# Image structural classification technologies based on statistical analysis of descriptions in the form of bit descriptor set


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**Abstract.** The problem of image recognition in computer vision systems is considered. We offer technologies for classifying visual objects using a statistical center based on a structural description of the image as a set of key point descriptors. The use of statistics for the bits of the description data helps to increase performance while providing sufficient classification performance. Results of experimental modeling and peculiarities of implementation of the developed approaches are discussed.



**Keywords:** computer vision, image classification, key point, descriptor, statistical center, nonparametric statistics, performance, classification results


## 1 Introduction

In today's computer vision systems, the use of data processing technology has become widespread, providing information about recognized visual objects as set of key points (KPs) of 100-1,500 pixels [1]. At the same time, each point reflects the properties of the image in the neighborhood of its coordinates and is described by a vector-descriptor with dimensions in 64… 512 components [2]. Due to the large volumes of visual data flows, there is an urgent need to use the mining apparatus to identify the most essential regularities in the content of the description of the visual objects in order to reduce computational costs while ensuring effective classification.

Considering the structure of the analyzed data, which contains numerous set of identical elements, it is promising to use the apparatus of mathematical statistics. Its tools are able to reveal the deep informational properties of descriptions, which are necessary for effective recognition of images [2-5].

The aim of the paper is to study the technologies of statistical analysis and nonparametric methods for the formation of innovative feature space, which provides effective classification of images by their structural description.

The tasks of the paper are the construction of mathematical models for the transformation of descriptions and the calculation of relevance in the synthesized space of features, the implementation of software modeling to evaluate the effectiveness of the developed modifications.

## 2 Formal problem statement

Traditionally, the system of structural pattern recognition $R = \langle V, T, U \rangle$ involves three main components [1]: $V$ – used method (comparison with the etalon in the feature space), $T$ – set of features used in training and recognition (set of descriptors of KPs), $U$ – set of recognized situations (set of classes given by samples). One of the particular cases $R$ is a "one-on-one" classification, when only one class is identified compared to others, that is $U = \{0,1\}$.

In our work, within the framework of recognition technology, effective modifications for features $T$ and related method $V$ have been proposed. If it is reliable assumption that the elements of description create the concentrated cluster structures, then it is possible to build a classification based on the cluster characteristics for the description data [6]. From the point of view of processing speed the most effective situation is when only cluster is created on a dataset and its properties are given by the statistical center [8]. The analysis and purposeful processing of the center proposed in the paper significantly increase the rate of performance.

The second area of research is the direct application of nonparametric statistics methods to the set of the bit description, which together with the acceleration of processing considers the peculiarities of the entire statistical picture of the data description.

## 3 Literature review

Detecting of deep regularities in the set of numerical data is a powerful tool for the robust distinguishing of dataset by their quantitative characteristics in the classification process.

Recent studies in the field of image analysis and processing have developed in the aspect of quantitative analysis regarding the structure of the analyzed data [7-11].

According to specific applications, authors of the contemporary research continue to offer effective measures to determine the similarity of object descriptions that are calculated and analyzed with the help of the key point descriptor sets obtained by detectors [8-14].

Particular attention is focused on the parameters of the proposed method performance [16-20]. Based on this, it is essential to use spatial analysis and processing of descriptor values in the form of a block system model, which makes it possible to statistically summarize the information and accelerate the implementation of classification procedures [4, 8].

Powerful statistical analysis tools in the practice of computer vision are nonparametric statistics methods that do not rely on information about type of distribution [4-6]. It seems natural to use them to analyze the properties of a random vector system, which in this case acts as a model for the analyzed object description.

The essence of the BRISK detector for determining the KPs of the image and the procedures of comparison of descriptors are analyzed in [19-22]. The possible ways of forming the description centers are discussed in [2, 3], moreover, modifications of the space of KP descriptors are considered in [8, 25]. Studies related to the use of structural descriptions when processing video streams are contained in the monograph section [26].

Reference to the software used in modeling the developed methods is given in [27].

## 4 Analysis and construction of feature space

Let the vector space of binary vectors of dimension $n$ defines the universe $B^n$, $card\ B^n = 2^n$. We will identify space $B^n$ with the set of descriptors which are the vectors constructed by the KPs detector for the image [2-3].

Consider the description of the analyzed image as a fixed finite subset $Z \subset B^n$ which consists of the vectors from $B^n$. In general, we can consider $Z$ as a multiset, since the description elements can be repeated or similar to each other. This approach promotes the representation of the visual object as a collection of its structural elements, and the value of each descriptor is the result of extracting meaningful features of the spatial fragments of the image. The set $Z = \{z_v\}_{v=1}^{s}$, $z_v \in B^n$, is composed of $s$ descriptors of KPs with binary values, generated by detectors such as ORB, BRISK, AKAZE [19-21].

Consider the set $Z$ in a structured matrix form $D = \left\{ \{d_{i,j}\}_{i=1}^{s} \right\}_{j=1}^{n}$ for the fixed value $n$ and specific sequence of $s$ descriptors of KPs. For simplicity, we consider $s$ to be the same for all etalons, whose finite set represents the recognized classes of images [2-3].

Suppose that the structural description $Z$ is characterized by the compact placement of elements around a center in the space $B^n$. This makes it possible for the available data to estimate the allowable limit for the distance within the neighborhood of the determined center and classify the description by calculating the number of its equivalent elements and the refined center used the established threshold.

It is clear that in the aspect of multi-class classification, the effectiveness of this method naturally depends on how well the computed centers will differ from each other in the applied feature space.

Let's interpret the sequence of bits of each descriptor $z_v$ (it is the row of the matrix $D$ ) as separate case of $n$ – dimensional discrete signal. We also construct for $Z$ the aggregated image $h(Z)$ of the "data center" in the form

$$h(Z)=(h_1,\ldots,h_j,\ldots,h_n),\ \mathrm{h_j}=\sum_{i=1}^{s}d_{i,j}\ , \qquad (1)$$

where $h_j$ are the sums of the elements of corresponding columns.

Let's call the vector $h(Z)$ the statistical center (SC) of the description and put its values at the basis of classification.

It is important for the practical implementation of recognition procedures that representation $h(Z)$ doesn't depend on the order of descriptors $z_v$ in the set $Z$ , that is, the model $h(Z)$ is invariant to mixing descriptors that corresponds to the arbitrary arrangement of rows in the matrix. This property makes it possible to receive descriptors in any order, taking into account the allowable geometric transformations of objects. In fact, the vector $h(Z)$ is a generalized image of an object in the $n$ – dimensional space $C^n$ of the vectors with integer nonnegative components since $h(Z)\in C^n$, $h_j\geq 0$. The range of values $h_j$ in (1) is determined directly by the calculation procedure and the number of descriptors $s$; due to the bit type of data, it can be considered as given: $h_j\in\{0,1,\ldots,s-1,s\}$.

In addition to the description, we will also refer to the normalized representation $h^s(Z)=(h_1^s,h_2^s,\ldots,h_s^s)$, where $h_i^s=h_i/s$ are obtained by normalizing values $h_i$ to the descriptor number $s$ of the description, $h_i^s\in[0;1]$. Vectors $h$ and $h^s$ can be considered as posteriori characteristics of the description, as they are calculated on the basis of input information.

## 5 Classification based on data center

Let's carry out a statistical analysis of the data of the binary matrix $D$ and on the basis of the values of the vectors $h$ or $h^s$ set a logical procedure for determining the fact of belonging an arbitrary vector $b\in B^n$ to the given description $Z\in B^n$ .

At the pre-processing stage, we calculate a vector whose components have the form $q_i=\rho(h^s,z_i)$, $i=1,\ldots,s$ , where $\rho(h^s,z_i)$ is a distance between vector $h^s$ and descriptor $z_i\in Z$ . The range of values for $\rho(h^s,z_i)$ is known, since the space of vectors is determined by the metric and value of the data. For example, the value of the Manhattan distance $\rho(h^s,z_i)=\sum_{v=1}^{n}\left|h^s(v)-z_i(v)\right|$ belongs to the segment $[0;n]$.

Let's rank the values $q_i$ by type $q_1\leq q_2\leq\ldots\leq q_s$ , then choose the median value $q_{s/2}$ from the sorted sequence. The distance value $q_{s/2}$ halves the whole set of descriptors and half of the descriptors will be in the neighborhood of the center $h^s$ with distance less than $q_{s/2}$ [2].

We choose the value $\alpha = q_{s/2}$ as the threshold for the distance $\rho\left(h^s, z_i\right)$ to classify the query for the assignment of an arbitrary vector $b$ to the set $Z$. This choice of the value $\alpha$ under the condition $\rho\left(h^s, z_i\right) \le \alpha$ provides equivalence with accuracy $\alpha$ for most vectors of description $Z$ and its center $h^s$.

Determining the threshold $\alpha$ by moving the sorted sample to the left or right of its center allows further to adapt the data content to the center value and can contribute to a more reliable classification.

After that we define a refined SC $h^{s*}$ for the subset of the descriptors selected by the threshold $\alpha$ with the help of the averaging the values of only the descriptors for which the condition $\rho\left(h^s, z_i\right) \le \alpha$ is satisfied:

$$h^{s*} = \frac{1}{s*} \sum_{i=1}^{s} z_i \chi(z_i), \quad \chi(z_i) = \begin{cases} 1, & \rho\left(h^s, z_i\right) \le \alpha, \\ 0, & \rho\left(h^s, z_i\right) > \alpha, \end{cases} \tag{2}$$

where $s*$ – the number of such descriptors, $\chi(z_i)$ – characteristic function as a result of logical analysis of distance.

We now apply the refined SC $h^{s*}$ to classify descriptors of the arbitrary description. The selected concentrated portion of the description data in the form (2) contributes to a more thorough identification of characteristics of data concentration in terms of differences with other descriptions.

In general, the classification using the SC for the image database will be represented by technology in the form of data processing steps:

1) analysis of the set of etalon descriptions of the image base to determine the SC and the threshold $\alpha$ for each etalon;

2) calculating the refined SC (2) for the set of etalons;

3) analysis of descriptor set that is the description of a recognized object for satisfaction of inequality $\rho\left(h^{s*}, z_i\right) \le \alpha$ with respect to each etalon;

4) counting the number of voices of descriptors that satisfy the condition $\rho\left(h^{s*}, z_i\right) \le \alpha$ for each etalon;

5) classification of the object on the basis of determining the etalon with the highest number of received votes.

The proposed technology gives the possibility of modification, for example, in stage 3 it can be competitively identified only one of the etalons based on the shortest distance to the refined center. Another development of the approach may be the use of weighting classification coefficients for single bits of the SC, which enhances the individual characteristics of the descriptions and aims to improve the quality of classification.

# 6 Application of nonparametric statistics apparatus

The vector $h(Z)$ is a characteristic of a structural description of a visual object. Another factor for distinguishing the descriptions presented by the matrix $D$ can be directly statistical distributions of data [2-3] or the parameters of these distributions for individual bits or blocks $D$ [3]. Such "indirect" approaches to performance analysis, instead of directly data values, often make it possible to successfully solve applied problems. The advantage is a significant reduction in the amount of computation. The disadvantages are related to some blurring in the image space when determining relevance.

Let's imagine the value $d_j = \{d_{i,j}\}_{i=1,\ldots,s}$ of the $j$-column bits of the matrix $D$ as the realization of some random variable $b_j$, $j = 1,\ldots,n$, which takes the binary values $b_j \in \{0,1\}$. We consider the column sequence as a system of independent random variables. On the basis of sampling $d_j$, we determine experimentally the mathematical expectation and variance of each of the quantities $b_j \in \{0,1\}$.

We now apply a nonparametric statistical criterion based on the experimental values of mathematical expectation and variance to evaluate the relevance of the distributions of the corresponding bits for the compared descriptions. A distinctive advantage of nonparametric criteria using numerical characteristics of distributions is their independence on the type of statistical data distribution [4, 5].

If the statistical characteristics $a_1, \sigma_1^2$ and $a_2, \sigma_2^2$ for two random variables are known ($a$ – mathematical expectation, $\sigma^2$ – variance), then the degree of closeness of these variables can be estimated on the basis of statistics [1, 3]:

$$\beta = \frac{\left[\left(\sigma_1^2 + \sigma_2^2\right)/2 + \left(\left(a_1 - a_2\right)/2\right)^2\right]^2}{\sigma_1^2 \sigma_2^2}. \tag{3}$$

At full coincidence of parameters $a_1, a_2$ and $\sigma_1^2, \sigma_2^2$ we have $\beta = 1$, and as their differences increase, the value $\beta$ increases indefinitely. Based on the introduction and application of the threshold $\delta_\beta$ for the criterion value $\beta$, we will construct a procedure for determining the relevance of the two descriptions and the classification.

Unlike parametric statistical criteria, the implementation of criterion (3) does not rely on statistical tables. In this case, there is a problem of determining the lower limit $\delta_\beta$ for the value $\beta_j$, which exceed indicates a significant difference between the studied object descriptions.

The value of expression (3) is calculated separately for each element $d_j$ of the bit array. At the same time it can be considered in sense of multidimensional distribution, where the parameters $a$, $\sigma^2$ are vectors containing the characteristics of the independent variable system. For a multidimensional situation, the criterion $\beta$ is given by a vector of values.

The application of criterion (3) in the relevance analysis of the descriptions makes it possible to significantly simplify the classification of the object in comparison with the traditional apparatus for accepting statistical hypotheses [4, 5] and does not depend directly on the type of probability distribution.

For example, consider the value of a single bit from a set of descriptors as a discrete random variable, described by distributions $p_0, p_1$, where $p_0$ – the probability of 0, $p_1$ - the probability of 1. Mathematical expectation of $\theta$ is defined as $M[\theta]=\sum_k \theta_k p_k = p_1$. The variance of $\theta$ is calculated as $D[\theta]=\sum_k (\theta_k - M[\theta])^2 p_k = p_0 p_1$ [4].

Based on the analysis of the values $b_1, b_2, \ldots, b_n$ from the system of independent bits, we obtain for each etalon description its image in the form of a representation by the vector values of the mathematical expectation $M = (M_1, \ldots, M_n)$ and variance $D = (D_1, \ldots, D_n)$. Further, on the basis of values $M$, $D$ by expression (3) and by applying the logical processing using a threshold $\delta_\beta$ for the value $\beta$, we can decide or reject the equivalence of the compared descriptions.

The most general model for a system of independent bits involves different probability values of occurrence of 1 in each single bit for a given etalon class. In this case, we have a distribution where in each bit values 1 or 0 appear independently. If $p_j$ is the probability of occurrence of 1 in the j-th bit, then we have a system of random variables given by the set of proper probabilities: $p_1, p_2, \ldots, p_n$. A specific set of values for these probabilities will determine the etalon class. That is, the etalon can be represented in a probabilistic way in the form $p_1, p_2, \ldots, p_n$.

The probability of a specific sequence of 0s and 1s is described by the product of $n$ probabilities $p_j$ or $(1 - p_j)$ depending on the value at the j-th position: 1 or 0. The probabilities $p_j$ are directly calculated based on the normalized distribution as $p_j = h_j / s$. For example, the probability of occurrence of a sequence (0,1,0,1,1,1) is a product $P(0,1,0,1,1,1) = (1 - p_1) \cdot p_2 \cdot (1 - p_3) \cdot p_4 \cdot p_5 \cdot p_6$.

A separate theoretical case of the analyzed distribution is binomial one when $p_1 = p_2 = \ldots = p_n = p$, that is, the case of coincidence of values $p_j$ for single bits from the list of descriptors. It means that the characteristic of the description is the value $p$. It is clear that, in such an idealized model, the different descriptions must have the different values $p$ to distinguish them.

Then the descriptor values provide a random vector of dimension $n$ with the parameter $p$ of occurrence of 1 in every single bit. The probability of occurrence of 1s in some specific sequence of 0s and 1s can be written as $C_n^k p^k (1 - p)^{n-k}$, where $C_n^k$ is a number of combinations. As we know, the binomial distribution is described by the parameters of mathematical expectation $M = np$ and variance $D = np(1-p)$. Values $M, D$ are the integral characteristics of the whole image and they can be directly applied in expression (3).

The threshold value $\delta_\beta$ for logic processing can be found by the fraction of the number of bits in the chain representation of the description, whose distributions have significantly different mathematical expectations according to the Z-criterion [3, 4]. For example, 75% of the bits of two test objects have significantly different mathematical expectations (i.e. 25% of them have no significant difference). We calculate the values of statistics $\beta_j$, $j = 1,\ldots,m$, rank the obtained values in ascending order, and reject the first 25%. The first remaining value is taken as the limit. Objects will be considered the different ones if at least 75% of the obtained statistic values $\beta_j$ exceed the threshold.

## 7 Experiments and results

We have performed a software modeling of the proposed classification technologies based on structural data description in C # Visual Studio 2017 using Open CV library tools [2-4, 27]. To conduct the investigation we took the images (Fig. 1) for which the structural descriptions were calculated using the BRISK detector (parameters s = 176, n = 512). Neighborhoods of KPs are shown in Fig. 1 as small rings. The first two images are visually similar to each other ("angel and demon"), which always causes difficulties in recognition even by human vision.

**Fig. 1.** Images with neighborhood of KPs

The calculated Manhattan distances $\rho(i,k)$ between statistical centers ($i,k$ - numbers of centers) for the images of Fig. 1 have the following values: $\rho(1,2) = 23$, $\rho(1,3) = 44$, $\rho(2,3) = 37$. Generally, it indicates a significant similarity between the values of the descriptions in the investigated feature space of SCs, since all values of distance in this example belong to the interval [0; 512]. The corresponding normalized values are $\rho^*(1,2) = 0.044$ , $\rho^*(1,3) = 0.085$ , $\rho^*(2,3) = 0.072$ . As we can see, even visually similar images in Fig. 1 can be distinguished by the value of the distance between the SCs.

Calculating the refined centers (2) on the basis of the threshold for half of the descriptors, we obtained: $\rho^*(1,2) = 0.052$ , $\rho^*(1,3) = 0.087$ , $\rho^*(2,3) = 0.076$ , therefore, the degree of differentiation between the SCs has obviously increased. This indicates a certain improvement in the effectiveness of classification.

The obtained number of votes for the elements of the etalons assigned to the corresponding class (Fig. 1) by comparing the distance between them and refined center with the boundary value is shown in Table 1.

**Table 1.** The number of classified elements in the description of etalons

| Class number | 1 | 2 | 3 |
|---|---|---|---|
| 1 | 44 | 29 | 11 |
| 2 | 36 | 44 | 20 |
| 3 | 32 | 27 | 44 |

As we can see, the number of votes on the diagonal of Table 1 is sufficiently greater than the values in the row and column, which confirms the effectiveness of the method when classifying the descriptors. The two visually similar images in Fig. 1 are also successfully differentiated. Thus, the formation of a concentrated subset (cluster) of the description using the refined SC with logical processing (2) provides effective classification.

The effectiveness of the application of nonparametric criterion (3) in the classification of visual objects was tested experimentally in the problem of distinguishing halftone silhouette images shown in Fig. 1. For each of the images, 500 ORB descriptors of dimension 256 have been generated. We can see that the images used in the experiment are visually similar to each other, which makes it possible to evaluate the sensitivity and performance of structural methods to distinguish such signals. It is clear that for significantly dissimilar images, recognition performance will be better.

Calculation of the criterion $\beta$ by the expression (3) for one-bit distributions of the first two similar images in Fig. 1 showed results which were quite close to the minimum value $\beta = 1$. All values for each of the 256 bits of the dataset were in the range 1.0–1.12. Choosing the threshold value $\delta_\beta = 1.006$ the necessary decision value $n_0 = 128$ (half of the total number of bits) is achieved. It means the ability to distinguish these essentially similar images in the constructed space of statistical features, which is based solely on the values of mathematical expectation and variance of data. Under the condition $\delta_\beta \geq 1.006$, these images are considered different by the proposed classification method. In Fig. 2 the curve 1 shows the dependence of the value $n_0$ on the threshold value $\delta_\beta$ .

The effect of impulse noise on the input image was also simulated: with a given probability p, the pixels of the image were changed by a randomly generated noise value in the range 0,…, 255 [1]. Experiments have shown that under the influence of impulse noise for images in Fig. 1 the curve of dependence of the number of equivalent bits $n_0$ required for statistical decision making on the threshold $\delta_\beta$ shifts to the right (Fig. 2, curve 2). Even for a significant noise value p = 0.7, each of the distorted images are recognized successfully by this measure when setting the threshold $\delta_\beta = 1.05$.

Software modeling has also shown that when calculating the criterion $\beta$ as a vector for substantially dissimilar images, a slightly higher threshold value should be set, for example, $\delta_\beta = 1.1$. It makes it possible to reliably identify each of the images in the experiment. The dependence of the value on the threshold value has the form shown in Fig. 2.

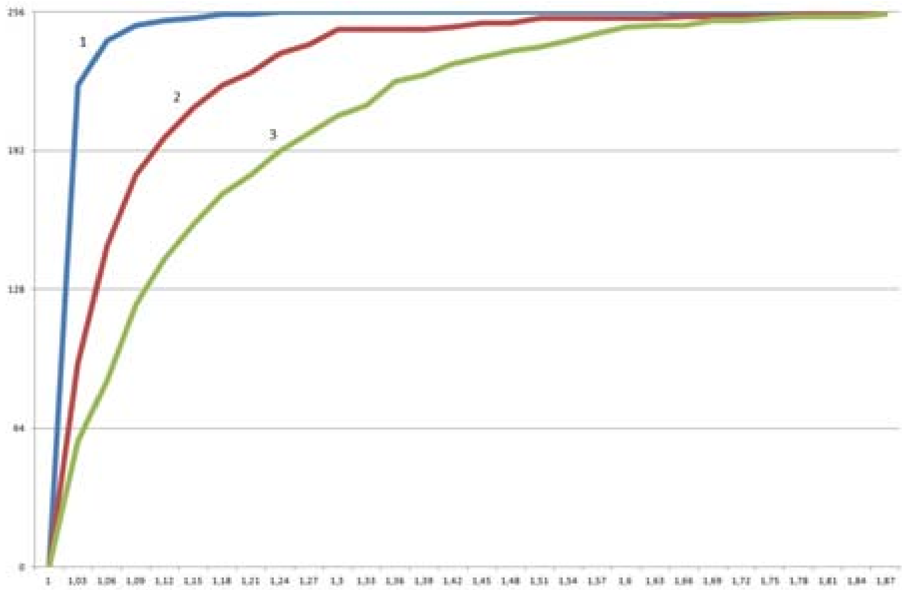


**Fig. 2.** Dependence of $n_0$ on threshold $\delta_\beta$: 1 - for similar images, 2 - for noise-affected images, 3 - for visually different images

As we can see from the obtained experimental results, effective classification actions of a logical plan with a threshold value $\delta_\beta$ for the analyzed images can only be performed in a quite small size range $\delta_\beta \in [1;1.1]$ (when choosing $n_0 = 128$). Obviously that closeness of $\delta_\beta$ to 1 is a criterion for identifying an etalon image among others, or when assigning a classified image to one of the etalons. In fact, the choice of the threshold value $\delta_\beta = 1.1$, as can be seen from Fig. 2, makes it possible to reliably identify each of the images analyzed in the experiment, including visually similar ones. The analysis of the results of the modeling showed that for an arbitrary set of images it is possible to set a common or individual threshold $\delta_\beta$ for each etalon, which gives an opportunity to classify the images to one of the etalons.

## 8 Conclusion

The statistic center and criterion (3) constructed in the paper are based on the evaluation of the properties of the bit structure formed on the data description, as they obtained by independent bitwise processing of a set of descriptors.

The formation of a concentrated subset in the form of clusters for description elements using a refined statistical center with logical processing provides a reduction in computational cost and effective classification by revealing significant patterns of description of the visual objects.

The use of nonparametric methods for the statistical analysis of descriptor bits using the mathematical expectation and variance makes it possible to classify even visually close images.

The scientific novelty of investigation is improvement of the methods of structural classification of images by introducing a statistical methods apparatus for a system of bit description, which facilitates the processing and enhancement of classification performance without reducing the efficiency.

The practical value of the paper is the developed mathematical and software models for the implementation of image classifiers in the computer vision.

The further development of the study is the creation of applications of multidimensional or block data structure based on set of bits.

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