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Shape Retrieval through Polygon Matching

Bryan E. Martínez, Antonio Camarena-Ibarrola, Karina Figueroa

Universidad Michoacana de San Nicolás de Hidalgo,
Facultad de Ingeniería Eléctrica,
Mexico

bryaneduardo24@gmail.com,
{antonio.camarena, karina.figueroa}@umich.mx

Abstract. Content-Based Image Retrieval consists in searching for images in large datasets by their shape, it allows for automatic annotation in images, image classification, automatic surveillance, and many other applications. In this work, we model objects as sets of triangles built from keypoints on their border. We use an invariant of these triangles to make them robust to affine transformations such as scaling, rotating, or shearing; this invariant is adapted as a hash for indexing purposes. The experiments show that this method is very effective, achieving 99% accuracy, outperforming state-of-the-art works with the same collection of images.

Keywords: Image retrieval, contour shape, transform invariant.

1 Introduction

Image repositories grow very fast and there is great interest in designing efficient and effective Content-Based Image Retrieval (CBIR) algorithms [19]. CBIR by content is normally accomplished by extracting features from the images such as shapes, textures, and colors.

This work focuses on shape-objects contained in images. Shape is one of the primary low level image features used in CBIR and one of the Contour-Based Descriptors (CBD). Although CBD has been widely used and many researchers have had good results, there are some problems regarding robustness since it is affected by noise and variability.

This is because only part of the shape information, that is contour information, is normally used. Also, in many cases, the shape contour is not available. For some applications, shape content is more important than contour features [22]. For these reasons and also because many images contain not just one but several objects, a perfect retrieval rate using only the shape information has not been possible so far [4].

There are generally two types of shape representation methods in the literature, that is Region-Based and Contour-Based [21]. Both approaches can be subdivided into Structural or Global methods, as shown in Fig. 1. Structural methods are typically used where partial matching is required, while Global methods are used when complete matching is needed. Different methods can be further distinguished between them, some work in space domain and others in some transformed domain [19, 22].

We are interested in both Structural and Global methods, and we use Fourier descriptors to create polygons. Structural methods have several drawbacks [21]: Since

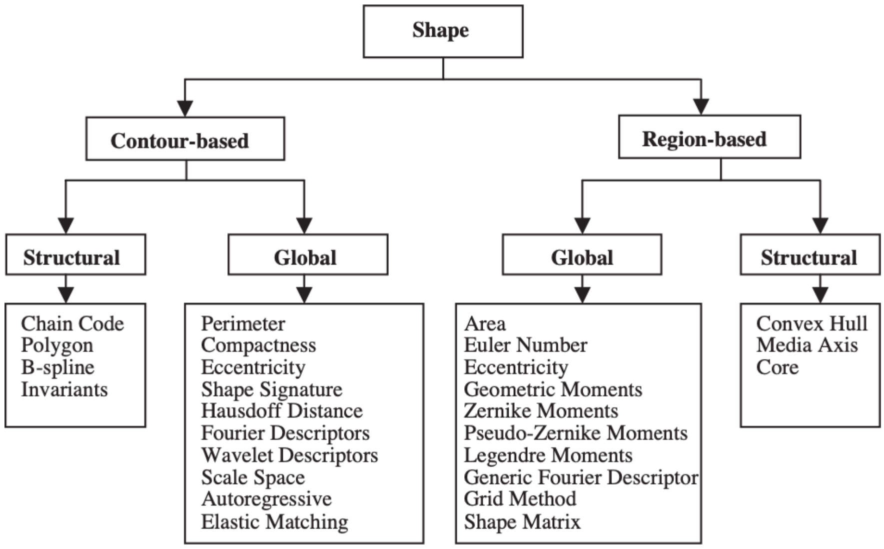


Fig. 1. Classification of shape representation and description techniques [22].

there is no formal definition for an object or shape, the number of primitives required for each shape is unknown. Variations of the object boundary may cause significant variations to local structures. In these cases, global features are more reliable. The shape and its representation is a many-to-one mapping.

Therefore, matching of one or more features does not guarantee full shape matching; Structural methods have higher computational complexity than conventional techniques. The distance or similarity measure used for Shape matching or shape retrieval should be invariant to many distortions including scaling, offset, noise contamination, partial occlusion, shearing, rotation, etc. Techniques for handling these distortions frequently rely either in the representation of the data or in the similarity or distance measure used [6, 12, 13, 16, 17].

Another issue that complicates the problem is the partial occlusion of objects due to the presence or other objects in the image [19]. Rotation invariance is also a challenge, some intended for achieving rotation invariance rely on the representation of the data at the expense of discrimination ability, while others rely on the distance measure used at the expense of efficiency [12].

In order to carry out Shape matching of image objects effectively, contour normalization techniques are widely used, as they save time and space during both feature extraction and similarity matching. The normalized sampled contour points are keypoints that compactly represent shapes. The conventional Shape matching and retrieval applications perform analysis methods of Equal Distance Normalization (EDN) on the shape contours. In addition to EDN, the boundary can also be normalized assuming the enclosed area of the shape captures all the information about the shape [17].

In assessing a method for shape retrieval six factors should be considered: (1) Retrieval accuracy, (2) Compactness of the features, (3) Generality for applications,

(4) Low computation complexity, (5) Robustness, and (6) Hierarchical coarse-to-fine representation [21, 22]. For large databases, sequential searching should be avoided, so shape descriptors should be indexable. Hash tables and M-trees are very used for these activities [6]. Shape recognition and retrieval are complex tasks on non-rigid objects, However, it can effectively be performed using a set of compact descriptors [17].

Shape representation is one of the most challenging aspects of computer vision because they are often more complex than color or texture. Moreover, color and texture can be quantified by a few parameters, unlike shapes that need hundreds of parameters to be represented explicitly [16]. Shape matching and indexing is an essential topic in its own right, and it is a fundamental subroutine in most shape data mining algorithms [12]. In conclusion, Shape is accepted as a stable visual feature for image recognition and retrieval due to its discriminate strength [19, 16, 22].

The rest of this work is divided as follows: First the state-of-the-art is reviewed in Section 2. In Section 3, we give a little description about polygons matching and some basic concepts to generate triangles by using curvature shape. In section 4 we explain our method as applied to the benchmark datasets described in Section 5. Finally, in Section 5 and 6 we show results and conclusions.

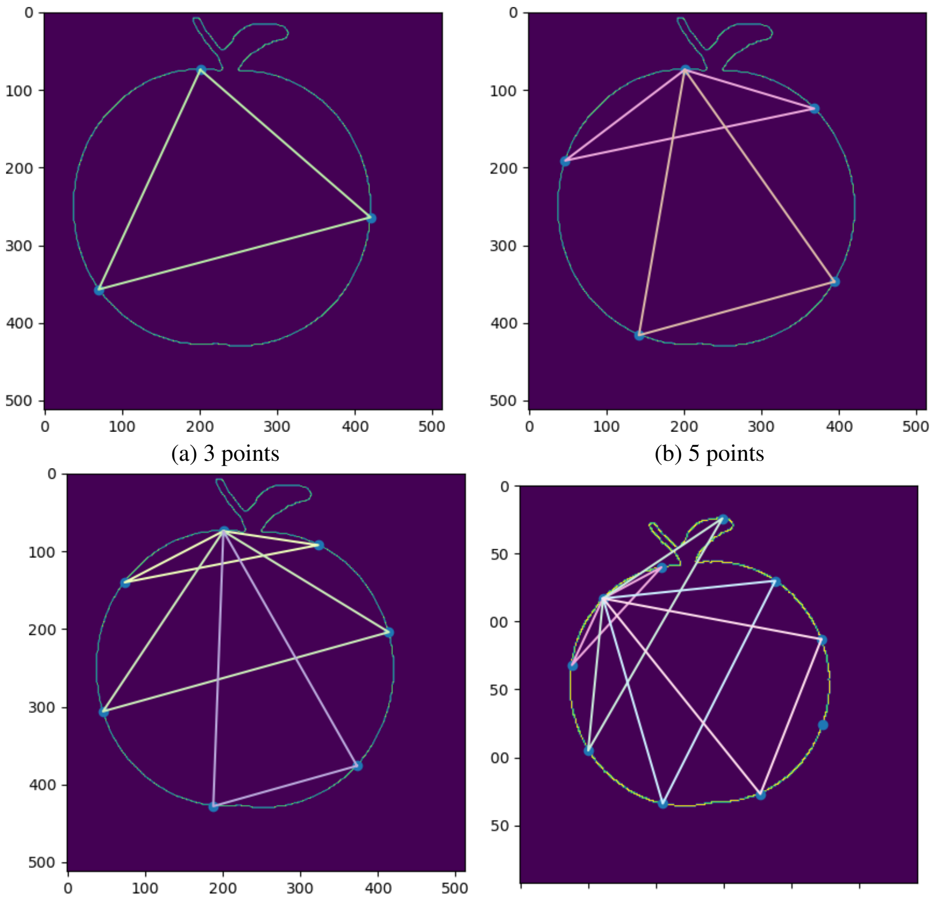
2 State of the Art

In early works features extracted from curvature shapes were sequences of values such as curvatures, angles, descriptor values, or polygon coefficients. The Curvature Zero Crossing Contours of the Curvature Scale Space (CSS) was used to represent the shapes of boundary contours of objects by five pairs of integer values. The significant advantage of this method is that it is indexable, and the aspect ratio of the CSS image is used to reduce the search range. Since the matching algorithm has been designed to use global information, it is sensitive to major occlusions, but minor occlusions do not cause problems [1, 16].

Another descriptor, used by many researchers, is the Zernike Moment Descriptor (ZMD), which has many desirable properties, such as rotation invariance, robustness to noise, expression efficiency, fast computation, and multi-level representation for describing the shapes. Kim & Kim showed that ZMD can be used as an adequate global shape descriptor for images in a large database [13]. The experimental results performed in a database of about 6,000 images in terms of exact matching under various transformations and the similarity-based retrieval showed that the proposed shape descriptor is very effective in representing shapes. Zhang and Lu evaluated ZMD and the CSS Descriptor [21].

The idea of getting patterns from curvature shapes led some researchers to use polygons, particularly triangles [4], these polygons represent shape curvature using the spatial positions distributed along the contour, they are quite popular among researchers even thought it focuses in the contour and neglects any information inside the shape [19].

Kumar and Mali remark the importance of selecting good keypoints at contour sampling for shape classification via contour matching [14]. In Boundary-Based Shape matching, Dynamic Time Wrapping (DTW) and Dynamic Space Warping (DSW) have



(a) 3 points (b) 5 points

(c) 7 points (d) 10 points

Fig. 2. Representing an apple shape contour with triangles using keypoints.

proved to be useful [3, 19]. Bartolini *et al.* proposed a Fourier-based approach for shape retrieval called WARP [6], they claimed that phase information provides a better accurate description of object boundaries than using only the amplitude of the Fourier coefficients, they use DTW to match images even in the presence of (limited) phase shifts, they also use proximity indices to speed-up the retrieval phase.

Alajlan *et al.* proposed a Shape Retrieval method using Triangle-Area Representation (TAR) for non-rigid shapes with closed contours [4]. The representation uses areas of triangles formed by boundary points to measure convexity at different scales (or lengths of triangle's edges). This representation is effective in capturing both local and global characteristics of a shape, it is invariant to translation, rotation, and scaling.

It is also robust against noise and some partial occlusion. In the matching stage, a Dynamic Space Warping (DSW) algorithm is used to search for the correspondence between the points of two shapes. A distance is computed based on the best alignment between two shape representations. The computational complexity for matching is

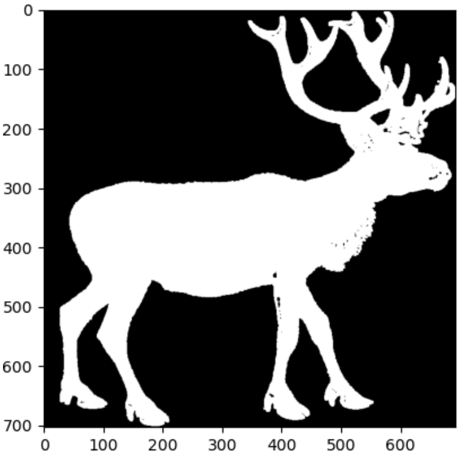


Fig. 3. Deer from the MPEG-7 Core Experiment CE-Shape-1 Dataset.

O(N^2), where N is the number of boundary points. A difficulty associated with DSW is the fact that the starting point of a contour shape is unknown, the same happens when working with rotation angles (i.e. Which angle is the first one?).

Rather than performing an exhaustive search for the correct starting point as in classical approaches, Alajlan proposed Algorithm HopDSW which finds the starting point efficiently [3]. HopDSW operates in a coarse-to-fine manner. The coarse search is global and uses a hopping step to exclude points from the search. Then, the search is refined in the neighborhood of the solution of the coarse search. A criterion for selecting the hopping step parameter is given thus reducing the number of starting point computations. For shape representation, Triangle Area Signature (TAS) is computed from triangles formed with the boundary points.

Paramarthalingam and Thankanadar proposed a procedure for generating normalized contour points from shape silhouettes, this procedure identifies the contour of any object in an image and uses the Object Area Normalization (OAN) method to split the object by its center into regions of equal area. They defined Six descriptors: The Compact Centroid Distance (CCD); the Central Cngle (ANG); the Normalized Points Distance (NPD); the Centroid Distance Ratio (CDR); the Angular Pattern Descriptor (APD); and the Multi-Triangle Area Representation (MTAR). These descriptors conform a feature vector to model the shape of the object [17].

Keogh *et al.* consider rotation to be the hardest distortion in shape matching and indexing. Regular approaches rely on data representation to achieve rotation invariance, they show how to speed up such approaches without loosing accuracy, they make use of existing shape representations and distance measures [12]. Yildirim *et al.* proposed a statistical approach [19], they compute the standard deviation of the angles between the shape centroid and all points around the contour. They quantize angle to integer values, then for each angle they extract three features: The number of contour repetitions; the average distance of the points at that angle to the centroid; and the standard deviation of those distances.

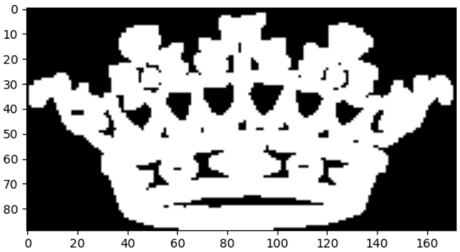


Fig. 4. Crown from the MPEG-7 Core Experiment CE-Shape-1 Dataset.

Kumar and Mali used the center of gravity of the shape of an object as a fixed point, then computed the perpendicular distance from each point on the object contour to the line passing through the fixed point as a geometrical invariant. In the matching stage, they used principal component analysis concerning the moments of the perpendicular distance function, their method is robust to translations and rotations [14].

Xu *et al.* used Partial Shape Matching (PSM) and Dynamic Programing (DP) for retrieval of vertebral boundary shape in X-ray images, their method called corner-guided DP, uses nine landmark boundary points as a multiple open triangle representation. Their method use linear transformations (translation, rotation, and scaling) on a shape to find the best match between two shapes [18].

Arjun and Mirnalinee proposed an iterative algorithm called multi-scale feature integration that use points on the shape curvature, these points are ordered according to their normalized distance to the contour. For feature extraction they use the angular pattern (AP), Binary AP (BAP), and Sequential Backward Selection (SBS) algorithms [5]. Abro *et al.* evaluated some features such as Fourier descriptors, Hierarchical Centroids, Moment-based descriptor and Shape Context Descriptors and showed that fusing several descriptors a better accuracy is achieved. They assessed fusion based on concatenation of features and fusion based on a discriminant correlation analysis achieving an accuracy of 90% [2].

Paramarthalingam and Thankanadar proposed the Object Area Normalization (OAN) method for generating normalized contour points from shapes, they split each object with respect to its centroid into segments of the same size using triangles. From these triangles, they define six contour-based geometric shape features and use them to recognize shapes [17].

Zhang *et al.* proposed an algorithm called shape classification network (SCN) based on convolutional neural networks based on LeNet5 since this basic structure have been used to recognize handwritten numbers achieving good results on MNIST dataset and they claimed it is a similar problem to object shape recognition [20]. Damen *et al.* use *edgelet* constellations for detecting objects in stream video [9]. Edgelets are edge segments and constellations of edgelets are used to characterize shapes even when they are partially occluded.

There are many works on the subject, we described here those with shape retrieval accuracy between 90% and 100%. We found that those works where 100% accuracy was reported, included in their tests just Rotation or Scaling, but not both. In very few works, the authors included shearing in their tests and those who did report an accuracy

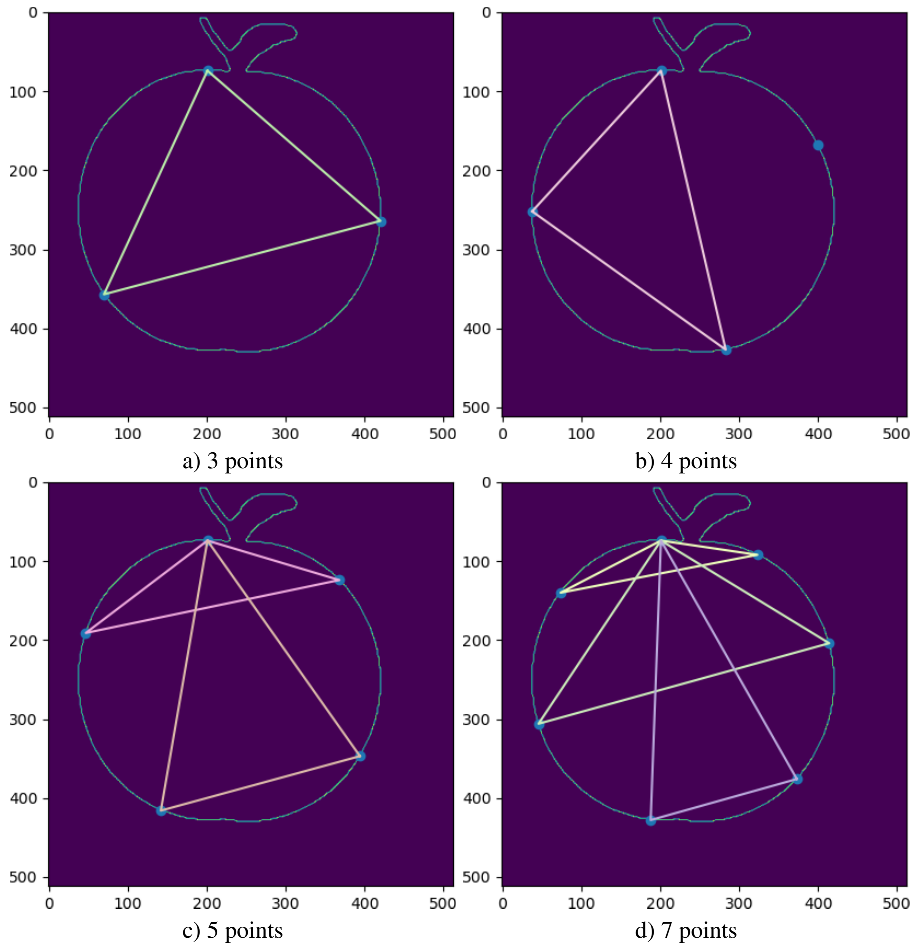


Fig. 5. Representing an apple shape contour with triangles using keypoints.

of about 80%. Those who are unfamiliar with the problem and need basic information should start with [11]. Those familiar with the problem but still need a survey may read [22], for more recent advances in the state-of-the-art may read [19].

3 Theoretical Framework

A generalized polygon is an ordered set of vertices, this notion generalizes the concept of the boundary of a polygonal shape because self-intersections are allowed [10]. Using Polygons to represent Contour shapes, the problem of contour matching is turned into a problem of accomplished polygon matching. For example, in Fig. 5, the contour shape of an apple is used to generate triangles from keypoints, a Start point (or main point) was chosen and you recognize it in Fig. 5 because it is common to all triangles, the number of triangles used to represent the shape is a free parameter and determines the number

Table 1. Results on the Normal Experiment using unmodified images.

Keypoints	Hits/Total	Accuracy
3	1394/1400	0.9957
4	1394/1400	0.9957
5	1394/1400	0.9957
6	1394/1400	0.9957
7	1394/1400	0.9957
8	1394/1400	0.9957
9	1394/1400	0.9957
10	1394/1400	0.9957

of points needed for that matter. In Fig 5 the representation of an apple is shown with 3, 5, 7, and 10 points. Observe that with less than 10 points the stem was not reached.

For the problem of matching polygons, Chavez *et al.* proposed seeing the sequence of vertices that define a polygon as a sequence of complex numbers and so as a small complex signal, then they defined a Fourier descriptor that is invariant under affine transformations of the polygon, including rotation, translation, scaling, and shearing [8]. For that purpose Chavez *et al.* built a collection of complex scalar functions on the space of plane polygons, if two polygons are affine related, the pseudo-hyperbolic distance between their associated values is a constant that depends only on the affine transformation involved, but independent of the polygons.

Point (x, y) in the plane is associated with the corresponding complex number $z = x + jy$, where $j = \sqrt{-1}$. A polygon in the plane, which is an ordered set of points, is then an ordered set of complex numbers, in which the order defines which are the consecutive vertices. Given polygons $Z = (z_,1, z_2, z_3, \ldots, z_n) \in \mathbb{C}^n$ and $W = (w_1, w_2, w_3, \ldots, w_n) \in \mathbb{C}^n$, where n is the number of vertices, matching W and Z is the problem of telling if there is an affine transformation f such that $Z = f(W)$ [7, 8, 10].

The approach to polygon matching under affine transformations involves the construction of complex scalar functions $\varphi_\ell : \mathbb{C}^n \to \mathbb{C}, \ell = 1, \cdots, \lfloor (n-1)/2 \rfloor$. Then, finding all the matching polygons in a collection can be achieved very quickly after mapping all the polygons in the collection to complex numbers. It is important to highlight that all similar polygons under affine transformations will be mapped to the same complex number φ_ℓ. This method assumes $n \geq 3$ (we need $n = 3$, because we are using triangles). Function $\varphi_\ell : \mathbb{C}^n \to \mathbb{C} \bigcup \{\infty\}$ is:

$$\varphi_\ell(z_1, z_2, z_3, \cdots, z_n) = \frac{\sum_{k=1}^{n} \lambda^{\ell k} z_k}{\sum_{k=1}^{n} \lambda^{-\ell k} z_k}, \tag{1}$$

where $\lambda = e^{\frac{2\pi j}{n}}$ and ℓ is any integer in $1, \ldots, \lfloor (n-1)/2 \rfloor$.

Table 2. Results on the Extended experiment with modified images.

Keypoints	Scaling (hits/total)	Rotation (hits/total)	Shearing (hits/total)	Average Accuracy
3	1388/1400	**1394/1400**	1394/1400	**0.9942**
4	1382/1400	**1394/1400**	1394/1400	0.9928
5	1397/1400	1379/1400	1394/1400	0.9928
6	1397/1400	1379/1400	1394/1400	0.9928
7	**1399/1400**	1379/1400	1394/1400	0.9933
8	**1399/1400**	1379/1400	1394/1400	0.9933
9	**1399/1400**	1379/1400	1394/1400	0.9933
10	1397/1400	1379/1400	1394/1400	0.9928

4 Description of the Proposal

In this section we will describe our method of contour shape retrieval. We built a proximity index, to do that we process each image in the following way:

1. First, the contour shape in the image has to be determined. We use the canny edge detector and eliminate holes to deal with images such as the crown shown in Fig. 4.
2. We determine the centroid of the contour shape and the nearest point to this centroid that is in the contour. These two keypoints, labeled as 1, and 2 define a line of reference. We translate the image so the centroid corresponds with the origin (0, 0).
3. We split the curvature shape by tracing lines at 120, 90, 72, 60, 51.42, 45, 40 and 36 degrees counter-clockwise with respect to the line of reference between keypoints 1, and 2. The points where these lines intersect with the contour are the keypoints labeled as 3, 4, 5, 6, 7, 8, 9, and 10. When the lines intersect 2 or more points of the contour (think for example of the contour of the Deer shown in Fig. 3), these points can be ordered from its distance to the centroid from the innermost to the outermost. We select as keypoint only the outermost thus favoring bigger triangles.
4. We create triangles starting from keypoint 2, and the keypoints at its left and right. Then add another triangle using always keypoint 2 and the keypoints at its left and right that have not been used until there are no more unused keypoints or until there is just a single keypoint available (we need keypoint 2 and two more to build a triangle).
5. For each triangle built in the previous step we use Equation 1 and compute the magnitude of the complex number that results from that transformation obtaining a single number per triangle.
6. Using the number determined in the previous step, add the triangle as well as its unique identifier to a hash table of size 256. The shape has an entry to the hash table for each triangle built from it.

Table 3. Accuracy obtained of our proposal contrasted with those obtained in similar works that use the same collection of images.

Author	Average Accuracy
SCN	0.7539
BAPmP	0.8797
(SCF + SCF) (DCA)	0.9196
SA-OAN	0.9434
DSW + Global	0.9508
Zernike moment descriptor	0.9588
Our proposal	**0.9942**

In Fig. 5 the importance of a good selection of keypoints is depicted. Using our method for selecting keypoints, the shape may be rotated, and still we select almost the same keypoints, very near as you may observe, this is important if we want the set of triangles to represent the shape.

5 Experiments and Results

For our experiments, we used the MPEG-7 Core Experiment CE-Shape-1 Test Set, which is the most commonly used dataset for the contour shape matching problem, this database consists of 1400 images from 70 classes of natural and artificial objects [15]. Figures 4 and 3 are examples from this collection of images. The set has two parts called A1 and A2, for scaling and rotation respectively. We conducted two experiments on retrieving images by content based on the contour shapes, in both experiments we use all triangles obtained from the query image to search for a match using the hash table.

For the first experiment, which we called the normal experiment, we used the original dataset without modifications. We varied the number of keypoints from 3 to 10, and in all cases we achieved an accuracy of 0.9957 as shown in Table 1. For 1400 queries in 1394 the system identified the shape correctly and failed only in 6. For the other experiment, which we called the extended experiment, the images of the dataset were modified by scaling, rotation, and shearing using the same parameters used by other researchers interested in this problem, these parameters are also used in known datasets such as Kimia99, and ETH-80, they are:

- **Scaling**: .1, .2, .25, .3 and 2.
- **Rotation**: 9, 36, 45, 90 and 150 degrees.
- **Shearing**: -.3, -.2, -.1, 0, .1 and .2.

Modified images were used to retrieve unmodified images. The results of the extended experiment are shown in Table 2. The best accuracies were obtained using 7-9 keypoints for scaling, 3-4 keypoints for rotation and 3-10 keypoints for shearing.

Surprisingly using only 3 keypoints the method works very well, leaving not very much room for improvement when using more keypoints. In Table 3 the achieved accuracy is contrasted with those obtained from the work of researchers that have used the same collection of images.

6 Conclusions and Future Work

We designed a contour shape matching/retrieval technique that is very robust under rotation due to the way the keypoints that conform the triangles are selected, and is also robust under Scaling and Shearing thanks to the use of invariant obtained with Equation 1. The features extracted are compact since only a few keypoints have to be stored. Extracting these features is a low complexity procedure.

Our method does not require the use of DTW algorithm or any aligning mechanism thanks to the way we select our keypoints, that is, the initial point is always about the same point, this fact is very important since it reduces the computational complexity for comparing features between objects. There are however two drawbacks, the method is sensitive to noise so it works very well when combined with a good noise removal technique. Also, our method works only with non-occluded shapes.

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