Non-linear Reflectance Model for Bidirectional Texture Function Synthesis

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Abstract

A rough texture modelling involves a huge image data-set - the Bidirectional Texture Function *(BTF). This 6-dimensional function depends on planar texture coordinates as well as on view and illumination angles. We propose a new non-linear reflectance model, based on a Lafortune reflectance model improvement, which restores all BTF database images independently for each view position and herewith significantly reduces stored BTF data size. The extension consists in introducing several spectral parameters for each BTF image which are linearly estimated in the second estimation step according to the original data. The model parameters are computed for every surface reflectance field contained in the original BFT data. This technique allows BTF data compression by the ratio 1:15 while the synthesised images are almost indiscernible from the originals. The method is universal, and easily implementable in a graphical hardware for purpose of real-time BTF rendering.*

1 Introduction

Recent virtual reality systems aim for preserving reflective properties of rough textures as close as possible to an original material during different illumination and view positions. The only way how to reach real visual perception of observed texture is to measure its reflectance properties. These global illumination and view dependent real material properties were introduced in work of Nicodemus [12] and called the 4D *Bidirectional Reflectance Distribution Function* (BRDF). BRDF describes relation between incident light from direction $\omega_i(\theta_i, \phi_i)$ and light reflected by observed material $\omega_v(\theta_v, \phi_v)$ (see Fig.2) and was approximated by variety of reflectance models applied to computer graphics object rendering. BRDF is insufficient for textures hence a *Bidirectional Texture Function* (BTF) was introduced in [1] to solve this constraint. BTF describes reflectance of each pixel (1) based on illumination and view position. Hence this function is dependent on illumination and view angles as well as on planar position on observed material surface (see Fig.2), i.e., $BTF(r_1, r_2, \omega_i, \omega_v) = BTF(r_1, r_2, \theta_i, \phi_i, \theta_v, \phi_v)$.

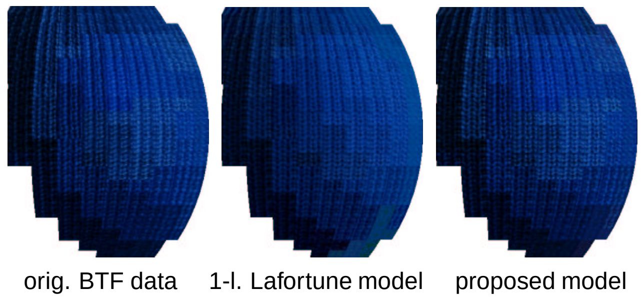


Figure 1. BTF rendering example.

BTF modelling is a new research area, one of the first BTF measurements were provided by Dana [1] but these BTF measurements suffer with image rectification. In [9] each pixel luminance was approximated by biquadratic polynomial, while chrominance was supposed to be constant. This approach (polynomial texture maps) suffers [11] with following specularity while grazing angles grow and with the diffuse material requirement. Several other solutions were published such as the per-pixel Lafortune model [2, 10], or extension [2] by additional lookup table to handle occlusion effects and to correct colour hue values, a slight modification of a two lobes Lafortune model was implemented in the graphic card processing unit [11]. Alternative approaches to BTF synthesis are based either on intelligent sampling techniques [8], [3, 4] or on adaptive multidimensional statistical models [6, 5]. In this paper an improvement of pixel-wise anisotropic one lobe Lafortune model [7] is proposed.

2 BTF data

BTF measurements comprehend whole hemisphere of light and camera positions in observed material sample coordinates according to selected quantisation steps. We used the Bonn University BTF dataset [14]. Fig.2 illustrates directional illumination source course above the sample for fixed view position. The BTF dataset contains 6561 images per texture sample (81 view and 81 illumination positions). All images are rectified to head-on view position ($\theta_v = 0^o, \phi_v = 0^o$) and resampled to obtain norm-textures of size 256×256 pixels. Effects presented in rough textures such as occlusions, self shadowing, interreflection or subsurface scattering are preserved and the size of samples is sufficient for some tiling methods e.g. [3, 4] but inadequate for efficient learning for some probabilistic models (e.g., discrete mixtures) [6, 5]. Unfortunately only measurements from the same view position are sufficiently rectified. Different view measurements suffer with registration errors even after the rectification process due to self-occlusion. Therefor the correct way how to model such a real measurements is to employ modelling step for each BTF subset comprehending all images obtained for a fixed view position. Such a BTF slice for a view position ω_v is a 5D function called *Surface Reflectance Field* $\mathcal{R}_v(r_1, r_2, r_3, \theta_i, \phi_i)$ which describes the radiance of the surface point $r = (r_1, r_2, r_3)$ where r_1, r_2 are planar coordinates on a sample and r_3 is the actual spectral band.

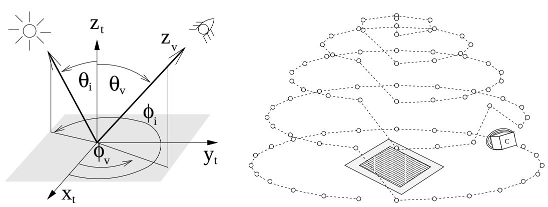


Figure 2. Relationship between illumination and viewing angles (left). Light vector trajectory above the sample (right).

3 BTF Reflectance Model

Single surface reflectance fields ($\mathcal{R}$) (i.e. 81 images - n_i) for an actual view position v can be per-pixel modelled using n_l-lobe Lafortune model [7] described in the following formula

$$Y_v(r,i) = \sum_{k=1}^{n_l} \rho_{k,v,r} (\omega_i^T \mathbf{C}_{k,v,r})^{n_{k,v,r}} \qquad (1)$$

where $\omega_i(\theta_i, \phi_i) = [u_x, u_y, u_z]^T$ and $\mathbf{C}$ is diagonal parameters matrix. As a texel is considered the set of pixels $\tau_v(r_1, r_2, r_3) = \mathcal{R}_v(r_1, r_2, r_3, \omega_i, \forall i)$, where $i = 1, ..., n_i$ and $v = 1, ..., n_v$ are illumination and view position indices respectively. One-lobe Lafortune model simplifies to

$$Y_v(r,i) = \rho_{v,r}(C_{v,r,x}u_x + C_{v,r,y}u_y + C_{v,r,z}u_z)^{n_{v,r}}$$

For every texel $\tau_v \in \mathcal{R}_v$ all the model parameters (ρ, C_x, C_y, C_z, n) can be estimated using for example the Levenberg-Marquardt non-linear optimisation algorithm [13].

During our testing it became obvious that the reflectance function approximation by one-lobe Lafortune model is unsatisfactory especially in cases of complex BRDF when the reflectance values are changing very fast during illumination movement. This situation occurs more apparently at higher grazing angles when the light shines in direction to camera causing significant specular reflections. The problem of one-lobe Lafortune model fitting for original data is illustrated in Fig.3. We computed BRDF for $\mathcal{R}_v - \theta_v = 60^o, \phi_v = 54^o$ of *knitted wool* as average value per individual colour spectrum through size of original $\mathcal{R}_v$ $N_x \times N_y$ (solid line) and compared it with BRDF obtained in the same way from estimated $\mathcal{R}_v$ (dashed line). From this we conclude that used one-lobe model is not able to follow such a steep changes of reflectance function, which are presented in variety of materials. This behaviour considerably depends on properties of individual material sample.

Generalisation of this model with additional reflectance

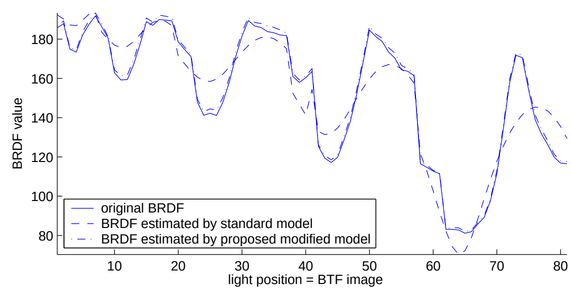


Figure 3. Comparison of original BRDF (solid line) and BRDF estimated by Lafortune model (dashed line) for complicated anisotropic material - ***knitted wool*** **for $\mathcal{R}_v - \theta_v = 60^o, \phi_v = 54^o$.**

lobes improve its performance however such a model still fails at grazing angles where the considerable difference between original and estimated reflectance values persists.

In addition the n_l lobes results in $n_l \times$ more parameter to store in graphic card, which we want to avoid and the lobes-fitting procedure is then more complex and time consuming. Even the general Lafortune model with all the parameters in parameter matrix $\mathbf{C}$ (not only the diagonal or symmetric ones) did not significantly improved the mentioned artifacts.

An introduced solution is Lafortune model extension by several spectral parameters specifying an unknown mapping function between original and the synthesised image histograms. We assume this function approximated by the polynomial expansion, which maps previous one-lobe Lafortune model BRDF to a new value according to equation

$$\hat{Y}_v(r,i) = \mathcal{M}_{r,v,i}(Y_v(r,i)) = \sum_{j=0}^{n} a_{r,v,i,j} Y_v(r,i)^j \qquad (2)$$

resulting in the new model expressed by the following formula:

$$\hat{Y}_v(r,i) = \sum_{j=0}^{n} a_{r,v,i,j}[\rho_{r,v}(\omega_i^T \mathbf{C}_{r,v})^{n_{r,v}}]^j \tag{3}$$

where $a_{r,v,i,j}$ are polynomial parameters specifying mapping function $\mathcal{M}_{r,v,i}$ between histogram values of the original BTF image to image $Y(r)$ synthesized according Lafortune parameters estimated in previous step and n is rank of this polynomial. The parameters $a_{r,v,i,j}$ are estimated by least squares fitting on the original mapping function quantised into 8 bits. Satisfactory results were obtained already with $n = 4$. Thus corresponding fifteen float numbers have to be stored with each BTF image.

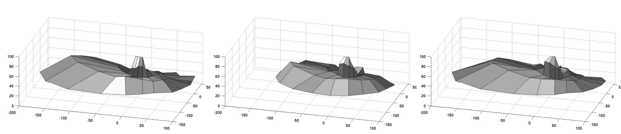
4 Results

During extensive tests performed on two BTF datasets from the University of Bonn: *knitted wool* and *proposte* the Lafortune model coefficients were estimated for all 81 surface reflectance fields $\mathcal{R}_v, \;\; v = 1 \ldots n_v$. Based on these parameters all BTF images were synthesised. For both materials the results of one-lobe Lafortune model were compared visually as well as numerically with the proposed model. For comparison the standard mean average distance (MAE) between original and estimated data was used.

In Fig.4 are depicted results for two different $\mathcal{R}_v$ – original images (upper row) in comparison with images synthesised by standard one-lobe model (middle row) and our modification (bottom row). From these images is apparent that the proposed method preserves colour hues and results in sharper images in comparison with the standard model. This is caused by stretching the histograms which results in increased contrast – distance of individual colour levels which enables to recognise for example two neighbouring colour levels which were in standard Lafortune result perceived as one colour hue.

The Fig.3 also depicts how the averaged BRDF computed by the proposed method (dash-dot line) follow the original average BRDF (solid line).

How the chosen model influence the shape of BRDF lobe in comparison with original measured BRDF lobe in texel $\tau(3, 13)$ of *knitted wool* is illustrated in Fig.5. Fig.6 demonstrates the performance of both methods on the whole BTF ie. for all 81 surface light fields $\mathcal{R}_v$ and for the both observed materials. The visual results and this figure leads us to assumption that *knitted wool* material covers much more complex anisotropic properties than *proposte* which can be almost correctly modelled by one-lobe Lafortune model. On the other hand the human eye is very sensitive for even smooth change of colour or brightness so proposed little difference between both method can be considerably visually apparent (check the Fig.4). The average errors overall the whole BTF for each RGB spectra and material are figured in Tab.1. The non-linear estimation of model parameters of all 81 surface reflectance fields $\mathcal{R}_v, v = 1 \ldots n_v$ comprised in BTF database for BTF image size 64×64 took less than one hour on PC Athlon 1.9GHz.



orig. BTF data 1-l. Lafortune model proposed model

Figure 5. Reflectance lobes for texel $(13, 3)$ of *knitted wool* and illumination $\theta_i = 75^o, \phi_i = 54^o$.

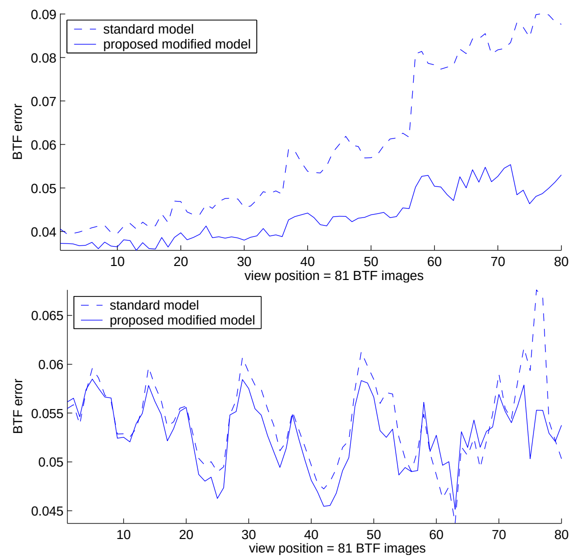


Figure 6. BTF error (MAE) for all view positions in *knitted wool* (top) and *proposte* (bottom) BTF database .

Results of BTF rendered on sphere using measured data, one-lobe Lafortune model results and proposed model results are depicted in Fig.1.

Table 1. Overall error (MAE) of synthesised BTFs.

	knitted wool			*proposte*		
method	R	G	B	R	G	B
1L Laf. mod.	0.0517	0.0655	0.0609	0.0441	0.0534	0.0649
	Average: **0.0594**			Average: **0.0541**		
Proposed 1L Laf. mod.	0.0453	0.0422	0.0423	0.0422	0.0525	0.0640
	Average: **0.0433**			Average: **0.0529**		

5 Conclusions

New reflectance model introduced in this paper enables to model BTF images visually indiscernible from their real

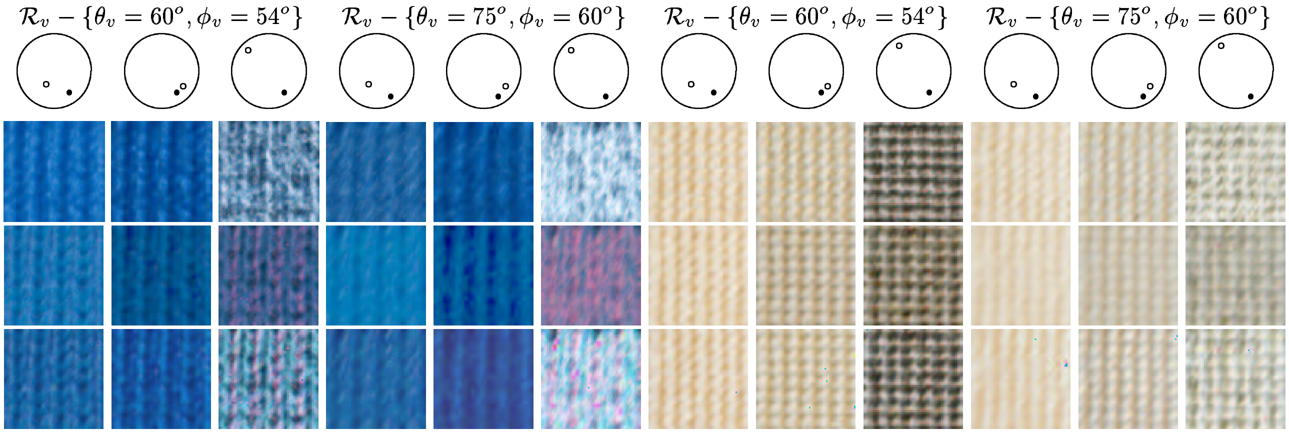


Figure 4. Synthesised BTF examples for materials: *knitted wool* **and** *proposte* **respectively. The first row describes mutual position of light (empty circle) and camera (filled circle) above the sample, the second row shows original raw BTF data . The third row shows results of standard Lafortune model and finally the fourth row illustrates results of the proposed model.**

measured counterparts. This pixel-wise anisotropic one lobe model offers - realism of perception and preserves real material appearance also in shadows and highlights areas at grazing angles unreachable by previously published models, - high compression of original BTF data, since only one lobe approximation is used, - easy computation and only a few additional parameters for each BTF image have to be stored independently on the image size. Method requires only little bit more computations per-pixel in comparison with standard Lafortune model but this is partly compensated by using of mostly only one-lobe model for parametrisation for each texel in surface light field. This parametrisation enables significant compression of original BTF data and make it possible to use this method in graphics hardware for BTF real-time rendering.

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