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Can image cues explain the impact of translucency on perceived gloss?

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Abstract

Gloss perception is a complex psychovisual phenomenon, whose mechanisms are not yet fully explained. Instrumentally measured surface reflectance is usually poor predictor of human perception of gloss. The state-of-the-art studies demonstrate that, in addition to surface reflectance, object's shape and illumination geometry also affect the magnitude of gloss perceived by the human visual system (HVS). Recent studies attribute this to image cues — the specific regularities in image statistics that are generated by a combination of these physical properties, and that, in their part, are proposedly used by the HVS for assessing gloss. Another study has recently demonstrated that subsurface scattering of light is an additional factor that can play the role in perceived gloss, but the study provides limited explanation of this phenomenon. In this work, we aimed to shed more light to this observation and explain why translucency impacts perceived gloss, and why this impact varies among shapes. We conducted four psychophysical experiments in order to explore whether image cues typical for opaque objects also explain the variation of perceived gloss in translucent objects and to quantify how these cues are modulated by the subsurface scattering properties. We found that perceived contrast, coverage area, and sharpness of the highlights can be combined to reliably predict perceived gloss. While sharpness is the most significant cue for assessing glossiness of spherical objects, coverage is more important for a complex Lucy shape. Both of these observations propose an explanation why subsurface scattering albedo impacts perceived gloss.

Introduction and Background

Gloss is an important property of objects and materials that has a large impact on how they look. The International Commission on Illumination names gloss among the four fundamental attributes of visual appearance, along with color, translucency, and texture [1]. According to the ASTM Standard Terminology of Appearance [2], gloss is *"angular selectivity of reflectance, involving surface-reflected light, responsible for the degree to which reflected highlights or images of objects may be seen as superimposed on a surface."* While numerous methods have been developed over the past century to measure gloss and surface reflectance properties, instrumentally measured gloss is a poor predictor of how glossy the measured material appears to a human eye [3, 4, 5], and it remains an open question how the human visual system (HVS) separates these reflections of the surround in the proximal stimulus. Interestingly, even when surface reflectance function is kept constant, its apparent gloss can vary considerably, being impacted by multiple factors, such as illumination [6, 7], and the 3D shape of an object it is presented in [8, 9].

These factors have motivated numerous studies on visual gloss perception. It is proposed that the HVS relies on statistical regularities in the image of the environment to perceive gloss – for instance, the skewness or a similar measure of luminance histogram asymmetry has been proposed as a candidate cue [10] (see [4] and [5] for a comprehensive review on gloss perception).

Marlow, Kim, and Anderson [11] attempted to explain the exact mechanisms of how and why the extrinsic factors affect gloss. They showed that variability of perceived gloss is well explained by specific image regularities: sharpness, contrast, coverage area, and depth of specular reflections. In the subsequent work, Marlow and Anderson [12] further explored how variation in surface geometry and illumination modulate sharpness, contrast, and coverage cues – and hence, perceived gloss.

The overwhelming majority of the studies on gloss perception have focused on fully opaque materials. However, many glossy objects and materials that we encounter in our daily lives are also translucent, such as water and ice, glass, plastic, marble, and human skin. If perceived gloss depends on image statistics, these statistics depend - among other factors - on material's translucency as well. Gigilashvili *et al.* [13, 14] asked human observers to judge glossiness of five spherical objects with identical surface reflectance but different translucency. They have observed that translucency impacted their judgments of gloss. While one group of observers considered opaque ones glossier, as they could use the objects as a mirror due to larger contrast, another group, on the other hand, considered translucent ones glossier as they shone more strongly. In the subsequent study, they used objects with a complex surface geometry that did not preserve the mirror image of the environment. In that case, translucent ones were selected by the majority [15]. Being inspired from these findings, Gigilashvili *et al.* [16] used computer graphics to carefully control subsurface scattering properties in the stimuli. They observed that even if surface reflectance is identical, subsurface scattering properties can affect perceived gloss. However, they noticed that this impact differs among shapes. For instance, if subsurface scattering albedo is negatively correlated with perceived gloss for spherical objects, the correlation is positive for a complex Lucy shape. Although Gigilashvili *et al.* [16] hypothesize that subsurface scattering properties may be modulating image cues proposed by Marlow and Anderson [12] in a similar manner as done by surface geometry and illumination, the credible explanation on why translucency affects perceived gloss is yet to be proposed.

While separate works in the past have demonstrated that on the one hand, translucency affects apparent gloss, and, on the other hand, apparent gloss depends on sharpness, contrast, and coverage area of the highlights, the objective of this study is to investigate why translucency modulates perceived gloss, why the impact of translucency on gloss differs among the shapes, whether these phenomena can be explained by the modulation of the image cues proposed in [11, 12]. Understanding how optical properties affect material appearance and exactly why, is vital for understanding humanly mechanisms of material appearance perception. The literature demonstrating that translucency impacts apparent gloss is itself limited, and to the best of our knowledge, this work is the first attempt to explain the underlying mechanisms of this impact, which is the key novelty of this work.

The article is organized as follows: we describe the research methodology in the next section. In the subsequent section, we first analyze the results, and then discuss them in context of the state-of-the-art. Finally, we conclude and propose directions for the future work.

Methodology

This section describes the research methodology. To investigate how image cues correlate with the impact of translucency on perceived gloss, we conducted psychophysical experiments with the visual stimuli used by Gigilashvili *et al.* [16]. As there is no universal way to quantify the image cues (proposedly used by the HVS) with image statistics, we decided to quantify perceived contrast, sharpness, and coverage area of the highlights psychophysically, similarly to [11, 12]. Marlow and Anderson assume that yet unknown image statistics exist that quantify these perceptual cues and *"whatever the appropriate image measurements are, they will have to accurately capture how each of these cues is perceived in a given context... For example, a perceptually relevant image-based measurement of specular contrast will have to capture how specular contrast is perceived in a given image" [12].* Our study is also based on the expectation that this assumption holds.

Experimental Protocol

Being inspired from [11, 12], we conducted four pair-comparison experiments, where observers were shown pairs of translucent objects, which they had to compare by one of the four criteria, in the following order, respectively: total glossiness, perceived contrast between specular and non-specular regions, perceived size of the highlights (coverage), and perceived sharpness of the highlights. The rationale behind using the pair-comparison experimental protocol is bi-fold: first of all, we wanted to be consistent with previous works [11, 16]; secondly, the pilot experiments, as well as previous studies have indicated that pair-comparison is semantically easier task for the observers, than triplet comparisons or more subjective magnitude estimation [16, 17]. QuickEval tool was used to host the experiments [18]. A sample comparison and the interface that have been used in the experiment are illustrated in Figure 1.

Instructions

Before the experiments, definition of gloss, definition of the respective cues, and real life examples of specular reflections were given. It was confirmed by the authors that observers had a clear understanding of the task. The above-mentioned ASTM definition was provided for gloss [2]. The definitions for contrast, coverage, and sharpness were taken from [12], and are as follows:

- Contrast – "the difference in luminance between a specular reflection and its surround";

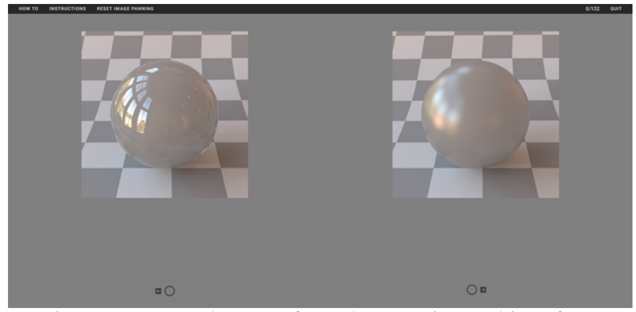

Figure 1: A sample scene from the experimental interface.

- Coverage – "the proportion of a visible surface area occupied by specular reflections";
- Sharpness – "the slope of the luminance gradient at the edge of a reflection";

Observers were allowed to ask questions during the experiment. The instructions were given before each experiment. They could access them anytime in the user interface. The instructions were as follows:

- Exp. 1, Glossiness: Choose the image with higher gloss;
- Exp. 2, Contrast: Choose the image with higher contrast;
- Exp. 3, Coverage: Choose the image with higher coverage;
- Exp. 4, Sharpness: Choose the image with higher sharpness.

Observation Conditions

Although a web-based tool was used to host the experiments [18], the observers completed the task in fully-controlled laboratory conditions. All experiments were conducted on a sRGB calibrated EIZO CG246 ColorEdge display, with a gamma of 2.2, a whitepoint color temperature of 6500K, and a luminance of 80 cd/m^2. The distance between display and observer was 60 cm. The display resolution was 1920×1080, and the image size was 13.55cm (both horizontally and vertically), occupying approximately 12.88° of the field of view. The experiments were performed in full display view. A progress indicator was shown in the top right corner of the display.

Observers

22 observers participated in all four experiments. The majority of the observers were first- and second-year Computer Science students with experience in image processing and color science. Three researchers from NTNU ColourLab have also participated in the experiments. All participants had normal color vision and normal or corrected-to-normal visual acuity.

Stimuli

We used a subset of the stimuli used by Gigilashvili *et al.* [16]. To explain the cross-shape differences observed in [16], two different shapes were used: a perfect sphere and a Stanford Lucy [19]. 12 different materials were selected per shape that varied in surface roughness (α), extinction coefficient (σ_T), and subsurface scattering albedo. The properties of these materials are given in Table 1. The images are illustrated in Figure 2. The

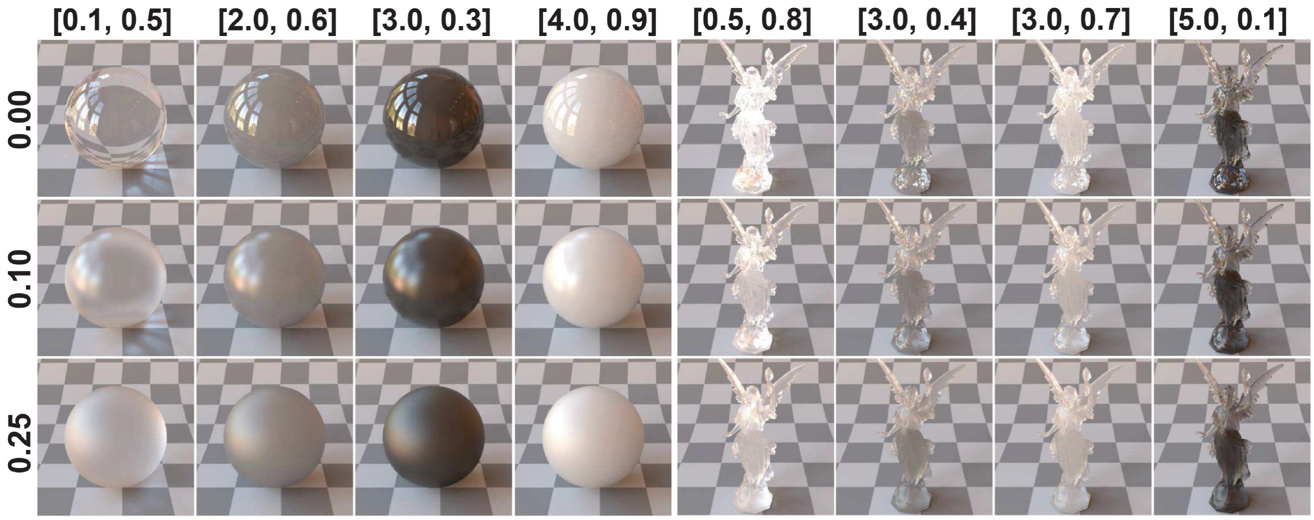

Figure 2: The images used in the experiment. The numbers on the left correspond to α for a given row, while a pair of numbers on top of the images correspond to σ_T and albedo for a given column. All images were used in and are reproduced from [16].

Table 1: The table summarizes material properties used to generate images of spherical (left, yellow), and Lucy (right, lilac) objects. Each row in each half of the table corresponds to each material (triplet of α, σ_T, and albedo).

Sphere			Lucy		
α	σ_T	Albedo	α	σ_T	Albedo
0	0.1	0.5	0	0.5	0.8
0	2	0.6	0	3	0.4
0	3	0.3	0	3	0.7
0	4	0.9	0	5	0.1
0.1	0.1	0.5	0.1	0.5	0.8
0.1	2	0.6	0.1	3	0.4
0.1	3	0.3	0.1	3	0.7
0.1	4	0.9	0.1	5	0.1
0.25	0.1	0.5	0.25	0.5	0.8
0.25	2	0.6	0.25	3	0.4
0.25	3	0.3	0.25	3	0.7
0.25	4	0.9	0.25	5	0.1

images had 512×512 pixel resolution, they were displayed on a neutral gray background. The objects were compared only with the objects of the same shape, which led to 132 comparisons per experiment for both shapes combined. On average, it took 8-10 minutes to complete one experiment. The stimuli were shown in a random order.

Analysis and Discussion

In this section, we present and discuss the results.

Z-scores

First of all, we calculated Z-scores for total glossiness scores to visualize which objects appeared glossier than others and to check whether the results from the previous work using these stimuli [16] are reproduced. Z-score plots are given in Figures 3 and 4 for sphere and Lucy, respectively. These plots are not directly comparable with similar plots in [16], because Z-score is a relative measure to the rest of the stimuli, and objects in [16] were compared primarily with objects with the same roughness, as well as with additional materials not addressed in this article. However, we can still compare and discuss overall trends. The trends are very much similar to that of [16]. Roughness has a significant impact on glossiness of spheres. When a sphere is smooth, a transparent one (i.e. low σ_T) and the ones with low albedo are considered glossier, while the ones with high albedo are less glossy. The differences within the same roughness group decrease for rougher spheres. Similarly to [16], the opposite trend was observed for Lucy. The differences are smaller for a smooth Lucy, and they increase for rougher objects. For rough Lucy objects, as in [16], if σ_T is low, or if both σ_T and albedo are high, Lucy appears glossier than others. The Lucy with low σ_T is significantly glossier than other materials with the same roughness and is equally glossy as smoother objects.

Gloss as a Weighted Average of the Cues

Afterward, similarly to previous works [11, 12], we analyze whether total gloss judgment can be presented as a weighted average of sharpness, coverage, and contrast. We followed the methodology presented in [11]. Marlow *et al.* [11] demonstrated that cues can be combined in a linear manner, and their best fit accounted for 94% of the variance in apparent gloss judgments.

Pair comparison data was converted into scores from 0 to 100, where the score for a given stimulus corresponds to the percentage of the cases out of all comparisons in a given experiment when a given stimulus was selected. Afterward, for each shape, total perceived gloss value is presented as a weighted average of the three perceived cues (Equation 1), where the weights sum up to 100% (Equation 2).

$$Gloss = W_1 \times Contrast + W_2 \times Coverage + W_3 \times Sharpness \quad (1)$$

, where:

$$W_1 + W_2 + W_3 = 1 \quad (2)$$

In order to find the best fit, we used a brute force approach to test all possible combinations of W_1, W_2, and W_3 that satisfy

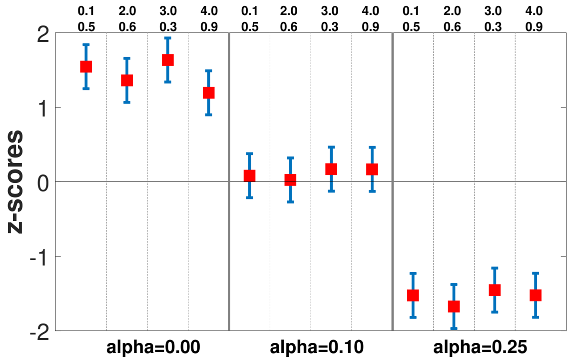

Figure 3: Z-scores for sphere. Z-scores are given on a vertical axis. The materials are grouped by surface roughness along the horizontal axis. The numbers on the top correspond to respective σ_T and albedo. Red squares correspond to the Z-score, while the whiskers extend to the 95% confidence interval. Identical variance is assumed.

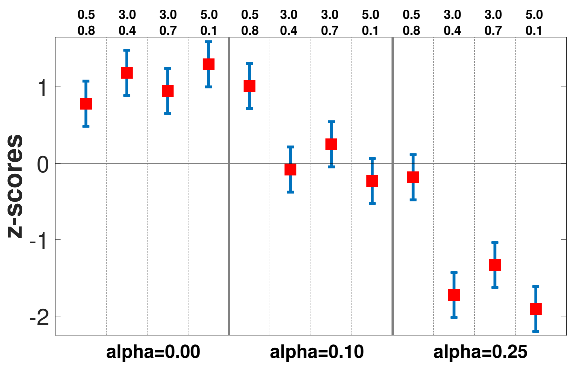

Figure 4: Z-scores for Lucy.

Equation 2, changing them with the steps of 0.01. The triplet of the weights with the least sum of squared residuals (i.e. the difference between actual total gloss and predicted total gloss for a given triplet) was selected, and is given in Equation 3 for sphere and Equation 4 for Lucy, respectively. With these models, the weighted average of the perceived cues accounted for 99% and 98% of the variance in total gloss judgments for sphere and Lucy, respectively (with a *p-value* orders of magnitude smaller than 0.01).

$$Gloss_{\text{Sphere}} = 0.1 \times Contrast + 0.3 \times Coverage + \mathbf{0.6} \times \textbf{Sharpness} \tag{3}$$

$$Gloss_{\text{Lucy}} = 0.2 \times Contrast + \mathbf{0.54} \times \textbf{Coverage} + 0.26 \times Sharpness \tag{4}$$

As we see from Equation 3, sharpness of the highlights has the largest weight, with coverage coming next, while contrast contributes just 10% to the sum. The model is different for Lucy (Equation 4); in this case, coverage weights most, while sharpness and contrast are relatively less impactful.

Heatmaps

To get a better understanding of how measured image cues co-vary with subsurface scattering properties, we produced heatmaps (Figure 5), and plotted the scores for all individual stimuli (Figure 6). Above-mentioned scores on a 0-100 scale are shown in a tabular format in Figure 5, where the higher the value – the green the cell; and the lower the value – the redder the cell. We can observe in the heatmap that the color difference among the roughness groups is very apparent for sphere and less apparent but still noticeable for Lucy, which is consistent with the Z-scores. If we refer to smooth objects, we can observe that for transparent (low σ_T) materials, contrast is rather low, which is also the case for the ones with high albedo. However, for transparent Lucy coverage is very high, which is not the case for sphere. For sphere, low albedo usually produces sharp highlights with high contrast and coverage. For Lucy, low albedo also produces somewhat higher contrast and sharpness, but coverage is rather low. For rough spheres with high albedo, slightly higher coverage compensates for low contrast and sharpness, in the end producing almost equal glossiness for all materials. For rough Lucy, high coverage is usually responsible for high total gloss values. On the other hand, rough Lucy with low albedo – although its contrast and sharpness are relatively high – has very small coverage, and hence, lower gloss.

Afterward, refer to the plots in Figure 6. The shape of the curves shows that all four scores are highly correlated for sphere, while their shape is less similar for Lucy. Low albedo usually leads to considerably larger contrast for all spheres. However, low albedo produces sharper highlights only for smoother spheres and is not capable of increasing sharpness for very rough ones. Therefore, the negative correlation between albedo and gloss disappears with the increase in roughness. However, low albedo slightly increases coverage in the latter case. As for Lucy, we can notice that it is usually high coverage that increases glossiness of low σ_T as well as high σ_T and high albedo materials, despite their sharpness and contrast being relatively low. When albedo is low, coverage goes down, while sharpness and contrast go up.

Discussion

We have once again demonstrated that subsurface scattering properties affect perceived magnitude of gloss, and the nature of this impact is different between the shapes, being largely consistent with [16]. Similarly to Marlow, Kim, and Anderson [11], we have been able to linearly combine perceived image cues, and the weighted average of contrast, coverage, and sharpness accounted for nearly 99% of the variation in perceived glossiness data. However, the weights differed dramatically between the two shapes. While sharpness was the most significant contributing predictor for sphere, it was coverage that contributed most to the total glossiness of Lucy. This observation is highly consistent with a recent study by Gigilashvili and Islam [17], where the authors reported that changing surface roughness had a stronger impact on the glossiness of a sphere than on that of Lucy, which the authors explained by blurring the nearly mirror-like reflection image of the surround that is observable on a simple spherical object and not on Lucy.

This can be an indication that observers primarily assess sharpness of the reflections when they are clear and contain semantic content, as is the case for sphere. On the other hand, complex shapes, such as Lucy, do not permit us to see the detailed image of the environment and rather produce homogeneous saturated areas of highlights. The clarity of the reflected image, which

Sphere

Alpha	sigmaT	Albedo	Total Glossiness	Contrast	Coverage	Sharpness
0	0.1	0.5	87.19	64.88	77.69	84.30
0	2	0.6	81.40	79.34	73.97	84.71
0	3	0.3	90.50	93.80	85.12	97.93
0	4	0.9	76.03	64.46	71.49	71.90
0.1	0.1	0.5	48.76	45.45	53.31	47.11
0.1	2	0.6	49.17	53.31	48.35	46.69
0.1	3	0.3	56.20	69.83	53.31	61.98
0.1	4	0.9	49.59	50.00	50.00	46.28
0.25	0.1	0.5	15.29	10.74	16.12	9.92
0.25	2	0.6	10.74	18.60	16.12	13.64
0.25	3	0.3	19.01	33.06	24.79	21.49
0.25	4	0.9	16.12	16.53	23.55	14.46

Lucy

Alpha	sigmaT	Albedo	Total Glossiness	Contrast	Coverage	Sharpness
0	0.5	0.8	75.62	46.28	92.56	58.26
0	3	0.4	79.75	77.69	73.97	79.34
0	3	0.7	74.79	61.16	79.34	63.64
0	5	0.1	83.88	86.78	71.49	88.02
0.1	0.5	0.8	70.25	69.83	78.51	64.88
0.1	3	0.4	44.63	57.02	38.43	54.55
0.1	3	0.7	51.65	46.28	45.87	47.93
0.1	5	0.1	40.91	62.81	37.60	55.79
0.25	0.5	0.8	42.98	37.60	47.11	33.88
0.25	3	0.4	10.74	17.77	9.92	16.12
0.25	3	0.7	19.42	14.46	22.31	19.01
0.25	5	0.1	5.37	22.31	2.89	18.60

Figure 5: The heatmaps show the scores for a material with properties specified in a given row. The scores range from 0 to 100 and show the percentage of the cases when a given stimulus was selected in a given experiment. The larger the score, the greener the cell; and conversely, the lower the score, the redder the cell. We can observe that redder cells are usually concentrated in high roughness (Alpha) rows. High albedo usually produces low contrast but high coverage for Lucy.

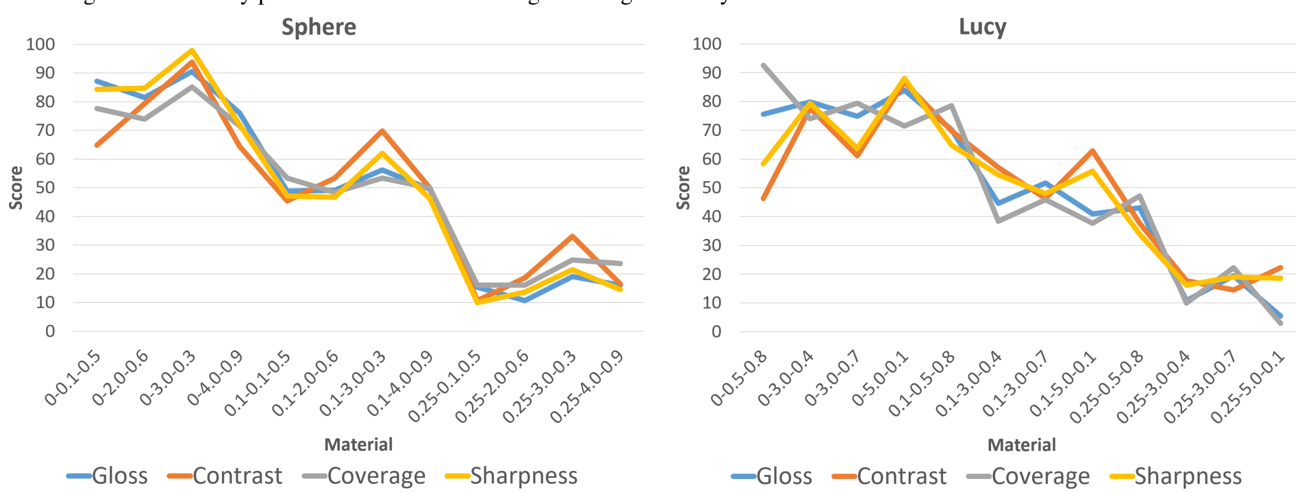

Figure 6: Total Glossiness, Contrast, Coverage, and Sharpness scores for each of the 12 materials. The material names are specified in the horizontal axis, in α-σ_T-*albedo* format. The scores range from 0 to 100 and show the percentage of the cases when a given stimulus was selected in a given experiment. We can notice that the curves are more aligned for sphere than this is the case for Lucy. Low σ_T or high albedo usually produces high coverage, and thus, relatively high glossiness for Lucy.

depends on sharpness as well as contrast, is what observers may be primarily assessing on spherical objects; on the other hand, the primary cue that observers base their judgments on for Lucy is the overall area covered by the highlights rather than sharpness and contrast. The latter fact demonstrates that the HVS has a poor ability to invert optics and recover reflectance, and highlights resulting from subsurface scattering are easily mistaken for specular reflections, as is the case for Lucy in this work. In post experiment interviews, the observers considered Lucy more challenging to assess in all four experiments, due to its complex shape.

Gigilashvili *et al.* [16] reported that the correlation between albedo and gloss was negative for smooth spheres, and positive for Lucy and rough spherical objects. The explanation for this can be albedo's negative impact on sharpness and contrast in the former case, and its positive impact on coverage in the latter case. However, the findings need to be taken with care, as the study is based on small subset of materials. It is important in future works to have better sampling of materials, and to change σ_T and albedo in small steps, while fixing all other parameters, to model more accurately how each individual subsurface scattering property modulates each individual image cue. Pair-comparisons need to be conducted with fixed roughness levels to capture the subtle variations, which may be hidden by large roughness differences.

Finally, this work was based on the assumption that there are measurable image metrics that quantify perceived gloss. We attempted to predict perceived gloss with handcrafted image statistics extracted from the pixel intensities, such as standard deviation divided by mean for contrast; number of pixels with intensity above a given threshold divided by the total number of pixels – for coverage; the slope of the intensity curve across the section starting from the highlights and ending in the neighboring areas, or no reference image quality metrics, such as Natural Image Quality Evaluator (NIQE) [20] – for sharpness. None of these statistics demonstrated performance comparable to that of psychophysically measured contrast, coverage, and sharpness. Therefore, automatic measurement of image cues and subsequent prediction of apparent gloss from pixel values remain an open question.

Conclusion and Future Work

This work partially reproduced the results from previous works, demonstrating that subsurface scattering contributes to perceived gloss, and this contribution varies between shapes [13, 14, 15, 16]. While previous works managed to model perceived gloss as a linear combination of perceived contrast, coverage area, and sharpness of the highlights for completely opaque materials, we have been able to repeat the same for highly translucent and transparent materials. We identified interesting trends in how subsurface scattering properties modulate these image cues that the human visual system proposedly relies on for gloss perception. Low albedo increases contrast between specular and non-specular parts and makes reflections appear sharper – that subsequently makes the reflected image of the surrounding more discernible. This can be why smooth spheres with low albedo appear glossier than the ones with high albedo. On the other hand, if surface roughness or a complex shape make it impossible to observe the reflected image, observers usually attend to the overall area covered by highlights. High subsurface scattering albedo in this kind of objects produces large areas of highlights, which are mistaken for specular reflections and stronger gloss.

While this work indicates that image cues explain why translucency impacts perceived gloss, we need denser sampling of materials to model this relationship. This should be addressed in the future. Apart from that, we have not been able to identify any handcrafted image statistics for quantifying contrast, coverage, and sharpness, that could potentially predict perceived gloss as precisely as done by their psychophysically measured counterparts. If such measures exist, their mathematical definition could make it possible to predict apparent gloss from image intensities alone. This topic deserves a rigorous study in future works.

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