A Comparative Study on Shape Retrieval Using Fourier Descriptors with Different Shape Signatures

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Abstract: *Shape is one of the most important features in Content Based Image Retrieval (CBIR). Many shape representations and retrieval methods exists. However, most of those methods either do not well represent shape or are difficult to do normalization (making matching hard). Among them, methods based Fourier descriptors (FD) achieve both well representation and well normalization. Different shape signatures have been exploited to derive FDs, however, FDs derived from different signatures can have significant different effect on the result of retrieval. In this paper, we build a Java retrieval framework to compare shape retrieval using FDs derived from different signatures. Common issues and techniques for shape representation and normalization are also analyzed in the paper. Data is given to show the retrieval result.*

Keywords: CBIR, Shape, Fourier descriptors, Retrieval.

1. Introduction

Owing to the rapid development of digital and information technologies, people now live in a multimedia world. More and more multimedia information is generated and available in digital form from varieties of sources around the world. Along with the information, people appear that want to make use it. Before one can use any such information, however, it will have to be located first. At the same time, the increasing availability of potentially interesting material makes this search harder. Currently, solutions exist that allow searching for textual information. Many text-based search engines are available on the World Wide Web, and they are among the most visited sites, indicating they foresee a real demand. Identifying information is, however, not possible for visual content, as no generally recognized description of this material exists. Multimedia databases on the market today allow very limited searching for pictures using characteristics like color, texture and information about the shape of objects in the picture.

Visual information plays an important role in our society, visual information may be represented in various forms, such as still pictures, video, graphics, 3D models, animation etc. One of the basic visual information needs to be processed is image, the need to find a desired image from a collection is shared by ordinary users as well as many professional groups, including journalists, design engineers and art historians. While it is attractive to provide higher level query using indexing methods such as keyword indexing and textual annotation to make use of facilitation of query language, such as SQL, from current database techniques, there are several drawbacks with these indexing methods [IP97]: (i) they do not conform to a standard description language, (ii) they are inconsistent, (iii) they are subjective, i.e. they might not capture the image content and (iv) they are time consuming. In order to overcome these drawbacks, recent researches on image retrieval focus on content based image retrieval (CBIR), which utilizes low level image features such as color, texture and shape. Several commercial and academic prototypes of CBIR systems have been developed recently to allow searching through image databases by image content. These include QBIC [Niblack et al 93], Photobook [PPS94], Virage [Bach et al 96] and VisualSEEK [SC96].

Shape is one of the most important low level image features due to that 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 CBIR. Applications on shape retrieval can be found in many areas, such as meteorology, medicine, space exploration, manufacturing, entertainment, education, law enforcement and defense.

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 accounted to obtain the shape representation. Common region based methods use moment descriptors to describe shape [TC88, TC91]. 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 [Hu62]. 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 exploit shape boundary information, these representation methods can be classified into global shape descriptors [Niblack et al 93], shape signatures [Davies97] and spectral descriptors [ZR72, HH98, YLL98]. 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.

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 overcomes 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 [TB97, YLL98]. 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 [TB97] and [YLL98] 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 [ZR72, Otterloo91], character recognition [PF77, Rauber94], shape coding [CB84], shape classification [KSP95] and shape retrieval [LS99, Sajjanhar97, HH98]. In these methods, different shape signatures have been exploited to obtain FD. However, FD derived from different signatures has significant different effect on shape retrieval. In this paper, we compare shape retrieval using FD derived from different shape signatures. The signatures considered are central distance, complex coordinates, curvature function, and cumulative angles. The rest of the paper is organized as following. In Section 2, we give the preprocessing techniques used in the boundary extraction. Section 3 describes different shape signatures and in Section 4, we discuss shape indexing using Fourier descriptors. Section 5 gives our experimental results and Section 6 concludes the paper.

2. Pre-processing

The shapes we consider in this paper are outline shapes which can be described as single plane closed curves. The shapes in our database are obtained either from silhouette real world objects or from user-drawn shapes, the shapes are in the form of gray level images. The preprocessing is to extract the boundary information, or coordinates of the boundary, from the shape. The block diagram for preprocessing is shown in Figure1.

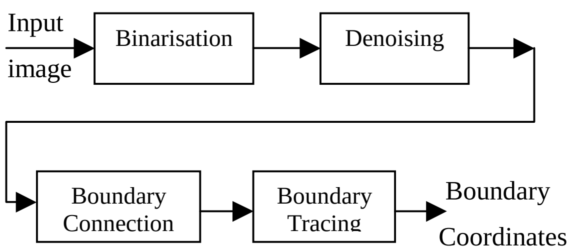
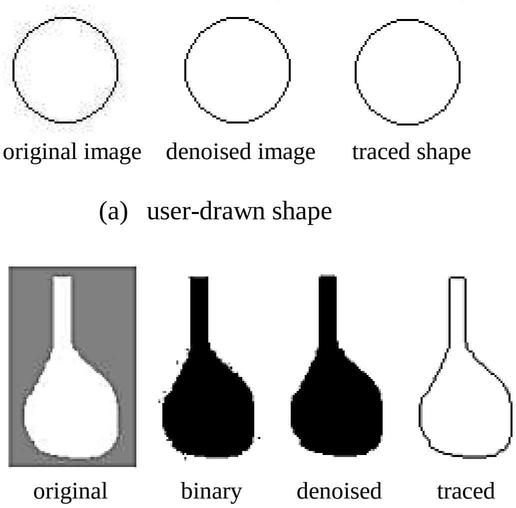


Figure 1. Preprocessing of shape image

The first step in the preprocessing is to binarizing the shape image, a simple thresolding is applied to convert the gray level shape image into binary image. In reality, shape images are often corrupted with noise, as a result, the shape obtained from the thresholding usually has noise around the shape boundary, therefore, a denoise process is applied. The denoising process eliminates those isolated pixels and those isolated small regions or segments. For the non-silhouette shape, the shape boundary is not always connected, therefore, a *m-connectivity connection* technique [GW92] is used to fill the gaps between boundary points. The shape is then traced using a *8-connectivity contour tracing* [Pavlidis82] technique to obtain the shape boundary coordinates. Some examples of preprocessing are shown in Figure 2.



(b) silhouette shape

Figure 2. Examples of preprocessing

3. Shape signatures

In general, a *shape signature* is any 1-D function representing 2-D areas or boundaries. Four shape signatures are considered in this paper, these are central distance, complex coordinates (position function), curvature and cumulative angular function. The reason for choosing these four shape signatures for test and comparison is because they are mostly used in recent FD implementations and have been shown practical for general shape representation [Otterloo91]. In the following, we assume the shape boundary coordinates ($x(t)$, $y(t)$), t = 0, 1, …, L-1, have been extracted in the preprocessing stage.

3.1 Complex coordinates

A *complex coordinates* function is simply the complex number generated from the boundary coordinates:

$$z(t) = x(t) + iy(t) \qquad (3.1)$$

In order to eliminate the effect of bias, we use the shifted coordinates function:

$$z(t) = [x(t) - x_c] + i[y(t) - y_c] \qquad (3.2)$$

where (x_c, y_c) is the centroid of the shape, which is the average of the boundary coordinates

$$x_c = \frac{1}{L}\sum_{t=0}^{L-1} x(t)\,,\; y_c = \frac{1}{L}\sum_{t=0}^{L-1} y(t) \qquad (3.3)$$

This shift makes the shape representation invariant to translation.

3.2 Centroid distance

The *centroid distance* function is expressed by the distance of the boundary points from the centroid (x_c, y_c) (3.3) of the shape

$$r(t) = ([x(t) - x_c]^2 + [y(t) - y_c]^2)^{1/2} \qquad (3.4)$$

Due to the subtraction of centroid, which represents the position of the shape, from boundary coordinates, the centroid distance representation is also invariant to translation.

3.3 Curvature signature

Curvature represents the second derivative of the boundary and the first derivative of the boundary tangent. The *curvature function* used in [KSP95] is defined as the differentiation of successive boundary angles calculated in window w:

$$K(t) = \theta(t) - \theta(t-1) \tag{3.5}$$

where

$$\theta(t) = \arctan\frac{y(t)-y(t-w)}{x(t)-x(t-w)} \tag{3.6}$$

however, this curvature function defined in this way has discontinuities at size of 2π in the boundary, therefore, in this paper we use

$$K(t) = \varphi(t) - \varphi(t-1) \tag{3.7}$$

where $\varphi(t)$ is defined in (3.8). Curvature is invariant under translation and rotation.

3.4 Cumulative angular function

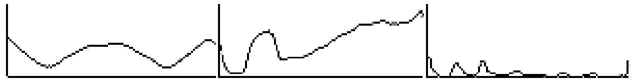
Shape can also be represented by boundary angles, but due to that the tangent angle function $\theta(t)$ (3.6) can only assume values in a range of length 2π, usually in the interval of $[-\pi, \pi]$ or $[0, 2\pi]$. Therefore $\theta(t)$ in general contains discontinuities of size 2π. Because of this, a cumulative angular function is introduced to overcome the discontinuity problem. The *cumulative angular function* $\varphi(t)$, defined by Zahn and Roskies [ZR72] is the net amount of angular bend between the starting position $z(0)$ and position $z(t)$ on the shape boundary

$$\varphi(t) = [\theta(t) - \theta(0)]\mathrm{mod}(2\pi) \tag{3.8}$$

In order to make it accord with human intuition that a circle is "shapeless", a *normalized cumulative angular function* $\psi(t)$ is used as the shape signature (assuming shape is traced in anti-clockwise direction)

$$\psi(t) = \varphi(\frac{L}{2\pi}t) - t \tag{3.9}$$

Three of the smoothed shape signatures of the shape in Figure 2(b) are shown in Figure 3.



(a) $r(t)$ (b) $\varphi(t)$ (c) $K(t)$

Figure 3. Shape signatures

All the four shape signatures described in this section are derived from shape boundary coordinates and are information preserving, i.e. they allow full reconstruction of the shape of the contour [Otterloo91]. This is a important property for shape representation.

4. Shape Indexing Using Fourier Descriptors

Fourier transformation on shape signatures is widely used for shape analysis, there are also some recent attempts to exploit it for shape retrieval [Sajjanhar97, HH98]. The Fourier transformed coefficients form the Fourier descriptors of the shape. These descriptors represent the shape of the object in a frequency domain. The lower frequency descriptors contain information about the general features of the shape, and the higher frequency descriptors contain information about finer details of the shape. Although the number of coefficients generated from the transform is usually large, a subset of the coefficients is enough to capture the overall features of the shape. The very high frequency information describes the small details of the shape, it is not so helpful in shape discrimination, therefore, they can be ignored. As the result, the dimensions of the Fourier descriptors used for indexing shapes are significantly reduced.

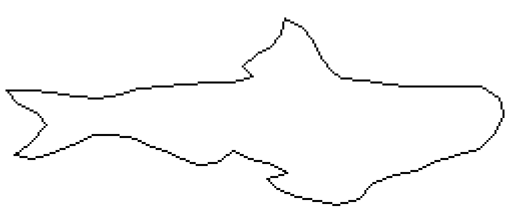
4.1 Shape size normalization

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. In order to facilitate the use of the fast Fourier transform (FFT), the number of sampled points is chosen to be power-of-two integer. The sampling process not only normalize the sizes 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 arclength 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 arclength 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 arclength sampling method apparently achieves the best equal space effect, because the use of arclength as parameter in the signature achieves the unit speed of motion along the shape boundary [Otterloo91]. Therefore, we choose the equal arclength sampling to normalize the sizes of the shapes. For each shape, we select 64 candidate points with equal arclength space between them. A example of shape normalization is shown in Figure 4. 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.

(a) original shape



(b) normalized shape

Figure 4. Shape size normalization

4.2 Discrete Fourier transform on shape signatures

For a given shape signature described in Section 3, $s(t)$, t = 0, 1, …, L, assuming it is normalized to N points in the sampling stage, the discrete Fourier transform of $s(t)$ is given by

$$u_n = \frac{1}{N}\sum_{t=0}^{N-1} s(t)\exp\left(\frac{-j2\pi nt}{N}\right), \quad n = 0, 1, \ldots, N\text{-}1$$

The coefficients u_n, n = 0, 1, …, N-1, are usually called Fourier descriptors (FD) of the shape, denoted as FD_n, n = 0, 1, …, N-1

4.3 Indexing shape using Fourier descriptors

In shape retrieval, user is only interested in the outline features of similar shapes, the position, size and rotation of the shapes is not important. In order to make model shape and data shapes comparable, the shape representations must be invariant to translation, rotation and scale. Shape invariance is difficult to achieve under spatial domain, most invariance techniques in spatial domain, especially rotation invariance techniques, involve large amount of computation. However, shape invariance is easy to achieve for the FDs. All the four shape signatures described in Section 3 are invariant under translation, therefore, the corresponding FDs are also translation invariant. Rotation invariant of the FDs are achieved by ignoring the phase information and by taking only the magnitude values of the FDs.

For complex coordinates signature, all the N descriptors except the first one (DC component) are needed to index the shape. The DC component depends only on the position of the shape, it is not useful in describing shape thus is discarded. Scale normalization is achieved by dividing the magnitude values of all the other descriptors by the magnitude value of the second descriptor. The invariant feature vector used to index the shape is then given by

$$\mathbf{f} = \left[\frac{|FD_2|}{|FD_1|}, \frac{|FD_3|}{|FD_1|}, \ldots, \frac{|FD_{N-1}|}{|FD_1|}\right]$$

For centroid distance signature and curvature signature, because the functions of (3.4) and (3.5) are real valued, there are only $N/2$ different frequencies in the Fourier transform, therefore, only half of the FDs in (4.3) is needed to index the shape. Scale invariance is then obtained by dividing the magnitude values of the first half of FDs by the DC component

$$\mathbf{f} = \frac{|FD_1|}{|FD_0|}, \frac{|FD_2|}{|FD_0|}, \ldots, \frac{|FD_{N/2}|}{|FD_0|}$$

The periodic cumulative angular function of (3.9) is itself invariant under translations, rotations and scales [PF77], therefore, the FDs derived form this signature can be directly used to index the shape. Also due to its real value, only half of the FDs including the DC component is needed to index the shape. The feature vector to index the shape is then

$$\mathbf{f} = [\ |FD_0|, |FD_1|, \ldots, |FD_{N/2}|]$$

Now for a model shape indexed by FD feature $\mathbf{f}_m = [f_m^{\ 1}, f_m^{\ 2}, \ldots, f_m^{\ Nc}]$ and a data shape indexed by FD feature $\mathbf{f}_m = [f_d^{\ 1}, f_d^{\ 2}, \ldots, f_d^{\ Nc}]$, since both features are normalized as to translation, rotation and scale, the Euclidean distance between the two feature vectors can be used as the similarity measurement

$$d = \left(\sum_{i=0}^{Nc} |f_m^{\ i} - f_d^{\ i}|^2\right)^{\frac{1}{2}}$$

where Nc is the truncated number of harmonics needed to index the shape.

5. Experiment results

FD method is widely used in shape analysis, however, the many FD methods often target particular applications. For example, Persoon and Fu [PF77] used FD for character recognition, Kauppinen et. al. used FD for military plane and character classification [KSP95]. In relation to shape retrieval, Huang et. al. use feature combining FD (using complex coordinates as shape signature) with invariant moments as filter to eliminate most irrelevant shapes from the query, after that a geometric indexing feature is used to refine the retrieval result. Due to too small the database composed of only cartoons, the retrieval result is largely irrelevant shapes. No data on recall and precision is reported. Sajjanhar [Sajjanhar] has conducted a comparison of shape retrieval using FD (using centroid distance) and that using other methods such as invariant moments and grid based method. Although detailed data on query precision and recall is given, there is same shortcoming as that in Huang et. al's work, i.e. the database is too small. Only 70 synthetic polygon shapes are used, each shape is a single class, making the evaluation result unconvincing as no information is given on how the "perceptual similarity" between shapes is obtained. In our experiment, we use the same 70 synthetic shapes used by Sajjanhar and 25 bottle shapes to create our shape database. For each of the 95 shapes, four similar shapes are created by affine distortion with different parameters, one scaled shape is also generated for each of the 95 shapes. Then for each of the 70 synthetic shapes, a rotated shape is also generated. This create a database of 640 shapes including the original shapes. The distorted shapes of the two shapes in Figure 2 are shown in Figure 4.

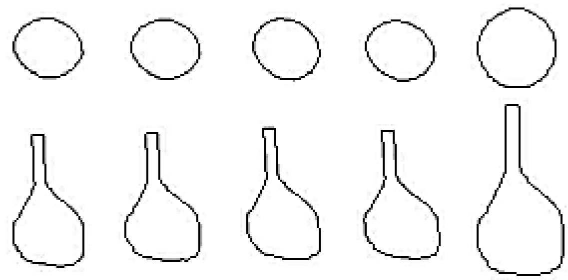


Figure 5. Distorted shapes of the shapes in Figure 2.

The database created in this way makes the evaluation more reliable. The performance of the retrieval is evaluated using precision and recall. Precision P is defined as the ratio of the number of relevant retrieved shapes r to the total number of retrieved shapes n. Recall R is defined as the ration of the number of retrieved relevant images to the total number m of relevant shapes in the whole database. Therefore

$$P = \frac{r}{n} \qquad\qquad R = \frac{r}{m}$$

In the experiment, we build a Java client-server framework to conduct the retrieval test. In the client site, a Java applet is used to run the query, since the applet can be embedded into Web page, the retrieval can be done online. We use 16 shapes selected from the database as query shapes, the average precision and recall of the retrieval result for each signature is given in Figure 6. Some retrieval screen shots are given in Figure 7, and online information for the shape retrieval can be accessed on: http://www-mugc.cc.monash.edu.au/~dengs/shape/src/JAIApplet.html

It is clear from the diagram that the retrieval performance using FDs derived from centroid distance is the best among the four. The performance of complex coordinates and cumulative angular function are comparable, while the performance of curvature function is entirely a failure. The results are not difficult to explain. Although central distance is derived entirely from boundary information, it also contains the region information of the shape, that is to say, centroid distance captures both local and global features of the shape. Therefore, it is safe to say, central distance is a shape representation between contour based representation and region based representation. The drawback of non-uniqueness of centroid distance can be overcome by using *signed centroid distance* [Otterloo91]. It is a desirable shape signature. The complex coordinates (or position function) and the cumulative angular function are purely boundary representation, they only capture the local features of the shape boundary, consequently, they are not as robust as the centroid distance. Although curvature is a very important feature of shape due to its importance for human shape perception, local curvature information only makes shape representation non-meaningful. Moreover, curvature is essential the second derivatives of shape boundary, it is very unreliable. For shape retrieval, only global curvature information such as convexity and concavity information of boundary segments is helpful.

6. Conclusions

In this paper we have compared shape retrieval using FDs derived from four shape signatures. Our results show that shape retrieval using FDs derived from centroid distance signature is significantly better than that using FDs derived from the other three signatures. The property that centroid distance captures both local and global features of shape makes it desirable as shape representation. It's robust and information preserving. Although cumulative angular function has been used successfully for character recognition, it is shown that it is not as robust as centroid distance in discriminating general shapes. The curvature function can be eliminated as shape representation for retrieval purpose as it is too sensitive to noise and distortion. The use of curvature as shape representation requires intensive boundary approximation to make it reliable.

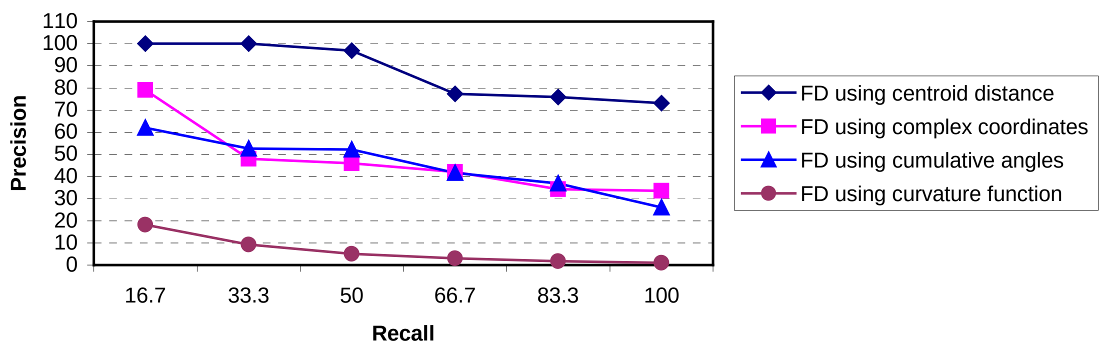
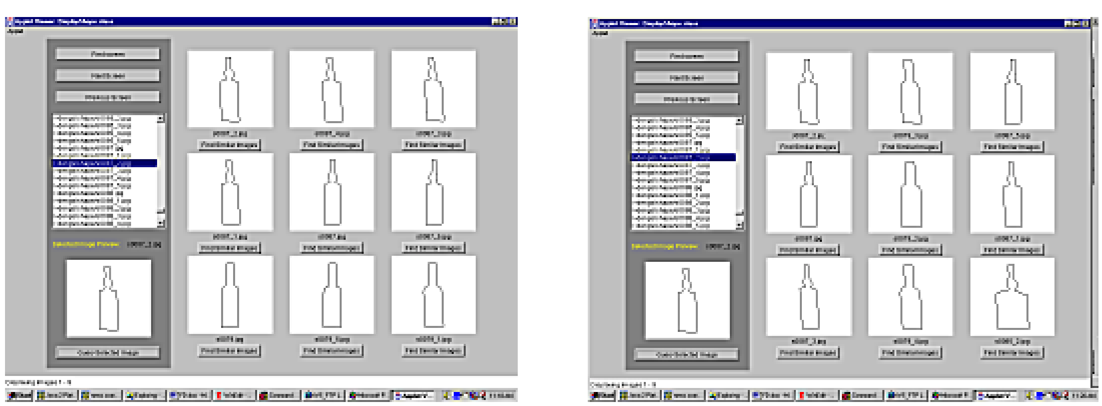
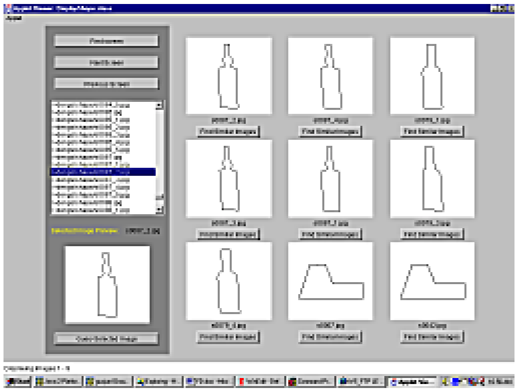


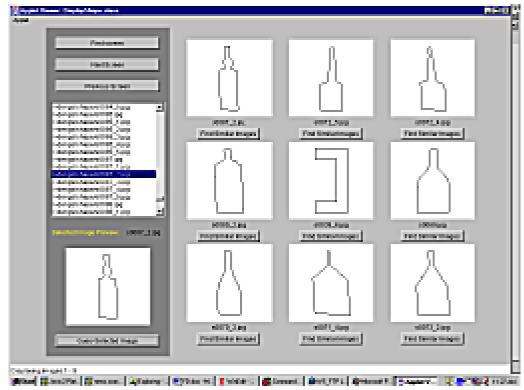
Figure 6. Precision and recall diagram. The numbers are in percentage.



(a) (b)



(c)



(d)

Figure 7. Screen shots of shape retrieval using FDs derived from (a) centroid distance (b) cumulative angle (c) complex coordinates (d) curvature.

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