Survey of Shape Based Boundary Methods for Leaf Retrieval

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Abstract. With explosive growth of plant species, it is becoming difficult for the botanists to manage the details of leaf. Moreover, extracting the specific leaf from the huge collection is a big job. Hence, an effort is done so as to help the botanists identify the specific leaf. The basic approach for leaf identification is based on textual information. But the effort involved in manual annotation is comparatively tedious and moreover it is impossible to represent the vast features of the image in limited keywords. Fundamentally, the identification of a plant is based on leaf. We present a summary of different boundary based methods for image retrieval of leaf. The methods have been explored for maple leaf and advantages and disadvantages have been highlighted.

Keywords: Image Retrieval, Image Processing, Leaf Identification, Boundary Based Identification, Shape Representation.

1 Introduction

With the emergence of multiple digital devices like cameras, mobiles etc, there have been a huge collection of digital images. However, this ever increasing digital collection has put forth a challenge for image retrieval. For image retrieval, textual annotation could be a possible option. But the issues like manual annotations and incomplete representation makes textual representation ineffective. Another option which defines retrieval based on image features is referred to as Content Based Image Retrieval (CBIR) CBIR provides retrieval based on image details like color, texture, color layout and shape. Considering human perspective, shape is a strong descriptor of image features.Shape is probably the most important property that is perceived about objects. Shape allows predicting more facts about an object than other features, e.g. colour. Thus, recognizing shape is crucial for object recognition. In some applications, it may be the only feature present which would help in recognising the shape e.g. logo recognition. Elaborate work has been proposed for many applications like face recognition, iris recognition, fingerprint recognition.

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The main focus of this paper is on image retrieval based on shape for identification of leaves. Looking into the surroundings, there exist millions of varieties of plant species. Managing this huge information in digital format requires lot of efforts. However, it has been explored that identification of leaf is very helpful in recognizing the plant. But identification of leaf is not an easy task. The reason behind this is that the contour of a leaf remains the same for same species. So besides contour, it is important to get into the interior details of leaf for recognizing the leaf appropriately.

For efficient retrieval, it is important that shape representation should be invariant of basic transformations and should be able to deal with noise. The effectiveness of shape based image retrieval system depends on the features used for representing the shape, the type of queries and the effectiveness of shape matching strategies. The steps required for shape based image retrieval are:

a) Convert image into binary form.
b) Use suitable edge detectors to extract edges from binary image.
c) Represent edges as feature vectors.
d) Match feature vector of query to that of database images to generate similar set of images.

In above steps identified, third point defines shape representation and fourth point defines shape matching. An effective shape representation is helpful in visual image information representation.

2 Classification and Approaches of Shape Representation

Shape representation can be classified into: Boundary Based Image Representation and Region Based Image Representation. Boundary based approach helps in representing information of image only at boundaries whereas region based approach represents details of image, including the interiors of the contour.

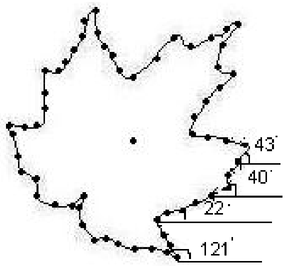
Various papers have been referred in context to Shape Based Image Retrieval for different applications. The approaches have been analysed and implemented for identification of leaves.

2.1 Tangent Angle Approach

In this approach, the image is broken into line segments and the curvature of the line segments is measured at the boundary points[1]. The tangent angle function at any point $P(x_n,y_n)$ is defined by the tangential direction of the contour. The formula for tangent angle approach is as follows:

$$\theta_n = \frac{y(n)-y(n-w)}{x(n)-x(n-w)}$$

where w is the small window to calculate tangential angle θ_n accurately. The tangential representation can be done by generating a plot of the length of the segment along the x-axis and the curvature of the segment along the y-axis.[2]



The image shows the boundary points highlighted. Thereby, at the boundary points, moving anticlockwise, tangential vectors are drawn and angles are measured. Also the distance between the consecutive points is measured.

Thus, the values are in the form of magnitude and angles, when started referring anticlockwise is as follows:

$$50\angle 121^{\circ},\ 33\angle 22^{\circ},\ 21\angle 40^{\circ},\ 31\angle 43^{\circ}$$

This method is able to maintain the details of the shape boundary by accumulating the values of curvature and magnitude [3]. To make the approach rotation invariant, cumulative angular function is calculated as follows:

$$\text{Cumulative Angular Function} = \theta(n) - \theta(ref)$$

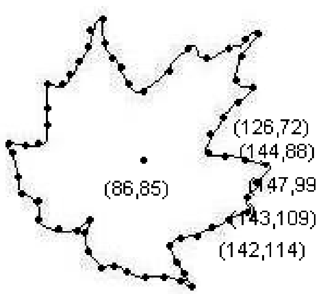
where $\theta(n)$ is the angle measured at the shape boundary and $\theta(ref)$ is the reference angle value. The additional advantage of this approach is that it is possible to regenerate the shape by reading the magnitude and angle values. The approach is scale, rotation and position invariant and the computational complexity is low.

2.2 Triangle Area Representation

In this method, the area is computed from the area of triangle formed by taking into consideration three consecutive boundary points [4]. The area is useful to calculate the curvature of the boundary shape.

Let the consecutive boundary points be $P_{n-ts}(x_{n-ts}, y_{n-ts})$, $P_n(x_n, y_n)$ and $P_{n+ts}(x_{n+ts}, y_{n+ts})$ where n belongs to [1,N] and t_s belongs to [1,N/2 -1] is even. Thus the area for these consecutive points would be given by:

$$TAR(n, t_s) = \frac{1}{2}\begin{vmatrix} x_{n-ts} & y_{n-ts} & 1 \\ x_n & y_n & 1 \\ x_{n+ts} & y_{n+ts} & 1 \end{vmatrix}$$



where the boundary points are traversed in clockwise direction and the values of TAR help to judge the contour. Positive TAR values refer for convex, negative TAR values refer for concave and zero values for straight line.

The array of the concave, convex and straight lines helps to understand the curvature of the boundary. A matrix is generated by taking 3 consecutive boundary points in anticlockwise direction and determinant value is calculated.

Mathematically,

$$TAR(, t_s) = \frac{1}{2} \begin{vmatrix} 142 & 114 & 1 \\ 143 & 109 & 1 \\ 147 & 99 & 1 \end{vmatrix}$$

= 142(109-99)-143(114-99)+147(114-109)
=142*10-143*15+147*5
=1420-2145+735=10(+ve value)

The value of the determinant helps to judge that the curve generated by the combination of 3 points(142,114) (143,109) and (147,99) is a convex curve. In this way, the complete shape is analyzed to be defined in the form of concave, convex or straight line and the output is an array of concave, convex and straight line representing the boundary. The method is scale, translation and rotation invariant [5].

2.3 Adaptive Grid Resolution (AGR)

In AGR, a square sufficient enough to cover the whole image is considered and overlaid upon the image [6]. The resolution of the grid cells varies from one portion to another according to the content of the portion of the shape. The interior dense portion of the image requires the higher resolution, thus smaller grids are required to represent the boundary whereas the areas of the image with coarser regions are represented with relatively big grids.

To represent the AGR image, quad tree is applied. Each node in the quad tree covers a square region of the bitmap. The level of the node in the quad tree determines the size of the square. The internal nodes represent ‘partially covered’ regions.

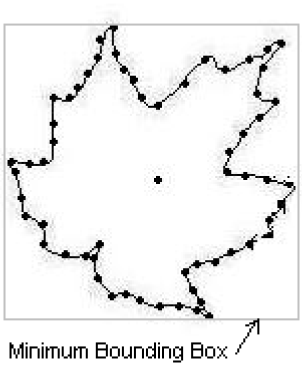


Image 1

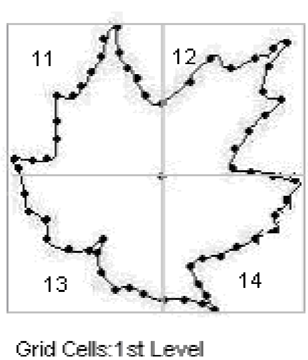


Image 2

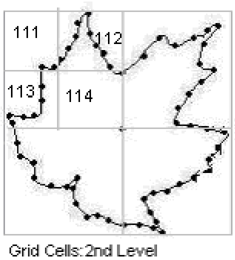


Image 3

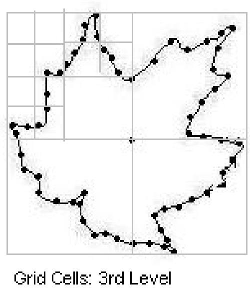


Image 4

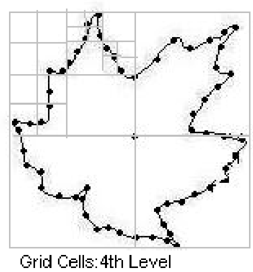
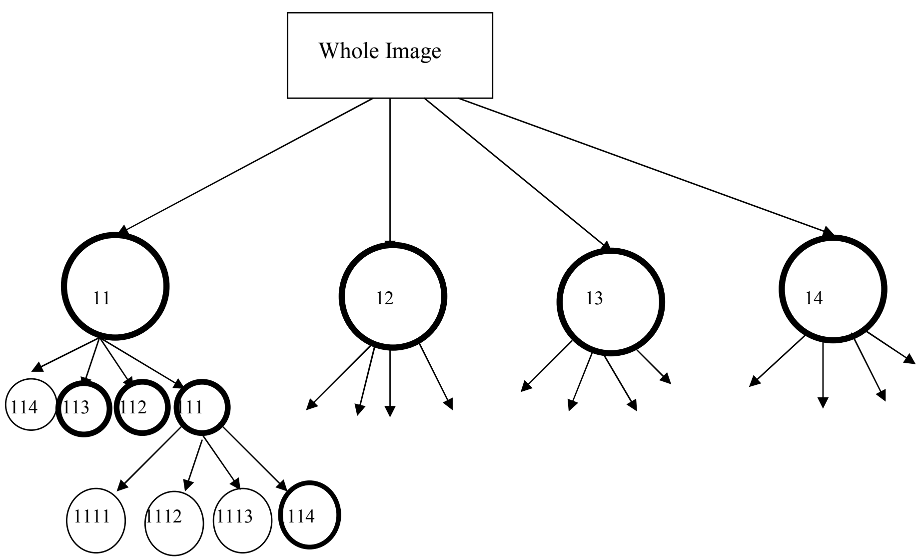


Image 5

As shown in the above sequence of the leaf images, the Image 1 depicts the image represented using minimum bounding box and a centroid at the centre. The Image 2 depicts the image represented as a grid of 4 cells. The centre of the bounding box is defined using centroid. The Image 3 depicts the grid cells further refined. Here grid 11 is segmented into four grids 111,112, 113 and 114. At the next level of defining grid cells, only those grid cells are sub-divided where the boundary pixels are prominent. The cell 114 need not to be divided as there are no pixels in the cell. In Image 4, the cell 111 is further divided into 1111, 1112, 1113 and 1114. Cell 112 is further into 1121, 1122, 1123 and 1124.The sub-division into further grid cells manages the accuracy of the depiction of data. Below a quad-tree has been generated using the grid based representation. Only those nodes are darkened where there is existence of pixels in the grids.



This approach is translation, scale and rotation invariant and the computational complexity is also low. This approach is important where the image boundaries are required to be explored in great details.

2.4 Bounding Box Approach

Bounding box approach computes homomorphism between 2D lattices and its shapes. To make bounding box, first the shape is normalized [7]. Then the image is broken into n columns, such that the dimensions of the columns overlap the image exactly, thus chopping the extra dimensions of the columns. The column segmented image is superimposed by m rows. The row dimensions are chopped which extend beyond the image. Then bounding box of each resulting pixel is calculated.

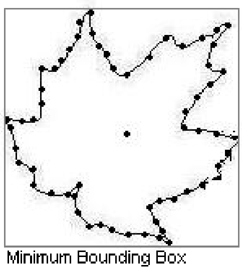


Image 1

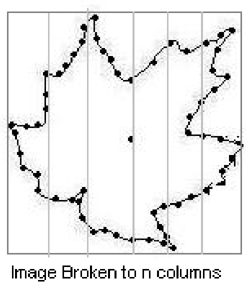


Image 2

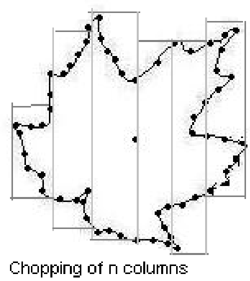


Image 3

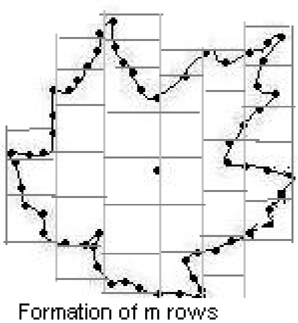


Image 4

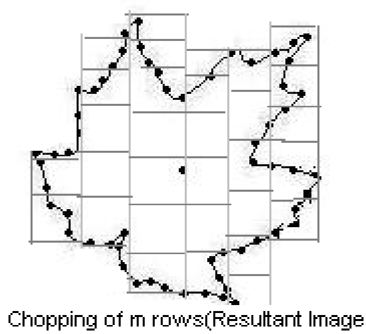


Image 5

The images above show the implementation of the bounding box method. Image 1 shows the bounding box for the image. The Image 2 is broken into n columns. The Image 3 shows the columns being chopped depending on the image boundaries. The Image 4 depicts the image segmented into m rows. Thus boundary box representation is a simple computational geometry approach to compute homomorphism between shapes and lattices. It is storage and time efficient. It is also invariant to rotation, scaling and translation invariant and has relatively higher computational complexity[11].

2.5 Directional Fragment Histogram (DFH)

A generic shape descriptor is computed using the outline of a region. The contour is defined to be formed of m elementary components. These elementary components are merged to form line segments having approximately same slope [8]. Thus the elementary components can be line segments or pixels. The computational details of the method are as given below:

Contour C= $ec_1, ec_2, ec_3, ec_4, ec_5 \ldots\ldots\ldots\ldots ec_n$
where $ec_1, ec_2, ec_3, ec_4, ec_5 \ldots\ldots\ldots\ldots ec_n$ are elementary components.
Segment 1= ec_1, ec_2, ec_3
Segment 2= ec_4, ec_5, ec_6

....
Segment n= $ec_7, ec_8 \ldots\ldots\ldots\ldots ec_n.$

Thus the contour is identified as combination of line segments which are represented as:

Contour C= Segment 1 , Segment 2, Segment 3……. Segment n . Such groups are called directional fragments[10].

Image 1 shows the elementary components. Image 2 represents the image as segments (red) and vertices (blue).The relative lengths of the individuals segments and their relative angles are calculated. The values can be tabulated as, magnitude of length of line segments along x-axis and angle between the line segments along y-axis where the angles are merged into 8 directions.

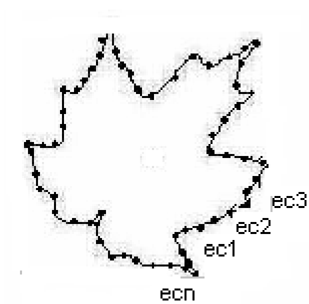


Image 1

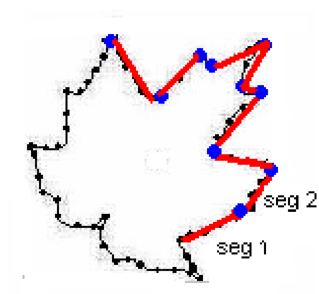
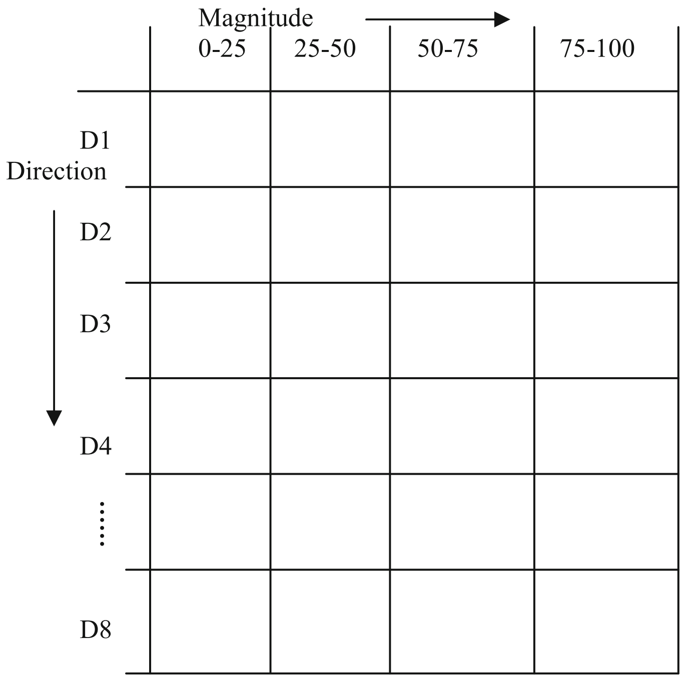


Image 2

Directional Fragment Histogram provides two kinds of information. At local level, it codes the relative length of elementary components within a given segment. At global level, DFH codes the elementary component's frequency distribution. The advantage of this method is that relative directions allow the representation to be rotation invariant by focusing on only directional changes.



To make the approach scale invariant, the length of the segment should be represented as ratio of the length of the segment to the total length of the contour. The drawback of the approach is that it approximates the directional values and hence does not capture accurate information like Chain code.

3 Summary and Conclusion

Several image retrieval methods have been discussed and their advantages and disadvantages of each have been mentioned after analyzing the methods in detail. For any boundary based shape representation, it is important that the description should be translation, scale and rotation invariant and should handle noise effectively. Feature vectors extracted to represent the shape boundary should be stored in such a manner that it reduces space complexity but improves efficiency in image retrieval. We can say that it is a process of making a trade-off between space and effectiveness.

Summarizing the results, we come to the conclusion that the tangent angle approach is an accurate approach for representing information. But it is too tedious to calculate the angles at each pixel and would also increase the space complexity. The triangle area representation makes a good representation of boundary contours in the form of concave, convex and straight line and overcomes the drawback of tangent angle by reducing the space complexity though both the methods are affine invariant. Adaptive Grid Resolution method has the advantage of matching the shape contour iteratively, grid wise. Thus, it's possible to match the shape contour at each level depending on the level of the accuracy required. Boundary box approach segments the image contour into small cells and is highly space and time efficient. Directional Fragment Histogram approximates the direction and magnitude values representing the boundaries.

Among the approaches discussed above, it is impossible to identify a method which can be defined as perfect for boundary representation, as every method represents the processing of pixels coordinates in an exclusive way. Moreover, the effectiveness of any approach depends upon the complexity of the leaf image.

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