Continuous Global Optimization in Multiview 3D Reconstruction

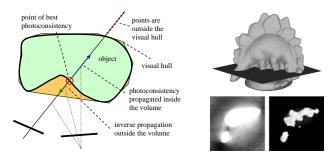
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Contributions

- The first formulation for *continuous* global optimization in the context of multiview 3D reconstruction
- Introduction of an energy model based on stereo-based regional terms without preliminary per-pixel disparity estimation



Volumetric propagation of photoconsistency. *Left:* Regional terms ρ_{obj} , ρ_{bck} are defined according to the location of maximal photoconsistency along visual rays through the current point. *Right:* This leads to considerable improvements in boundary alignment compared to silhouette-based formulations.

Energy Model

The following energy functional is considered:

$$E(S) = \int_{R_{obi}^{S}} \rho_{obj}(x) \, dx + \int_{R_{brk}^{S}} \rho_{bck}(x) \, dx + \nu \int_{S} \rho(x) \, dx,$$

where R^S_{obj} and R^S_{bck} denote the interior and exterior region with respect to S, and ρ_{obj} , ρ_{bck} and ρ are regional and classical surface-based photoconsistency functions, respectively.

Convex Formulation

• Introducing a binary-valued function to label object and background region yields:

$$\begin{split} E(u) = & \int_{V} (\rho_{bck}(x) - \rho_{obj}(x)) u(x) dx + \nu \int_{V} \rho(x) |\nabla u| dx \\ \text{s. t. } u \in \{0,1\} \,. \end{split}$$

Relaxation of the above binary constraint leads to the following convex formulation:

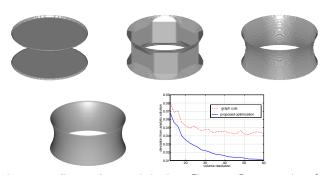
$$\begin{split} E(u) = & \int_{V} (\rho_{bck}(x) - \rho_{obj}(x)) u(x) dx + \nu \int_{V} \rho(x) |\nabla u| dx \\ \text{s. t. } u \in [0,1] \,. \end{split}$$

 The relaxed functional is minimized by solving the respective Euler-Lagrange equation

$$(\rho_{bck} - \rho_{obj}) - \nu \operatorname{div}\left(\rho \frac{\nabla u}{|\nabla u|}\right) = 0$$

via linearization and Successive Over-Relaxation.

• Thresholding the result by some $\mu \in (0,1)$ leads to a *global* optimum of the original binary energy model (see [1]).

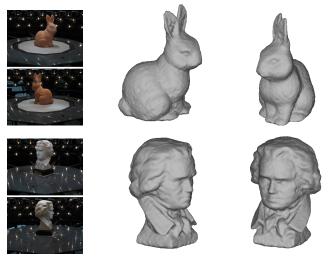


Continuous vs. discrete shape optimization. *First row:* Reconstruction of a synthetic catenoid with 6-conn., 26-conn. graph cuts and the proposed optimization, respectively. *Second row:* Analytic solution and plot of the deviation of the recovered surface (26-conn. graph cuts) from the ground-truth for increasing volume resolution.



Middlebury data sets (48/47 images). One of the input images and reconstructed surface.

data set	completeness	accuracy
dinoRing	99.4 %	0.43 mm
templeRing	97.8 %	0.72 mm



Bunny and Beethoven data sets (33 images). Two of the input images and reconstructed surface

- [1] Chan, Esedoglu, Nikolova: Algorithms for finding global minimizers of images segmentation and denoising models, SIAM J. Appl. Math., 2006.
- [2] Kolev, Klodt, Brox, Esedoglu, Cremers: Continuous Global Optimization in Multiview 3D Reconstruction, EMMCVPR, 2007.
- [3] Kolev, Klodt, Brox, Cremers: Propagated Photoconsistency and Convexity in Variational Multiview 3D Reconstruction, PACV, 2007.