Experiments with a low-cost system for computer graphics material model acquisition

Holly Rushmeier, Yitzchak Lockerman, Luke Cartwright and David Pitera Yale University, Department of Computer Science, New Haven, CT, USA

ABSTRACT

We consider the design of an inexpensive system for acquiring material models for computer graphics rendering applications in animation, games and conceptual design. To be useful in these applications a system must be able to model a rich range of appearances in a computationally tractable form. The range of appearance of interest in computer graphics includes materials that have spatially varying properties, directionality, small-scale geometric structure, and subsurface scattering. To be computationally tractable, material models for graphics must be compact, editable, and efficient to numerically evaluate for ray tracing importance sampling. To construct appropriate models for a range of interesting materials, we take the approach of separating out directly and indirectly scattered light using high spatial frequency patterns introduced by Nayar et al. in 2006. To acquire the data at low cost, we use a set of Raspberry Pi computers and cameras clamped to miniature projectors. We explore techniques to separate out surface and subsurface indirect lighting. This separation would allow the fitting of simple, and so tractable, analytical models to features of the appearance model. The goal of the system is to provide models for physically accurate renderings that are visually equivalent to viewing the original physical materials.

1. INTRODUCTION

There are many computer graphics applications that require visual simulation of the physical world. Applications include animation, games, virtual reality training simulators and architectural and industrial design. In these applications varying levels of accuracy for material appearance models are required. In many cases there is a much greater need for models with visual richness than for models with a high level of numerical accuracy in individual spatial and angular measurements. An inexpensive acquisition system that can produce approximate data for complex materials would often be more useful in an application than access to a highly accurate instrument for making detailed light scattering measurements. In this work we present the design of and initial tests of components in an inexpensive system for acquiring computer graphics material appearance models.

Visually rich materials are characterized by spatial variations of light scattering properties, small scale geometric variations and subsurface scattering. The state of the art for acquiring the data to model such materials is to use multi-light, multi-camera position systems that record the light scattered from a surface patch of material. The resulting data is referred to as a bidirectional texture function BTFs, originally introduced by Dana et al.¹ in 1999. While capturing visual richness, raw BTFs are not suitable for many graphics applications. Many applications require models that are compact to reduce memory requirements. The models must also facilitate importance sampling for use in an efficient light simulation scheme for rendering. Finally, models are most useful if they can be edited easy to achieve particular visual effects. Some approaches for fitting analytic models to BTF data have made progress towards these requirements,² but compactness and editability in particular are generally limited. In the design of new material specification systems^{3,4} we haven taken the approach that more efficient and compact models can be produced by fitting models to components of material appearance, rather than attempting to model all effects bundled together. Furthermore, separating components of appearance allows for more efficient adaptive sampling of individual materials to capture the components that are most critical to model for that particular material.

Send correspondence to HR H.R.: E-mail: holly@acm.org



Figure 1. Material appearance is often simply modeled by specifying surface reflectance (left), small scale surface structures (center), and subsurface scattering (right). All three components may vary with light wavelength and with position on a surface.

2. APPEARANCE COMPONENTS

In our work we seek to estimate the different individual components of material appearance by separating out the direct and indirect components of scene illumination.

2.1 Components of Material Appearance

Material appearance models need to capture spectral, directional and spatial variations in a surface. In many graphics rendering systems (e.g. Maya⁵) these models are encoded as image maps on the surface of a model. Spectral variations are typically encoded as variations in red, green and blue (RGB) scattering parameters. Directional characteristics are encoded by variations in the directionality of the bidirectional reflectance distribution function(BRDF). BRDFs are typically represented by a Lambertian component and a specular lobe, with the lobe modeled by a model such as the Cook-Torrance or Blinn.⁶ The directional variation of scattering is also the result of small but visible changes in surface orientation modeled as bump maps, surface normal maps or height maps.⁶ Subsurface scattering, which results in light leaving a material some distance from where it entered, is represented by parameters for the fraction of light absorption and scattering per unit length that light travels through a material. Typically a dipole model is used to compute subsurface scattering efficiently.⁷

Our goal in material appearance modeling for graphics rendering then is to estimate the surface reflectance, small scale surface structure and subsurface scattering as a function of position on a surface. Many systems have been devised to measure these parameters.⁸ Fundamentally each system uses light sources and sensors to probe the material properties. The goal in each system is to configure the sources and sensors to minimize the time and expense to obtain a model at a particular level of accuracy. Surface reflectance systems from other disciplines, e.g. the scanning gonio-photometers described by Apian-Bennewitz,⁹ measure directional reflectance of spatially homogeneous at a high level of accuracy. For graphics applications though spatial variations and a lower level of absolute accuracy are required.

2.2 Components of Scene Radiance

Over the past ten years there has been a great deal of work in computer vision in separating light at a sensor into components that have undergone different scattering events between the source and the sensor. A classic separation technique is to use a polarized light source to separate surface and bulk reflectance, since surface reflectance does not change the polarization, but bulk reflectance does. More recently work has focused on using high spatial frequency patterns^{10–12} and temporal variations.^{13,14} In our work here we focus on spatial patterns, rather than temporal variations for separation.

Nayar et al.¹⁰ introduced high spatial frequency illumination to separate direct and indirect illumination. The light radiance L received by a sensor is the sum of direct illumination L_d that has undergone just one scattering event, and global illumination L_g that has undergone multiple scattering events. Their essential observation was that if spatial on/off patterns of light of high spatial frequency are used to illuminate scenes, and the fraction of surface illuminated with the "on" pattern is c, the radiance received from a directly lit spot is $L_d + cL_g$, and from other spots just cL_g . Reversing the on off patterns of illumination to get two images, each location has a maximum value $L_d + cL_g$ and a minimum value cL_g . The values of L_d and L_g can then be calculated.

In practice, Nayar et al. point out many problems with the technique. One issue is that projector and camera pixels do not line up, so there is not a clean line between lit and unlit locations. Rather than just using two reversed patterns, multiple shifts of a high frequency pattern are needed. Another problem is that projectors always have some residual illumination even in black areas, to that has to be accounted for. Another major problem is that some multiple subsurface scattering emerges from the same location it entered, so it is impossible to completely capture the multiply scattered light. We use the basic framework introduce by Nayar et al., taking into account these practical problems.

Simultaneous with the work of Nayar et al., Tariq et al.¹¹ presented a technique for estimating subsurface reflectance using high spatial frequency patterns. They focus on capturing scattering on human faces. While surface interrelations are present on faces, on many areas on the face there is no effect. They propose estimating the dipole scattering properties of a point on the face by matching the variation of scattered light from the point with the variation of scattering from known materials as a pattern of high spatial frequency illumination is moved across the face. We propose that the basic idea of building a library of material signatures for subsurface scattering under high frequency illumination, coupled with a technique to detect the effect of surface interreflections can be used as a basic technique for material modeling.

Reddy et al.¹² considered the problem of differentiating between different types of global scattering. They propose differentiating between near and far scale effects by designing suitable spatial patterns. They focus on scene analysis from a single viewpoint and single light direction. Since we want to differentiate specifically between surface interreflections and subsurface scattering, and wish to compute small scale surface structure, we differentiate between surface effects by using multiple lighting directions.

Our basic observation is that the influence of a point on the illumination of other surface points is fundamentally different for subsurface scattering from a flat surface than for a non-flat surface with surface scattering. For a flat subsurface scattering surface, the spatial pattern of the multiply scattered light L_g is independent of lighting direction. For a non-flat surface, the spatial distribution of L_g changes with light directions.

3. EQUIPMENT

Our system design consists of three sets of cameras and projectors. Each camera/project pair is clamped together, so that the camera view is nearly coincident with the point of original of the projection pattern.





Figure 2. System setup: an individual projector clamped to a Rasperry Pi (left) , the system of three camera/projector pairs (right).

For local control at each of three camera/project positions we use Raspberry Pi Model B motherboards (each costing just less than \$20). For cameras we use the Raspberry Pi 5MP Camera Board modules (about \$15 each).

The cameras have resolution of 2592x1944 pixels. We use AAXA KP-100-02 P2 Jr Pico projectors at a price of about \$200 each. The Pico Jr takes a maximum input resolution of 1920x1080 pixels. We experimented with a less expensive pocket projector, but found that the light level of the projector was not stable over time.

Each camera/processor is mounted rigidly next to one of the projectors, as shown in Fig. 2. Each of these assemblies is support by a tripod, rather than a fixed support system to allow flexibility in our experiments. We found that to have the cameras and projectors in focus, and to evenly illuminate overlapping areas with the projectors, we needed to locate the assemblies approximately one meter from the test surface. Limits on the flexibility of the Pi cameras limited how narrow the camera field of view can be, and so the level of spatial resolution we can achieve. As a result our system has a relatively low spatial resolution of at best 0.3 mm per pixel on our test samples. The minimum camera exposure time is limited by the projector refresh rate. In our experiments we typically took exposures of 0.15,0.4 and 0.85 seconds to capture a larger dynamic range than available in a single image.

The Raspberry Pi processors are connected via ethernet connection to a Dell Vostro 420 seriesdesktop computer running Windows 7. We use a python script to run the desktop computer as a server, with each of the Pi's as clients. The script for the patterns to be projected and pictures to be taken from the cameras is distributed to the Pis, and at the end of the acquisition the images are returned to the server as a zip file of jpg images.

We calibrated the camera, and so light source, positions using the MATLAB¹⁵ cameraCalibrator with the 10mm per checkerboard-block pattern. We use a MacBethTM chart for color calibration and grey scale linearization, using the MATLAB scripted written by Akkayak et al.¹⁶ The cameras and projectors vary in their color characteristics, and the cameras use automatic white balancing. Along with the main MacBethTM chart calibration, each image includes a mini-MacBethTM chart (visible in Fig. 2) for further refinement.

Because the projector and camera pixels are not aligned, and because the projector checkerboard patterns are not perfectly sharp, the checkerboard edges are blurred across as many as 5 image pixels (where the pattern is projected from a non-zero angle to the surface normal). To estimate global scattering, however, it is desirable to have a relatively high spatial frequency pattern. We experimented with various sized patterns, and used a pattern that projected onto about 10 image pixels when the pattern was projected normal to the reflecting surface. We take images of the pattern shifted 8 times for each sample.

We use our results to compute normals from photometric stereo, so we need to have substantially different lighting directions. We also want to have one view that had highest surface resolution, so we positioned one camera normal to the test surface.

4. PROCESSING

Our software processing is performed in MATLAB.

Following Nayar et al., given the images for multiple shifts of a checkerboard pattern the estimate of the value of $L_d + 1/2L_g$ is obtained by simply taking the maximum value for each pixel over all images. The estimate of $1/2L_g$ is obtained by taking the minimum. The direct illumination can then be estimated by subtracting the minimum from maximum component. The direct component is then used to solve for the surface normals by solving three simultaneous equations formed by setting the dot product of the known light directions with the unknown surface normals equal to the observed values of L_d .

There are three major practical problems produce significant artifacts in the results – the non-uniformity in the subsurface scattering component, specular reflections and cast shadows. Since the subsurface scattering varies continuously from the center of each illuminated square to the center of each dark square, it is not possible to obtain spatially flat values for the maximum and minimum values without single pixel shifts across each illuminated square. As a result there is always some residual pattern of edges in the resulting directly and indirect images. To reduce this effect, we use a median filter on the indirect image and subtract it from the fully lit (i.e. non-checkerboard image) to obtain the directly lit image.

Specular reflections and cast shadows respectively give over- and under- estimates of the diffusely reflected light, producing significant errors in the photometric normals. The classic remedy for this is to use a larger number of light directions, and discard very high and very low values. Our three light system prevented us from taking this approach, although placing the sample on a turntable would allow additional lighting directions without additional physical camera/hardware pairs.

5. RESULTS

We present results for three common materials commonly found in architectural interiors – a synthetic marble-like tile, carpet, and wood.

The marble-like material has spatially varying subsurface scattering. The top row of Fig. 3 shows images of the high spatial frequency grid projected on the sample from each of the three lighting directions. The differences in the apparent grid sizes are due to the different angles that the projected light has to the surface normal for the three different lights. The second and third rows show the maximum and minimum values from the grid patterns for the three light directions. The minimum values are essentially a plot of the subsurface scattering in the tile. The spatial variation is the same for the three lighting directions, as is expected for a flat sample. That is, the magnitude of light scattered from each surface point varies with the angle of incidence, but portions of the surface affected by the scattered light from the point are the same, independent of light direction. The images of the third row is the direct illumination after the indirect is subtracted from the fully lit image when the light comes from the direction normal to the surface. The values in this image, when divided by the values reflected under the same conditions from a SpectralonTM target can be used as the diffuse reflectance for the tile.



Figure 3. Synthetic marble sample: top row- grids projected from each of three projectors, middle row- maximum value for each projector, lower row - minimum value for each projector, right: direct surface reflectance.

There is a bright spot in the lower left of the leftmost images that include direct illumination. This was caused by specular reflection from the top of the surface. Thus far in our system we have not attempted to remove specular reflections, or to use the presence of the bright spot to estimate the specular component of reflectance. There is a dark area in the upper left of the rightmost images. This was due to the projector from that direction not illuminating the full area shown in the image.

The wood sample, Fig. 4 exhibits both subsurface scattering and interreflections. The wood also has some specular reflectance, and cast shadows. The top row of Fig. 4 shows the full illuminated sample for one light direction (left), and the maximum value from the high spatial frequency illuminated samples (right). Because the globally scattered light is cut in half in the left image, the shape of the sample is more evident. The second row of images shows the minimum values for each of the three light conditions. The images show a change in the spatial distribution of the global light component. This change indicates that the light is from interreflections. Light scattered from a point via surface reflection (rather than subsurface) to other surfaces will be different for different light directions. The left image is lit from above, and all surfaces receive some direct illumination. There is global scattering from all surfaces that are within grooves. In the center and right images, surfaces in the grooves don't receive light, or receive less, and so the global scattering pattern changes.



Figure 4. Results for a wooden sample with geometric relief: top row – original full illumination from one source direction and maximum of grid illuminated images from that direction, second row – minimum of grid illuminated images for the three directions, showing different spatial distributions of scattered light, third row – gray scale of direct illumination for the three illumination directions, relit images from photometric stereo, showing artifacts from presences of cast shadows.

The third row of images Fig. 4 shows a grey scale image after the fully lit image for each lighting direction is adjusted to remove the global light effects. The shape of the surface is even more evident. There is clearly a



Figure 5. Results for six carpet samples, shown from left to right illuminated with a grid, illuminated with an inverse grid, with maximum image values, minimum image values, and estimated directly scattered light.

cast shadow in the center of the center image. This causes problems for computing properties in the shadowed area. However, the center image also provides useful data for the small scale grooves in the surface of the wood that are just barely evident in the images. The three corrected images are used to compute the normals using photometric stereo. The bottom row shows the computed normals lit from new light directions. There are obvious artifacts at locations where surfaces were in shadow, particularly cast shadows, in the adjusted direct illumination images.

Results for five carpet samples are shown in Fig. 5. As in the results for the synthetic marble, the spatial pattern for the globally scattered light was nearly identical for the different lighting directions. In the case of the carpet, the high spatial frequency of the carpet texture masks the checkerboard edge artifacts in the minimum/maximum images. The results show the dramatic increase in globally scattered light when the carpet fibers have a high scattering coefficient. Scattering in the green carpet in the upper right of the sample set is virtually nil relative to the scattering in the white carpet in the middle of the left column.

6. DISCUSSION AND RECOMMENDATIONS

The results shown here show that it is possible to separate out material effects with low end camera and projectors. A major limitation is poor spatial resolution, with 0.3mm still being too crude for many applications.

6.1 Subsurface Scattering

The results for subsurface scattering show that this approach to material scanning can be used to create spatial maps of scattering, even though the complete global component can't be obtained. Tariq et al. proposed using a standard library of signatures of different type of scattering for the variation of pixel radiance with illumination pattern be used to determine dipole scattering coefficients. They do this by comparing the signatures to a library of signatures for known materials. More recently Gkioulekas et al.¹⁷ have proposed high accuracy rendering and material dictionaries to obtain volume scattering parameters using a high end measurement device. In a similar spirit, we propose estimating the scattering parameters from scan lines through the checkerboard illuminated images. The variation of radiance across the direct and indirect illuminated regions can be compared to a library of checkerboard renderings for known materials created by a physically accurate system such as Mitsuba.¹⁸ Figure 6 show an example plot of a variation from one of the images of synthetic marble, and Mitsuba renderings for two types of materials with subsurface scattering.

The development of an automatic system to extract parameters would need to segment the maps of direct and indirect into some small number of different materials. Then for each region, sample on-off checkerboard pairs would need to be automatically located and their cross-sections matched to cross-sections from a library of Mitsuba renderings.

Extracting the parameters would take significant effort, and the level of accuracy of the parameters required for rendering is not known. For example, in the wood sample in this work the level of subsurface scattering is



Figure 6. Examples of plotting scattering variations from a physical sample (a) and Mitsuba renderings (b) and (c).

very low relative to the surface reflectance. It is not clear that performing the subsurface scattering calculations would have a noticeable impact on rendered images except in extreme situations (e.g. a laser spot focused on the sample in a dark room). There has been limited work in graphics on the perception of scattering. General guidelines were discussed in¹⁹ and the phase function was studied in.²⁰ We hope to use the scattering results from our system to examine the impact of different scattering parameter estimates on renderings of materials relative to viewing the physical material.

6.2 Surface Scattering – Normals and Specularity

The results show that we can obtain estimates for diffuse reflection and for surface normals. However, some specular component of the reflectance is needed for a full model, and the effect of specular reflections needs to be removed from the calculation of the normals. Further, the effect of shadows on the normals calculation needs to be eliminated.

One approach to overcoming cast shadows and to estimate the directional specular reflectance of a surface is to add more light projectors to the system. As more projectors are added, the system crosses from being a simple inexpensive system to an expensive difficult to calibrated system. Another way to increase the effective number of light sources is to reposition the sample, and reuse the existing light sources. The disadvantage of this is that precision calibration is needed to merge the observation. The relatively crude spatial resolution of the current camera system makes this difficult, and the spatial quality of the results would be degraded. A compromise might be to add a light, and provide additional statistical information from measuring a repositioned sample, rather than using the light sources for the repositioned object directly in calculations.

Similar to the problem of subsurface scattering parameter estimates, more data is needed on the level of accuracy needed for the estimation of small scale surface variations and specular reflectance estimates. Clearly other surface properties affect how visible the small scale geometry is. Differences in shape perception of details caused by material surface appearance properties has already been recognized as a problem when using 3D printing to reproduce scanned shapes.²¹

Materials such as carpet don't have well defined surface normals. However, as shown by Wu et al.,² many BTF data sets can be approximated as sums of BRDFs with different surface normals. Experiments are needed to see if such an approximation can be extracted for a subsurface/surface normal/surface reflectance model that adequately models complex materials such as carpet.

7. CONCLUSIONS

We have presented the results of experiments of a system set up to acquire material appearance properties using low cost cameras and projectors. A major shortcoming of the system is the low spatial resolution. The system does provide us with data that allows us to move forward experimenting with methods to estimate material models, and with how accurate models have to be to faithfully produce renderings of materials. Further development of the system we have described needs to improve on its current limitations on spatial and directional sampling.

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