COST #254
IEEE Slovenia Section-R8
University of Ljubljana

International Workshop on Intelligent Communications and Multimedia Terminals

Ljubljana, Slovenia, November 1998
Edited by Jurij F. Tasič, Urban Burnik

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Terminal Equipment and Signal Processing for Multimedia Communications

Lectures

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How to Control the Level of Detail in the Framework of Object-Level Description

Jaka Krivic, Aleš Jaklič, Aleš Leonardis, Franc Solina
Computer Vision Laboratory
Faculty of Computer and Information Science
University of Ljubljana
Tržaška 25, 1001 Ljubljana, Slovenia
(jakak, alesj, alesl, franc)@razor.fer.uni-lj.si

Abstract

In this paper we propose an enhancement of the SEGMENTOR system for modelling range image data with superellipsoids, which enables us to modify the degree of detail of the descriptions. The basic idea is that the space inside the model is transformed. We show that this approach is successful in the model recovery stage.

1 Introduction

We percept the world around us as being made of parts. Detecting those parts in images has been one of the goals of the computer vision. The part structure as well as the shape of individual parts can be recovered. Such a description of an image has the advantage of being compact and useful for higher-level processing. The parts can be modeled by various models. Superquadrics are volumetric part models the computer vision community has paid attention to [1, 2, 3]. Representations of superquadrics are very compact and there are robust methods for recovery of an individual superquadric [3].

Recover-and-Select paradigm is used to recover parametric models from images [4]. It has been practically used in an object-oriented form in a system called SEGMENTOR [5]. This is a system for range image segmentation and modeling. Superellipsoids were used as models. The system has been relatively well tested [6]. The one deficiency of the system is its sensitivity to the degree to which the parts of an object could actually be modeled by superellipsoids. Since our goal is to use the systems' output for object classification, we first wanted to make it less sensitive to that. At the same time we wanted to be able to set how *'detailed'* an image desctription should be. For example we could get one model from an image of one's hand instead of getting one for each finger and a palm if we wanted a more detailed description.

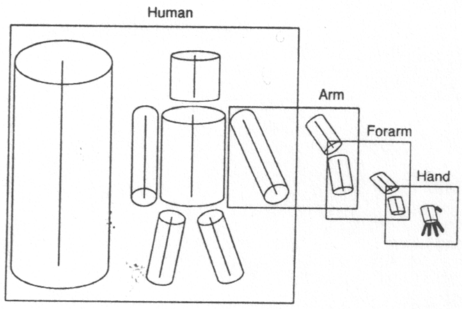


Figure 1: A hierarchy of different levels of part descriptions

The rest of this paper is organized as follows: SEGMENTOR and its basics are described in section 2, the modification is discussed in section 3 along with the presentation of experimental results and followed by conclusions.

2 SEGMENTOR

SEGMENTOR is an object-oriented framework for image segmentation and recovery of parametric models from range images [7, 5]. The main object is a description, which consists of a set of points called *region*, and a parametric model, in our case superellipsoid. The model should fit the region as accurately as possible. The measure of fitting is the *error function*. The framework uses Recover-and-Select paradigm [4], which consists of three stages:

1. Placing seed descriptions,
2. Growing of descriptions,
3. Selection of descriptions.

Growing and selection are performed several times. For the purposes of this paper we shall only describe the growing stage in greater detail; the interested reader should see [4, 7].

Growing of a description affects both the region and the parametric model. First, an efficient search for more compatible points is performed in the vicinity of the region. The newly included points have to be eight-connected to the region and their distance to the present model has to be less than the *max_point_distance* parameter. On this updated region a model recovery is performed. It consists of finding the superellipsoid parameters:

$$SE = (a_1, a_2, a_3, \epsilon_1, \epsilon_2, \phi, \theta, \psi, p_x, p_y, p_z) \quad (1)$$

Parameters a_i determine the size, shape is determined by ϵ_i, orientation by Euler angles ϕ, θ, ψ, and position by the components of translation vector p_i. Recovery is actually a minimization of an error function, which is based on the so called ***inside - outside*** *function*:

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

This function maps to value 1 for the points that lie on the surface of the superellipsoid. It is used to calculate the radial Euclidean distance and also the error function (see [7]), which are both of our interest. Radial Euclidean distance is used in region growing when including new points. Error function is used directly for model recovery.

3 Roughness: the level of detail

The basic idea of the proposed enhancement was to transform the space inside the model. Points lying inside the model would be virtually moved closer to the surface thus reducing the influence of local deviations on the distance and overall error function. Intuitively that would mean less detailed descriptions and also better descriptions of objects that cannot be modeled well by superellipsoids.

This is done by manipulating the inside-outside function. The function (2) is multiplicated with a *'roughness factor'* for the points that lie inside the model:

$$F_1(x,y,z) = \begin{cases} F(x,y,z) & f \geq 1 \\ (F(x,y,z)-1)r+1 & 0 \leq f < 1 \end{cases}$$

$$r \in [0,1], f = F(x,y,z) \quad (3)$$

Using value 1 for r produces normal descriptions with full details. Values less than 1 would produce less detailed descriptions. Typical recovery using changed inside-outside function (3) can be seen in

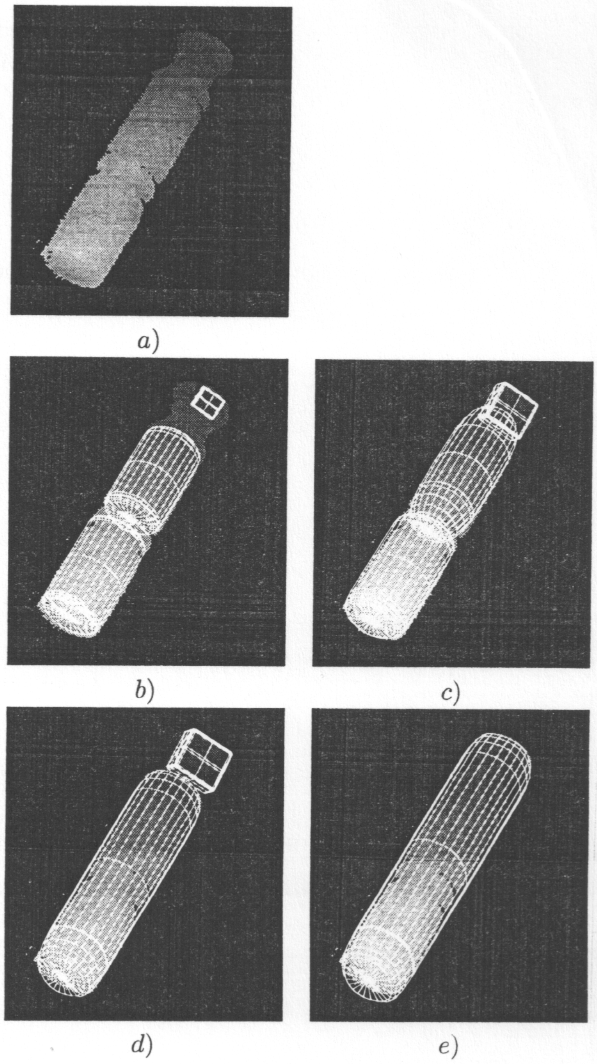
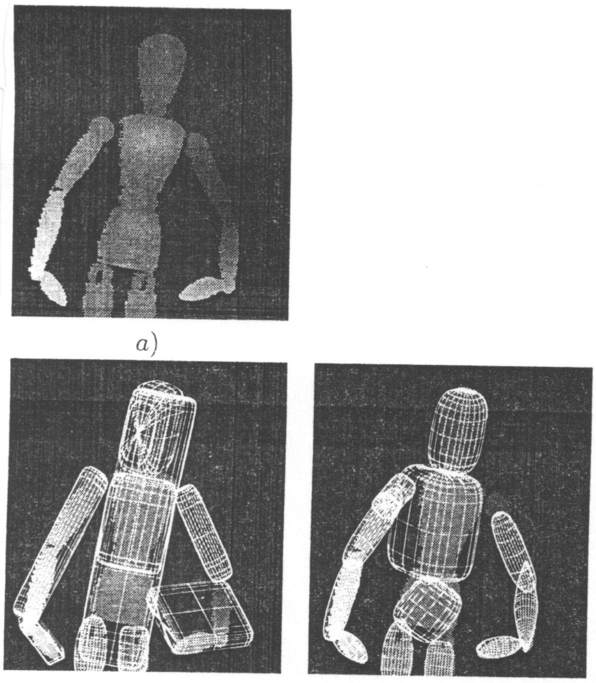


Figure 2: Typical recovery using F_1. a) original image, b) $r=1$, c) $r=0.5$, d) $r=0.3$, e) $r=0.1$

Figure 2. The range images were obtained in our laboratory with the help of a Dr. Wolf structured light range scanner. By changing the roughness factor less detailed descriptions of the object can be recovered.

On images of relatively simple objects this works fine. But when dealing with more complex objects, there is a problem. The regions are overgrown as one can see on Figure 3. Input was an image of a human-like model. We expected the recovery to behave like it did on models' right arm. Since the hand was almost stretched, it would seem that the forearm and the upper arm together are one part of the object. Models' left arm, however, is contracted; but the recovery produced a single superellipsoid for both the hand and the forearm. There is also a superellipsoid that covers models' head and chest that shouldn't be there. In part this is due to the lack of background



a) b) c)

Figure 3: Recovery of a more complex object. a) original image b) $r = 0.1$ c) $r = 1$

information, but the major cause is better evaluation of larger models.

We tried to correct this problem by virtually moving only those points that were originally closer to the surface of the model. The *inside-outside* function is then

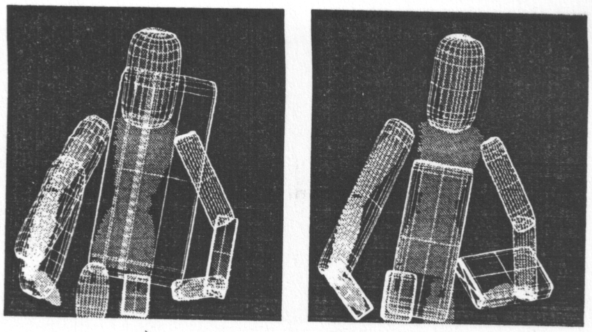
$$F_{21}(x,y,z)=\begin{cases} F(x,y,z) & d \geq 0 \\ (F(x,y,z)-1)r+1 & -D \leq d < 0 \\ F(x,y,z) & d < -D \end{cases}$$

$$r \in [0,1]$$

$$d = 1 - \frac{1}{\sqrt{F(x,y,z)}} \tag{4}$$

In this case d is a distance from the superellipsoid surface to the given point (x, y, z), expressed relatively. For example, if D has a value of 1, only the points that lie inside the model and their distance to the surface is less then one half of the distance from the center to the surface, are given a new reduced distance. That would give a model that is too large for the given region, higher error.

On Figure 4 one can see that there is some improvement. A variant of $F_{21}(x, y, z)$ was also tried:



a) b)

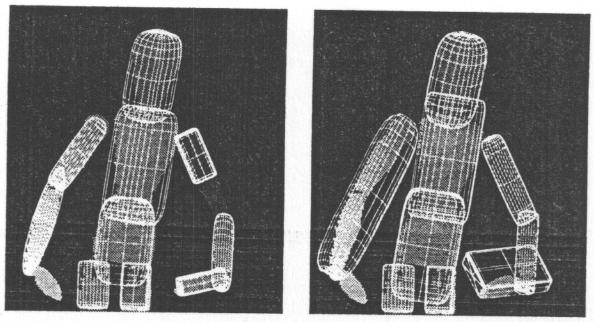
Figure 4: Recovery using F_{21}. a) $r = 0.1$, $D = 1$ b) $r = 0.1$, $D = 2$

$$F_{22}(x,y,z)=\begin{cases} F(x,y,z) & d \geq 0 \\ (F(x,y,z)-1)r+1 & -D \leq d < 0 \\ F(x,y,z) & d < -D \end{cases}$$

$$r \in [0,1]$$

$$d = \sqrt{x^2+y^2+z^2}\left(1 - \frac{1}{\sqrt{F(x,y,z)}}\right) \tag{5}$$

The $F_{22}(x, y, z)$ as inside-outside function only reduces distance to the points that are inside the model up to D units (i.e. pixels) from the surface. Some typical reconstructed descriptions can be seen in Figure 5. Again, there is slight improvement compared to the $F_1(x, y, z)$ (3).



a) b)

Figure 5: Recovery using F_{22}. a) $r = 0.1$, $D = 20$ b) $r = 0.1$, $D = 40$

4 Conclusions

In this work our goal is to develop a modification to the SEGMENTOR modeling system using superellipsoids as models, which would enable us to set the level of how detailed a description recovered from an image should be. That would also improve the systems' deficiency when dealing with objects that can not be modeled by superellipsoids.

The effort was directed to two stages of the process: the growing stage and the model recovery stage. The model recovery stage worked well, since we could control the degree of detail and get semantically right descriptions (see Figure 2). There was, however, a problem with the growing stage. The regions grew over their semantic boundaries. The regions were overgrown because if the model recovered for that region was larger than the region would suggest (usually it was), then the points in the vicinity of the region would also lie in the model and therefore be included when growing stage was engaged. This would be also true for the points that lie on another part of the object. In several growing iterations the region would grow over two (or more) parts of the object.

That leads to a conclusion that the two stages should be dealt with separately. The model recovery stage could be done in a way that we proposed. In the growing stage some other approach would probably produce better results. We could, for example, trace the models error and decide if growing should continue or not.

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