A New Fourier Shape Descriptor Using Smallest Rectangle Distance

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Abstract— Shape is one of the main features in content-based image retrieval (CBIR). This paper proposes a novel CBIR technique based on shape feature. This technique uses the distances between the boundary points of a shape and the smallest rectangle that covers it. The proposed technique is a Fourier based technique and it is invariant to translation, scaling and rotation. The retrieval performance between some commonly used Fourier based signatures and our Smallest Rectangle Distance (SRD) signatures has been tested using MPEG-7 database. Experimental results are shown that the SRD signature has better performance compared with many of those signatures.

Keywords-Content based Image Retrieval (CBIR); Shape; Smallest Rectangle Distance (SRD); Fourier Descriptors.

I. Introduction

Because of the increasing amount of digital images and weakness of traditional text based image retrieval systems, content based image retrieval (CBIR) systems was introduced in the early 1990's [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]. A block diagram of CBIR systems is shown in Fig. 1. Color, texture and shape are the main low-level features for CBIR. In CBIR systems, a feature vector for each image is automatically extracted based on these low-level features. Then, 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.

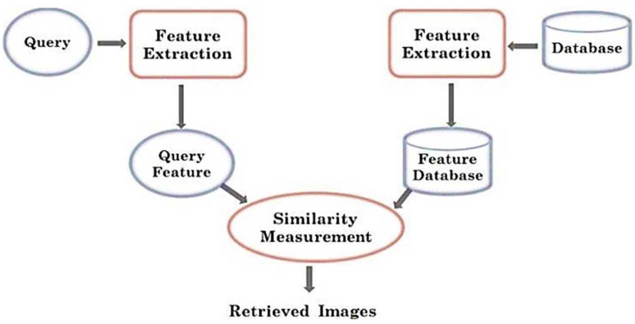

Figure 1. Block diagram of CBIR systems.

In this paper, we propose a new shape based image retrieval technique that uses the distances between the boundary points of a shape and the smallest rectangle that covers it.

The rest of the paper is organized as follows: Section II is related works. The proposed method is presented in Section III. The experimental results are studied in Section IV and Section V is conclusion.

II. Related Works

Shape is the importance feature for recognition of objects in an image [3]. There are two classes of techniques in shape based 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 computed as (1).

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

The a_n coefficients are called the Fourier descriptors of the shape. The Fourier descriptors are invariant to translation, scaling and rotation, if we use them as (2).

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

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

A. Radial Distance (RD)

The feature vector of this signature is the distance between each boundary point *(x_t , y_t)* and the centroid point of the shape *(x_c , y_c)* [6]. See Fig. 2(a). Equation (3) is the feature vector of this descriptor.

$$RD(t) = \sqrt{(x_t - x_c)^2 + (y_t - y_c)^2} \quad (3)$$

B. 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-x_c)* and the complex part is *(y_t-y_c)* [7]. See Fig. 2(b). Equation (4) is the feature vector of this descriptor.

$$CC(t) = (x_t - x_c) + j(y_t - y_c) \quad (4)$$

C. Polar Coordinate (PC)

The feature vector of this signature at each boundary point is a complex number. The real part is the RD signature and the complex part is the angle between this radial and *x* axis [8]. See Fig. 2(c). Equation (5) is the feature vector of this descriptor.

$$PC(t) = RD(t) + j\theta(t) \quad (5)$$

D. Angular Function (AF)

This signature considers the changes of directions for some boundary points of a shape (with *s* step) [4].

The feature vector of this descriptor is computed as (6). See Fig. 2(d).

$$\varphi(t) = \frac{\big(y(t) - y(t-s)\big)}{\big(x(t) - x(t-s)\big)} \quad (6)$$

E. 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 the RD signature and the complex part is same as the AF signature [8]. See Fig. 2(e). Equation (7) is the feature vector of this descriptor.

$$ARC(t) = RD(t) + j\varphi(t) \quad (7)$$

F. 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 [9]. See Fig. 2(f).

G. 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* [10]. See Fig. 2(g).

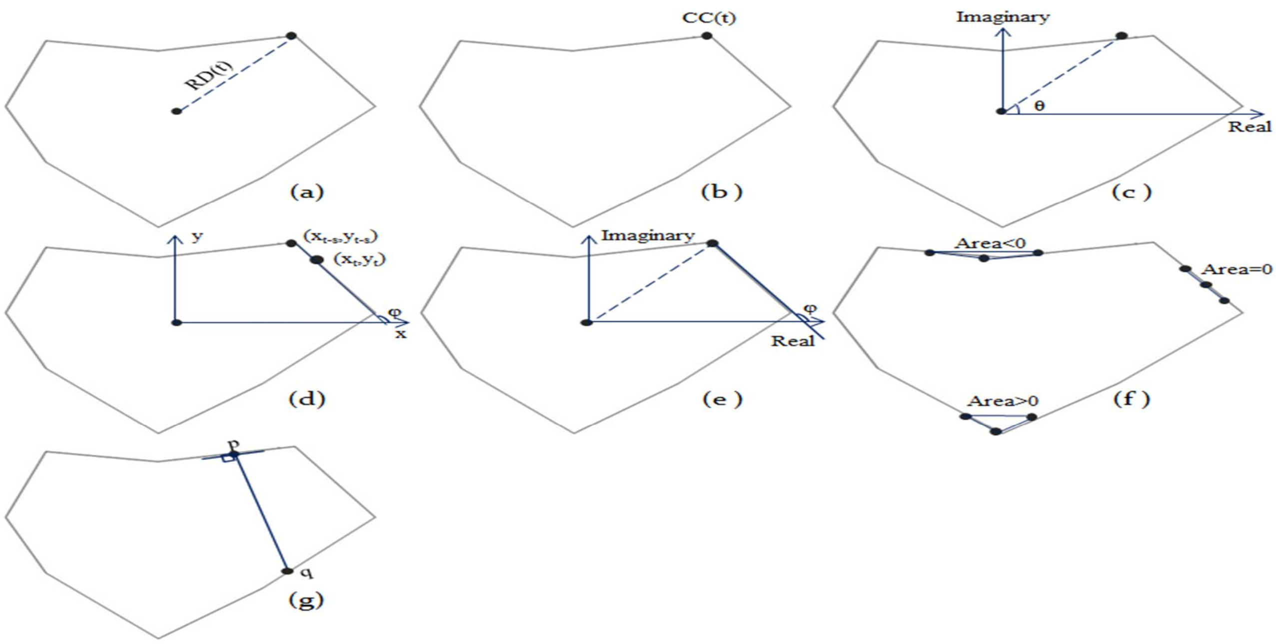

Figure 2. Fourier shape signatures: (a) Radial Distance (RD) signature; (b) Complex Coordinate (CC) signature; (c) Polar Coordinate (PC) signature; (d) Angular Function (AF) signature; (e) Angular Radial Coordinate (ARC) signature; (f) Triangle Area Representation (TAR) signature; (g) Chord Length Distance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

III. THE PROPOSED METHOD

The proposed method is a boundary based approach. In the first stage, the smallest rectangle that covers a shape is obtained. Then, we consider *N* points in each length sides and *M* points in each width sides of the rectangle. We should get them according to the length and width size of the rectangle. Then, the opposite points of them on the shape's surface, is obtained. Therefore we select *2(N+M)* points on the rectangle and *2(N+M)* points on the shape. The important phase of the proposed method is computing the distances between these opposites' points. Fig. 3 shows this process. Fig. 3(a) is the original shape and Fig. 3(b) shows the smallest rectangle that covers the shape and arrows show the distances between the opposite points on the surfaces of the rectangle and the shape. For simplicity, a few number of points only used in this figure. The feature vector size of our smallest rectangle distance technique (SRD) is *2(N+M)*. Each corners of the rectangle, can be the start point. The number of selected points on the length and width side of the rectangle can be different or same. The last stage is getting discrete Fourier transform of the signature *SRD(t)* as (1). The SRD signature is invariant to translation, scaling and rotation.

The SRD signature is translation invariant because it is obtained according to the smallest rectangle that covers a shape.

The SRD signature is scale invariant because the obtained distances are normalized. If a distance is from the length side of the rectangle, it is normalized by dividing this distance by the width of the rectangle. Similarly, if a distance is from the width side of the rectangle, it is normalized by dividing this distance by the length of the rectangle.

The SRD signature is rotation invariant by using the magnitude values of the descriptor and ignoring the phase information. Therefore, the Fourier coefficients of the SRD signature are used as (8).

$$a_n = \frac{1}{(2(N+M))} \sum_{t=0}^{(2(N+M))-1} SRD(t) e^{\frac{-j2\pi nt}{2(N+M)}}$$

$$n = 0, 1, \dots, ((2(N+M)) - 1)$$

$$fd = [|a_1|, |a_2|, \dots, |a_{N+M}|] \quad (8)$$

IV. EXPERIMENTAL RESULTS

For performance measurement and comparing the proposed technique with other commonly used shape signatures, we use part B of the MPEG7 database [11]. It consists of 1400 images that are classified into 70 classes. Each class has 20 similar images. Fig. 4 shows some samples of this database. All the 1400 shapes in the database are used as queries in our 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 [12]. They are calculated as (9) and (10), respectively.

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

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

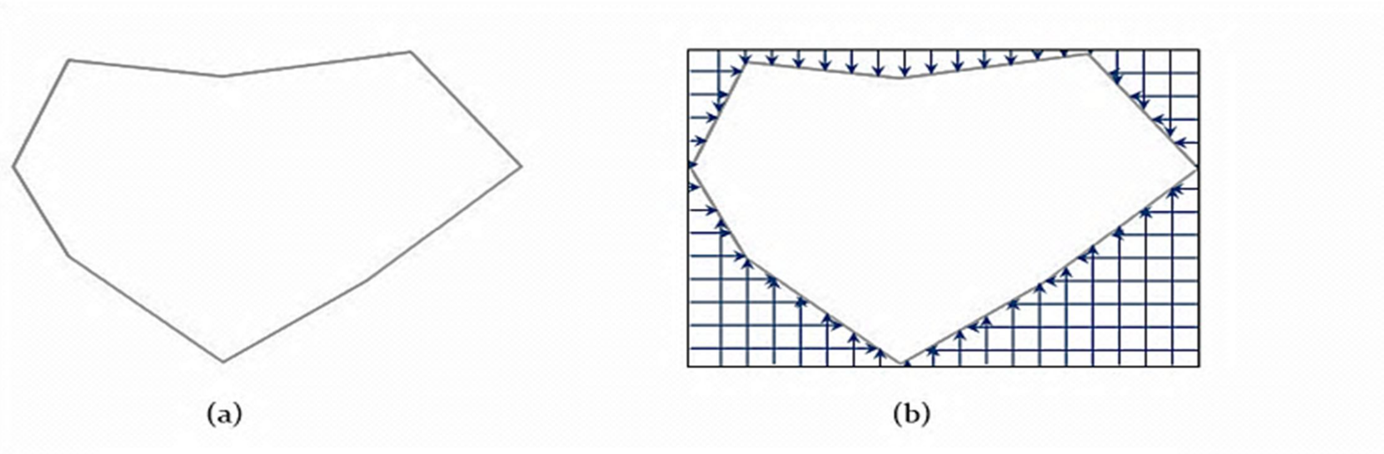

Figure 3. The Smallest Rectangle Distance (SRD) signature: (a) The original shape; (b) Computing the distances between the boundary points of the shape and the smallest rectangle that covers it.

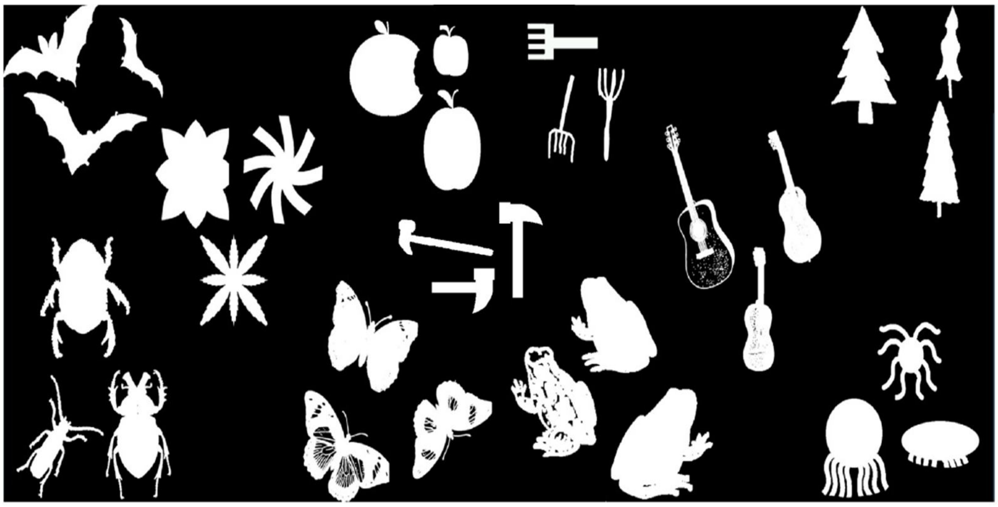

Figure 4. Samples of 11 calsses of shapes from set B of the MPEG-7 database.

Table 1 shows the average of precision for low and high levels of recalls (recall ≤ 50% and (recall > 50%) for the SRD signature and seven well-known signatures. It is clears that the performance of the SRD signature is higher than sixth of them. It is only less than the RD signature. For better comparison, Fig. 5 shows the precision-recall curve of the proposed SRD method and three of those shape signatures (RD, CC and CLD). It is obvious that the precision-recall curve of the SRD method is higher than the CLD and CC signatures and it is less than the RD signature. It is concluded that, the proposed method has a good performance in comparison with some of well-known shape signatures.

TABLE I. THE AVERAGE PRECISION FOR HIGH AND LOW LEVELS OF RECALL FOR THE SRD AND OTHER FOURIER DESCRIPTORS ON THE MPEG DATABASE

Signatures	**Precision**	
	Recall ≤ 50%	***Recall > 50%***
RD	75.69	41.77
SRD	67.87	34.61
CC	64.76	22.59
PC	64.40	35.12
ARC	58.93	26.83
TAR	58.70	23.54
CLD	57.80	24.00
AF	57.39	27.88

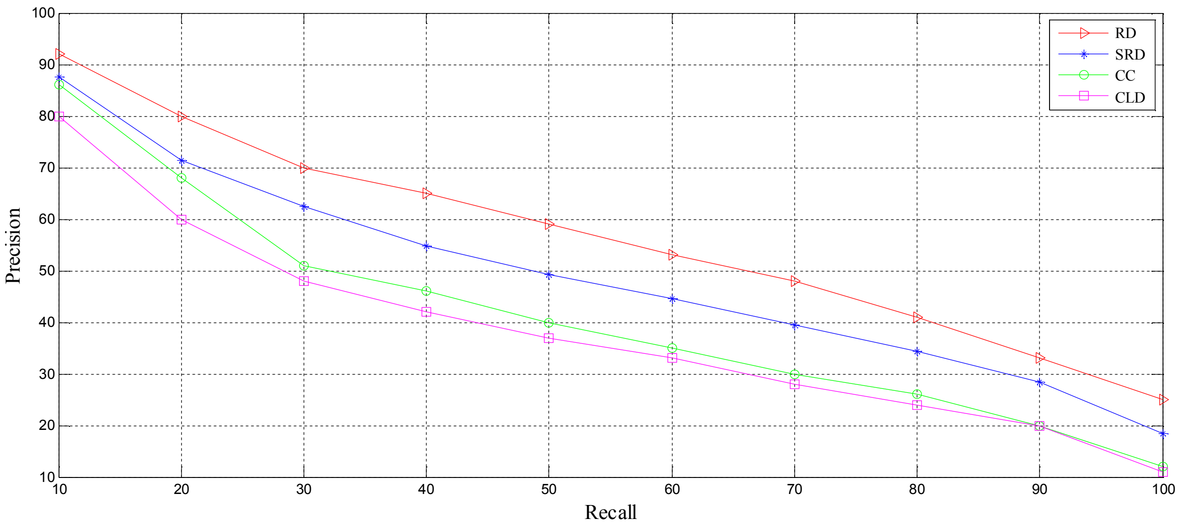

Figure 5. The precision-recall curves of the proposed method (SRD) and some well-known shape signatures.

V. Conclusion

One of the important low-level features in content-based image retrieval is shape. This paper proposes a new CBIR system based on shape feature. This is based on boundary points of shapes. The smallest 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, is selected. The distances between the opposite points on the surfaces of the rectangle and the shape, is computed as feature vector.

The proposed method that is called smallest rectangle distance (SRD) is a Fourier based descriptor and it is not sensitive to translation, scaling and rotation. The proposed SRD signature is compared with seven commonly used Fourier based descriptors (RD, CC, PC, AF, ARC, TAR and CLD). Experimental results are shown that the average of precision for low and high levels of recall for the SRD signature is higher than sixth of those commonly used signatures.

References

[1] Suchismita Das, Shruti Garg and G. Sahoo, “Comparison of Content Based Image Retrieval Systems Using Wavelet and Curvelet Transform,” The International Journal of Multimedia & Its Applications (IJMA) Vol.4, No.4, pp.137-154, August 2012.

[2] Nidhi Singhai and Prof. Shishir K. Shandilya, “A Survey On: Content Based Image Retrieval Systems,” International Journal of Computer Applications (0975 – 8887) Volume 4 – No.2, pp. 22-26, July 2010.

[3] N. Alajlan, I. El Rube, M.S. Kamel and G. Freeman, “Shape retrieval using triangle- area representation and dynamic space warping,” Patern Recognition, vol. 40, pp. 1911-1920, 2007.

[4] Akrem El-ghazal, OtmanBasir and SaeidBelkasim: “Farthest point distance: Anew shape signature for Fourier descriptors,” Signal Processing: Image Communication 24, pp. 572-586, 2009.

[5] R.C. Gonzalez, R.E. Woods, “Digital Image Processing,” Addison-Wesley, Reading, MA, 2002.

[6] K.L. Tan, and L. F. Thiang, “Retrieving similar shapes effectively and efficiently,” Multimedia Tools and Applications, Kluwer Academic Publishers, Netherlands, pp.111–134, 2003.

[7] D.S. Zhang, G. Lu, “A comparative study of curvature scale space and Fourier descriptors,” Journal of Visual Communication and Image Representation 14, pp.41–60, 2003.

[8] I.Kunttu and L.Lepisto, “Shape-based retrieval of industrial surface defects using angular radius Fourier descriptor,” IET Image Processing, 2007, 1, (2), pp.231–236, 2007.

[9] Yang Mingqiang, Kpalma Kidiyo and Ronsin Joseph, “A survey of shape feature extraction techniques,” Pattern Recognition, Peng-Yeng Yin (Ed.), pp.43-90, 2008.

[10] D.S. Zhang and G. Lu, “Study and evaluation of different Fourier methods for image retrieval,” Image and Vision Computing 23, pp.33–49, 2005.

[11] F. Mokhtarian, M. Bober, “Curvature Scale Space Representation: Theory Application and MPEG-7 Standardization,” first ed., Kluwer Academic Publishers, Dordrecht, 2003.

[12] RitendraDatta, DhirajJoshi, Jia Li and James Z. Wang, “Image Retrieval: Ideas, Influences, and Trends of the New Age,” ACM Computing Surveys, Vol. 40, No. 2, Article 5, Publication date: April 2008.