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Edge Histogram Descriptor, Geometric Moment and Sobel Edge Detector Combined Features Based Object Recognition and Retrieval System

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Abstract: Shape is one of the high level features that play an important role in the object recognition and perception. Object shape features provide a powerful clue to object identity. In this paper, we have implemented the approach by combining three feature descriptor i.e. edge histogram descriptor, geometric moment, and Sobel edge detector techniques recognize the objects in the images that is invariant with the changes , scaling, rotation, and orientation. Since edges play an important role in image perception and it is frequently used as a feature descriptor in image retrieval so we select the Edge Histogram Descriptor, EHD, as a feature vector which represents the spatial distribution of five types of edges. We also select geometric moment invariant as another shape feature vector which is extensively used to extort global features, can improve the previously recognition rate to a significant measure. Due to Sobel operator's smoothing effect, it is less sensitive to noise present in Images. On the other hand, smoothing affects the accuracy of edge detection. So next we select Sobel edge detection as a third feature vector that extract the shape features. Finally, we combined the all three shape features that form the 3 dimensions feature vectors of the entire image. Experiment results conclude that the proposed scheme has a very good performance in respect of the precision recall.

Keyword: Edge Histogram Descriptors, Geometric Moment, Sobel Edge Detector.

I. INTRODUCTION

For image retrieval, Object shape features can be used to provide powerful information, because humans can recognize objects solely from their shapes. Basically, the shape contains semantic information about an object, and it is different from other elementary visual features, such as color or texture features .Shape representation compared to other features, like texture and color, is much more effective in semantically characterizing the content of an image [1]. However, the challenging task of shape descriptors is the accurate extraction and representation of shape information. The construction of shape descriptors is even more complicated when invariance, with respect to a number of possible transformations, such as scaling, shifting and rotation, is required [2]. The overall performance of shape descriptors can be divided into qualitative and quantitative performances. The qualitative characteristics involve their retrieval performance based on the captured shape details for representation. Their quantitative performance includes the amount of data needed to be indexed in terms of number of descriptors, in order to meet certain qualitative standards [3] as well as their retrieval computational cost. While studies have been extended to content-based three dimensional (3D) shape retrieval methods [4], still pattern recognition by 2D shape descriptors can be used in many practical tasks, for example in image matching, multi temporal image sequence analysis, shape classification and character recognition. Furthermore, their quantitative characteristics which still remain superior make them widely used and effective [5].

Various shape descriptors exist in the literature, mainly categorized into two groups: contour-based shape descriptors and region-based shape descriptors. Contour-based methods need an extraction of boundary information which in some cases may not available. Such methods completely ignore the important features inside the boundaries. Region-based methods, however, do not rely on shape boundary information, but they take into account all the pixels within the shape region. Region-based image retrieval methods, firstly apply segmentation to divide an image into different regions/segments, by setting threshold values according to the desirable results. Whereas the boundary of an image can be obtained by applying any edge detection method to an image [6]. Therefore, for generic purposes, both types of shape representations are necessary.

In this study, a computer vision system recognizing objects in capturing images is established using Edge Histogram Descriptor (EHD), Geometric Moment (GM) and Sobel Edge Detector. The rest of the paper is organized as follows. In Section 2, Geometric moment invariants descriptor is described. Section 3 deals with the Edge Histogram Descriptor. In section 4 Sobel edge detection methods are described. In Section 5, proposed methodology and their efficiency is presented. In Section 6, the shape-based descriptors are calculated and evaluated against each other in both terms of retrieval and computational complexity performance. The paper concludes in Section 7.

II. GEOMETRIC MOMENT INVARIANTS

Moment invariants are widely used technique in many approaches of pattern recognition. The use of Geometric Moment of image processing and pattern recognition was first implemented by Hu and ALT [7]. They came up with the idea to utilize the approach of known mathematician

Boole, Sylvester and Cayley. These moments remain unaffected if the image endures changes like-

- Scaling
- Translation
- Rotation
- Orientation

Hu declared that if f(x, y) is a discrete hybrid function and has nonzero values in a finite region of x, y plane, then the moment succession { μ_{pq} } uniquely describes the f(x, y).

$$\mu_{pq} = \sum_{x=0}^{l-1} \sum_{y=0}^{w-1} x^p y^q f(x,y)$$

Where p, q = 0, 1, 2,……∞, while the product of x^p and y^q is the source function for this moment and the set of n moments contain all μ_{pq} for $p+q \leq n$, i.e. there are ½ (n+1)(n+2) entities [8]. As the segment of the image is finite region a moment set can be generated which will have distinct information of the image segment. For two-dimensional images these moment invariants give the distinct features. They are the peculiarities of connected regions in binary images that are invariant to scale translation and rotation. They characterize a simple calculated region behavior in a set that can be utilized for recognition of shape or any area. η_{pq} are denoted as normalized central moments.

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}$$

Where

$$\gamma = \frac{p+q}{2} + 1 \text{ , } p+q = 2, 3, 4\ldots$$

From second and third normalize moment Hu derived a set of seven invariant moments and this set of moment from $\phi 1$ to $\phi 7$ be invariant to change in size, rotation and translation [9].

$$\phi_1 = \eta_{20} + \eta_{02}$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$

$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$

$$\phi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} - \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} + \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} - \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

$$\phi_6 = (\eta_{20} - 3\eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 + 4(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})]$$

$$\phi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} - \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (\eta_{21} + \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

III. EDGE HISTOGRAM DESCRIPTOR

The edge histogram descriptor (EHD) is one of the widely used methods for shape detection. It basically represents the relative frequency of occurrence of 5 types of edges in each local area called a sub-image or image block. The sub-image is defined by partitioning the image space into 4x4 non-overlapping blocks as shown in figure 1. So, the partition of image definitely creates 16 equal-sized blocks regardless of the size of the original image. To define the characteristics of the image block, we then generate a histogram of edge distribution for each image block. The Edges of the image block are categorized into 5 types: vertical, horizontal, 45-degree diagonal, 135-degree diagonal and non-directional edges, as shown in Figure 2. Thus, the histogram for each image block represents the relative distribution of the 5 types of edges in the corresponding sub-image.

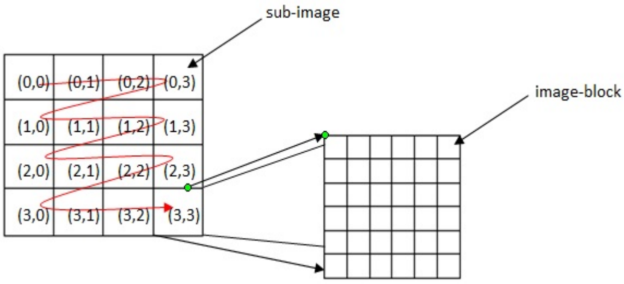

Fig 1. Definition of Sub-image and Image-block in the EHD

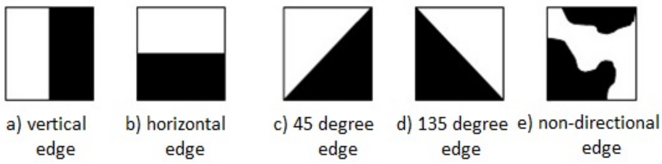

Fig 2. Five Types of Edges in the EHD

A. *Semantics of Local Edge Histogram*

A simple method to extract an edge histogram in the image-block is to apply digital filters in the spatial domain. To this end, first divide the image-block into four sub-blocks as shown in Figure 1. Then, numbering the labels of the four sub-blocks. The average gray levels for the four sub-blocks are represented at (i,j)th image-block as $a_1(i,j)$, $a_2(i,j)$, and $a_3(i,j)$ respectively. Also, filter coefficients for vertical, horizontal, 45-degree diagonal, 135-degree diagonal, and non-directional edges can be represented as $f_v(k)$, $f_h(k)$, $f_{d45}(k)$, $f_{d135}(k)$, and $f_{nd}(k)$ respectively, where k = 0,…,3 represents the location of the sub-blocks. We have the coefficients of the vertical edge filter as shown in Figure 3-a). Similarly, we can represent the filter coefficients for other edge filters as shown in Figure 3 – b), c), d) and e).

1	-1
1	-1

a) Vertical Edge Filter

1	1
-1	-1

b) Horizontal Edge Filter

$\sqrt{2}$	0
0	$-\sqrt{2}$

c) dia45 Edge Filter

0	$\sqrt{2}$
$\sqrt{-2}$	0

d) dia134 Edge Filter

2	-2
-2	2

e) nond Edge Filter

Fig 3. Filters for Edge Detection

B. *Non-Normative Global Edge Histogram*

High retrieval performance cannot be achieved only by applying the local histogram alone. It may not be enough. Rather, we may need edge distribution information for the whole image space as well. That is, beside the local histogram, we need the global histogram. The global edge histogram represents the edge distribution for the whole image space. Note that the bin values for all global histograms can be obtained directly from the local histogram. Since there are five edge types, the global edge histogram also has five bins. Consequently, we have total 80 bins (local) + 5 bins (global) = 85 bins .

IV. SOBEL FEATURE EXTRACTION

Shape information can be measured in the context of edge image of the original grayscale image in the database. In this paper the Sobel operator is selected as a shape descriptor that creates the edge image of the original grayscale image. Sobel operator not only determines the shape of an image, but also the shape of a particular region that is being searched for.

The Sobel operator determines the edge by applying a 2-D spatial gradient on an image and emphasizes regions of high spatial frequency that correspond to edges. The basically Sobel operator is used to find the approximate absolute gradient magnitude at each and every point in an input grayscale image. The Sobel operator which consists of a pair of 3×3 matrix is shown in figure 4. One matrix is simple and the other rotated by 90° [10].

$$\underset{Gy}{\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}} \qquad \underset{Gx}{\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}}$$

Fig 4. Sobel operator

Figure 5 shows the results of applying the Sobel operator vertically and horizontally relative to the pixel grid and with combined together.

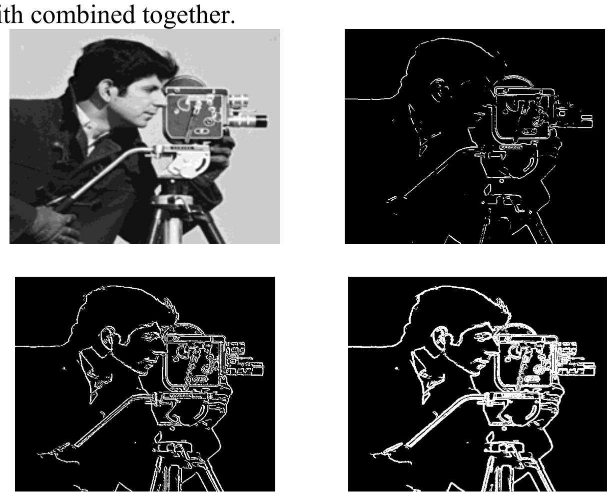

Fig 5. Edge Detection with Sobel Operator

These matrices are designed to determine edges vertically and horizontally relative to the pixel grid. Both matrices can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (i.e. Gx and Gy). To find the absolute magnitude of the gradient and the orientation of that gradient at each point, these measurements can then be combined together to find. The gradient magnitude is given by:

$$|G| = \sqrt{Gx^2 + Gy^2}$$

Typically, an approximate magnitude is computed using:

$$\alpha = a\tan^{-1}\left[\frac{Gy}{Gx}\right]$$

The Sobel operator may be slower with respect of computation than the other edge detection operator, but this operator is less sensitive to noise due to its larger convolution kernel that smoothes the input image to a greater extent. The operator also generally produces considerably higher output values for similar edges, compared with the other operators.

V. STRUCTURE OF THE PROPOSED METHOD

Figure 6 depicts the block diagram of the proposed image retrieval technique. First of all user supplies a query image which will be entered into the retrieval system where it is converted into a grayscale image after that Shape feature is extracted by applying the edge histogram descriptor, Geometric moment and Sobel edge detection. Then combines the all three shape features to generate 3 dimension query feature vector Q_f. This query feature Q_f is compared against the database images features which is already stored in the feature database and calculates the similarity between the query feature vector Q_f and each target feature vector f'. Based on the similarity ranks, finally it retrieved a given number of target images from the image DB.

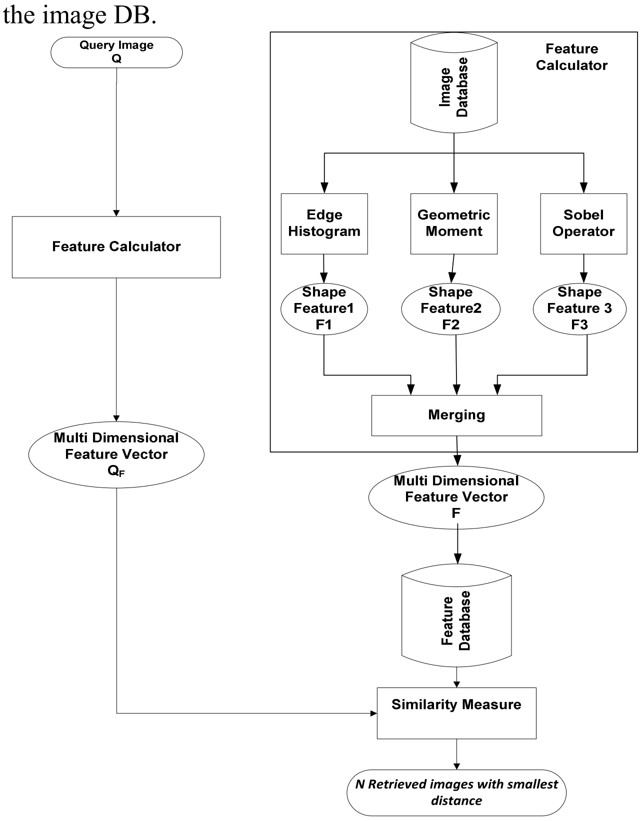

Fig 6. Block Diagram of The proposed work

Proposed Algorithm

Algorithm 1: Global Shape Feature Extraction
Purpose: to extract global features from an image.
Input: RGB/Gray image.
Output: 3-dimension feature vector F.
Procedure:
{
F1= Edge Histogram Descriptor ( );
F2= Geometric Moment Descriptor ( ):
F3= Sobel Edge Detector ( ):
Return ([F1, F2, F3]);
}

Edge Histogram Descriptor ( )
{
Step1: Convert the RGB image I into gray image Ig.
Step2: : divide the eeg image into 4*4 blocks
Step3: Calculate the local edge histogram as described in section III.
Step4: percentage of the number of pixels that correspond to an edge histogram is calculated.
Step5: Calculated the global edge histogram by applying the same procedure described in section III on the entire image and then calculate the percentage of the number of pixels that correspond to a global edge histogram bin.
Step6: Save both local and global histogram values in feature vector F1.
Step7: return the Feature Vector F1.
}

Geometric Moment Descriptor ()
{
Step1: for extracting the geometric moments the colored images I am converted to grayscale I_g.
Step2: Sobel edge Detection is applied to get the edge contours of the objects.
Step3: From these edges detected images the seven geometric moments are calculated as described in section II.
Step4: Save the seven moments to feature vector F2.
Step5 : Return the moment vector F2 consisting of 7 attributes calculated
}

Sobel Edge Detector:
{
Step1: Convert the RGB image I into Gray Scale image I_g.
Step2: : divide the I_g image into 4*4 blocks
Step3: calculate the local edge by applying a Sobel Operator mask on each image block in both x and y direction.
Step4: calculate the global edge by applying a Sobel Operator mask on entire image in both x and y direction.
Step5: After the edges are identified and marked, Calculate and store percentage of the total number of pixels in the each block are edges, into the feature vector F3.
Step5: Return the Feature Vector F3 consisting of 36 feature vector in which 32 from local edge and 4 from global edge.
}

Algorithm 2: Image Retrieval system
Purpose: to retrieve similar images on the basis of Query Image.
Input: gray shape image.
Output: N similar images with smallest distance with Query Image.
Procedure:
{
Step1:- Input the query image Q.
Step2:- Extract the Global Shape Features of Q with the help of Algorithm 1(as previously explained)
Step3:- Combining the F1, F2 and F3 hybrid feature of Query image and save these on the multidimensional feature vector Q_F.
Step4:- Calculate the similarity measure between Query Image and Images stored in the database by applying Euclidean Distance between Query feature vector Q_F and each target feature vector F_D whose feature is already stored in the database. Where F_D stands for Feature of database Image.
Step5:- On the basis of Euclidean distance retrieve the N similar images with smallest distance.
}

VI. EXPERIMENTAL RESULT AND ANALYSIS

To check the effectiveness of the proposed retrieval system this section deal with the details of performance evaluation that includes the image database, the evaluation metrics, and the result of our method and performance comparison with existing methods.

A. Image Database

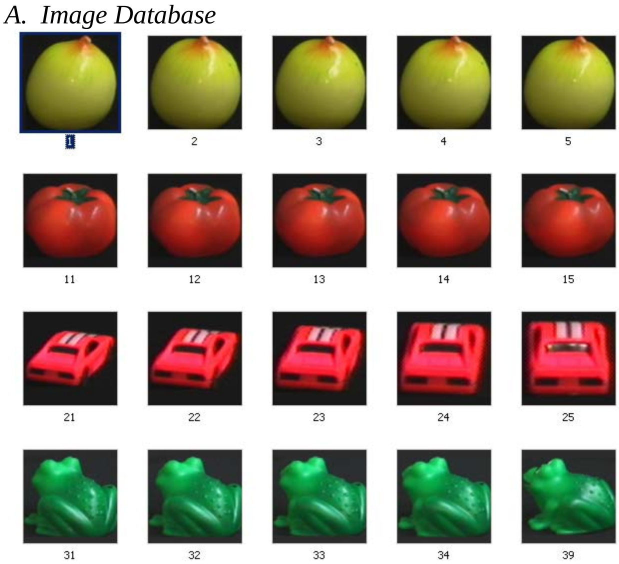

Fig 1. Some example of image data set

The image dataset is taken from the Caltech dataset. This image database consists of 150 images with 15 object categories. And each object category contains 10 images.

B. Evaluation Matrices

For retrieval efficiency, we have considered two parameters, namely recall and precision. We calculated recall and precision value in case output after applying the edge Histogram descriptor, Generic moment descriptor, and Sobel edge detection for the shape feature extraction. For the similarity measurement, we have used the Euclidian distance Metrics. In our experiment, the precision and recall are calculated as:

$$precision = \frac{\text{No. of relevant images retrieved}}{\text{Total no. of images retrieved}}$$

$$recall = \frac{\text{no.of relevant images retrieved}}{\text{Total no. of relevant images in the database}}$$

C. Result Snapshots

Fig 8 to fig 16 shows the result snapshots of the proposed method

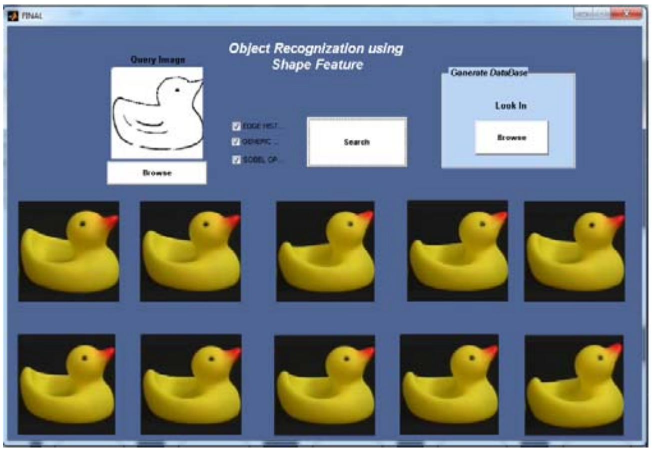

Fig 2. Output of the proposed method on Duck image

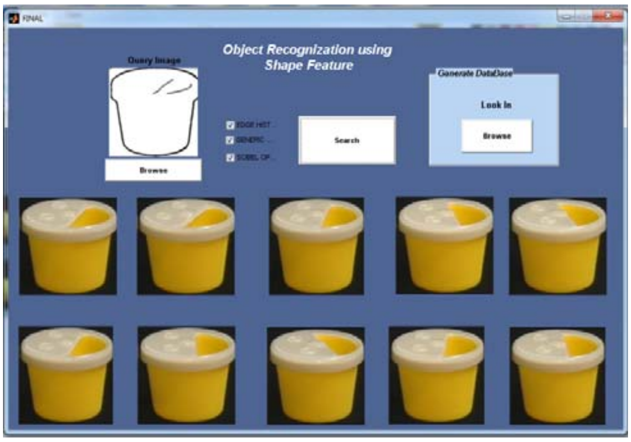

Fig 3. Output of the proposed method on Cup image

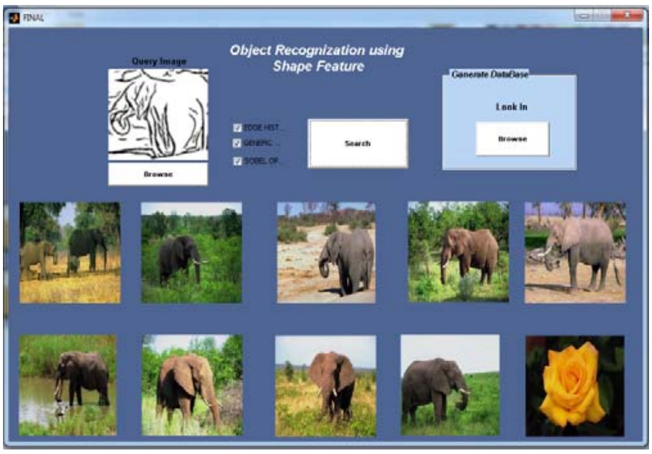

Fig 4. Output of the proposed method on elephant image

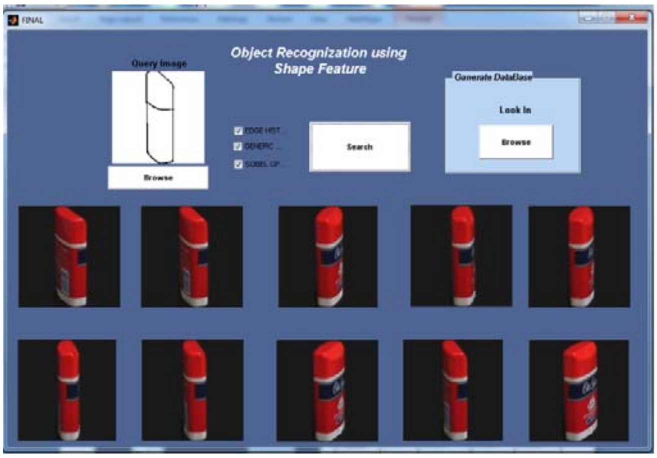

Fig 5. Output of the proposed method on stick box image

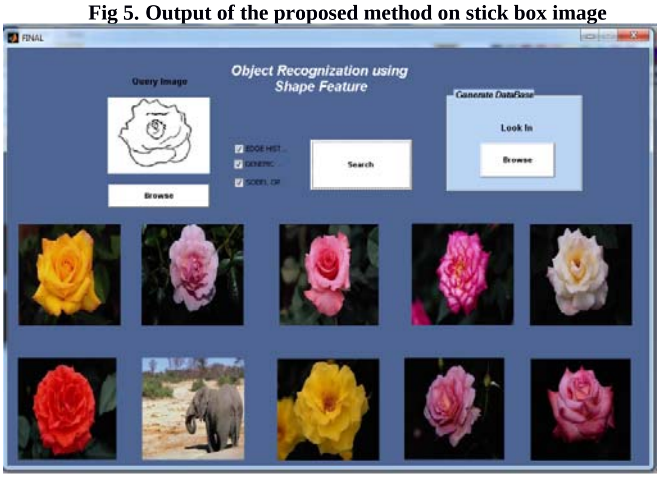

Fig 6. Output of the proposed method on flower image

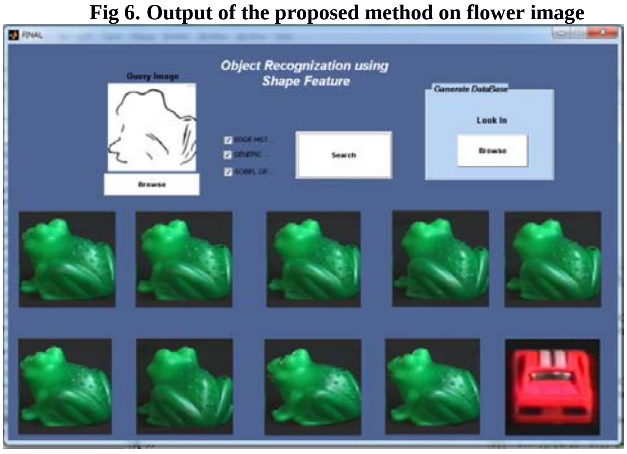

Fig 7. Output of the proposed method on frog image

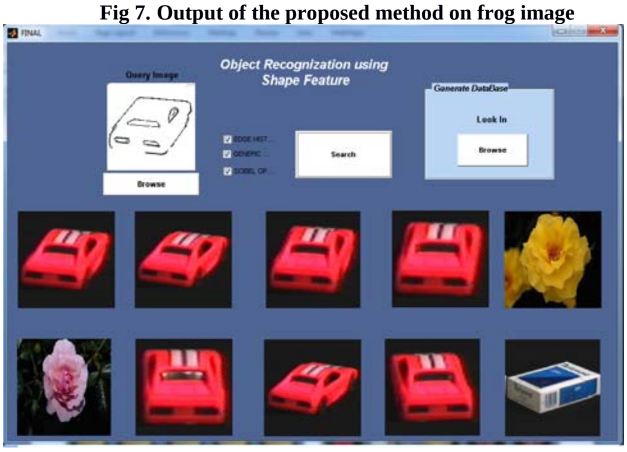

Fig 8. Output of the proposed method on Car image

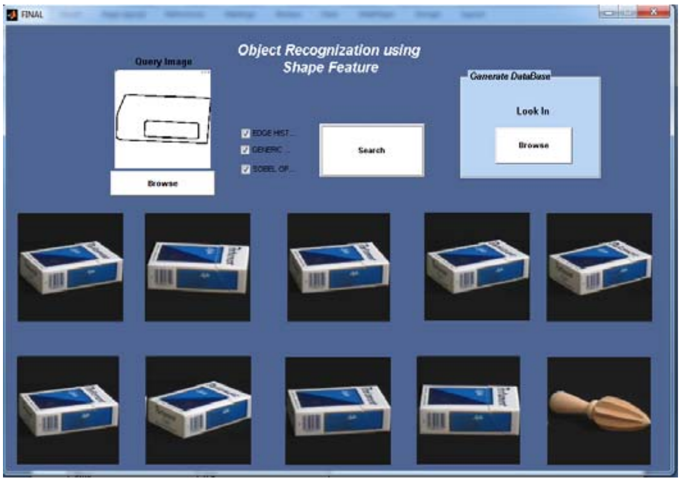

Fig 9. Output of the proposed method on cigarette box image

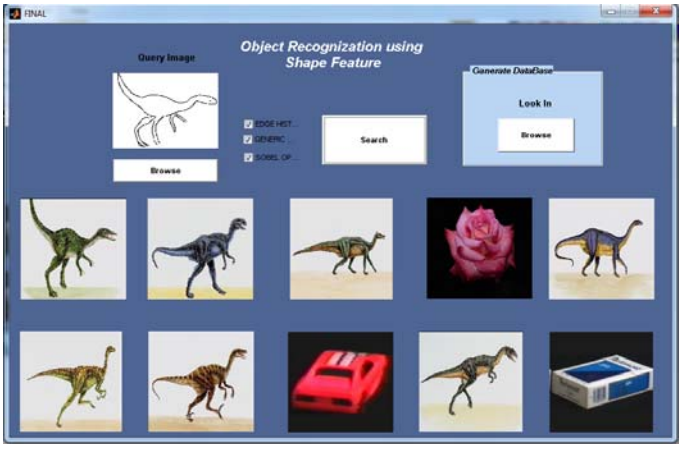

Fig 10. Output of the proposed method on dinosaur image

D. Retrieval Results:

We implement the proposed method on the Wang image database. The experimental results in terms of average precision and recall using the proposed method is shown in Table 1. And the graph is shown in figure 16.

Table 1 Average precision/Recall calculation of the proposed method against other method

Semantic Name	The proposed method
Car	0.9
Dinosaur	0.7
Duck	1
Elephant	1
Flower	0.9
Frog	0.9
Cup	1
Ring	0.6
Cigarette Box	0.9
Stick Box	1

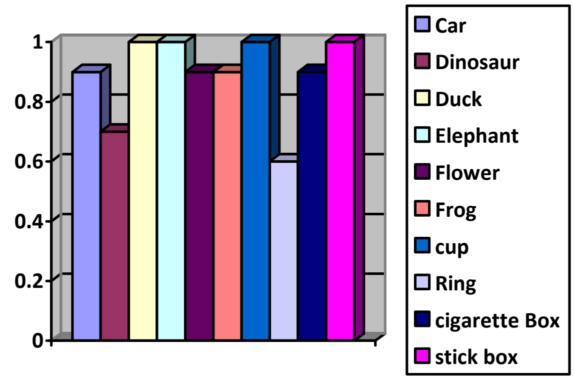

Fig 11. Result graph of the proposed method on different images

VII. CONCLUSION:

In this paper, we proposed a framework for the object detection and retrieval using combined features, i.e., Edge histogram, Geometric moments and Sobel edge detection. Experimental results on the test image dataset shown that our proposed method outperforms in terms of precision and recall. In the future, the larger benchmark image dataset will be used to further evaluate the effectiveness and efficiency of our proposed method.

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