Range Data Processing: Representation of Surfaces by Edges

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Abstract: Representation of surfaces by edges is an important and integral part of a robust 3-D model based recognition scheme. Edges in a range image describe the intrinsic characteristics about the shape of objects. In this paper we present three approaches for detecting edges in 3-D range data. The approaches are based on computing the gradient, fitting 3-D lines to a set of points, and detecting changes in the direction of unit normal vectors on the surface. These approaches are applied locally in a small neighborhood of a point. The neighbors of a 3-D point are found by using the k-d tree algorithm. As compared to previous work on range image processing, the approaches presented here are applicable not only to sensed range data corresponding to any one view of the scene, but also to 3-D model data obtained by using the Computer-Aided Geometric Design (CAGD) techniques or the 3-D model data obtained by combining several views of the sensed object. A comparison of the techniques is presented and their performance is evaluated with respect to signal-to-noise ratio.

1. Introduction

An efficient and invariant representation of surface of 3-D objects is of fundamental importance in model based recognition of 3-D objects and their manipulation by robots [1]. In CAGD field, surface/boundary representations include Coons patches, bicubic surface patches, Bezier methods and B-splines. In our work related to CAGD based 3-D vision, we are investigating several surface and volume based approaches which allow the generation of computer representations and geometric and functional models of complicated realizable 3-D objects in a *systematic manner* [1, 2]. In this paper we present three approaches for extracting edges in the range data. Although in general, the edge detection techniques have the drawback in that the edge responses must be grouped, thinned and linked in order to produce a reasonable object description in terms of coherent regions, they have the additional feature in that once the line segments are found, the theory of 3-D line semantics can be directly applied and edges can be very useful in 3-D shape recognition.

2. Edge Detection in Range Images

Edge points correspond to those object points which lie on significantly different regions of the surface. Like the edge detection in intensity images, a number of techniques have been used for the segmentation of range images [3, 4, 5]. These techniques have been applied to one view of the range image; they have not been applied to 3-D model data. The 3-D edge detector of Zucker and Hummel [6] is not directly applicable to find the edges in a surface based representation, where only the (x,y,z) coordinate points are available.

3. Algorithms for Surface Characterization by Edges

In the following, we present three algorithms for edge detection. They can be used on both the range image and the 3-D model data.

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Technique 1 - Gradient Approach: A second derivative formulation for discrete case is used to calculate magnitude and direction of an edge at each point similar to the work by Sugihara [5]. We used four 3x3 edge operator to calculate both edge magnitude and edge direction at each point. In general, most edges in intensity images are step edges. But the edges in range images can be either step or roof edges. As a result we cannot get all the edges in a range image by edge operators used on intensity images. Preferably, for range images an edge operator should be sensitive to roof edges.

The four operators each for different direction are as below.

```
 1  1  1     1  1 -2     1 -2  1    -2  1  1
-2 -2 -2     1 -2  1     1 -2  1     1 -2  1
 1  1  1    -2  1  1     1 -2  1     1  1 -2
0 degree    45 degree   90 degree   135 degree
```

Compared to this work, Sugihara used just two neighboring points to calculate edge magnitude. This is just a second derivative at a point in a given direction theta. He did not do any preprocessing and as shown in the next section it is more sensitive to noise than our technique.

The simplest technique for thinning is to retain only those edge points whose magnitude is a local maximum based on edge direction. An edge element is said to be present at a point if:

1. The edge magnitude of the central point exceeds some threshold value.

2. The edge magnitude at the central point is larger than its two neighbors in a direction normal to the direction of the edge at this point subject to the condition that the directions of the two neighboring points are the same as that of the central point.

To link edge points, we used both edge magnitude and edge direction. By edge direction, the candidate successor or candidate predecessor is found. Among those, maximum edge magnitude point is selected as successor or predecessor. Thus all the linked edge points have relatively large edge magnitude.

Technique 2 - Line Fitting Approach: In this approach we do not assume that the data is in the form of an image. Normally it is in the form of a list of (x,y,z) points and it can be *nonuniformly spaced*. The neighbors of a point are found by using the k-d (k=3) tree algorithm to organize the data. The k-d tree is a binary tree of k-dimensional keys which is organized such that at each subdivision step, the data are split at the median along the axis having the greatest spread in vector element along that axis. The data can be organized in O(nlog n) time and it allows the determination of m-nearest neighbors of a given query in O(log n).

After getting neighboring points in 3-D space, we calculate the unit direction vector from the center point to its neighboring points. The two of these direction vectors lie on a straight line if they point exactly opposite direction. If we find two or more than two straight lines within a certain threshold (related to the differences of the direction vectors), then the center point and all its neighboring points lie on a plane and it is not an edge point. Conversely, If we find only one straight line or no straight line, then it is an edge point.

Technique 3 - Surface Normal Approach: Here we make use of the simple fact that the points on a plane have the same normal vectors and assume that the normals at each surface point are given. These are provided by our CAGD based 3-D modeling approach [2] and many times they are computed in a range segmentation technique. In this approach we calculate the change of direction of normal vectors in the neighborhood of a point. The neighbors of a point are found by using k-d (k=3) tree algorithm as in technique 2. We used 8 neighboring points to calculate the change of direction of normal vectors. If the difference of unit normal vectors is greater than a certain threshold value, then it signifies the presence of an edge point.

4. Results

In this section we present results on sensor data obtained from laser scanners and 3-D model data obtained from CAGD [2]. A comparison of the methods is also given.

Fig. 1 shows range data on two industrial objects, named the "Green Piece" and the "Renault Piece." The 3-D sensor data on Green Piece was obtained by using the White Scanner and the data on Renault Piece was obtained by using the INRIA laser scanner. These two objects have about 5000 and 2000 surface points in one view, respectively.

Fig. 2 shows the linked edge results on the objects shown in Fig. 1 by using the gradient approach. White and gray edge points in this figure depict convex and concave edges. In Fig. 2(a), note that most of the holes, circles and surface scratches are correctly obtained, although a few of them show some gaps. In Fig. 2(b) convex and concave edges are properly labeled.

Fig. 3 shows the edge point results on the objects shown in Fig. 1 by using the line fitting approach. These edge points can be thinned as in technique 1. These results are not as good as the results of the gradient technique. It is because of the greater sensitivity of this technique with respect to noise.

Fig. 4(a) shows one view of the 3-D CAGD model of the Green Piece. The model has about 12,000 points with a resolution of 0.1 inches.

Fig. 5(a) shows the points in one view of the 3-D CAGD model of the Renault Piece. It has about 6000 points with a resolution of 0.2 inches.

Fig. 4(b) and 5(b) show the results on Green Piece and Renault Piece 3-D CAGD model data using the line fitting technique. Note that very good edge points are obtained in these cases.

Fig. 4(c) and 5(c) show the results on Green Piece and Renault Piece 3-D CAGD model data using the surface normal based approach. Note that good results are obtained. However, by comparing the results on the same data by line fitting technique, we find that line fitting technique produces better results.

4.1. Evaluation of Techniques with Respect to Signal-to-Noise Ratio

Technique 1 is analyzed by adding some noise to each range value in the image. The noise is normally distributed with zero mean and a given standard deviation. The signal-to-noise ratio (SNR) is defined as the difference of range values of neighboring pixels in a roof edge divided by the standard deviation of Gaussian white noise. The effect of noise is found by determining the number of incorrect edges. There are two cases for incorrect edges: (i) edge finding algorithm finds an edge where there is no edge, (ii) edge finding algorithm misses an edge where there is an edge. The classification error is the number of incorrect edges divided by the total number of edges in a noise free image. Fig. 6 compares the performance of the proposed technique with Sugihara's technique with different SNRs and the table given below shows the classification errors. Note that our technique has consistently lower classification errors and thus it is less susceptible to noise.

SNR	Present Technique		Sugihara's Technique	
	wrong edges	% error	wrong edges	% error
20	0	0	0	0
10	0	0	0	0
5	3	6	5	10
2	29	58	30	60
1	41	82	47	94

Total # of actual edges = 50

Technique 2 is analyzed in a similar way as technique 1. Here, the SNR is defined as the resolution (minimum distance of data points) divided by the standard deviation of Gaussian white noise. Fig. 7(b) shows the graphical results on the ideal cube data of Fig. 7(a) and the results are given below for various SNRs.

SNR	# of wrong edges	% error
20	0	0.0
10	8	6.9
5	66	56.9
2	more than 116	100
1	more than 116	100

Total # of actual edges = 116

If SNR is small, we cannot get good results. If SNR is less than 5, this technique doesn't work well.

To analyze the sensitivity of technique 3, the noise is added to the angles (alpha, beta and gamma) which a unit normal vector makes with the x, y and z axis. Here the SNR is defined as pi / 2 divided by the standard deviation of Gaussian white noise. Fig. 7(c) and the table given below show the results. It is noted that this technique is more sensitive to noise than the technique 2.

SNR	# of wrong edges	% error
20	12	10.3
10	25	21.6
5	94	81.0
2	more than 116	100
1	more than 116	100

Total # of actual edges = 116

5. Conclusions

In this paper we presented three different approaches to detect edges in range data. These algorithms are not limited to single view of an object; they are applicable to complete 3-D surface data as well. Comparison of these results with a curvature based approach and the development of 3-D matching techniques using these results are currently under investigation.

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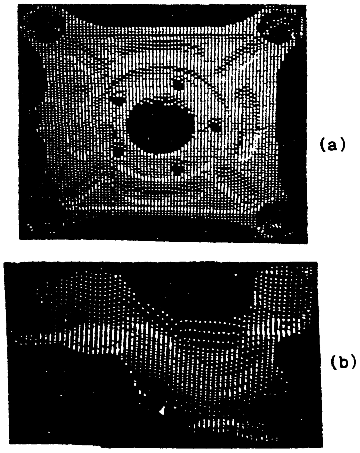

Fig. 1 Sensed objects used for finding edges.
(a) Green Piece (b) Renault Piece

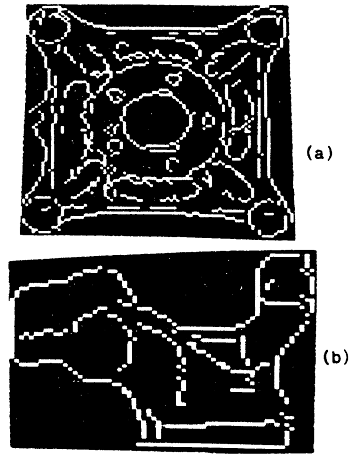

Fig. 2 Linked edges by using the Gradient technique.
(a) Green Piece (b) Renault Piece

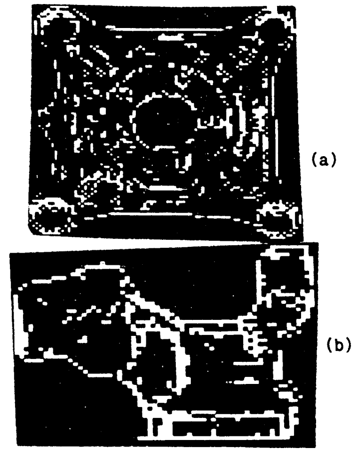

Fig. 3 Edge points by using the line fitting technique.
(a) Green Piece (b) Renault Piece

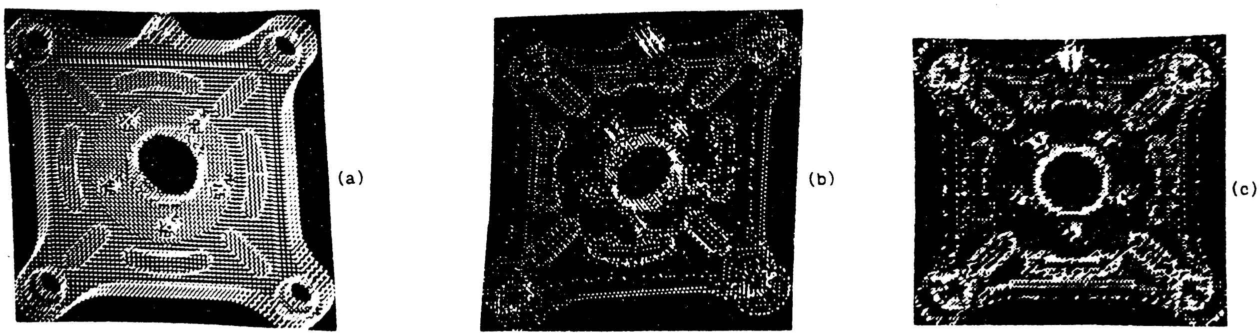

Fig. 4 3-D CAGD model and edge points of Green piece.
(a) 3-D CAGD model data
(b) Edge points by using line fitting technique
(c) Edge points by using surface normal based technique

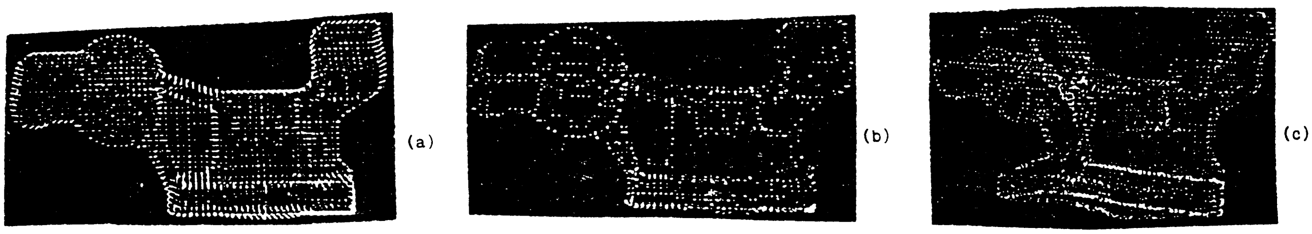

Fig. 5 3-D CAGD model and edge points of Renault piece.
(a) 3-D CAGD model data
(b) Edge points by using line fitting technique
(c) Edge points by using surface normal based technique

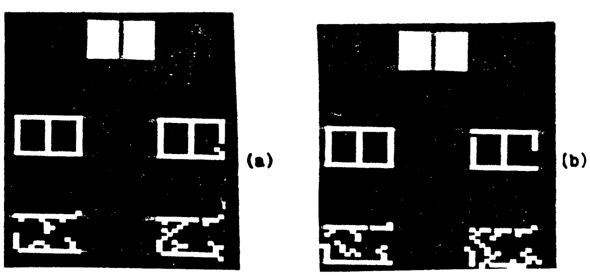

Fig. 6 Comparision of our gradient technique and Sugihara's approach.
(a) Our technique (b) Sugihara's approach

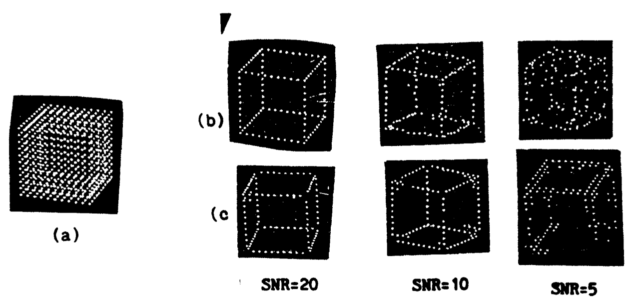

Fig. 7 Analysis of line fitting technique and surface normal based technique by changing SNR.
(a) Synthetic cube model
(b) Line fitting technique
(c) Surface normal based technique

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