (232, 152, 104), (232, 152, 120), (232, 152, 136), (232, 168, 104), (232, 168, 120), (232, 168, 136), (232, 168, 152), (232, 184, 152), (232, 184, 168), (248, 168, 136), (248, 168, 152), (248, 184, 152), (248, 184, 168)}. The power of set $E = 43$. The quantized colors that appeared in the training template with a probability of at least ε=0.001 were selected for set E.

In Fig. 4, the template is shown.

In Fig. 5, a, the binary image is presented. In addition to large areas (hands, face, exposed neck and chest), there are scattered areas.

In accordance with the third stage, the binary image is clustered. In accordance with the fourth stage, the probabilities of clusters appearing in the binary image are calculated. In accordance with the fifth stage, the most priority clusters are selected.

In Figs. 6–8, the highest priority clusters are shown with their numbers n and the probability of clusters appearing in the binary image p_n with the size of the Moore neighborhood $D = 4.5$. These clusters can be interpreted semantically. Thus, the first cluster corresponds to human hands, the second cluster corresponds to the face and exposed area of the neck and chest, and the third cluster corresponds to a separate area of the chest and is semantically related to the second cluster.

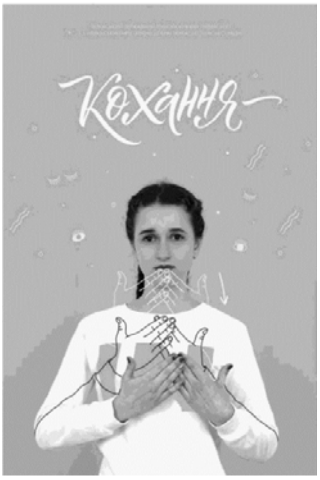

Figure 3 – The quantized grayscale image with $\Delta = 16$

Figure 4 – Template

Figure 5 – The binary image

Figure 6 – The cluster $n = 1$ (D=4.5, $p_1 = 0.4949$)

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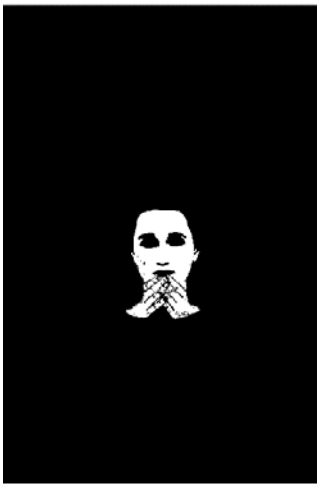

Figure 7 – The cluster $n=2$ (D=4.5, $p_2=0.4625$)

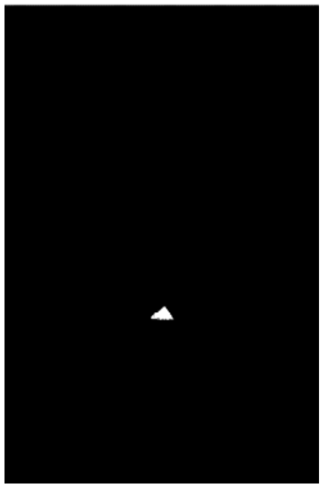

Figure 8 – The cluster $n=3$ (D=4.5, $p_3=0.0170$)

In Figs. 9–10, a binary and color image is shown, obtained by combining three clusters (the probability of each of these clusters appearing in the binary image is not less than $\gamma=0.01$).

Figure 9 – The binary image of three clusters

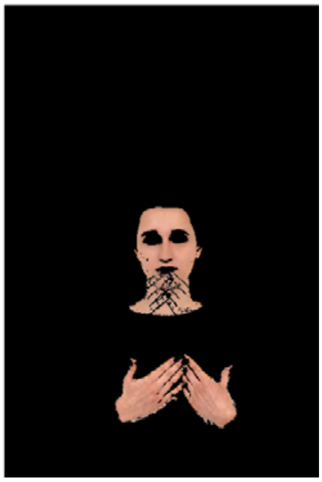

Figure 10 – The color image from three clusters

In Figs. 11–16, the most important clusters are shown with their numbers and the probability of clusters appearing in a binary image with a Moore neighborhood size. These clusters can also be interpreted semantically.

Figure 11 – The cluster $n=1$ (D=9, $p_1=0.3195$)

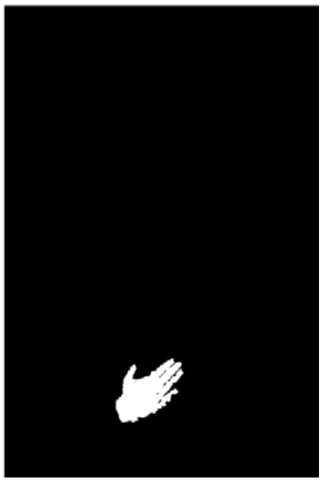

Figure 12 – The cluster $n=2$ (D=9, $p_2=0.2530$)

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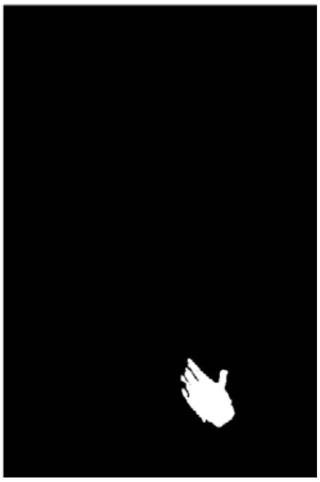

Figure 13 – The cluster $n = 3$ (D=9, $p_3 = 0.2195$)

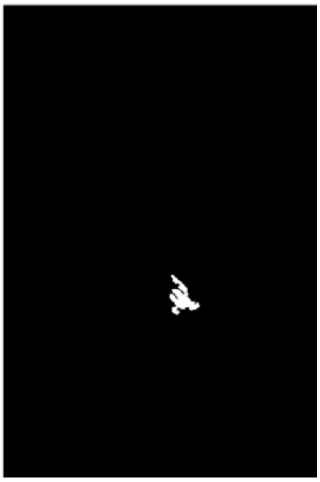

Figure 14 – The cluster $n = 4$ (D=9, $p_1 = 0.0522$)

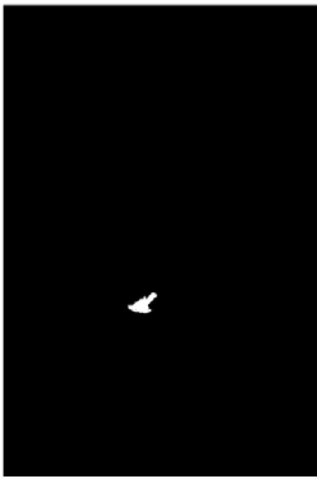

Figure 15 – The cluster $n = 2$ (D=4.5, $p_2 = 0.4625$)

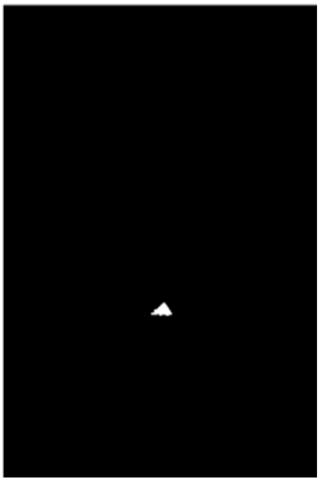

Figure 16 – The cluster $n = 3$ (D=4.5, $p_3 = 0.0170$)

Thus, the first cluster corresponds to a person's face, the second cluster corresponds to the right hand, the third cluster corresponds to the left hand, and the fourth, fifth, and sixth clusters correspond to a separate area of the neck and chest and are semantically related to the first cluster.

In Figs. 16–17, a binary and color image is shown, obtained by combining six clusters (the probability of each of these clusters appearing in the binary image is not less than $\gamma = 0.01$).

Figure 17 – The binary image of six clusters

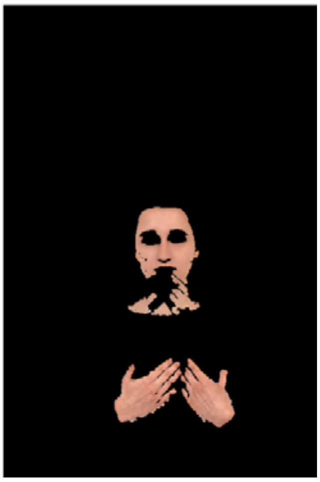

Figure 18 – The color image from six clusters

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Calculate the number of white points in a binary image

$$N = \sum_{n_1=1}^{N_1} \sum_{n_2=1}^{N_2} Q(n_1, n_2), \ N << N_1 \times N_2 .$$

The results of comparing the proposed method of intelligent image analysis based on clustering with the existing DBSCAN method are presented in Table 1.

Table 1 – Comparison of the proposed image analysis method based on clustering with the existing DBSCAN method

Accuracy		Computational complexity	
proposed	existing	proposed	existing
0.98	0.80	N^2	$(N_1 \times N_2)^2$

6 DISCUSSION

One of the most well-known density-based clustering methods, DBSCAN, is widely used to identify connected regions in images. However, its use in analyzing color images is accompanied by a number of limitations, namely:

– the algorithm is characterized by high computational complexity due to the need for sequential neighborhood search for all image points;

– it does not guarantee accurate clustering based on color characteristics, which reduces the selectivity of region extraction;

– with significant color diversity, the image may form an excessive number of clusters, which complicates subsequent interpretation;

– requires the specification of a neighborhood radius, the incorrect selection of which significantly affects the accuracy of clustering.

In view of these shortcomings, this paper proposes a new method for analyzing color images that implements a different principle of cluster formation. Unlike the traditional approach, where clustering is performed directly in the color space of the original image, the developed method uses clustering of the binary representation of the image. At this stage, only white points are taken into account, which allows limiting the search for neighborhoods to only significant elements and thus significantly reducing the computational complexity.

The proposed method includes preliminary quantization of color components, followed by binarization of quantized colors based on a training template containing the most probable colors. This reduces the number of unique color values and, accordingly, reduces the number of clusters formed.

A feature of the developed method is the replacement of the neighborhood radius with a logical check of the pixel's belonging to the white color, which increases the accuracy of clustering and resistance to variations in the color palette.

Additionally, an approach is proposed to use the training template not in its entirety, but only through the selection of quantized colors with the highest probability of occurrence. This technique reduces the influence of minor artifacts and noise that arise when the operator forms the template.

The use of normalized threshold values makes it possible to use probabilistic estimates of the occurrence of quantized colors and clusters, which further improves the accuracy of selecting informative image elements.

Thus, the developed method eliminates the key limitations inherent in the traditional DBSCAN algorithm, providing increased accuracy and speed of image element extraction.

The results of a comparative analysis (Table 1) confirm that the proposed method demonstrates high accuracy and performance compared to DBSCAN. According to experimental data (Figs. 9–10, 17–18), the use of the Moore neighborhood $D = 4.5$ allows for more accurate extraction of binary image elements with fewer clusters formed, which further confirms the effectiveness of the proposed approach.

CONCLUSIONS

The urgent task of improving the efficiency of color image analysis methods has been successfully solved through the development of a comprehensive approach based on the use of digital signal processing algorithms and machine learning methods.

The scientific novelty.

1. The method for analyzing color images has been proposed, which is based on the integration of digital signal processing methods and machine learning algorithms, thereby improving the accuracy and speed of extracting informative elements from images. It is based on the sequential application of several interrelated techniques, each of which is aimed at optimizing individual stages of analysis and preliminary data processing.

2. The technique for quantizing the three-color components of a training template to reduce the number of colors represented and, accordingly, reduce the computational complexity of subsequent operations. By reducing the number of color combinations analyzed, the speed of binary image formation is increased without a significant loss of information.

3. The technique for selecting the most priority colors of the training template based on a probabilistic assessment of their occurrence, which is aimed at increasing the reliability of color feature extraction. The use of a normal-

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ized threshold value allows for the adaptive selection of colors with the highest probability of occurrence, which increases the accuracy of the training template formation and reduces the influence of insignificant color variations.

4. The technique for quantizing the three-color components of the original color image by reducing the number of color clusters, which optimizes the process of image element selection, prevents the appearance of redundant segments, and contributes to more accurate segmentation and subsequent classification of objects.

5. The technique for creating a binary image based on a set of quantized colors from a training template. As a result of its application, the image contains only the most probable colors, which improves the accuracy of subsequent clustering. This limitation of the color space ensures the extraction of elements belonging exclusively to the specified color areas and prevents the formation of false clusters associated with unspecified colors.

6. The technique of extracting binary image elements based on clustering is aimed at improving the accuracy of selecting objects of various shapes and sizes. A distinctive feature of this approach is an improved mechanism for forming point neighborhoods: inclusion in the neighborhood is carried out by checking only the nearest white points, which eliminates the need for empirical specification of the neighborhood radius. This also ensures the elimination of random noise emissions (clusters of minimum power) and automatic determination of the number of elements to be extracted, which increases the overall efficiency of the analysis.

7. The technique for selecting the most important elements of a binary image is based on a probabilistic assessment of the frequency of cluster occurrence. The use of a normalized threshold allows for the objective selection of the most informative elements of a binary image, thereby increasing the accuracy of the final analysis.

The comprehensive application of the above techniques provide a highly effective method for analyzing color images, capable of adaptively processing complex visual scenes, minimizing computational costs, and increasing the reliability of structural element extraction through the coordinated use of digital signal processing and machine learning tools.

The practical significance. The developed approach expands the capabilities of color image analysis through the comprehensive application of quantization, training template-based binarization, clustering, and selection of the most significant clusters. The proposed method improves the efficiency of computer systems for image analysis and synthesis, ensuring more accurate, faster, and more stable extraction of informative elements from a visual scene.

Prospects for further research. A promising direction is the application of the developed method to a broader class of statistical analysis and machine learning tasks, including automatic classification, segmentation, and recognition of complex visual structures, as well as integration with modern neural network architectures for intelligent computer vision systems.

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DECLARATIONS

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

Authors’ contributions: Fedorov Eugene: technique for quantizing the three-color components of the training template and technique for quantizing the three-color components of the original color image; Khramova-Baranova Olena: technique for selecting the most important colors in the training template and technique for selecting the most important elements of a binary image; Utkina Tetyana: technique for extracting binary image elements; Galytska Helen: technique for generating a binary image; Nesen Ivan: numerical study of the effectiveness of the proposed method and perform a comparative analysis with traditional approaches.

Data availability: The manuscript has associated data in a data repository https://github.com/fedorovee75/ArticleAnalysingColorImages/.

Software availability: The manuscript has no associated software.

Use of artificial intelligence tools: The authors confirm that they did not use artificial intelligence technologies in creating the submitted work.

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МЕТОД АНАЛІЗУ КОЛЬОРОВИХ ЗОБРАЖЕНЬ НА ОСНОВІ ЦИФРОВОЇ ОБРОБКИ СИГНАЛУ ТА МАШИННОГО НАВЧАННЯ

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АНОТАЦІЯ

Актуальність. В останні десятиліття спостерігається стрімкий розвиток технологій цифрової обробки сигналів і методів штучного інтелекту, що значно розширило можливості аналізу та інтерпретації візуальної інформації. Кольорове зображення, як складний багатовимірний сигнал, містить дані про геометричні, спектральні та текстурні характеристики об’єктів. Ефективна обробка таких даних вимагає інтеграції методів фільтрації, сегментації та перетворення сигналів з алгоритмами машинного навчання для вилучення прихованих закономірностей і високорівневих ознак.

Метою роботи є створення методу аналізу кольорового зображення на основі квантування, бінаризації, кластеризації та вибору пріоритетних кластерів.

Метод. Запропонований метод поєднує цифрову обробку сигналів і машинне навчання для підвищення точності та швидкості вилучення інформативних елементів. Він включає декілька взаємопов’язаних методик: квантування трьох колірних компонентів навчального шаблону знижує кількість перевірених кольорів і прискорює формування бінарного зображення; відбір найбільш пріоритетних кольорів навчального шаблону на основі ймовірності появи з нормованим порогом, що підвищує точність виділення значущих ознак; квантування трьох колірних компонентів вихідного кольорового зображення, що оптимізує сегментацію і запобігає надлишковим кластерам; створення бінарного зображення на основі множини квантованих кольорів навчального шаблону, що виключає помилкові кластери і підвищує точність кластеризації; вилучення елементів бінарного зображення на основі кластеризації з перевіркою околиць тільки білих точок, що усуває шум, дозволяє виділяти елементи різної форми і автоматично визначати їх кількість; вибору найбільш пріоритетних елементів бінарного зображення з імовірнісною оцінкою, що підвищує достовірність аналізу.

Результати. Метод реалізований в Matlab і перевірений на спеціалізованій базі даних. Порівняння з традиційними підходами показало підвищення точності та стійкості вилучення елементів при скороченні часу обробки за рахунок оптимізації кількості кольорів і виключення надлишкових кластерів.

Висновки. Комплексне застосування квантування, бінаризації, кластеризації та вибору пріоритетних елементів забезпечує точний, швидкий і адаптивний аналіз кольорових зображень. Метод розширює функціональні можливості систем обробки візуальної інформації і може застосовуватися для завдань статистичного аналізу, інтелектуальної обробки зображень, сегментації та класифікації складних візуальних структур.

КЛЮЧОВІ СЛОВА: аналіз зображень, навчальний шаблон, квантування, бінаризація, кластеризація, машинне навчання, цифрова обробка сигналів.

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