A review work on image retrieval of content-based and shape-based method

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Abstract

More and more images have been generated in digital form around the world, due to the decreasing storage and processing costs and the internet. There is a growing interest in finding images in huge collections or from remote databases. In order to find an image, the image has to be narrated or represented by certain features. Shape is a significance visual feature of an image. Looking for images using shape features has attracted much recognition. Shape is one of the primary low-level image features exploited in the newly emerged content-based image retrieval (CBIR). Many shape methods exist. We study many shape representation and description techniques in the literature. However, in this dissertation it has been shown that Fourier descriptor-based methods have better performance for contour-based image search whereas shock graph based skeletal methods shows better accuracy for interior based image search depending on the applications.

Keywords— retrieval, Texture, Fourier descriptor, shape descriptor

I. INTRODUCTION

Retrieval of images from large-scale database has become of concern to an ever-increasing segment in the field of computer vision for browsing, searching and retrieving information. CBIR (content-based image retrieval), one image retrieval area has developed, which aims to avoid time complexity of traditional textual descriptions-based retrieval. CBIR retrieves images based on their visual similarity to a user-supplied query image or user-specified image features and searches for the important content of the image; color, texture and shape. Where there is no information about color and texture, shape-based retrieval is very important that includes potential uses, like crime prevention, medical diagnosis, and retail catalog, military, registration, prototype formation, hand written character recognition.

II. BACKGROUND

An important task in image analysis is the discrimination of objects based on their appearance. Various properties of appearance such as texture, color and shape can be measured [1]. Shape is a powerful tool for describing objects and differentiating between them, and has been extensively applied in many areas of computer vision. If shape has to be defined, there is no universal definition of what shape is. The word 'figure' is used for shape [1,14]. Shape is an important visual feature or outline of something and it is one of the primary features for image content description. It is difficult to define perceptual shape features and measures the similarity between shapes. In the shape-based image retrieval, visual transformation of shape is an important issue for shape matching [9]. It is desirable that small changes in the shape boundary should result in the small changes in the shape descriptor. If any large changes in the shape boundary of the object result in very slight changes in the shape descriptor, then the shape descriptor is considered not sensitive and we will get the robustness of result [3]. Researcher either try to reduce sample point or developed the matching algorithm in such a way that deal with the reducing the time complexity. Some other factors like loss of information make the shape-based representation and retrieval task difficult. In a typical shape representation technique, a 3-D real object is projected onto a 2-D plane, which results in the loss of one-dimensional information. Therefore, to get all the feature information from images, shape retrieval techniques are generally classified into two types of methods: contour-based and interior-based methods. It is because that shape retrieval is based on whether shape features are extracted from the contour only or the whole shape interior. Each type of method is further divided into local and global feature extraction approaches [2,6]. These approaches are based on whether the shape is represented as a whole or by segments. Contour-based approaches had been more frequently used in comparison to interior-based ones mainly due to the facts that human is thought to discriminate shapes predominantly by their contour features and also shape contours are the only available feature to use in many applications. Global contour shape techniques take the total shape contour as the shape representation. However, there are a few limitations in contour-based methods. Firstly, contour shape descriptors are generally sensitive to noise and variations as they only use small part of the shape information. Secondly, the shape contour is not available in many cases. Thirdly, shape content is more important than the contour features in some applications [4,7]. Given these problems, some of the promising contour-based techniques such as the moment method, Fourier descriptor (FD), generic-Fourier descriptor (GFD) and wavelet-Fourier descriptor

(WFD) had been developed [9,4]. The interior-based approaches showed better performance than the contour-based ones in handling instability, which existed in an image database where partial matching was needed. Particularly, skeleton-based interior approaches exhibited superior performance in comparison to the contour-based approaches by providing topological and geometrical information as well as revealing robustness against the visual transformations [1,10]. Main drawbacks of interior-based local approaches were failure to capture global features of a shape and computational complexity in calculating the similarities. If the interior-based features are connected to the global shape features, then the method was able to cope well with shape defections. However, the interior-based methods, like skeleton-based feature matching, were more complex than contour-based methods [10,12]. An extensive research had been performed to handle the complexity of similarity measure for skeletal-based method. Our recent work also proposed a set of new methods to reduce complexity of the interior-based skeletal method.

III. Problem Statement

The problem we found is that both interior and contour-based local or global methods have limited applications. Using only contour or interior information failed to perform correct retrieval of a shape in some cases. Therefore, combination of contour and interior features was the next logical progression as shape descriptors. In terms of using the combined features, it had been indicated that shape-based trademarks needed to be interpreted using different algorithms for global and local structures [11]. Using this strategy, the sample images were compared separately to the local and global features of the query images. Curvature and centroid distance were used for describing the local feature while Zernike moments were employed to extract the global feature by computing the first 4-order 15 Zernike moments to achieve the most effective measurement of the global shape. The similarity was computed by utilizing the Euclidean distance to the range [0, 1] and setting up a threshold of 0.3. However, there were some drawbacks. One problem was the lack of incorporating the relationships between the adjacent boundary points in computation. Also, the presence of factorial calculations made the computation of Zernike moment complex and thus an approximation was needed. However, the retrieval accuracy could not be guaranteed if the approximation was used. Moreover, using a threshold value made the system database dependent. An effective solution for those drawbacks was proposed by Heng et al. [6] by combining two shape features for representing and matching. In their work, contour-based descriptor included the histogram of centroid distances and represented the relationship among two adjacent boundary points and the centroid. In the feature matching strategy, a statistics-based method was proposed to compute the dissimilitude values between shape feature vectors of images. The combination of contour and interior-based descriptor might have increased the computational time. However, the computational complexity was not analyzed in their study. Also, comparison analysis with respect to other combined feature-based approaches was absent.

In our work, we have shown Fourier-based methods shows better performance among the contour-based method where contour information is available. However, to represent an image from intrinsic point of view we need the region-based descriptor. In this case, shock graph-based interior features show best performance among the region-based shape retrieval methods. Also, we have also checked the combination of Fourier descriptor-shock graph (FD-SG) method in [8]. Moreover, it does not affect the accuracy at a lower computational complexity. To the best of our knowledge, a shock graph is a robust descriptor for shape retrieval. Although the shock graph was a computationally complex method, a less complex computation was performed in our previous study [8,13]. Also, we do not observe any increment of complexity arising from combining FD because it is one of the simplest ways for contour-based feature extraction. Moreover, the most notable advantage of different FD methods over many other contour-based shape descriptors is simple to compute and normalize; each descriptor has specific physical meaning and captures both global and local features. In our recent study, we performed a number of experiments on combined feature of Fourier descriptor and shock graph. We have also provided a comparative study between contour and region-based approaches.

IV. Fourier Descriptor as a Contour Feature

Most FD-based works are dedicated to the character recognition and object classification. The complex coordinates and the cumulative angle function are dominantly used to derive FD [3,13]. However, Zhang and Lu found that, for general shapes, the centroid distance function was the most desirable shape signature to derive FD. They also found that 10 FD features were sufficient to represent shape and it was a significant reduction in the dimensions of FD, where 60 FD features were usually used. Thus, we apply the centroid distance-based Fourier descriptors as shape contour features.

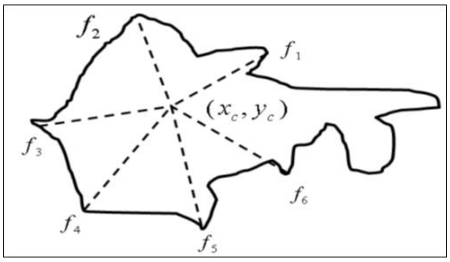

Figure 1:Shape features: Centroid Distance

In general, Fourier descriptors are derived from a shape signature (Fig. 1). A shape signature, f(t), is any 1-D function representing 2-D areas or boundaries. For a given shape, a shape signature can be defined as a closed curve C which in turn is represented by a one-dimensional function f(t). The f(t)is complex and periodic at every time t. As f(t) is complex for period T, we have f(t+nT)=f(t),where 0<t<T. Different shape signatures have been used to derive FD [3].

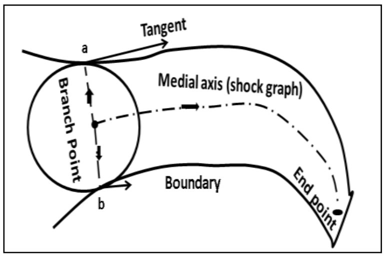

Figure 2: Shape features: Shock graph

During the experiments, we used centroid distance-based (Fig.2) shape signature. In order to find the centroid distance-based shape signature, we initially extract the boundary points of a shape contour. We assume that the shape boundary coordinates (x(t), y(t)), t= 0, 1, …, N-1, are extracted where t usually means the arc length. In our implementation, the shape boundary points are extracted through an 8-connectivity contour tracing technique(Lu, 2002). Finally, the centroid distance function is expressed by the distance of the boundary points to the centroid (x_c, y_c) of the shape and shown as in equation (1)

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

Consequently, the discrete Fourier transform is defined by using the shape signature as in equation (2)

$$F_n = \frac{1}{N}\sum_{t=0}^{N-1} f(t)\exp\left(-\frac{j2\pi nt}{N}\right), \quad n \in Z \quad \ldots\ldots.. (2)$$

The coefficients F_n, n=0,1,…,N-1,are used to derive Fourier descriptor of the shape. Using the city block distance, we get the similarity measurement, Cb_n for Fourier descriptor.

Shock-Graph as an Interior Descriptor

Medial axis is one of the important skeleton-based interior features, which is known to be better than the contour-based approaches for shape retrieval [12] Medial axis can be defined as the locus of the centers (called singularities or shock points) of maximal circles which touches the boundary at least at two points, as in Fig. 2. The points which touches the boundary are referred to as characteristic points (a and b in Fig.2). Shock graph is an idea which arises from the concept of medial axis augmented with some additional dynamic properties. According to the type of tangency and the number of touching points on the boundary, a shock point can be of first, second, third or fourth order. The loci of all the shock points in Fig. 2 give the Blum's medial axis and also the idea of the whole shock graph [12,6].The second and fourth order shocks are the generic cases of shock orders which are involved in occurring instability in shape retrieval. The second order shocks are the sources of flow while the fourth order shocks are termination points of flow, which represent branch and end points, respectively. These end and branch points are used as interior shape descriptors in our proposed approach to represent and retrieve an image from a database. At the beginning of the feature extraction stage, we adaptively select the nodes (shock points) of the images corresponding to the given query [7].The time complexity of the selection algorithm is O(x), where x is the number of nodes. For matching, we use shock point matching and edit operations in a discrete way. The matching cost between shock graphs is measured by discretizing the graph into branch or end nodes. It is assumed that two segments of shock graphs be discretized at sample nodes. These nodes can be considered as elements of a matrix (x by y). Let C (i,j)and d ([k, j], [l, j]) be the matching cost of graphs and segments, respectively. Therefore, the cost of shock point matching C (i, j) is

$$C(i,j) = \min_{k,l}\left[C(i-k, j-l) + d([i-k,i],[j-l,j])\right] \cdots\ldots \; (3)$$

Here, the number of sub-problems solved by a dynamic programming algorithm is (x×y) where x and y are the number of shock points (nodes) between graphs from the query and data image. Therefore, computing the matching cost C(i, j)needs complexity of order O(xy). To deal with a visual transformation, we consider deform cost resulting from the edit operation like contract and splice cost[13]. The total cost is the sum of the shock point matching cost and deform cost. The total matching cost, M_q can be written as in equation (4).

$$M_q = C(i,j) + D_q \; \cdots\cdots\; (4)$$

Where C(i,j), D_q and q represent matching cost, deform cost and the number of images, respectively.

FDSG Scheme

we obtained similarity measurements for two descriptors. Our proposed FDSG scheme combines Fourier descriptor with shock graph to get a generic similarity value to handle the robustness in retrieval. Thus, the proposed similarity measure G for a combined descriptor is defined in the equation (5).

$$G = w_1 Cb_n + w_2 M_q \; \cdots\cdots\cdots \; (5)$$

Where w_1 and w_2 represent the combination factors which have constant values. In our experiment, w_1 is set to 0.00001 and w_2 is set to 1 to make the measurement scale similar. Here, G is the generic similarity value between a query and database images. By applying algorithm 1, it is possible to calculate the generic similarity measure value for the two descriptors. The first step of the algorithm measures the similarity using the city block distance and the second step measures similarity by edit distance of shock graph. This combination shows an improved performance in retrieval without increasing the computational complexity. The total complexity of shock graph method is O(xy), [total complexity= (selection algorithm = O(x)) + (shock points matching = O(xy)) + (deform cost = O(x)) = {O(x) + O(xy) + O(x)} = max{O(xy), O(x)} = O(xy)]. In applying Fourier descriptor, all the boundary points are considered and we apply fast Fourier transform for saving computation [3]. If the boundary points are sampled to the power of two, for example, 32 or 64 points, then the sampling may result in a loss of boundary features. Therefore, all the points on the shape boundary are applied in our implementation. The computation of FD is O(x), when x

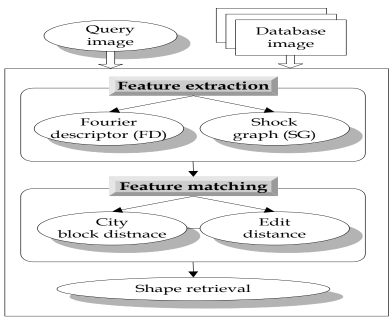

Figure 3: Overall flow of the proposed method

is the number of the boundary points. Therefore, the total complexity of the proposed FDSG method is O(xy) and the feature combining does not add any complexity. However, complexity does not fully explain the running time; the efficiency of an algorithm heavily depends upon data size [4]. A problem with complexity O(xy) is still NP hard; however, it is possible to decrease the running time by reducing the sample points in shock graph method [8]. However, it's a matter of concern about the running time when the database is too large.

The Figure 3 depicts the overall flow of the proposed method. When a query is presented, the features are extracted by the Fourier descriptor and shock graph descriptor. It is then matched against the database images by both local and global similarity measures. This leads to two types of similarity values: shock graph-based edit distance measure and Fourier descriptor-based city block distance measure. Finally, the images are retrieved according to the similarity values.

V. EXPERIMENTAL RESULT AND COMPARISON ANALYSIS

Today, more and more audio-visual information is available from many sources around the world. Also, there are people who want to use this audio-visual information for various purposes. However, before the information can be used, it must be located. At the same time, the increasing availability of potentially interesting material makes this search more difficult. This challenging situation led to the need of a solution to the problem of quickly and efficiently searching for various types of multimedia material interesting to the user. Moreover, MPEG-7 not only enables this type of search, but also enables filtering. Thus, MPEG-7 will support both push and pull applications. Shape descriptors depend on shape database. Ideally, all retrieval test should be done on a standard shape database. In MPEG-7, there are two shape databases, one consisted of trade marks is for region-based shape test, it is not publicly available. The other is for contour-based shape test, it is consisted of only marine fishes which may be judged by ordinary observers as being too many similarities in most cases.

DATA SET USED FOR SHAPE RETRIEVAL

We compared the performance of each descriptor on MPEG-7 dataset. This dataset is very useful for testing similarity-based retrieval and the shape descriptors robustness to various arbitrary shape distortions. To verify the performance of the proposed combined shape retrieving algorithm, we tested it on the MPEG-7 CE Shape-1 Part-B dataset. In some experiments [6], this database is used as trademarks. We used this dataset without any kind of change to get the performance results in the presence of instability in the dataset. This image database includes 1,400 images of 70 classes and each class has 20 images. We use a shock graph as an interior-based shape descriptor by applying the method described earlier. The adaptive algorithm is used to reduce the number of shock points [8]

RETRIEVAL PERFORMANCE FOR REGION OR INTERIOR BASED FEATURE

To verify the performance of the shock graph based region approach, we tested it on the MPEG-7 dataset (Image Processing Place). We used this dataset without any kind of change to get the performance results in the presence of instability in the dataset. Retrieval performance of that approach is excellent in Fig. 5 up to the 3rd retrieval both for transformed and non-transformed images. Moreover, retrieval rate is 100% where instability does not occur in the database (e.g. bone images in Fig.5). Comparative study has not been provided due to the unavailability of skeleton-based shape retrieval approaches which use MPEG-7 database. We have also tested our approach with a Kimia dataset of 216 images [11]. It is clear from Fig. 4 that our method performed the same or better than the recent approaches [2]. We see that, up to the 3rd retrieval, the region based approach shows the same performance as the recent [10] and better performance for the 5th to the 10th retrieval (except for the 4th retrieval). The skeletal graph method [2] shows better performance only for the 4th retrieval and has a sharp fall after the 5th retrieval. The gradient vector approach [5] shows lower performance than our approach after the 4th retrieval. Therefore, in terms of retrieval performance, the approach [5] are not as good as our approach. Though shock graph approach [12] has almost the same performance as our approach, however, the method is avoided due to its computational complexity. Therefore,

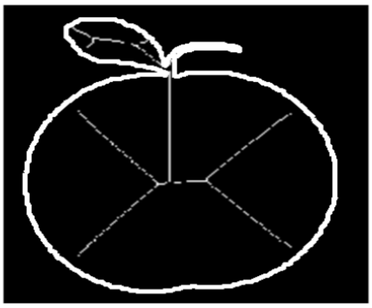

Figure 4: Apple image with boundary and medial axis

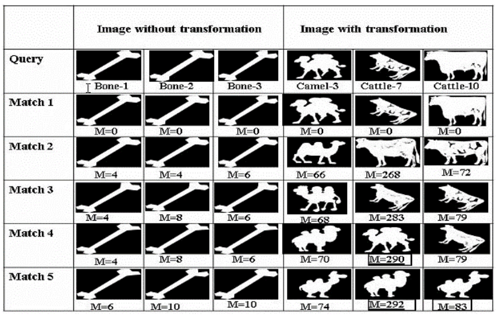

Figure 5: Distance measure (matching cost) for shape retrieval using 3 groups of 15 images (bone, camel and cattle) from the MPEG-7 database

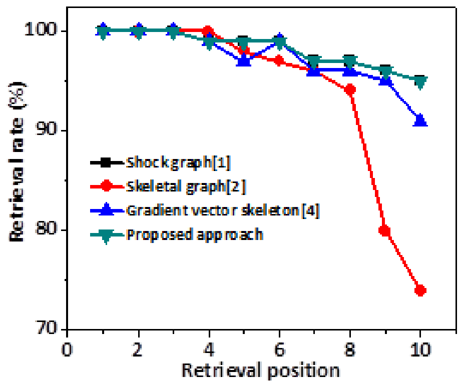

Figure 6: Comparing shape retrieval performance (in percentage, up to 10th retrieval) of our approach to some other skeletal-based approaches using the Kimia 216 database (Sebastian T. B., 2005; Bai, 2008)

shock graph method does not affect the accuracy at all. Fig. 4 shows a shape of an apple image which is represented by a medial axis with its boundary. Feature matching is conducted by measuring the distance between the feature vectors of the query image and the database images. Firstly, using city block distance, [3] we get the similarity measurements for the images with respect to query images. In the second step, interior-based distance measurement is obtained by using shock graph-based edit distance [8]

RETRIEVAL PERFORMANCE FOR CONTOUR BASED FEATURE

In contour based methods, Fourier descriptor and curvature scale space descriptor are more promising for image retrieval; in region based methods, geometric moments, grid method and Zernike moments are more promising for image retrieval. All the five methods tend to have relatively low precision when the database is large [4]. On average, FD is better than CSSD, while FD is much easier to derive, match, normalize and more compact compared with CSSD. Therefore, we view that FD should also be include as shape descriptors in MPEG-7. Although it is reported in that GD outperforms FD, however, the database is small and the shapes are mostly synthetic polygons. In our experiment, retrieval using GD has a fast drop on precision and recall. In fact, it usually can only hit .those scaled (zoomed), mirror and flip shapes, shapes with even slight skew are missed out from the retrieval. Images in the same class are considered to be similar. In our implementation, the shape boundary points are extracted through an 8-connectivity contour tracing technique [3]. It has been found that the increased number of FDs over 60 does not significantly improve the retrieval performance [4]. The actual retrieval performance is not changed significantly when the number of FDs is reduced to 10. Therefore, we used 10 FDs to represent and retrieve a shape. The common retrieval performance measure precision and recall are used as the evaluation of the query results. 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 indicates accuracy of the retrieval. 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 indicates the robustness of the retrieval performance.

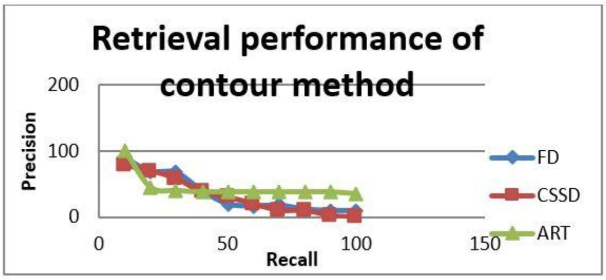

Figure 7: Retrieval performance of contour-based method

Table 1 shows that the shock-graph distance generates good retrieval accuracy up to the 5th retrieval with respect to the query, an apple. The contour-based Fourier descriptor also produces an excellent retrieval performance for the apple query. Both methods are effective in distinguishing an apple images from the beetles or the bat images. Furthermore, the accuracy is not affected at all and all the apple images are retrieved successfully by FD-SG method when two descriptors are combined. However, there are some images which are not possible to be retrieved only by using a contour or an interior-based feature. Table 2 shows that shock graph has poor performance in retrieving bat images. Using shock graph, 3 bats are retrieved out of 5 while all the bats are retrieved by FD method. On the other hand, the shock graph method produces good retrieval performance in retrieving beetles. However, FD method fails to distinguish a bat from beetles and no beetles are retrieved at all. In fact, shape images may have the same contour with different interior details. A standard database like MPEG-7 contains all sorts of images and that is why only using interior or contour detail may generate erroneous retrieval performance. Therefore, interior and contour features should be compared separately in order to enhance the retrieval performance during the feature matching stage.

Table 1: Shape retrieval result

Query: Apple			
Images	**FD**	**SG**	**FDSG**
Apple	27.9136	0	27.913598
Apple	55.8272	17	72.827195
Apple	83.74079	14	97.740793
Apple	111.6544	17	128.65439
Apple	139.5680	23	162.56799
Bat	167.4816	26	193.48159
Bat	195.3952	45	240.39518
Bat	223.3088	40	263.30878
Bat	251.2224	49	300.22238
Bat	279.1360	41	320.13598
Beetle	307.0496	89	396.04957
Beetle	334.9632	90	424.96317
Beetle	362.8768	97	459.87677
Beetle	390.7904	113	503.79037
Beetle	418.7040	124	542.70396

It will be beneficial to use the combination of both local interior and global contour features simultaneously. The proposed FDSG method shows an improved performance in Table 2, where only one descriptor fails to produce correct retrieval. Table 2 shows that the retrieval accuracy increased for the bat image. Moreover, this combination makes the distance larger between images of different groups. Based on the experiment results, it is possible to say that our proposed method has the retrieval robustness and is appropriate for fine matching which can further be used for image indexing. Thus, it will be better to combine the contour-based Fourier descriptor (of low computational complexity) with shock graph-based interior descriptor to improve the retrieval accuracy without increasing computational complexity. Therefore, combination of Fourier descriptor and shock graph should be used as a general descriptor for an optimum retrieval performance. The Fig.7 depicts a performance comparison of FDSG method with Fourier descriptor (FD) and shock graph (SG) method. We performed our experiment on MPEG-7 database. The black, red and blue lines represent the performance of FD, SG and FDSG, respectively. Here, we observe the performance up to 5th retrieval of images according to a query image. The retrieval rate of FD (shown in the black line) is not as good as SG and FDSG method up to 3rd retrieval. In fact, FD shows very poor performance at 4th or 5th retrieval. On the other hand, SG and FDSG methods show excellent performance (100%) up to 3rd retrieval. However, the performance of SG is not as good as FDSG after 3rd retrieval. Actually, FDSG method incorporates both the SG and FD as a combined descriptor. The use of interior and contour features makes the method suitable for all types of images. Therefore, the performance of FDSG is better than FD and SG up to 5th retrieval (Fig. 7)

Table 2: Shape retrieval result (2)

	Query: Bat			Query: Beetle		
Images	FD	SG	FDSG	FD	SG	FDSG
Bat	21.32750	0	21.32750	10.67262	290	300.67262
Bat	42.65502	30	72.65502	32.00013	232	264.00013
Bat	63.98253	44	107.98253	53.32764	290	343.32764
Bat	85.31004	50	135.31004	74.65515	253	327.65515
Bat	106.63755	70	176.63755	95.98266	278	373.98266
Beetle	127.96506	290	417.96506	117.31017	0	117.31017
Beetle	149.29257	153	302.29257	138.63768	166	304.63768
Beetle	170.62008	82	252.62008	159.96519	176	335.96519
Beetle	191.94759	149	340.94759	181.29270	189	370.29270
Beetle	213.27510	64	277.27510	202.62021	182	384.62021
Bird	234.60261	31	265.60261	223.94772	223	446.94772
Bird	255.93012	28	283.93012	245.27523	207	452.27523
Bird	277.25763	137	414.25763	266.60274	193	459.60274
Bird	298.58514	135	433.58514	287.93025	207	494.93025
Bird	319.91265	55	374.91265	309.25776	236	545.25776

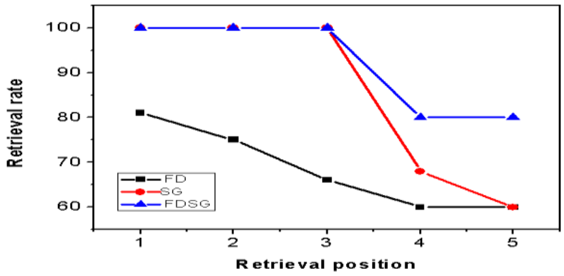

Figure 8: Performance graph comparing Shock graph and Fourier descriptor

The table 2 shows comparative discussion on contour and region based methods for shape retrieval. From the table, it can be concluded that FD based contour methods are applicable for simple contour based method and computation is very simple. However, this method is not applicable for image of complex interior details. On the other hand, region based shock graph method show robustness in handling instability and accuracy is high for complex image recognition. Though the accuracy is high, however, it is a complex method. So, the performance of contour or region based method depend on which images we are applying for.

CONCLUSION:

There are two groups of approaches: contour-based versus region-based. Contour-based approaches are more popular than region-based approaches. Because it is believed that human being discriminates shapes mainly by their contour features. The majority of real world objects have clear contours which are readily available. Therefore, contour methods can easily find applications. Contour based methods usually involve less computation than their region-based counterparts. However, contour shape descriptors are more easily affected by noise and variations than region-based shape descriptors because they use less shape information than region-based methods. Region based methods are usually more robust and application independent. However, they usually involve more computation and region shape descriptors usually need more storage than contour-based descriptors. Comparatively, global feature-based methods are promising for shape based image retrieval. Particularly, in contour based methods, Fourier descriptor and curvature scale space descriptor are more promising for image retrieval; in region based methods, Shock graph based methods are more promising for image retrieval.

FURTHER RECOMMENDATION

A detailed comparative study of our approach applied to a real-life image database is under investigation. Our future concern for retrieving shape will be how we can reduce and analyses the complexity of retrievals method of shock graph and Fourier descriptor without affecting the accuracy. Classification of images using combined features (obtained from Shock graph- Fourier descriptor) can be left for future work. Finally, we will work on developing application software that will perform shape retrieval task in a user friendly manner.

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