



Discriminative outlines parts for shape retrieval [☆]



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ABSTRACT

In this paper we propose a new method for shape retrieval using only discriminative parts which are sufficient for the recognition of many objects and their classes. The discriminative outline shape is firstly determined by performing psycho-visual tests and then described with geometric attributes of high curvature points located along the outline. This obtained description is invariant to scale change, rotation, mirroring and deformation. To study the performance of our approach, global approach which deals with the whole contour and partial approach which is based on the discriminative part are compared. Experiments conducted on our data set and a selection of MPEG-7 dataset demonstrated the usefulness of this approach and the results obtained are presented and discussed.

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1. Introduction

This work is made by inspiring from human behavior when recognizing some objects without having the whole details of their forms. Indeed, several studies [17–19] have shown that when people look at objects, they often spontaneously segment them into parts. Our interest concerns the particular parts which allow the identification of the remaining parts by deduction. In this case, the visual perception captures the most important characteristic features of the shape to infer an initial recognition and so, details are added to complete the recognition task [1–3,34].

Our interest is to deal particular parts which allow the object identification by abstracting the remaining parts. In order to locate these parts, psycho-visual tests have been conducted on a sample of persons from different profiles by giving them some partial images of familiar object (cat, bottle, bird, hammer). When images contain discriminant parts, people recognize these objects easily in spite of incomplete information on the shape (see Fig. 1). However, when the same test is achieved with other parts of the same sample of images, the recognition was ambiguous in certain cases and impossible in others. This is the key idea of our work, thus, our approach will concern:

- determining the discriminative part,
- description of the discriminative parts such that will be invariant to translation, rotation and scale change,
- shape retrieval based on the discriminative part.

The paper is structured as follows. In Section 3, we present our method for the selection of discriminative parts of shapes. Section 4 is devoted to outline shape description. Based on this description, we show in Section 5 how to achieve the matching process and particularly when discriminative part is used. Finally, results of experiments are presented and discussed.

2. Previous work

Shape recognition problem is considered as an active field in computer vision; it has seen rapid progress in recent years. Several methods have been proposed and the challenge is to recognize a large number of shapes without compromising effectiveness and efficiency of the results. Many of these methods use shape boundary to achieve shape matching and retrieval. A well known 2D shape representation is the curvature scale space (CSS) [4] selected as the standard object contour-based shape descriptor for MPEG-7 [5]. However, the CSS representation has two drawbacks: First, it tends to diffuse the effects of a feature far away from its location as coarser scales are considered. This may be undesirable if such features have perceptual significance. Second, it is computationally expensive, therefore an optimization of the method is proposed in [6] including a set of marginal-sum features summarizing the CSS

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Fig. 1. Psycho-visual test: First row: Discriminative parts, Second row: Insignificant parts of objects, Third row: The selected Objects.

image. The main contribution focused on execution efficiency and invariance to rotation and reflection.

Adamek and O'Connor [7] proposed an efficient algorithm (MCC) for shape representation invariant to several kinds of transformations including some articulations and modest occlusions. The optimal matching of two shape representations is achieved using dynamic programming. The MCC achieved 84.9% retrieval accuracy on the MPEG-7 data set. However, it is computationally expensive $O(N^3)$.

In [8], Belongie et al. considered a shape as a set of reference points represented by the shape context descriptor. A shape context at a reference point captures the distribution of the remaining points relative to it. A much faster algorithm was proposed in [9], the authors used the shape context of a particular reference points corresponding to the end points of the shape skeleton. The reported results on MPEG-7 data set is 79.92%.

A representation using areas of triangles formed by the boundary points to measure the convexity/concavity of each point at different scales is proposed in [10] and optimized in [23]. The method captures both local and global characteristics of shape. The matching is achieved using dynamic space warping. The method reported high accuracy in shape retrieval but a high cost too.

Inspired by some perceptually human customs, the authors of [31] exploit two properties in the shape retrieval and recognition problems. The first one is that, people would tend to neglect small deformation of the shape and only use the main structure of the shape for retrieval. Second, if the shape consists of main structure and inward parts, people would tend to neglect the inward parts and only regard the shape as the main structure. To model these customs, the authors use the two morphological operators, dilation and erosion with an adequate number of iterations to fill the gaps representing small details of the shape. The proposed representation is applied to improve the retrieval performances of a popular shape matching method named Inner-Distance Shape Contexts (IDSC) [32], and then the Locally Constrained Diffusion Process (LCDP) method [33] is exploited to further enhance the retrieval performance. The authors reported a retrieval rate of 98.56% on MPEG-7 dataset.

Daliri and Torre proposed in [29,30] an approach to object classification. They represent a shape using a string of symbols describing each point of the contour by the attributes: distance and angle. The point-to-point matching is evaluated by the shape context [8] and the alignment of two shapes is achieved by

dynamic programming. After, each contour is transformed into a string of symbols and the edit distance is used to compute the similarity between strings of symbols. The recognition is obtained by the nearest-neighbor procedure [30] and a learning-based algorithm using SVM [29]. The method reported high accuracy, but has high complexity too, since it involves all contour points and uses expensive matching method (shape context), added to the starting point problem.

The majority of shape recognition methods match the whole query descriptor to the database shape descriptors, which leads to difficulties in handling the problem of major deformation of some parts. There are some relevant works dealing with partial matching:

- Bai et al. [28] address the following problem: Given a significant part of a contour shape as a query, the goal is to find similar shapes containing the query part, by solving three problems: length problem, scale problem, and distortion problem. The performance of the proposed approach depends strongly on the key points positioning. The authors assumes that the contour query exists in their database. Therefore, to handle small misalignment of parts of contour segments, a shape similarity measure based on shape context [8] is used.
- Chen et al. [35] propose a local shape matching method based on the Smith–Waterman algorithm to efficiently find similar parts of two shapes without requiring exhaustive search for all possible parts.

Authors in [37] use particle filters to establish perceptually correct correspondences between point sets characterizing shapes. Ten parts of shapes of different classes from the MPEG-7 data set are used as queries. Each part is matched to the entire database (all 1400 shapes), based on the PF correspondence and Procrustes Alignment.

A novel efficient partial shape matching is proposed in [38]. Authors use sampled points from the silhouette as a shape representation. Retrieval results on MPEG depend on the number of sampled points.

Authors in [36] proposed a method for the extraction of discriminative parts in order to achieve shape matching whatever the errors in image segmentation.

In [39], a learning based shape descriptor for shape matching is demonstrated. Formulated in a Bag-of-Words (BoW) like framework, the proposed method summarizes the local features extracted

from certain shape to generate an integrated representation. The experiments conducted do not take the parts of shapes as queries.

In our approach, we propose a solution to this problem under the following constraint: the considered objects have some features on their boundary contour, discriminating them from other objects. These discriminative parts correspond to open curves extracted from the entire shape curve. Obviously, the recognition is possible only when these parts are visible in the query shape. Therefore, shape classes are denoted by the corresponding discriminative parts and the matching problem consists to extract first, the discriminative part of the query shape and submit it to partial matching with all shapes of the data set.

A method for shape representation and matching based on quasi invariant features associated to corner points located along the shape outline is then proposed. This representation is used in a second phase in visual recognition of particular objects having a discriminative part. The matching of two shapes consists to establish the optimal correspondences of features associated to corner points.

The main contributions of this paper are:

- Psycho-visual tests for selecting discriminative parts for each class of objects for recognition. The experiments are conducted in order to select the useful parts for recognition.
- Textual Description of partial outline shape.
- A method for achieving shape retrieval based on discriminative parts with low complexity and handling the occlusion problem or deformation for shape retrieval.

3. Discriminative parts of shapes

3.1. Notion of discriminative in the state of the art

The notion of discriminative has been used in some recent works.

In [41], authors study the importance of the visual shape for recognizing objects. They claim also that there is a large consensus that human vision represent shapes in terms of component parts and their relationships.

Authors in [40] discuss several geometric factors that determine how human vision parses shapes into parts, and determines their perceived salience. They have also reviewed evidence suggesting that part segmentation is carried out rapidly and early in visual processing, and that the allocation of visual attention to objects can be part-based.

To recognize actions using any two consecutive frames of an action video, two perceptually important features, the optical flows and Canny edges are employed [24]. Each feature alone may have weak discrimination power. However, the combination of the two cues can exhibit distinctive stable semantic characteristics. These features are extracted within local patches, the mean orientation of the optical flow and Canny edge features is adopted. A feature is considered to be discriminative, if it satisfies the following property: their occurrence frequency is high in the target action class but low in other classes [24].

Articulated configuration of human body parts for effective action classification are studied and from daily observation, some typical poses in each action class, which can describe the action very well are found [25]. Additionally, these poses often occur with high frequency while any subject performs the action. Therefore these poses, are considered as discriminative and representative of the action class. Very often one can recognize an action class by just observing a local pose, for example, a pose of a leg or an arm when other parts of the human body are occluded.

Appearance descriptors and shape descriptors are combined using discriminative learning for 3D human pose estimation [26].

Neither shape nor appearance features are self-sufficient for a robust estimation of human poses, they have the potential to complement each other because one may not be sensitive to conditions that affect the other.

Discriminative features are also used in image analysis. Discriminative visual features to image classification and retrieval are proposed by extracting the SIFT features from the foreground image [27]. The selected discriminative features are common to each category and they improve the category specific information by means of the classification performance.

In this work, we are interested to study the role of some important parts of outline shape for the achievement of object recognition.

3.2. Definition

A part of outline shape is discriminative if:

- it allows the recognition of the corresponding object without ambiguity,
- it changes weakly in the different object instances,
- it allows to infer the corresponding object even if there is a missing of other parts,
- it rarely occurs in the other object classes.

The discriminative outline part may be common to a class of objects. Fig. 2 illustrates two discriminative outline parts of two objects.

Generally, the discriminative part has the same form for all objects of a given class. However in some object classes it changes from an instance to another. For example, for birds, if we assume that the discriminative part is the beak (Fig. 3), in the same class, the beaks of a canary, a parrot or a flamingo are not the same. Therefore, we take into account these specificities and we model the different discriminative parts.

3.3. Locating

Automatic locating discriminative parts has been studied and many approaches have been proposed. The most relevant approach [28] is based on the assumption that the instability of the position of critical points is marginal and then makes a *strong* assumption that the displacement of most of the critical points is small. A high number of parts must constitute the database which is another disadvantage.

Our aim in this work is:

- to reduce the number of representative parts and to consider only some parts of each class of objects,
- to describe the representative parts such that the position of critical point does not influence in the retrieval step.

We consider in this work only objects having a discriminative outline part distinguishing them from the other classes. To determine recognizable object set, we perform psycho visual tests on a sample of people. The test consists to show the assumed discriminative outline part of the object and hide the remained shape and ask people to guess the identification. If the majority of responses confirm the hypothesis, we add this object to our object database models. Otherwise, the supposed part is not discriminative, so we eliminate the object from the set of recognizable objects.

Experiments have been conducted on a sample of 30 persons from different profiles: gender, age, study degree, and separated into 3 groups. Shapes are selected from our dataset and decomposed into visual parts. Three sets are created by regrouping different parts of shapes so that inference of parts from the same shape is made more difficult to the subjects.



Fig. 2. Example of discriminative outline parts (in blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



Fig. 3. Two discriminative parts for the same bird class.

Table 1
First sample of made experiments.

The shape and Outline	Part of the shape	Recognition rate	Non Recognition rate	Ambiguity rate
		100%	0%	0%
		20%	70%	10%
		40%	0%	60%
		30%	70%	0%

Table 2
Second sample of made experiments.

The shape and Outline	Part of the shape	Recognition rate	Non Recognition rate	Ambiguity rate
		100%	0%	0%
		10%	80%	10%
		0%	50%	50%

Tables 1–3 address sample of results obtained for this stage. For each part of object which has been shown to subjects, we give the number of persons having identified correctly the object, non identified, or had ambiguity for identification (no response is given or many responses are given).

3.4. Discussion

From these tests, we can assert that human may visually recognize objects seeing only the supposed discriminative part of the form. In fact, among the performed experiences, discriminative

Table 3
Third sample of made experiments.

The shape and Outline	Part of the shape	Number of subjects	Recognition rate	Ambiguity rate
		100%	0%	0%
		30%	40%	30%
		50%	0%	50%
		0%	70%	30%

parts of shapes are sufficient for shape retrieval. In other side, this is useful because this will decrease the complexity of shape retrieval and handle the occlusion problem or deformation.

4. Outline shape description

In a previous work [11], we have proposed a representation of outline shapes that decomposes a shape into hierarchical parts obtained by a sweeping of the shape following the direction of the length of the rectangle of minimum area encompassing it. The resulting representation is a global descriptor which gives topological information about the shape and local descriptor that describes geometric attributes of the part boundaries.

Inspired from this representation, in the present work, we decompose the outline shape into elementary contours by means of curvature points in a circular direction. Quasi-invariant attributes (angle, relative length) are associated to the junctions of these elementary contours. We assume that shapes have already been extracted from images in the form of closed contours. Automatic shape extraction from images is outside the scope of this paper.

Chetverikov algorithm [12] is used again to locate curvature points. This method depends on two parameters: an angle α and a distance d whose values are set empirically to $(150^\circ, 5 \text{ pixels})$ giving the best location of curvature points along shape contours. However, applying these values to several kinds of shapes (smooth, sharp, polygonal contours) we can get two kinds of points:

- superfluous points: generation of points which don't represent a true curvature,
- missing points: important curvature points are not detected.

To locate all significant curvature points independently of the parameters values, we first apply the Chetverikov's method using values of the parameters (α, d) that give a maximum number of points (even if we generate superfluous points). Then we eliminate unwanted ones by introducing a third parameter which corresponds to the angle (β) between three successive curvature points. Only curvature points for which the angle β is less than a given threshold are considered. The result of this application is illustrated by Fig. 4.

Once curvature points are located, the contour is partitioned into elementary contours by means of these points. Each curvature point is described by three parameters: (degree of concavity or convexity, angle, relative length) (see Fig. 5):

- Degree of concavity or convexity d_i of the curve defined by the current curvature point and the next one: Is computed as the ratio of r and the distance of the correspondent chord of the curve, where r is the maximum of distances from points on the curve to the associated chord. In case of concave resp. convex segments, this attribute takes a negative resp. positive value, obviously when the segment is a line the degree of concavity or convexity is zero. The sign is added here to r in order to distinguish the concave from the convex curve.
- Angle: Is the internal angle a_i formed by three successive curvature points (the considered point, its predecessor and its successor). The value considered is normalized and then divided by 2π .
- Relative length: is the ratio l_i of the lengths of the segments defined by (current point and the previous one) and (current point and the next one).

The description of the outline shape having n curvature points is obtained as a grouping of all curvature points descriptors represented by the quasi-invariant attributes (convexity, angle, relative length) and will have the following expression:

$$D = \{(d_0, a_0, l_0), (d_1, a_1, l_1), \dots, (d_{n-1}, a_{n-1}, l_{n-1})\}$$

To compute the descriptor of the outline shape illustrated by Fig. 6, we start from the point P_0 and for all 12 curvature points, three attributes are computed. The result is given by:

- (0.15, 0.16, 1.13), (0.14, 0.43, 0.42), (0.08, 0.47, 54), (0.07, 0.65, 5.89),
 (0.24, 0.21, 0.61), (0, 0.36, 1.90), (0.69, 0.31, 0.11), (0.08, 0.49, 4.18),
 (0.20, 0.46, 1.26), (0, 0.16, 0.97), (0.11, 0.62, 0.84), (0, 0.62, 1.14).

4.1. Properties of the description

4.1.1. Invariance of the description to affine transformations

Scale change:

Let C be a contour of shape with the descriptor D . We assume now that the shape is scaled. The descriptor is obtained using the curvature points P_i located with Chetverikov's algorithm. Down-

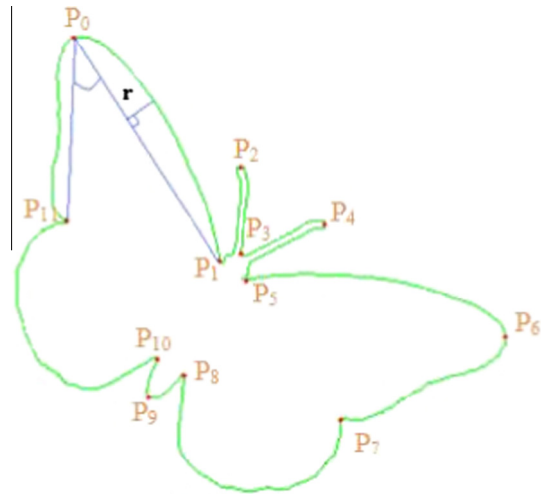


Fig. 5. Geometric attributes of the shape contour: ($r, \text{angle}(P_{11}P_0P_1), P_{11}P_0/P_0P_1$).

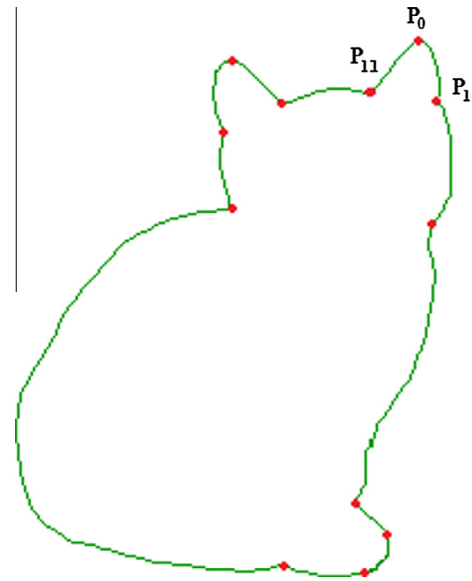


Fig. 6. Example of shape contour and located curvature points.

scaling a shape will remain all curvature points, and their location will be achieved in the same way. However, when the size of the shape becomes very small, the distance d used in the algorithm of Chetverikov must be set to a new value regarding the scale. This exception is valid for any other descriptor. The scaling up of the shape will give the same descriptor (see Fig. 7).

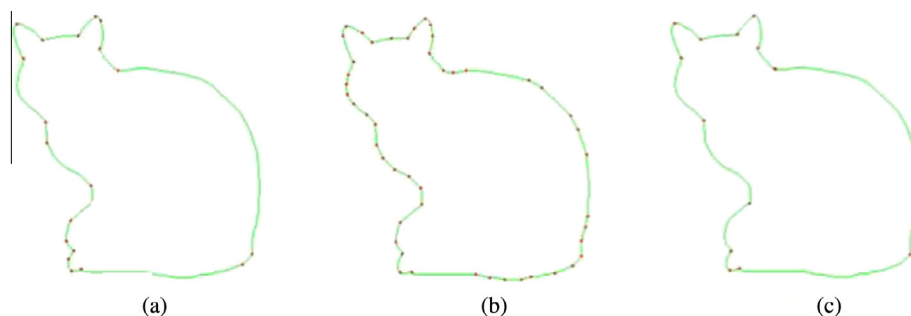


Fig. 4. Curvature point located using Chetverikov algorithm for (a) $\alpha = 150^\circ, d = 5$ pixels, (b) with $\alpha = 170^\circ, d = 7$ pixels, the maximum number of points are generated, (c) refinement of Chetverikovs algorithm with $\beta = 140^\circ$ and then superfluous points are eliminated.

Translation, Rotation, Reflection:

These properties are trivial because all values (d_i, a_i, l_i) are computed as ratios (see Fig. 8).

Optimized description

Any shape is described using structured file easy for storing and indexing.

5. Shape matching

The proposed shape descriptor based boundary, is as a cyclic sequence of curvature points descriptors. To align two shape representations, the starting points must be matched. This requires to define a unique starting point for each shape, which is not practically possible because feature vectors of similar objects may differ due to small deformations.

In order to solve this problem, one feature vector is taken as a reference, and the second feature vector is shifted considering different feature values. For each shift, the distance between the two vectors is computed. The minimum value of this distance is considered for the matching. In our approach, the similarity measure is defined at two levels: similarity between curvature points and similarity between two shape descriptors.

5.1. Curvature similarity measure

Similarity $S(C_i, C_j)$ between two curvature points C_i, C_j of two shapes (S_Q, S_M) is defined as the Euclidean distance given by the Eq. (1):

$$S(C_i, C_j) = |d_i - d_j| + |a_i - a_j| + |l_i - l_j| \tag{1}$$

where

- i, j are two elementary contours of shapes S_Q and S_M ,
- d_i, d_j are the convexity or concavity degrees of the curvature points C_i, C_j ,
- a_i, a_j are relative angles associated to the curvature points C_i, C_j ,
- l_i, l_j are the relative lengths associated to the curvature points C_i, C_j .

The point to point matching process may leads to erroneous result due to some deformation adding or missing some curvature

points in the same region. Therefore, we have introduced the neighboring notion in the curvature points matching.

As we have to shift the shape having the minimum number of curvature points considering the other one as a reference, for curvature point C_i of the shifted shape S_Q we establish the correspondences with C_{j+k}, C_{j-k} , where C_j is the corresponding curvature point of the shape S_M and k is the number of neighbors. Therefore, C_i is matched to the nearest candidate having the smallest matching cost. In this case the elementary distance between two curvature points is called the neighboring distance N_d defined by:

$$N_d(C_i, C_j) = \min\{S(C_i, C_j), j = i - k \dots i + k\} \tag{2}$$

5.2. Global similarity measure

To match two feature sets with difference in the set sizes, different solutions are possible. In [13], the shape curve is sampled with a compact set of points, dummy points are added to each set in order to establish a point to point matching.

Another solution consists to normalize the size of the two feature sets to a given value. For example, in [14], the authors proposed an alternative shape modeling based on the CSS representation in which, the matching of the transformed CSS image feature is achieved after a phase normalization transform. The dimension of resulting feature space is reduced via subspace projection methods.

In our case, we call global similarity S^g , the distance between two shapes based on the distance between their curvature points. Let S_Q, S_M be two shapes with respectively n, m curvature points respectively. Since the similarity measure is defined for a pair of curvature points, the global similarity for a given shift j , $S_j^g(S_Q, S_M)$ is computed as follow:

$$S_j^g(S_Q, S_M) = \sum_{i=1}^{\min(n,m)} |N_d(C_i, C_j)| + \delta, \tag{3}$$

$$\delta = |n - m| * avg|N_d(S_i, S_j)|, i = 1 \dots \min(n, m) \tag{4}$$

The global similarity is defined as the sum of two terms: the first one is the distance resulting from the mapping of two elementary contours sets having the same size. We map the smallest shape $(Min(n, m))$ to the other one. However, the second term expresses the unmapped contours, so to penalize them, we define this term by the number of remaining contours multiplied by the average value of neighboring distance computed over all matched contours.

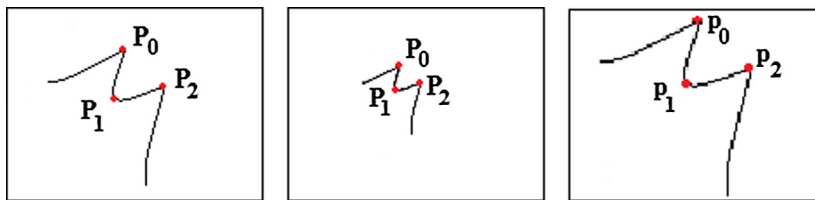


Fig. 7. From left to right: Initial part of shape, the down-scaled part to 50%, the up-scaled part to 130%.

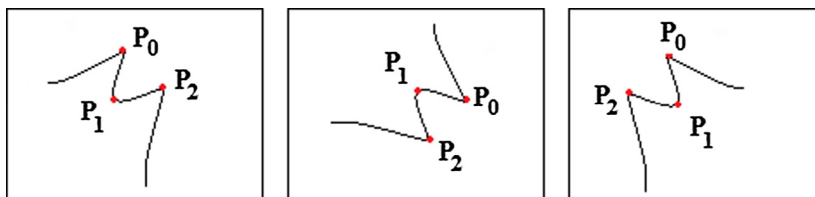


Fig. 8. From left to right: Initial part of shape, the rotated part, the reflected part.

This manner to calculate the matching cost implies that if we are comparing two shapes having similar form but not the same number of points, the matching cost will not be increased considerably by adding the second term, since the point to point cost is cheap. However if the two shapes are dissimilar, the unmapped points will inherit from the matching cost of the mapped ones, this will discard this shape from the top retrieved results.

5.3. Matching process

As a result, the matching of a shape query S_Q and a set of shapes $(S_{M_1}, \dots, S_{M_p})$ consists to compute for each pair (S_Q, S_{M_i}) , $i = 1 \dots p$, the global similarity $S_j^g(S_Q, S_{M_i})$, where j denotes the number of shifts.

At this level, we compute the distance between the two shapes at each shifting. So, we have to find the best matching which produces the minimum value for the computed distance. We define $S^{g^*}(S_Q, S_{M_i})$ as the minimal global similarity of a pair of shapes (S_Q, S_{M_i}) , computed as the smallest value of $S_j^g(S_Q, S_{M_i})$ from all possible shifts, as follow:

$$S^{g^*}(S_Q, S_{M_i}) = \min_j S_j^g(S_Q, S_{M_i}), j = 1 \dots \text{Min}(n, m) \quad (5)$$

where j is the number of shifts which corresponds to the minimum number of curvature points of (S_Q, S_{M_i}) . Therefore, to find the best matching between the query shape and the whole database, the minimal global similarity of the query and each entry is computed and the matching results are ranked according to this similarity measure. The most similar shapes to S_Q are those having the smallest values of S^{g^*} .

5.4. Learning

As the discriminative part of an object class changes very weakly from an instance to another and is invariant to scale change and rotation, we reduced the number of training images from 3 to 6 images per class (see Fig. 9). Unlike to other methods for which the running time of the learning process is very important, our method builds models instantaneously thanks to its invariance, therefore it improves the performance of the learning stage.

To build our models which denote a set of classes, we have to extract the corresponding discriminative parts. To do this, we take a sample of images of the same class, where the discriminative part is visible. Then, for each image, we locate curvature points along the outline shape, and we calculate the corresponding descriptor.

The discriminative part associated to the object class corresponds to the common part of all computed descriptors. Therefore, we define the common part of two shapes as the most similar longest curve (continuous curve) along the two shapes contour. Similar curves means that for each pair of curvature points, the neighboring distance is less than a certain threshold.

Finally, the discriminative part associated to the class model is an open curve composed of a sequence of curvature points, such as their geometric attributes are the average values of the corresponding attributes of the training shapes. Therefore, our database models is a set of descriptors denoting discriminative parts associated to our recognizable objects.



Fig. 9. Training images of cat.

5.5. Discriminative part matching

In this stage, we predict the presence/absence of an instance of modeled classes in the test image. We can formulate this problem as the response to the following question: does a modeled object X correspond to the query image? To answer to this question, we have to develop a new matching algorithm, because in previous section, we match whole shapes, so we have to calculate the distance between a query shape and the database shapes, and rank the resulting answers according to the similarity measure defined in formula (5). In this case, the top results may be visually similar to the query, or may be very dissimilar (the query class doesn't appear in the database). However, when we talk about matching discriminative parts (models) to the query shape, we have to find a sequence of curvature points in the query similar to the discriminative sequence of the model. Therefore, we have to check for each model entry in the database models, if the corresponding discriminative part descriptor is similar to a part of the query descriptor.

Let be D_s a discriminative part with n elementary contours (an open curve) associated to a given class Cl and S_Q a query shape with m curvature points. Both S_Q and D_s are represented by the descriptors detailed in Section 4. To check if D_s could be matched to a part of S_Q , we have to shift D_s along S_Q boundaries until a match will be found. We can say that D_s belongs to S_Q (S_Q is an instance of class Cl) if for each mapped pair of curvature points, the neighboring distance defined in Eq. (2) is less than a threshold T . The matching algorithm is presented below:

Algorithm: Model Matching

```

DB: database models with  $p$  models
 $S_Q$ : query shape with  $m$  elementary contours
Begin
  matched = false;
  For ( $k = 1$ ;  $k \leq p$ ;  $k++$ )
  Do
     $D_s$ : discriminative part of class  $Cl_k$  having  $n$  curvature
    points
    For ( $i = 1$ ;  $i \leq m$ ;  $i++$ ) Do
       $j = 1$ ;
      While ( $j \leq n$ ) and ( $N_d(C_i, C_j) < T$ ) Do
         $j++$ ;
      If  $j > n$  then matched = true;  $Cl(S_Q) = k$ ; break;
    EndIf;
  EndFor;
  If matched = true then  $S_Q \in Cl(S_Q)$  else  $S_Q \notin DB$ 
  EndIf;
EndFor
End

```

5.6. Partial shape matching

The model matching stage let us know if the query shape belongs to the modeled classes. If the response is yes, the discriminative part is located along the query contour. Therefore, in the retrieval step, the query is first submitted to model matching process, then the extracted open curve corresponding to the

discriminative part will be submitted to the shape matching with the dataset images. The matching consists to map the discriminative part of the query to the most similar open curve of the dataset shapes, and then retrieves in the top responses, shapes having the smallest matching cost.

To establish the similarity measure between two open curves, we adopt the same principle as in formula (3). However, since we deal with open curves, the size (number of points) of the whole shape doesn't have any impact on the matching, because we look for the most similar part common to both the dataset shape and the discriminative part of the query. So, anyway the two parts should have the same size. The partial similarity S^p will concerns

the query part P_Q (with n points) and a shape part P_S , for a given shift j is given by:

$$S^p(P_Q, P_S) = \sum_{i=1}^n |N^d(C_i(P_Q), C_i(P_S))| \tag{6}$$

In the same way the minimal partial similarity between a query part P_Q and a shape S (with m points) is given by:

$$S^{ps}(P_Q, S) = n S_j^p(P_Q, P_S), j = 1 \dots \min(n, m), P_S \in S \tag{7}$$

Therefore, to retrieve the most similar shapes to a query, we use the following algorithm:

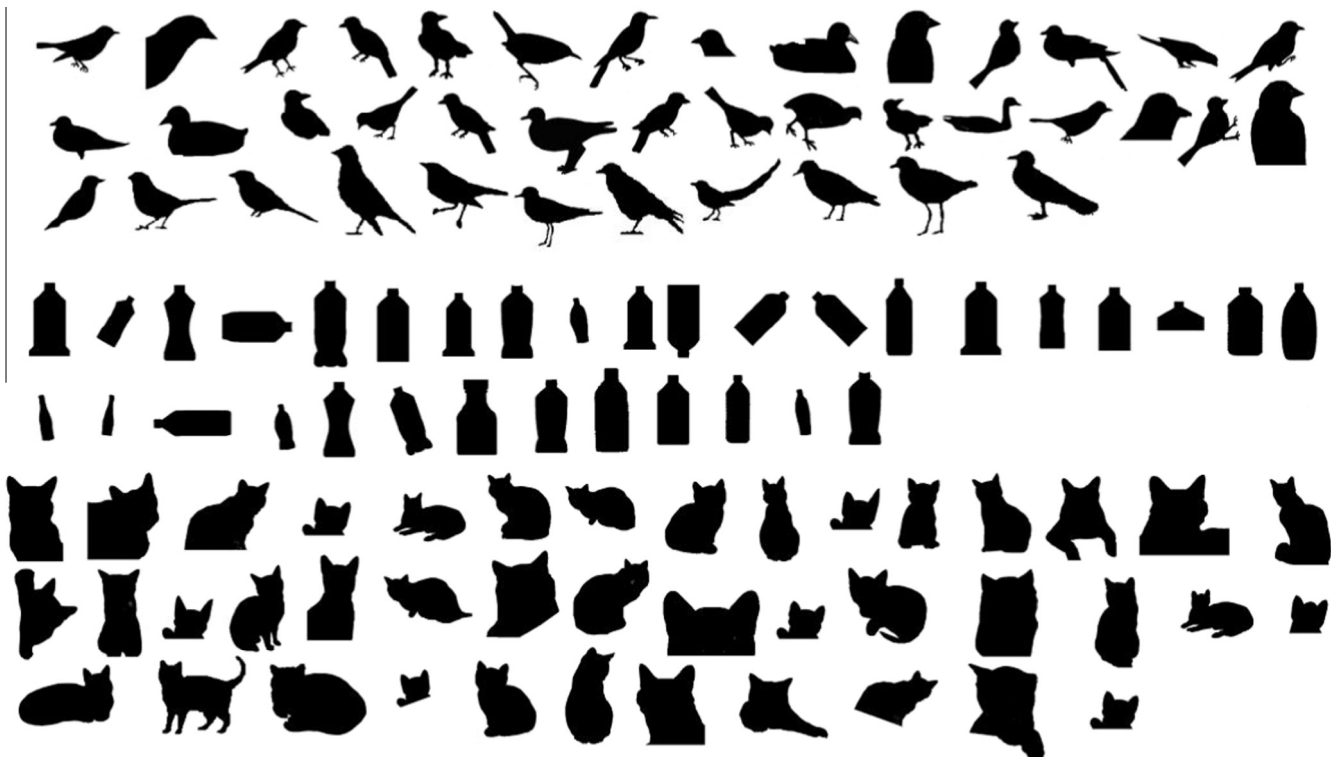


Fig. 10. Object classes of the built dataset, part 1.

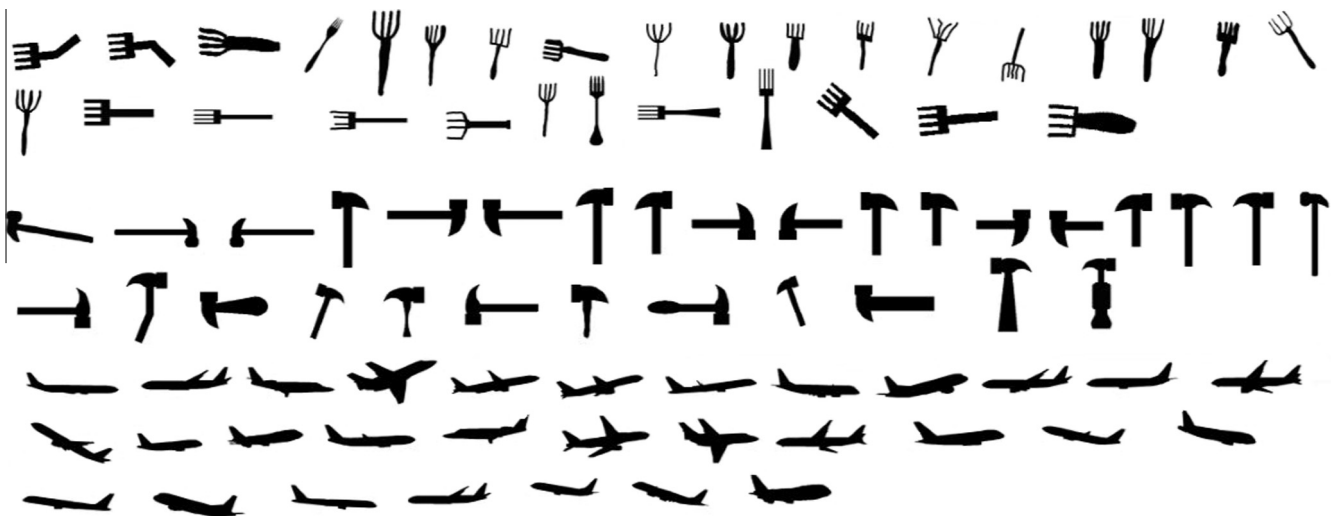


Fig. 11. Object classes of the built dataset, part 2.












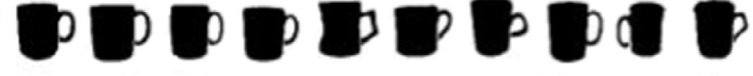


Query	Top ten results
	
	
	
	
	
	
	

Fig. 12. Shape retrieval from the MPEG7 dataset. Query shape in the first column, in the second column we give the most similar shapes to this query among the 1400 images of the dataset.

Algorithm Partial Shape Matching

- DBT: database of test images (p images)
- S_q^d : discriminative part with m curvature points of the query shape.
- S_p^i : denotes a part of i^{th} shape of the database.

Begin

For each shape S_i ($i = 1$ to p)

Begin

- Extract S_p^i the most similar part to S_q^d
- Save $S^{p*}(S_p^i, S_q^d)$

End

Sort $S^{p*}(S_p^i, S_q^d)$ in the ascending order

End.

- Bird (5 training images, 40 test images),
- Bottle (2 training images, 33 test images),
- Cat (6 training images, 41 test images),
- Fork (3 training images, 30 test images),
- Hammer (2 training images, 30 test images),
- Airplane (4 training images, 30 test images).

A sample of this images is illustrated by Figs. 10 and 11.

Our database models is built in an off-line stage by extracting the discriminative part of each class from the training images. Furthermore, our test data is considered as our own images presented

6. Performance evaluation

6.1. Used data and hardware platform

The hardware platform used in the performed experiments is composed by

To evaluate our method, we have built a set of 6 classes of images from different sources (own dataset, MPEG-7 Core Experiment CE-Shape-1 closed-contour database [15], Kimia’s dataset [16]). This set contains the following categories:

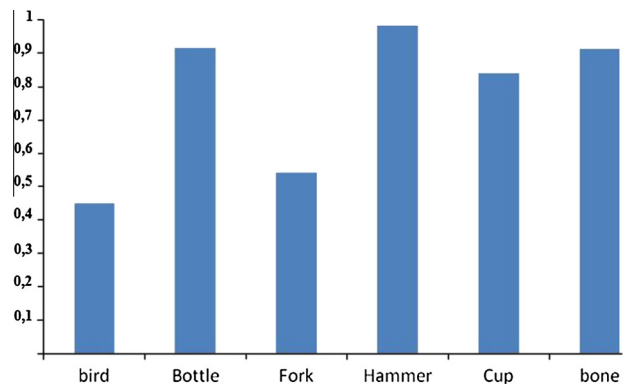


Fig. 13. Recognition rate of the six classes of Fig. 12.

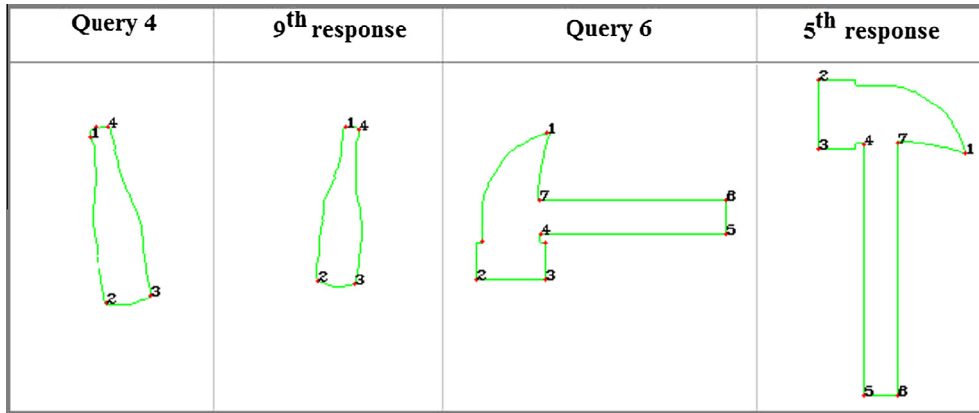


Fig. 14. Detailed point to point matching, pairs of curvature point having the same number are matched.







Query \ Precision						
[20] Method	90.90	90.90	100	90.90	100	100
Our method	100	100	100	100	100	100

Fig. 15. Examples of recognition rate obtained for some shapes.


































	Query	1	2	3	4	5	6	7	8	9	10
TSDIZ[21]											
BAS[22]											
GM											

Fig. 16. Examples of results of shape retrieval for three methods.

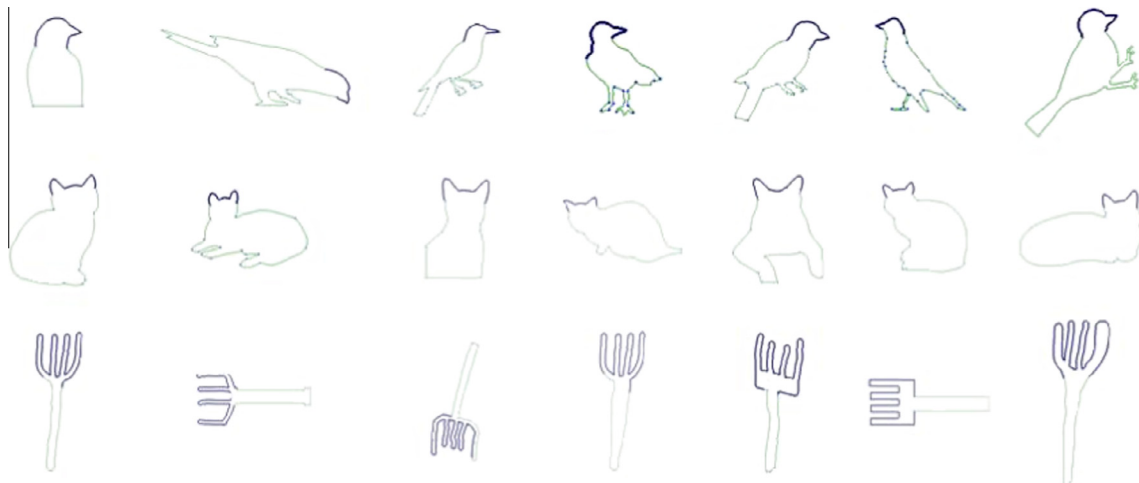


Fig. 17. Extracted discriminative parts represented in bold.

above. The goal of the experimentation stage is to compare the results of shape retrieval in two cases: global matching and partial matching. In other words, we want to know what is more efficient for shape retrieval: the whole shape or a discriminative part of the shape?

Both partial approach (using the discriminative part) and global approach (using the whole shape) are performed giving three kinds of experiments:

- In the first one, the query shape is submitted to the whole MPEG-7 dataset, therefore, a global matching is achieved between the query and each image of the dataset.
- In the second one, we deal with our own dataset (see Figs. 10 and 11). The discriminative part of the query shape is first extracted and submitted to both global matching (whole shape)

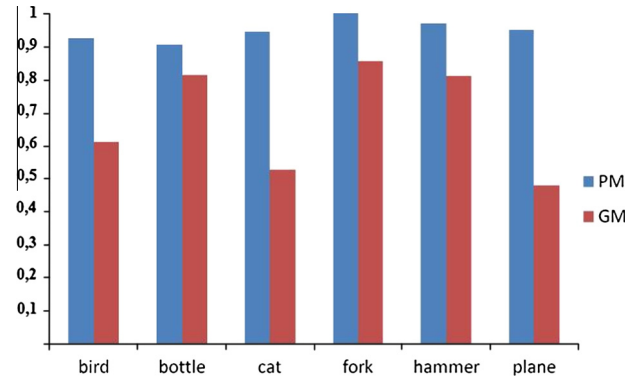


Fig. 19. Whole results of shape retrieval in case of partial and global matching.

Query	Discriminative part	Top ten results

Fig. 18. Results of the partial matching and global matching for same queries. For each query (first column), the corresponding discriminative part is extracted (second column) and the top ten retrieved shapes from the whole dataset is given in the third column, where the top row is the result of partial matching and the down one illustrates the global matching (the whole contour of the query is submitted).

Table 4
Retrieval results on 10 test images shown in column 1. Column 2 shows most significant contour parts. Columns 3–7 show most similar database segments to the detected contour parts, and column 8 gives the recognition rate over the top ten retrieved results.

	Query	R1	R2	R3	R4	R5	RR
Bat							70
Beetle							70
Bird							30
Butterfly							100
Cattle							20
Deer							70
Elephant							10
Guitar							60
Horse 1							40
Horse 2							50

and partial matching (discriminative part) to compare the retrieved results from the whole dataset and decide which method performs better: global or partial matching.

- The third one achieves a comparison of our partial matching method and the partial approach developed in [28]. Additional tests are achieved to show the effectiveness of our method.

6.2. Global shape matching

In this experiment we evaluated the performance of the global matching (GM) on the MPEG-7 database [15], which is a challenging dataset due to the wide variety of shape classes and the visual similarity of some shapes of different classes. The submitted queries are whole shapes selected from this dataset and the retrieval stage consists to match the query to all images of the dataset (1400) according to the presented matching process. The results are ranked from the most similar to the less one, then the top ten responses are retrieved.

Some examples of shape retrieval with the GM method are illustrated in Fig. 12. The obtained results demonstrate that our method handles geometric transformations as translation, rotation, scale and reflection. However, the method is quietly sensible to deformations. A summary of the obtained results of the GM method over a selection of MPEG7 dataset (6 classes of 20 images each) illustrated by Fig. 12, is given in Fig. 13. For each instance of a given class we retrieved the top ten results and computed its recognition rate which corresponds to the number of correct answers (shapes of the same class) by the number of retrieved answers. The highest scores are associated to regular classes (weak difference in the instances).

In order to show how the point to point matching is achieved, two examples (from Fig. 12) are detailed in Fig. 14. The labels associated to curvature points of each pair represent the matching result.

The proposed GM method have been compared to recent works. In the first work, the authors propose to decompose the shape boundary into perceptually significant entities with associated local boundary features [20]. In their experiment, they considered a dataset of 219 shapes (11 to 12 shapes per class) selected from different sources: MPEG-7, Kimia’s dataset, etc. Therefore, we have selected their reported results for MPEG-7 queries and compared them to our results retrieved from the whole MPEG-7 dataset

	Query	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	RR
Bat												50%
												70%
												100%
Beetle												70%
												70%
												80%
Bird												30%
												70%

Fig. 20. Retrieval results on 10 test images shown in column 1. Column 2 shows three different contour parts of the same class, Columns 3–12 show most similar shapes retrieved, the red contour is the matched part to the query, and column 13 gives the recognition rate over the top ten retrieved results (in red the best reported score for the same example). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(see Fig. 15). We notice that our method outperforms [20] method for glass, heart, and car images and gives a recognition rate = 100% for all selected queries.

The second example shows the visual image retrieval for an MPEG-7 query. The top ten retrieved images from the whole MPEG-7 dataset are illustrated in Fig. 16 with three methods: first row, shape representation using tensor scale descriptor with influence zones TSDIZ [21], followed by shape representation with beam angle statistic BAS [22] and at last, our method for global matching. The irrelevant responses are highlighted with a red rectangle, thus, our method outperforms the BAS [22] and is very close to TSDIZ [21].

6.3. Partial shape matching

As our proposed method for partial matching is constrained by specific object categories, we have built our own dataset so that in the same class we can find a large variety of postures and forms (objects of the same class can be visually very dissimilar). Therefore, in this experiment, the challenge is to recognize a shape with a small part of its contour even in presence of significant deformation which is a very interesting result. To achieve this experiment,

the first task to operate is to extract the discriminative part from the query, so, we have to apply the model matching algorithm presented in Section 5.5. The obtained result is an open curve delimited by two curvature points. Some examples of extracted discriminative parts are shown in Fig. 17.

In the partial matching, the submitted queries are the extracted discriminative part. The query is submitted to the matching with the whole dataset using the algorithm SHAPE RETRIEVAL presented in Section 5.6. In order to prove the performance of the proposed method, the same query is submitted to both global matching GM and partial matching PM. In each case the top ten results are reported. A sample of obtained results from every class is presented in Fig. 18.

In all tests the best answers are always given by the partial matching method, which affirm the goal of our investigation. Fig. 19 shows the results of shape retrieval of each image of our dataset for the two proposed methods: partial and global matching. For each class we compute the average value of the retrieval rate (number of correct answers on the number of retrieved images). The obtained retrieval rate for all classes of our dataset is 94, 93% for partial matching method and 68, 25% for the global matching.

Butterfly												100%
												100%
												90%
Cattle												30%
												100%
												80%
Deer												60%
												40%
												80%
Elephant												10%
												40%
												60%

Fig. 21. Continuation of Fig. 20.

6.4. Generalized partial shape matching applied to MPEG-7 dataset

As our partial matching works under specific constraints (specific objects and discriminative contour parts), we have not found in the literature works that achieve experiments in the same conditions as us. However, as cited previously in Section 2, to make our method comparable to other works, we can generalize our partial approach and consider an arbitrary part of the contour rather than discriminative part in the matching process.

To achieve this goal, a comparative experiment is conducted by taking the results reported in [28] as a reference. In fact, the authors generated a set of 58,000 contour segments using the shapes of the 70 classes of the MPEG-7 Shape 1 Part B dataset. The query is an open contour issued from a contour grouping procedure that generates what they called the most significant contour, which is the part of contour that represent the best their shape. The matching process consists to find and rank the part of contour that matches the best this query among the remaining shapes of the MPEG-7 dataset. This experiment uses 10 examples, the authors illustrated the top five responses and reported the recognition rate (number of correct responses) for the top ten retrieved responses. The obtained results are shown in Table 4.

In order to compare our partial approach to [28], we have used the same examples with the same contour parts, we have reported the top ten results and the obtained recognition rate for each query. Furthermore, for each example we have extended the test to two other contour parts to show that the recognition rate depends strongly on the selected part for the partial matching, which enforces our hypothesis of the usefulness of the discriminative part in the partial matching. The obtained results are illustrated in Figs. 20–22.

For the same queries as those cited in [28], we have obtained very close scores. However, our method gives very higher scores



Fig. 23. Kimia's data set, 25 instances from six categories.

Guitar												40%
												60%
												40%
Horse 1												50%
												80%
												50%
Horse 2												40%
												50%
												50%

Fig. 22. Continuation of Fig. 21.

when other contour parts are submitted. We notice that the matched contour parts are visually similar to the query even when sometimes the response does not belong to the same class as the query.

6.5. Generalized partial shape matching applied to Kimia dataset

In this experiment, we achieve shape retrieval using the proposed partial matching on Kimia’s 25 shapes (see Fig. 23). For each class, two different parts of the contour are submitted as queries to show the dependence of the results on the considered part, therefore, the whole shape is submitted for the retrieval with the global matching and compared to the partial results. The details of this experiment are presented in Tables 5 and 6 where the first column corresponds to the query, the next five columns give the top five retrieval responses ranked from the most similar to the query to the less one and the last column shows the retrieval rate which corresponds to the number of relevant responses on the number of shapes of the class. Each shape is submitted at three times, the first two rows correspond to a partial matching and the third one represents the global one.

As the selected data set does not contain objects with discriminative parts as defined in our approach, except may be the shape hand which can be recognized with some fingers, we have tried to extract the most representative part of each shape as a query in the first time, in the second time an arbitrary part is submitted. Therefore, we can easily notice that the best performance is obtained in the first case. For example, in the query hand the first part records a retrieval rate of 100% even in presence of occluded shape (third response), but since the characteristic part is visible the matching is achieved correctly. However, the second one performs less well

Table 5 Partial and global retrieval on Kimia’s 25 shapes data set.

Query	R1	R2	R3	R4	R5	RR
						100
						75
						100
						100
						75
						100
						100
						50
						100

Table 6 Partial and global retrieval on Kimia’s 25 shapes data set.

Query	R1	R2	R3	R4	R5	RR
						100
						75
						100
						100
						50
						100
						100
						60
						100

because it could not distinguish the original shape from the other ones. Another conclusion is that when objects have not a characteristic part, the global matching performs better than the partial one, the obtained results show that all first responses in global matching are correct.

We performed all the experiments on a PC with a 1.7 GHz 64 bit CPU and 1 GB RAM. The running time of algorithms took less than 1 min to finish the similarity retrieval with 10 query parts against 1400 shapes. Note that the programming language we used is C++ and OpenCV library.

6.6. Discussion

Experiment 1 shows the performance of the first approach noted global matching. In fact, the obtained results show the power of the method to handle the shape matching under several transformations as translation, rotation, scale, reflection and even small deformation. However, the method is weakly sensible to huge distortions. The conducted tests over a selection of the MPEG-7 database give satisfying results. In experiment 2, we achieve a shape retrieval for two matching schemes: global approach and partial approach. The principal goal of this experiment is to demonstrate that the partial shape modeling and matching can perform better than classical approaches (using the whole contour). The key idea of this approach is based on certain characteristics of shapes in the nature so, we cant apply it to any kind of objects, for this reason, we have built our own dataset. Therefore, we have conducted the same experiments (same data set, same

queries) for the two approaches. The obtained results show clearly that the partial approach performs better than the global one, this result is obtained thanks to the stability of the form of the discriminative part along instances of the same class. However, when the discriminative part is heavily distorted in the query, the method fails. The GM gives similar responses as the PM when the query shape is generic, it means it is similar to some shapes of the dataset (geometric transformations or small deformations).

In the third experiment, we have shown clearly that the retrieval rate depends strongly on the submitted part. The same shape can be decomposed in different ways, but the best results are obtained only when judicious parts are selected. This conclusion was given implicitly in [28], the authors conclude in their discussion that: *we can observe that some query parts can get very good retrieval results but some cannot. The first one is if the part is too simple, it will be not unique and there will be a lot of parts accidentally similar to it. The second reason is if the part is too unique, the system cannot find the other parts except the part which is exactly the same with it.*

Therefore, the best part to submit should occur in the different instances of the same class and may not belong to other classes, which are the main characteristics of what we have called the discriminative part.

7. Conclusion and future works

In our contribution we used the knowledge extracted from the geometry of the shapes of several objects. The most characteristic parts which discriminate an object from the others are then used for the modeling and the retrieval step of object recognition step. Therefore, we have proposed in a first step a shape representation contour based method (global approach) using geometric attributes of curvature points. And next, we have developed a second representation (partial approach) based on discriminative parts. To evaluate the two methods, two matching schemes have been proposed, the several experiments conducted have validated our reasoning. Therefore, we can resume the key points of our work as follows:

- the model gives rich information about the object class in a compact descriptor;
- the retrieval method uses a partial representation which facilitates the matching process;
- the model building is achieved with a very few training images;
- the method is invariant to translation, rotation, medium scale change, mirroring and deformation;
- this approach can be used to classify a large range of images using a small open curve.

Experimental study have demonstrated the usefulness of the partial modeling for shape retrieval. Moreover, this method can be applied to other problems, we can use it in categorization for example, to determine the kind of birds through the form of their beaks or feet, or the species of trees using the kind of leaves.

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