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PLENARY PAPER II

DISASSEMBLY

APPLICATIONS

LOGISTICS

PLENARY PAPER III

ROBOT VISION

REVERSE ENGINEERING BY MEANS OF
RANGE IMAGE INTERPRETATION

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Abstract: Reverse engineering of shape strives to construct CAD models of existing objects. Automatic construction of CAD models from range images requires the segmentation of the 3D data points into subsets that correspond to individual models. We present the results of our approach to segmentation and modeling of range images which enables the reconstruction of a compact geometric representation in the MDL sense which may consist of different types of models. *Copyright © 1998 IFAC*

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1. INTRODUCTION

Reverse engineering of shape is a process of creating geometric models of existing objects for which no such model is available. Typical applications of reverse engineering are when one needs to produce a copy of an existing part but no original plans are available, where the design is carried out by means of real-scale clay or wooden models, to generate custom fits to human surfaces etc. Since CAD/CAM systems are ubiquitous in modern manufacturing, the goal of reverse engineering is the creation of surface or solid models so that the advantages of CAD/CAM technologies can be exploited.

The reverse engineering procedure consists of the following basic steps (Várady *et al.*, 1997):

(1) Data capture
(2) Preprocessing
(3) Segmentation and surface fitting (model recovery)
(4) CAD model creation

In this paper we concentrate on the segmentation and surface fitting step. We present a method of simultaneous segmentation and recovery of parametric models from range data that we developed and which is successfully applied in a project funded by the European Union with the goal of building an intelligent reverse engineering system (Martin and Várady, 1996; Martin and Várady, 1997).

The outline of the paper is the following: first the reverse engineering problem is defined in more detail. Next, the problem of range image segmentation is addressed and the recover-and-select method is introduced. In the fourth section results of the recover-and-select method in recovery of planar surfaces, spheres, cylinders and superquadrics are shown. In conclusions we point out the relevance of this system in the framework of intelligent assembly and disassembly.

2. REVERSE ENGINEERING

One needs to make a distinction between the concept of a 3D copier and a 3D scanner. Just like a photocopier, a 3D copier takes a solid shape and produces another object of just the same shape. A scanner on the other hand, in 2D, recognizes the characters and figures, thus providing a text file and graphical structures, and in 3D, creates a geometrical model of the data. In this way we can not only copy the original shape but derive new shapes, make variations and analyze properties. A complete automatic 3D scanner is still only a research goal. For a state of the art survey in reverse engineering see (Várady et al., 1997).

The first important step is data acquisition. Optical methods are the broadest and most popular due to their non-contact nature and relatively fast acquisition rate. Different tactile methods make up the other large category. There are several categories of optical methods. We use a structured lighting device which in subsequent images projects stripes of light of different width which enables the computation of 3D coordinates of points in the scene. A cloud of 3D surface points which makes up a range image is only a starting point on the way of creating CAD models. Further data reduction has to be achieved by partitioning the points into separate parts during the process of segmentation and fitting of models to these separate parts. Range images may be corrupted with noise or some data might be missing which makes their processing even harder.

3. RANGE IMAGE SEGMENTATION

A central problem in computer vision is segmentation, where each piece of information must be mapped either to a shape primitive or discarded as noise. At the same time, there should be a minimum number of such primitives applied, to get as compact a description as possible. Given a range image as input we want to divide the original point set into subsets, one for each part or component that can be represented by a suitable model. The approaches to segmentation can be broadly divided into two categories: *edge-based* and *region-based*. The first tries to find boundaries in the point set representing edges between different surfaces (i.e., sharp edges or discontinuities). The second tries to infer connected regions of points with similar properties (i.e., groups of points all having the same normal). A good survey of segmentation techniques is in (Besl and Jain, 1985).

Next, a model must be fitted to the data points of each segment. If segmentation is isolated from model recovery, as it is commonly done, we may be confronted with regions which can not be

described with chosen models. We have argued repeatedly that segmentation and model recovery (fitting) should be approached simultaneously (Bajcsy et al., 1990; Leonardis et al., 1997). Therefore we proposed a new *Recover & Select* technique for simultaneous segmentation and model recovery which can use almost any kind of models (Leonardis et al., 1995; Leonardis, 1996). We demonstrated segmentation and recovery of range images using surface patches, superquadrics and other types of parametric volumetric models (spheres, cylinders etc.), as well as any desirable combination of them.

3.1 *Recover & Select Paradigm*

We present here a brief general outline of the Recover-and-Select paradigm. For details the reader is referred to (Leonardis, 1993; Leonardis, 1996). The paradigm consists of two intertwined stages: model-recovery and model-selection. At the model-recovery stage, a redundant set of models is *independently* initiated in the image and allowed to grow, which involves an iterative procedure combining data classification and parameter estimation. Since all of the models are initiated independently, they can be of completely different types involving both linear and/or nonlinear estimation procedures to determine the parameters of the models. The output of the model-recovery procedure comes in the form that is independent of the particular type of models; namely, each of the recovered models is characterized by the points it covers, the error, and the corresponding parameters. The final outcome of the model recovery procedure for a model m_i consists of three terms:

(1) The region R_i, which represents the domain of the model and encompasses $n_i = |R_i|$ image elements that belong to the model,
(2) the set of model parameters a_i (N_i denotes the cardinality of this set), and
(3) the error-of-fit measure ξ_i which evaluates the conformity between the data and the model.

While this description is general, i.e., independent of a particular choice of models, specific procedures designed to operate on individual type of models can differ significantly. This is primarily due to the matching and fitting processes which depend on the type of models and on the choice in defining the measure of the distance between the model and the data.

All the recovered models are then passed to the selection-procedure which is defined as the quadratic Boolean problem based on the Minimum Description Length (MDL) principle (Kovačič et al., 1997; Solina and Leonardis, 1998). The solution is a subset of all recovered models which
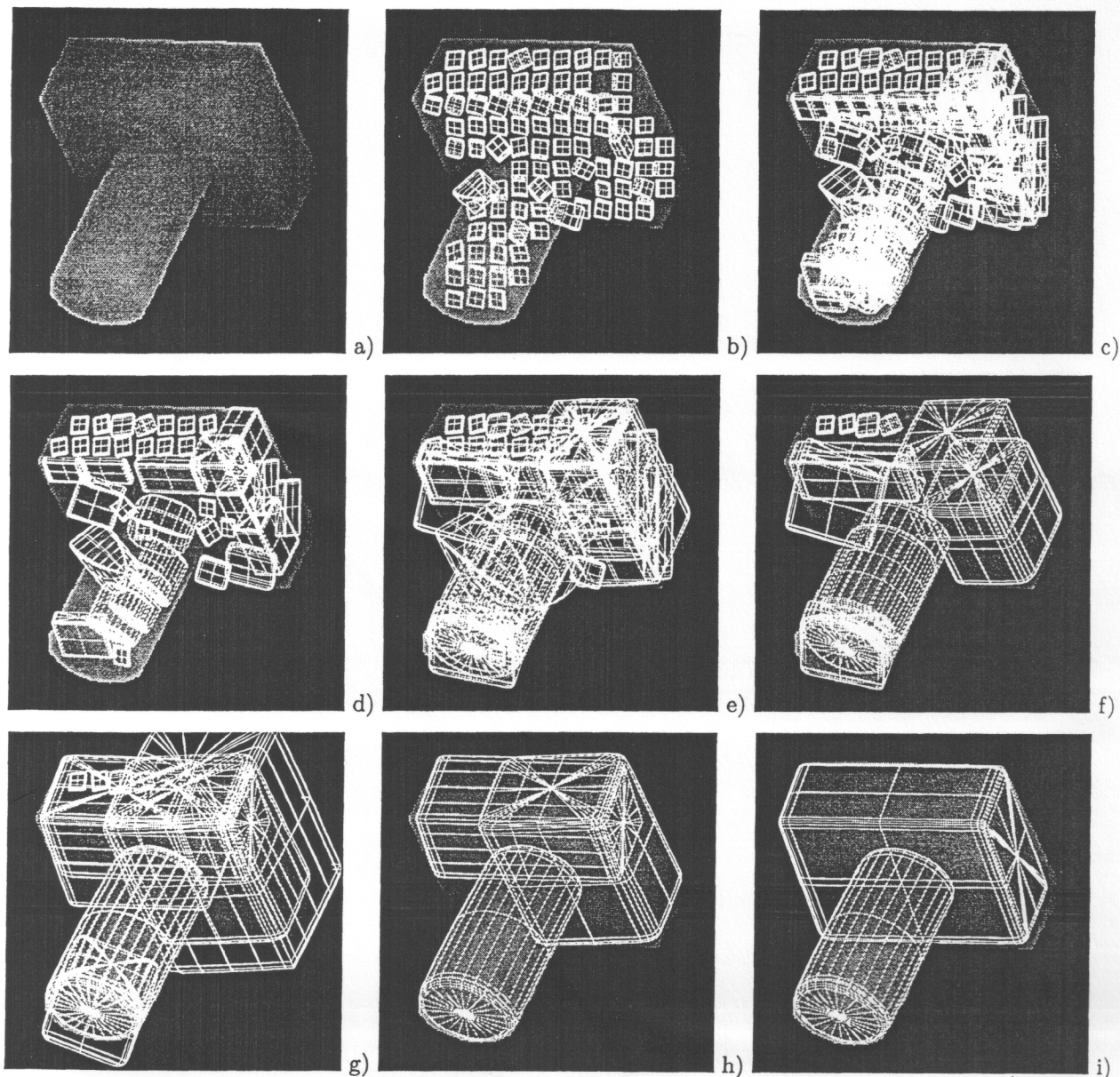
Fig. 1. A simple composition of a block and a cylinder. a) input range image, b) initial superquadric seeds, c) models after the first iteration of growth, d) remaining models after the 1st selection, e) models after the 2nd iteration of growth, f) remaining models after the 2nd selection, g) models after the 3rd iteration of growth, h) remaining models after the 3rd selection, i) two remaining superquadric models after the 4th iteration of growth and 4th selection (Jaklič, 1997).

yields the simplest overall description. To increase the computational efficiency of the method, model-recovery and model-selection are combined in an iterative fashion. The recovery of currently active models is interrupted by the model-selection procedure which selects a set of currently optimal models that are then passed back to the model-recovery procedure. This process is repeated until the remaining models are completely recovered.

At the model-recovery stage models determine their own domain of applicability by developing (growing) only where there is a close correspondence between the data and the models. Then, at the model-selection stage, the recovered models (many of whom may be partially or even completely overlapped) compete (on the basis of the MDL principle) to be selected in the final description, meaning that the selection procedure determines which models are better suited to describe different parts of the image. In the first example in this paper we employ superquadrics, in the second planar surface patches and in the third example a combination of planar surface patches, spheres and cylinders. Other combinations of different models are also possible (Leonardis et al., 1996).

4. RESULTS

The experiments were performed using our own object-oriented system "Segmentor" for image
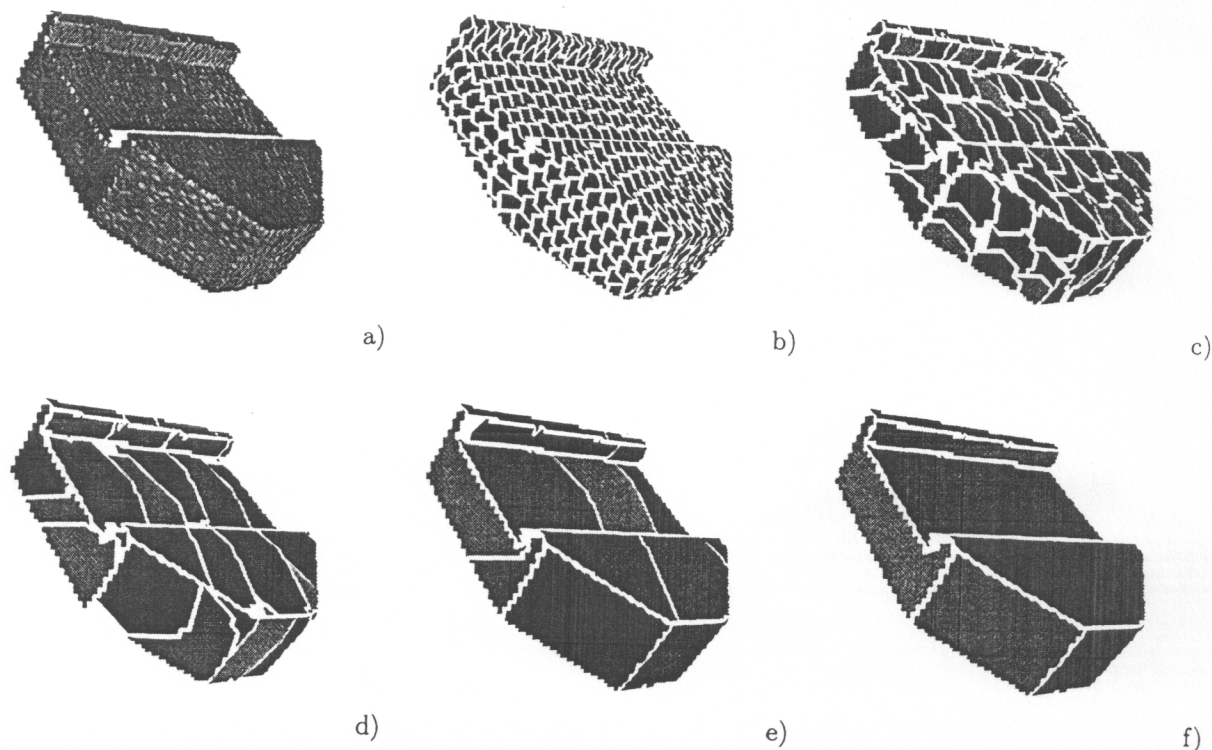
Fig. 2. a) original range image, b) regions of planar seed descriptions, c) regions after 1st selection, d) regions after 2nd selection, e) regions after 3rd selection, f) final planar regions (Kverh *et al.*, 1997).

segmentation based on the Recover-and-Select paradigm which is publicly available (Jaklič *et al.*, 1996; Jaklič, 1997). Due to self-occlusion, a single range image is not sufficient for a complete object description. Multiple images must be taken from several viewpoints and registered in order to produce complete and accurate 3D description. For a given scene an optimal number of views can be determined (Maver and Bajcsy, 1993). We may merge range images or merge partial models recovered from these range images (Jaklič, 1997).

4.1 *Recovery of superquadrics from range data*

Superquadrics are volumetric models suitable for modeling simple objects such as postal packages—successfully demonstrated in a pilot application (Solina and Bajcsy, 1989)—or for part-level description of articulated objects (Solina, 1996). Superquadrics are an extension of basic quadric surfaces and solids (Solina and Bajcsy, 1990). The superquadric surface is defined by the following implicit equation:

$$\left(\left(\frac{x}{a_1}\right)^{\frac{2}{\epsilon_2}} + \left(\frac{y}{a_2}\right)^{\frac{2}{\epsilon_2}}\right)^{\frac{\epsilon_2}{\epsilon_1}} + \left(\frac{z}{a_3}\right)^{\frac{2}{\epsilon_1}} = 1 \, , (1)$$

where a_1, a_2, a_3 define the superquadric size, and ϵ_1 and ϵ_2 define a smoothly changing family of shapes from rounded to square. A superquadric

in general position requires six additional parameters. A detailed description of using superquadrics for segmenting and modeling range data can be found in (Leonardis *et al.*, 1997). Fig. 1 shows the recovery sequence for a simple composition of a block and a cylinder.

4.2 *Recovery of surfaces from range data*

Surface models offer a more fine grained, local and adaptive shape representation (Leonardis *et al.*, 1995; Kverh *et al.*, 1997). Fig. 2 shows the recovery sequence for a machine part. We use the following planar surface model:

$$ax + by + cz + d = 0. \qquad (2)$$

4.3 *Recovery of planes, spheres and cylinders from range data*

In general, a more compact representation is possible by concurrent recovery of volumetric and surface models. In (Leonardis *et al.*, 1996) we used a combination of planar surfaces and superquadrics. In (Kverh and Leonardis, 1998) we used planes, spheres and surfaces of 2nd order instead of superquadrics. When several different models are used at the same time, they must all be fully grown before the selection is performed. In short, we first independently recover each of them, and finally select models from all sets of
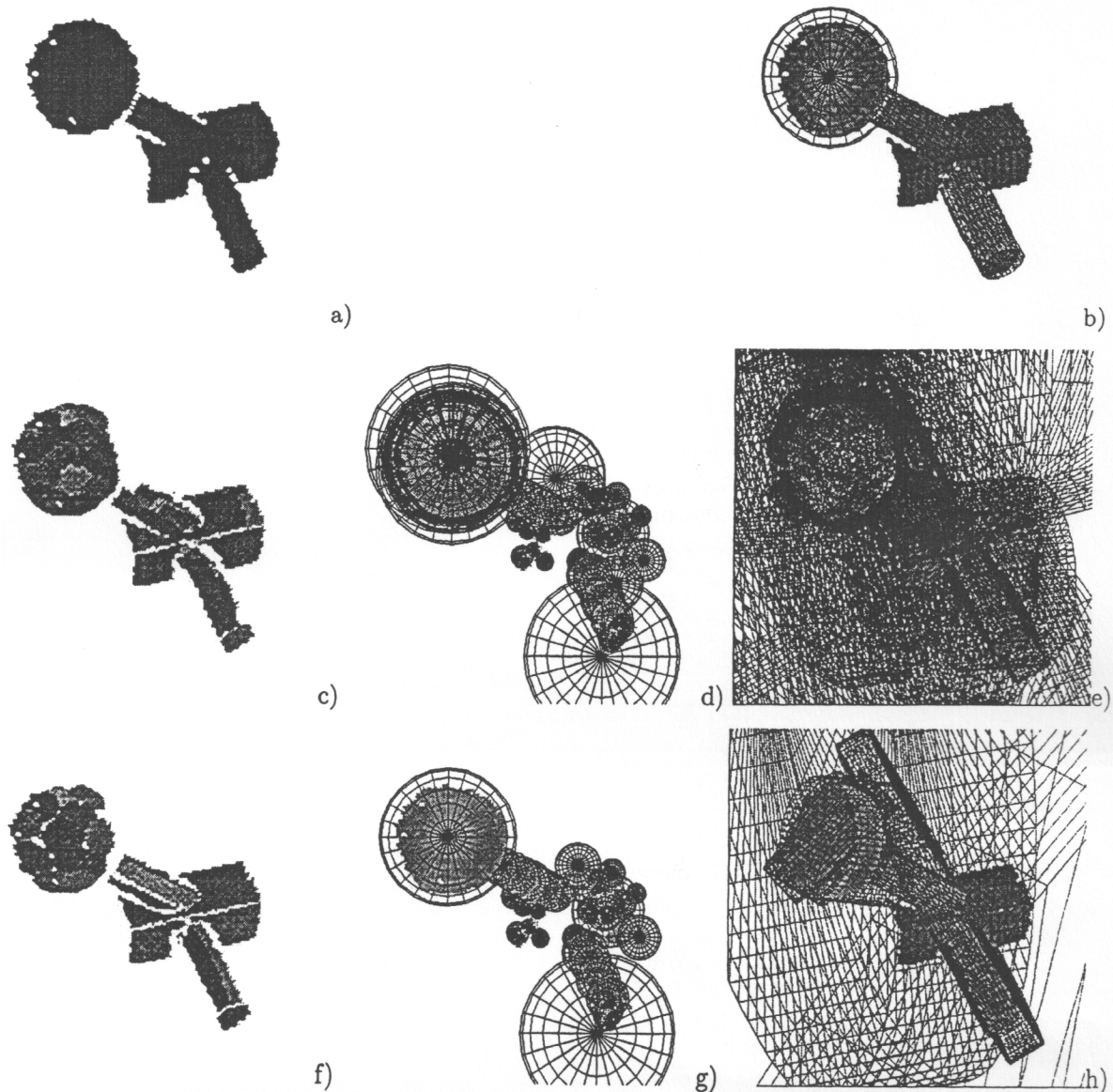
Fig. 3. a) original range image, b) final description made out of one sphere, two cylinders and two planar surface patches, c) intermediate planar regions, d) intermediate spherical regions, e) intermediate cylindrical regions, f) final planar regions, g) final spherical regions, h) final cylindrical regions.

models again using the MDL principle. The model for spheres is straightforward:

$$(a - x)^2 + (b - y)^2 + (c - z)^2 - r^2 = 0 . \quad (3)$$

The cylinder model is slightly more complex:

$$\left\| (\mathbf{p} - (\rho + \frac{1}{k})\mathbf{n}) \times \mathbf{a} \right\| - \frac{1}{k} = 0 , \quad (4)$$

where $\mathbf{p}$ is a directional vector of a point in 3D, ρ defines the smallest distance between the coordinate center and the surface of the cylinder, parameter k is the inverse of the cylinder radius, $\mathbf{n}$ is a unit vector along the axis of the cylinder and $\mathbf{a}$ is a unit vector normal to the cylindrical surface so that the scalar product $\mathbf{n} \cdot \mathbf{a} = 0$. Vectors $\mathbf{n}$ and $\mathbf{a}$ are each defined by three parameters: φ, ϑ

and α. Fig. 3 shows the recovery sequence for an articulated object.

Our code for segmentation and modelling the range data is public-domain and is available via anonymous ftp at `razor.fri.uni-lj.si` in `/pub/software/bojank/segmentor.tar.gz`. The segmentation of range images with superquadrics can be tested via Internet as well. The appropriate http address is `razor.fri.uni-lj.si/~ danijels/ segmentor/segmentor.html`.

5. CONCLUSIONS

We have outlined the problem of reverse engineering the shape of objects. Segmentation and modeling of range images is a crucial step in this process. We present results of the Recover-and-

Select method in segmenting and modeling range images using different types of parametric models.

One can employ different types of models in the Recover-and-Select paradigm depending on the complexity of shapes or required accuracy. Incomplete or approximative models (i.e., superquadrics) can be used for collision checking, manipulation or assembly and disassembly. For CAD purposes one requires more accurate models where blends and free-form surfaces play an important role and models with surfaces common in mechanical engineering (cylinders, cones etc.).

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