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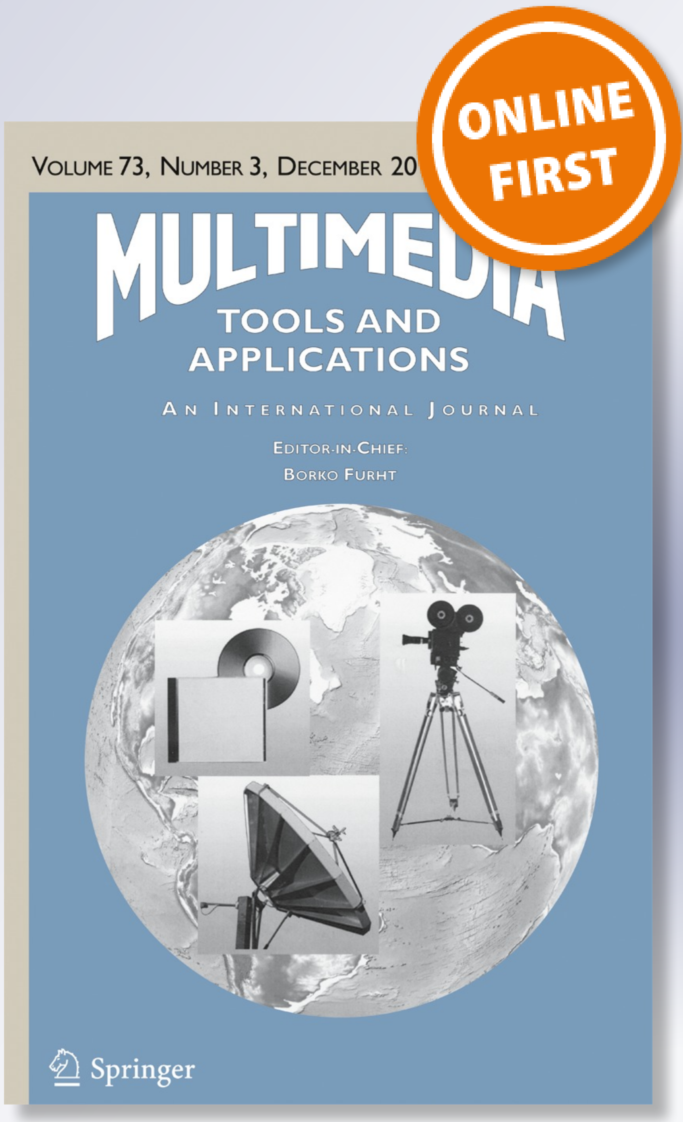

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Efficient descriptor for full and partial shape matching

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Abstract In this paper we present a new approach for full and partial shape retrieval based on a shape descriptor invariant to geometric transformations, reflection and deformation. The proposed description is a set of features that capture simultaneously global and local properties of the shape. To achieve the best matching, we propose a novel matching algorithm based on Dynamic Time Warping. The proposed method is evaluated in two cases: partial and full matching. The experimental results demonstrate that our approach outperforms existing methods of partial shape retrieval and gives comparable results for full shape retrieval.

Keywords Shape description · Shape retrieval · Shape matching · Partial matching · Full matching

1 Introduction

Shape matching is an important task in computer vision applications such as content-based image retrieval, shape classification, object recognition. For shape description, contour-based method is the approach usually used in this field due to the rich features can be extracted from the contour. Many works [1, 4, 6, 8, 29, 37] described a shape by a set of points extracted along the contour curve, following different manner of sampling and modelling. Much of them deal with the whole shape, therefore the matching problem is how to match two closed contours under translation, scale and rotation transform and even in

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case of some deformations. However, very few papers give solutions when large parts of the shape are occluded or missed and this problem remains still open.

In the present work we are interesting to full and partial shape representation and matching. We can formulate the problem of partial shape matching as follow: Given two curves as an input, where the first one is open and the second one is closed, we have to find what part of the second curve that matches the best with the first curve. This kind of matching is useful in many applications involving shape comparison in case of occlusion or deformation. Moreover, this problem is more complicated than whole-to-whole shape matching, since we have to recognize objects when only a small part of them is visible and probably noised or distorted.

In this paper we propose a new method for shape representation based on a set of features that are able to handle geometric transformations and deformation. The key point of this representation is that it can perform partial shape matching so as full shape matching.

We begin this paper by presenting a review of previous works related to this area. The next section is devoted to our method for shape representation. Next, we explain the main idea of the proposed algorithm for partial and full shape matching. In the last section we present and discuss the different experiments conducted on MPEG7 data set. Finally, a conclusion is given.

2 Previous works

Many works have been devoted for shape matching which concern 2D or 3D objects. The main problem of this challenge is the finding of sufficient features able to do the correct match whatever the nature of image.

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 [38]. 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 [19] including a set of marginal-sum features summarizing the CSS image.

Adamek and O'Connor [2] proposed an efficient algorithm (MCC) for shape representation invariant to several kinds of transformations including some articulations and modest occlusions. In the proposed approach, contour convexities and concavities at different scale levels are represented. Then, a new measure for the curvature was proposed based on the relative displacement of a contour point with respect to its position in the precedent scale level. The optimal matching of two shape representations is achieved using dynamic programming. Shape is considered by Belongie et al. [9] a 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. Corresponding points on two similar shapes have similar shape contexts, therefore, the transformation that best aligns two shapes can be estimated. The key parameter measuring the performance of this method, is the number of sampling points, thus, for a faithful representation of the shape, the number of points should be the highest possible and so the complexity. A much faster algorithm was proposed in [47], the authors used the shape context of a particular reference points corresponding to the end points of the shape skeleton.

A recent approach is proposed in [5] and optimized in [3]. The representation utilizes the areas of triangles formed by the boundary points to measure the convexity/concavity of each point at different scales. The method captures both local and global characteristics of a 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 [22] 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, dilatation 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) [30], and then the Locally Constrained Diffusion Process (LCDP) method [48] is exploited to further enhance the retrieval performance.

Daliri and Torre proposed in [15, 16] an approach to object classification. They represent a shape using a string of symbols describing each point of the contour by two attributes: a distance and an angle. First they compute the center of mass of the shape, and for each point they calculate its distance to this center of mass normalized to its maximum distance. These distances are transformed into four different symbols : S, M_1, M_2 and L (for small, medium 1, medium 2 and long distances). Next, for each point P_j over the contour, two points P_{j-k} and P_{j+k} are considered (k^{th} point clockwise and counterclockwise). The angle created by these three points is computed and quantized in eight different bins $(A_1, A_2, .., A_8)$ between $[0, \Pi]$. A representation at different scales can be obtained by changing the value of k. The point-to-point matching is evaluated by the shape context [9] 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 [16] and a learning-based algorithm using SVM [15]. 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.

Objects in images and videos, are represented by mono-view features such as the integral projection method proposed in [34], or usually represented by multi-view features, such as color, shape and texture [20, 33].

Partial shape representation and matching is a challenging problem, it has been recently the focus of many works [11, 12, 14, 18, 25, 27, 35, 36, 40].

Chen et al. [12] presented a partial shape matching method based on the Smith-Waterman algorithm. They represented the shape by a sampling point sequence described by two local features, the turning angle and the distance across the shape. The matching process is achieved by including Smith-Waterman algorithm to dynamic programming.

In [11], the authors proposed a partial shape matching algorithm based on MCMC (Markov chain Monte Carlo). The shape contour is represented by a set of ordered landmark points, selected and updated by a posterior distribution. In this approach, the matching output is a set of multiple matched segments that are not connected.

The work presented in [18] proposes a new indexing structure under partial matching. The partial matching is achieved between two shock graph nodes using the earth mover's distance approach, which allows partial matches in a natural way.

Partial matching has been also used to solve the problem of affine distortions of partially occluded shapes; an example is given in [35], where the shape is described by a sequence of ordered affine-invariant segments based on the curvature scale space. The matching of two sequences is achieved by the Smith-Waterman algorithm.

In [14], the authors proposed an algorithm that performs whole-to-part 2D curve matching under similarity transform (translation, rotation and uniform scaling), and extended it to a more complex problem which is part-to-part curve matching, where the curve is parameterized by scale invariant signature corresponding to the integral of absolute curvature. To extract the signature, they Compute curvature of the curve at equal arc length intervals-sampled points along the integral of unsigned curvature axis.

In [40], the main motivation is the use of partial shape similarity to perform object-based image labelling. The object is first decomposed into regions by means of color segmentation, then B-splines are fitted to them to compute feature points with local maximum curvature. The matching step identifies potential partial matches between two distance matrices corresponding to two candidate regions by sub-matrix method.

Latecki et al. [25, 27] developed an elastic partial shape matching technique to model partial occlusion and distortion of shapes. They consider a part of shape as a query and search a corresponding part from a whole shape that best matches it, the matched part is supposed to be a distorted version of the query. In this approach, the discrete curve evolution process (DCE) [23] is first applied to the shape to extract a set of sampling points, then the angle between the tangent line at every sample point and the x-axis is computed. The obtained sequence is the considered shape descriptor. The matching algorithm is inspired from two techniques: Dynamic Time Warping [10, 42] and the Longest Common Subsequence [17, 46], which result into a new method called minimum variance matching (MVM) [26] that reduces the problem of optimal alignment between two sequences to a shortest path in a Directed Acyclic Graph (DAG). The main contribution of the proposed approach is its elasticity in the matching process, so it can skip dissimilar points.

In the same context as [27], Michel et al. [36] proposed another partial shape matching method based on a spatially non-uniform contour sampling that provides a local descriptor, scale and rotation invariant. The matching algorithm is a variant of an existing Dynamic Time Warping (DTW) technique [41], where the point-to-point match cost weighs more points that represent a large portion of the contour and less the points which represents a smaller one. The authors consider also the matching of two closed contours as a special case, to avoid the exhaustive consideration of the alignments of two cyclic strings for every possible initial match; they used a fast matching technique proposed in [44].

The most relevant references to our work are [27] and [36] and used for experimental comparison with the proposed method.

Despite the numerous contributions in this field, the score of all proposed methods for many data sets does not reached a high value. Our aim in this work is to reach a higher score. In our approach, the problem of partial matching is formulated as follow: having a whole query shape, we aim to retrieve the most similar shapes from a data set. Instead of performing a whole-to-whole shape matching, we select a part (open curve) of the query shape and we search for the best part of the other shapes that best matches it. To make the problem more challenging, we suppose that the two parts to match don't have the same size neither the same orientation and can be reflected. Furthermore, they are not identical, some distortions may exist in each one, and even the two initial shapes may contain distorted or articulated parts. Performing such shape matching under all these constraints needs a powerful shape descriptor and a flexible matching algorithm.

A new shape descriptor is then proposed which is scale, rotation and reflection invariant and can handle some articulations and deformation.

Dynamic Time Warping technique is adapted to our needs, in order to perform an efficient whole-to-whole shape matching algorithm. For the part-to-part matching, another algorithm is proposed. The key idea is to skip the matching of dissimilar points in both query and shape to match, this allow us to skip local distortions of the parts to match.

Our main contributions in this paper are:

- A new shape descriptor based on corner points invariant to geometric transformation and reflection.
- An efficient partial and full shape matching algorithm which performs a correct matching even if some deformations exist in the two parts to match.

3 Shape descriptor

Sampling the contour of a shape into a set of points is a common approach used for shape representation [1, 4, 6, 8, 29, 37], [21, 27, 31, 36]. The size of the sampling points, the manner they are extracted and the features associated to them determine the power of the shape descriptor to handle different transformations (scale, rotation,reflection, deformation, and articulation) and its computation complexity. Furthermore, the results of the shape matching depend strongly on the shape representation.

In our description a dense and rich set of sampling points corresponding to corner points along the contour is used. If they are located with high accuracy, theses points give pertinent information about the form with reduced set of points compared to uniform sampling or other sampling methods. Furthermore, corner points are invariant to translation, rotation and medium scale change. Many works have been devoted to the problem of corner point's detection and localization [13, 28, 32, 43], most of them depend on a parametrization function. Among them, the method developed in [13] is selected and used. It depends on two parameters a distance and an angle, the values giving the best results are fixed empirically to 7 for the distance and 150° for the angle.

The shape descriptor robustness depends on the selected features for describing each point or segment of the outline shape. A rich set of features can be used at this level: turning angle, equiangular distance, curvature, distances to particular points of the contour, distance radii, triangle area, inner distance, etc. A feature can be considered as a global descriptor if its value is computed relatively to all other points, in this case each point embeds global information about the shape. This kind of descriptors is sensible to whole shape transformations as articulations and deformations. Some relevant works are: shape context [8], curvature scale space [37], triangle area [4], average distances to all other points [36], inner distance [29].

At the other hand,a local descriptor is computed in a close neighboring of the considered point; its value is preserved while the neighboring is unchanged. Such features are sensible to local deformations as noise such as the turning angle [27, 45], tangent vector [39].

In our work, the shape descriptor is a sequence of corner points taken in the counter clockwise direction. Each corner point is described by a combination of three features (see Fig.1):

- The inner angle θ_i associated to a corner point P_i: is the inside angle defined by P_{i-d}, P_i, P_{i+d}, where d is an empiric distance from the corner point to P_{i-d}, P_{i+d} in two opposite directions. The inner angle is invariant to translation, scale, rotation, reflection, other corner point's deformation or articulation.
- The relative central distance d_i related to the distance joining the considered corner point P_i and the center of mass of the whole shape. Its value is normalized relatively to the maximal central distances of all points. It is invariant to translation, rotation, scale (normalized value), reflection; it can be altered by some deformations and articulations.
- The relative length L_i of the segment $P_i P_{i+1}$ compared to the whole contour length, where P_{i+1} is the next corner point. It is invariant to translation, scale, rotation, reflection (we have just to consider a clockwise direction), articulation, but sensible to important deformations of the whole shape.

The third feature depends on a global attribute of the shape, which is the center of mass. The center of mass or the gravity center of a shape is a point calculated relatively to the density of all shape points. It changes weakly when small deformations or articulation is achieved on the shape. The center of mass CM (X_m, Y_m) associated to a shape S is defined by the first moment order as:

$$X_m = M_{10}/M_{00}, Y_m = M_{01}/M_{00} \tag{1}$$

where $M_{pq} = \sum_i^l \sum_j^k (i^p j^q f(i, j)$ and f is the intensity function defined by $f(i, j) = 1 \forall, (i, j) \epsilon S$

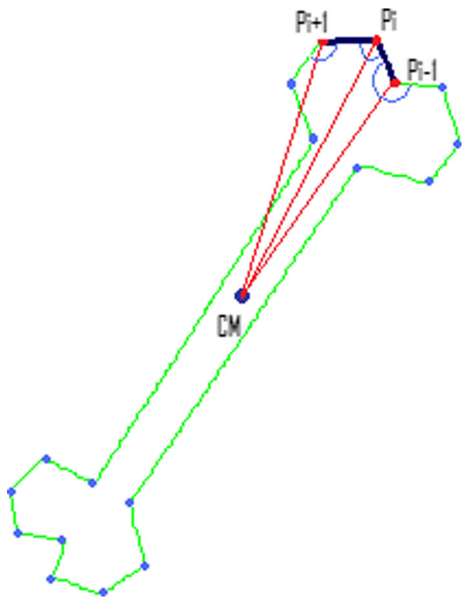


Fig. 1 Features of shape descriptor related to three corner points P_{i-1}, P_i, P_{i+1}: (240.25°, 0.8, 0.02), (116.56°, 0.88, 0.03), (129.80°, 0.81, 0.02)

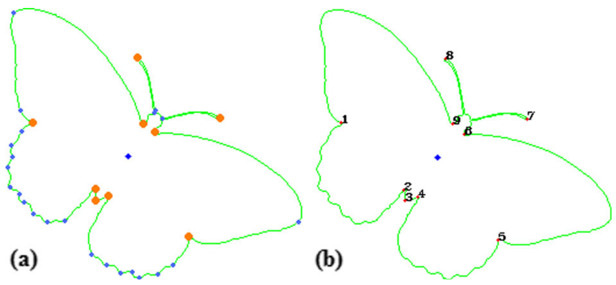


Fig. 2 **a** Coarse and refined points in red resp. blue color, **b** Features of some coarse points: $P_1(285.80°, 0.56, 0.14)$, $P_2(315°, 0.25, 0.01)$, $P_3(81.86°, 0.29, 0.01)$

To make our representation independent from some local details which vary in the same class of shapes, we group corner points into two sets: *coarse* and *refined* points. In fact, when a corner point is very concave or very convex (synonymous of small value of the inner angle), it has an important role in the matching process, since it is more characteristic in the determination of the form and its occurrence in the different instances of the same class is more probable.

A *coarse* point P_i is defined by an inner angle θ_i verifying $(\theta_i < \theta)$ for high convexity or $(\theta_i > 360 - \theta)$ for high concavity, where θ is an angle fixed empirically. *Refined* points correspond to the rest of corner points; they are characterized by more largest inner angles. Figure 2 illustrates coarse points in red and refined points in blue, in addition a detailed description of the coarse points set is given.

4 Shape matching

The matching process consists to compare descriptors in order to find the best correspondences between them that minimize the similarity measure. Two trivial problems arise, the sequences size and the starting point of each sequence of the descriptor. To align two sequences of different length, a solution is given by the Dynamic Time Warping algorithm (DTW) [41, 42]. In this case, the optimal match that gives minimum distance is obtained by compressing or expanding the two sequences using the mapping of one point to many or many points to one.

In practice to match two sequences of points $S_1(P_1..P_n)$, $S_2(q_1..q_m)$ using DTW algorithm, we have to find the optimal path that starts with the pair (P_1, q_1) and ends at (P_n, q_m) and minimizing the matching cost of each point of S_1 and S_2. First, a $(n \times m)$ matrix D is constructed, where D_{ij} is initialized to the distance between the points (P_i, q_j), D is updated dynamically by the recursive formula (2):

$$D(i, j) = D(i, j) + min\{D(i-1, j), D(i-1, j-1), D(i, j-1)\} \tag{2}$$

Once the matrix updated, the minimum cumulative distance is equal to $D(n, m)$. The optimal path is obtained by back tracking the matrix D from $D(n, m)$ to $D(1, 1)$ using the backward formula (3).

$$D(i, j) = D(i, j) + min\{D(i+1, j), D(i+1, j+1), D(i, j+1)\} \tag{3}$$

Another constraint is generally added to this algorithm which excludes some point matching of S_1 and S_2 from the optimal path search. To restrict the moves that can be made from any point, the warping window is adjusted to a limited band. Generally the width of this band is set to 10 % of the length sequences [42]. In addition, the best possible matching is obtained when the starting point in each sequence is correctly selected. Unfortunately, the problem of starting point remains unsolved in many cases. A trivial solution consists to make a circular shift of the point sequence and consider all possible starting points. Therefore, for each shift the minimum matching cost is computed with DTW, and the starting point generating the best matching is considered.

In our approach, the matching process is achieved in two phases: the coarse matching and the local matching. As seen in the previous section, some corner points are more characteristic for the shape description than others, therefore in a first time only coarse points participate in a preliminary matching step, next the remaining points limited between two coarse points are matched by intervals using DTW algorithm. The detailed method is explained in the next subsection.

4.1 Points matching

To match two sets of point descriptors, we have to define a similarity measure between a pair of points. In our description, this measure corresponds to the Euclidean distance between each feature of the point descriptors. Let $P_i\,(\theta_i, d_i, L_i)$, $P_j\left(\theta_j, d_j, L_j\right)$ be the descriptors of two points to match, the similarity measure SP_{ij} between P_i, P_j is given by the (4).

$$SP_{ij} = \sqrt{\alpha_1\left(\theta_i - \theta_j\right)^2 + \alpha_2\left(d_i - d_j\right)^2 + \alpha_3\left(L_i - L_j\right)^2} \tag{4}$$

Where $\alpha_1, \alpha_2, \alpha_3$ are the weights associated to each feature and have the role to control each feature in the point-to-point matching.

4.2 Coarse matching

In the coarse matching we generate the key point-to-point matching; only the most important points are considered in this step. This idea is motivated by the fact that the matching of all corner points at the same time can be altered considerably by multiple local deformations of shape. To avoid this problem we propose to decompose the shapes to match into parts by the mean of coarse points. The matching of these points which are considered as a reference allow us to obtain a subsets of corner points delimited between two reference points that are the candidate to match in the next step.

Instead of dynamic programming algorithm which match all points of shapes, in this phase we want to obtain only the most correct matching pairs, even we skip some points. Therefore, we try to put in evidence the most similar parts first. This reasoning seems to be more realistic than DTW method, we can have two shapes of the same class that presents some deformations each one, contrary to our method, DTW can't skip these deformations.

Another advantage of our method is a non-exhaustive search for the starting point. As we use in this step few points for preliminary matching, this leads to an implicit solution for the starting point problem. Instead of an exhaustive search of all possible starting points, we reduce this search to coarse points only, which reduce considerably the complexity. The best starting point pair is selected so that the similarity measure given in (4) is minimal.

To establish the coarse matching between two shapes S_i, S_j having respectively n_i, n_j coarse points, we map the shape having the minimal number of points to the other one in an ordered way. First, the starting point pair is fixed. Next, the best match is explored in two opposite directions in order to give the correct response even in case of reflection. For each point of S_i, we establish the best correspondence with the immediate point of S_j and its successor; this will allow elasticity in the matching without losing the notion of sequence. We reduce the space of search to two candidates in order to preserve our hypothesis which consist to deal with key points. So if we compare two similar shapes we suppose that these characteristic points are not so far from one to another and the differences may rather occur in the refined points positions. The cumulative point-to-point matching cost, having the minimal value (by taking all possible shifts of the coarse points of the shape with minimal number of points) corresponds to the coarse similarity measure CS_{ij} between S_i and S_j, as described in algorithm 1, and given by the formula (5).

$$CS_{ij} = min_{k=1}^{n_i} \sum_{l=1}^{n_j} min\left(SP_{kl}, SP_{k(l+1)}\right) \tag{5}$$

Figure 3 shows two examples of coarse matching, the red points are the coarse points and the blue ones correspond to the refined points. Points having the same labels are the

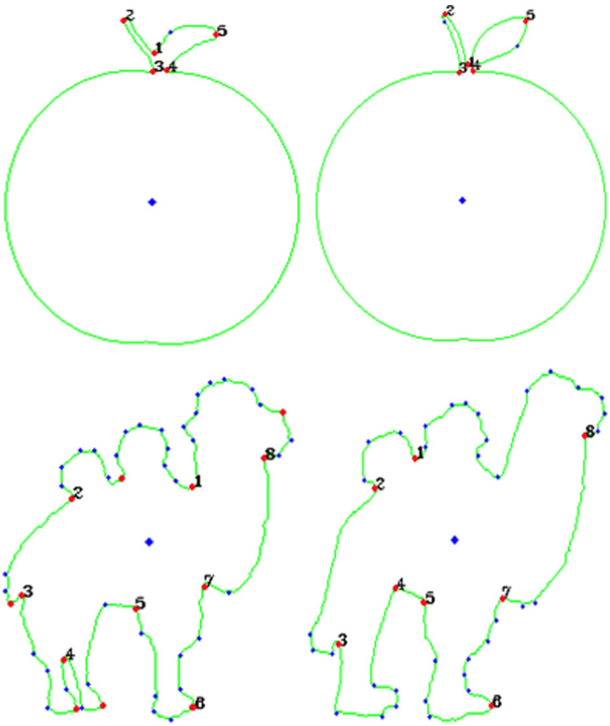


Fig. 3 Coarse matching of two pairs of shapes

ALGORITHM 1: *Coarse Matching* (S_i, S_j)
Begin
- Input: S_i, S_j two shapes having respectively n_i, n_j coarse such as $n_i \leq n_j$
- Output: CS_{ij} The minimal coarse similarity measure between S_i, S_j
For $k = 1$ to n_i
    Do $l = 1$
    While $l \leq n_j$
    Do
        If $SP_{kl} < SP_{k(l+1)}$ **Then**
        $CS_{ij}[k] = SP_{kl}$, $l = l + 1$,
        Else
        $CS_{ij}[k] = SP_{k(l+1)}$, $l = l + 2$
        EndIf
    EndWhile
    EndFor
Sort CS_{ij}, Minimal coarse similarity=$CS_{ij}[1]$
End

matched pairs. For the apples we have the same number of coarse points in each image, the matching gives the correct correspondences for each shape, and for the camels the size of the point sets is different, so the shape having less points than the other is mapped to the other, some coarse points remain unmapped, they will be matched in the next step. However

ALGORITHM 2: *Refined Matching* (I, I')
Begin
- Input: $I_i = [P_{i,1}..P_{i,p}]$, $I'_i = [P'_{i,1}..P'_{i,q}]$: two sets of points
- $D(p \times q)$: the distance matrix of I_i, I'_i
- W: the size of the warping window
- Output: RS_i The optimal refined similarity measure between I_i, I'_i
- The $(p \times q)$ elements of DTW array set to ∞
$DTW[0, 0] = 0$
For $k = 1$ to p
    Do
        For $l = max(1, k - w)$ to $min(q, k + w)$
        Do
$Val = Min(DTW[k - 1, l], DTW[k, l - 1], DTW[k - 1, l - 1])$
$DTW[k, l] = D[k, l] + Val$
        EndFor
    EndFor
$RS_i = DTW[p, q]$
End

we notice that instead of some parts that exists in the second image and not in the first one (camel 1 with two separated legs and one joined leg and camel 2 with two joined legs), the matching result is intuitive and the mapping of points is achieved correctly.

4.3 Refined matching

At this level the remaining points delimited between the pairs of coarse points issued from the previous matching stage, are put into correspondence, interval by interval with respect to the matching order of their boundary points. As the coarse matching is already established, each interval has only one candidate interval to be matched with it. However, the two intervals to match haven't systematically the same size, at the other hand we must match all points of the two sets, and therefore in this situation dynamic time warping is the appropriate solution. Let (P_i, P_{i+1}) be a pair of successive coarse points matched with the pair $\left(P'_i, P'_{i+1}\right)$. The interval I_i defined by the two points P_i, P_{i+1} contains p points: $\left\{P_{i,1}..P_{i,p}\right\}$ should be matched to the interval I'_i defined by the two points P'_i, P'_{i+1} which contains q points: $\left\{P'_{i,1}..P'_{i,q}\right\}$.

As explained in Section 4, to establish the DTW matching of I, I' we should construct the matrix $D(p \times q)$, where each element D_{ij} is initialized to the distance between the points $\left(P_{i,k}, P'_{i,l}\right)$ which corresponds to the similarity measure between the two point descriptors given by (4). D is updated dynamically by formula (2) in order to compute the minimal matching cost of the points of I_i, I'_i.

4.4 Whole shape matching

The full matching consists to match two entire shapes. As explained above, this task is achieved in two times: a preliminary matching and a refined matching. The combination of

ALGORITHM 3: *Partial Matching* (Q, S')
Begin
- Input: Input: $Q = q_1..q_n$ the query part,
S' a candidate shape with m points
- Output: $PS_{QQ'}$ is an array of m elements
for storing partial similarity costs between Q and Q'
For j:=1 to m **do**
$k = j$
For i:=1 to n **do**
    if $SP^P_{ik} < SP^P_{i(k+1)}$ then
    k=k+1;
    else
    $PS_{QQ'}[j] = PS_{QQ'}[j] + SP^P_{i(k+1)}$
    $k = k + 2$
    EndIf
    EndFor
EndFor
Sort $PS_{QQ'}$
Partial similarity cost=$PS_{QQ'}[1]$
End

the results of the two steps corresponds to the matching cost of a pair of shapes. Let S_i, S_j be two shapes with n resp. m points, having n_i resp. n_j corner points. Therefore, the similarity measure S_{ij} between S_i, S_j is computed as follow:

$$S_{ij} = \sum_{i=1}^{min(n_i,n_j)} CS_{ii} + \sum_{i=1}^{min(n_i,n_j)} RS_i \tag{6}$$

5 Partial matching

Associate a part of a shape to a part of another shape is more complicated than full shape matching, but very useful in case of occlusion or distortion, if the common part is still visible in the two shapes. In our approach, we aim to achieve a partial matching using an arbitrary part of a shape to retrieve the best responses from an image database. To make the problem more challenging, we suppose that the query part and the matched part can be distorted. In addition, this matching takes into account geometric transformations, reflection and the starting point. As the context of partial matching is different from the full matching, the proposed solution at this level is not identical to the previous one. Some adaptations of the proposed full matching method are made in order to handle the partial matching constraints.

5.1 A modified similarity measure

First, the descriptor of the selected part should be as independent as possible of the whole shape descriptor to be able to give correct responses even in occlusion or considerable deformation. At this effect, the point-to-point matching is adjusted so that local features contributes more than global ones, the priority is assigned to the inner angle compared to the relative central distance and relative segment length. This adjustment is made by changing the weights of each attribute in formula (4) as follow:

$$SP_{ij}^{P} = \sqrt{\left(\alpha_1' \left(\theta_i - \theta_j\right)^2 + \alpha_2' \left(d_i - d_j\right)^2 + \alpha_3' \left(L_i - L_j\right)^2\right)} \tag{7}$$

Where $\alpha_1 = \alpha_1' = 5, \alpha_2 = \alpha_2' = 3, \alpha_3 = 20, \alpha_3' = 2.$

5.2 Selecting dominant points

The second constraint is that we suppose the occurrence of some deformations in both the query part and the part to be matched. As we are face to matching two open curves represented by two sequences of points, the key idea consists to consider characteristic points only and skip unwanted points from each part to reach the optimal match. Therefore, the DTW matching algorithm could not be applied in this situation, since in DTW all points of the query and the candidate part should be mapped.

To extract the most important points of the query part, we compare the descriptors of points in a local neighboring of size is equal to 2 and we introduce an alignment condition to eliminate the less important points in this neighboring as follow:

Let $q_1..q_k$ be the sequence of points of the query part Q. If $q_i, q_{i+1}, q_{i+2}, q_{i+3}$ are four successive points of Q, then q_{i+1} should be eliminated if the angle formed by q_i, q_{i+1} and q_{i+1}, q_{i+2} is less than θ' (θ' is a large angle). If q_{i+1} satisfies this condition, it is discarded and the same test is achieved again with q_i, q_{i+2} and q_{i+2}, q_{i+3} in order to eliminate q_{i+1} (resp.q_{i+2}) or maintain them.

In this processing, we can eliminate at most two successive points at the same time to avoid creating large gaps in the query sequence. The goal of this operation is to eliminate points located on a nearly straight line contour ($\theta' \approx 180\circ$) that are less discriminative than the others.

For example in Fig. 4.a, we consider a query part delimited by the sequence of 20 points, by applying the previous operation, only red points are considered for the matching, therefore the query part sequence is updated with the new 14 points as shown in Fig. 4.c.

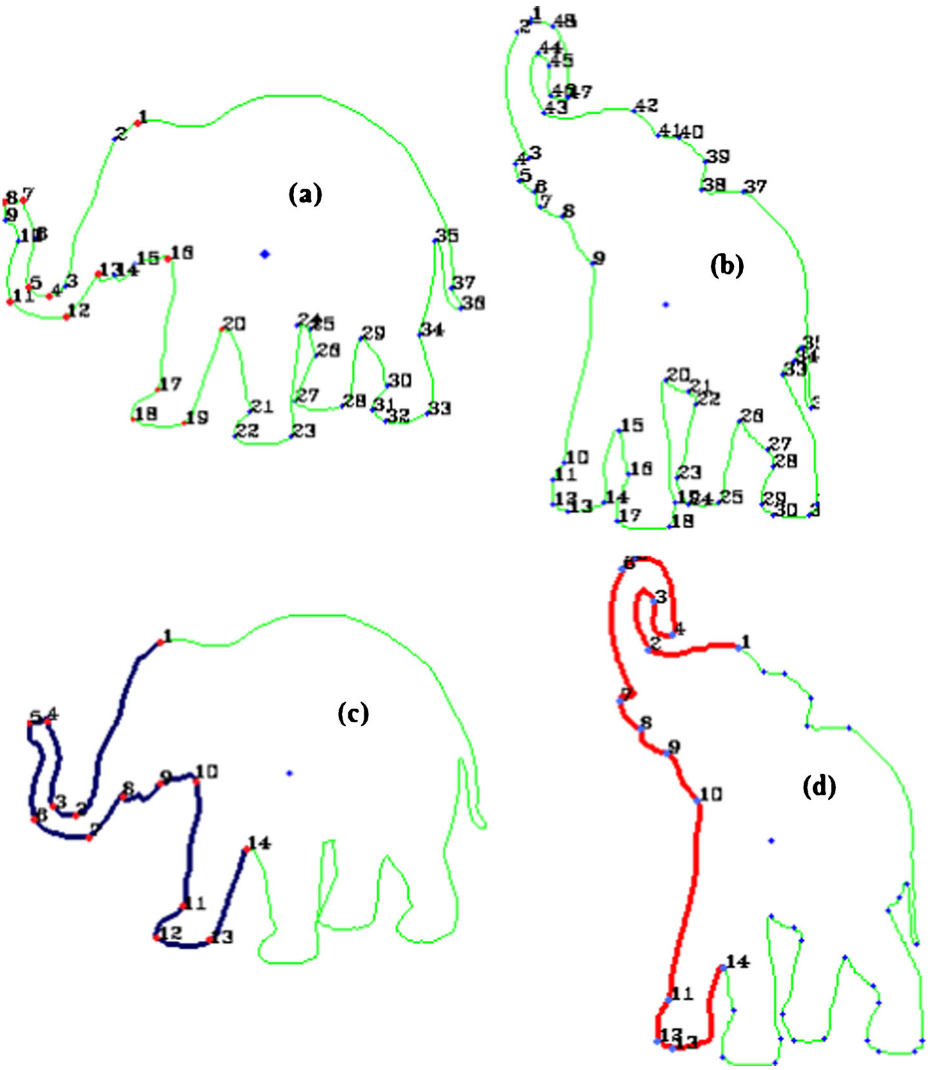


Fig. 4 Partial matching: **a** The query shape to match using the part defined by the points 1..20, **b** The candidate shape, **c** The points sequence retained for the matching, **d** The associated part of the candidate shape

5.3 Matching

The matching of the new query sequence resulting from the characteristic point's extraction is submitted to the partial matching by shifting it along the sequence of points of the candidate image, by taking parts having at least the same size and at most the twice size as the query. Indeed, each point can be associated to two successive candidate points from the second shape, in the worst situation the size of the second associated part is equal to $size(query) \times 2$. All points of the query should be matched. However, in the candidate part we can skip some points (at most one point) to allow a certain elasticity that skips some deformations, without losing the global aspect of the part.

To find the part Q' of a shape S' that best match the part $Q = q_1..q_n$ of a shape S (already reduced as explained previously), we select an arbitrary point P_s of S' which will be supposed as the first point of Q'. Therefore, the partial point similarity defined by (7) of q_1 , P_s and q_1 , P_{s+1} is computed in order to determine the best point that will be matched to q_1. The process is repeated sequentially with the next pair of points Q, Q' until matching all points of Q. The cumulative sum of partial point similarity corresponds to the partial matching cost. The part Q' of S' minimizing this cost is extracted and considered as the best part that match Q (see Fig. 4).

6 Experimentation

Our experimental study focuses on the two proposed methods of partial and full matching. All conducted experiments have been performed based on the MPEG7 Core Experiment CE-Shape-1dataset [24]. This database consists of 70 different classes of objects from different kinds: animals, foods, engines, objects, etc. Each class contains 20 instances of the same object class taken in different postures, resulting in 1400 different shapes.

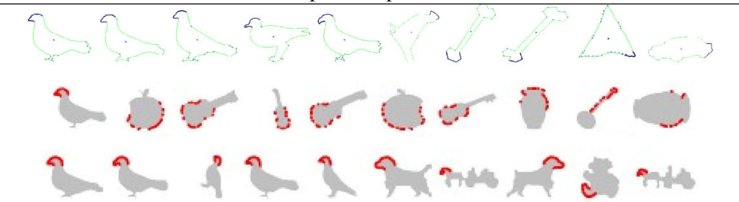
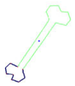
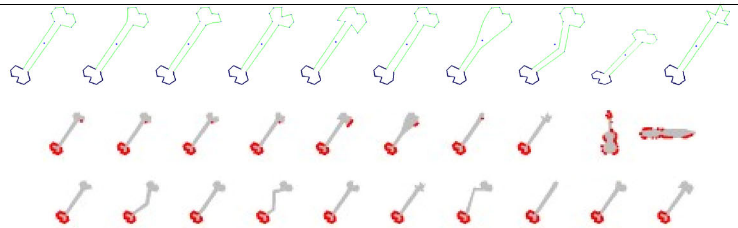
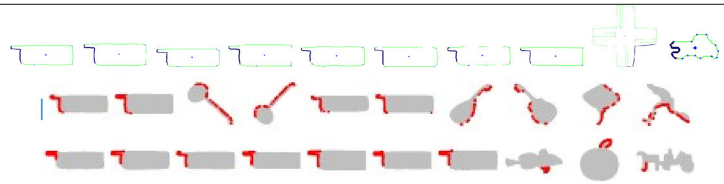
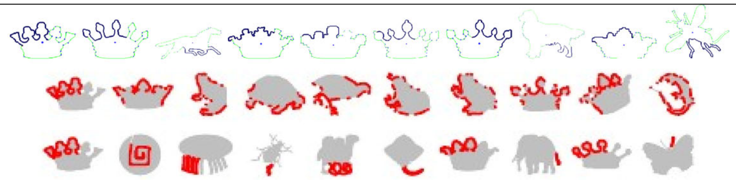
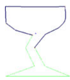
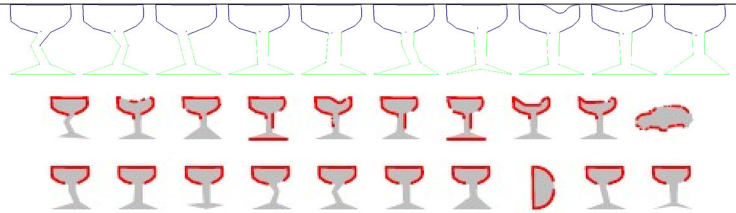
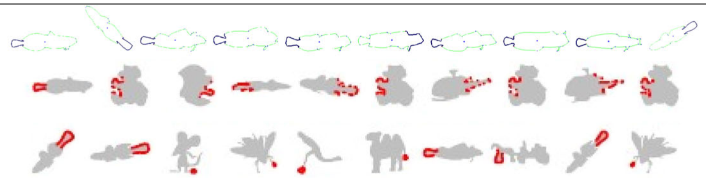
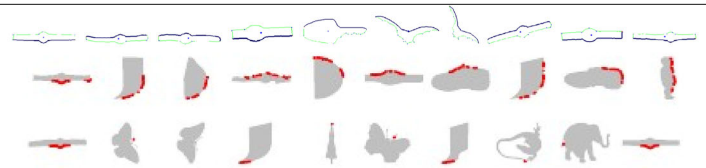
6.1 Partial matching

6.1.1 Results

Our partial approach has been compared to the most relevant works [27, 36]. The experiment performed in [27] on the MPEG7 data set consists to select 5 shapes out of each shape class, for a total of $350(5 \times 70)$ shapes. The partial matching is achieved on 10 queries corresponding to open contours extracted from some shapes of the selection. The reported results presented the top five responses retrieved from the selected 350 shapes. In [36] the same experiment is performed using the same queries but the retrieval is generalized to the whole MPEG7 data set and the top ten responses are reported. To be able to compare their results to [27], authors implemented the method presented in [27].

In our partial matching experiment, we have performed the same experiment as described in [36]. Therefore, we have conducted the same test on the same 10 queries using the same selected part of the ten shapes. Each query is submitted to the whole MPEG7 data set (1400) for the retrieval, and the top ten responses are reported. The obtained results are illustrated in Table 1. The first column shows the query shape with the part to match highlighted in a blue contour. The second column reports the top ten results of the three methods, illustrating the matched part in blue or red: the first row represents the results of our approach, the second row corresponds to the approaches [27, 36]. The third column gives the number of correct responses (shapes of the same class) among the 10 responses for each method.

Table 1 Partial matching results on 10 examples of MPEG7, for our approach and [27, 36]

Query	Top ten responses	Score
		6 5 1
		10 10 8
		8 7 4
		7 3 4
		10 9 9
		8 2 1
		7 2 3

The recognition rate of our method (86 %) outperforms those of Michel et al. [36] and Latecki et al. [27] (67 %, 35 %).

6.1.2 Discussion

In fact, in [27] when authors establish the partial elastic matching called Minimum Variance Matching (MVM), they associate a directed acyclic graph (DAG) to the two sequences to match. Therefore the optimal correspondence is obtained by finding the shortest path on the DAG. To skip outliers and allow elasticity, the authors tolerate jumps in columns, which means that all points of the query must be matched but not necessary to successive sequence of points. However, as shown in Table 2, when these jumps are important i.e associated points are dispersed, this yields to singular point matching and results in losing the meaning of the sequence and the visual similarity of the matched part to the query. Therefore, the probability to achieve a correct partial matching decreases considerably.

The method developed by Michel et al. [36] performs better than [27]. However, as the shape descriptor used corresponds to the set of distances computed from a sampled point to the others points of the same part, the partial matching results depend on the size of the selected query part and the details it contains. Thus, for small parts the results could be ambiguous, and high accuracy is obtained for more important parts, since its descriptor is more discriminative.

In our approach the results are more intuitive, the retrieved shapes present visually similar part as the query even they don't belong to the same class as the query. To allow the matching elasticity, we assume a more realistic hypothesis that tolerates skipping points from both the query and the matched part, but in a restricted neighboring to avoid singular point matching. Furthermore, our shape descriptor is based on corner points, therefore naturally, the size of the point sequence is very reduced compared to the points generated by the discrete curve evolution method used in [27] or the dynamic sampling proposed in [36]. In addition, the features associated to corner points are more discriminative in the representation of the shape details.

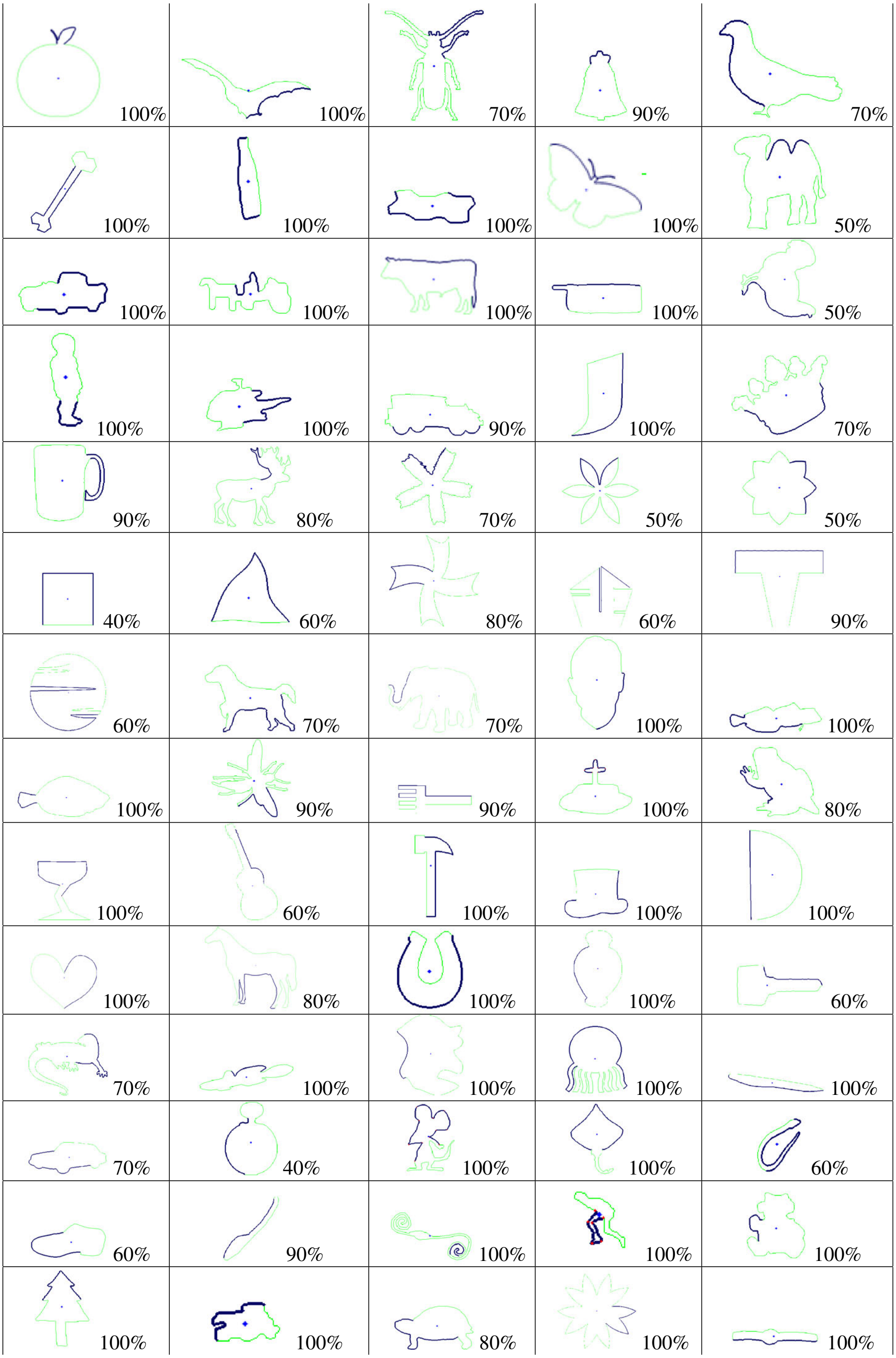
To confirm the results obtained in the previous experiment with 10 queries, the partial matching is generalized to all classes of the MPEG7 shapes. For each class, a part is submitted to the partial matching with the whole data set and the top ten similar shapes are retrieved. Table 2 illustrates the obtained results, the query part is highlighted with blue, the recognition rate of the query is reported, and it corresponds to the percentage of correct answers. The recognition rate of the 70 shapes corresponds to 85, 57 %.

6.2 Whole matching

6.2.1 Efficiency of the shape descriptor

Experiments are conducted to illustrate the efficiency of our shape descriptor and our matching algorithm for full shape matching. In this experiment we matched closed to closed contour using the approach developed in Section 4, the test is performed on a selection of 660 shapes (33 classes $\times$20) of the MPEG7 data set, each shape is submitted for full matching with the 1400 shapes of the data set, the 40 ranked responses are retrieved to compute the number of correct responses. The bull's eye score obtained for the selected classes is reported in Fig. 5, the recognition rate of the tested selection is 82, 85 %. In the same figure we have reported the results obtained for the same classes with the multi-scale representation method for non-rigid shapes with a single closed contour (MCC) proposed by Adamek

Table 2 Partial matching results of the whole MPEG7 classes



100%	100%	70%	90%	70%
100%	100%	100%	100%	50%
100%	100%	100%	100%	50%
100%	100%	90%	100%	70%
90%	80%	70%	50%	50%
40%	60%	80%	60%	90%
60%	70%	70%	100%	100%
100%	90%	90%	100%	80%
100%	60%	100%	100%	100%
100%	80%	100%	100%	60%
70%	100%	100%	100%	100%
70%	40%	100%	100%	60%
60%	90%	100%	100%	100%
100%	100%	80%	100%	100%

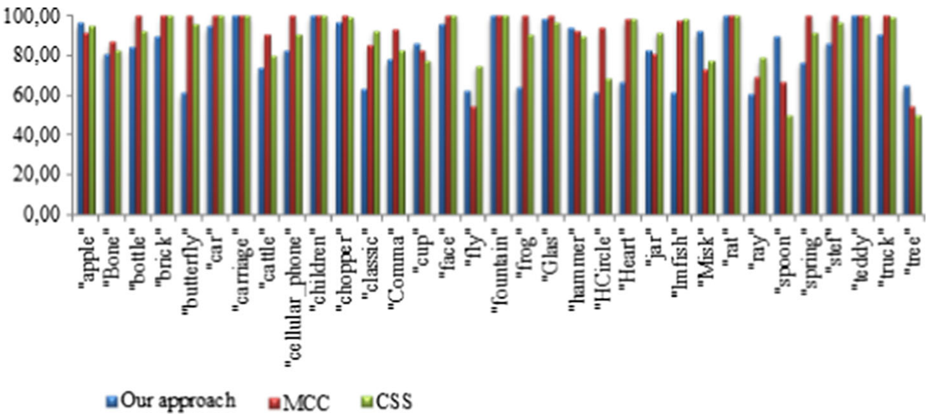


Fig. 5 Bull's eye score of some MPEG7 classes

and Connor [1], and an optimized version of the curvature scale space approach (CSS) developed in [7].

Qualitative results of some examples of the selection are presented in Fig. 6, where the first column corresponds to the query and the second one illustrates the top 20 responses.

6.2.2 Discussion

The obtained results show that the proposed method for closed to closed contour matching performs well even in case of some deformations as for apple example (Fig. 6) where the top 20 responses are correct in spite of missed parts in responses 19 and 20, and additional parts in response 13, and so for cattle, glas, spoon examples. Moreover, the method gives

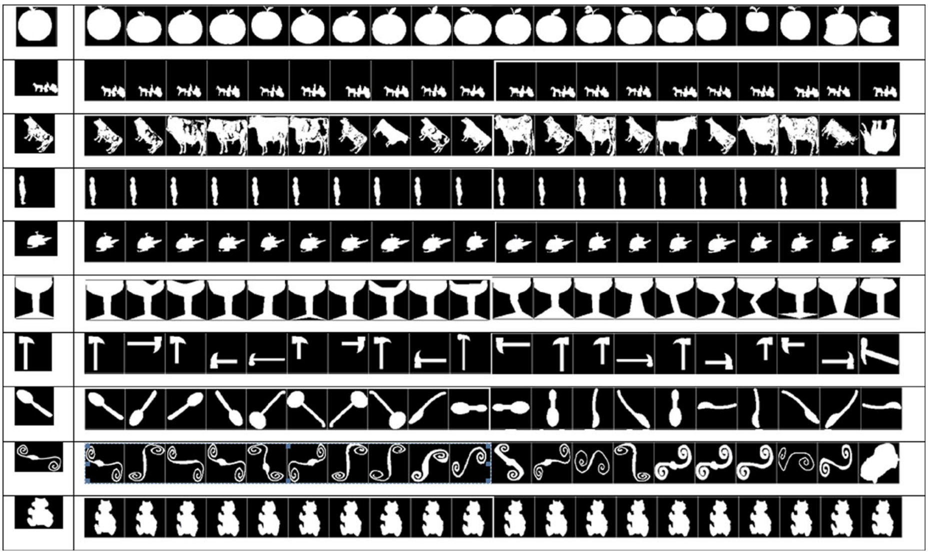


Fig. 6 Examples of shape retrieval using full matching on MPEG7 shapes

satisfying results in case of rotation, scale change and reflection. The plot of Fig. 5 demonstrates that our approach gives comparable results relatively to two well known methods [1, 7] in the state of art of shape modeling and matching.

6.2.3 Handling articulated shapes

Despite that the proposed approach has been developed essentially for partial and full matching problems, it is also able to handle some articulated shape matching. In fact, we have extracted a reference example from [29] of two articulated shapes abeetle and an octopus for a further comparison. The approach proposed in [29] provides different solutions for articulated shapes matching and classification, based on the inner distance. One of these methods uses the inner-distance to build a shape descriptor based on shape contexts called SC. Another one extends the SC by considering the texture information along shortest paths called IDSC. In the original example, the authors compared the performance of shape retrieval for SC and IDSC, they submitted the queries to the whole MPEG7 data set retrieval, the top one to nine matches are reported for each variant of their approach.

For our comparison, the same test is achieved in the same conditions using the full matching approach. Figure 7 recapitulates the results of each approach, the left column shows the two shapes to be retrieved, the three right rows show the top 9 retrieved shapes for each approach and the last column reports the score of the correct answers of each method. The obtained results demonstrate the competitiveness of our approach compared to a dedicated approach for articulated shape matching.

6.2.4 Partial matching at different rates

In this experiment, we submit a whole shape for global matching and we compare the obtained results with the partial matching by considering different parts of the initial shape. Table 3 illustrate this experiment on two examples: apple and bat. In the query column we

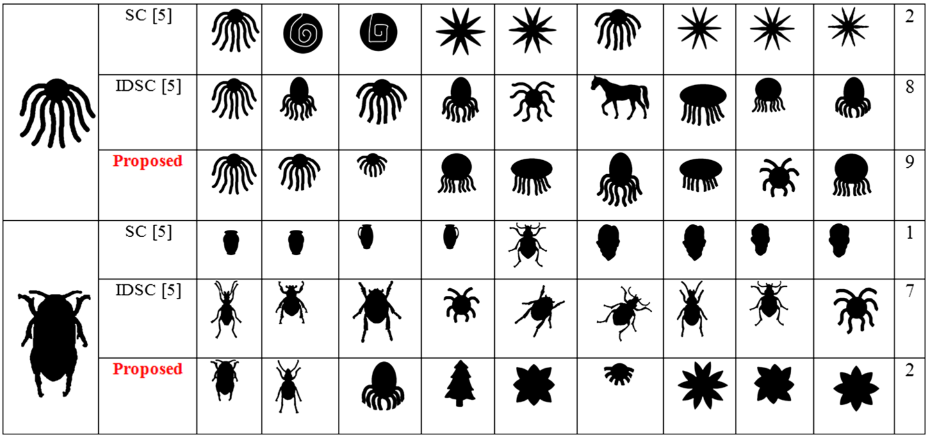
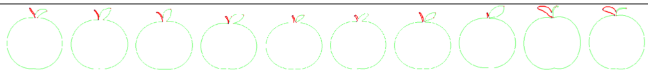
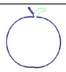
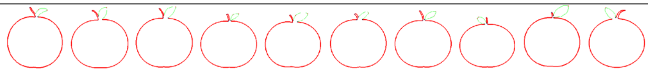
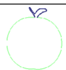
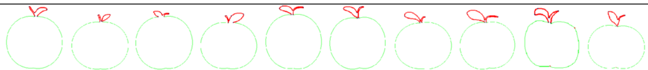
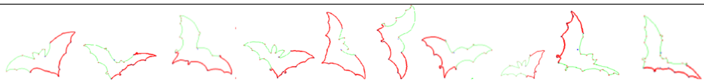


Fig. 7 Two retrieval examples an octopus and beetle of the MPEG7 shapes, for comparing SC, IDSC [5], and our approach

Table 3 Comparison of retrieval results in case of global matching and partial matching with different query parts

Query	Top ten responses	Score
		10
		10
		10
		5
		10
		8
		10
		4

can find in the first row the submitted shape for global matching, the bottom rows show the parts of contour in blue submitted for partial matching. The top ten retrieved shapes are reported and ranked by the similarity measure, in case of partial matching , the matched parts are highlighted in red. The last column reports the score of the retrieval result, it represents the number of shapes belonging to the same class as the query.

6.2.5 Discussion

The obtained results show that the retrieval rate does not depend systematically on the size of the submitted part, we can obtain a high score with a very small part (third query of apple example). Moreover, two parts of approximately the same size (third and fourth query of apple example) can give a very different result (one is more discriminative than the other). In addition, for some query parts the partial matching outperforms the global matching (first and second query of bat example).

Throw the previous observations, we can conclude that the choice of the submitted part is crucial to achieve the best retrieval score. the size of the query is not the most important parameter, the best results are obtained for parts that are characteristic in the shape class and are common to all instances of the class, as an example we can observe that for the last query of the bat example the submitted part is present in only 4 bats of the 20 shapes of the class, therefore only theses instances were retrieved, the global matching with this shape will decrease the retrieval accuracy because of the non common part (bat ears) included in the matching.

7 Conclusion

In this paper we have proposed an efficient descriptor invariant to rotation, scale and reflection; it also captures global and local information about the shape. We used this descriptor to achieve full and partial shape matching with novelty at two levels:

- In the full matching the coarse to refined matching provides an optimal solution for local deformations and reduces considerably the search of the optimal starting point.
- The partial matching assumes that the parts to be matched are both weakly distorted and gives a solution to skip outliers.

Our experimental results demonstrate the effectiveness of the two proposed approaches. The partial shape retrieval method outperforms existing methods and the full shape retrieval gives comparable results.

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