BTF PREDICTION MODEL USING UNSUPERVISED LEARNING

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ABSTRACT

The impressions evoked by textures are called affective textures, and are considered to be important in evaluating and judging the quality of an object. And, technologies for understanding and controlling sensory textures are needed in product design. In this study, we propose a BTF prediction method using DNN as a first attempt to generate textures based on affective texture recognition. The method uses a series of continuously varying viewpoint angles of a texture image as the input signal. This method enables the generation of texture images with continuously changing angles. We tested the validity of the proposed method by using textile, wood and paper. The results show that the proposed method is effective for predicting diffuse reflection optical properties and irregular and regular patterns.

KEYWORDS

PredNet, Machine Learning, BTF, Affective texture.

1. INTRODUCTION

The impression evoked by the surface properties (texture) of a material is called "affective texture," and is considered to be important in evaluating and judging whether an object is good or bad [1,2]. Therefore, technologies to understand and control affective textures are needed in product design. The reflectance characteristics of an object's surface, which are closely related to the affective texture, are represented by the Bidirectional Reflectance Distribution Function (BRDF) and the Bidirectional Texture Function (BTF) [3,4]. Because of its accuracy, it is widely used in texture representation. Conventional BRDF and BTF acquisition methods, however, require measurement with dedicated equipment, which is time and facility consuming and resource intensive. For this reason, Researchers have conducted studies on prediction and interpolation of BRDFs and BTFs [5].

On the other hand, in the research related to deep learning, which has been rapidly developing in recent years, methods related to image generation, such as Generative Adversarial Networks (GANs), have been used in various applications, such as image resolution enhancement and image style conversion [6, 7]. These methods have also attracted attention in texture representation due to their expressive power and generation accuracy [8]. The realization of texture representation using image generation methods based on deep learning will make it possible to reproduce and edit a wide variety of textures.

In this study, we propose a BTF prediction model using a Deep Neural Networks (DNN) as a first attempt to generate textures based on affective texture perception. We also verify the accuracy and clarify the effectiveness of the proposed method.

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2. RELATED WORK

In the field of computer graphics (CG), techniques for reproducing realistic images have been developed. Since accurately reproducing the appearance of an object's surface is essential for realistic computer graphics, BRDF and BTF, which represent the characteristics of reflections on an object's surface, are used as reproduction techniques. Especially for BTF-based systems, a large number of texture images are collected under diverse conditions using specialized acquisition equipment in advance [4, 9]. However, time and huge amounts of data are problems for collection by measurement devices. To solve this problem, studies on BTF generation using DNNs are being reported [8, 5]. since BTFs require a large amount of data to be measured in advance, it is very useful to reproduce the entire BTF data set from a small number of BTFs.

On the other hand, researchers have conducted interdisciplinary texture studies in psychophysics, engineering, and brain physiology [10,11]. Some examples of research on rendering methods include the use of BTF for cloth [12,13]. However, in these studies, BTF is measured using measurement devices, and it takes a great deal of time to perform the measurement. In this study, we attempt to reduce the measurement time by predicting and interpolating the BTF.

In addition, image generation has been an active area of research related to deep learning, and the latest studies have shown remarkable results [14]. In recent years, research on texture generation using GANs has been reported [15], but no research using time series data has been reported. However, it has been reported that Predictive-coding based DNN (PredNet [16]) (Fig.1), a learning model for time series data, can predict optical illusions, which is one of the perceptual processes of the brain [17]. Therefore, there is a possibility that we can predict texture, which is a cognitive processing of the brain, by applying this model. In this study, we attempt to predict the change in texture due to changes in the angle of view using the PredNet framework. In this study, we use the BTF dataset, in which the viewpoint angle changes continuously, as the training data.

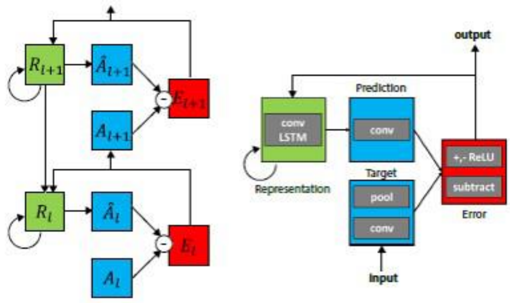

Figure 1. PredNet [16]

3. METHOD

In this study, we propose a BTF prediction model using PredNet. Fig. 2 shows an overview of the proposed method. The PredNet used in this method is a DNN with time-series image data as input and output. The method uses a series of continuously varying viewpoint angles of a texture image as the input signal. This method enables the prediction of texture images with continuously changing angles.

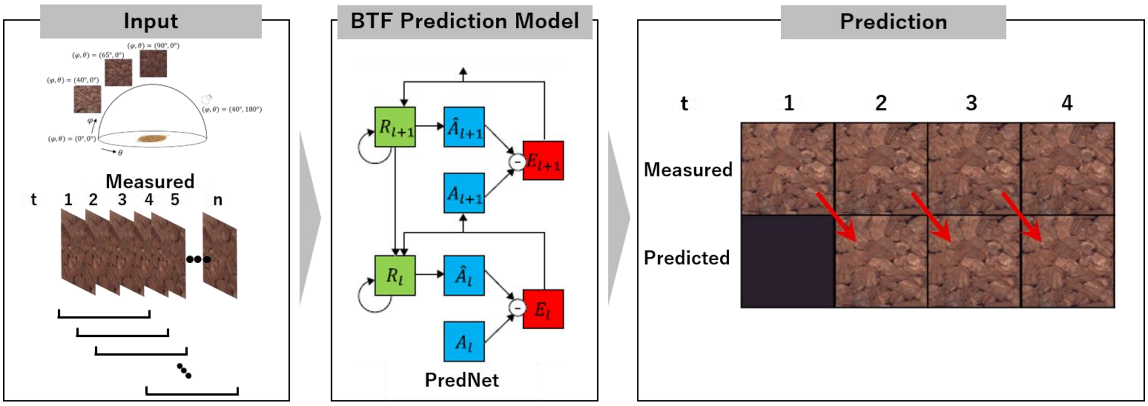

Figure 2. Concept of our proposal method

3.1. Material

The target material was measured using an OGM-CCD camera measuring device manufactured by Digital Fashion. The OGM-CCD consists of a sample stand, a metal halide light source, and a CCD camera, and it is capable of measuring the optical axis in two axes and the sample stand in two axes, for a total of four axes of angular rotation. In this study, we use the images this device captures as BTF. Table 2 shows this system's measurement conditions. We measured the

Table 1. Measurement conditions

Viewing		Illumination	
Elevation	Azimuth	Elevation	Azimuth
30~90°（every 1°）	0, 90, 180, 270°	30~90°（every 5°）	0, 90, 180, 270°

Table 2. Measurement materials

Conditions			Materials		
	Reflection property	Pattern	Textile	Wood	Paper
A	Diffuse	Irregular			
B	Diffuse	Regular			
C	Specular	Irregular			
D	Specular	Regular			

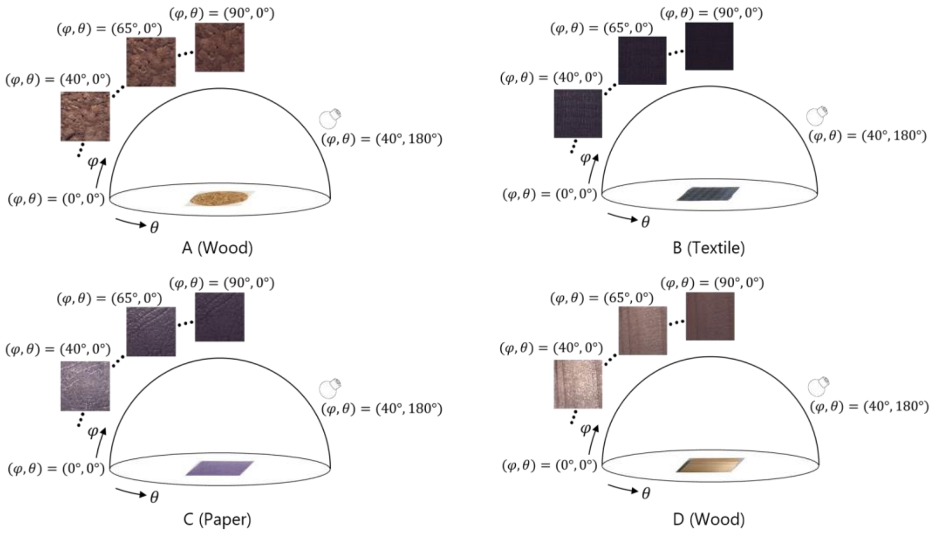

Figure 3. Measurement method and obtained images

elevation angle of the viewpoint at every 1° , the azimuth angle between the viewpoint and the light source at every 90° , and the elevation angle of the light source at every 5°.

We selected textile, wood, and paper as the measurement materials for BTF. For each material, we treated four conditions: material with diffuse reflection property and irregular pattern (condition A), material with diffuse reflection property and regular pattern (condition B), material with specular reflection property and irregular pattern (condition C), and material with specular reflection property and regular pattern (condition D). We measured a total of 12 materials. Table 1 shows the materials we used for the measurements.

We obtained Each of the 11,396 BTFs for each material. Fig.3 shows some of the measurement results for each material. Fig.3 shows the visibility of the viewpoint in relation to the position of the viewpoint and the light source.

3.2. Dataset

Based on the measured BTFs, we created a dataset for learning, verification, and testing. We sampled each material at 2° intervals so the change in viewpoint elevation angle would be continuous, and we used 10 images as one set (Fig.4). In this study, we used 66336 sets for training, 8292 sets for verification, and 691 sets to test each material. We divided the data sets randomly.

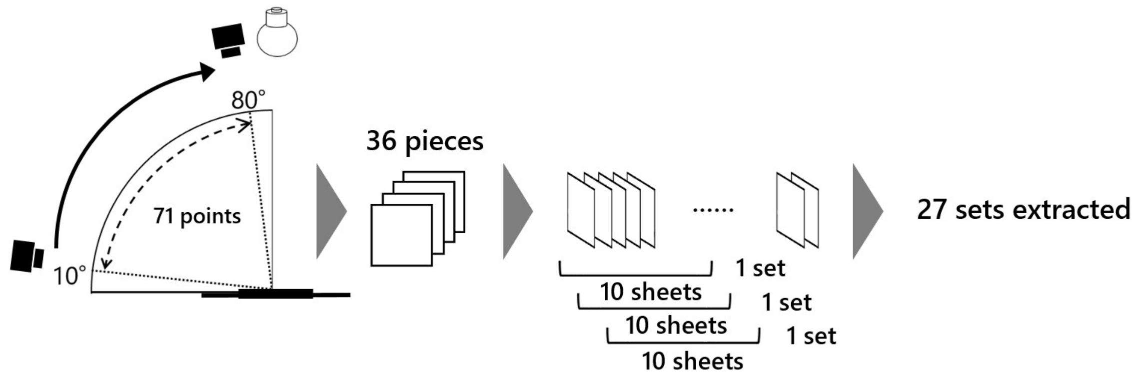

Figure 4. Overview of dataset creation

4. RESULT AND DISCUSSION

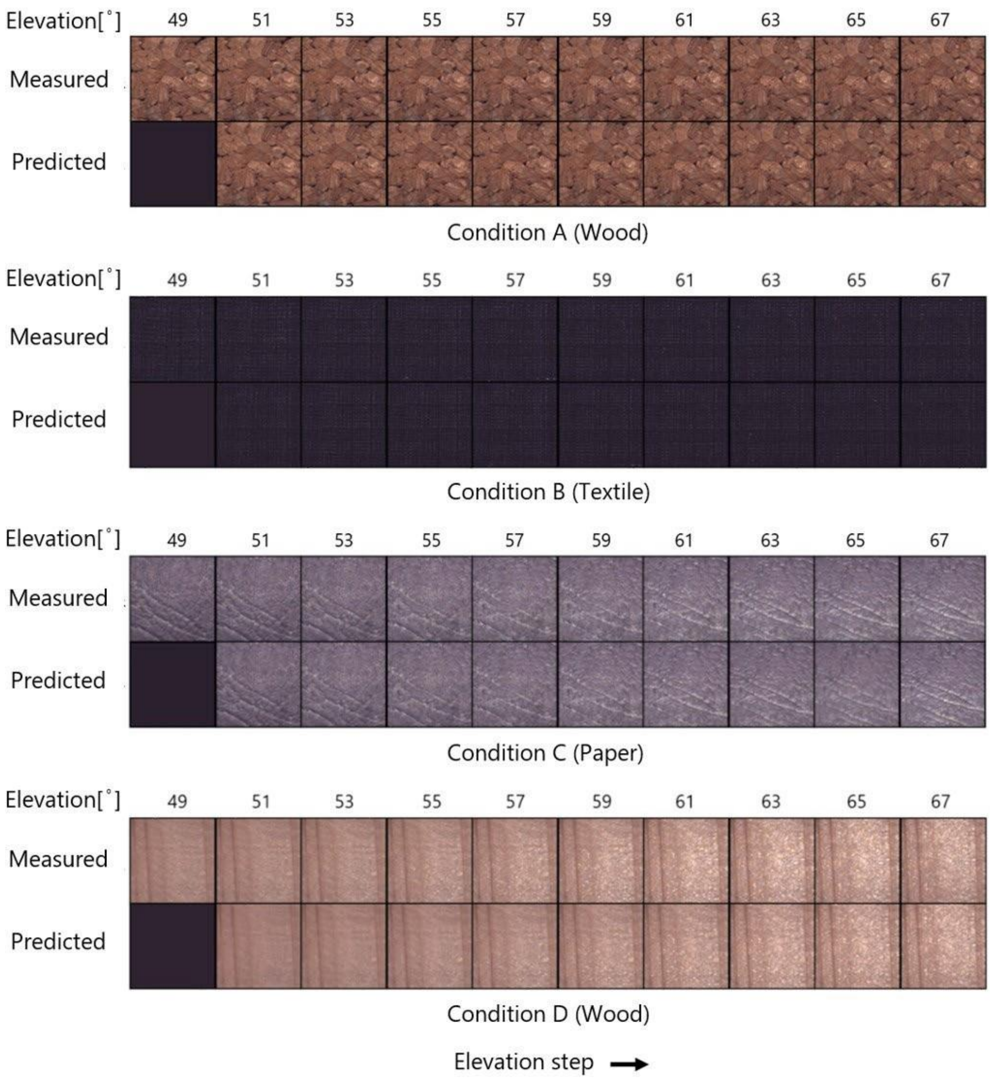

Figure 5. Example of prediction results (Azimuth of viewpoint: 180◦, Elevation of light source: 65◦, Azimuth of light source: 0◦)

We conducted the prediction of future frames using the series of images as input data. We used the BTFs measured in the previous section as the input images to the network. The network structure has four layers, a convolutional filter size of 3 × 3, and the number of filters is 3, 48, 96, and 192, starting from the lower layers. Adam was used as the model optimization algorithm. The hyperparameters for learning were set based on previous studies [16].

Examples of BTF prediction results are shown in Fig.5. For all materials and conditions, the predicted images are similar to the measured images. We confirmed that predictive capabilities of PredNet are effective in generation BTFs.

Furthermore, to quantitatively verify the effectiveness of the proposed method, we evaluated the accuracy of BTF prediction for each material. We used SSIM [18] to evaluate accuracy; SSIM is an index that assumes that the similarity of image structure contributes to near human image quality degradation; the similarity is calculated from luminance, contrast, and structure. Image

Table 3. Average of SSIM in test data

Conditions			Materials			**Average of conditions**
	Reflection	Pattern	Textile	Wood	Paper	
A	Diffuse	Irregular	0.982	0.987	0.991	0.987
B	Diffuse	Regular	0.986	0.986	0.984	0.986
C	Specular	Irregular	0.923	0.982	0.990	0.965
D	Specular	Regular	0.947	0.971	0.985	0.968
Average of materials			0.960	0.982	0.988	

compression guidelines for digitized documents state that SSIM is indistinguishable from the original image at 0.98 or higher, degradation is visible when enlarged at 0.90-0.98, and degradation is obvious at 0.90 or lower [19]. Table 3 shows the average SSIM values in the test data. The table shows that the values are high under all conditions. The SSIM results thus confirm that the reflective characteristics and patterns are accurately predicted under all conditions.

A comparison of materials shows that the values for cloth are lower than those for wood and paper. When we look at the SSIM of each of the 12 materials, we find that the SSIM of fabrics with specular reflectance characteristics is particularly low. A comparison of the different conditions shows that the condition with specular reflectance characteristics has a slightly lower SSIM value than the condition with diffuse reflectance characteristics. To examine these factors, we focused on the SSIM for each angle of the predicted results (Fig.6). Fig.6 shows that the SSIM values are high for each viewpoint elevation angle for conditions A and B, which are diffuse reflection characteristics. On the other hand, the SSIM values are low in the specular reflection conditions, condition C and D, where specular reflection begins to appear. Comparing the measured and predicted images for conditions C and D in Fig.7 with a viewpoint elevation angle of 55◦ , where the change in SSIM values is large, we confirmed that the predictions of the glossy areas were not sufficient. These results suggest that, due to the characteristics of PredNet, this method is not accurate enough to predict steep pixel value changes that would cause specular reflections to appear. Therefore, a new model that shows high accuracy even in steep changes due to angular changes will be considered.

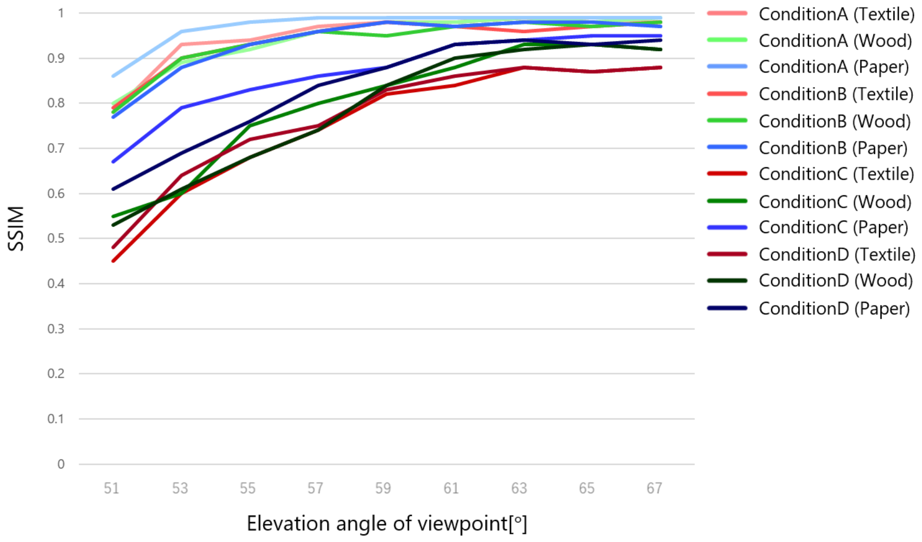

Figure 6. SSIM with change in elevation angle of viewpoint

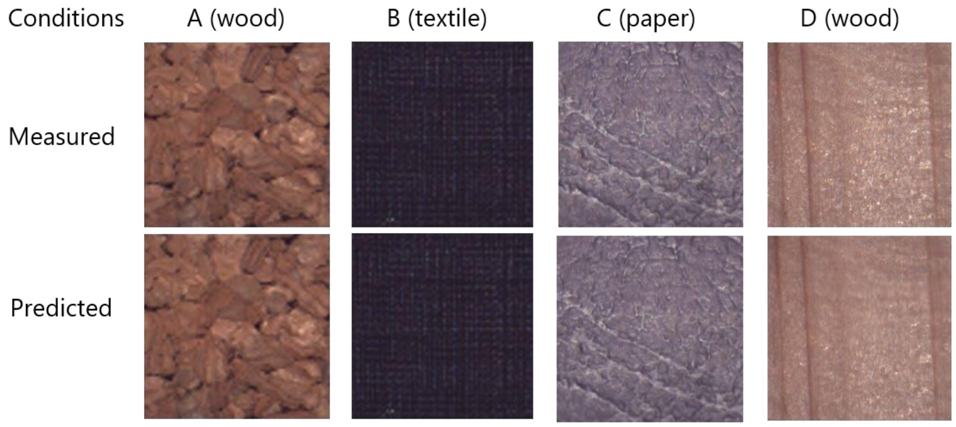

Figure 7. Measured and predicted images for a viewpoint elevation angle of 55◦

5. CONCLUSION AND FUTURE WORK

In this study, we developed a BTF prediction model for texture generation based on affective texture perception. We used PredNet for prediction, and build the model by training a BTF dataset with a series of continuously varying angles. We determined the proposed method's effectiveness by calculating the predicted images' SSIM for 12 materials with various optical properties. The results show that the proposed method is effective for predicting diffuse reflection optical properties and irregular and regular patterns.

In the future, we will study a new model that shows high prediction accuracy even for steep texture changes due to angular changes.

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