Shape and Reflectance from Scattering in Participating Media

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Abstract

Most shape and reflectance acquisition methods use the light reflected from objects’ surfaces. When the reflection cannot be observed, e.g., when the object’s surface is black matte or highly specular, its shape and reflectance are difficult to acquire. In this paper, we propose a method that can measure shape and reflectance with another approach. Our method involves the use of the scattering of reflected light in a participating media instead of using only the light reflection. We place the target in a participating medium and focus a laser beam on it. Cameras can observe the scattering of reflected light toward all reflection angles even if they can only observe light reflected toward the cameras. Experimental results showed that our method can acquire the shape and reflectance of various surfaces.

1. Introduction

In recent years, the demand for photorealistic 3D imagery in many sectors such as cinema and gaming has risen dramatically. Hardware advances have increased the available computation power to the point where rendering very complicated scenes with hundreds of light sources and millions of polygons is now feasible for professionals with dedicated machines. However, modeling such scenes requires highly realistic models for the objects that appear in the scene. Such models are expensive when created by graphics artists. Therefore, the problem of automating the process of obtaining realistic object models has attracted many researchers.

An object model comprises two components: shape and spatially varying reflective characteristics.

Most active ranging techniques focus a laser or structured light onto the target and use its reflection for shape acquisition. It is difficult to observe the reflection of many real-world objects, including highly specular objects and black matte objects. Although many approaches for measuring such surfaces are proposed [6], they can be applied to only a specific reflection property.

On the other hand, almost all previous studies on acquiring reflective characteristics use light reflection, including diffuse and specular reflection. One of the drawbacks of the previous studies is that dense observation, i.e., the situation where many cameras surround the object, is required for observing specular reflection. A few methods, including a method with ellipsoid mirror [13], resolve this problem, but these methods can only work for fixed surface points and cannot be used for unknown shapes.

This paper proposes an approach for measuring the shape and reflectance of such challenging objects simultaneously. Our approach involves the use of the scattering of reflected light in participating media instead of using only the reflected light. An overview of our approach is illustrated in Figure 1. We place a target object in a tank filled with participating media and focus a laser beam onto the surface of the object. In this situation, the path of the incident laser beam and the reflected light in all directions, which can otherwise not be observed in a clear air environment, can be observed as scattered light. Using the scattered light, we estimate the 3D position of the reflecting point and reflectance parameters. Our approach can be applied to measure black materials because the incident light path gives enough information to estimate the reflection points, and it can also measure specular objects with a few observations because the reflected light in all directions, which is necessary to acquire reflectance, is captured by each image.

The rest of this paper is organized as follows. An overview of related work is presented in Section 2. System configurations are presented in Section 3. Our shape acquisition and reflectance parameter estimation methods are explained in Sections 4 and 5. In Sections 6 and 7, we present the experimental results and conclude our paper.

2. Related Work

The active illumination techniques focus a light/light stripe onto a target object and estimate the 3D position of the reflected point of the light with the stereo method. Most of these methods are designed under the assumption that surfaces of targets are Lambertian surfaces, which reflect incident light in all directions, in order to make it easy to detect stereo correspondences. However, many objects in
the real world do not satisfy this assumption: objects with non-Lambertian surfaces such as mirror-like objects are difficult to measure because such surfaces reflect incident light toward a specific direction and these reflections make difficult to detect point correspondences. There are several approaches [6] to measure non-Lambertian surfaces, such as specular flow [1], methods that use polarization [12], and methods that use known patterns, shape-from-distortion, phase-shifting [3], shape-from-heating [4], and light-path triangulation [8]. These methods require special devices and/or can be applied to only a specific reflection property.

Some studies on reflectance acquisition define constraints on the object shape, such as restriction on the target object surface to be planar. For example, the gonioreflectometer developed by Li et al. [10] works only on planar samples of materials to obtain high-density nonparametric BRDF (Bidirectional Reflectance Distribution Function) models. Aside from the shape limitation, the drawback of this method is the usage of multiple moving parts, making the operation of the device very slow. It takes approximately 10h for a single point reflectance extraction. Mukaigawa et al. [13] propose a method that addresses the speed problem of gonioreflectometers by introducing ellipsoidal mirrors that converge the different angle reflections from the planar object surface to a single direction in such a way that the observing camera is not required to move. Another method to tackle the speed problem was proposed by Lu et al. [11]. Their technique is mainly applicable to nonrigid materials such as fabrics. The material is wrapped around a right-circular cylinder and irradiated by a parallel light source. This allows to observing multiple reflection angles of the material from a single frame.

While the above studies employ the approach of using only the reflected light, our approach uses the scattering of reflected light which enables us to observe the reflected light toward all directions indirectly. A study closely related to ours was performed by Hullin et al. [5]. They used fluorescent material for observing laser trails and succeeded in capturing transparent objects that are difficult to measure using most vision-based methods. However, reflectance acquisition is out of the scope of this method. An acquisition method for scattering objects, i.e., translucent objects, was developed by Inoshita et al. [7]. Their method also actively uses scattering for shape acquisition but does not focus on reflectance acquisition. Shape acquisition of underwater objects [9][2] is also related to our work. However none of the methods focus on reflectance acquisition.

3. System Configuration

Our system configuration is shown in Figure 1(b). The system consists of a transparent, e.g., glass or acrylic, liquid tank filled with a participating medium, cameras, and a laser pointer unit. We place the target object inside the tank and focus the laser beam on its surface. The cameras are placed such that they can observe the scattering of light in the entire tank. All cameras are calibrated in advance. Note that we have to take into account refraction on the liquid tank walls: the incoming rays toward the cameras will be refracted from the liquid tank wall because the refraction rate of air and that of the participating media differ, and hence traditional $3 \times 4$ projection matrices will prove ineffective. Fortunately, there has been much research on refraction calibration in vision systems [9]. We will discuss a method to this calibration method in Section 6.

Images are obtained while a target object is submerged in the water solution inside the tank. There are two settings for image acquisition: object area detection and parameter estimation. We employ the background subtraction method for object region detection. For this detection, it is necessary to illuminate the object and create a contrast with the black background of the tank. Figure 2(a) shows a sample of the source images we obtained for object region detection.

On the other hand, to obtain source images for parameter estimation, all light sources except the laser beam are turned off.
off. In this study, we do not allow simultaneous illumination with multiple lasers. This makes the following image processing and estimation phases simpler to implement and compute. Figure 2(b) shows a sample of the source images we obtain for estimation of the scattering and reflectance parameters.

Figure 2. Images for (a) object area detection and (b) scattering and reflectance parameters estimation

4. 3D Reconstruction

In this section, we describe the details of processes to obtain the necessary data for parameter estimation: the 3D location of the reflection point and the 3D orientation vector of the laser beam. Our method is similar to Hullin’s method except that we use a point laser instead of a slit laser.

A fraction of the reflected light scatters back to the object surface results in secondary reflections. These secondary reflections are very hard to model because we know neither the object shape nor the BRDF at those locations before the estimation phase. Therefore, it is necessary to mask out the object surface. We extract the object area by using the background subtraction method and the source images for parameter estimation are masked with the detected object area.

The detection of the laser beam in images has a three-fold importance: First, it enables us to limit the search area for the reflection point; second it is required for 3D reconstruction of the incidence direction; and lastly, the laser region and its immediate surroundings where second scattering of laser light occurs can not be modeled with the reflectance and scattering formulations we use and therefore should be masked from the image, as the object region was. We binarize the masked input images, and apply the Hough transform to the binary image and estimate the laser beam line in the images. The immediate surroundings of the laser beam line are masked from the images; in this work, we empirically determined the size of surroundings. The pixel with the highest pixel value is detected from a set of pixels on the laser beam lines and is used as the reflection point on the image. Using the stereo method, we calculate the 3D position of the reflection point and the 3D laser beam direction.

Note that our method detects one 3D point on the object’s surface from each image. Moving the laser unit and taking multiple images, we acquire the point cloud of object surfaces.

The surface normal of each point on the object surface must be known prior to parameter estimation as the object reflectance depends on the angles between the normal and the incident ray. We use the simple approach of finding the principal axis of the neighbors of the target point. The neighbors are the \( n_{nbr} \) closest sample points on the object surface. The principal axis is the eigenvector corresponding to the smallest eigenvalue of the covariance matrix \( C \). The covariance matrix for \( n_{nbr} \) points is calculated by the following equations:

\[
c = \frac{1}{n_{nbr}} \sum_{i=1}^{n_{nbr}} p_i \tag{1}
\]

\[
C = \sum_{i=1}^{n_{nbr}} (p_i - c)(p_i - c)^T, \tag{2}
\]

where \( p_i \) is the \( i \)th closest point. The value of \( n_{nbr} \) is iteratively increased until the second largest eigenvalue of the covariance matrix is bigger than half the value of the biggest eigenvalue. In this way, we ensure that the neighboring sample point cloud is not too close to linearity.

5. Scattering and Reflectance Parameter Acquisition

5.1. Scattering Model

The scattering effects of the participating media can be modeled in a simplified form with the single scattering assumption. We use the model described in Narashimhan et al.’s work[14]. The three scattering parameters are the scattering coefficient (\( \beta \)), the extinction coefficient (\( \sigma \)), and the Henyey–Greenstein parameter (\( g \)). Figure 3 illustrates the scattering along a single ray path and the notation we will use throughout this section. The variables that affect the contribution of a single light ray path to the observed luminance of a pixel are \( d_1 + d_2 + d_3 \) and \( \theta \). \( d_1 + d_2 + d_3 \) represents the total distance a light ray travels in the medium, and as shown in figure 3, \( \theta \) is the angle of scattering. The light radiance at a single path without taking the BRDF of the object into consideration is

\[
I = I_0 e^{-\sigma (d_1 + d_2 + d_3)} \ P(\theta, g) \tag{3}
\]

\[
P(\theta, g) = \frac{1}{4\pi} \frac{1 - g^2}{[1 + g^2 - 2g \cos(\theta)]^{3/2}} \tag{4}
\]

5.2. Reflectance Model

We use a modified form of the Cook–Torrance model for the reflectance model. We transform the parameters \( k_s, k_d, \)
and $R_d$ in the Cook–Torrance BRDF model,

$$D = \frac{1}{4\pi m^2(\hat{n} \cdot \hat{h})^4} e \left( \frac{a R_d^2 - 1}{m + (a R_d)^2} \right)$$

$$F = \frac{1}{2} \frac{(g - c)^2}{(g + c)^2} \left( 1 + \frac{(c(g + c) - 1)^2}{(c(g - c) + 1)^2} \right)$$

$$e = \hat{v} \cdot \hat{h}, \quad g = \sqrt{n_o^2 + c^2} - 1$$

$$G = \min \left\{ 1, \frac{2(\hat{n} \cdot \hat{h})(\hat{n} \cdot \hat{v})}{\hat{v} \cdot \hat{h}}, \frac{2(\hat{n} \cdot \hat{h})(\hat{n} \cdot \hat{i})}{\hat{i} \cdot \hat{h}} \right\}$$

$$f_r = k_d R_d \frac{\hat{n} \cdot \hat{l}}{\pi} + k_s \frac{DFG}{\hat{n} \cdot \hat{v}}, \quad k_s + k_d = 1$$

and define a reflectance model,

$$\mu = R_d + k_s - R_d k_s, \quad s = \frac{k_s}{\mu}$$

$$f_r = \mu \left( \frac{d \hat{n} \cdot \hat{l}}{\pi} + s \frac{DFG}{\hat{n} \cdot \hat{v}} \right), \quad s + d = 1$$

where $\hat{n}$, $\hat{l}$, $\hat{v}$ and $\hat{h}$ are the surface normal, incident light direction, view direction, and the half angle between $\hat{l}$ and $\hat{v}$, respectively. Here, the parameter $\mu$ represents the overall brightness of an object and is between 0 (black-body) and 1 (lossless reflectance).

### 5.3. Observation Model and Reference Object

Unlike direct observations, light scattering is a volumetric concept and the pixel values are a result of the integration of all the light power through a pixel’s coverage area (e.g. the red dashed line in figure 3). This is a bounded line integral and can be notated as follows:

$$E(u, v) = \int_{d_{3,0}}^{d_{3,1}} V(x, y, z) \, \mathrm{d}l$$

Here, $d_{3,0}$ and $d_{3,1}$ denote crossings of the pixel ray with the two sides of the tank; $V(x, y, z)$ is the volumetric light intensity distribution function given by the product of equations 3 and 7:

$$V(x, y, z) = I_0 \beta e^{-\sigma(d_1 + d_2 + d_3)} P(\theta, \phi) f_r.$$

Pixel values obtained from the images are scaled as a whole with the combined multiplicative effect of six factors: the ISO settings, the shutter speed, and the aperture size of the camera; the light power of the laser pointer; the scattering parameter $\beta$; and the overall brightness of the target object $\mu$. While it is possible to fix the first five factors, as the target object changes the brightness varies. The other reflectance parameters do not affect the pixel values globally. It can be said that those parameters impart the “shape” of the observed brightness distribution over pixels and the overall brightness imparts a “scale” to it. We propose to separate the process of finding a best match for the shape from finding the correct scale for the brightness function by normalizing it with its mean value $^1$.

$$G_N(u, v) = n_{samp} \frac{G(u, v)}{\sum G(u, v)}, \quad (10)$$

where $G(u, v)$ is a pixel value on the pixel coordinates $(u, v)$, and $n_{samp}$ is the number of pixels used for parameter estimation.

When an object is rendered or photographed, its brightness is measured in pixel values ranging between 0 and 255 for 3-channel, 24-bit imagery. On the other hand, object radiance and irradiance on the object surface are measured in $\text{W/m}^2\cdot\text{sr}^{-1}$ and $\text{W/m}^2\cdot\text{sr}^{-1}$, respectively. Thus, the parameter $\mu$ has units $\text{sr}^{-1}$.

The reference object is required to create a mapping between the physical world with the computer world. We use a white Lambertian plate as the reference and choose its $\mu$ to be 1.

### 5.4. Estimation of Scattering Parameter

The reference object is used for estimating the scattering parameters, $\sigma$ and $g$. The “shape” of the observed brightness is controlled by $\sigma$ and $g$, when we use a white Lambertian plate, i.e., we set $\mu = 1$ and $d = 1$, $s = 0$. In order to evaluate the difference of the “shape” we use the difference of normalized pixel value and normalized simulated value $E(u, v)$ for the error function:

$$E(\sigma, g) = \sum_{(u, v) \in S} |G_N(u, v) - S_N(\sigma, g, u, v)|, \quad (11)$$

where $S_N(\sigma, g, u, v) = N(E(u, v))$ and $S$ is a set of pixels that are outside the object area. We find the optimal parameters $\sigma_{opt}$ and $g_{opt}$ that minimize the error with the Nelder–Mead method.

$$(\sigma_{opt}, g_{opt}) = \min \mathcal{E}$$

$^1$The notation “$N(f) = n_{samp} \frac{\int f(u, v)}{\sum_{(u, v) \in S} f(u, v)}$” is used throughout this section.
For estimating the “scale” for the brightness function, the ratio of the scaling factors of the observed and simulated brightness, denoted by $R$, is calculated.

$$R = \frac{\sum_{(u,v) \in S} G_X(u,v)}{\sum_{(u,v) \in S} E(u,v)}$$

Here, $R$ represents the combined effects of the ISO settings, the shutter speed, and the aperture size of the camera; the light power of the laser pointer; and the scattering parameter $\beta$. $R$ is thought to be constant provided these effects are unchanged. When another object with unknown parameters is introduced into the system, its $\mu$ is found by the following equation:

$$\mu = \frac{1}{R} \frac{\sum_{(u,v) \in S} G(u,v)}{\sum_{(u,v) \in S} E(u,v)}$$

### 5.5. Estimation of Reflectance Parameters

Estimation of reflectance parameters is essentially the same as the estimation of scattering parameters with the difference that the image formation model is more complicated. This phase is performed after the parameters $\sigma_{opt}$ and $\theta_{opt}$ are obtained. It is possible to control the concentration of the medium, so the estimation phase for scattering parameters need not be repeated.

The variables that are to be estimated in this phase are $s$, $m$, in the Cook–Torrance model; therefore, the error function depends on these two parameters. The observed and simulated brightness functions are scaled in the same way as the estimation of the scattering parameters.

$$\mathcal{E}(s,m) = \sum_{(u,v) \in S} |G_X(u,v) - S_X(s,m,u,v)|$$

Similar to the previous phase, the Nelder–Mead method is used to find the optimal values $s_{opt}$, $m_{opt}$ that minimize the error.

$$(s_{opt}, m_{opt}) = \min_{s,m} \mathcal{E}(s,m)$$

### 6. Experiments

#### 6.1. Implementation

Our measurement system, shown in Figure 4, consists of a 60 cm $\times$ 60 cm $\times$ 60 cm liquid tank with 9-mm-thick crystal-clear acrylic walls, two DSLR cameras (Canon D7000 with zoom lenses, 4948 $\times$ 3280 pixels) and a 5 mW green laser module ($\phi = 1$ mm). In this experiment, we estimated the reflectance parameters of only the green channel; however, our method can easily be extended to estimate other color channels by using different-colored lasers.

To avoid the reflection of light on the liquid tank surfaces, we covered the background wall of the liquid tank with black matte sheets. We used 0.5 mL milk diluted in 180 L water as a participating medium.

To reduce the effect of refraction, we placed the cameras orthogonally against the liquid tank surfaces and at a distance of 4 m from the water tank. The cameras were calibrated using Zhang’s method [15]; however, as mentioned in Section 3, refraction in the liquid tank that cannot be modeled by a $3 \times 4$ projection matrix must be considered.

**Refraction Correction** A ray direction in the liquid tank is modeled by Snell’s law as follows:

$$\frac{\sin \theta_{air}}{\sin \theta_{water}} = \frac{n_1}{n_2},$$

where $\theta_{air}$ and $\theta_{water}$ are incidence and refraction angles, and $n(=1.333)$ is the refractive index of the scattering material. The direction can be calculated using the 3D position and orientation of the liquid tank surface, and therefore we first calibrated the cameras before adding the participating medium to the liquid tank, after which we estimated the 3D location of the liquid tank surfaces. We placed a chessboard pattern on the liquid tank surfaces and measured their 3D positions.

![Figure 4. System implementation. Left: a liquid tank filled with diluted milk and a laser unit. Right: a DSLR camera mounted 4m away from the liquid tank surface.](image-url)
We evaluate the precision of the shape reconstruction by using a planar reference object (object 1). The planarity of the point cloud obtained after 3D reconstruction can be assessed in two ways: (1) the distance of each point from the plane obtained by applying a singular value decomposition to the point cloud and (2) the angle between the normals associated with each point and the normal to the SVD plane. We sampled 107 points on object 1 for evaluation. Figure 6 shows the reconstructed mesh from the point cloud. The average distance from the SVD plane is 0.1272 mm, which corresponds to approximately 0.5 pixel in input images, and there are no outliers with distance greater than 1 mm from the SVD plane. Therefore, we conclude that our approach returns acceptable results for shape reconstruction. The average angle with the SVD plane normal was 0.5291°.

Next, we analyze the stability of the error function under the cases of estimation of the scattering parameters and estimation of the reflectance parameters. As previously explained in Section 5.3, we perform scaling to eliminate the effect of constants, including the scattering parameter $\beta$. Therefore, estimation is performed only for $g$ and $\sigma$. The error function described in Section 5.4 was for samples obtained from a single image. We expand this by summing the error functions obtained corresponding to multiple images taken by the two cameras to stabilize possible errors due to image noise and other anomalies that cannot be estimated.

Figure 7 shows the error function for the estimation performed on a total of 109 frames per camera from the two cameras. From the figure, it is clear that there are no multiple local minima, and the global minimum is not situated in an ill-posed location or the edges. We find $g_{opt} = 7.602 \times 10^{-1}$ and $\sigma_{opt} = 2.2857 \times 10^{-3}$ mm$^{-1}$. The RMS error per sample is 0.65%. This shows that the optimum parameters and our image formation model with the Lambertian BRDF assumption can accurately simulate the observations.

Figure 8 shows the logarithm of the error functions corresponding to one point on objects 1-3, respectively. The reflection from the surface of object 4 cannot be detected; therefore, its $\mu$ is estimated to be 0, and other reflectance
parameters are not important.

The error function corresponding to object 1 has its minima along the $s = 0$ line. The error function of object 2 has a single global minimum around the large $s$, small $m$ area. While the blue tape has an observable specular glow, the highly directive nature ($g >> 0$) of the water–milk solution causes a specular glow that is oriented toward the ceiling and hence is not visible from the tank sides. Therefore, our method cannot detect the specularity of the blue tape, and the error function minima is on the $s = 0$ line. The metallic duct tape has a rougher surface than the tablespoon. This is correctly shown in the results as a unique global minimum around the large $s$, large $m$ area.

### 6.3. Rendering Results

We present two types of rendering results: a spherical object that takes the reflectance of one of the objects, and the reconstructed object surface. In both cases, the BRDF is uniform. The area indicated by the blue lines in figure 9(a)-(d) show the area scanned with the laser pointer. The images are converted to grayscale with the value of the green channel.

The rendering results show that our method can generate a considerably accurate estimate for the shape and BRDF of the target objects.

### 7. Conclusion

In this paper, we proposed a novel method to obtain the shape and reflection of real-world objects, utilizing the scattering phenomenon. Detecting the path of the incident laser from images, we estimate the reflection points, and the reflectance parameters are estimated from scattering.

Extending our method to nonparametric BRDF acquisition is a future goal. While nonparametric BRDF estimation requires dense observation, our approach utilizing the scattering of reflected light can reduce the number of observations.

### References


Figure 9. Rendering results. (a)-(d): Target object. The area scanned with the laser pointer is indicated by the blue lines. (e)-(h): Spheres rendered using estimated reflectance parameters. In (g), two different materials shown in (c) are used for rendering. (i)-(l): Reconstructed shape and reflectance.


