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Texture Synthesis with Desired Visual Impressions Using Deep Correlation Feature

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***Abstract*—We propose a texture synthesis method with desired visual impressions, to realize product designs suitable for individual needs. First, we conducted an evaluation experiment and quantified visual impressions of texture images. After that, we modeled the relationship between the quantified visual impressions and the image feature extracted from the convolutional neural network. Based on the obtained model, we updated the features to have the desired visual impressions and generated texture image. Finally, we confirmed the effectiveness of our method by conducting a verification experiment.**

I. Introduction

Manufacture of mass production and mass consumption has so far been carried out. However, manufacturing products that better suits individual needs is nowadays regarded as important to differentiate products.

Texture is the surface properties of objects, and the impressions of a texture, such as “luxury” and “smoothness,” are important factors in the preferences or quality judgments of objects [1]. Therefore, texture control techniques are needed in various manufacturing scenes to create the ideal impression.

Many texture synthesis methods have so far been made [2]. An algorithm for transferring an image style by using VGG-19 which is a convolutional neural network for object recognition [3] has been proposed [4]. However, there is currently no research that manipulates the visual impression felt from images in texture synthesis.

In this research, we propose a texture synthesis method that can control the visual impressions felt from images. To this end, we conduct the following tasks: quantification of visual impressions on texture images; modeling of the relationships between visual impression and image features extracted from a convolutional neural network; and texture synthesis with the desired visual impression. Finally, we verify the effectiveness of our method by conducting an evaluation experiment using images generated by our method. Fig. 1 shows an overview of our approach.

II. Quantification of visual impressions

We conducted a subjective evaluation experiment to quantify visual impressions of texture images. Prior to this experiment, we collected 25 Japanese adjectives to evaluate visual impressions, and 29 texture images, including images collected from the PerTex texture database [5] (V01-V29). The participants in this experiment were 20 Japanese in their 20s (15 men; 5 women; average=22.2; SD=1.01). They evaluated 25 adjective scales about 29 images in 5 stages.

We performed factor analysis to rate the data using the unweighted least squares method and the Promax rotation. As a result, 4 factors were extracted (Fig 1 upper left). We interpreted each factor as follows: Factor 1 is “freshness” because “youthful” and “sporty” have high factor loading; Factor 2 is “roughness” because “slick” and “smooth” have high negative factor loading; Factor 3 is “robustness” because “firm” and “heavy” have high factor loading; and Factor 4 is “crudeness” because “fine” has high negative factor loading and “unlikable” has factor loading. We quantified the obtained factor scores as the visual impressions of the texture images.

III. Modeling

We modeled the relationship between the quantified visual impressions and the image features. We extracted deep correlation features [6] using a pre-trained VGG-19 [3], and we used them as image features of texture images. They consist of 4 elements: Gram matrix, Deep correlations, Diversity, and Smoothness. Because the Gram matrix represents the image style [4], it can be considered to be highly related to visual impressions of texture images. For this reason, we used the Gram matrices extracted in pooling layers 1, 2, 3, and 4 as the features to be modeled. The dimensions of them were 64×64, 128×128, 256×256 and 512×512, respectively.

In order to model the relationships, we performed a Lasso regression by setting the factor scores as dependent variables and the Gram matrices as independent variables. In this research, since the Gram matrices are high-dimensional features with respect to the number of texture images, over-fitting was expected. In Lasso regression, significant parts are selected from independent variables, and regression model is constructed while preventing over-fitting, which is why we used this method.

First, as a result of a regression using all Gram matrices as independent variables, the Gram matrix extracted in pooling layer 4 was not selected. This suggests that features extracted in deep layers are important for object recognition and are not related to the visual impressions of the texture images. Therefore, we focused on the Gram matrix extracted in pooling layer 1, 2 and 3 and again performed regression. TABLE I shows the results of the Lasso regression. We constructed the

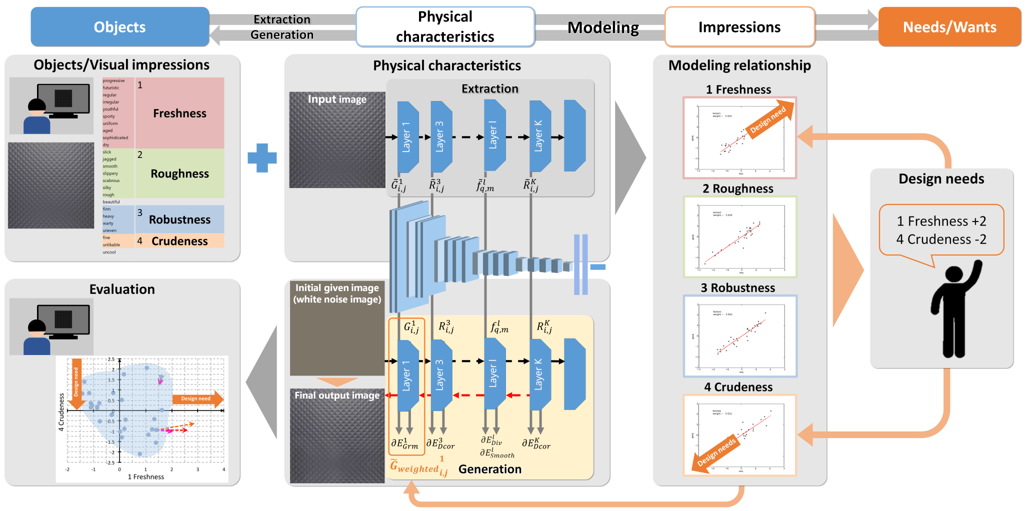


Fig. 1: Overview of our proposed method.

regression models with high precision and modeled the relationships between the visual impressions and image features.

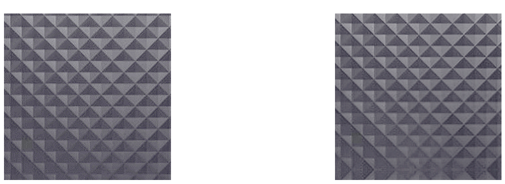
TABLE I: Results of Lasso regression.

Independent variables	64×64	128×128	256×256
Coefficient of determination	0.65	0.83	0.91

IV. Texture Synthesis

Based on the obtained model, we updated the Gram matrix to have the desired visual impressions. By using the Gram matrix of an original image as an initial value, we searched for optimal features with desired (promotion or suppression) factor scores near the initial value using a gradient method. Based on the redesigned Gram matrix and the other features of the original image, we generated a texture image from white noise image using the method of Sendik et al. [6].

Figure 2 shows the results of generating a V07 image with promoted "freshness." An image was generated that emphasized the horizontal and vertical edges while maintaining the entire structure of the original images. These results suggest the effectiveness of our method.



(a) Original image. (b) Generated image.

Fig. 2: Results of generation from updated features.

V. Effect verification experiment

We conducted an evaluation experiment to verify whether the impressions of the image generated by our method changed as designed. We used 8 texture images as stimuli: the original images of V07 and V12, images with promoted "freshness," images with suppressed "crudeness," and images with both impressions changed. We used the same 25 adjectives used in the previous experiment as the evaluation words. The participants in this experiment were 15 Japanese in their 20s (7 men; 8 women; average=21.7; SD=1.29). They evaluated 25 adjective scales about 8 images in 5 stages.

After comparing the evaluation scores of the original images and the generated images, we confirmed that the impression had changed as designed in V07 with both impressions changed, V12 with promoted "freshness," and V12 with both impressions changed. We also confirmed an expansion effect outside the range of the impression space obtained in the previous experiment (Fig. 1 lower left). From these results, we confirmed the effectiveness of our method.

VI. Conclusion

We proposed a texture synthesis method that can control visual impressions. First, we modeled the relationships between the visual impressions and image features of texture images. After that, based on the obtained model, we updated image features to have desired visual impressions , and generated texture images. In addition, we confirmed the effectiveness of our method by conducting a verification experiment.

In the future, we will generate texture images with various visual impressions changed and verify the effects. As a result, our method will contribute to manufacturing that better satisfies individual needs.

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