Image-Based Illumination for

Electronic Display of Artistic Paintings

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Abstract

Visual impressions from two-dimensional artistic paintings greatly vary under different illumination conditions, but this effect has been largely overlooked in most poster productions and electronic display. The light-dependent impressions are more pronounced in oil paintings and they arise mainly from the non-diffuse specular reflectances. We present an efficient method of representing the variability of lighting conditions on artistic paintings utilizing both simple empirical reflectance models and an image-based lighting method. The Lambertian and Phong models account for a significant portion of image variations depending on illumination directions, and residual intensity and color variations that cannot be explained by the reflection models are processed in a manner that is similar to the image-based lighting methods. Our technique allows brush strokes and paint materials to be clearly visible with relatively low data dimensionality.

CR Categories and Subject Descriptions: I.3.3 [Computer Graphics]: Picture/Image Generation; I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism – Color, shading, shadowing and texture; I.4.1 [Image Processing and Computer Vision] Digitization and Image Capture - Reflectance

Additional Keywords: Image-based lighting, Illumination, Reflectance, Artistic Painting, Phong Model, Diffuse Reflectance, Texture Model.

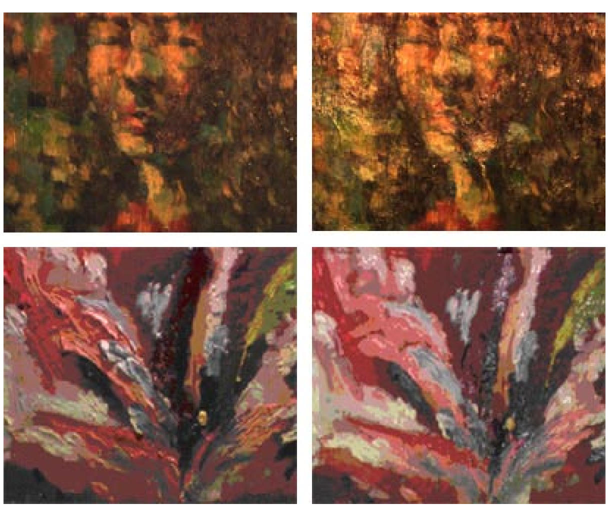

Figure 1. Paintings under different lighting conditions

1 Introduction

The difference between the visual impressions from a real painting in an art museum and from its photographed posters or images displayed on a CRT monitor is quite striking. The well-known reasons for the visual discrepancy include the inaccurate color reproduction and size difference. However, the visual impressions resulting from brush strokes, paint materials and canvas textures have been largely overlooked mainly due to the lack of appropriate means to display them in a reproduced image. The visual perception of those effects arises to a large extent from the non-Lambertian specular reflections and the appearance of a painting (especially oil painting) varies greatly depending on the illumination conditions. People in an art museum change their viewpoints occasionally to better appreciate the surface texture of a painting under various lighting environments. Figure 1 shows two oil paintings under different light directions. A straightforward way to provide all the visual information would be to photograph a painting under all the possible illumination conditions and let a person change the conditions electronically in a computer. However, the data dimensionality would be prohibitively high, especially in a web environment.

The ideal way of dealing with all the lighting and viewing variabilities is to employ accurate physical reflectance models based on the Bidirectional Reflectance Distribution Function (BRDF). However, most non-Lambertian physical models are quite complex and estimation of their parameters from real scenes is intricate. There have been data-driven approaches that render a scene under a novel lighting condition based on a set of input images acquired under known or unknown illumination conditions. These image-based relighting methods employ some form of data reduction schemes such as those based on eigenspace to lower data dimensionality and they linearly combine basis images to generate a novel view based on the linearity of light. For the paintings with both diffuse and non-Lambertian specular reflectances, the main difficulty in applying those methods lies in that they are limited to a single reflectance type from diffuse surfaces and specular reflections are not generally considered.

In this paper, we present a new strategy of efficiently displaying artistic paintings under a range of lighting conditions using a combination of input images and reflectance models. This approach partly takes advantage of the compactness of reflection models and also partly of the image-based methods' ability to account for image variation without rigorous modeling. To explain this concept, we represent the image irradiance I as:

$$I = f(\Theta) + r$$

where $f(\Theta)$ and Θ are the reflectance model function and its parameters, respectively, and r is the residual, i.e., the difference between the measured image and the image predicted by the model. If $f(\Theta)$ is highly accurate physically, the residual is negligible and the image I can be compactly represented. If $f(\Theta)$ is only approximate, on the other hand, the residual r should be kept to maintain image information. Instead of the original images, this set of residuals can be used for image-based relighting together with $f(\Theta)$. When $f(\Theta)$ can account for a significant portion of multiple reflection components, the residual r becomes much smaller than the original image I and the data size for the image-based relighting part becomes much smaller. The reflectance model part $f(\Theta)$ allows both diffuse and specular reflections to be considered. Since it can be approximate, we use the Lambertian model for diffuse reflectance and the emprical Phong model for the specular reflectance for its simplicity. The residual r takes into account all the inaccuracies in modeling, measurement errors in image capture, and the intensity and color variations unmodeled in $f(\Theta)$ such as self-shadowing, sub-surface scattering and interreflections. In our work presented in this paper, the main variability is in lighting directions and we fixed the viewing direction. We show that our simple modeling using the Phong model keeps the residual very low for most of the paintings we experimented with and the total data size for displaying an oil painting under a wide range of illumination angles is kept very small.

2 BACKGROUND AND PREVIOUS WORK

The Bidirectional Reflectance Distribution Function (BRDF) [Nicodemus 77] provides the most fundamental basis for the characterization of surface reflectance properties. There have been a large number of techniques developed to accurately and compactly represent the BRDF such as those that use linear basis functions [Cabral 87], [Sillion 91], and physically based analytic models [Torrance 67], [Cook 81], [He 91]. [Dana 99] presents the Bidirectional Texture Function (BTF) that captures textures under pre-integrated lighting conditions. Empirical models have been widely used in computer graphics [Phong 75], [LaFortune 97].

Image-based relighting methods have been developed that allow a scene to be rendered under novel lighting conditions, based on a set of input images. They include [Shashua 92], [Nimeroff 94], [Belhumeur 96], [Teo 97], [Nishino 99], [Georghiades 99], [Wood 00] and [Debevec 00]. Most of the methods are based on diffuse reflections and specular reflections have not been explicitly taken into account. Like our work presented in this paper, they assume fixed viewpoint. On the other hand, objects can be rendered with novel lighting from new viewpoints in [Wong 97] [Levoy 96][Gortler 96].

[Epstein 95] and [Ramamoorthi 01] suggest that low-dimensional lighting models are adequate to model reflections including non-Lambertian reflections. However, specular reflections are widely spread spatially in the test and sharp specularities are not considered. [Lin 00] suggest a method for separately combining diffuse and specular reflections linearly for generating novel views.

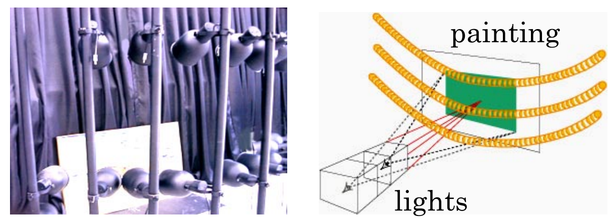

Figure 2. Light arrangement

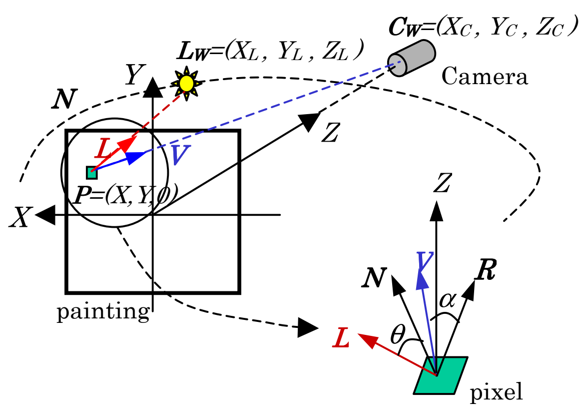

Figure 3. Imaging geometry

3 APPROXIMATION OF REFLECTION COMPONENTS

3.1 Acquisition of Image Irradiance from Painting

As in the field of photometric stereo and other related fields ([Debevec 00], [Georghiades 99], [Malzbender 01]), we collect multiple images of a static 2-D painting with a static color camera under varying illumination conditions. Figure 2 shows the arrangement of lights in circular arc. The camera and lights are calibrated, i.e., the position and orientation of the camera and the lights are known. For the work presented in this paper, only one circular layer of lights has been used.

Figure 3 shows the imaging geometry. The painting plane is taken as the reference *X-Y* plane and its normal direction is taken as the *Z* direction. Since the position and dimensions of the painting in the field of camera's view are known, the position of each pixel can be determined as $\boldsymbol{P}=(X,Y,0)$, and the illumination direction $\boldsymbol{L}$ and the viewing direction $\boldsymbol{V}$ for each pixel is given as:

$$\boldsymbol{L}=\frac{\boldsymbol{L}_W-\boldsymbol{P}}{\left\|\boldsymbol{L}_W-\boldsymbol{P}\right\|},\qquad \boldsymbol{V}=\frac{\boldsymbol{C}_W-\boldsymbol{P}}{\left\|\boldsymbol{C}_W-\boldsymbol{P}\right\|}\tag{1}$$

Where $\boldsymbol{L}_W$ is the position of the light and $\boldsymbol{C}_W$ is the position of the camera center. The surface orientation $\boldsymbol{N}$ remains unknown, but its deviation from the *Z* direction varies depending on the blush touch and thickness of paint.

3.2 Approximate Physical Reflection Models

Each image in the set can be represented as the combination of diffuse and specular reflections as:

$$I(x,y,\phi) = I_d(x,y,\phi) + I_s(x,y,\phi) + r(x,y,\phi)$$

where $I_d(x,y,\phi)$ and $I_s(x,y,\phi)$ are the diffuse and specular reflections, respectively, ϕ denotes the lighting angle, and the residual $r(x,y,\phi)$ is the difference between the modeled image irradiance and measured image $I(x,y,\phi)$. Since we are not particularly interested in rigorous physical modeling of the reflection components but only in finding good and simple numerical representations that can approximately account for the variation of the image appearance depending on the lighting directions, we used the Lambertian model for the diffuse term and an empirical model for the specular term. Any discrepancy between the measurement and the approximation will remain in the residual $r(x,y)$.

The Lambertian diffuse term in each image pixel (x,y) is given as:

$$I_d = C_d\,(\boldsymbol{N}\bullet\boldsymbol{L}) = C_d\cos\theta,$$

where C_d is the coefficient that accounts for the albedo and the scale factor from the Lambertian BRDF, and θ is the angle between $\boldsymbol{L}$ and $\boldsymbol{N}$ (see Figure 3.2). When the directions of $\boldsymbol{L}$ and $\boldsymbol{N}$ are close to the *Z* direction, it can be shown that I_d also varies depending on the cosine of the lighting angle and it reaches its maximum when $\boldsymbol{L}$ is closest to $\boldsymbol{N}$, i.e.,

$$I_d\,(x,y,\phi) = C_d\,(x,y)\cos[\phi-\xi(x,y)],$$

where ϕ is the azimuth angle of light in the *XYZ* coordinates (see Figure 3) and $\xi(x,y)$ is the value of ϕ when $\boldsymbol{L}$ is closest to $\boldsymbol{N}$.

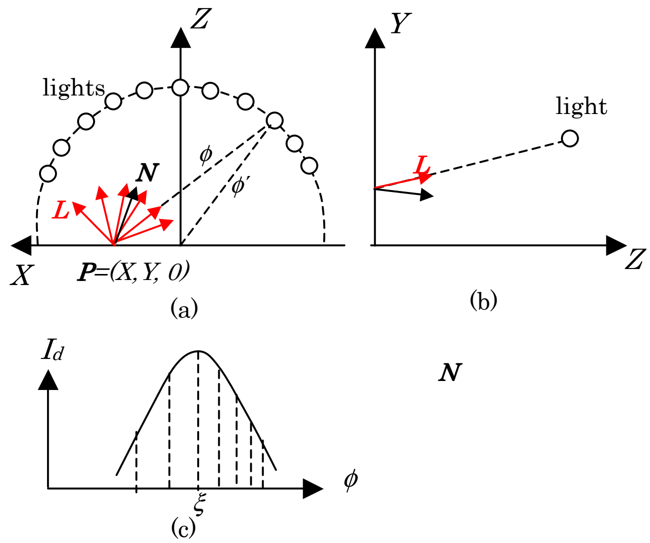

Figure 4. Light arrangement: (a) top view of the *XYZ* space, (b) side view of the *XYZ* space. (c) Illustration of I_d variation.

Figure 4 (a) and (b) show our light arrangement for image capture. The lights are placed in a circular arc. The angles of the lights about the Y axis (denoted as ϕ' in Figure 4 (a)) are uniformly sampled. However, the actual light angle ϕ for an off-center pixel should be adjusted according to Equation (1) and this results in non-uniform light sampling. Figure 4 (c) illustrates the variation of I_d at a pixel with this adjusted non-uniform sampling. Note that the effect of non-uniformity becomes negligible when the distance to the lights is much larger than the painting size.

We use the Phong model for approximating the single-lobe specular term. It is up to the capability of this empirical model how small the residual term $r(x,y)$ becomes. We further simplify this model for our approximation as described below. The specular reflection is represented as:

$$I_s = C_s\,(\boldsymbol{V}\bullet\boldsymbol{R})^n,$$

where $\boldsymbol{R}$ is the light reflection unit vector (mirror of $\boldsymbol{L}$ about $\boldsymbol{N}$), C_s is the coefficient for the Phong reflectance and n represents the shininess of surface. Since $\boldsymbol{R} = 2(\boldsymbol{L}\bullet\boldsymbol{N})\boldsymbol{N}-\boldsymbol{L}$, the specular reflection by this Phong model is given as:

$$I_s = C_s\,[2(\boldsymbol{L}\bullet\boldsymbol{N})(\boldsymbol{V}\bullet\boldsymbol{N})-\boldsymbol{V}\bullet\boldsymbol{L}\,]^n$$

Since the surface normals of each local surface in a painting do not deviate significantly from the *Z* direction, we can make an approximation of $\boldsymbol{N}\approx\boldsymbol{V}$ and the specular reflection is further simplified as:

$$I_s = C_s\,[\boldsymbol{N}\bullet\boldsymbol{L}\,]^n = C_s\cos^n\theta\,.$$

Including the above specular term, the image variation is represented as:

$$I(x,y,\phi) = C_d(x,y)\cos[\phi - \xi(x,y)] \\ + C_s(x,y)\cos^{n(x,y)}[\phi - \xi(x,y)] \\ + r(x,y,\phi)\ . \qquad (2)$$

Due to the approximations we made, the diffuse and specular terms in Equation (2) may not carry precise physical meaning but they are simply an analytical approximation of the reflection variation. All the inaccuracies in modeling, measurement errors in image capture, and the intensity and color variations unmodeled in $f(\Theta)$ such as self-shadowing, sub-surface scattering and interreflections, remain in the residual $r(x,y,\phi)$. The parameter ξ carries partial information about the surface normal with our lighting arrangement and the parameter n represents the surface shininess in the Phong model. Note that both ξ and n vary from pixel to pixel. For a given set of measured images $I(x,y,\phi_k)$ under sampled illumination at ϕ_k, the parameters $n(x,y)$ and $\xi(x,y)$ and the coefficient color images $C_d(x,y)$ (for R, G ,and B) and $C_s(x,y)$ (for R, G, and B) can be estimated in the minimum least-squares sense.

In addition to the residual images $r(x,y,\phi)$, the estimated two color images $C_d(x,y)$ and $C_s(x,y)$ and the two parameter images $n(x,y)$ and $\xi(x,y)$ are all that are needed for generating a view under novel lighting at ϕ using Equation (2) . The residuals $r(x,y,\phi_k)$ are obtained from all the frames (e.g., 40), but if their intensities are small, compression will be very effective and the their total size will be small. We can reduce the $r(x,y)$ data by keeping only low dimensional data in eigenspace after a principal component anlaysis (PCA).

3.3 Computation of Model Parameters

The approximate two-lobe reflectance model described in Equation (2) is a nonlinear function of eight parameters: three diffuse coefficients, three specular coefficients, one coefficient for $\xi(x,y)$, and one coefficient for $n(x,y)$. This function is difficult to optimize because it is non-convex, and in particular it is exponential in one of the free parameters.

We perform a two-stage optimization to minimize the residual. In the first stage, the parameter ξ is chosen heuristically based on the lighting angle for which intensity is maximized. The parameter ξ is then held fixed while the remaining seven parameters are optimized. By holding ξ fixed, we can establish a good initial estimate of the parameter n without complications due to the coupling of the two terms. Then, in the second phase, all eight parameters are optimized simultaneously. We use an interior-reflective Newton method for both stages, for which the Matlab implementation requires about 0.25 seconds of processing for each pixel.

An example of the quality of the fitting procedure is shown for a sharply specular pixel in Figure 5, and a diffuse pixel with broad specularity in Figure 6. The sharp specularity of the pixel in Figure 5 causes saturation of the sensor, which needs to be considered when fitting the parameters. In the first stage of the optimization, we naively fit the parameters as if the data has no saturation. However, in the second stage we do not penalize models which saturate the sensor at lighting angles where the measurement is saturated. The result is a model which tends to saturate the sensor at the same lighting angles as were observed, as can be seen in Figure 6.

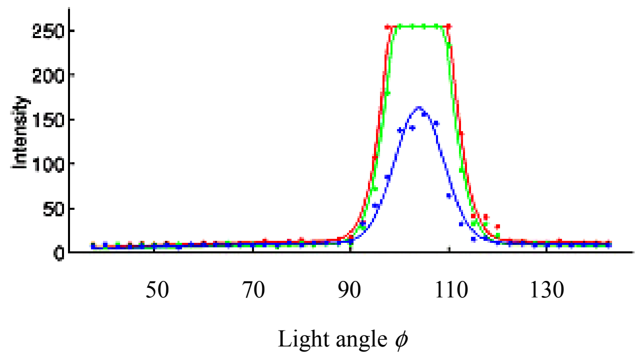

Figure 5. Parameter fit of a saturated, sharply specular pixel

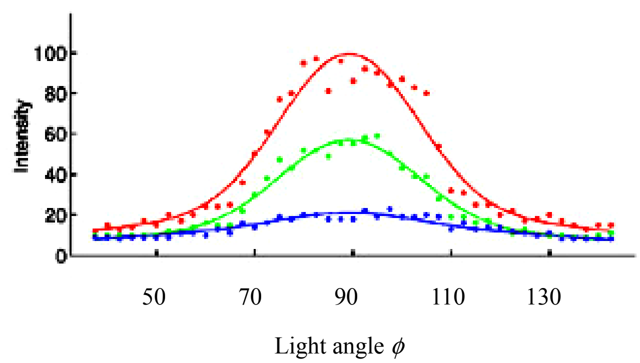

Figure 6. Parameter fit of a diffuse, broadly specular pixel

4 EXPERIMENTAL RESULTS

Images were captured from from both oil and watercolor paintings. Nine samples from a set of 43 oil painting images are shown in Figure 7. Figures 8, 9 and 10 show an image captured with the illumination angle ϕ=90° in (a), its residual image in (b), and the relative values of the eight recovered coefficients in (c)-(f). The parameters in Figure 8 and 10 were recovered from a set of 22 images taken at 5 degree intervals, while the set in Figure 9 were recovered from a set of 43 images taken at 2.5 degree intervals. Note that the residual images in Figures 8, 9 and 10 are contrast-enhanced for better visibility. Without the enhancement, the intensities are too low since the RMS fitting errors are 7.0, 7.1, and 5.8 grey levels, respectively. As suggested by Figure 6, error is greatest near the specular peaks. Figure 10 shows the recovered reflectance parameters of a watercolor. Since the watercolor painting is nearly completely diffuse, no specular texture is visible. Figure 11 shows reconstructions of the paintings, as they would be seen from novel lighting directions.

Figure 7. Nine of the 43 images.

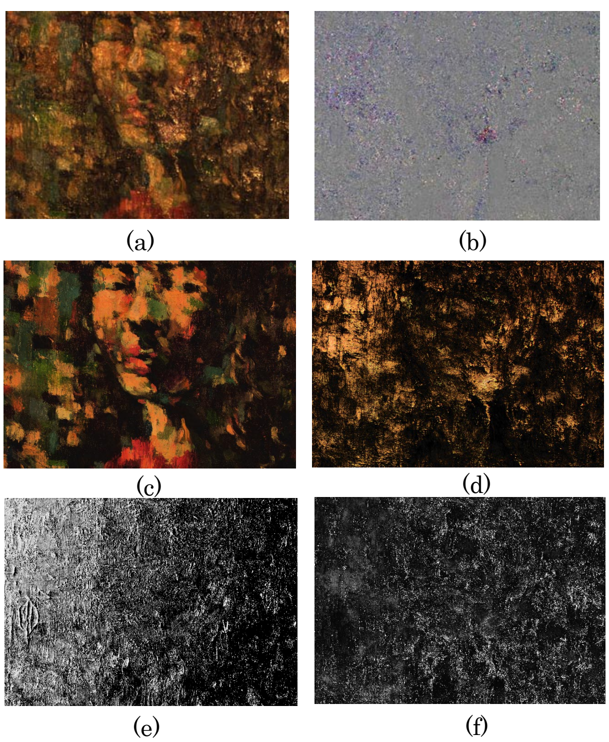

Figure 8. Oil painting: (a) Captured image $I(x,y,\phi=90°)$, (b) Residual $r(x,y,\phi=90°)$, (c) Diffuse $C_d(x,y)$, (d) Specular $C_s(x,y)$, (e) Surface structure $\xi(x,y)$, (f) Surface shininess $n(x,y)$

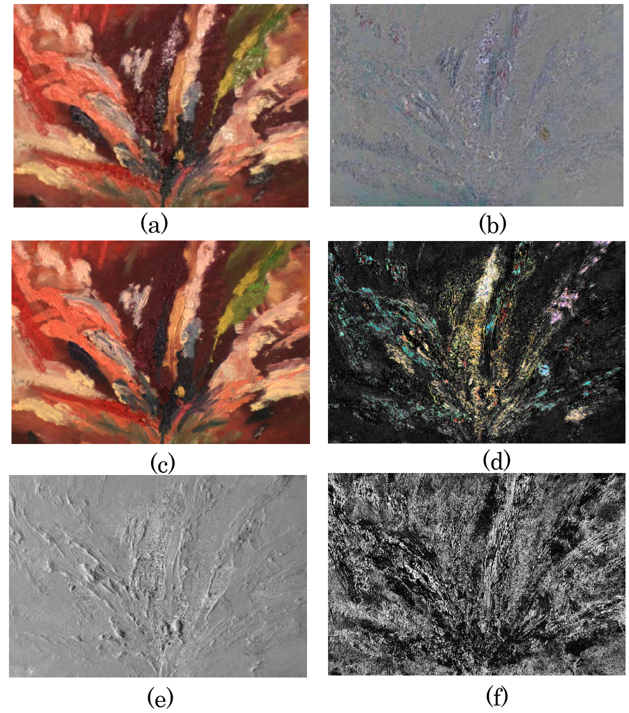

Figure 9. Oil painting: (a) Captured image $I(x,y,\phi=90°)$, (b) Residual $r(x,y,\phi=90°)$, (c) Diffuse $C_d(x,y)$, (d) Specular $C_s(x,y)$, (e) Surface structure $\xi(x,y)$, (f) Surface shininess $n(x,y)$

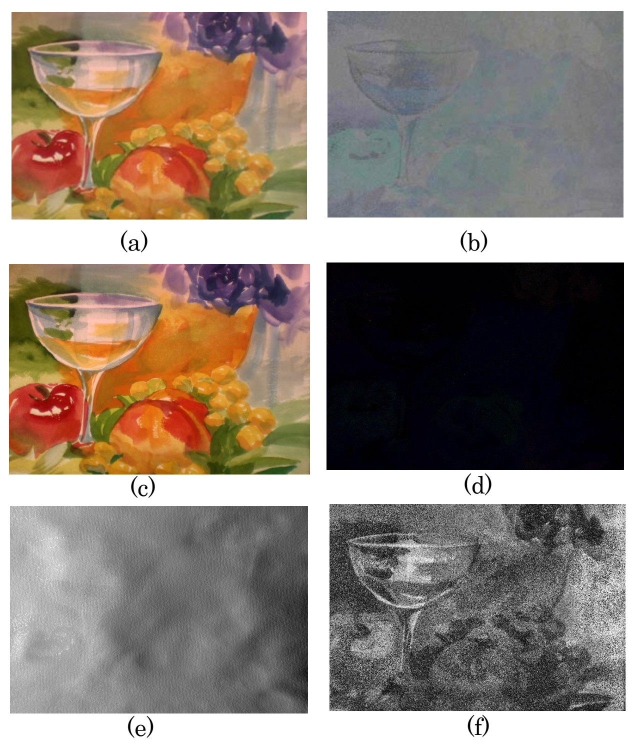

Figure 10. Water color painting: (a) Captured image $I(x,y,\phi=90°)$, (b) Residual $r(x,y,\phi=90°)$, (c) Diffuse $C_d(x,y)$, (d) Specular $C_s(x,y)$, (e) Surface structure $\xi(x,y)$, (f) Surface shininess $n(x,y)$

The residuals are compressed using principle components analysis, and used to tradeoff between storage size and fidelity of reproduction. Figure 12 shows this tradeoff for the painting shown in figure 7. An RMS error of less 4 grey levels is achieved using 13 coefficients.

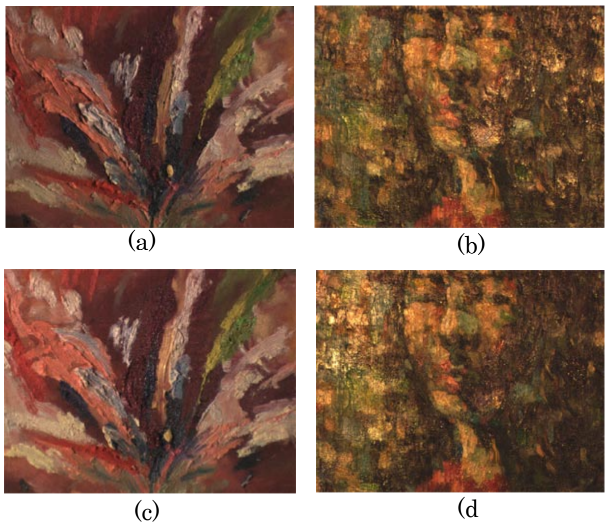

Figure 11. (a) One of the 22 captured oil painting images. (b) One of the 43 captured oil painting images. (c) The image in (a) under a novel illumination direction. (d) The image in (b) under a novel illumination direction.

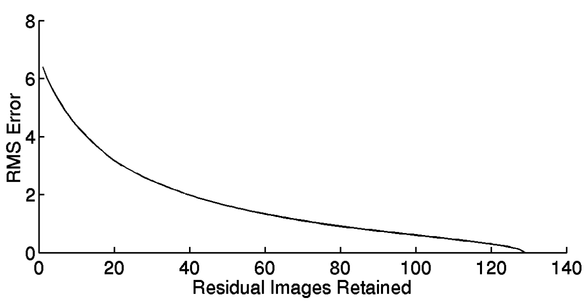

Figure 12. Reproduction accuracy as a function of the number of residual images retained

5 CONCLUSIONS AND FUTURE WORK

We present a new method for visualizing artistic paintings under a range of lighting directions. It combines simple empirical reflectance models with the image-based lighting approaches. We show that important 3-D effects in paintings such as brush strokes and canvas texture can be visually reproduced with low data dimensionality. We plan to include physical color models for more efficient and accurate estimation reflection parameters. They include the dichromatic and neutral interface reflection models.

We are interested in creating artificial illumination environments similar to those of good art museums. We intend to extend the range of lighting directions vertically, and develop an interactive editor for combining images under multiple lights and for modifying the recovered parameter maps to generate better subjective realism. Of particular interest is to create natural ambient lighting critical for reproducing museum-grade lighting environments.

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