

An Improved Shape Signature for Shape Representation and Image Retrieval

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Abstract—The Fourier Descriptor (FD) is a powerful tool for shape analysis and many signatures have been proposed to derive Fourier descriptors. These shape signatures lack of important information in articulation and part structures of complex shapes. In this study, the Inner-Centroid Distance (ICDs) signature which is based on the Centroid Distance signature and Inner-Distance is developed to overcome the shortcomings of existing signatures. The retrieval performance is evaluated by using standard shape database and commonly used performance measurement. The experimental results demonstrate that the proposed signature performs better than the comparison algorithm.

Index Terms—shape signature; Fourier descriptor; inner-distance; image retrieval

I. INTRODUCTION

Shape is one of the most important information for image analysis and probably most conservative and robust feature of human visual perception, which tends to simplify scenes and objects to their basic primitives. Psychological studies have suggested that shape is one of the most important visual attributes to characterize objects. Gladilin [1] imposed the observation to the following postulate: shape is a feature of object geometry that is invariant w.r.t. translation, rotation and scaling.

The shape descriptors have been actively studied over decades and can basically be subdivided into two major groups: contour-based shape descriptors (or so-called boundary-based descriptors) and region-based shape descriptors. Region-based techniques describe images as a density function of a 2D-distributed random variable. These methods are usually applied to complex scenes, which can not be reduced to clearly shaped objects and has to be analyzed “as a whole”. The region based algorithms of interest are Zernike Moment Descriptor (ZM), Hu Moment Descriptor (HM), Geometric Moment Descriptor (GM), and Grid Descriptor (GD). They have some advantages of global characteristic and can be applied to generic shapes, but the drawback of regular moments is that there is redundant information in the moments since the bases are not orthogonal and high-order moments are sensitive to noise. Contour-based shape features characterize the properties of the spatial

positions of the pixels that lie on the boundary of an object. The most common used contour-based feature extraction techniques are: Fourier descriptors (FD), Shape Contexts (SC), curvature descriptors (CDs), signature or chain code-based descriptors. But, these descriptors may not be suitable for complex shapes that consist of several disjoint regions, since they are often based on a single contour.

Currently, almost all of the affine invariant shape descriptors are contour-based, and few of them are region-based. Among these affine invariant shape descriptors, Fourier descriptors have proven to be better than other contour-based shape descriptors and some region-based approaches [2-3]. During the last decade, many signatures have been proposed to derive Fourier descriptors. The Centroid Distance, the Complex Coordinates (CC), the Chord-Length Distance (CLD), the Triangular Centroid Area (TCA), and the Angular Function (AF) are common-used signatures. Recently, some progress has been made in performance improvement for content-based image retrieval. In [4], Fourier descriptors were extended to Generic Fourier Descriptors (GFD), which is derived by applying two-dimensional Fourier transform on a polar-raster sampled shape image. Bartolini et al. [5] have described an accurate retrieval technique using the phase information of Fourier descriptors and time warping distance. Kunttu et al. [6] introduced a multi-scale Fourier descriptor for shape-based image retrieval. By adopting the wavelet and Fourier transform, the proposed multi-scale descriptor improves the shape retrieval accuracy of the traditional Fourier descriptors. El-ghazal et al. [7-8] proposed a novel signature, named farthest point distance (FPD), and compared it with other frequently used shape signatures. Furthermore, the desirable characteristics of Fourier descriptors, such as low computation complexity, clarity and coarse to fine description, make it a popular descriptor in many applications. For instance, it was used in [9] for human target identification, or more recently, in [10], for mice behavior recognition.

In this study, we propose a novel signature, named Inner-Centroid Distance (ICD) and compared it to other commonly used signatures, like the Centroid distance, the

Complex Coordinates (CC) and the farthest point distance (FPD). The retrieval performance is evaluated by using standard shape database and commonly used performance measurement. The paper is organized as follows: Section 2 gives a brief description of frequently used shape signatures. Section 3 introduces the proposed signature in detail. Comparative studies to compare the proposed signature with other shape signatures are presented in section 4. Conclusions and suggestions derived from the study are presented in Section 5.

II. SHAPE SIGNATURES

In general, a shape signature is the way of representing 2-D boundaries by using a 1-D function, usually for describing a unique shape and capturing the perceptual feature of the shape. Three of the most commonly used shape signatures are considered in this study; they are Centroid Distance (CD), Complex Coordinates (position function), and Farthest Point Distance (FPD). Brief descriptions of these shape signatures are presented in the following sections. The reason for choosing these three shape signatures for comparison is because they are mostly used in recent FD implementations and have been shown practical for general shape representation. In the following stage, we assume the coordinates of shape boundary points (x_i, y_i) $i = 0, 1, \dots, N-1$ have been extracted in the preprocessing stage.

2.1 Centroid Distance

The Centroid Distance function represents the distance between the boundary points (x_i, y_i) and the centroid (x_c, y_c) of the shape. Other common names for this signature are the radial distance. Due to the subtraction of the centroid from boundary coordinates, the centroid distance representation is also invariant to translation.

$$CD_i = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \quad (1)$$

The centroid, which is the average of the boundary coordinates, is computed as follows:

$$x_c = \frac{1}{N} \sum_{i=0}^{N-1} x_i \quad y_c = \frac{1}{N} \sum_{i=0}^{N-1} y_i \quad (2)$$

where N denotes the number of boundary points.

2.2 Complex Coordinators

The Complex Coordinates function is generated by treating each boundary coordinate pair (x_i, y_i) as a number on a complex plane. Another frequently used name for this signature is position function.

$$C_i = x_i + 1i * y_i \quad (3)$$

In order to achieve translation invariant, the shifted coordinates function is obtained by subtracting of the centroid from the boundary coordinates of the shape.

$$CC_i = (x_i - x_c) + 1i * (y_i - y_c) \quad (4)$$

where (x_c, y_c) is the centroid of the shape.

2.3 Farthest Point Distance

The Farthest Point Distance (FPD), proposed by Akrem El-g hazal, aiming to overcome some of the shortcomings of existing techniques, such as ignoring distances between corners. The value of the signature at a given point A is defined as the distance between A and the point farthest from it, say B. The signature is calculated by adding the Euclidean distance between point A and the centroid C to that between the centroid C and the farthest point. The FPD signature at boundary point (x_i, y_i) is calculated as follows [8-9].

$$FPD_i = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} + \sqrt{(x'_i - x_c)^2 + (y'_i - y_c)^2} \quad (5)$$

where (x'_i, y'_i) is the farthest point from (x_i, y_i) , and (x_c, y_c) is the centroid of the shape.

III. DERIVATION OF FOURIER DESCRIPTORS

The Fourier Descriptor (FD) is a powerful tool for shape analysis and has been successfully applied to many shape representation applications. The outstanding characteristics, such as simple derivation, perceptually meaningful, and robust to noise, make it a popular shape descriptor. These descriptors represent the shape of the object in a frequency domain and avoid the high matching cost of using shape signatures in spatial domain. Generally, the Fourier Descriptors is obtained by applying Discrete Fourier Transform (DFT) on a shape signature function derived from shape boundary coordinates. Then, the Fourier coefficients are used for shape features. The 1-D discrete Fourier transform of an signature $z(t)$ is given by:

$$a_n = \frac{1}{N} \sum_{t=0}^{N-1} z(t) e^{-j2\pi n t / N} \quad n = 0, 1, \dots, N-1 \quad (6)$$

The coefficients a_n are called the Fourier descriptors.

Rotation invariance of the Fourier descriptors can be achieved by ignoring the phase information, only taking into consideration the magnitude values. Scale invariance for real-valued signatures can be established by dividing the magnitude of the first half descriptors by the DC

components $|a_0|$, which represents the average energy of the signature. Additionally, since the $|a_0|$ is always the largest coefficient, and consequently the values of the normalized descriptors should be in the range of 0~1.

$$V = \left[\frac{|a_1|}{|a_0|}, \frac{|a_2|}{|a_0|}, \dots, \frac{|a_{N/2}|}{|a_0|} \right] \quad (7)$$

Then, the acquired Fourier descriptors are invariant to rotation, scale, and translation. The low-frequency descriptors contain information about the general features of the shape, while the higher represent the finer details. Since the number of generated coefficients is often large, a subset of the coefficients is enough to capture the overall features of the shape. The very high-frequency descriptors is not so helpful and can be ignored. As a result, the dimensions of the shape features used for image retrieval are significantly reduced.

Once the features are extracted from the indexed images, the retrieval of images becomes the measurement of similarity between these features. Zhang [11] evaluated a number of commonly used similarity measurements, Minkowski Distance, Cosine Distance, χ^2 statistics, Histogram Intersection, Quadratic Distance and Mahalanobis Distance. The results show that city block distance and χ^2 statistics measure outperform other distance measure in terms of both retrieval accuracy and retrieval efficiency. Thus, the similarity measure used in our experiment is city block distance. The similarity between two shapes A and B described by Fourier descriptors V_A and V_B is given by:

$$d(A, B) = \sum_{i=0}^{N-1} |V_A(i) - V_B(i)| \quad (8)$$

IV. PROPOSED INNER CENTROID DISTANCE (ICDs)

In this section, we present a novel signature, the Inner-Centroid Distance (ICDs) signature which is based on the Centroid Distance (CD) signature and Inner-Distance [12-13]. The ICDs is developed to overcome some of the shortcomings of existing signatures, such as ignoring articulation and part structures of complex shapes. In the Centroid Distance signature, only the distances of the boundary points from the centroid of the shape are concerned and thus the features extracted from CDs cannot characterize the fundamental properties of the complex shape boundary. The inner-distance is articulation insensitive and more effective at capturing complex shapes with part structures and is proved as a natural replacement for the Euclidean distance in shape descriptors. So, inner-distance is used here to extend the Centroid Distance (CD) signature for image retrieval.

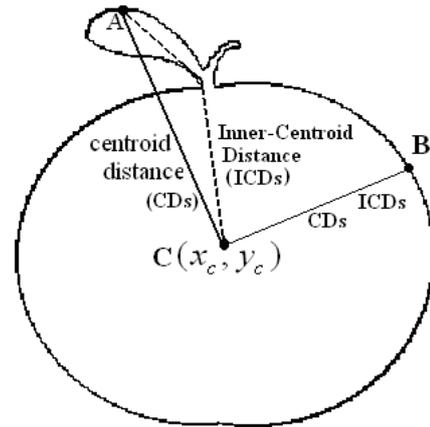


Figure 1. Basic concept of the Inner-Centroid Distance (ICDs) signature

The inner-distance is defined as the length of the shortest path between landmark points within the shape silhouette in [14]. Consider two points $x, y \in O$, where O is a shape defined as a connected and closed subset of R^2 . The inner-distance between x and y , denoted as $d(x, y; O)$, is defined as the length of the shortest path connecting x and y within O . If shape O is convex or the line segment connecting x and y falls entirely within the silhouette, the inner-distance between x and y reduces to the Euclidean distance.

Figure 1 depicts how the Inner-Centroid distance is calculated. For point A , part of the line segment AC is out of the shape silhouette. Thus the inner-distance between A and C (Centroid point) is calculated as the length of the shortest path within O , which is denoted by dashed line. For point B , the Inner-Centroid distance is the Euclidean distance between C and B . It indicates that the inner-distance is influenced by part structure and characterizes some fundamental properties of the complex shape boundary.

V. EXPERIMENT AND ANALYSIS

To verify the retrieval effectiveness of the proposed signature, comprehensive comparisons are carried out between our method with three popular Fourier Descriptors which are derived from centroid distance signature, complex coordinates and farthest point distance, respectively. The retrieval tests are conducted on the standard contour shape database, MPEG-7 CE-1 Part B. Precision and the recall, the commonly used retrieval performance measurement, are used as the evaluation of the retrieval accuracy and efficiency.

5.1 Database & Measurement

The standard contour shape database MPEG-7 CE-1, consists of three parts, Set A, Set B and Set C. Set B represents general shapes from natural objects and is for similarity-based retrieval which tests overall robustness of the shape representations. It consists of 1400 images of 70 groups, and 20 similar shapes in each group. Samples of the images from this subset are depicted in Figure 2.

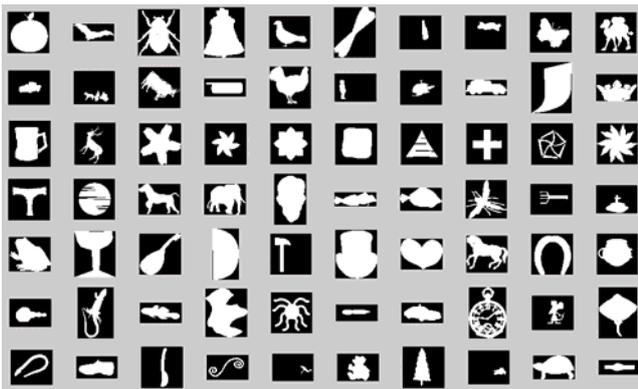


Figure 2. Shape database MPEG-7 CE-1 Part B

Precision and the recall are the commonly used performance measurement in image retrieval. Precision P is defined as the ratio of the number of retrieved relevant images n_r to the total number n_{all} of retrieved shapes, i.e. $P = n_r / n_{all}$. It indicates the accuracy of the retrieval and the speed of the recall. Recall R is defined as the ratio of the number of retrieved relevant shapes n_r to the total number m_{all} of relevant shapes in the whole database, i.e. $R = n_r / m_{all}$. Recall R indicates the robustness of the retrieval performance.

5.2 Results and analysis

In the implementation procedures of shape signature, two parameters needed to be defined: the boundary points of shape and the number of features. The boundary points of shape are often resampled to a number of power of two to save computation cost of fast Fourier transform. The resampling may result in the loss of boundary features and affect the retrieval performance. Therefore, in our implementation, the entire boundary points of the shape are used in terms of accuracy. As for the number of the Fourier features that used in the experiments, Zhang [2] have found that 15 Fourier descriptors are sufficient to describe a shape. Their test reveals that when the number of FD features is above 15, the retrieval precision does not improve significantly with increased number of FD features; the retrieval precision does not degrade significantly when the number is reduced down to 10 FD features. Our experiments have confirmed the conclusion and the number of features used in our implementation is 15.

Table 1 shows the average precision for low and high recalls for the proposed ICDs and the competing signatures. From Table 1, it can be seen that our methods achieve the best scores whether in the case of low recall or high recall, where as the Complex Coordinates signatures' performance is the lowest. This improvement is obtained by characterizing fundamental properties of the complex shape boundary. Additionally, due to the tendency of capturing farthest corners, the Farthest Point Distance (FPD) performs a little better than Centroid

Distance (CD) signatures in the low recall case, and yield comparable results in the high recall case.

TABLE 1.

THE AVERAGE PRECISION FOR LOW AND HIGH RECALLS

Signature	Low recall (for recall \leq 50%)	High recall (for recall $>$ 50%)
The Inner-Centroid Distance (ICDs)	78.23	44.51
The Centroid Distance (CDs)	75.17	42.18
The Complex Coordinates (CCs)	67.59	31.92
The Farthest Point Distance (FPD)	75.82	42.13

Figure 3 illustrate the precision and recall curve using MPEG-7 database Part B. From the plots, we can see that the proposed signature outperforms the competing techniques. The experiment results indicate that the proposed method is more suitable for complex shape retrieval.

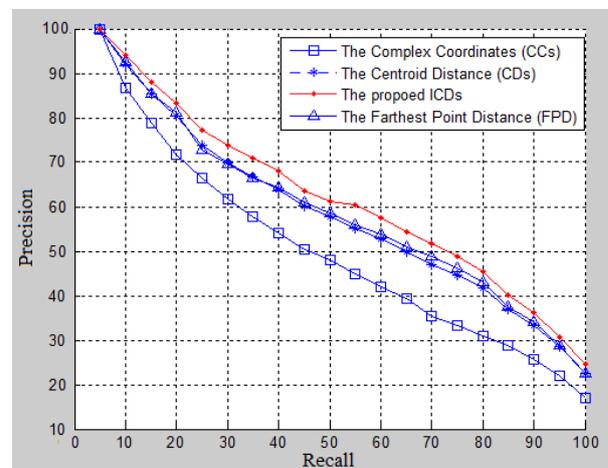


Figure 3. Precision-recall curves of the proposed and compared techniques

VI. SUMMARY AND CONCLUSIONS

A novel shape signature, named Inner Centroid Distance signature (ICDs), for Fourier descriptors and image retrieval is presented in this study. The proposed ICDs characterized the fundamental properties of the complex shape boundary and is developed to overcome some of the shortcomings of existing signatures, such as ignoring articulation and part structures of complex shapes. Comparable studies are conducted by comparing it to three commonly used signatures, the Centroid

Distance (CDs), the Complex Coordinates (CCs) and the farthest point distance (FPD). The retrieval performance is evaluated by using standard shape database and commonly used performance measurement. The experimental results demonstrate that the proposed signature performs better than the comparison algorithm.

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