A shape-from-shading framework for satisfying data-closeness and structure-preserving smoothness constraints

Rui Huang
rui@cs.york.ac.uk
William A.P. Smith
wsmith@cs.york.ac.uk

Department of Computer Science
University of York
UK

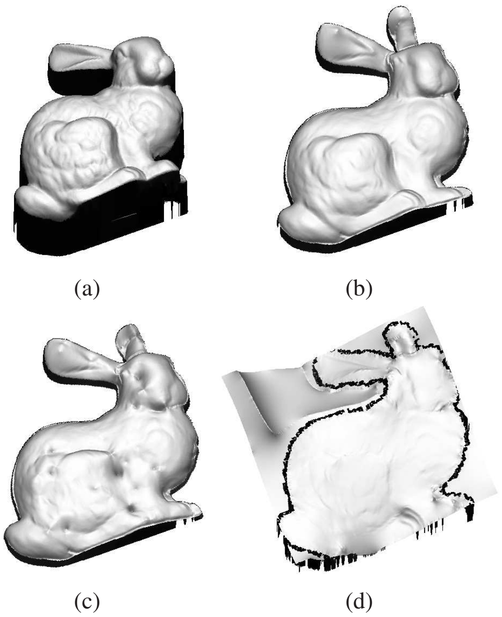

Figure 1: Surfaces recovered for the Stanford bunny. From (a) to (d): ground truth, proposed algorithm, [3], [2].

A key problem in shape-from-shading is how to simultaneously satisfy data-closeness and regularisation (such as surface smoothness) constraints. This paper makes two contributions towards solving this problem. The first is to describe a smoothness constraint which preserves surface structure by adaptively smoothing according to the intensity gradient magnitude. The second is to derive a framework which seeks to strictly satisfy this constraint while maintaining zero brightness error. Experimental results on both synthetic and real world imagery demonstrate that our method is both robust and accurate and outperforms a number of existing techniques.

We propose an alternative regularisation constraint which employs information about the intensity gradient in all directions over a local neighbourhood. For a pixel (x,y), we define the local neighborhood as $\Omega(x,y) = \{(x+1,y),(x-1,y),(x,y+1),(x,y-1)\}$. We precompute the change in incident angle between all pairs of neighboring pixels:

$$S((x_1,y_1),(x_2,y_2)) = \frac{|\arccos(I(x_1,y_1)) - \arccos(I(x_2,y_2))|}{\Delta S_{max}}, \quad (1)$$

where ΔS_{max} is the largest change in incident angle over the image. We define a weight between adjacent pixels based on the magnitude of the change in incident angle: $W((x_1,y_1),(x_2,y_2)) = e^{KS((x_1,y_1),(x_2,y_2))}$, .

The total of the weights between a pixel and its neighbors is given by:

$$Z(x,y) = \sum_{(i,j)\in\Omega(x,y)} W((x,y),(i,j)). \quad (2)$$

The surface normal at pixel (x,y) at iteration $t+1$ is given by the weighted average of its neighboring normals at iteration t:

$$\mathbf{N}^{(t+1)}(x,y) = \frac{\boldsymbol{\mu}^{(t+1)}(x,y)}{\|\boldsymbol{\mu}^{(t+1)}(x,y)\|}, \quad (3)$$

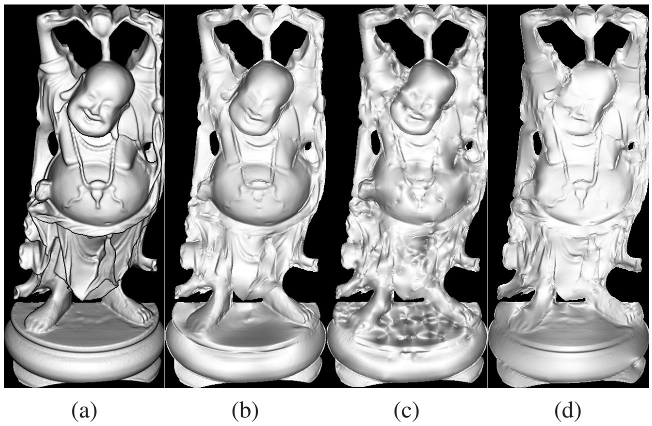

Figure 2: Frontal View of Mesh. From (a) to (d): ground truth, proposed algorithm, [3], [2].

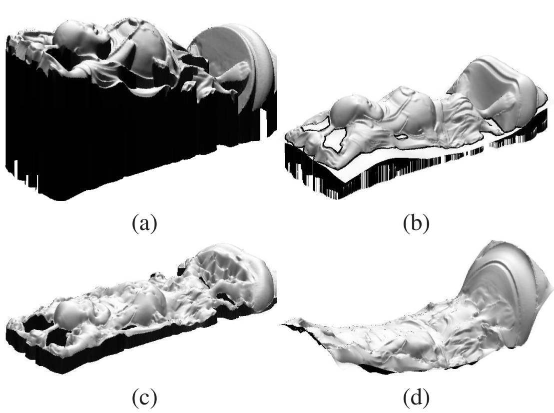

Figure 3: Surfaces recovered from the input image shown in the left panel of Fig. 2. From (a) to (d): ground truth, proposed algorithm, [3], [2].

where

$$\boldsymbol{\mu}^{(t+1)}(x,y) = \sum_{(i,j)\in\Omega(x,y)} \mathbf{N}^{(t)}(i,j)\frac{W((x,y),(i,j))}{Z(x,y)}. \quad (4)$$

A summary of our algorithm is as follows:

1. Obtain $\mathbf{N}^{(0)}(x,y)$ using negative gradient initialisation [3]
2. Repeatedly apply (3) until convergence
3. Rotate normals back to cone: $\mathbf{N}(x,y) = \Theta\mathbf{N}^{(\text{final})}(x,y)$
4. Stop if converged, otherwise iterate to step 2

To obtain surface height estimates, we integrate the field of surface normals using the algorithm of Frankot and Chellappa [1].

[1] R. T. Frankot and R. Chellappa. A method for enforcing integrability in shape from shading algorithms. *IEEE Trans. Pattern Anal. Mach. Intell.*, 10(4):439–451, 1988.

[2] Tom S. F. Haines and Richard C. Wilson. Belief propagation with directional statistics for solving the shape-from-shading problem. In *Proc. ECCV*, pages 780–791, 2008.

[3] P. L. Worthington and E. R. Hancock. New constraints on data–closeness and needle map consistency for shape–from–shading. *IEEE Trans. Pattern Anal. Mach. Intell.*, 21(12):1250–1267, 1999.