A psychophysically-based model of surface gloss perception

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ABSTRACT

In this paper we introduce a new model of surface appearance that is based on quantitative studies of gloss perception. We use image synthesis techniques to conduct experiments that explore the relationships between the physical dimensions of glossy reflectance and the perceptual dimensions of glossy appearance. The product of these experiments is a psychophysically-based model of surface gloss, with dimensions that are both physically and perceptually meaningful and scales that reflect our sensitivity to gloss variations. We demonstrate that the model can be used to describe and control the appearance of glossy surfaces in synthetic images, allowing prediction of gloss matches and quantification of gloss differences. This work represents some initial steps toward developing psychophysical models of the goniometric aspects of surface appearance to complement widely-used colorimetric models.

Keywords: Visual perception, material perception, appearance, gloss, light reflection models

1. INTRODUCTION

Color and *gloss* are two fundamental attributes used to describe surface appearance. Color is related to a surface's *spectral* reflectance properties. Gloss is a function of a surface's *directional* reflectance properties. Many models have been developed for describing color, from the simple RGB model used in video and computer graphics, to the more sophisticated Munsell, XYZ, and CIELAB models that have grown out of the science of *colorimetry*[30,7]. These colorimetric models have made it easier to describe and control color because the models are grounded in the psychophysics of color perception. Unfortunately similar psychophysically-based models of gloss have not been available.

Current physical models of gloss are based on quantitative studies of light reflection[6,8,28,23,14,24], and although great progress has been made in the accuracy and generality of these models, for the most part their parameters are visually unintuitive, and interactions among the parameters make it difficult to specify the appearance of glossy surfaces. Conversely, the most widely-used model of apparent gloss[11] is based on dimensions derived largely by intuition and scaled one-at-a-time, under highly restricted material, illumination, and viewing conditions. It has proved difficult to use this model to predict glossy appearance, because of the multidimensional nature of gloss perception under natural conditions[1]. A model of gloss that is grounded in both the physics of light reflection and the phenomenology of gloss perception could greatly facilitate the process of describing and controlling surface gloss properties.

In this paper we introduce a new model of surface appearance that is based on quantitative studies of gloss perception. We have used image synthesis techniques to conduct experiments that explore the relationships between the physical dimensions of glossy reflectance 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 to produce a *psychophysically-based* gloss model, with dimensions that are both physically and perceptually meaningful and scales that reflect our sensitivity to variations in gloss. We will show that the model can be used to describe and control the appearance of glossy surfaces in synthetic images, allowing prediction of gloss matches and quantification of gloss differences. This work represents some initial steps toward developing psychophysical models of the *goniometric* aspects of surface appearance to complement widely-used colorimetric models.

2. BACKGROUND

The earliest studies of gloss perception are attributed to Ingersoll[12] who in 1914, examined the appearance of glossy papers. In 1936, Hunter[11] observed that there are at least six different visual phenomena related to apparent gloss. He defined these as:

<u>specular gloss</u> – perceived brightness associated with the specular reflection from a surface
<u>contrast gloss</u> – perceived relative brightness of specularly and diffusely reflecting areas
<u>distinctness-of-image (DOI) gloss</u> – perceived sharpness of images reflected in a surface
<u>haze</u> – perceived cloudiness in reflections near the specular direction
<u>sheen</u> – perceived shininess at grazing angles in otherwise matte surfaces
<u>absence-of-texture gloss</u> – perceived surface smoothness and uniformity

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In 1937, Judd[13] formalized Hunter's observations by writing expressions that related them to the physical features of surface *bi-directional reflectance distribution functions* (BRDFs). Hunter and Judd's research established a conceptual framework that has dominated work in gloss perception to the present day. Their gloss dimensions have been used as the bases of many important industrial metrics for gloss measurement and specification, however there has been considerable difficulty in correlating these metrics with object appearance under natural conditions[18]. Although Hunter and Judd's dimensions can certainly be observed and measured, few experiments have been done to evaluate if these are the dimensions people actually use to judge gloss.

In 1987 Billmeyer and O'Donnell[1] published an important paper that tried to address the issue of gloss perception from first principles. Working with a set of white, gray, and black paints with varying gloss levels, O'Donnell collected ratings of the perceived differences in gloss between pairs of samples and then used *multidimensional scaling* techniques to discover the dimensionality of apparent 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 Hunter's distinctness-of-image gloss, while the appearance of low gloss surfaces is better described by a measure like contrast gloss. This work is significant because it is the first to study the multidimensional nature of gloss perception without preconceptions about what the dimensions might be.

In the vision literature, studies of gloss have focused primarily on its effects on the perception of shape from shading. Todd[25] and Mingolla[16] found that gloss generally enhances the perception of surface curvature. Blake[2] found categorical changes in surface appearance and shape depending on the 3d location of the specular highlight. Braje[4] 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[17] also studied interactions between shape and gloss, and found that subjects are poor at matching the Phong[21] parameters of bumpy surfaces with different frequency and amplitude components. Only recently[22] has the perception of material properties per se become an active subject of study in the vision community.

There is still much work to be done in this area. First, with the exception of Billmeyer and O'Donnell's experiments there has been little study of gloss perception from first principles. Hunter and Judd's studies of apparent gloss were groundbreaking and insightful, but their dimensions were defined a priori. To really understand gloss perception we need to conduct experiments that identify and quantify without preconception, the dimensions people actually use to judge gloss. Second, previous studies of gloss perception have only looked at flat, directly illuminated surfaces in unstructured 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 understand how we perceive gloss under natural conditions, we need to study three-dimensional objects in realistic environments. Fortunately, image synthesis gives us a powerful tool to study gloss perception. Physically-based image synthesis methods let us make realistic images of complex objects in globally-illuminated scenes, and gives us precise control over object and scene properties. By using image synthesis techniques to conduct experiments on gloss perception we should be able to make significant progress toward the goal of developing a psychophysically-based gloss model that can be used to describe and predict the appearance of glossy surfaces.

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 the perception of color. Many of the earliest experiments focused on determining the *dimensionality* of color perception, culminating with Young's trichromatic theory[9]. Following this, further experiments were done to find *perceptually meaningful axes* in this three-dimensional color space. Hering's work[10] on opponent color descriptions, falls into this category. Finally, many experiments have been done to scale these axes to create *perceptually uniform* color spaces and estimate *just noticeable differences* (JNDs) in color. Munsell, Judd, and MacAdam's efforts are good examples (see Wyszecki[30] 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:

- 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 to create a *perceptually uniform* gloss space and predict *just noticeable differences* in gloss

Finally we will use the results of these experiments to develop a psychophysically-based model of gloss that can be used to relate the physical dimensions of glossy reflectance to the perceptual dimensions of glossy appearance.

3.2 Experiment 1

3.2.1 Approach

The purpose of Experiment 1 is to determine the dimensionality of gloss perception and to find perceptually meaningful axes in visual gloss space. To do this we've designed an experiment based on multidimensional scaling techniques. Multidimensional scaling[3] (MDS) is statistical method for finding the latent dimensions in a dataset that 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. MDS can produce solutions in any number of dimensions to achieve the best fit to the data. The goodness of fit, known as the *stress* of the solution, is given by:

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

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.

Plotting stress as a function of the dimensionality of the solution produces a curve that drops sharply as dimensions are added that explain more of the data and declines more slowly as superfluous dimensions are added. Standard practice is to choose the dimensionality indicated by the inflection point in the stress curve. MDS algorithms come in a variety of flavors that differ in the form of the stress function used. We use a variant called weighted Euclidean non-metric MDS 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 that lets us test hypotheses about the functional forms of the dimensions and their orthogonality (see Borg[3] for further details).

3.2.2 Procedure

To study 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 the MDS algorithm uses to construct a representation of visual gloss space.

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 decided 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.

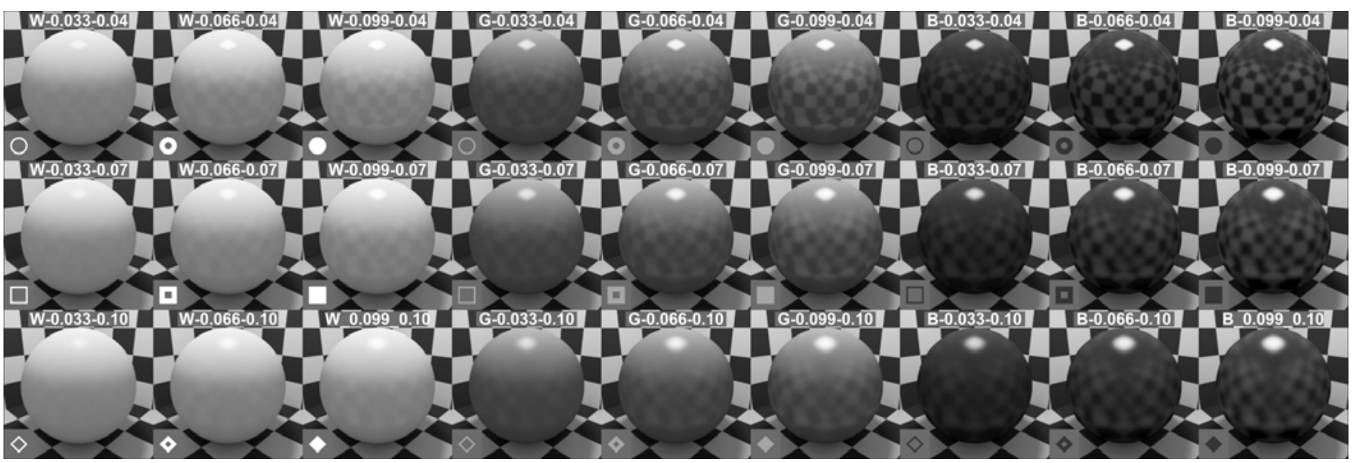

Figure 1: Composite image of the stimulus set used in Experiment 1. Labels indicate the diffuse color (ρ_d ;white, gray, black), ρ_s , and α values. Symbols are included as an aid for interpreting subsequent figures.

A composite image of the stimulus set used in Experiment 1 is shown in Figure 1. The environment consisted of a sphere enclosed in a checkerboard box illuminated by an overhead area light source. Images were generated with a physically-based Monte Carlo path-tracer that used an isotropic version of Ward's light reflection model[28]:

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

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. We chose Ward's model because we wanted the objects in the stimulus set to represent the gloss properties of real materials, and Ward provides parameters that describe a range of measured glossy paints. Our stimulus set spans 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; black, gray, and white) which are the diffuse reflectance factors corresponding to Munsell values (N2, N5, and N9). The 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 1.

In the final stage of the image synthesis process, scene radiances calculated by the rendering algorithm are mapped to numerical values used to drive a display device. This process is known as *tone reproduction*. The goal of the tone reproduction process is to produce a displayed image that accurately captures the appearance of the scene. In our case, choosing a tone reproduction operator presented a challenge because the visible reflection of the light source created images with high dynamic ranges. We experimented with a number of tone reproduction operators including simple clipping and gamma compression as well as Pattanaik et al.[20]and Ward-Larson et al.'s[29] high dynamic range operators, but they all produced objectionable artifacts such as halos and banding. We settled on Tumblin's[27] Rational Sigmoid operator which compresses highlights without abrupt clipping and allows all other scene radiances to be directly reproduced by the display.

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 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[5] MDS algorithm.

3.2.3 Results

Recall that our goal in this experiment is to discover the dimensionality of gloss perception for our stimulus set and to find perceptually meaningful axes in this space. To do this we observed how the stress value varied with the dimensionality of the MDS solutions. Our analysis showed that the stress value dropped sharply with the change from a 1-dimensional to a 2-dimensional solution, but declined more slowly with the addition of higher dimensions that were probably only accommodating noise in the dataset. From this pattern we inferred that under the conditions of our experiment apparent gloss has two dimensions. The two-dimensional gloss space recovered by the MDS algorithm is shown in Figure 2.

We must now identify perceptually meaningful axes in this 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 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 <u>qualitatively</u> similar to the *contrast gloss* and *distinctness-of-image (DOI) gloss* attributes Hunter observed and so we will name these 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 <u>quantitative</u> formulation of the relationships between these perceptual dimensions and the physical parameters used to describe surface reflectance properties.

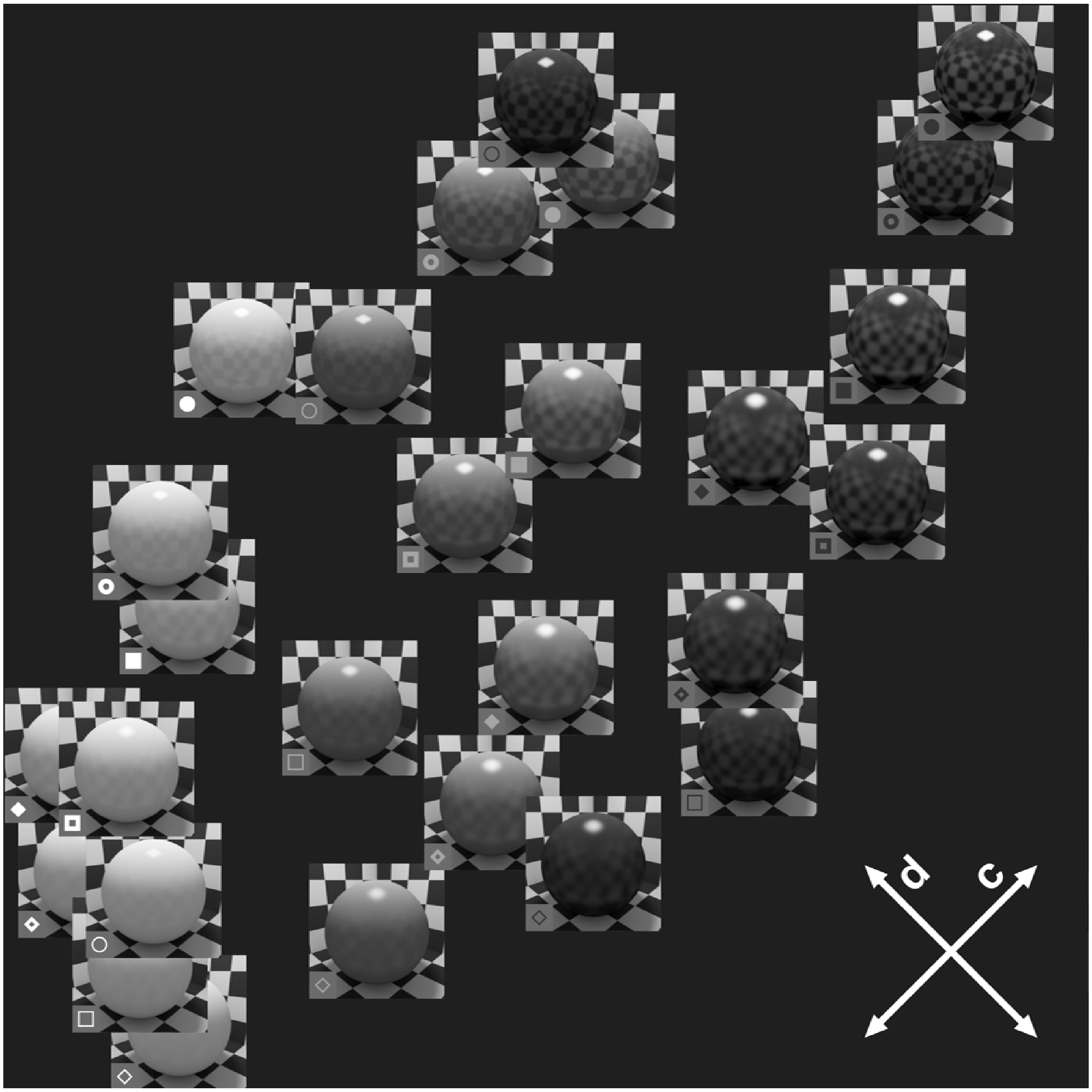

Figure 2: Two-dimensional MDS solution for Experiment 1.

3.3 Experiment 2

3.3.1 Approach

In Experiment 1 we discovered the dimensionality of gloss perception for our stimulus set and identified perceptually meaningful axes in this gloss space. The purpose of Experiment 2 is to place 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.

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[26]. 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. Just noticeable differences (JNDs) can be derived from measures of dispersion of the magnitude estimates[26].

3.3.2 Procedure

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 parameters intermediate to those in the original set. In the *contrast gloss* 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* study, α was varied in 10 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.

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 study, subjects viewed single images from the 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 an on-screen slider.

3.3.3 Results

Our goal in these experiments is to derive psychophysical scaling functions that relate changes in apparent gloss along the perceptual dimensions discovered in Experiment 1 to variations in the physical parameters of the light reflection model. To achieve this goal we tested various hypotheses about functional relationships, 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 3 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 2) it is clear that *c* varies with diffuse reflectance, since the white, gray, and black objects form distinct clusters that occupy different

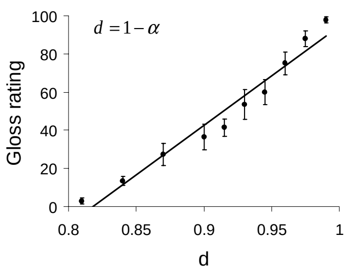

Figure 3: Magnitude estimates and fit for DOI gloss *d*.

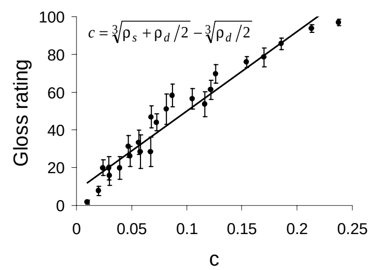

Figure 4: Magnitude estimates and fit for contrast gloss *c*.

ranges along the *c* dimension. Our first hypothesis was that *c* is a simple function of the physical contrast (luminance ratio) of the reflected black and white patches in the image plane 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 CIELAB *(L)*. 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. Finally, we tested a third hypothesis that when judging gloss, subjects' lightness estimates are based on object-space features rather than image-plane features (i.e. subjects show a form of constancy, compensating for blur-related losses in image contrast). 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 4 plots the data from the contrast gloss study, which shows how subjects' gloss ratings relate to this final formulation for the *c* dimension. The line was obtained through linear regression and provides a good fit to the data (r^2 = 0.94). 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 this region of gloss space.

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

$$d = 1 - \alpha \qquad (3)$$

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

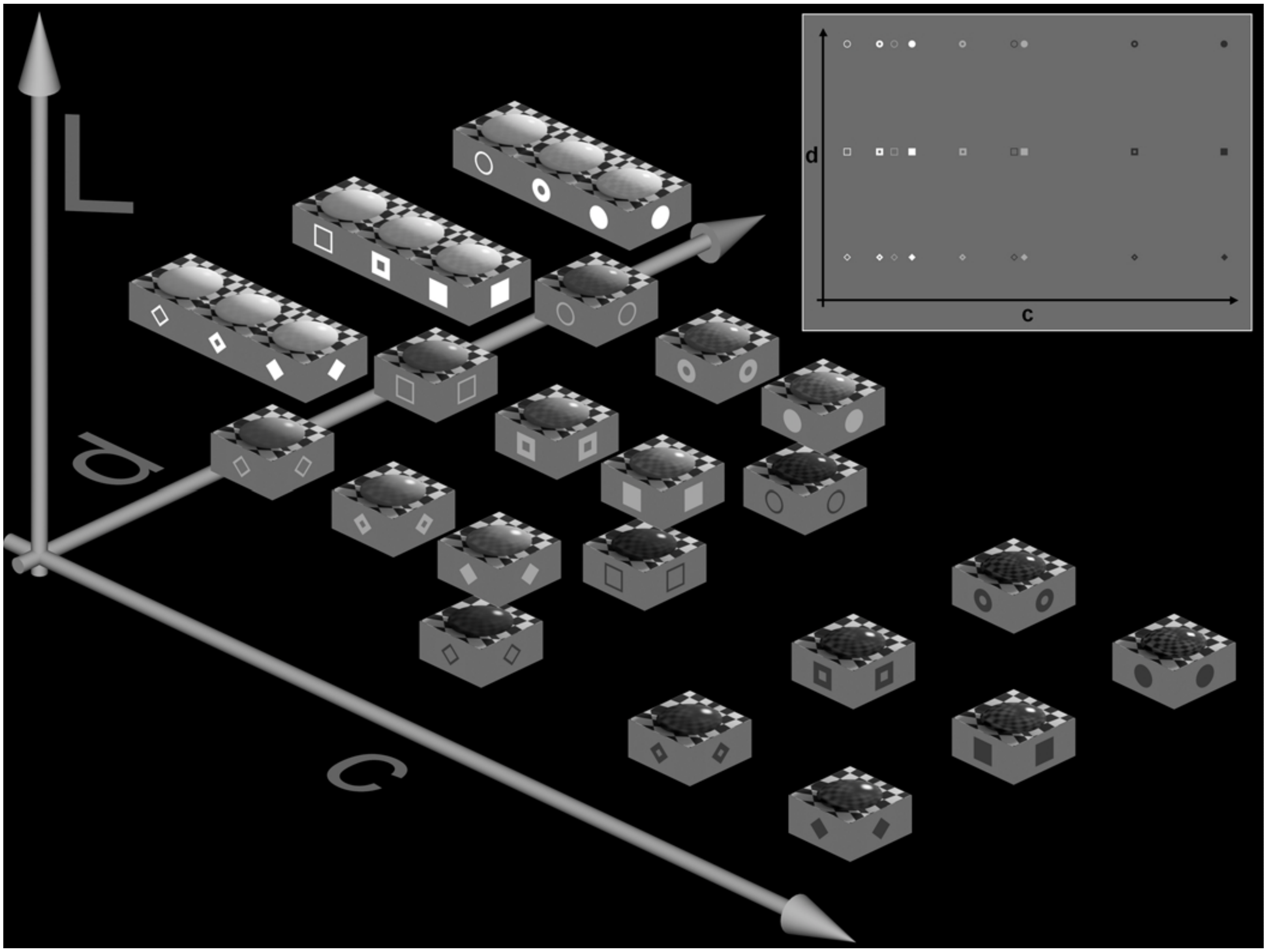

Figure 5: The perceptually uniform gloss space derived from Experiment 2.

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

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

Figure 5 shows a visualization of the perceptually uniform gloss space defined by the metrics with the stimuli from Experiment 1 placed at their predicted locations. The contrast gloss (c) and DOI gloss (d) axes 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.

4. A PSYCHOPHYSICALLY-BASED GLOSS MODEL

To take full advantage of this new space, we are going to rewrite the parameters of Ward's physically-based light reflection model in perceptual terms to create a psychophysically-based model that can be used to describe both the physical and visual characteristics of our glossy surfaces. To do this, we need to introduce a perceptually linear parameter related to a surface's 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, where f is the CIELAB lightness function normalized in [0,1]:

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

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

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

Figure 6 illustrates the influence of the diffuse component on apparent gloss. Here the solid curve plots the maximum contrast gloss *c* achievable for surfaces with different lightness values (derived by enforcing energy conservation of the BRDF). This curve defines the envelope of gloss space with respect to surface 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 within the range of stimuli we tested, however this should not be too much of a limitation because the stimulus set actually covers a substantial range of glossy paints. The model may also be applicable outside this range, but we feel that the model parameters should be constrained to the space of physically plausible BRDFs that can be expressed by the Ward model. In particular we feel that the Ward model's α value should not be much larger than 0.2 because the specular component of the BRDF is not normalized for such broad lobes, and it is unclear that the *c* and *d* dimensions remain independent in the extreme low gloss domain.

5. APPLYING THE MODEL

In the previous section we used the results of our experiments to develop a psychophysically-based gloss model. In this section we demonstrate the power of the model by showing how it can be used to facilitate the process of describing and controlling surface appearance in realistic image synthesis.

5.1 Gloss matching

Many studies of gloss perception[11,1] 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 7 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 7 shows the results produced with our psychophysically-based gloss model. Here the objects have been assigned the same perceptual gloss values (c = 0.057, d = 0.96), and they appear similar in gloss despite differences in their lightnesses. Using the dimensions provided by the new model should make it much easier to create objects that have the same apparent gloss.

5.2 Isogloss contours

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

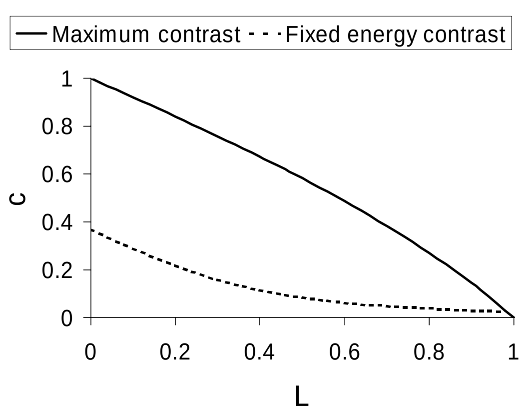

Figure 6: Effect of surface lightness on contrast gloss.

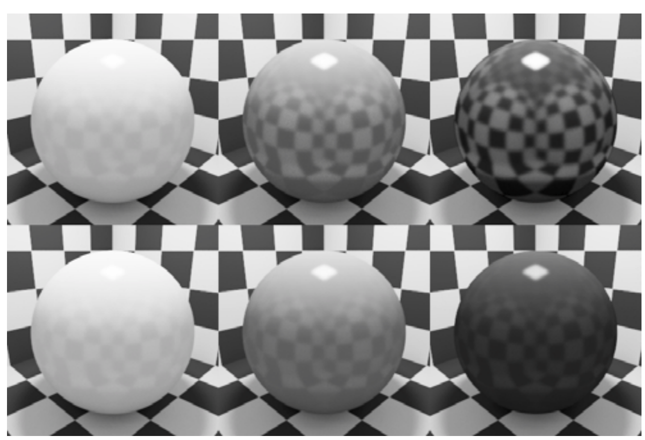

Figure 7: Matching apparent gloss: white, gray, and black objects having the same physical gloss parameters (top row) and perceptual gloss parameters (bottom row).

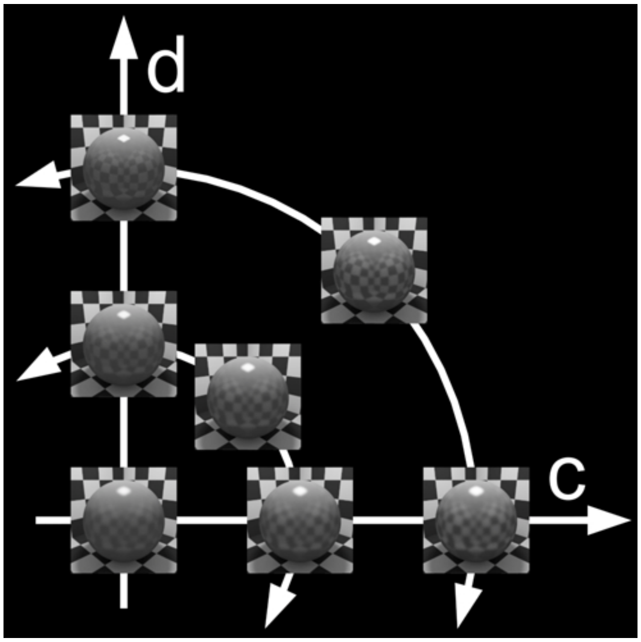

Figure 8: Isogloss contours: objects along the contours are equally different in apparent gloss from the central object.

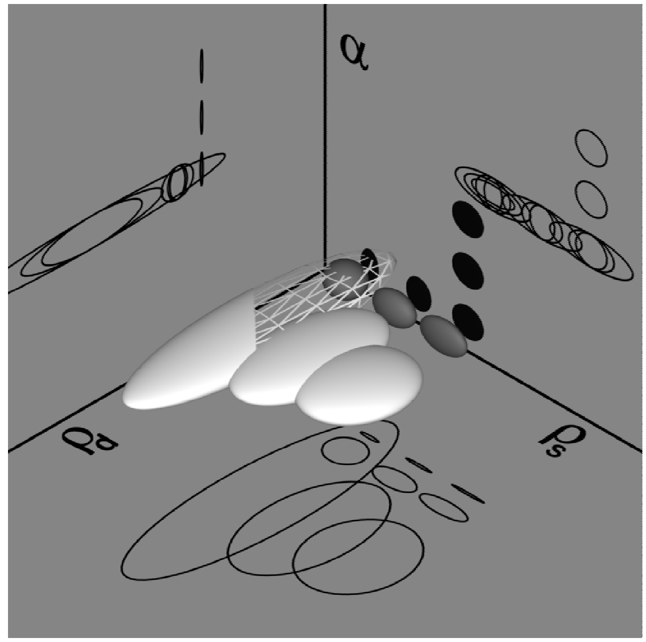

Figure 9: Just noticeable differences in gloss: the ellipsoids indicate the changes in material properties required to produce visible differences in gloss from the materials defined by their centers.

chroma (*a,b*) produce perceptually equal changes in color appearance.

The perceptually uniform gloss space our model is based on has similar properties. Figure 8 shows *isogloss 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 = 0.022 = 0.04/1.78).

It's important to realize that because the gloss space is two-dimensional, two objects judged to be equally different in gloss from a reference object may have different reflectance properties. For example, the two objects at 12 and 3 o'clock in Figure 8 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, suggesting that subjects found them to be equally "glossy", but in different ways.

5.3 Just-noticeable differences in gloss

A major goal in the development of colorimetry was the formulation of color difference metrics that could be used to predict visible differences in color. Color difference metrics have great value in science and industry where they can be used to predict required precision and acceptable tolerances in measurement and manufacturing processes. In 1942 MacAdam[15] performed a series of experiments to estimate just noticeable differences in chromaticity within the CIE XYZ color space. When these JNDs are plotted on the chromaticity diagram they form the so-called *MacAdam ellipses*.

We have attempted to estimate measures analogous to the MacAdam ellipses for visible differences in gloss. In the absence of direct experiment, Torgerson[26] suggests that just noticeable differences can be estimated from measures of dispersion in the ratings given to stimuli in a scaling task. Following this procedure, we calculated JNDs for c and d as the average standard deviation of the distribution of differences between the gloss values predicted by the regression lines in Figures 3 and 4 and the actual ratings made by the subjects. We multiplied this value by 0.954 to adopt a 75% discrimination criterion. We excluded near-endpoint stimuli from our calculations to eliminate range-related constraints on dispersion, which could lead to artificially small JNDs[19]. The JND formula is:

$$JND = 0.954 * average(\sigma_i) \quad \text{where} \quad \sigma_i = stdev(gloss\_measured_{i,n} - gloss\_predicted_i) \tag{9}$$

Here i is the number of stimuli included in the calculations (20 and 8 respectively for c and d), and n is the number of measures taken on each stimulus (27 for both c and d). This method yields JNDs for c and d as 0.031and 0.017 respectively.

Figure 9 shows these values plotted in terms of the physical parameters of the Ward model for a subset of the stimuli tested in Experiment 2. The ellipsoids indicate the changes in material properties necessary to produce just noticeable differences in gloss for each of the stimuli. The horizontal ρ_d ,ρ_s plane relates to *c*, the contrast gloss dimension. The vertical axis relates to *d*, the DOI gloss dimension. There are several things to notice. First, in general, the lighter objects (high ρ_d) require larger changes in material properties than darker ones (low ρ_d) to produce noticeable differences in gloss. This is because for a fixed ρ_s, lighter objects show less contrast gloss than darker ones. However it should also be noted that the effect of increasing ρ_s is proportional to the object's ρ_d value: increasing ρ_s reduces the size of a JND more for lighter objects than for darker ones. Finally, the stimuli along the vertical axis show that the effect of α on JNDs is constant over the range of stimuli we tested. Although direct measurements of gloss JNDs should be done before any definitive claims are made, these JND estimates are consistent with observers' subjective reports and also suggest interesting directions for future study.

6. CONCLUSIONS

In this paper we've introduced a new model of surface gloss that is grounded in the psychophysics of gloss perception. Using image synthesis techniques, we conducted two experiments that explored the relationships between the physical dimensions of glossy reflectance and the perceptual dimensions of glossy appearance. The product of these experiments is a psychophysically-based model of gloss where the dimensions of the model are perceptually meaningful, the scales of the dimensions are perceptually uniform, and gloss differences can be quantified. We have demonstrated that the model can be used to describe and control the appearance of glossy surfaces in synthetic images. Although we feel that these results are promising, there is much more work to be done.

First, we want to make clear that at this time, the model we've developed is only predictive of appearance within the range of glossy paints we studied, under the imaging and viewing conditions we used. Although we believe our results will generalize well, if the goal is to develop a comprehensive psychophysically-based model of surface gloss, 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 affect apparent gloss. 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 be more salient and add dimensions to "gloss space".

A potential criticism of using image synthesis techniques to study gloss perception is that because of the dynamic range limitations of display devices, if there are visual gloss attributes related to the absolute intensity of surface reflections, these attributes may not be accurately represented by images, which could lead to underestimation of their importance. The clear utility of images as visual representations of objects and scenes and the well known dynamic range adaptations of vision, suggest that this may not be the case, however further studies are necessary before the results of our experiments can be generalized from predicting appearance in the imaging domain to predicting appearance in the real world.

Clearly there is more to do, but hopefully this work represents some initial steps toward developing psychophysical models of the goniometric aspects of surface appearance to complement widely-used colorimetric models.

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