A New Shape Segmentation Approach for Active Vision Systems

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Abstract

Vision systems are becoming an integral part of many automated manufacturing processes involving localisation and identification of 3D shapes. Active vision offers a practical solution to such problems. In this paper, we present a new solution to extract 3D shapes from a structured light image. The 2D striped image is segmented into regions corresponding to quadratic surfaces. A fuzzy analysis of the stripes properties allows to locate discontinuities and to model stripe parts. These parts are tracked in consecutive images and matched in order to create regions. We present segmentation results obtained with a real scene consisting of multiple objects of arbitrary shapes.

1. Introduction

Sensing of 3D shapes can be exploited in different applications such as : inspection, bin-picking, assembly or vehicle motion. Many 3D sensing methods using active or passive vision are currently under investigation [1]. Active triangulation methods, so-called structured light methods [2],...[6], consist in projecting on the scene a visible light from a source with a known pattern geometry . The scene is viewed with an imaging sensor looking off the emission axis. Knowing the position of an image point on the detector, as well as the lateral distance between the projector and the camera, and the projection angle of the light source, the 3D point location can be computed. When the source is a plane of light, the range information manifests itself in the apparent deformation of the projected stripe.

Our work deals with the development of a segmentation method for structured light images produced with a stripe scanning technique. We suppose that surfaces are "regular" enough and that they can be approximated by second order patches. The algorithm includes three steps :

- image preprocessing for extracting the stripe skeleton and locating its discontinuities,
- tracking process for grouping 2D stripe parts that present enough common features,
- shape recovery via triangulation for computing 3D points, and least square minimisation for modeling quadratic faces.

In this paper , we focus on the algorithms developed to solve the segmentation problem. The 3D sensor and the shape recovery method are described in [6].

2. Image preprocessing

2.1 Extracting the stripe skeleton

The variable range between sensor and objects causes defocussed images for the projected stripe. Consequently, we must extract the skeleton of the projected pattern which represents the intersection between a perfect plane and the 3D scene. In order to eliminate the background noise, we determine a minimum intensity threshold by applying a statistical method to a set of randomly chosen image points. On each line of the thresholded image where the intensity can be modeled by a discrete function I(x), the most representative pixel is the one which receives the maximum of energy. To identify and to locate accurately this unique maximum, we convolute the I(x) function with a symmetric exponential filter [6],[7]. Then a statistical computation is used to reduce a possible bias on the maxima location and to estimate the standard deviation of the signal I(x). Simultaneously, breaking points which correspond to occluding boundaries between faces are detected and the stripe is divided into several parts.

2.2 Locating stripe curvature discontinuities

Our aim is to approximate each laser stripe by a set of adjacent second order curves. To do that, we locate stripe discontinuities such as angular, retrogression or bending points. Let $x = L(y)$ be the noisy curve resulting from the previous processing (fig 1a). Discontinuities correspond to maxima or zero crossing of the second derivative of $L(y)$. We compute this derivative via a symmetric exponential filter [7] which reduces the truncature noise, by preserving the discontinuities location (fig. 1b).

In order to perform an accurate curve analysis, a Kalman filter controlled by a qualitative method is used to evaluate the residual noise of L''. The control method uses the Student test results for updating the predicted errors variance.

The analysis of the smoothed L'' signal consists in locating its zero crossing and its maxima, in order to subdivide L(y) into second order approximable curves (fig. 1d). We have established a decision-making function using fuzzy information such as the smallness of $L''(y)$ and the straightness of a set of adjacent points of L(y). Such information cannot be correctly analyzed by a boolean process. Our curve analysis uses a fuzzy logical operation

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based on the comparison between the current value of L" and those of the previous points.

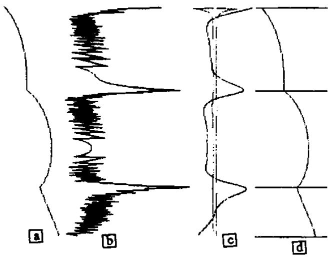

Figure 1. Laser stripe processing
a) L(y)- **b)** L"(y) before smoothing- **c)** L"(y) after smoothing - **d)** Discontinuities on L(y)

3. Image segmentation via stripe parts tracking

3.1 Stripe part model

Grouping similar stripe parts in homogeneous 2D regions involve modeling these curves. We identify each part with a parabolic model which can be written :

$$x = a y^2 + by + c$$

A curve fragment is described by the parameters a,b,c, and their variance/covariance, by the 2D coordinates of its two end points and by a fuzzy value attached to their type (breaking, bending, retrogression or angular point).We also consider another fuzzy value which caracterizes the straightness of the curve.

3.2 Matching and fusion process

The problem we address here is to "track" each curve fragment in the sequence of images acquired when scanning the 3D scene. Presently, we assume that the curve motion can be modeled by a translation and a small rotation in the image plane. This rotation is first order approximated, in order to keep the consistency of the parabolic model. For each fragment of a new image, we find which fragment might correspond to it, by calculating the distance between each parameter of this fragment and the corresponding parameters of the set of fragments which have not been matched. We use the so called Battacharyya distance [7] which takes into account the variance/covariance of the parameters. Other criteria are considered in this matching process , such as:

- the overlapping of the fragment projections on the vertical image axis, which allows us to avoid the matching of similar curves belonging to different regions,
- the likeness between the corresponding fragment end points which is generally stronger in case of curves issued from the same object face.

The decision process is controlled by a fuzzy logical operation on the fuzzy values that we have associated to these distances and criteria.

3.3 Experimental results

The algorithms we propose in this study have been implemented on a PC computer and tested on indoor scenes including planar and curved objects. Figures 2 shows the striped image of a scene superimposed on its multi-level image (a) and some regions (b,c,d) extracted with the segmentation process.

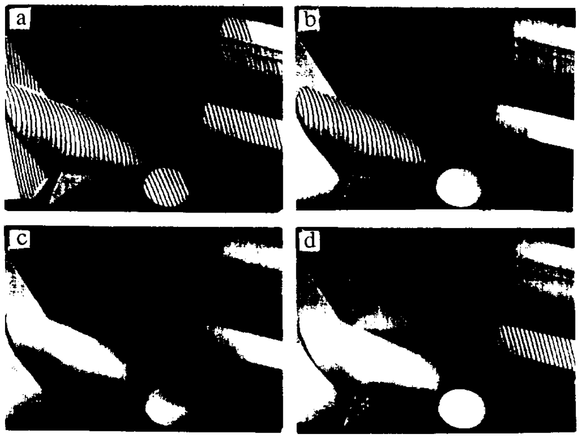

Figure 2. Some segmentation results

4. Conclusion

We have presented algorithms for solving the segmentation problem when sensing 3D scenes with structured light vision. Presently, we are improving our recursive shape recovery method which uses an analytic representation, and we are also developing algorithms for modeling the face boundaries.

5. References

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