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# SEGMENTATION OF RANGE IMAGES

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## ABSTRACT

The range image (RI, gives the distance from an observer) segmentation task is motivated by 3D object reconstruction from multiple RI of an object. To simplify the task of object reconstruction a particular RI is segmented to regions that can be precisely described by a parametric model. The output of segmentation is the list of regions with attached surface models and the image describing the topology of regions. When a sequence of range images is once segmented, the correspondence between particular views can be established and 3D model of the object can be recovered. The aim of this article is to introduce a field of research activity which is applicable not only to computer vision problems.

Key words: range image, segmentation, discontinuity, differential geometry.

## 1 MOTIVATION

This work presents a segmentation method which can be used as the first step towards the 3D object reconstruction from range images (RI is the map which gives the distance of surface points to an observer. See (Jarvis, 1983) for basic principles of range image formation.).

It is assumed that a sequence of range images covers the whole surface of the object. Furthermore, it is assumed that adjacent images overlap so that it is possible to find Euclidean transformations between images from observed data. Euclidean transformations can be computed using constrained minimization problem (Sabata, 1991) if corresponding points in overlapping images are found.

To make the correspondence task less computationally intensive, rough transformation estimate can be found from quadric description of surface patches (Yu, 1991). Instead of comparing a **great** number of data points, small number of similar parametric models is matched (Vayda, 1991). Exact transformations are then obtained using the *iterative closest point algorithm* (Besl, 1992).

Having the sequence of range images and the list of correspondences and Euclidean transformations, the geometrical model can be inferred by the *probabilistic fusion* of the range data from multiple sources (Bove, 1990).

The rest of this paper deals with the segmentation of a surface into $C^0$ and $C^1$ continuous low order polynomial patches which is the basic procedure to obtain candidates for matching surface patches.

## 2 SURFACE SEGMENTATION PROCEDURE

The aim of surface segmentation is to group and label pixels from the image into connected sets of points (regions) so that:

1. No region overlaps $C^0$ discontinuity and no region is $C^1$ discontinuous.

2. All regions satisfy a parametric model.

Both 3D model reconstruction and surface segmentation are highly domain dependent tasks. We restrict ourselves to piecewise continuous surfaces which can be described by a parametric model (Bajcsy, 1990). One continuous surface patch is modelled by *2nd* or *3rd* order polynomial function. It is simple but still feasible surface description.

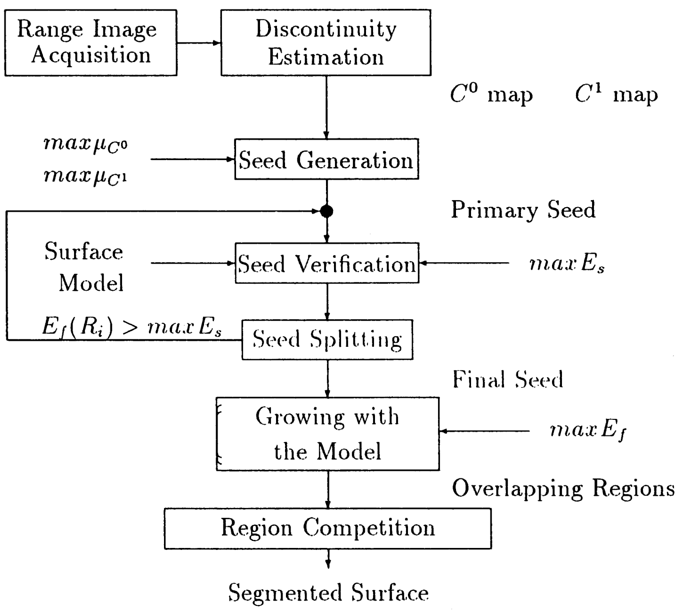


**Figure 1:** *Surface Segmentation*

The whole segmentation procedure based on the region growing method (Marik, 1992) is outlined in Fig. 1. The region growing is an iterative process that starts from an initial region called *seed* region. The seed region is described by a parametric model. All pixels in 4-neighbourhood of the region are attached to the region if they do fit the model. The model is updated in the process of growing to describe all data included in the region. The process of growing and model evaluation is repeated while there is any point neighbouring the region and fitting its model.

In the next sections we will describe seed generation from surface discontinuities and the region growing method.

## 2.1 SURFACE DISCONTINUITY ESTIMATION

The aim of discontinuity estimation is to exclude points near surface discontinuities from seed regions. Small neighbourhood of every pixel (typically $7 \times 7$ points) is approximated by $2nd$ order polynomial patch. $C^0$ and $C^1$ discontinuity measures are then evaluated from the approximation. The $C^0$ discontinuity is measured by the residual error of fit. The $C^1$ discontinuity is computed as the maximal angle between surface normals at the point. The method invariant to view point changes is used to compute $C^1$ surface discontinuities (Pajdla, 1993). The $C^0$ and $C^1$ discontinuity maps are the output from this step.

## 2.2 SEED GENERATION

Given $C^0$ and $C^1$ discontinuity maps, the *primary seed* is generated. The set of primary seeds $PS = \{R_i\}$, where $R_i$ is a region so that:

1. $\forall\ R_i \in PS, \forall\ R_j \in PS, i \neq j \Rightarrow R_i \cap R_j = \emptyset$,
2. $\forall\ R_i \in PS$ and $\forall\ x \in R_i$: $\mu_{C^0}(x) < max\mu_{C^0}$ and $\mu_{C^1}(x) < max\mu_{C^1}$, where $\mu_{C^0}$ and $\mu_{C^1}$ are measures of the discontinuity strength.

The actual value of $max\mu_{C^0}$ and $max\mu_{C^1}$ depends on the range image acquisition process. In general the lower *signal/noise* ratio is, the higher both $max\mu_{C^0}$ and $max\mu_{C^1}$ must be.

## 2.3 SEED VERIFICATION AND SPLITTING

Due to the local nature of the discontinuity estimation it is not possible to find all points corresponding to surface discontinuities using simple thresholding. Given the structure of surface parametric model and the maximal fit error $maxE_s$, the set of final seeds $FS = \{R_i\}$ is generated. Every $R_i \in FS$ must satisfy the following condition: $E_f(R_i) < maxE_s$, where $maxE_s$ is the maximal fit error allowed for one seed patch.

Every $R_i \in PS$ is subjected to the error-of-fit test. If the test is not successful, the region $R_i$ is split into at least two regions $R_{ij}$, $j > 1$. Region growing with interior model is used to extract regions $R_{ij}$ from $R_i$. The growing process starts at the point $\hat{x} \in R_i$ for which holds:

$$\mu_{C^0}(\hat{x}) = min\{\mu_{C^0}(x)\}, \quad \mu_{C^1}(\hat{x}) = min\{\mu_{C^1}(x)\}, \quad x \in R_i.$$

and stops when there are either no more seed points or the fit error meets the limit $maxE_s$. New regions are appended to the list of all seed regions. The whole *test-and-split* process is repeated until all $R_i \in FS$ do not well satisfy their models.

## 2.4 REGION GROWING WITH SURFACE MODEL

Every $R_i \in FS$ is used as an independent seed for region growing with the interior model. Every seed region is approximated by a polynomial with the lowest possible order to satisfy the error-of-fit test $E_f(R_i) < maxE_f$. Then, the growing with surface model is applied while there are any data compatible with the model. If there are any points not already included in the region, model order is increased and growing continues. We typically start with $1st$ polynomial and stop with $2nd$ or $3rd$ order polynomial model.

The output of this growing procedure is the list of independently grown regions that may possibly overlap. To obtain a set of disjoint regions, we have to decide where to place

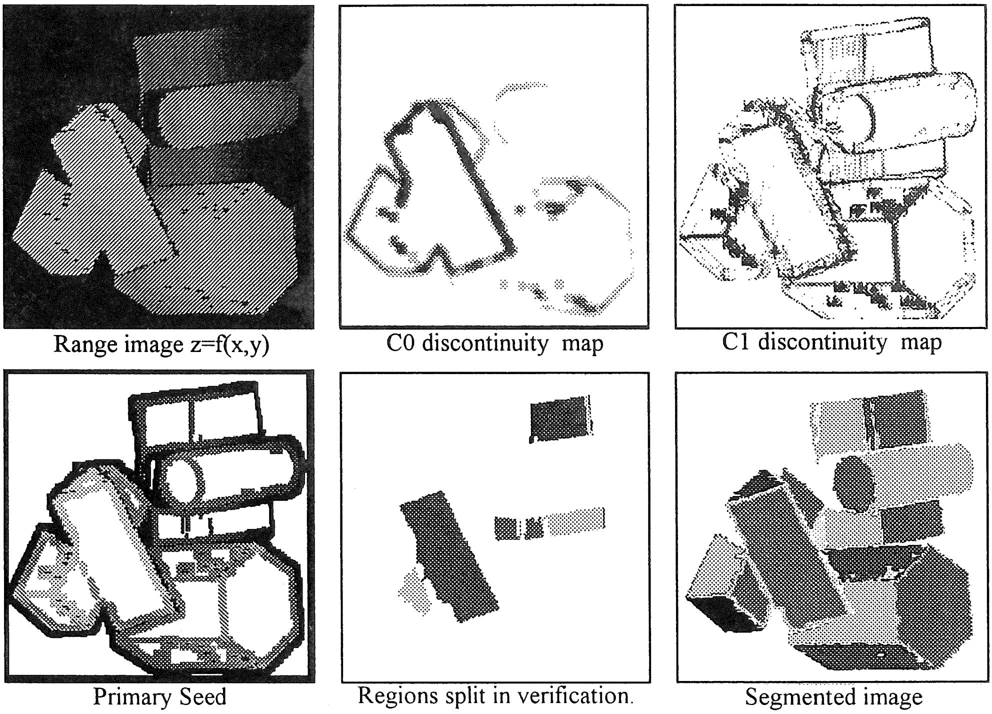


Figure 3 : Segmentation of range image data.

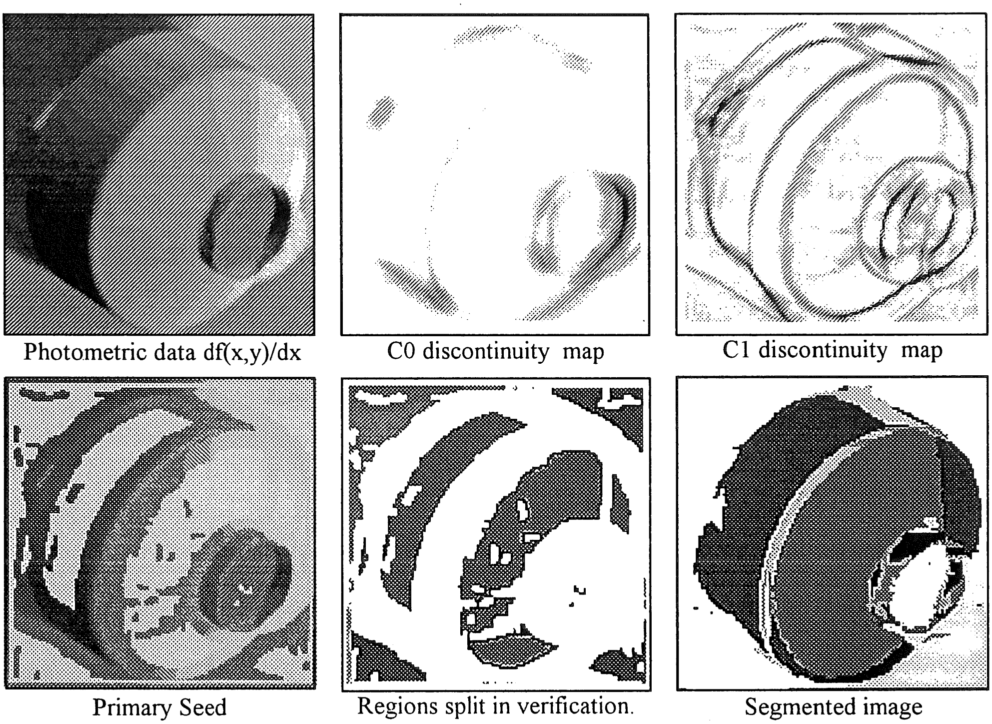


Figure 4 : Segmentation of Photometric stereo data.

the boundaries of overlapping regions. Every point in overlapping areas are assigned to that region the model of which fits better the point.

Having finished the growing step of the surface segmentation algorithm the set of disjoint regions $\{R_i\}$ with following properties is obtained:

$$E_f(R_i) < maxE_f, \quad R_i \cap discontinuity = \emptyset.$$

## 2.5 EXPERIMENTS

We present experiments with (a) real range data captured by laser range finder and with (b) data obtained from photometric stereo technique (Woodham, 1991).

Figure 2 shows an example of range image segmentation. All surface patches were modeled with $1st$ and $2nd$ order polynomial. Thresholds for primary seed generation were set to $max\mu_{C^0} = 5$ per pixel, $max\mu_{C^1} = \frac{2\pi}{3}$. Maximal error of fit $E_s$ was set to 1 per pixels. Maximal error of fit in the process of growing $E_f$ was set to 2 per pixel.

Figure 3 shows segmentation of photometric stereo data. The image contains one partial surface derivative, $\frac{\partial f(x,y)}{\partial x}$. The original surface consists of a cone and 2 cylinders. The image of the surface derivative has been segmented using $3rd$ order polynomial models. Thresholds for primary seed generation were set to $max\mu_{C^0} = 5$ per pixel, $max\mu_{C^1} = \frac{2\pi}{3}$. Maximal error of fit $E_s$ was set to 2 per pixels. Maximal error of fit in the process of growing $E_f$ was set to 3 per pixel. It can be observed, that continuous surface patches are broken to more than one region. It stems from the fact that a derivative of a quadric is not a low order polynomial.

## 3 CONCLUSIONS

We have shown general segmentation method applied to the segmentation of range images and photometric stereo data.

The possible improvement in segmentation could be achieved if a boundary model was added to support the region interior model. The boundary of a region can be modelled as an elastic membrane (Witkin, 1988). The growing in directions which keeps boundary energy as small as possible would inhibit long and narrow shaped regions.

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