A Shape from Shading Approach Using General Lambertian Reflectance Map

R Balasubramanian, Rama Bhargava and Manoj Kumar

Department of Mathematics, Indian Institute of Technology Roorkee, Roorkee, India- 247 667

The present paper contains a linear and general approach to shape from shading (SFS). In this approach, we have linearized depth, \( Z(x,y) \) and used general Lambertian reflectance model instead of Lambertian model. The brightness of a Lambertian surface is independent of viewing direction, while the brightness of a rough diffused surface is dependent to the viewing direction and increases as the viewer approaches the source direction. Hence, there are many surfaces (plaster, clay, sand, cloth etc.), which significantly deviate from the Lambertian reflectance model. On the other hand, the general Lambertian reflectance model works equally well for rough as well as smooth surfaces. The algorithm has been tested on several synthetic and real (Lambertian and rough diffused objects) images and the results are shown.

1. Introduction

Shape recovery of object surfaces is a primary goal of computer vision. Shape from Shading (SFS) is one of the main techniques of the 3D reconstruction in computer vision and has very broad spectrum of applications viz., in medical science, astrophysics, earth science etc. SFS means the recovery of shape from gradual variation of shading in one or more images. The SFS has been attracting many researchers since last two decades, started by Horn and Brooks [1]. SFS deals with the recovery of shape from image brightness and it depends on surface orientation, light source direction and reflectance of the surface. The recovered shape can be represented in several ways: depth \( Z(x,y) \), surface normal \( (n_x, n_y, n_z) \) or surface gradient \( (p, q) \). The depth can be considered as the relative surface height above the \( xy \) plane. The surface normal is the orientation of a vector perpendicular to the tangent plane on the surface object. The surface gradient \( (p, q) = \left( \frac{\partial Z}{\partial x}, \frac{\partial Z}{\partial y} \right) \) is the rate of change of depth in \( x \) and \( y \) directions. The surface slant \( \phi \) and tilt \( \theta \), are related to the surface as \( (n_x, n_y, n_z) = (\sin\phi, \sin\phi\sin\theta, \cos\phi) \), where \( l \) is the magnitude of surface normal. The unit surface normal \( \hat{n} \) and surface gradient \( (p, q) \) are related as given in [1]:

\[
\hat{n} = \frac{(-p, -q, 1)}{\sqrt{1 + p^2 + q^2}}
\]

Various methodologies have been given since the introduction of the field of SFS. Zhang et al. [2] categorized SFS techniques into four approaches namely, minimization approach: Zheng et al. [3], Lee et al. [4]; propagation approach: Bichsel et al. [5]; local approach: Lee et al. [6]; linear approaches: Pentaland [7], Tsai et al. [8]. In minimization approaches, solution is computed by minimizing an energy function over the entire images by calculation of variation methods. The propagation approaches start from a single reference points, or a surface point where the shape is either known or can be uniquely determined (such as singular points) and propagate the shape information across the whole image. Local approaches derive the shape by assuming local surface type and using local constraints about the surface being recovered. Linear approaches convert the nonlinear problems of SFS into linear problems through the linearization of the reflectance map. Here in this paper, the linear approach, given by Tsai and Shah [8], has been used.
Table 2
Standard deviation of Z error for synthetic images.

<table>
<thead>
<tr>
<th>Images</th>
<th>L R Model</th>
<th>G L R Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Synthetic Vase</td>
<td>16.8</td>
<td>16</td>
</tr>
<tr>
<td>Mozart</td>
<td>35.4</td>
<td>35.3</td>
</tr>
<tr>
<td>Canadian Tent</td>
<td>139.2</td>
<td>138.4</td>
</tr>
<tr>
<td>Banana function</td>
<td>37.3</td>
<td>37.1</td>
</tr>
<tr>
<td>Cylinder</td>
<td>36.9</td>
<td>36.6</td>
</tr>
<tr>
<td>Ellipsoid</td>
<td>38.5</td>
<td>38.4</td>
</tr>
</tbody>
</table>

L R Model: Lambertian Reflectance Model.
G L R Model: General Lambertian Reflectance Model.

The graph between the average depth (Z) error and the number of iterations for the Mozart image, which is showing, as the number of iterations increase, the average (Z) error decreases, which shows the convergence of algorithm. In case of synthetic images, we have normalized the output depth values by the proposed algorithm, in the range of given true depth value, then compared it with the mean and standard deviation of depth error. For each synthetic image, we have shown depth error for the two cases: Lambertian reflectance map and general Lambertian reflectance map. The error is minimum for synthetic base while maximum for Canadian tent. Canadian tent is more erroneous because of its sharp edges and non-smoothness.

6. Conclusions

The presented algorithm is very simple, fast and general. The algorithm computes the depth value at each point by using only one shaded image. The results on synthetic and real images demonstrate our method. The distinction of use of Lambertian and general Lambertian models can be observed in the rough parts of the image viz., the hat of Lena (possibly made up of cloth) and real vase (possibly made up of clay). However, the method works equally well for rough and smooth surfaces, but the inter-reflection and self shadow factors are ignored in this algorithm. So for these factors, this work can be extended in future.

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Balan. Raman is an Assistant Professor and head of the Vision, Graphics and Image Processing Laboratory (CVGIP lab) in the Department of Mathematics at Indian Institute of Technology Roorkee since February 2006. He has worked as a Lecturer of Mathematics in the Department of Mathematics at Indian Institute of Technology Roorkee from September 2004 to February 2006. He has worked as a faculty of Computer Science and Information Systems at Birla Institute of Technology and Science, Pilani, India in 2003-04. He has worked as a Post Doctoral Associate at VIZ lab, Electrical and Computer Engineering Department, Rutgers, the State University of New Jersey, USA from July 2002 to April 2003. He was also a Post Doctoral fellow in Computer Engineering and Computer Science (CECS), University of Missouri-Columbia (MU), Missouri, USA, from October 2001 to June 2002. He received his Ph.D. in Mathematics (2001) from Indian Institute of Technology, Madras, India. He received his B.Sc and M.Sc in Mathematics from University of Madras in 1994 and 1996 respectively. He has more than forty research papers in various reputed international journals and conferences (including IEEE-IJCNN, IEEE-ICIP and LNCS). His areas of research include Computer Vision, Graphics, Satellite Image Analysis, Scientific Visualization, Imaging Geometry and Reconstruction problems.

Rama Bhargava is working as Professor in the department of Mathematics, at Indian Institute of Technology Roorkee since 1979. She has been working in the field of Computational Fluid Dynamics, Computer Graphics and Mobile Computing. An Australian Endeavor award winner in 2008. She has been recipient of DAAD fellowship also. She has an expertise in Finite element and has shifted herself now in Computer Graphics and Image Processing.

Manoj Kumar has received his M.C.A. degree from Jawaharlal Nehru University (JNU), New Delhi in 2003. He is pursuing Ph.D. in the Department of Mathematics, IIT Roorkee. His area of research is Computer Vision and Digital Image Processing.