

# A Voronoi based Shape Analysis for Image Comparison

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**ABSTRACT:** Geometric structures like contours and skeletons are useful in shape analysis. An incremental Voronoi vertex labelling algorithm are used for curve reconstruction, medial axes and dominant points (DPs) detection from non-uniform and possibly sparse data, sampled from the barriers of geometric objects. It can handle set of curves, outliers and sharp corners. The proposed system uses the concept of shape matching to improve the system performance. The system takes an input image which have some variations from the original image. By taking the dominant points our approach can able to say there is a matching or not. The system have high efficiency than the existing system.

**KEYWORDS:** Shape Analysis, Voronoi Diagram, Delaunay Triangulation, Computational Geometry, Medial axis, 2D point sets, Shape Reconstruction, Modelling, Curves and Surfaces, Dominant Points, Curve Reconstruction.

## I. INTRODUCTION

Recouping shape representations of an object from its boundary samples is a difficult task in variety of fields like computer graphics, computer vision and computational geometry. There are different kind of representations such as curves and skeletons, evolved from the point set, provide treasured perceptive of geometry of the analogous object. Such geometric systems have an important function in shape analysis, through advancing the computational performance and minimizing the storage specifications.

The proposed system uses a integrated Voronoi based architecture for curve reconstruction, medial axes and dominant points (DPs) detection from non-uniform and sparse data, sampled from the boundaries of geometric objects. Figure 1 shows the proposed framework having various shape representations sampled alongside the shape of a fish. Our shape representations vary from accurate polygonal curves (Figure 1a) extent the input points to DPs polygonal approximations (Figure 1c) which attains high-degree of data compression. Additionally, further approximates medial axes (Figure 1b) of the object from its input samples.

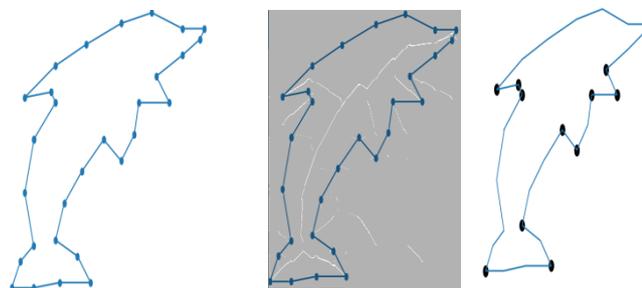


Figure1 (a)

(b)

(c)

Output of Curve Reconstruction(a),Medial Axis(b),Dominant Points(c)

An incremental Voronoi vertex labelling algorithm is introduced to extract those shape representations from points sampled along the simple closed curves. A hypothetical evaluation of the incremental labelling algorithm for smooth curves is given below non-uniform sampling method. Here the system is capable of reconstructing objects with outliers, sharp corners, collection of curves and works with sparse data.

Dominant points are also used for shape matching. The concept of shape matching is introduced to increase the improve the system performance.

Paper is organized as follows. Section II, describes the survey on the various shape representation methods. In Section II, the proposed method is presented. In Section IV, the implementation of the proposed method. Experimental results are presented in Section V. Finally, Section VI concludes the research.

## II. RELATED WORK

### CURVE RECONSTRUCTION

Fernando de Goes et al [1] introduced a robust 2D shape reconstruction and simplification algorithm. Here the input is a defect-laden point set with noise and outliers. They introduced an optimal-transport driven approach where the input point set is considered as the sum of uniform measures on 0- and 1-simplices. A fine to coarse scheme is developed to construct the resulting structure through the greedy decimation of a Delaunay triangulation of the point set. The proposed method performs well with line drawings to grayscale images, with or without noise, features, and boundaries.

Jun Wang et al [2] introduced a robust algorithm for reconstructing the 2D curve from unorganized point data with a high level of noise and outliers. By constructing the quadtree of the input point data, grid-like boundaries of the quadtree can be extracted, and smoothen the boundaries using a modified Laplacian method. Then the skeleton of the smoothed boundaries is computed and hence the initial curve is generated by circular neighboring projection. After that, a normal-based processing method is applied to the initial curve to get smooth jagged features at low curvatures areas and recover sharp features at high curvature areas. As a result, the curve is reconstructed accurately with small details and sharp features can also be preserved.

Subhasree Methirumangalath et al [3] introduced a reconstruction problem to compute a polygon which best approximates the geometric shape induced by a given point set,  $S$ . The input point set can either be a boundary sample or a dot pattern. A Delaunay-based, unified method for reconstruction is proposed irrespective of the type of the input point set. From the Delaunay Triangulation (DT) of  $S$ , exterior edges are iteratively removed subject to circle and regularity constraints to obtain a resultant boundary which is termed as ec-shape and it is similar to a simple closed curve. The time and space complexities of the algorithm is  $O(n \log n)$  and  $O(n)$  respectively, where  $n$  is the number of points in Set  $S$ .

Jiju Peethambaran et al [4] introduced a fully automatic Delaunay based sculpting algorithm for approximating the shape of a finite point of set  $S$ . The algorithm outputs a relaxed Gabriel graph (RGG) that consist of most of the Gabriel edges and a few non-Gabriel edges induced by the Delaunay triangulation. Holes are characterized through a structural pattern called body-arm formed by the Delaunay triangles in the void regions. RGG is created through an iterative removal of Delaunay triangles subjected to circumcenter (of triangle) and topological regularity constraints. This algorithm doesn't require tuning of any external parameter to approximate the geometric shape of the point set and hence human intervention is eliminated.

Jiju Peethambaran et al [5] proposed a Voronoi based algorithm for closed curve reconstruction. The algorithm computes one of the poles (farthest Voronoi vertices of a Voronoi cell) and hence the normals at each sample point by drawing an analogy between a residential water distribution system and Voronoi diagram of the given input samples. The algorithm then categorize Voronoi vertices as either inner or outer concerning the original curve and subsequently construct a piece-wise linear approximation to the boundary and the interior medial axis of the original curve for a class of curves having bi-tangent neighborhood convergence (BNC). The algorithm can reconstruct sparsely and non-uniformly sampled curves with sharp corners, outliers, and a collection of curves.

S.Ohrhallinger et al [6] proposed areconstruction algorithm. This algorithm manages the distance between geometrically consecutive points. The algorithm is based on local feature size and developed as a minimum local feature size along intervals between samples. HNN crust algorithm is used. The reconstruction algorithm works by connecting the nearby points. The new sampling condition, smooth curves can be reconstructed from even fewer points, typically half of the state-of-the-art bound, in the limit roughly one third.

Amal Dev Parakkat et al [7] proposed an algorithm for curve reconstruction. Here a novel non-parametric curve

reconstruction algorithm based on Delaunay triangulation has been introduced and it has been theoretically proved that the proposed method reconstructs the original curve under  $\varepsilon$ -sampling. Starting from an initial Delaunay seed edge, the algorithm starts by finding an appropriate neighboring point and adding an edge between them. The proposed algorithm is capable of reconstructing curves with different features like sharp corners, outliers, multiple objects, objects with holes, open curves, etc.

Subhasree Methirumangalath et al [8] proposed a hole detection technique in a planar point set. Outer boundary detection (shape reconstruction) is an extensively studied problem whereas, inner boundary (hole) detection is not a well-studied problem because detecting the presence of a hole is itself a difficult task. The proposed method uses a Delaunay triangulation based strategy to detect the presence of holes and an algorithm to reconstruct them. This algorithm is a unified one that reconstructs holes, both for a boundary sample (points sampled only from the boundary of the object) as well as for a dot pattern (points sampled from the entire object). Also, the method is a non-parametric one that detects holes irrespective of its shape.

Parakkat et al [9] proposed a Delaunay triangulation based algorithm to compute a polygonal approximation of the curve. The process starts by removing the longest edge of each triangle into a resulting graph. Further, each vertex of the graph is checked for a degree constraint to compute simple closed/open curves. Assuming  $S$ -sampling, we provide a theoretical guarantee which ensures that a simple closed or open curve is a linear approximation of the original curve. The proposed method handles the input point set without outliers, identifies the presence of noise in a noisy point set. The algorithm can also be able to detect closed or open curves, disconnected components, multiple holes, and sharp corners. S. Ohrhallinger et al [10] proposed a "fit connect" which is a reconstructing algorithm used for manifold reconstruction. FITCONNECT algorithm is based on the HNN crust algorithm. Extending the HNN crust algorithm by identifying the nearest neighbor to handle samples polluted by high noise extents. Additionally, it simplifies the output curve without losing features and denoises it. The fit connect algorithm extends HNN-CRUST seamlessly to connect both samples with and without noise, performs as local as the recovered features and can output multiple open or closed piece-wise curves.

### Medial Axis

The medial axis is (the closure of) the set of points in  $O$  that have at least two closest points on the object's boundary  $\partial O$ . In 2D, the MA of a plane curve is the locus of the centers of circles that are tangent to curve in two or more points, where all such circles are contained in  $O$ . This structure is defined for objects of 2D and higher dimensions. The skeleton is a concept closely related to the MA. MA is a powerful shape descriptor used in shape analysis and for feature extraction. Shape approximations can also be done using the Medial axis.

Joachim Giesen et al [11] proposed a Voronoi edge algorithm. The algorithm starts by labeling the vertices of the Voronoi diagram of the set of sample point  $S$  of the smooth boundary of a planar shape  $O$ . For the classification we use a curve reconstruction algorithm that picks Delaunay edges from the Delaunay triangulation of  $S$  that connect the points in  $S$  in the same way as they are connected along  $\partial O$ . The algorithm proves that the medial axis of the union of Voronoi balls centered at Voronoi vertices inside  $O$  has a simple structure than a general union of balls.

Yanshu Zhu et al [12] proposed a system for computing the medial axis transform of an arbitrary 2D shape. The instability of the medial axis transform can be overcome by using a pruning algorithm guided by a user-defined Hausdorff distance threshold. The stable medial axis transform can be approximated by using spline curves in 3D to produce a smooth and compact representation. These spline curves are computed by minimizing the approximation error between the input shape and the shape represented by the medial axis transform. A noise pruning algorithm for the medial axis transform can also be proposed and integrated into the framework. This noise pruning algorithm filters noise in the medial axis transform robustly and provides a good initial medial axis transform for optimization in our framework.

Pan Li et al [13] proposed a method to compute a medial axis transform. They introduced an efficient method, called Q-MAT, that uses quadratic error minimization to compute a structurally simple, geometrically accurate, and compact representation of the MAT. They introduced a new error metric for approximation and a new quantitative characterization of unstable branches of the MAT, and integrate them in an extension of the well-known quadratic error metric (QEM) framework for mesh decimation. Q-MAT is fast, removes insignificant unstable branches effectively, and produces a simple and accurate linear approximation of the MAT.

Dominant Points

The dominant point or corner point is a popular notion in pattern recognition, especially in shape representation. The most critical role of dominant points is that they are partitioning points for the decomposition of a curve into meaningful parts. Dominant Points (DP) focussed on the highly compressed linear approximation that best approximates the input shape. A dominant point on a curve has local maximum curvature. Detection of the dominant point results in better shape approximation.

Wen-Yen Wu [14] proposed the system for dominant point detection. Here an improved method is used for determining the region of support in the dominant point detection. Instead of setting the regions of support for points independently, the region of support dynamically depending on the previous region of support. The breakpoints are considered as the candidates of dominant points, it will reduce the computation time on both the determination of supporting region and curvature estimation. The method is insensitive to noise and it is robust on the scale and orientation changes.

Majed Marji et al [15] proposed a new algorithm for detecting dominant points and polygonal approximation of digitized closed curves is presented. It uses an optimal criterion for determining the region of support of each boundary point, and a mechanism for selecting the dominant points. The algorithm does not require an input parameter and handle shapes that contain features of multiple sizes efficiently. Also, the approximating polygon gives the symmetry of the shape.

D.S Guru et al [16] proposed a novel boundary-based corner detection algorithm. The proposed method computes an expected point for every point on a boundary curve. A new 'cornerity' index for a point on the boundary curve is the distance between the point and its corresponding expected point. The larger the cornerity index, the stronger to prove that that the boundary point is a corner point. A set of rules is worked out to guide the process of locating true corner points. The proposed approach is invariant to image transformations like rotation, translation, and scaling.

Asif Masood [17] proposed an algorithm for polygonal approximation based on dominant point (DP) deletion. The proposed algorithm initially takes all the breakpoints and starts eliminating one by one until the required level of approximation is obtained. First of all, a local optimization of a few neighboring points is performed after each deletion. Although the algorithm does not guarantee to get an optimal solution, the combination of local and global optimization is expected to produce optimal results. The algorithm is extensively tested on various shapes with varying numbers of DPs and error thresholds. It incorporates both local and global optimization which results in a very high quality of results.

J peethambaran et al [18] introduced an Incremental labeling of Voronoi vertices for shape reconstruction. It is a unified framework capable of extracting curves, medial axes and dominant points (DPs) from non-uniform and possibly sparse data, sampled from the boundaries of geometric objects. The algorithm computes the normals at each sample point through poles and use the estimated normals and the corresponding tangents to determine the inner and outer location of the Voronoi vertices concerning the original curve. The vertex classification helps to construct a linear approximation to the object boundary and the interior medial axis of the original curve. Extreme curvature portions induce specific labeling patterns of the Voronoi diagram and these labeling patterns are utilized to identify dominant points on the input curve. It can handle a collection of curves, outliers and shape corners.

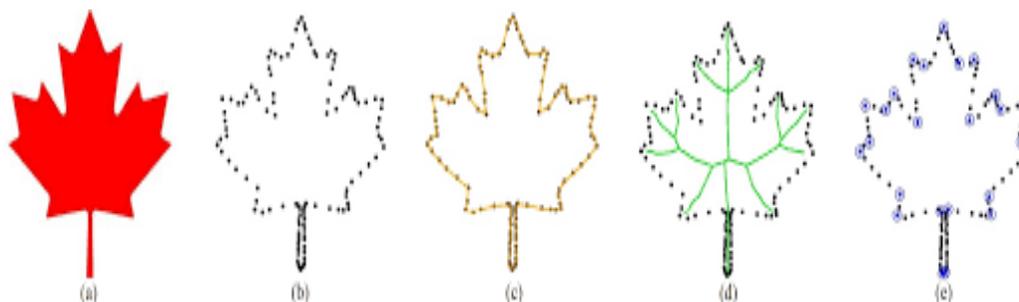


Fig 2.1: (a).Representative image (b).point set (c).reconstructed curve (d).medial axis (interior) (e).dominant points (Image courtesy [18])

### III. PROPOSED SYSTEM

#### 3.1 SYSTEM ARCHITECTURE

Developed an incremental voronoi based algorithm for reconstructing curves, medial axis and detection of dominant points. It can manage collection of curves, outliers, sharp corners, reconstruct curves with sparse data. The extracted Medial axis have high approximation quality. Here the approximation quality is constrained by sampling density of point set and the flatness of the original shape. It is equipped for distinguishing Dominant Points (DPs) at particular positions on the shapes and subsequently, producing polygons that hold the morphology of the shape with a plausible precision. The concept of shape matching is analysed by using dominant points, i.e. by taking an image and flipped image, we can say that there is a matching or not.

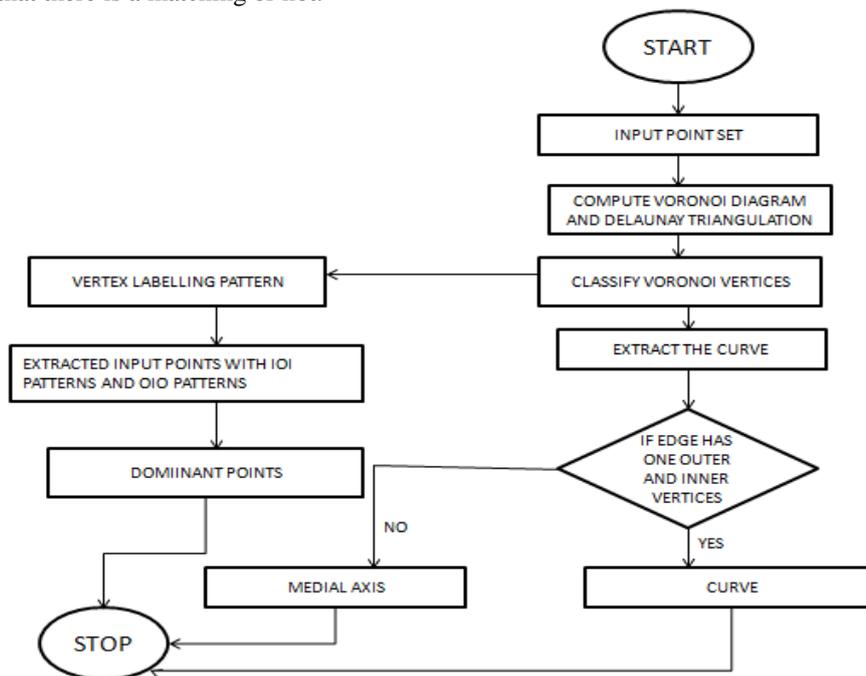


Fig 3.1: System overview of Shape analysis

Here the Fig 3.1 represents the overall design of the shape analysis. In the Input set the voronoi diagram is constructed. After that the shape is approximated, curve is reconstructed. Then the skeleton or medial axis of the input is approximated. Dominant point detection gives better shape approximation. Shape analysis is performed by using curve reconstruction, medial axis approximation and dominant point detection.

Shape matching can be done using dominant points. The dominant points of input set and dominant points of the flipped input set are used and check whether there is a matching or not.

#### 3.2 SHAPE ANALYSIS AND SHAPE MATCHING

There are different ways for shape analysis and shape matching. The different steps used for both shape representations are:

1. Curve Reconstruction
2. Medial Axis
3. Dominant Points

The Voronoi diagram (VD) comprises of bounded and unbounded Voronoi cells. A cell  $V_p$  is said to be unbounded if the sample  $p$  lies on the convex hull of  $P$ . Unbounded Voronoi cells initiate what is called as infinite edges, whose one vertex lies at infinity. All Voronoi vertices with the exception of vertex at infinity are finite. Two unbounded and one bounded Voronoi cells of a Voronoi diagram constitute an extreme Voronoi vertex.

3.2.1 Incremental labelling in pseudo-concavities

In any closed curve, concave parts present terrific problems for reconstruction. Henceforth, we clarify the marking process through picking a concave part of a basic closed curve. Marking for convex curves is fairly straightforward and simple. Entire Voronoi vertices are at first named as outer(labelled utilising the dark blue points in Fig 3.2).Incremental marking in a pseudo-concavity begins with an EVV.Beginning from the EVV, the marking procedure advances to nearby unvisited outer Voronoi vertex contiguous it. A couple of outer Voronoi vertices experience label changes from outer to inner during the incremental labelling procedure.

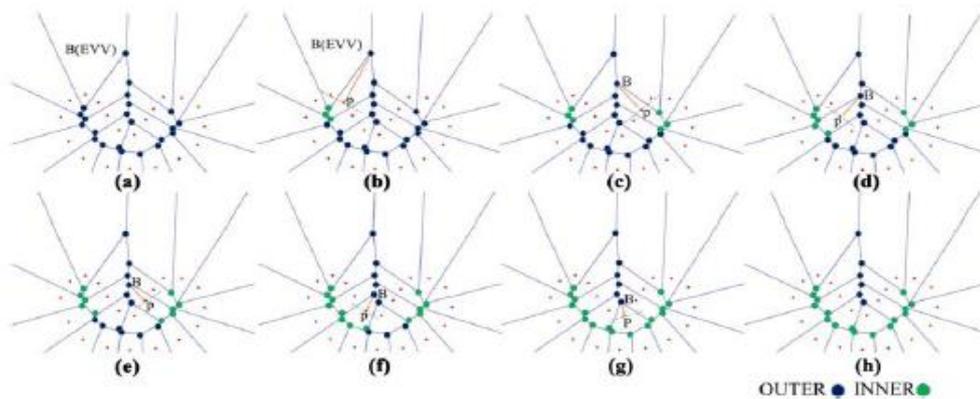


Fig 3.2 Representation of incremental labelling in a concave portion of a closed planar curve(Image courtesy[18])

Inside the figure, red dots comprises the input points sampled from the curve, green and dark blue vertices, individually, denotes the inner and outer (w.r.t original curve) Voronoi vertices in the characterization. Incremental labelling begins from an EVV and advances in the direction of the high curvature points inside the concavity.

For a Voronoi cell  $V_p$  of a sample point, the outer Voronoi vertex in which the marking procedure begins denotes to its source Voronoi vertex (SVV). Every example  $p$  in  $P$  has its own Voronoi cell  $V_p$ , and thus one of the vertices of  $V_p$  subjected to the marking process is destined to be the SVV of  $p$ .The line  $L$ , symmetrical to  $B_p, p$ , partitions the plane into half planes assigned as  $H_1(p)$  and  $H_2(p)$ . Utilising the vector,  $B_{\{p\}} - p$  and  $L$ ,use the Label transition rule for a Voronoi vertex.

Definition 5 . Label transition rule

Let  $B_i$  be an outer Voronoi vertex of a Voronoi cell  $V_p$  of a sample point  $p$  and  $B_p$  be the source Voronoi vertex of  $V_p$ ,  $B_i$  is marked as inner if  $B_p$  and  $B_i$  lie on either side of  $L$ .

3.2.2 Algorithm

The basic geometric form,for example the Voronoi Diagram VD, upon whereupon the complete algorithm is structured.

Algorithm 1: IncrementalLabel(B)

Input: Branch Voronoi vertex, B

1. Let  $p$  be the unpaired sample in the three Voronoi cells of B;
2. Pair  $p$  with B;
3. Apply state transition rule (Definition 5) to B in  $V_p$  ;
4. if there are no neighboring outer and unvisited vertices for B then
5. return;
6. end
7. else if there is one neighboring outer and unvisited vertex for B then
8. Let  $B_{new}$  be the outer neighboring vertex of B;
- 9.IncrementalLabel( $B_{new}$  );
10. end
11. else

12. Let  $B_{new1}$  and  $B_{new2}$  be the outer neighboring vertices of  $B$ ;
13. `IncrementalLabel( $B_{new1}$ );`
14. `IncrementalLabel( $B_{new2}$ );`
15. `end`

The source vertices compute the poles of the samples and the vectors,  $B_p - p$  and  $L$ , estimate the normal and tangent at  $p$ , independently. In this way, all the Voronoi vertices of  $V_p$  beyond  $p$  whilst seen from  $B_p$  are named as inner. The proof is that the Voronoi vertices lying past the evaluated tangent  $L$  of  $p$  likewise lie interior of the actual curve and thus can be determined as inner.

The labelling procedure advances to any nearby unvisited outer Voronoi vertices of  $B_p$  (Figures 3.2 c to 3.2 f) and continued till not any nearby unvisited outer Voronoi vertices for the contemporary  $B_p$  (allude to Figure 3.2 g). The incremental labelling in pseudo-concavities is supplied in Algorithm 1. Whilst the primary recursive call (line 7 of Algorithm 1) allows to cross a single Voronoi branching, the second recursive call (lines 11 and 12 of Algorithm 1) allows to traverse the two new Voronoi branchings relating to two inner pseudo-concavities. The entire Voronoi vertices are visited precisely as soon as during the `IncrementalLabel` on  $B_p$ .

Algorithm 2: `ExtractShapes(P)`

Input: Point set  $P$

Output: `curve(P)`

1. Construct `Vor(P)` and its dual `Del(P)`;
2. Label all the vertices of `Vor(P)` including the INFINITE vertex to outer;
3. Pair up the samples in unbounded Voronoi cells with INFINITE vertex;
4. Construct a heap priority queue,  $PQ$  containing EVV  $s$  lying outside the convex hull of  $P$ , sorted in the descending order of their circum radii of the dual Delaunay triangles;
5. while  $PQ$  not empty do
6.  $B = \text{root}(PQ)$ , delete  $B$  from  $PQ$ ;
7. `Incremental_Label(B)`;
8. end
9. Extract the graph, `curve(P) = {e | edge e ∈ Del(P) and Dual(e) has outer and inner vertices}`;
10. Extract the graph, `MAT (P) = {e | edge e ∈ Vor(P) and e has either two inner or outer vertices}`;
11. return `curve(P)`;

The Voronoi vertex naming in our methodology depends on an incremental methodology and henceforth in expansion to the MA approximation, the technique can likewise be able to reconstruct the boundary of the input sample.

### 3.2.3. Curve and Medial Axis Extraction

We expect that no four points are co-circular and henceforth every finite Voronoi vertex has a degree of 3. A pseudo-code for curve reconstruction is given in Algorithm 2. It begins with the development of `Vor(P)` and its dual `Del(P)`. Every Voronoi vertex model is outfitted with the label and visited fields to follow along of the vertex label and the visited status during the incremental labelling. All the Voronoi vertices are instantiated to unvisited in the starting. Beneath dense sampling, EVVs of infinite Voronoi edges brought up by any nearby samples from pseudo-convex portions lie interior of `Conv(P)`. For convex portions, the convex hull is a direct estimate to the original shape and subsequently, those vertices likewise lie inside the interior of the original shape. Along these lines, we mark all such EVVs as inner. Remaining all last Voronoi vertices are marked outer at the beginning of the incremental labelling process. Within the following track, a heap-based priority queue,  $PQ$  of all the outer EVVs, is made, in which the EVVs are arranged within the decreasing range of the circumradii of the corresponding dual Delaunay triangles. In every emphasis, the procedure selects the root component from  $PQ$  and executes the vertex labelling process yielded in Algorithm 1. When the incremental labelling has been carried to entire EVVs in  $PQ$ , it extricates the curve and MAT from `Del(P)` via utilizing `Dual()` function which offers the dual Delaunay edge of a Voronoi edge. The procedure can be intended to cope with closed curves.

The number of Voronoi vertices is straight as far as the point set size,  $n$ . Considering every Voronoi vertex is traversed precisely as soon as in the `IncrementalLabel()` process, loop of Algorithm 2 costs as it were  $O(n)$ . Different tasks along with label initialization, and curve and MAT extractions take linear time. The worst case time complexity of the algorithm is  $O(n \log n + k \log k)$ , where  $k = \text{no of EVVs}$ , and occurred because of the computation of VD.

### 3.2.4. Dominant Point Detection

The labelled VD acquired through the incremental labelling (Algorithm 1) may be additionally utilised for distinguishing the points with high curvature values (or DPs). The patterns are shaped out of the names of three consecutive Voronoi vertices along the Voronoi cell boundary, where every pattern includes vertices with same labels at either side and a centre vertex with an alternate label as appeared in Figure 8. After all Voronoi vertices are marked either as inner or outer, we have as it were such labelling sequences called IOI and OIO patterns (here, inner is condensed as I and outer is condensed as O). In non-uniform sampling, the Voronoi cells of points from curvature extremes in general have either IOI or OIO patterns on their Voronoi cells. These can guide into a basic and on spot extraction conspire for DPs.

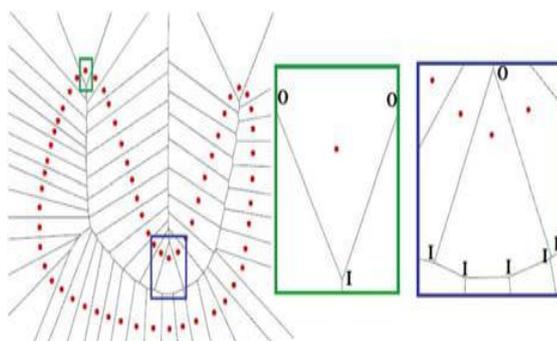


Fig 3.3. Different labelling patterns on the Voronoi cells of dominant points. (Image Courtesy [18])  
Green and blue boxes represent examples of OIO and IOI patterns, individually.

Input points with IOI or OIO patterns on their Voronoi cells are separated as DPs. The DP extraction comprises a direct traversal over the Voronoi cells, a consistent circular movement over the vertices of a cell for recognising the mentioned patterns and a consistent time area test for the pattern vertices. Consequently, the time complexity of DP extraction is  $O(n \log n)$ , for the most part because of VD computation.

### 3.2.5. Shape Matching using Dominant Points

We can use the concept of dominant points for shape matching. That is here we can check two images i.e. an original image and a flipped image to find out there is a matching or not. Here we will take the dominant points of the both image and its flipped image to find out whether there exists a matching or not.

### 3.2.6. Shape Matching using Curve Reconstruction

We can use the concept of curve reconstruction for shape matching. That is here we can check two images i.e. an original image and a flipped image to find out there is a matching or not. Here we will take the input set of reconstructed curve of both image and its flipped image to find out whether there exists a matching or not.

## IV. IMPLEMENTATION

The basic system was implemented in python. The system performs two operations simultaneously shape analysis and shape matching.

### 4.1. Curve Reconstruction

Here an incremental voronoi based algorithm is used for curve reconstruction. Here a curve is reconstructed by using the input as point set. A voronoi and delaunay triangulation is computed. After that classify the voronoi vertices into outer and inner. After that take the edge that is a delaunay edge which having both outer and inner vertices. when the incremental labelling have tested above all EVVs (extreme voronoi vertex), which results in extraction of the curve.

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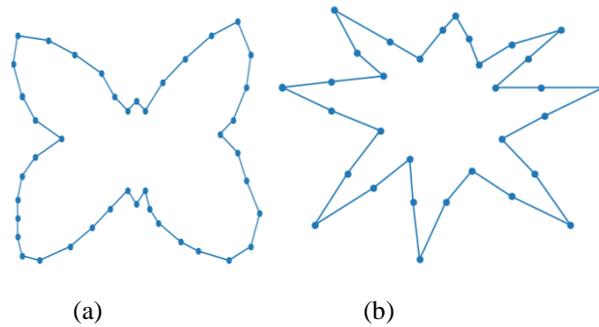


Fig 4.1 Curve reconstruction of butterfly,star

#### 4.2. Medial Axis

Here an incremental voronoi based algorithm is used for medial axis approximation. Here both voronoi and delaunay triangulation are computed. After applying the incremental labelling procedure take the EVV s, extract the MAT by using a Dual() function producing the dual Delaunay edge of a Voronoi edge. After a edge with two inner or outer vertices are considered to a medial axis, in which the edge is a voronoi edge.

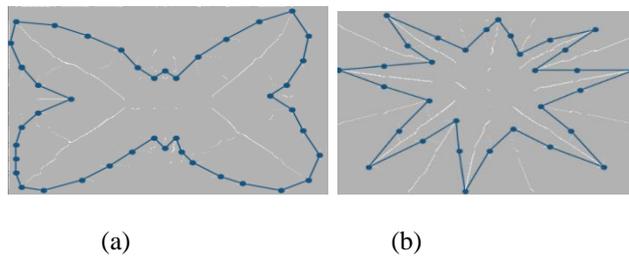


Fig 4.2 Medial Axis of butterfly,star

#### 4.3. Dominant Points

Here an incremental voronoi based algorithm is used for dominant point detection. The labelled VD acquired via the incremental labelling can be additionally utilised to distinguish the areas with high curvature values (or DPs). Here the dominant point is the point with maximum curvature. Extreme curvature positions results in specific labelling designs of the Voronoi diagram (VD) and these labelling patterns are used to distinguish DPs on original shape.

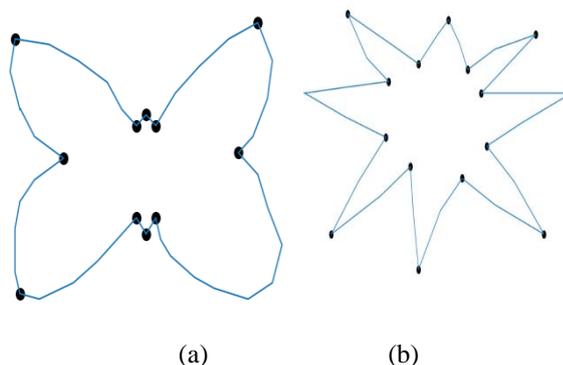


Fig 4.3 Dominant Points of butterfly,star



4.4. Shape Matching

Shape matching is a important concept in image processing. We will introduce the shape matching by using the concept of dominant points and curve reconstruction. The main advantage of this technique is it have high data compression. ie shape matching have different applications like finger point identification, pattern recognition etc. Shape matching using dominant points can be achieved by using a one to one correspondence between two shapes. Shape matching can also be performed in case of curve reconstruction. Here we will compare two matching techniques to find out which one is best. The metric used to compare both concepts is by using euclidean distance.

**V. EXPERIMENTAL RESULTS**

Here we demonstrate the results using shape matching using curve reconstruction and dominant points.

*Shape Matching*

In this section, we compare shape matching using reconstructed curve (RC) and dominant point detection (DP). Here the table shows difference in matching when the image is rotated along the angle of 180.

Input	RC	DP
Butterfly	0.148	0.08
Fish	0.364	0.07
Shark	0.178	0.079
Star	0.285	0.092
Leaf	0.330	0.0107

The table below shows difference in matching when the image is rotated along the angle of 90.

Input	RC	DP
Butterfly	0.187	0.008
Fish	0.380	0.060
Shark	0.156	0.073
Star	0.636	0.009
Leaf	0.340	0.0101

Here both table show the difference between shape matching in case of both curve reconstruction and dominant point detection. Here the observed result yields a shape similarity measure. Here euclidean distance is the distance function which is used to measure the difference between two shapes. When the difference is smaller, we can conclude that more similar the shapes are.

Euclidean distance is the straight line distance between two pixels. If  $p=(p_1,p_2)$  and  $q=(q_1,q_2)$  then the distance is given by

$$d(p,q) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2}$$

Here the observed result shows better matching by using dominant points. By using dominant point, the input image and the flipped image gives the better result. A better shape matching is obtained by using dominant points.

## VI. CONCLUSION

Introduced a multi-functional Voronoi and Delaunay based Structure for reconstructing Curves, Medial axis approximation and DP detection. The vital role of the structure is a general incremental procedure that characterises the Voronoi vertices into outer and inner regarding the original shape. Under non uniform sampling method, an incremental algorithm can build a piecewise direct estimation to smooth, closed and planar curves. The test outcomes show the methodology is equipped for reconstructing curves from sparse data. It can likewise manage group of curves effectively and seize sharp corners and outliers. The proposed system can extend the shape analysis to shape matching by using dominant points.

In future one can extend the work to 3D and also extend the structure for the reconstruction of objects with holes by using a hierarchical incremental labelling.

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