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Does higher refractive index mean higher gloss?

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Figure 1: *Index of refraction (IoR) affects both gloss and translucency, because materials with high IoR transmit little light and reflect most of it. In this example, IoR equals to 1.10, 1.33 [water], 1.50 [glass], and 2.41 [diamond], from left to right, respectively. Reproduced from [GTHP21].*

Abstract

According to Fresnel equations, the amount of specular reflection at the dielectric surface depends on two factors: incident angle and the difference in refractive indices of inner and outer media. Therefore, it is often assumed that the higher the refractive index of the material, the glossier it looks. However, gloss perception is a complex process that, in addition to specular reflectance, depends on many other factors, such as object's translucency and shape. In this study, we conducted two psychophysical experiments to quantify the impact of refractive index on perceived gloss for objects with varying degrees of translucency and surface roughness. For some objects a monotonic positive relationship between refractive index and perceived gloss was observed, while for others the relationship was found to be non-monotonic. Afterward, we evaluated how the refractive index affects image cues to gloss and tried to explain psychophysical results by image statistics.

CCS Concepts

• ***Computing methodologies*** → ***Perception;*** *Reflectance modeling; Image processing;*

1. Introduction

Gloss is one of the four main components that define total appearance of objects and materials, along with color, texture, and translucency [Poi06; Eug08]. Given the importance of gloss as a perceptual attribute, it has been of academic interest to study the different factors that influence its perception [LOPH13; CK15].

According to Fresnel equations that describe the reflection and transmission of electromagnetic radiation at the boundary between two materials, the amount of reflectance at the dielectric surface depends on two factors: incidence angle and the difference in the refractive indices of the two media [AYB06] (Fig. 2). If we assume that the outside medium is fixed, for a given incidence, increasing the index of refraction (IoR) of a material, will make it more reflective, and therefore, more glossy [Fau19]. Faul [Fau19; Fau21] has demonstrated that Fresnel effects play a significant role in gloss perception and constancy, and synthetic images rendered without accounting for Fresnel effects may not be optimal for studying gloss perception. Specular reflections are directly associated and often interchangeably used with the concept of gloss [Hun37; HH87]. However, specular reflection is an optical property of a material, while gloss can be a perceptual attribute seen by the human visual system (HVS) [AST17; Poi06]. IoR has long been known to affect optical measurements of reflectance and gloss [AYB06], and the HVS has been demonstrated to be capable of visually estimating IoR to a certain extent [FJM11].

Since a higher IoR produces stronger reflections, a usual assumption is that such materials are glossier [Fau19; AYB06]. However,

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gloss perception is a complex psychovisual process, and the link between optical properties and perceived gloss is not straightforward [LOPH13; CK15]. To the best of our knowledge, no study has demonstrated psychophysically that an increase in material's IoR universally and monotonically increases perceptual gloss. Gigilashvili *et al.* [GTHP21] demonstrated that IoR affects perceived translucency because high IoR objects reflect most of the incident light and refract little, while low IoR materials permit most of the incident light to penetrate the subsurface (see Fig. 1). Gigilashvili *et al.* [GSW*21; GTPH19] argued that gloss perception studies are almost exclusively conducted on opaque media and demonstrated that subsurface scattering can also affect visual cues to gloss, which led the authors to propose that it is essential to consider interactions between gloss and translucency. This means that in addition to a direct link to the amount of reflection, IoR can also indirectly affect gloss by its impact on translucency. We, therefore, suggest to psychophysically quantify the impact of IoR on perceived gloss for transparent, translucent, and opaque objects.

The contributions of this work are as follows:

- Creation of a new database with a broad range of opaque, translucent, and transparent objects, accompanied by the corresponding perceived gloss ratings obtained from a magnitude estimation experiment.
- Creation of a Python framework for rendering automation in Mitsuba.
- Study of the impact of index of refraction on perceived gloss, based on a pair comparison and magnitude estimation experiments.
- Analyzing image statistics to explore which image cues get affected by the change in the IoR.

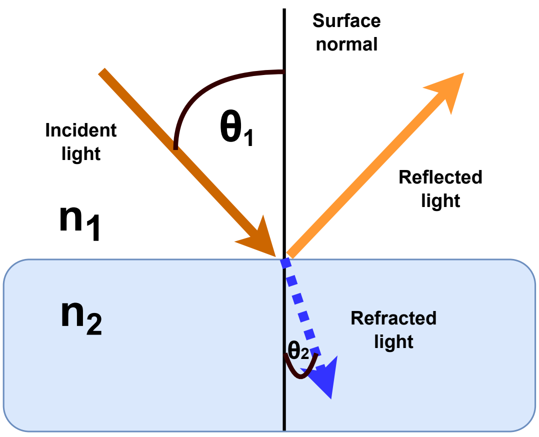

Figure 2: *When the incident light hits the boundary between the two media with mismatching indices of refraction, part of it gets specularly reflected, while the rest gets refracted and continues propagation into the second medium. The amount of reflectance depends on the angle of incidence θ_1 and the indices of refraction (n_1 and n_2) of the two media. According to the Snell–Descartes law of refraction, $n_1 \sin\theta_1 = n_2 \sin\theta_2$. Throughout this paper, n_1 is assumed to be equal to 1, while we vary n_2. The light is assumed to be unpolarized.*

- Discussing the implications of IoR's impact on gloss for future computer graphics and material appearance research followed by the outline of future directions.

In this paper, section 2 presents general concepts of gloss and translucency in the context of material appearance research. Section 3 describes the research methodology. Section 4 presents the results and analysis. Afterward, section 5 offers the discussion of the results. Lastly, section 6 discusses limitations of the work and proposes ideas about possible future work before concluding in section 7. Further data is appended as the *Supplementary Material* and *Supplementary Material 2*.

2. Background and Related Work

Given that one of the main objectives of this work was to generate a database with opaque, translucent and transparent materials, this section describes general concepts of material appearance, including translucency and gloss.

2.1. Gloss

In general, the concept of gloss is related to the degree of perceived shininess of an object, which includes transparent objects, such as glass, or opaque but highly reflective objects such as mirrors. More formally, the definition of gloss is given as follows: *"Gloss (of a surface) — the mode of appearance by which reflected highlights of objects are perceived as superimposed on the surface due to the directionally selective properties of that surface."* [CIE87]

Given that the definition of gloss is perceptual, it is of interest to study the response of the human visual system and the factors that influence glossiness perception [LOPH13]. Faul [Fau19] describes six main factors that impact gloss perception: shape of the object, illumination type, presence of a floor (weather the object is resting on a surface), albedo, roughness, and the index of refraction. For instance, environment lighting is important, since it allows to cover the whole surface of the object, thus, 360° panoramic images are commonly used as environment maps to light the scene; typically, glossy objects have their surface covered by a distorted version of their surroundings [Fau19]. Furthermore, the perceived glossiness of an object tends to increase with the curvature of the surface [GI22], thus, it is common to find spherical shapes in gloss perception studies [Fau19; GTHP21; PFG00]. Different perceptual types of gloss have been identified, such as distinctness-of-image gloss, which primarily depends on surface roughness, and contrast gloss, which stems from the observation that darker objects usually look glossier than lighter ones since the highlights stand out more with higher contrast [PFG00]. Roughness of an object is critical, and lower roughness generally leads to more glossy surfaces as they preserve the image of the surroundings to a greater extent; the presence of diffuse and specular reflections characterize glossy surfaces, where the distribution of these reflections is described as a lobe shape; moreover, a lower roughness in the surface causes the lobe shape to be narrow, which leads to better defined edges in the reflected image in the surface, causing a higher impression of gloss with better defined highlights [Fau19]. In the case of IoR, real life objects have values ranging from 1.00 (vacuum) to 3.0, and common daily objects usually have IoR values in the range of 1.33 (water) to 1.5 (acrylic) [Fau19; GSW*21].

The HVS is believed to utilize the statistical regularities present in the images to perceive gloss [GTPH20]. For instance, Motoyoshi *et al.* [MNSA07] famously hypothesized that the HVS uses skewness of the luminance histogram or a similar asymmetry measure to distinguish between glossy and matte surfaces. The correlation between skewness and gloss was observed by Gigilashvili *et al.* [GTPH20] as well, but the authors argue that this observation should be taken with care and overall understanding of the complex scene also plays a role. Wiebel *et al.* [WTG15] analyzed the natural images and concluded that standard deviation is a better correlate of perceived gloss than skewness. Marlow *et al.* [MKA12; MA13] varied the surface geometry of materials and the structure of the light field in order to analyse their impact on perceived gloss, concluding that sharpness, contrast, and coverage area of the highlights are correlated with perceived level of glossiness. Different works have attempted to explain perceived gloss with various image statistics, such as luminance contrast [THS17; LPDH10] or size, number, and strength of the specular highlights [QCSD14; QCSD15]. The emergence of sophisticated deep learning models revealed that deep neural networks outperform handcrafted features in predicting perceived gloss, and they even mimic the human gloss perception by making similar mistakes [SAF21]. A thorough review on gloss perception can be found in [LOPH13; CK15; GT23].

2.2. Translucency

In basic terms, we refer to a translucent object as a material with an appearance between opaque and transparent, which transmits light diffusely and blurs the see-through image [AST17; Eug08].

Translucent objects reflect portion of the incoming light, while the rest is refracted. The light that propagates through the translucent material may get absorbed, or it may scatter multiple times and re-emerge from a different part of the object [XWG*14; GTHP21]. This phenomena is described by the Radiative Transfer Equation (RTE), which models the material with the following wavelength-dependent parameters:

- σ_a: the absorption coefficient.
- σ_s: the scattering coefficient.
- P: the phase function, which models the angular distribution of scattered light.

σ_T denotes the extinction coefficient, also referred as the density of the material, which is defined as the sum of absorption and scattering coefficients:

$$\sigma_T = \sigma_s + \sigma_a \tag{1}$$

Furthermore, the albedo of a material is defined as the ratio between σ_a and σ_T; thus, the albedo describes how much is the proportion of scattering with respect to the sum of absorption and scattering coefficients:

$$Albedo = \frac{\sigma_s}{\sigma_T} = \frac{\sigma_s}{\sigma_s + \sigma_a} \tag{2}$$

The exact psychovisual mechanisms of perception of translucency remain a topic of active research. Fleming and Bülthoff [FB05] famously proposed that instead of reverse engineering optics in the scene, the human visual system instead uses image statistics to tell translucent and opaque objects apart. Edges that face away from the incident illumination are often bright and contain useful cues to translucency [FB05; GWA*15]. Furthermore, it has been demonstrated that the luminance contrast between specular and non-specular parts of the object co-varies with translucency – translucent objects producing softer shadows, i.e., lower contrast around bumpy areas [Mot10; GUT*22]. However, Fleming and Bülthoff [FB05] showed that luminance histogram alone does not explain translucency perception and spatial information is also important. This was later substantiated by Marlow *et al.* [MKA17], who noticed that intensity co-varies with surface normal direction and object's geometry when the material is opaque but not when it is translucent. Translucency and 3D shape perception seem to be closely interconnected, where the luminance distribution resulting from specular reflections, subsurface scattering, and self-occluding contours plays a major role [MA21]. In recent years, similarly to gloss, unsupervised machine learning has been used to create a perceptually meaningful representation for translucency as well [LSX23].

Perceived translucency of a given material is not constant, and it can vary across conditions: for instance, back-lit objects usually appear more translucent than front-lit ones [XWG*14]. A comprehensive review on translucency perception mechanisms can be found in [GTHP21]. The authors argue that translucency perception is influenced by multiple factors:

- **Intrinsic factors:** The material's internal parameters, such as absorption and scattering coefficients, the phase function, and IoR.
- **Extrinsic factors:** The object scale/thickness, surface roughness, shape, caustics, the illumination direction, motion, etc.

3. Methodology

This section describes the stimuli generation, the design of the experiments, and data collection.

3.1. Stimuli generation

We used Mitsuba 0.6 physically-based renderer [Jak10] to generate the stimuli for the experiment. Vogl's light probe *At the Window* [Vog] was used as an environment map, similarly to the demonstrations in [GTHP21] and Fig. 1. In order to generate a dataset with a broad range of opaque, translucent and transparent appearances, we went through a trial-and-error-based parameter tuning process and eventually selected a total of 21 materials each one with 5 levels of index of refraction (IoR), which results in a total of 105 different images of spherical objects. The 21 materials (M01-M21) result from the combination of different parameters, namely: three levels of surface roughness α = [0.01, 0.1, 0.5], albedo = [0.1, 0.5, 0.8], and σ_T = [0, 1, 5]. It is worth mentioning that when σ_T=0, albedo is undefined, or in simple terms, varying albedo does not make a difference (see Eq. 2). That's why the dataset includes 21 ($3 \times 3 \times 2 + 3$) and not 27 ($3 \times 3 \times 3$) images. Each of these materials was rendered with five different IoR: 1.1, 1.33, 1.5, 2.0, and 2.41. Table 1 shows a summary of the 21 different material groups and their corresponding parameters, while Fig. 3 shows an example of some of these material groups. The complete dataset is shown in *Supplementary Material S1*. Full resolution images can be found in *Supplementary Material 2*. A framework for rendering automation in Python and Mitsuba was created, which can be found at this GitHub repository.

All images were rendered with the resolution of 512×512 pixels and with 4096 samples per pixel. The surface for all materials was modeled using the rough dielectric BSDF surface scattering model [WMLT07] in Mitsuba 0.6, and Mitsuba's homogeneous participating medium was used to model subsurface scattering. External IoR was set to 1.0 (vacuum), and isotropic scattering phase function was used. The renderings were tonemapped and exported as .png images, by using the *ldrfilm* directive in Mitsuba, which corresponds to low dynamic range images with sRGB encoding.

Material group	α	Albedo	σ_T
M01	0.01	–	0
M02	0.1	–	0
M03	0.5	–	0
M04	0.01	0.1	1
M05	0.01	0.5	1
M06	0.01	0.8	1
M07	0.1	0.1	1
M08	0.1	0.5	1
M09	0.1	0.8	1
M10	0.5	0.1	1
M11	0.5	0.5	1
M12	0.5	0.8	1
M13	0.01	0.1	5
M14	0.01	0.5	5
M15	0.01	0.8	5
M16	0.1	0.1	5
M17	0.1	0.5	5
M18	0.1	0.8	5
M19	0.5	0.1	5
M20	0.5	0.5	5
M21	0.5	0.8	5

Table 1: *Summary of the 21 different material groups designed.*

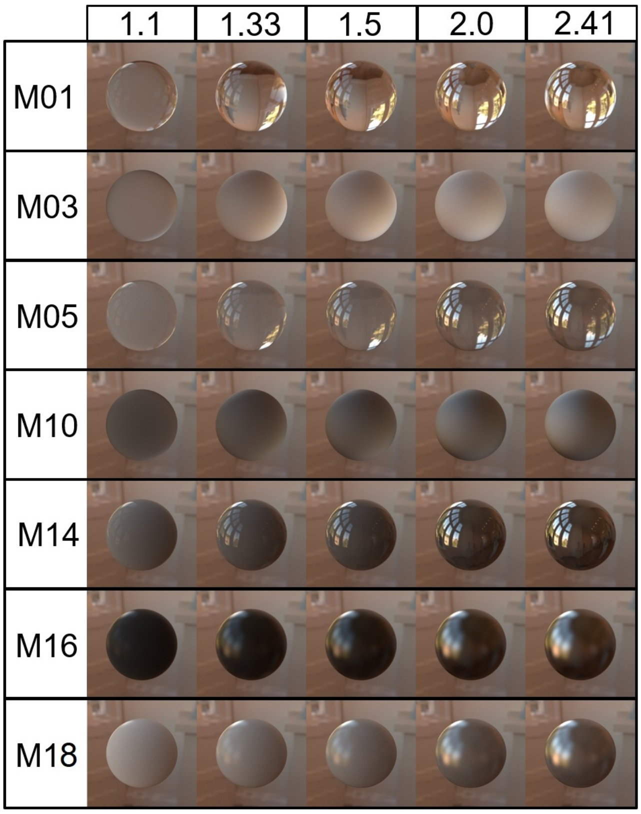

Figure 3: *Examples of some of the designed material groups. The rows correspond to material groups, while columns correspond to different levels of refractive index.*

3.2. Experimental design

The experiments were hosted on the QuickEval platform [VDFP*15] and conducted under controlled laboratory conditions. The stimuli were shown on a color-calibrated Eizo CG246 display, with a resolution of 1920×1080 pixels, sRGB encoding, 2.2. of gamma, 80 $\frac{cd}{m^2}$ peak luminance, and D65 white point. Furthermore, a chin rest was used to ensure a constant viewing distance of 60 cm. The complete experiment (parts 1 and 2) had a duration of approximately 20 minutes, and the definition of gloss was provided to the observers at the beginning of the experiment.

The experiment had two parts: a two alternative forced-choice (2AFC) pair comparison and magnitude estimation.

- **Part 1 - Pair comparison.** Pairs of images were shown and the observer had to select the one that appeared glossier. Only the identical materials with different indices of refraction were compared, with 10 comparisons per material group and 210 comparisons in total. The order of the images was randomized. An example of the experiment is shown in Fig. 4
- **Part 2 - Magnitude estimation.** The observer was shown each of the 105 images individually and asked to rate the level of glossiness from 0 (least glossy) to 100 (most glossy). The order of images was randomized. An example of the experiment is shown in Fig. 5. The observers went through a training where the definitions of gloss as a concept were given and examples of what low gloss and high gloss implies were brought. We did not visually illustrate materials with gloss=0 and gloss=100, which was intentional to avoid bias, since there is no universal conceptual definition of minimum and maximum gloss (e.g., if we included materials with high/low IoR or gloss, should they be opaque or translucent? light or dark? Will this selection affect gloss magnitude itself?).

3.3. Observers

17 observers voluntarily participated in the experiment, including 3 females and 14 males representing 11 different nationalities. All

observers had a certain level of knowledge related to computer graphics and color imaging. The average age of the observers was 25 years, and all of them had normal or corrected-to-normal visual acuity.

4. Results and Analysis

4.1. Pair comparison experiment

Table 2 shows a summary of the pair comparison experiment, in particular, separating two different scenarios:

- **Case A:** comparisons where a material with higher IoR was considered glossier, as hypothesized.
- **Case B:** comparisons where a material with lower IoR was selected glossier than the one with higher IoR.

For each material group the percentages of cases A and B are presented. While for the majority of the materials higher IoR commonly led to higher gloss, there are several notable exceptions that do not conform to this rule. The table illustrates that for materials M03, M11, M12, M20, and M21, the percentage of case B is higher than 10%; in particular, for material M03, the objects with lower IoR were selected as glossier in 42.94% of the comparisons. All of those materials have high α and albedo (when $\sigma_T \neq 0$).

Z-score plots and comparison matrix heatmaps for representative cases are shown in Fig. 6. Similar plots for all other materials can be found in *Supplementary Materials S2-S3*. Z-scores are based on Thurstone's law of comparative judgement [Thu27], assuming that subjects assess samples' qualities that are Gaussian random variables. The standard normal cumulative distribution function (CDF) is used to find the probability of picking a given sample in a given comparison. Z-score is its inverse CDF, showing how many standard deviations away is that sample from the mean. It is usually assumed that all samples are independent and have equal variance [TG11] (hence the identical size of confidence intervals). If the 95% confidence intervals that are shown as error bars do not overlap, the qualities of the two images are significantly different with 95% confidence.

For M05 (as shown in Fig. 6) and most materials (see *Supplementary Material S2*) perceived gloss monotonically increases as IoR increases, which is consistent with the literature. The differences among IoR levels are almost always significant with no overlap between 95% confidence intervals. For materials such as M12, M20, and M21, the relationship is non-monotonic and increase in IoR initially leads to slight decrease in perceived gloss, while those with IoR of 2.0 and 2.41 are still considered the glossiest. The only obvious exception is Material M03. Its perceived gloss peaks at IoR=1.50 and starts decreasing for higher IoR values.

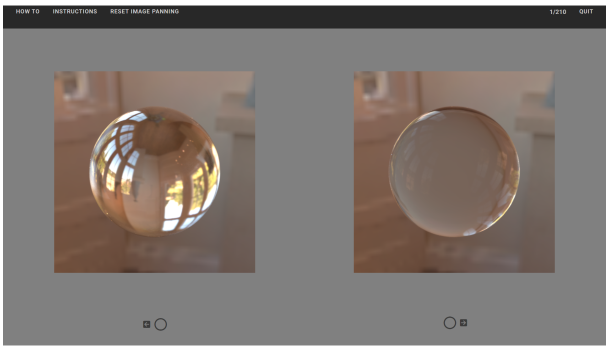

Figure 4: *Example of pair comparison experiment.*

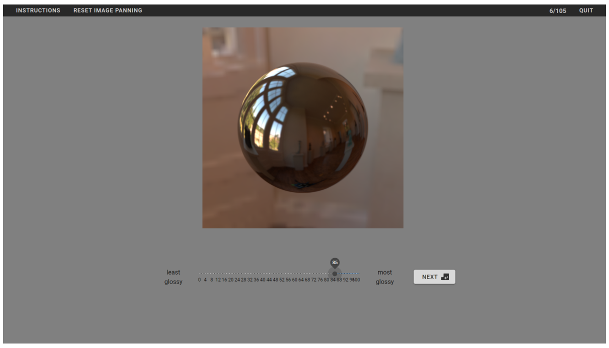

Figure 5: *Example of magnitude estimation experiment.*

When material has a smooth surface (low α), specular reflections are clearly visible and become more expressed as the IoR increases (see M05 in Fig. 3 and 6). On the other hand, rough surfaces blur the reflectance image, which makes specular reflections indiscernible. When IoR is low, more light penetrates the subsurface as demonstrated by [GTHP21]. It has been also demonstrated previously that subsurface scattering can contribute to perceived glossiness [GSW*21]. This can potentially reveal the mechanism that explains how materials with high α and albedo but lower IoR can produce more highlights than those with higher IoR. However, M03 is a special case. The material itself is transparent with no scattering or absorption taking place in the subsurface. The light is scattered on the surface, which removes specular highlights (see M03 in Fig. 3 and 6). However, when IoR ranges from 1.33 to 1.5, larger amount of light gets refracted into the material, propagates through it and gets focused on the other side of the object (see right parts of the object) as internal caustics, which produces highlights and according to literature, can be potentially mistaken for specular reflections [GSW*21; GTPH19].

Fig. 7 and Fig. 8 show the pixel-wise differences between images of M03 and M05, respectively. The differences between images of group M05 are more clear as compared to M03, given that in M05 the specular highlights are much more noticeable and better defined, and these change with the IoR. The large differences in the right part of the image (the light is incident from the left) are noticeable for M03 due to internal caustics.

4.2. Magnitude estimation experiment

We conducted one-way analysis of variance (ANOVA) for IoR's effect on mean opinion score (MOS) of perceived gloss magnitudes. The effect of IoR turned out significant at the 95% significance level ($F(4,100)=3.25$, $p<0.05$). ANOVA is a method to compare means among multiple groups [Kim17]. It uses difference of vari-

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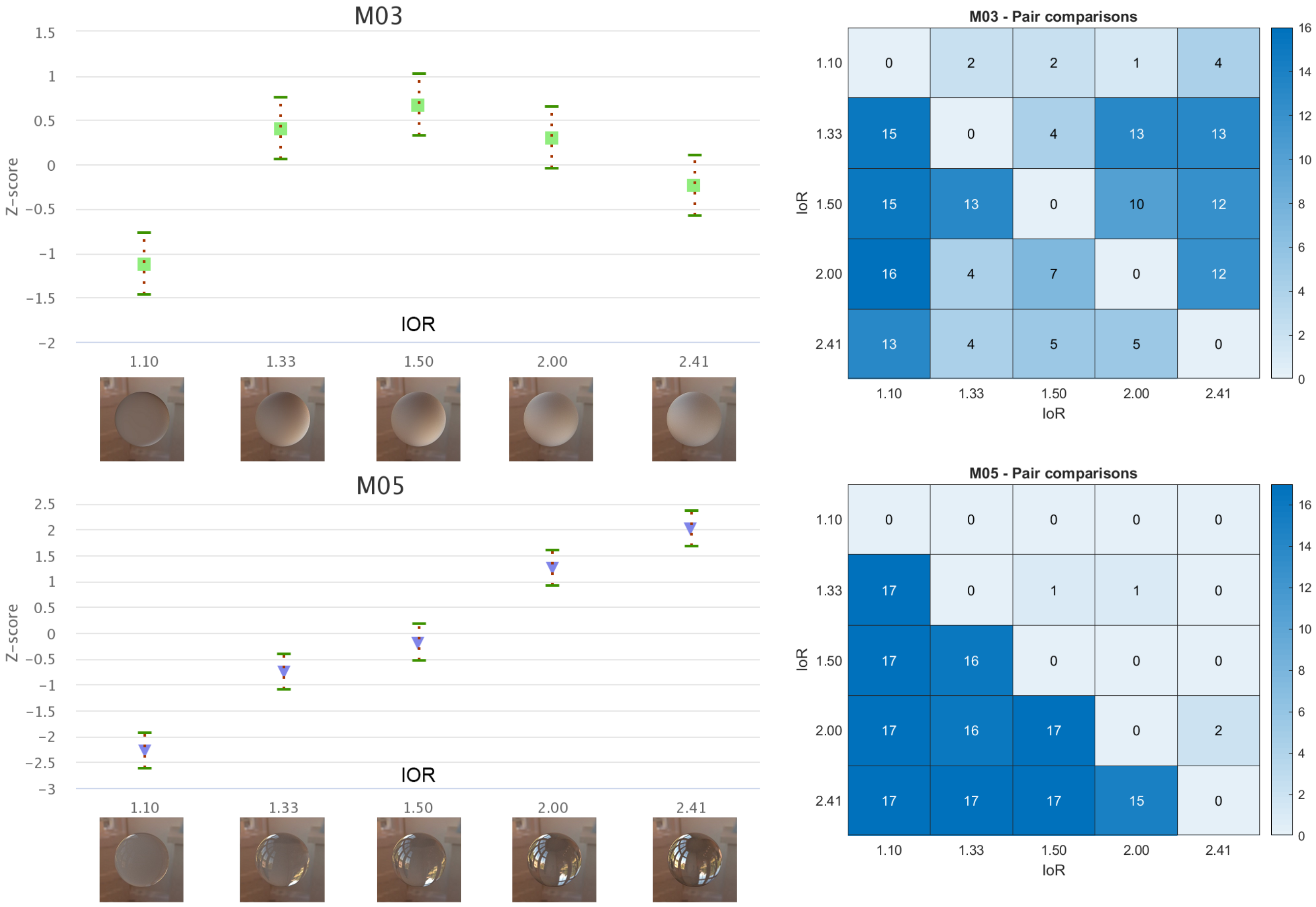

Figure 6: *Comparison between results of materials M03 and M05 from the pair comparison experiment. The figures show Z-scores (left) and comparison matrix heatmaps (right). The whiskers extend to the 95% confidence intervals in the Z-score plots. Respective images are shown below the plots.*

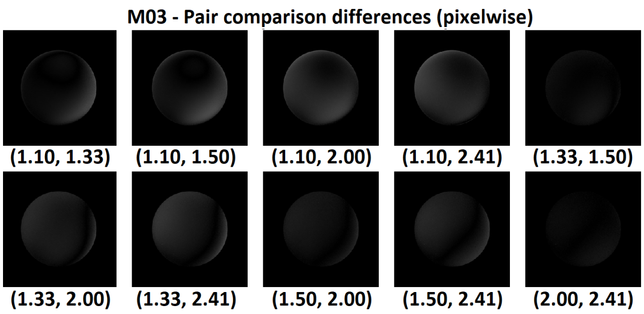

Figure 7: *The figure shows the pixel-wise absolute differences for each of the 10 pair comparisons for material group M03, each figure legend indicates the images being subtracted, i.e., the pair, (1.10,2.41) denotes the difference between these images with different IoR.*

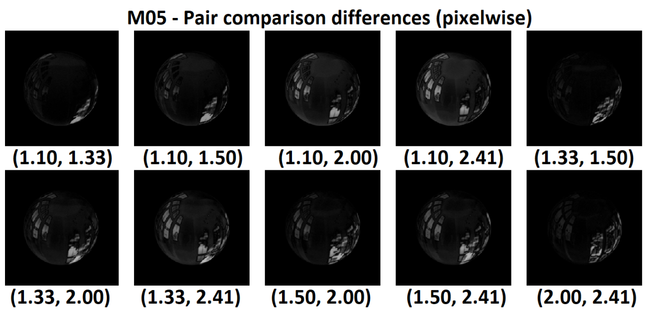

Figure 8: *The figure shows the pixel-wise absolute differences for each of the 10 pair comparisons for material group M05, each figure legend indicates the images being subtracted, i.e., the pair, (1.10,2.41) denotes the difference between these images with different IoR.*

Material group	Total Case A	Total Case B	Case A [%]	Case B [%]
M01	159	11	93.53%	6.47%
M02	157	13	92.35%	7.65%
M03	97	73	57.06%	**42.94%**
M04	165	5	97.06%	2.94%
M05	166	4	97.65%	2.35%
M06	170	0	100%	0%
M07	159	11	93.53%	6.47%
M08	164	6	96.47%	3.53%
M09	167	3	98.24%	1.76%
M10	154	16	90.59%	9.41%
M11	142	28	83.53%	**16.47%**
M12	125	45	73.53%	**26.47%**
M13	169	1	99.41%	0.59%
M14	165	5	97.06%	2.94%
M15	169	1	99.41%	0.59%
M16	167	3	98.24%	1.76%
M17	166	4	97.65%	2.35%
M18	167	3	98.24%	1.76%
M19	164	6	96.47%	3.53%
M20	150	20	88.24%	**11.76%**
M21	127	43	74.71%	**25.29%**

Table 2: *Results from pair comparison experiment. For each material group the percentages of cases A and B are presented. Case A: comparisons where a material with higher IoR was selected as glossier; Case B: comparisons where a material with lower IoR was considered glossier. Occurrences of case B with more than 10% of comparisons are highlighted in orange.*

ances. F distribution is a reference distribution of variance ratios. For given groups, the F-statistic is calculated, which is equal to the ratio between inter- and intra-group variances. High F-statistic implies that variation between the group means is larger than that within the groups. This can be an indication to reject the null hypothesis, which usually assumes that the means of all groups are equal. In our case, the groups are different IoR values.

Fig. 9 shows the Pearson linear correlation coefficient between the IoR and the gloss rating (MOS) for each material group. Pearson linear correlation coefficient measures the linear correlation between the two sets of data [SBS18]. It is calculated as the covariance of the two sets divided by the product of their standard deviations, with 1 and -1 corresponding to perfect positive and negative linear relationships, respectively, and 0 showing the lack thereof.

In almost all cases the correlation is highly positive, which indicates that as the IoR increments, the gloss impression increases. However, materials M03 and M10 had a correlation of -0.62, and 0.52, respectively. This can be explained by the fact that both M03 and M10 have non-linear relationship between the IoR and gloss. Fig. 10 shows a comparison of M03 and M04 materials, with respect to the gloss rating (MOS) for each IoR; M04 follows a monotonically positive relationship with the increase of IoR (as most of the materials), while M03 does not follow any kind of linear relationship with the IoR. Similar boxplots for all materials are included in the *Supplementary Material S4*.

Table 3 shows the results from the magnitude estimation experiment. The table shows the gloss rating based on the MOS of the observers, where the rows are the material group, and the columns are the IoR. Fig. 11 shows the MOS as a function of IoR. Three different clusters emerge based on their α, which indicates that surface roughness has the largest effect on perceived gloss. MOS increases as the IoR increases. However, the slope is substantially steeper for smoother objects. In other words, the smoother the object, the higher is the impact of IoR on perceived gloss. And conversely, IoR has weaker effect on perceived gloss when objects are rough. (green curves in Fig. 11).

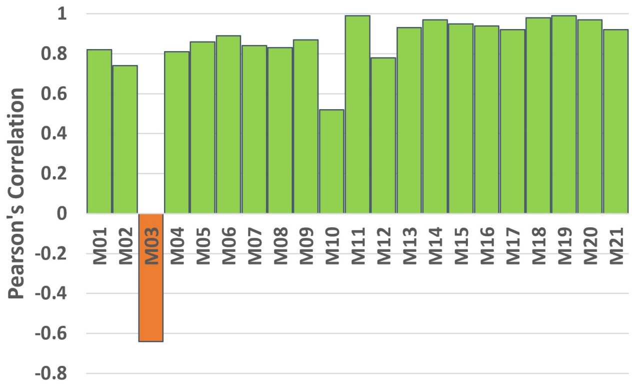

Figure 9: *Pearson's linear correlation coefficient between the index of refraction (IoR) and the gloss rating (MOS) for each material group.*

Material group	Gloss rating (MOS) for each IoR				
	1.10	**1.33**	**1.50**	**2.00**	**2.41**
M01	52.24	78.82	82.12	89.53	91.59
M02	25.82	49.12	48.12	56.53	53.12
M03	11.41	12.00	13.35	10.53	10.24
M04	53.53	75.18	84.76	88.29	89.47
M05	43.76	68.76	76.59	81.82	87.18
M06	39.00	63.24	67.47	78.35	82.35
M07	25.06	43.00	51.35	55.41	56.88
M08	19.12	37.35	44.76	49.76	49.88
M09	15.24	32.24	37.94	41.41	46.41
M10	8.18	13.88	13.41	12.71	13.47
M11	6.76	7.71	9.35	11.06	13.12
M12	6.82	7.35	7.18	7.00	12.53
M13	52.94	67.88	75.71	87.06	89.41
M14	45.94	55.88	64.76	84.65	87.65
M15	35.71	55.41	62.88	73.94	83.18
M16	23.71	39.00	42.53	51.65	56.18
M17	14.47	33.12	38.24	44.41	53.59
M18	14.29	26.24	30.35	44.82	51.53
M19	4.53	7.82	7.82	15.06	17.47
M20	7.06	8.12	7.82	12.65	17.65
M21	8.24	8.24	9.00	10.06	14.35

Table 3: *Results from magnitude estimation experiment. The table shows the gloss rating based on the mean opinion score (MOS) of the observers, where the rows are the material group, and the columns are the index of refraction (IoR).*

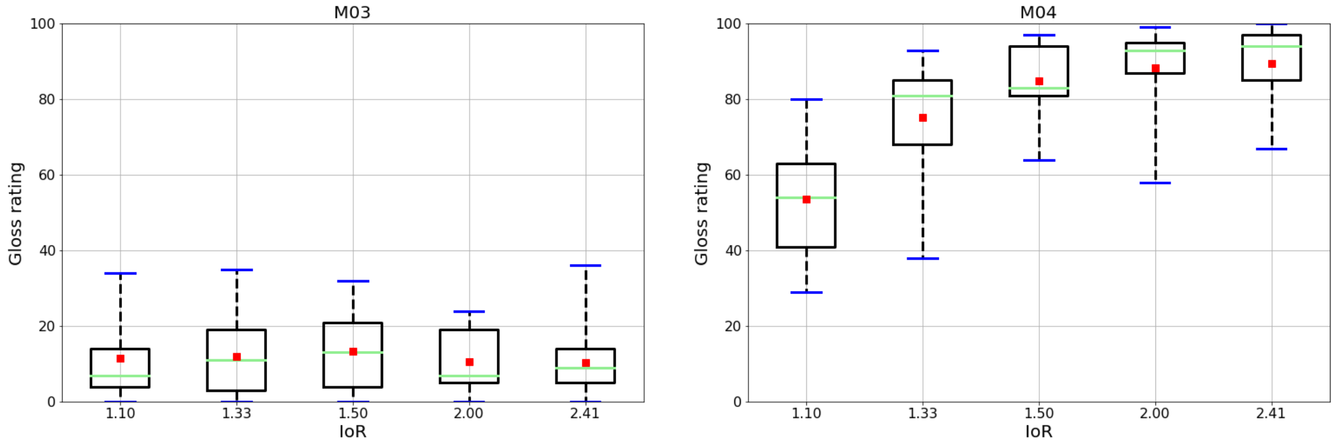

Figure 10: *Comparison of M03 and M04 material groups, with respect to the gloss rating (MOS) for each IoR. The red square in the box plots indicates the MOS, the green line is the median, the size of the box corresponds to the inter quartile range (Q1-Q3), and the blue lines indicate the maximum and minimum. M04 follows a monotonically positive relationship with the IoR (as most of the materials), while M03 does not show this behaviour.*

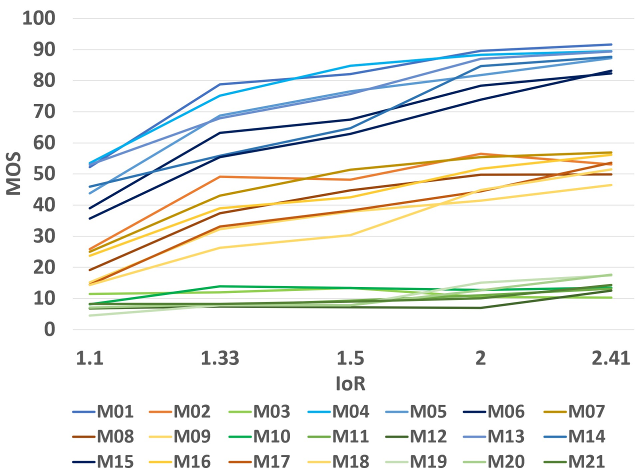

Figure 11: *Gloss rating for all materials, based on the mean opinion score (MOS) of the observers. The curves are color-coded by* α*: blue for those with* α*=0.01, orange-yellow for 0.1, and green for 0.5. We can see the clear separation between* α *levels. The slopes of the curve also depend on the* α *level.*

4.3. Image statistics analysis

Multiple works suggest that image statistics, especially those in the luminance channel, can be used to some extent to predict perceived gloss [MKA12; MA13; GTPH20; MNSA07; WTG15; MAS*23]. We analyzed whether these statistics co-vary with IoR.

All images were converted from RGB to grayscale since the most relevant cues are supposedly encapsulated in the luminance information. Afterward, a mask was applied in order to retrieve only the pixels belonging to the sphere. The luminance values were normalized in the [0,1] range, and the four image statistics selected for the analysis were: mean luminance of the object, standard deviation, skewness and kurtosis of the luminance histogram, similarly to [GTPH20]. Table 4 shows the Pearson's linear correlation coefficient between the IoR and the image statistics of the luminance histogram for each material group. For some statistics, such as mean, the correlation can be strongly positive or negative, depending on the material, while if the results for all materials are aggregated (the last row of the table), there is almost no correlation. The most consistent trend is shown for standard deviation that is usually highly positively correlated with IoR. Fig.12 shows the standard deviation as a function of IoR. Similar plots for other statistics can be found in the *Supplementary Material S5*. The sole obvious exception is above-mentioned Material M03, whose IoR has no correlation with standard deviation. This could potentially explain the lack of correlation between its IoR and perceived gloss, since standard deviation is proposedly covariant with perceived gloss [WTG15; MAS*23]. However, this question needs a further, more thorough study in future works.

5. Discussion

The magnitude estimation experiment has demonstrated that IoR and perceived gloss are positively correlated. This is especially true for objects with smooth surfaces. However not all materials follow a linear or monotonically increasing relationship (Fig. 10), and in the case of highly scattering rough materials (i.e., M03, M10) the correlation is lower or even inverse. This is consistent with pair comparison experiments, where similar materials with different IoR were compared.

In objects with smooth surface (i.e., M05), which permit mirror reflections, increase in IoR and consequent increase in the amount of specularly reflected light makes reflected image stand out more and produce higher coverage of the specular highlights, which can be responsible for its glossier appearance (refer to Fig. 8).

Rough surfaces, on the other hand, blur the reflections and do

Material group	Pearson correlations between IoR and image statistics (luminance histogram)			
	Mean	STD	Skewness	Kurtosis
M01	0.97	0.84	-0.70	-0.71
M02	0.98	0.72	-0.91	-0.84
M03	0.90	-0.01	-0.57	-0.70
M04	1.00	0.92	-0.96	-0.92
M05	-0.98	0.95	-0.96	-0.87
M06	-0.99	0.98	0.14	-0.95
M07	0.99	0.88	-0.92	-0.95
M08	-0.98	0.93	-0.84	-0.97
M09	-0.99	0.96	0.23	-0.85
M10	1.00	0.99	-0.67	-0.75
M11	-0.97	0.99	0.92	-0.99
M12	-1.00	0.85	0.92	-0.73
M13	1.00	0.97	-0.86	-0.89
M14	-0.45	0.99	0.55	-0.36
M15	-0.95	0.99	0.91	0.77
M16	1.00	0.98	-0.94	-0.97
M17	0.01	1.00	0.17	-0.43
M18	-0.93	0.99	0.83	0.34
M19	1.00	0.99	-0.88	-0.80
M20	0.39	1.00	-0.14	-0.74
M21	-0.88	0.93	0.89	-0.63
Average	0.01	0.90	-0.18	-0.66

Table 4: *The table shows the Pearson's linear correlation coefficient between the IoR and the image statistics of the luminance histogram for each material group. STD stands for standard deviation. The last row shows the average of all 21 materials.*

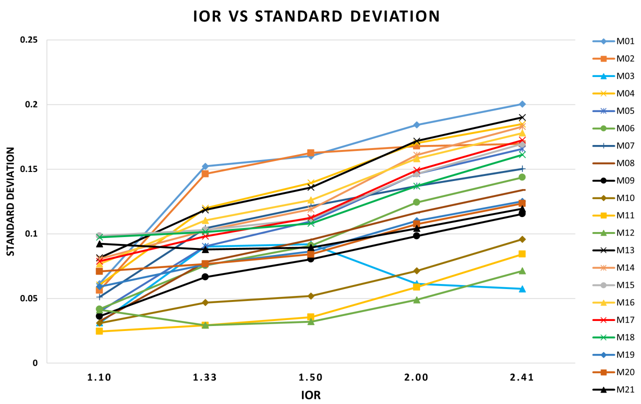

Figure 12: *The graph shows the mean standard deviation of the luminance histogram (vertical axis) as a function of the IoR (horizontal axis), for each material.*

not exhibit clear specularities, which creates ambiguity regarding its gloss, especially if large amount of light penetrates into the subsurface and re-emerges from a different point. It has been demonstrated previously that subsurface scattering may affect gloss cues, and internal caustics can be mistaken for specular reflections [GSW*21; GTPH19]. In this case, the increase in IoR, which decreases the amount of subsurface light penetration, can negatively affect gloss. The extreme case of this is a fully transparent material (M03) with rough surface. There is no subsurface scattering inside the material (σ_T=0), and the scattering only happens on the surface. There are no visible specular reflections to assess its gloss. When its IoR is large, most light is reflected diffusely from the surface without sharp highlights. However, when its IoR is lower, the light is refracted into its volume. The curved geometry of a sphere, which acts like a lens, converges refracted light to form sharp and bright internal caustics on a different edge of the object, which may be mistaken for specular reflections [GTPH19; GSW*21] and hence, affect its apparent gloss.

From the luminance statistics analysis we can observe that the standard deviation is the most positively correlated with the change in IoR, which is logical, since, generally, a change in the IoR changes the contrast of the image; for instance, the superimposed reflections on the surface and the specular highlights are stronger and better defined. Interestingly, the materials whose IoR is not positively correlated with perceived gloss, also exhibit no correlation between IoR and standard deviation.

This once again highlights the complexity of gloss perception, which cannot always be reliably predicted by surface reflectance. A holistic approach is needed to understand how different optical parameters interact with one another and whether or not they produce highlights. This especially applies to transparent and translucent materials that permit large amount of subsurface light transport.

This findings have significant implications for many applications, such as material modeling, prediction of perceptual effects in computer graphics, and appearance reproduction using additive manufacturing. For example, understanding the relationship between material's refractive index and perceived gloss may decrease the need for costly trial-and-error process in 3D printing. Furthermore, here we assume the IoR of the external medium (n_1) to be fixed. However, it is the difference between the refractive indices of the two media (n_1 and n_2) that affects the amount of reflected light, not the absolute value of n_2 alone. Therefore, the findings have implications not only for modeling a given material, but also for visualization of that material in different media; for instance, how perceived glossiness changes in underwater scenes.

6. Limitations and Future Work

This study was limited to a spherical shape. Spheres permit sharp mirror reflections of the environment when micro-scale roughness is low, which makes them a common choice for studying perceived gloss [PFG00; FDA03; XB08; vAWP16; GTPH20]. Since this was the first step on this particular topic, variation of material properties was prioritized. However, it is known that shape and illumination affect perceived gloss [GI22; GT23]. Therefore, future works should explore whether these findings generalize to other shapes and illumination conditions. Since micro-scale surface geometry affects how IoR is related to perceived gloss, we hypothesize that similar impact can be observed for macro-scale shape differences as well (due to sharpness of the highlights, interreflections, etc.). Object's scale (even if the shape is fixed) can also impact the result, since it affects translucency and luminance statistics [UTB*19; GTHP21]. Illumination structure is another significant variable, whose impact on gloss has been studied before [FDA03; AKLM18]. Furthermore, illumination direction can also have an impact: for instance, if IoR is low and the object is back-lit, much of the light refracted into the subsurface may reach the camera and produce highlights, as shown in [GTHP21]. Each of these aspects merit a separate quantitative study with carefully selected subset of materials. It is especially interesting to further study the materials that did not conform to the expected positive correlation between IoR and gloss, such as M03, and investigate whether this peculiarity holds for other shapes. For instance, sphere acts like a lens due to its curvature and forms strong internal caustics when both IoR and subsurface scattering are low (such as in M03). Future works may visualize M03 in other shapes with different curvatures. This will also help to isolate the impact of reflection and refraction geometries.

Besides, it is worth pointing out that the experiments were conducted in a low dynamic range environment. Future work should explore the similar research question in high dynamic range (HDR) scenes by using HDR displays or physical objects. Finally, we believe that future work should aim creation of a robust model that will incorporate above-mentioned findings and predict perceived magnitude of gloss based on optical properties, including but not limited to index of refraction, extinction coefficient, and albedo. This could be done for instance by applying conventional multivariate regression techniques or also by applying machine learning regression models, i.e., support vector machines, decision trees, and neural networks.

7. Conclusions

A new dataset of opaque, translucent and transparent objects was created to study the impact of index of refraction on perceived gloss. For this purpose, two psychophysical experiments were conducted. The results of this study show that for objects with smooth surface, the perceived gloss increases with the IoR, exhibiting a monotonically increasing behaviour. However, this is not always the case for rough objects, especially, when they permit large degree of subsurface light transport. When surface is rough and sharp specular reflections are absent, lower IoR permits larger amount of light to penetrate the subsurface, which may produce image cues to gloss. Future work should cover more shapes and illumination conditions and answer the questions on to what extent the current observations generalize.

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