https://doi.org/10.2352/CIC.2025.33.1.26

Ghiblification and color richness in material appearance: How human observers and image quality metrics perceive them?

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Abstract

Distortions introduced during the reproduction of digital images can lead to substantial changes in their color composition. The motivations for altering images range from practical purposes, such as image compression and color quantization to reduce file size, to more aesthetic applications like style transfer using generative AI. In this work, we investigate how the reproduction of color images affects material appearance, in particular, the perception of gloss and translucency. We applied different image quality distortions to natural images of glossy and translucent objects. Additionally, we Ghiblified them – a recent viral social media phenomenon of mimicking the Japanese anime style using generative AI style transfer. Afterward, we conducted a series of user studies to evaluate the fidelity of gloss and translucency reproduction. The experimental results represent how the reproductions are perceived by image quality metrics and open up a new direction for material appearance studies.

Introduction

The life of a modern human is unimaginable without digital images. We encounter a daily plethora of digital imagery that plays a significant role in many aspects of our lives, from education to industrial inspection, medical imaging, and entertainment. The rapid development of digital image processing and generative AI provides ample opportunities to edit and manipulate those images in numerous ways [1, 2]. The objectives and intentions of editing can be different: technical limitations of the reproduction pipeline [3, 4], compression [5], or artistic and aesthetic effects [4]. Although compression and cross-media color reproduction problems have been around for a long time [6], the style transfer and artistic stylization of images gained widespread use after large language and vision models became commonly available. A vivid illustration of this is a viral social media phenomenon called "Ghiblification" – a neologism, which means using generative AI to transfer photographs to the anime style, which resembles the artistic style of the Japanese animation studio, Studio Ghibli [7], example of which is illustrated in Fig. 1.

Image reproductions have one thing in common: they can affect colors and their distributions, which may (e.g., in artistic style transfers) or may not (e.g., digitizing heritage objects) be desirable or intended, depending on the application. Color distribution in the image, on its part, has been demonstrated to affect material appearance [8, 9].

Material appearance plays a significant role in many domains, such as 3D printing, electronic commerce, aesthetic medicine, cosmetics, or cultural heritage reconstruction – to name a few [8, 10]. In this work, we focus on two fundamental attributes of appearance: gloss and translucency.

Figure 1. *Image stylization not only changes the visual appeal of the photograph, but also affects overall color distribution and material appearance of the depicted objects. The original photograph shown here (left) was converted to a Studio Ghibli style (right) using ChatGPT.*

Figure 2. *Examples of the original photographs used in the experiments. The top row – gloss experiments, bottom row – translucency experiments.*

Our understanding of physiological and psychological mechanisms of gloss and translucency perception remains limited [8]. However, the state-of-the-art works indicate that appearance attributes, such as color, gloss, and translucency, impact each other, and for gloss and translucency perception, the human visual system (HVS) relies on color and intensity distribution cues in the image, such as sharpness and contrast [8, 10, 11, 12]. Therefore, we hypothesize that color reproduction and specifically, the richness of color in the image, impacts perceived gloss and translucency. Gigilashvili *et al.* [13, 14] have shown that color and translucency perception are closely related.

To test our hypothesis, we created a dataset of photographs of translucent and glossy objects that we encounter in our daily lives. Afterward, to affect color richness and overall distribution in the images, we pursued two strategies: first, we Ghiblified them using generative AI to produce a cartoon-like appearance of the materials; second, we applied common image quality and image processing distortions, such as JPEG compression, color quantization, and dynamic range clipping. Afterward, we conducted two user studies, where human users rated how accurate gloss and translucency reproduction were, respectively.

Few works have addressed the impact of image quality on material appearance. For instance, Gigilashvili *et al.* [15] studied how image blur affects perceived translucency, while Aketagawa *et al.* [16, 17] studied the impact of different display properties on perceived roughness, transparency, and gloss. Besides, color has been analyzed in the context of generative AI [18]. However, to the best of our knowledge, this is the first study that addresses gloss and translucency appearance in generative AI images.

Methodology

Dataset Preparation

We photographed natural and indoor scenes depicting glossy and translucent objects that we interact with daily, such as foliage, toys, and kitchenware. We also photographed selected objects from the Plastique artwork collection [19], previously used for material appearance studies [20]. In total, we selected 10 glossy and 10 translucent objects, examples of which are illustrated in Fig. 2. Afterward, for each original image, we generated two Ghiblified versions of it and two different levels of color quantization, posterization, dynamic range clipping, and JPEG compression - creating 10 versions of the original image, shown in Fig. 3. In total, we had 100 test images (10×10) per appearance attribute, and 200 images in total.

Photographing

All images used in this study are original and were captured in two different locations. A part of the images for the dataset were taken outdoors. Translucent objects were photographed against the light, with the sun positioned behind the object at a slight angle, since backlit objects appear more translucent [10, 21]. Glossy objects were captured at the same location using front lighting from the sun, also slightly angled. For these outdoor images, the camera settings were: aperture f/3.5, ISO 100, and shutter speed ranging from 1/1000 to 1/2500 seconds, adjusted based on the sun's position. Indoor images were taken under natural light near a window. Translucent objects were shot with backlighting using settings of f/3.5, ISO 100, and a shutter speed of 1/400 seconds. Glossy objects were photographed with side lighting from the window and a wall background, using f/3.5, ISO 400, and a shutter speed of 1/160 seconds. A Canon 6D DSLR camera was used to capture all photographs.

Distortions and stylization

Image quality distortion using traditional algorithms. To begin with, 13 common image quality distortions were chosen and applied to the reference images. Visually inspected by the authors, four distortion types were chosen out of this pool of 13 distortions that impacted translucency and gloss the most. The applied distortion types are clipping, color quantization, JPEG compression, and posterization. The distortion types were applied in two distinct levels in a way that there would be a clear difference between the distortion levels themselves and the reference image, plus care was taken to preserve the content of the images in the more severe distortion level. Clipping thresholds were set to 200 and 180, where pixel values above the threshold were set to 255. Color quantization [22], which reduces the number of unique colors, was implemented using palette sizes of 16 and 8 colors. Visually, color quantization introduces banding to the images in smooth regions. Repeated JPEG compression [23] involved saving and reloading the image twice using JPEG quality levels of 20 and 10, respectively. Posterization [24], in contrast to color quantization, is applied per image channel, creating abrupt transitions and artifacts on the image. Posterization levels were controlled via quantization to 16 and 8 tonal levels per channel.

Ghibli stylization using generative AI. A stylization applied to the original images was done using AI. We used ChatGPT to convert the images into a Ghibli-inspired style. As with the other distortions, we generated two levels of stylization. The first version was created using the prompt: *"Apply Ghibli stylization to the following images while preserving the original shapes and colors accurately, without introducing any new elements."*. For the second version, we aimed to retain the glossiness and translucency, respectively, features of the original objects, using the prompt: *"Apply the same Ghibli stylization to the following images, but retain the translucency/glossiness of the original object as much as possible."*. The first prompt was used as level 1, and the second prompt as level 2 of this stylization type. The same prompt usually does not produce identical results, so we used the same prompt once for all images, but multiple attempts have shown that the resulting images are qualitatively similar.

User Study

Experimental protocol

We conducted a pair-comparison category judgment user study using the QuickEval platform [25], where the observers were shown a pair of images at a time: the original photograph and one of the ten reproductions side-by-side. The task of the observer was to rate how accurately the test image reproduces the gloss or translucency appearance of the material in the original image, respectively, on a Likert-type 1 to 7 point scale. The following instruction was given for the gloss experiment: *"How accurately does the test image reproduce the glossiness of the material shown in the reference image? Please rate on a scale from 1 to 7, where 1 means 'not accurate at all' and 7 means 'highly accurate.' Focus solely on glossiness, disregard other material attributes or the overall image quality."*. The instruction was identical for the translucency experiment, except for replacing "glossiness" with "translucency". In both cases, this instruction was followed by the technical definition [26] (as per the ASTM dictionary of the standard appearance terminology) of gloss and translucency, respectively. The order of the reference images, as well as the test images for each reference image, was randomized. The observers first took the gloss experiment, followed by the translucency experiment in the same sitting. In total, they took on average 20 minutes to rate 200 images.

Screen Calibration

We used an Eizo CG279X monitor with a resolution of 2560×1440 and a pixel density of 109 ppi, calibrated to sRGB viewing standard (brightness: 80 cd/m^2, temperature: D65, gamma: 2.2, color gamut: sRGB). The distance of the observers to the screen was controlled by a physical obstacle and was fixed to 78 cm, which is 2.3 times the screen height.

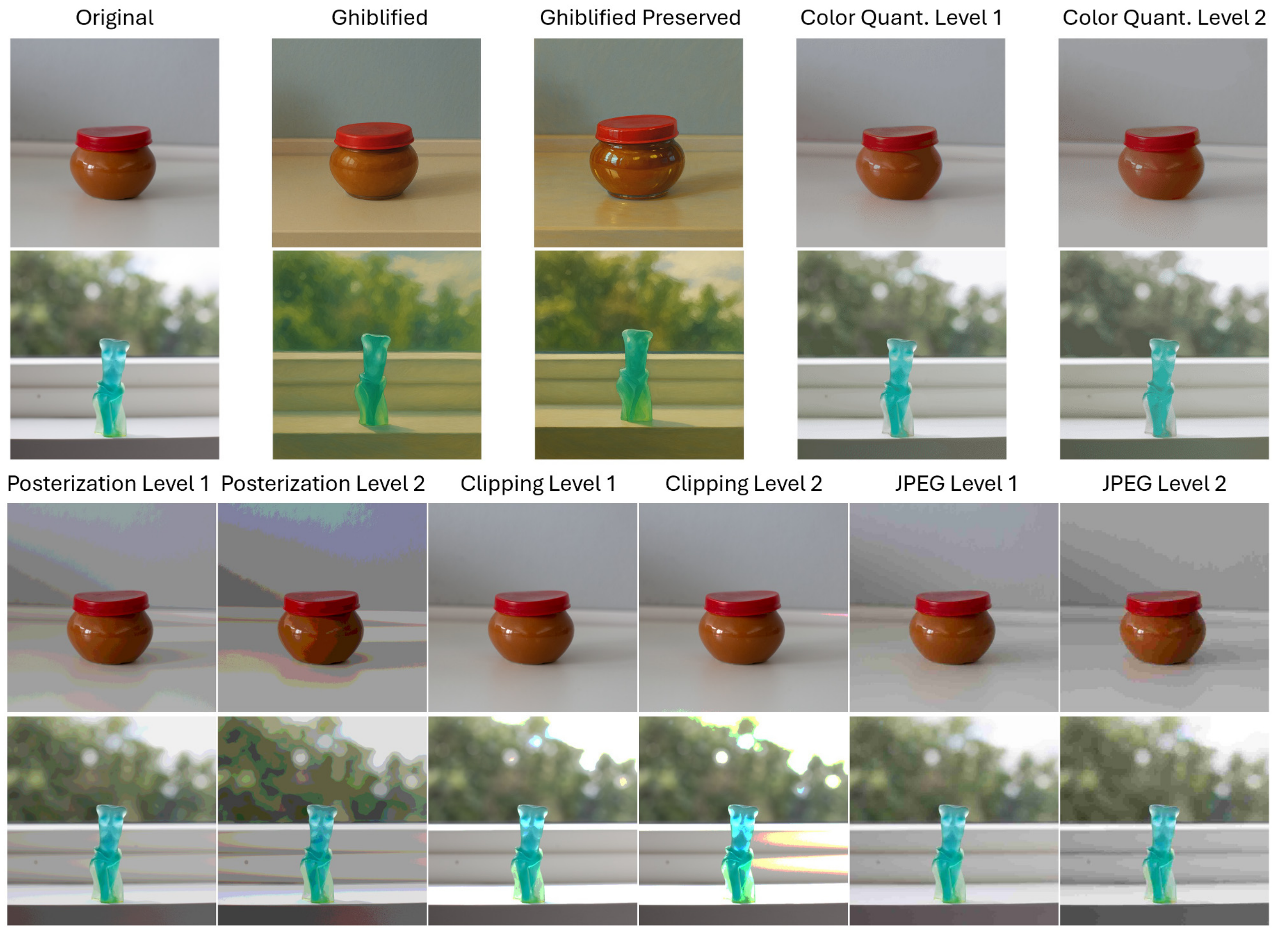

Figure 3. *Illustration of all 10 distortions and stylization applied to the original images shown in the top left. The images in the respective top rows (jam jar) were used for gloss experiments, while the cyan bust figurine shown below was used for studying translucency.*

Observers

19 observers, 11 male and 8 female, participated in the experiment. All of them had normal color vision and normal or corrected-to-normal visual acuity (self-reported). Most of them were graduate students at the computer science department. However, only 13 of them had previous experience with material appearance. The median age of observers was 29.

Results & Discussion

After the user study, we calculated the Mean Opinion Score (MOS) of images. To encounter the difference between individual scaling, the Z-Score for each image was also calculated (Eq. 1).

$$Z_{i,j} = \frac{x_{i,j} - \mu_j}{\sigma_j} \quad (1)$$

where: $Z_{i,j}$ is the Z-score for image i and observer j; $x_{i,j}$ is the raw rating given for image i by observer j; μ_j and σ_j are the average and standard deviation of all scores for observer j, respectively.

Figs. 4 and 5 show the raw MOS of each distortion type aggregated over all images and observers. We see that overall, the MOS values are above average, but none of them reached *”highly accurate”* maximum value. Fig. 4 shows that moderate clipping does not substantially affect gloss reproduction, being closest to *”highly accurate”*. However, gloss reproduction quality was considered less satisfactory when color quantization was applied. For JPEG compression and posterization, the performance depended on the degree of degradation. While the first levels demonstrated relatively better results, the second levels were rated significantly worse in gloss reproduction quality. The opposite is true for Ghiblified images. The reason for the average of the MOS of the Ghiblification level 2 for both attributes being higher than level 1 is that, Ghiblification is not necessarily a degradation of the images, and the second level's prompt explicitly instructed to preserve the gloss and translucency, respectively.

As for translucency (Fig. 5), clipping degrades translucency reproduction by far more than any other method. The second level of clipping is the closest to the *”not accurate at all”* label. The impact of the magnitude of a given degradation (difference between two levels) is more apparent for translucency: the second level of each degradation usually results in substantially worse (except Ghiblification) reproduction. On the other hand, when explicitly requested to retain translucency, the Ghiblified version exhibited better preserved translucency appearance than it was the

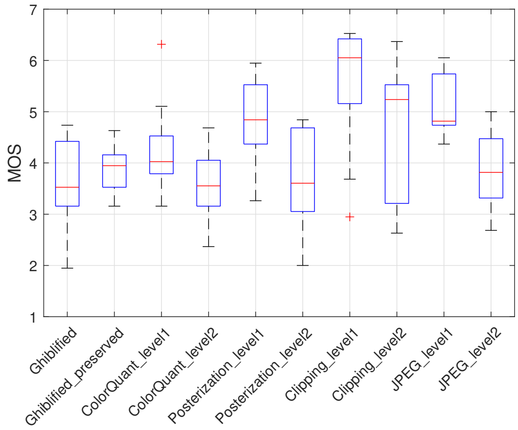

Figure 4. The distribution of MOS for each distortion on gloss. The central mark in red indicates the median, and the bottom and top edges of each box show the 25th and 75th percentiles, respectively. The outliers are plotted individually using the '+' marker symbol.

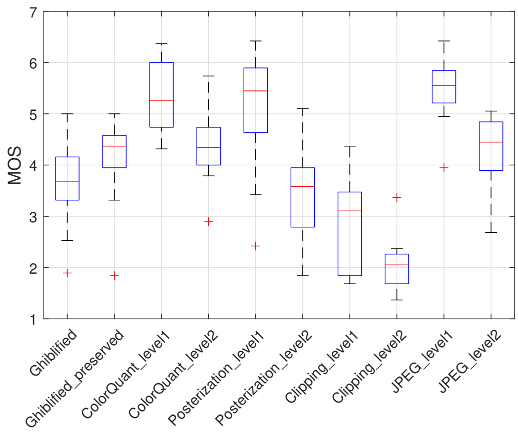

Figure 5. The distribution of MOS for translucency.

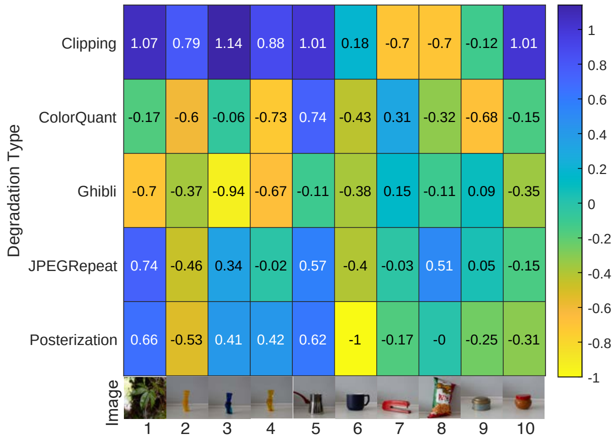

Figure 6. Gloss mean Z-Scores per image and distortion averaged over level 1 and 2.

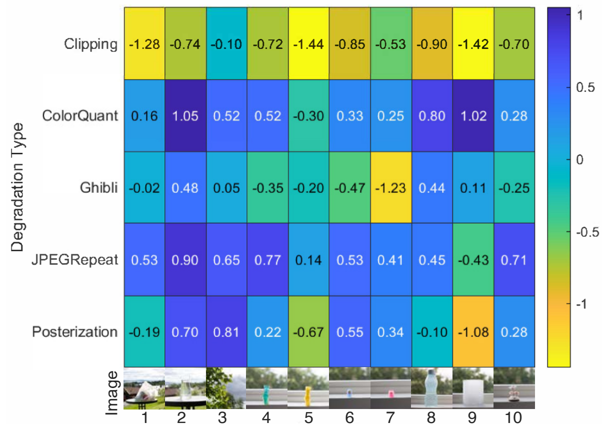

Figure 7. Translucency mean Z-Scores per image and distortion averaged over level 1 and 2.

case for gloss.

Figs. 6 and 7 show the heatmaps of Z-Scores of gloss and translucency, respectively, where each row is a distortion type and each column is an image. The small icon of each original image is shown at the bottom. The heatmaps show the mean of the Z-Scores for the two distortion levels. Comparing colors across the rows will indicate the difference in the impact of each distortion method, while comparing colors across the columns will show how much this effect varies depending on the content of the image. We can see in Fig. 6 that clipping has the least impact on gloss reproduction (more blue cells), while color quantization and Ghiblification affect more (more red cells). For translucency (Fig. 7), clipping degrades translucency reproduction quality most. However, comparison of the columns shows that the effect can vary substantially among images.

The same method may have a larger impact on one image and less on another. For instance, clipping had a large impact on the gloss in images 7 and 8, while it largely retained the glossiness in images 1 and 3 (as sorted from left to right in Fig. 6). For images 2 and 6, posterization had by far larger impact than clipping. Fig. 8 (a-b) correspond to clipping level 2 for images 1 and 8, respectively. Considering the intensity composition and dynamic range of each image, specular highlights are largely retained for (a), while they look more unnatural, saturated artifacts for (b), which explains the difference. Images (c-d) represent clipping and posterization for image 2. Clipping retains specular reflections along with the 3D shape cues, and gloss remains natural, while posterization results in large homogeneous areas, where the location of the highlights is inconsistent with the 3D shape and, hence, as previously demonstrated [27], does not evoke perception of gloss. In general, images with strong gloss cues and mirror-like appearance, e.g. image 5, are less affected.

Content dependency is also observed for translucency. Ghiblification did not retain translucency for Fig. 7 image 7, but worked well for Fig. 7 image 2. Fig. 8 (e-f) show that it clearly replicates the see-through cues and background for image 2, while changes the shape for image 7 (cf. Fig. 2), making its translucency gradient weaker. For image 9, color quantization retained translucency, while posterization deteriorated it, since color quantization retained smooth luminance gradient, while posterization converted it to uniform regions with abrupt transition and opaque look (g-h).

Furthermore, we explored how the objective image quality metrics perform on our dataset. Seven Full-Reference (FR) and

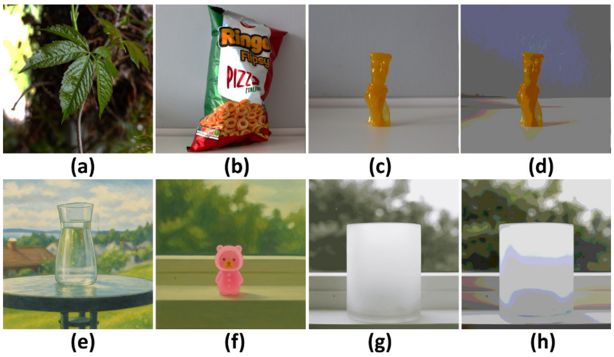

Figure 8. Top row – gloss; bottom – translucency. (a-c) clipping level 2; (d,h) posterization level 2; (e-f) Ghiblification level 2; (g) color quantization level 2. It seems that the impact of each distortion is highly content-dependent.

five No-Reference (NR) image quality metrics, with some metrics measuring quality in the spatial domain and some in the frequency domain, were chosen. The metrics are Mean Squared Error (MSE) (FR) [28], Structural Similarity (SSIM) (FR) [29], Multi-scale Structural Similarity (MSSIM) (FR) [30], Feature SIMiliarity Index (FSIM) (FR) [31], Local Entropy Difference (Entropy-Diff) (FR) [32], Haar wavelet-based Perceptual Similarity Index (HaarPSI) (FR) [33], Multi-Scale Gradient Wavelet (MSGW) (FR) [34], Image BLUR Metric (NR) [35], Cumulative Probability of Blur Detection (CPBD) (NR) [36], Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) (NR) [37], Natural Image Quality Evaluator (NIQE) (NR) [38], and Perception-based Image Quality Evaluator (PIQUE) (NR) [39].

Figs. 9 and 10 show the correlations between image quality metrics and the MOS (not Z-score). Some of these quality metrics increase their scores as the image quality improves, such as SSIM and MSGW, and others decrease. The quality metrics before the vertical line mostly have a positive correlation both for translucency and gloss, because they increase the scores as the image quality improves. The quality metrics after the vertical line decrease the score as the image quality improves. The reason for these correlation values to be low is that in Ghiblification, the pixel-by-pixel comparison that most FR image quality metrics have is less relevant, because AI stylization slightly changes the overall image structure, which is why the overall correlation that is for all distortions is low. We tried removing Ghiblification scores and recalculated the correlations. The correlation increased substantially for BRISQUE and slightly for all other metrics. On the other hand, we notice that in general, NR metrics often fail to capture perceptually relevant changes, especially for translucency. The structure-based metrics showed higher correlations with gloss perception. The correlation values show that image quality metrics can explain the variation in MOS to a certain extent, indicating the influence of the distortions on the MOS. However, observers rated gloss and translucency, not image quality. Thus, objective image quality metrics do not fully explain the variation in MOS, and observers rely on various cues other than those specific to image quality, in their judgments.

Conclusion

This study investigated how image distortions affect the perception of translucency and gloss. We conducted a user study

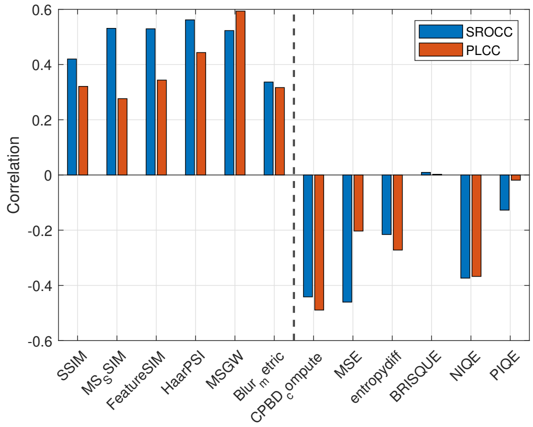

Figure 9. The correlations of metrics for gloss. The vertical line separates the quality metrics that increase the score as the image quality improves from the metrics that decrease the score when quality improves. SROCC – Spearman Rank Order Corr. Coef.; PLCC – Pearson Linear Corr. Coef.

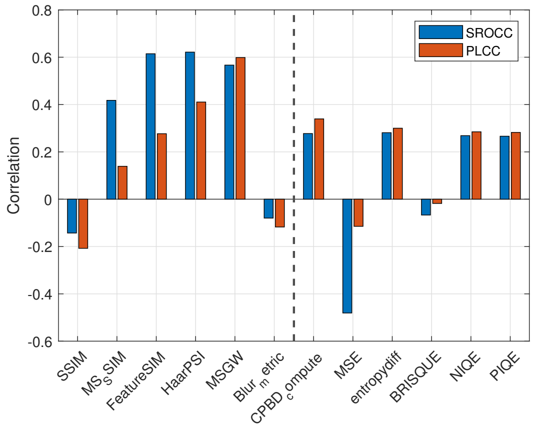

Figure 10. The correlations of metrics for translucency.

and analyzed subjective ratings alongside a range of objective image quality metrics. The subjective scores show that the perception of gloss and translucency is strongly influenced by distortions and is highly content-dependent. A deeper analysis of object and background color distributions in the future may shed more light on the underlying reasons for content-dependent differences. The analysis of the objective scores shows that there is ample room for the development of objective metrics that understand gloss and translucency. Future work will extend the study to a broader set of images and explain the subjective scores with image statistics. Due to potential scoring bias, an alternative experiment may employ relative judgments rather than an absolute one. Plus, a second series of user studies could be conducted in which observers would rate the overall image quality; then, the relationship between image quality and perception of gloss and translucency could be further investigated. Generative AI-based stylization retained gloss and translucency better when the model was explicitly instructed to do so. However, it often inadvertently changed image structure, introducing artifacts. Prompting strategies and the ability of the generative AI models to reproduce material appearance merit a separate future study on their own.

Acknowledgment

Mobina Mobini is supported by the Research Council of Norway through the "Quality and Content" project (#324663).

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