

# Image-based Extraction of Material Reflectance Properties of a 3D Rigid Object

M. Erkut Erdem, İ. Aykut Erdem, Volkan Atalay

Dept. of Computer Engineering, Middle East Technical University, Ankara, Turkey  
{erkut, aykut, volkan}@ceng.metu.edu.tr

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## Abstract

*In this study, we concentrate on the extraction of reflectance properties of a 3D rigid object from its 2D images and the other aim of this work is rendering the object in real-time with photorealistic quality in varying illumination conditions. The reflectance property of the object is decomposed in diffuse and specular components. While the diffuse components are stored in a global texture, the specularity of the object is represented by a single Bidirectional Reflectance Distribution Function (BRDF). In the rendering phase, these two components are combined to obtain the behavior of the real surface property of the object.*

Categories and Subject Descriptors (according to ACM CCS): I.3.7 [Modeling packages; Color, shading, shadowing, and texture; Virtual reality]:

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## 1. Introduction

3D model reconstruction has many application areas varying from 3D virtual environments, computer games, visualisation of cultural heritage to 3D visualisation of the products in e-commerce applications. In this study, our goal is the extraction of material reflectance property of a 3D object from a set of images when the geometry of the object is known. This technique can be easily adopted to image-based model reconstruction frameworks such as <sup>8</sup> to improve the appearance quality of the obtained 3D models.

In literature, various methods are proposed to model the appearance of an object. The most common method is texturing. In most of these studies, the model is represented as a triangular mesh, and each triangle is associated with one of the images for texture extraction. However, this approach may cause discontinuities on the triangle boundaries if adjacent triangles are associated with different images. To overcome this problem, mostly blending <sup>4,2</sup> is used. Also alternatively, surface particles concept can be used in extracting the texture <sup>8</sup>. However, the main weakness of texturing is that it does not capture the true physical characteristics of the object surface, i.e. it ignores changes in illumination and viewing conditions. Therefore, some more complex but physically more ac-

curate models are introduced. As an example, light fields are one way beyond the texture maps where the idea is representing the radiance as a function of position and viewing direction. In this study, we use another complex and popular model, Bidirectional Reflectance Distribution Functions (BRDFs) to represent the appearance of the object.

Traditionally, BRDFs are measured by using special devices known as gonioreflectometers. However, recently image-based techniques are introduced where there is no need to use any special device. In general, these techniques are used for modeling any homogenous or spatially varying surfaces. For example, Debevec et al. <sup>6</sup> use BRDFs for rendering architectures in varying illumination conditions. Even BRDFs can be used for modeling the human skin <sup>9,?</sup>. These image based measurement techniques can be mainly grouped in two categories. While some try to acquire the reflectance property from just one image <sup>10,11</sup>, the others try to capture this information by using multiple views <sup>6,9,3</sup>. We also use a multiple image set to reconstruct the appearance of the model. Since in computer graphics, reflection is modeled by a combination of diffuse and specular components, we decompose the overall reflectance data into these two components. While we are storing the diffuse component in a global texture, the specular component is represented

as a single BRDF. Furthermore, interactively rendering of the object with photorealistic quality is achieved due to this decomposition.

The rest of the paper is organized as follows: Section 2 describes the reflectance model we used. Section 3 and Section 4 explain details of estimation of diffuse and specular components respectively. Section 5 describes the interactive rendering process and Section 6 presents the experimental results and the conclusion.

## 2. Reflectance Model

The amount of reflection depends on the material property of the object. In this study, we use BRDFs to represent the reflectance. In short BRDFs are the functions that describe how light is reflected when it interacts with a surface. While BRDFs ignore some other concepts such as subsurface scattering, fluorescence, phosphorescence and polarization, they still give more realistic results than the other conventional methods. We can use the following function notation for BRDF,  $BRDF_{\lambda}(\vec{u}, \vec{v})$  where  $\lambda$  is the wavelength of the incoming light;  $\vec{u}$  is the incoming light direction; and  $\vec{v}$  is the viewing direction. Since in our study, we work on RGB color space, we can omit the wavelength ( $\lambda$ ) in the function notation and use the BRDF as a 4D function for each color channel.

Finding an efficient way to represent BRDFs is another difficult problem. Historically, tabular representation of BRDFs is used. But since it is not an efficient and compact way, some parametric models are introduced. Either the sampled reflectance data are used to fit a physically plausible model or more compact forms such as splines, spherical harmonics, spherical wavelets, etc. are obtained from the sampled data. In this study, we use the parametric representation proposed by Lafortune et. al. <sup>5</sup> because the model is simple and compact and it can represent natural reflection phenomena such as off-specular reflection, increasing reflectance and retro-reflection. It has the following representation:

$$f(\vec{u}, \vec{v}) = \rho_d + \sum_i [C_{x,i}(u_x v_x + u_y v_y) + C_{z,i} u_z v_z]^{N_i} \quad (1)$$

where  $\vec{u}$  is the incoming light direction,  $\vec{v}$  is the viewing direction,  $\rho_d$  is the diffuse component,  $N_i$  is the specular exponent, and the ratio between  $C_{x,i}$  and  $C_{z,i}$  indicates the off-specularity of lobe  $i$  of the BRDF  $f$ . In this study, we only use one lobe representation. The diffuse component ( $\rho_d$ ) and specular terms ( $N$ ,  $C_x$  and  $C_z$ ) of each surface point are estimated individually. Basically while the diffuse components are stored in a global texture, a single BRDF with  $\rho_d=0$  represents the specularity of the whole object.

## 3. Estimation of Diffuse Components

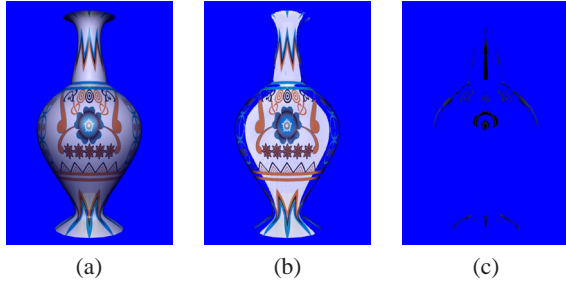
Diffuse reflection is the view-independent component of the reflection. When light interacts with the surface of an object, the incident light is scattered in various directions. For the ideal case which assumes Lambertian surface, light is scattered equally in all directions. In our computations, we also assume a Lambertian surface. In general  $\rho_d$  is estimated as the minimal pixel value among the acquired input images where the corresponding surface point  $p$  is visible. But this initial estimation is inaccurate when  $p$  belongs to a shadow area in one of the input images. In our approach we are storing  $\rho_d$  of each surface point  $p$  in a global texture. This texture is extracted by using surface particles concept proposed in <sup>8</sup>. However, initially, an unshading phase proposed by Rocchini et. al. <sup>2</sup> is applied to the input images to remove the illumination effects like shadows and specular highlights. This unshading phase requires a system setup where six point light sources are placed around the camera at the known positions and during each shot only one of the light sources are activated and six images are acquired for each view.

### 3.1. Computing Illumination-invariant Images

For each view, the illumination effects such as shadows, specular highlights, etc. can be eliminated by inspecting pixel values in the images. While the pixels having lower intensities correspond to shadow areas, the unsaturated pixels correspond to specular highlights. To obtain the corresponding illumination-invariant images for each view, we need to compute the diffuse component  $\rho_d$  of each surface point  $p$  that is visible in that view. The diffuse component can be reconstructed by assuming a Lambertian surface. This can be formulated as the following linear system of equations  $\rho_d \mathbf{l}_i \cdot \mathbf{n} = c_i$  where  $\mathbf{l}_i$  is incoming light direction,  $\mathbf{n}$  is the surface normal and  $c_i$  is the observed color value in input image  $i$ . After removing the shadows and specular highlights in the input images, for a surface point this linear equation can be solved if at least three different color values are observed in the input images for each view. If this is not the case, some bad pixels may occur in the output image. While Rocchini <sup>2</sup> estimates the values of these bad pixels by interpolating from neighboring pixels, we don't need to fully reconstruct the illumination-invariant image since we use surface particle concept in texture extraction. In Figure 1(a)&(b), for a view one of the input images out of six and corresponding illumination-invariant image are shown.

### 3.2. Extracting Texture for Diffuse Components

Once the illumination-invariant images are computed, the diffuse component of the object's surface appearance is stored in a global texture. In constructing the texture, the surface particles concept is used like in <sup>8</sup>. The model is composed of surface particles with three attributes: position, nor-



**Figure 1:** (a) An input image, (b) computed illumination-invariant image, (c) corresponding residual image.

mal and color. The main idea is in extracting the global texture, instead of assigning triangles to images, particles are assigned to images. Each surface particle is associated with a pixel on the texture. The value for that particle can be determined from the image where the particle is visible and whose normal vector produces the minimum angle with the particle normal. The particle is projected to this image and the corresponding color in the image is assigned to the corresponding pixel in the global texture.

#### 4. Estimation of Specular Component

Specular reflection is the view-dependent component of the reflection. Estimation of specular component requires mainly two steps: collecting the reflectance data from the images and fitting a single BRDF to the reflectance data.

##### 4.1. Collecting Reflectance Data

After computing illumination-invariant images, the residual images are obtained by taking difference between the input images and corresponding illumination-invariant images. In Figure 1(c), a residual image is shown. In collecting reflectance data, we use a similar approach to the one proposed by Lensch et al. <sup>3</sup>, but since we are decomposing the reflectance as the combination of diffuse and specular components, the reflectance data obtained from the residual images contain only the specular reflectance. The idea is that for a set of surface points in the object, the corresponding radiance samples are collected from each residual image where the point is visible. Also local incident light direction  $\vec{n}$  and viewing direction  $\vec{v}$  are determined and stored for that view. These vectors can be easily determined since the position of light source, the camera position and position of the surface point are known and the corresponding radiance values can be found by projecting the surface point to the images. The radiance values are proportional to the color value at the projected pixels, the brightness of the point light source and the squared distance from the light source to the surface point. These collected data are used in the BRDF fitting process.

##### 4.2. Fitting a BRDF model

As mentioned in Section 2, we use Lafortune BRDF model to represent the specularity of the object. Lafortune model has four parameters (See Equation 1). Since we work on RGB color space, three different models are fit for each color channel. However, for each model,  $\rho_d$  is assumed to be zero since we are fitting only the specular data. The remaining parameters can be determined by using Levenberg-Marquardt optimization technique as stated in the original work by Lafortune <sup>5</sup>.

#### 5. Interactive Rendering

In the rendering phase, we need to combine diffuse and specular components of the object. Therefore the rendering is performed in two passes. In the first pass, the object is rendered using global texture containing the diffuse component, and in the second pass, the specular component is added to the diffuse component by blending. This can be seen in Figure 2. Since specular component is represented by a single BRDF, we need to render the model using fitted parameters.

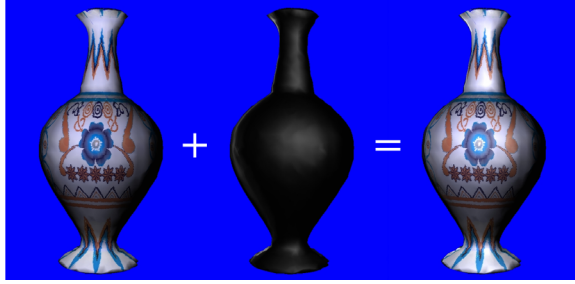
Normally, rendering of a model using parametric representation of BRDF requires evaluation of BRDF for each surface point for the current viewing and incoming light directions. In real-time rendering, these evaluations must be recomputed when the view or the position of the light source changes. But this results very low rendering speeds in current graphics hardware. To interactively render BRDFs some algorithms are developed where texture maps are used to store the parameters of BRDF models <sup>7,1</sup>. In our work, we choosed to use Kautz and McCools <sup>7</sup> method which is based on separable decompositions of BRDFs. Separable decompositions approximate a high-dimensional function  $f$  using a sum of products of lower-dimensional functions  $g_k$  and  $h_k$ :

$$f(x, y, z, w) \approx \sum_{k=1}^N g_k(x, y) h_k(z, w) \quad (2)$$

In their work, Kautz and McCool stated that  $N = 1$  has proven to be visually adequate for many BRDFs. So the process turns out to be separating the 4D function as products of two 2D functions. These functions are preevaluated and stored as cube-maps and rendering can be done in one pass by using multi-texturing feature of OpenGL.

#### 6. Conclusions and Future Work

In this study, we describe a method to separate diffuse and specular components of reflectance. We store the diffuse component as a global texture and fit a Lafortune BRDF model to the reflectance data obtained from residual images to represent the specularity of the object. We generate artificial test data by using a 3D modeling tool with 3 different objects. The first and second objects are a ceramic vase and pot



**Figure 2:** In rendering phase, diffuse and specular components are combined to form a photorealistic appearance.

and the last one is a pepsi can. Test objects are rendered from 20 different viewpoints, totally having 120 images(6 images for each view). All the processing is done on a 2 GHz Pentium4 PC. The geometry of the objects are obtained using A. Mulyim's<sup>8</sup> 3D reconstruction method. For each test object, total number of faces and execution times of our method is shown in Table 1. As it can be observed from the table, for the vase object the execution time is higher since the texture detail is complex. Interactive rendering of the reconstructed objects can be performed with around 20 fps on the same PC. The reconstruction results for the other objects can be seen in Figure 3. As a future work, a more complete extraction of reflectance properties can be done by fitting multiple BRDFs for each material exist in the object and associating each surface point with these BRDFs. However, the main problem is interactive rendering of these multiple BRDFs.

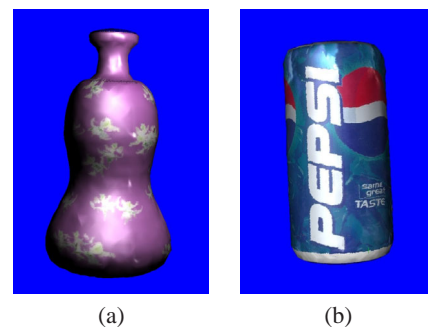
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**Table 1:** This table lists for each model, the number of faces and corresponding execution times.

Model	Number of Faces	Execution Time(in sec.)
vase	3478	953
pot	3804	455
pepsi can	3926	433

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**Figure 3:** Reconstructed (a) pot model, (b) pepsi can model.