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Development of Effective Methods for Structural Image Recognition Using the Principles of Data Granulation and Apparatus of Fuzzy Logic

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ABSTRACT The processes of intelligent data processing in computer vision systems have been researched. The problem of structural image recognition is relevant. This is a promising way to assess the degree of similarity of objects. This approach provides the simplicity of construction and the high reliability of decision making. The main problem of an effective description of characteristic features is the distortion of fragments of analyzed objects. The reasons for changing the input data can be the actions of geometric transformations, the influence of background or interference. The elements of false objects with similar characteristics are formed. The problem of ensuring high-quality recognition requires the implementation of effective means of image processing. Methods of statistical modeling, granulation of data and fuzzy sets, detection and comparison of keypoints on the image, classification and clustering of data, and simulation modelling are used in this research. The implementation of the proposed approaches provides the formation of a concise description of features or a vector representation of unique keypoints. The verification of theoretical foundations and evaluation of the effectiveness of the proposed data processing methods for real image bases is performed using the OpenCV library. The applied significance of the work is substantiated according to the criterion of data processing time without reducing the characteristics of reliability and interference immunity. The developed methods allow to increase the structural recognition of images by several times. Perspectives of research may involve identifying the optimal number of keypoints of the base set.

INDEX TERMS Characteristic features, computer vision, classification, data granulation, etalon, fuzzy logic, interference, keypoints, structural image recognition, uniqueness index.

I. INTRODUCTION

The modern information systems require the solution of applied problems of computer vision. Computer vision is a section of information technology [1] that researches the capabilities of tools to extract information from images. Data are received from various sensors. The result of the work should provide an emulation of human visual perception.

The main problem in this area is the emulation of the behavior of little-studied and poorly understood processes of human perception of visual information [2], [3].

A person can use the accumulated experience and knowledge to make decisions [4] for the interpretation of a visual image.

The existing problems relate to the possibility of obtaining high-quality and fast recognition of visual objects [5]–[8]. For example, the identification of human faces [9]–[11], document templates, fingerprints, antiques, vehicles.

The existing methods of computer vision are deterministic; the result of their work depends only on the input data [12]–[14].

The methodological aspects of structural image recognition are presented in [9], [10], [15]–[19]. The papers

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mentioned above [9], [10], [15]–[19] does not contain the consideration of the fuzziness, incompleteness, redundancy and inconsistency of input data during the development of modern information systems. There is also no practical implementation of the proposed method of structural image recognition in [10], [11].

Structural models for recognizing the shapes and positions of parts of animal body have been demonstrated in the scientific work [16]. Geometric relations of the coordinates of keypoints as well as the tools for deep learning are used as the base of the described method. The approach, based on learning deep neural networks for tracking a person's posture during movement, is presented in the analyzed paper [17]. The multi-iteration algorithm for constructing the harmonic graph in [18] involves the phased modeling of the skeleton structure. The deep generative model in [19] allows to restore the gaps on the image. Thus, the results of research [16]–[19] relate to the structural recognition of objects using deep learning methods. This paper proposes methods that are focused on the vector representation of keypoints in the form of descriptors, and the learning is based on the etalon comparison.

The solution to the problem of recognition is significantly complicated by changes of the object under the influence of geometric transformations. The external environment in the form of background and interference around the object affects significantly [11]. These factors lead to the distortions of individual fragments of the analyzed objects. Elements of false objects with similar characteristics are formed [10].

The existing methods for analyzing objects on images of real visual scenes do not allow to effectively and fully solve complex problems of recognition [5]–[8], [12]–[19] connected with distortions of parts of objects. The model for their construction is unable to take into account external interference and the resulting false descriptions.

The literary sources [20]–[24] show the possibilities and efficiency of using the apparatus of fuzzy logic in the intelligent information systems. The results obtained due to the implementation of fuzzy tools are useful for the development of methods of structural image recognition. There is no description of computer vision tasks and the application of fuzziness in the systems of image identification in [20]–[24].

The analyzed scientifically-practical literary sources [1]–[3], [5]–[8], [12]–[19], [25]–[32] have shown that the problem of structural image recognition is relevant. The tasks of computer vision require further research, development, and improvement. It is necessary to apply a systematic approach [32] to develop effective methods for structural image recognition.

The development of effective methods for structural image recognition using the principles of data granulation [33] and the apparatus of fuzzy logic [22] is promising. This methodology allows us to organize high-quality and high-speed tools for recognizing visual objects using the mechanisms of computational intelligence.

The research aim is to create effective methods of image recognition on the base of the construction of a unique concise structural description. It is proposed to solve the problem by granulating the values of the features. To determine the degree of membership of the researched object to the etalon class, it is recommended to use the apparatus of fuzzy logic.

Taking into account the certainty coefficients during the structural recognition of images allows us to detail the influence of the description elements on the final result. The compression of descriptions allows us to reduce the time spent. The designers of the information system should take into account possible interference during the identification of objects. The classification of sets of unique keypoints allows to reduce the impact of interference and decrease the number of false matches.

The objectives of this research are:

- Construction of models for the formation, processing, and comparison of compressed structural descriptions in the form of a subset of unique characteristic features;
- Performing the computer simulation to research the effectiveness of method modifications in comparison with known approaches.

The paper proposes and demonstrates:

- The principles of data granulation during the structural description of the values of the features (Section III). This approach provides mechanisms for creating effective methods of object recognition on the base of the construction of a unique concise structural description;
- The role of fuzzy logic during determining the membership of keypoint to the etalon class (Section IV). The application of the membership function allows to reduce the size of the dataset and increase the speed of image recognition;
- Methods for determining the "uniqueness" indexes during the structural method of image recognition (Section V). The result of the application of the developed scheme is a compact subset or vector description of unique keypoints;
- The method for the implementation of the element's classification during the structural representation of the values of the features (Section VI). It is possible to apply the apparatus of fuzzy logic to determine the degree of membership of the researched object to the etalon class. The method provides the damping of interference if it is present in the information system;
- Methods for constructing the basic set of descriptions during structural image recognition (Section VII). A scheme for description transformation during the formation of informative features has been created. The implementation of these methods provides the formation of a concise description to reduce the recognition time without reducing the reliability factor;
- The results of the approbation of the developed methods during structural image recognition (Section VIII). Testing was carried out based on real images. The analysis of the performed experiments confirmed the increase in the speed of the structural object recognition. The result

was obtained without reducing the reliability and noise immunity characteristics.

The paper proposes the methodology for the design of information systems. The mechanisms allow us to identify subsets of unique features and transform structural descriptions of images through classification.

II. BACKGROUND

Today there is a need to process many related images [34].

The existing methods of the structural description of images need to be improved due to the large time and resource costs [35], [36].

The computer vision provides the following classification of recognition tasks [37]–[39]:

- Object identification – search for object instances on the image. It is possible to work with the input data in a distorted form. The visual features of the object are preserved. The tasks can be solved in different ways depending on the specific field of application;
- Detection tasks – search for any areas according to the specified criteria, without clear visual features. For example, diagnostics in medicine, video surveillance systems, systems for finding people and faces in photographs;
- Tasks of image segmentation – the identifying the related areas. It is possible to separate the background from the object in front of it;
- Tasks of image classification – labeling incoming images from a set of classes depending on the content of the images;
- Classification tasks through localization – simultaneous search for the location of elements of different classes on the image with the subsequent labeling depending on the elements found.

The methods of structural image recognition are implemented on the base of descriptions in the form of a set of keypoints. Keypoints (characteristic features, special points, characteristic points, points of interest, primitives) are formed on the base of the information of "significant" fragments.

The comparison of keypoints in the feature space is implemented by calculating the similarity measure for certain sets [40]–[42]. Object classes are defined as a finite combination of etalon sets. High quality of identification or recognition of the objects under research is achieved by a successful description of the differences between the etalons. The more significant the difference between the elements of descriptions or the more significantly their composition differs, the higher the probability of correct recognition [43].

The performance indicator of recognition due to the transformation of the system of features can be improved tenfold [15], [42]. For example, granulation of description elements [36] can provide:

- The necessary compression of the features size;
- Effective transformation of space;
- Formation of subsets of the most informative features to effectively reduce computational costs [41], [44].

In the methods of structural image recognition, the individual keypoints of description elements are represented by vectors from space B^n with real components. The structural description of the object is a finite multiset $O \subset B^n$ [15].

There are many methods for detecting and matching keypoints on the image, for example, BRIEF, ORB, BRISK, FREAK, AKAZE, LATCH, SIFT, SURF, which use a binary representation for image features [30], [41], [45].

For research, Speeded Up Robust Features (SURF) [30], [41], [45] was chosen as one of the effective and fast methods for structural analysis of visual objects.

This choice is based on the following factors: the ranges of values of the descriptors of the SURF method can be both positive and negative; the SURF method is good at recognizing blurry or rotated images.

The SURF method is used to construct descriptions of objects for the following tasks: comparison of images [30]; search for objects on images [15]; 3D reconstruction of the territory infrastructure [20]; recognition of road signs [45]; automatic recognition of bacteria in blood tests [41], etc.

SURF is used to find objects on the image, but it does not work with the objects (it does not select the object from the background). The method considers the image as a whole and searches for features of this image. In this case, the features can be inside the object, on the background, at the points of the border of the object and the background. This method does not work well for objects of simple shape and without a pronounced texture. SURF does not find keypoints inside such objects. The points can be found on the border of the object with the background or only on the background. The object under research cannot be recognized on another image or another background for this reason.

The SURF method forms $O \subset B_1^n$ (finite multiset) from the subset $B_1^n \subset B^n$ of vectors $o = (o_1, \ldots, o_n)$, $o \in O$, $n = 64 \vee 128$. The subset B_1^n is defined as the set of n-dimensional real vectors, the Euclidean norm of which is equal to 1:

$$\|o\| = \sqrt{\sum\nolimits_{i=1}^{n} o_i^2} = 1. \tag{1}$$

In practice, this condition is implemented in an approximate form

$$B_1^n = \{o | o \in B^n, \quad \|o\| \approx 1\}. \tag{2}$$

The SURF description can contain hundreds of vectors, that significantly slows down processing [15]. The problem of reducing the number of vectors involves the construction of a concise description O^* on the base of the image $\Omega : O \rightarrow O^*$.

The variant of the description is the formation of a subset $O^* \subset O$ of significantly lower capacity by applying the procedure of selecting (reducing) features from O.

"The reduction of numerous features" is the method of data compression to reduce costs for recognition. In the recognition theory, this process is called the formation of the subset of "significant", "unique" or "informative" features [15], [43], [44].

The main criterion for assessing the similarity of elements B_1^n is the metric ρ. Most often, the Euclidean metric from ρ is used as B_1^n. The criterion of the equivalence of keypoints $o_i,\ o_j$ is the value $\rho(o_i, o_j)$ that does not exceed the prior value of the threshold δ_o.

Two keypoints are equivalent if the condition $\rho(o_i, o_j) \leq \delta_o$ is met. The similarity of values of features in the middle of the description and between the descriptions is estimated by the Euclidean distance

$$\rho(o_i, o_j) = \sqrt{\sum\nolimits_v [o_i(v) - o_j(v)]^2} \tag{3}$$

between the vectors $o_i,\ o_j$ of keypoints.

The degree of similarity of features between each other within the description and the description base can be estimated based on the construction of the relations between numerous features [46]. The implementation of the apparatus of similarity relations provides new opportunities for improving recognition by taking into account the individual features of the description.

The threshold δ_o is defined as the percentage (accuracy) of the maximum possible value [47].

The choice of δ_o also depends on the processing procedure applied. Threshold values δ_o may vary. For example, during training procedures, during establishing the equivalence of keypoints, during classification. The established relation of equivalence of elements O at a fixed value δ_o determines the partition O.

The application of this method provides the reliability of recognition, allows to evaluate the parameters of objects under the conditions of the spatial distortion. Using the principles of data granulation and the apparatus of fuzzy logic allows to improve the existing approaches. Also, the quality improves and the speed of structural image recognition for applied problems of computer vision increases.

III. PRINCIPLES OF DATA GRANULATION DURING THE STRUCTURAL DESCRIPTION OF FEATURE VALUES

The ability to granulate information is an important property of intelligent recognition systems. These structures use semantics to formalize the problem solving [48]. During granulation, clear and fuzzy approaches are divided [37].

Data granulation during the structural representation of objects is represented by two aspects:

- Description in the form of vector through the multiset by classifying its elements [42];
- Description in the form of the grouping of similar elements on the base of the properties of uniqueness or cluster analysis [43].

The fundamental difference of the first approach is the priori given base set, which defines the classes for the description elements.

An information granule is the subset of the universum through which the relation of similarity (indistinguishability, equivalence) is defined. A granule is the combination of atomic elements [15], [37], [48].

As a result, such universum or description can be represented as a set of granules. The basics of the theory of measure and relations are developed on the base of a combination of granules. The measure of the granule is calculated as the sum (integral) of the values of the membership function of the elements.

The measure $d(A)$ of the discrete granule A is defined as

$$d(A) = \sum_{a \in A} \mu_A(a), \tag{4}$$

where $\mu_A(a)$ is the value of the membership function to granule A, $\mu_A(a) \in [0,\ 1]$ [7].

For clear representations $\mu_A(a)$ takes binary values 0 or 1. The operations over granules are performed according to the laws of set theory [49], [50]. The granules can include each other, form hierarchies. Data granulation is implemented in a specific method and depends on several parameters. The formulation of the question about optimal granulation based on the apparatus of fuzzy logic is possible.

IV. THE ROLE OF FUZZY LOGIC FOR DETERMINING THE MEMBERSHIP OF KEYPOINT TO THE ETALON CLASS

The membership function $\mu_A(a)$ is applied for each etalon $O(q)$ from the set Q. The distance between the vector description (descriptor) of the point of interest and other vectors of characteristic features is calculated for each keypoint. The total number of identical features is calculated separately for each keypoint and points of interest within the same etalon.

Two features are considered to be the same if the distance between the vectors of their descriptors is less than an acceptable error ε.

The value of the acceptable error ε is selected by the experiment and depends on the base of etalons Q.

Using the membership function $\mu_A(a)$ assumes that all etalons of the same class are dependent on each other [51]. The characteristic feature can be unique within the same class of etalons, but repeated within other classes. Adding the new etalon to the class involves recalculating the descriptors of characteristic features of all etalons within this class. The analysis using the membership function is repeated.

The coefficient of "uniqueness" τ of each characteristic feature can be determined as:

$$\tau = e/\text{total}, \tag{5}$$

where e – is the number of identical unique features within one etalon $O(q)$; total – the total number of identical unique features of the base of etalons Q.

The characteristic feature is removed from consideration if the value τ is less than a predetermined threshold δ_o. If this keypoint is repeated in other etalons of the etalon base Q, the primitive is eliminated automatically. The exclusion of "non-unique" keypoint from the researched set allows to reduce the size of the dataset and increase the speed of image recognition.

The quality and speed of recognition improve at $\tau \rightarrow 1$, and the size of the dataset decreases. The reduced size of the dataset positively affects the structural SURF method, which assumes the storage of all keypoints and their descriptors.

V. METHODS FOR DETERMINING THE "UNIQUENESS" INDEXES DURING THE STRUCTURAL METHOD OF IMAGE RECOGNITION

For the element o_i of description $O = \{o_i\}_{i=1}^{I}$, we can define the number of repetitions h_i:

$$h_i = \sum_{j=\overline{1,I}} 1(\rho(o_i, o_j) \leq \delta_o), \tag{6}$$

where

$$1(\rho(o_i, o_j) \leq \delta_o) = \begin{cases} 1, & \rho(o_i, o_j) \leq \delta_o, \\ 0, & \text{otherwise}. \end{cases} \tag{7}$$

$h_i \in C_+$ is the number of elements O, which are equivalent to the element $o_i \in O$ with an accuracy of δ_o in accordance with the predicate $1(\rho(o_i, o_j) \leq \delta_o)$, C_+ is the set of non-negative numbers.

Let's consider a finite set $O = \{O^i\}_{i=1}^{Q}$ of descriptions corresponding to the dataset of images from etalons Q. For each keypoint $o_{ij} \in O^i$ of the etalon with i-number, let's calculate the uniqueness indexes α_{ij}, β_{ij}:

$$\alpha_{ij} = h_{ij}/s_i, \quad \beta_{ij} = h_{ij}^s/(s-s_i), \ \alpha_{ij} \in [0,\ 1], \ \beta_{ij} \in [0,\ 1], \tag{8}$$

where h_{ij} is the number (6) of similar elements for o_{ij} for i-etalon; s_i – the number of characteristic features of i-etalon; h_{ij}^s – the value (6) for o_{ij} in the base of etalons, excluding the etalon with i-number;

$$s = \sum\nolimits_i s_i \tag{9}$$

the total number of the description elements for base O.

For the elements of each etalon, let's calculate the values of indexes (8) and integral indicators

$$\sum\nolimits_j \alpha_{ij}, \quad \sum\nolimits_j \beta_{ij}. \tag{10}$$

In the general case $s_i \neq s_q$ for $i \neq q$.

The index α_{ij} shows the degree of repeatability of j-element within i-etalon. The index β_{ij} reflects the degree of repeatability of j-element in the descriptions of the rest objects of the base, except for i. The index β_{ij} may be considered more significant for recognition. The closer β_{ij} to zero, the more unique the element is among the rest of the elements of the base. The sum $\alpha_{ij} + \beta_{ij}$ reflects the degree of uniqueness of the element in the whole base. The integral indicators (10) characterize the general uniqueness of the elements of etalon within the base.

The research of values $\{o_{ij}, \alpha_{ij}, \beta_{ij}\}$ and integral indicators allows to practically estimate the degree of distinguishability of the objects of the base when applying the structural classification. The analysis of uniqueness indexes α_{ij}, β_{ij} allows us to build and apply the procedures of reduction of the features both within the etalon and within the base.

Filtering is carried out by constructing the predicate of "importance" of the element in the new description.

On the basis of the calculated characteristics, it is possible to select groups (granules) of rarely or frequently repeated keypoints. The characteristic features can be the basis for constructing the similarity of objects. The efficiency of recognition depends on the threshold value δ_o and the number of generated unique features.

The following methods for features reduction are proposed:

1. The etalons are processed independently. A tuple of g features with the smallest values α_{ij} is determined.
2. For each etalon, a tuple of g unique features among other etalons is formed, i.e. with the lowest values β_{ij}.

The increase in the processing speed of image recognition for these methods is s_i/g. The transformation of the feature space is carried out at the preliminary stage and does not affect the recognition time.

The second method is more promising and affects efficiency. The criterion β_{ij} reflects the degree of difference between the etalons. Features with high value α_{ij} are intensively repeated within the description. The keypoints with the maximum value α_{ij} contain the information component and affect the results of recognition.

VI. THE METHOD FOR THE IMPLEMENTATION OF THE CLASSIFICATION OF ELEMENTS DURING THE STRUCTURAL REPRESENTATION OF FEATURE VALUES

The definition of the term "granule" (Section III) and the proposed methods for calculating uniqueness indexes (Section V) allow us to form the elements of the description base in the system of classes. This approach granulates elements into groups and significantly reduces the processing time [15], [37].

Classes can be defined on the basis of characteristics α_{ij}, β_{ij}. The variant of "thinning" the set of features is possible.

By classifying different elements in the base $U = \{u_1, u_2, \ldots, u_i, \ldots, u_l\}$, we can obtain the representation of etalon in the form of a multiset [42]. The membership of the point o in the multiset A is established through calculating the characteristic function

$$\chi_A(Z) = \begin{cases} 1, & o \in A, \\ 0, & o \notin A. \end{cases} \tag{11}$$

The verification $o \in A$ is performed by comparing o with the elements U on the base of $\rho(o, u_i)$ (or other measure).

The class u_* of element o is determined by discrete optimization

$$u_* = \arg\min_{u_i \in U} \rho(o, u_i), \quad \rho(o, u_*) \leq \delta_o, \tag{12}$$

on the set U. Classification (12) includes checking the condition $\rho(o, u_*) \leq \delta_o$.

The proposed approach allows us to remove individual image elements from consideration.

On the base of (12) for k base classes for the etalon $O(q)$, we obtain the vector representation

$$\varphi(j) = \{\varphi_1, \varphi_2, \ldots, \varphi_i, \ldots, \varphi_k\}, \quad \varphi_i \in C_+, \tag{13}$$

where φ_i is the multiplicity of occurrence of i-base element.

On the base of the proposed classification (12) and vector description (13), the transformation $O \rightarrow \varphi$ is performed. This transformation is performed from the multiple representations to the vector description φ of finite dimension k with components from C_+.

The result of the classification and transformation of the description is determined by the parameter δ_o. Implementation (12) additionally provides jamming of interference if it is present in the information system.

Due to the proposed transformation (13) the granulation of the structural description is performed in the form of clusters of closely related elements. In this research, this transformation is interpreted as the classification. Such classification differs from traditional clustering.

"Representatives" of clusters are specified by the set U a priori. The method of classification on the base of U is similar to the transformation under the system of orthogonal functions [48]. The main difference is that the elements U do not require orthogonality. In the resulting system of features, there is no need to restore the elements.

The object recognition during the multiset representation is carried out by calculating and minimizing the distance

$$\rho(A, B) = \frac{\sum_i w_i \left|\varphi_A(u_i) - \varphi_B(u_i)\right|}{\sum_i w_i \max\left[\varphi_A(u_i), \varphi_B(u_i)\right]}, \tag{14}$$

where w_i are the weighting factors, for this research

$$\sum_i w_i = 1; \tag{15}$$

$\varphi_A(u_i), \varphi_B(u_i)$– is multiplicity for the representation of A and B sets in the projection of the base element $u_i \in U$.

The two-level classification system is obtained by implementing data granulation using (12) or (13) for elements O. For this system, the class of the object is defined as

$$j = Class_2\left[Class_1\left[O, U\right]\right], \tag{16}$$

where $Class_1$ – is the classification at the level of description elements in the base U; $Class_2$ – is the classification of the transformed description in the base O.

VII. METHODS FOR CONSTRUCTING THE BASE SET OF DESCRIPTION FEATURES DURING STRUCTURAL IMAGE RECOGNITION

The creation of the successful base set $U = \{u_i\}_{i=1}^k$ provides an effective classification according to the proposed method (Section VI). The set U is a thesaurus, the description features of which find their place in the representation $\varphi(q)$. The thesaurus is the combination of terms that describe the subject area with an indication of the semantic relations between them. The elements, which are relevant to the set u_i, are the synonymous objects. During recognition, such objects are formally indistinguishable.

Let's assume that S is the input number of features. Calculation of uniqueness indexes and classes is based on the analysis of the symmetric matrix of distances

$$M = \left\|m_{i,j}\right\|_{s\times s}, \tag{17}$$

where $m_{i,j} = \rho(o_i, o_j)$. Distances reflect the relations between the elements in the form of the degree of equivalence [52]. For each o_i it is possible to define the characteristics of the total and average connectivity

$$d_i(o_i) = \sum\nolimits_{j=1}^{s} m_{i,j}, \quad \overline{d_i} = \frac{1}{s-1}\sum\nolimits_{j=1, j\neq i}^{s} m_{i,j}, \tag{18}$$

where the elements of i-row or column of the matrix M are used.

The smaller the values (18), the stronger the i-element is related to the rest elements from the description.

In order of decreasing the level of connectivity, let's arrange the elements, for example, in the form of

$$d_{\min} = d_1 \leq d_2 \leq \ldots \leq d_s = d_{\max}. \tag{19}$$

A rating list is created, according to which the most informative elements are selected (max d_i).

Another method of analysis is to count the number of elements with which the analyzed element is related to in accordance with (8). As a result, we obtain the required order of the elements.

Both methods involve checking the condition $r_{i,j} \leq \delta_r$. Only "significant" relations are analyzed.

The proposed models of data processing (8), (18) are the basis for constructing the set U and establishing the number k. The increase in processing speed is inversely proportional to the number of base classes k. The space of features is compressed.

The methods of forming the base set U are the reduction of features according to the values of characteristics (8), (18) and the clustering over the set of elements of the base under research [42]. The elements U are selected as the representatives of the clusters. The scheme of description transformation during the formation of the informative features or vector representation is shown in Figure 1.

VIII. RESULTS OF APPROBATION OF THE PROPOSED METHODS DURING STRUCTURAL IMAGE RECOGNITION

The software simulation has been carried out for already existing methods of structural image recognition [5], [10], [11], [32], [53], [54] and for the developed methods on the same experimental image bases.

The Python 3.6 language in the Visual Studio 2019 environment and the OpenCV library [55] have been used. The software platform can run on Windows, Android, iOS, Windows Phone, Mac OS X and Linux.

Twelve 300 × 300 pixel-sized images (Figure 2) were selected for the research. The pictures were downloaded from the base of portraits of famous film actresses [56].

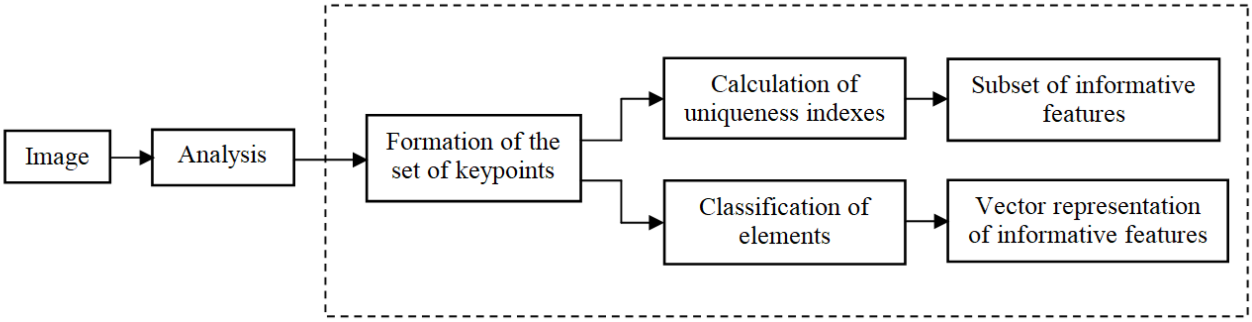

FIGURE 1. Scheme of image description transformation.

TABLE 1. Values of uniqueness indexes for image No. 1 in Figure 2.

No. of keypoint	1	2	3	4	5	6	7	8	9	10	Amount
α_{ij}	0.32	0.55	0.38	0.31	0.28	0.45	0.53	0.37	0.44	0.69	38.16
β_{ij}	0.27	0.49	0.26	0.39	0.34	0.47	0.46	0.48	0.43	0.67	33.89

FIGURE 2. Examples of images from the base of portraits of famous film actresses.

The number of SURF features in their descriptions was:

- The average value: 195, 184, 216, 152, 228, 214, 196, 198, 177, 192, 207, 224 for existing methods of structural image recognition [5], [10], [11], [32], [53], [54];
- 91, 87, 97, 85, 99, 92, 89, 90, 92, 86, 95, 98 for the developed methods of structural image recognition with the further definition of the set of unique keypoints in the concise description that contains only 10 primitives.

It is known that the time of image recognition is proportional to the number of selected unique keypoints. The apparatus of fuzzy logic is used at the stage of preprocessing of the image base under research. This approach allows to eliminate the increase in time at the stage of recognition. It should be noted that for some tasks of structural image recognition the speed of data processing is not critical [5], [9]–[11], [14]–[18], [20], [27], [28], [32], [42], [43], [53]. The results of this research may be useful, for example, in robotics, remotely piloted aircraft, where the criterion of image processing speed is decisive.

The results of the experiments showed that for different image bases at the threshold of $\delta_o < 0.45$ for many keypoints (more than 84%), not a single similar feature is determined. At the threshold of $\delta_o > 1.77$ all features become equivalent to each other. In these situations, it is impossible to form a subset of unique features [54].

To obtain the set of unique keypoints, the most appropriate values of the thresholds are $\delta_o = 0.59$ and $\delta_o = 0.78$.

Table 1 contains the values of the uniqueness indexes (8) for the first 10 keypoints and the index for describing image No. 1 in Figure 2.

The represented keypoints (Table 1) have rather close values (8). The resulting range of values for describing image No. 1 in Figure 2 is from 0.25 to 0.75.

Figure 3 contains a histogram of repetitions of characteristic features for the description of image No. 1 of Figure 2. The results of the research showed that there is a group of unique features (Figure 3), which can be taken as a basis for forming a compact description.

Table 2 contains the numbers and values of indexes for the 10 most unique keypoints.

Figure 4 shows the set of generated keypoints and a subset of 10 unique keypoints.

The criterion of uniqueness is the main for obtaining a concise description. The number of keypoints can be reduced

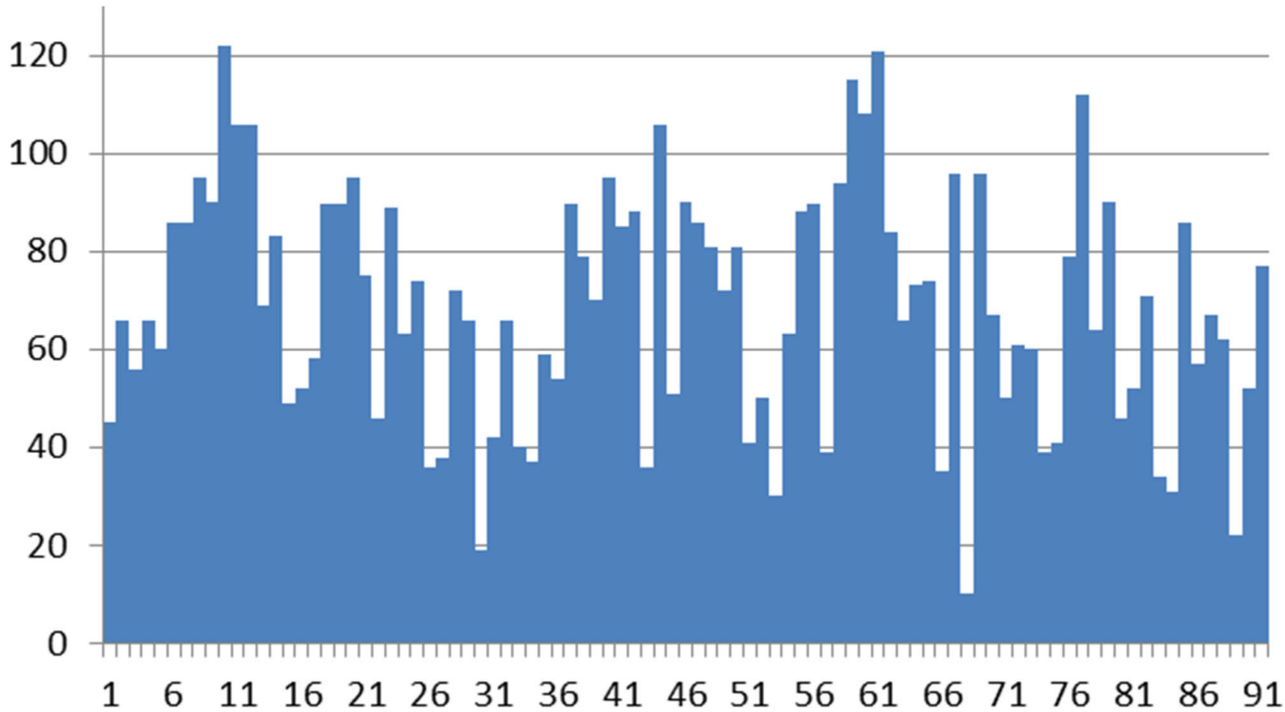

FIGURE 3. Histogram of repetition of feature values for the description of image No. 1 with images No. 2 – No. 12 of Figure 2.

TABLE 2. Values of uniqueness indexes for the selected keypoints.

No. of keypoint	**67**	**29**	**88**	**83**	**82**	**21**	**50**	**14**	**70**	**44**
α_{ij}	0.10	0.12	0.12	0.15	0.18	0.21	0.22	0.24	0.25	0.26
No. of keypoint	**67**	**29**	**88**	**52**	**83**	**25**	**82**	**65**	**42**	**26**
β_{ij}	0.07	0.10	0.11	0.17	0.17	0.19	0.20	0.21	0.23	0.24

at once by 9 times. The probability of correct recognition based on the concise description out of 10 unique keypoints in the absence of interference is not reduced.

The recognition time in this experiment decreased 3.4 times. Reducing computational costs directly depends on the size of the image base. The positive effect exceeds 120 times with the number of images of 45. The experiment on the base of the selection of unique features on the image has shown that the positive effect for 12 etalons is about 75 times.

The research confirmed that the number of false matches for the system of unique keypoints of images is significantly less than for full descriptions. At the threshold of $\delta_o = 0.59$ the number of false matches decreases from 92–94% to 12–30%, and at the threshold of $\delta_o = 0.45$ – from 52% to 8%.

The presented histograms in Figure 5 show that the number of similar keypoints of image No. 1 in Figure 2: own 10 unique features (a), 10 unique features within the whole base (b) without using the threshold δ_o.

These histograms confirm the possibility of recognition on the base of the classification of keypoints [54]. The base set is 10 unique characteristic features.

In this research, the value of the acceptable error ε is specified within [0.1; 0.4], threshold δ_o – within [0.5; 0.8]. The experiments have confirmed the effectiveness of the membership function.

Besides, the classification was carried out when images were distorted by additive interference with a Gaussian distribution. The number of keypoints always increases with interference. The experiment showed a 4-fold increase in characteristic features. During recognition on the base of sets of unique keypoints of etalons, the number of false matches at the threshold of $\delta_o = 0.45$ reduces from 46% to 1.8%. The probability of recognition does not reduce. The number of coincidences for the object under research is 92%. The results were obtained for the base of 75 images of gold earrings [57]. Examples of research objects are shown in Figure 6. You can verify the level of complexity of the experimental samples.

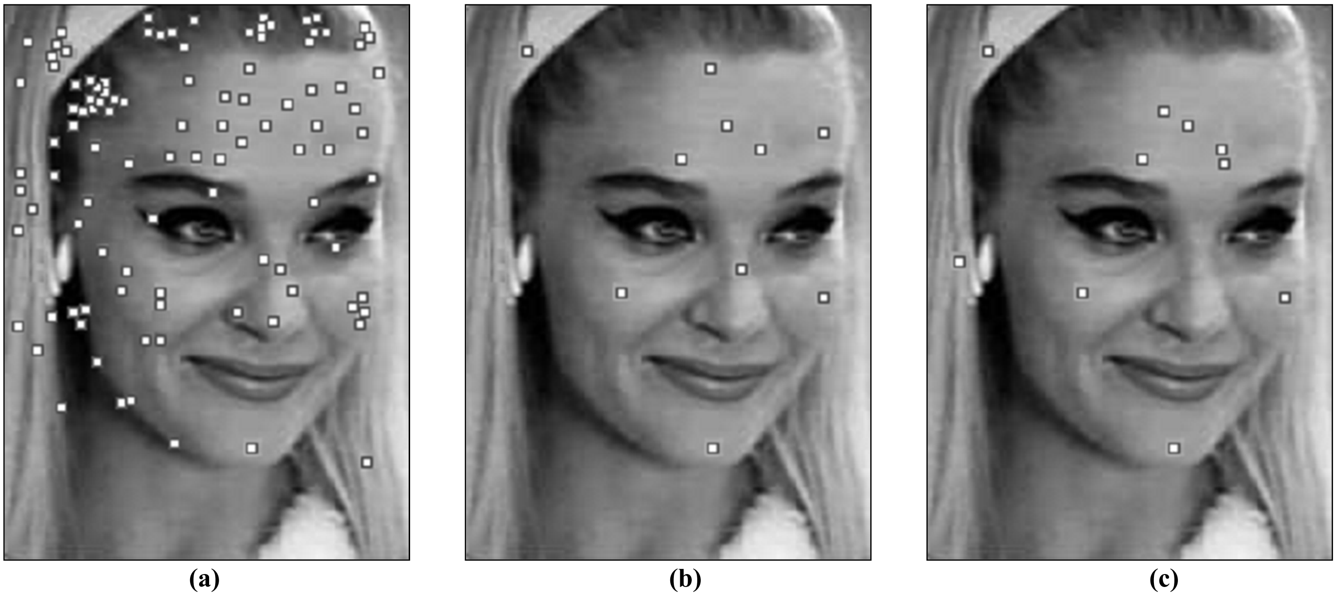

FIGURE 4. The result of the experiment with image No. 1 of Figure 2: (a) Set of 91 keypoints. (b) 10 unique keypoints. (c) 10 unique keypoints in the base of 12 images in Figure 2.

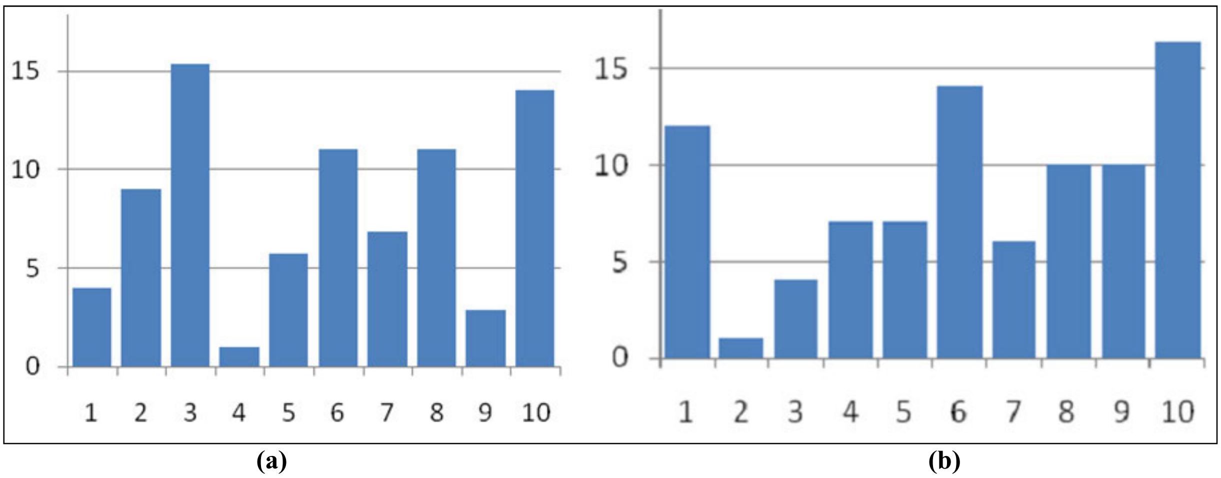

FIGURE 5. Histograms of similar keypoints of image No. 1 of Figure 2: (a) Own 10 unique features. (b) 10 unique features within the whole base without using the threshold.

FIGURE 6. Examples from the base of images of gold earrings.

The proposed methods of structural image recognition can perform recognition on the basis of one unique feature. This case is possible if the input image is not subjected to distortion and interference. For the applied tasks the number of unique features should be more than 10. The number of keypoints depends on the requirements for the conditions of application of the developed software application. The practical number of classes of characteristic features, as shown by the experiment, is in the range from 10 to 15.

IX. CONCLUSION

The methods for identifying subsets of unique features and transformation of structural descriptions of images by classification are proposed. The described ideas are based on the principle of similarity of values in the space of finite-dimensional real vectors. This approach provides the granulation of the structural representation. The implementation of the methods provides the formation of the concise description in order to reduce the recognition time without reducing the reliability factor.

The result of applying the developed methodology is the compact subset or vector description of unique and informative keypoints. Reducing the number of characteristic features allows us to reduce the probability of false identification of objects on the image.

The research contributes to the body of knowledge by creating the effective methods of object recognition based on the construction of the unique concise structural description. This technique is based on the granulation of the values of the features. The apparatus of fuzzy logic is used to determine the degree of membership of the object under research to the etalon class.

The application tasks have confirmed the efficiency of input data compression. The important stage during searching the significant keypoints is the formation of the base set for the classification of elements.

Approbation of the proposed methodology was demonstrated on real bases. The practical value of research was confirmed by experiments. The applied significance of the work was substantiated according to the criterion of processing time without reducing the characteristics of reliability and interference immunity. The test results of the developed approaches have shown the increase in the processing speed of structural image recognition by several times.

Further prospects of research focus on identifying the optimal number of keypoints of the base set, that allows to determine the number of classes of characteristic features.

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