Constructing Coherent Boundaries

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Abstract

This paper presents a new approach to the problem of gap bridging and junction detection. Perceptual groupings and evidence from existing boundaries are combined to produce joins which are consistent with the initial image structure. In particular, a new definition of co-curvilinearity, which distinguishes between true and false co-curvilinearity, is given. Structural quantities are computed for all potential joins. A local non-iterative algorithm selects the best joins and/or junctions which satisfy specific structural conditions. No assumption, domain restriction, or model is needed. The current implementation is fully presented together with the results obtained.

Keywords: *Gap bridging, Perceptual grouping, Junction detection, Connectivity.*

1 Introduction

Since the earliest attempts at computer vision and pattern recognition, it wa realised that reducing an image into a set of connected boundaries helps wit compressing visual data and eliminating noise, whilst retaining topological an geometric properties. Connected boundaries play fundamental roles in inferrin shapes [9], recognising objects, and $3D$ interpretation of scenes [2].

When trying to extract boundary representations of images, the main proble encountered is the large number of discontinuities (or gaps) between boundar fragments of the same physical contour and near junction points. These gap originate from noise distortion, weak contrast, and the intrinsic nature of conven tional smoothing operators such as $\nabla^2 G$, which blur details of image structur near junction points.

Our goal is to reconstruct junctions and boundaries so that they are coheren and in accord with the initial image structure. The method should be suitable fo general purpose computer vision systems, *i.e.* it should be knowledge-free. Such process should, of course, incorporate perceptual organisation capabilities akin t

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humans [13, 17, 8, 3, 10]. Many existing techniques for reconstructing junction and bridging gaps already include these features. However, these techniques lac the crucial stage of checking the plausibility of the new constructions with th evidence locally present in the existing contours and in the raw image. It is ou primary task to present a local algorithm, which combines perceptual groupin factors and specific structural conditions to bridge gaps and reconstruct junctions

2 Related work

Many existing techniques are based on perceptual grouping, such as proximity continuity, connectivity and co-curvilinearity [17, 8, 3, 10]. It is agreed that suc capabilities must also be present in machine vision systems if they are to hav generality and function in real scenes.

Co-curvilinearity, in particular, was identified as one of five viewpoint-invarian features which are necessary and sufficient for inferring shape and obtaining robus curve descriptions [7, 11]. It accounts for most, if not for all, groupings done b human visual system. In [6], angles are detected and grouped into junctions.

In [11], curves that terminate in a local neighbourhood are candidates fo linking with each other by line segments. The neighbourhood is defined in term of the acceptable distance d between the ends of the curves; d is taken as a fractio of the curve length with a fixed minimum length. A local non-iterative proces selects the most co-curvilinear (or least bent) joins among neighbouring curves.

Mohan & Nevatia extended the perceptual grouping factors to account fo parallelism, symmetry, T-junctions, corners and U-structures [12]. Line segment are gradually grouped into predefined shapes, termed *collated features*, that ar thought to be omni-present in images.

The major problem with these techniques is that they lack a crucial stage which is to check whether the selected bridges are consistent with the evidenc already present and the structure of the raw image, and thus may produce wron junctions. Additional imperfections can also be identified:

- When using line-segments rather than bounday fragments the obtaine boundaries lack smoothness.
- Predefined shapes used in [12] limit the sphere of applicability of such tech niques to man made objects.
- Thresholding on angles as in [6] has the undesirable effect of eliminatin simple L-junctions, which are so common in everyday scenes.
- The measurements presented for the co-curvilinearity in [11, 6] do not di tinguish between genuine and false co-linearity, as shown in **Figure** 1. Genuin co-curvilinearity involves two disconnected boundary fragments (segments) of th same physical boundary of a narrow band. The very nature of conventional ope ators and tessellation effects result in the eventual displacement of sections of th boundary by a few pixels.

Another critical problem associated with previously outlined approaches is en suring the right choice of size for the neighbourhood. Small windows lead t wrong bridges, and large windows bring into consideration other segments tha may interfere with the correct bridges.

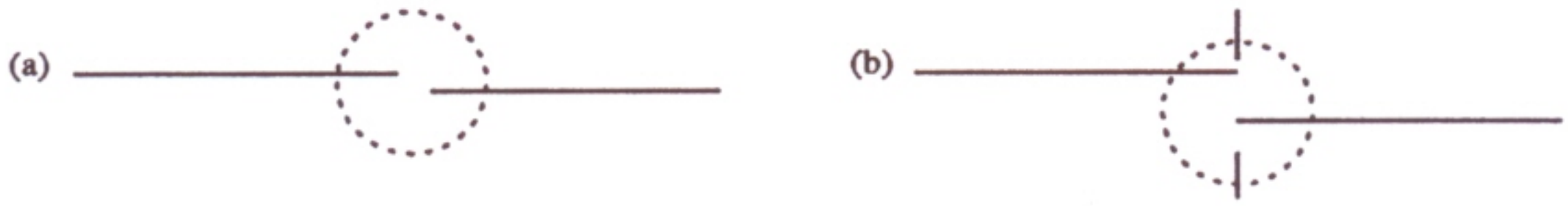

Figure 1. *(a) shows a genuine colinearity. (b) false colinearity. These two case need to be distinguished.*

3 Our approach

We shall present an approach to junction detection and gap bridging which of fers solutions to the problems identified above. Our approach uses curves rathe than line segments, we combine perceptual groupings with evidence from exist ing boundaries and the initial raw image to connect boundary fragments. Co curvilinearity, proximity, contrast and continuity are used to predict potentia joins between boundary fragments which terminate in the same neighbourhood A suitable band, based on the prediction stage, is then chosen for each potentia join. Structural quantities are computed from intensities in this band to verif the plausibility of the predicted joins with image structure. This approach ha some similarities with Canny's technique for edge detection [1]. Parts of the con tour around the point of interest (*i.e.* evidence) are examined to decide on th entire segment using hysterisis thresholding (*i.e.* verification). Finally, a loca non-iterative process based on ordering and partitioning selects the plausible join and junctions.

3.1 Input used

The initial boundary fragments are extracted from Spacek's *first difference magni tude surface* [15] (see **Figure** 2), which combines both edge strength and boundar thinning. Spacek computes gradient components $\partial f/\partial x$ and $\partial f/\partial y$ by convolvin the initial image $f(x, y)$ with two linear filters defined by: $abs(x).x/(x^2 + y^2)$ an $abs(y).y/(x^2 + y^2)$. *Ridge* points are obtained by checking for a local maximun in the direction of the gradient vector. A non-maximum suppression technique i applied to eliminate false points.

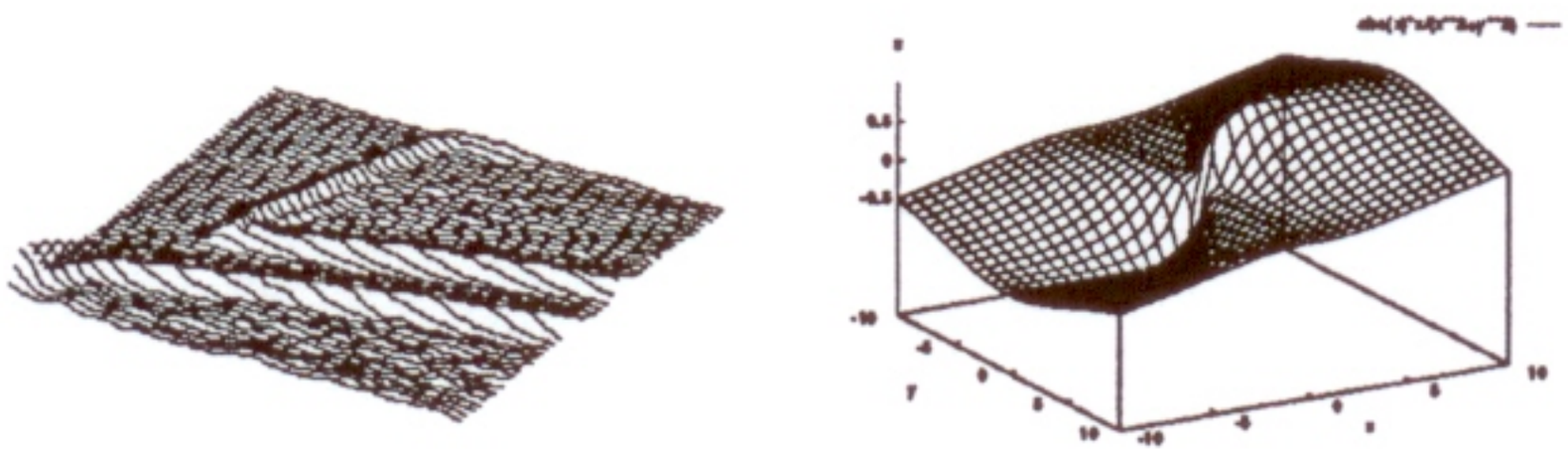

Figure 2. *Left: first difference magnitude surface. Connected boundaries are en coded along ridges (not shown here) using an 8-connected grid. Right: Spacek' finite difference template for $\partial f/\partial x$.*

3.2 Potential joins

Each boundary fragment, and its end points, are used to build the *adjacency graph*, in which co-terminations form the nodes and boundary fragments form the arcs (dual links) between them.

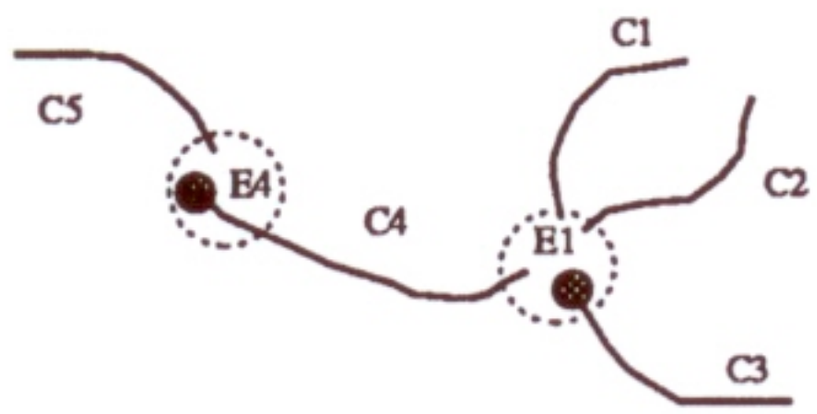

Figure 3. *The nodes (dots) created at E_1 and E_4 capture the connectivity.*

A node captures the neighbouring co-terminations (see **Figure** 3 for illustration). A single node is created at E_1. This node *attracts* neighbouring co-terminations at a distance *radius* from it; *radius* is a global parameter (see results section). The choice of E_1 is purely arbitrary.

The term *join* henceforth is used to refer to an abstract entity which denotes the perceptual and structural characteristics of a link between two bounday fragments.

Potential joins are searched for in the *adjacency graph* between neighbouring fragments. For every pair of neighbouring fragments, the following entities are computed:

3.2.1 Perceptual coherence

- The difference in contrast dc of the two boundaries involved in the join.
- The co-curvilinearity cl of the section PP' (defined later).
- End point proximity embodied in $d = \overline{QQ'}$.
- The eventual boundary which the join would give rise to, and its total length l.

Let P and P' be two points belonging respectively to B and B' such that $\overline{PQ} = \overline{Q'P'} = b$, where b is a global control parameter. Since the vectors $\vec{PQ}$ and $\vec{Q'P'}$ could be assimilated to the tangents to B and B' at Q and Q' respectively, the co-curvilinearity is defined as follows (see **Figure** 4):

$$cl(j) = \begin{cases} 0 \text{ if } PQ \bigcap Q'P' = \infty \\ \text{(straight join)} \\ \widehat{\vec{PQ}\ \vec{Q'P'}} \text{ if } PQ \bigcap P'Q' = I \\ \text{(angled join)} \\ 0 \text{ if } PQ \bigcap P'Q' = \emptyset \text{ and } W \leq 2 \\ \text{(tessellation effect)} \\ \pi \text{ if } PQ \bigcap P'Q' = \emptyset \text{ and } W > 2 \\ \text{(wrong co-curvilinearity)} \end{cases}$$

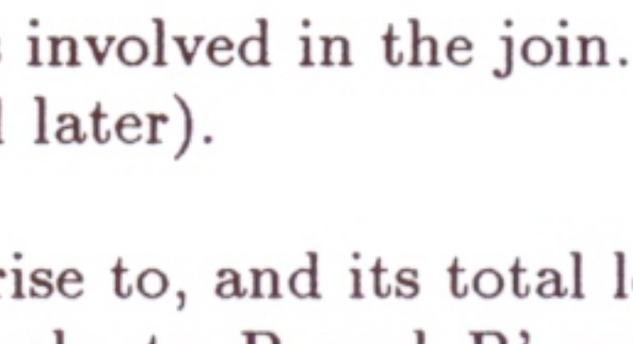

Figure 4. *Computing perceptual characteristics of a join.*

where I is the intersection point (when it exists) between lines PQ and $Q'P'$, and $W = d(PQ, P'Q')$ the distance between the lines PQ and $Q'P'$ when parallel. $\emptyset$ is the empty set. Note that $cl \in [0, \pi]$. This definition distinguishes between

false and true co-curvilinearity by construction. Joins with small values of cl are preferred over joins with larger values. $cl = \pi$ indicates that there is no perceptual evidence at all for the join.

3.2.2 Structural coherence

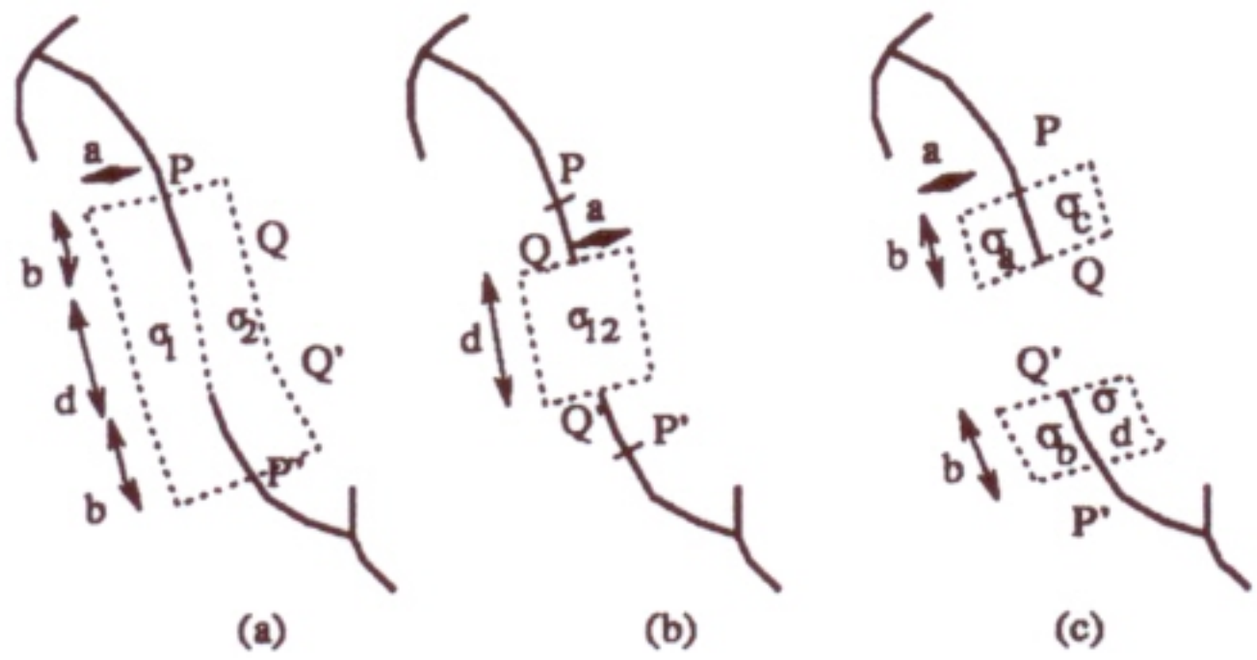

Figure 5. *Explanative figure for computing the consistency of a join with image structure.*

The differences in image intensities at the location of a gap cannot be used directly. Edge detectors would not fail at these locations in the first place, if these differences were relevant. However, we still can measure the uniformity of the intensities on each side of a potential join. This will give hints on whether the gap is a genuine one or not. To do so, we compute σ_1,σ_2 and σ_{12} the standard deviations in image intensity along and across a potential join (see **Figure** 5 (a) & (b)).

The physical reason behind these measurements is that image intensities are uniform on both sides of a genuine join, *i.e.*, σ_1 and σ_2 are less than a certain threshold and less than σ_{12}. In case of a 3-way junction though, only one side is uniform and there is no uniformity of intensity across the potential join.

3.3 Selected joins

Potential joins are ordered in a list with respect to the following criteria of comparison: let j be a join, cl_j, d_j, l_j and dc_j respectively its co-curvilinearity, length, total length of the eventual new boundary, and the difference in contrast between the boundaries involved. The ordering is done by the following set of rules:

1) $|cl_j - cl_{j'}| > \varepsilon_{cl}$ & $cl_j < cl_{j'} \Longrightarrow j < j'$ **2)** $|cl_j - cl_{j'}| > \varepsilon_{cl}$ & $cl_{j'} < cl_j \Longrightarrow j' < j$

3) $\frac{d_j}{d_{j'}} < \varepsilon_d \Longrightarrow j < j'$ **4)** $\frac{d_{j'}}{d_j} < \varepsilon_d \Longrightarrow j' < j$ **5)** $\frac{l_j}{l_{j'}} < \varepsilon_l \Longrightarrow j' < j$

6) $\frac{l_{j'}}{l_j} < \varepsilon_l \Longrightarrow j < j'$ **7)** $TRUE \Longrightarrow j' = j$

These rules are applied in order (*i.e.* 1,2,3,4,5,6 and 7). The first one to have its left hand side conditions satisfied decides on the ordering between j and j'. Rules 1 and 2 reflect the preference for joins that will result in the best co-curvilinearity first. If no decision can be taken on the basis of co-curvilinearity, *i.e.* there is no

strong evidence that one join is more co-curvilinear than the other, the proximity factor is used to decide on the ordering. This is embodied in rules 3 and 4. A very short join is much preferred over a long one. If still no decision can be taken on the basis of the proximity factor, *i.e.* there is no strong evidence that a join is much shorter than the other, preference is given to joins that will result in longer boundaries. Rule 7, when reached, indicates that joins j and j' are not discernable on the basis of the above grouping factors. This level of ambiguity hardly ever occurs. The constants ε_{cl}, ε_d and ε_l are positive thresholds in [0..1].

However, a join j is genuine only when the following structural conditions hold: $\sigma_1(j) \leq T_1$, $\sigma_2(j) \leq T_2$, $T'_{12} \leq \sigma_{12}(j) \leq T_{12}$, the bridge QQ' does not cross any other boundary, and the resulting boundary does not cross itself. Where T_1, T_2 and T_{12} are local thresholds. The use of thresholds seems unavoidable in this context.

Automatic thresholding techniques can be roughly classified into two categories: one based on statistical concepts, the other on preserving the geometric structure of images [16]. We adopt the former strategy in computing local thresholds: Let σ_a, σ_b, σ_c and σ_d be the standard deviations in intensity levels in the specified locations in **Figure** 5 (c). The sigmas represent evidence near strong edges found by the edge detector. We define local thresholds: $T_1 = max(\sigma_a(j), \sigma_b(j))$, $T_2 = max(\sigma_c(j), \sigma_d(j))$, $T'_{12} = min(\sigma_{ac}(j), \sigma_{bd}(j))$, $T_{12} = max(\sigma_{ac}(j), \sigma_{bd}(j))$.

The last condition is equivalent to Canny's hysterisis thresholding technique [1]. Joins which do not satisfy these conditions are marked as candidates for a 3-way junction (see next section).

Similarly, a junction is genuine (see **Figure** 6), only if the following structural conditions hold: $\sigma_1(j) \leq \sigma_a(j)$, $\sigma_2(j) \leq \sigma_b(j)$, $\sigma_{12}(j) \leq \sigma_{ab}(j)$, and the bridge $Q''J$ does not cross any other boundary.

The junction point J is the nearest point on PP' to Q'' (see **Figure** 6).

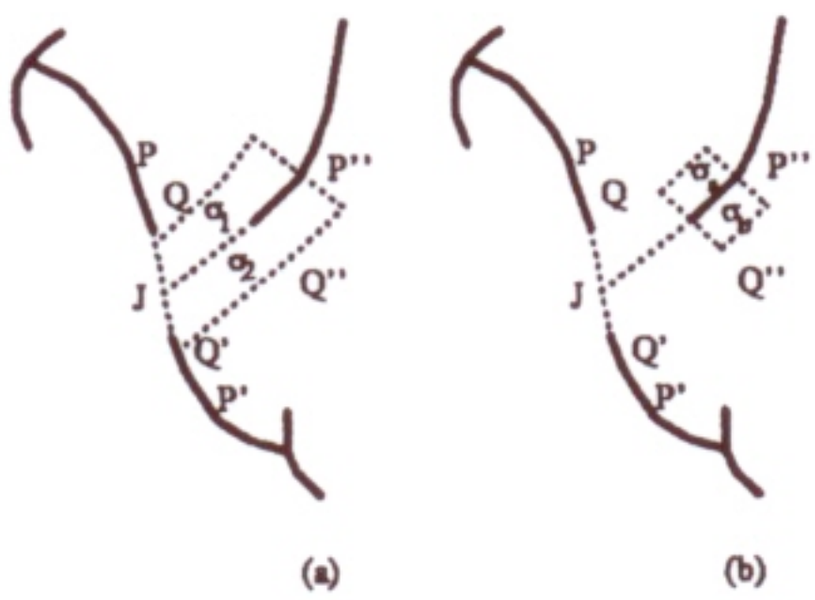

Figure 6. *Explanative figure for computing the structural coherence for 3-way junctions.*

3.4 Bridging strategy

The general idea lies in partitioning the ordered set of potential joins at a boundary end-point into two sets. One set consists of simple joins between pairs of boundaries. When fused, each will give rise to a single boundary. The other set comprises joins to be each combined with an additional boundary not involved in the first set in order to produce 3-way junctions. Joins of each set satisfy the

structural conditions. Moreover, they are consistent[1] with each other and wi joins of the other set. It is only after computing these sets that bridging a junction reconstruction are performed.

Fused boundaries are deleted from the global list, and the adjacency grap is updated accordingly. Attributes of newly created boundaries, such as contra and length, are also updated. Final boundaries are collected with the topologic structure and junction points.

Line segment's points and corner's points are generated using an adaptation midpoint line scan-conversion algorithm [5] to produce chain codes.

At this stage, we draw the attention to the following points:

• Contrary to previously described techniques, our approach offers a soluti to the neighbourhood problem discussed earlier

• No assumption or domain limitation is needed

• The complexity of the approach is governed by the number of end-poin $2n$ (where n is the number of boundaries) and the local computations at ea end-point. These local computations are proportional to the radius r, as will empirically shown in the results section. It follows that the overall complexity $O(2nr)$.

4 The results

The parameters that govern our bridging process are l_{min} and *radius* for the glob control, ε_{cl}, ε_d and ε_l for local perceptual grouping, and a, b for computing t standard deviations and co-curvilinearity. Most of these parameters were fixed f all experiments. Typically, $l_{min} = 3$, $(\varepsilon_{cl}, \varepsilon_d, \varepsilon_l) = (0.175, 0.50, 0.175)$, $a = 3$ pixe and $b = 5$ pixels.

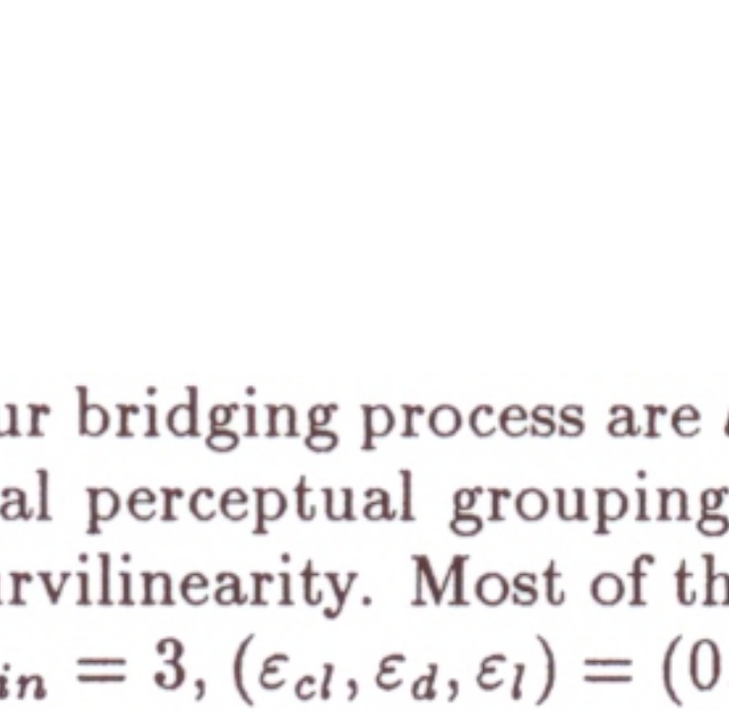

Figure 7. *From top to bottom: A* 250×100 *image of step edges at various contrast boundary fragments detected and boundaries obtained using our bridging algorithm Panel intensities are 64,190,96,158,112,142,120,134,124 and 130. Edge finde responses are rounded to the nearest pixel position, hence the zigzags.*

The performance has been tested on a variety of synthetic and real image

[1] Two joins are said consistent if they do not have a boundary in common and do not cro each other. A binary image is used locally to compute intersections.

The first synthetic image is a reproduction of the data used by Fleck [4] to test the output of various edge detectors. This image represents step edges at various contrasts (**Figure** 7). The panels were first smoothed with a Gaussian of standard deviation 1 cell and then corrupted with Gaussian noise of standard deviation 1 intensity unit to simulate real imaging conditions.

It is apparent that the structural conditions for detecting gaps work well, even in cases of very low contrast. In this experiment only one gap out of 26 was not bridged. This miss is actually due to the fact that the co-curvilinearity of this join is π, and thus is not eligible for bridging on the basis of perceptual grouping.

The second synthetic experiment involves noisy step edges. The panels were first smoothed with Gaussian of standard deviation 1 cell and then corrupted with Gaussian noise of increasing standard deviation (**Figure** 8).

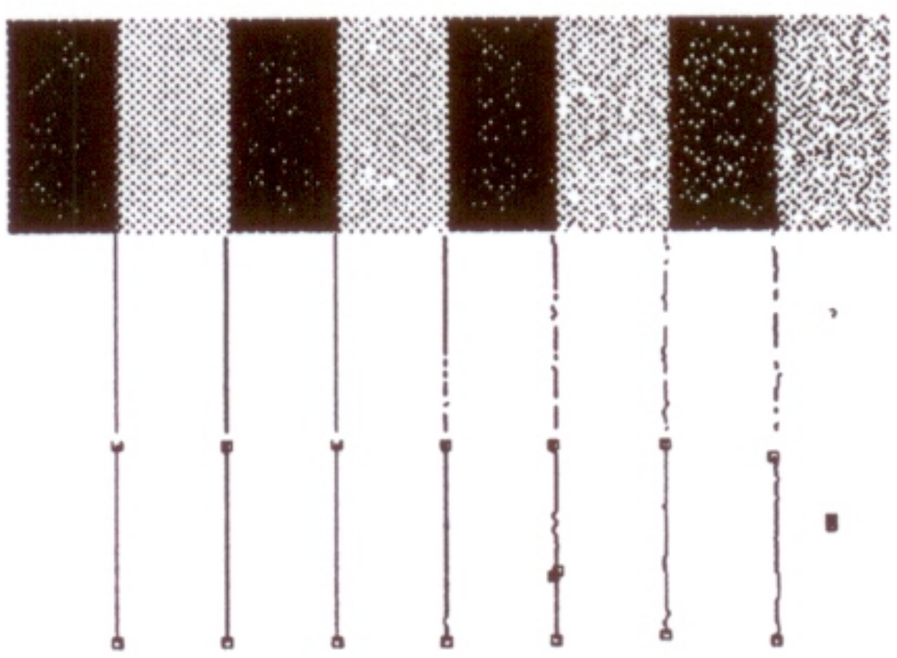

Figure 8. *From top to bottom:A* 400 × 100 *image of noisy step edges, boundary fragments detected, and boundaries obtained using our bridging algorithm. Panel intensities are 27 and 227, and the boundaries occur between two cells. Odd-numbered panels are corrupted with Gaussian noise of standard deviation 8.0,16.0,32.0 and 64.0 units. Even-numbered panel boundaries are not corrupted.*

The first real image shows a pair of scissors on a mouse pad (**Figure** 9).

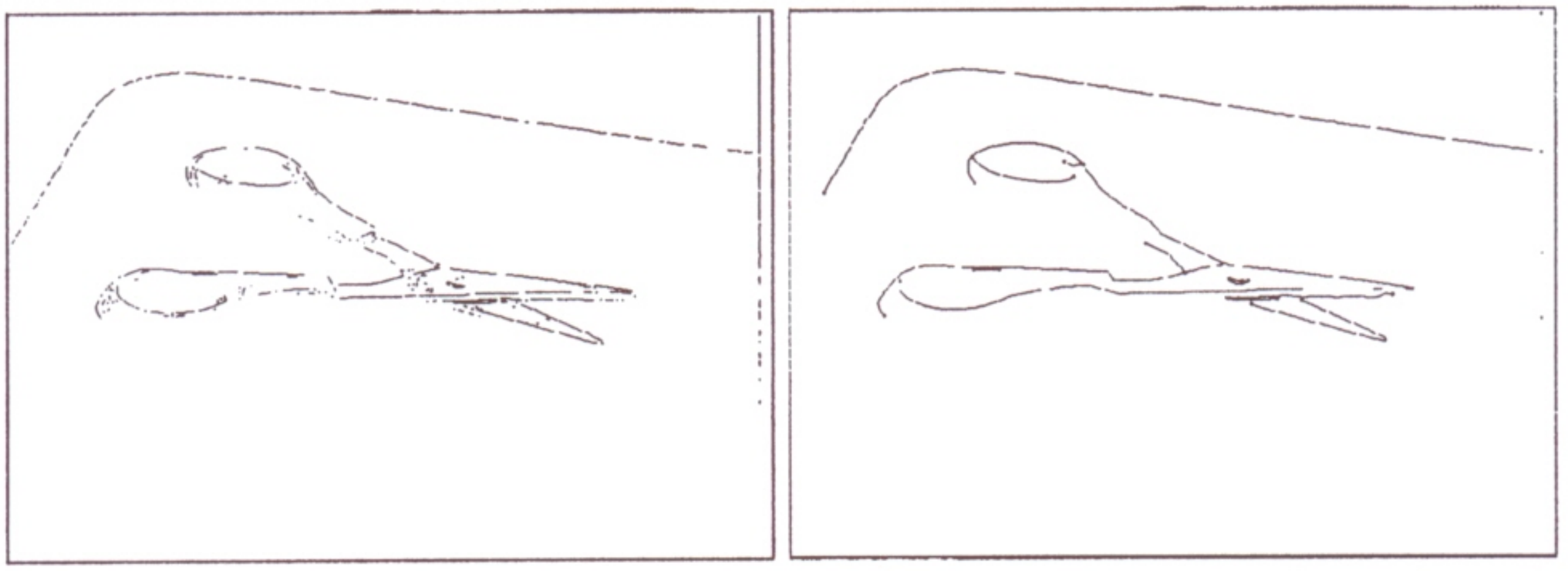

Figure 9. *Left: boundaries extracted from* 1^{st} *difference magnitude surface of a pair of scissors. Right: final boundaries obtained* ($r = 40$). *Junctions are marked with dots.*

The table below shows the performance obtained with a *SPARC station EL* when processing **Figure** 9.

r(pixels)	time(s)	% reduction
20	5.6	69
25	6.7	70
30	8.0	70
35	8.4	70
40	10.0	70
45	10.6	70
50	11.7	70
55	12.9	70
60	14.3	70
65	15.7	70

Table 1: *Recorded measurements from processing the scissors.*

The reduction factor (Table 1, 3^{rd} column) is: $f = 1 - \frac{final\ boundaries}{initial\ boundaries}$. The tim recorded are for the bridging process to run, including the construction of the tw graphs and I/O operations. For this particular image, $r_{opt} = 25$ is the optimu radius. Radii $r > r_{opt}$, produce the same boundaries as $r = r_{opt}$. r_{opt} depen strictly on the quality of the input. The graph $(r, time)$ confirms our claim th the complexity of the approach is $O(2nr)$.

For the above values of r, on average 83% of the joins were selected on th basis of a strong co-curvilinearity, 14% on the basis of proximity and 3% on th basis of the total length. The order in which co-curvilinearity and proximity we applied was not important.

The second experiment is a (768 × 576) picture of various objects (see **Fig ure** 10). Final boundaries for this image (see **Figure** 10) were obtained usin the radius $r = 11$. Out of 160, only 44 boundaries were retained, which gives reduction factor of 72%. All 3-way junctions were successfully solved. 38% of th joins were based on co-curvilinearity, 10% on proximity, 51% on the total lengt of the newly produced boundary, and only 1 join was ambiguous.

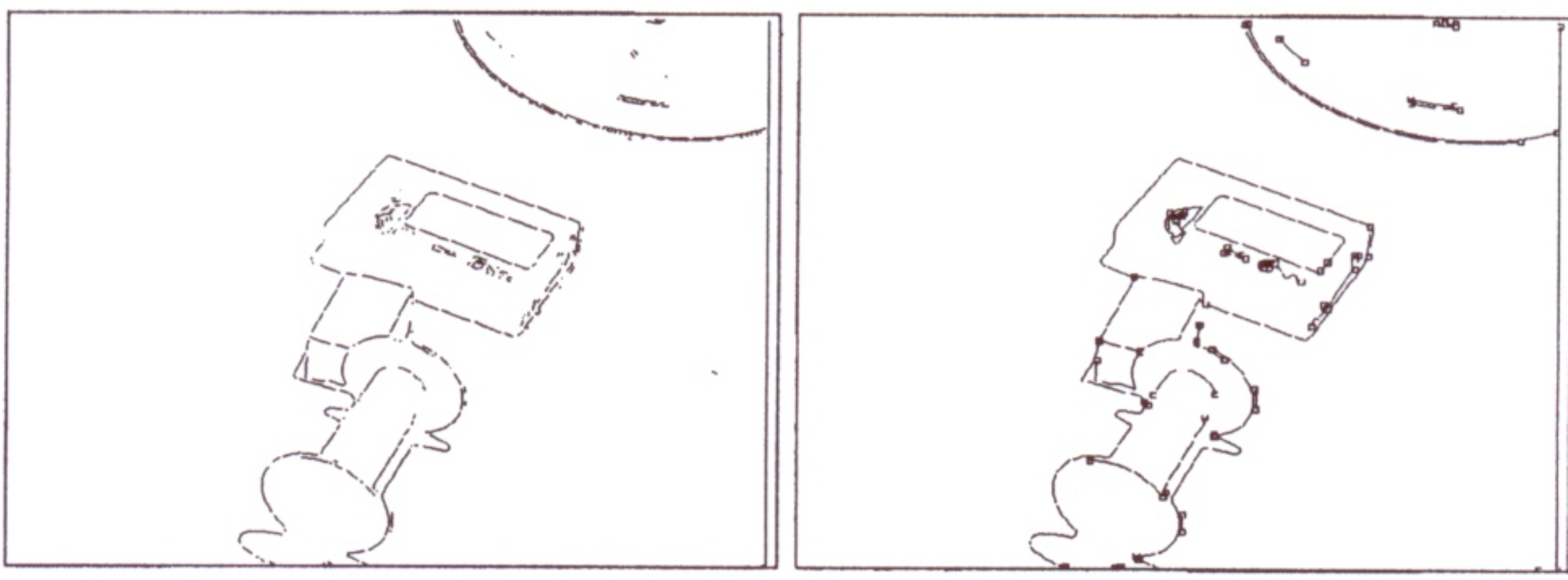

Figure 10. *Left: Input to our system: boundaries extracted from first differenc magnitude surface of an image of a few objects. Right: final boundaries obtaine* ($r = 11$). *Detected junctions and end-points are marked with squares.*

5 Conclusion

We have presented an approach to gap bridging which constructs coherent boundaries in images using both perceptual groupings and image structure criteria. The underlying characteristic of the approach is consistency with the initial image, which makes it suitable for general-purpose computer vision systems. The authors successfully used these boundaries for correspondence computation [14].

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