Single-Image Reflectance Estimation for Relighting by Iterative Soft Grouping

Abstract

Reflectance values for image-based relighting are often estimated from grouped pixels with similar reflectance, but such groupings are difficult to compute with certainty for sparse image data. To address this problem, we propose an iterative method that aggregates BRDF data in a single image with known geometry and lighting by soft grouping, where pixels contribute to one another’s estimate according to their degree of reflectance similarity. Estimation of specular reflectance is further improved by albedo-independent soft grouping of pixels based on shape continuity. With recovered reflectances, we demonstrate realistic relighting for synthetic and real scenes, including surfaces with spatially-varying reflectance.

1. Introduction

Photographs have commonly been used in computer graphics for realistic rendering of scenes. In this field of image-based rendering, attention has mainly been focused on synthesizing scenes from various viewpoints. Besides viewpoint, another important factor in appearance is the lighting condition, and there has been increasing effort on varying illumination in image-based environments.

A straightforward approach to relighting scenes is to capture a set of images under densely sampled illumination directions. To obtain such dense measurements for human faces, Debevec et al. [3] constructed a light stage for acquiring reflectance fields, and with linear combinations of these images, they are able to relight faces according to any desired illumination environment consisting of distant light sources. Koudelka et al. [4] performed similar sampling and can render surfaces for arbitrary light source positions by selection of appropriate rays from the images.

Dense illumination sampling is difficult to obtain for most scenes, but with reduced sampling, illumination effects such as specular reflections cannot in general be accurately rendered for unsampled lighting directions by image interpolation [7]. To handle novel illumination conditions, scenes have been decomposed into geometry and reflectance, where estimated reflectance models can approximate a continuous bi-directional reflectance distribution function (BRDF). There exist many methods for shape recovery, including range scanning and stereo, and several methods have been proposed for reflectance estimation.

Among the approaches for BRDF recovery are image-intensive techniques that utilize special measurement devices [14], curved material samples [9], or model arbitrary BRDFs that include shadows and interreflections [4]. Other methods that employ large image sets include Sato et al. [12], which estimates both object shape and parameters of the Torrance-Sparrow reflectance model [13], and Wong et al. [15], which stores apparent BRDFs in terms of spherical harmonic coefficients without need for scene geometry.

To avoid the need for large sets of images and multiple illumination conditions, some previous methods process BRDF data aggregated from predefined groupings of pixels with similar reflectance. Given these groupings, Yu and Malik [17] solve for reflectance model parameters of architecture with consideration of lighting from the sun, sky and environment. In subsequent work, Yu et al. [16] compute the reflectances in a room while accounting for both direct and indirect illumination. Also for inverse rendering under general illumination conditions, Ramamoorthi and Hanrahan [11] present a mathematical formulation of the problem as a deconvolution of lighting and the BRDF. Using just a single image, Boivin and Gaglowicz [1] compute reflectance parameters for surfaces by fitting increasingly complex reflectance models until the fitting error falls below a threshold.

While these methods assume a prior reflectance grouping, formation of these groups for reflectance estimation is a difficult task, especially when local reflectance variations often exist. To address this problem, Lensch et al. [6] present a method for clustering reflectances by iterative splitting and refitting of reflectance models to a user-specified number of materials. Spatially-varying reflectances are preserved by expressing the BRDF of each pixel in terms of basis BRDFs of its cluster. Nishino et al. [10] assemble reflectance data from point correspondences among multiple views with fixed lighting to estimate reflectance parameters as well as the illumination environment.

In our work, the goal is also to aggregate BRDF infor-
mation for reflectance estimation, but with substantially reduced data. For broader applicability, our approach takes as input only a single image, and with such limited data, we cannot perform clustering as in [6] where 20-25 images are captured. In fact, a single image is insufficient for estimating the reflectance of independent pixels, so some form of data aggregation becomes necessary.

Determination of pixel groupings is, however, a challenging problem. With just a single BRDF sample for each pixel, it cannot be known with full certainty whether two pixels share the same reflectance. Furthermore, the presence of spatially-varying BRDFs will complicate the partitioning of pixels. To deal with this uncertainty, we propose a soft reflectance grouping where pixels contribute in varying degrees to one another’s reflectance estimate. In computing the reflectance of a given pixel, the BRDF data of other neighboring pixels are each weighted by their reflectance similarity to the examined pixel, so that pixels which are more likely of the same reflectance are more strongly grouped while less similar pixels have relatively little impact on the estimation. By computing these soft groupings separately for each pixel, spatially-varying reflectance is also modelled in this framework.

Because of initially imprecise soft groupings, we progressively refine reflectance estimates by iterating the process. In successive iterations, updated soft groupings produce improved reflectance values, which in turn leads to more accurate comparisons of pixel similarity and better soft groupings. To further improve results, we make more complete use of BRDF information by partially grouping pixels that have similar reflectance except for albedo. On a continuous surface, it is typical for reflectance to vary only in albedo, so we take advantage of this characteristic to provide more data for estimation of non-albedo reflectance parameters. Under this scheme, we have been able to obtain reasonable reflectance estimates which have been effectively used for relighting scenes.

2. Overview

An overview of our algorithm is illustrated in Figure 1. It takes as input a single image, geometry that can be obtained by range scans or other means, and the light source position. For ease of explanation, we assume a single light source, though our method can easily be extended to multiple lights. With this input, we determine the shadowed pixels for which we handle separately as explained in the following section. Section 3 also describes the subsequent computation of initial reflectance values.

The reflectance models we use are a Lambertian model for diffuse reflectance and a single isotropic lobe from the Lafortune model [5] to represent other reflectance effects, such as specular reflection. In terms of light direction $L$,
surface normal $N$ and viewing direction $V$, reflectance at a point $x$ is formulated as

$$I(x) = \rho(x)N(x) \cdot L + [c_1(L \cdot V) + c_2(N(x) \cdot L)(N(x) \cdot V)]^n$$

(1)

where the albedo $\rho$ and the Lafontaine coefficients $c_1$, $c_2$ and $n$ are the four reflectance parameters we aim to recover for each image pixel.

With the rough initial reflectance estimates, we begin the iterative refinement process. For each non-shadowed pixel, reflectance similarities are computed for neighboring pixels as presented in Section 3.1. These similarity values serve as weights in an optimization process for computing new reflectance parameters. A similar procedure is then performed for updating the non-albedo parameters, using shape continuity weights described in Section 3.2 and another optimization. This estimation routine, detailed in Section 4, is repeated until the change in reflectance parameters falls below a certain threshold.

With the computed reflectance values, the scene can be rendered for arbitrary illumination conditions. In our method, the effects of interreflections within the scene can be modelled within an apparent BRDF represented by the reflectance model. A more complex reflectance model, such as a Lafontaine model with multiple lobes, should better fit an apparent BRDF with interreflections, but in this paper we use the model in (1) for simplicity.

3. Neighborhood support

Since estimating the reflectance of a single pixel from a single observation is an underconstrained problem, it is necessary to gather additional data to compute a feasible estimate. This data can be derived from neighboring pixels with similar reflectance, but uncertainty also exists on which pixels indeed share reflectance characteristics.

To account for this uncertainty, we propose a method with varying local support from neighboring pixels. Pixels with reflectance that seem similar to the examined pixel are more likely to share the same reflectance, and therefore their data should be emphasized in the estimation process. The less similar a pixel is to the examined pixel, the less likely it is of the same reflectance, and consequently it should have less influence on parameter estimation. The dependence of a pixel’s reflectance on neighboring pixels can be seen as a form of regularization, with the similarity measure acting as weight to reduce smoothing over discontinuities.

We incorporate two forms of neighborhood support in our estimation framework: reflectance similarity and shape continuity. Our reason for using shape continuity is based on the observation that many continuous surfaces are made of the same material, and differences in reflectance on a surface mainly result from albedo texture. We take advantage of this property to gain additional data for estimating non-albedo reflectance parameters. In this section, these two types of soft groupings are presented.

3.1. Reflectance similarity

Because of the typical sparsity of specular reflections in a single input image, it is difficult to initially determine differences in specular reflectance among the image pixels. Despite this problem, the albedo value of pixels can be approximated using the Lambertian model of diffuse reflectance. From the known surface normals $N$ and primary light position $L$ of the scene, the albedo $\rho_k(x)$ of pixel $x$ can be computed as

$$\rho_k(x) = \frac{I_k(x)}{N(x) \cdot L}$$

(2)

where $k = R, G, B$. Light from scene interreflections may also be incident upon the scene point at $x$, but a calculation using only the primary source nevertheless provides a useful initial value. For ease of explanation, we will assume in this paper that the scene is illuminated by a white light source, while modifications could be made to handle lights of different colors.

With the computed albedo values, we formulate initial reflectance similarity of pixel $y$ with respect to $x$ as a function of their albedo distance in RGB color space:

$$r_x(y) = \frac{1}{1 + \|\rho(y) - \rho(x)\|}.$$  

(3)

After the initial iteration when the other reflectance parameters are available, we compute the reflectance similarity using a weighted sum of parameter differences:

$$r_x(y) = \frac{1}{1 + \|R(y) - R(x)\|}$$

$$R = [\alpha_1 \rho, \alpha_2 c_1, \alpha_3 c_2, \alpha_4 n]^T.$$  

(4)

where $R$ is a vector of weighted reflectance parameters.

The reflectance for image regions shadowed from the primary light source cannot be independently estimated without at least determining the principal indirect illumination sources of each point. Because of the difficulty in this, the shadowed areas are computed from the known geometry and the primary light position, and are excluded from the reflectance estimation process. Reflectance values for these regions must nonetheless be determined for relighting purposes, so we associate these shadowed pixels with image pixels for which a reflectance is computed.

After a final reflectance is computed, we determine the reflectance of each shadowed pixel in a simple manner. The chromaticity of the pixel is compared with the chromaticities of the pixels that border the shadow region. For those border pixels whose chromaticity difference is less than a
3.2. Shape continuity

While direct comparisons between pixels are made for reflectance similarity, shape continuity is measured by aggregating along a path between pixels. Although a large sum of incremental shape differences generally do not indicate a change in surfaces, a large difference between adjacent pixels can signal a discontinuity in material. Consequently, we formulate a shape continuity measure that penalizes sharp changes in depth and surface normals while discounting small ones. Additional shape characteristics such as curvature could easily be incorporated for a more detailed shape quantity.

We compute the path taken for aggregating shape differences using the Bresenham line-drawing algorithm [2]. Although points on an imaged surface might not all be connected to one another by straight-line paths, in most cases a straight path provides sufficient support for reflectance estimation, and it avoids the need to search among various paths to determine true continuity.

Let the path between pixels \( x \) and \( y \) be denoted as an array \( P \) of pixel coordinates, including the endpoints. Then the shape continuity value of pixel \( y \) with respect to \( x \) is formulated as

\[
s_x(y) = \sum_{k=1}^{\text{length}(P)} \left[ \beta_1 \frac{1}{1 + d(P(k+1)) - d(P(k))} + \beta_2 \left( N(P(k+1)) \cdot N(P(k)) + 1 \right)^2 \right] + r'_{x}(y)
\]

where \( d \) is the depth and \( N \) is the unit surface normal. \( \beta_1, \beta_2 \) are empirical weights that tradeoff depth and surface normal factors. The term \( r'_{x}(y) \) represents the difference in specular reflectance parameters between \( x \) and \( y \). Although \( r' \) is unrelated to shape continuity, we include this term to reduce the likelihood of grouping pixels from different materials that are present on the same continuous surface. We express \( r' \) as in (4) but without albedo:

\[
r'_{x}(y) = \frac{1}{1 + \|R'(y) - R'(x)\|}
\]

\[
R' = [\alpha_2 c_1, \alpha_3 c_2, \alpha_4 n]^T.
\]

4. Iterative Reflectance Estimation

The measures of reflectance similarity and shape continuity presented in the previous section are used to drive an iterative procedure for refining reflectance estimates. From the initial reflectance (albedo) values computed in (2), we repeatedly update the reflectance parameters of the pixels until a termination criterion is met.

The iterations are performed in two steps. In the first step, we do a soft grouping of pixels weighted by reflectance similarity. For each pixel \( x \), its new reflectance values are computed according to

\[
\arg \min_{r'\in[0..1]^3} \sum_{x'\in W_x} r_x(x')[I(x') - \hat{I}(x')]^2
\]

where \( W_x \) is a window centered around \( x \) not including shadowed pixels. \( \hat{I} \) is computed from (1), and \( r \) is from (4), except for the first iteration when \( r \) is calculated from (3). This equation is computed using the Levenberg-Marquardt minimization algorithm with multiple initial seeds.

In the second step, the non-albedo reflectance parameters are re-estimated with a soft grouping weighted by shape continuity. Similar to the first step, the reflectance for \( x \) is

\[
\arg \min_{s\in[0..1]^3} \sum_{x'\in W_x} s_x(x')[I(x') - \hat{I}(x')]^2
\]

where the albedo of \( \hat{I} \) is taken to be its estimated value in (5).

These steps are repeated until the change in estimated reflectance values falls below a threshold \( t \):

\[
\frac{1}{|I'|} \sum_{x \in I'} [R_{\text{new}}(x) - R_{\text{old}}(x)]^2 < t
\]

where \( I' \) is the set of unshadowed image pixels.

To include as much BRDF data as possible in the estimation, the window size should be large. The initial values of reflectance similarity, however, may be inaccurate, especially between distant pixels. To both reduce the negative effects of early reflectance uncertainty and increase data aggregation, we utilize a small 5x5 window for the first iteration, and progressively enlarge it through subsequent iterations. If the window grows to a maximum size of 99x99 before termination, the size will no longer be increased.

With the final reflectance estimates and scene geometry, the image can clearly be relit for arbitrary illumination conditions. Shadows are cast according to the geometry and light positions, and pixel intensities within the cast shadows result from global illumination computation [16, 8].

5. Results

In this section, we present our results for reflectance estimation and relighting. First, we examine the performance for a synthetic scene, to more clearly demonstrate the features of our algorithm and to provide comparisons of relighting results to ground truth. Following this, we view the results for a real scene.
5.1. Synthetic scene

The synthetic scene, depicted in Figure 2, consists of a book, a smoking pipe and a ceramic container on a wooden table. Some challenging features of this scene are the complex texture on the container and table, and also the different materials that form the smoothly-shaped pipe.

The relighting results in Figure 2 with different lighting directions can be seen to closely approximate the ground truth images. Highly textured objects such as the container and the wooden tabletop are handled properly. Although specular reflection exists on only a few areas of the container in the original image, it is accurately rendered on other parts of the surface for different lighting. In particular, it can be noticed on the container that although golden-colored areas in the original image are entirely diffuse, they exhibit correct specular characteristics for other illumination conditions, since our shape-continuity soft grouping method effectively transferred reflectance properties of the material across albedos. An effect like this could not happen without albedo-independent grouping. Different materials that together form one surface, such as the pipe, are not incorrectly soft grouped because they exhibit different reflectance in the original image.

Figure 3 illustrates the iterative refinement in reflectance estimates via relighting results for a novel illumination direction. The first image displays a relighting after an intermediate iteration, and the specular reflections on the ceramic container appear as if there are two light sources in the scene. Specularities from the original image are still present, since their underlying diffuse reflectance has not yet been fully estimated, and the specularities for the new lighting condition appear dim, since the specular reflectance parameters have not completely been transferred across the container. At a later intermediate step, the specular reflectance parameters are closer to the true values. The final relighting closely resembles the ground truth image. Much of the diffuse reflectances were approximately correct from the beginning, since this synthetic example contains no noise and was rendered with Lambertian diffuse reflectance. Interreflection, though, perturbs some of the initial albedo estimates.

5.2. Real scene

The real image we process is of a ceramic cat (with range data, courtesy of Ko Nishino) that is shown in Figure 4. From the original (leftmost) image, the computed diffuse reflectance is exhibited in the second image, rendered with the same illumination as the original. The albedo values that describe the diffuse reflectance appear to fit the ceramic cat. The last two images display relighting results for two different illumination directions. The reflectance appearance in these relighting results seem reasonable, though some specular reflections are slightly broad, which results from the precision level of the geometry.

For a second example, we altered the reflectance of the ceramic cat so that the white areas became matte, as shown in Figure 5. With this image, the relighting results of our algorithm are presented in the last two images. It can be noticed that although the yellow paws are part of a continuous surface with the body of the cat, the specular property of the paws is not spread to the body, and the matte property of the body is not passed to the paws in our soft grouping scheme.

6. Discussion

Although the use of only a single image can greatly increase the applicability of a reflectance estimation method, natural limitations arise from having such scant data. Reflectance estimates certainly improve in accuracy when more BRDF data is available. While our method attempts to gather as much of this data as possible from the image, it is nevertheless bounded by the reflectance information that is present. A planar surface generally provides far less BRDF information than an object that exhibits a wide range of surface normals. Also, if a shiny material does not exhibit specular reflections in the given image because of its orientation, this lack of information belies the true reflectance of the surface when estimating parameters. Because of this, the inclusion of additional images, either from different viewing positions or with different lighting conditions, could significantly enhance the data.

Since our method is presented with little data, this uncertainty can potentially lead to errors in soft grouping, such as strongly associating pixels of different materials. An automatic method cannot be completely accurate given only a single image, but it nevertheless provides a useful tool. While manual segmentation is perhaps the only perfectly reliable way to form groupings, this task is tedious for complex textures and can often be circumvented by the use of our algorithm.

The precision of reflectance estimation of course depends upon the representational ability of the reflectance model employed. Since our model is intended to represent an apparent BRDF that includes interreflections, a relatively complex model would be more suitable, though at a cost of greater computation. Estimation accuracy also relies heavily on accurate geometry and lighting information.

7. Conclusion

In this paper, we have presented a method for aggregating BRDF data in a single image for estimation of reflectance parameters and subsequent relighting. To account
Figure 2. Synthetic images and relighting results

Figure 3. Effect of iterations on relighting

Figure 4. Real image and relighting results
for uncertainty in grouping pixels with limited information, our algorithm forms soft groups with variable support from neighboring pixels. Albedo-independent pixel grouping is also introduced for improving estimates of specular parameters. By computing these soft groups on a per pixel basis, spatial variations of reflectance can be captured within our estimation framework.

In future extensions of this work, we plan to improve the performance and robustness of our current implementation by increasing the dimensionality of the reflectance model and by including more detailed shape descriptors, such as various curvature measures, in the shape continuity formulation. Another area for further investigation would be to develop a user interface for providing simple information that can reduce the reflectance uncertainty which arises from limited data.

References