# BRDF Estimation with Simple Measurement and Data-driven Model 

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#### Abstract

In this paper, we proposed a method for measuring surface reflectance under multiple lighting by using simple devices. In order to establish this method, we first applied principal component analysis (PCA) to MERL BRDF database for compact representation. For estimating BRDF under multiple lighting, lighting component is obtained from the image captured by omnidirectional camera. Through the optimization process using these basis and lighting component, an appropriate set of vertex data necessary for estimating unknown BRDF are selected. By performing the optimization process, our method allows us to estimate unknown BRDF efficiently. Finally, to obtain weighting coefficient for linear combination, the measured data of selected vertex are projected onto the basis of $B R D F$. We verified that our method can estimate the surface reflectance with high accuracy by comparing the results between ground truth and estimated data.


## Introduction

A development of 3D printer may provide the next revolution for rapid proto-typing in the field of manufacturing industry. Before now, this rapid proto-typing was operated only in the virtual world such as computer simulation and virtual reality system. The use of real object by making 3D printer becomes a real possibility in rapid proto-typing, since the shape and hand feeling can offer a sense of reality. Our group proposed a novel display system for rapid proto-typing in which computer graphics can overlap with real object through the projection map and flat panel display as shown in Fig.1 [1, 2]. To make practical use of our proposed system for the rapid proto-typing with 3D printing, we need various bi-directional reflectance function (BRDF) information for arbitrary material appearance such as metal, plastic, ceramic, and others.

It is well-known that many kinds of BRDF measurement method or instrument have been developed. The conventional methods employed prudent approach for acquiring the geometry and spatially-varying BRDF of 3D objects by moving the light arm around the target object $[3,4]$. These method were possible to


Figure 1. Developed display system for rapid proto-typing
acquire the accurate BRDF directly with many trials, whereas it was necessary to keep the large space and tangled calibrations. Recent researches make a compact and easy-to-use measurement system possible by using a single camera and rotating table $[5,6]$. In this method, they estimated the three variables such as specular reflectance, diffuse reflectance, and roughness under the condition that information of geometry and incident light are known. They attempted to derive the BRDF profile by fitting the measured data to reflection model such as Beckmann and GGX. The demonstrated result was feasible for the surface reflectance of real object such as ceramic and rubber. However, the model-based estimation sometimes produced undesirable results since no perfect reflectance model exists for various BRDF of material appearance and fitting misalignment is occurred at the part of specular and diffuse reflection.

In this paper, therefore, we propose a data-driven method for estimating surface reflectance by calculating linear combination of the basis which is generated from MERL BRDF database. This approach can expect to fit preciously between measured data and BRDF model derived from reality-based data. Moreover, our method employ directly matching between measured pixel value and radiance, although almost of data-driven method calculated the matching between reflectance and result of linear combination. This idea can estimate accurate appearance of real 3D objects even if these objects were measured under general light condition with multiple lights.

## Related Works

A compact and easy-to-use measurement system of BRDF was developed by the contribution of computer science. Dong et al. [5] proposed the method which acquires spatially varying isotropic surface reflectance and geometry data of target object under unknown lighting. This method is greatly simplified compared with conventional because it is only necessary to capture the feature of target object by using video camera with rotating table. In their method, they estimate simultaneously four variables such as specular reflectance, diffuse reflectance, surface roughness, and lighting information around the target object through optimization calculation. By calculating this complex problem, they were possible to estimate both BRDF and environment light. However this estimation algorithm causes less convergence and more computational cost since some ill-posed conditions bring considerable disruption to this estimation.

To avoid this problem, Domon et al. modified the method proposed by Dong et al [6]. They used the environmental image captured by omni-directional camera to derive incident light component for the reduction of computational cost. By fitting the various BRDF model, this method estimated three variables such as specular reflectance, diffuse reflectance, and surface roughness. They demonstrated that their method can estimate BRDF rapidly and accurately compared with the Dong's method. However, these model-based estimation method sometimes causes misalignment on the estimated BRDF. It is important to select the best reflectance model for comprehensive estimation of BRDF.

On the other hand, there are some data-driven methods for estimating unknown BRDF. Nielsen et al. [7] proposed the method for estimating the surface reflectance efficiently with simple devices. This method applied principal component analysis (PCA) to various reflectance data with fitting as compact representation. Using these basis and an iterative optimization process, an appropriate BRDF data set with sampling directions are selected. Finally, the measured data of selected sampling directions is projected onto these basis, and weighting coefficients are obtained by linearly representing for unknown material. This method allows us to significantly reduce the time and effort for measurement of unknown surface reflectance. However, it has limitation that this method can be applied only under the condition that measured data is obtained by a single point light. Since this limitation vitiates the practical use, therefore, we improve the Nielsen's method by using direct matching between measured pixel value and radiance under the multiple illuminated condition.

## Analysis of BRDF Data for Our Purpose

## MERL BRDF Database

We make use of BRDF dataset of Mitsubishi Electric Research Lab (MERL) acquired by Matusik [8] for learning the statistics of real world BRDFs. There are 100 materials in this database with BRDF measurement made for all three color channels i.e. Red, Green, and Blue. These measurements were based on Rusinkiewicz [9] half vector parameterization of the BRDF. In this parameterization, four angles are generally used to describe the BRDF, namely theta half $\theta_{\mathrm{h}}$, theta difference $\theta_{\mathrm{d}}$, phi difference $\varphi_{\mathrm{d}}$ whereas phi half $\varphi_{\mathrm{h}}$ is not considered for isotropic BRDFs. However, it has been shown previously proposed by Romerio et al., it is effective that the 2D bivariate approximation of the 3D BRDF is sufficient for modeling BRDF of various materials [10]. This approximation reduces the dimensions of the BRDF significantly because theta half and theta difference are only used to describe the BRDF as shown in Fig.2. Therefore, for each color channel of a material sample, we have a total of $90 \times 90=$ 8100 measurements at one degree intervals. Finally, for three color channels, this amounts to a total of $8100 \times 3=24300$ measurements.

Next, we construct a matrix $H$ of BRDF data for all materials. In order to prepare this data for post-processing later, it is necessary to arrange the BRDF data that is represented in bivariate space of all 100 materials in $H$. Thus, the BRDF data of each material is arranged in $H$ with $M$ rows and $N$ columns, where $M$ is the number of sampling directions and $N$ is the number of materials. Normally, the BRDF values of specular and diffuse


Figure 2. Data representation


Figure 3. Top 5 Principal Components.


Figure 4. Plot of cumulative sum of Eigen values.
surfaces are scaled differently each other. If these values are used with original scaling, then future numerical analysis will generate bad result. To address this issue, we normalize BRDF data in real space.

## Principal Component Analysis

For acquiring BRDF of new materials efficiently, we further reduce the dimensions of matrix $H$ by performing Principal Component Analysis (PCA) using covariance matrix of the form $H^{\mathrm{T}} H$. After analyzing the reconstruction error using different number of basis vectors, it is observed that PCA is able to capture the correlations among various BRDFs adequately. The first 5 principal components are visualized in Fig.3. The color scale represents the intensity of reflectance, the vertical axis represents theta half, and the horizontal axis represents theta difference. A plot of cumulative sum of eigen values is shown in Fig. 4. This Figure demonstrate that the dimension of BRDF data is reduced significantly. Therefore, in this paper, we use the first 5 principal component in follow processing. All BRDF is approximated with first 5 principal components denoted by Eq.1.

$$
\begin{equation*}
f_{r}=b_{1} \times c_{1}+b_{2} \times c_{2}+\cdots+b_{5} \times c_{5} \tag{1}
\end{equation*}
$$

where $f_{r}$ is the BRDF, $b$ is the vector of principal component, and $c$ is the principal component score.

## Implement of Proposed Method

## Estimation Algorithm

Our proposed method requires three measurements, which are captured images of target object, environmental image for incident lights, and geometry data of target object. Here, to improve the limitation by Nielsen's method as mentioned related works, our estimation algorithm is based on the rendering equation proposed by Kajiya et al. [11]. This rendering equation describes the total amount of light emitted from a point $x$ along a particular viewing direction, and it is given by a function for incoming light and BRDF, as is denoted by Eq. 2 .

$$
L_{o}\left(x, \overrightarrow{\omega_{o}}\right)=\int_{\Omega} \begin{align*}
& f_{r}\left(x, \overrightarrow{\omega_{L}}, \overrightarrow{\omega_{o}}\right)  \tag{2}\\
& \quad \times L_{i}\left(x, \overrightarrow{\omega_{i}}\right) d \overrightarrow{\omega_{i}},
\end{align*}
$$

where x is the location in space, $\overrightarrow{\omega_{l}}$ is the direction of the incident light, $\overrightarrow{\omega_{o}}$ is the direction of the outgoing light, and $\Omega$ is the unit hemisphere. $L_{o}\left(x, \overrightarrow{\omega_{o}}\right)$ indicates the total specular radiance directed outward along direction $\overrightarrow{\omega_{0}}$ from a particular position x . Moreover, $f_{r}\left(x, \overrightarrow{\omega_{i}}, \overrightarrow{\omega_{o}}\right)$ is the proportion of light reflected from $\overrightarrow{\omega_{l}}$ to $\overrightarrow{\omega_{o}}$ at position $\mathrm{x}, L_{i}\left(x, \overrightarrow{\omega_{i}}\right)$ is the incident light derived from hemisphere. In this equation, we replace the integral calculation with the dot product of the vector. The converted equation, as is denoted by Eq. 3 .

$$
\begin{equation*}
L_{o}\left(x, \overrightarrow{\omega_{o}}\right)=\overrightarrow{L_{l}}\left(x, \overrightarrow{\omega_{l}}\right) \cdot \vec{f}\left(x, \overrightarrow{\omega_{l}}, \overrightarrow{\omega_{o}}\right) \tag{3}
\end{equation*}
$$

As a result of PCA processing, the BRDF can be represented by a linear combination of principal components and principal component score as shown in Eq.2. Therefore, we can substitute this equation for the BRDF term of Eq.3. The equation after substitution is denoted by Eq. 4 .

$$
\begin{align*}
L_{o}\left(x, \overrightarrow{\omega_{o}}\right)= & \overrightarrow{L_{l}}\left(x, \overrightarrow{\omega_{l}}\right) \cdot \overrightarrow{b_{1}}\left(x, \overrightarrow{\omega_{l}}, \overrightarrow{\omega_{o}}\right) \times c_{1}+ \\
& \overrightarrow{L_{l}}\left(x, \overrightarrow{\omega_{i}}\right) \cdot \overrightarrow{b_{2}}\left(x, \overrightarrow{\omega_{i}}, \overrightarrow{\omega_{o}}\right) \times c_{2}+\cdots  \tag{4}\\
& +\overrightarrow{L_{l}}\left(x, \overrightarrow{\omega_{l}}\right) \cdot \overrightarrow{b_{5}}\left(x, \overrightarrow{\omega_{l}}, \overrightarrow{\omega_{o}}\right) \times c_{5}
\end{align*}
$$

In our estimation algorithm, $L_{o}\left(x, \overrightarrow{\omega_{o}}\right)$ is the observation value of target object and $\overrightarrow{L_{l}}\left(x, \overrightarrow{\omega_{l}}\right)$ is the incident light component captured with Ricoh Theta by 360 -degree camera. This equation is applied to all n pixels on which the object is projected. We represent them in the form of a matrix as shown in Eq. 5.

$$
\left[\begin{array}{c}
L_{o}\left(x_{1}\right)  \tag{5}\\
\vdots \\
L_{o}\left(x_{n}\right)
\end{array}\right]=\left[\begin{array}{ccc}
\overrightarrow{L_{l}}\left(x_{1}\right) \cdot \overrightarrow{b_{1}} & \cdots & \overrightarrow{L_{l}}\left(x_{1}\right) \cdot \overrightarrow{b_{5}} \\
\vdots & \ddots & \vdots \\
\overrightarrow{L_{i}}\left(x_{n}\right) \cdot \overrightarrow{b_{1}} & \cdots & \overrightarrow{L_{i}}\left(x_{n}\right) \cdot \overrightarrow{b_{5}}
\end{array}\right] \times\left[\begin{array}{c}
c_{1} \\
\vdots \\
c_{5}
\end{array}\right]
$$

By calculating the inverse matrix in this equation, we are possible to derive the unknown principal component score. Here, it is noted that the above calculation is highly over constrained since 5 unknown coefficients and a lot of linear equations exist. Therefore, by selecting an appropriate subset from this large number of equations, the number of necessary BRDF measurements can be significantly reduced for BRDF estimation. In the next section, we consider an optimization process to efficiently estimate the coefficients value of principal components. If such a small subset of equations can be found, any new material can be measured by using the only a few pixels corresponding to the selected set of equations.

## Selection of Suitable Pixels for Acquisition

To select an appropriate subset rows, it is necessary to perform an iterative optimization for reducing the condition number of the linear system of equations described above. In the case of the condition number which is the ratio between the highest eigen vakue and the smallest eigen value is low, the matrix is wellconditioned. On the other hand, in the case of the condition number is high, the matrix is ill-conditioned. The following stepwise manner shows the details of optimization process for selecting the matrix with good condition.
I. Pick a subset of $L$ rows from the matrix of dot product between the luminance value and the principal components of BRDF. Let us represent this row subset with matrix X.
II. Select one row from subset X and outside of X respectively, and swap their row.
III. Perform the PCA calculation on the covariance matrix XTX to obtain eigen values and calculate the condition number of X by using these eigen values.
IV. If the new condition number is smaller than the condition number of previous matrix, then hold the newly inserted row in the set X , otherwise return set X to the previous state.
V. Repeat from step $\Pi$ to step IV until the matrix does not change.
VI. Repeat step I through step V several times, and finally select the matrix with the lowest condition number among all solutions.

The iterative procedure described above allows us to obtain an optimal matrix for estimating the BRDF with high accuracy. This obtained sets of equations can also be referred to as the most informative set. Next, we calculate the inverse matrix by using only the obtained set.

## Verification for Our Method

In order to validate our proposed method, we first describe experiments on the MERL BRDF database itself. To avoid over fitting, we split the data into two groups: 90 materials for training, and 10 materials for testing. Next, we render these images under environment image provided by Debevec [12]. Figure 5 shows the root-mean-squared error of normalized values between reconstruction and ground truth. In this verification, we estimate the BRDF with four different number of pixels: using $5,10,20$, and all pixels, which are derived from optimization process. From this RMSE results, it is apparent that the estimation by using 5 pixels is hard to make stability. On the other hand, the accuracy of estimation using 20 pixels is equivalent to the estimation using all pixels.

Figure 6 shows the reproduction images by using the result from our proposed method. In the case of 20 pixels, comparing between reproduced image and ground truth, it can be confirmed that the BRDF are estimated with high accuracy through our proposed method. On the other hand, in the case of 5 pixels and 10 pixels, their appearances of reproduction are different from ground truth. Therefore, it is concluded that the data included more than 20 pixels is required for accurate estimation in this condition.
Next, we also evaluated the validity of our proposed method with actual image. In this validation, we prepared three kinds of material such as gold electroplating metal, alumite treatment metal, and paper as shown in Fig.7. We captured the image of target object by using Nikon D5100 equipped with an AF-S NIKKOR $24-120 \mathrm{~mm}$ lens. Also, we captured an environmental image with Ricoh Theta V 360 degree view camera.

Here, since the target object has two shapes which are a corrugated shape and flat shape, the ground truth BRDF was measured the flat sample by using gonio-photometer. And, the estimation of BRDF was performed by using captured data of the corrugated sample. By comparing these BRDFs, we verified the accuracy of proposed method. Figure 8 shows the result of measurement by using gonio-photometer and our proposed method. Blue line in this figure shows the result of measurement by goniophotometer, and red line shows the result of our estimation.


Figure 5. Root-mean-squared error of normalized values between reconstruction and ground truth


Figure 6. Rendered image for verifying our proposed method


- Gonio-photometer - Our proposed method


Figure 8. Estimation result of our proposed method


Figure 9. Rendered image by using our proposed method

It is apparent that estimated BRDF in gold and alumite material are significantly matched to the ground truth. Therefore, our proposed method has accuracy for BRDF estimation even if the target objects have 3D shape. On the other hand, the BRDF of paper material has a few difference between from 10 to 30 degree of BRDF angle. This difference seem to generate from the difference of shape, since it was difficult to fit in the corrugated shape at the case of paper. Figure 9 shows the reproduction image by using the result from our proposed method and ground truth image. By comparing these images, it is obvious that visual appearance of all material are very similar.

## Conclusion and Future Work

In this paper, we proposed an accurate and practical method for measuring surface reflectance by using a data-driven model and the rendering equation. With the use of data-driven estimation, we can obtain an important set of samples for BRDF estimation. This effort conduces to the reduction of calculation cost within estimation accuracy. With the use of the rendering equation, we can obtain the BRDF directly from the captured images. This idea makes it possible to estimate BRDF even if the lighting components exist in the measurement condition. It is very useful contribution in the practical work for rapid proto-typing.

On the other hand, we verified the accuracy of our proposed method by using relatively simple object. From the practical point of view, it is necessary to evaluate our method with more complex shape. In addition, the material appearance of target object was limited to isotropic and uniform. Therefore, we will apply our proposed method to the anisotropic and spatially varying BRDF as the future work.

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