Extreme Curvature Scale Space for Efficient Shape Similarity Retrieval

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Abstract: *The description of the object shape is an important characteristic of the image; several different shape descriptors are used. This paper presents a novel shape descriptor which is robust with respect to noise, scale and orientation changes of the objects. It is based on the multi scale space approach to identify shapes. The descriptor of a shape is created by tracking the position of extreme curvature points in a shape boundary filtered by low-pass Gaussian filters of variable widths. The result of this process is a several contours map representing the extreme curvature points of the shape as it is smoothed. The maxima of these contours are used to represent a shape. We demonstrate object recognition for three data sets, a classified subset of database SQUID, the set of silhouettes from the MPEG-7 database and the set of 2D views of 3D objects from the Columbia Object Image Library (COIL-100) database. The results prove the performance and robustness of the developed method and its superiority over Curvature Scale Space (CSS) in shape with shallow concavities.*

Keywords: *Multi scale analysis, CSS, shape similarity, image database retrieval.*

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1. Introduction

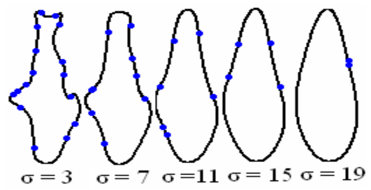
Shape representation/description and matching is a central and challenging problem in image processing and computer vision which arises in many applications since shape is an inherent property of most objects. A large number of shape representation methods have been introduced in the literature [9, 19]. These methods can be classified into two categories: Region based and contour based. Each of these groups is further subdivided into two subgroups containing global or structural approaches.

Region-based descriptors work on a shape as a whole taking into account all the pixels within a shape. Common methods use moment descriptors to describe shape [6, 19]. These include geometric moments, Legendre moments, Zernike moments and pseudo-Zernike moments. Region-based methods are more suited to general applications. However, they are more computationally intense and most approaches need to normalize the image to achieve common geometrical invariances. These normalizations introduce errors, sensitivity to noise, and thus inaccuracy in the recognition process.

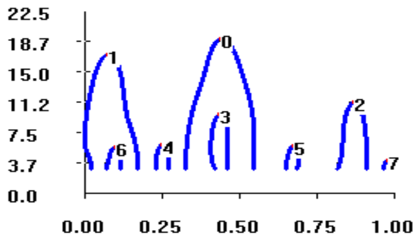
Contour based shape representation only exploits shape boundary information. These representation methods are more popular than region-based approaches in the literature. This is because silhouette contours contain detailed information about the shape of objects, and because in many of the shape applications, the shape contour is the only interest, whilst the shape interior content is not important. Different feature based contour are employed for shape similarity retrieval. In Query by Image Content (QBIC) system a set of simple global descriptors like area, circularity, eccentricity, axis orientation and bending energy are used to represent an object. These descriptors can only discriminate shapes with large dissimilarities; therefore, they are not suitable to be standalone shape descriptors. The basic idea in shape signatures is to represent shape by a one dimensional function derived from shape boundary points. Many shape signatures exist [11], including centroid distance, curvature signature and cumulative angles. Shape signatures are local representations of shape features and are extracted from spatiall domain; as a result, they are sensitive to noise. Slight changes in the boundary can cause large error in the matching.

The curvature of a curve has salient perceptual characteristics [13, 17] and has proven to be useful for shape recognition [18]. Asada and Brady [3] have developed a description they refer to as the “curvature primal sketch” as a fundamental and comprehensive intermediate image representation. The description is a multi scale structure based on the extraction of changes in curvature.

Mokhtarian and Boder [21] developed the Curvature Scale Space (CSS) technique which was one of the features selected to describe objects in the MPEG-7 standard. The CSS image of a planar curve is computed by convolving a path-based parametric representation of the curve with a Gaussian function of increasing variance σ^2, extracting the zeros of curvature of the convolved curves, and combining them in a scale space representation for the curve. These zero curvature points are calculated continuously while the planar curve is evolved by the expanding Gaussian smoothing function as shown in Figure 1.

a) A fish shape. b) Contour smoothing.



c) The resulted CSS image.

Figure 1. Curvature scale-space filtering for a closed contour.

Over the past few decades, the CSS technique has been extensively investigated and applied for solving various problems in the field of computer vision and image processing [14, 28].

In [30], the problem of extending the curvature scale-space technique to represent open curves is addressed. Various approaches to deal with the endpoint problem of open curves are considered, and one which allows us to handle the evolution of the open curves as a special case of the evolution of closed curves is selected. The convergence theory of evolved open curves is established, and the CSS shape representation is investigated.

Ye and Androutsos [22] proposed a new affine invariant shape descriptor called the Principal Component Analysis (PCA)-whitening CSS descriptor. It is used to transform the original shape contours into their canonical forms, in which the effects of scaling and skewing are eliminated. Next, CSS images are extracted from the canonical contour shapes. The maxima of the CSS images are the affine invariant shape descriptors. Image retrieval experiments on a 1890 silhouette image database show a promising retrieval rate of 91.02% using the proposed descriptor, which over performs its affine parameterization based counterpart by 10.03%.

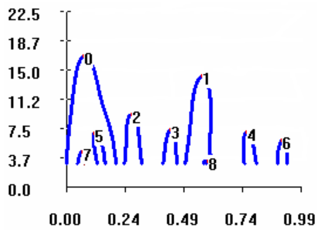
To reduce the computational cost of CSS descriptor, Baojiang and Liao [29] proposed Direct Curvature Scale Space method (DCSS). DCSS is defined as the CSS that results from convolving the curvature of a planar curve with a Gaussian kernel directly. To compute a scale space image, DCSS is much cheaper than CSS.

Mark *et al.* [10] have introduced the Eigen-CSS search for shape retrieval. A new feature vector for shape representation has been created and called the marginal sum feature vector which is composed of row-sum and column-sum of the raw CSS image. Then, the PCA (called as Eigen-CSS) is used in the matching stage.

The CSS representation has proven to be robust under noise, scaling, orientation and translation changes, its drawbacks are mainly due to the problem of shallow concavities on the shape [26, 29].

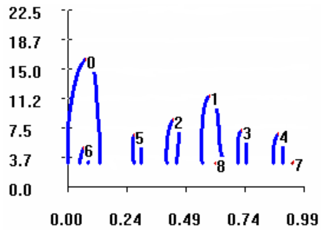
It can be shown that the shallow and deep concavities may create the same large contours on the CSS image. Therefore, a shallow concavity may be matched with a deep one during the CSS matching. As an example, the two shapes in Figures 2-a and c are different shapes. However, their CSS image in Figures 2-b and d are quite similar.

a) A shape with a shallow concavity on the boundary.



b) CSS image.

c) A shape with a deep concavity on the boundary.



d) CSS image.

Figure 2. Two different shapes and their CSS images.

This problem was previously analyzed in [2] by adding more information to the CSS image maxima. However, the proposed strategies depend on some empirical parameters that need to be fine tuned and raise the computational costs significantly [24].

Several methods integrate curvature extrema of the smoothed shape exists, in [5], the curvature zero-crossing points from a Gaussian smoothed boundary are used to obtain primitives, called tokens. The feature for each token is its maximum curvature and its orientation, and the similarity between two tokens is measured by the weighted Euclidean distance. Since the feature includes curve orientation, it is not rotation invariant. A remedy is proposed in [25] by using the concept of “force equilibrium” in order to normalize the shape orientation.

Lee and Atkins [16] exploit local curvature extrema to divide the border into a set of indentation/protrusion segments by construct extended curvature scale space image. The zero-crossings of the partial derivative of the curvature function with respect to path length variable for each smoothing scale are determined and their positions are recorded on the image along with their concavity or convexity property. The most important difference between this method and CSS is the functionality of his contour map. CSS image are designed to analyse point features, while extended curvature scale space image analyse indentation and protrusion curve segments, which can be organised into hierarchical structures.

In [23], the shape contours are smoothed using linear diffusion of the contour. A diffusion scale proportional to the contour dimension is chosen, improving the uniform scaling invariance. The relative positions of the smoothed contours curvature extremes are compared, resulting in a shape similarity measure. This method is compared with the resulting from comparing the maxima of the scale-space maps of the CSS. It is shown that those maxima always coincide with a curvature extreme at the maximum scale. Retrieving examples using the proposed method are compared with the results of a CSS implementation. A visual improvement of the retrieving results was found. The results were also compared with a polygonal approximation based method.

Andrei *et al.* [13] proposed a multiscale, morphological method for the purpose of shape-based object recognition. A connected operator similar to the morphological hat-transform is defined, and two scale-space representations are built, using the curvature function as the underlying one-dimensional signal. Each peak and valley of the curvature is extracted and described by its maximum and average heights and by its extent and represents an entry in the top or bottom hat-transform scale spaces.

From the above works based on curvature information, we can deduce two important remarks: First, it is clear that will be of great benefit to integrate the curvature characteristic for shape description in any efficient shape descriptor, secondly, the CSS descriptors can fail to distinguish shallow concavity from deep concavity on the shape boundary. Consequently, dissimilar shapes can be described as similar shapes because of this failure. To take into account these observations, we propose a new descriptor based on the presentation of extreme curvature points in multi scale space. The proposed descriptor makes two changes to curvature scale space method: It substitutes the use of curvature extrema for curvature zero crossings and it adds the value of the curvature in each extremum as an additional feature on each of the matched points.

The remainder of the paper is organized as follows. In section 2 we present a new scale space descriptor and its properties. A shape distance measure is introduced in section 3. In section 4, several retrieval examples are shown and a comparative analysis between CSS and our descriptor are presented. Finally, the conclusion and future investigations are discussed in section 5.

2. Proposed Descriptor

The proposed descriptor is based on scale space analysis and extreme curvature. Intuitively, curvature is a local measure of how fast a planar contour is turning. Therefore, it can be defined as the derivative of the tangent angle to the curve. Let $f(u)=\langle (x(u), y(u)) | u \in [0, 1]\rangle$ be the parametric representation for a given curve of shape, where u is the normalised curvilinear abscise. And let $\langle g(u,\sigma)/\sigma \geq 0\rangle$ be set of Gaussians where, for a given σ, $g(u, \sigma)$ is given as follows:

$$g(u,\sigma)=\frac{1}{\sigma\sqrt{2\pi}}e^{\frac{-u^2}{2\sigma^2}} \tag{1}$$

The set of the smoothed curves $\langle f(u,\sigma)/\sigma\,{}^{3}0\rangle$ is a multi scale representation of the curve of shape $f(u)$. Those smoothed curves are obtained by the convolution of $f(u)$ with the set of Gaussians $g(u, \sigma)$ for different values of σ.

A set of a multi scale curvature $K(u, \sigma)$ that corresponds to the set of curve of shape $\langle f(u,\sigma)/\sigma \geq 0\rangle$ can be defined as follows:

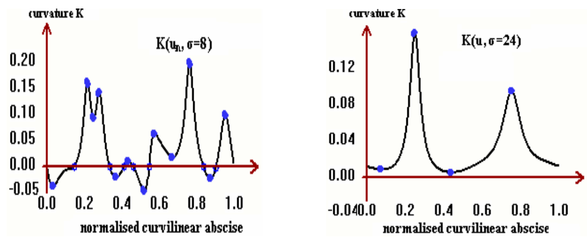
$$K(u,\sigma)=\frac{x_t(u,\sigma)y_{tt}(u,\sigma)-x_{tt}(u,\sigma)y_t(u,\sigma)}{\left(x_t^2(u,\sigma)+y_t^2(u,\sigma)\right)^{3/2}} \tag{2}$$

Where x_t, y_t et x_{tt}, y_{tt} are respectively the first and second derivatives of x and y with respect to t.

Let $P=\{P_{i(\sigma)}\}_{i=1}^{N}$ be the set of minima that is the set of points such as $K(u, \sigma)$=0 (set of inflection points). If we assume that the curvature $K(u, \sigma)$ is continuous between two consecutive minima $P_{i(\sigma)}$ and $P_{(i+1)(\sigma)}$, Rolle's theorem applies, there is always an extremum $m_{i(\sigma)}$ (minimum or maximum) of $K(u, \sigma)$ located at point $P_{mi(\sigma)}$ between these points $P_{i(\sigma)}$ and $P_{(i+1)(\sigma)}$.

Note that, the extremum of curvature $K(u, \sigma)$ is not unique between two inflection points. It could have several minima and maxima between two curvature zero-crossing points as shown in Figure 3.

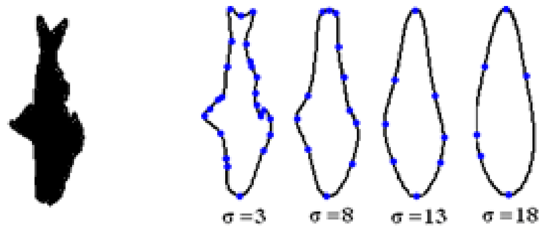
a) Example of fish shape and its curvature function of the smoothed shape at b and c.



b) σ=8. c) σ=24.

Figure 3. Curvature function representation. All extreme curvature points are presented by bold points.

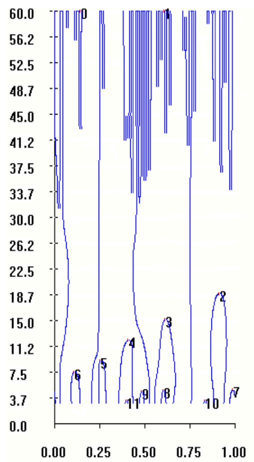
We propose to describe each extremum curvature point $P_{mi(\sigma)}$ of the curve $f(u, \sigma)$ by the vector $E_{i(\sigma)}(u_{i(\sigma)}, \sigma, m_{i(\sigma)})$, with $u_{i(\sigma)}$ in [0, 1] is the normalised arc length, σ is the width of the Gaussian kernel, and $m_{i(\sigma)}$ is the curvature at point $P_{mi(\sigma)}$. As a result, a set of extremum curvature points can be extracted from each smoothed contour shape description in multi scale representation. Figure 4 shows the obtained results of the smoothed curves in multi scale representation for given shape and their associated extreme curvature points.



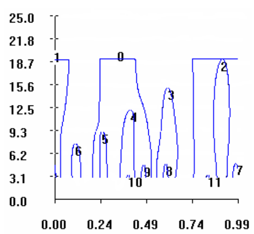
a) Scale σ increases. b) From left to right: σ = 3, 8, 13, 18. The points marked on the boundary are the extreme curvature points.

Figure 4. The evolution of shape boundary.

The locations of extreme curvature $P_{mi(\sigma)}$ on $\langle f(u,\sigma)/\sigma \geq 0\rangle$ described by vector $E_{i(\sigma)}(u_{i(\sigma)}, \sigma, m_{i(\sigma)})$ are determined at different levels of the scale. The process starts with σ=3, and at each level, σ is increased by $\Delta\sigma$, chosen as 0.1 in our experiments. As a result we can display the resulting points in (u, σ) plane, where u is the normalised arc length and σ is the width of the Gaussian kernel. The result of this process can be represented as a binary image of the curve as shown in Figure 5-a.



a) The evolution of extreme curvature points of fish shape in (u, σ) plane.



b) The extracting process of extreme curvature points stops when the curvature zero-crossing points disappear.

Figure 5. Extreme curvature points representation.

The intersection of every horizontal line with the contours in this image indicates the locations of extreme curvature on the corresponding evolved curve. For example, by drawing a horizontal line at σ=8, it is observed that there are 12 extreme curvature points. These points can also be found on the boundary of the shape in Figure 4 for σ= 8.

It is clear, as the scale σ increases, the infection points become less, and therefore, at the highest scale, the boundary is smooth and there is no inflection points, but our proposed process continue to extract some extreme curvature points as shown above in Figure 3-c, correspond to σ=24, the contour of the fish shape given in Figure 3 has four points of extreme curvature, and has no inflection points. Therefore, even in case of no zero curvature points we can find extreme curvatures points. Hence, the problem is the condition for terminating the processes, i.e., for which value of σ we must stop our algorithm. To solve this problem, we propose to take into account only the extreme curvature points between each pair of successive zero-curvature points. So, our algorithm for determination of the extreme curvature points stops when the curvature zero-crossing points disappear (the number of curvature zero-crossing points will be zero) as shown in Figure 5-b.

The final descriptors contours are composed of all maximum curvature points from the binary image obtained. Hence, the peaks are then extracted out and sorted. In the case of incomplete contour map, (exp: Peaks 0 and 1 in Figure 5-b), we take into account both its branches.

Small contours of the binary image obtained are related to noise or small ripples of the curve. As a result, small maxima are not included in this representation.

Finally, the proposed descriptor are composed of all maximum points $E_p(u_p, \sigma, m_p)$ in the binary image, where u_p is the normalized arc length, σ is the width of the Gaussian kernel and m_p is the curvature at which the E_p is obtained.

As shown in Figure 5-b, there are 10 complete contour map and 2 incomplete contour map (peaks 0 and 1). Each incomplete map is described by both its branches, thus there are 14 peaks of the corresponding descriptor for the fish shape. Finally, the descriptor is presented as:

{(0.246, 19.1, 1.645); (0.075, 19.0, 2.14); (0.44, 19.0, 0.688); (0.75, 19.0, 0.66); (0.91, 18.9, 0.875); (0.619, 15.10, 1.98); (0.41, 12.10, 1.80); (0.26, 9.10, 1.64); (0.11, 7.50, 1.88); (0.99, 4.80, 1.35); (0.61, 4.70, 1.21); (0.49, 4.60, 1.09); (0.40, 3.20, 0.98); (0.84, 3.20, 0.73)}

The proposed descriptor makes two changes to curvature scale space method, it substitutes the use of curvature extrema for curvature zero crossings and it adds the value of the curvature in each extremum as an additional feature on each of the matched points. One of the great benefits to integrate the curvature characteristic is to distinguish between shape with shallow concavity and shape with deep concavity.

2.1. Invariance and Robustness

The proposed descriptor is based on the curvature function which is computed starting from an arbitrary point on the outline. If the starting point is changed, then there is a cyclic shift along the normalised arc length of the peaks in the binary image obtained. In order to solve this problem, when a similarity measure is computed, all possible shifts need to be investigated.

A rotation transformation on a closed boundary curve translates the initial point of the parameterisation process; i.e., a rotation of the object usually causes a circular shift on its representation, which is determined during the matching process. Note that, the same shape presented in tow different orientations with same starting point generate two identical images binary.

Each peak is described by tree features: Normalised arc length, width of the Gaussian kernel, and curvature. It is evident that all are invariant to translation.

Scale invariance is achieved by normalizing all the shapes into a fixed number of boundary points, every shape is represented by the *x* and *y* coordinates of its boundary points, to normalise the arc length in our case, the boundary is resampled and represented by 200 equally distant points in SQUID database and 256 in MPEG-7 and Columbia Object Image Library (COIL) database.

3. The Matching Algorithm

Correspondence-based shape matching measures similarity between shapes using point-to-point matching; every point on the shape is treated as a feature point.

After extracting the maxima of every model, they are normalised so that the horizontal coordinate u varies in the range [0, 1]. The maxima of every model are sorted according to their normalised u-coordinates during the process of maxima extraction.

Let $F^I = \left(u_i^I, \sigma_i^I, k_i^I\right)_{i=1,\dots,N}$ be a set of features of an input image *I*, where *N* is the number of all detected peaks in image binary. And $F^S = \left(u_j^S, \sigma_j^S, k_j^S\right)_{j=1,\dots,M}$ be a set of features of a stored image *S*, where *M* is the number of all detected peaks in image binary of *S*.

The similarity between two shapes is measured by the sum of the peak differences (the two curvature extremes must be of the same kind (maxima or minima)) between all the matched peaks and the peak values of all the unmatched peaks [7]. In order to find the minimum cost of the match between an image and a model, the algorithm must consider all possible ways of aligning the high-scale contour maxima from both binary images, and compute the associated cost. The distance function below was employed to obtain the minimum of all matching $MATCH_{ij}$ between F^I and F^S.

$$dist(F^I, F^S) = \min_{ij}\left\{MATCH_{ij}\right\} \tag{3}$$

And the matching $MATCH_{ij}$ is the sum of the Euclidean distance of the matched peaks and the unmatched peaks between $\left(u_i^I, \sigma_i^I, k_i^I\right)_{i=1,\dots,N}$ and $\left(u_j^S, \sigma_j^S, k_j^S\right)_{j=1,\dots,M}$.

$$MATCH_{ij} = \sum_{\substack{matched\\peaks}} \sqrt{(u_i - u_j)^2 + (\sigma_i - \sigma_j)^2 + (k_i - k_j)^2} + \sum_{\substack{unmatched\\peaks}} \sigma_i + \sum_{\substack{unmatched\\peaks}} \sigma_j \tag{4}$$

4. Experimental Results

We have implemented a system for the indexing and retrieving of shapes. The software has been developed in visual C++. To test the reliability of the proposed method for shape based object recognition, we used three data sets, the SQUID database [1], which contains 1099 images of marine creatures described by their shapes. The MPEG-7 CE1-B database [15], which contains 70 classes. In each class, there are 20 similar shapes (samples of shapes are shown in Figure 6), and the COIL database [8] which contains 7200 images.

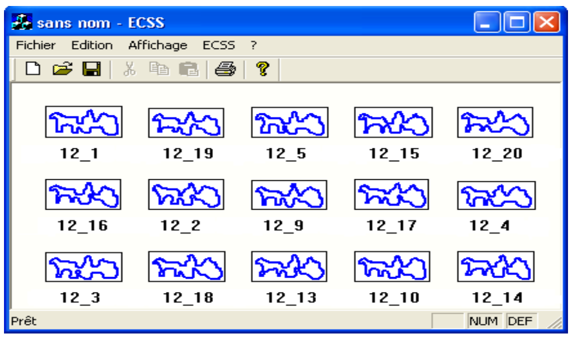
4.1. MPEG-7 Database

Using a convivial user interface provided by the system, a shape already existing in the database as shown in Figure 6 can be used as a query (query by example) by the user. The system retrieves shapes similar in shape to the user query from the database in decreasing order of similarity using the k-nearest neighbour algorithm.

Figure 6. Samples of shapes from set B of the MPEG-7 database.

An example of query shape in database MPEG-7 is shown in Figures 7 and 8.

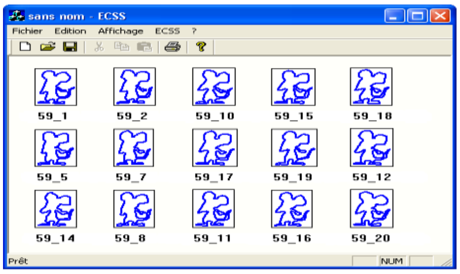
a) Query shape.



b) The obtained 15 similar shapes using K-nearest neighbour algorithm.

Figure 7. Results of shape retrieval.

a) Query shape.



b) The obtained 15 similar shapes using K-nearest neighbour algorithm.

Figure 8. Results of shape retrieval.

The obtained results are similar to those that a user could find visually.

To check the importance of our method, we have extract from the proposed descriptor, three others descriptors, by replacing the Three parameters (u, σ, m) in each extremum by parameters: (u, σ), (u, m) and (m, σ), and after, we have realized a comparative study. The distance used in the descriptor composed of points features (m, σ) is presented in [23], and in the other descriptors we have used the same measure used in CSS [2].

The retrieval performances of our methods are assessed using the precision-recall curves. Precision P is defined as the ratio of the number of retrieved relevant shapes r to the total number of retrieved shapes n, i.e., $P=r/n$. Precision P measures the accuracy of the retrieval and the speed of the recall. Recall R is defined as the ratio of the number of retrieved relevant images r to the total number m of relevant shapes in the whole database, i.e., $R=r/m$. Recall R measures the robustness of the retrieval performance. For each query, the precision of the retrieval at each level of the recall is obtained. The result precision of retrieval using a type of shape descriptors is the average precision of all the query retrievals using the type of shape descriptors.

The precision and recall of proposed descriptor and the tree descriptors deduced from it are shown in Figure 9.

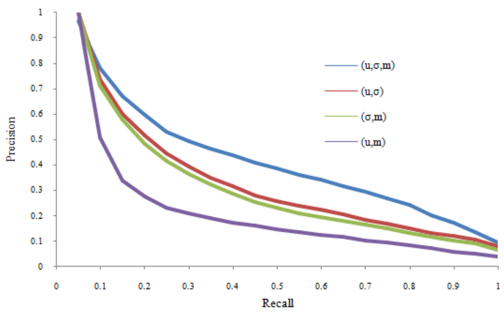


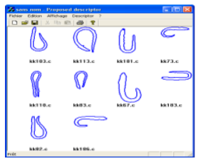
Figure 9. Precision-recall curves of the proposed descriptor and the tree descriptors deduced from it.

It can be seen from the precision-recall charts that the proposed descriptor (u, o, m) outperforms significantly the other descriptors. This results prove the performance of the proposed method and the importance to adds the value of the curvature in each extremum as an additional feature on each of the matched points which are known to be more stable than curvature inflection points [12, 27].

4.2. Database SQUID

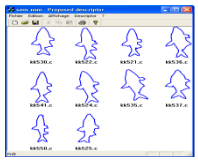
The second experiment consists of 1099 images of marine animals from SQUID project. Each image consisted of just one object on a uniform backgtound. An example of query shape is shown in Figure 10.

a) First target shape.



b) Teen first's matching images.

c) Second target shape.



d) Teen first's matching images.

Figure 10. Results of shape retrieval.

The obtained results are similar to those that a user could find visually. The returned shapes having different orientations.

To show the performance of the proposed descriptor in case of shape with shallow concavities, we propose to use a classified subset of database SQUID. The objects in the database are divided into 13 different categories, each containing 8 distinct objects. The whole database is presented in Figure 11. Abbasi *et al.* [2] sign that these objects are selected carefully so that the within-class similarity is reasonably high. There are also particular characteristics it from other groups.

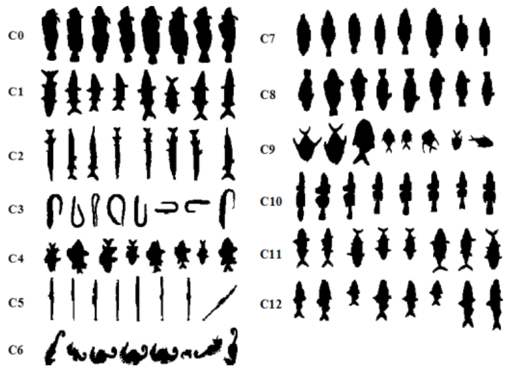


Figure 11. Classified database used for objective evaluation.

The procedure of evaluating and marking the performance of the system is the same as in [2]:

- Choose one of the objects in class one as the input query, and determine the first n outputs of the system. These are the most similar images of the database to the input according to the system. n= 15 is chosen for this test.

- Count the number of outputs which are in the same class as the input and let the result be a measure of performance of the system for that particular object.
- Repeat the previous steps for all members of class one. Determine the performance of the system for class one by summing up the performance measures of all members of this class.
- Determine the performance measures for all classes, repeating the above steps.
- Finally, sum up the performance measures of all classes and find the performance of the system for the whole classified database.

Using this method, we measure the performance of the proposed descriptor and compare it them with CSS.

The result of the objective evaluation is presented in Table 1. We can make the following observations from this comparison:

- The proposed descriptor is better than CSS in the groups 02, 05 and 12 containing shapes with shallow concavities. The groups 02, 05 and 12 have been improved by 23.44%, 28.12% and 20.31%, respectively. This signifiant improvement are mainly due to the value of the curvature integrate in each extremum of proposed descriptor.
- We can observe also an improvement in groupe 0 containing shapes with deep concavities by 4.69%.
- A very good performance measure of the proposed descriptor is observed for groups 03 and 07, the result for group 03 is 100%. We observe that the shape in group 03 having different orientations. This proves that our proposed descriptor is invariant to rotation.
- The proposed descriptor fails to detect the mirror-shape of the input shape, even if such a mirror-shape is included in the database. However, many shapes in group 04 and 08 are symmetric, so very poor results are observed for proposed descriptor with respect to CSS. The drop in the performance measure of the proposed descriptor for group 11 is also considerable.
- The proposed descriptor and CSS have an insignificant difference in other groups and the results obtained are good.

Table 1. Proposed descriptor results in comparison with the CSS.

Classes	0	1	2	3	4	5	6	7	8	9	10	11	12	Average
Pdesc	68.75	60.94	76.56	100	35.94	85.93	43.75	90.63	43.75	75	84.37	46.88	76.56	70.18
CSS	64.06	59.37	53.12	100	53.12	57.81	57.81	92.19	56.25	78.13	100	70.31	56.25	69.01
DIFF	4.69	1.57	23.44	0	-17.18	28.12	-14.06	-1.56	-12.5	-3.13	-15.63	-23.43	20.31	1.17

It can be seen that if we use the proposed descriptor, the improvement of objective evaluation is about 1.17%, which is good. The improvement is significant of shape with shallow concavities, i.e., groups 02,05 and 12.

4.3. COIL Database

The image database used, in third experiment, is the COIL-100 [8] of 100 objects. Each object was placed on a motorized turntable which was rotated through 360 degrees with respect to a fixed camera. Images of the objects were taken at pose intervals of 5°. This corresponds to 72 images per object making a total of 7200 gray-scale images. The objects have a wide variety of complex geometric and reflectance characteristics. The images are size normalized. In Figure 12, the frontal pose of each object is shown. We have used the COIL database as it is known as a very standard object image database and it has several images of the same object taken at different poses.

Figure 12. Objects of the COIL-I00 image database.

The recall and precision obtained by the proposed descriptor and CSS are shown in Figure 13.

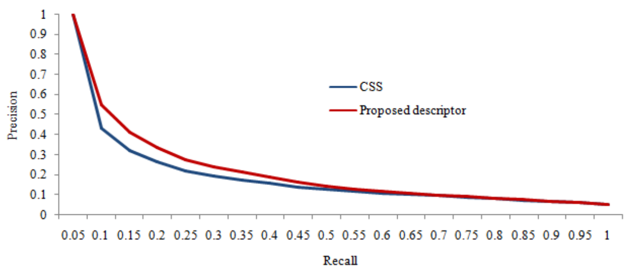


Figure 13. Precision-recall curves of the proposed descriptor and CSS.

It can be seen from the test experiment results shown in Figure 13 that the proposed descriptor outperforms the CSS descriptor, therefore it can be efficiently used for 2D/ 3D model search and retrieval.

4.4. Computation Efficiency

It is desirable to have a fast scheme to retrieve images from a database. The retrieval scheme described above computes sequentially the distance of a given query image with the images in the database.

In order to calculate the algorithm complexity of the proposed descriptor, the feature extraction and the retrieval are tested on the Windows7 of a Core(TM) i5 PC with 4096M memory. The time taken for the feature extraction and the retrieval on MPEG-7 is given in Table 2. It can be seen from Table 2 that the average time of shape processing (computation of descriptor) is the most important computing time in this retrieval system.

Table 2. The average time of feature extraction of proposed descrtiptor for 1400 shapes (ms).

	Total Time of 1400 Shapes	Average Time Each Shape
Feature Extraction	438897	313,50
Retrieval Query	230883	164.91
Total	669780	478,41

This time depends on the complexity of the shape request. We also remark in our retrieval system that the CPU time ranged between 95ms and 316ms for a query on a database and the average time of feature retrieval for all database is 164.91ms. The average of feature and retrieval on database is 478,41ms; this value proves that our system is fast.

Table 3. The average time of feature extraction of CSS for 1400 shapes (ms).

	Total Time of 1400 Shapes	Average Time Each Shape
Feature Extraction	219126	156,52
Retrieval Query	228126	162,95
Total	447252	319,47

It can be seen from Table 3, that the proposed method requires more computation time than CSS. This weak difference (0,158 second) are due to the supplementary treatment used to extract extreme curvature after calculating curvature zero crossings of treated shape. It is possible to reduce the time requirement of proposed descriptor by using the techniques presented in [29, 10].

5. Conclusions

In this paper, a new method for shape similarity retrieval has been proposed. The proposed descriptor is invariant to common geometrical transformations and robust to noise. It is based on the curvature scale space theory and extreme curvature. The representation of descriptor is created by convolving a shape boundary with low-pass Gaussian filters, extracting the extreme curvature of the convolved shape boundary and combining them in a scale space representation of curve. The result of this process is a several contours map. The maxima of these contours are then extracted out as descriptors to index shape. The method was tested on a SQUID database of 1099 images of marine animals, Mpeg-7 database and coil-100 database. With regard to evaluation of the method, we examined an objective test involving a classified subset of the database. The results show the promising performance of our method and its superiority over CSS in shape with shallow concavities. In our future work we intend to combine the proposed descriptor with other descriptors based color and texture and we investigate the possibility to extend the proposed approaches to 3D objects.

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