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Comparative Performance Analysis of Centroid Distance Based Fourier Descriptor as Contour Feature

Research Article

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Abstract: Retrieving images from large collections or from remote databases is an important issue for many real life applications of CBIR (content based-image retrieval). Different shape features are used in order to represent and retrieve images. In content based image retrieval (CBIR) area, shape is an important visual content and attracted much attention these days. Also, we must need a good shape descriptor for image representation perfectly. In this paper, it has been shown that Centroid distance based Fourier descriptor shows better performance as contour feature for shape based retrieval. Also, a comparative performance analysis of different contour based image features along with Fourier descriptor have been presented in this paper. The whole process is implemented on MPEG-7 database by using MATLAB. The experimental result shows that Centroid distance based Fourier descriptor along with city block distance shows high retrieval accuracy around 96.33% and low computational complexity.

Keywords: *Shape extraction ● Fourier descriptor ● City block distance ● Computational complexity*

1. Introduction

The present world is the world of information technology, day by day information system increased a lot. With the overwhelming growth of internet, personal computer, mobile phone and digital camera huge number of images are received by online and offline databases. It is difficult to searching a particular image from the huge number of image databases. Image identification and classification is also difficult, which are essential in various real life applications. So, image retrieval has become a familiar topic in computer science research. Color, texture features are needed to represent an image obviously; however, shape is the most important feature for image understanding. This is a very important sign of image segmentation. It plays an important role in the image retrieval fields because of its effective and powerful representation (Ankur Gupta. 2018). Shape classification applies in several sectors e.g. Crime prevention (Iqbal et al., 2016), Medical Imaging (Kitanovski et al., 2017), Trademark, Fingerprint identification and so on.

There are some challenging issues in CBIR; Visual transformation (occlusion or articulation) and computational complexity matter a lot for shape retrieval. (Klein P, 1998; Zaboli H, 2007). In order to get the accuracy or robustness of retrieval the shape descriptor should not sensitive to visual transformation; that means a small change in the shape should give small changes in the descriptor. Another important issue is to reduce the computational complexity for matching and indexing of the shapes. To deal with the problem of computational complexity, one way is to reduce sample point and the other is to develop an algorithm or technique that deals with reducing the time complexity (Khanam et al., 2010).

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According to the literature, shape retrieval techniques can be divided into two categories: contour-based and interior-based methods. The reason for this is that, depending on the application or retrieval objective, shape retrieval is dependent on the shape's contour or interior detail of a shape (Anaraki et al. 2017). Generally, interior based methods show robustness in retrieval with high complexity. However, contour-based methods are faster to compute and perform with low computational complexity. Moreover, contour based techniques take the whole shape contour as shape representation and people are supposed to discern shapes primarily by their contour features. In many applications, shape contours are the only available feature which is why compared with region-based shape representation contour-based shape methods are more popular in the literature. So, we are interested to work with contour based shape techniques. We can see a few limitations in contour-based methods; sensitive to noise and variation. Therefore, some contour-based approaches, such as the moment method, Fourier descriptor (FD), generic-Fourier descriptor (GFD), and wavelet-fourier descriptor (WFD) (Khare et al., 2018) have been developed to address these issues (Zang et al.2004, and Lu et al. 2002). Among the various shape representations Fourier descriptors are easy to derive and compact in terms of representation. Also, FD is a popular descriptor because of its eligible characteristics, these are: low computational complexity, high performance accuracy. Also the advantages of FD over many other shape descriptors are: simple to compute, retrieval speed, each descriptor has specific physical meaning, simple to do normalization, making shape matching a simple task etc (Zang et al.2004, and Lu et al. 2002).

Our goal of this paper is to choose a good descriptor which gives a good result for shape retrieval. However, in the literature of image processing, there are many retrieval methods which are sensitive to noise, translation or rotation and some other methods which are with high computational complexity. There are many retrieval techniques which give us a good accuracy with high computational complexity or many techniques with low computational complexity which can't give a good accuracy. To address these problems, particularly, we use Centroid distance based Fourier descriptor as contour feature. We will show the outstanding performance of Centroid Fourier descriptor (CFD) as contour based shape feature. Where the application is simple; to avoid computational cost, CFD can be a good contour based shape descriptor. As we know, Fourier descriptor (Zang et al.2004, and Lu et al. 2002) shows good accuracy at low computational cost, proposed CFD can be used for shape retrieval efficiently. Here, we use the City block distance to obtain the similarity measurement of the different shapes applying the CFD descriptors. Our method is implemented by MATLAB 2014 software in MPEG-7 database.

The rest of this paper is organized as follows. Section 2 introduces the premise of our suggested method: the Centroid distanced based Fourier descriptor (CFD), as well as the CFD algorithm. We detailed our experimental results in section 3 of this paper. In section 4, the complexity analysis, as well as the comparative study, is discussed. Finally, in section 5, we discuss the findings as well as future research.

2. Proposed method of shape based image retrieval

Our paper is organized into two stages; which are feature extraction and image retrieval. The feature extraction is the basic stage of our work, the aim of this stage is extract image by using a perfect image descriptor. Here, we have used the Centroid distance based Fourier descriptor (Liao et al., 2021) which performance is better than among other Fourier descriptors (Zhang et al., 2002). When the feature extraction is done, City block distance is used for shape retrieval.

2.1. Centroid distance based Fourier descriptor as shape feature

The Fourier Transformation is an important image processing tool which is one kind of general form of the Fourier series. The Fourier Transformation is a method which convert the general form (signature) of an image (or a function) into an alternative form of *sine* and *cosine* components.

The Fourier series corresponding to the periodic function $f(x)$ is defined as

$$f(x) = \frac{a_0}{2} + \sum_{n=1}^{\infty}[a_n \cos(nx) + b_n \sin(nx)] \qquad (1)$$

Where a_0, a_n, b_n are constants and $\sum_{n=1}^{\infty} a_n \cos(nx)$ is the even component and $\sum_{n=1}^{\infty} b_n \sin(nx)$ is the odd component where n = 1,2,3,……… . By using these even and odd component we obtain the Fourier coefficients a_n and b_n.The Fourier descriptor converts the time domain into the frequency domain. Time domain measure the change of a signal with respect to the total time and the frequency domain measure how fast a signal is change. In this paper, we have worked with various types of shapes. Shape is often unclean with noise, defects and distortions which is unwanted and make an undesirable signal. To represents an effective and proper image we have to ignore this undesired signal. The time domain can't separate the desire signal and the undesired signal. However, the desire signal and the undesired signal are separable in frequency domain and then filter out this noise by very simple filter Medfilt2 command which is a MATLAB code. Frequency domain is translation, scale and rotational invariant as well as calculations are easier in frequency domain.

FD's are derived from a shape signature. There are several types of shape signatures have been used to derive Fourier descriptor. Centroid distance function is the most desirable shape signature among other FD's like affine FD's, area FD's, chord length FD's, curvature function FD's etc (Zhang et al., 2002). In this paper we work with the Centroid distance function. In general, a shape signature $f(t)$ is any 1-D function which represents 2-D area or boundary. The 1-D signature function to represents a shape is,

$$f(t) = ([x(t) - x_c]^2 + [y(t) - y_c]^2)^{1/2} \qquad (2)$$

Where, *x(t)* and *y(t)* are the boundary coordinates and (x_c, y_c) is the centroid of the shape. To get a signature of a shape; firstly, we need to calculate the boundary points *x(t)* and *y(t)* where t is the arc length. The boundary points of the shape are extracted through the contour tracing by moores law. Here we use 8-connectivity contour technique [Niblack et al., 1993]. The centroid (x_c, y_c) of the shape boundary is calculated by the equation.

$$x_c = \frac{1}{N}\sum_{t=0}^{N-1} x(t) \ \ and \quad y_c = \frac{1}{N}\sum_{t=0}^{N-1} y(t)$$

The shape signature $f(t)$ is rotation invariant. The FT of the function $f(t)$ is computated as given by the equation,

$$F_n = \frac{1}{N}\sum_{t=0}^{N-1} f(t)\exp\left(-\frac{2\pi int}{N}\right), n \in \mathbb{Z} \qquad (3)$$

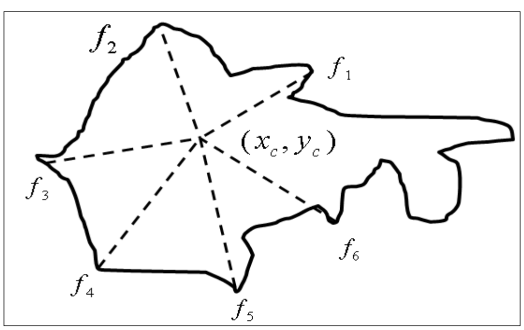


Figure 1. Shape contour using centroid distance

Figure 1 shows the shape boundary with centroid distance. After getting some descriptors from some shape, we calculate the similarity between two images, one is query image and other is database image. Here, we use city block distance as a similarity measurement.

2.2. Algorithms for proposed method

In this section, we described step by step algorithm for finding the contour based Fourier descriptor and city block distance measure without any built in functions.

Fourier descriptors algorithm

Step-1: input a query image p_1.

Step-2: input database images $(p_1, p_2, p_3, \dots\dots, p_n)$.

Step-3: Find the x-coordinates of image boundary, $x_1(t)$.

Step-4: Find the y-coordinates of image boundary, $y_1(t)$.

Step-5: Find the average of x-coordinates, x_c .

Step-6: Find the average of y-coordinates, y_c .

Step-7: Find the shape signature(centroid distance) for each images,

$$f(t) = ([x(t) - x_c]^2 + [y(t) - y_c]^2)^{1/2}$$

Step-8: Find Fourier descriptor using the shape signature

$$F_n = \frac{1}{N}\sum_{t=0}^{N-1} f(t)\exp\left(-\frac{2\pi int}{N}\right), n \in \mathbb{Z}$$

Step-9: Find the City block distance measure using the Fourier descriptor.

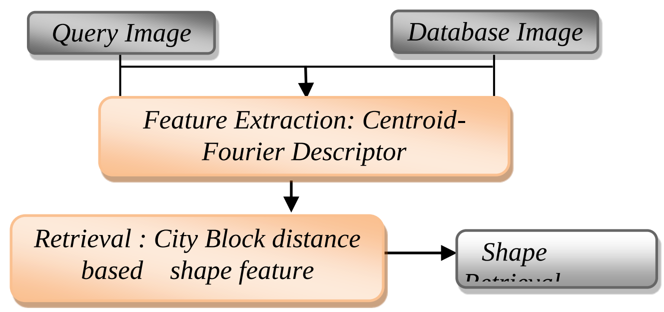


Figure 2. Overall framework of Centroid Fourier Descriptor (CFD) based Shape Retrieval.

Figure 2 shows the overall framework of our proposed method, where, the feature extraction step extracts data images by Centroid Fourier descriptor and then we measure the similarity between query image and database images by city block distance.

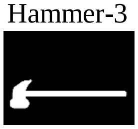
3. Experimental results and discussion

Our proposed method is tested on **MPEG-7** CE Shape-1 Part-B database images which contain a 1400 images (apple, bat, battle, butterfly, bone, tree, heart etc.) of 70 groups and each groups has 20 images and we use the mathematical software MATLAB to analyze the numerical results as well as to get graphical representation. However, as our method is contour based, at the beginning, shape signature must be computed and then, features are extracted according to centroid distance Fourier descriptor. We have extracted contour of an image through an 8-connectivity contour tracing technique(Niblack et al., 1993). Then, City block distance between the centroids are calculated to measure the similarity between query image and the data images. To test our proposed method of image retrieval, we have used 15 images from three different groups (cup, hammer and shoe), where 3 images from each group will be used as a query images from the respective groups. We assign each image based on the minimum centroid distances from table-1. The contour-based Centroid Fourier descriptor produces an excellent retrieval performance for the query; cup, hammer, shoe even for same animals of similar shapes.

Table 1. City Block similarity (distance) measurement for 15 images (query: cup-1, hammer-3 and shoe-5)

Image No.	Image	Distance for query **cup-1**	Distance for query **hammer-3**	Distance for query **shoe-5**
1	Cup-1	**13735813.55**	50654742.74	105405618.6
2	Cup-5	**1849796.269**	45146320.7	102313174.4
3	Cup-7	**4012337.62**	39628854.72	98967105.99
4	Cup-10	**15838605.54**	32178130.94	92623576.86
5	Cup-18	**30105813.78**	20984736.15	82443847.9
6	Hammer-3	35643068.24	**10993083.99**	72452195.74
7	Hammer-7	40386724.97	**200.5489376**	60458869.26
8	Hammer-10	50643327.89	**10992414.28**	50466697.49
9	Hammer-11	61157031.63	**21985163.39**	38473948.36
10	Hammer-17	71814055.19	36977912.52	**21481199.24**
11	Shoe-5	85558772.86	48970084.29	**11489027.46**
12	Shoe-6	95362181.88	**20963410.76**	**595700.987**
13	Shoe-10	144203612.8	65955005.19	**6095893.441**
14	Shoe-11	145075252.7	88948331.66	**12489219.92**
15	Shoe-12	125966298.6	87939926.09	60480814.34

Table 2. Result of retrieval according to query image (Cup-1, Hammer-3, Shoe-5)

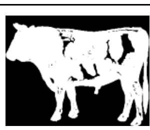
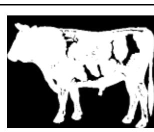
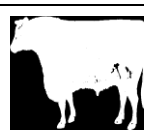
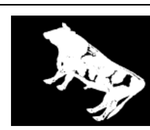
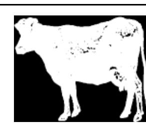
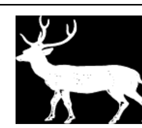
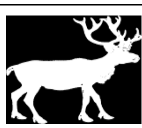
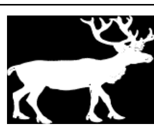
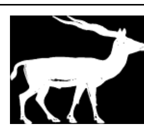
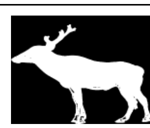
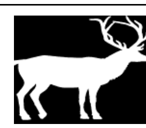
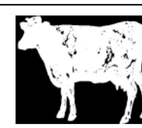
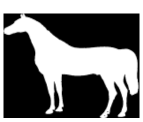
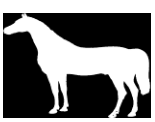
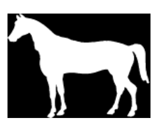
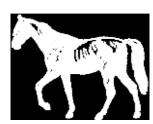
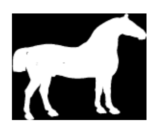
Query Image	Retrieved Images				
Cup-1 					
Hammer-3 					
Shoe-5 					

In the above Table-2, we see that the first group is accurate up to 5 images; second and third group is accurate up to 4 images. For the second experiment, we have been used 15 another images from three different groups (cattle-6, deer-1, horse-1) and we have been used 3 images as a query images from different groups. We assign each image based on the minimum centroid distances from table-3.

Table 3. City Block similarity (distance) measurement for 15 images (query:cattle-6, deer-1 and horse-1)

Image No.	Image	Distance for query **cattle-6**	Distance for query **deer-1**	Distance for query **horse-1**
1	Cattle-7	**10071122.65**	64288150.66	101824691.3
2	Cattle-8	**5523726.796**	56240754.85	92070100.14
3	Cattle-8	**5023322.628**	48193705.46	86386317.91
4	Cattle-10	**15071526.82**	30145501.43	72800092.09
5	Cattle-12	25118576.24	**20198452.16**	66358120.7
6	Deer-1	**17516620.05**	**12050826.01**	54134252.83
7	Deer-6	45219603.16	**3020.39799**	45254810.07
8	Deer-8	58266652.49	**12049624.62**	36989110.58
9	Deer-12	65314105.99	**210970771.93**	29837703.14
10	Deer-16	74578985.72	29374890.55	21041289.92
11	Horse-1	79750011.95	35146654.97	**10302273.68**
12	Horse-2	84594927.3	41577291.56	**5060731.977**
13	Horse-6	90301525.54	49233195.8	**1806654.101**
14	Horse-9	96720940.14	57631988.26	**14850002.52**
15	Horse-11	103717315.6	66489121.95	**14897402.07**

Table 4. Results of retrieval according to query image (cattle-6, deer-1, horse-1)

Query Image	Retrieved Images				
					
					
					

In the above table-4, first group is accurate up to 4 images, second group is accurate up to 4 images and third group is accurate up to 5 images successfully.

In this study, we consider the performance up to fifth retrieval of images according to the query image. From our experimental results we observe that CFD based shape retrieval shows excellent performance (100%) up to fourth or fifth retrieval. Finally, from the whole experiment we found that CFD method with city block distance shows very fast and high retrieval accuracy around 96.33% with low computational complexity. The performance rate comparison graph up to fifth image according to our experimental results is presented here in this section.

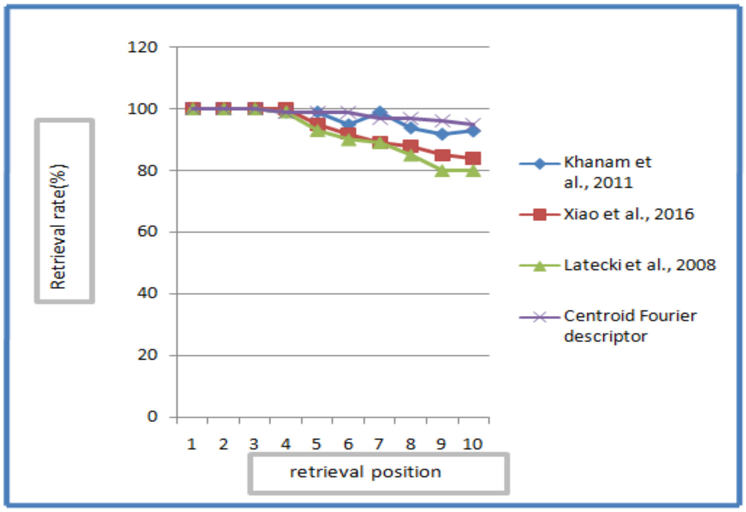


Figure 3. Retrieval rate (%) of different methods up to fifth retrieval position.

From figure 3, it can be explained that centroid Fourier descriptors shows the same retrieval performance up to fifth and better performance after fifth retrieval (Khanam et al., 2011, Xiao et al., 2016 , Latecki et al., 2008) using MPEG-7 database.

4. Complexity vs. performance analysis

Computational complexity means how much time taken by the program. Computational complexity is the rate of growth of time taken with respect to input. Computational complexity plays very important role to justify the performance of an algorithm from others algorithm for a same problem. As, we use only the boundary point (contour) of an image so, the computational complexity of Fourier descriptor is $O(n)$, where n is the number of the boundary points as well as the proposed similarity measure is also linear $O(n)$, where n is the total number of data, The total complexity of the proposed methods is $O(n)$. So, the computational complexity of our proposed method is linear. This is the robustness of our methods that low computational complexity with better accuracy.

Table 5. Complexity analysis of different shape features using MPEG-7 database

Approaches	Time complexity	Comments
Discrte shock graph (Khanam et al., 2011)	$O(n^2)$	Time complexity problem.
Skeleton representation with K-NN(k-nearest neighbor (Bai et al., 2008)	$O(n^2)$	Computationally heavy. Choosing best k may be difficult and need a large number of data.
Centroid-Fourier Descriptor (proposed)	$O(n)$	Simple and computational complexity is less than other methods.

Table 6. Performance analysis of different shape features using MPEG-7 database

Performance Comparison		
Method	Advantage	Disadvantage
Boundary Moments(Jie-xian, 2010)	Easy to apply and can reduce the dimension of boundary. It is easy to appliance. Less noise-sensitive shape descriptors.	Difficult for higher associate with higher order momnet.
3.Proposed Centroid-Fourier Decriptor Method	i. Represent shape as a 1D signal which is easier to analyze than to analyze 2D signal.	Not applicable for two images with the same contour but of different interior details.

	ii. Overcomes the noise sensitivity and difficult normalization in the shape signature representations. iii. simple to compute; iv. each descriptor has specific physic meaning; v. simple to normalize making shape matching a simple task; vi. capturing both global and local features;	
4. Chain Code Representation (Dengsheng et al., 2004)	describe an object by a sequence of unit-size line segments	it is very sensitive to boundary noise and variations.
5.Shock graph based skeletal method (Khanam et al., 2011)	i. superior in handling instability ii. Better retrieval accuracy iii. Robust against visual transformation	i. Computationally complex. ii. Not applicable for image where only contour information is available

From the table 5 and 6, we see that the computational complexity of proposed method is less than other shape based methods. It can be concluded that CFD based contour methods can be used in shape retrieval to make our computation simple. However, this method does not show robustness for the images with same contour with complex interior detail. On the other hand, region based methods have better performance in the case of handing images with complex interior detail. Though the accuracy is high, region based method are computationally complex. So, the success of a contour or region-based approach is dependent on the images being used.

6. Conclusions

Depending on the application or retrieval objective, shape retrieval is dependent on the shape's contour or interior detail of a shape. Generally, interior based methods show robustness in retrieval with high complexity. However, humans are assumed to discriminate shapes primarily based on their contour aspects. Moreover, contour-based methods are faster to compute and perform with low computational complexity. Therefore, compared with region-based shape representation contour-based shape methods are more popular in the literature. In this study, we did our shape retrieval experiment with contour-based approaches. Particularly, among the contour based methods, we have shown that Centroid Fourier descriptor with city block distance shows better retrieval performance with low computational complexity. Comparing with another shape based methods using MPEG-7 database, we see that our method is highly accurate and less computational complex than other methods. The total computational complexity of our method is linear $O(n)$ which is challenging for a process. Our method shows excellent accuracy (100%) up to 4th retrieval and finally, from the whole experiment we found that Centroid FD method with city block distance shows very fast and high retrieval accuracy around 96.33% with low computational complexity. As a future work we will apply our approach in a real life image database for trademark image retrieval.

References

Ankur G A. (2018). A review on various approaches for content based image retrieval based on shape, texture and color features. *International Journal of Academic Research and Development, 3:77-180*.

Anaraki A T, Sheikh U U, Rahman A A H A and Omar Z (2017). An Alphabetic Contour- Based Descriptor for Shape-Based Image Retrieval. *IEEE International Conference on Signal and Image Processing Applications, Malaysia.*

Bai X and Latecki L J. (2008). Path similarity Skeleton Graph Matching. *IEEE Trans. Pattern Anal. Mach. Intell*, 30:1282-1292.

Iqbal K, Odetayo M, James A, Iqbal R, Kumar N, and Barma S. (2016). An efficient image retrieval scheme for colour enhancement of embedded and distributed surveillance images. *Neurocomputing, 174:413-430*.

Julio C F, Francisco G, Nelo M and Ialis C and Junior P. (2016). Contour Based Feature extraction for image classification and Retrieval. *IEEE*.

Klein P and Sebastian T B. (1998). Indexing Based on Edit Distance Matching of Shape Graphs. *Multimedia storage and archiving systems III*, 25-36.

Khanam S, Jang S and Paik W. (2011). Fast and Simple 2D Shape Retrieval Using Discrete Shock Graph. *IEICE TRANS. INF. & SYST,* 10 (94): 2059-2062.

Kitanovski I, Strezoski G, Dimitrovski I, Madjarov G, and Loskovska S. (2017). Multimodal medical image retrieval system. *Multimedia Tools and Applications, 76:2955-2978*.

Khare M, Srivastava P, Gwak J, and Khare A. (2018). A Multiresolution Approach for Content-Based Image Retrieval Using Wavelet Transform of Local Binary Pattern. *Springer International Publishing AG, part of Springer Nature*, 529–538.

Liao N N, Guo B, Li Z and Zheng Y. (2021). An Advanced Fourier Descriptor Based on Centroid Contour Distance. *Journal of Physics: Conference Series*, 1735(1):012002.

Loncaric S. (1998). A Survey of Shape Analysis Technique. *Pattern Recognition*, 983-1001.

Misra S, Verma A K. (2018). Content Based Image Retrieval Using K-Means Algorithm. *International Journal of Applied Engineering Research* . 13:5562-5564.

Niblack W, Barber R, Equitz W, Flickner M, Glasman E, Petkovic D, Faloutsos C. and Toubin G. (1993). The QBIC project: querying image by content using color, texture and shape. *In proceeding of SPIE storage and retrieval for image and video database*.173-187.

Rahaman, M D A. (1997). Integral Transforms and Boundary value problems. *College, Mathematical methods*, 2 :189-223.

Van T T, Van Thinh N T and Manh Le T M. (2018). The method proposal of Image Retrieval based on K- means Algorithm. *Spinger*, 481-490.

Sebastian T B, Klein P N and Kimia B B. (2004). Recognition of shapes by editing their Shock Graphs. *IEEE Trans. Anal. Mach. Intel*, 26(5) :550-571.

Zaboli H, Rahmati M. (2007). An Improved Shock Graph Approach for Shape Recognition and Retrieval. *Proceedings of the First Asia International Conference on Modeling & Simulation. AMS,438-443*.

Zeng J , Y.-g. Z. (2010). A Novel Shape Representation and Retrieval Algorithm: Distance Autocorrelogram. *Journal of Software*, 1022-1029.

Zhang D , Lui G. (2005). Study and evaluation of different Fourier methods for image retrieval. *Image and vision computing, 23(1):33-49*.

Zhang D S and Lu G. (2002). A Comparative study of Fourier descriptors for shape representation and retrieval. *The 5th Asian Conference on computer vision, Melbourne, Australia*, 23-25.

Zhang D, and Lu G. (2004). Review of shape representation and description techniques. *Pattern Recognition*, 1-19.

Zhang X Z, Ling B W K, Lun D P K, Cao J, Dai Q. (2016). Image Retrieval Based on Discrete Fractional Fourier Transform Via Fisher Discriminant. *Circuits Syst Signal Process*.