Toward a Psychophysically-Based Light Reflection Model for Image Synthesis

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ABSTRACT

In this paper we introduce a new light reflection model for image synthesis based on experimental studies of surface gloss perception. To develop the model, we've conducted two experiments that explore the relationships between the physical parameters used to describe the reflectance properties of glossy surfaces and the perceptual dimensions of glossy appearance. In the first experiment we use multidimensional scaling techniques to reveal the dimensionality of gloss perception for simulated painted surfaces. In the second experiment we use magnitude estimation methods to place metrics on these dimensions that relate changes in apparent gloss to variations in surface reflectance properties. We use the results of these experiments to rewrite the parameters of a *physically-based* light reflection model in *perceptual* terms. The result is a new *psychophysically-based light reflection model* where the dimensions of the model are perceptually meaningful, and variations along the dimensions are perceptually uniform. We demonstrate that the model can facilitate describing surface gloss in graphics rendering applications. This work represents a new methodology for developing light reflection models for image synthesis.

Keywords

I.3.7 Three-Dimensional Graphics and Realism, Human Factors, Experimentation, Light Reflection Models, Gloss, Visual Perception.

1. INTRODUCTION

Color and *gloss* are two fundamental visual attributes used to describe the appearances of objects in synthetic images. In a typical graphics rendering application a user specifies an object's color as an RGB triple and describes its gloss in terms of the parameters of a light reflection model such as Phong [Phon75].

In addition to RGB, many rendering applications allow users to describe color in more perceptually meaningful color spaces such as HSV, Munsell, or CIELAB, that have grown out of the science of colorimetry [Wysz82]. Working in these spaces makes it easier to specify color, because the dimensions of the spaces are representative of our visual experience of color, and the scaling of the dimensions is perceptually uniform.

Unfortunately similar perceptually-based spaces for specifying

Figure 1: Coffee mugs with different gloss attributes.

surface gloss do not yet exist. At the present time the parameters used to describe gloss are either based on ad-hoc lighting models such as Phong, or are motivated by research into the physical aspects of light reflection [Blin77, Cook81, He91, Ward92, Schl93, LaFo97, Stam99]. In either case, the visual effects of the parameters are relatively unintuitive and interactions among different parameters make it difficult to specify and modify surface gloss properties. A light reflection model grounded in the visual psychophysics of gloss perception would greatly facilitate the process of describing surface gloss properties in computer graphics renderings, and could lead to more efficient and effective rendering methods.

In this paper we introduce a new light reflection model for image synthesis based on experimental studies of surface gloss perception. To develop the model, we have conducted two psychophysical studies to explore the relationships between the physical parameters used to describe the reflectance properties of glossy surfaces and the perceptual dimensions of glossy appearance. We use the results of these experiments to rewrite the parameters of a *physically-based* light reflection model in *perceptual* terms. The result is a new *psychophysically-based light reflection model* where the dimensions of the model are perceptually meaningful, and variations along the dimensions are perceptually uniform. We demonstrate that the model is useful for describing and modifying surface gloss properties in graphics rendering applications. However, the long-term impact of this work may be even more important because we present a new methodology for developing psychophysical models of the goniometric aspects of surface appearance to complement widely used colorimetric models.

2. BACKGROUND

To develop a psychophysically-based light reflection model for image synthesis we first need to understand the nature of gloss perception.

In his classic text, Hunter [Hunt87] observed that there are at least six different visual phenomena related to apparent gloss. He identified these as:

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specular gloss – perceived brightness associated with the specular reflection from a surface

contrast gloss – perceived relative brightness of specularly and diffusely reflecting areas

distinctness-of-image (DOI) gloss – perceived sharpness of images reflected in a surface

haze – perceived cloudiness in reflections near the specular direction

sheen – perceived shininess at grazing angles in otherwise matte surfaces

absence-of-texture gloss – perceived surface smoothness and uniformity

Judd [Judd37] operationalized Hunter's definitions by writing expressions that related them to the physical features of surface reflectance distribution functions (BRDFs). Hunter and Judd's work is important, because it is the first to recognize the multidimensional nature of gloss perception.

In 1987 Billmeyer and O'Donnell [Bill87] published an important paper that tried to address the issue of gloss perception from first principles. Working with a set of black, gray, and white paints with varying gloss levels, O'Donnell collected ratings of the apparent difference in gloss between pairs of samples and then used multidimensional scaling techniques to discover the dimensionality of perceived gloss. He concluded that for his sample set and viewing conditions (flat samples, structured/direct illumination, black surround) the appearance of high gloss surfaces is best characterized by a measure similar to distinctness-of-image gloss, while the appearance of low gloss surfaces is better described by something like contrast gloss.

In the vision literature, studies of gloss have focused primarily on its effects on the perception of shape from shading. Todd and Mingolla [Todd83, Ming86] found that gloss generally enhances the perception of surface curvature. Blake [Blak90] found categorical changes in surface appearance and shape depending on the 3d location of the specular highlight. Braje [Braj94] found interactions between apparent shape and apparent gloss, showing that a directional reflectance pattern was perceived as more or less glossy depending on the shape of its bounding contour. More recently Nishida [Nisi98] also studied interactions between shape and gloss, and found that subjects are poor at matching the Phong parameters of bumpy surfaces with different frequency and amplitude components.

Finally, in computer graphics, while there has been extensive work on developing physically-based light reflection models, there has been relatively little effort to develop models whose dimensions are perceptually meaningful. One exception is Strauss's model [Stra90], a hybrid of Phong and Cook-Torrance, that describes surface properties with five parameters: color, smoothness, metalness, transparency, and refractive index. He reports that users find it much easier to specify surface gloss with this model than with others.

There is still much work to be done in this area. First, with the exception of Billmeyer and O'Donnell's work there has been little investigation of the multidimensional nature of glossy appearance from first principles. Hunter's observations about visual gloss phenomena are insightful but we need studies that quantify these different appearance dimensions and relate them to the physical properties of materials. Second, all previous gloss studies have looked exclusively at locally illuminated surfaces in uniform surrounds. This practice is understandable given the difficulty of controlling complex environments, but it's strange considering that one of the most salient things about glossy surfaces is their ability to reflect their surroundings. To really understand how we perceive surface gloss, we need to study three-dimensional objects in realistically rendered environments. Fortunately, image synthesis gives us a powerful tool to study the perception of surface gloss. Physically-based image synthesis methods let us make realistic images of three-dimensional objects in complex, globally-illuminated scenes, and gives us precise control over object properties. By using image synthesis techniques to conduct psychophysical experiments on gloss perception we should be able to make significant progress toward our goal of developing a psychophysically-based light reflection model that can describe the appearance of glossy materials.

3. EXPERIMENTS

3.1 Motivation

In many ways the experiments that follow are analogous to early research done to establish the science of colorimetry. In that work, researchers wanted to understand the relationships between the physical properties of light energy, and our perception of color. Many of the earliest experiments focused on determining the *dimensionality* of color perception, culminating with Young's trichromatic theory [Helm24]. Following this, further experiments were done to find *perceptually meaningful axes* in this three-dimensional color space. Hering's work [Heri64] on opponent color descriptions, falls into this category. Finally, many experiments have been done to scale these axes and create *perceptually uniform* color spaces. Munsell, Judd, and MacAdam's efforts to develop uniform color scales are good examples (see [Wysz82] for a review).

Although we recognize the great effort involved in the development of color science, our overall goals with respect to understanding gloss are similar: we are conducting experiments to understand gloss perception with the goal of building a psychophysical model of gloss that relates the visual appearance of glossy surfaces to the underlying physical properties of the surfaces.

- In Experiment 1 we will use multidimensional scaling techniques to reveal both the *dimensionality* of gloss perception, and to suggest *perceptually meaningful axes* in visual "gloss space"
- In Experiment 2 we will use magnitude estimation techniques to place quantitative metrics on these axes and create a *perceptually uniform* gloss space.
- Finally we will use these results to develop a psychophysically-based light reflection model for image synthesis.

Gloss is a visual attribute of a wide variety of materials including plastics, ceramics, metals, and other man-made and organic substances. Eventually we would like to develop a model that can explain the appearances of all these kinds of materials, but initially we need to restrict our studies to a manageable subclass. To start, we've chosen to study a set of achromatic glossy paints. We chose paints because they exhibit a wide variety of gloss levels from flat to high gloss; their reflectance properties have been measured extensively so there are good models to describe their physical characteristics, and they are widely used in art and industry, so hopefully our findings will be immediately useful.

3.2 Experiment 1: Finding the perceptual dimensions of gloss space

3.2.1 Purpose

The purpose of Experiment 1 is to determine the dimensionality of gloss perception for painted surfaces in synthetic images and to find perceptually meaningful axes in this visual gloss space. To do this we've designed an experiment based on multidimensional scaling techniques.

3.2.2 Methodology: Multidimensional scaling

Multidimensional scaling (MDS) is statistical method for finding the latent dimensions in a dataset [Borg97]. Multidimensional scaling takes a set of measures of the distances between pairs of objects in a dataset and reconstructs a space that explains the dataset's overall structure. This concept is best illustrated by example.

Table 1 shows a matrix of the distances between a number of U.S. cities. This matrix indicates how far one city is from another but gives no sense of their spatial relations. If this *proximity matrix* is used as input to the PROXSCAL MDS algorithm [Busi97], it attempts to reconstruct the spatial positions of the cities to best explain the proximity measures.

The two-dimensional MDS solution produced by the algorithm is shown in Figure 2, where you can see that MDS has recovered the true spatial layout of the cities (the outline of the U.S. map is overlaid for reference). Since distances in a space are unaffected by rotations or inversions, MDS solutions are only specific up to these transformations, and it is the experimenter's job to find meaningful axes in the solution.

Although a two-dimensional MDS solution is shown in Figure 2, MDS can produce solutions in any number of dimensions to try to achieve the best fit to the data. The goodness of the fit is known as the *stress* of the solution. The stress formula used in the example is:

$$stress = \sum_{i,j} \left[\delta_{i,j} - d(x_i, x_j)\right]^2 \tag{1}$$

where $\delta_{i,j}$ are the input proximities, x_i and x_j are the recovered locations in the n^{th} dimensional solution, and d is a measure of the distance between them. The MDS algorithm attempts to minimize the stress for each of the solutions.

Figure 3 plots the stress values for solutions running from 1 to 5 dimensions. The stress curve will drop sharply as dimensions are added that explain more of the data and will decline more slowly as further superfluous dimensions are added. Standard practice is to choose the dimensionality indicated by this inflection point in the stress curve. The stress curve in Figure 3 indicates that a two-dimensional solution provides the best fit to the data, but this is to be expected since the dataset is inherently two dimensional, and error in the proximity measures is negligible, providing a perfect two-dimensional fit. In typical experimental datasets, noise in the data results in a stress curve that drops then asymptotes as greater-than-necessary dimensions are added.

MDS algorithms come in a variety of flavors that depend on the form of the stress function the algorithm uses. In our work we use a variant called *weighted Euclidean non-metric MDS* [Borg97] that allows us to combine data from multiple subjects, compensate for individual differences, and analyze datasets where the proximities may only reflect ordinal rather than interval relations in the data. We also use a second variant called *confirmatory* MDS [Borg97] which let us test hypotheses about the functional forms of the dimensions and their orthogonality.

	Atl	Chi	Den	Hou	LA	Mia	NYC	SF	Sea	DC
Atlanta	0									
Chicago	587	0								
Denver	1212	920	0							
Houston	701	940	879	0						
LA	1936	1745	831	1374	0					
Miami	604	1188	1726	968	2339	0				
NYC	748	713	1631	1420	2451	1092	0			
SF	2139	1858	949	1645	347	2594	2571	0		
Seattle	2182	1737	1021	1891	959	2734	2406	678	0	
DC	543	597	1494	1220	2300	923	205	2442	2329	0

Table 1: Proximity matrix of distances between U.S. cities.

Figure 2: MDS reconstruction of the U.S. map.

3.2.3 Experimental Procedure

3.2.3.1 Stimuli

To apply MDS to the problem of finding the dimensionality of gloss perception, we first need to construct a stimulus set with objects that vary in gloss, and then collect measures of the apparent differences in gloss between pairs of objects in the set. These apparent gloss differences then serve as the proximities that the MDS algorithm uses to construct a representation of visual "gloss space".

A composite image of the stimulus set used in Experiment 1 is shown in Figure 4. The environment consisted of a sphere enclosed in a checkerboard box illuminated by an overhead area light source. Images were generated using a physically-based Monte Carlo path-tracer that used an isotropic version of Ward's [Ward92] light reflection model:

$$\rho(\theta_i, \phi_i, \theta_o, \phi_o) = \frac{\rho_d}{\pi} + \rho_s \cdot \frac{\exp[-\tan^2 \delta / \alpha^2]}{4\pi\alpha^2 \sqrt{\cos\theta_i \cos\theta_o}} \tag{2}$$

where $\rho(\theta_i,\phi_i,\theta_o,\phi_o)$ is the surface BRDF, θ_i,ϕ_i, and θ_o,ϕ_o are spherical coordinates for the incoming and outgoing directions, and δ is the half-angle between them. Ward's model uses three parameters to describe the BRDF: ρ_d – the object's diffuse reflectance; ρ_s – the energy of its specular component, and α – the spread of the specular lobe. Our reason for choosing Ward's model is that we wanted the objects in the stimulus set to be representative of the gloss properties of real materials, and Ward gives parameters that represent measured properties of a range of glossy paints. The parameters used in our stimulus set span this range. Each parameter was set to three levels. ρ_s values were (0.033, 0.066, 0.099), α values were (0.04, 0.07, 0.10), and ρ_d was set to (0.03, 0.193, 0.767) which are the diffuse reflectance factors corresponding to Munsell values (N2, N5, and N9). The

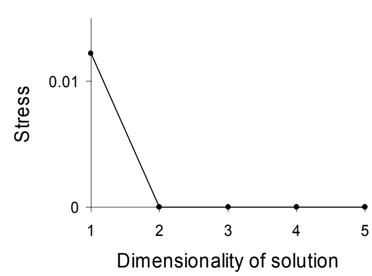

Figure 3: Stress vs. dimensionality graph for MDS solution.

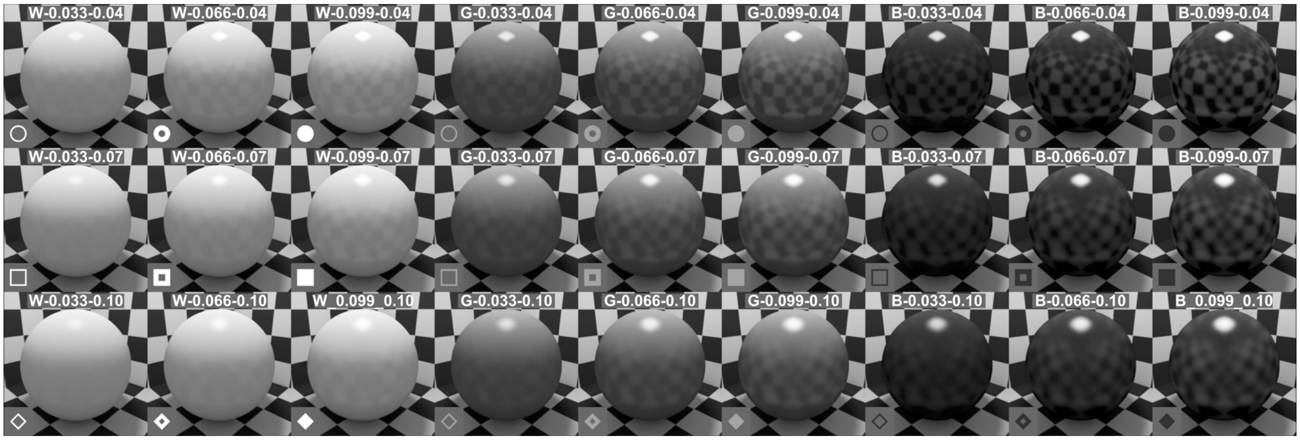

Figure 4[†]: Composite image of the stimulus set used in Experiment 1. Labels indicate the diffuse color (white, gray, black), and ρ_s and α values. Symbols are included as an aid for interpreting subsequent figures.

black and white checks in the checkerboard surround were completely diffuse and had ρ_d's of 0.03 and 0.767 respectively. By using all combinations of the ρ_d, ρ_s, and α parameters for the sphere objects, we produced the 27 images shown in Figure 4.

Choosing a tone reproduction operator to map from calculated image radiances to display values presented a challenge because the images had high dynamic ranges caused by the visible reflection of the light source. We experimented with a number of tone reproduction operators including simple clipping and gamma compression as well as Pattanaik [Patt98] and Ward-Larson's [Ward97] high dynamic range operators but we abandoned these methods because they produced objectionable artifacts such as halos and banding. We settled on Tumblin's [Tumb99] Rational Sigmoid function which compresses the light source highlight without abrupt clipping and allows all other scene values to be directly mapped to the display.

One of the consequences of the limited dynamic range of display devices is that any gloss attribute related to the absolute intensity of a highlight is not likely to play much of a role in how glossy surfaces appear in images. Given the amount of effort that has gone into developing physically accurate light reflection models for realistic image synthesis, addressing the particular dynamic range problems caused by trying to display images of glossy surfaces is certainly a subject that merits future work.

3.2.3.2 Procedure

Nine subjects participated in Experiment 1. The subjects were the first two authors and seven graduate and undergraduate Computer Science students. All had normal or corrected to normal vision. With the exception of the authors, all were naïve to the purpose and methods of the experiment.

In the experimental session, the subjects viewed pairs of images displayed on a calibrated SXGA monitor. Minimum and maximum monitor luminances were 0.7 and 108 cd/m^2 and the system gamma was 2.35. The images were presented on a black background in a darkened room. The monitor was viewed from a distance of 60 inches to ensure that the display raster was invisible. At this viewing distance each image subtended 3.2 degrees of visual angle.

Subjects were asked to judge the apparent difference in gloss between the pair of objects shown in the images. They entered their responses using a mouse to vary the position of a slider that was displayed below the images. The ends of the slider scale were labeled "0, small difference" and "100, large difference". A readout below the slider indicated the numeric position along the scale.

Subjects judged the apparent gloss differences of all 378 object pairs in the stimulus set. The pairs were presented in random order. For each subject, the apparent gloss differences measured in the experiment were used to fill out a 27 x 27 proximity matrix. All nine proximity matrices were used as input to the PROXSCAL MDS algorithm using the weighted Euclidean non-metric stress formulation.

3.2.4 Analysis/Discussion

Recall that our goal in this experiment is to discover the dimensionality of gloss perception for the painted surfaces and to find perceptually meaningful axes in this gloss space. To do this we observed how the stress varied with the dimensionality of the MDS solution. Figure 5 plots stress values for solutions running from 1 to 5 dimensions. The stress value drops significantly with the change from a 1-dimensional to a 2-dimensional solution, but declines more slowly with the addition of higher dimensions which are probably only accommodating noise in the dataset. *From this pattern of results we infer that under these conditions apparent gloss has two dimensions.*

The two-dimensional gloss space recovered by MDS is shown in Figure 6. In the Figure, MDS has placed the objects at locations that best reflect the differences in apparent gloss reported by the subjects.

As stated earlier, since distances in this space are invariant under rotation, inversion or scaling, it is our job to look for perceptually meaningful axes in the space. The cross in the lower right corner of the diagram indicates two important trends in the data that are related to properties of the reflected images formed

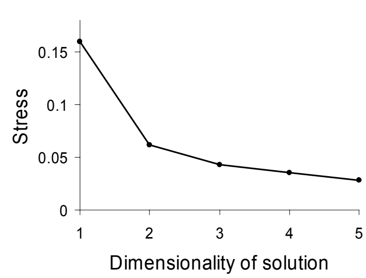

Figure 5: Dimensionality vs. stress graph for Experiment 1.

[†]Gloss appearance parameters are specified for the display conditions described in the experiments. Appearance in the printed images is subject to the limitations of the printing process.

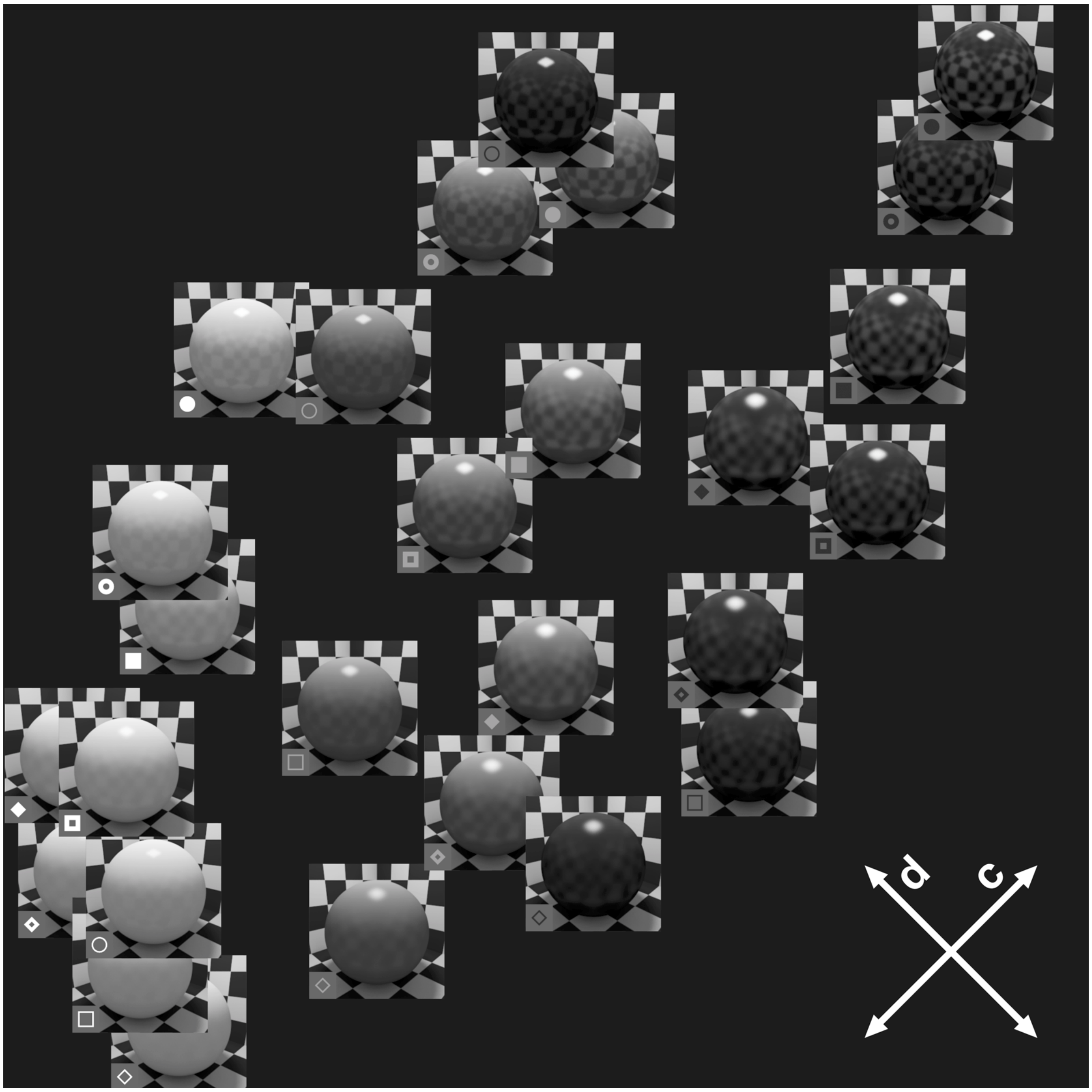

Figure 6†: Two-dimensional MDS solution for Experiment 1.

by the surfaces. First, the *apparent contrast of the reflected image* increases from the lower left to the upper right of the diagram. Second, the apparent sharpness or *distinctness of the reflected image* increases from lower right to upper left. We believe these dimensions are qualitatively similar to the *contrast gloss* and *distinctness-of-image (DOI) gloss* attributes Hunter observed and so we will name our dimensions *c* for contrast gloss and *d* for DOI gloss. However, to foreshadow the results of the next experiment, we will differ significantly from Hunter (and Judd) in the quantitative formulation of relationship between these perceptual dimensions and the physical dimensions used to describe surface BRDFs.

3.3 Experiment 2: Creating a perceptually uniform gloss space

3.3.1 Purpose

In Experiment 1 we discovered the dimensionality of gloss perception and identified perceptually meaningful axes in visual gloss space for painted surfaces in synthetic images. The purpose of Experiment 2 is to place psychophysical metrics on these axes and rescale them to create a perceptually uniform gloss space. To do this we've designed an experiment based on magnitude estimation techniques.

3.3.2 Methodology: Magnitude estimation

Magnitude estimation is one of a family of psychophysical *scaling* techniques designed to reveal functional relationships between the physical properties of a stimulus and its perceptual attributes [Torg60]. In the basic magnitude estimation procedure, subjects are presented with a random sequence of stimuli that vary along some physical dimension, and they are asked to assign a number to each stimulus that indicates the apparent magnitude of the corresponding perceptual attribute. Magnitude estimates are then used to derive a psychophysical scale.

3.3.3 Experimental Procedure

3.3.3.1 Stimuli

Two magnitude estimation studies were performed in Experiment 2 to scale the perceptual gloss dimensions found in Experiment 1. In both cases the stimuli used were subsets of the stimuli used in Experiment 1, supplemented by new stimuli with

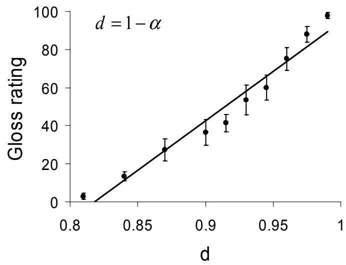

Figure 7: Magnitude estimates and fit for DOI gloss *d*.

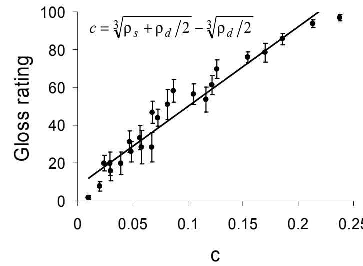

Figure 8: Magnitude estimates and fit for contrast gloss *c*.

parameters intermediate to those in the original set. In the *contrast gloss* scaling study 24 images were used, showing objects with combinations of ρ_d levels of (0.03, 0.087, 0.193, 0.420, 0.767) (black, dark/medium/light gray, white) and ρ_s levels of (0.017 0.033, 0.050, 0.066, 0.083 0.099) (low to high specular energy), the α parameter was fixed at 0.04 (small spread) to make variations along the contrast gloss dimension as salient as possible. In the *DOI gloss* scaling study, α was varied in 11 levels from 0.01 to 0.19 (small to large spread), and the ρ_d and ρ_s parameters were fixed at 0.03 (black) and 0.099 (high specular energy) to make variations along the DOI gloss dimension as salient as possible.

3.3.3.2 Procedure

The subjects in Experiment 2 were the same as those in Experiment 1, and the same display techniques, viewing conditions, and data gathering methods were used.

In each magnitude estimation study, subjects viewed single images from the new stimulus sets. Images were presented in a random sequence and each sequence was repeated three times. On each trial subjects were asked to judge the apparent glossiness of the object in the image on a scale from 0 to 100 by adjusting the on-screen slider.

3.3.4 Analysis/Discussion

Our goal in these experiments is to derive psychophysical scaling functions that relate changes in apparent gloss along the perceptual dimensions we discovered in Experiment 1 to variations in the parameters of the physical light reflection model. To achieve this goal we tested various hypotheses about functional relationships between the physical and perceptual dimensions, first with least squares fitting techniques on the magnitude estimation data and then with confirmatory MDS on the full dataset from Experiment 1. This approach allowed us to verify that the scaling functions are task independent and to determine whether the perceptual dimensions are orthogonal.

First we examined the *d* (DOI gloss) dimension. Our hypothesis was that *d* is inversely related to the α parameter. In Figure 7 subjects' gloss ratings are plotted versus the function $d = 1 - \alpha$. The line was obtained through linear regression and the r^2 value of the fit was 0.96. Polynomial fits only increased r^2 by less than 0.01 so we concluded that the relationship is linear.

Interpreting the *c* (contrast gloss) dimension was less straightforward. In the MDS solution from Experiment 1 (Figure 6) it is clear that *c* varies with diffuse reflectance, since the white, gray, and black objects form distinct clusters that occupy different ranges along the *c* dimension. Our first hypothesis was that *c* is a simple function of the physical contrast (luminance ratio) of the black and white patches in the reflected image but this provided a very poor fit to the data ($r^2 = 0.76$). Our second hypothesis was that "contrast" in this situation is a function of the *difference in apparent lightness* of the two patches, where lightness is defined as in CIELAB [Fair98]. This second formulation provided a much better fit to the magnitude estimation data ($r^2 = 0.87$). However when we tested this second hypothesis on the full dataset from Experiment 1 using confirmatory MDS, we found that the fit was poor for surfaces with large α values where the physical contrast in the image plane drops as the reflected image gets blurrier. We then tested a third hypothesis that subjects' lightness judgments are based on inferred object-space reflectance values rather than image-space intensity values (i.e. subjects show lightness constancy [Fair98], compensating for blur-related image contrast losses). This hypothesis is formalized in Equation 4 which we derived using standard integration techniques under the assumption of small α values and high environmental contrast.

Figure 8 plots the data from the contrast gloss scaling study, which shows how subjects' gloss ratings relate to this final formulation for the *c* dimension. The line was obtained through linear regression and is a good fit to the data with an r^2 value of 0.94. This result shows that subjects appear to be compensating for the decrease in physical image contrast caused by blurring in making their judgments of the lightnesses of the reflected patches. Using this formulation also decreased the stress value in a subsequent confirmatory MDS test on the full dataset, which indicates that the *c* and *d* axes are independent, and therefore orthogonal in gloss space.

Equations 3 and 4 show the final formulas for the *c* and *d* axes. These formulas define psychophysical metrics that relate changes in apparent gloss along these two axes to variations in the physical parameters of the light reflection model.

$$d = 1 - \alpha \tag{3}$$

$$c = \sqrt[3]{\rho_s + \rho_d/2} - \sqrt[3]{\rho_d/2} \tag{4}$$

These axes are perceptually linear, but to make the space perceptually uniform, we need to find weighting factors for the axes so that distances in the space can be measured. These weights are given as a byproduct of the confirmatory MDS tests we ran which lets us write the distance as:

$$D_{ij} \propto \sqrt{[c_i - c_j]^2 + [1.78 \cdot (d_i - d_j)]^2} \tag{5}$$

Figure 9 shows a visualization of the perceptually uniform gloss space with the stimuli from Experiment 1 placed at their predicted locations. The Figure shows the contrast gloss (*c*) and DOI gloss (*d*) dimensions form a two-dimensional space, (which is also shown in the inset), and surface lightness (*L*) (which we will incorporate in the following section) is an orthogonal third dimension.

Like perceptually uniform color spaces, this perceptually uniform gloss space has a number of important properties. For example, it allows us to:

- predict the visual appearance of a glossy paint from its physical reflectance parameters

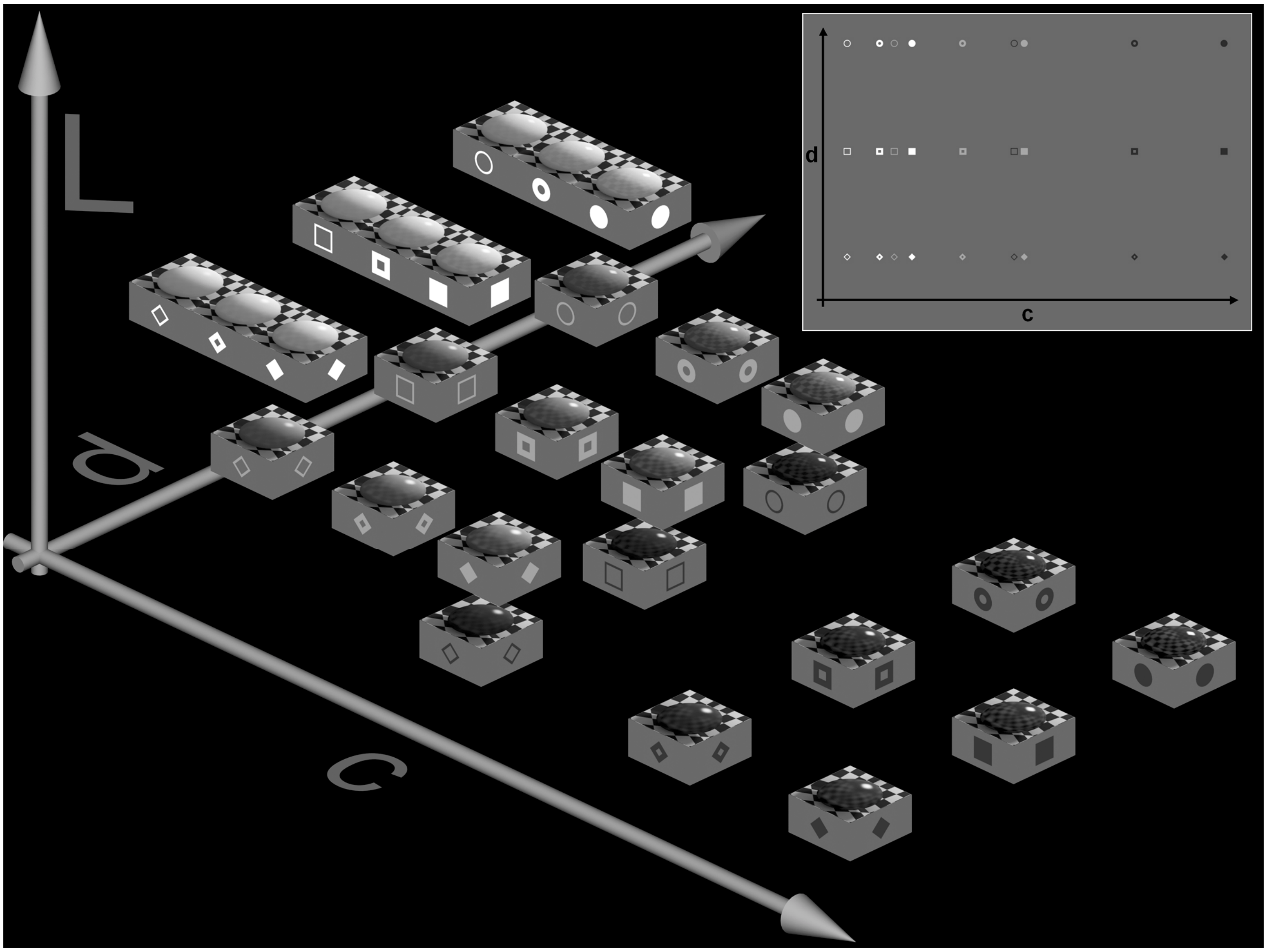

Figure 9[†]: The perceptually uniform gloss space derived from Experiment 2.

- compare two paints with respect to the two visual gloss dimensions
- produce paints with different physical reflectance values that match in terms of apparent gloss
- calculate isogloss contours that describe paints that differ equally in apparent gloss from a standard.

4. A PSYCHOPHYSICALLY-BASED LIGHT REFLECTION MODEL

To take full advantage of this new space, we are going to rewrite the parameters of the physically-based light reflection model (Equations 6,7,8) in perceptual terms to create a psychophysically-based light reflection model that can be used to describe both the physical and visual characteristics of the paints we studied. To do this, we need to introduce a perceptually linear parameter related to diffuse reflectance. For compatibility with perceptually uniform color spaces we chose CIELAB lightness (L). This final addition allows us to express the physical parameters in terms of the perceptual ones through the following equations:

$$\rho_d = f^{-1}(L) \tag{6}$$

$$\rho_s = \left(c + \sqrt[3]{f^{-1}(L)/2}\right)^3 - f^{-1}(L)/2 \tag{7}$$

$$\alpha = 1 - d \tag{8}$$

where f is the CIELAB lightness function normalized in [0,1].

Figure 10 illustrates the influence of the lightness of the diffuse component on perceived gloss. Here the solid curve plots the maximum contrast gloss c achievable for different lightness values (derived by enforcing energy conservation of the BRDF). This defines the envelope of gloss space with respect to lightness. We also plotted how contrast gloss varies with lightness for a fixed energy of the specular lobe. This curve shows that for the same specular energy, contrast gloss is smaller for lighter objects. That is to say, if two surfaces are painted with black and white paints having the same physical formulations, the black surface will appear glossier than the white one.

Strictly speaking, the model we've developed is only predictive

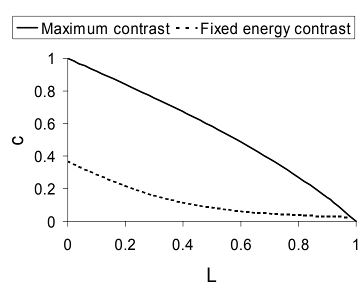

Figure 10: Effect of surface lightness on apparent gloss.

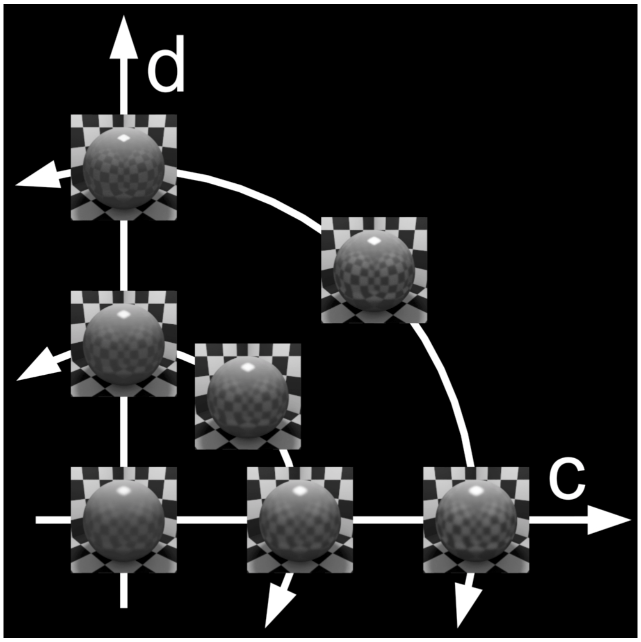

Figure 11[†]: Isogloss difference contours.

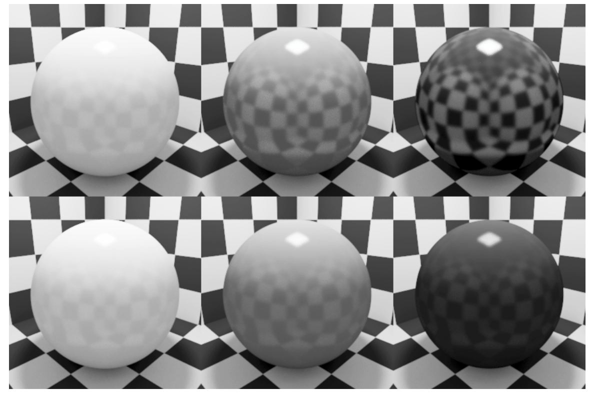

Figure 12[†]: Matching apparent gloss: white, gray, and black objects having the same physical gloss parameters (top row) and perceptual gloss parameters (bottom row).

within the range of our stimuli, which covers a substantial range of measured glossy paints. However we feel confident that the model can be applied outside this range to cover the space of physically plausible BRDFs expressible using the Ward model, but we believe that the physical parameters should be maintained in the range of the ones measured for real materials. In particular, the α value should not be much larger than 0.2 since the specular lobe of the BRDF is not normalized for larger values [Ward92].

5. APPLYING THE MODEL

In the previous section we used the results of our gloss perception studies to develop a psychophysically-based light reflection model for image synthesis where the dimensions of the model are perceptually meaningful and variations along these dimensions are perceptually uniform. In this section we demonstrate the power of the model by showing how it can be used to facilitate the process of describing surface appearance in graphics rendering applications.

5.1 Describing differences in apparent gloss

One of the benefits of working in a perceptually uniform description space is that steps along the dimensions produce equal changes in appearance. This is true of uniform color spaces such as CIELAB where equal numerical steps in lightness (L) or chroma (a,b) produce perceptually equal changes in color appearance.

The perceptually uniform gloss space our light reflection model is based on has similar properties. Figure 11 shows *isogloss difference contours* with respect to the object in the lower left corner of the diagram (c = 0.087, d = 0.93). According to the model, the objects falling on the circular contours are equally different in apparent gloss from the reference object. The concentric circles show two degrees of isogloss difference (Δc = 0.04, Δd = 0.22 = 0.04/1.78).

It's important to observe that because the gloss space is two-dimensional (c,d), objects equidistant from a reference object may have different reflectance properties even though they will be judged to be equally different in gloss from the reference. For example, the two objects at 12 and 3 o'clock in Figure 11 have very different reflectance properties: the one at 12 o'clock produces a sharp but low contrast reflection, while the one at 3 o'clock makes a blurry but high contrast reflection, still the model predicts that they will be judged to be equally different in gloss from the reference object. This prediction was supported by an informal ranking study we ran using the stimulus set from Experiment 1. Objects whose parameters fell along isogloss contours with respect to a low gloss reference object received similar rank values implying that they appeared equally "glossy" but in different ways.

This demonstration shows that our model provides the ability to specify differences in apparent gloss. This should make it much easier to modify object gloss properties in controlled ways in graphics rendering applications.

5.2 Matching apparent gloss

Many studies of gloss perception [Hunt87, Bill87] have noted that apparent gloss is affected by the diffuse reflectance of a surface, with light colored surfaces appearing less glossy than dark ones having the same finish. This effect is illustrated in the top row of Figure 12 where the white, gray and black objects have the same physical gloss parameters (ρ_s = 0.099, α = 0.04) but differ in apparent gloss with the white sphere appearing least glossy and the black sphere appearing most glossy. This phenomenon makes it difficult to create objects with different lightnesses that match in apparent gloss. The bottom row of Figure 12 shows the results produced with our psychophysically-based gloss model. When the objects are assigned the same perceptual gloss values (c = 0.057, d = 0.96) they appear to have similar gloss despite differences in their lightnesses. This property of the model should make it much easier to create objects that have the same apparent gloss, since the parameters that describe object lightness (L) and gloss (c,d) have been decoupled.

5.3 A new tool for modeling surface appearance in computer graphics

In the previous subsections we have demonstrated that our new model has two important features: it allows us to describe differences in apparent gloss, and it lets us make objects match in apparent gloss. These features should make it much easier to specify surface appearance in graphics rendering applications. To demonstrate how the model might be used, Figure 13 shows a prototype of a perceptually-based color/gloss picker for painted surfaces that could be incorporated into an application. We add color to the model by assuming (as suggested in [Astm89] and [Aida97]), that surface chromaticity and apparent gloss are

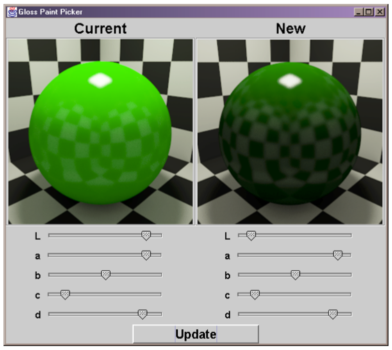

Figure 13†: Prototype of a perceptually-based color/gloss picker for painted surfaces. Surface appearance is specified by three color parameters CIELAB lightness (*L*) and chroma (*a,b*) and two gloss parameters (*c*) contrast gloss and (*d*) distinctness-of-image gloss.

relatively independent. For consistency with the lightness parameter *(L)* we use CIELAB chroma (*a,b*) to specify color. In the interface, surface appearance is specified by these three color parameters and by the two gloss parameters (c,*d*).

Figure 14 shows an image where this five parameter color/gloss description has been used to match the apparent gloss of the dark red and light blue mugs. Notice that the glossy appearance of the mugs is similar even though they differ significantly in lightness and color. This image suggests that psychophysically-based light reflection model we have developed through our experiments may be usefully applied under more general conditions, however further testing and validation are clearly necessary.

6. CONCLUSIONS/FUTURE WORK

In this paper we've introduced a new light reflection model for image synthesis based on experimental studies of surface gloss perception. To develop the model we conducted two experiments that explored the relationships between the physical parameters used to describe the reflectance properties of glossy surfaces and the perceptual dimensions of glossy appearance in synthetic images. We used the results of these experiments to develop a psychophysically-based light reflection model where the dimensions of the model are perceptually-meaningful and variations along the dimensions are perceptually uniform. We've demonstrated that the model can facilitate the process of describing surface appearance in graphics rendering applications. Although we feel that these results are promising, there is clearly much more work to be done.

First, we want to make clear that strictly speaking, the model we've developed only accurately predicts appearance within the range of glossy paints we studied, under the viewing conditions we used. Although we believe our results will generalize well, if the goal is to develop a comprehensive psychophysically-based light reflection model for image synthesis, many more studies need to be done: 1) to investigate different classes of materials like plastics, metals, and papers (possibly requiring different BRDF models); and 2) to determine how object properties like shape, pattern, texture, and color, and scene properties like illumination quality, spatial proximity, and environmental contrast and texture affect apparent gloss. Additionally, even though in our experiments we found that apparent gloss has two dimensions, we fully expect that for other materials and under other conditions different gloss attributes such as sheen and haze may play a greater role. Finally, we feel that a very important topic for future work is to develop better tone reproduction methods for

Figure 14†: Demonstration that the model can be used effectively in a typical rendering application (3D Studio MAX™). The model was used to make the dark red and light blue mugs match in apparent gloss.

accurately reproducing the appearance of high dynamic range glossy surfaces within the limited ranges of existing display devices.

By using physically-based image synthesis techniques to conduct psychophysical studies of surface appearance, we should be able to make significant progress in these areas. This will allow us to develop models of the goniometric aspects of surface appearance to complement widely used colorimetric models.

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