IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 5 October 2023, accepted 8 November 2023, date of publication 13 November 2023,
date of current version 16 November 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3332291

RESEARCH ARTICLE

Statistical Data Analysis Models for Determining the Relevance of Structural Image Descriptions

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This work was supported via funding from Prince Sattam bin Abdulaziz University project number PSAU/2023/R/1444.

ABSTRACT The aim of the research is to improve the effectiveness of image recognition methods according to the description in the form of a set of keypoint descriptors. The focus is on increasing the speed of analysis and processing of description data while maintaining the required level of classification efficiency. The class of the image is provided as a description of the etalon. It is proposed to transform the description by implementing a statistical system of features for non-intersecting data fragments. The developed method is based on the aggregation of data distribution values within the description, the basis of which is the bit representation of the descriptors. Statistical features are calculated as the frequency of occurrence of the fixed value of a fragment on a set of description data and thus reflect the individual properties of images. Three main classifier models are analyzed: calculating the measure of data relevance in the form of distributions; assigning each of the descriptors to defined classes (voting); using the apparatus of statistical data analysis to decide on the significance of the difference between the distributions of the object and etalons. The results of software modeling of methods and calculations of statistical significance of differences based on distributions for training sets of images are represented. Using distributions instead of a set of descriptors increases the processing speed by hundreds of times, while the classification accuracy is maintained at a sufficient level and does not deteriorate compared to traditional voting.

INDEX TERMS Computer vision, data fragment, descriptor, image classification, keypoint.

I. INTRODUCTION

Constructing effective classification solutions for images of visual objects in modern computer vision systems is one of the most important and complex tasks. This is due to the multidimensional nature and significant amounts of analyzed data. When implementing structural methods, the images of visual objects are presented as a set of keypoint descriptors. Descriptors are numerical vectors of high dimension [1], [2]. Binary detectors Oriented FAST and Rotated BRIEF (ORB) [3], Binary Robust Invariant Scalable Keypoints (BRISK) [4] have a dimension of 256 and 512 components. At the same time, the number of descriptors (description composition) reaches 500–1500. In this case, transformation by presenting data as a system of its fragments or integrated statistical distributions significantly reduces the dimensionality and contributes to a significant simplification of the applied implementation of methods [1]. The results of this implementation are studied in detail in [2], [5], [6]. The primary tool is the apparatus of

The associate editor coordinating the review of this manuscript and approving it for publication was Andrea De Marcellis.

spatial-statistical data analysis. It is based on the aggregation of descriptor values from the object description by calculating new integrated features based on the analysis of a set of fragments [2], [7].

An important factor is the research of the distinguishing properties of the statistical feature system, including the hierarchical representation of data. It can be created based on distributions for basic fragments with a size of 1 bit. This direction is in line with the ''Content-Based Image Retrieval'' (CBIR) research section [8], [9] for computer vision systems. It is related to the implementation of intelligent recognition technologies based on image composition with a variety of levels of information representation. In general, the apparatus of generating, transforming, and analyzing descriptions of visual data in the form of a set of keypoint descriptors refers to this direction. The important point in the applied sense is the cluster representation of the description as an effective means of integration for the synthesis of high-level solutions [8], [10], [11].

The aim of the research is to improve the effectiveness of image recognition methods according to the description in the form of a set of keypoint descriptors. The focus is on increasing the speed of analysis and processing of description data while maintaining the required level of classification efficiency.

The research objectives are to study the efficient probabilistic data models in terms of processing speed in order to calculate the relevance of descriptions for classification purposes. It is important to study the effectiveness of implementing these models in classification methods, as well as to conduct an experimental assessment of the proposed approaches based on the results of the analysis of the image base.

The article proposes:

1) Formal models for constructing statistical features in the form of data distributions for the classification task. The breakdown of descriptors into non-intersecting fragments, which are the basis for creating a probabilistic system of features, is analyzed in detail. The implementation of the ideas provided ensures the effectiveness and increases the speed of the classifiers.
2) The process of calculating distribution values and constructing features on a set of descriptor blocks. We consider a scheme of a spatial method of representing data by accumulating bit values for fragments. Methods for calculating the relevance of probabilistic representations of image descriptions, which are the basis of classification, are analyzed. We propose a scheme for constructing the classifier based on the generated system of features.
3) The results of software modeling. We have developed the software models to implement the proposed data representation models and to construct a classification method. We have tested the image database. According to the results of the experiments, the proposed classification method has confirmed its efficiency, increased speed, and efficiency for the image classification task.

II. REVIEW OF THE LITERATURE

Recognition of the images of visual objects is a key task of computer vision and artificial intelligence theory in general [1], [2], [12], [13], [14], [15]. Formally, the features of its theoretical formulation are considered in the works [1], [16], [17], [18]. The methods' speed performance problem has been studied in [5], [10], [19], and [20]. Now researchers are focusing more on developing methods for classifying images, which is aimed at effective applied implementation. Particular interest is caused by methods development based on comparison with etalon descriptions, which ensures consistent processing [9], [11], [21], [22].

It should be noted that image keypoint descriptors are a modern and effective tool for representing descriptions of visual objects [3], [4], [20], [23]. This apparatus ensures invariance to geometric transformations of images, high-speed performance of data analysis, and provides decent classification performance. A finite set of binary vectors (descriptors) obtained by the keypoint detector creates a description of the etalon or recognizable image. An etalon is a selected image for which a description is generated. A set of etalons sets the basis for classification. Formally, a recognizable class in such a formulation [2], [21] has the form of an infinite set of images obtained from the image of a particular etalon by applying to it various sets of geometric transformations of shift, scale, and rotation. In this case, the keypoint detector provides invariance to the transformations.

Various aspects of the descriptor apparatus application are studied in many researches. Researchers are interested in reliability of keypoint extraction [24], [25] and effective models for comparing sets of descriptors [26], [27], including the implementation of ensembles on their bases [8], [28], [29]. An effective application tool is the aggregation of a set of descriptors into data distribution vectors to speed up classification to avoid costly linear search when calculating the relevance of descriptions [6], [7], [25], [26]. A description in the form of a set of descriptors is used for a wide range of computer vision tasks: identification, tracking objects or their parts, evaluating characteristics etc. [9], [22], [30].

Taking into account the multidimensional and spatial nature of the image signal and the determined set of features, statistical approaches [2], [7], [8], [31] and approaches related to spatial data analysis have become most widespread in solving object classification problems, which significantly simplifies processing processes [1], [10], [20]. Specialized neural network software is also being developed, based on the preliminary creation and training of a classification neural network within a fixed database of images [11], [19], [20], [21]. Today's limitations of such systems are long-term training and the dependence of the effectiveness of their application on the training base.

Despite the presence of practically effective systems with the implementation of machine learning tools, the study and justification of new methods of object recognition continue [6], [22], [23], [31], [32].

The implementation of the apparatus of statistical methods into the classification process gives significant advantages [5], [8]:

1) The construction and use of data distributions instead of data values significantly reduce the number of calculations [2], [33].
2) The use of distributions for data fragments preserves the classification ability of features and makes it possible to control the effectiveness of classification as a parameter [7], [17].
3) The statistical methods have a precise mathematical justification and are successfully used in modern approaches [18], [34], [35].

In our research, statistical methods are used in several ways: to form aggregate features based on a set of descriptors, to determine distributions according to the data fragments, and to verify the hypothesis on the difference significance between pairs of data distributions. But the implementation of statistical approaches, as well as any other methods, requires a detailed study of their effectiveness and performance on the available data regarding the requirements of the applied task.

One of the perspective directions of research in the aspect of improving the performance of structural methods is the implementation of spatial bitwise processing of a set of descriptor vectors [1], [2] and hierarchical tools of data presentation [15], [34], [36]. Such approaches by generalizing data transformation significantly simplify and speed up classification. At the same time, it is effective to combine methods and implement a complex of approaches to improve performance, namely: reducing the number of descriptors in the description [37], statistical processing with the identification of the most informative components [16], [29], [30], [33], [35], [37]. The possibility of implementing training procedures in such classifiers, where etalon descriptions of classes are considered to be given, also contributes to further improvement of their performance.

Today, the applied performance of modern neural network systems, such as Tiny YOLO, EfficientNet, Pelee, and SqueezeNet [12], [13], for the image classification task is difficult to surpass. However, these systems are known to require long-term training on a large set of partially labeled data. At the same time, the result and efficiency of classification depends entirely on the data used for training.

Our proposed approaches, based on the direct measurement of image features in the form of a set of descriptors, also should exist and be implemented in computer vision systems. Their advantage is the possibility of operational and radical change in the composition of classes. For the functioning of these methods, only representatives of classes are needed, namely, etalon images. We calculate the descriptions of the etalon in the form of a set of descriptors, and after that the method is ready for use. The method is universally suitable for any set of etalons, which can be quickly changed for a specific task.

III. PROBABILISTIC DATA MODELS FOR THE SYSTEM OF FRAGMENT

Let's take a finite set Z of binary vectors $z \in Z$, $z \in B^n$, $z = (z_1, z_2, \ldots, z_n)$ of the n-dimension from the space B^n of any binary vector $z_i \in \{0, 1\}$, $i = 1, \ldots, n$. $Z = \{z(r)\}_{r=1}^{s}$, $z(r) = (z_1(r), z_2(r), \ldots, z_n(r))$, $s = card\ Z$ is the number of vectors in the set Z. Example of Z can be a set of keypoint descriptors that create the image description [1], [4]. Modern detectors ORB and BRISK [3], [4] can be applied for forming a set of keypoint descriptors. In Figure 1, we show the example of an information element of set Z in the form of a binary vector with a volume of 16 bits. Let's interpret the sequence of bits of each of the descriptors $z(r) \in Z$ as readings of the n-dimensional discrete signal.

0	1	1	1	0	1	0	0	1	0	1	1	0	0	1	1

FIGURE 1. View of the vector from the set Z at $n = 16$.

Let's perform a bitwise analysis of the composition of set Z and proceed to presentation Z with a probabilistic model $Z \to P$ in the form of vector $P = (p_1, \ldots, p_n)$, where p_i – the posterior probability of the appearance of the value 1 in the bit with number i. We calculate the vector $P = (p_1, \ldots, p_n)$ using the values of individual bits for the set of vectors Z, where the value p_i is the frequency of occurrence of 1 in the set of bits from their total number s in the set.

The vector $P = P(Z)$ obtained as a result of such a transformation is the secondary integrated representation of the data set Z (image features). Using the vector P instead of the set Z with many elements makes it possible to accelerate the making of the classification decision (hundreds of times) due to the aggregation of data through the transformation of a set of vectors into one vector [1], [2], [7], [11].

It is important for implementing image recognition procedures based on the vector value $P(Z)$ that representation $P(Z)$ does not depend on the sequence of descriptors $z(r)$ in the set Z, i.e. representation by the model $P(Z)$ is invariant to the mixing of descriptors in the description's composition. The fact is that, in the conditions of geometric transformations, descriptors of description Z are formed in an arbitrary order. The vector P is a generalized multidimensional probabilistic image of a visual object in the n-dimensional space of all vectors with component values within the interval [0, 1]. Another advantage is the ability to analyze and evaluate the relevance of images with different numbers of elements of the vector P, including as a tuple of blocks.

In general, the distribution p_i of values by the i-th bit for the object description can be considered near to binomial, which is defined by Bernoulli's formula [8]. According to this model, the value of the probability $P_s^{(i)}(v)$ of the appearance of the number v of units at the place of the i-th bit in the description of s vectors can be defined as follows:

$$P_s^{(i)}(v) = C_s^v p_i^v (1 - p_i)^{s-v}, \tag{1}$$

where C_s^v is the number of combinations, p_i is the distribution parameter, which from a traditional point of view is equal to the probability of the appearance of a single bit for the i-th component in the set Z, and from an applied point of view, it is equal to the i-th component of vector P.

If we specify $\Theta(Z, \beta_Z)$ as the data distribution for the description Z with a vector of parameters β_Z, and $\Theta(E, \beta_E)$ as the corresponding distribution of the etalon with a vector of parameters β_E then we can represent the classification by determining some probability measure $\Omega\left[\Theta(Z, \beta_Z), \Theta(E, \beta_E)\right]$ between a pair of descriptions and optimizing the values Ω on a set of etalon descriptions [2], [17]. Another way is to establish the fact of a statistically significant difference between distributions $\Theta(Z, \beta_Z)$ and $\Theta(E, \beta_E)$ by testing the statistical hypothesis $H\left[\Theta(Z, \beta_Z), \Theta(E, \beta_E)\right]$ [30].

Calculation of the measure of relevance Ω and testing the hypothesis H are based on the posterior values of multidimensional distributions Θ for a set of features of the researched objects that differ in parameter values. The implemented probabilistic data model makes it possible to implement classification by establishing the degree of closeness between the images of the analyzed objects or the fact of their significant difference.

As a result, we interpret the image described by bit images of descriptors of description Z as a probability map

$$p_i = \left[\sum\nolimits_{r=1}^{s} z_i(r)\right]/s, \tag{2}$$

that for the values of the vector p_i integrates the spatial information of description Z by adding the bit values of the individual descriptors to obtain a compressed aggregate model of the input data representation. In (2), i is the bit number and r is the vector number in the description Z.

Note that calculation (2) for the binary vectors z_i is equivalent to determining the mathematical expectation (as well as the median) by the set of individual bits of these vectors.

For example, if the set Z contains ORB descriptors for the image keypoints then the vector $P = \{p_i\}_{i=1}^{256}$ summarizes the characteristics of the image by representing the frequency of occurrence of a unit in each of the 256 bits. Figure 2 shows an experimental example of the values of the vector P of 256 bits for one of the test images.

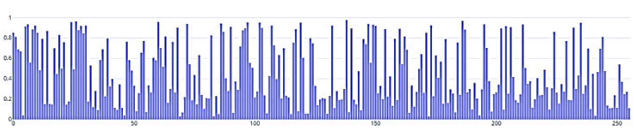

FIGURE 2. Experimental example of the vector P.

The vector P can be the basis for constructing the classifiers, which reduces the time of training or classification due to the processing of one vector instead of hundreds of vectors traditionally [11], [35].

For a fixed value n and a specific sequence of keypoint descriptors s, the set Z can be represented in the structured form of a binary matrix $Z = \left\{\{z_i(r)\}_{r=1}^{s}\right\}_{i=1}^{n}$. To simplify the analysis, let's assume that the value s is the same for all etalons, the finite set of which represents recognized classes of object images [1], [2].

As the parameter n of the size of the descriptor reaches several hundred (for the BRISK descriptor the value is $n = 512$, for the ORB descriptor $n = 256$), one way to reduce the dimensionality of the data to be processed is to split the keypoint vector-descriptor on a sequences of m fragments ($m \ll n$), that covers it fully. The synthesized data blocks have a size of $b = n/m$ and create a sequences structure for each descriptor [7], [11].

In this case the BRISK descriptor of 512 bits can be represented, for example, by the sequence of 512 fragments of one bit with the values 0 and 1 or by sequence of 256 fragments of 2 bits that take one of the binary values 00, 01, 10, 11, or by sequence of 128 fragments of 4 components, each of which has the format of a tuple of double elements within the range from 0000 to 1111 (the number of such values is equal to 2^4 =16), etc. As a result of such representation based on a set of bits, the description Z can be transformed into a matrix of integers with m columns and s rows (Table 1) [7].

Table 1 shows a block representation of the description.

TABLE 1. Block representation of the data structure Z.

Number of descriptor	Number of block				
	1	…	j	…	m
1	$z^1(1)$	…	$z^j(1)$	…	$z^m(1)$
…	…	…	…	…	…
s	$z^1(s)$	…	$z^j(s)$	…	$z^m(s)$

Based on the data model as the combination of values inside the fragments, let's introduce a new reflection $Z \to Q$ from the space of binary vector-descriptors of keypoints into a set Q of the distributions of the values of their components (as blocks), which makes it possible to construct the classifier for recognition of the visual objects based on a set of fragments of significantly fewer dimensions [1]. The distribution according to the fixed fragment with a number j, $j = 1, \ldots, m$ is represented in the form of the vector of integers $q_j = (q_1, \ldots, q_w)_j$, where, q_{kj}, $k = 1, \ldots, w$ is the frequency of the occurrence of k-th value of the fragment at the j-th place of the chain amid all description descriptors, the number of which is $s = \sum\limits_{k=1}^{w} q_k$ for any number j.

The values $p_k = \frac{q_k}{s}$, $k = 1, \ldots, w$, are the relative frequencies (probability estimates). Sometimes the name "posterior probabilities" is used for them [7], [8]. At the same time $w = 2^b$, $\sum\limits_{k=1}^{w} p_k = 1$.

In general, the set Q can be considered in the form of the system

$$Q = \left\{ q_j = (q_1, \ldots, q_w)_j \right\}_{j=1}^{m}, \tag{3}$$

for every one of the m fragments. The data Q can be represented as a matrix with w columns and m rows. For the normalized case, we have the distribution scheme

$$Q_{norm} = \left\{ p_j = (p_1, \ldots, p_w)_j \right\}_{j=1}^{m}. \tag{4}$$

For example, in the case of using the BRISK descriptor, when splitting into bytes, for $n = 512$ we get $m = 64$, $w = 256$, therefore, for the set Z the matrix $Q(Q_{norm})$ contains the frequencies (relative frequencies) of the occurrence of all acceptable values of byte-sized fragments.

In the example of Figure 1, we can consider eight pairs of sequential bits. For each pair of bits of description from s vectors, we determine the probabilities of the appearance of four possible combinations 00, 01, 10, 11, which are described by the values w_1, w_2, w_3, w_4. For the ORB descriptor with a size of 256, there will be 128 of such fours. As a result, we will get the matrix Q of probabilities with the size of 4×128. In this way, we can obtain a representation of the set Z at different levels of the hierarchy, which is determined by the number of bits b in the data block.

Based on the base system of one-bit distributions P by spatial analysis of values for combinations of fragments, the hierarchical model of the feature system can be implemented [1], [2], [7]. If we calculate the values of the column sum (1-bit fragment) for the matrix Z of the description, then we obtain the vector $t = (t_1, \ldots, t_j, \ldots, t_n)$, $t_r = \sum_{i=1}^{s} z_i(r)$, which is equivalent to the not-normalized value for distribution model P.

The vector t is an integral feature of the lowest level relative to the description Z, which preserves the property of invariance to geometrical transformations of the analyzed object inherent in keypoint descriptors.

Based on the features t_j, we can determine the features u_k of the highest level of the hierarchy by adding values t_j for each of the constituent components in the system of not-intersecting blocks

$$u_k = \sum\nolimits_{i=k}^{k+b-1} t_j, \tag{5}$$

where $k = 1, b+1, 2b+1, \ldots, n-b+1$ is the number of the bit from which the current fragment begins; $b = n/m$ is the block size in the bits.

The features (5) implement cross-correlation processing of the data matrix Z with a rectangular mask of size $b \times s$ [17]. By calculating according to (5), we obtain an integer vector u_k of dimension m. The parameter m is a characteristic of the degree of integrality for the system of fragments.

The vector values $u = (u_1, \ldots, u_k, \ldots, u_m)$ can be used as the statistical features for classification. They are calculated based on the bit-by-bit analysis of the columns of the matrix Z. The processing according to (5) depends on the value of the parameter b and implements the spatial processing (integration of distribution values) on the existing set of descriptors. Due to such a simple model for calculating functions (5), all of them for an arbitrary fragment size are determined quite simply (logically or by adding integers) based on previously obtained 1-bit values.

Based on the representation (5), the traditional hierarchical recognition method can be implemented based on calculating the relevance value of distribution systems for the input object and the etalon base [1]. This method is based on the calculation of relevance with the etalons of the values of the feature system u_k with different degree of data integration, determined by the size of the block.

The range of the integer values for the features u_k can be determined by the size of the fragment: $u_k \in \{0, \ldots, sb\}$. The resulting vector u is an integrated characteristic of the object description. It can be individually normalized by the number of descriptors or the fragment size.

The amount of values for the features (5) varies from one number to the vector of size n (the number of descriptor bits) and decreases with increasing fragment size. When $m = 1$, we have $b = n$, that is, each descriptor contains one fragment, and the value u_1 is determined by one value and is equal to the sum of the bits of the entire description. If $m = n$, we have another boundary situation: n of 1-bit fragments, and u_k is calculated as the sum of the column of the matrix Z.

The models of (2), (4), (5) implement the procedures to reduce the information redundancy of the spatial signal due to the permissible reduction (in terms of the recognition quality) of the degree of distributive ability of the feature system when presenting the description [14].

The processing (5) is a kind of spatial analysis of the fragment values for the set of descriptors along coordinates. Other examples of such processing are filtering or decomposition of the descriptor according to the system of orthogonal functions [17].

IV. METHODS OF CONSTRUCTING CLASSIFIERS ACCORDING TO TRANSFORMED DESCRIPTIONS

Classification of visual objects according to their description in the form of a set of keypoints descriptors or aggregated statistical characteristics of the description is carried out by the following methods:

1) By calculating the degree of relevance Ω of the descriptions (or their integrated characteristics in the form of distributions or hierarchical presentation) for a classified object and etalons, followed by the determination of the object class with the maximum value of the relevance value [1], [2], [10].
2) By assigning individually each of the object descriptors to one of the etalons with the determination of the etalon that received the largest number of class votes [7], [11], [37].
3) Using the apparatus of statistical data analysis to make decision H about a significant difference between the distributions of data for describing the object and

etalons with the definition of the etalon, which has a non-significant difference [8], [33], [35].

With this approach, according to the apparatus of statistical testing of hypothesis $H\,[\Theta(Z, \beta_Z), \Theta(E, \beta_E)]$, two opposite hypotheses are implemented at the specified level of significance: null one regarding the absence of significant differences between the researched objects Z, E and alternative one regarding the presence of such differences. Modern data analysis apparatus has a wide range of statistical criteria, particularly the two-sample t-test [38]. This test is to compare statistically two samples based on their mathematical expectations $\overline{Z}$, $\overline{E}$. Note that the t-test can be used to compare both independent (unpaired) samples and dependent (paired) samples. The difference in the application of these variants lies in the choice of the statistic $t(t_{\text{unpair}}\ \ or\ \ t_{\text{pair}})$, the value of which is compared with the critical value of $t_{\text{critical}}(t_{\text{critical1}}\ or\ t_{\text{critical2}})$. According to the test at $|t| < t_{\text{critical}}$ the hypothesis is accepted that there is no significant difference between Z and E, and at $|t| < t_{\text{critical}}$ the alternative hypothesis is accepted.

Based on the comparison of the hierarchic representations (5), it is possible to calculate the relevancy Ω for the descriptions A and C as the Manhattan distance ρ between the vectors $u(A)$, $u(C)$ at the fixed level of the hierarchy

$$\rho[u(A), u(C)] = \sum_{j=1}^{m} \left|u_j(A) - u_j(C)\right|. \tag{6}$$

For the balanced consideration of the influence of the components when evaluating the relevance value, it is possible to apply the normalized values:

$$\rho^{*} = \frac{\rho}{sm}, \tag{7}$$

where sm is the product of the number of descriptors s and the number of fragments m used in (7) to normalize the value of the Manhattan distance (6) to obtain an evaluation for (6) between 0 and 1.

The measures (6), (7) can be calculated both at individual levels of the hierarchy with a subsequent generalization or logical analysis of the obtained values or in an integrated form by adding the values of the measures at the aggregate set of levels of the hierarchy.

The values (6), (7) increase in stages as the final amount is reached. Based on this fact, it is possible to implement the methods for further reducing the number of calculations, stopping the process when the sum in (6) reaches some critical threshold relative to the difference in descriptions [16], [17].

On the basis of the ensemble of measures (6) at various values $m = 1, \ldots, n$, it is possible to construct the hierarchical measure that takes into account the entire range of the distribution capacity of the proposed feature system.

An alternative for criterion (6) to determine the degree of difference of the integrated descriptions u is the application of the metric for comparing the sets [1], [8].

Let's perform the classification by optimizing measures of the form (6), (7) on the set of etalons. The analyzed object will be assigned to the etalon with the smallest distance. We can apply a similar method for sets of distributions (3), (4) of the object and etalons.

In Figure 3, we shown the classification scheme based on the calculation of the degree of relevance between the integral representation of the components of the object description and the etalons (distributions or hierarchical representation).

A special case of (6) can be a direct comparison of the values of vectors P for the object and etalons.

The second method of classification is implemented by determining the degree of relevance between individual descriptors of the object and some "centers" of etalons obtained from their presentation P by discretizing the components of the vector P to a binary set of values {0,1} [2].

The variants of implementing the third method are implemented, for example, by comparing the distributions of object data and etalons through the application of a two-sample t-test for means – both for bit-by-bit comparison of the vectors, which are integrated representations of the objects and for comparing such vectors as a whole [33], [35].

The classification scheme according to methods 1 and 3 is shown in Figure 3.

Thus, compression (encoding) is proposed for a set of binary vectors as a description of an object based on the statistical characteristics of this set. More detailed set of descriptors analyzing schemes are described in our papers [1], [2], [35]. The scheme in Figure 3 generally illustrates the algorithmic description of the main steps of the proposed classification method.

V. EXPERIMENTAL RESEARCHES

The proposed approaches were tested on the example of the emblems of universities of 400 × 540 size using the tools of the OpenCV library [1], [2], [31], [39]. Illustrations of images and marked keypoint coordinates are shown in Figure 4.

We have applied BRISK descriptors of dimension $n = 512$ and number 700 in each description.

In our previous research we used descriptors of the "float" and "integer" type generated by the SIFT and SURF detectors. Their information components are data bytes. The effectiveness of these methods has been confirmed by numerous experiments. However, recently, due to applications (mobile devices and systems), binary descriptors such as ORB and BRISK have been used more often. They gain in processing speed, give the possibility for data fragmentation and statistical analysis since every their bit has an information load for classification.

Fig. 5 shows an example of the generated distribution (in integers) relative to the fragment values for descriptors of the description of two emblems (blue and yellow) by the first two bits.

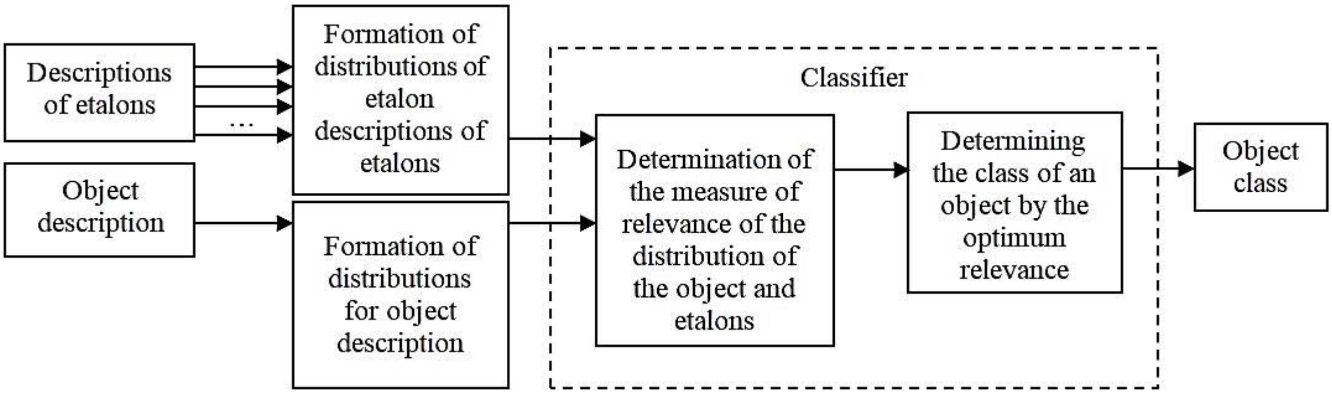

FIGURE 3. Classification scheme.

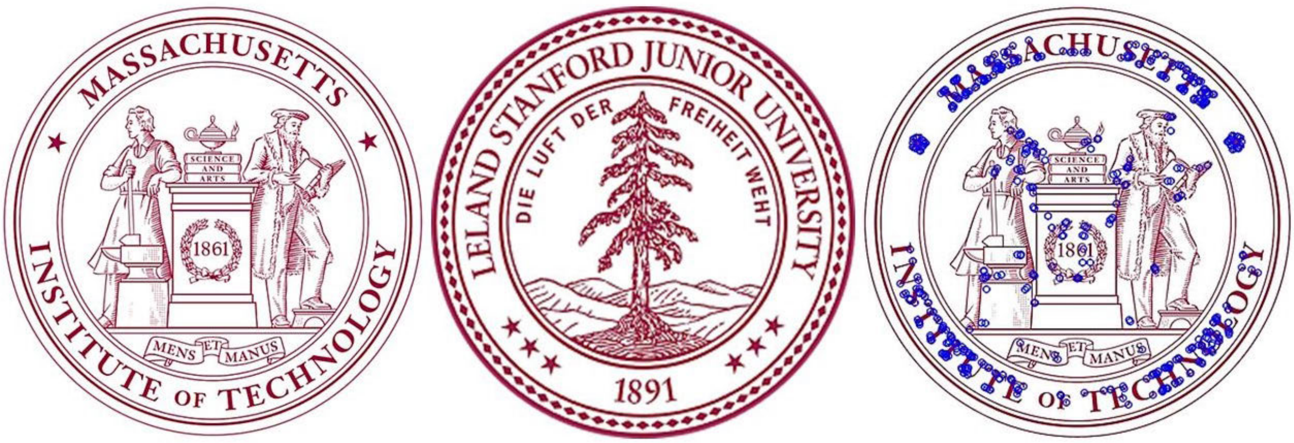

FIGURE 4. Images of the emblems of universities and highlighted coordinates of keypoints.

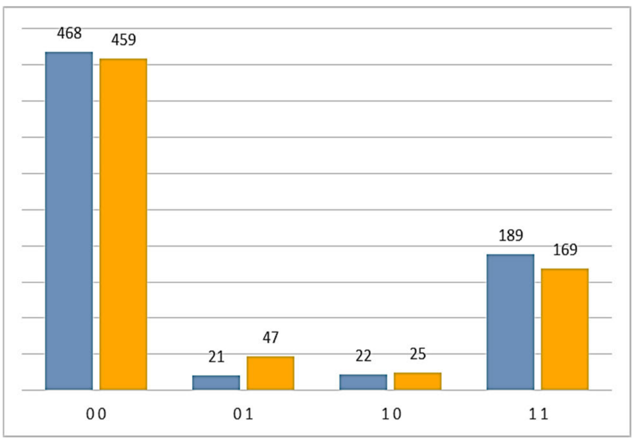

FIGURE 5. Example of distributions for images of icons by 2 bits.

The experimental Table 2 obtained on the basis of the simulation results contains the values of the classifier $\rho^{*'}$ (7) for descriptions of emblem images, depending on the number of descriptors (16…700) of the description and the number of bits (1…8) in the distribution blocks.

TABLE 2. The value of the classifier (7) depends on the number of bits.

Number of descriptors	Number of distribution bits			
	1	2	4	8
700	0.059	0.084	0.143	0.319
500	0.061	0.086	0.149	0.326
100	0.071	0.110	0.204	0.450
50	0.106	0.165	0.290	0.570
30	0.108	0.175	0.320	0.600
16	0.127	0.210	0.402	0.699

The measure of similarity according to the voting method (calculating the number of similar descriptors with an equivalence threshold of 20% of the maximum value of the Hamming distance) for these two emblems equals 0.12.

According to the result of comparing the values of Table 2 with the values obtained for images significantly different in content (we have compared the image of the emblem with the image of the coat of arms of the city), it turned out that the value in the column for 1 bit is about 50% higher and in the column for 8 bits is 20% more. This fact confirms sufficient possibilities for distinguishing objects using the distribution model even in the case of a small number of bits in a fragment, which is significant from the point of view of processing speed.

Let's estimate the amount of available computational costs for the implementation of the considered methods in comparison with traditional approaches. The calculation time using software models in seconds is recorded in Table 3.

TABLE 3. Time estimates (in seconds) during computer simulation.

Number of descriptors	Voting	Number of bits in distribution			
		1	2	4	8
700	10.7	0.008	0.011	0.028	11
500	6.4	0.006	0.01	0.017	6.2
100	0.48	0.002	0.002	0.007	1
50	0.11	0.001	0.002	0.004	0.915
30	0.08	0.001	0.001	0.003	0.527
16	0.045	< 0.001	<0.001	0.002	0.315

According to the results of the estimation of the processing time in Table 3, it is clear that the proposed approach based on distribution features has significant computational advantages over traditional voting procedures for description descriptors since the value of the time estimation for determining relevance for this approach is about 1300 times less for a 1-bit representation and 400 times less for a 4-bit representation. At the same time, the calculation time for the 8-bit version is almost equal to the costs for the traditional method. However, the main costs are spent purely on the formation of distributions and not on the relevance calculation.

Computational cost analysis for the developed data analysis models showed that the computation time for distribution-based modifications compared to the traditional voting method decreased by about 1000 times. Specifically, the values were 8 ms for bit analysis and 11 ms for bit-pair analysis, while voting took almost 11 seconds. In this case, the gain in processing speed increases in proportion to the number of descriptors in the description. Analysis models for one and a pair of bits give approximately the same performance indicators, but it is clear that as the number of distribution links increases, the calculation time also increases. In general, the developed methods provide a significantly higher speed of functioning of the recognition system.

We have carried out detailed statistical calculations for the third method of classification. A significant difference between data of the descriptions of two different emblems of universities is confirmed by the two-sample t-test with different dispersions. The test is applied to a system of description fragments, taking into account the independent nature of the samples.

Under the specified method at the level of a separate fragment with its distribution, the decision is made for each of the objects regarding the significance of the differences between the corresponding mathematical expectations.

For one-bit fragments, we have the distributions given in Table 4.

Note that for a fragment length greater than 1, coding was previously introduced for the convenience of numerical processing. For example, for the two-bit case, fragments 00, 01, 10, 11 are assigned the values of 1, 2, 3, 4. Table 5 shows the results of applying the test for two-bit fragments.

Continuing similar calculations for fragments of lengths 4 and 8, let's summarize the results of the calculations in Table 6, from which it is clear that as the length of the fragment increases, the share of significantly different fragments increases.

As a supplement to the fragment-by-fragment comparative analysis, let's conduct a study on the homogeneity of vectors, which are entirely composed of previously considered mathematical expectations of the distributions of individual fragments. So, for example, based on Tables 4 and 5 for one- and two-bit cases, respectively, it is assumed to compare columns containing the mathematical expectations of fragments and marked with $\overline{x}$.

Based on the paired character of the compared columns, let's apply the paired two-sample t-test, which indicates about significant difference of the researched objects at different fragment lengths, despite even a significant reduction in the lengths of the compared sequences when the size of the fragments increases (Table 7).

Analysis of calculated Tables 6 and 7 shows that for a different number of bits in the fragment, there is a significant statistical difference between descriptions of different objects in the space of statistical images, which confirms the practical feasibility of using a block representation for descriptors. As can be seen from the tables, even a decrease in the length of sequences of mathematical expectations with an increase in the length of fragments demonstrates their significant difference, which, in turn, is a confirmation of the effective recognition of the researched objects and the efficiency of the proposed approach in general.

As can be seen from Tables 6 and 7, the calculations according to the t-test are evidence for establishing significant differences between emblem objects, which are visually different. The effectiveness of fragmentation naturally increases with increasing fragment size.

The developed models of the classifier have been also used on the example of images of people's cartoons (politicians, artists, scientists). The illustrations of the etalon images and generated keypoint coordinates are shown in Figure 6.

The number of calculated descriptors in the description of each of the etalons is $s = 500$. We have applied more practical methods of classification 1 and 2 with the additional use of data hashing to speed up the processing [5], [8]. Input images were subjected to displacement, rotation, and scaling transformations.

TABLE 4. Results of the application of the two-sample t -test with different dispersions in the case of one-bit fragments, $\bar{x}$– mathematical expectation, $t_{\text{critical 1}}$ = 1.96 (at the $\alpha = 0.05$ significance level).

Fragment number	Emblem 1: Number of identical fragments 0	Emblem 1: Number of identical fragments 1	Emblem 1: $\bar{x}$	Emblem 2: Number of identical fragments 0	Emblem 2: Number of identical fragments 1	Emblem 2: $\bar{x}$	Application of the t -test: t_{unpair}	Application of the t -test: Conclusion of a significant difference
1	489	211	0.301	506	194	0.277	1.002	No
2	490	210	0.300	484	216	0.309	-0.349	No
3	314	386	0.551	277	423	0.604	-2.005	Yes
…	…	…	…	…	…	…	…	…
512	447	253	0.361	413	287	0.410	-1.869	No

TABLE 5. Results of fragment-by-fragment application of the two-sample t-test with different dispersions in the case of two-bit fragments, $\bar{x}$ – mathematical expectation, $t_{\text{critical 1}}$ = 1.96 (at the $\alpha = 0.05$ significance level).

Fragment number	Emblem 1: 00	Emblem 1: 01	Emblem 1: 10	Emblem 1: 11	Emblem 1: $\bar{x}$	Emblem 2: 00	Emblem 2: 01	Emblem 2: 10	Emblem 2: 11	Emblem 2: $\bar{x}$	t_{unpair}	Conclusion of a significant difference
1	468	21	22	189	1.903	459	47	25	169	1.863	0.573	No
2	213	101	236	150	2.461	175	102	263	160	2.583	-2.038	Yes
3	139	70	44	447	3.141	144	62	50	444	3.134	0.108	No
…	…	…										…
256	347	88	45	220	2.197	302	115	40	243	2.320	-1.724	No

(Emblem 1 and Emblem 2 columns 00–11: Number of identical fragments; last two columns: Application of the t -test.)

TABLE 6. Number of significant differences for fragment features according to the two-sample t-test.

	The number of bits in the fragment: 1	2	4	8
Number of fragments with significant differences (at the 0.05 level)	259 of 516 (50.59%)	130 of 256 (50.78%)	76 of 128 (59.38%)	42 of 64 (65.63%)

TABLE 7. Application of the paired two-sample t-test for sequences from mathematical expectations, $t_{\text{critical 2}}$ = 1.998 (at the $\alpha = 0.05$ significance level).

Fragment size	t_{pair}	Conclusion of a significant difference
1	-15.288	Yes
2	-11.773	Yes
4	-8.684	Yes
8	-7.662	Yes

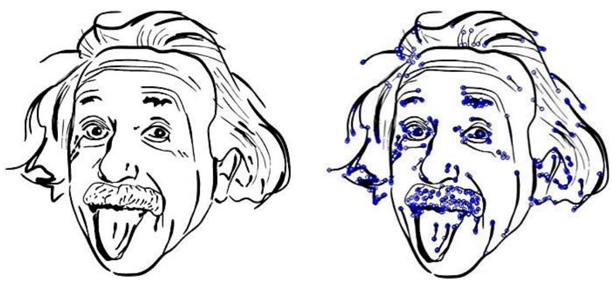

FIGURE 6. Example of an etalon image with keypoint coordinates.

Based on the conducted experiments with the images shown in Figure 6, we have obtained the results, which confirm high-quality indicators of recognition of visual data with significantly lower computational costs in terms of classification time. The obtained estimates of the classification time coincide with the data in Table 3.

To evaluate the developed approaches in the aspect of universality, we have conducted the research using software models with images from the database of human faces [40], where small subsets of 5 etalon images have been taken.

An example of the image with the keypoint coordinates is shown in Figure 7. We have carried out the modeling according to method 2 and calculations according to method 3, which generally confirmed the obtained conclusions.

In our research we have implemented the development of the proposed technologies with the use of probabilistic data models in the aspect of analyzing the relevance and evaluating the significance of the differences in distributions by classes of etalons [2], [11], [35].

The purpose of this research was to evaluate the performance of the method based on distributions of real image

FIGURE 7. The image from the database [39] with keypoint coordinates.

data. The demonstrated experiments confirm the operability and high speed of the proposed method, as well as the possibility of effective distinguishing implementation or identification for real images. In addition, we have used the hypothesis testing as an alternative for making decisions. This has confirmed the effectiveness.

It should be noted that the developed methods have confirmed their effectiveness on small sets of etalons and require an in-depth study of their effectiveness for volumetric applied databases of visual data.

VI. CONCLUSION

The implementation of probabilistic models and statistical criteria for the intellectual analysis of empirical data in the form of structural descriptions of images makes it possible to determine the quality factor of the constructed feature space from different points of view to classify visual objects in computer vision systems. The application of the model of block-bit representation and statistical analysis for the values of data fragments contributes to the improvement of the effectiveness of the object recognition process, which is confirmed by an increase in the recognition level when the fragment size increases in the description structure.

Thus, the article contains the following contribution:

1) We have developed and generalized in single key the probabilistic models of data analysis previously developed by the authors.
2) We have proposed the method for implementing estimates of a significant difference between distributions.
3) We have confirmed the effectiveness of the proposed methods for classification based on modeling and statistical calculations using real data.

The use of a variety of statistical criteria in the applied experiment gave identical conclusions about the significance of differences in object descriptions, which emphasizes the objectivity of the research.

Analysis of the system of data blocks for a set of descriptors based on probabilistic models is a perspective direction for a significant reduction in computing costs. Probabilistic data presentation not only contributes to a significant acceleration (in experiments more than a thousand times) of classification procedures but also provides a rather high level of differentiation of images. At the same time, time costs for implemented models are proportional to the number of description descriptors and depend on the methods of generating input data.

The applicative significance of the research is to confirm the feasibility of implementing probabilistic models, block structure, and statistical analysis to transform the description of the object as an effective approach for solving image recognition tasks.

The application of the considered models for determining relevance without forming distributions for the recognized image can be considered perspective based only on generated etalon distributions obtained at the preliminary processing stage. Another direction is the research of methods for image databases of large volumes.

ACKNOWLEDGMENT

This study is supported via funding from Prince Sattam bin Abdulaziz University project number PSAU/2023/R/1444. The authors acknowledge the support of the Department of Informatics, Kharkiv National University of Radio Electronics, and the Department of Higher Mathematics, Kharkiv National Automobile and Highway University, Ukraine, in numerous help and support to complete this article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest to report regarding the present research.

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