# Grouping of Straight Line Segments and Circular Arcs for Scene Analysis

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## Abstract

We introduce an approach for the extraction of 2D features from intensity data. Using perceptual organization, hierarchies of 'low-level' features are generated based on parallelism, symmetry, continuation and intersection. Previous work by Lowe [7] provides an excellent introduction to the idea behind perceptual grouping of straight lines and the significance of features. Mohan and Nevatia [8] perform perceptual grouping of image boundaries that leads to the identification of surfaces and objects in a scene. Our local grouping algorithm is inspired by the formalism defined by Etamadi et al. [3] which is extended to include circular arcs. Our procedure is as follows: edges extracted from the intensity image are recursively grouped and segmented into straight line segments and circular arcs. Perceptual laws are then applied to identify the possible relationships between all pairs of lines and arcs. A measure of significance is assigned to every detected grouping. This measure reflects the amount of valuable information contained in the grouping. The hierarchies extracted can be combined to obtain closures that may be interpreted as the borders of visible surfaces in a scene. Results obtained for complex indoor scenes are presented.

## 1 Introduction

A key problem area in computer vision is the extraction of meaningful features that can make easier the interpretation of intensity data. Humans isolate object boundaries and relationships among image elements before recognizing them. This phenomenon called perceptual organization can be summarized by a set of laws defined as follows [5][6]: 1) *Proximity* - elements which are closer together tend to be grouped together, 2) *Similarity* - elements that are similar in physical attributes are grouped together, 3) *Continuation* - elements that lie along a common line or smooth curve are grouped together, 4) *Closure* - there is a tendency for curves to be completed so that they form enclosed regions, and 5) *Symmetry* - regions which are surrounded by symmetrical borders are perceived as coherent figures.

Most previous research in this field concentrated on forming perceptually significant groupings among straight line segments [7] and curves [8]. Applying perceptual organization to curves gives good results but it costs a lot in computer time. On the other hand, straight line segments give incomplete descriptions of the visible surfaces of non-polyhedral objects. To fill the gap between these two extremes, an approach was developed that includes circular arcs in the process of perceptual grouping. The combination of circular arcs with straight line segments increases the amount of structural information that can be extracted from intensity data without increasing significantly the complexity of the analysis.

In this paper, we present an approach to find perceptually significant groupings among straight line segments and circular arcs. This algorithm is particularly inspired by the formalism defined by Etamadi et al. [3] which is concerned with the formation of self-consistent groupings. In the next sections, we describe the global hierarchy of the system (section 2). Then we explain in detail every step of the process. First, edges detected by the Canny operator [1] are linked into contours using an algorithm introduced by Nevatia and Babu [9] (section 3). Based on a parallel algorithm developed by Etamadi [2], contours are segmented into straight line segments and circular arcs (section 4). Perceptual laws are then applied to identify the possible relationships between any pair of characteristics extracted in the previous stage. Additionally, a measure of significance is assigned to these 'low-level' features based on parallelism, symmetry, continuation and intersection. This measure reflects the amount of valuable information contained in each grouping (section 5). Then, we present typical results obtained for complex indoor scenes and show how we can use the measure of significance in filtering unlikely groupings (section 6). Finally, a discussion and some conclusions are presented including some future works concerned with this new approach for grouping straight line segments and circular arcs (section 7). The ultimate goal of this research is the localization, description, and recognition of objects in a cluttered scene explored and analyzed by an autonomous mobile robot. The hierarchies of groupings extracted with the presented algorithms form the starting point towards this goal.

## 2 Overview of the approach

This section describes the basic concepts and steps involved in the extraction of perceptually significant groupings from a set of straight line segments and circular arcs. The approach essentially organizes structural information contained in intensity data to find regularities and extract meaningful 2D groupings.

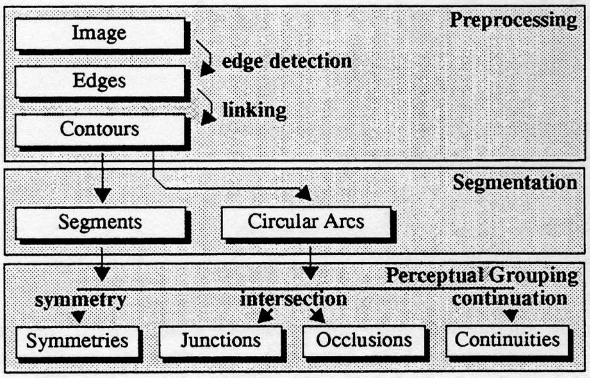


Figure 1 Hierarchy

The goal of our research is to extract hierarchies of features that can serve as a basis for the analysis of complex indoor scenes. Since we start with the assumption that the scenes are composed of man-made objects of unknown shape, features must be found to distinguish one object from another. Based on the fact that most man-made objects have boundaries that may be well approximated by groups of linear and circular segments, a choice was made to look for groupings among straight line segments and circular arcs that can be extracted from intensity data.

The framework of our approach includes three phases: 1) preprocessing of the image to decrease the amount of information for analysis, 2) segmentation of contours into straight line segments and circular arcs, and 3) perceptual grouping of characteristics based on parallelism, symmetry, continuation, and intersection. The whole process is sketched in Figure 1.

# 3 Preprocessing

This module first extracts edges from the intensity image using a Canny edge detector [1]. These edges contain the basic structural information from which all groupings will be derived. Open and closed contours are then extracted based on a tracking algorithm presented by Nevatia and Babu [9]. The purpose of the linking process is to group single edge points based on connectivity. The Canny edge detector preserves connectivity information by tracking maxima of gradient magnitude based on their orientation. Contours obtained must be approximated so as to overcome local noise. Representation of contours in a more manageable form results in better performance of grouping algorithms.

# 4 Segmentation

Obtaining straight line segments is straightforward, and these have been used by many researchers in computer vision [4][7][10]. Less time has been devoted to the extraction of higher order representations such as circular arcs [11]. Based on a parallel approach developed by Etamadi [2], the contours obtained in the previous stage are segmented into two types of characteristics: straight line segments and circular arcs.

The segmentation algorithm is based on *local symmetry* (not to be confounded with the symmetry groupings to be discussed in Section 5.4) which is inherently scale independent and requires no threshold. It operates on individual contours of three or more edge pixels to extract straight line segments and circular arcs. In this way, each contour may be processed in parallel and the results linked at the end. The algorithm operates in three passes. Each contour is first broken into sub-contours which respect a local symmetry assumption. On the second pass, these sub-contours are linked into segments based on cocurvilinearity and colinearity criteria. The segments are finally classified as straight line segments or circular arcs based on a simple deviation criterion. More details are given in the next three sub-sections.

## 4.1 Near Symmetry Segmentation

Figure 2 shows a graphical representation of a twelve pixels long contour. Let us suppose that processing begins at the endpoint labeled $B$. Since sub-contours less than four pixels long are inherently symmetric, we label $B$ and $C$ as the endpoints of the starting sub-contour. We first calculate the position of $D$ the midpoint of the sub-contour. Next we find the position of $E$ by dropping a perpendicular from $D$ onto the line joining the endpoints of the sub-contour. The sub-contour is said to be *locally symmetric* if the difference between $BE$ and $EC$ is less than $1/\sqrt{1+L^2}$ where $L$ represents the current length of the sub-contour in pixels. The value $1/\sqrt{1+L^2}$ represents the difference of the distances in the case of a one pixel deviation from a straight line.

Processing continues by jumping to the next pixel along the contour and determining the symmetric state of the new sub-contour. In Figure 2 the whole process is clearly illustrated. Symmetric and asymmetric states are respectively indicated by symbols $s$ and $a$. The process iterates until the sub-contour has been in an asymmetric state three consecutive times or until any other sub-contour of three pixels is again a candidate as the possible start of a new segment. The set of pixels from the starting point to the last symmetric state point are grouped to form a segment.

## 4.2 Segment Linking

Since each segment is associated with a single contour, connectivity information associated to a contour simplifies the linking procedure. Two adjacent segments will be grouped if they have the same relative direction

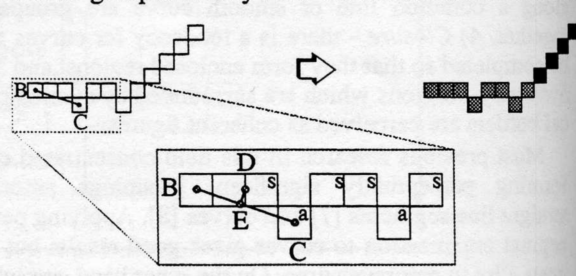


Figure 2 Segmentation pass applied to a simple contour

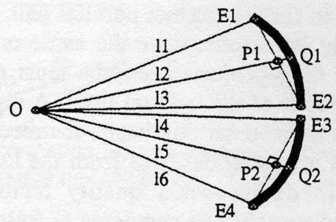


Figure 3 Linking two adjacent segments

of curvature. Figure 3 shows two adjacent curved segments with the parameters needed for the calculation. Using a least-squares circular arc fitting, the position of $O$, the combined center of curvature, is determined. The relative direction of curvature of segments is computed simply by comparing the lengths of segments $OPi$ and $OQi$, where $i$ identifies the segment.

Combination of segments is based on cocurvilinearity and colinearity criteria. A *basic criterion* imposes that adjacent endpoints be within 3 pixels and that segments have the same relative direction of curvature. Cocurvilinearity is respected if any pair of two lengths from $l1$, $l2$, $l3$, $l4$, $l5$ and $l6$, differ by less than $\sqrt{2}$. Indeed, given the segmentation procedure, $\sqrt{2}$ is the maximal distance between any point on one of the two segments and the least-squares circular arc fitted to the two segments. To evaluate colinearity, endpoints $E1$ and $E4$ are joined by a straight line segment and the maximum deviation between this line and the segments to be linked is computed. Colinearity is respected if the basic criterion (see above) is verified and the maximum deviation between the two segments is less than 2 pixels. Segments that respect cocurvilinearity or colinearity are joined into a new segment. The procedure is repeated until no more adjacent segments along a contour may be combined. The next subsection describes how segments are classified as straight line segments or circular arcs.

### 4.3 Classification

Classification of segments is based on the colinearity criterion. For any segment, a maximum deviation of less than 2 pixels means that the segment is linear and can be classified as a straight line segment. If this deviation condition is not respected, it means that the segment has a uniform non-zero curvature and it is therefore classified as a circular arc. Typical results obtained for an indoor scene are shown in Figure 4.

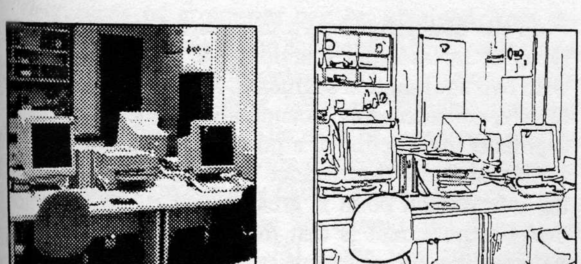

Figure 4 Simple object segmentation: (a) intensity image, and (b) segmentation where thin contours represent straight line segments and thick contours circular arcs

## 5 Perceptual Grouping

The goal of the grouping process is to find relationships between any pair of characteristics to extract 2D features of the objects in the scene. By using perceptual organization, hierarchies of 'low-level' features based on parallelism, symmetry, continuation, and intersection are generated. Previous work by Lowe [7] provides an introduction to the idea behind perceptual grouping of straight lines and the significance of features. Mohan and Nevatia [8] perform perceptual grouping of image boundaries that leads to the identification of surfaces and objects in a scene. Our local grouping algorithm is particularly inspired by the formalism defined by Etamadi et al. [3]. This formalism concerned with the formation of self-consistent groupings of straight lines from which all higher level groupings may be derived is extended to include circular arcs. Additionally, a measure of significance is assigned to every detected perceptual grouping. This measure reflects the amount of valuable information contained in the grouping.

Any pair of straight lines and arcs may respect laws of parallelism, symmetry, continuation, or intersection. An important requirement is that any higher level grouping should be derivable from the generated 'low-level' hierarchies. Based on this assumption, any proposed grouping must be exclusive and respect strict definitions for parallelism, symmetry, continuation, and intersection. Invariance to scale factor is also desirable for the purpose of computer vision. The hierarchy developed must facilitate the elimination of unlikely combinations of characteristics at an early stage.

Based on these requirements, three different types of hierarchies are defined. These hierarchies are concerned with pairs of straight lines, pairs of arcs and pairs of one straight line and one arc, respectively, and are illustrated in the form of tree structures in Figure 5. The distinction between intersecting and non-intersecting junctions is important since non-intersecting junctions may be interpreted as occlusions that represent the overlap of two

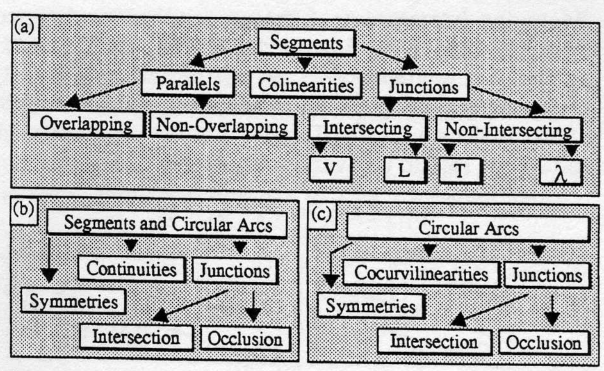


Figure 5 Hierarchies of groupings: a) pairs of segments, b) pairs of segment and circular arc, and c) pairs of circular arcs.

visible surfaces in a scene. In the next subsections, we describe all those relations in details and the measure of significance that is attached to each of these groupings.

## 5.1 Straight Line Segment Groupings

As can be seen in Figure 5a, seven types of groupings may be obtain by the combination of two straight line segments. These grouping emerge from parallelism, colinearity, and intersection relationships. In the following we devote our discussion to these type of straight line segment groupings.

### 5.1.1 Overlapping Parallel Line Pairs

Let us first define the following *colinearity criterion.* When the difference of orientation between two straight segments is less than $\varphi_c$, the angle of colinearity, these segments are labeled as candidates for parallelism or colinearity. Parameters $Li$, $LPi$, $\varphi i$, $\sigma''$ and $\sigma^{\perp}$ will be use in the discussion. They respectively represent the length, the projected length onto the so-called 'virtual line', the orientation and the standard deviation along and perpendicular to the direction of the straight line segment $i$. The standard deviations $\sigma''$ and $\sigma^{\perp}$ are used to incorporate uncertainty in the position of segments extracted in the previous stage. For now, grouping is realized without any uncertainty model. Since no uncertainty values are computed, the standard deviations are replaced by constant values in our implementation.

Given a pair of segments $S1$ and $S2$ as illustrated in Figure 6a, the first step in the search for overlapping parallels is to parameterize 'virtual line' $VL$. The orientation angle $\varphi_{VL}$ corresponds to a weighted average of the orientation of $S1$ and $S2$. The coordinates of $M$, the midpoint of $VL$, are calculated in the same way using $M1$ and $M2$, the midpoints of $S1$ and $S2$, respectively:

$$\varphi_{VL} = \frac{(L1 \times \varphi_1 + L2 \times \varphi_2)}{L1 + L2},$$

$$M_X = \frac{(L1 \times M1_X + L2 \times M2_X)}{L1 + L2} \text{ and}$$

$$M_Y = \frac{(L1 \times M1_Y + L2 \times M2_Y)}{L1 + L2}$$

Next we compute the coordinates of $P1$, $P2$, $P3$ and $P4$ as the intersection of the perpendiculars dropped from the endpoints of $S1$ and $S2$ onto $VL$. The endpoints of $VL$ correspond to the pair of points $Pi$ and $Pj$ which are separated by the largest distance. The length of $VL$ is denoted $L^{VL}_{1,2}$. The straight line segments $S1$ and $S2$ are said to be overlapping parallels if

$$L^{VL}_{1,2} \leq LP_1 + LP_2 - \sigma''_1 - \sigma''_2$$

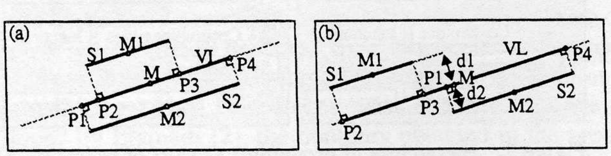


Figure 6 Overlapping (a) and non-overlapping (b) pair of parallel straight line segments

In order to form a perfect parallel pair, two overlapping straight lines must have the same orientation and the sum of their projected lengths must correspond to twice the length of the 'virtual line'. A measure of significance is defined on this basis; it reflects how much any parallel grouping deviates from the ideal case. Etamadi et al. [3] define such a 'quality' factor for overlapping parallel straight line segments as follows:

$$Quality = \frac{LP_1 + LP_2 - \sigma''_1 - \sigma''_2}{2 \times L^{VL}_{1,2}}$$

This definition ensures that the quality factor is always in the range of 0.0 to 1.0 where a value of 1.0 represents a perfect grouping. This definition also ensures self-consistency of the groupings.

### 5.1.2 Non-Overlapping Parallel and Colinear Line Pairs

Given the definition of an overlapping parallel line pair described in the previous subsection, the algorithm for finding non-overlapping parallel and colinear groupings follows naturally. Let us consider the pair of segments illustrated in Figure 6b. Straight line segments $S1$ and $S2$ are labeled as candidates for non-overlapping parallel or colinear grouping if:

$$L^{VL}_{1,2} > LP_1 + LP_2 - \sigma''_1 - \sigma''_2$$

In order to form a perfect colinear or non-overlapping parallel grouping, two straight line segments must have the same orientation and the sum of their projected lengths must correspond to the length of $VL$. To differentiate between non-overlapping and colinear pairs, the distances $d1$ and $d2$, which correspond to the lengths of perpendiculars dropped from $M$ onto the prolongation of segments $S1$ and $S2$, respectively, must be computed. If distance $di$ is less than or equal to $\sigma^{\perp}i$, the segments are colinear. Otherwise the segments represent a non-overlapping parallel straight line grouping. The measure of significance for these types of grouping is defined as follows:

$$Quality = \frac{LP_1 + LP_2 - \sigma''_1 - \sigma''_2}{L^{VL}_{1,2}}$$

### 5.1.3 Intersecting Junctions

In the hierarchy shown in Figure 5, we defined two types of intersecting junctions for groupings involved with two straight line segments. Any pair of intersecting lines is considered as a candidate $V$ junction. A pair of segments intersecting at a point on one of the segments is disqualified if the distance between each endpoint and the intersection point is greater than $\sigma''_i + \sigma^{\perp}_j$. An additional requirement is that the difference of orientation between the two segments must be in the range $\varphi_{min}$ to $\varphi_{max}$. To ensure consistency of the grouping, $\varphi_{min}$ is selected as equal to $\varphi c$ the colinearity angle threshold.

For a perfect $V$ junction, the intersection point $I$ shown in Figure 7a lies exactly at the extremities of the

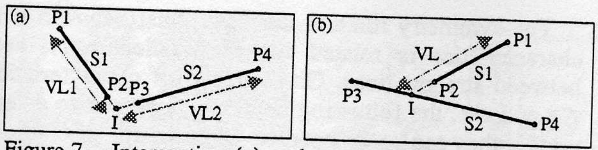


Figure 7 Intersecting (a) and non-intersecting (b) pairs of straight line segments

straight line segments. In the case of an intersecting junction, the purpose of the significance measure is to penalize groupings having an intersection far away from the endpoints of the segments. Based on this assumption, we define the factor of quality as follows:

$$Quality = \frac{L1 + L2}{L_1^{VL} + L_2^{VL}}$$

To avoid any ambiguity between almost intersecting an intersecting junctions, two segments that satisfy the above requirements and that have a distance less than $max|\sigma_i^{''}, \sigma_i^{\perp}|$ between their closest endpoints are labeled as a $V$ junction. An $L$ junction can be seen as a particular case of a $V$ junction where $\varphi_{max}$ corresponds to $\pi/2$ and $\varphi_{min}$ to $\pi/2 - \varphi c$. For consistency reasons, the $\varphi_{min}$ of an $L$ junction corresponds to the $\varphi_{max}$ associated to the $V$ junction type.

### 5.1.4 Non-Intersecting Junctions

A non-intersecting junction is one which results from the overlap of two visible surfaces in a scene. A junction is labeled as non-intersecting if it has not already been labeled as an intersecting junction and the intersection point lies on one of the straight line segments.

For perfect $\lambda$ or $T$ junction between two straight line segments, the intersection point $I$ shown in Figure 7b lies exactly on an endpoint of one of the segments. In order to penalize groupings between distant segments, we define the following measure of quality using $L1$ and $L_1^{VL}$ associated to the straight line segment which does not include the intersection point:

$$Quality = \frac{L1 - \sigma_1^{''} - \sigma_2^{\perp}}{L_1^{VL}}$$

## 5.2 Straight Line Segment and Circular Arc Groupings

Four types of groupings can be obtained from the combination of straight line segments with circular arcs. In the following we will devote our discussion to continuation and intersection between straight line segments and circular arcs. The case of symmetry will be discussed at the end since the principles are the same as for groupings between any pair of characteristics.

We now describe how to extend the formalism defined by Etamadi et al. [3] to the formation of self-consistent groupings of circular arcs. Since definitions used before concerned only straight line segments, it appears natural to describe circular arcs using straight line segments.

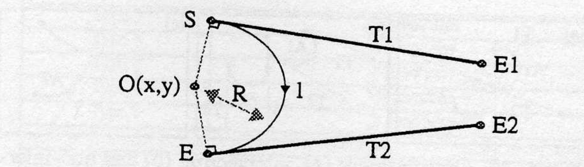


Figure 8 Circurlar arc segmentation

The assertion can be made that junctions between any type of characteristic occur at their extremities. As a result, the knowledge of the endpoints coordinates and orientations of two characteristics may lead to the identification of a junction between them. On the basis of this and the need for consistency, we chose to describe a circular arc by the straight line tangents at its endpoints.

Figure 8 illustrates the segmentation of a typical circular arc for the purpose of junction search. Since the endpoints and the center of any circular arc have known coordinates, one may easily compute the orientation of $T1$ and $T2$ using simple trigonometry. To ensure consistency with straight line groupings, tangent segments must be of the same length as the circular arc which they come from. From the rotation direction of the circular arc, the coordinates of $E1$ and $E2$, the unknown endpoints of the tangent segments, may be computed. With this representation of circular arcs, the algorithms of the previous section may be used to find any pair of straight line and circular arc satisfying the continuation, intersecting, or non-intersecting criteria.

### 5.2.1 Continuities

The continuity relation that may exist between straight line segments and circular arcs is related to the colinearity relation between two straight line segments. Since the proposed representation for a circular arc is in the form of two tangent segments, the colinearity algorithm described in the previous section is used to identify pairs of straight line segment and circular arc that form continuity groupings. An exemple of continuitie between a straight line segment $S$ and a circular arc $A$ is shown in Figure 9a.

### 5.2.2 Intersecting and Non-Intersecting Junctions

Given the framework defined in the last subsection, the definition of intersecting and non-intersecting junctions between straight line segments and circular arcs follows naturally. As one can see in Figure 9b and 9c, an intersecting junction between segment $S$ and arc $A$ corresponds to junction types $V$ or $L$ while a non-intersecting junction correspond to $\lambda$ or $T$ junction types.

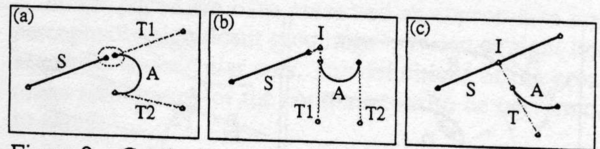


Figure 9 Continuity (a), intersecting (b) and non-intersecting (c) pairs of a straight line segment and a circular arc

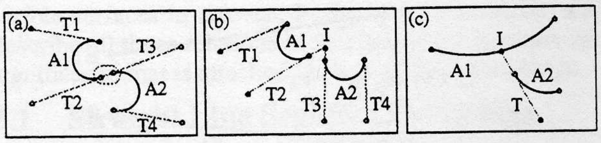


Figure 10 Cocurvilinear (a), intersecting (b) and non-intersecting (c) pairs of circular arcs

## 5.3 Circular Arc Groupings

As presented in Figure 5c, four types of groupings may be obtained from the combination of two circular arcs. These groupings emerge from symmetry, cocurvilinearity, and junction relationships. Figure 10 shows how tangents may be used to extract cocurvilinearities and intersection based junctions. In the next subsection symmetrical groupings between any pair of straight line segments and circular arcs are discussed.

## 5.4 Symmetric Groupings

Symmetry is a measure of the structural relationship between two characteristics. Mohan and Nevatia [8] define symmetry as a one-to-one mapping between the points on two curves. The symmetry axis is the locus of the midpoints of the lines joining points at equal length ratios along the curves. Let $l1$ and $l2$ be the respective lengths of curves $AX$ and $CY$ as shown in Figure 11a. Point $X$ of $AB$ will be mapped to point $Y$ of $CD$ if and only if the following criterion is verified.

$$\frac{l1}{AB} = \frac{l2}{CD}$$

For the detection of symmetry between two characteristics, only the extremities of the curves need to be matched since the match for other points on the curves is implicit. In summary, extracting symmetries involves matching of curves rather than edges.

Some heuristics for finding possible pairs of symmetric characteristics have been proposed by Mohan and Nevatia [8]. The first one says that the length of the shorter of the two curves should be no less than one third of the length of the longer curve. Another heuristic is concerned with a minimum overlap ratio.

An algorithm was developed to find symmetries between straight line segments and circular arcs. It is based on the definitions proposed by Mohan and Nevatia [8] and the overlapping parallel straight lines groupings introduced by Etamadi et al. [3]. Given that symmetries may be evaluated only from the endpoints of characteristics and the need for consistency, a circular arc is described by a straight line joining its endpoints.

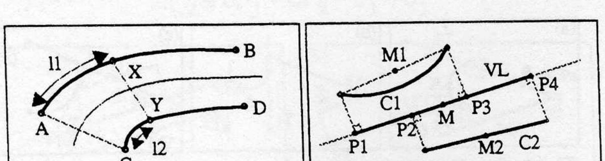


Figure 11 (a) Symmetry definition and (b) Symmetric pair of straight line segment and circular arc

The symmetry relation that may exist between two characteristics is related to the parallelism relation between straight lines. Given a pair of characteristics $C1$ and $C2$, the following heuristics are used to determine if they can be grouped on the basis of symmetry.

1) The acute angle between the straight line segments representing the two characteristics must be less than a given value $\varphi s$, called the limiting angle of symmetry. Since symmetries having an angle larger than 90° are intuitively better represented by junctions, our search is limited by assigning a value of 90° to $\varphi s$. Mathematically:

$$|\varphi_{c1} - \varphi_{c2}| \le \varphi s$$

2) There should be some overlap between the two curves. Symmetry is validated if the weighted sum of the projected lengths onto the symmetry axis is larger than the length of the symmetry axis. We define $rOverlap$ as the minimum ratio of overlap needed for a pair of characteristics to be a candidate for symmetry grouping.

$$L^{VL}_{1,2} \le (LP_1 + LP_2 - \sigma''_1 - \sigma''_2) \times (1 - rOverlap)$$

3) The length of the shorter of the two curves must be greater than the length of the longer curve weighted by $rOverlap$, the minimum ratio of overlap.

$$Min(L_{c1}, L_{c2}) > Max(L_{c1}, L_{c2}) \times rOverlap$$

Figure 11b shows a pair of one straight line segment and one circular arc. The first step of the algorithm is to verify whether the orientation and length criteria are respected. Then $VL$ is parameterized. The overlapping criterion is then verified. If all conditions are satisfied, the candidate pair is accepted as a symmetric grouping.

For a perfect symmetric grouping, the sum of the projected lengths of the two characteristics corresponds to twice the length of the proposed symmetry axis. Based on this definition, the following measure of significance is defined for symmetric groupings:

$$Quality = \frac{LP_1 + LP_2 - \sigma''_1 - \sigma''_2}{2 \times L^{VL}_{1,2}}$$

Three different types of hierarchies representing the basic relations that may exist between straight line segments and circular arcs have been presented. Figure 12 illustrates some significant perceptual groupings extracted for a complex indoor scene.

# 6 Experimental Results

The above grouping algorithms have been successfully applied to many other intensity images of indoor scenes. Three close-up views are shown in Figure 13a. Figure 13b shows the result of applying the Canny edge detector to these images. Figure 13c shows results of the segmentation pass where thick contours represent circular arcs and thin contours straight line segments. In order to show how the measure of significance may be used effectively in filtering unlikely groupings, we have

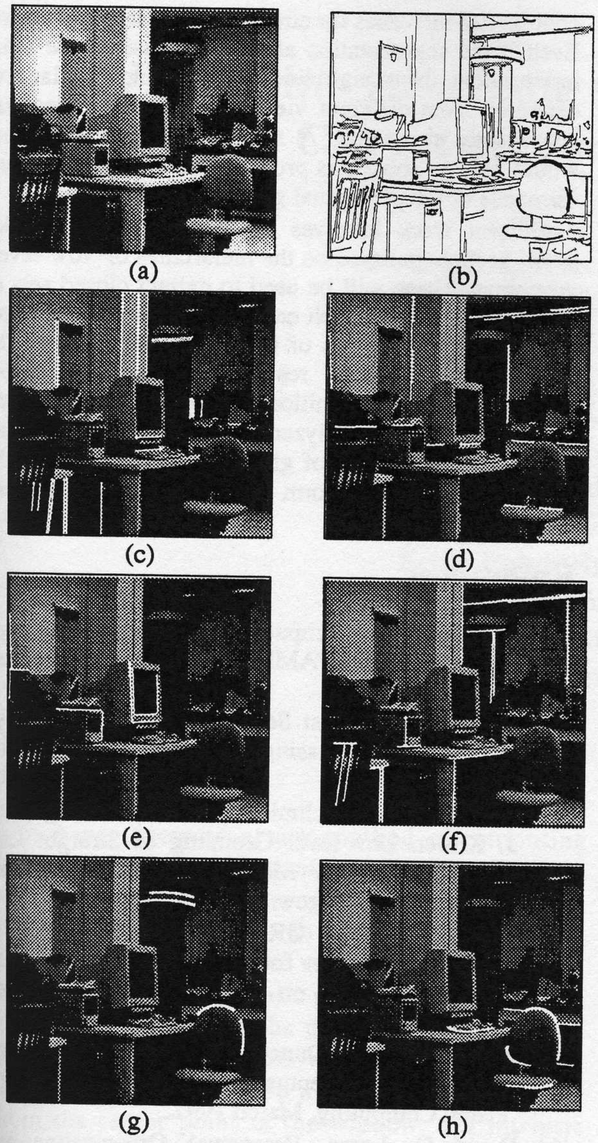


Figure 12 Some exemples of groupings extracted for a complex indoor scene: (a) original image, (b) straight line segments and circular arcs extracted, (c) overlapping parallels, (d) colinearities, (e) $L$ junctions, (f) $\lambda$ junctions, (g) symetric pairs of circular arcs, and (h) straight line segment and circular arc junctions

applied the grouping algorithm twice to the set of straight line segments and circular arcs extracted from the left image in Figure 13a, using different values of the quality factor. Figure 14 shows the results of segmentation with identification numbers and characters allocated to lines and curves, respectively. Table 1 shows all groupings having a measure of significance greater than or equal to 0.5. Table 2 illustrates the results for a quality factor of 0.8. The different types of grouping are numbered as follows:

| Pair of straight line segments | |
|---|---|
| Type 1 | Overlapping parallels |
| Type 2 | Non-Overlapping parallels |
| Type 3 | Colinearities |
| Type 4 | L Junctions |
| Type 5 | T Junctions |
| Type 6 | V Junctions |
| Type 7 | $\lambda$ Junctions |
| Pair of circular arcs | |
| Type 8 | Cocurvilinearities |
| Type 9 | Junctions |
| Type 10 | Occlusions |
| Type 11 | Symmetries |
| Pair of one straight line segment and one circular arc | |
| Type 12 | Continuities |
| Type 13 | Junctions |
| Type 14 | Occlusions |
| Type 15 | Symmetries |

Table 1 Groupings obtained with a 0.5 limiting quality factor

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Type 1 | 1-2 | 1-12 | 3-4 | 5-6 | 11-12 | | |
| Type 2 | 1-11 | 2-11 | 2-12 | 3-5 | | | |
| Type 3 | 4-5 | | | | | | |
| Type 4 | 1-10 | | | | | | |
| Type 5 | | | | | | | |
| Type 6 | 1-5 | 1-7 | 2-3 | 2-7 | 2-8 | 2-9 | 3-7 |
| | 3-9 | 3-11 | 4-11 | 5-7 | 5-9 | 5-11 | 6-7 |
| | 6-9 | 6-11 | 7-9 | 7-11 | 7-12 | 8-9 | 8-11 |
| | 8-12 | 9-11 | 9-12 | | | | |
| Type 7 | 4-9 | | | | | | |
| Type 8 | a-h | c-d | e-f | | | | |
| Type 9 | a-g | b-c | b-g | d-g | e-g | e-h | f-g |
| | g-h | g-i | | | | | |
| Type 10 | g-h | | | | | | |
| Type 11 | b-d | b-e | b-g | d-e | d-g | e-g | |
| Type 12 | | | | | | | |
| Type 13 | 1-a | 2-a | 2-d | 2-g | 3-g | 3-i | 4-a |
| | 4-d | 4-i | 5-a | 5-g | 6-a | 6-g | 6-i |
| | 7-a | 7-g | 7-i | 8-a | 8-g | 8-i | 9-a |
| | 9-d | 9-e | 9-f | 9-g | 9-i | 10-e | 10-g |
| | 11-b | 11-d | 11-g | 11-h | 12-c | 12-d | 12-e |
| | 12-g | | | | | | |
| Type 14 | 2-h | 4-g | 9-g | 10-b | 12-a | 12-b | |
| Type 15 | 1-a | 4-h | 5-a | 6-a | 7-a | 9-g | 10-g |

Table 2 Groupings obtained with a 0.8 limiting quality factor

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Type 1 | 5-6 | 11-12 | | | | | |
| Type 2 | 1-11 | 2-11 | 2-12 | | | | |
| Type 3 | 4-5 | | | | | | |
| Type 4 | | | | | | | |
| Type 5 | | | | | | | |
| Type 6 | 4-11 | 5-7 | 8-9 | 8-12 | 9-12 | | |
| Type 7 | | | | | | | |
| Type 8 | a-h | c-d | e-f | | | | |
| Type 9 | b-c | f-g | g-h | | | | |
| Type 10 | | | | | | | |
| Type 11 | b-d | b-e | b-g | d-e | | | |
| Type 12 | | | | | | | |
| Type 13 | 2-a | 3-i | 6-a | 9-e | 11-b | 12-d | 12-g |
| Type 14 | | | | | | | |
| Type 15 | 5-a | 6-a | 7-a | | | | |

# 7 Discussion and Conclusions

In this paper, we have presented an approach to find perceptually significant groupings between straight line segments and circular arcs. The definitions of the groupings allow many of the computations to be performed in parallel.

The algorithm presented is an extension of the formalism defined by Etamadi et al. [3] concerned with the formation of self-consistent groupings. The process can

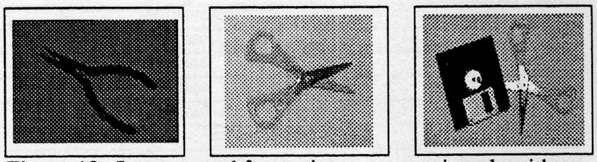

Figure 13a Images used for testing our grouping algorithms

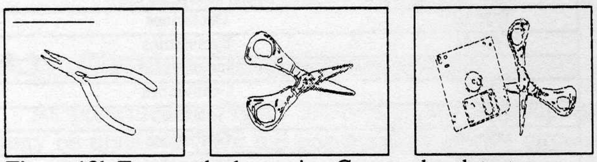

Figure 13b Extracted edges using Canny edge detector

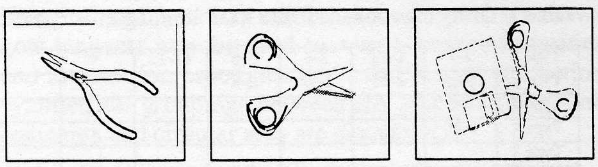

Figure 13c Straight line segments and circular arcs extracted

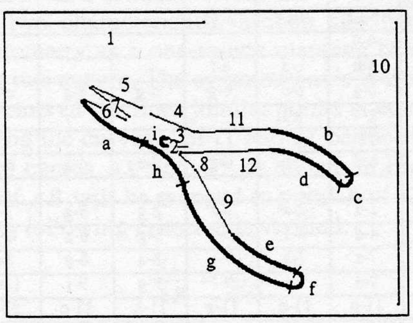


Figure 14 Identifications used to create Table 1 and Table 2

be summarized as a four-step algorithm: 1) edge detection, 2) edge linking, 3) segmentation, and 4) grouping of straight line segments and circular arcs on the basis of perceptual laws. Additionally, a measure of significance is assigned to the extracted 2D features. This factor is an important attribute of the system since it reflects the amount of valuable information contained in each grouping. Measures of significance make it possible to handle the rapid increase in the number of extracted groupings by focussing attention on the better ones.

In the present implementation of the algorithm no consideration is made of the extraneous characteristics in the neighborhood of a candidate grouping. This results in the extraction of invalid groupings like the $\lambda$ junction formed by the straight line segments 4 and 9 in Figure 17. This grouping has two extraneous segments (3 and 8) in the area separating the segments 4 and 9. Also, no noise model is used to compute the uncertainty in the position of the extracted characteristics. Instead, the standard deviations $\sigma^{\parallel}$ and $\sigma^{\perp}$ are replaced by constants. This may cause errors in the calculation of the tangents at the endpoints of the circular arcs and result in the extraction of invalid groupings. The importance of the errors made in the calculation of the endpoint coordinates increases for circular arcs of high curvature. Even if the segmentation algorithm is said to be scale independent, the straight line segments and circular arcs extracted from different views of the same object are not exactly the same. A scale integration algorithm would help to solve this problem and increase the performance of the perceptual grouping algorithm.

Current work involves the construction of 'mid-level' groupings based on the hierarchies of 'low-level' groupings. These will be used to extract closed sets of segments and arcs which can be interpreted as the borders of visible surfaces of the objects in a scene. The ultimate goal of this research is the localization, description, and recognition of objects in a cluttered scene explored and analyzed by an autonomous mobile robot. The hierarchies of groupings extracted with the presented algorithms form the starting point towards this goal.

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