Planar shape decomposition made simple

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The psychophysical, ecological, and computational aspects of planar shape decomposition into parts have been studied for more than five decades [9]. Although a complete theory of object recognition remains an impossibility, it is believed that our ability to recognize objects by their silhouette alone is related to simple rules by which the visual system decomposes shapes into parts [4]. In computer vision, object detection and recognition has deviated from such studies, but understanding visual perception towards learning better representations is always relevant.

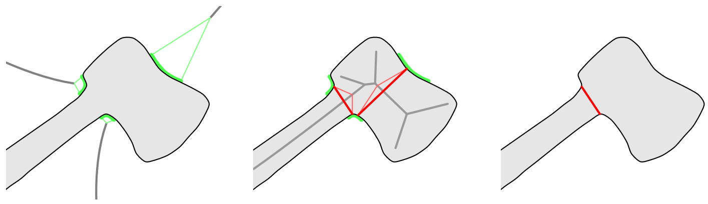
Recent work on the subject has introduced ever more complex computational models relying on combinatorial optimization [6, 7]. The main focus of such models is *convexity*, although the support from psychophysical studies is limited or absent [8]. The most recognized rules underpinning shape decomposition are the *minima rule* [4] and the *short-cut rule* [11], along with the definition of *part-cuts* [10]. However, attempts to reflect these rules into simple computational models still resort to optimization and new ad-hoc rules [5]. Although the medial axis has been one of the first representations used even before the formulation of these rules [1], it is not frequently used today. On the other hand, quantitative evaluation has been practically impossible until recently [3].

In this work, we revisit the problem assuming the medial axis representation and introduce a new computational model referred to as *medial axis decomposition* (MAD). Contrary to common belief [5], we argue that this representation is both efficient and robust, at least as far as decomposition is concerned, and as long as a part hierarchy [9] is not sought. We show that it is possible to incorporate all rules suggested by psychophysical studies into a computational model that is so simple that one nearly "reads off" part-cuts from the medial axis. In doing so, we suggest a stronger definition of part-cuts concerning local symmetry such that the list of candidate cuts is linear in the number of minima. We also shed more light into the relation of minima to convexity by relaxing the latter to *local convexity*. Contrary to global optimization models, this guarantees robustness [9].

The main ideas of our work are illustrated in Fig. 1. As in most related work, a shape is decomposed into parts by defining a number of part-cuts which are line segments contained in the shape. According to the minima rule [4], the part-cut endpoints are points of *negative minima of curvature* of the shape boundary curve. But it is known [2] that such points are exactly projection points (boundary points of minimal distance) of end vertices of the exterior medial axis (the medial axis of the complement of the shape). Moreover, as shown in Fig. 1a, one may get from a medial axis vertex not just one boundary point but an entire arc. We call this arc a *concave corner* or simply *corner*. It is readily available and involves no differentiation, contrary to all previous work. We show there are advantages over the common single-point approach.

There is no constraint as to which pairs of minima (corner points) are candidate as part-cut endpoints, hence all prior work examines all possible pairs. On the contrary, as shown in Fig. 1b, we only consider pairs of points that are projection points of the same point of the interior medial axis (of the shape itself). Similarly to *semi-ligatures* [1] and single-minimum cuts [5], a cut may also have only one corner point as endpoint [11]. In either case, endpoint pairs are readily available by a single traversal of the medial axis. Comparing to the conventional definition, which requires part-cuts to cross an axis of local symmetry [10], this is a stronger definition in agreement with the definition of *necks* [9]. Contrary to common belief, we show that it can actually be in accordance to psychophysical evidence [3]. For each corner, we only select one cut per medial axis branch; this is a simple and intuitive rule that has not been observed before.

Now, given a candidate list of cuts, the *short-cut* rule [11] suggests that priority be given to the shortest over all cuts incident to each corner point; but it does not specify how many should be kept. On the other hand, convexity-based approaches attempt to find a minimal number of



(a) exterior (b) interior (c) cuts

Figure 1: Main elements of our method. (a) Exterior medial axis and concave corners (in green) as boundary arcs that are each the projection of one medial axis end vertex (minima rule). (b) Interior medial axis and candidate cuts (in red) whose endpoints are contained in corners and are projection points of the same medial axis point; only one such cut is selected per corner and medial axis branch. (c) Final cuts according to short-cut and convexity rules: the shortest cuts are selected for each corner such that each shape part is locally convex at the corner, roughly forming an interior angle less than π (up to tolerance).

cuts such that each shape part is convex [7]. Clearly, a concave smooth boundary curve segment would require an infinite partition, so convexity is only sought approximately. But negative minima of curvature are points where the shape is locally maximally concave. They are therefore the first points where one should establish convexity by cutting. Hence we introduce a *local convexity* rule whereby the minimal number of cuts is selected such that the interior angle of each part is less than π (up to tolerance) at each corner. Selection is linear in the number of candidate cuts and again, all information is merely read-off from the (exterior) medial axis. The final cuts are shown in Fig. 1c.

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