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Image Statistics as Glossiness and Translucency Predictor in Photographs of Real-world Objects

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Abstract. We interpret our surrounding based on the visual stimuli, and perceive objects and materials around us to have various attributes, like color, glossiness, and translucency. We analyze the three-dimensional world based on the two-dimensional images detected by our retina. The state-of-the-art works conclude that the human visual system has a poor ability to fully understand and invert the complex optical nature of light and matter interaction. Some authors rather propose that the human brain calculates image statistics to perceive appearance, demonstrating correlation between perceptual attributes and various statistical metrics. However, the illustrated examples are usually unrealistic nearly-perfect stimuli, making real-life robustness of the findings questionable. In this study, we analyzed image statistics of photos of real world objects, and assessed the performance of statistical image metrics proposedly used by the human visual system. We identified very interesting trends, as well as limitations.

Keywords: Material appearance · image statistics · gloss · translucency

1 Introduction

Appearance is a complex psychovisual phenomenon that implies attributing particular characteristics to surrounding objects based on the interpretation of the visual data. CIE 175:2006 [23] (as quoted in [5]) defines appearance as *"the visual sensation through which an object is perceived to have attributes as size, shape, colour, texture, gloss, transparency, opacity, etc."* The CIE identifies color, gloss, translucency and texture as four major appearance attributes [23]. Appearance measurement has been developed towards hard metrology, i.e. instrumental measurements [12, 18, 30], and soft metrology relying on psychophysics [8, 22, 27].

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While we orient ourselves in the 3-dimensional world we still interpret the environment based on the 2D retinal images. And we do pretty well: humans with normal vision can easily distinguish glossy and matte or translucent and opaque objects; furthermore, we are good at identifying materials, easily distinguishing ceramics from wax or human flesh from plastic dummies. Although multisensory information, like tactile or auditory, facilitate this process, the crucial amount of information is extracted from the above-mentioned 2D retinal images. Fleming and Bülthoff [6] have proposed that the human visual system (HVS) has poor optics inversion abilities, and that it relies on simple image cues to interpret material properties. Motoyoshi [21] tried to correlate image statistics with material properties, and found indications that skewness, or a similar measure of luminance histogram asymmetry, might be used by the HVS to judge surface properties. The finding is further supported and manifested by Landy [15]. Marlow and Adelson [16] demonstrated that sharpness, contrast and coverage area of the highlights are correlated with perceived level of glossiness. Qi et al. [24] tried to find correlation between perceived glossiness and various statistics of specular highlights, like spread, size, number, strength, and percentage coverage, and found a statistically significant correlation between the percentage of the highlight coverage and perceived glossiness.

Image statistics have been used for studying perceived translucency as well. Motoyoshi [20] manipulated images of various materials and concluded that *"spatial and contrast relationship between specular highlights and non-specular shading patterns is a robust cue for perceived translucency of three-dimensional objects"*. On the other hand, it has been also shown that image statistics alone do not entirely explain the complex nature of appearance perception and they are usually subject to multiple photo-geometric constraints [2, 13, 14, 16].

Although the above-mentioned findings are interesting, they are oftentimes based either on the synthetic stimuli, rendered in constrained and unrealistic environments, or few photographs taken in limited conditions. The studies using large photograph databases have no access to the physical ground truth of the material (e.g. [25, 31]), while wherever the ground truth is available, the number is stimuli is low (e.g. [21]).

The novelty of this study is using a photograph dataset with full access to the ground truth physical stimuli. We had a particular motivation for using photographs in this study. The vast majority of the authors using computer generated stimuli do not account for imperfections and artifacts present in the real world. As computer vision emerges, with autonomous vehicles among the most prominent applications, in-the-wild performance of particular metrics becomes vitally important for material identification. Therefore, we decided to extract image statistics not from the synthetic stimuli, but from photographs of real world objects coming with unintended artifacts, and to study the robustness of image statistics, as predictors for actual material appearance. We photographed objects with varying degree of gloss and translucency and described them with statistical metrics known to be correlated with them.

The paper is organized as follows: in the next section, we present the acquisition setup and methodology. The results are presented and discussed in Sections 3 and 4, respectively. Finally, we draw conclusions and summarize the potential directions for the the future work.

2 Methodology

2.1 Stimuli

We photographed spherical resin objects from the *Plastique* collection [28]. The objects have been created by an independent artist with an intention to be used in material appearance research. The resin substrate material is colored with different combinations of blue, yellow and white colorants, followed by different levels of surface processing (polishing). The objects come in three levels of surface coarseness that affects apparent gloss of the materials. We photographed 30 spheres in total with 3 different levels of surface roughness, 3 hues, and various levels of translucency (Fig. 1). It is worth mentioning that the objects have several visible artifacts, like scratches on the surface and bubbles in the volume, that make them good targets for testing the robustness of image-based metrics. The close-ups of some of the objects are shown in Fig. 2. Renderings of spherical

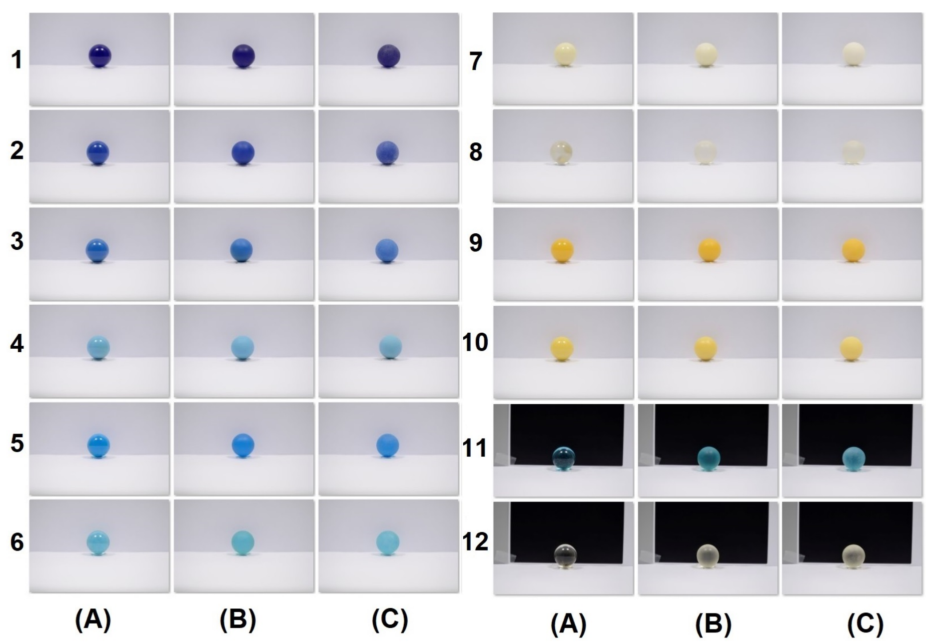

Fig. 1. The resin objects used as targets. Column A - objects with smooth surface; Column B - rougher objects; Column C - the roughest among the three. Objects in the same row are made of the identical material and differ only in surface processing.

objects are very commonly used in computer graphics for studying appearance (e.g. [22, 29]), and a simple curved shape of a sphere ensures apparent specular reflections, as well as distinctness of image gloss, that are very widely used cues for glossiness assessment by the HVS [8, 9, 22].

2.2 Image Acquisition

The objects were photographed in a GretagMacbeth Spectralight III viewing booth under diffuse D50 illumination with around 4900K color temperature. The illuminant is placed on the ceiling of the viewing booth, placing all objects under top-lit geometry - the most commonly encountered illumination geometry, both outdoors under sunlight, as well as in an office environment. The light intensity on the bottom of the viewing booth was 1858 lux, as it was directly exposed to the light, while it was 900 lux on the background. The acquisition setup is shown in Fig. 3.

The objects were placed on a white matte paper. Metal rings were used to fix the position of the spherical objects. In order to avoid possible bias from highly specular metal rings, they were covered with a white tape sticker. The immediate background of the object was white for opaque objects, while translucent objects were photographed twice, with black and white backgrounds. A Nikon D3200 camera was used with ISO 100, shutter speed 1/250 sec., F-stop 2.2, and 50mm focal distance. The object was located around 50 centimeters away from the camera. The camera was characterized using a MacBeth ColorChecker. The estimates of CIE XYZ values were obtained by a regression-based method using manufacturer-provided and camera-acquired color coordinates of the color checker patches. The color correction matrix was found by the least squares approximation. The spheres were segmented from the images of 3008×2000 pixels.

We are aware of the limitations related to the acquisition pipeline. Although the camera response function (CRF) has not been measured or estimated, the non-linearity of the CRF that is typical to consumer cameras might have affected the results. It is especially worth highlighting that the limited dynamic range of the acquisition system and clipping of the high luminance information could have impacted the recorded luminance histogram and its statistical moments.

2.3 Analysis of the Data

Only manually segmented images were studied and the background is not included in the statistics. It has been proposed that chromatic information has negligible impact on gloss perception [9, 22, 27]. In depth analysis of this is beyond the scope of this work. We assume that the vital portion of the information needed for glossiness estimation is embedded in luminance, and therefore, analyze the luminance channel Y from CIE XYZ. We found luminance histograms for each of the segmented objects and calculated the first four moments of it. Finally, the following statistical measures have been considered for the analysis: skewness and kurtosis of the luminance histogram, coverage of the highlights,

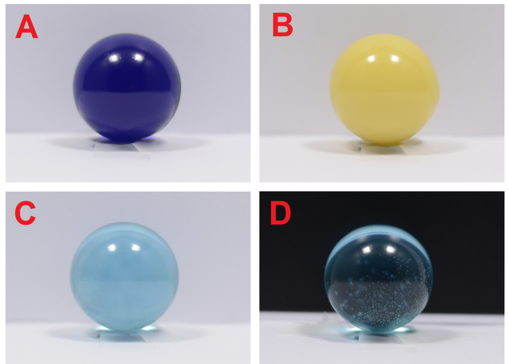

Fig. 2. The difference in contrast as well as in the reflected image is apparent between the dark blue and yellow smooth-surfaced objects (A and B). The object shown in illustrations C and D is the same, but its appearance differs due to the change in the background color. Some artifacts and bubbles are visible in image D.

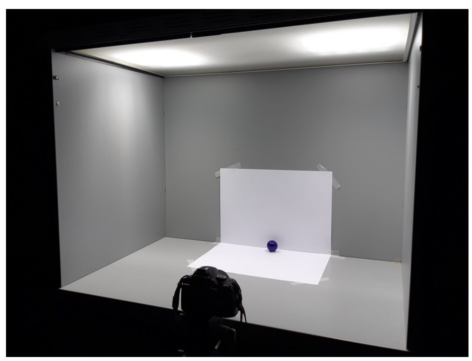

Fig. 3. The setup used for image acquisition.

mean luminance of the object, and standard deviation of the luminance distribution. The coverage was defined as the percent of the total surface covered by the areas which were larger than 20 pixels and had luminance value above 0.9 (luminance is normalized to 0-1 range, 1 corresponding to the largest luminance recorded by the acquisition system. We do not report cm/m^2 measurements). A correlation between gloss and the size of the highlights has been reported in the literature [16, 17]. Finally, we used these five statistical metrics for clustering the objects.

3 Results

The images of the 30 objects are shown in Figure 1. Objects shown in rows 11 and 12 are the same as the ones in rows 6 and 8, respectively, but photographed

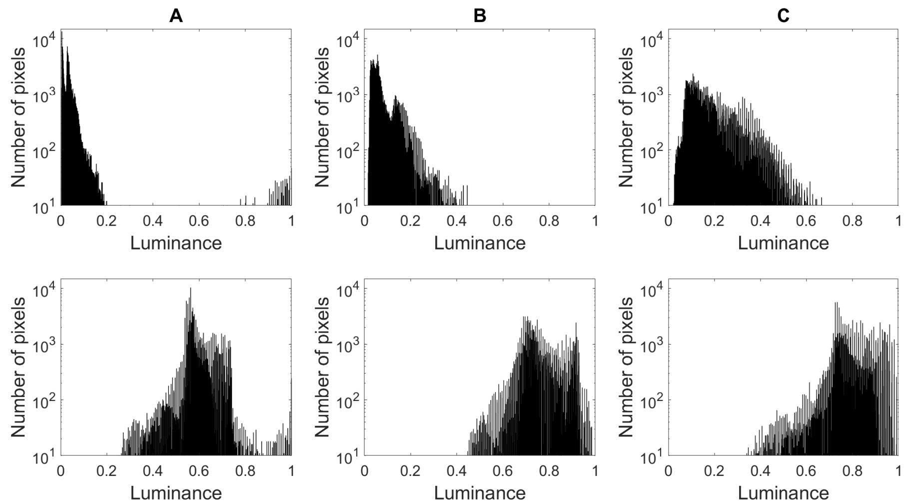

Fig. 4. Luminance histograms for segmented images. Top row - dark blue objects (row 1 in Fig. 1); bottom row - white objects (row 7 in Fig. 1). Column A - smoothest objects; Column C - roughest objects. The histograms show that the smoothest objects are positively skewed. As the mean luminance is lower, the skewness is stronger for the dark blue one. The histogram of the roughest white object is negatively skewed.

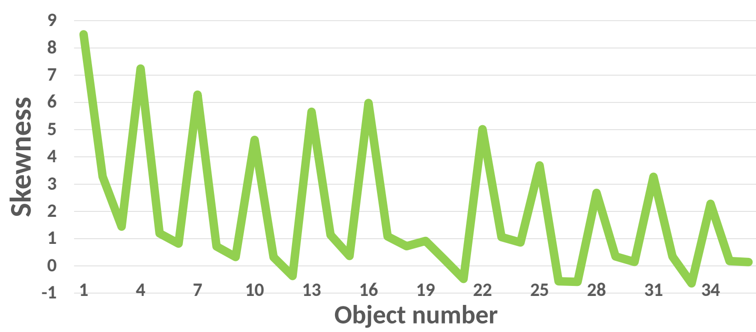

Fig. 5. Skewness of the luminance histogram for each segmented object (as to be counted from left to right, and top to bottom, in Fig. 1. Clear regularity of the triplets is visible in the pattern.

with the black background. Two major histogram asymmetry metrics have been studied: skewness and kurtosis. How the luminance histogram varies among different colors and levels of surface roughness is illustrated in Fig. 4. The results for skewness are shown in Fig. 5-6. As we see from the plots, the luminance histogram of the objects with smoother surface, i.e. higher gloss (difference in perceptual glossiness is apparent among the three levels of surface coarseness, although not quantified psychophysically), has always a positive skew, and the skewness is higher than that of the rougher, i.e. less glossy objects. Skewness difference between the two other surface levels is visible, but not large. A clear regular pattern for the triplets is visible in Fig. 5. If we refer to rows 1-4 in Fig. 1, the objects vary from darkest blue in row one, to lightest blue in row four. As we increase lightness of the object, the skewness of the luminance histogram decreases. Row 7 stands out on the plot with its low histogram skewness. This can be explained with the fact that the object is white, close to the illumination color. As the specular reflections on the surface are also whitish, they cause less skew in the luminance distribution, than for the low luminance bluish objects, where the tail of the distribution was high luminance specular highlights.

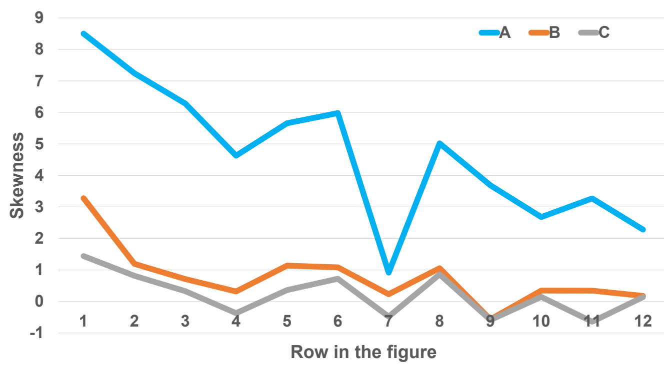

Fig. 6. Skewness of the luminance histogram for each segmented object. Each curve corresponds to each level of surface coarseness, as shown in columns in Fig. 1. Numbers in horizontal axis correspond to the rows in Fig. 1.

While skewness measures asymmetry towards particular direction, either positive, or negative skew, kurtosis measures general "tailedness" of the distribution in both directions. Kurtosis for glossiest class of the objects is highest, and generally follows the same pattern, as it is for the skewness (refer to Fig. 7). However, the distinction between the two other classes is negligible with this measure.

The surface coverage by specular highlights was equal to zero for all rougher objects (columns B and C in Figure 1). The only exception was row 7, where the whitish color of the object biased our calculations and led to unreasonably many false positives. On the other hand, the coverage did not differ significantly among the smooth objects (column A), and the specular highlights covered around 0.8% of the total visible area of the sphere.

Mean luminance for each object is summarized in Fig. 8. Studying mean luminance can be interesting for two reasons: first of all, overall shininess of the object, as observed in [9], can evoke gloss perception in itself; secondly, it has been demonstrated [16, 22] that contrast between specular and diffuse areas, has significant impact on perceived gloss. Considering that specular highlights are white and nearly identical on all objects, we assume that mean luminance of the object is inversely correlated with the contrast gloss - i.e. higher the mean

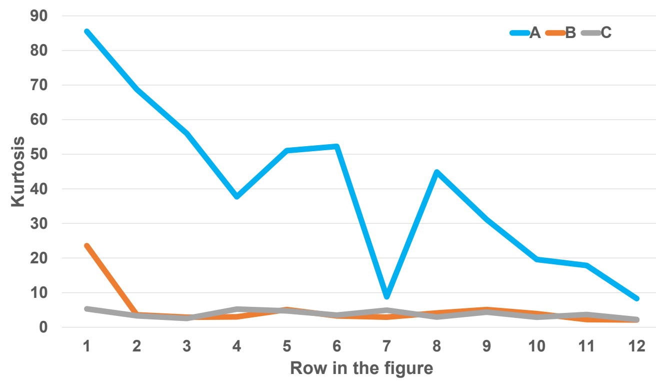

Fig. 7. Kurtosis of the luminance histogram for each segmented object. Each curve corresponds to each level of surface coarseness, as shown in columns in Fig. 1. Numbers in horizontal axis correspond to the rows in Fig. 1.

luminance of the entire object, lesser is the contrast between specular and diffuse areas. The objects with smoothest surface have less mean luminance than objects made of the identical material but with rougher surfaces. This can be explained with the fact that the substrate white material is exposed to the surface due to scratches, artifacts and irregularities presented on the rough surface.

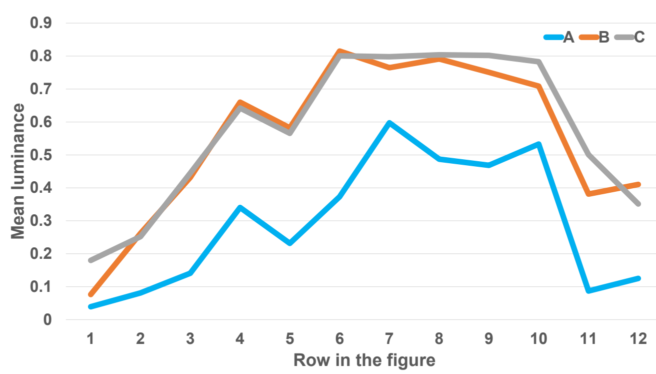

Fig. 8. Mean luminance for each segmented object. Each curve corresponds to each level of surface coarseness, as shown in columns in Fig. 1. Numbers in horizontal axis correspond to the rows in Fig. 1.

In contrast with the findings by Wiebel *et al.* [31], standard deviation of the luminance distribution is a poor predictor for surface coarseness class in our study (refer to Fig. 9). However, it significantly rises when the background of the object is changed from white to black. This might be a good indication that impact of the background on the luminance variance is a result of volume scattering - thus, used as a predictor of translucency for see-through objects.

In addition to this, we hypothesize that complexity of the scene might impact the statistics. We photographed objects in one additional condition placing a checkerboard-covered cube close to the object (the setup is shown in Fig. 10). The general trend is that rougher the surface is, the smaller the impact of the cube on statistical measures. This can be explained with the fact that the smooth surface has a good distinctness-of-image reflection, and the image reflected from the surface significantly impacts the statistics, while rough surfaces diffuse the light and no pattern is visible on the surface reflections. This trend deserves further attention.

Afterwards, we compared the metrics for the identical objects between white and black background photographing conditions (the results for rows 6 and 8 are compared with the results for rows 11 and 12, respectively). Interestingly, skewness and kurtosis decrease when the background is changed to black. To some extent, this can be accounted for many white-colored artifacts of the object which are visible on the black background only. As expected, mean luminance is decreased for black background due to absorption of the energy by the background, and thus, less back-reflections. Finding the ratio of the luminance measured on white and black backgrounds is an established technique for transmittance measurement of the flat objects (e.g. [10]). This observation holds at some extent for spherical objects as well. Also, as already discussed above, standard deviation changes significantly due to change in the complexity of the background. It has been demonstrated [9] that translucency, when objects are placed on a white background, can make objects look glossier. Here we observe that white background leads to more skewed luminance histograms that itself is proposedly related to gloss. Therefore, there might be a gloss-translucency cross-attribute interaction that is described by changes in image statistics. However, this needs further experimental evidence.

Finally, we conducted clustering to validate our hypothesis that the five statistical measures are good predictors for object class (smooth, moderately rough, and highly rough surfaces). We used *k-means* clustering with 3 clusters. Falsely detected highlight coverages for objects in the seventh row were manually set to 0. The cluster was defined as the centroid being the mean of all points in that particular cluster. Maximum number of iterations was set to 1000. Cluster centroids were initialized using *k-means++ algorithm* [3]. All objects with rougher surfaces (columns B and C) ended up in the same cluster. A small separate cluster was objects 1A and 2A, i.e. dark blue objects with low mean luminance, with the highest positive skew in luminance histogram. Four smooth-surfaced objects 7A, 10A, 11A, and 12A were clustered together with rough objects. While all other smooth objects were grouped together in a separate cluster. Clustering gives us an indication that five variables, the five statistical descriptors we use, might be enough to separate very smooth and glossy objects from rougher and less glossy objects. However, they fail describing intra-group differences.

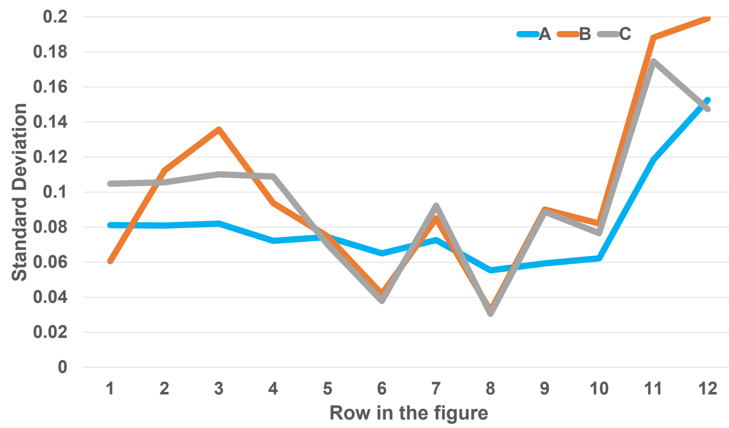

Fig. 9. Standard deviation of the luminance histogram for each segmented object. Each curve corresponds to each level of surface coarseness, as shown in columns in Fig. 1. Numbers in horizontal axis correspond to the rows in Fig. 1.

4 Discussion

We have observed that as the surface becomes rougher, skewness and kurtosis of the luminance histogram decrease, and the distribution becomes less tailed. While glossy objects look solid opaque, like billiard balls, rougher surfaces look milkier, and at some extent evoke illusion of subsurface scattering via surface scattering only that is not surprising considering that the HVS has poor optics inversion ability [6]. This can be an indication in support for Motoyoshi's proposal [20] that blurring non-specular regions, i.e. squeezing the tails towards the center, reflected in decreased skewness and kurtosis, can enhance translucency perception. On the other hand, it has been observed earlier [7] that translu-

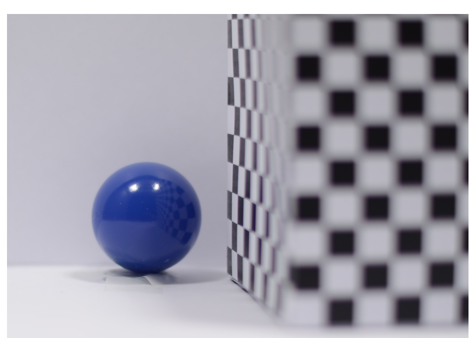

Fig. 10. A cube next to the object is covered with a checkerboard texture that is reflected on the surface of the sphere affecting its image statistics and appearance.

cency perception declines with blurring the entire object or image, i.e. when we decrease variance and histogram asymmetry. However, this proposal certainly needs validation psychophysically.

Although specular highlights are small and very simple in texture (just saturated blobs), covering less than 1% of the total visible area of the sphere, they strongly skew the luminance histogram, and evoke strong perception of gloss. Interestingly, van Assen *et al.* [4] have studied photographs with various patterns of highlights (disk, square, window etc.), and found that simpler specular highlights evoke stronger gloss perception than more complex ones. However, the role of the highlights should not be exaggerated, as the perception of gloss is a complex cognitive process and neither specular reflections are the only source of the highlights, nor all highlights evoke perception of glossiness. To demonstrate this, we have superimposed specular highlights of a smooth surface to a rougher surface of the identical materials (Fig. 11). In one case, the target rough object has relatively homogeneous texture, while in the other case, there are very apparent scratches and visual artifacts that help observers deduce the surface composition of the object. While glossiness for the former object looks reasonably realistic, the latter object does not look glossy as the highlights start looking more like artifacts. Presence of roughness cues limit perception of glossiness, although the statistical metrics are similar to that of glossy objects. This once again demonstrates photo-geometric constraints limiting the usage of image statistics as an appearance predictor. Interestingly, the HVS can still be tricked in particular scenarios when additional cues are missing (the manifestation of this phenomenon is the viral *glossy legs* illusion [19]).

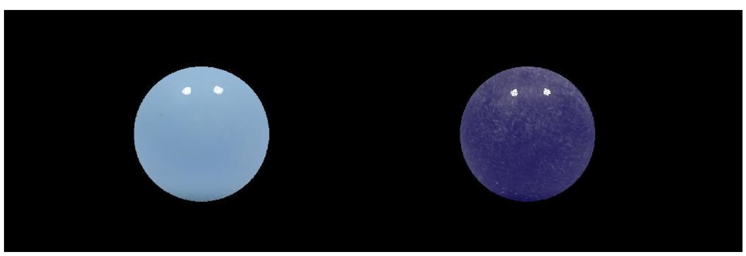

Fig. 11. While both highlights are artificial, the left object looks glossier due to the lack of artifacts, while the scratches help us know the right object is not smooth, i.e. not glossy.

Hunter [11] names contrast gloss, i.e. contrast between specular and diffuse areas, among one of the types, or dimensions of gloss. Pellacini *et al.* [22] have demonstrated that darker objects look glossier than lighter ones, and this effect has also been observed in other studies [9, 16, 29]. Although we did not have a direct measure for contrast in this work, considering that highlights were nearly identical among objects, we assumed that mean luminance of the entire object is inversely correlated with the contrast gloss. It has been demonstrated that up-to some threshold rough and light surfaces might look glossy [8, 24]. Moreover, it has been proposed that luminance information associated with shininess might significantly increase perceived glossiness [9]. Although mean luminance alone cannot be a good predictor for apparent gloss of the materials, it might carry rich information regarding contrast and distinctness-of-image (another dimension of gloss according to Hunter [11, 12]), and could be eventually included in the perceptual gloss model.

Standard deviation turned out a poor predictor of surface roughness class in our study. This interestingly contradicts with Wiebel *et al.* [31], who studied natural images, observed a strong positive correlation between standard deviation of luminace histogram and gloss, and found it a better predictor for gloss than skewness. Although we have not conducted perceptual measurements of our stimuli, we can draw some qualitative parallels. The inconsistency can be explained with the type of objects depicted in authors' natural images. If we examine the images illustrated in [31], we notice that images considered glossy consist of large segments of contrasting luminances, i.e. photographed complex shaped objects yield high number of pixels with highlights and also high number of dark pixels with shading - leading to large standard deviation. Unlike theirs, the highlights covered less than 1% of our stimuli, while the luminance gradient on the rest of the sphere was relatively homogeneous. This led to strong skew but was not enough for yielding high standard deviation in the luminance histogram.

Distinctness-of-the-reflected-image, the mirror image of the surrounding we can see on very glossy surfaces is another cue for glossiness. The background and surrounding vary dramatically in dynamic scenes, and hardly ever are as simple in real life, as studied in the laboratory conditions. Image statistics are neither static, nor consistent among different conditions. We observed that even a minor change in the environment (Fig. 10) can affect image statistics that makes its possible use by the HVS and even by machines, questionable. On the other hand, appearance is also dynamic; even though the HVS has ability to perceive some appearance attributes consistently across different conditions, i.e. demonstrates some constancy (e.g. color constancy), the constancy is valid up-to certain extent only, and completely fails in many conditions. While the vast majority of the studies trying to explain appearance with image statistics rely on a few images in very limited conditions, it remains an open question how appearance and image statistics co-vary. We have shown above that particular image statistics are promising and deserve further attention, but for more solid conclusions, psychometric measurements are needed. Understanding how image statistics correlate with perceived appearance can be beneficial in two ways:

– It can unveil further mechanisms that are used by the HVS to interpret the surrounding.
– It can have commercially significant applications in computer vision. Many image statistical metrics are extremely efficient computationally, and might be used for material identification and quality assurance. Moreover, generality across different conditions might not be the mandatory requirement for image statistics. Many computer vision applications are limited to very spe-

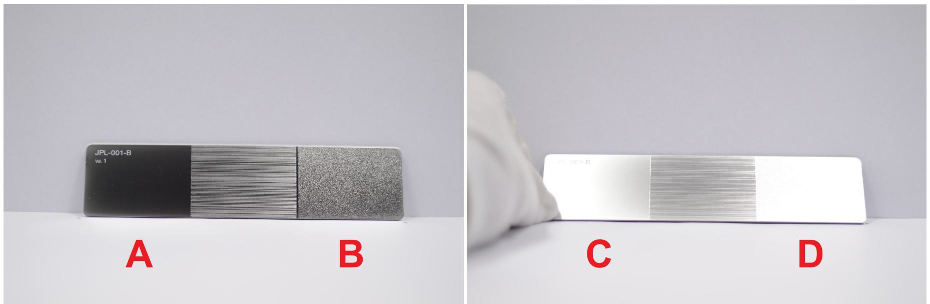

Fig. 12. The object shown in the left and right photos is the same. However, even a slight change in illumination angle leads to dramatic changes in its appearance. If the smoothest (region A) and the roughest (region B) surfaces are distinguishable in the left image, they (regions C and D) look nearly identical in the right one due to dynamic range limitations.

cific conditions by nature, and limits of particular statistics might not have vital importance, as long as a correlation between statistics and appearance is established for given (application-specific) conditions.

Finally, we should mention that above-discussed variation in luminance distributions was observed due to the curvature of the spherical objects. Our findings might not be applicable to other surfaces, especially to the planar ones. To demonstrate this, we tried photographing flat plastic and metallic samples from the JIDA Standard Sample dataset [1]. We have observed two interesting phenomena that made studying image statistics of these samples unreliable:

– Because the surface is flat, all points on small objects are under approximately the same illumination geometry that makes it impossible to see specular and diffuse areas separately, and the entire part of the patch looks rather homogeneous, essentially cutting down the luminance histogram to a single luminance value. This can be seen in the left image of Fig. 12, where the leftmost part of the patch (region A) is smooth and glossy, albeit homogeneous under given conditions.
– The samples, especially the metallic ones, are extremely prone to appearance changes even with a slight change in illumination geometry. This is demonstrated in Fig. 12.

Although haze and absence-of-textures on low gazing angles (further dimensions or types of gloss) could be observed on the flat patches, these phenomena are beyond the scope of this work and should be addressed in the future.

5 Conclusion and Future Work

We have taken photographs of real world objects and studied correlation between image statistics and actual physical surface properties. Although very clear positive skew of the luminance histogram is characteristic for smooth (and presumably glossy) surfaces, the robustness of the metric is challenged by complexity of the surrounding and semantic understanding of the scene and surface geometry. Furthermore, mean luminance can be correlated with contrast gloss, while change in variance across different conditions can be a predictor for translucency. It is worth mentioning that the dynamic range of our acquisition system was limited, and analysis of the high dynamic range data could reveal further interesting trends. Complex shapes and wider range of the materials should also be covered. While difference in perceptual gloss was assumed between smooth and rough surfaces, the statistics should be correlated with actual psychophysical measures in the future. Finally, more statistical measures, like entropy, and chromatic information should also be included in future studies and the performance of simple image statistics should be compared with that of the complex machine learning (e.g. *deep learning*) models. It has been demonstrated recently [26] that unsupervised learning techniques outperform image statistics and even supervised learning techniques in prediction of human perception. This is an interesting avenue that not only provides basis for reliable computer vision systems, but can also reveal curious mechanisms of the human vision.

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