Chapter 5

Shape Feature Extraction for Image Retrieval with FRAR Model
CHAPTER 5

SHAPE FEATURE EXTRACTION FOR IMAGE RETRIEVAL WITH FRAR MODEL

5.1. Introduction

Shape of an object is the characteristic surface configuration represented by its outline or contour. Similar to texture and edge, shape is regarded as a low-level visual feature to retrieve images from a large collection of images. In this chapter, we extend the same Full Range Auto Regressive model presented in chapter 2 for extraction of shape features and its usage is highlighted for proposing a new image retrieval system.

5.1.1. Feature based shape analysis

The feature based shape analysis procedure systematically computes the necessary ingredients for shape categorization. It includes encoding, feature detection, structural description and semantics of shape by its feature classification and similar measures. It consists of four discrete sequential processes: shape encoder, feature decoder, feature classifier and shape analyzer. Each process has specific representation schemes, searching algorithms, definitions and required knowledge in order to process the data to produce the required output. The shape encoder transforms the shape images into syntactic shape
representations. The feature detector considers the syntactic data and searches all the shape features during the process of feature extraction. The feature classifier classifies the shape features into specified classes and measures the categorical typicality of shapes. The shape analyzer compares the extracted shape features, examines the shapes, determines the categorical prototype and computes their categorical membership within a group of shapes.

5.1.2. Shape descriptors

In content based image retrieval system, the characteristics of shape are used to identify and distinguish objects [Lonc98]. Shape descriptors are classified into boundary based (or contour based) methods and region based methods. This classification depends on whether the shape features are extracted from the contour or the whole region. Shape descriptors further can be divided into structural (local) descriptors and global descriptors. The sub divisions are based on whether the shape is represented as a whole or represented by segments.

Shape is one of the primitive features for image content description. The content description of the shape is difficult to define, because measuring the similarity between shapes is too complex. Therefore, the shape features are extracted and measure the similarity between the extracted features to overcome this complexity. The shape descriptor features [Rysz07] are computed from object contour such as circularity, aspect ratio, discontinuity angle irregularity, length irregularity, right-angled area, sharpness and directedness. The features based on contour are formulated with necessary variables as follows.
Let $n$ - number of sides of a polygon enclosed by segment boundary,

$A$ - Area of polygon enclosed by segment boundary

$P$ - Perimeter of polygon enclosed by segment boundary

$C$ - Length of longest boundary chord

$p_1, p_2$ - Greatest perpendicular distances from longest chord to boundary, in each half-space either side of line through longest chord

$\theta_i$ - Discontinuity angle between $(i-1)^{th}$ and $i^{th}$ boundary segment.

$r$ - Number of discontinuity angles equal to the right-angle within a specified tolerance

$M$ - Total length of straight-line segments parallel to the mode direction of straight-line segments within a specified tolerance.

1) Circularity: $cir = \frac{4pA}{p^2}$

2) Aspect Ratio: $ar = \frac{p_1 + p_2}{C}$

3) Discontinuity Angle Irregularity: $dar = \sqrt{\frac{\sum |\theta_i - \theta_{i+1}|}{2\pi(n-2)}}$

The difference between the discontinuity angles of the polygon segments made with its adjoining segments.

4) Length Irregularity: $lir = \sum \frac{|L_i - L_{i+1}|}{K}$

where $K = 2P$ for $n > 3$ and $K = P$ for $n = 3$. 

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5) Right-Angleness:

\[ r_{a} = \frac{r}{n}. \]

It measures the proportional discontinuity angles which are approximately right-angled.

6) Sharpness:

\[ s_{h} = \sum \max \left( 0, 1 - \left( \frac{\theta - \frac{\pi}{2}}{\frac{\pi}{2}} \right)^{2} \right). \]

It measures the proportion of sharp discontinuities (over 90°).

7) Directedness:

\[ d_{ir} = \frac{M}{\sum P_{i}}. \]

It measures the proportion of straight-line segments parallel to the mode segment direction.

The region-based shape descriptor utilizes a set of Zernike moments to calculate the feature vector within the center of the image. In image retrieval system, a set of lower order moments are used to discriminate among different images. The most common lower order moments are geometrical moments, central moments, the normalized central moments, moment invariants, Zernike moments and the Legendre moments. The Curvature Scale Space (CSS), Beam Angle Statistics (BAS), Contour Salience (CS), Tensor Scale Descriptors (TSD), Moment invariants, and Segment Salience (SS) are the different shape descriptors used for extracting the feature vectors.
5.2. Related work on shape based CBIR

Shape is a very important feature to human perception and the human beings tend to perceive scenes being composed of individual objects, which can be identified by their shapes. Shape is very simple for the user to describe, either by giving an example or by sketching. Once the images or scenes are decomposed into individual objects they can be exploited to facilitate object recognition. A query by example may specify: (a) An object or a part of an object and (b) The semantic or structural content of an image.

Three primary issues are involved in shape based image retrieval. They are representation, similarity measures and indexing of shape. In region based techniques, all the pixels within a shape are taken into account to obtain the shape representation. Common region based methods use moment descriptors to describe shape [Cho88]. The first seven invariant moments, which are derived from the second and third order normalized central moments are proposed by Ming-Kuei Hu [Ming62]. The moments combine the information across the entire object rather than providing information at a single boundary point. The first few terms of the invariant moments of Fourier series captures the general shape properties such as contour based representations, overall orientation, and elongation while the later terms capture finer detail. However, unlike Fourier series, it is difficult to obtain higher order invariant moments.
Contour based shape representation exploits only the shape boundary information. These representation methods can be classified into global shape descriptors, shape signatures [Davi97] and spectral descriptors [Jain95]. Mostly shape signatures such as complex coordinates, curvature and angular representations are the essential local representations of shape features. They are sensitive to noise and not robust. In addition to this, the shape representation using shape signatures require intensive computation during similarity calculation, due to normalization of rotation invariance. T. Venugopal and V. Kamakshi Prasad [Venu08] proposed a method for representing a shape. It is an adaptation of Fourier theory based descriptors integrated with Freeman Code.

Shape features of objects or regions have been used in many content-based image retrieval systems [Gary92, Gros90]. Compared with color and texture features the shape features are usually described after images have been segmented into regions or objects. Since robust and accurate image segmentation is difficult to achieve, the use of shape features for image retrieval has been limited to specific applications where the objects or regions are readily available.

In Fariborz Mahmoudi et. al., [Fari03] method for extracting feature vector for non-segmentation shape-based image indexing and retrieval. This feature considers the correlation between the neighboring edges. Also it includes the information of continuous edges, lines of images and describes major shape properties of images. The edge oriented autocorrelogram algorithm is used for non segmented shape based image
indexing and retrieval. John P Eakins, et al., [John03] suggested an investigation on comparative effectiveness of a number of different shape features and matching techniques in the retrieval of multi-component trademark images.

A robust and effective shape feature known as the compound image descriptor (CID), combines the Fourier Transform (FT) magnitude and phase coefficients with the global features [Shan05]. The underlying FT coefficient has shown analytically invariant to rotation, translation, and scaling. The global features, besides being incorporated with the FT coefficients to form the CID, are also used to filter out the highly dissimilar images during the image retrieval process. Thus, they serve a dual purpose of improving the accuracy and hence the robustness of the shape descriptor and of speeding up the retrieval process, leading to the reduction of query response time.

In [Yupe05] Yupeng Li et. al., modified version of Generic Fourier Descriptor (GFD) that operates on edge information within natural images from the COREL image database for shape-based image retrieval. Measuring the edge-texture characterization also reduces the complexity inherent in over sensitive edge maps.

In shape based image retrieval, shape representation generally looks for shape features based on boundary information or the entire content of the shape. The Curvature Scale Space (CSS) method [Mokh86] represents 2D shapes with different resolutions. Maxima (peaks) of CSS images are used to describe the shape to perform the matching between
two curves under analysis. The matching scheme is based on the Euclidean distance between the peaks of the CSS images and to retrieve shapes invariant of translation, rotation and scaling, it tries to identify the best match between the CSS peaks. This scheme is very complex and expensive. Carlos W. D. De Almeida [Carl06] proposed a hybrid system for shape based image retrieval using the curvature scale space and Self Organizing Map (SOM) methods.

Various techniques are reported in the literature that aims to represent objects based on their shapes. Each of these techniques has both advantages and disadvantages. Fourier Descriptor (FD) technique has attractive properties such as rotational, scaling and translational invariance. Akrem El-ghazal et. al., [Akre07] modeled a technique and presented a shape registration method for extracting Fourier descriptors with Curvature Scale Space and Zernike Moments (ZM) in shape-based image retrieval.

Most of the existing methods are based on the geometric equations of curves which are computed by processing an entire image. These processes are computationally intensive, and do not take advantage of the Gestalt rules of human vision. Hence, Zheng et. al., [Zhen07], proposed a method by applying certain mechanisms based on the human visual perception process.

Some of the shapes techniques existing in the literature are contour based image retrieval process. In these methods, the contour based shape descriptors include Fourier descriptors [Pers77], Wavelet
descriptor [Yang98], and Curvature scale space descriptor [Abba99]. Since their computations are based on the boundary pixels, they cannot represent shapes with the complete boundary information. In the case of region-based shape descriptors, both the boundary and interior pixels of the shape are exploited. These region based descriptors are applicable to generic shapes and shape distortions. A Generic Fourier Descriptor (GFD) proposed by D. S. Zhang [Zhan04], is one of the region based shape descriptor. GFD is extracted from spectral domain by applying 2-D Fourier transform (FT) on polar raster sampled shape image.

There are many drawbacks and issues in these existing methods of image retrieval system. They are: discontinuous, unclear edge orientations, redundant feature extraction, reduction in speedup retrieval process, discrimination of shapes with large dissimilarities, and the complexity inherent in over sensitive shape boundaries. In order to overcome these issues we propose an extension of FRAR Model for shape based CBIR System, and the same is presented in the next section.

5.3. The proposed shape based image retrieval with FRAR model

In this section, we propose a novel model for computing and analyzing the content of the image using shape boundaries. For this purpose the Full Range Auto Regressive model has been first applied for detecting the edges in 2D monochrome images as discussed in the algorithm 4.1 of chapter 4. After extracting the edges from the input image with the FRAR model, the closed edges are considered for the extraction of shape based features. The closed edges of the input image are bounded with rectangular grid and are considered for feature
extraction, if the area of the shape within the grid has at least one fourth of its bounded area. The shape based general features of bounded grids are extracted along with the auto correlation functional features of each bounded sub images. The procedure for extraction of shape based features and the generation of feature set of the input image is discussed in the following sub sections.

5.3.1 Extraction of shape features

Initially, the image under analysis is extracted with the edge map using FRAR model as discussed in chapter 4. The closed edges in the extracted edge map are bounded with rectangular grids. Apply ones in the positions of the bounded area of shapes within the grid and zeros for non bounded area of shape within the rectangular grids as mentioned in the equation 5.1. Finally, the rectangular grid of each sub-image is represented in a matrix of size \((m \times n)\) as shown in the equation 5.2.

\[
f(x,y) = \begin{cases} 
1, & \text{if the presence of shape area within the grid} \\
0, & \text{otherwise} 
\end{cases} \quad \text{... (5.1)}
\]

\[
G_{m,n} = \begin{bmatrix} 
 f(0,0) & f(0,1) & \cdots & f(0,n-1) \\
 f(1,0) & f(1,1) & \cdots & f(1,n-1) \\
 \vdots & \vdots & \ddots & \vdots \\
 f(m-1,0) & f(m-1,1) & \cdots & f(m-1,n-1) 
\end{bmatrix} \quad \text{... (5.2)}
\]

where \(m\) and \(n\) are the number of rows and columns of the rectangular grid.

Figure 5.1 shows the shape of a sub image bounded with rectangular grid and its corresponding edge map computed with equations (5.1) and (5.2).
After extracting the edge map of the image, the image is subdivided into sub images according to their presence of shapes. Here, a sub image is considered with its grid representation matrix grid $G_{m,n}$ shown in equation (5.2). Then, the shape based general features such as Area, Perimeter and Coordinates of the Centroid and Mass are computed for the rectangular grid in which it satisfies the one fourth of its presence of shape as per the following equations. The procedure for the generation of shape based general features is discussed in the following sub sections.

**Centroid:**

The Centroid of each bounded shapes are defined as the respective positions of the rectangular grid of the input image with the positional values either 0 or 1. Let the coordinates of $(X_c, Y_c)$ of the Centroid (C) be defined as follows.

$$X_c = \frac{\sum_x \sum_y f(x,y) \times x}{\sum_x \sum_y f(x,y)} \quad \ldots \ (5.3)$$

$$Y_c = \frac{\sum_x \sum_y f(x,y) \times y}{\sum_x \sum_y f(x,y)} \quad \ldots \ (5.4)$$

$$C = f(x_c, y_c) \quad \ldots \ (5.5)$$
where \((x,y)\) are the positional coordinates and \(f(x,y)\) is set to 1 for pixels within the shape and 0 otherwise as discussed in equation (5.1).

**Area**

Area is defined as the number of pixels in the region described by the shape. The real area of each shape may be taken into consideration to get the real size of a region and is represented on grid to compute the area \((A)\) of the each shape with the following equation (5.6).

\[
A = \sum_x \sum_y f(x,y)
\]  

... (5.6)

For example, in the Fig. 5.2 the total area represented by the shape is 28 square units because the total pixel inside the shape region is 28 and is represented in the grid.

![Figure 5.2. Demonstration of areas as shape descriptor](image)

**Perimeter**

Perimeter is defined as the number of outermost pixels of the bounded rectangular shape with the equation (5.7).

\[
P = 2((m-1) + (n-1))
\]  

... (5.7)

where \(m\) and \(n\) are the number of rows and column of the bounded rectangular grid. For example in Fig. 5.3, the total number of pixels in the outermost area of the rectangular grid is 32.
Mass

Mass of a shape is defined as the average mean ($\bar{x}$) of the pixel values of the rectangular shape.

$$\text{Mass} (M) = \left[ \frac{\sum_{i=1}^{n} x_i}{n} \right]$$

where $x_i$ is the pixel value of the shape and $n$ is the number of pixels within the shape.

Hence, the part of feature set $F_{Gk}$ is computed with the above mentioned general features viz. Centroid co-ordinates ($C_i, C_j$), Area ($A_k$), Perimeter ($P_k$), and Mass ($M_k$) of the $k^{th}$ bounded shape of the input image are represented as follows.

$$F_{Gk} = \{C_i, C_j, A_k, P_k, M_k\}$$

5.3.2 Extraction of shapes with auto correlation features

The auto correlation functional features of all the bounded rectangular sub images are extracted to form the feature set of the input image. The feature vectors are computed with the auto correlation coefficients using the positional differences $p$ and $q$ as discussed in the section 2.4.3 of chapter 2. The computed auto correlation coefficients are considered as feature vectors and are represented below.
where $A_{c_{k,0}}, A_{c_{k,1}}$ to $A_{c_{k,m,n}}$ are the auto correlation functional features.

### 5.3.3 Generation of feature set

The feature set is generated with the shape based feature vectors for all the bounded rectangular sub images of their general shape features and the auto correlation functional features. The feature set of the input image under analysis is represented as follows:

$$F_t = \{F_{G_1}, F_{A_1}, F_{G_2}, F_{A_2}, \ldots, F_{G_n}, F_{A_n}\}$$

(5.11)

where $F_{G_1}, F_{G_2}, \ldots, F_{G_n}$ are the shape based general feature vectors and $F_{A_1}, F_{A_2}, \ldots, F_{A_n}$ are the auto correlation coefficients of the input image.

Finally, the feature database $F$ is established to store the feature set of all the images available in IDB.

### 5.4. Algorithm

In order to retrieve the shape based images from the heterogeneous databases, two phases are followed. In the first phase, the feature database of the IDB is established first. Hence, algorithm 5.1 is used to establish the feature database of the entire image available in the IDB with the auto correlation and shape based FRAR Model. The next algorithm 5.2 is also used to retrieve the top $m$ relevant images of the target image with the image database. The steps involved in the establishment of feature database and retrieval of relevant target images are discussed in the following two algorithms.
Step 4: Calculate the Euclidean distance between the feature set of the target image and feature sets of the images available in IDB and store the results.

Step 5: Sort the computed results of Euclidean distance obtained from step 4 in ascending order.

Step 6: List the top $m$ results and retrieve the relevant $m$ images from the Image database.

End

Procedure edge_extract()
{
    Step 1: Input the monochrome image of size (M x M).

    Step 2: Define three matrices $T_s$, $T_d$ and $T_o$ each of size (M x M) with all elements initialized to zero.

    Step 3: For $i=1, ..., M-2$
            For $j=1, ..., M-2$
            For $k=i, ..., i+2$
            For $l=j, ..., j+2$
                Estimate smooth image $T_s$ from the input image by using equation (4.1).

    Step 4: Find the resultant matrices $T_d$ by subtracting original image $I_i$ with the smooth image $T_s$

    $T_d(i,j) \leftarrow I_i(i,j) - T_s(i,j)$

    Step 5: Find the Confidence Limit (CL) of $T_d$ as in equation 4.6

    Step 6: Find $T_o(x, y)$ by comparing each pixel with CL

    if $T_d(x, y) >= CL$ then
        $T_o(x, y) \leftarrow [T_o(x, y)]^2$
    else
\[ T_e(x,y) \leftarrow 0 \]

endif

**Step 7**

For \( i=1, \ldots, M-1 \)

For \( j=1, \ldots, M-1 \)

For \( k=i, \ldots, i+2 \)

For \( l=j, \ldots, j+2 \)

Find edge map by calculating CL as in equation 4.6 and apply non-maxima suppression algorithm using calculated CL.

\[
\text{if } T_d(x,y) \geq CL \text{ then }
\]

\[
T_d(x,y) \leftarrow 1
\]

else

\[
T_e(x,y) \leftarrow 0
\]

endif

Procedure shape_feature()

{

**Step 1**

: Identify the closed edges of the edge map of the input image.

**Step 2**

: Bound the closed edges with rectangular grid.

**Step 3**

: Fill the grid values either "1" for presence of shape content or "0" for other as mentioned in the equation 5.1.

**Step 4**

: Eliminate the shapes present in the rectangular grid if the area less than \( \frac{1}{4} \)th of the bounded rectangular grid area and count the number of shapes considered \( (n) \) for feature extraction

**Step 5**

: Calculate the shape based general features such as Centroid \( x \) and \( y \) coordinates of Centroid \( (c_i, c_j) \), Area \( (A_k) \), Perimeter \( (P_k) \) and Mass \( (M_k) \) of the selected \( k^{th} \) rectangular grid area as discussed in the sub sections of 5.3.
Step 6: Establish the general shape based feature set $F_{Gk}$ with the features computed in step 5 viz.

$$F_{Gk} = \{C_i, C_j, A_k, P_k, M_k\}$$

Step 7: Calculate the auto correlation features of the $k^{th}$ rectangular sub-image with the positional difference $p$ and $q$ of the input image as mentioned in equation 5.10 viz.,

$$F_{Ak} = \{A_{c_{0,0}}, A_{c_{0,1}}, \ldots, A_{c_{m,n}}\}$$

Step 8: Repeat Step 2 Through Step 7 for all the $n$-bounded shape contours of the input image and find the feature vectors of each bounded shapes.

Step 9: Establish the feature set of the input image as mentioned in the equation 5.11 and store the established feature set for all the $n$-rectangular bounded shapes.

End

5.5. Experiments and Results

To validate the effectiveness of the proposed shape based image retrieval system, experimentation is performed with the images in the image database that contains five hundred 2-D monochrome images of size (256 × 256). The total images are grouped into 10 classes with 50 images of each class. Some sample images of the respective classes are shown in figure 5.4.
Figure 5.4. Sample images considered for shape features.
All these input images are subjected to extraction of shape features as proposed in this chapter. First edge maps are bounded and extraction of closed edges are detected and bounded with rectangular grids. The shapes within the bounded rectangular grids are considered in which the grid area of the shape within the grid with at least one fourth of its bounded rectangular area as described in section 5.3. For example, the edge map of the original image Flow03 presented in figure 5.5(a), is shown in figure 5.5(b). The closed edge bounded with rectangular grid of the edge map is presented in figure 5.5(c). We then put ‘1’ in the position of the shape within the rectangular area and ‘0’ otherwise for shape analysis, as described in section 5.3.1.
Fig 5.6: Target image based on shape retrieval
Figure 5.7. The retrieval of top 10 ranked images with the proposed model

The common retrieval performance measure Precision and Recall are used as the evaluation of the query results. The feature set for all the 500 images have been extracted and stored in the feature database. With the target image FLOW03, the results are compared with the existing Fourier Descriptor model. In the retrieval process, the first 10 retrieved images are flowers and the first image is the target image. In our database there are 50 flowers and our model retrieves within the rank 50 for the last flower. Hence, the precision/recall is 100%. The result precision of retrieval is the average precision of all the query retrievals used, as given in table 5.1. From the table 5.1, the 10% of recall level of the target image of our model is 100% and 60% the existing Fourier Descriptor model. Similarly, the different retrieval rate of our FRAR model is compared with the existing Fourier Descriptor model for all the images in the classes. The average retrieval performance of the proposed shape based FRAR model 84% is compared with the existing Fourier Descriptor model [Deng02] is 57%. Hence, the proposed shape-based FRAR model provides efficient results over the existing method.
Table 5.1. Comparison result of proposed method with Fourier descriptor

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Average: FD Model 57.04 and Proposed FRAR Model **84.05**
5.7. Conclusion

In this Chapter, the Full-Range Auto regressive model is extended for shape-based CBIR system using auto correlation function. After detecting the edges with the FRAR model, the feature sets are generated with the general shape based features and the auto correlation features for the images and stored in the feature database. With the feature sets of the target images of various classes, the relevant images are retrieved and ranked. The performance of the proposed shape based image retrieval of various classes and compared with the existing Fourier Descriptors model.