Contour Shape Descriptor for 2D Image Retrieval

Pushpalatha S.Nikkam* and Priyanka Mathapati** and Pratibha Badiger***, Dr. Nagaratna P. Hegde**** and Dr. B. Eswara Reddy*****
* Assistant Professor, SDMCET, Dharwad, JNTUCE, Anantapur, Andhrapradesh.
geetasrikant@gmail.com.
**Student, SDMCET, Dharwad.
priyanka.math1991@gmail.com.
*** Student, SDMCET, Dharwad.
****Honorary Professor, Dept. of CSE, Vasavi College of Engineering, Hyderabad.
*****Professor, Dept. of CSE, JNTUCE Anantapur, Andhrapradesh

Abstract: Recognizing contour of any object in a digital image is a challenging task. This paper presents an efficient method to identify the contour of an object in a given image and retrieve similar images. Initially major noise in an image is removed using bilateral filters and then threshold is applied to eliminate small noises. Canny Edge detection technique is used to get the edges in an object. The morphological dilation, erode and flood fill techniques are used to draw the contour of the object. The shape features are computed using the area, bounding box, perimeter, and centroid of the contoured image. Shape based image retrieval depends on measuring of similarity between shapes represented by their features. The distance measures such as Euclidean, Canberra, Manhattan are used to retrieve similar image from the database. The experimental results are tabulated using precision and recall graph.

Keywords: Shape, Centroid, Euclidean, Canberra, Manhattan Distances, Canny Edge detection.

Introduction

Now-a- days searching for an image from a huge database or remote database become tedious task. From web point of view, if we give a query as an image we may not obtain the exact one or we may get irrelevant images which are of less use. So to conquer this issue an effective shape descriptor is used, in order to retrieve images very efficiently. The innovation has created from the first original standard text based image retrieval to today's semantic based and content based image retrieval [1]. Image retrieval build on content (CBIR) is an approach utilized to get similar images in huge image database. The most difficult part of it is to cross the barrier between the powerful and semantic theory and flat level features.

There are three ways to extract images and is based on semantics, content and text. Presently text based approach is utilized more widely than other approaches. The most popular is Google Image search. In this approach, using Key words which are explanations over images, we can extract the images. This approach has two demerits. First of all, each image in the database has to be annotated manually. For this annotation, a lot of time for human effort and a large database is needed. The output of the retrieval is built on the criteria that how images have been understood so that we may not always get expected outcomes. This is because those different key words could be annotated with the same image.

The second approach is Content Based Image Retrieval (CBIR) is utilized to get similar images from an image database like Wang [2]. The most difficult part of it is to cross the barrier between the powerful semantic theory and flat level features. Among the feature representation of image such as shape, color and texture, this paper concentrates only on shape. Based only on operations of contour (shape) images are retrieved. Hence contour shape accomplishes only boundary of the image. Shape comparison and intolerance refers to approaches for image comparison. Contour based strategies pick up ubiquity since it is typically easy to acquire and is enlightening adequately in numerous applications. Shape is mainly considered for object recognition. There are various applications used in shape matching such as medical image, object recognition and character recognition etc. Shape based object recognition in natural image has been more practical and attracting more attention in computer vision community.

Shape representation searches for better techniques to capture the core of shape components with the goal that it gets to be less demanding to store, to transmit, to contrast against and to recognize a shape. In order to represent feature of the shape, descriptor is used which is the quantitative value used for evaluating image retrieval. There are diverse descriptors available and described in the literature survey. Implementing a new method of descriptor is the challenging task. There are two groups of descriptors like Contour and Region based descriptors as shown in Fig.1. There are some of attributes (properties) associated with shape signatures such as rotation, translation and scaling variance.

In the boundary based method, shape features are extracted from boundary line and objects are represented in terms of their external attributes where as region based method, features are extracted from the whole shape region. In this paper, we concentrate on Contour (boundary) to determine the better description of shape for 2D images.

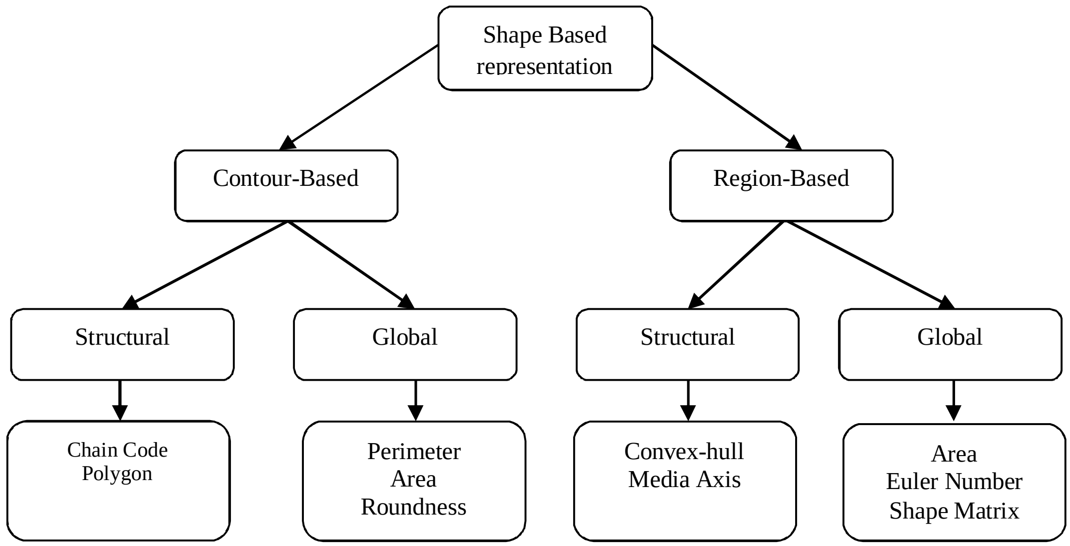


Fig 1: Shape Classification

Literarure Survey

Shape is the one of the important feature of the image. Since it is a low level attribute, its analysis in the today's world became challenging task. There are many researches going on the design and analysis on contour or boundary of the image. There are two main classification based on shape description and representation such as contour and region methods. The distribution is made out on two criteria of shape attributes such as contour only or which are acquired from the whole shape area.

Roshi Choudhary et al. [3] explored concepts on matching of LBP and color moment. He used two technologies to illustrate about Wang dataset. He experimented on attributes of image such as using color moment on color feature and by using local binary pattern on texture feature on Gray images. For both texture and color attributes of the images multiple feature vectors are taken and images are retrieved efficiently.

Irnia Mocanu et al. [4], proposed that diverse shape descriptors for shape matching and analysis such as centroid – radii, turning angle method, Fourier descriptor, distance histogram techniques. He experimented based on contour images for shape retrieval and representation. He proposed that Fourier and centroid –radii method possess best performance for image retrieval where as turning angle at the worst. This author also showed comparison time for these descriptors and told that both Fourier and centroid – radii methods will take less comparison time where as turning angle takes higher comparison time.

A.M Patil and Reshma Chudhary et al. [5] proposed that retrieval of content based images depends on colour and shape and the combination of both on Wang dataset. They proposed an algorithm which improves the accuracy and performance of image retrieval. They considered the approximate shapes rather than taking exact shape in order to enhance the rate of the shape based retrieval. The combination of color and shape increases the performance and accuracy of the resultant. Their proposed methodology increased an average of 44% to 72% by increasing average precision value.

P.Bhuvaneshwari et al. [6] presented a study on different shape descriptors. Mainly on the contour based such as Fourier Descriptors, Curvature Scale Space and region based like Angular Radial Transform (ART), Image Moment Descriptors, Zernike Moments Descriptor (ZMD), Geometric Moments Descriptors (GMD) and Grid Descriptors (GD). They said shape descriptors for contour based are simple and for region-based are robust.

Lei Ma and Bitao Jiang et al. [7], proposed a paper on edge grouping for object detection by using new method. This new method helps in detecting contours under complex background when some of the contours of the object are missed during extraction of the contour. In this paper they have done 3 works: firstly on Turn Angle Probabilistic Sequence model (TAPSM) for shape (contour) of the image, secondly based on sequential search on TAPSM edge grouping is done, thirdly development of probabilities for linear discrimination weight in order to estimate similarity between the model and detected lines. This proposed method is implemented on remote sensing images.

Yun Wen Chen et al. [8], presented RFC a new feature invariant descriptor mainly used on planar shapes. Random

Composite Feature helps to extracts features using analysis on spectral and statistical. He told that, without using normalization the proposed system overcomes existing representation of shapes methods. He experimented on MPEG-7 dataset and shapes are retrieved using above method and also experimental results which keeps precision values above 85% for this dataset.

Objective

The main objective of this project is to design and implement a new shape signature (descriptor) which encompasses contour of the image, for 2D image retrieval. Based on given query as an image, the contour of an image will be extracted and the feature vector is to be determined and manipulated for the contour image. This will be considered to as Distance vector which will be used to retrieve similar images from large database. Moreover the descriptor must show invariance for rotation, scaling, and transform.

Segmentation Methodology

The methodology is based on contour-based shape feature, where an image is undergone a number of segmentation processes and based on final segmentation results contour is detected. Shape features are computed from this contour as shown in Fig.2.

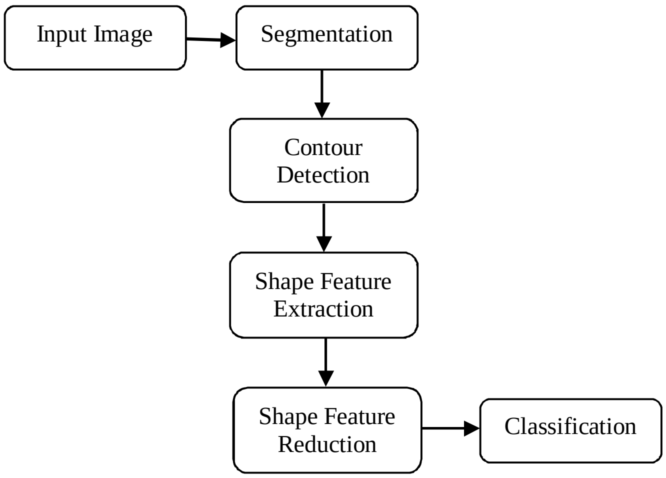


Fig 2: Flow diagram of Segmentation methodology

Segmentation

Segmentation is done to segregate the object of interest from the background. It refers to the process of partitioning an image into groups of pixels which are homogenous with respect to certain characteristics. Different groups should not overlap each other and neighboring groups must be heterogeneous. Segmentation methods are more oriented towards area than oriented towards pixels. The result of segmentation is the division of the image into connected areas. Segmentation divides an image into meaningful regions.
Images from the WANG [2] dataset are segmented in two steps. First every image goes through mean shift segmentation. To perform mean shift segmentation EDISON method [9] is used. Edge Detection and Image Segmentation (EDISON) System uses mean shift based segmentation method.

Edge Detection and Image Segmentation (Edison) System

EDISON has a graphical user interface, which makes the task of selecting and segmenting an image easier. On opening a new segmentation window we can load the image which needs to be segmented. Once the image is loaded we have to check the option Segment under operation and Overlay boundaries. The segmented result is shown in Fig.3. below:

Bhattacharya Coefficient

Once the initial segmentation is done by the mean-shift algorithm, many small regions are available. To merge small regions, these regions are to be defined using some descriptor. Here we describe the region using color histogram. The color histogram is computed using RGB color space.

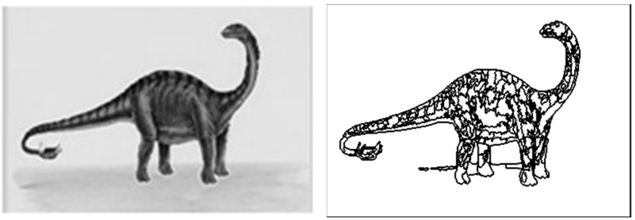


Fig 3: Initial Segmentation Result
(a) Original Image. (b) Segmented Image output

Histogram bins for RGB images are used for shape feature representation. The shape is calculated in terms of edges. Histogram bins selected are 16X16X16 so as to hold a large amount of image information. When a histogram bin is plotted it is easy to find out whether two histogram bins are similar in color or not. This similarity is found using one of the most absolute unbiased Bhattacharyya coefficient defined in the below equation 1:

$$\boldsymbol{\rho(P, P') = \sum_{i=1}^{N} \sqrt{P(i)P'(i)}} \quad \ldots\ldots 1$$

Where P(i) and P'(i) represent two bins in two different histograms shown in the equation 2, with probabilities P(i=1) to P(i=N) and P'(i=1) to P'(i=N). Since P(i) and P'(i) symbolize the probability distributions

$$\boldsymbol{\sum_{i=1}^{N} P(i) = \sum_{i=1}^{N} P'(i) = 1} \quad \ldots\ldots 2$$

The Bhattacharyya coefficient has a simple geometric interpretation as the cosine of the angle between N dimensional vectors. The equation 3(c) represents N dimensional vectors.

$$\boldsymbol{(\sqrt{P(1)} \ldots \sqrt{P(N)}\ )^T and (\sqrt{P'(1)} \ldots \sqrt{P'(N)}\ )^T} \quad \ldots\ldots 3$$

Thus, if the two distributions are identical, then cosine of angle between vectors is given in the equation 4

$$\boldsymbol{\cos(\theta) = \sum_{i=1}^{N} \sqrt{P(i)P'}} \quad \ldots\ldots 4$$

If the two bins are identical then the equation 5 holds good.

$$\boldsymbol{\cos(\theta) = \sum_{i=1}^{N} \sqrt{P(i)P'(i)} = \sum P(i) = 1} \quad \ldots\ldots 5$$

Thus consequently θ=0.
Now the user has to interact to recognize the object and the background so that the similar regions are merged. Here the Bhattacharyya coefficient is used to measure the similarity between the regions. When two regions are of similar content then their histogram will be very similar. Once the histogram are very similar, the Bhattacharyya coefficient is very high i.e. the cosine of the angle between them is very small. Hence the Bhattacharyya coefficient is simple and efficient method to represent the regions and similarity between them. Coupling the Bhattacharyya and maximal similarity rule the region merging process works well. The output image from the EDISON system is fed as input to the maximal similarity based region merging algorithm. It is an interactive method. The interactive information is markers. These markers are input by the users to approximately specify the position and main features of the background and object. The markers are simple strokes. The green color is used to mark the object and the blue color is used to mark the background. It has to be noted that only a small portion of the object and background regions are marked by the user. The less the marker by the input user, the more convenient and robust the algorithm is.

Hand-Drawn Markers
After the segmentation, the user has to specify the object and background by drawing some markers. The markers can be of strokes, curves, lines on the image. The pixels which are inside the object marker region are called object marker regions. The pixels inside the background marker region are called as background marker regions. Green color is used to mark the object and Blue color is used to mark the background. After marking the object and background each region will be identified as one of the three kinds of regions: the object region marker, the background region marker and the non-marker region. This automatic assigning of each of the non-marker regions with the correct label of either object or background region will completely extract the object contour. To guide the merging of the regions, the object is marked with green color and background is marked with blue color as shown in the Fig.4. Here 4(a) is the mean shift segmented image and 4(b) is the segmented image, which is marked with markers.

Fig 4: Hand-drawn Markers.
(a) Mean shift segmentation. (b) The interactive input by the user

To detect the object contour, each of the non-marker regions has to be automatically assigned with the correct label of either background region or object region. The marker background region is denoted by RB and the set of marker object regions is denoted by RO. The sets of non-marker region are denoted by N.

Maximal Similarity Merging Rule

As only the smaller portion of the object or background is marked by the user, it is challenging to detect accurately the contour of the object from the background. The marker acts as a seed and the starting point of the algorithm for merging and the non-marker regions are gradually labeled as either the region of object or background. In order to identify all the non-marker regions based on the input of object and background markers, the maximal similarity merging rule is used.

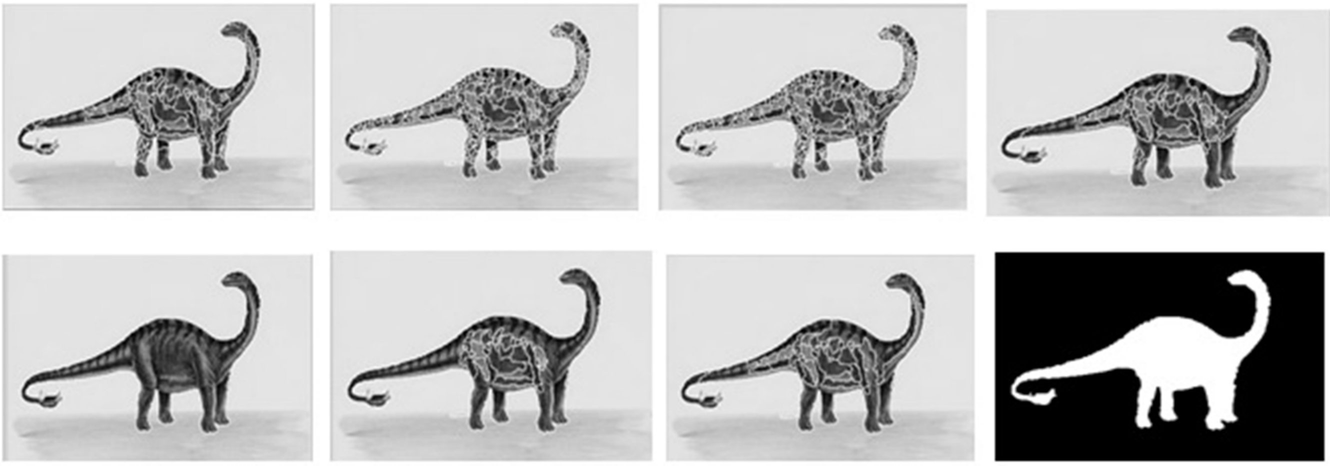


Fig 5: Region merging process

The merging strategy follows by linking of the quadrants from adjacent tiles, in the vertical and horizontal directions, is performed in three steps. First, quadrants in a tile are merged using the adaptive nested design strategy. Second is the horizontal linking that connects quadrants from adjacent overlapping tiles. Finally, column merging connects quadrants from vertically overlapping tiles as shown in Fig.5.

Then the similarity of different regions will be computed by the method and the regions will be merged based on the maximal similarity rule with the aid of the markers. Finally object can be extracted from the background once the merging process terminates.

Contour Detection

Fig 6: Contour Detection
(a) Segmented result by MSRM (b) Contour extracted.

Initially contour is detected from the segmented image followed by the region merging algorithm. The result is as shown in Fig.6 (a). Thus obtained image is subject to binarization and the contour is obtained as shown in Fig.6(b).
Boundary of an object could be an interior boundary or an exterior boundary. Interior boundary contains the pixels which belong to the object itself and the pixels of exterior boundary belong to the background. In other words, the exterior boundary of an object is identical to the interior boundary of the background [10]. Boundaries tend to correspond to object outlines rather than interior edges. This is necessary to detect a clear contour of the object.

Extraction Of Features

Extraction of features is one of the prerequisites of identification and recognition. There are some of features to be operated on contour of the image in order to retrieve. Features like area, bounding Box, perimeter, minor axis length, major axis length etc are used. This work involves some of algorithms for computing area, bounding box and perimeter as follows.

Area: The area indicates number of pixels on the contour. The area can be calculated based on contour of the image as shown in Fig.7 (a) and Fig.7 (b).

area_img= regionprops (edge_image).Area;

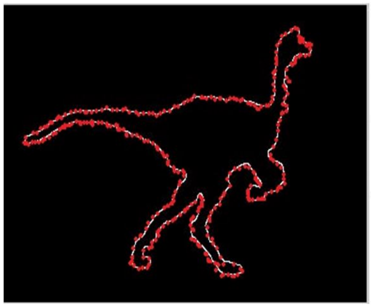


Fig 7(a): Area of the image.

Fig 7(b): Displaying Top 10 images based on area.

Bounding Box: This feature returns 1-by-p*2 the smallest rectangle consisting the region where p is the number of image dimensions. This can be computed as same as area feature as shown in Fig. 7(c) and Fig.7 (d).

bounding_box= regionprops (edge_image).BoundingBox;

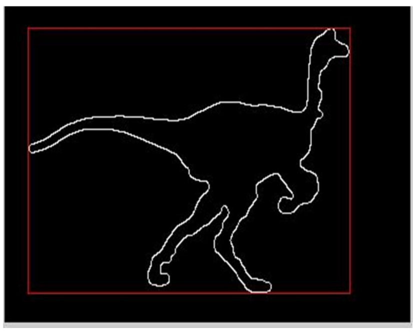


Fig 7(c): Bounding Box Image.

Fig 7(d): Displaying Top 10 images based on Bounding Box.

Perimeter: This feature gives back a scalar that determines the distance around the boundary of the image region. In other words it is the number of pixels along the exterior boundary of the object of interest. The regionprops calculate the perimeter by computing the distance between each connecting pair of pixels around the contour of the image region. This feature can be computed as shown in Fig. 7(e) and Fig.7(f).

perimeter_Img = regionprops (edge_image).Perimeter;

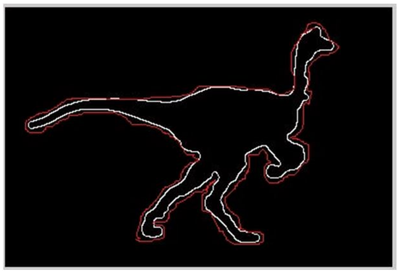


Fig 7(e): Perimeter Image

Fig 7(f): Displaying Top 10 images for perimeter.

Table 1: Elapsed time for Segmentation methodology

CLASS	Elapsed Time for Existing System using Euclidean Distance(in seconds)
	TOP 10
BUILDING	1.25
DINOSAUR	1.22
FLOWER	1.39

Non Segmentaion Methodology

In this paper, the image retrieval is based on operations on contour of the image.

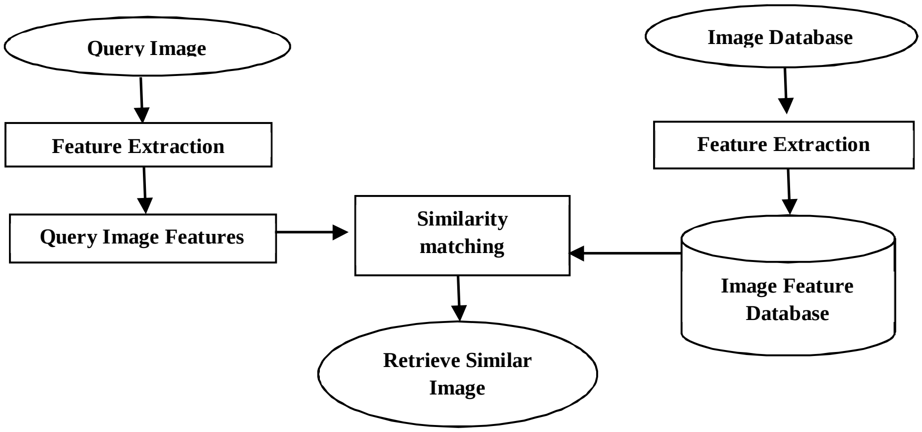


Fig 8: Flow Diagram Non Segmentation methodology.

The Fig.8 shows, Flow diagram of proposed system. In this system, a query image is given for that feature is extracted and it will be saving in filename.mat format in the database. Similarly the same features are extracted for all other images in the database. In similarity matching module, feature of query is matched with features of images from huge database. Once the matching is done, similar images are retrieved.

Boundary Extraction

Here contour of images can be get by applying morphology to images. Morphology involves

a. Dilation
b. Flood Fill and
c. Erosion.

Based on shapes (contours), morphology set process the images. In morphological operations, the estimation of each pixel in the result image (output) depends on an examination of the comparing particular given input recommended image pixel with its neighborhood.

DILATION

The main rule of this Dilation is the estimation of the output pixel is the maximum estimation of all other pixels in the input_pixel's neighborhood. In case of the binary image, output pixel is made to 1 if any of the pixels in the image is set to

the worth (value) 1. This operations as a rule uses a structuring elements for expanding and growing the shapes comprised in the input image. The image is made dilated in OpenCV with visual C++ as below:
dilate (canny_image, dilated_img,elementDilate);

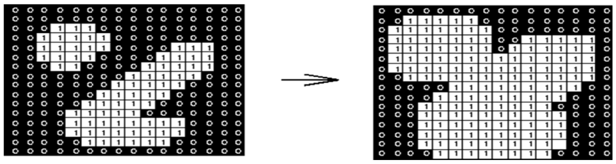


Fig 9: Effect of Dilation using 3X3 structuring element.

EROSION

This operation mainly highlights the boundary of the image with white pixels. The main rule of this operation on output image is the estimation of the output pixels is the minimum estimated value of all other pixels in the input_pixel's neighborhood. In the case of binary image, output pixel is made to 0 if any of the pixels in the image is set to worth (value) 0. Erosion operation on the image can be done in OpenCV with Visual C++ language is as follows:
erode (floodFilled, erode_img ,erode_img ,kernel);

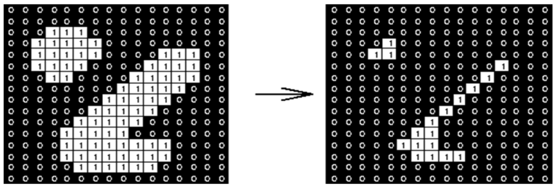


Fig 10: Effect of Erosion using 3X3 structuring element.

FLOODFILL

This operation is mainly done to fill the regions and holes that are detected in the dilated image. Flood fill is also termed as Seed Fill. This is an algorithm which chooses the area connected with a given node in array of multi-dimensional. This operation is used on the background pixel of the dilated image, beginning from points determined in locations. This is also termed as Boundary Fill, when this operation is applied on the image in order to fill the particular boundary area.
The dilated image is made flood filled in OpenCV with Visual C++ as shown in Fig.11.
floodFill (dilated_img , floodFilled, cv :: Point (0, 0), 0 , 0, cv ::Scalar(), cv :: Scalar (),8 + (255 << 8) + cv :: FLOODFILL_MASK_ONLY);

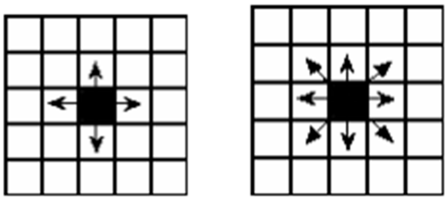


Fig 11: 4- way and 8-Way FloodFill.

In order to retrieve images based on contour of the image is given in algorithm below:
1. Read a query Image
2. Convert to gray scale and apply bilateral filter
3. Apply threshold
4. Apply Canny Edge-Detection Technique
5. Apply Dilation, FloodFill and Erode the image
6. To get contour Subtract Erode image from Flood fill image
7. Get centroid point of contour image
8. Apply Euclidean, Manhattan and Canberra distance formulas to store feature vector
9. Divide each feature vector by maximum of the respective distance
10. Get minimum and maximum distance values to set histogram range
11. Perform comparison between query image feature and rest of image features from database

12. Retrieve similar images.

(a) (b) (c) (d)

(e) (f) (g) (h)

Fig 12: Steps involved in extracting contour.(a) Original Image,(b) Filtered Image,(c) gray image,(d) Canny edge detected image,(e) dilated image,(f) flood filled image,(g) eroded image,(h) contour image of Class Dinosaur.

Some of the computations to be carried out on this contour image are done as follows:

Feature Space Set

Feature Space set is the quantitative in nature which is operated on Contour of the image to get certain values. Detecting Feature alludes to strategies that go for computation of abstractions of image data and at every point in the image making local decisions in order to indicate image feature of that type is present at that point or not. There are many feature are available to be performed on image such as area, bounding box, edges, region of interests (ROI), Corners , centre, eccentricities, energy, entropy etc. In this paper, feature is taken as **centroid**. Centroid is the geometrical point of the image means it is the centre point of the whole contour image. The centroid can be displayed in MATLAB as follows:

SysCentroid = regionprops (canny_image, 'Centroid');

The centroid point for the images is shown below in Fig.13 (a). for DINOSAUR Class and Fig.13 (b). for FLOWER Class. The centroid is different for diverse images.

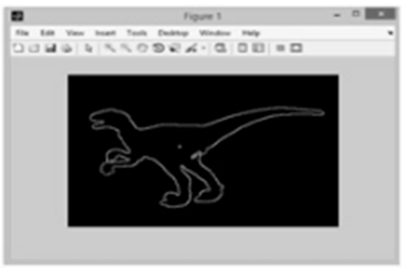


Fig 13 (a): Displaying Centroid point for Dinosaur Class

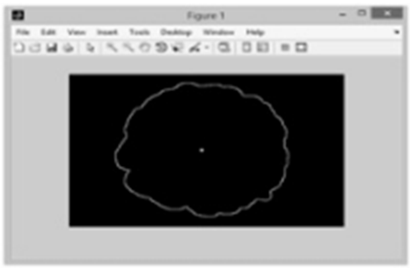


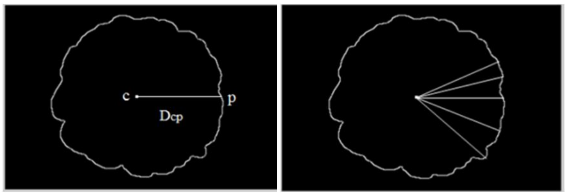
Fig 13 (b): Displaying Centroid Point for the Flower Class.

In this paper, the distance is calculated from centroid of the image to contour pixels in such a way that it covers all edges.

Euclidean Distance

This is well known straight line distance and it is the measure of the length of the line segment connecting two pixels. We are taking the contour image for shape analysis of the image; we calculate the distance by using Euclidean formula from centroid point of the contour image to the boundary pixel in such way that it covers all edges as shown in Fig.14. In this paper, we are going to analyze the contour by applying Euclidean formula for the class Flower if two pixels that are considered coordinate (X_1, Y_1) and (X_2, Y_2):

$$Dcp = \sqrt{(X1 - X2)^2 + (Y1 - Y2)^2} \quad \ldots\ldots 4$$



(a) From centroid (b) Centroid to Pixel on edges
Fig 14: Calculating Euclidean distance

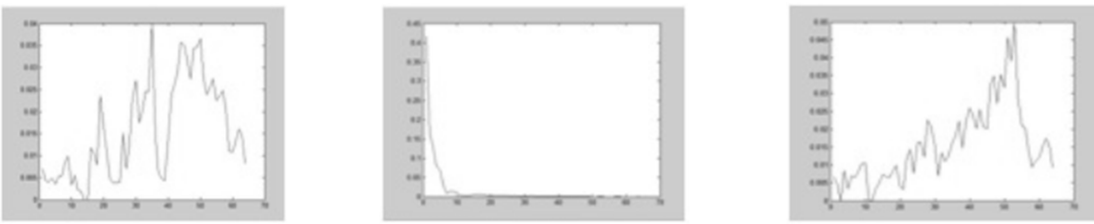
Canberra Distance
Canberra Distance is the scalar measure of the distance between the set (pair) of point in a Vector space. The procedure is same as above but only we need to change the formula of the Canberra Distance as follows:

Dcp = $sum(abs(x1 - y1)/(abs(x2 + y2)$ …………………………………………………………….5

Manhattan Distance
This Distance is also known as **City Block Distance**. This distance measure assumes that it is possible to travel directly along pixel grid lines in going from one pixel to next. Diagonal moves are not allowed. Here, by using this formula the distance is calculated as shown in above figure.

Dcp =$\sum(X1 - X2) + (Y1 - Y2)$ ……………………………………………………………….6

Histogram
Histogram is used to represent the distribution of numerical information in graphical manner. This is the estimation of probability distribution of the quantitative variable (termed as continuous variable). The histogram is plotted for feature values as shown below Fig.15.



(a) Euclidean Distance b) Canberra Distance (c) Manhattan Distance
Fig 15: Histogram representation using different distance measures.

Experimental Results
In this paper, the benchmark dataset Wang [2] is used to test on proposed system. This dataset consists of 1000 images and 10 classes. Each class has 100 images and contains African, bus, building, dinosaur, elephant, horse, flower, mountain, food, and beach. The result is taken for retrieval of Top_set 10, Top_set 15, Top_set 20 correct results. These results are taken for **Euclidean, Canberra and Manhattan distances**.
The experiment has been carried out on OpenCV in order to get contour of image followed by MATLAB (R2014 a version) to get feature vector and retrieve images.
Image retrieval by using Euclidean distance:

Top 10 Images:

Top 15 images:

Fig 16 (a): Displaying Top 10 images using Euclidean Distance.

Fig 16 (b): Displaying Top 15 images using Euclidean Distance.

Top 20images:

Figure 16 (c): Displaying Top 20 images using Euclidean Distance.

Image retrieval based on Canberra Distance.
For Top 10 images.

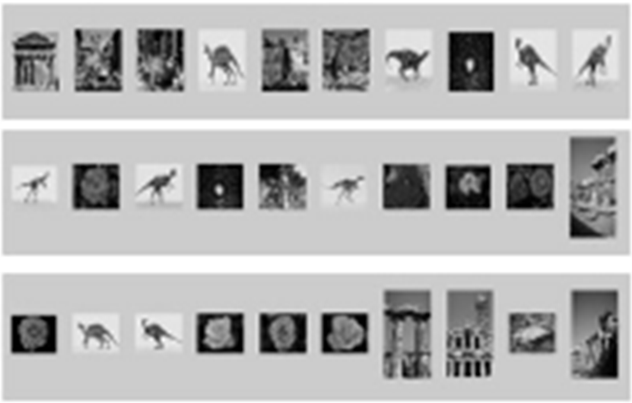


Fig 17: Displaying Top 10 images using Canberra Distance.

Image Retrieval based on Manhattan Distance.
For Top 10 Images.

Fig 18: Displaying Top 10 images using Manhattan Distance.

As per results compared from all three distance measures, Euclidean distance measure yields better .Manhattan yields average where as Canberra the worst. Even though different distance measures are used to retrieve images, thereby it indicates operations on contour images are very important step. Elapsed time of each retrieval for Top 10, Top 15, Top 20 images for Euclidean, Canberra and Manhattan distances respectively.

Table 2: Elapsed time for Euclidean Distance

CLASS	**Elapsed Time For Euclidean Distance(in seconds)**		
	TOP 10	TOP 15	TOP 20
BUILDING	0.73	0.89	1.10
DINOSAUR	0.71	0.91	1.08
FLOWER	0.72	0.93	1.10

Table 3: Elapsed time for Canberra Distance

CLASS	**Elapsed Time For Canberra Distance(in seconds)**		
	TOP 10	**TOP 15**	**TOP 20**
BUILDING	0.76	0.94	1.11
DINOSAUR	0.82	0.95	1.11
FLOWER	0.74	0.93	1.12

Table 4: Elapsed time for Manhattan Distance.

CLASS	**Elapsed Time for Manhattan Distance(in seconds)**		
	TOP 10	**TOP 15**	**TOP 20**
BUILDING	0.98	1.12	1.11
DINOSAUR	0.97	1.17	1.19
FLOWER	0.96	1.15	1.37

Precision and recalls are the basic measures used in evaluating search strategies. These both are based on an understanding and measure of relevance. Precision is the ratio of number of relevant images retrieved to the total number of irrelevant and relevant images retrieved.

$$\text{Precision} = \frac{Number\ of\ Relevent\ Images\ Retrieved}{Number\ of\ Irrelevant\ Images + Relevant\ Images\ retrieved}$$

Recall is the ratio of number of relevant images retrieved to the total number of relevant images in the database.

$$\text{Recall} = \frac{Number\ of\ Releveant\ Images\ retrieved}{Total\ number\ of\ relevent\ images\ in\ Database}$$

The precision and Recall curve is shown in below Fig.19.

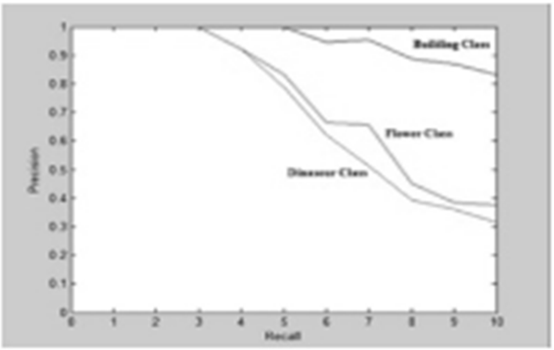


Fig 19: Precision v/s Recall Curve for a Proposed System.

Table 6: Precision and Recall For Euclidean Distance

Class	Precision Value			Recall Value		
	TOP 10	Top 15	TOP20	TOP 10	TOP 15	TOP 20
‘BUILDING’	100%	100%	90%	30%	50%	60%
‘DINOSAUR’	100%	93%	90%	30%	46.66%	60%
‘FLOWER;	100%	93%	90%	30%	46.66%	60%

Table 7: Precision and Recall For Canberra Distance

Class	Precision Value			Recall Value		
	TOP 10	Top 15	TOP20	TOP 10	TOP 15	TOP 20
‘BUILDING’	80%	73.33%	80%	26.66%	36.66%	53.33%
‘DINOSAUR’	80%	80%	70%	26.66%	40%	46.66%
‘FLOWER;	70%	60%	55%	30%	30%	36.66%

Table 8: Precision and Recall for Canberra Distance

Class	Precision Value			Recall Value		
	TOP 10	Top 15	TOP20	TOP 10	TOP 15	TOP 20
'BUILDING'	90%	80%	90%	30%	40%	60%
'DINOSAUR'	90%	73.33%	80%	30%	36.66%	53.33%
'FLOWER'	50%	40%	40%	16.66%	20%	26.66%

By these experimental results, for a non segmentation method we can say that the Euclidean Distance is the best method for matching similarity in retrieval of image and takes less computational time when compared to segmentation method as well as it gives better performance.The procedure that is followed in order to extract the contour of the image for segmentational method is too lengthy with poor retrieval of images.This problem is overcome by applying centroid feature for a non segmentation method and yeilds better retrival of images.

Acknowledgement

I would like to thank **Dr. Jagadeesh Pujari**, Head of Department, Information Science & Engineering, SDMCET, Dharwad for his valuable suggestions and expert advice. I would also like to thank my students Dharmveer Choudhary, Shruthi Haveri and Soumya M, 6th semester students of Information Science & Engineering, SDMCET, Dharwad for the support towards completing paper work.

Conclusion

In this paper, we implemented a new shape descriptor for non segmentation method which is used to calculate feature vector for both query image and images from huge database. Using different distance measures such as Euclidean, Canberra and Manhattan query image is matched with other images from database and images are retrieved for non segmentation method. This novel descriptor takes less computational time and yields better performance compared to segmentation method as well as overcomes the problems with invariance such as scaling, rotation and translation. We mainly used L1 norm of histogram for image retrieval in non segmentation method.

References

[1] http://www/eie.polyu.edu.hk/`enhchan/imagesf.pdf.
[2] http://wang.ist.psu.edu/doc/related.
[3] Roshi Choudhary, Nikita Raina, Neeshu Chaudhary, Rahmi Chauhan , Dr, R.H Goudar ,"An Integrated Approach to Content Based Image Retrieval", ICACCI - 2014
[4] Irina Mocanu ,"Image Retrieval By Shape Based On Contour Techniques A Comparative Study", 4th International Symposium on Applied Computational Intelligence and Informatics, 2007, 219-223.
[5] A.M. Patil, Reshma Choudhary, "Content Based Image Retrieval Using Color and Shape Features", International Journal of Advanced Research in Electrical and Electronics and Instrumentation engineering, Vol 1, Issue 5, Nov -2012.
[6] P.Bhuvaneshwari,Preeti D'Silval, "Various Shape Descriptors in Image Processing- A Review" , IJSR, ISSN: 2319 7064, 2013.
[7] Lei Ma,Bitao Jiang, " Edge Grouping With A Novel Shape Model For Object Detection", 7th International Conference on Image and Graphics , 2013.
[8] Yun Wen Chen, Yan Qiu Chen, "Invariant Description and Retrieval Of the Planar Using Radon Composite Features", IEEE Transactions Signal Processing, Vol 56, 2008.
[9] Tanjinder Kaur, Harsirman Singh, "Novel Method for Edge Detection For Gray Scale Images using VC++ environment" , International journal of advanced computer research, Volume-3, Issue-13 December-2013,Number-4, ISSN (print): 2249-7277
[10] C. Christoudias, B. Georgescu, P. Meer, "Synergism in Low Level Vision", Intl Conf on Pattern Recognition, 2002, 4, pp. 40190
[11] B.Chanda, D. Dutta Majumder, "Digital Image Processing and Analysis", PHI Learning.