Improving Environment Modelling by Edge Occlusion Surface Completion

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Abstract

Reconstruction of 3D models from range images usually focuses on complex objects completely contained in the field of view. Using range images to reconstruct a whole environment is challenging because of many occlusions. The focus of this paper is the reconstruction of the corners and edges of partially occluded simple-shape objects like furniture pieces in a indoor scene. Little research has been done on reconstructing obscured surface parts. We introduce a new approach to detect and complete occlusions. The proposed approach is based on good boundary and surface continuation and explores architectural constraints as well. Results on real images confirmed improvement of environment modelling and the perception of the scene objects.

1 Introduction

Range images are used in a wide range of applications. So far they have been used extensively in object recognition [12, 6], reverse engineering [3], and other applications, nearly all focusing on small and rather complex objects and scenes. While extending the use of range images to a whole environment rather than well-delimited objects (an important example of these applications is the CAMERA EU project [5]) new issues arose.

Occlusion is a major cause of information loss: even in moderately complicated scenes it is either impossible or impractical to obtain complete range scans [14]. On the other hand, an exhaustive description of the observed objects or environment is needed for some applications, like construction of a 3D model [5] and environment object recognition.

The problem we wish to solve is the reconstruction of partially occluded simple-shaped areas. The solution is a procedure to fill in the gaps without performing extra scans inferring the unseen parts by exploiting the surroundings.

There have been few attempts in the literature to reconstruct occluded surfaces [2, 7]. This research reconstructed fully surrounded occlusions where the object has been split. The proposed work represents an effort to extend the range of resolvable/reconstructible occlusions. We propose a method for reconstruction in cases when significant portions of object boundaries are occluded (eg. a corner). The detection and reconstruction is based on establishing a foreground - background relation between regions during the analysis of region boundaries. In particular, the background region is occluded by the foreground region and reconstruction starts from its boundary. Back-foreground classification is hardly studied in literature [13, 9, 11], but most of the relevant research investigates two dimensional context. In our case we have the depth information provided by the range data and we use this information to disambiguate the situation. Once occlusions are detected reconstruction can be achieved by applying the principles of *good surface continuation*, that is, the occluded surface keeps the same shape as its visible part [9, 11], and *good boundary continuation*, that is, the occluded boundary keeps the same slope as its visible part. Moreover we exploit *architectural constraints* to bound the occluded surface. This can be a wall, a floor, a door, a window etc. [4, 8]. Experiments show reconstructed simple shaped surfaces inside a fairly complex scenario. The occlusions considered here arise very commonly in typical man-made environments.

2 Proposed Method

The proposed method can be divided into two consecutive phases: Occlusion Detection and Occlusion Recovery.

2.1 Occlusion Detection

Images are segmented (using the algorithm described in [10]) and detected surfaces are considered in pairs. Their

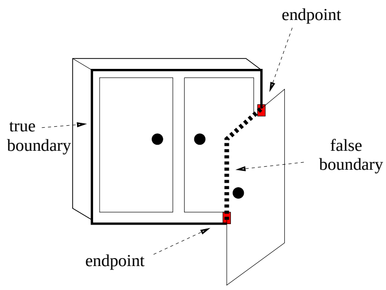


Figure 1. Endpoints and boundaries between adjacent surfaces.

boundaries are compared and if depth values associated with adjacent surface boundaries are similar, the surfaces are contiguous and so not occluded in the area surrounding those boundaries. The boundaries between the wall and cupboard shown in figure 1 are examples of boundaries between contiguous surfaces. We call them *true boundaries*. If instead, depth values associated with adjacent surface boundaries are different, it means that the surface closer to the sensor is in foreground and the other one is in background. In this case the boundary of the background surface is a *false boundary*. In figure 1 the boundaries between the door and cupboard are examples of false boundaries.

We have to establish a foreground-background relation for each pair of adjacent regions. We start by extracting the boundaries of each region. The boundary $\mathbf{B}_l$ of region l is the set of points x_i defined as:

$$\mathbf{B}_l = \{x_i \in l \quad AND \quad \exists x_j \in n_{x_i} | x_j \notin l\} \tag{1}$$

where n_{x_i} is the neighbourhood of x_i. We then proceed by grouping into the same segment boundary points that have the same pair of neighbour regions. That is, each boundary point $x_i \in \mathbf{B}_l$ is associated to $y_i \in \mathbf{B}_h$, where h is a region different from l, so that:

$$\begin{array}{c} y_i \notin l \quad AND \\ \forall y_j \notin l \quad dist(x_i, y_j) > dist(x_i, y_i) \end{array} \tag{2}$$

We call $x_i \in l$ and $y_i \in h$ *associated points* and we label x_i with h. The two regions l and h are so identified as *adjacent*. The goal of the foreground-background classification phase is to distinguish between false and true boundaries for each adjacent region. The analysis is based on the depth information of associated points. We introduce a voting algorithm to establish whether two adjacent region boundaries are at the same distance. If this is not the case, we establish which boundary is in the background and which is in the foreground. In the last case, the boundary points belonging to the background surface represent a *false boundary*.

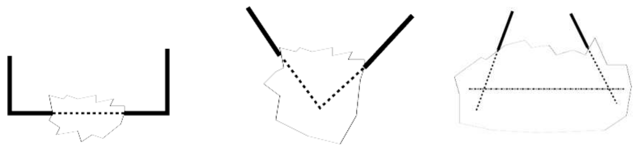


Figure 2. Proposed reconstruction rules

Once false and true boundaries have been identified it is possible to detect the points when the background surface boundary is occluded. We call them *endpoints*. The endpoints are the ends of the background surface true boundaries and they lie just next to the false boundary endpoints. Figure 1 shows the endpoints for the example case. It is important to detect endpoints because they represent the starting points for the reconstruction.

2.2 Occlusion Recovery

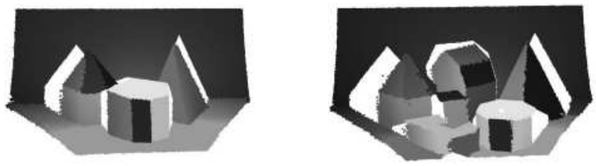
The key to reconstruction is to identify which part of the occluded region can potentially be connected behind the occlusion. The proposed method is based on the concept that the occluded area is filled in with the same type of surface as that of the visible area. For each boundary endpoint we estimate the direction of its continuation within the occluded area. Endpoint prolongation is performed according the Gestalt principle of good continuation and proximity in some form or order, e.g. linearity, co-circularity [9], closure [11]. In this way we are able to bound the surface which is going to be reconstructed. We can distinguish three possible cases based on the relation between visible boundaries lying in the proximity of an intersection with the occluded surface.

case A) coincident boundaries;

case B) convergent boundaries;

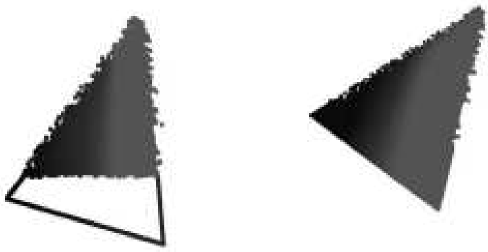
case C) divergent or parallel boundaries.

This cases are represented in figure 2. In all the three cases the hidden boundary is the continuation of the visible one. However, in the case A, the boundary extensions across the occluded area are coincident to the line connecting endpoints; in the case B, the boundary extensions over the occluded area intersect within the occluded area; in the case C, the boundary extensions over the occluded area do not intersect. The last case needs an architectural constraint to limit boundary extensions. In the work presented here, we assume that the extensions do not pass through walls or the floor. This may overextend some surfaces; the alternative would be more conservative and not reconstruct these cases - awaiting instead additional data.



a) b)

Figure 3. Scenario 1 (a) and 2 (b) before reconstruction.



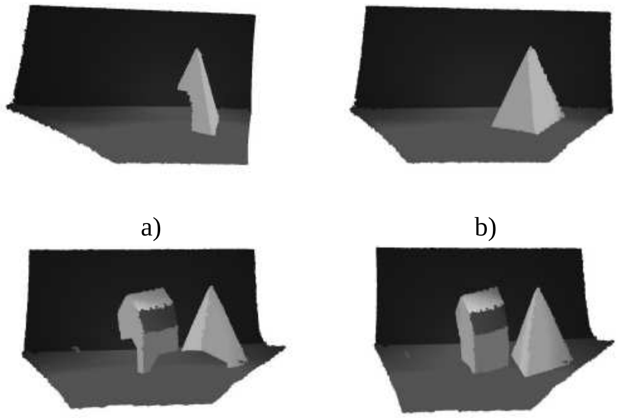
a) b)

Figure 4. Reconstruction of left pyramid side into scenario 2: extended boundaries (a) and reconstructed surface (b).

Hypothetical surfaces can then be created by extending the visible surface regions into the identified bounded area. The method to estimate the occluded surface is based on the hypothesis that the surface does not change its shape within the occluded area. Given an occluding pixel and an occluded surface we intersect the ray from the sensor through the occluding point with the occluded surface. As this ray overlaps the optical ray of the laser scanning beam, the reconstructed pixel is placed in a position that could actually have been sensed by the sensor. For planes there is usually one intersection. For cylinder and spheres we usually find two intersections and select the one contiguous with the observed surface.

3 Experimentation

We applied our method to different range images acquired by a Perceptron LRF scanner available at [1]. These images are proposed as a test-set in order to evaluate image segmentation performance. We used this test-set to evaluate the proposed occlusion reconstruction algorithm. The figure 3 shows complex object scenarios (for which figure6.a and 6.b represent the intensity image). They contain many objects and many occlusions arise when the scene is scanned



a) b) c) d)

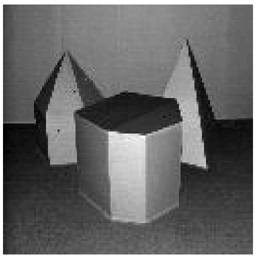
Figure 5. Scenario 1: pyramid before (a) and after (b) reconstruction. Scenario 2: *little house* **and pyramid before (c) and after (d) reconstruction.**

by laser system. In order to apply architectural constraints the wall and the floor were extracted. These scenarios have several example of the analyzed occlusion cases. For example the floor and the wall were recontracted applying the case A rule, the left side of the pyramid in scenario 1 was reconstructed applying the case B rule, while the left side of the pyramid in scenario 2 was reconstructed applying the case C rule (see figure 4). Figure 5 shows occluded

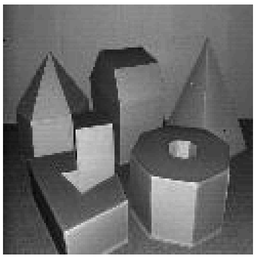
	Tot occl	True detect	False detect	Correct recon.	Not recon.	Incor. recon.
sc.1	6	6	-	4	1	1
sc.2	14	11	-	9	1	1
sc.3	8	7	-	7	-	-
sc.4	7	6	-	5	-	1
total	35	30	-	25	2	3

Table 1. Occlusions statistics.

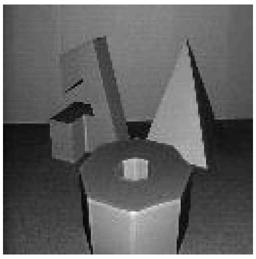
objects as they appear before and after the reconstruction. These reconstructions appear *visually acceptable* and their perception is improved. In order to evaluate performance of our method, we generate statistics based on the number of occlusions detected and correctly or incorrectly resolved. In particular, we verified by hand, for each image, the number of actual occlusions, the number of occlusion correctly detected and reconstructed. The object shape ground truth was available in [1]. The number of actual occlusions was estimated by hand. The Table 1 summaries our statistics based on four different images seen in figure 6. The results show



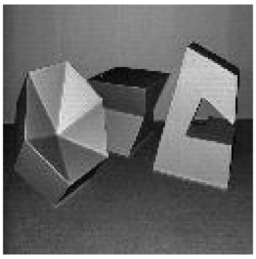
a)



b)



c)



d)

Figure 6. Intensity images of the reconstructed scenarios

that our process is quite good at detecting occlusions (30 of 35) with 5 undetected because the latter are generated behind adjacent surfaces instead of depth discontinuities. Of the 30 detected occlusions 25 were correctly reconstructed, 2 not reconstructible and 3 incorrectly reconstructed.

4 Conclusion

A new approach was proposed in order to reconstruct occlusions arising when a scene is scanned by a laser system. In particular, a method was presented for reconstruction in cases when a significant portion of object boundaries (e.g. corners) are occluded. The reconstruction extended the portion of a scene that can be modelled without the need of additional expensive range scanning.

Experiments demonstrated the improvements obtained by introducing good continuation of boundaries and surface and architectural constraints. In particular, we were able to successfully detect most of the occlusions (no false detections arose) and the reconstructed part appeared as expected based on human perception. The recovered surface should be thoroughly investigated to avoid an incorrect reconstruction. A wider knowledge on the environment could be useful to this case. There were 3 cases where the reconstruction extended beyond the original object because the environment constraints were not strong enough to stop reconstruction before the floor.

Acknowledgements

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