Interactive Object Surface Retexturing using Perceptual Quality Indexes

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Abstract

This paper presents an intuitive retexturing system for editing object surfaces in images interactively. In the conventional retexturing methods, users were required to select texture images from a texture database. On the other hands, our system requires users to respond intuitive terms of material perception. Then, based on the user response, an optimal texture image is selected for the retexturing. For calculating an optimal texture image, we develop a material texture database with perceptual quality scores. The database is constructed on the basis of our subjective experiments with nine perceptual quality indexes which were suggested by Fleming et al. (2013). In the actual retexturing system, first, a user captures or selects an image including a retexturing target. Second, a target object region is extracted by Lazy Snapping which is an interactive image segmentation technique. Third, as to represent a target surface, the user sets the perceptual quality parameters and preferred object materials. Then, based on the user settings, an optimal texture is calculated from our material texture database. Finally the user achieves a retextured object image by adopting the optimal texture. For realizing interactive retexturing system, we have implemented our algorithm on tablet computers with Android and Windows OSs.

Introduction

Retexturing is a technique for editing object materials and surface appearance in images. For instance, by using a retexturing system, we can easily control visual appearance and impression of object materials such as interiors, outdoor objects, and cloths. Retexturing system is an effective graphics software tool for image appearance editing in such as post-production processes and product designs. This technique allows us to simulate the object appearance with expensive, valuable and high-quality materials.

Several retexturing approaches have been proposed. Tsin et al. proposed to replace near-regular texture patterns in a plane by learning a statistical texture model and lighting distributions from a sample image [1]. Oh et al. applied a retexturing technique into their image editing system by using depth information from distortions of the texture [2]. Liu et al. presented an approach based on user-assisted lattice extraction for near-regular texture [3]. A PCA analysis of obtained geometric and lighting deformation was also applied for controlling texture regularity. Textureshop is a pioneer system based on shape-from-shading approaches to recover a rough set of normals for an object in a photograph [4]. Based on the recovered normals, distorted texture on the object can be synthesized in Textureshop. 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]. Their key contribution is to interpolate missing data from available exemplars.
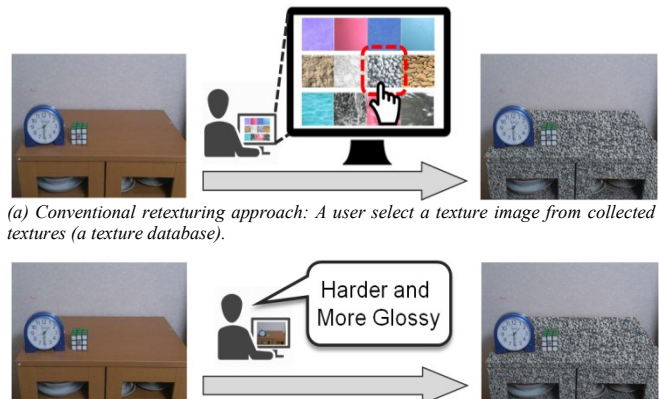
(a) Conventional retexturing approach: A user select a texture image from collected textures (a texture database).

(b)Proposed retexturing approach: A user respond intuitive terms of material perception.

Figure 1. Concepts of conventional and proposed retexturing approaches

As described above, the conventional approaches could reproduce fine appearance of retextured objects by recovering object geometric information (such as surface normals) and lighting conditions. 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, as shown in Fig.1(a), 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.

In this research, we propose a retexturing system for editing object material appearance interactively. Our system does not request users to select a texture image from a texture database. Alternatively, as shown in Fig.1(b), users just respond intuitive terms of material perception. For realizing intuitive user operation, we apply the perceptual quality indexes and material categories [7] as user parameters. Then, based on the user parameter settings, an optimal texture image is applied for the retexturing. For calculating optimal texture, we constructed a material texture database with perceptual quality scores.

As a similar concept, Khan et al. introduced image-based material editing based on material appearance [8]. However, they focused on the material editing by controlling physical properties such as transmittance and BRDF. On the other hand, our method focuses on the object material editing by controlling perceptual properties such as senses of transparency and glossiness.

The rest part of this paper is organized as follows. In the next section, we describe how to develop the material texture database with perceptual quality scores. First, we briefly introduce the previous study by Fleming et al. [7]. They conducted subjective experiments with material images for analyzing perceptual
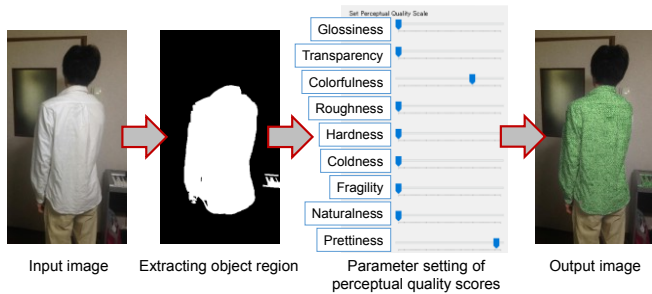
Figure 2. Practical example of user operation through an Android application.
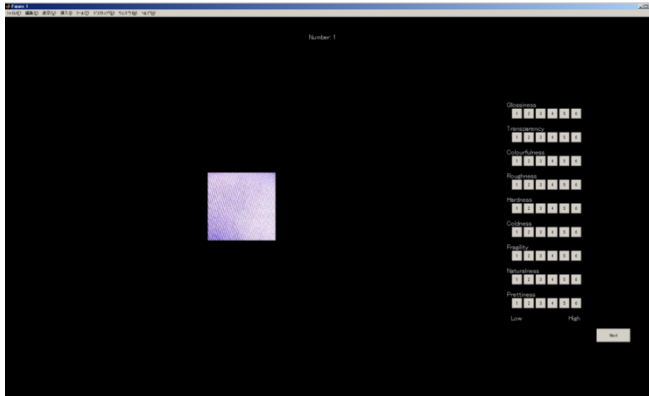

Figure 3. Screenshot displayed in our experiments. Subjects rated texture patch images by using nine perceptual quality indexes located at the right side.
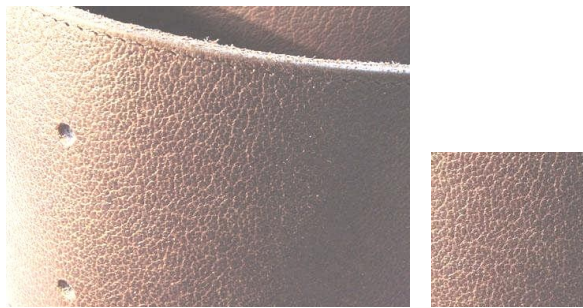

Figure 4. Comparative images of the previous study [7] with our experiments, (left) An material image used in the previous studs, (right) An material patch image used in our experiments.

Figure 5.Material texture examples prepared for conducting our experiments and developing our database.

qualities and material appearance. Then, we show our experimental methods and results toward the development of the material texture database with perceptual quality scores. In the third section, we present the overview and algorithms of our retexturing system. The algorithms mainly consist of (1) interactive object region extraction, (2) surface normal recovery of the object region, (3) optimal texture calculation by using the material texture database, and (4) texture synthesis for retexturing. In the fourth section, the interactive retexturing system is practically implemented on tablet computers. Figure 2 shows the practical example of our system as Android OS application. In addition, results and limitations of our retexturing system are also discusses. In the final section, we conclude our paper and describe future work.

Database Construction of Material Textures by Visual Experiments

Toward our intuitive retexturing system, we develop a material texture database with perceptual quality scores in advance. In this section, first, we briefly introduce the previous study by Fleming et al. [7]. They have investigated perception qualities by using material images. This previous study is based on our experiments for developing the material texture database. Then we describe our experimental methods and results for developing the material texture database.

Brief Overview of Previous Experiments

Fleming et al. conducted experiments to investigate the interactions between material classification and judgments of material qualities in both visual and semantic domains. Nine students viewed 130 images of materials from 10 different classes (fabric, foliage, glass, leather, metal, paper, plastic, stone, water, and wood). The stimuli images were selected from the MIT-Flickr material database [9], which sizes were 512 × 384 pixels. Then subjects rated each image in accordance with nine perceptual properties (glossiness, transparency, colorfulness, roughness, hardness, coldness, fragility, naturalness, and prettiness) based on a scale of 1 to 6.

Their results suggested that subjects assigned material qualities to different material classes both visually and semantically, even though subjects were not informed that the 130 different images consisted of 10 material classes. They also suggested that the visual estimation of perceptual properties and the separation of different material classes are closely related.

Our Experimental Strategy

Here, we conducted subjective experiments for developing a material texture database. Our experiments were based on the previous study [7]. Figure 3 shows the screenshot which is presented to subjects. In our experiments, we used ten material categories explained in the previous section. Each category contained ten texture images. Then we prepared one hundred texture images (10 categories × 10 textures / category) in total. The texture images were selected from the MIT-Flickr material database and MPI-VIPS database [10]. The images were trimmed and resized to 200 × 200 pixels. As shown in Fig.4, the previous study employed the images which subjects could recognize the object shapes and shading. Alternatively, our experiments employed texture patch images. Compared with the previous study, it was difficult for subjects to recognize the object shapes and materials from the patch images. Figure 5 shows the examples of displayed images.

Ten students participated to the experiments. They rated one hundred texture images which were randomly displayed on a color-calibrated monitor (EIZO ColorEdge CG 221-BK with Adobe RGB gamut). In addition, for investigating the repeatability of subject ratings, we selected ten images from the one hundred images and displayed them again. Then subjects rated one hundred ten texture images in total. The viewing distance and angles were 80 cm and 4 visual degrees. For the perceptual quality rating, the participants were instructed to evaluate the texture images based on the nine perceptual quality indexes and assign a suitable rating for each perceptual quality index on a scale of 1 to 6. The definitions of nine perceptual quality indexes were the same as the previous study (see [7]).

Our Experimental Results

Figure 6 shows the experimental results for each category. We obtained similar results compared with the previous study. However differences (variations) between rated scores of ten images for each category were less than those in previous results. It seems that this is caused by employing the material images of texture patches in our experiments, though the previous employed material images with object shapes (see Fig.4).

(a) Fabric *(b) Foliage* *(c) Glass*

(d) Leather *(e) Metal* *(f) Paper*

(g) Plastic *(h) Stone* *(i) Water*

(j) Wood

Glossiness
Transparency
Ccolourfulness
Roughness
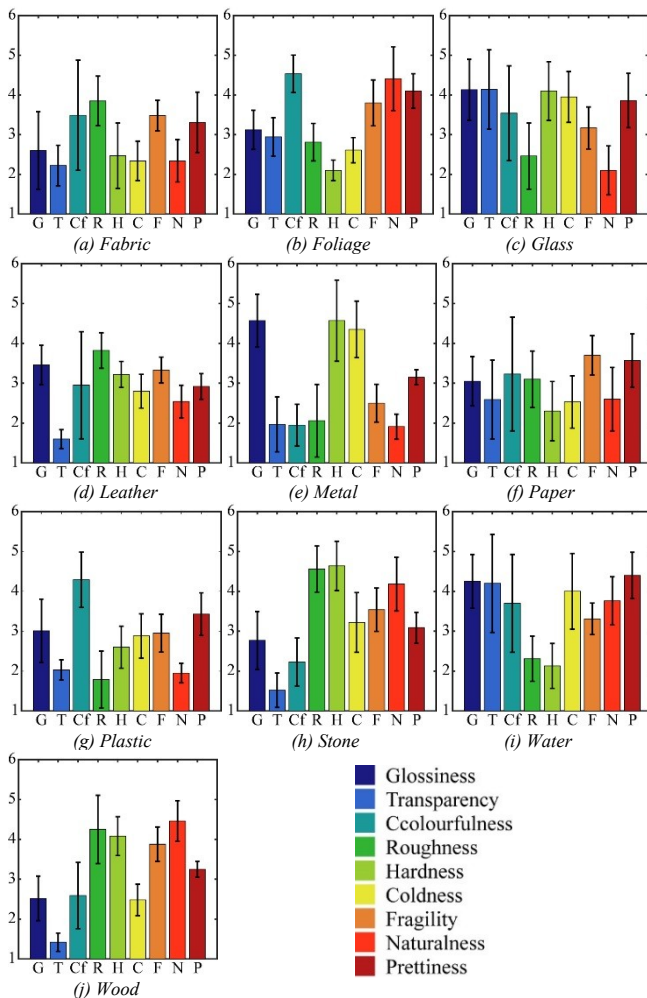Hardness
Coldness
Fragility
Naturalness
Prettiness

Figure 6. Our experimental results for each material category (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.

Figure 7 shows an example result of the repeatability investigation. The differences between first and second rated scores were less than one for almost all images used in the repeatability task. This result suggests that the subjects stably assign perceptual quality scores, even if they repeatedly evaluate material textures of patch images.

Figure 8 shows an example of perceptual quality scores of each material texture image, and Figure 9 shows the score-ordered material texture images for some material categories and perceptual quality indexes. As shown in these figures, the perceptual quality scores of material texture images are well correlated with our intuitions. Through our subjective experiments, we constructed our material texture database with nine perceptual quality scores.
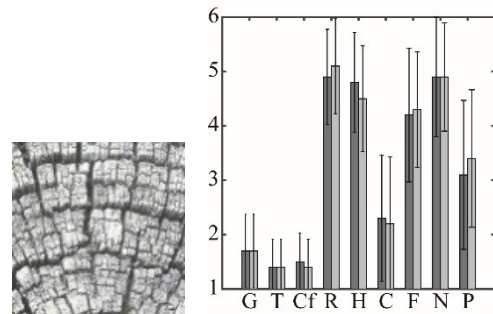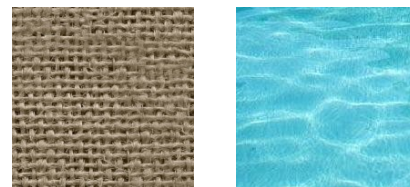

Figure 7. Example result (wood texture) of repeatability Investigation. The two color types of bars represent first and second rated scores.

(left) G:1.5, T:2.2, Cf:2, R:4.5, H:2.6, C:2.4, F:3.6, N:3.1, P2.9
(right) G: 4.1, T:4.9, Cf:5, R:2.2, H:1.4, C:5, F:2.9, N:4.7, P4.9

Figure 8. Examples of material textures with nine perceptual quality scores (see also the caption of Fig.6).

3.7 3.8 3.9 4.1 4.5

4.6 4.7 4.8 5.0 5.2

(a) Glossiness scores of Glass and Metal materials

1.8 1.9 2.7 3.8 4.2

4.3 4.5 4.6 4.8 5.0

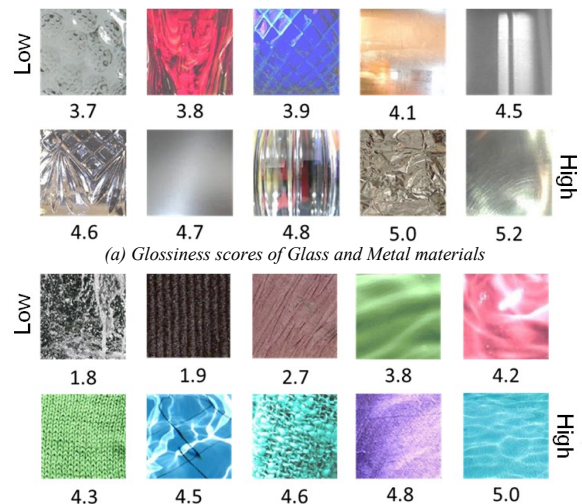*(b) Colurfulness scores of Fabric and Water*
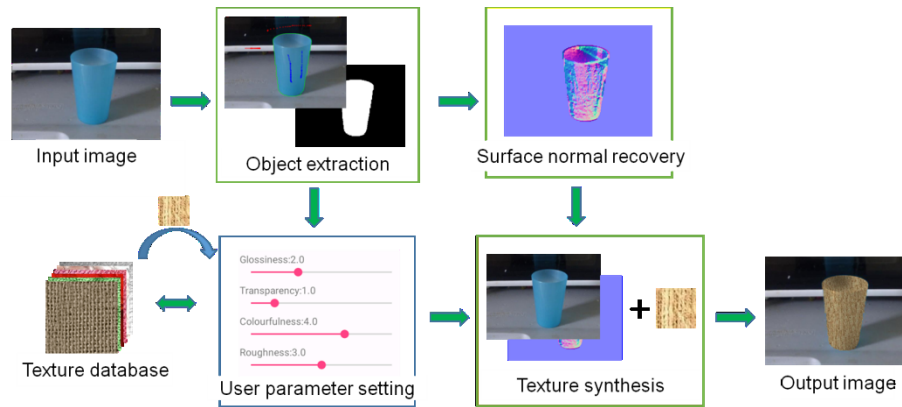
Figure 9. Score-ordered material texture images.
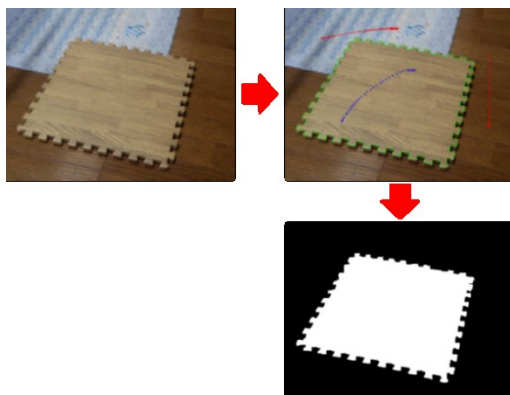
Figure 10. Overview of our retexturing system.

Figure 11. Example of object region extraction. Red line and blue line in upper right image were scribbled by a user.

System Overview and Algorithm

In this section, we describe algorithms in our retexturing system. Figure 10 shows the overview of our retexturing system. First, we extract target object regions in an input image. Second, surface normal of the extracted object regions is calculated. Then the user set the perceptual quality parameters and preferred object materials. Then, based on the user settings, an optimal texture is calculated from our material texture database. Finally the user achieves a retextured object image by adopting the optimal texture.

Object Region Extraction

First, a target object region in an input image is extracted. In this region extraction (segmentation), we applied the Lazy Snapping technique [11] which was an interactive image segmentation method. Lazy Snapping requires users to conceptually group the foreground object against its background through the interactive object marking steps. Instead of tracing the object boundary, Lazy Snapping allows users to use lines and curves to extract target object regions. The object region extraction (segmentation) algorithm is based on the combination of The Graph Cut with pre-computed over-segmentation. Figure 11 shows the example of object region extraction.

Surface Normal Recovery

Next we recover surface normal of segmented regions for realizing proper texture mapping on the object surface. In this normal recovery process, we used a technique proposed by Zelinka

et al [7]. Their method assumed a Lambertian reflection model. At the brightest point in the image, the surface normal point is facing to the light source. On the other hand, the darkest point of the image lies on a silhouette (right angle to the light source) and its normal aligns with the reverse image gradient. Based on this assumption, the surface normal at each pixel of target object region can be recovered.

Optimal Texture Calculation

An optimal texture is calculated based on the material texture database (see the previous section). Users intuitively set preferred target materials and perceptual quality scores through the user interface. As described in the previous section, the nine perceptual quality indexes (glossiness, transparency, colorfulness, roughness, hardness, coldness, fragility, naturalness and prettiness) and ten material categories (fabric, foliage, glass, leather, metal, paper, plastic, stone, water and wood) are applied as the user parameters.

Then, based on the preferred object materials and the perceptual quality scores by users, we calculate the optimal texture from the texture database. In this calculation, we employ the Euclidean distance of perceptual quality scores between the user setting and the subjective evaluation as follows.

$$d = \sqrt{\sum_{i=1}^{n} (u_i - t_i)^2} \,, \tag{1}$$

where n is the number of perceptual quality types by user setting parameter (maximum $n = 9$), u_i is the user setting scores and t_i is the texture scores in the material texture database. As shown in this equation, the perceptual quality indexes of which users does not set the scores are not are ignored for the optimal texture calculation. Figure 12 shows the examples of the calculated optimal texture.

Texture Synthesis for Retexturing on Surface

The selected texture through the above user setting is a small square patch. Then we synthesize a larger texture for suitable texture mapping to the object surface normal. For this texture synthesis, we apply the Jump Map technique [12]. A jump map is a parallel image to a texture which records for each pixel a small set of similar pixels within the image. A texture is produced from a seed point by iteratively copying pixels from the input to the output. Figure 13 shows an example of synthesized fabric texture.

Finally we map the synthesized texture on the object surface by using the recovered surface normal. This process provides appropriate angle-dependent appearance in terms of shading and texture scale.

(a) (User parameter setting) Categories: Fabrics and Leather, Perceptual qualities: Glossiness = 1.6 and Prettiness = 4.2. (Calculated optimal texture) Category: Fabrics, (Perceptual qualities: Glossiness = 1.6 and Prettiness = 4.1.

(b) (User parameter setting) Categories: Glass and Stone,, Perceptual qualities: Colourfulness = 4.2 and Hardness = 5.5. (Calculated optimal texture) Category: Glass, Perceptual qualities: Colourfulness = 4.1 and Hardness = 4.5.

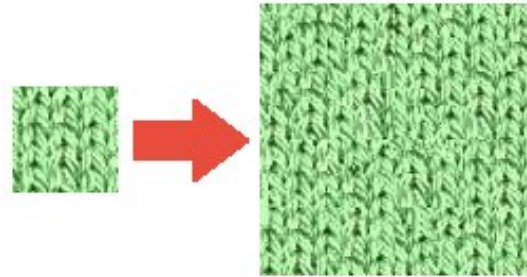Figure 12. Examples of user parameter settings and calculated textures.

Figure 13. Example of synthesized fabric texture by the Jump Map technique.

Implementation and Results

In this section, we describe how to implement our retexturing system on computers. We also demonstrate retexturing results through our developed retexturing system.

System Implementation and User Interface

We implemented our system on tablet computers on Android and Windows OSs. Figure 14 shows the user interface (UI) of our retexturing system as a Windows application (see also Figure 2 and 12 for our system as an Android application). Users need to operate the following four steps on this user interface. First, a user captures and selects an input image (upper left in the UI in Fig.14. Second, he/she marks a few lines for extracting a target object region (bottom left in the UI). Third, they set desired perceptual quality scores and preferred object materials (center parts in the UI). Then, based on the user settings, a calculated optimal texture from our material texture database is displayed. Finally the user pushes the "synthesis" button for achieving a retextured object image using the selected texture (right side in the UI).

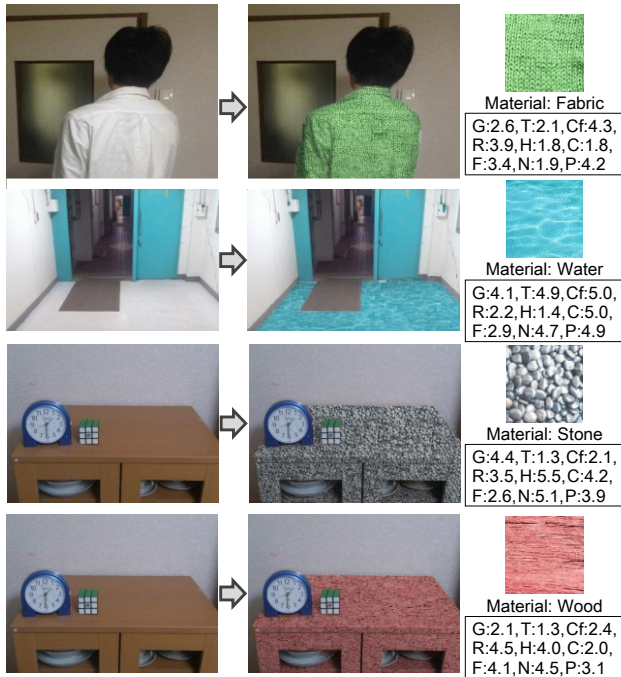Figure 14. Unser Interface of our retexturing system on the Windows OS.

Figure 15. Retexturing examples. The right side shows calculated materials and perceptual quality scores (see also the caption of Fig.6).

Figure 16. One of limitations in our retexturing system: a failure case due to the use of a nonuniform-shaded texture.

Results and Discussions

Figure 15 shows examples of our retexturing results. As shown in these examples, our system provides intuitive retexturing results based on the user interactive responds (settings). On the other hand, some material textures cannot provide appropriate results. Figure 16 shows one of our limitations. As shown in this figure, it is difficult to synthesize and map a continuous texture on object surface from a nonuniform-shaded texture patch. Our retexturing system also cannot provide object with highlights or specular (such as material of "metal" and "glass"), because our system does not address appropriate BRDF calculation.

Conclusions

This paper presented an interactive and intuitive retexturing system for editing object surfaces in images. For realizing the interactive and intuitive system, we applied the perceptual quality indexes and material categories as the user setting parameters. Our system will be helpful in image appearance editing and product design demonstration for general users.

As a future work, we must increase the number of texture images in our database for practical use. In particular, we develop the database with appropriate material textures for the retexturing. We also need to address objects with highlights (specular) such as metal and glass.

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Acknowledgments

Author Biography

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