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Shape Retrieval Using Smallest Rectangle Centroid Distance

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Abstract

Shape is one of the main low level features in content based image retrieval systems (CBIR). This paper proposes a novel CBIR technique based on shape feature. In this technique feature extraction is based on a rectangle that covers a shape. The proposed signature is a Fourier based technique and it is invariant against translation, scaling and rotation. The retrieval performance between some commonly used Fourier based signatures and our Smallest Rectangle Centroid Distance (SRCD) signature has been tested using the MPEG-7 database. Experimental results show that the SRCD signature has a good performance compared with those shape signatures.

Keywords: *Content based Image Retrieval (CBIR); Shape; Smallest Rectangle Centroid Distance (SRCD); Fourier Signatures*

1. Introduction

Because of the increasing amount of digital images, we need efficient image retrieval systems. Most of the image retrieval systems are text based. Text Based Image Retrieval (TBIR) systems have some disadvantages. One of them is that subjects of some image are hard to express. The other problem of TBIR systems is that annotation is never complete and this process is boring and time consuming. So, in the early of 1990's, Content Based Image Retrieval systems (CBIR) were introduced [1]. CBIR is a technique which uses visual contents, normally called as features, to search images from large scale image databases according to users' requests in the form of a query image [2]. Color, texture and shape are the main low-level features for CBIR. A block diagram of CBIR systems is shown in Figure 1. In CBIR systems, feature vector for each image of database is automatically extracted based on the low-level features. These feature vectors stored in the database of feature vectors. Then, the feature vector of the query image is extracted. After that, the similarity distance between the feature vector of the query image and the feature vectors of the database's images are computed. Finally, system retrieves similar images to the query based on their similarity values.

In this paper, we propose a new shape based image retrieval signature. This method is a Fourier based signature and exploits the rectangle that covers a shape for feature extraction.

The rest of the paper is organized as follows: Section 2 is related works. The proposed technique is presented in Section 3. The experimental results are analyzed in Section 4 and Section 5 is conclusions.

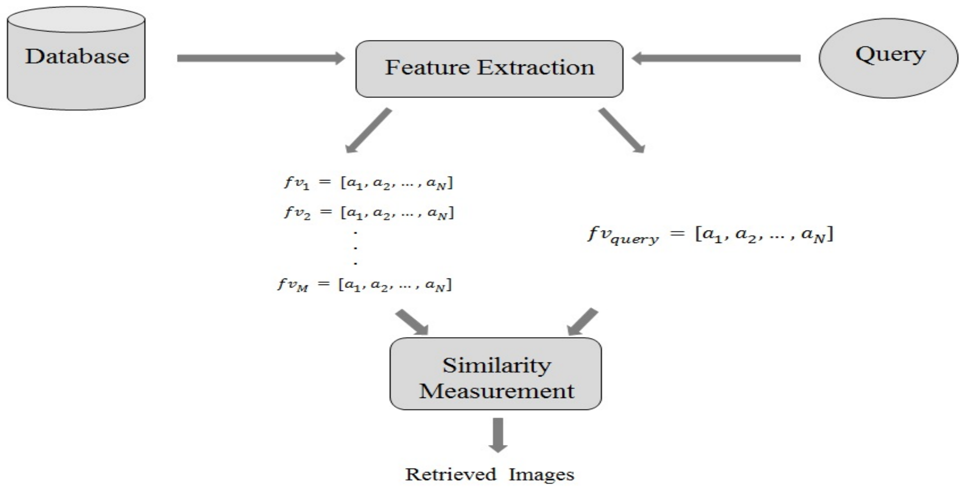

Figure 1. Block Diagram of CBIR Systems

2. Related works

Shape is one of the most important features for recognition of objects in an image [3]. There are two classes of techniques in shape based image retrieval. Region based techniques and boundary based techniques. A region based technique uses whole shape region but a boundary based technique only uses boundary points of shapes in feature vector extraction.

Region based techniques often involve intensive computations and fail to distinguish between objects that are similar [4]. Thus boundary-based techniques are more efficient than region based techniques. Several number of techniques have presented that are based on boundary of shapes.

One important class of boundary based techniques is Fourier descriptors (FD). In the FD methods, the Fourier transformed boundary is used as a shape feature [5]. The discrete Fourier transform of a signature *r(t)* is shown in Equation (1).

$$a_n = \frac{1}{N}\sum_{t=0}^{N-1} r(t)e^{\frac{-j2\pi nt}{N}} \qquad n = 0, 1, \ldots, N-1 \tag{1}$$

The a_n coefficients are called the Fourier descriptors of the shape. The Fourier descriptors are invariant to translation, scaling and rotation, if their coefficients are used as Equation (2) [6].

$$fd = \left[\frac{|a_1|}{|a_0|}, \frac{|a_2|}{|a_0|}, \ldots, \frac{|a_{N/2}|}{|a_0|}\right] \tag{2}$$

Some commonly used Fourier based signatures are complex coordinate (CC), polar coordinate (PC), angular function (AF), triangular area representation (TAR), chord length distance (CLD) and angular radial coordinate (ARC).

2.1. Complex Coordinate (CC)

The feature vector of this signature at each boundary point (x_t,y_t) is a complex number. The real part is $(x_t\text{-}x_c)$ and the complex part is $(y_t\text{-}y_c)$ [7]. See Figure 2(a). Equation (3) is the feature vector of this descriptor.

$$CC(t) = (x_t - x_c) + j(y_t - y_c) \tag{3}$$

2.2. Polar Coordinate (PC)

The feature vector of this signature at each boundary point (x_t,y_t) is a complex number. The real part is the distance between that point and the centroid point of the shape (radial distance). The complex part is the angle between this radial and the x axis [8]. See Figure 2(b). Equation (4) is the feature vector of this descriptor.

$$CD(t) = \sqrt{(x_t - x_c)^2 + (y_t - y_c)^2} \qquad PC(t) = CD(t) + j\theta(t) \tag{4}$$

2.3. Angular Function (AF)

This signature considers changes of directions for some boundary points of a shape (with s step) [9]. See Figure 2(c). Equation (5) is the feature vector of this descriptor.

$$\varphi(t) = \frac{(y(t) - y(t-s))}{(x(t) - x(t-s))} \tag{5}$$

2.4. Triangle Area Representation (TAR)

The feature vector of this signature is the area formed by each sequential three boundary points of a shape. It distinguishes between concave and convex regions [10]. See Figure 2(d).

2.5. Chord Length Distance (CLD)

In this signature, the feature vector at each boundary point p is the distance between that point and another boundary point q, such that pq be a vertical line to the tangent vector at p [11]. See Figure 2(e).

2.6. Angular Radial Coordinate (ARC)

The feature vector of this signature at each boundary point is a complex number that the real part is same as CD and the complex part is same as AF signature [8]. See Figure 2(f). Equation (6) is the feature vector of this descriptor.

$$ARC(t) = CD(t) + j\varphi(t) \tag{6}$$

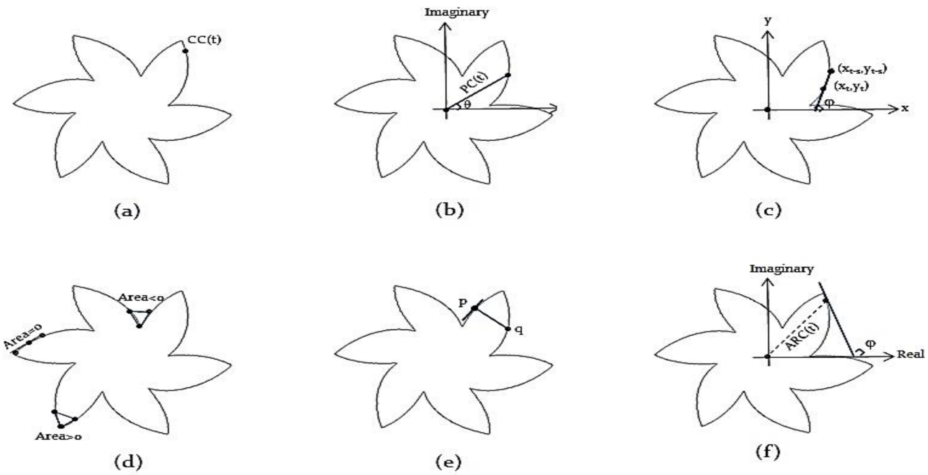

Figure 2. Fourier Shape Signatures: (a) Complex Coordinate (CC) Signature; (b) Polar Coordinate (PC) Signature; (c) Angular Function (AF) Signature; (d) Triangle Area Representation (TAR) Signature; (e) Chord Length Distance (CLD) Signature; (f) Angular Radial Coordinate (ARC) Signature

3. The Proposed Signature

We have been introduced a shape signature (SRD) in our previous work [12]. In this paper, we propose a new shape signature that is based on the SRD signature. The new shape signature has better performance compared with the SRD and other signatures that were discussed in Section 2. In the first stage, the smallest rectangle that covers a shape is extracted. Then, we consider p points in each length sides and q points in each width sides of the rectangle. These selected points should have a same distance with each other. The feature vector of the proposed signature is complex. Therefore, two values for each one of those $2(p+q)$ selected points on the rectangle's surface should be obtained. They are defined as:

1. The real part is the distance between a rectangle's point (x_r,y_r) and the opposite point of it on the shape's boundary (x_t,y_t). This element is called *dRectangle*.
2. The imaginary part is the distance between the (x_t,y_t) point and the centroid point of the shape (x_c,y_c). This element is called *dCentroid*.

In the SRD signature only *dRectangle* was used for feature extraction. Equation (7) shows the feature vector of our smallest rectangle centroid distance (SRCD) signature. Figure 3 shows the process of computing this signature.

$$SRCD_i = dRectangle_i + j\ dCentroid_i \qquad i = 1,2,\dots,(2p+2q) \qquad (7)$$

Because of using the rectangle that covers a shape, the SRCD signature is not sensitive against translation. The SRCD signature is invariant to scale if the feature vector's element became normalized. For normalization of the real part of the SRCD, they must be divided to the length (L) or width (W) of the rectangle. The imaginary part of the SRCD must be divided to the R whereas R is the distance between the centroid of the shape and the farthest point of it on the shape's boundary. Thus, for scale normalization, the feature vector of the SRCD signature should be modified as (8).

$$SRCD_i = \left(\frac{dRectangle_i}{W} + j\,\frac{dCentroid_i}{R}\right) \qquad i = (1 \sim p)$$
$$SRCD_i = \left(\frac{dRectangle_i}{L} + j\,\frac{dCentroid_i}{R}\right) \qquad i = (p+1 \sim p+q)$$
$$SRCD_i = \left(\frac{dRectangle_i}{W} + j\,\frac{dCentroid_i}{R}\right) \qquad i = (p+q+1 \sim 2p+q)$$
$$SRCD_i = \left(\frac{dRectangle_i}{L} + j\,\frac{dCentroid_i}{R}\right) \qquad i = (2p+q+1 \sim 2p+2q) \qquad (8)$$

When two shapes of same class have different directions, the SRCD feature vectors of them have different directions, too. By getting discrete Fourier transform of the SRCD signature, it will be invariant to rotation.

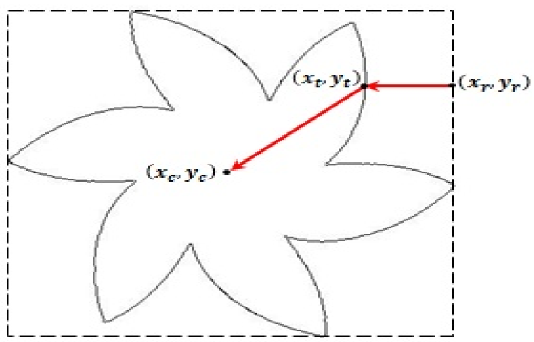

Figure 3. The Smallest Rectangle Centroid Distance (SRCD) Signature

4. Experimental Results

For performance measurement and comparing the proposed technique with other commonly used shape signatures, we used part B of the MPEG-7 database [13]. It consists of 1400 images that are classified into 70 classes. Each class has 20 similar images. This database is suitable to test for similarity, scaling, rotation and translation invariance. Figure 4 shows one sample of each class in this database. All the 1400 shapes in the database were used as queries in the experiments. Euclidean distance has been used for similarity measurement. The retrieval performance is measured in terms of precision and recall. Precision measures the retrieval accuracy, whereas recall measures the capability to retrieve relevant items from the database [14]. They calculate as (9) and (10), respectively.

$$Precision = \frac{\#\, relevance\ retrieved\ images}{total\ \#\, retrieved\ images} \qquad (9)$$

$$Recall = \frac{\#\, relevance\ retrieved\ images}{total\ \#\, relevant\ images\ in\ DB} \qquad (10)$$

Table 1 shows the average of precision for different levels of recalls for the SRCD signature and seven other signatures. In our experiments, we consider 64 coefficients of Fourier descriptors for all of the signatures. It is clear that the performance of the SRCD signature is higher than all of them. For better comparison, Figure 5 shows the precision-recall curves of the proposed SRCD and three other Fourier shape signatures (SRD, CC and CLD). The number of descriptors of the signatures in these curves is 32 It is obvious that the precision-recall curve of the SRCD method is upper than the others. It is concluded that the proposed method has a good performance in comparison with some of well-known shape signatures.

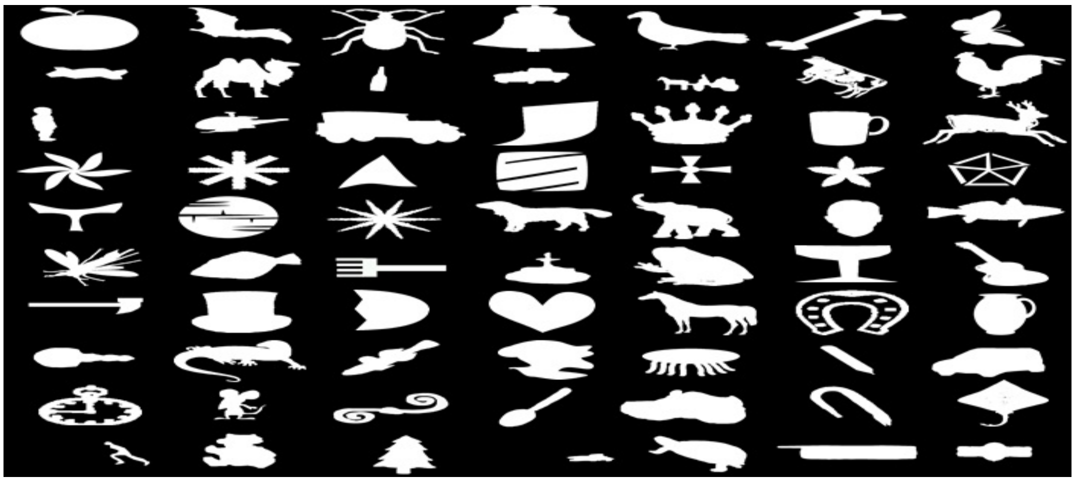

Figure 4. 70 Classes of Shapes from Set B of the MPEG-7 Database

Table 1. The Average Precision for Different Levels of Recalls for the SRCD and other Shape Signatures using the MPEG-7 Database

Shape Signatures	Average Precision		
	Total Recall	Recall > 50 %	Recall ≤ 50 %
SRCD	71.60	38.20	54.90
SRD	67.67	34.61	51.14
PC	64.40	35.12	49.76
CC	64.76	22.59	43.68
ARC	58.93	26.83	42.88
AF	57.39	27.88	42.66
TAR	58.70	23.54	41.12
CLD	57.80	24.00	40.90

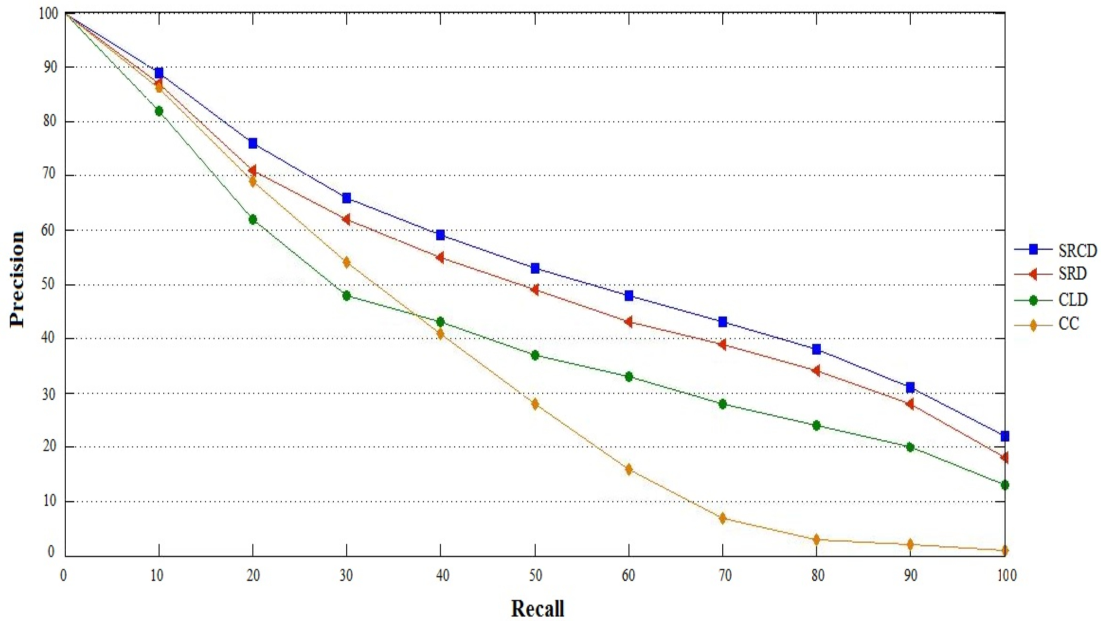

Figure 5. The Precision-recall Curves of the SRCD, SRD, CLD and CC Signatures on the MPEG-7 Database

5. Conclusions

One of the most important low-level features in content-based image retrieval is shape. This paper proposes a new shape based retrieval technique. This is based on boundary points of shapes. The feature vector of this signature is complex. First, the rectangle that covers a shape is considered. Then, some points on four sides of the rectangle and opposite points of them on the surface of the shape are selected. The distances between the opposite points on the surfaces of the rectangle and the shape, is computed as the real part of the feature vector. The imaginary part of the signature is the distance between the obtained points on the surface of the shape and the centroid point of it. The proposed SRCD signature is a Fourier based descriptor and it is not sensitive against translation, scaling and rotation. The SRCD signature was compared with some commonly used Fourier based descriptors. Experimental results have shown that the performance of the proposed signature is better than those descriptors.

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