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# Expert System for Segmentation of 2.5-D Image

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**Abstract**

This paper presents an expert system for the segmentation of a 2.5-D image. The results of two segmentation approaches, edge-based and region-based, are combined to produce a consistent and reliable segmentation. Rich information embedded in the 2.5-D image is utilized to obtain a view independent surface patch description of the image, which can facilitate object recognition considerably.

## 1. Introduction

Image segmentation is a central problem in image understanding system development and many techniques have been developed with varying degrees of success[1,2]. Segmentation of an image is the most difficult and important stage, since later stages of image interpretation are heavily dependent on the segmentation result. Many difficulties are encountered in the intensity image segmentation due to the inherent noise in the image and the fact that intensity values may not reflect the physical events in the scene.

Unlike the intensity images, 2.5-D images (called needle map, or surface orientation map) provide much more rich information about the objects in the scene. 2.5-D image is obtained by photometric stereo method[6,7,8], where 3 images are taken from the same camera location with 3 different lighting directions. Early use of 2.5-D image for object recognition was transforming the needle map into Extended Gaussian Image(EGI), where each surface normal vector is mapped onto Gaussian sphere, and then compared it with the model EGI for object recognition and pose determination. But this approach works only for non-occluded objects and the same EGI may represent different objects.

The appearance of 3-D object varies depending on the viewpoint. To handle the problem of arbitrary viewing directions, viewpoint independent surface characteristics are used that are general enough to describe both polyhedra and curved objects[4]. Surface patches are the features that directly link perception to the objects perceived, hence conveys more information about possible objects. Segmentation of 2.5-D image requires pixels to be grouped together into a relatively small set of view-independent symbolic surface primitives.

There are two approaches to segment an image: edge-based and region-based approaches. Edge-based approach looks for places where significant property changes take place. Unfortunately, edge detection invariably produces spurious edges and misses some real edges. Region-based approach starts with seed regions and grows the regions using the homogeneity constraints. The result depends on the seed regions and either oversegments or undersegments.

The expert segmenter presented in this paper utilizes the rich information embedded in the 2.5-D image and integrates two approaches in segmenting the image into meaningful view-independent 3-D surface patches.

## 2. Expert System and Image

In recent years there has been widespread interest in developing expert systems for application areas that involve complex decision processes. A number of expert systems have been developed and implemented for medical diagnosis, computer configurations, speech understanding etc[10].

The essential features of of an expert system are its modularity and its heuristic power. Modularity provides easy handling and updating large data sets, while heuristic power allows solving the combinatorial explosion of facts by developing adequate reasoning strategies. The expert system approach to image segmentation is motivated by the combinatorial aspect of image analysis and the

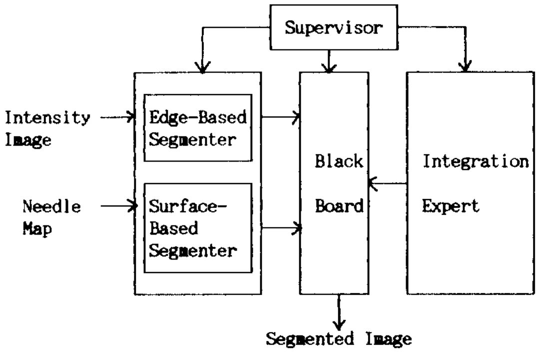


Figure 1. System Block Diagram

necessity to develop strategies involving perceptual as well as semantic knowledge about the scene[3].

Figure 1 is the system block diagram of the expert image segmenter. Domain specific knowledge is represented as a set of production rules in the IF <antecedent fields> THEN <consequent fields> form. The antecedent consists of various facts about the intermediate segmentation and boolean functions and the consequent is made up of invocations to appropriate procedures. Low level image expert invokes basic image processing algorithms for initial image segmentation. The rule base in the integration expert ia partitioned into several specialty rule base, such as edge rules, region rules, and junction rules, to enable fast rule matching. The various levels of segmentation data are kept in a global database, the blackboard. The various specialty knowledge sources in the integration expert produce changes to the blackboard that lead incrementally to final segmentation. Communication and interaction among the knowledge sources take place solely through the blackboard. Supervisor provides user interface to update rules or to supply parameters for procedures if needed. Control is implemented in a simple manner. If no rule fires in the current phase, next rule set is invoked to start the next phase processing.

## 3. Low Level Image Expert

### 3.1 Edge-Based Segmenter

Edge detection process serves to simplify the analysis of image by dramatically reducing the amount of data to be processed, while at the same time preserving useful structural information. In this research first derivative of Gaussian (Canny operator) is used as edge operator. Averaged Lambertian image is convolved with horizontal and vertical edge operator, producing gradient magnitude and edge orientation images. Non-maximum suppression is applied to generate edges of single pixel width.

Simple thresholding on the edge detection output results in a streaking problem of edge contours, where edge points may fluctuate above and below the threshold due to noise. In order to avoid the streaking problem, edge contour is traced first based on connectivity and direction, then thresholding is performed on the whole contour using the average edge magnitude of the contour. Edge contours whose contrast are below the threshold but length is longer than minimum are stored in the background data base for future use during integration.

Since edge contours are cumbersome to manipulate and to describe, each edge contour is divided into edge segments at important feature points. We use curvature extrema (corner) and zero crossing (inflection point) as our knot points[9] to segment the edge contours. An edge orientation list associated with an edge contour is convolved with the first derivative of Gaussian to compute curvatures along the contour. First we identify three regions in the edge contour curvature output: zero curvature region, positive curvature region, and negative curvature region. A corner is located if a curvature extremum is between two zero curvature regions. An inflection point is found if a small zero curvature region is bordering two non-zero curvature regions of opposing signs. Once these knot points and curvature property of each edge segments are determined, line or conic fitting is performed to verify the segmentation.

### 3.2 Surface-Based Segmenter

To handle the problem of arbitrary viewing directions, viewpoint invariant surface characteristics are needed that are general enough to describe both polyhedra and objects with arbitrary curved surfaces. Differential geometry states that local surface shape is uniquely determined by the first and the second fundamental forms. Gaussian and mean curvature combine these first and second fundamental forms in two differing ways to obtain scala surface features that are invariant to rotation and translation.

Let f(u,v) be a bivariable function describing a surface. Gaussian(K) and mean curvatures(H) are related to the two principal curvatures($k_1, k_2$) and are computed by the following equations.

The partial derivatives $f_u$, $f_v$, $f_{uu}$ $f_{uv}$ $f_{vv}$ are estimated by least squares local quadratic surface fit around N by N (we used 5 by 5) window. Due to noise in needle map, we use estimated partial derivatives even though needle map is already in partial form. Once Gaussian and mean curvatures are estimated at each pixel, their signs provide ten basic surface types (peak, pit, ridge, valley, flat, minimal, saddle ridge, saddle valley, positive high curvature, negative high curvature). Table 1 shows the surface type labels from the K,H signs.

$$K = k_1 k_2 = \frac{LN - M^2}{EG - F^2}$$

$$H = \frac{1}{2}(k_1 + k_2) = \frac{1}{2}\frac{EN - 2FM + GL}{EG - F^2}$$

*where*

$$f_u = \frac{\partial f(u,v)}{\partial u}, \quad f_v = \frac{\partial f(u,v)}{\partial v}$$

$$E = (1 + f_u^2), \quad F = f_u \cdot f_v, \quad G = (1 + f_v^2)$$

$$L = \frac{f_{uu}}{\sqrt{1 + f_u^2 + f_v^2}}, \quad M = \frac{f_{uv}}{\sqrt{1 + f_u^2 + f_v^2}}$$

$$N = \frac{f_{vv}}{\sqrt{1 + f_u^2 + f_v^2}}$$

Table1. Surface types from surface curvature signs

| | $K < 0$ | $K = 0$ | $K > 0$ |
|---|---|---|---|
| $H < N_{ext}$ | Negative High curvature region | | |
| $H < 0$ | saddle ridge | Ridge | peak |
| $H = 0$ | minimal | flat | none |
| $H > 0$ | saddle valley | valley | pit |
| $H > P_{ext}$ | Positive high curvature region | | |

If mean curvature at a pixel is greater than the prescribed threshold, that pixel is labeled as positive high curvature surface without regard to Gaussian curvature. Similarly negative high curvature surface type is assigned when mean curvature is less than the threshold. The threshold value is not critical, because these regions will eventually be removed.

High curvature surface types are introduced to facilitate segmentation by preventing the same surface types with different surface orientations from being labeled as the same region. Also these high curvature regions provide supporting cues in assigning edge types to the edge segments generated by the edge-based segmenter.

The initial surface-based segmentation result usually contains many small isolated regions due to the surface irregularity and lighting conditions. The small noisy regions are removed by the shrinking and expanding operations. Shrinking reduces each region size maintaining its gross shape. High curvature regions are not affected by the shrinking operation, but participates in expansion operation. The grouping of the same surface type pixels provides rough initial surface-based segmentation.

## 4. Integration Expert

Two independent segmentation results are combined into a final segmentation by the integration expert through the consistency and global constraints check. Low level processes can produce partitions only on a nonsemantic basis, since low level image operations are inherently based on local information. The role of the integration expert is to fuse the two imperfect outputs from two knowledge sources into a coherent and consistent segmentation.

**4.1 Region Adjacency Graph:** The surface-based segmentation is symbolic partitions of an image where symbols represent ten surface types. Connected component analysis produces an output which attaches different region number for each connected region and builds a region adjacency graph(RAG). The nodes of a RAG are attached with other geometrical information about a region such as area, centroid, boundary length, surface types, and elongation index.

Region analysis starts by cleaning the small regions adjacent to a large region and artifact regions created by surface-based segmentation. An artifact region appears as a narrow strip adjacent to a high curvature region.

**4.2 Edge Type Labeling and High Curvature Region Removal:** The refined surface-based segmentation is put into registration with the edge segments. By examining the region where an edge segment lay we can assign physical meaning to the edge segment. If an edge segment is inside a negative high curvature region, it is labeled as a convex edge. Likewise an edge segment inside a positive high curvature region is labeled as a concave edge. This is the case, where consistent evidences from two segmentation processes reinforce each other producing reliable information. Edge segments which are not assigned a label are either noisy or possibly region boundaries. These edge segments are discarded or used for region splitting depending on their relationship with other edges or regions.

High curvature regions are then removed by allowing adjacent non-high curvature regions to expand into the high curvature regions. The erosion of high curvature regions is repeated until the expansion reaches edge points or encounters other non-high curvature regions.

The removal of high curvature regions results in a segmented image where each region is bounded by edge segments or new region boundaries are formed. Association of regions and edge segments are achieved by traversing the region boundaries once again. After this traversal, the region slot of each edge segment is updated with the regions which borders the edge segment. Likewise, the edge slot of each region is also updated with the edge segments encountered.

**4.3 Edge Refinement** : Since regions and their associated edge segments are known, we can connect open edge segments and find junctions reliably using the region information. Two open edge segments which borders the same region are combined into one segment if their end point orientation is less than a certain degree. Edge segments of similar tangent direction which do not share a common region are connected only if they are close enough. Edge segments which have only one region associated with them are removed, since they are spurious edges.

**4.4 Junction Detection:** An open edge segment is checked with another edge segment which shares a common region by computing their intersection point. The intersection point becomes a junction and the open edge segments are extended to the junction. The remaining open edge segments, which already assigned a convex or concave label, are extended to a nearby edge segment. These edge segments become the shafts of T junctions.

**4.5 Region Merging and Splitting:** The above processes will produce a segmented image with each region surrounded by edge segments without any gap. Now we have to check whether each region can be merged with an adjacent region to form a larger region or a large region should be split into smaller regions. Two regions are never merged if they have a common edge segment separating them.

Since our surface classification is based on local surface property, region homogeneity criterion is a surface patch fitting error of the region. Merge is allowed if the error of the biquartic polynomial fit of the merged region is less than an error bound. Similarly a region is split if the surface fitting error is greater than the error bound. We define the fitting error as follows.

$$Error = \sum_{i \in R} \frac{\cos^{-1}(N_i \cdot \hat{N}_i)}{M}$$

where $N_i$ is the measured normal from the needle map, $\hat{N}_i$ is the normal computed from the surface fitting, and M is the number of pixels participating in the surface fitting.

4.6 Surface Cluster Graph: If multiple occluded objects are in the scene, they must be separated from each other for recognition. The edge type provides the clue. The surface patches are grouped into another graph structure called a surface cluster graph(SCG), where all the nodes in the graph belong to a single object. A SCG is a subgraph of a RAG such that every node in the SCG is connected to another node by at least one convex edge. A SCG corresponds to a distinct object in the image.

Building surface cluster graphs from the RAG is carried out by inference, using the type of edge between two surface patches. Let $S_i$ and $S_j$ be two adjacent surface patches. The following rules hold.

- . $S_i$ occludes $S_j$ if their common boundary is a limb or part of a T junction
- . $S_i$ and $S_j$ are connected if their common boundary is a convex edge.
- . $S_i$ and $S_j$ may or may not be connected if their common boundary is a concave edge.

Building a SCG starts with the largest region and adjacent regions sharing convex edges are directly linked to the region. These new regions become the leaves of the expanding graph. This step is repeated until all the leaf nodes do not have any more region sharing convex edges. This process is repeated until all the regions belong to one SCG.

## 5. Experiments and Conclusion

Experiments were performed on several scenes. Fig. 2 shows one of the result. Segmentation is a difficult process and uncertainties are inherently involved. Expert system approach presented above can reduce the uncertainties by integrating various segmentation cues from two knowledge sources, namely edge-based and surface-based initial segmentation, into a meaningful and reliable segmentation. The output of the integrated segmentation is an explicit and rich description of surface type and boundaries of each region which facilitates recognition, localization, and pose determination of objects in the image.

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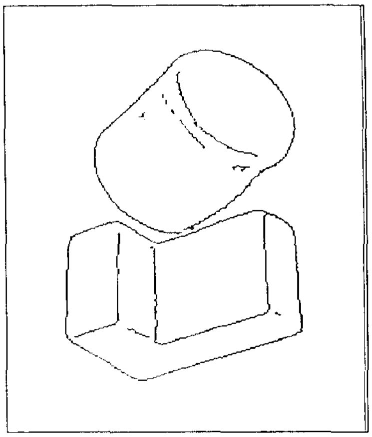
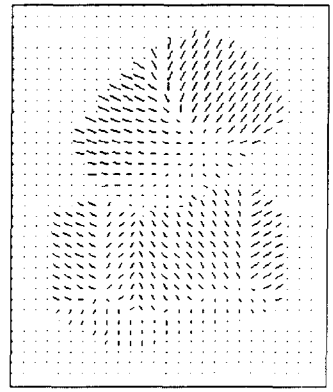
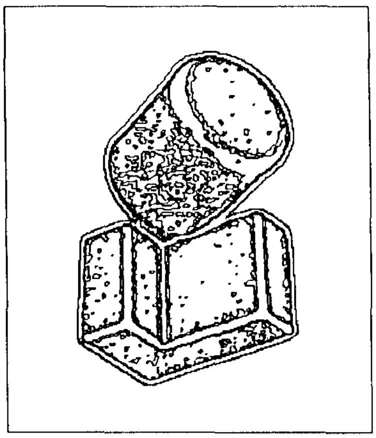


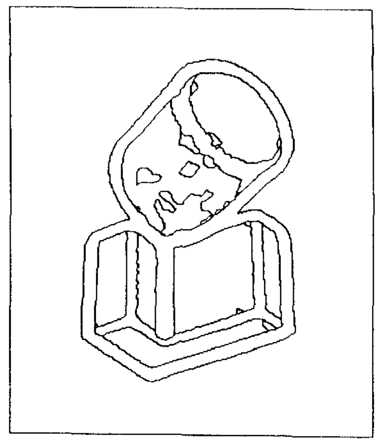
(a) Edges after contour thresholding



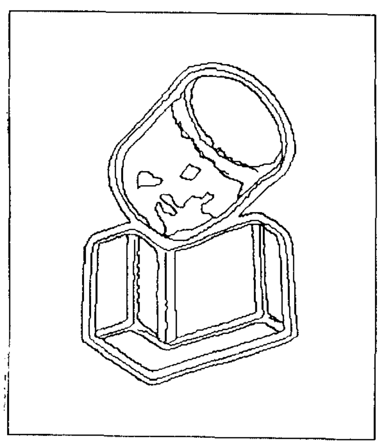
(b) Needle Map



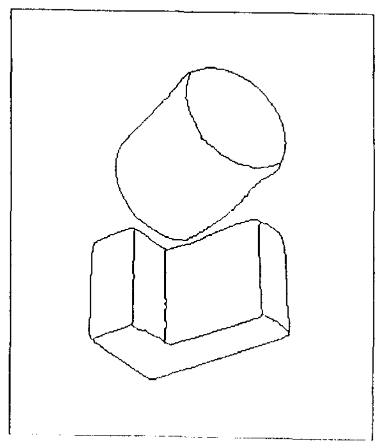
(c) Initial Segmentation



(d) After shrink and expand



(e) Edges superimposed on
refined segmentation



(f) Final segmentation

Figure 2. Image of a stair and cylinder