Original Article

The Research of Image Classification Methods Based on the Introducing Cluster Representation Parameters for the Structural Description

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Abstract — *The results of the development of high-speed methods for classifying images in computer vision systems using the description as a set of keypoints descriptors are presented. Classification methods based on the system of cluster centers parameters, which are independently constructed for the etalon descriptors set, are researched. The competitive voting of the descriptors of the object being recognized on a set of etalon centers is proposed. An optimal way of comparing the sets of cluster centers for an object and etalons is applied. Experimental estimation of the efficiency for the two presented classification methods in terms of computation time and classification accuracy based on the results of applied dataset processing are shown. Based on the research, a conclusion about the effectiveness of classification technologies using cluster centers for structural descriptions of images to ensure decision-making in real-time is made.*

Keywords — *Computer Vision, Descriptor, Image Classification, Keypoint, ORB Detector.*

I. INTRODUCTION

Achieving high-performance indicators for classification methods in modern computer vision systems requires solving several pressing problems associated with the multidimensional nature of data [1]–[3].

When introducing structural methods of classification, descriptions of visual objects are presented as a set of keypoint (KP) descriptors – high-dimensional numerical vectors [4]–[7].

Descriptions with binary components using detectors ORB, BRISK [7], [8] contain 256 bits and 512 bits, respectively. The number of descriptors in the description reaches from 500 to 1500 elements. In such a situation, the transformation of the feature space by representing it as a cluster system significantly simplifies their application implementation [4], [9], [10]. The main tool, in this case, is

the apparatus of cluster data analysis, based on the establishment of metric relations on the set of description descriptors and the definition of groups close in value from the description of the object and etalons [9]–[11].

An important problem is the choice of models for establishing a correspondence between the parameters of the cluster representation of various descriptions [12], [13]. These parameters include the center of the cluster, which can be determined based on several approaches, the main of which are the median and modifications of the mean value [10], [11]. These researches are related to the direction of Content-Based Image Retrieval (CBIR) [14], [15] in the development of computer vision systems. This approach is aimed at introducing intelligent recognition technologies based on image content with a hierarchy of present information presentation [16]–[18]. The formation of a data description as a set of KP descriptors and a cluster representation of the description are means of generalization for the synthesis of high-level productive solutions [9]–[11], [14], [15].

The computational advantage of classification by a set of centers of description clusters in comparison with the traditional classification approach directly behind description descriptors is justified because instead of calculating the relevance of sets, relevance is determined based on their limited number of characteristics [19]–[21].

If the cardinality of the description from KP descriptors is from 200 to 300 (and sometimes up to 1000) elements, then the number of centers can be reduced to 2–10 elements of the same dimension.

Relevance is calculated by analyzing the volumetric set of etalons; in applied problems, it reaches values from 100 to 1500, therefore, the performed transformation significantly (thousands of times) reduces the amount of necessary calculations [4], [10]. Such acceleration necessitates the clustering of the data of the recognized object and some

reduction in the degree of fragmentation.

This is because of the formation and application of generalized characteristics – a set of centers of description. Here, the clustering of the etalon data of the dataset is performed at the preparatory stage and does not directly affects the performance of the classification [22], [23].

The processing process, where for each description it is necessary to form an independent system of clusters, can realize a detailed analysis of the information about the description of the etalon data [10]. Because of independent processing, it is possible to synthesize individual cluster centers for each etalon [24]. This approach will contribute to a deeper identification of differences and increase the efficiency of the classification.

In [10], [25], measures of similarity between a precedent and a situation are studied, which are given by a variety of factors, and in [5], models and the process of establishing relevance for spatial structures of features synthesized on a set of KPs are considered.

Strengthening the influence of individual factors as parameters of a system of independent clusters makes it possible to create an information system. The structure of the system assumes that the classification decision is made independently (and possibly in parallel) for each etalon by a committee. Each element is adapted only to its etalon image [15]. Recognition systems with an architecture that includes the selection of an optimal committee representative, because of independent and consistent assessment, as a rule, have applied efficiency [26]–[28].

The purpose of the paper is to research the effectiveness of varieties of the structural method of image classification based on the formation of cluster systems of features by introducing models to determine the relevance of the transformed descriptions using the voting and optimal comparison apparatus.

The tasks of the research are to process data models to calculate the relevance of descriptions based on the indicators of a cluster presentation, which is efficient in terms of data processing speed. And also the study of the effectiveness of implementing these models based on the results of an experimental evaluation of the proposed approaches for the applied image base.

II. CLUSTER REPRESENTATION MODEL IN THE SPACE OF FEATURES

Consider base E of descriptions of images of etalons with dimension $N : E = \{E_1, E_2, \ldots, E_N\}$. Each etalon description E_i represents a separate class in the recognition problem and has the form of a finite set of KP image descriptors: $E_i = \{e_v(i)\}_{v=1}^s$, where s is the number of KP descriptors in the description [4], [10].

Each descriptor $e_v(i)$ characterizes some neighborhood of the KP image and is an element of vector space R^n of finite

dimension $n : e_v(i) \in R^n$ with real, integer, or binary components. We consider the power of descriptions of etalons to be equivalent to simplify the analysis:

$$card(E_1) = card(E_2) = \ldots = card(E_N) = s . \qquad (1)$$

This condition can always be practically achieved by selecting elements from a set of larger sizes.

Let us apply the mapping $E \rightarrow T$ from the space of images (set of descriptors) to the set T of disjoint clusters formed according to some principle [9]–[11]. A cluster is a subset of the description. Each image of E_i etalons is now transformed to M of its non-intersecting $T_k(E_i)$ subsets:

$$E_i = T(E_i) = \cup_{k=1}^M T_k(E_i) , \ k = \overline{1, M} ,$$

$$T_k(E_i) \cap T_j(E_i) = \varnothing . \qquad (2)$$

For set $T_k(E_i)$ of the elements of each cluster, we determine its center parameter $b_{k,i}$, $k = \overline{1, M}$, which is the key characteristic of the constructed cluster system for the analyzed data. Note that clustering and centers $b_{k,i}$ can be determined based on a fairly wide variety of procedures [9]–[11], [14], [15], [24], [25].

Because of the cluster representation, we form image E_i of the etalon in the form of M disjoint subsets of clusters $T_k(E_i)$ with centers $b_{k,i}$, $M * N$ – the total number of created clusters and centers for the base of etalons.

The recognizable visual object is similarly described by a finite set $Z = \{z_v\}_{v=1}^s$, where $z_v \in Z$ are KP descriptors, $s = card\ Z$.

Similarly to the processing of etalons, we apply the cluster partition of the set Z through reflection $Z \rightarrow T$; as a result, the description of the object image will be represented by M clusters:

$$Z = T(Z) = \{T_k(Z)\}_{k=1}^M , \ T_k(Z) \cap T_j(Z) = \varnothing . \qquad (3)$$

For each cluster $T_k(Z)$, we define the parameters of centers $b_k(Z)$, which apply in the classification process. For simplicity, we consider the number of M clusters to be identical for the input image and etalons.

III. CLASSIFICATION BASED ON CLUSTER REPRESENTATION

Consider the classification of the type "object – etalon" based on the calculation of the relevance value of their structural descriptions [10], [24], [25].

Instead of a complete set of description elements, we will apply a sped up classification scheme based on the use of centers b_k of the system of clusters of an object and an etalon.

The determination of the relevance of the etalon-object is implemented as a comparison of the sets of the centers of the object and etalons with the subsequent determination of the most relevant representative among the etalons of the base.

Let us introduce some distance ρ in vector space R^n. An example can be the Euclidean or Manhattan distance, and in a binary vector space, the Hamming metric, which is more computationally efficient in terms of volume of calculations [5], [6].

Let's count $M \times M$ of all distances $\rho(T_{k_1}(Z), T_{k_2}(E_i))$, $k_1, k_2 \in [1,2,\ldots,M]$ between the cluster systems of etalons and the recognized object by calculating the distances $q = \rho(b_{k_1}(Z), b_{k_2}(E_i))$ between the elements of the sets of centers of the object and the i-th etalon and denote them as $\{q_a\}$, $a = 1,2,\ldots,M^2$. Based on the values of set $\{q_a\}$ using traditional approaches, we can calculate the distances between the sets: bond distance, nearest neighbor, farthest neighbor, Hausdorff, and others, or their many modifications associated with logical analysis or processing of values q_a [15], [24], [29]. The average bond distance here has the form

$$\rho_{av}(T_k(Z), T_k(E_i)) = \frac{1}{M^2} \sum_{a=1}^{M^2} q_a . \qquad (4)$$

One of the modifications for determining the distance is calculated by adding three minimum elements of the preliminary ranked sample $q^* = q_1 \leq q_2 \leq \ldots \leq q_{M^2}$ for the set of distances [10]:

$$\rho_{3m}(T_k(Z), T_k(E_i)) = \sum_{a=1}^{3} q_a^* . \qquad (5)$$

Distance (5) simultaneously possesses the properties of both differential and integral metrics.

It is obtained because of the addition of three independent minima.

As an alternative to (5), consider adding the nearest neighbor distances separately for each of the object centers

$$\rho_{NN}(T_k(Z), T_k(E_i)) = \sum_{a=1}^{M} \min_{j=1,\ldots,M} \rho(b_a(Z), b_j(E_i)) . \qquad (6)$$

Distance models (5), (6) do not guarantee that a single center of the etalon will correspond to an individual center of an object.

Determination of a center with such properties is based on the use of the Hungarian method for the optimal assignment

of the most acceptable center of the etalon to each center of the object [5], [30].

Let us apply the Hungarian method for the optimal establishment of a correspondence between two sets of cluster centers b_1, b_2. They were obtained for descriptions Z_1, Z_2 considering the possible influence of noise [31], which leads to deviations from their ideal values.

The result of introducing the Hungarian method is the formation of the maximum matching for the elements of two sets with the minimization of the total cost. It can be estimated as the sum of the distances between pairs of individual components in b_1, b_2. The comparison process is formally reduced to an optimization problem

$$R(x) = \sum_{i=1}^{M} \sum_{j=1}^{M} \rho(b_{1i}, b_{2j}) x_{ij} \to \min , \qquad (7)$$

where $b_{1i} \in b_1$; $b_{2j} \in b_2$; x_{ij} is a binary feature; $x_{ij} \in \{0,1\}$, which is 1 if the i-th and j-th elements match.

The solution of problem (7) with constraints on the uniqueness of the correspondence of features from the compared sets

$$\begin{cases} \sum_{j=1}^{M} x_{ij} = 1 \forall i = \overline{1,M}, \\ \sum_{i=1}^{M} x_{ij} = 1 \forall j = \overline{1,M} \end{cases} \qquad (8)$$

minimizes the total distance (7) between sets of centers b_1, b_2.

The total number of cluster centers in our task is small (3...5), optimal methods can be successfully applied with insignificant requirements for processing speed.

The showed generally accepted distances and expressions (5), (6) for the sets of vectors could be applied directly to descriptions E_i and Z, but with a much larger amount of computation.

Classification of an object according to description Z based on the calculated distances (4)–(6) between the centers of the data under consideration is carried out traditionally by determining the smallest value among the values for a variety of etalons

$$Z \to E_a : a = \arg \min_{i=1,\ldots,N} \rho(T_k(Z), T_k(E_i)) . \qquad (9)$$

An independent cluster representation for descriptions in the etalon dataset also helps to simplify the implementation of classification procedures of the "object descriptor – etalon" type relative to individual elements of the description

of the recognized object. This approach is more universal in ensuring that the potential effects of interference on the image and filtering are considered in the process of classifying the occurrence of false KPs caused by interference. Here, the clustering of the object description, as a rule, is not used (this also reduces the computational costs). Each object description descriptor finds "its etalon class" by competitive comparison with the generated set $\{b_j(E_i)\}$ of etalon centers.

For each object descriptor $z_v \in Z$ we determine the closest of all etalon centers $\{b_j(E_i)\}$ according to the nearest neighbor procedure

$$d = \arg\min_{i} \rho(z_v, b_j(E_i)), \quad d \in \{1,2,\ldots,N\}, \quad (10)$$

where ρ is the distance between the object descriptor and center $b_j(E_i)$; $i \in \{1,2,\ldots,N\}$; $j \in \{1,2,\ldots,M \times N\}$.

In fact, (10) implements the multivalued characteristic function $d: R^n \to \{1,2,\ldots,N\}$, which determines the etalon class by a separate descriptor from the object description.

According to the results (10) $\forall z_v \in Z$ the number of $r_1, r_2, \ldots, r_N$ votes of $z_v \in Z$, elements assigned to one center $\{b_j(E_i)\}$ of the description E_i is calculated:

$$r_i = \sum_{v=1}^{s} f[z_v \to \{b_j(E_i)\}], \quad (11)$$

where f is a logical function that determines the assignment of element z_v to the center with the number j of the cluster

of the etalon E_i.

The procedure for implementing function f to ensure filtering of interference should be based on the threshold value δ_f for the value of the minimum among the distances calculated to each of the available centers $\{b_j(E_i)\}$ clusters for all etalons [4], [10], [25], [32].

The object's image is classified according to the received values of $r_1, r_2, \ldots, r_N$ votes as

$$Z \to E_j : j = \arg\max_{i} r_i. \quad (12)$$

According to the classification (10)–(12), the input image will be referred to the etalon that will collect the largest number of votes of its KP descriptors.

IV. ANALYSIS OF COMPUTER SIMULATION RESULTS

The developed models of classifiers apply to the example of images of Pokemon [33]. The software environment was used – IntelliJ IDEA 2020 and IDLE with the means of the OpenCV library and the Java programming language [34], [35]. An illustration of the images is shown in Fig. 1. For modeling, ORB descriptors of dimension $n = 256$ are used.

Fig. 2 shows an example of the results of clustering an image into 3 clusters by the k-means method, where the colors show the coordinates of the descriptors from different clusters. You can see that the elements within the existing clusters have common properties. For example, almost all contour points are assigned to one cluster (blue).
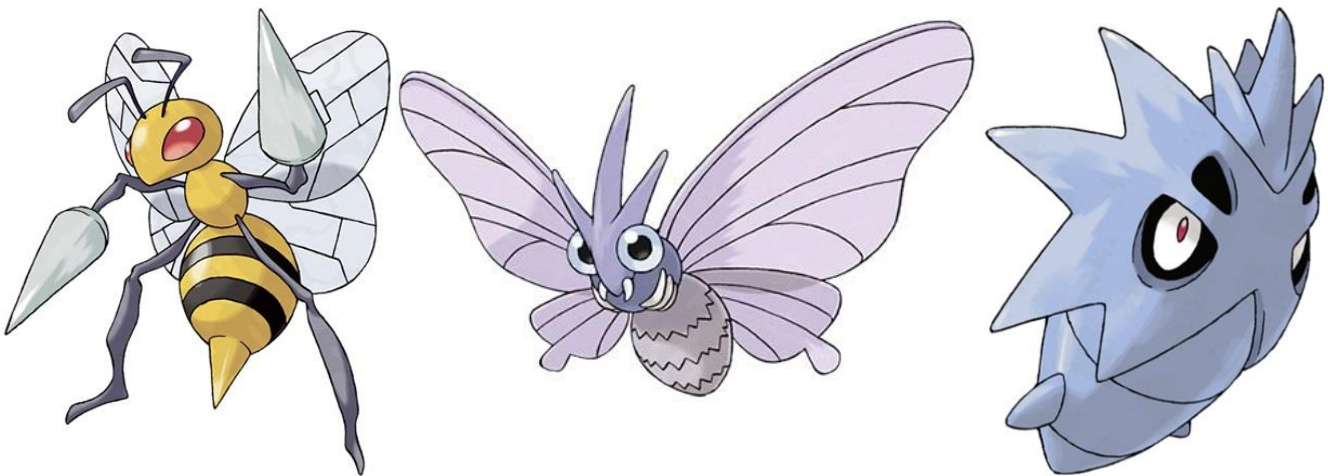

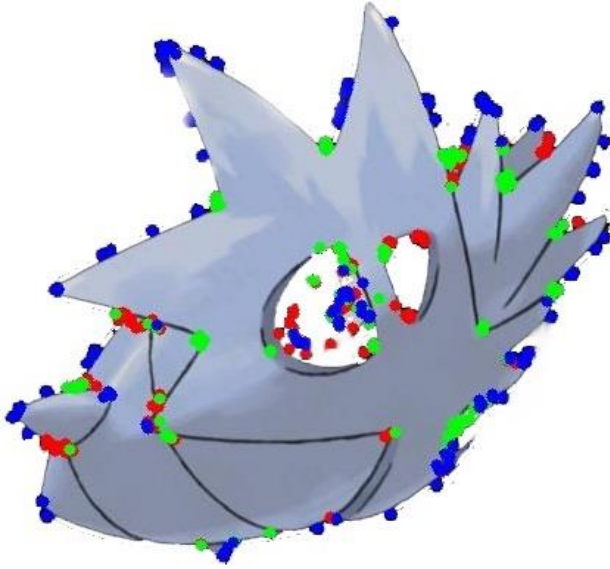**Fig. 1 Examples of analyzed images**

Fig. 2 Clustering result for 3 clusters

The essence of software modeling was reduced to the applied implementation of two types of classifiers:

– Using voting descriptors (10)–(12);

– Based on the establishment of the optimal ratio between the centers of the clusters (7)–(9).

The first method implements the principle of classification "object descriptor – etalon", and the second – "object – etalon". They base both approaches on an independent cluster system formed for each of the etalons.

The classification was carried out according to the scheme when a set of descriptors (the first method) or a set of centers of the cluster representation of one etalon (the second method) were compared with the set of centers of clusters for 10 etalons from the base [24], [33], [36]. Variants of descriptions with ORB descriptors of 300 KP, 500 KP, 1000 KP, and 1500 KP were considered. The results of calculating the normalized number of votes (in percent) for the input images Fig. 1 (etalons No. 3, No. 5, No. 6) on a set of 10 etalons at $s = 500$ are shown in Table 1. The resulting maxima are highlighted with a marker in Table 1.

The first method successfully classifies the input images, and the advantage of the maximum over the nearest value in the line (other base images) is quite confident of all input images. Experiments have shown that for the selected base of etalons, the number of used KP descriptors practically does not affect the result. For all considered quantities (300, 500, 1000, 1500) of KP, it obtained similar indicators.

The integrated representation of the descriptions of the etalon base can explain this as fixed sets of cluster centers.

The results of a classification in the value's form of the shortest distance using the second approach based on the Hungarian method to determine the optimal matching between the centers of the clusters of the input image Fig. 1 (etalon No. 3, No. 5, No. 6) and an etalon (etalons No. 1–No. 10) for 500 KPs are shown in Table 2. To describe the input image, clustering was repeated, otherwise, the result would have been predicted because of the complete coincidence of centers. The resulting minima are highlighted with a marker in Table 2.

Based on the simulation results, we see a confident classification for the considered etalons. The value of the shortest distance calculated according to the Hungarian method is significantly less compared to other etalons. Here, the etalon No. 6 is classified the best (third row of Table 2).

Table 1. Classification results by the first method

Input images	Etalons									
	1	2	3	4	5	6	7	8	9	10
3	7.4	8.8	23.8	9.6	12.6	7	6.8	9.4	6.6	8
5	11	9.8	10.2	7.2	29.8	9.2	3.8	5.8	3.2	10
6	9.6	9.8	8.2	12	9.4	26	6.6	4.8	5.6	8

Table 2. Classification results by the second method

Input images	Etalons									
	1	2	3	4	5	6	7	8	9	10
3	212	230	133	242	201	197	224	193	179	198
5	248	182	227	276	133	221	238	193	199	214
6	232	196	227	248	211	49	212	213	183	106

Analysis of experimental data (Tables 1 and 2) for the considered base of etalons shows a more confident classification by the first method compared to the second method. This can be explained by a more detailed analysis of the data components in the first method. It bases the second method solely on the integral characteristics of descriptions based on the results of clustering. Experiments have confirmed the possibility of effective applied application of optimal mathematical approaches (Hungarian method) for problems where data are presented in a concentrated cluster form. Direct application of these methods to input data as several hundred descriptor vectors is impossible because of implementation time constraints.

Based on the results of software modeling, it estimated the amount of time for implementing the considered methods. It devotes the major part of the program to the search and description of KPs using the ORB detector of the Open CV library [8], [36]. The parameter of the number of KPs does not significantly affect the speed of the second method (this is its advantage); it is determined solely by the number of clusters [37], [38]. With an increase in the number of KPs, the implementation time of the first method increases uncritically. The implementation time for one act of classification for both methods ranged from 1.1–1.5 seconds for the studied image data, the number of KP scans, the clustering method, and the hardware used.

V. CONCLUSIONS

Introducing a cluster representation on a set of description descriptors helps to improve the temporal characteristics of the classification through the use of cluster centers with the provision of the required level of performance.

Analysis and processing of grouped data make it possible to form a hierarchical structure with a variable parameter of detail and to identify properties of the image description that are significant for classification.

The contribution of the research lies in improving the method of structural classification of images by the description as a set of descriptors of keypoints based on introducing independent cluster data structures for etalons and the use of their parameters for classification.

Practical recommendations for this research are the effective use of integrated features for groups of image description descriptors, including the optimal adoption of a classification decision.

The practical significance of the work:

– Improving performance when calculating the relevance of images and classification;

– Confirmation of the effectiveness of the proposed feature models on the examples of images;

– Development of applied software models for research and implementation of classification methods in computer vision systems.

Research prospects may be associated with a deeper study of the scope and conditions for the application of the classification types "object descriptor – etalon" and "object – etalon".

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