Correlation Analysis between Wood Eigen Textures and Perceptual Qualities

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Abstract

In this paper, we analyzed the relationship between wood Eigen textures and the human perception. First, we developed a database of one hundred wood textures. Then, through our experiment that was designed based on the Fleming's subjective experiment (Journal of Vision, 2013), nine types of perceptual quality scores were assigned to each texture. The perceptual qualities are glossiness, transparency, colorfulness, roughness, hardness, coldness, fragility, naturalness, and prettiness. Second, we statically analyzed the one hundred wood textures using the principal component analysis (PCA). The PCA bases of the wood texture database are called "wood Eigen textures." Finally, we obtained correlation coefficients between weights of wood Eigen textures and perceptual quality scores. Our results showed the first wood Eigen texture (the first principal component) was correlated with the perceptual qualities of "glossiness" and "coldness." The second one was correlated with the perceptual qualities of "coldness" and "colorfulness." Based on the analysis, we demonstrate a texture generation technique for arbitrary perceptual qualities.

Introduction

According to the developments of available software packages such as Adobe Photoshop and Gimp, it becomes easier for general users to edit images. Representative examples of image editing are tone and color compensations, contrast improvement, noise removal, and image quality improvement. Furthermore, recent software with advanced image editing techniques has executed inpainting (image interpolation of missing regions) and image retargeting (image resizing considering objects in the image).

While many image editing techniques have been implemented in available packages, texture and material appearance editing [1-4] is still difficult in practical implementation. One of the material appearance editing techniques is retexturing (also called "texture replacement" or "material replacement"). Retexturing is a technique to edit materials and textures in an image by replacing a texture of object surface. Zelinka et al. proposed an intuitive and interactive retexturing system based on texture synthesis and shading manipulation using recovered surface normal [5]. Recently Diamanti et al. proposed a method to edit materials by a discrete set of annotated exemplars [6]. These conventional approaches could reproduce fine appearance of retextured objects. However, these methods required users to collect texture images (exemplars) in advance. This texture collecting process requires some efforts and becomes a barrier for general users. In addition, users are required to select a texture image from collected textures (texture database). This texture selection makes users difficult to use a retexturing system intuitively. Due to these reasons, when using a suitable texture for human intuition such as "cooler feeling" or "more soft impression," users have to search textures from a huge database. This process was an obstacle to easy uses.

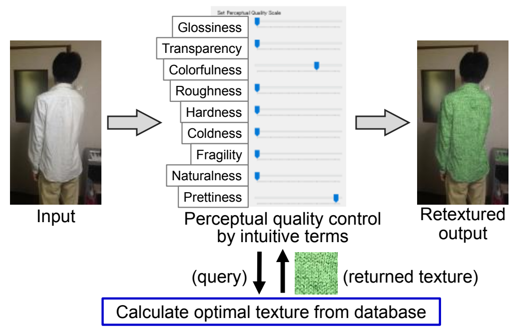


Figure 1. Our retexturing system in the previous study [7]

In our previous study [7], we have developed a system for intuitively retexturing (Fig.1). In this system, a user controls perceptual quality indexes for selecting a texture. Based on this user inputs, an optimal texture is selected for the retexturing. For obtaining an optimal texture, we developed a material texture database with perceptual quality scores. The database was constructed on the basis of our subjective experiments with nine types of perceptual quality indexes which were suggested by Fleming et al. [8]. Then, for obtaining an optimal texture, we calculated the Euclidean distance of perceptual quality scores between the user setting and the subjective evaluation.

Our previous study has provided intuitive and interactive retexturing for users. However, the number of texture images with perceptual quality scores was only one hundred for ten material categories (ten textures for each category). Due to this limitation, the system sometime returned a non-appropriate texture which was not suitable for user intuitions. For overcoming this problem, it was required to generate a new texture from limited texture exemplars, which is suitable to user material perception.

Generating a new texture with suitable perceptual quality scores is a challenging problem. One of the solutions is a PCA-based technique. Recently, Serrano et al. analyzed the relationship between human perception and principal components of BRDF database [9]. Based on this approach, they had controlled the intuitive BRDF appearance. Similarly, our research focuses on the relationship between human perception and material texture database. Then, we employed the PCA-based approaches for analyzing the relationships between material perception and principal components of a texture database.

In this research, for generating a new texture with preferred perceptual qualities, we analyzed the relationship between principal components of a material texture database and the human perception. As the first step of texture analysis using the PCA-based approach, this paper focuses "wood" material. Wood is one of the important materials in our daily life. Several researches focused wood texture analysis using image features [10]. In our study, first, we develop a wood texture database with perceptual quality scores through subjective experiments. Next, the PCA is applied to the wood texture database. The PCA bases of the wood texture database are called "wood Eigen textures." Finally, we analyses correlation coefficients between weights of wood Eigen textures and perceptual quality scores. We also demonstrate the texture generation using our analysis.

Construction of Wood Texture Database with Perceptual Quality Scores

Experimental strategy

Our study focuses the relationship analysis between principal components of a wood material texture database and the material perception. Then, in order to construct a wood texture database with perceptual qualities, we conducted subjective evaluation experiment. Our experiments were based on the previous study by Fleming et al. [8]. Figure 2 shows the screenshot which was presented to subjects. Wood texture stimuli were displayed one by one.

The number of wood textures in our database is totally 100 images which consists of 20 images of Flickr Material Database (FMD) [11] and 80 images taken by ourselves. All of the textures are trimmed and resized from the original image to 256 × 256 pixels. Texture examples are shown in Fig.3. The 100 wood textures were presented to subjects in random order.

The display in the experiment was Eizo CS 230 which was the calibrated monitor and the color gamut was sRGB. Assuming a viewing angle of 4 degrees, viewing distance was approximately 80 cm (Fig.4). The experiment was conducted in a dark room. Subjects started the experiment after dark adaptation of 2 minutes.

Ten students rated each texture stimulus in accordance with nine perceptual properties (glossiness, transparency, colorfulness, roughness, hardness, coldness, fragility, naturalness, and prettiness) based on a scale of 1 to 6. For the evaluation, click on the "1"-"6" buttons on the right side of the screen and input. Before the experiment, the subjects were instructed to read the definition of the perceptual quality indexes [8]. The definitions of the perceptual qualities are as follows:

Glossiness: How glossy or shiny does the material appear to you? Low values indicate a matte, dull appearance; high values indicate a shiny, reflective appearance.

Transparency: To what extent does the material appear to transmit light? Low values indicate an opaque appearance; high values indicate the material allows a lot of light to pass through it.

Colourfulness: How colorful does the material appear to you? Low values indicate a grayish, monochrome appearance; high values indicate a colorful appearance, which could be either a strong single color or several colors.

Roughness: If you were to reach out and touch the material, how rough would it feel? Low values indicate that the surface would feel smooth; high values indicate that it would feel rough.

Hardness: If you were to reach out and touch the material, how hard or soft would it feel? How much force would be required to change the shape of the material? Low values indicate that the surface would feel soft; high values indicate that it would feel hard.

Coldness: To what extent would you expect the surface to feel cold to the touch? Low values indicate that the material would typically feel warm or body temperature; high values indicate that the material would feel cold to the touch.

Fragility: How fragile or easy to break is the material? Low values indicate that the material is highly resistant and could not easily be broken; high values indicate that a small amount of force would be required to break, tear, or crumble the material.

Naturalness: How natural does the material appear to be? To what extent is the material in its most natural, common state? Low values indicate that the material appears unnatural; high values indicate that it appears natural.

Prettiness: How pretty or visually attractive is the material to you? Low values indicate the material is ugly or unattractive; high values indicate that it is attractive or beautiful to the eye.

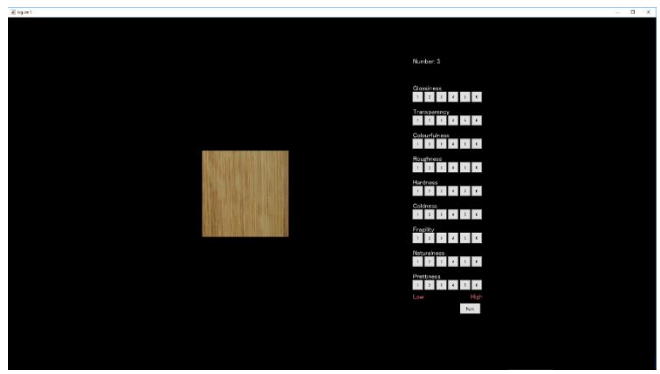


Figure 2: Screenshot of our subjective experiment

Figure 3: Wood texture examples in our database

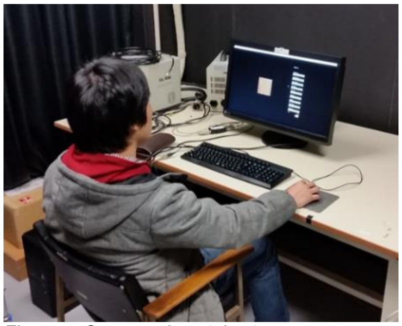


Figure 4: Our experimental setup

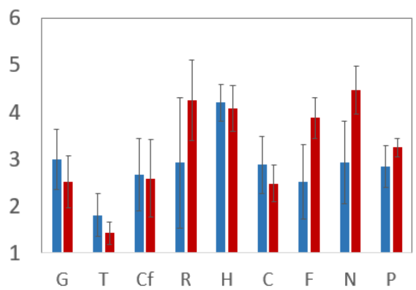


Figure 5: Perceptual qualities of the wood texture database in this study (blue) and the results of our previous study [7] (red) (G: Glossiness, T: Transparency, Cf: Colorfulness, R: Roughness, H: Hardness, C: Coldness, F: Fragility, N: Naturalness, and P: Prettiness). Error bars represent standard deviations of the mean.


(a) Textures used in this study


(b) Textures used in our previous study [7]

Figure 6: Comparison of textures


(left) G:3.7, T:1.6, Cf:4.0, R:3.7, H:4.4, C:2.7, F:2.1, N:3.4, P:3.5
(right) G: 2.4, T:1.2, Cf:2.1, R:5.4, H:4.3, C:2.9, F:3.8, N:4.6, P:2.6
Figure 7: Wood texture examples with perceptual quality scores. (see also the caption of Fig.5).


Figure 8: Average of wood texture database


Figure 9: Normalized first to tenth wood Eigen textures

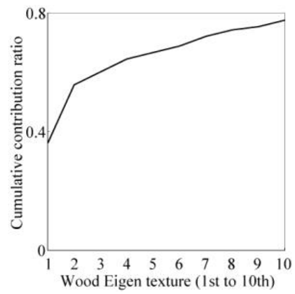


Figure 10: Cumulative contribution ratio of wood Eigen textures

Experimental results

Figure 5 shows our experimental results (blue bars). The scores are averages of ten subjects. We also show the results of our previous study [7] in Fig.5 (red bars). The number of wood texture in this study is 100 images. On the other hand, that in our previous study is only 10 images because our previous study focuses not only wood material but also other materials such as metal and fabric. These results in this study are similar to those in our previous study. In addition, our results are also similar to the results by Fleming et al. [8]. As shown in these results, even though we used different wood textures, the averages have similar tendencies. On the other hand, as shown in Fig.5, it should be noted that the scores of roughness, fragility, naturalness are slightly lower than those of our previous study. This is because the wood texture used in our database were mainly consists of not only natural textures but also processed plates, while the wood textures in our previous study [7] were mainly natural textures (Fig.6). Figure 7 shows an example of perceptual quality scores of each wood textures.

Wood Eigen Texture by PCA

Here, we applied the principal component analysis (PCA) technique to the wood texture database. Wood textures were converted to the YCbCr color space, respectively. The YCbCr color space is more appropriate compared with RGB color space, because we can directly extract luminance information which represents texture patterns. The size of each wood textures is 256 ×256 pixels for each color channel. Then 100 wood textures were transformed as Matrix representation: $\mathbf{I} \in \mathbb{R}^{(256\times256\times3)\times100}$. The PCA was applied to the Matrix of texture database $\mathbf{I}$.

Figure 8 shows the average of the texture database, and Fig.9 shows the wood Eigen textures which are the PCA bases of the texture database. The cumulative contribution ratio is shown in Fig.10. As shown in Fig. 8 and 9, the first and second wood Eigen textures are very smooth. On the other hand, the wood Eigen textures after the third component include roughness and wood structural components. Wood textures of approximately 60% can be recovered by linear combinations of first and second wood Eigen textures.

Correlation Analysis and Application

Correlation analysis between wood Eigen textures and perceptual qualities

For analyzing the relationship between wood Eigen textures and perceptual qualities, first, a linear regression $Q_X = aw_n + b$ was calculated, where Q_X was perceptual scores in the experiments, and w_n was the weights of the n-th wood Eigen texture P_n. Then, we calculated correlation coefficients between each perceptual quality score Q_X and weights W_n. Table 1 shows the correlation coefficients. If the absolute value of the correlation coefficient is closer to 1, the appearance change with arbitrary perceptual qualities can be accurately performed by the linear equation based on the wood Eigen textures. From Table 1, we can see the first wood Eigen texture is well correlated with glossiness and coldness. The second one is well correlated with colorfulness, coldness. These results suggest that perceptual qualities can be controlled by changing the weights of wood Eigen textures.

Application to wood texture generation

Now, we attempt to generate a new wood texture with arbitrary perceptual quality scores by using the above analysis results. In this study, the texture generation is performed by changing weights of the first and the second wood Eigen textures. Assuming that the original image is I_{input} and the first and second wood Eigen textures are P_1 and P_2, the generated image I_{output} can be expressed as $I_{output} = I_{input} + w_1'P_1 + w_1'P_2$. By changing the weights, we also control perceptual qualities of wood textures. The examples of the texture generation are shown in Fig.11. Since the correlation coefficient after the third principal component was low, this study used only intrinsic textures up to the second principal component.

Table 1: Correlation coefficients between perceptual qualities Q_X and weights P_n of first and second wood Eigen textures

	First	Second
Glossiness	0.43	-0.01
Transparency	0.01	0.30
Colorfulness	0.29	0.68
Roughness	0.22	-0.46
Hardness	-0.07	-0.03
Coldness	-0.43	-0.59
Fragility	0.26	-0.45
Naturalness	0.36	-0.40
Prettiness	0.23	0.37

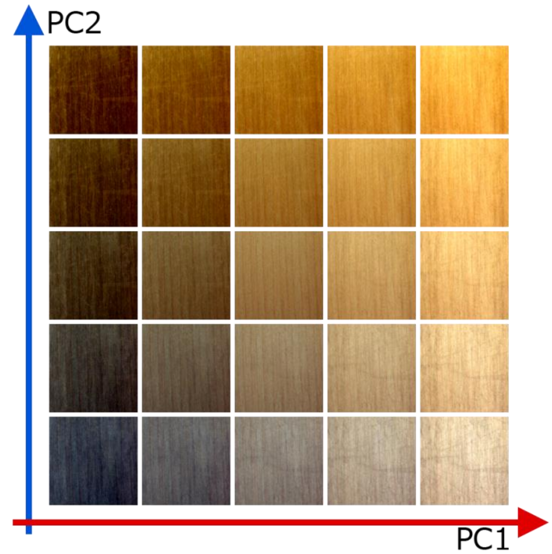
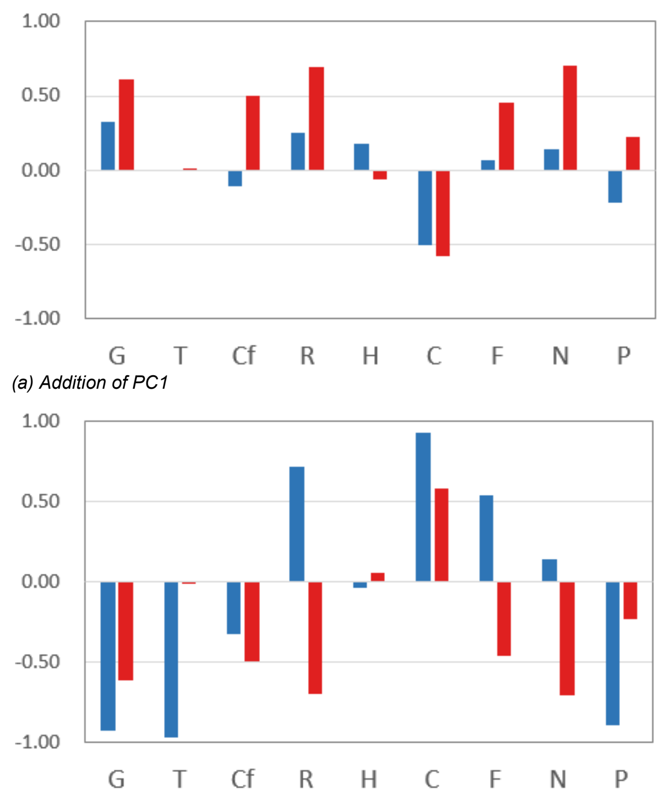
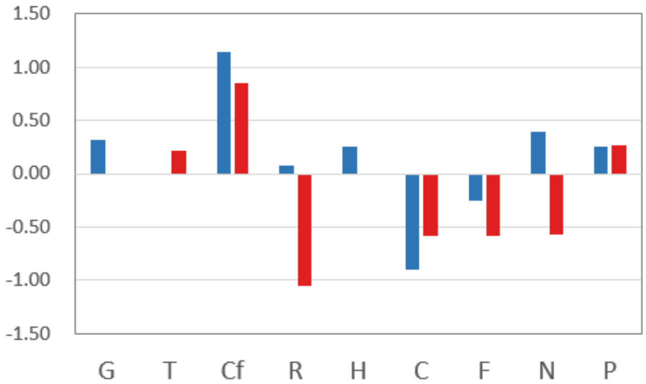


Figure 11: Example of texture generation. PC1: manipulation by the first wood Eigen texture, and PC2: done by the second one.

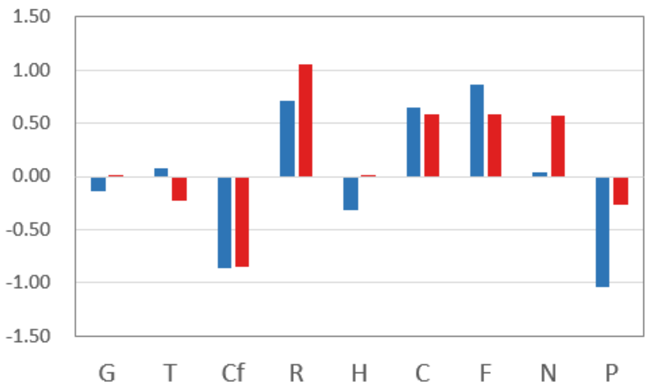


(a) Addition of PC1

(b) Subtraction of PC1



(c) Addition of PC2



(d) Subtraction of PC2

Figure 12: Results of validation experiments using generated textures in perceptual quality space (blue are subjective evaluation scores and red are estimated scores. See also the caption of Fig.5).

Validation experiment using generated textures

We conducted subjective experiments for validating the feasibilities of perceptual quality controls of generated wood textures. For the experiments, sixteen textures were selected from the wood texture database. In this experiment, the textures with various perceptual qualities were generated by adding or subtracting the weights of the first or the second wood Eigen textures for every four textures. Then thirty-six textures were evaluates (sixteen original textures + sixteen generated textures) in total. The other setups and strategies of validation experiments were in the same manner as the previous subjective experiments for constructing the database with perceptual quality scores.

Figure 12 shows the results of our validation experiment. In these figures, first, we calculated the difference between a perceptual score of an original texture and a perceptual score of a generated texture that corresponds to the original one. Then we calculated the averages of all of subjects for each four textures (added first / second component and subtracted first / second component are consist of four textures for each group, respectively). In addition, the predicted perceptual quality scores for each wood texture were predicted by using the results of linear regression equations in the previous section.

In the correlation analysis described above, the first wood Eigen texture is well correlated with glossiness and coldness, the second one is well correlated with colorfulness, coldness. As shown in Fig.12(a) and (b), correlations between subjective scores and predicted scores are close to 1 in the perception of glossiness and coldness. Additionally, as shown in Fig.12(c) and (d), correlations between subjective scores and predicted scores are close to 1 in the perception of colorfulness, coldness. Moreover, except for roughness and fragility, the changing directions of perceptual quality scores in subjective scores are almost same as those in predicted scores. As shown in Fig.9, roughness and fragility will be related to the third and the subsequent wood Eigen textures. From the above discussions, it is suggested that perceptual qualities of wood texture can be manipulated by adding or subtracting wood Eigen textures.

Conclusions

In this research, we analyzed the relationships between wood Eigen textures and the perception. First, we developed the wood texture database with perceptual quality scores. The database consists of one hundred wood textures. Then all of the textures were evaluated by using the nine types of perceptual quality indexes, i.e. glossiness, transparency, colorfulness, roughness, hardness, coldness, fragility, naturalness, and prettiness. Next, we obtained the wood Eigen textures by using the PCA technique. Then, we analyzed the correlation between wood Eigen textures and perceptual quality scores. As the results, the first wood Eigen texture is well correlated with glossiness and coldness. Additionally, the second one is well correlated with colorfulness, coldness. Based on the analysis, we generated new wood textures with arbitrary perceptual qualities by manipulating first and second wood Eigen textures. From the validation experiments, the subjective perceptual quality scores of the generated wood textures were well correlated with the predicted one.

In this paper, we focused on wood textures as the first step of the PCA-based material texture generation for arbitrary perceptual qualities. Definitely, it is also important to investigate common material textures such as metal, fabric, paper, leather and so on [8]. As future work, we need to analyze textures of other categories and generate other material textures with arbitrary perceptual qualities. In addition, as shown in the results of the correlation analysis, the perceptual qualities were depended each other. Then, when controlling the weights of Eigen textures, several perceptual qualities changes simultaneously. This sometime causes undesirable texture appearance. We need also investigate the technique to manipulate each perceptual quality score independently. Furthermore, as an application of this study, the texture generation technique should be incorporated into the retexturing system [7] as further future work.

Acknowledgments

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References

[1] L-Y.Wei, S. Lefebvre, V. Kwatra and G. Turk, "State of the art in example-based texture synthesis," Eurographics, State of the Art Report, pp.93-117, 2009.

[2] S. Zelinka, and M. Garland, "Jump map-based interactive texture synthesis," ACM Transactions on Graphics, Vol.23, No.4, pp.930-962, 2004.

[3] W. Matusik, Z. Matthias, and F. Durand, "Texture design using a simplicial complex of morphable textures," ACM Transactions on Graphics (Proc. SIGGRAPH). Vol. 24. No.3, pp.787-794, 2005.

[4] E. A. Khan, E. Reinhard, R. W. Fleming, and H. H. Bülthoff, “Image-based material editing,” ACM Transactions on Graphics (Proc. SIGGRAPH) Vol.25, No.3, pp.654-663, 2006.

[5] S. Zelinka, H. Faung, M. Garland, and J. C. Hart, “Interactive material replacement in photographs,” Proc. Graphics Interface, pp.227-232, 2005.

[6] O. Diamanti, C. Barnes, S. Paris, E. Shechtman, and O. Sorkine-Hornung, “Synthesis of complex image appearance from limited exemplars,” ACM Transactions on Graphics, Vol.34, No.2, pp.22:1-22:14, 2015.

[7] K. Hirai, W. Suzuki, Y. Yamada and T. Horiuchi, “Interactive object surface retexturing using perceptual quality indexes,” Proc. IS&T Electronic Imaging (Material Appearance 2017), pp.80-85, Jan. 2017.

[8] R. W. Fleming, C. Wiebel, and K. Gegenfurner, “Perceptual qualities and material classes,” Journal of Vision, Vol.13, No.9, pp.9:1-9:20, 2013.

[9] A. Serrano, D. Gutierrez1, K. Myszkowski, H-P. Seidel, and B. Masia1, “An intuitive control space for material appearance,” ACM Transactions on Graphics (Proc. SIGGRAPH Asia), Vol.35, No.6, pp.186:1-186:12, 2016.

[10] S. Katsura, Y. Mizokami, and H. Yaguchi, “Perceived quality of wood images influenced by the skewness of image histogram,” Optical Review, Vol.22, No.4, pp 565-576, 2015.

[11] L. Sharan, R. Rosenholtz, and E. Adelson, “Material perception: What can you see in a brief glance?,” Journal of Vision, Vol.9, No.8, p.784, 2009.

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