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APPEARANCE TRANSFORMATION OF 3D OBJECTS DEPICTED IN IMAGES

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Abstract

In this work we propose a method that facilitates transport of a material appearance between objects depicted in two different images. The approach consists of two steps performed on both the material and original images, capturing the object material, and the object of interest itself. The diffuse and specular reflection components are separated by removing specular highlights from the material image. The diffuse components of both images are then used to obtain the surface normals of depicted objects by application of shape from shading algorithm (SFS). The robustness of the method is limited mostly by precise estimations of surface normals and the light direction needed to acquire a reflectance of depicted objects.

As this process contains some ambiguities, we do some assumptions about the scene depicted in these images. We assume the objects are lit by a single white directional light source, and object's diffuse color is not a white. We also assume that there are specular highlights depicted within the images.

We have validated the method by a transfer of a real car paints onto an image of abstract 3D shape.

ACM Computing Classification System 1998: I.3.6, I.3.7
Additional Key Words and Phrases: shape from shading, appearance, reflection components separation

1. INTRODUCTION

The reflection model can be described as a function including various parameters related to color and geometry. Models for describing light reflection on an object surface are called *illumination models* and are widely used for rendering realistic images. In practice it could be useful to recover unknown reflectance properties from image data. Although the nature of the problem of recovering unknown reflectance parameters from image is underconstrainted, there are some works devoted to this problem. In [Robles-Kelly and Hancock 2005] is described a method for estimating surface radiance function from single images of smooth surfaces made of materials whose reflectance function is isotropic and monotonic. Under conditions in which the light source and the viewer direction are identical, this method can estimate a tabular representation of the surface radiance function. Classification of reflectance properties of surfaces from an image based on predictable statistics of the typical natural illumination is described in [Dror et al. 2001]. Properties of the object's surface reflection in [Tominaga and Tanaka 2000] are obtained by the color histogram analysis. In the process of the reflection analysis it is reasonable to separate the specular and diffuse reflection. Papers [Tan and Ikeuchi 2005] and [Tan et al. 2006] discuss the problem of this separation.

In this paper we present a problem of transfering a material appearance between two objects in images and solution of this problem under certain simplifying assumptions. To our knowledge there is no work devoted to this specific problem so far. Although, for the sake of simplicity we assume that depicted objects are lit by the white light source, the method [Tan et al. 2004] to estimation of the color of the illuminant could be used in general case.

2. SEPARATION OF THE SPECULAR COMPONENT

Let us consider the dichromatic reflection model, where the color of highlight is a linear combination of specular and diffuse color. This model proves adequate for most materials such as inhomogeneous dielectrics. Under assumption, that the scene is lit by the white source and the diffuse color of the object is not desaturated, the diffuse component can be obtained by the projection along the illumination direction. Color of pixels in the specular highlight region of the image creates an highlight cluster in RGB color space, see Figure 1.

Maximum chromaticity is defined by the following formula:

$$\sigma(\mathbf{x}) = \frac{max(I_r(\mathbf{x}), I_g(\mathbf{x}), I_b(\mathbf{x}))}{I_r(\mathbf{x}) + I_g(\mathbf{x}) + I_b(\mathbf{x})}, \tag{1}$$

where $\mathrm{I}_r(\mathbf{x})$, $\mathrm{I}_g(\mathbf{x})$ and $\mathrm{I}_b(\mathbf{x})$ are R, G and B components of the pixel at the image coordinates $\mathbf{x}$. Let $\mathbf{d}$ is a vector in the RGB space defined as $(\mathrm{I}_r(\mathbf{x}),\mathrm{I}_g(\mathbf{x}),\mathrm{I}_b(\mathbf{x}))$, where $\mathbf{x}$ are coordinates of the pixel of the object in the image with $\sigma(\mathbf{x}) = \max\{\sigma(\mathbf{y})|\mathbf{y}\in \Omega\}$. Ω is a region in the image where the object is inhered in. Let $\mathbf{s}$ is a vector in the RGB space defined as $(1, 1, 1)$ representing the direction of the illumination color. Diffuse component $\mathbf{c}(\mathbf{x})$ of the pixel at $\mathbf{x}$ with color $\mathbf{p}(\mathbf{x})$ in the highlight cluster is then computed as the intersection of the line in the direction $\mathbf{s}$ passing through $\mathbf{p}(\mathrm{x})$ with the line in the direction $\mathbf{d}$ passing through point (0,0,0). In other words, the diffuse component of the pixel at the coordinates $\mathbf{x}$ with the color $\mathbf{p}(\mathbf{x})$ is given by the following formula:

$$\mathbf{c}(\mathbf{x}) = \mathbf{p}(\mathbf{x}) + \mathbf{s}\frac{(-\mathbf{p}(\mathbf{x}) \times \mathbf{d}).(\mathbf{s} \times \mathbf{d})}{\|\mathbf{s} \times \mathbf{d}\|^2} \tag{2}$$

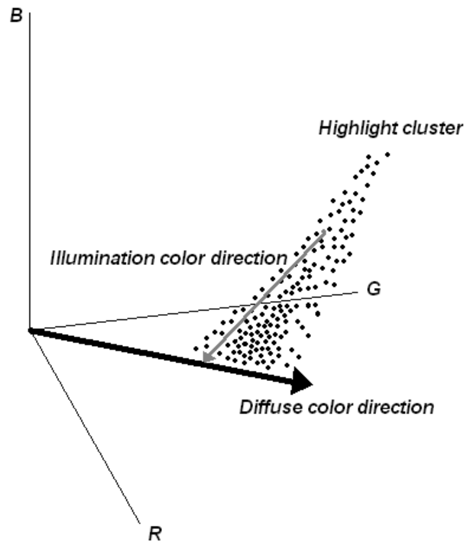


Figure 1. Color histogram in the RGB space.

Specular component can be derived by $\mathbf{p}(\mathbf{x})$ - $\mathbf{c}(\mathbf{x})$. Figure 2 shows an image of the sphere on top and two images obtained by decomposition into the diffuse and specular components.

As clamping in the color space produces saturation of the color, it is reasonable to use one of the HDR color formats such as RGBE.

To evaluate errors we use mean square error. We have decomposited specular and diffuse component of the sphere. We also rendered sphere with omitted specular component and have compared it with result of decomposition. We have evaluated error of the diffuse component to 2.10^{-6}. Error was evaluated by the following formula:

$$e = \frac{1}{|\Omega|} \sum_{\mathbf{x} \in \Omega} (\Delta(\mathbf{x}))^2, \tag{3}$$

where $|\Omega|$ is amount of pixels in region Ω of images and Δ is distance between two RGB colors and

$$\Delta(\mathbf{x}) = \sqrt{(I_r(\mathbf{x}) - I'_r(\mathbf{x}))^2 + (I_g(\mathbf{x}) - I'_g(\mathbf{x}))^2 + (I_b(\mathbf{x}) - I'_b(\mathbf{x}))^2}. \tag{4}$$

Each component of the RGB color varies from 0 to 1. I'($\mathbf{x}$) is rendered image with omitted specular component and I($\mathbf{x}$) is acquired diffuse component image. Mean square error of the specular component was 10^{-5}.

3. SHAPE FROM SHADING

The purpose of this section is to calculate the normal vector $\mathbf{N}(\mathbf{x})$ at surface point from an image of a surface. Let $\mathbf{I}(\mathbf{x})$ is a greyscale image of the diffuse component, then according to Lambertian reflection it can be written as

$$\mathbf{I}(\mathbf{x}) = \eta(\mathbf{N}(\mathbf{x}).\mathbf{L}), \tag{5}$$

where $\mathbf{L}$ is the illumination direction, η is the composite albedo and $\mathbf{N}(\mathbf{x})$ is the surface normal at the image plane coordinates $\mathbf{x}$. Obtaining of the 3D shape from a single shaded image is ill-proposed problem, therefore most of the algorithms incorporates regularization. The common assumption about surface shape is that the surface is locally spherical.

Most of the shape from shading methods require known direction of illumination. Authors in [Zheng and Chellapa 1991] discussed a method for estimation of the illumination direction and surface diffuse component. This method is based on the statistics of the derivatives of the image intensities in particular directions. Although for the images of perfect sphere this method works quite well, for relatively complex images results

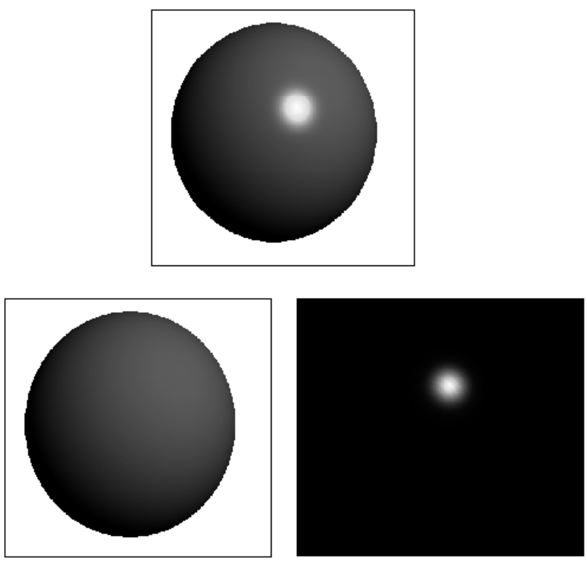


Figure 2. Original image and its diffuse and specular component image.

are not very encouraging. The recovered shape can be expressed as depth Z($\mathbf{x}$) or surface normals, where Z directs toward the camera. An iterative method based on the discrete approximation of the surface gradients is proposed in [Tsai and Shah 1994].

Horn and Brooks have proposed to use the unit normal rather then the gradient [Brooks and Horn 1989]. This method is based on the minimization of $\int_{\Omega}(\mathbf{I}(\mathbf{x})$-$\mathbf{N}(\mathbf{x}).\mathbf{L})^2 \mathrm{d}\mathbf{x}$, where Ω is a region in xy-plane. We adopted the iterative scheme for minimisation of a functional, where the surface normal is updated by taking a local average, and adjusting it either toward or away from the source.

4. TRANSFORMATION OF THE APPEARANCE

Proposed method requires two input images, first one is the material image $\mathbf{I}_1(\mathbf{x})$, depicting the object with required material appearance. Second input image is the object image $\mathbf{I}_2(\mathbf{x})$ it is the original image of object which some appearance we would like to change. The goal of this method is to change pixels of the object in original image $\mathbf{I}_2(\mathbf{x})$ to achieve the material appearance of the object depicted in material image $\mathbf{I}_1(\mathbf{x})$.

The color vector $\mathbf{p}(\mathbf{x})$ of the pixel of the object at the coordinates $\mathbf{x}$ can be described as follows:

$$\mathbf{p}(\mathbf{x}) = (\mathbf{N}(\mathbf{x}).\mathbf{L})\mathbf{d} + w_i(\mathbf{x})\mathbf{s}, \tag{6}$$

where $\mathbf{d}$ is the diffuse color vector, $\mathbf{s}$=(1,1,1) is the illumination color, $\mathbf{H}$ is the bisector vector between the light and the viewing direction, and $w_i(\mathbf{x})$ is the function of $\mathbf{N}(\mathbf{x}).\mathbf{H}$. First term represents the diffuse component of the pixel at the coordinates $\mathbf{x}$, and second term represents the specular component. Applying the decomposition described in Section 2 to each of the input image produces a specular component image and a diffuse component image. To estimate the geometry of both objects depicted in input images a shape from shading method is used. Results of proposed steps are captured in Figure 3.

To estimate the surface normals, method described in [Brooks and Horn 1989] have been used. Let $\mathbf{N}_1(\mathbf{x})$ is the normal map of the object in the material image $\mathbf{I}_1(\mathbf{x})$ and $\mathbf{N}_2(\mathbf{x})$ is the normal map of the object image $\mathbf{I}_2(\mathbf{x})$. Let $\mathbf{x}_1$ are coordinates of the most brightest pixel in the specular component image of the material image and $\mathbf{x}_2$ in the specular component of the object image. Let the bisector vector $\mathbf{H}_1$ is $\mathbf{N}_1(\mathbf{x}_1)$ and $\mathbf{H}_2$ is $\mathbf{N}_2(\mathbf{x}_2)$. Let $\mathbf{L}_1$ represents illumination direction in the material image and $\mathbf{L}_2$ in the object image. $\mathbf{L}_1$ is obtained as the reflection $\mathbf{L}_1 = 2(\mathbf{E}.\mathbf{H}_1)\mathbf{H}_1$ - $\mathbf{E}$ and similarly $\mathbf{L}_2 = 2(\mathbf{E}.\mathbf{H}_2)\mathbf{H}_2$ - $\mathbf{E}$, where $\mathbf{E}$ = (0,0,1).

Let $\mathbf{A}$ and $\mathbf{B}$ are tabular representations of a mapping form $\mathbb{R}$ to RGB space

$$A = \{(\mathbf{N}_1(\mathbf{x}).\mathbf{L}_1, d(\mathbf{I}_1(\mathbf{x}))) \mid \mathbf{x} \in \Omega_1\} \tag{7}$$

$$B = \{(\mathbf{N}_1(\mathbf{x}).\mathbf{H}_1, s(\mathbf{I}_1(\mathbf{x}))) \mid \mathbf{x} \in \Omega_1\} \tag{8}$$

where $d(\mathbf{I}_1(\mathbf{x}))$ is diffuse component of $\mathbf{I}_1(\mathbf{x})$, $s(\mathbf{I}_1(\mathbf{x}))$ is specular component of $\mathbf{I}_1(\mathbf{x})$ and Binary tree data structure storing $\mathbf{A}$ and $\mathbf{B}$ stores pairs of the dot products and the color. For each pixel coordinates $\mathbf{x}$ of the object in the material image, the dot product $\mathbf{N}_1(\mathbf{x})$. $\mathbf{L}_1$ and the diffuse component $d(\mathbf{I}_1(\mathbf{x}))$ are stored into $\mathbf{A}$. Similarly, for each pixel coordinates $\mathbf{x}$ of the object in material image the dot product $\mathbf{N}_1(\mathbf{x})$. $\mathbf{H}_1$ and its corresponding specular component $s(\mathbf{I}_1(\mathbf{x}))$ are stored into $\mathbf{B}$.

Transfer of the material appearance is achieved by changing pixels colors of the object in $\mathbf{I}_2(\mathbf{x})$. For each pixel coordinate $\mathbf{x}$ of the object in $\mathbf{I}_2(\mathbf{x})$ we determine the $\mathbf{d}(\mathbf{x})$ and $\mathbf{s}(\mathbf{x})$. We select two elements (a_1,c_1) and (a_2,c_2) from $\mathbf{A}$. The first element (a_1,c_1), where $a_1=\max\{a \mid a \leq \mathbf{N}_2(\mathbf{x}).\mathbf{L}_2, (a,c) \in A\}$ is the pair which has first higher component closest to $\mathbf{N}_2(\mathbf{x}).\mathbf{L}_2$, while the second element (a_2,c_2) where

$a_2=\min\{a \mid a \geq \mathbf{N}_2(\mathbf{x}).\mathbf{L}_2,\ (a,c) \in A\}$ has its dot product lower component closest to $\mathbf{N}_2(\mathbf{x}).\mathbf{L}_2$. The color $\mathbf{d}(\mathbf{x})$ is then defined as the linear interpolation of the color components c_1 and c_2. The color $\mathbf{s}(\mathbf{x})$ is defined as the linear interpolation of color components c_3 and c_4 of two elements (b_1,c_3) and (b_2,c_4) from $\mathbf{B}$, where $b_1=\max\{b \mid b \leq \mathbf{N}_2(\mathbf{x}).\mathbf{H}_2,\ (b,c) \in B\}$ and $b_2=\min\{b \mid b \geq \mathbf{N}_2(\mathbf{x}),\ \mathbf{H}_2,\ (b,c) \in B\}$, respectively. Then pixel color of the object at coordinates $\mathbf{x}$ in the original image is changed as follows:

$$\mathbf{I}_2(\mathbf{x}) = \mathbf{d}(\mathbf{x}) + \mathbf{s}(\mathbf{x}). \tag{9}$$

5. RESULTS

Proposed method was tested on multiple synthetic images using Phong and Cook-Torrance illumination model. Best result has been obtained in the material image $\mathbf{I}_1(\mathbf{x})$ with a single sphere and with the same light and viewer direction.

Figure 4 shows a material appearance transfer from yellow sphere with the shininess coefficient 30 to the blue teapot with the shininess coefficient 100. The direction of the light in case of the sphere was (0,0,1) and estimation was $\mathbf{L}_1 =$ (-0.002,-0.001,1). In the case of the teapot the light direction was (0,-0.4,1) and the estimation of the light direction was $\mathbf{L}_2 =$ (-0.02,-0.18,0.983). Inaccuracies in normal estimations were affected by errors in the light direction estimations of the Zheng & Chellappa's method.

We evaluated mean square error according to Eq. 3 in diffuse transport to 0.038 and specular transport to 0.058. In Figure 5 we show the differences in RGB space between result of this transfer and exact rendered image. In the upper part of teapot are some inaccuracies in specular component. In the diffuse component are inaccuracies at the boundaries caused by shape from shading algorithm.

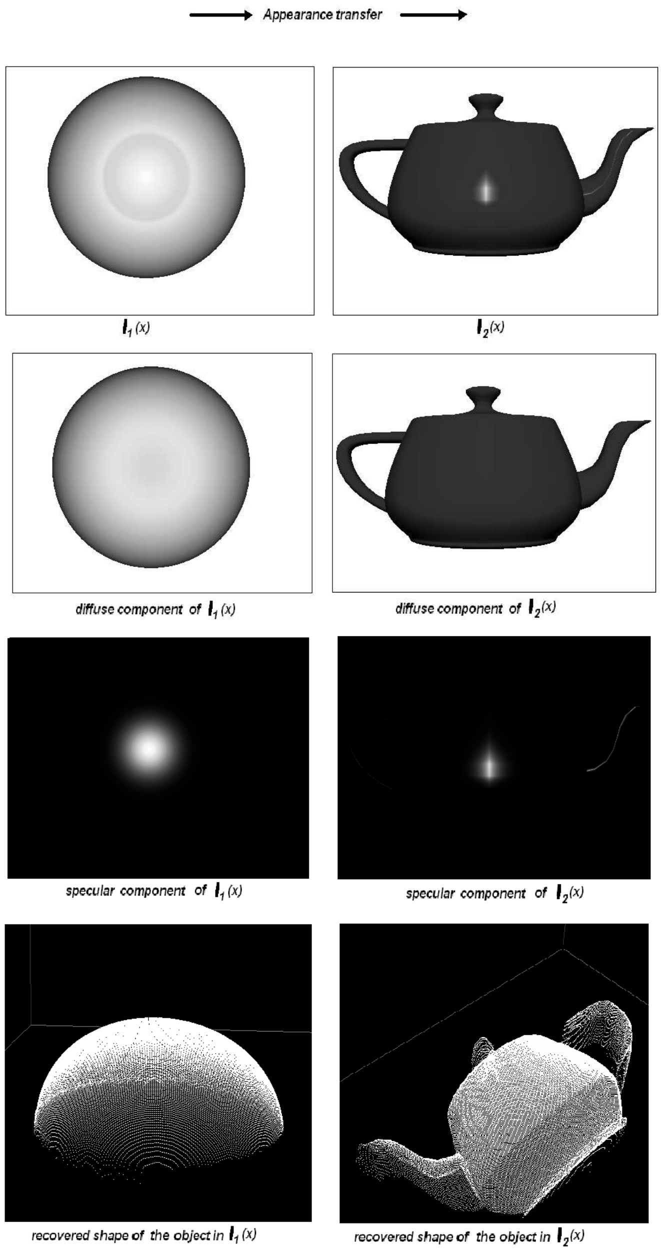


Figure 3. Steps required in the process of the transfer.

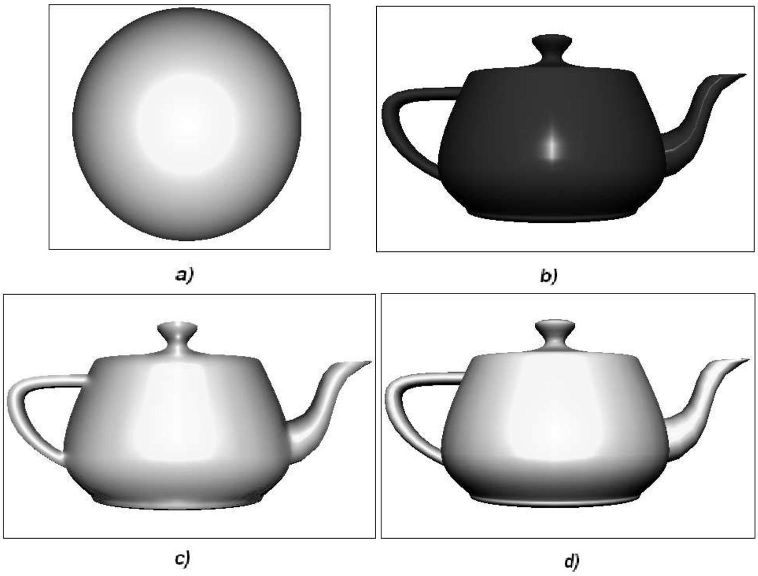


Figure 4. Material transfer from yellow sphere to the teapot. a) The source image $\mathbf{I}_1(\mathbf{x})$. b) The target image $\mathbf{I}_2(\mathbf{x})$. c) The material appearance of the object in $\mathbf{I}_1(\mathbf{x})$ transfered to the object in $\mathbf{I}_2(\mathbf{x})$. d) The original object from $\mathbf{I}_2(\mathbf{x})$ rendered with the same material parameters as the parameters of the object in $\mathbf{I}_1(\mathbf{x})$.

Figure 6 shows result of the appearance transfer from the sphere with the metallic car painting to the yellow teapot. Estimation of $\mathbf{L}_1$ is (-0.16,-0.136,0.98) and $\mathbf{L}_2$ is (-0.0768,0.252,0.96). The Horn and Brooks algorithm tends to oversmooth the recovered normal map, which leads to losing of the boundaries. The problem of improper estimation of the geometry of the object in the material image $\mathbf{I}_1(\mathbf{x})$ leads to certain noise in the result. This noise is due to errors in the recovered normal map which leads to the constructions of structures $\mathbf{A}$ and $\mathbf{B}$ in which some element may have the dot product component higher then some others elements, but the color component consists of the color with lower intensity.

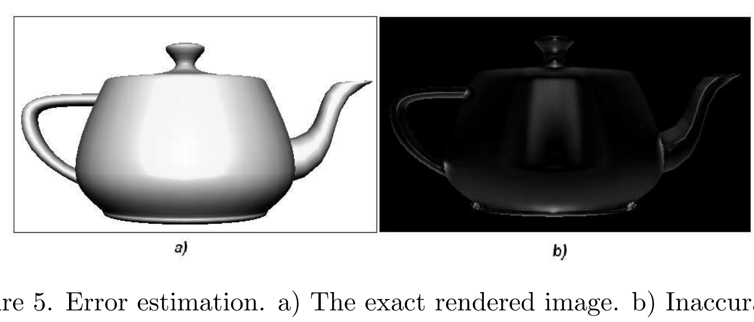


Figure 5. Error estimation. a) The exact rendered image. b) Inaccuracies of the result.

6. CONCLUSION

We have developed method which gets material of the object from single image and applies it to another image. The bottleneck of this method is the inaccuracy of the classic shape from shading algorithms. Despite not encouraging results of these approaches there can be some improvement accomplished by involving a user interaction to the shape recovering process as proposed in [Yasuyuki et al. 1999]. An attempt to decrease the dependency on the shape from shading algorithm of the proposed appearance transformation method may also increase the accuracy.

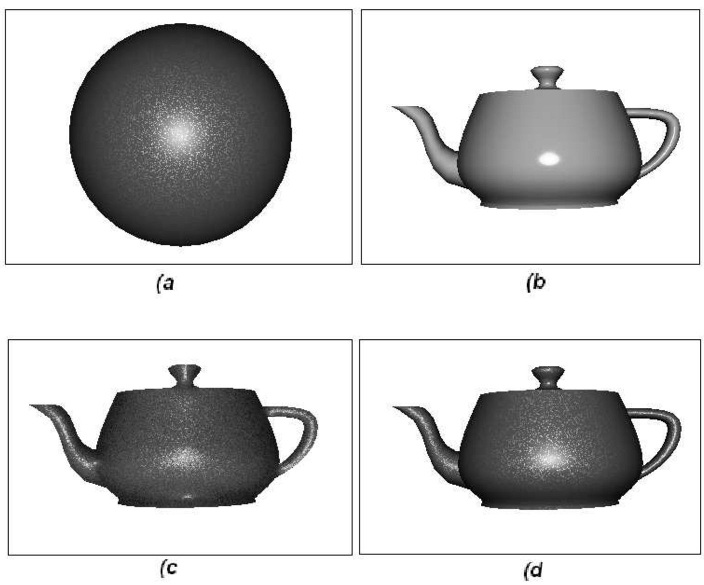


Figure 6. Transferring sparkling material from the sphere to the teapot. a) The source image $\mathbf{I}_1(\mathbf{x})$. b) The target image $\mathbf{I}_2(\mathbf{x})$. c) The material appearance of the object in $\mathbf{I}_1(\mathbf{x})$ transfered to the object in $\mathbf{I}_2(\mathbf{x})$. d) The original object from $\mathbf{I}_2(\mathbf{x})$ rendered with the same material parameters as the parameters of the object in $\mathbf{I}_1(\mathbf{x})$.

Another improvement of the proposed method may be achieved by generalization of the assumption of the illumination and the object's surface composition. For example color changes in pearlescent paintings produces ambiguity errors in the process of the extraction of the diffuse component. Incorporating an environment map analysis may allow appearance transformation of the material surface which reflects surroundings.

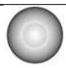
scene	exact light direction	estimated light direction	exact **H**	estimated **H**
	(0,0,1)	(-0.002,-0.001,1)	(0,0,1)	(-0.002,-0.001,0.999)
	(0,-0.4,1)	(-0.02,-0.18,0.983)	(0,-0.196,0.981)	(-0.012,-0.067,0.997)
	(0,0,1)	(-0.012,-0.016,0.999)	(0,0,1)	(-0.006,-0.008,0.999)
	(-1,-1,0.4)	(-0.4,-0.011,0.8)	(-0.503,-0.503,0.704)	(-0.23,-0.006,0.973)

Table 1. Vectors estimations.

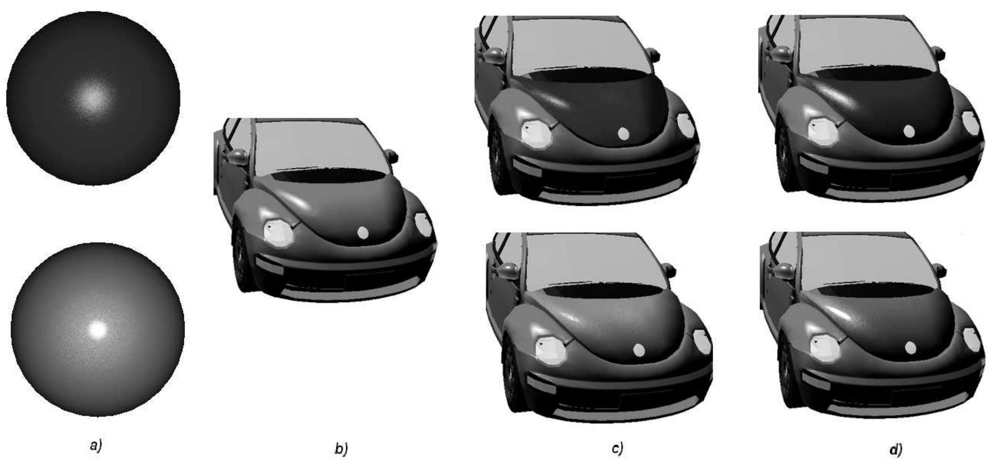


Figure 7. Multiple material transfer to a specific regions. a) Source images. b) The target image. c) Source material applied onto the bonnet of the car. d) Bonnets rendered with the same material parameters as the parameters of the object in source images.

experiment	relative error
	2.476%
	5.365%
	14.837%
	11.989%

Table 2. Relative errors.

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