Translucent Material Transfer Based on Single Images

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(a) Source (b) Target (c) Depth Map (d) Final Result

Figure 1: *Transfer the material of green grapes to an egg while maintaining the specular lighting and translucent effect.*

1 Introduction

Extraction and re-rendering of real materials give large contributions to various image-based applications. As one of the key properties of modeling the appearance of an object, materials mainly focus on the effects caused by light transportation. Therefore, understanding the characteristics of a complex material from a single photograph and transferring it to an object in another image becomes a very challenging problem.

Khan et al. [2006] present an image-based material editing method which can produce translucent or transparent materials in place of the original diffuse objects or re-render the objects with arbitrary BRDFs in a single high dynamic range photograph. However, the experiential models in their system sometimes is not convenient to create very realistic images, using real materials as input should be considered. Moreover, this approach employs a re-texturing method instead of simulating the real mechanism of light transport in translucent material, that will also affect the synthesis quality.

In this paper, we present a novel framework to transfer real translucent materials such as fruits and flowers between single images. We define a group of information which can model the attributes during the extraction and transfer process. Once we extract those information from both the source and target images, we can easily produce a realistic photograph of an object with target-like materials and suitable shading effects in the environment of sources.

2 Algorithm Details

2.1 Re-rendering Translucency in Single Image

Translucent materials have two main special light effects: white highlight differed from metals and irradiance reduction with the distance of light transmission from the incident point to the outgoing point. Following the above issues, we first cut out the object from the target image and segment out the highlight set H from the set O including all the pixels within the contour of the object by the highlight detection method in [Khan et al. 2006]. Then we re-render the new material of an object as follows ($C(x, y)$ is the pixel color at point (x, y) in images):

$$C_{object}(x,y) = \begin{cases} C_H(x,y), & if(x,y) \in H \\ C_O(x,y), & otherwise \end{cases} \tag{1}$$

For set O, we employ the dipole diffusion equation from [Jensen and Buhler 2005] and TSM rendering method from [Dachsbacher and Stamminger 2003] to approximate the translucent part of object. Considering the outgoing vector for every point in the image equals the view vector $v = (0, 0, 1)$, it can be rewritten as:

$$\begin{aligned} C_O(x,y) = & \frac{1}{\pi} F_t(\eta, v) \int_A R_d(\|(x,y) - (x_{in}, y_{in})\|) \\ & E(x_{in}, y_{in}) dA(x_{in}, y_{in}), \end{aligned} \tag{2}$$

where $F_t(\eta, v)$ is the Fresnel transmission coefficient and η represents the relative index of refraction ($\eta = 1.3$ in our experiments). $R_d(\|(x, y) - (x_{in}, y_{in})\|)$ is the diffuse reflectance function, and $E(x_{in}, y_{in})$ is the irradiance at a given point on the surface.

For the highlight set H, we employ the specular lighting part of Phong model. Consider H as *a gloss map* of the object, $C_H(x, y)$ can be rewritten as:

$$C_H(x,y) = \begin{cases} C_O(x,y) H \sum_{i=1}^{n} I_i max\{N \cdot h_i, 0\}^m, \; if \; (N \cdot \omega_i > 0) \\ 0, \quad otherwise, \end{cases} \tag{3}$$

where $C_O(x, y)$ is the surface color at point (x, y), I_i is the intensity of the ith incident light L_i, ω_i is the direction of incident light and m is the specular exponent which can control the sharpness of the specular highlight ($m = 5$ in our experiments).h_i is the halfway vector for the L_i given by

$$h_i = \frac{\omega_i + v}{\|\omega_i + v\|}, \tag{4}$$

where v is the view vector set to be (0,0,1) in our experiments.

Finally, after departing the highlight set H, we still have 3 parameters to solve: the object shape information Ω, the information of incident lights L_i (including the direction ω_i and intensity I_i), and the diffuse reflectance function R_d. Therefore, our material extraction algorithm contains three main steps: shape recovery, light detection and BSSRDF estimation.

2.2 Material Extraction and Transfer

Shape recovery We adapt the shape from shading method in [Khan et al. 2006] to reconstruct the depth map Z of an object. W assume

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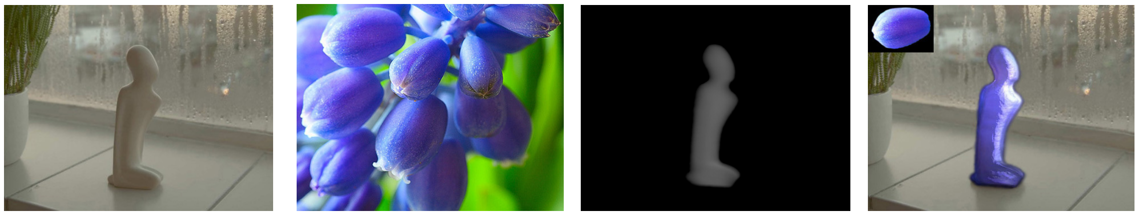

(a) Source (b) Target (c) Depth Map (d) Final Result

Figure 2: *Transfer the material of purple flowers to an sculpture while maintaining the specular lighting and translucent effect.*

the global convexity as follows:

$$Z = (1 - \alpha) D_{base} + \alpha D_{detail} \tag{5}$$

where the base layer D_{base} encodes global convexity and the detail layer D_{detail} encodes high frequency. We can increase the coefficient α to fit the shape recovery from simple geometries to more complicated objects (0.6 is good for most objects). Furthermore, we utilize the bilateral filter to post-process these two layers, so we can control the smoothness of the recovery depth map by the value $\sigma_{spatial}$ in the bilateral filter. A bigger $\sigma_{spatial}$ will make the final depth map smoother. Next, a normal map N is subsequently computed from Z by using the gradient field method in [Khan et al. 2006]. As BSSRDF is a global rendering equation which needs the entire shape information of an object, with the assumption of symmetry, we create a back depth map Z_b by just mirroring Z. The corresponding back normal map N_b is also generated.

Light detection We separate incident lights L_i into the light for highlight $L^{highlight}$ and lights for translucency L_i^{trans}. We propose a voting algorithm to calculate the light parameters for highlight based on our recovered normal map of points in set H and the halfway vector theory of Phong model (Equation 3). In Phong model, specular lights are the most intense when the halfway vector (h in Equation 4) points to the direction of the normal vector n at one point of the object surface, so we use the view vector $v = (0, 0, 1)$ and the normal of every point p in set H to reverse the direction $\omega^{highlight}$of its corresponding highlight with the Equation 4. Finally we compute the weighted average of all calculated direction of highlight to vote out the main direction $\widetilde{\omega}^{highlight}$ of $L^{highlight}$. We utilize the method in [Lopez-Moreno et al. 2010] to detect the lights L_i^{trans} for translucency (including the direction ω_i and the intensity I_i). That method performs a two-step analysis of the pixels' luminance along and within the contour of an object. Finally, we set both $L^{highlight}$ and L_i^{trans} as the entire incident lights L_i for the computing of $C_H(x, y)$ while the intensity ratio of $L^{highlight}$ is usually set to 0.5 and 0.5 for left lights. When calculating $C_O(x, y)$, we just use L_i^{trans} as the incident lights L_i.

BSSRDF estimation We adapt the approach in [Munoz et al. 2011] to estimate the BSSRDF model from the given single image. Based on the previously recovered object shape and light information, and the approximated diffuse profile R_d by piecewise constant functions, the dipole diffusion equation is formatted into a linear system, which can be solved using the Quasi-Minimal Residual (QMR) method. Furthermore, because R_d is an exponential function, to get a more precise result, we also fit the piecewise constant function into the form of $f(x) = ae^{bx} + ce^{dx}$. We have also tried this BSSRDF estimation method on common photographs not just HDR images, and the results show good effect as well.

In the final transfer step, we re-render the new realistic appearance of chosen object with those information got in previous steps and the rendering equation we mentioned in Section 2.1.

3 Results and Conclusion

In this paper, we present a novel translucent material transfer algorithm, which can extract the translucent material information from a single natural image and transfer it to an object in another image. As Figure 1 shows, our algorithm reproduces the translucent effect of green grapes in the source image and maintains the highlights in the right position with the right color. In Figure 2, the purple translucency and white highlight of the target material is all depicted in the source sculpture object. The limitation of our algorithm is that currently our shape recover step depends on the shape from shading technique, so we can just do such transfer on some objects without many surface details. In the future, we plan to accelerate our algorithm to real-time level and extend the algorithm to video editing field which can supply more shape information for BSSRDF estimation and re-rendering.

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