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Implementation of Shape Descriptor Based On Distance Interior Ratio for Image Retrieval

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Abstract— We propose a method to improve the accuracy, query time and the quality of shape-based image retrieval. We exemplify precise shape descriptor named DIR (Distance Interior Ratio) that is invariable to rotation and scaling. Here histogram based shape matching of given query image with the dataset is done. An experimental result shows a higher retrieval rate (performance) and efficient query time.

Keywords— Structural histogram, Shape Matching, Bounding Box, Shape Recognition

I. INTRODUCTION

There is a growing interest in searching images in huge collections or from remote databases. Finding for images using shape features has grabbed the attention. Shape is an important feature used for describing image content. There are many shape description and representation techniques. Shape representation generally looks for effective and perceptually important shape features based on either shape boundary information or boundary plus interior content. Perceptually similar shapes usually means rotated, translated, scaled shapes and affinely transformed shapes. A good shape descriptor should be not be application dependent. It should perform well for all types of shapes. Shape matching or discrimination refers to methods for comparing shapes. It is used in model based object recognition where a set of known model objects is compared to an unknown object detected in the image. For this purpose a shape description scheme is used to determine the shape descriptor vector for each model shape and unknown shape in the scene. Image retrieval is the process of identifying images (objects) in a large database that are similar to a given image [1].
Effectual shape features must have necessary properties such as:
identifiability: shapes which are observed perceptually similar by human have the same feature translation, rotation and scale invariance: the extracted features must not be effected by location, rotation and scaling changing of the shape.

Affine invariance: the "straightness" and "parallelism" of lines are preserved by linear mapping from 2D coordinates to other 2D coordinates when there is affine transformation. Using sequences of translations, rotations, scales, shears and flips affine transform can be constructed. The extracted features should be invariant with affine transforms.

Noise resistance: features must be the same whatever be the strength of the noise in a given range that affects the pattern i.e., they must be as vigorous as possible against noise

Occultation invariant: the feature of the remaining part must not change compared to the original shape when some parts of a shape are occulted by other objects.

Statistically independent: two features must not be statistically dependent. This specifies the compactness of the representation.

Reliable: as long as one deals with the same pattern, the extracted features must remain the same.

Shape feature representation and extraction plays an crucial role in the below categories of applications:

Shape recognition and classification: determining whether a given shape matches a model appropriately or which of prominent class is the most similar.

Shape retrieval: seeking for all shapes in a consistently huge database of shapes that are similar to a query shape. Normally all shapes from the query are determined within a given distance on the first few shapes which have the smallest distance.

Shape alignment and registration: translating or transforming one shape in part or in whole, so that it best matches another shape.

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Shape approximation and simplification: shape constructing of fewer elements like points, segments, triangles, etc., which is still similar to the original.

II. SHAPE DESCRIPTOR

Some set of numbers that are produced to describe a given shape feature is Shape descriptor. A descriptor attempts to quantify shape in ways that agree with task-specific requirements (or human intuition). Smashing retrieval sharpness (accuracy) requires a shape descriptor be able to efficiently find correspondingly similar shapes from a database. Generally, the descriptors are in the vector form. Shape descriptors should meet some requirements such as the descriptors should be fair enough i.e. complete to characterize the gist of the information items, descriptor vector size must not be too large, the reckoning of distance between descriptors should not be difficult; else the it takes longer time for execution and the descriptor should be invariant to noise, scaling and rotation.Efficiency and accuracy are the two requirements to be achieved. Region-based and Contour-based methods [7,8], are the two families of shape representations that have been proposed. The contour-based contemplate the information obtained from the shape contour, while the region-based method considers the global (universal) information of the pixels within the shape. The examples of established method of shape descriptor include shape context [1], centroid distance [7], Contour Point Ditribution Histogram (CPDH) [9] and distance distribution. A pairwise distance descriptor called D2 proposed by Osada et al.[5]. One problem of D2 is the existence of homometric pairs [6], which are pairs of objects with different shape but similar distance distribution. Whether the line segment crosses the boundary or not the pairwise distance distribution does not take into account.

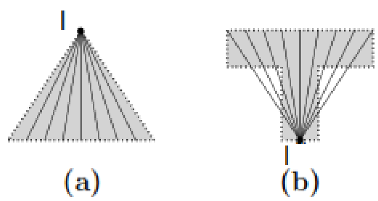

Fig. 1. The distance interior of shapes:
(a) Triangle and (b) T

As in the above Figure 1 (a) and (b) two of the objects with different shape but similar distance distribution.

Shape is described by the edge pixel. By region based method we get the internal information of the object (image), meanwhile by contour based method we get shape information of the contour points of an image (object). So, here we taking the combination of region based and contour based shape representation method for defining shape descriptor for image retrieval application. Influenced by the line segment classification, we nominate a histogram-based shape descriptor called Distance Interior Ratio (DIR). The distribution of the fraction of the line segments lying in the polygon and the length of the line segments on the contour points is known as DIR. By using the DIR descriptor, the two shapes in Figure 1 are different. The DIR of all line segments of shape (a) equals 1, while it is strictly less than 1 for some line segments in shape (b).

A. *Distance Feature*

Given a set $L = \{l_1,l_2,..l_n\}$ of *n* arbitary points on the boundary of a simple polygon that is extracted from binary image. Let [*lm*] be the line segment connecting the two points $l,m \in L$.

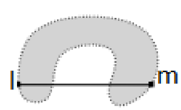

Fig 1.(a) A line segment [lm]

Let d_{lm} represent the Euclidean Distance of [lm]. The Euclidean distance can be computed as

$$d_{lm} = \sqrt{(lx - mx)2 + (ly - my)2}$$

Let d^r_{lm} be the DIR, i.e. is the fraction of line segment lying inside the polygonand length of the line segment.To calculate d^r_{lm}, let $Q(l,m) = \{q_1,\ldots..,q_k\}$ be the digital line segment from point l and m where l_i for $1 \leq i \leq k$ is a pixel on the Q(l, m) and k is |Q(l, m)|. In this research, we use Bressenham's Algorithm [3] for approximating a digital line segment. Since we only consider only binary images, we assume that the intensity $f(q_i)$ of every pixel q_i is either 1 or 0. Let d^{in}_{lm} be the number of pixels p_i with $f(q_i) = 1$.The DIR is given by d^{in}_{lm}/k. The shape information is transformed to a feature space F, where each line segment [lm] is represented by the point (d_{lm}, d^r_{lm}). The x-axis represents the Euclidean distances between the vertices of L and the y-axis corresponds the DIR of L. The ranges of the x-axis and the y-axis are [d_{min}, d_{max}] and [d^r_{min},d^r_{max}] respectively, where d_{min} is the minimum Euclidean distance between points in L and d_{max} , d^r_{min} and d^r_{max} correspondingly.

B. Structural Histogram

Given two positive integers' c and r, the feature space F is equally divided into c×r blocks. The x-axis and the y-axis are divided into c (column) and r (row) blocks respectively. The interval of each block on the X-axis is (d_{max}-d_{min})/c and the Y-axis is (d^r_{max}-d^r_{min})/c.

Let (*l*, *m*) denote a block in F where *l* and *m* are the index on X-axis and Y-axis respectively. The interval of each block is denoted by [x_l, x_{l+1}], [y_m, y_{m+1}]. Let *hist*(*l*, *m*) be the number of points that fall into [x_l, x_{l+1}], [y_m, y_{m+1}]. To avoid scaling problem, *hist*(*l*, *m*) is normalized by dividing the total number of points in the feature space. Normalization of *hist*(*l*, *m*) is done by dividing the total number of points in the so as to avoid scaling problem.

We have,

$$hist(l,m) = \frac{2}{n(n-1)} \sum_{i=0}^{n} \sum_{j=1}^{n-1} g(d_{ij}, d^r_{ij}, x_l, x_{l+1}, y_m, y_{m+1})$$

Where

$$g(d_{ij}, d^r_{ij}, x_l, x_{l+1}, y_m, y_{m+1}) = \begin{cases} 1, if\ d_{ij} \in [x_l, x_{l+1}]\ and\ d^r_{ij} \in [y_m, y_{m+1}] \\ 0, otherwise \end{cases}$$

The Structural Histogram image of different classes are computed and are stored in Feature space dataset.Figure 2.1 (a) and (b) represent the Structural Histogram image of the classes Apple and Bone respectively.

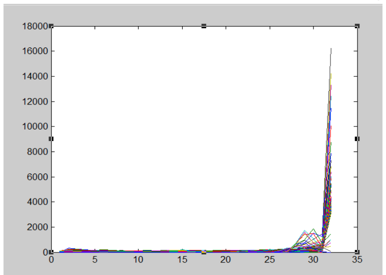

Fig 2.1(a)Structural Histogram representing the image of Class Apple

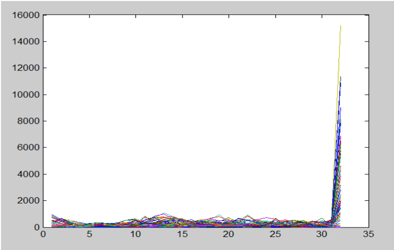

Fig 2.1(b) Structural Histogram representing the image of Class Bone

The distribution of the classified distances of A, denoted by Hist(A), is a c × r histogram matrix of hist(l,m), where $0 \le l \le c - 1$ and $0 \le m \le r - 1$.The histogram of the images belonging to different classes are shown in Fig 2.1 (a) and (b)

The L_1 norm is adopted to find the similarity between two descriptors of shape A and B,let D(A,B) be the distance between two descriptor.It is computed as

$$D(A,B) = \sum_{i=0}^{r-1} \sum_{j=0}^{c-1} |hist_A(i,j) - hist_B(i,j)|$$

III. METHODOLOGY

A. Edge Pixel Detection

Here, since the descriptor is primarily based on contour shape representation, edge (boundary) pixels should be detected .If a

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pixel has less than eight neighbors then that pixel is the contour pixel.

B. Picking 'n' points

Different images will have different edge pixel count. This count varies from image to image and is in the range of few hundreds to few thousands .Considering the complexity involved in computation we restrict the no. of edge pixel count to 1000. If the edge pixel count is less than 1000 then all the points are considered for computation. If the edge pixel count is greater than 1000, we restrict it to 1000.These 1000 are chosen so as to cover the entire boundary in a uniform fashion. For this we have introduced novel method of Bounding Box. A tight BB covers the boundary edge pixels of the object (image). Then it is divided into four quadrants as shown in Fig 3.1

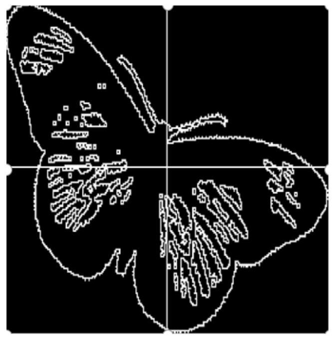

Fig 3.1 Bounding Box

The number of pixels chosen from each quadrant is proportional to the percentage of edge pixels originally held in that quadrant. For Quadrant isolation we do masking. The final edge points from the quadrant are chosen so that they uniformly uniformly span the entire edge information in that quadrant.

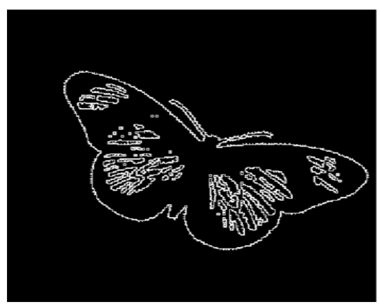

Fig 3.2 Picking 'n'(1000) pixel points

If no edge pixels are found in a quadrant care is taken that pixels are selected from remaining quadrants as shown in Fig 3.3

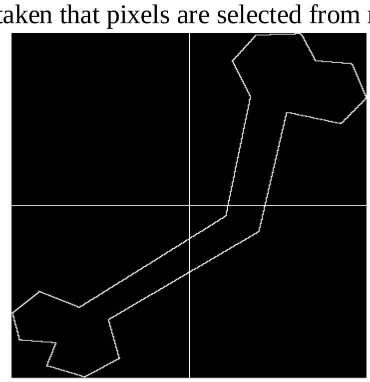

Fig 3.3 No image falls in First Quadrant

Shape signature for all 1400 image is computed and kept in database which is an offline activity.

IV. EXPERIMENTAL RESULT

The performance of DIR descriptor is evaluated using the MPEG7 CE-Shape-1 [4] dataset. For the distance interior ratio histogram matrix, we choose c = 64 and r = 32.The dataset (MPEG7 CE-Shape-1) consists of 1400 images. It has 70 classes and each class containing 20 shapes. The retrieval efficiency for some classes is shown in the Table1. The result is tabulated for full retrieval (Top 20), Top 15 and Top 10 correct results.

Table 1.Group Performance

GROUP PERFORMANCE IN PERCENTAGE (%)			
Class	Top 20	Top 15	Top 10
'APPLE'	70	93.333	100
'BAT'	70	73.333	90
'BEETLE'	60	66.667	80
'BELL'	95	100	100
'CAR'	100	100	100
'CARRIAGE'	100	100	100
'RAT'	95	100	100
'SPOON'	60	80	100
'SPRING'	70	86.667	100
'STEF'	65	80	90
'TEDDY'	100	100	100
'WATCH'	85	93.333	90

V. CONCLUSION

We proposed a descriptor called Distance Interior Ratio (DIR), which is a distance-based descriptor. The proposed descriptor is easy to compute and requires less space. The retrieval performance is encouraging compared to other descriptors available in the literature.

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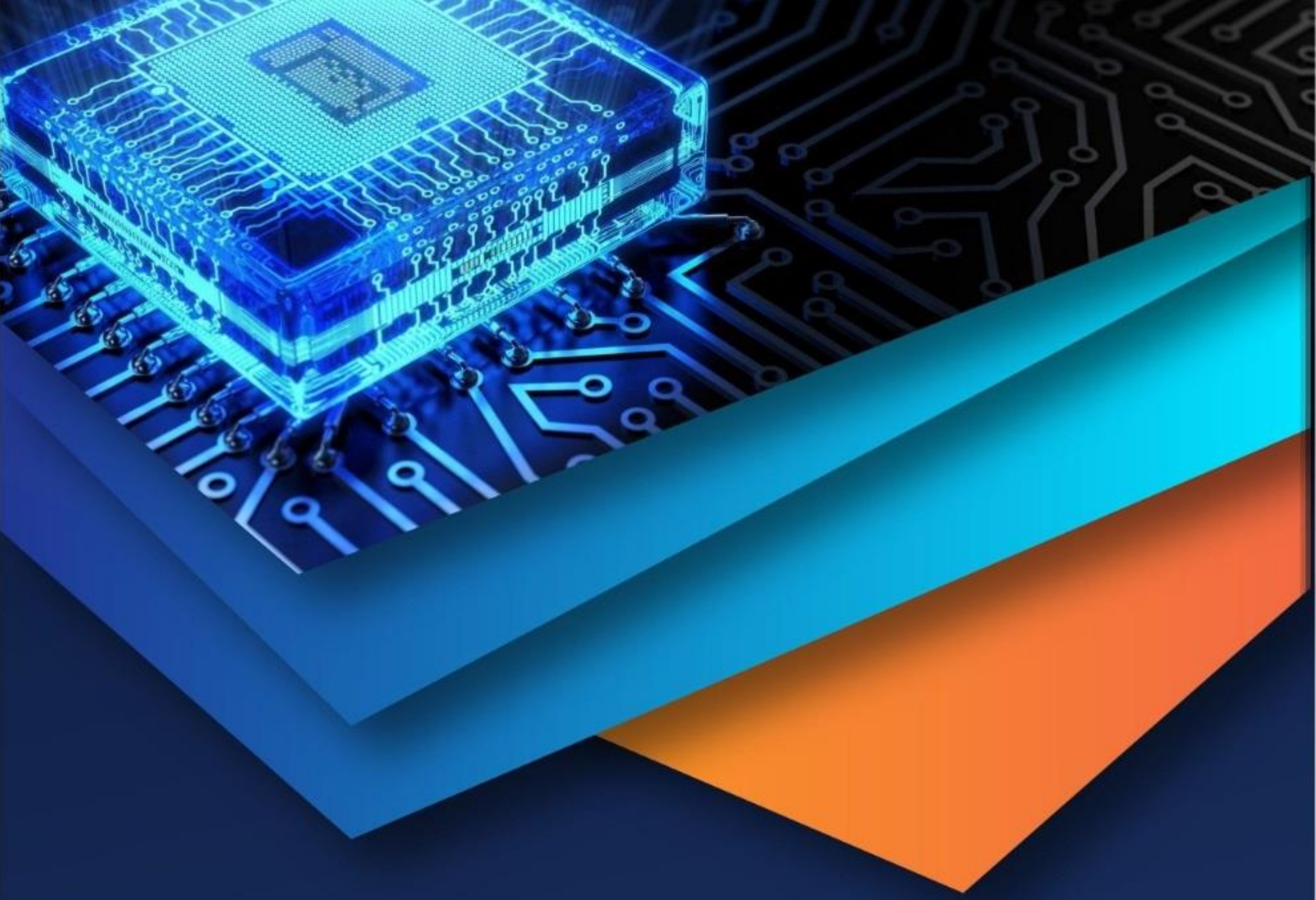

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