A Novel Approach to Shape Based Image Retrieval Integrating Adapted Fourier Descriptors and Freeman Code

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Summary
Accurate recognition of a shape depends on its representation. Therefore an efficient representation of shape information is the basic task of computer vision. We present a novel method of representing a shape. It is an adaptation of Fourier theory based descriptors integrated with Freeman code. To obtain a good boundary description, we choose to define it in an 8-connectivity. Fourier Descriptors have a disadvantage of giving equal weights to all its 8-neighbors. So, the Fourier coefficient formula must be completely recomputed so that horizontal and vertical neighbors are given more weight when compared to the diagonal neighbors. Diagonal neighbors are identified using Freeman code. Under Java retrieval framework, we compare our proposed results with the existing Fourier descriptors and validate the proposed method.

Key words:
CBIR, Feature Database, Fourier Descriptors, Image Retrieval, Shape Representation, Re-sampling,.

1. INTRODUCTION

Shape is a very important feature to human perception. Human beings tend to perceive scenes as being composed of individual objects, which can be best identified by their shapes. Besides, as far as query is concerned, shape is simple for user to describe, either by giving example or by sketching. Once images or scenes are broken down into individual objects, they can be exploited to facilitate object recognition.

One of the key issues raised in the object recognition, is the efficient retrieval of the objects. In this paper, we will focus our presentation on the retrieval of the popular image [1]. Recently, several prototypes [7], [11] etc., and commercial systems like QBIC [2] [15], VisualSeek [13], Photobook [9], Netra, SPIE [17] have been implemented in order to address this problem. The retrieval process is based on the content, and more particularly on the visual object features.

For images, low level visual features are color, texture, shape and spatial localization. However, among these features, shape is the most important because it represents significant regions or relevant objects in images. Ideally, shape segmentation would be automatic and efficient, but it is either impossible or difficult with heterogeneous images. Segmentation algorithms generally compute regions sharing several properties. Nevertheless, each calculated region does not correspond to a relevant entire object. Since obtaining high-level objects is very important in image retrieval, human intervention is needed to give a few orientations. After obtaining relevant objects, suited representations must be chosen among multiple existing models. Segmentation aspects will not be presented in this paper.

Shape retrieval involves three primary issues: shape representation, shape similarity measure and shape indexing. Among them, shape representation is the most important issue in shape retrieval. Various shape representation methods, or shape descriptors, exist in the literature, these methods can be classified into two categories: region based versus contour based. In region based techniques, all the pixels within a shape are taken into account to obtain the shape representation, they are given in section 2. Common region based methods use moment descriptors to describe shape [21],[22].Region moment representations interpret a normalized gray level image function as a probability density of a 2D random variable. The first seven invariant moments, derived from the second and third order normalized central moments, are given by Hu [26]. Because moments combine information across an entire object rather than providing information just at a single boundary point, they capture some of the global properties missing from many pure contour-based representations: overall orientation, elongation, etc. The first few terms of the invariant moments, like the first few terms of a Fourier series, capture the more general shape properties while the later terms capture finer detail. However, unlike Fourier series, it is difficult to obtain higher order invariant moments and relate them to shape. Comparing with region based shape representation, contour based shape representation is more popular. Contour based shape representation only exploits shape boundary information, these representation methods can be classified into global shape descriptors [15], shape signatures [25] [29] and spectral descriptors

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[24], [6], [23]. Although simple to compute and also robust in representation, global descriptors such as area, circularity, eccentricity, axis orientation used in QBIC can only discriminate shapes with large dissimilarities, therefore, it is usually suitable for filtering purpose. Most shape signatures such as complex coordinates, curvature and angular representations are essentially local representations of shape features, they are sensitive to noise and not robust. In addition, shape representation using shape signatures require intensive computation during similarity calculation, due to the hard normalization of rotation invariance. As the result, these representations need further processing using spectral transform such as Fourier transform and wavelet transform.

The retrieval process computes the similarity (from an appropriate distance for each feature) between source and target features, and sorts the best similar objects according to their similarity value. To improve the retrieval effectiveness, both textual and visual descriptions are used. The system must be flexible since images may belong to different domains.

The rest of the paper is organized as following. In Section 2, we give different shape representation techniques, fourier descriptors and an exhaustive study of different image retrieval systems available. Section 3 describes about proposed system, algorithms for creating feature database and image retrieval. Section 4 gives our experimental results and Section 5 concludes the paper.

2.Shape Representations

2.1 Fourier descriptors:

Starting at arbitrary point (x_0,y_0) in the boundary, coordinates pairs $(x_0,y_0),(x_1,y_1),(x_2,y_2),\ldots\ldots,(x_{k-1},y_{k-1})$ are encountered in the traversing boundary, say ,in clockwise direction. These coordinates can be expressed in the form $x(k)= x_k$, $y(k)= y_k$. With this notation the boundary itself can be represented as sequence of coordinates $z(k)=[x(k),y(k)]$, for $k=0,1,2,,\ldots\ldots.k-1$. Each coordinate point can be treated as complex number $z(k)= x(k)+jy(k)$, $k=0,1,\ldots,.k-1$ be the boundary sequence. The FD is defined as the Discrete Fourier Transform of $Z(k)$

$$Z(k) = \tfrac{1}{K}\sum_{n=0}^{K-1} z(k).e^{-2\pi nk/K}$$

Eq 2.1

where $k=0,1,\ldots\ldots..k-1$.

The reason why Fourier descriptors are used for the feature matching are FD describe the shape in terms of its spatial frequency content. Begin by representing the boundary of the shape as a periodic function (in one of a few possible ways). Expand this in a Fourier series; obtain a set of coefficients that capture shape information. These coefficients are called as Fourier descriptors using eq 2.1. It will be shown that DC term --- centroid of the region, Add in the +/- 1st terms --- best fitting ellipse, Add in the next pair --- best fitting hourglass And so on.

The Fourier descriptors offer a shape description in which we can "tune" the degree of precision according to our needs to make effective tradeoffs among accuracy, efficiency and speed of recognition, and the compactness of the representation.

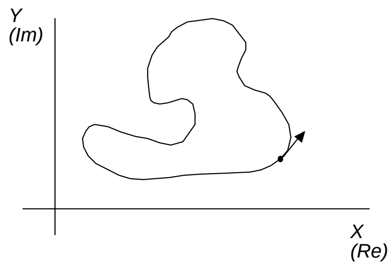


Fig 2.1.a

If we make repeated traces of the contour of fig 2.1.a

$$u(t) = x(t) + jy(t) = u(t+nT)$$

For n = 1, 2, 3,…… this is periodic
Expanding $u(t)$ in a complex Fourier transform

$$u(t) = \sum_{-\infty}^{\infty} u_n e^{jn\omega_0 t}$$

$$u_n = \frac{1}{T}\int_0^T u(t)e^{-jn\omega_0 t}dt$$

$$= a_n e^{j\alpha_n} \qquad -\infty < n < \infty$$

Where $j=\sqrt{-1},\ \omega_0 = \dfrac{2\pi}{T}$

we can pick $T = 2\pi$

The period is made equal to 2π by choosing the speed at which we circumnavigate the shape properly.

Properties of FDs:

The reason why FD are used for the feature matching are the coefficients can also be normalized to eliminate the effects of scale, translation, and rotation.

Translation Normalization**.** An is translation normalized due to the translation invariance of z(k).
Rotation Normalization**.** Ignore the phase information of an and only retain the magnitude of $z(k)$.
Scaling Normalization**.** All the other coefficient magnitudes are normalized by $|z_0|$.

2.2 Existing System:

In the object recognition, the shape matching process efficiency is essential. Consequently, a compact and reliable shape representation and a well-suited similarity distance are necessary. An interesting shape description should be invariant to translation, rotation, scaling and starting point transformations [5], [30]. In general, shape representations are classified into two categories: boundary-based and region-based [1]. The first one describes the considered region by using its external characteristics (i.e. the pixels along the object boundary) while the second one represents the considered region by using its internal characteristics (i.e. the pixels contained in the region). Several shape description approaches were developed in the two categories. For example, area, compactness, bounding box for the region-based category, and perimeter, curvature for the boundary-based category may be cited [1], [5], [30]. These techniques are simple to implement, but they do not accurately describe the shape, and they do not satisfy all the previous properties. They are just large approximations of shape.

A simple method to represent a contour is Freeman code (chain code), a coding method of closed shape by approximation of the continuous contour with a sequence of numbers, each number corresponding to a segment direction. Freeman's code is usually employed in a 4-neighborhood given in fig 3.1 (where 4 possible directions may be used) or in an 8-connectivity given in fig 3.2.1.e (that gives an 8-directional chain code) [5], [30]. This representation is compact and is invariant to the geometric transformation translation. However, it depends on rotation and scaling transformations. Moreover, it is difficult to manage Freeman's code with complex shapes.

The two most interesting methods of
shape description are the Fourier theory-based method and the Moment theory-based method. As far as the former approach is concerned, the Discrete Fourier Transform (DFT) is generally used to describe the shape feature from its boundary. They give a sequence of complex coefficients called Fourier Descriptors [5], [4], [16], [10], [12]. These coefficients represent the shape of an object in the frequency domain where the lower frequencies symbolize its general contour, and where the higher frequencies represent the details of its contour. Only a few coefficients are required to describe even quite complex shapes. In [12], a modified Fourier descriptor method is proposed in order to take into account the discretization noise. Fourier descriptor representation is not only compact and accurate, but also invariant to geometric transformations. The latter method uses region-based moments to characterize the contour of an object. A set of 7 moments identified by Hu, is invariant to geometric changes. These moments are called invariant moments [5], [30].

Spectral descriptors include Fourier descriptors (FD) and wavelet descriptors (WD), they are usually derived from spectral transform on shape signatures. With Fourier descriptors, global shape features are captured by the first few low frequency terms, while higher frequency terms capture finer features of the shape. Apparently, Fourier descriptors not only overcome the weak discrimination ability of the moment descriptors and the global descriptors but also overcome the noise sensitivity in the shape signature representations. Other advantages of FD method include easy normalization and information preserving. Recently, wavelet descriptors have also been used for shape representation [20],[23]. Wavelet descriptors have the advantage over Fourier descriptors in that they achieve localization of shape features in joint-space, i.e., in both spatial and frequency domains. However, the use of wavelet descriptors involves intensive computation in the matching stage due to wavelet descriptors are not rotation invariant. For example, both [20] and [23] use best matching method to measure similarity between two feature vectors of the two shapes, this is impractical for higher dimensional feature matching. Therefore, wavelet descriptors are more suitable for model-based object recognition than data-driven shape retrieval, because for shape retrieval, which is usually conducted online, speed is essential.

Many FD methods have been reported in the literature, these include using FD for shape analysis [24], [27], character recognition [10], [18], [12] shape coding [3], shape classification [7] and shape retrieval [14], [19], [6], [24]. In these methods, different shape signatures have been exploited to obtain FD. However, FD derived from different signatures has significant effect on shape retrieval. Shape retrieval using FD derived from different shape signatures have been compared and it is shown that Shape retrieval using FD derived from centroid distance signature is significantly better than other signatures[29].

3. Our Proposition

3.1 Proposed Method

In our image retrieval prototype, we integrate two shape descriptors namely recomputed version of Fourier Descriptor and Freeman code [8]. We store Freeman code in the database in order to compute rapidly the contour of objects in images with no loss of information. It is an important capability, since the user may select a previous extracted shape as a formulation example of his query. To obtain a good boundary description, we choose to define it in an 8-connectivity (or an 8-neighborhood) where horizontal, vertical and diagonal directions are allowed, since in a 4-connectivity, only vertical and horizontal directions may be followed as given in fig 3.1. An illustration of Freeman code is given in Figure 3.2.1.e.

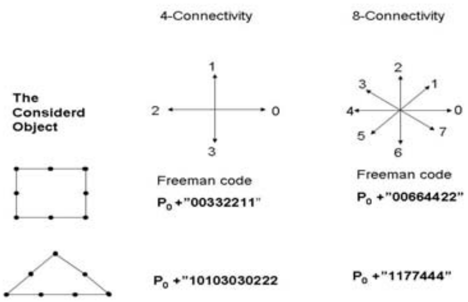


Fig 3.1

The Freeman code approach is not sufficient to compare different shapes [28]. It is the reason why we have integrated freeman code with recomputed version of Fourier descriptors, because for us all information on the shape of an object is contained in the pixels or points belonging to its boundary.

Our proposition is different from other works because we consider the object border in an 8-neighborhood, which involves that the points or the samples are not equidistant. The 8-connectivity gives a better contour, and the number of points may be less important than with a 4-connectivity. However, as the sampling step in not constant, the well-known results of Fourier theory [3] can not be reused. So, the Fourier coefficient formula must be completely recomputed so that horizontal and vertical neighbors are given more weight when compared to the diagonal neighbors as given in eq 3.1 and table 3.1.

$$k=0,\quad \begin{bmatrix} c_0(x) \\ c_0(y) \end{bmatrix} = \begin{bmatrix} \frac{1}{T}\sum_{n=1}^{N}\left[\frac{x_{n-1}+x_n}{2}\right]\Delta t_n \\ \frac{1}{T}\sum_{n=1}^{N}\left[\frac{y_{n-1}+y_n}{2}\right]\Delta t_n \end{bmatrix}$$

$$k\neq 0,\quad \begin{bmatrix} c_k(x) \\ c_k(y) \end{bmatrix} = \begin{bmatrix} -\frac{1}{\gamma T}\begin{bmatrix} \left(x_N.e^{-\gamma t_N} - x_0.e^{-\gamma t_0}\right) + \\ \left(\frac{1}{\gamma}\sum_{n=1}^{N}\frac{\Delta x_n}{\Delta t_n}\left[e^{-\gamma t_n} - e^{-\gamma t_{n-1}}\right]\right) \end{bmatrix} \\ -\frac{1}{\gamma T}\begin{bmatrix} \left(y_N.e^{-\gamma t_N} - y_0.e^{-\gamma t_0}\right) + \\ \left(\frac{1}{\gamma}\sum_{n=1}^{N}\frac{\Delta y_n}{\Delta t_n}\left[e^{-\gamma t_n} - e^{-\gamma t_{n-1}}\right]\right) \end{bmatrix} \end{bmatrix}$$

where

$$\Delta t_n = t_n - t_{n-1}, t_0 = 0.$$

$$N = \text{point number}$$

$$0 \le k \le N-1.$$

$$\gamma = j\frac{2\pi}{T}k, tn = \sum_{i=1}^{n}\Delta t_i.$$

$$\Delta x_n = x_n - x_{n-1}, x_0 = 0.$$

$$x_n = \sum_{i=1}^{n}\Delta x_i, y_n = \sum_{i=1}^{n}\Delta y_i.$$

Eq 3.1

3.2 Image Retrieval System:

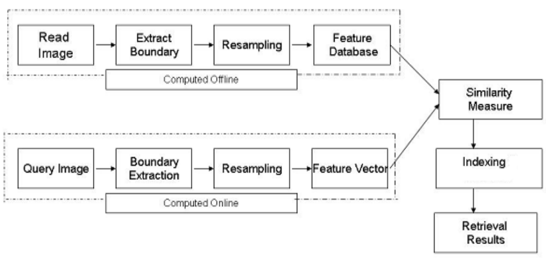


Fig 3.2

We programmed the integrated freeman code with recomputed version of Fourier descriptor formula presented in equation 3.1 and literature on FD [29] under JAVA Framework, and compare our results with results obtained with the on MPEG-7 shape database. To estimate the quality of our method, we implemented too the inverse DFT. Fig 3.2 shows a block diagram of our image retrieval model. The input images are taken from MPEG-7 part B Shape database [34] .
Image retrieval model consists of two major modules i) Feature database creation, it is explained in section 3.2.1 and ii) Query image Retrieval, it is explained in section 3.2.2.
This tests allows us to judge our results in relation to the already available results in the following literature [29], [4], [32], [10], [16] from objects whose sampling step is constant.

Code	0	1	2	3	4	5	6	7
Δx_n	1	1+j	j	-1+j	-1	-1-j	-j	1-j
Δt_n	1	$\sqrt{2}$	1	$\sqrt{2}$	1	$\sqrt{2}$	1	$\sqrt{2}$

Table 3.1

All the previous test types concerned only object whose shape is simple. That is why, we tested our program on heterogeneous databases like MPEG-7, SIID.

MPEG-7 shape database consists of 1400 images in 70 different categories, each image shape category in turn consists of 20 related images.

3.2.1 Steps for creating Feature database from large image database

i) Read image
ii) Boundary extraction
iii) Re-sampling the boundary of shape with large grid space
iv) Extract the shape features.
v) Store the extracted features in the feature database with an index
vi) Repeat the above steps for all the images present in the image database.

i) **Read an image :**
An image is loaded by giving its URL address in the image retrieval system interface.

ii) **Boundary extraction:**
In this procedure we are using Contour based method which requires only external characteristics such as boundary. Internal characteristics of the shape are ignored as shown in figure 3.2.1.a, and figure 3.2.1.b.

To extract the Boundary we used morphological Boundary extraction procedure [30]. X = A-(AΘB) where A is input image B is the structuring element as shown in fig 3.2.1.c X is the extracted boundary of A. A is the image shown in fig3.2.1.a and X is the boundary extracted image as shown in fig 3.2.1.b

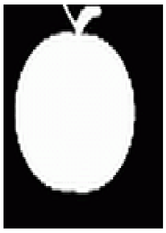


Fig3.2.1.a

Fig 3.2.1.b

1	1	1
1	1	1
1	1	1

Fig 3.2.1.c

iii) **Re-sampling and Normalization:**

Before applying Fourier transform on the shape signature, shape is first sampled to fixed number of points. In general, objects shape and model shape can have different sizes. Consequently, the number of data points of the object and model representations will also be different. For matching purposes, the shape boundary or the shape signature of objects and models must be sampled to have the same number of data points. The sampling process not only normalizes the size of shapes but also has the effect of smoothing the shape. The smoothing eliminates the noise in the shape boundary and the small details along the shape boundary as well. The number of resolution levels at which the shape signature will be decomposed is determined by the length of the shape boundary. By varying the number of sampled points, the accuracy of the shape representation can be adjusted. The larger the number, the more details the shape is represented, consequently, the matching result will be more accurate. In contrast, a smaller number of sampled points reduces the accuracy of the matching results, but improves the computational efficiency. There are generally three methods of normalization (i) equal points sampling; (ii) equal angle sampling; and (iii) equal arc-length sampling. Assuming *K* is the total number of candidate points to be sampled along the shape boundary. The equal angle sampling selects candidate points spaced at equal angle $\theta = 2\pi/K$. The equal points sampling method selects candidate points spaced at equal number of points along the shape boundary. The space between two consecutive candidate points is given by L/K, where L is the total boundary points.

The equal arc-length sampling method selects candidate points spaced at equal arc length along the shape boundary. The space between two consecutive candidate points is given by P/K, where P is the perimeter of the shape boundary. Among the three sampling methods, the equal arc-length sampling method apparently achieves the best equal space effect, because the use of arc-length as parameter in the signature achieves the unit speed of motion along the shape boundary [27]. Therefore, we choose the equal arc-length sampling to normalize the sizes of the shapes. For each shape, we select 64 candidate points with equal arc-length space between them. A example of shape normalization is shown in Figure 3.2.1.d. As can be seen, the normalization successfully eliminates the noise and small details of the shape which can affect robustness of shape matching, while successfully extracts the outline feature from the shape and also keeps key salient points (sharp bend points) which is important to shape representation.

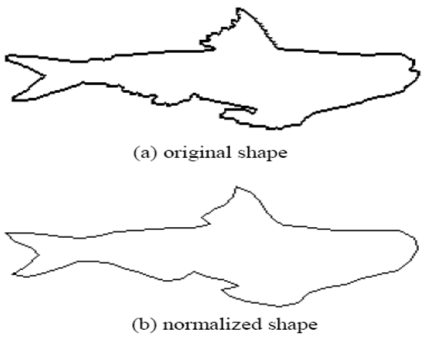
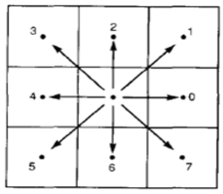


Fig 3.2.1.d

Chain Code:- Chain codes are used to represent a boundary by a connected sequence of line segments of specified length and direction. Typically this representation is based on 4 – or 8-connectivity of the segments direction of each segment is coded by using numbering scheme such as shown in fig 3.2.1.e



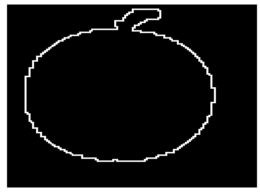
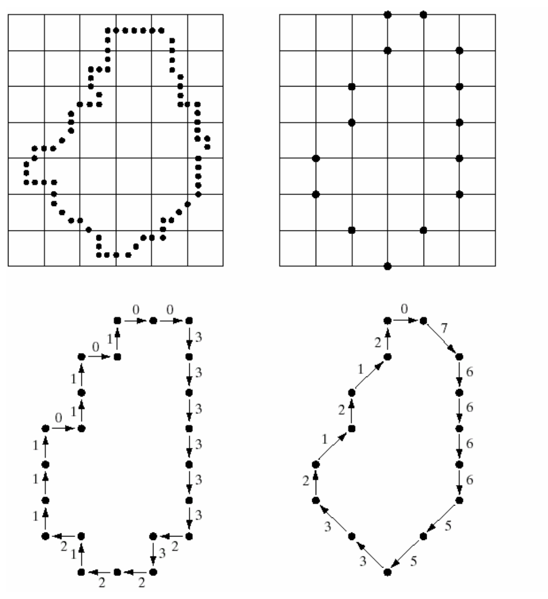


Figure3.2.1.e **Fig .2.1.f**

Digital images usually are acquired and processed in a grid format with equal spacing in the x- and y-directions, so a chain code could be generated by following boundary in, say, a clock-wise direction and assigning direction to the segments connecting every pair of pixels. Generally this method is unacceptable for two principal reasons: (1) The resulting chain of codes tends to be quite long, and (2) any small disturbances along the boundary due to noise or imperfect segmentation cause changes in the code that may not be related to the shape of the boundary.

An approach frequently used to circumvent the problems just discussed above is to resample the boundary by selecting the large grid space as illustrated in figure 3.2.1.g .

We will get fig 3.2.1.f after re-sampling the image given in fig 3.2.1.b with a large grid space. In our system we used a 5X5 Structuring element for re-sampling.



4- directional chain code 8-directional chain code

Fig3.2.1.g

iv) Feature Extraction:
Features of image are extracted by applying Discrete Fourier Transforms on shape boundary and they are called as Fourier descriptors. In this procedure 8-neighbours are used and all the neighbors are given equal weights. In fact we know that horizontal and vertical neighbors are nearer than diagonal neighbors by √2 times so the original DFT given in Eq 2.1 must be recomputed and the Fourier Descriptors formula given in Eq 3.1 which will give more weights to 4- neighbors.

In this formula we trace the boundary of shape and the boundary pixels are coded using chain code method as given in fig 3.2.1.e. All the diagonal neighbors are identified using their chain code values as shown in the table 3.1and their features (FD) are multiplied by 1/√2. Diagonal neighbors have their chain code as odd numbers (1, 3, 5, and 7). Thus horizontal & vertical neighbors are given more weightage than diagonal neighbors

v) Feature Database: All the extracted features (FD's) of the image are stored in the separate database Known as Feature Database.

vi) All the above 5 steps are repeated for all the images and their features are stored in the feature database with indexing.
Feature Database is created offline and it is one time process as shown in fig 3.2 .

3.2.2 Algorithm for shape retrieval

i) Read query image
ii) Boundary extraction
iii) Re-sampling the boundary of shape with large grid space
iv) Extract the shape features of query image.
v) Similarity Measure

step i) to step iv) are same as given in section 3.2.1.

v) Similarity Measure:
In the proposed methodology Euclidian distance given in equation 3.2.1.2 is used as measure of similarity. When a query image is given its features are extracted and stored in feature vector, they are compared against features which are stored in the feature data base. The difference d between Query features (FD^Q) and target features in database (FD^T) are stored. Features of the Images having less difference are more similar. All the images are indexed according to the difference between Query features and database features. Thus related images are retrieved. Shape retrieval is an online process to increase the performance of the Image retrieval system Feature database is created offline as shown in fig 3.2.

$$d = \left(\sum_{i=1}^{N} | FD_i^Q - FD_i^T |^2\right)^{\frac{1}{2}}$$

Equation 3.2.1.2

4. Experimental Results:

To validate the effectiveness of our approach for image retrieval, we have performed experiments over MPEG-7 Database [34]. A database consisted of 1400 shapes is created from set B of the MPEG-7 contour shape database. The shapes in set B are grouped into 70 classes of perceptually similar shapes. In our current retrieval system, the visual features used are Fourier Descriptors computed from eq 3.1

We programmed our formula presented in equation 3.1 on a Java online indexing & retrieval framework, compared our results with results obtained on the DFT presented in equation2.1 which is already given in [29], [10] and recomputed again. Our output from Java online indexing & retrieval framework is shown in fig 4.1, in which a query image and part of the output is shown. The query image is bottle-01, the first six retrieved images are also bottles. In our database there are 20 bottle's and our system gave rank 48 for the last bottle to be retrieved, all the ranks of the relevant retrieved images are given in fig 4.1 above Query image. For this image the Precision is 41% for 100% Recall.

The common retrieval performance measure – Precision and the Recall [14] are used as the evaluation of the query results. All the 1400 shapes features have been extracted and stored in the feature database. Out of these 10 images are used as queries. For each query, the precision of the retrieval at each level of the recall is obtained. The result precision of retrieval is the average precision of all the query retrievals used, as given in table 4.1. The average retrieval performance of each FD is shown in Fig 4.2. It is clear from the figure 4.2 that the retrieval performance of the proposed method outperforms retrieval performance of the FD preserving the invariance to the geometric transformations. Average precision and recall of the existing system i.e Fourier descriptors is around 57% as given in [10],[29] and for our proposed methodology it is around 82%, as illustrated in the Precision –Recall graph given in fig 4.2 and table 4.1, thus our approach is efficient.

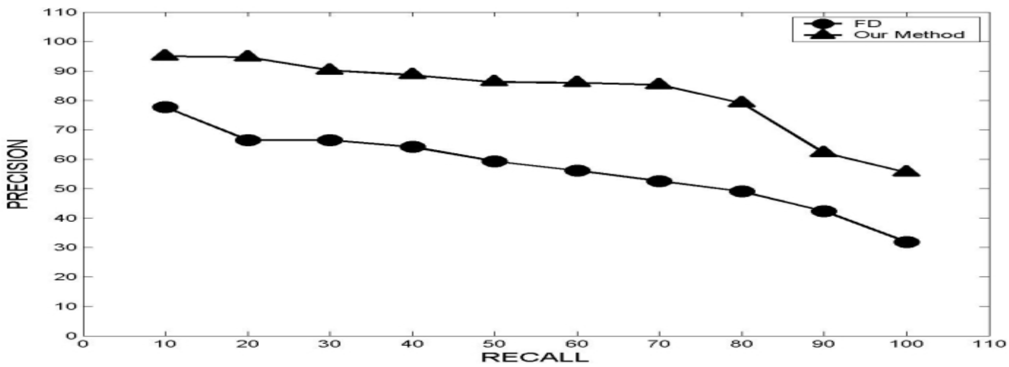


Fig 4.1

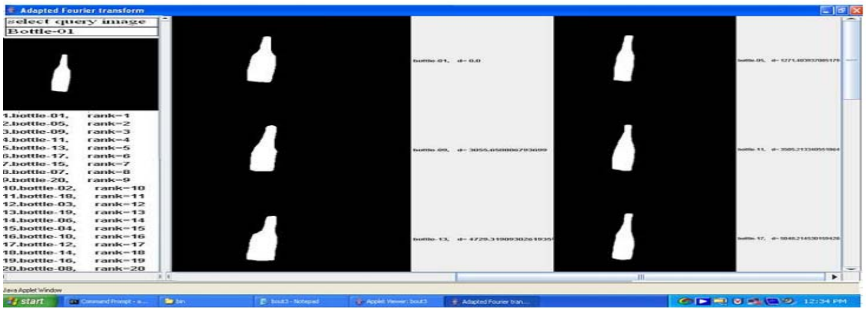


Fig 4.2

Precision Recall Table of Fourier Descriptor

image/recall	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%	
apple-8	66.6	57	60	53.3	52.6	50	50	42.1	28.5	25.3	
apple-18	100	100	66.6	66.6	66.6	66.6	48.27	51.6	40.9	40	
apple-1	100	45	50	50	50	46.1	31.8	29.6	25	24.6	
bottle-1	100	100	100	100	71.4	48.8	45.1	48.4	48.6	50	
bottle-16	66.6	57	60	53.3	52.6	50	50	42.1	28.5	25.3	
bone-1	100	80	85.7	80.3	83.3	85.7	77.7	66.6	66.6	20.4	
bone-4	50	50	60	61.5	55.5	57.14	58.3	57.1	29.5	20.8	
bone-2	100	80	85.7	80	76.9	80	82.3	69.5	66.6	20.8	
brick-2	28.5	40	42.8	50	46.1	46.1	46.6	48.4	54.4	50	
brick-7	66.68	66.6	54.5	47.5	35.7	36.8	36.8	34.7	34.7	35.7	
	77.838	67.56	66.53	64.25	59.07	56.724	52.687	49.01	42.33	**31.29**	**56.7289**

Precision Recall Table of proposed Methodology

apple-8	100	80	85.7	66.65	58.8	54.4	56	44.4	35.2	31.2	
apple-18	100	100	66.6	66.6	71.4	66.6	51.8	42.8	43	35.9	
apple-1	50	66.6	50	53.3	35.7	40	42.4	45.7	47.3	38.4	
bottle-1	100	100	100	100	100	100	100	100	100	100	
bottle-16	100	100	100	100	100	100	100	100	100	100	
bone-1	100	100	100	100	100	100	100	88.8	41.9	44.4	
bone2	100	100	100	100	100	100	100	88.8	41.9	41.6	
bone-4	100	100	100	100	100	100	100	80	50	43.4	
brick-2	100	100	100	100	100	100	100	100	90	55.7	
brick-7	100	100	100	100	100	100	100	100	72	60.6	
	95	94.66	90.23	88.655	86.59	86.1	85.02	79.05	62.13	**55.12**	**82.2555**

Table 4.1

5. CONCLUSION

The shape feature is essential in the content-based image retrieval. It must be accurate, compact and it should be invariant to certain geometric transformations. In this paper we have made a study on Fourier descriptors, presented how we describe the shape feature in our prototype and discussed the advantages and disadvantages of several shape representations. We have implemented two methods. The first one is an existing well-known approach, which is Fourier descriptor as given in [29]. The second one is an adaptation of Fourier descriptors integrated with freeman code. As the boundary is expressed in an 8-neighborhood, which involves a restricted point number and a better contour, the sampling step is not constant. It is the reason why, we could not reuse the Fourier descriptors and we had to compute their adapted formula integrated with freeman code to give more weights to horizontal and vertical neighbors than diagonal neighbors. After different kinds of experimentation on MPEG -7 Shape database, the proposed method has given interesting results over the existing methods.

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