2D Shape Reconstruction Based on Combined Skeleton-Boundary Features

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Abstract

Reconstructing a shape into meaningful representation plays a strong role in shape-related applications. It is motivated by recent studies in visual human perception discussing the importance of certain shape boundary features as well as features of the shape area; it utilizes certain properties of the shape skeleton based on symmetry axes combined with boundary features based on curvature to determine protrusion strength. The main contribution of this paper is the combination of skeleton and boundary information by deploying the symmetry –curvature duality method to simulate human perception based on results of research in visual perception. The experiments directly compare our algorithm with experiments on human subjects. They show that the proposed approach meets the human perceptual intuition. In comparison to existing methods, our method gives a perceptually more reasonable and stable result. Furthermore, the noisy shape reconstruction demonstrates the robustness of our method ,experiments of different data sets prove the invariant representation of the combined skeleton-boundary approach.

Keywords: Protrusion, Symmetry-curvature duality, Contour, Bamboo boundary, Merging point.

1. INTRODUCTION

In all the research areas such as image retrieval and computer graphics, character recognition, image processing, and the analysis of biomedical images [1],the skeleton plays a major role for object representation and recognition. Skeleton-based representations [2] are the abstraction of objects, which contain both shape features and topological structures of original objects. Because of the skeleton's importance, many skeletonization algorithms [3] have been developed to represent and measure different shapes. A recent study on human perception [4] demonstrated that curvature properties of the boundary and the area properties of the enclosed regions affect the observers' identification of contour segments. Similar to previous results from [5],their experiments showed that negative minima of contour curvature depict segment boundaries. Additionally segment identification was determined by contour length, the turning angle at part boundaries and the width at the part's base. Motivated by these results, the proposed approach mimics the procedures of human perception assumed in [4] by combining concepts of skeleton and boundary in shape analysis. Our method shows that 'junction points' of the skeleton can provide the possibility of important protrusions. Boundary information as mentioned in [4], including contour length, the turning angle at part boundaries and the width at the part's base, can determine the probability of important protrusions. The proposed reconstruction is then based on a definition of protrusion strength, based on both curvature of boundary points and their structural correspondence. Recently Bai et al. [6][7] presented robust approaches to compute a perceptually reasonably pruned discrete 2D skeleton of a single boundary. The author utilizes [8] this skeleton approach. It establishes a correspondence between structural information and boundary. Due to its robustness, we use this skeleton approach. Of course any skeleton algorithm offering 'junction points' is applicable.

2. PRELIMINARIES

Shape Reconstruction is an emerging field. It mainly splits into two classes of approaches: boundary and region based. Generally segmentation is best suited for uniform boundary images. Hence Segmentation splits the shapes into regions and the boundary of that particular region or contour is taken for processing. In [6], the author, segments the image into many number of contour based skeletal representation. In [7] Discrete skeletal evolution he identifies the skeleton evolving algorithm to identify the complete stable skeletal representation of the input image. In[9],The author utilizes the boundary feature and skeleton structure to decompose the input image. In the following sections, it will be seen that 'junction points' of the skeleton play a crucial role in finding a correct decomposition. The motivational connection between junction points and protrusions is the observation that a junction point emanates from the merging of two protrusions. Hence, if the junction points are known, the positions of protrusions can be predicted and the protrusions can be classified as parts or non-parts based on their strength. The experiments directly compare our algorithm with experiments on human subjects. This is mainly achieved through the crucial junction point information with the important boundary features.

3.Methodology of the proposed work

The image is seen into two classes. One from the outer shape boundary. The other is from the segment of the shape and its corresponding segment boundary or contour. The shape boundary is computed from the high positive maximum of the curvature and the segment boundary or contour is computed from the negative minima of curvature. In[10],the author explains between the axes that track the curvature maxima (positive axes and the curvature minima (negative axes) using a second derivative. In fig 3.1 it is depicted as follows.

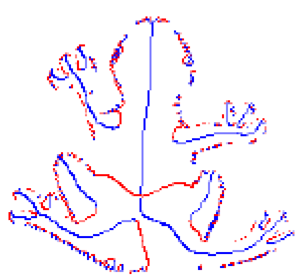

Fig3.1 Positive (shown in blue) and negative (shown in red) axes

A. Reconstruction.

Deforming a given shape to a target shape has been a topic of interest in shape analysis In a skeleton based representation, [11],[12],[13],[14],[15] one can obtain new shapes simply by modifying a skeletal representation. Note that even though small changes in the shape boundary may lead to significant changes in the shape skeleton, the opposite is not true [16]. Suppose we edit our skeletal representation by changing attributes or deleting/inserting a primitive. Since we have lost information as a result of excessive regularization, we cannot construct the new shape boundary simply by propagating the edited skeleton, as in [17],[18]. Therefore, we suggest an alternative solution by considering the transformations or diffeomorphisms, [19],[20], that transform one disconnection point set into another. Note that when such a transformation is found, it can be used to form a dense correspondence between two shape domains. The new shape boundary after the skeletal edit operations can be formed by applying the computed transformation to the original boundary points. In contrast to skeleton scale space methods which smooth the boundary first and then compute the skeleton, we, in a dynamic way, continuously smooth the shape boundary and record its interested points using visual data exploration and pixel connectivity till the whole boundary becomes simple enough. Hence we get the boundary as well as the skeleton representation collectively called as bamboo skeleton as in fig 4.2.1. As such, in[21][22],[23], the proposed representation is an unlabeled attributed point set and forms a trade-off between unstructured point sets, and in [24],[14],[25],[26]skeletal graphs. Skeletal points moving with a faster speed than the non-skeletal points can be detected by the minima of the gradient which are indirectly related to curvature maxima. We include the parameters symmetry curvature duality, protrusion strength, width and the segment length. The relevant measure (high positive curvature maximum) for computing the boundary end point. Skeletal points moving with a faster speed than the non-skeletal points can be detected by the minima of the gradient which are indirectly related to curvature maxima. Hence it is worth exploring the algorithms that jointly determine point correspondences and estimate local deformation, [11], In[27] the author represents the unique ,consistent and stable bamboo skeleton for all number of contour produced in [7].

B.Exploring point correspondences and local deformation.

The construction of skeleton is via maximal circles that are inscribable inside the shape and touch the shape boundary at more than one point. In this construction, circle radius plays the role of time of arrival in the symmetry axis function. Considering the envelope of maximal circles, one can reconstruct the shape boundary.

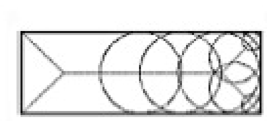

Fig3.b.1 maximal circles

In[28], [29],[30],While all of these constructions lead to the same representation, they inspired many others having different properties and being computed with different algorithms No matter which major branch is chosen as a reference axis, the same axis must be chosen for similar shapes. Since there are two major axes of the same type, there is an ambiguity in the process. If the descriptions of two similar shapes depend on different coordinate frames, the matching algorithm will be unable to determine the similarities of shapes. This situation may necessitate creating at least two descriptions. To overcome this problem, we use each negative major symmetry branch as a reference axis for one half of the shape. Hence, the shape is described as two halves with each half having its own coordinate frame This approach decreases the computation time of the matching algorithm drastically.

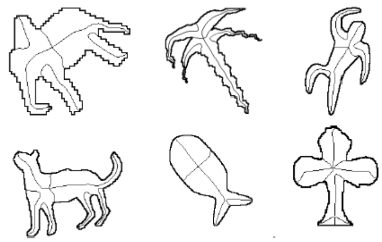

Fig 3.b.2 Symmetry axes for sample shapes after pruning.

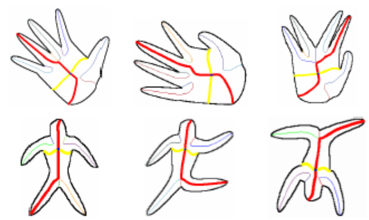

Fig 3.b.3
The major branches of the hand and human shapes.
Positive major symmetry branches are shown in bold red and
negative major symmetry branches are shown in bold yellow.

The *skeleton S* of a boundary *B* is the locus of the centers of maximal disks in correspondence to [10]. We use the discrete definition of a skeleton as given in [5]: using 8-neighborhood, a skeleton is a connected, thin point set $S = \{s_1 ... s_n\}$ describing a geometric graph embedded in R2.
A shape *boundary* is a vector of points $B = \{b_1 ... b_m\}$.
An *endpoint* $E_i \in S$ is a skeleton point having only one neighbor.
A *junction point* $J_k \in S$ is a skeleton point with three or more neighbors.
Given a junction point J_k of a skeleton, there is a set of corresponding boundary points intersecting with the maximal disk centered at J_k.We call these boundary points *tangent points* $t_i \in B$ of the junction J_k.
The shortest path between a pair of endpoints on a skeleton graph is called a *skeleton path P* ([31]). We call a partial path between junction or endpoints a *branch*.
With these definitions, we will now describe our decomposition approach. The goal is to find the end points of the part *lines* ([5]), i.e. straight connections between a pair of boundary points entirely inside of the shape boundary.
We first compute the skeleton using the Discrete Skeleton Evolution method as proposed in [5]. This approach first computes the skeleton based on Blum's medial axis definition. Then iterative skeleton pruning (removing end branches) is performed based on a relevance measure which describes the importance of the respective branch for shape reconstruction. The pruning process ends when only major relevant branches remain. We follow [10] and utilize a single threshold as stop criterion. Our experiments showed that this leads to visually correct skeletons in all examples. After the pruned skeleton is obtained, we choose 'relevant' (high positive curvature)pairs of tangent points as candidates to merge the shape boundary. The visual significance, and therewith the final decision for merging computed as protrusion strength and symmetry curvature duality is as follows.

There is a connection between positive curvature maxima of the shape boundary and the skeleton in the sense that each curvature maximum gives rise to a skeletal boundary [32]. This connection is often used to extract the skeleton. When the skeleton is extended to include branches that arise from curvature minima, a richer set commonly referred to as local symmetry axes is obtained [33].The skeletal arc formed out of curvature minima contains the end points one at the boundary having high positive curvature and the other at the symmetry axes on the base skeleton with high negative curvature. The protrusion strength is used to identify the junction point with curvature minima.

Following [9], our merging is guided by the following two rules:
(1) Merging focuses on the turning angle of the part boundary, where the
tangent points have positive maxima of curvature.
(2) Segment identification performance (i.e. strength of protrusion) is related to the segment length and the width at the part's base

Protrusion strength:
With *c*(.) denoting the curvature in a boundary point (concavities having negative curvature), compute the sum of curvature $C(i, j) = (c(l_i) + c(r_j))$ for all $(l_i, r_j) \in T_L \times T_R$. Also, for each (l_i, r_j) compute the *protrusion strength*, which is defined as follows:

$$P(l_i, r_j, b_k, r) = \frac{|b_k - r|}{|l_i - r_j|}$$

Where $|l_i - r_j|$ is the Euclidian distance of l_i and r_j , r is the radius of the maximal disk, see fig.3. b_k is the length of branch with junction point J_k, i.e. the length between J_k and the respective endpoint E. However, if another junction point $\hat{J}$ is between J_k and E, which led to a cut before, b_k is defined as the (shorter) branch length between J_k and $\hat{J}$. With a given threshold T , the pair $(\hat{l}_i , \hat{r}_j)$, which minimizes the curvature value, is selected amongst all pairs of points with $P(l_i, r_j, b_k, r) > T$ $C(\hat{i},\hat{j}) = \min\{C(i, j)\}$
.

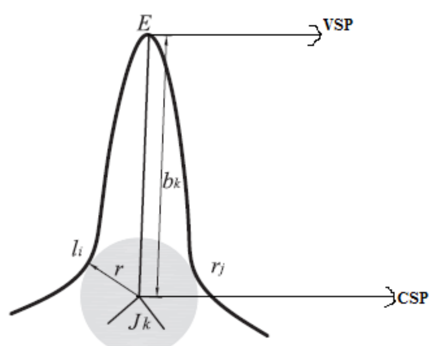

Fig 3.b.4 Computation of protrusion strength.

The skeleton branch is a line segment connecting the end points one at the boundary having curvature maximum and the other at the junction point of the symmetry axes/base skeleton having curvature minimum. The segment terminates at the curvature extremum of the opposite type.

C. Combining symmetry axes and curvature minima
According to symmetry-curvature duality theorem,[34]the tangent point $t_i \in B$ *and the junction point* $J_k \in S$ *are the* curvature extremum of the opposite type. According to the author in [9], $J_k \in S$ is a point with curvature minimum. ,$t_i \in B$ is a point with curvature maximum. According to symmetry axis the curvature maximum point gives raise to the boundary. Hence using pixel connectivity we connect all those $t_i \in B$,to obtain the boundary of the ununiform shape. This $E_i \in S$ is called as valance skeleton point (vsp)and $J_k \in S$ is called as core skeleton point (csp).This vsp is a point that can be used for merging and modifying the input image into another skeletal representation.

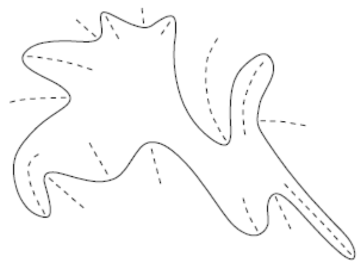

Fig 3.c.1

An illustration of the Symmetry-Curvature Duality Theorem

In [9] the protrusion strength is used to identify the inner most point as junction point having high negative curvature where as our proposed method utilizes the by the symmetry –curvature duality theorem to compute the outer most point as valance skeletal point having high positive curvature and that can be used for further processing .

4 Experiments

4.1 Experiment on Abstract Shapes

Figure 4.1.1 gives the original data set with darkened boundary parts for test. The data set has different levels of part significance with respect to the part base line and the elongation: the base width for the test segment increases from top to bottom, the segment length for the test segment increases from left to right. The least significant segment is therefore located in the bottom row, left column. The result in [4] shows the trend that it was harder for observers to identify the segments of shapes shown at the bottom and left side compared to those at the top and right side of figure 4.1.2 For example, only about 40−50 percent of the observers identified the defined segment in (row/column) 3,1 and 4,1 as 'significant'.

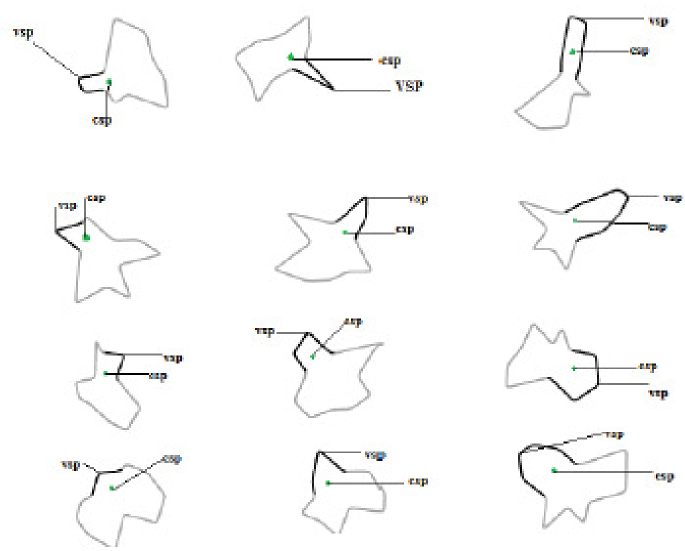

FIGURE 4.1.1

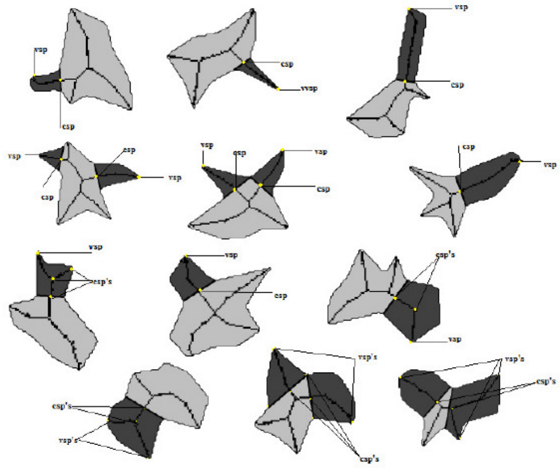

FIGURE 4.1.2

4.2 Experiments on Different Shapes.

A. Existing Method

The first and second row has seven shapes from the existing approach. It is different for any number contours.

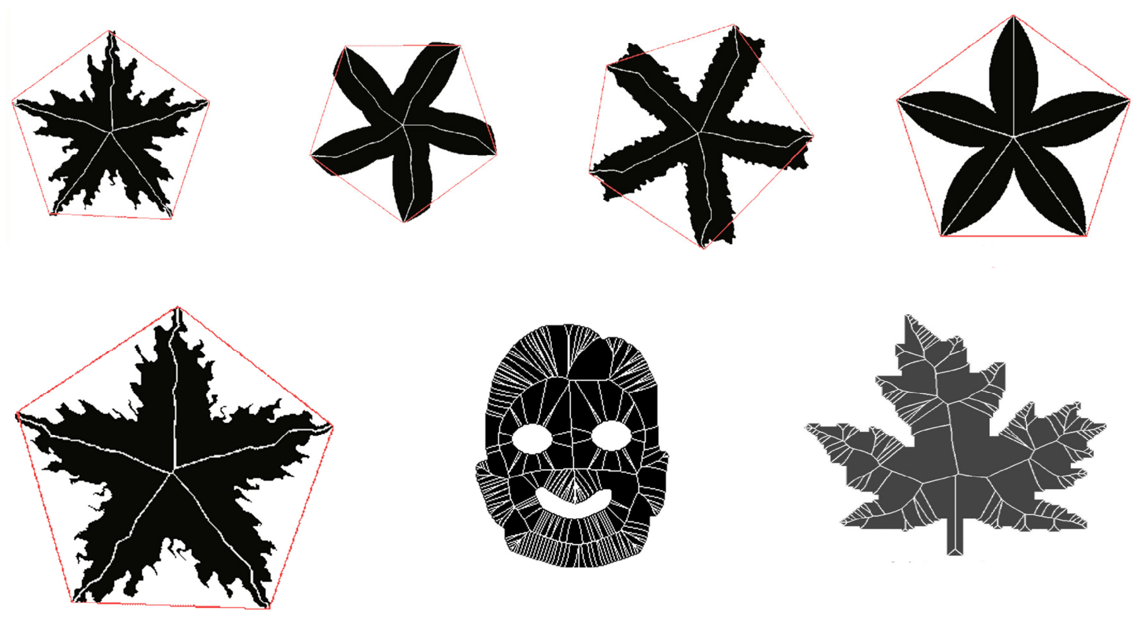

FIGURE 4.2.A.1

B.Proposed Bamboo skeleton Representation

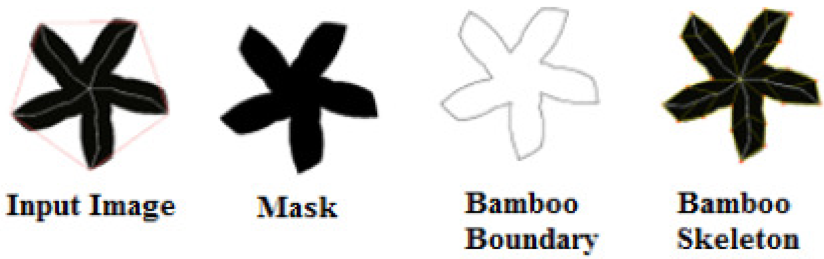

FIGURE 4.2.B.1

In [33]The first and second row has seven shapes from our approach. It is common for any number of contours.

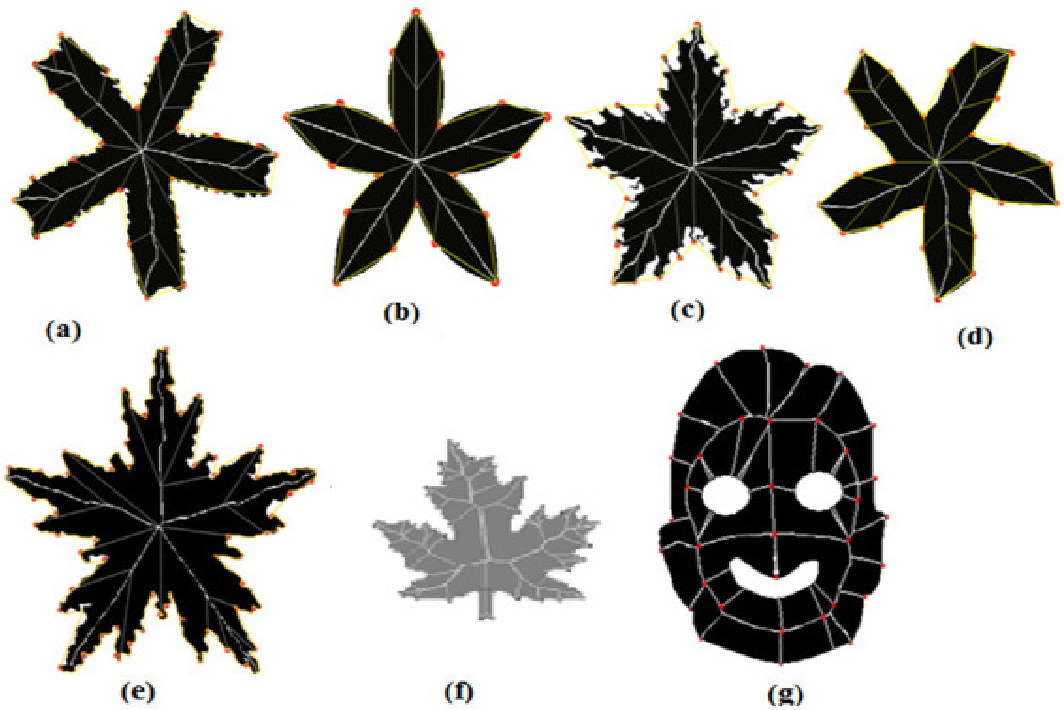

FIGURE 4.2.B.2

C.Proposed Merging Point Computation

In [35] the merging points are computed and labeled.

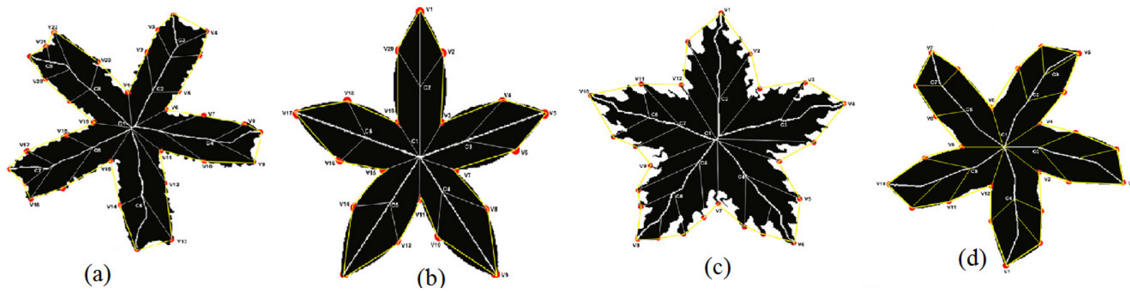

FIGURE 4.2.C.1 Merging points computed by our approach. The results is in accord with the experiment in[4]

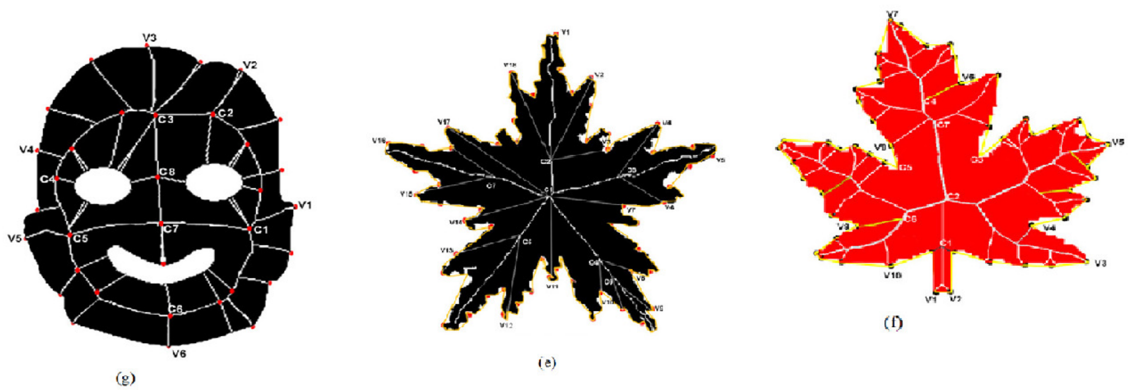

FIGURE 4.2.C.2:Merging points computed by our approach. The results is in accord with the experiment in [4]

4.3. Reconstruction results of our approach on different shapes.

This experiment shows reconstruction of different shapes, taken from [7], Figure 4.3.1 shows some results of the proposed algorithm. The consistent reconstruction of the object in row1 is especially remarkable, although heavily distorted by noise.

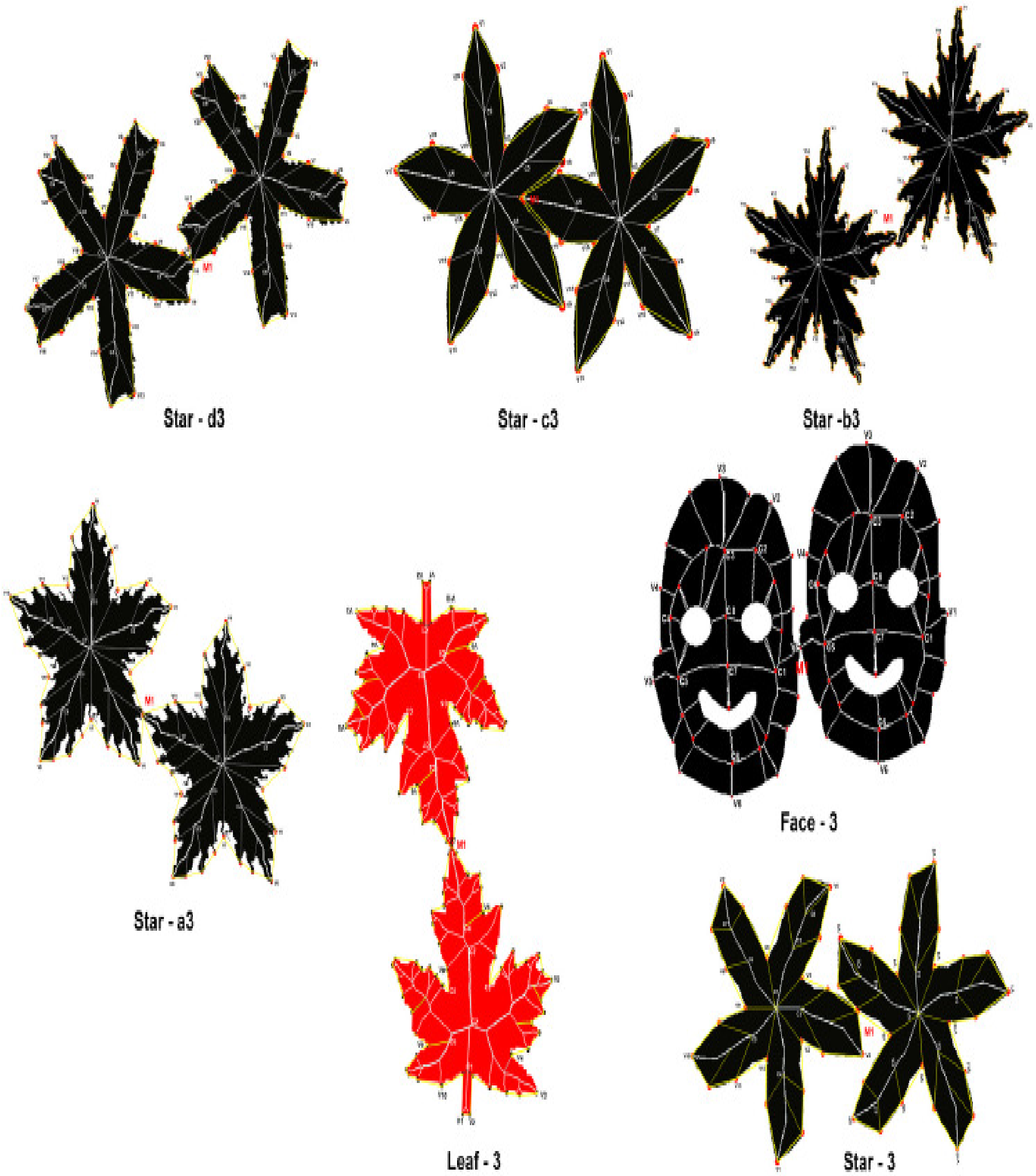

FIGURE 4.3.1 Transformed skeletal representation

4.4 Comparison
In the first row the existing pruning method with DCE produces different contour representation for the input image. The second row depicts the proposed skeleton representation.

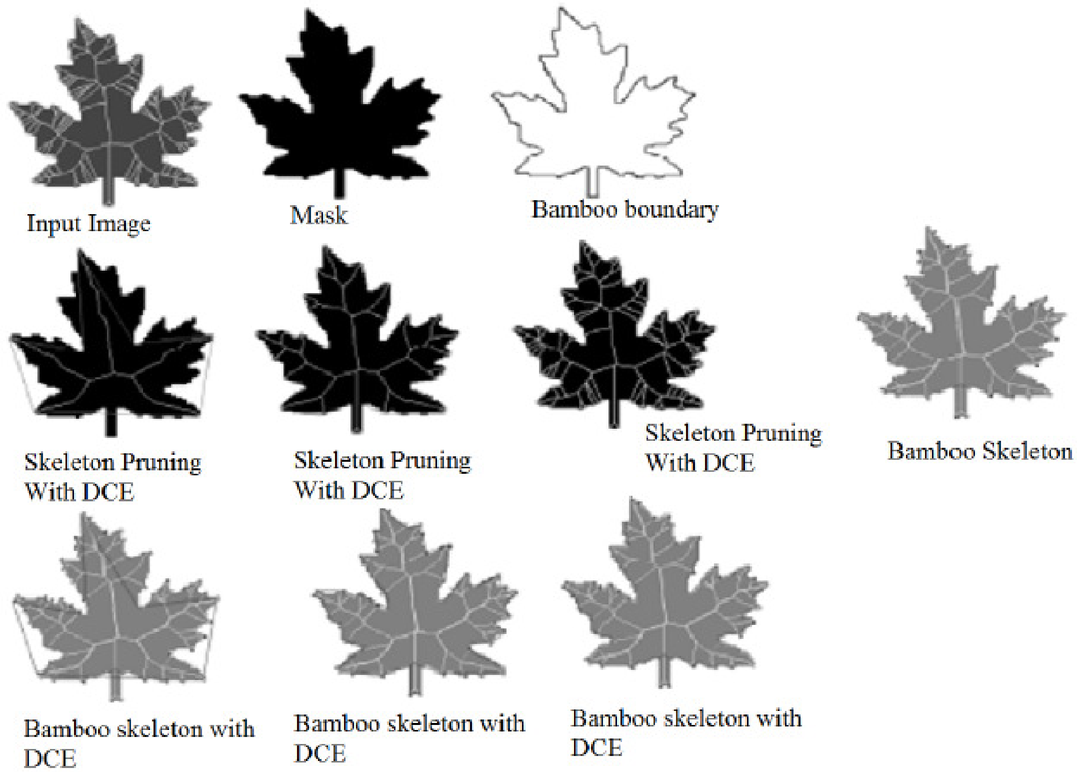

FIGURE 4.4.1.

1. It gives the same common skeletal representation for three different contour against that of the existing DCE method. It reduces the unused storage space for the particular shape representation as in contour1.
2. The boundary deformation is reduced ,In the contour 2 in which the boundary points that are essential for shape representation are not included in contour2 whereas in the proposed representation the boundary points are computed using symmetry –curvature duality based protrusion method and the skeletal arc have been included in contour2 of the proposed method, and hence the boundary deformation is reduces to the great extent.
3. The number of skeletal arc is discrete, unique and standard for all the contour representation. The proposed skeletal representation is unique and stable and satisfies the skeleton topology.
4. Merging of two input images could be achieved to produce new recombinant skeletal representation. The following fig represents merging of two input images to produce transformed or merged images that can be used for producing the new real time objects. The computed boundary points can be used in merging two images so as to transform the existing skeletal representation into a modified recombinant skeletal representation that can be used for generating real time objects.
5. The bamboo skeletal representation is suited for ununiform contour based shape representation against the existing method which is finds difficulties in ununiform contour based images.

4.5 Robustness to Noise

In this experiment, noise was added to data extracted from [7] to show the robustness of the decomposition method. Figure 8 presents 4 groups of shapes, each containing a basic shape in different poses. These poses show non-rigid deformations. Since the approach is based on robust skeleton detection and important boundary features, the reconstruction result is consistent. Figure 9 gives the decomposition result for two shapes with evolved noise. It indicates that the increasing noise does not influence the merging result.

4.6 Invariant Representation

A shape cantered coordinate frame allows one to describe the organization of the primitives in a way that is robust to changes in scale, rotation and articulation. This coordinate frame can be formed by designating the prominent branches of the shape as the reference axes.

5. Conclusion and future scope

The proposed method is best suited for 2D object representation. It can be extended for 3D images also. Any modifications developed in the generated real time objects can also be studied and accordingly the work can be extended from objects point of view and its representation.

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