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RANGE IMAGE PROCESSING FOR BIN-PICKING OF CURVED OBJECT

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ABSTRACT

This paper describes a model based robot vision system for bin-picking of curved object utilizing range images. Surface properties and 3-D shape of the object are derived from the range image. This system extracts an object and detects its location and orientation based on models. The object is to be represented by a set of quadric curved surfaces. The Gaussian and the mean curvature are used as the local measure of the surface shape. In this work, workpieces are mainly composed of cylindrical surfaces such as pipe-joints. Models are defined as a list of cylindrical surfaces and their relationships. The object of the specified type is detected in the scene. Cylindrical components are extracted from the segmented regions. They are compared with models, the type and the pose of the object are obtained, and then the gripping point is determined from the model.

INTRODUCTION

Machine vision is one of the most important sensor to realize a flexible robot. Without sensing work environments, robots can deal with the only parts which are placed in carefully controlled position and attitude. Vision sensor can offer the information to recognize the environments. It has a great advantage that it can get global information about circumstances without any tactile device.

In many conventional vision systems, binary or intensity images have been processed to detect the position and the orientation of objects [1, 2, 3]. Boundaries of the objects were detected from brightness changes and the 2-D projections of the objects were recognized in the image. It has been difficult to recognize the object in a heap or to determine the 3-D shape.

Range images provide the 3-D structures in the scene. Surface properties and 3-D shape of the object can be derived from them. Ikeuchi and others used range information and the extended gaussian image obtained from the photometric stereo method [4]. This system could pick up such a simple object as a doughnut. Recently Ikeuchi used a CAD model [5]. The attitude of the object is analyzed based on the visible forms of the object generated from the model. Similar approach can be found in the 3DPO system [6]. This system utilized range data and hypotheses about the object's pose.

In this paper, we describe a model based robot vision system for bin-picking of curved objects utilizing range images. Surface properties and 3-D shape of the object can be derived from the range image. Comparing the surface properties with object models, the curved objects like pipe-joints are easily distinguished and identified. The location and the orientation of the object are also obtained. The object can be picked up by using the extracted properties.

OVERVIEW OF THE SYSTEM

To recognize a curved object, we consider the region as a set of curved surfaces. This approach is often used in region-based approaches based on the range image analysis [7]. Curvature properties are used to segment curved surfaces. As the extracted properties are compared with ones in the models, the object of the specified type is detected. Figure 1 shows the outline of the system.

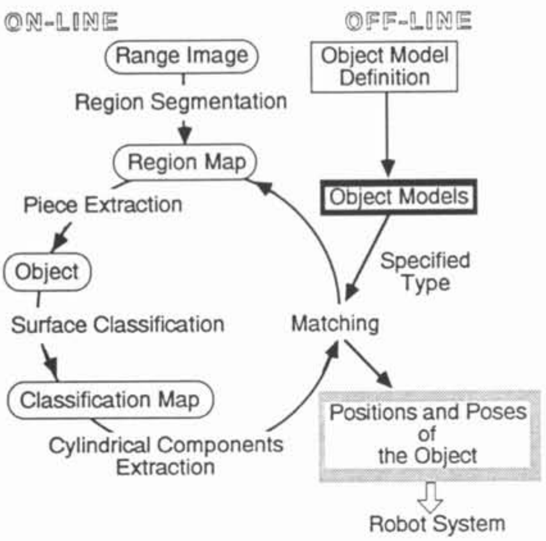
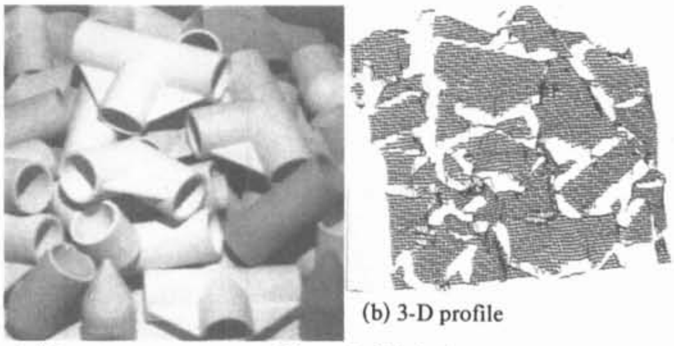


Figure 1. Processing flow of the system

RANGE FINDER

Range images are acquired from the Liquid Crystal Range Finder (LCRF); a high speed and high resolution range imaging system based on the Gray coded pattern projection by a LCD optical mask [8, 9]. This system is based on an active triangulation by projecting 2-D light patterns in the scene sequentially. This system has a great advantage that every pixel in the image has range data



(a) Input scene Figure 2. Original scene

except for in shadow regions. It can provide a dense range image in the form of three 256 x 256 arrays, in which each pixel has the value of X, Y, Z in global coordinates. Figure 2 shows an intensity image of the scene and its 3-D profile.

OBJECT MODELS

This system deal with several kinds of pipe-joints in which primitive cylinder parts are combined differently. Figure 3 shows the seven experimental objects. In this system geometrical models are utilized to identify the object and to detect the pose of it. They are described as a list of cylindrical components' properties and their relationships. The object can be identified by examining their cylindrical components and relationships among them. Figure 4 shows the model of T-type joint. It is described as a set of three cylinders.

REGION SEGMENTATION

To specify the object in a pile of workpieces, the input scene has to be segmented into meaningful regions. The object of interest can be extracted utilizing the object contours, which are found in range images directly. They are not brightness changes in intensity images, but structural changes. The following points and lines are taken as features for a segmentation:

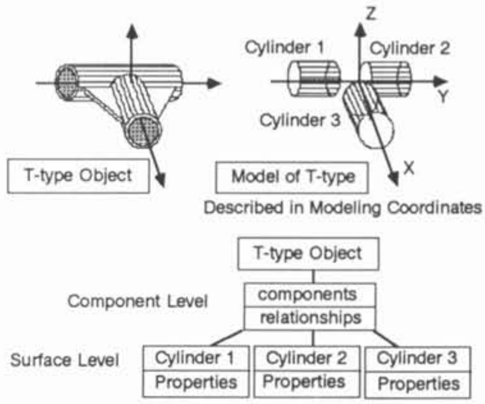
(a) Shadow : non-illuminated regions when illuminating a pile. Range data can not be acquired in such regions.
(b) Jump edge : the points where the surface is discontinuous. This can be found easily in range images.
(c) Roof edge : the points where the surface orientations are discontinuous. Concave roof edges are usually found where two objects are in contact each other.

Local surface orientations are calculated at each pixel by fitting the plane over the local surface.

CURVED SURFACE CLASSIFICATION

The object surface is analyzed based on the Gaussian curvature and the mean curvature [10]. These curvatures show the local surface changes. Using sign of these curvatures, each pixel in the image is labeled as its surface type. There are 6 types : 1) planar, 2) convex or 3) concave elliptic, 4) convex or 5) concave conical, and 6) hyperbolic, as shown in Table 1. These labels are independent of any

Figure 3. Objects



(a) Model constitution

```
Model type : T-type
     components    : 3
     relationships : (1,2) collinear
                     (2,3) orthogonal
                     (3,1) orthogonal

  == Cylinder 1 ==
                 radius  :      34.1 mm
                 length  :      30   mm
             axis (direction)  (0.0, -1.0, 0.0)
                  (position)   (0, -35, 0) (mm)
             gripping point    (0, -35, 0) (mm)
  == Cylinder 2 ==
                 radius  :      34.1 mm
                 length  :      30   mm
             axis (direction)  (0.0, 1.0, 0.0)
                  (position)   (0, 35, 0) (mm)
             gripping point    (0, 35, 0) (mm)
 == Cylinder 3 ==
                 radius  :      34.1 mm
                 length  :      30   mm
             axis (direction)  (1.0, 0.0, 0.0)
                  (position)   (35, 0, 0) (mm)
             gripping point    (35, 0, 0) (mm)
```

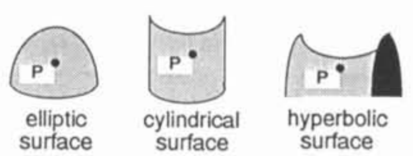
(b) Property list

Figure 4. Object model (T-type)

Table 1. Surface type labels

K \ H	H > 0	H = 0	H < 0
K > 0	convex elliptic	———	concave elliptic
K = 0	convex cylindrical	planar	concave cylindrical
K< 0	hyperbolic		

K: Gaussian Curvature H: Mean Curvature



translation and rotation of the object.

After the surface types are derived over the whole region, the adjacent pixels which have the same label are merged into one region. The object surface is segmented into regions of the same properties. Figure 5 shows a surface classification map of T-type object.

CYLINDRICAL COMPONENTS EXTRACTION AND MODEL MATCHING

Object models are used to identify the object and to prepare the point for gripping. The object is identified by examining the number of cylindrical components and the relationships among them.

Cylindrical components of the object are extracted from the cylindrical region. As they are combined smoothly in each pipe-joint, plural components are sometimes included in one cylindrical region. Each cylindrical region is examined whether it consists of one component or not. A cylindrical region is traced and split by the constricted portion where the region doesn't have the sufficient width (Fig. 6). After checking a cylindrical region in Figure 5, it is subdivided into three components shown in Figure 7. The principal axis of each component is calculated by fitting a quadric surface to these regions.

The object type is determined by matching with models in database. The location and the orientation of the object are determined by examining relative position of the components. The gripping point is selected out of the several candidates in the model. The wireframe in Figure 7 displays the detected T-type object. Other kinds of pipe-joints, L-type and tripod-type are analyzed in the scenes shown in Figures 8 and 9.

In the experiment, the objects of the specified type are detected in the pile. Figure 10 shows the system. Figure 11 shows the experimental scene. When T-type is specified, two objects are detected from the scene. Detected objects and their 3-D profile are shown in Figure 12.

CONCLUSIONS

We have described the model-based bin-picking system utilizing range images. The curved object such as pipe-joints can be identified and the position and the pose of it are detected by this system. The object is segmented into quadratic curved surfaces and their relationships are examined. Objects which are mainly cylindrical are dealt with in this paper. Our approach can be applied to objects which have other quadratic surfaces, if the relationships among them are predescribed. At present object models are made by hand operations. It is the subject for a future study to generate the model effectively, for example, by integrating with a CAD model.

We have assumed that detected objects are not occluded and the extracted properties are reliable. If these assumptions are not true, the backtracking procedure is required to analyze occluded objects. This approach is now progressing.

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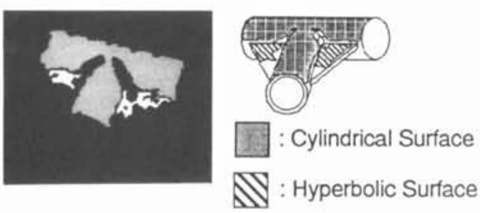


Figure 5. Surface classification map

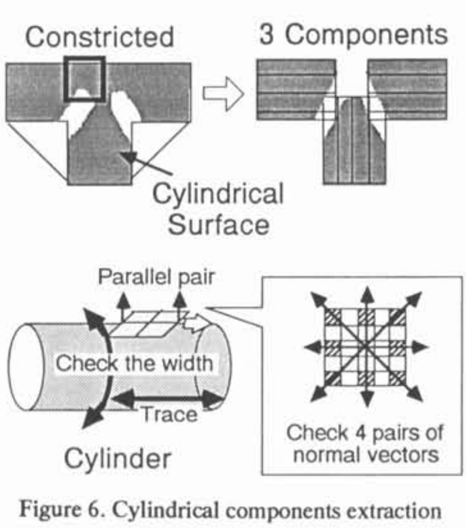
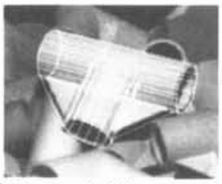


Figure 6. Cylindrical components extraction

(a) Extracted components

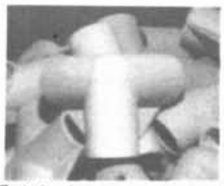


(c) Detected object

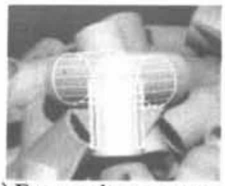
```
Cylinder (total number) = 3
    == Cylinder 1 == Length  35.47 mm
        Axis position  ( 86.7, 147.9, 135.9) mm
        Axis direction (-0.338992, 0.939071, 0.568425e-01)
    == Cylinder 2 == Length  33.59 mm
        Axis position  ( 72.9, 115.0, 119.5) mm
        Axis direction (0.800385, 0.254827, 0.542629)
    == Cylinder 3 == Length  33.39 mm
        Axis position  (106.2, 94.4, 131.9) mm
        Axis direction (-0.348002, 0.934629, 0.732284e-01)
Relations
        (1,2) (2,3) : Orthogonal
        (3,1) : Collinear
Object type         T-type
    orientation     theta = 1.91722 (rad)
                    gzai = 1.51392 (rad)
    location        (96.5, 121.1, 133.9) mm
```

(b) Result of recognition

Figure 7. T-type detection



(a) Original scene



(b) Extracted components

```
Cylinder (total number) = 3
    == Cylinder 1 == Length  41.72 mm
        Axis position  (75.6, 90.1, 131.4) mm
        Axis direction (0.958748, 0.56412e-01, -0.278602)
    == Cylinder 2 == Length  43.3 mm
        Axis position  (58.7, 109.8, 133.3) mm
        Axis direction (-0.95714e-01, 0.934053, -0.344069)
    == Cylinder 3 == Length  44.2 mm
        Axis position  (53.7, 82.4, 119.3) mm
        Axis direction (0.306959, 0.359602, 0.881171)
Relations
        (1,2) (2,3) (3,1) : Orthogonal
Object type         Tripod-type
    orientation     theta = 1.67291 (rad)
                    gzai = 1.92204 (rad)
    location        (58.7, 109.0, 133.6) mm
```

(c) Result of recognition

Figure 9. Tripod-type detection

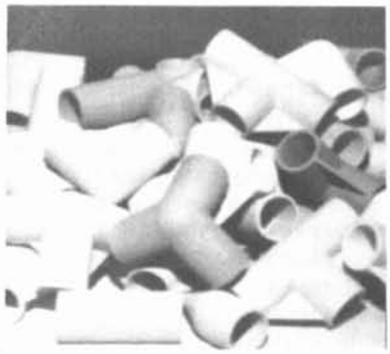
(a) Original scene

(b) Extracted components

```
Cylinder (total number) = 2
    == Cylinder 1 == Length  50.01 mm
        Axis position  (128.3, 47.0, 128.7) mm
        Axis direction (0.973556, 0.118082, 0.195563)
    == Cylinder 2 == Length  37.85 mm
        Axis position  (101,0, 69.8, 140.8) mm
        Axis direction (-0.176645 0.830453 0.52834)
Relations
        (1,2) : Orthogonal
Object type         L-type
    orientation     theta = 1.78038 (rad)
                    gzai = 1.01415 (rad)
    location        (101.2, 69.0, 140.3) mm
```

(c) Result of recognition

Figure 8. L-type detection



(a) Original scene

(b) 3-D profile of the scene

Figure 11. Experimental scene

Figure 10. Appearance of the system

(a) Detected Object

(b) 3-D profile of the objects

Figure 12. Experimental result