IPSJ Transactions on Computer Vision and Applications Vol.5 114–118 (July 2013)

[DOI: 10.2197/ipsjtcva.5.114]

Express Paper

Efficient Modeling of Objects BRDF with Planned Sampling

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Received: March 11, 2013, Accepted: April 24, 2013, Released: July 29, 2013

Abstract: In this work we propose a novel method for modeling and synthesizing objects appearance based on planned sampling. The proposed method can efficiently model the BRDF of an object with uniform and isotropic reflectance using a small number of light source directions. This is achieved by utilizing together the knowledge of the object's shape along with the statistics of various BRDFs. The method considers the shape of the object, compact basis representing variations in a reflectance dataset, a fixed view direction and all possible light source directions around the object. Then using an iterative optimization process which simulates the contribution of each light source in modeling the object appearance, our method identifies the most suitable set of light source directions for efficiently modeling the BRDF of the object's material. The selected light sources are then used to acquire actual images of the object for recovering its reflectance properties. Experiments conducted using several objects with varying shapes and a small number of light sources optimally selected by the method validate the effectiveness of the proposed approach in modeling object appearance.

Keywords: reflectance modeling, bivariate BRDF, object shape, optimization, planned sampling

1. Introduction

Modeling object shape and reflectance is essential for synthesizing the realistic appearance of real world objects. While there exist several solutions for recovering the shape of the object very few methods make effective use of it for planned sampling of reflectance.

It is well known that the Bidirectional Reflectance Distribution Function (BRDF) $f(\theta_i, \phi_i, \theta_v, \phi_v)$ can fully characterize the optical properties of materials effectively. However capturing the BRDF tends to require dense measurement of objects appearance, and it is still a challenging task to use a sparse set of images of a given object with an arbitrary shape for modeling its appearance. In this work we propose a method for planned sampling of objects for BRDF modeling using very few images.

Some researchers have proposed efficient measurement methods by taking objects shape into consideration [6], [7]. However most real world objects exhibit significant variations in object shape and reflectance which motivates the need of adaptive sampling strategies for modeling the BRDF of materials comprising the object using a small number of observations.

In this work our contributions include a new method which can find the most suitable light source directions for modeling the BRDF of materials comprising the object from a fixed view position thus significantly reducing the effort required for such measurements. We introduce the idea of using knowledge of object shape with the statistics of BRDF dataset for efficient modeling. Besides we present a complete framework for sufficiently sampling the uniform material comprising the object using as few light sources as possible in a planned manner.

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2. Related Work

Lensch et al. [5] developed an approach for modeling the object appearance by clustering various materials comprising the object and then used the lafortune BRDF model as a fit to the observed samples. Later in Ref. [6] they extended this approach and developed a method for planned sampling of object appearance by finding a set of advantageous measurement directions. They used an uncertainty measure for quantifying suitable directions based on estimated parameters of lafortune model from observations which results in incremental learning of the reflectance as more views become available.

Zickler et al. [7] developed an approach using radial basis functions (RBFs) and reflectance sharing. Their method performs scattered data interpolation in mixed spatial and angular domain using RBFs for modeling a nonparametric reflectance function from a sparse set of images of an object with known shape. They were able to reduce the desired number of images in case of objects with uniform materials but stopped short of describing any principled approach for selecting suitable measurement directions.

Lawrence et al. [10] developed an inverse shade tree framework for representing and editing non-parametric material BRDFs.

This framework allowed them to reduce the high dimensional datasets into a compact representation that can be edited easily. However their method requires building a regularly sampled data matrix before factorization can be applied which eventually requires dense sampling of materials under consideration.

More recently Chandraker et al. [8] described a semi parametric regression based approach for BRDF estimation of objects composed of uniform materials and showed that BRDF estimation is possible under the limiting case of a single input image. Based on these insights Lombardi et al. [9] developed an approach for estimating the BRDF for objects with multiple materials using a parametric reflectance model and Markov Random Fields (MRFs). Although both of these approaches are fairly attractive however using very few observations often leads to inaccuracies specially at grazing angles where the behavior of the observed reflectance changes significantly and too few observations are often insufficient for modeling a diverse set of materials accurately.

Ali et al. [11] proposed an optimization method for sampling the BRDF at a single point on the surface and here we build upon their work and couple the knowledge of object geometry with BRDF statistics from a fixed view position for recovering the BRDF of the materials comprising the object. We propose a principled approach for finding the most suitable set of light source directions and show that by using a small number of images captured using light source directions suggested by our method it is possible to recover the bivariate BRDF of the materials, thus modeling the objects appearance efficiently.

3. Proposed Method

3.1 Reflectance Modeling of Objects

We propose an optimization method for the planned sampling of objects composed of uniform materials which enables the selection of most suitable set of light source directions for modeling BRDFs of the unknown materials comprising the object appearance. In our approach, we assume a fixed view direction and a known object geometry, besides we capture images of an object by rotating a point light source around it. We propose to consider the statistics of real-world BRDFs for efficient selection of light source directions.

3.2 BRDF Statistics

We make use of the MERL BRDF dataset [1], [2] for learning the statistics of real world BRDFs. There are 100 materials in this dataset and the measurements were made using Rusinkiewicz half vector parameterization [4] of the BRDF. In this parameterization four angles are used to describe the BRDF namely: theta half (θ_h), theta difference (θ_d), phi difference (ϕ_d) where as phi half (ϕ_h) is not considered for isotropic BRDFs. However it has been shown previously by Romeiro et al. [3] that the 2D bivariate approximation of the 3D BRDF is sufficient for modeling variations in materials as long as the observed radiance shows little change when the light and view vectors are rotated about the half vector. This minimization reduces the dimensions of the BRDF significantly as (θ_h) and (θ_d) are only used to describe the BRDF. The parameterizations are visualized in **Fig. 1**.

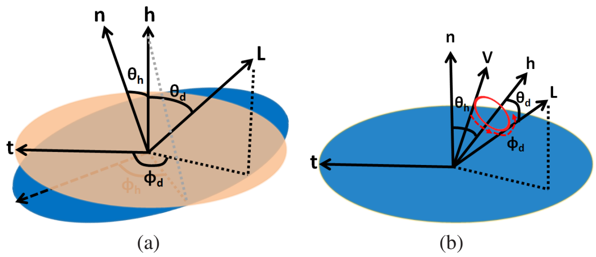


Fig. 1 (a) Rusinkiewicz, (b) 2D Bivariate parameterization.

Using this representation, the BRDF data corresponding to all materials is organized in a matrix $\mathbf{H}$ preserving the correspondence of angles in bivariate space such that each material is placed in a different column. The dimensions of $\mathbf{H}$ after all materials are placed in it is $X \times Y$, where X is the number of sampling directions and Y is the number of materials. Normally BRDF values of specular and matt surfaces are scaled differently (high dynamic range). If these values are used with the original scaling then future analysis will associate more importance to the noise in specular highlight as compared to non-specular components. To address this issue, the natural logarithm of all observations in $\mathbf{H}$ is computed.

Then to model the statistics of these existing BRDFs of uniform materials we perform Principal Component Analysis (PCA) of $\mathbf{H}^{\mathbf{T}}\mathbf{H}$ and obtain a compact representation in the form of basis. Let us represent this compact basis with $\mathbf{V}_K$, with K being the number of basis.

3.3 Optimal Selection of Light Sources

Notations: Let us represent the set of M light sources around the object with $\mathbf{Q} = \{Q_1, Q_2, ..., Q_m, ..., Q_M\}$ while set $\mathbf{P} = \{P_1, P_2, ..., P_w, ..., P_W\}$ contains optimally selected light sources (empty initially). $\mathbf{N}$ represents all surface points of the object while $\mathbf{S}_m = \{s_{m,1}, s_{m,2}, ..., s_{m,r}, ..., s_{m,R}\}$ represents the visible and illuminated points of the object for the light source Q_m. The matrix $\mathbf{G_P}$ contains statistics of existing BRDFs collected for the selected set of light sources in set $\mathbf{P}$.

Next we describe an optimization procedure whose objective is to find a small set of light source directions around the object which will then be used for reconstructing complete BRDFs. The procedure described here will achieve this by simulating the contribution made by each light source in modeling the appearance of the object using the statistics of existing BRDFs.

Using this procedure we want to build a matrix $\mathbf{G_P}$ which is a subset of $\mathbf{V}_K$. However unlike $\mathbf{V}_K$ which contains all sampling directions (θ_h, θ_d) matrix $\mathbf{G_P}$ only contains samples $\mathbf{S}_m \subset \mathbf{N}$ for selected light sources. For instance, if an object consists of 100 surface normals then this results in providing 100 different sampling directions for a given light source. The matrix $\mathbf{G_P}$ will be used later for linearly reconstructing the BRDF of the unknown material using a small set of observations which requires that we build the matrix such that its condition number is minimal.

We intend to select sampling directions from $\mathbf{V}_K$ for a particular light source into $\mathbf{G_P}$ if they decrease the condition number of the matrix. The condition number is used here as a measure of uncertainty in modeling the object appearance with a given

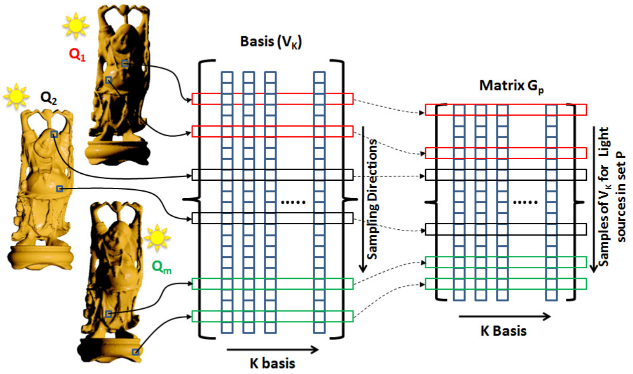


Fig. 2 The overview of the proposed method. Matrix $\mathbf{G_P}$ is built using a subset of unique sampling directions from $\mathbf{V}_K$ by evaluating all light sources in $\mathbf{Q}$. At the end of the optimization process of Section 3.3 $\mathbf{G_P}$ contains samples corresponding to the selected light sources in set $\mathbf{P}$.

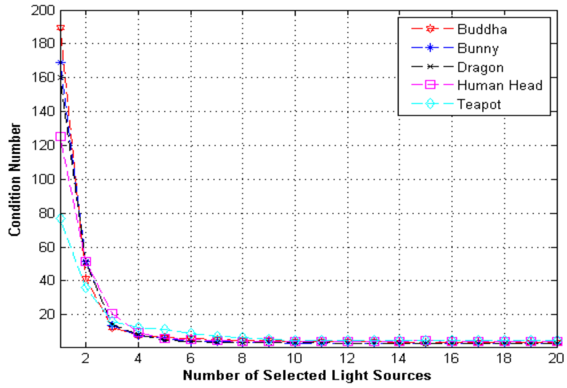


Fig. 3 The decrease in condition number for several objects used in the experiments is shown as more light sources are selected. It can be observed that no change in condition number occurs after a small number of light sources ranging from 5-9 are selected.

light source. It tells us how inaccurate the resulting solution will be after an approximation using the selected light source and its corresponding samples in $\mathbf{G_P}$ is obtained.

The stepwise iterative procedure for selecting light sources is described below and summarized in **Fig. 2**.

(1) Choose a light source direction from $\mathbf{Q}$ and obtain object surface points $\mathbf{S}_m \subset \mathbf{N}$.
(2) Then $\forall s_{mr} \in \mathbf{S}_m$ the local surface angles $(\theta_i, \phi_i, \theta_v, \phi_v)$ are reparameterized to half angle representation (θ_h, θ_d) which serves as an index into the rows of matrix $\mathbf{V}_K$.
(3) Select samples (θ_h, θ_d) from $\mathbf{V}_K$ $\forall s_{mr} \in \mathbf{S}_m$. These samples are then placed in matrix $\mathbf{G_P}$. The samples from $\mathbf{V}_K$ for different color channels are grouped one after the other in $\mathbf{G_P}$.
(4) Calculate the condition number of $\mathbf{G_P}$. The condition number can be obtained by calculating the ratio of maximum and minimum Eigen values of $\mathbf{G_P^T G_P}$.
(5) Repeat steps 1 to 4 for all light sources in $\mathbf{Q}$ one at a time.
(6) Select the light source direction which gives the lowest condition number for matrix $\mathbf{G_p}$. Add the light source to the selected set $\mathbf{P}$.
(7) Update $\mathbf{G_P}$ to contain unique samples from $\mathbf{V}_K$ $\forall s_{mr} \in \mathbf{S}_m$ of the selected set of light sources in $\mathbf{P}$.
(8) Repeat steps 1 to 7 until the condition number of $\mathbf{G_P}$ can no longer be minimized after the addition of a new light source to set $\mathbf{P}$.

This method provides a principled approach for evaluating the contribution of each light source in modeling the appearance of objects. At the end of this optimization process a set of most suitable light source directions for sampling the appearance of the object will be obtained in set $\mathbf{P}$ and matrix $\mathbf{G_P}$ will contain the corresponding samples from $\mathbf{V}_K$ with a sufficient and optimized set of constraints for reconstructing the unknown material effectively. **Figure 3** shows a plot of condition number for several objects as it decreases with the selection of more light sources.

3.4 Discussion

In Section 3.5 matrix $\mathbf{G_P}$ will be used for the reconstruction of the BRDF of materials comprising the object and is involved in inversion in a linear system. Therefore the choice of condition number for obtaining an optimized set of samples in $\mathbf{G_P}$ emerges to minimize the uncertainty in modeling the object appearance for a given light source. It provides a metric which without making any new measurements can tell when the linear system is stable enough to be solvable reliably. Besides, it estimates the sensitivity of the output to a small change in input which is essential to the minimization of modeling error of the BRDF of an unknown material using the light sources in set $\mathbf{P}$.

Moreover the light source directions selected by this procedure are based on the statistics of a diverse set of materials including numerous commonly found materials therefore it can generalize well for modeling the appearance of the same object even when it is composed of different types of materials.

Further, a light source is selected based on the criteria of the minimum condition number of $\mathbf{G_P}$. Given a fixed view, a light source direction and an object shape the resulting samples (θ_h, θ_d) selected from $\mathbf{V}_K$ will always be the same. Based on this when the first light source in selected into $\mathbf{P}$ the corresponding matrix $\mathbf{G_P}$ will give some condition number for samples of every evaluated light source direction. Among them the minimum value will be the same and will result in the selection of the same light source direction irrespective of how many times this procedure is repeated.

This same principle applies to the selection of other light sources. Repetitive selection and addition of samples for different light sources based on minimum condition number than the previous iteration leads to a continuous decrease in the condtion number of matrix $\mathbf{G_P}$. This condition number eventually comes closer to one as indicated in Fig. 3 thereby guaranteeing the convergence of $\mathbf{G_P}$ to an optimized set.

Besides it must be mentioned explicitly that the procedure described above is a simulated run and does not need actual measurements to be made as it evaluates light sources using existing BRDF measurements.

3.5 Reconstruction of BRDF Using Selected Light Sources

We capture the images of the object using selected light source directions and then reconstruct the BRDF of the material. For reconstruction, the linear system of equations needs to be established appropriately and the simplistic formulation using basis can be expressed as:

$$\mathbf{V_K c} + \mathbf{m} = \mathbf{b} \quad (1)$$

where $\mathbf{c}$ represents the coefficients vector, $\mathbf{b}$ is the newly acquired material sample and $\mathbf{m}$ is the mean vector of $\mathbf{H}$.

However while selecting the light sources we simultaneously built the matrix $\mathbf{G_P}$ containing sample from $\mathbf{V}_K$ for all light sources in set $\mathbf{P}$. Let us update our linear system to reflect this as:

$$\mathbf{G_P c} + \mathbf{m_P} = \mathbf{b_P} \quad (2)$$

where $\mathbf{b_P}$ contains actual measured pixel values of the object acquired using selected light sources in set $\mathbf{P}$, $\mathbf{m_P}$ contains the mean of $\mathbf{H}$ corresponding to the selected sampling directions of $\mathbf{G_P}$.

The organization of samples in $\mathbf{b_P}$ follows a similar arrangement to that of $\mathbf{G_P}$. The only unknown in Eq. (2) is $\mathbf{c}$ and solving for it involves taking the pseudo inverse of matrix $\mathbf{G_P}$. The system of equations with this modification can be expressed as:

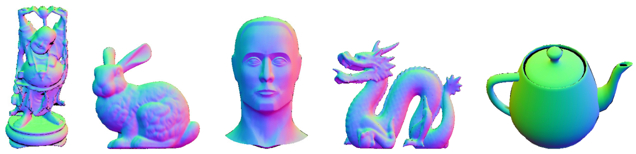
$$\mathbf{c} = (\mathbf{G_P^T G_P})^{-1}\mathbf{G_P^T}(\mathbf{b_P} - \mathbf{m_P}) \quad (3)$$

After calculating the coefficient $\mathbf{c}$ the BRDF of the material comprising the object can be reconstructed using Eq. (1) treating vector $\mathbf{b}$ to be the only unknown. While performing the reconstruction, all color channels are treated independently and separate reconstruction is performed for each of them.

4. Experimental Results

In order to evaluate the effectiveness of the proposed method, experiments are conducted using several objects such as: Buddha, Bunny, Dragon, Person Head, Teapot and Sphere. Some of these objects are shown in **Fig. 4**. MERL dataset [2] is used in these experiments which covers numerous commonly found materials i.e., plastic, metals, fabrics, wood and rubber. We calculate the percentage error (RMS/L2 Norm) metric between the actual measured BRDF and the reconstructed BRDF using the selected light sources.

We use 1,000 light sources distributed randomly around the object for analysis and a value of $K = 45$ is used as these basis capture more than 99% of the variance in the dataset thus representing the diverse materials compactly. Using a very small value of K can adversely affect the reconstruction of matt surfaces which have a smaller magnitude as the basis representation will treat such values as insignificant components. Further, in order to perform an unbiased evaluation, the dataset is divided into two groups i.e., a basis set and a test set of materials. The basis set has 80 materials while the test set contains 20 materials. All materials are randomly distributed among the two sets. Further 10 such random configurations are constructed and the results presented in **Table 1** are averaged for all such groupings.



(a) (b) (c) (d) (e)

Fig. 4 Some of the objects used for experiments (a) Buddha (b) Bunny (c) Human Head (d) Dragon (e) Teapot.

Table 1 summarizes the results for several objects. For each model we evaluate the performance using two sets of selected light sources. We also compare the performance of informed selection using the method of Section 3.3 with that of the random selection. Since random results vary over multiple runs we report the mean and standard deviation obtained over several runs. For the Buddha and Bunny models, 7 light sources are selected and it can be seen that no significant change in error occurs for informed selection as the number of light sources is increased to 9. Likewise for the Dragon, Teapot and Sphere objects no significant change in error is observed with the addition of 2 more lights sources. However in case of the Head object we do observe an improvement when the number of light sources is increased from 5 to 7.

It must be mentioned explicitly that the second set of light sources for all objects in Table 1 is deemed most suitable by the method of Section 3.3. However we select even fewer sources taking into account a relatively small change in the condition number with increasing light sources. This effect is also quite evident in Fig. 3. We need more light sources for modeling the BRDF of teapot model because its 3D model has only 1,195 vertices compared to 32,458 for buddha and 35,432 for the bunny models. The human head model is also relatively sparse with 4,540 vertices. The results for random selection for the sphere object are closer to informed selection because this shape does not exhibit directionality and the smoothly varying surface creates enough distinct normals and is less dependent on the directionality of light sources due to its similar curvature at all angles.

Besides, the object geometry does influence the required number of light sources for an object. However for a given light source, the variations in surface normals provide different (θ_h) values while different light source directions provide variations in (θ_d). If an object exhibits fewer variations in surface normals i.e., (θ_h) then it will require more observations for reliable reconstruction. Considering this the difference in the number of light sources which define (θ_d) should not be significantly large for different shapes and the same phenomenon is exhibited in the results in Table 1.

Finally we provide detailed results in **Fig. 5** for all 100 materials from the MERL dataset and compare it with bivariate ap-

Table 1 Detailed experimental results for several objects.

Model Name	Selected Light Sources	Percentage Error Informed Selection	Percentage Error Random Selection	Std. Dev. Random Sel.
Buddha	7	4.47	9.1	1.8
	9	4.31	8.17	1.73
Bunny	7	4.67	9.36	1.92
	9	4.27	7.65	1.73
Dragon	5	4.95	10.1	2.3
	7	4.45	8.81	2.12
Head	5	5.62	11.2	2.7
	7	4.83	9.8	2.25
Teapot	9	4.91	11.5	2.98
	11	4.72	9.2	2.43
Sphere	5	4.97	7.95	1.63
	7	4.48	7.26	1.1

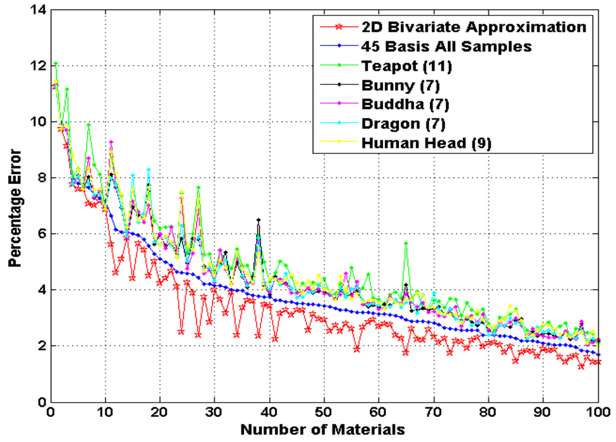


Fig. 5 Reconstructed BRDF using different models is compared with bivariate approximation and all samples and 45 basis for all 100 materials. The number in brackets indicates the number of light sources used for the reconstructions.

(a) (b)

Fig. 6 (a) Original Measured BRDF (yellow phenolic) (b) Reconstruction using 7 light sources for the bunny model.

proximation and all samples. As we select light sources based on the properties of various materials and not for a specfic material, the estimated BRDF and bivariate results appear correlated. Besides, visual renderings for the reconstructed BRDF using the bunny model and an environment map are shown in **Fig. 6**. The environment map for this rendering is used from Debevec [12]. This demonstrates that a small number of light source directions selected in an appropriate manner can yield fairly good reconstructions of the BRDF from diverse object shapes.

5. Conclusion

In this paper we proposed a new method for modeling the BRDF of the uniform materials comprising the objects appearance using a small number of light sources with a fixed view direction. Our method achieved this by evaluating the contributions made by different light sources in modeling the object appearance using statistics of existing BRDFs. The detailed experimental results conducted on several objects with diverse shapes using the MERL BRDF dataset validate the effectiveness of the proposed method compared to random selection. In future we plan to extend this to objects with spatially varying BRDFs in an appropriate manner.

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(Communicated by *Hiroshi Ishikawa*)