Visible Surface Reconstruction with Accurate Localization of Object Boundaries

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Abstract
An important problem in 3D reconstruction from multiple perspective views is the accurate recovery of surfaces near the discontinuities (object boundaries and creases). A common limitation of many techniques based on regularization methods is the poor quality of the results near the surface discontinuities. In this paper, we present a reconstruction method that is able to perform the surface recovery with an accurate preservation and localization of the discontinuities. The method is based on an iterative optimization algorithm. Experimental results using both synthetic and real data are presented for proving the effectiveness of the proposed approach.

Keywords: visible surface reconstruction, area matching, object boundaries.

1. Introduction

An important class of techniques for the automatic 3D reconstruction of scenes is that based on regularization. Such methods are based on the minimization of a functional that imposes a smoothness constraint on the reconstructed visible surface. In the recovery of surfaces from stereo images the regularization method may be applied both to the interpolation of sparse 3D data obtained from feature matching, and to the recovery of dense depth maps by area matching. Surfaces and depth maps generally exhibit discontinuities at occlusions between different objects and at surface creases. The regularization method yields a smooth surface and then performs poorly in the proximity of the discontinuities, where the accuracy is most important. In fact the importance of boundaries and creases is crucial since they carry the most significant information on the object’s shape.
Blake and Zisserman [1] and Terzopoulos [2] proposed a method for surface recovery, which consists in a modification of the thin-plate spline method. This method allows the localization and insertion of surface discontinuities not known in advance. The method is able to preserve both jumps and creases during the reconstruction process. However, in the presence of strongly converging perspective views, the quality of the information available near the object’s boundaries is quite poor, so that this method does not have enough information to reconstruct the object’s silhouette with sufficient accuracy. In this paper, we present a method for surface recovery which is able to perform an accurate localization of the boundaries and creases. The method is based on an iterative optimization algorithm that minimizes a functional similar to that of Terzopoulos [2] and provides a set of surfaces that describe the objects and their boundaries. A segmentation algorithm is then applied to the perspective projection of the resulting surfaces. This algorithm partitions such surfaces and, for each object, it determines a close curve that encircles it. The last step of the procedure uses the luminance edges for refining the position of the boundaries. In order to do so, it applies a deformation force to such curves in order to ”pull” them toward the projection of the object’s silhouettes. Experimental results on the application of the proposed algorithm on both synthetic and real images are presented. The algorithm has, in fact, been tested on sequences acquired with a trinocular camera system.

2. The Algorithm

The surface to be reconstructed is thought of as a function (depth map) of two coordinates. The method here proposed determines both the best surface fitting the data and the jumps and creases along the surface. We denote by K_1 the set of jumps and by K_2 the set of creases. The method starts with the minimization of the functional:

$$\varepsilon(u, K_1, K_2) = \int_{\Omega\setminus(K_1\cup K_2)} \left|\nabla^2 u\right|^2 dx + \\ + \int_\Omega \Phi(x,u)dx + D(K_1, K_2),$$

where Ω is the image domain, $x=(x_1, x_2)$, and

$$\left|\nabla^2 u\right|^2 = u^2_{x_1x_1} + 2u^2_{x_1x_2} + u^2_{x_2x_2}$$

as for the thin plate spline. By minimizing the first term of the functional we tend to preserve surface continuity and rigidity (absence of folding) except at the set of discontinuities. Through the second term of the above expression we try to keep the surface as

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close as possible to the given data. For surface interpolation from sparse depth data we have

$$\int_\Omega \Phi(x,u)dx = \sum_{i=1}^{N} \alpha(u(x_i) - d_i),$$

where d_i denote the surface points obtained from feature matching. For the recovery of a dense depth map by area-matching we have:

$$\Phi(x,u) = [L(P_l(x)) - R(P_r(x))]^2$$

where P_l and P_r denote the projection of space points on a pair of images L, R. The last term is given by:

$$D(K_1, K_2) = c_1|K_1| + c_2|K_2|$$

where $|\cdot|$ denotes the length of the line. This term penalizes the length of the discontinuity curves, therefore it is aimed at preventing the minimization process from producing a set of degenerate (small) surfaces in the neighborhood of each 3D point. Following Terzopoulos [2] we represent the discontinuity curves by means of continuity control functions ρ and τ such that $\rho(x)=0$ if $x \in K_1$, $\rho(x)=1$ if $x \in \Omega \setminus K_1$, and $\tau(x)=0$ if $x \in K_2$, $\tau(x)=1$ if $x \in \Omega \setminus K_2$.

The minimization process of the functional $\mathcal{E}$ consists of a multistage algorithm. During each stage of the algorithm, the control functions $\rho(x)$ and $\tau(x)$ are treated as fixed functions. Hence, at each stage, the functional becomes convex and therefore it is optimized by a relaxation method. At the start of each stage, an improved estimate of the discontinuities is computed from the solution obtained in the previous stage. The discontinuities should be placed along the most significant changes of depth. This problem is therefore equivalent to an edge detection problem, so that discontinuity curves are detected at each stage by using a modified version of the Canny [3] edge detection algorithm, applied to the last estimated depth function u. Finally, the shape of the discontinuity curves is refined by means of a joint analysis of the depth map and color edges. The curves are "pulled" toward the closest color edge that lies in the proximity of a region with high depth gradient and that exhibits the same local orientation as the surface jump, if present. This deformation is moreover performed in such a way as to increase the local smoothness of the curve by using an active contour model.

We also experiment an approximation of the length of the discontinuity curves by means of a differentiable functional [4]: we consider a smooth function ρ and we replace $|K_1|$ in $\mathcal{E}$ by the functional:

$$\int_\Omega \left[\varepsilon |\nabla \rho|^2 + \frac{1}{4\varepsilon}(1-\rho)^2 \right] dx,$$

then the term $|K_2|$ is replaced by an analogous functional. It can be shown that the resulting functional converges as $\varepsilon \to 0$ to the original functional $\mathcal{E}$ in a variational sense: the minimizers $(u_\varepsilon, \rho_\varepsilon, \tau_\varepsilon)$ of the approximating functionals converge as $\varepsilon \to 0$, in an appropriate metric, to the minimizers (u, ρ, τ) of $\mathcal{E}$. The approximating functionals are attractive from a numerical point of view because they can be discretized by standard finite elements/differences and then minimized by a descent method.

Experimental Results

Experiments with the proposed algorithm have been carried out with both synthetic and real images. While the experiments with synthetic data had the aim of proofing the correct behavior of the proposed method in each situation, the experiments with real data were aimed to show the actual performance in the case of complex 3D scenes and noisy data.

Figures 1 and 2 show the results obtained from the reconstruction of a clipped pyramid, where the cloud of 3D points are obtained through an area-matching technique from a synthesized stereo pair. Figure 1 shows the reconstructed surface, whose shape results to exactly coincide with the synthesized one. Figure 2a) and 2b) show, respectively, the maps of the jumps and the creases, ρ and τ.

The test with real data has been carried out with a 3D point cloud provided by an optimized area-matching technique [5], using three views from a video-conferencing sequence acquired with a trinocular system. Figure 3 shows one of the three views, from which the 3D point cloud shown in fig. 4 has been obtained. Due to the nature of the observed scene and the poorness of the 3D informaiton in the vicinity of object boundaries [5], it makes no practical sense to search for creases in such a data-set. For this reason, only the map of the depth jumps $\rho(x)$ is determined in this case. Figure 5 shows the map of depth jumps superimposed to the original view. The algorithm is able to automatically segment the given point cloud into the sub-surfaces, each representing the one of the different objects present in the scene.

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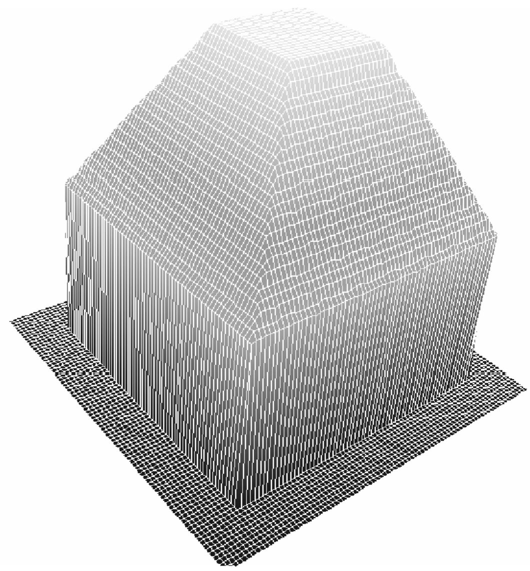
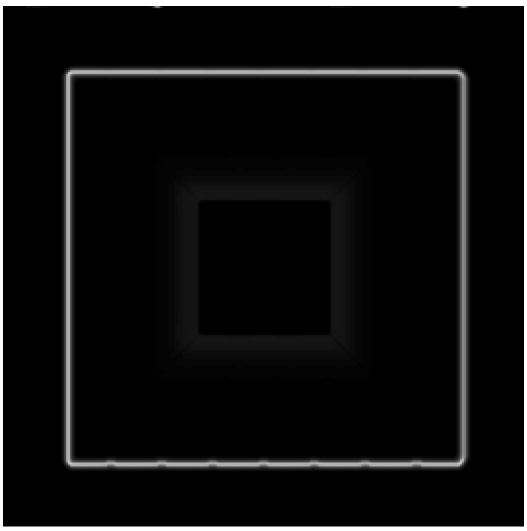


Figure 1. *The reconstructed surface of the synthetic clipped pyramid.*



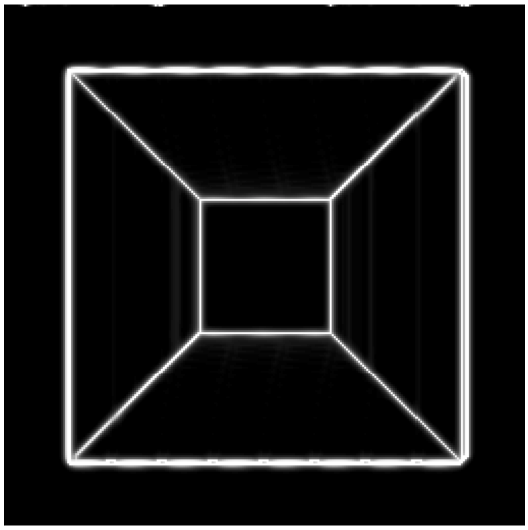


Figure 2. *The obtained discontinuity maps: a) the depth jumps $\rho(x)$; b) the creases $\tau(x)$.*

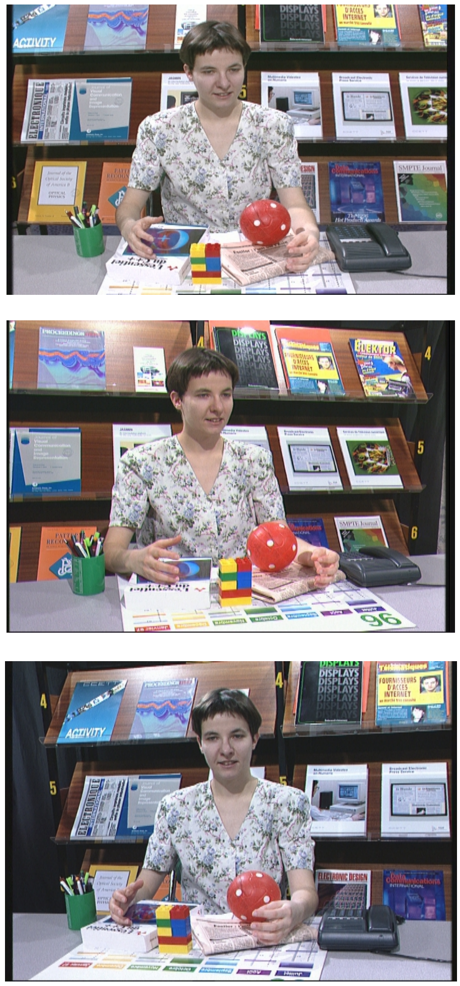


Figure 3. *The three views of the scene, acquired by the trinocular system.*

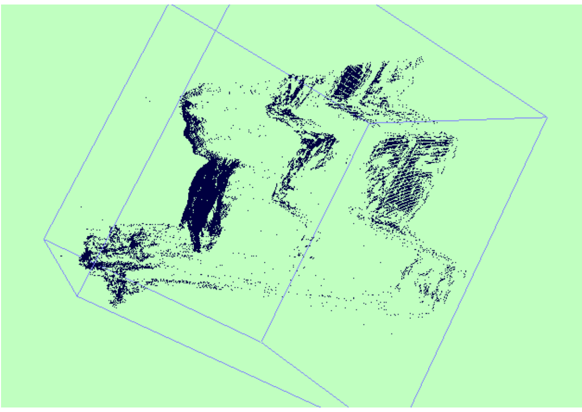


Figure 4. *The 3D point cloud, used as input for the proposed algorithm, obtained by the area-matching algorithm [5] from the images of fig. 3.*

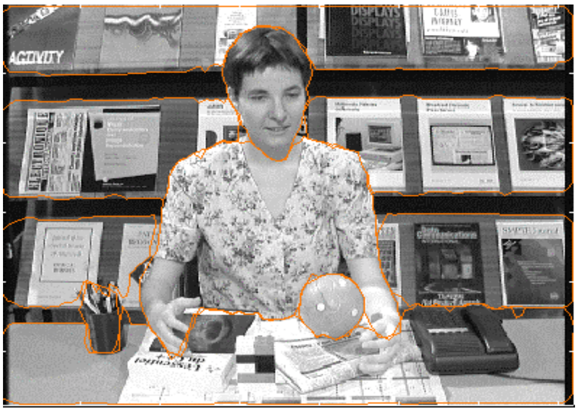


Figure 5. *The final segmentation of the given point cloud into sub-surfaces. The borders of the surfaces determined by the algorithm match exactly to the actual objects' boundaries.*