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ESTIMATING SURFACE ROUGHNESS FOR REALISTIC RENDERING OF FRUITS

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ABSTRACT

One important factor to render realistic images of a virtual object is a bidirectional reflectance distribution function (BRDF) that mainly governs the appearance of the object. Many BRDF models have therefore been developed. A physically-based BRDF based on the microfacet theory is widely used in many applications. The goal of this paper is to estimate the roughness parameter of a physically-based BRDF model from microstructrues measured by using laser scanning microscopies in order to render realistic images of fruits. We investigate two types of microscopies, a confocal laser scanning microscopy and a two-photon excitation microscopy, and demonstrate that the two-photon excitation microscopy is suitable for rendering fruits.

1. INTRODUCTION

A bidirectional reflectance distribution function (BRDF) plays an important role to synthesize realistic images of virtual objects. The BRDF significantly affects the appearances of virtual objects. Modeling of BRDFs is one of the major research topics in computer graphics and many BRDF models have been developed. Among them, a BRDF model based on microfacet theory [1] is widely used in many applications since it can produce highly realistic images.

The goal of our research is to estimate the parameters for the existing microfacet-based BRDFs to render realistic fruits. The microfacet-based BRDF consists of three terms; a Fresnel reflectance, a normal distribution function, and a shadowing-masking function. In this paper, we focus on the normal distribution function which is considered to be the most important factor for the microfacet-based BRDFs. For reproducing the appearance of existing materials, the user has to adjust the parameters of the BRDFs. Usually, this can be done by taking a set of photographs of the material sample and fit the parameter to the measured data. In this paper, we employ a different approach. We directly measure microstructures of surfaces and estimate the parameters for physically-based BRDFs.

We tried two different types of laser microscopies: confocal laser microscopy and two-photon excitation confocal laser microscopy. We measured surface microstructures of an apple and estimated the roughness parameters of normal distribution functions. We compared the synthetic images with photographs to validate the results. We found that using two-photon excitation confocal laser microscopy produces much better results.

2. RELATED WORK

In this paper, we focus on the physically-based BRDFs based on the microfacet theory [1]. The physically-based BRDFs determine the reflections from the surface based on the distribution of the microfacets on the surface. The physically-based BRDF usually represented as a product of a Fresnel, a shadowing-masking, and a normal distribution function. A detailed discussion on the microfacet-based BRDFs can be found in [4]. The most important factor among these terms is the normal distribution function (NDF) and several expressions have been proposed for NDF. Commonly used NDFs are: Beckmann distribution, Phong distribution, and GGX distribution [10].

The physically-based BRDFs are widely used and can produce realistic images for different materials.

We directly measure microstructures of surfaces to estimate the parameters of the physically-based BRDFs. Dong et al. also employ the same approach; they measure microstructures of metals [3]. They use a confocal laser microscopy that measures the reflected intensities of a laser beam illuminating the material sample. However, as they mentioned in [3], this device may not be used for highly scattering materials, such as foods. We use two-photon excitation microscopy to address this problem.

3. OVERVIEW

Fig. 1 shows an overview of our framework for modeling realistic appearances of fruits. The macroscopic structure of a fruit sample is measured by using an X-ray CT scanning system. We first apply a Gaussian filter in order to

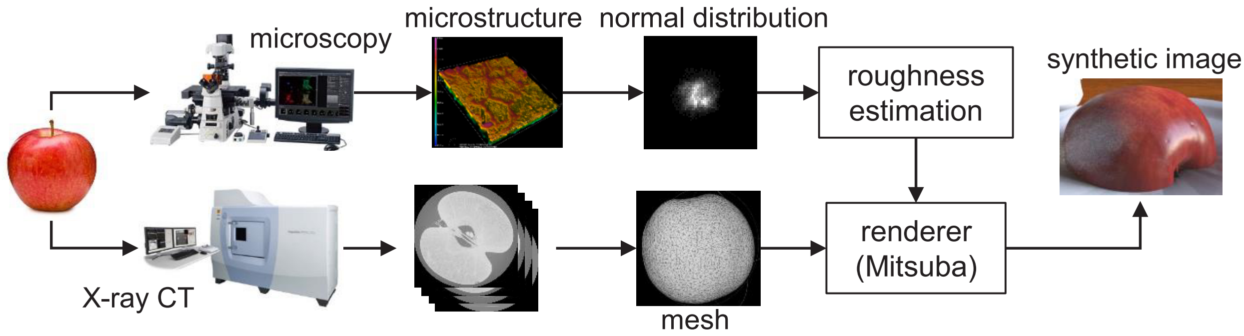


Figure 1: Our framework for modeling realistic food appearances.

remove the noise in the CT volume and then isosurfaces are extracted by using the marching cubes algorithm [7]. We further apply a few iterations of Laplacian smoothing operator to the isosurfaces to obtain smooth surfaces. The microscopic structure on the surface of the fruit is measured by using laser scanning microscopies. From the surface microstructure, we estimate a roughness parameter of the microfacet-based BRDF. Then, synthetic images of fruits are created by a path tracer [5].

In this paper, we apply our framework to the rendering of an apple. We focus on the estimation of the surface roughness parameter for the BRDF from the measured microstructures of the apple. We examine two types of laser scanning microscopies and compare the results. The results are evaluated by comparing the synthetic images and the photographs of the apple.

4. LASER SCANNING MICROSCOPY

We use two types of microscopies, namely, a confocal laser scanning microscopy (CLSM) and a two-photon excitation microscopy (TPEM). We briefly describe the mechanisms of these two types of microscopies.

CLSM is an optical imaging device that uses a spatial pinhole placed at the confocal plane of the lens to eliminate out-of-focus light [6]. This device can reconstruct three-dimensional structures from the images obtained by collecting a set of images at different depths.

Another type of the laser scanning microscopy we use is TPEM [2]. This device can also acquire thin three-dimensional structures on a microscopic scale. Different from CLSM described above, TPEM measures fluorescent light excited by a laser beam illuminating a sample. The microstructure is obtained in the form of three-dimensional volume data structure; the intensity of the fluorescent light is recorded at each voxel. The microfacet is obtained by extracting an isosurface from this volume data.

5. MICROFACET-BASED BRDF

The microfacet-based BRDF is generally expressed by the following equation.

$$f_r(l,v) = \frac{F(l,h)G(l,v,h)D(h)}{4(n\cdot l)(n\cdot v)}, \tag{1}$$

where l and v are directions of light and view, respectively, and h is the half vector between l and v. n is the normal vector at the calculation point. F is the Fresnel reflection function, G is the geometry function related to the shadowing/masking between microfacets, and D is the normal distribution function describing how microfacet normals are distributed around direction h. For the Fresnel function, we use the Schlick's approximation [9] and the refraction index is experimentally determined. The geometry function G is computed from the normal distribution function D.

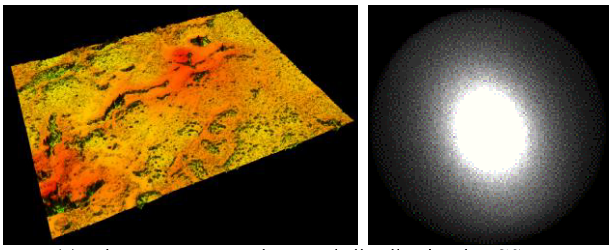
In Eq. 1, the normal distribution function D is the most important and has significant effects on the appearance of the object [3]. We also focus on the normal distribution and we assume the following normal distribution function proposed by Walter et al [10].

$$D(h) = \frac{\alpha^2}{\pi((n\cdot h)^2(\alpha^2-1)+1)^2}, \tag{2}$$

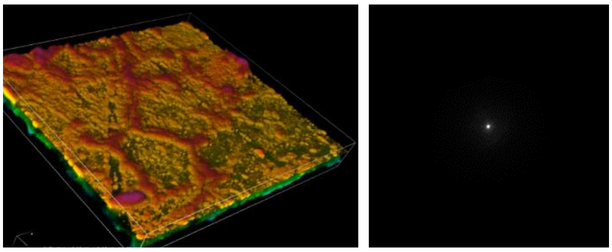
where α is a parameter controlling the surface roughness. We compute this roughness parameter from the microstructures measured by laser scanning microscopies.

6. ESTIMATION OF SURFACE ROUGHNESS

The CLSM provides us with a height map representing the surface microstructure. We can directly compute the normal distribution function from this height map. When using the TPEM, however, the volumetric microstructure near the surface is obtained. In this case, we extract an isosurface in the same way as the method for extracting the isosurface



(a) microstructure and normal distribution by CSLM



(b) microstructure and normal distribution by TPEM

Figure 2: Measured microstructures and corresponding normal distribution functions by using CLSM (a) and TPEM (b). The left images show mircostructures and the right images show normal distribution functions computed from the microstructures.

from the X-ray CT volume (see Section 3). We use the isosurface to compute the normal distribution function (NDF), $D(h)$.

The NDF is computed by using the part of the isosurface/height map that is visible from the average normal direction, i.e., the vertical direction. We represent the NDF by using a cube map texture. Each texel of the texture stores the number of normal vectors that lie within the solid angle represented by the texel. We then normalize the cube map texture so that the following equation is satisfied [4],

$$\int_\Omega D(h)(n \cdot h) d\omega = 1, \tag{3}$$

where Ω represents a set of directions over the hemisphere above the surface.

Finally, the surface roughness is estimated by fitting the GGX function (Eq. 2) to the measured NDF computed as above. We optimize the roughness parameter in the GGX function to minimize the squared difference between the GGX function and the measured NDF. We use the Levenberg-Marquardt method [8] for the optimization.

7. RESULTS

We applied our framework to the rendering of an apple. We cut a small piece near the surface and measured its microstructures by using CLSM and TPEM.

Fig. 2 shows microstructures measured by the two microscopies. The left image in Fig. 2(a) shows the height map

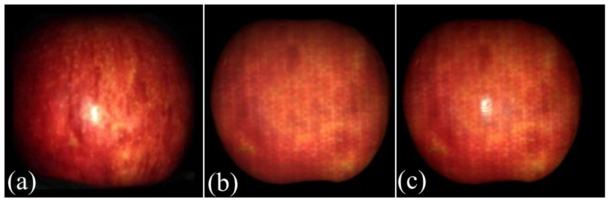


Figure 3: Comparison of synthetic images with photographs. (a) is a photograph. (b) and (c) are synthetic images rendered with roughness parameters estimated by using microstructures measured by CLSM and TPEM, respectively.

measured by CLSM. The dimension of the height map is $1424.30\mu m \times 1068.22\mu m \times 121.18\mu m$. The height map is represented with 2048×1536 grid points. The right image in Fig. 2 (a) shows the NDF computed from the height map. The left image in Fig. 2(b) shows the volume measured by TPEM and its dimension is $318.2\mu m \times 318.2\mu m \times 50.0\mu m$. The size of the volume is $512 \times 512 \times 50$. The right image in Fig. 2(b) shows the NDF computed from the isosurface extracted from this volume. As shown in these images, the NDF computed from the microstructure measured by TPEM has a sharp peak at the center of the distribution while the NDF computed from that measured by CLSM is much smoother.

We then fit the roughness parameter of the GGX function to these normal distribution functions. We compare the rendered images with the photograph of the apple. Fig. 3 shows the results. Fig. 3(a) shows the photograph of the apple. Figs. 3(b) and (c) show the synthetic images rendered with the parameter estimated by using the microstructures measured with CLSM and TPEM, respectively. We extract the diffuse texture from the photographs. The index of refraction for computing the Fresnel term is manually adjusted. This comparison indicates that the synthetic image corresponding to TPEM (Fig. 3(c)) is much similar to the photograph than that corresponding to CLSM (Fig. 3(b)). This comparison implies that, for measuring microstructure of fruits, TPEM works much better than CLSM. This is because fruits are in general highly scattering medium. CLSM measures the reflected light as well as the scattered light, resulting in the incorrect NDF.

Finally, Fig. 4 shows an image of the synthetic apple illuminated by an environment map. We use the roughness parameter that is same as that used for Fig. 3(c). As shown in this image, a highly realistic image is created.

8. CONCLUSIONS AND FUTURE WORK

In this paper, we reported experimental results for measuring surface microstructures of an apple by using two types

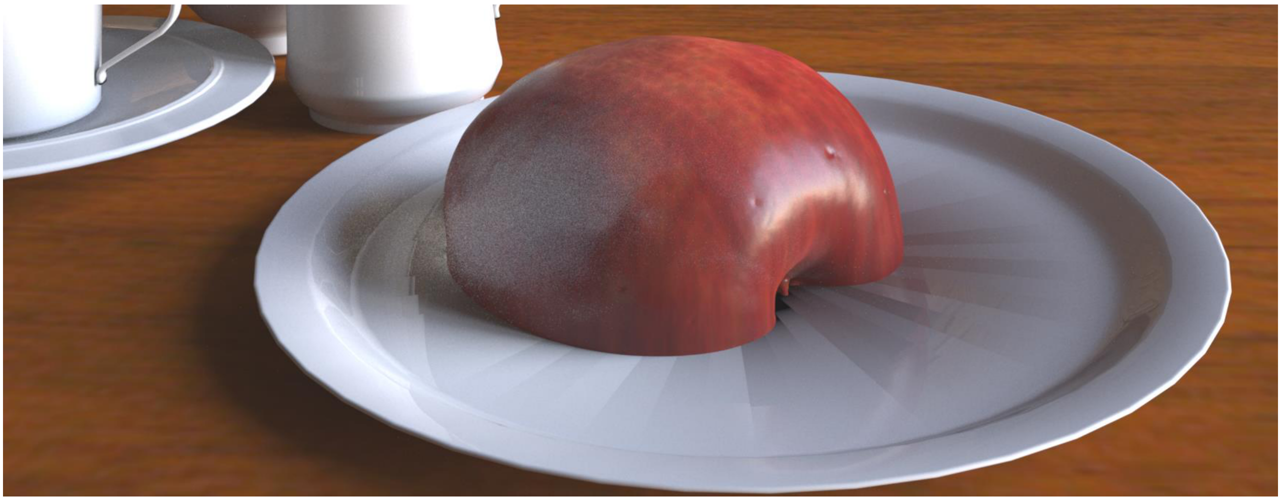


Figure 4: A rendered scene with a synthetic apple by using the microstructure measured by TPEM.

of laser scanning microscopies: a confocal laser scanning microscopy and a two-photon excitation microscopy. From the measured microstructures, we computed the normal distribution functions and fit the roughness parameters of GGX function to the measured data. From the comparisons, we concluded that CLSM is not suitable for measuring microstructures of fruits. In future, we would like to extend our framework to estimating different optical parameters other than the surface roughness for different types of foods.

ACKNOWLEDGEMENTS

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