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BTF Image Recovery based on U-Net and Texture Interpolation

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Abstract

Bidirectional Texture Function (BTF) is one of the methods to reproduce realistic images in Computer Graphics (CG). This is a technique that can be applied to texture mapping with changing lighting and viewing directions and can reproduce realistic appearance by a simple and high-speed processing. However, in the BTF method, a large amount of texture data is generally measured and stored in advance. In this paper, in order to address the problems related to the measurement time and the texture data size in the BTF reproduction, we a method to generate a BTF image dataset using deep learning. We recovery texture images under various azimuth lighting conditions from a single texture image. For achieving this goal, we applied the U-Net to our BTF recovery. The restored and original texture images are compared using SSIM. It will be confirmed that the reproducibility of fabric and wood textures is high.

1.Introduction

In recent years, realistic image reproduction technologies have been developed in the field of computer graphics (CG). When reproducing realistic CG, it is indispensable to accurately reproduce the appearance of the object surface. The appearance of the object is significantly influenced by the color, unevenness, texture, and reflection characteristics of the object. A bidirectional reflectance distribution function (Bidirectional Reflectance Distribution Function, BRDF) and a texture mapping using a bidirectional texture function (Bidirectional Texture Function, BTF) are frequently used for reproducing the CG appearance.

BRDF is a function that shows the reflectance characteristics of object surfaces and the ratio of the incident and the reflected light intensity at a certain point on the object surface. The surface shape and material can be reproduced by using the BRDF and calculating the light reflection. CG by BRDF is correctly reproduced by physical shape and reflection characteristics. Once BRDF measurement is completed, even if conditions such as lighting and camera (viewpoint) position change, it can be repeatedly recovered by the recalculation. However, the disadvantage is that it takes time to measure and calculate BRDF.

A wide range of researches has been proposed based on BRDF for speeding up measurement methods and for restoring BRDF using one or a few images without measurements using deep learning [1, 2].

Bidirectional Texture Function (BTF) is a 7-dimensional function that depends on the illumination and viewpoint directions at a certain coordinate. It shows sample images measured by various combinations of illumination and viewpoint directions. Although the physical shape of the object surface is unknown, it can represent the appearance of the object surface and reproduces irregularities, textures, and Shitsukan. BTF data is generally used for texture mapping, which is a technique for reproducing the appearance of CG. BTF is a technique in which a large number of texture image datasets are prepared in advance. A texture image that corresponds to the lighting and viewing conditions to be reproduced is selected and mapped from the dataset to a CG scene. The BTF-based method does not need BRDF measurement and calculation time in the CG reproduction processes. Compared to the BRDF-based rendering method, the BTF-based method have advantages in both measurement and calculation time. Since the texture image is reproduced simply by mapping it into the scene, if there is no texture under the suitable conditions that completely match the situation, a similar one will be substituted. In this case, the restoration accuracy will be reduced compared to the BRDF-based rendering. However, with regard to the reality of CG, it is more important whether humans feel reality without perceptual incompatibility rather than physically accurate reproduction. Therefore, if human beings are able to reproduce within a range that does not feel perceptual incompatibility with reality, they can see realistic CG appearance. The BTF-based method is often used in the CG reproduction because it can be reproduced with little rendering cost with maintaining a certain level of quality. However, it is necessary to collect a lot of texture images under various conditions in advance. It takes much time to collect data. Even with a single texture, the appearance changes depending on various conditions such as lighting and viewing directions. Therefore, image measurements are required for each condition. In addition, the texture image database is enormous. Furthermore, the collection is very difficult due to the requirement of special measurement instruments. Measuring samples to create a texture mapping database would take a lot of time, and the advantage of the BTF-based technique would be decreased. When the difficulty of data collection disappears, the problem of the BTF-based texture mapping will be solved.

Since the measurement of BTF images requires a huge amount of measurement from various directions of illumination and viewing directions, various researchers have developed measurement methods [3, 4]. Although researches on BTF have been proposed, no method has been proposed for recovering BTF from one or several images.

Recently, the BRDF-based CG can be reproduced by deep-learning techniques [1, 2]. On the other hand, deep-learning-based BTF restoration method have not been proposed yet. Since BTF requires a lot of data measurement in advance, it is very useful to restore the entire BTF dataset from a small number of BTF images.

In this paper, we propose a BTF image recovery method from a single image using deep learning. Our method focuses on the illumination direction change for a specific material texture. The difference between input and output images depends on shading due to the lighting directions. Therefore, we considered that U-Net [5], which can learn while maintaining the characteristics of the local region, is suitable for the method of this study.

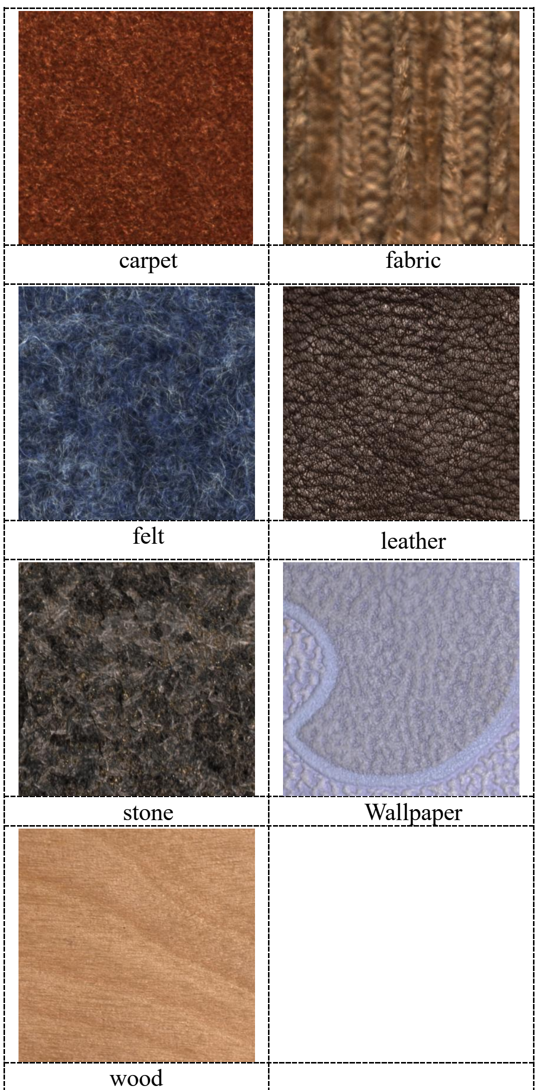

Figure 1. Examples of 7 categories of BTF images

Table1: BTF database details

	Light	Camera
Azimuth	-178°～180° 2° increments	-
Elevation angle	15°～75° 15° increments	0°
Per sample：900 images		
Per category：12 samples		
Total：75600 images		

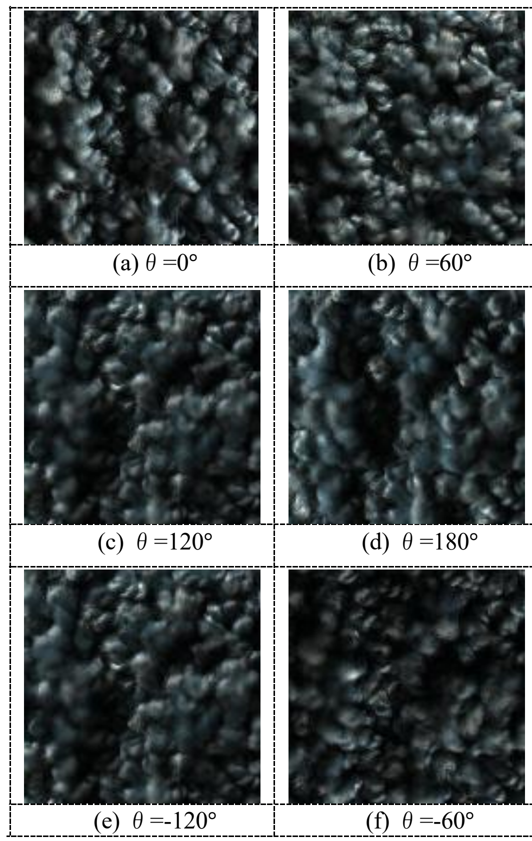

Figure 2. BTF image of "carpet" generated by changing the azimuth angle of illumination

2. Database Construction for Deep Learning

2.1. Overview of BTF database

In order to create a network for recovering BTF images under arbitrary conditions, data under various conditions is required as training data. In this study, we constructed the BTF image database using UBO2014Datesets [6] published by Weinmann et al.

In UBO2014Datasets, BTF is measured by shooting from the 21801 direction by combining the 151 light source directions and the 151 viewing directions for each sample.

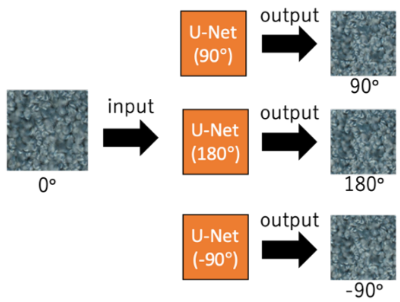

Figure 3. Image restoration process using U-Net

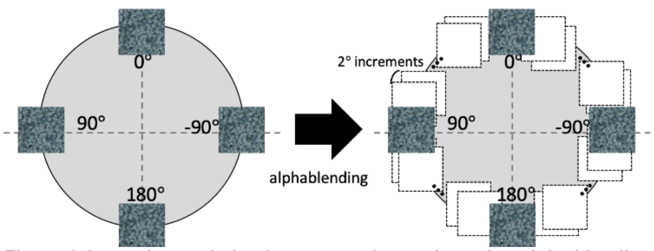

Figure 4. Image interpolation between major angles using alpha blending

There are seven categories of data content: "carpet", "fabric", "felt", "leather", "stone", "wallpaper", "wood." Each category includes 12 samples. The total number of samples are 84 types. An example of each category is shown in Fig. 1.

2.2. Database generation result

In this study, we need a dataset with different illumination positions. Then, we constructed a dataset with different illumination azimuth and zenith angles. Table 1 shows the details of the database. There were 900 images per a sample, and it was constructed in the same way for all 84 samples in 7 categories. Finally, a total of 75600 images were prepared. All image sizes are 400 × 400 pixels. Fig. 2 shows an example of a "carpet" image with changing the azimuth of the lighting directions.

3. Proposed BTF Image Generation

The azimuth angle of the illumination directions is recovered for 360°. In this study, we recovered 180 images with the interval of 2° increments. First, we recovered texture images under 90. 180, and -90° illumination directions changes from a base texture image (0° illumination direction) using U-Net. Second, we generate an arbitrary image by the interpolation between two of the 0, 90. 180, and -90° illumination directions. The details of our method is as follows.

3.1. Texture recovery by U-Net

Figure 3 shows the procedure for our image recovery using U-Net. U-Net learn the difference of appearance due to the illumination directions for each sample. The input image is set as the 0° azimuth illumination angle. In the U-Net, we recover 90, 180, and -90° from the 0° texture images. The deep networks were learned independently for each illumination angle.

Generative adversarial networks such as CycleGAN [7] and StarGAN [8] were tested for recovering the BTF image recovery because the image generation with the illumination position change is regarded as domain transformation. However, the purpose of this study is to faithfully reproduce the partial change of appearance due to the difference in lighting position in a texture and not due to the overall feature of the image. For this reason, we tried to learn the appearance difference due to illumination position changes using U-Net. Thus, the U-Net can maintain local features, and to generate an image with converted illumination angle.

3.2 Angle interpolation with alpha blending

Figure 4 shows the procedure for interpolating the angle between the images by alpha blending. We generated an image of an arbitrary azimuth angle from two of the 0, 90. 180, and -90° illumination directions. In this study, we generated 180 images which cover 360° azimuth angle with the interval of 2 degrees. We interpolated images based on the alpha blending between paired images (0° and 90°, 90° and 180°, 180° and -90°, and -90° and 0°).

4. BTF Image Generation Results

4.1 BTF image generation using U-Net

Figure 5 shows the original image and the B TF image recovered by U-Net under the main four illumination directions. To evaluate the reproducibility of the generated BTF image, we used SSIM as the evaluation scale. Table 2 shows the average SSIM calculation results for each category of BTF images generated using U-Net. As shown in Table 2, the restoration accuracy varies from category to category. Among them, fabric and wood show particularly high values. In other words, fabric and wood texture images can be well recovered by U-Net.

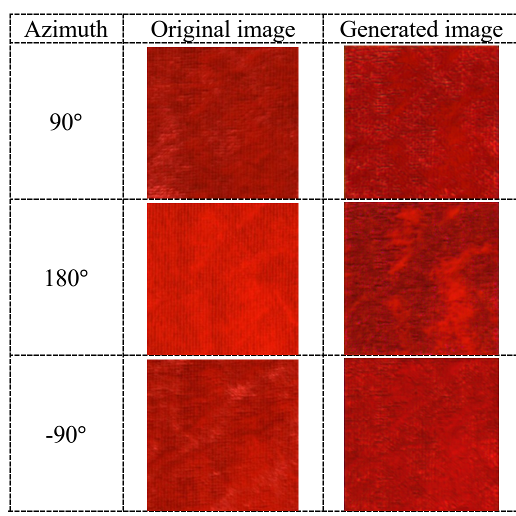

Figure 5. Example of BTF image and original image generated using U-Net (fabric)

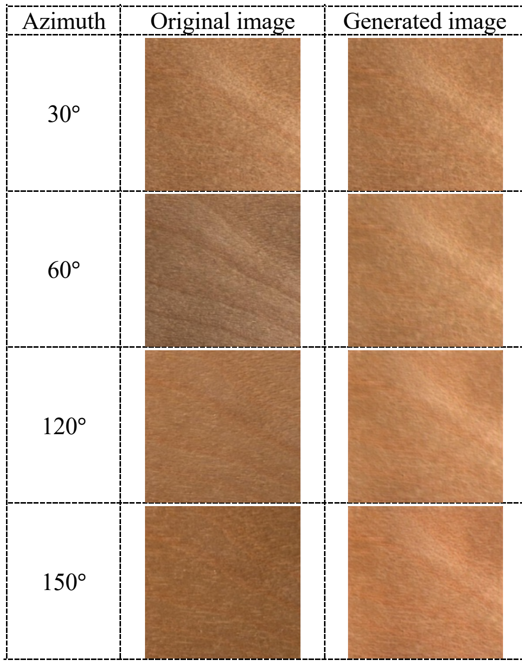

Figure 6. Example of BTF image interpolated using alpha blending (wood)

Table2: Average SSIM for each category of BTF images recovered using U-Net

Category	SSIM
Carpet	0.674
Fabric	0.948
Felt	0.527
Leather	0.866
Stone	0.596
Wallpaper	0.665
Wood	0.926

Table3: Average SSIM of BTF images angularly interpolated by alpha blending

Category	fabric	wood
SSIM	0.955	0.954

4.2 BTF image interpolation result by alpha blending

Figure 6 shows the original image and the recovered BTF images by the alpha blending interpolation between the main four illumination using alpha blending. Table 3 shows the average SSIM of the images obtained by interpolating the angles of fabric and wood textures which were generated by U-Net and the alpha blending. As shown in Table 2, the fabric and wood textures were accurately recovered in the BTF image generation by U-Net. In addition, as show in Table 3, it can be seen that fabric and wood textures can be also recovered by the interpolation with the alpha blending with high accuracy.

5.Conclusions

In the BTF database construction, there is a difficulty on the cost of equipment and time. Researches has been conducted on efficient measurement methods to solve this BTF-measurement problem. However, no method for recovering BTF images from a single image has been proposed. In this paper, we proposed a method to recover BTF images from a single image using deep learning. Since local changes are important for appearance changes due to lighting position, images under the main four lighting directions were generated using U-Net. After that, the BTF image was recovered by interpolating the image of the angle between the images under the main four illumination by the alpha blending. Fabric and wood textures have high reproducibility in recovered images using U-Net and the interpolation. As a result of the BTF recovery, the average SSIM of fabric and wood images was 0.955, and 0.954, respectively.

The restoration accuracies of the fabric and wood textures were high. On the other hand, the other five categories were not recovered with good accuracy. Therefore, as future work, it is necessary to improve a restoration method for each category.

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Author Biography

Naoki Tada received the B.E. degree from Chiba University in March 2019. He is currently a student of a master's course program in the Department of Imaging Sciences, Chiba University. His research interests are material perception and imaging technologies. Especially, he is now constructing a BTF recovery using deep learning.