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Searching for Colors of 3D Translucent Objects

Davit Gigilashvili, Dipayan Chowdhury, and Jon Yngve Hardeberg;
Department of Computer Science, Norwegian University of Science and Technology; Gjøvik, Norway

Abstract

3-dimensional translucent objects exhibit large spatial variations of color, and it remains unclear what colors humans choose cognitively to represent monomaterial 3D translucent objects. Previous works asked human observers to match translucent object with a most representative uniform color patch. Matched colors were compared with the average color of the object, which turned out to be a poor predictor of the match. In this work, we conducted a more thorough analysis of the color matching experiments and investigated whether matched color is systematically overestimated or underestimated relative to the average color in any particular axis in the CIELAB space. Afterward, we conducted K-means clustering of the pixel colors to extract a palette of dominant colors of the translucent object and compare the palette with observers' match. And finally, we went through a psychophysical experiment to quantify perceived color differences between pairs of 3D translucent objects. We explore whether perceptual color differences can be predicted with traditional color difference formulae using pixel-wise averages or dominant colors from the K-means clustering.

Introduction

Color perception and communication play a vital role in our daily lives. However, color alone does not fully convey how different objects and materials look. For better specification of their look, other attributes, such as translucency, gloss, and texture should be considered that often impact each other [1]. Modern color technologies enable us to measure and reproduce colors to a certain extent [2, 3]. Colorimetry is usually limited to point measurements of uniform colors. However, the reality we live and orient in, rarely manifests perfectly uniform colors. 3D objects that we interact with have large spatial as well as temporal variations of color (e.g., due to shadows) that are hard to capture and communicate with point colors (Fig. 1). 2D spectral captures, measuring bidirectional reflectance or subsurface scattering, shed more light on material properties, but they still do not provide a reliable predictor of a single color cognitively assigned to the object by humans. We, for practical reasons, still assign single color labels to different objects. For instance, we say that an apple is red, but exactly what kind of red is it? Often it has textures of other hues, some yellowish or greenish parts too – does this affect its redness? There is little experimental evidence that the human visual system actually captures a single well-defined color per object [4], and experimental attempts of doing so usually end in large inter- and intra-observer variation [4, 5, 6].

Many materials around us are translucent – letting light through, which makes their color highly inconsistent across illumination conditions [7, 6, 8]. Controlling appearance of translucent material is an open problem in multiple industries, 3D printing [9, 10] and winemaking [11] can be named among many.

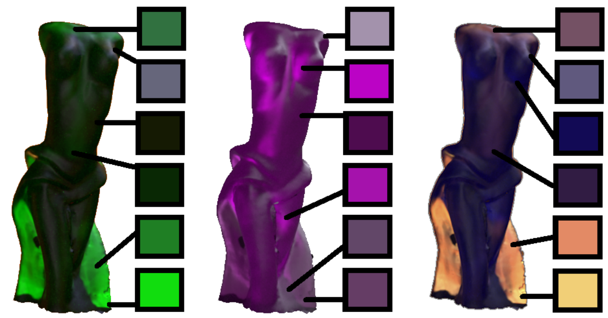

Figure 1: 3D translucent objects exhibit very large spatio-temporal variation of color, which makes it challenging, if not infeasible, to capture their colors with single point measurements. Reproduced from [8].

Point measurements on flat material samples acquired in controlled conditions rarely generalize to diverse dynamic scenes, different illumination conditions, object shapes, and scales [7, 12]. This also makes challenging to quantify color differences between 3D objects [13]. While averaging point measurements at multiple spatial locations can be suggested as a potential workaround for opaque objects [14], this may not generalize to translucent objects, because, in comparison with opaque objects, their color gets affected by background, thickness, and surface geometry to a very large extent. This large spatial variation among object's different regions and temporal variation among the scenes, made us explore what colors such objects are associated with and how humans choose a single representative color for 3D translucent objects, which is an interesting cognitive problem.

Two works by Gigilashvili *et al.* [6, 8] addressed the topic of perception, measurement, and communication of colors for highly translucent objects. In [6], the authors reported color matching and color naming experiments. Images of real and virtual translucent objects were shown in different environments, and the observers had to name their color and pick a single uniform color patch that in their opinion best represented the overall color of the 3D translucent object. The authors showed that color of a given material varies substantially across conditions and average color is not a reliable predictor of what is considered object's dominant color. In a recent position paper [8], we discuss color of translucent objects as an open problem in a broader context and bring especially challenging examples from color naming, color matching, and color difference measurement research.

In this paper, we further extend the aforementioned works [6, 8] and conduct additional data collection and analysis to gain deeper insights into the implications of the recent research done on the topic. In particular, this paper extends the previous works as follows:

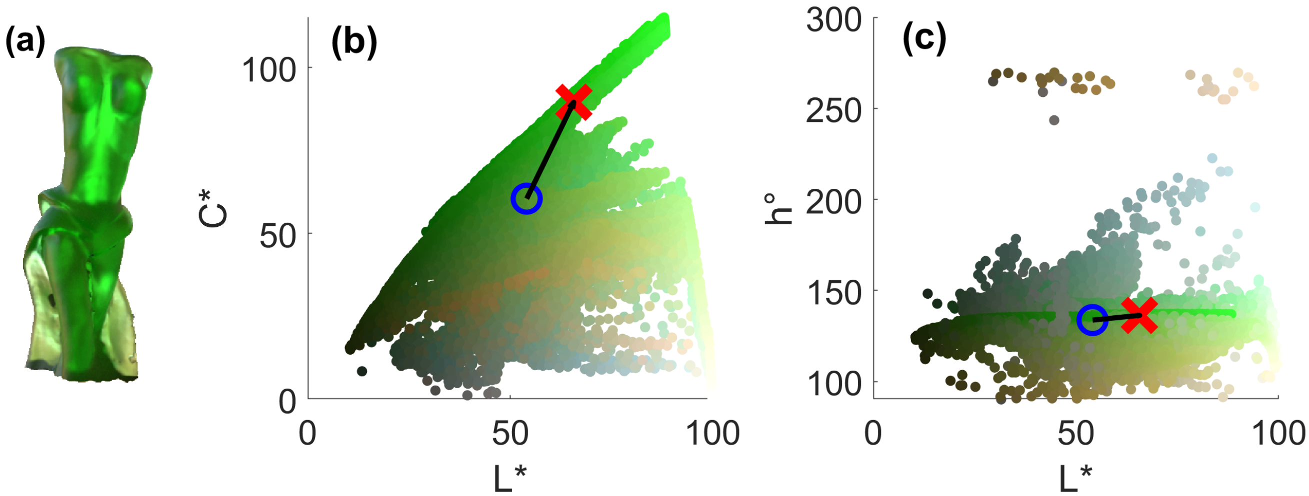

Figure 2: The translucent object (a) and distribution of its pixel colors in the CIE lightness-chroma (b) and lightness-hue planes. The blue circle marks object's average color, while the red X corresponds to the color that was picked by observers as the most representative color according to [6]. We can observe that colors of different parts of the object vary substantially.

- Previous works primarily reported differences between pixel-wise averages and perceptually picked dominant colors in terms of ΔE; in this work, we thoroughly quantify the directionality of differences by visualizing the co-location of average and matched colors in the CIE L*C*h color space;
- After demonstrating that simple pixel-wise average is a poor correlate of what humans pick, we conduct K-means clustering to extract the palette of dominant colors. It may happen that one of the cluster centroids is a better representation of object's overall color.
- Previous works briefly reported the magnitudes of perceptual color differences among 3D translucent objects that were obtained through psychophysical experiments. In this work, we use calculated color difference to predict perceptual color difference between two translucent objects and compare multiple color difference metrics as well as different ways to extract object's color for quantifying color differences.

Matched Colors in the L*C*h Space

Gigilashvili *et al.* [6] showed a collection of synthetic images and photographs of real objects that displayed highly translucent objects of different hues in different environments. They asked human observers to use a color picker and pick a single most representative uniform color. The observers saw the entire image including the background. The instruction implied that the entire object was made of the same material by referring to it in a singular form (*"navigate through the color space and pick one color that best represents the translucent material that the object is made of"*). They showed both visually as well as by calculating CIELAB ΔE color differences that the color picked by observer highly deviates from object's pixel-wise average color. This is consistent with a similar study conducted on curved 3D transparent objects [15]. A plot similar to Fig. 2 was shown in the recent position paper [8], where we demonstrated the high dispersion of object's colors in the CIELAB space and the large distance between average and matched colors.

While ΔE could potentially give an idea of the difference between average color and the most representative color, we are especially interested in the directionality of these differences. For this purpose, we plotted average and matched colors from [6] in the CIE L*C*h space, illustrated in Fig. 3. The pairs belonging to the same object are linked with an arrow. The plot of the L*-C* plane shows that most arrows are pointed diagonally toward positive L* and C* directions, which illustrates that in almost all cases observers pick lighter and more chromatic colors as the most representative than the simple average. The only exception is the blue object that appeared dark gray on a red background (see G1 in Fig. 5) and was matched with pure black instead. The picture is slightly different when it comes to hue angle. The plots in the L*-h plane show that the hue angle does not change much, and the hues are matched consistently with the average hue. The only exception is a highly translucent light blue object on a red background (G2 in Fig. 5), whose average color is dark low chroma red but is matched with dark green (140 degree shift in hue from red to green).

Extracting Dominant Colors

As mentioned above, translucent objects usually exhibit large spatial variation of color. Therefore, reducing its color appearance to single representative can be an ill-posed problem as pointed out previously [8], and it can be potentially better represented by a palette of multiple dominant colors. Clustering, such as K-means clustering, is commonly used for dominant color palette extraction and retrieval in fashion and design applications [16, 17, 18].

We followed the similar approach and conducted K-means clustering on the images. Only object pixels were considered, while background was ignored. K-means algorithm requires the number of clusters to be specified by the user [19]. Therefore, we had to choose the optimal number of colors in the palette. For this, we conducted clustering with the number of clusters ranging from 2 to 10. For each number of clusters and individual image, we calculated average Silhouette score [20] and within-cluster sum-of-squares of point-to-centroid distances (WSS) [21]. Then the results were averaged for all 48 images. These two criteria were

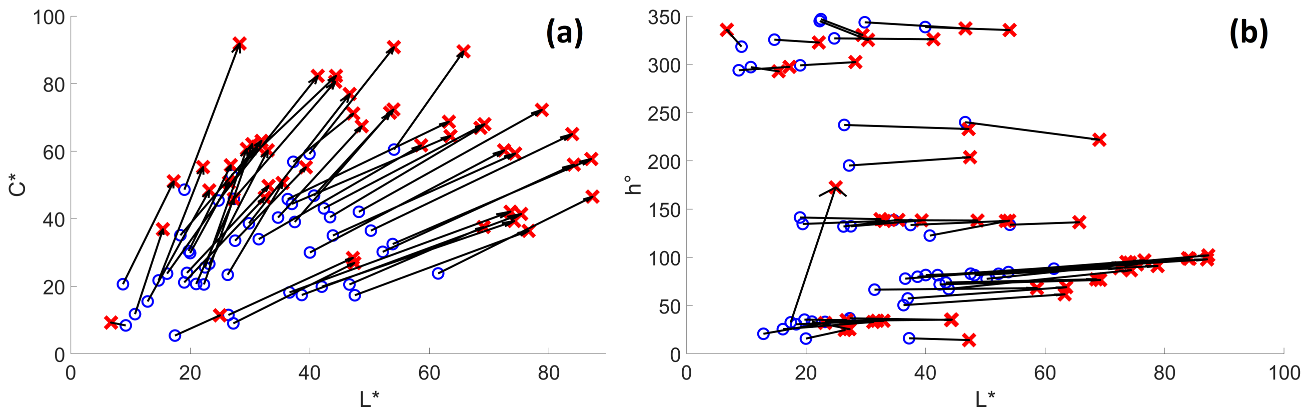

Figure 3: Blue circles correspond to average colors of the 48 objects used by Gigilashvili *et al.* [6], while the red X marks the colors matched by the observers. Each pair of the average-matched color is linked with an arrow. The arrows are directed toward the top-right corner of the L*-C* plot (a), which confirms previous proposals that observers pick lighter and more chromatic colors. Plot (b) illustrates the L*-h plot. Hue angle remains unchanged for the vast majority of the objects.

used to determine the optimal number of clusters. Higher Silhouette scores are preferred. The higher the Silhouette score, the more similar the point is to its own cluster and the more different it is from other clusters. WSS decreases as the number of clusters increase. Therefore, we used the elbow method [21] to identify the optimal balance between the metric value and the simplicity of the palette. The scores are illustrated in Fig. 4. The Silhouette score slightly decreases, but the decrease is subtle from 2 to 3 clusters. The sharpest elbow appears to be at 3 clusters for the WSS. Therefore, we decided to proceed with 3 clusters. We used MATLAB's *kmeans()* function with squared Euclidean distance metric and maximum of 100K iterations.

The resulting palettes, along with the images themselves, their average colors, and those matched by observers in [6] are shown in Fig. 5. We can see that the palette colors vary for a given object and strongly depend on the illumination conditions. While the three cluster centroids seem similar in front-lit and more diffuse environments (e.g. 1A, 1E, 2H, 3G, 6E, etc.), the palettes offer high diversity when objects are back-lit and show strong shine-through cues (e.g. 1C, 4B, 4C, 5C, 2F etc.).

It is interesting to explore whether any of the palette colors are closer to the matched color than the average. Fig. 6 shows CIEDE2000 color differences between the matched color and the four candidates (average and the three centroids from the palette). The plot illustrates that the average is hardly ever closest to the matched color among the four; the only exception is the black-appearing blue object in 1G. The values are the largest for the E and G columns. The histogram in Fig. 7 shows that the distance difference to the matched color between the best-matching centroid and the average is large in many cases. In other words, some of the palette colors from the K-means clustering can give us a substantially clearer idea of the most representative color than the simple average. Furthermore, we analyzed whether the centroid closest to the matched color was the one with highest chroma and lightness, as such colors are usually picked by the observers (Fig. 3). It turned out that in 64.8% of the cases, the closest centroid among the three was the one with the highest sum of L* and C* (according to the Binomial cumulative distribution function, the chance probability of this is 9.39×10^{-6}, with $\frac{1}{3}$ success probability on each trial), while in 81.3% of the cases, the closest

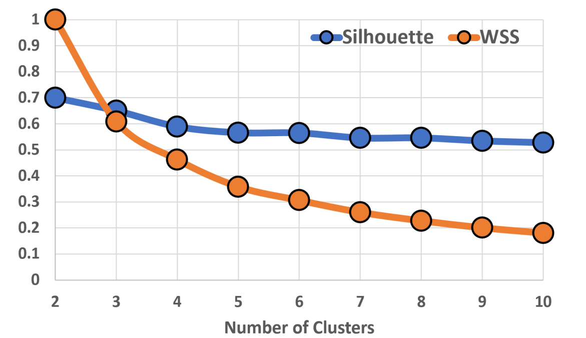

Figure 4: The Silhouette Score and within-cluster sum-of-squares (WSS) for K-means clustering, when the cluster number ranged from 2 to 10. WSS is normalized in 0-1 range, while absolute values are reported for the Silhouette Score. Higher value is preferred for the Silhouette Score and the lower number for WSS. The results are average for all 48 images.

centroid had either highest L* or highest C* (1.71×10^{-4} chance probability, with $\frac{5}{9}$ success probability on each trial). This further demonstrates the utility of K-mean in predicting the best match.

Color Differences

While matching 3D translucent objects to respective colors remains an open problem, it is also important to explore measuring color differences between them, which will have implications for appearance reproduction in various settings. The psychophysical experiment on color differences using 3D translucent objects was introduced in [8]. We used synthetic images of translucent objects that came in three hues – red, green, and blue, three levels of translucency-opacity, and four illumination conditions. We used a grayscale method to scale perceived color differences (ΔV). The example is shown in Fig. 8. For each trial, the hue and illumination condition were the same and objects differed only in opacity. Each pair was compared against grayscale references that were later transformed into a numerical scale. The details about calibration and experimental protocol can be found in [8]. We presented ΔV magnitudes for each scenario and concluded that color difference for a given pair of objects can vary substantially among illumination conditions (Fig. 9). For instance, when ob-

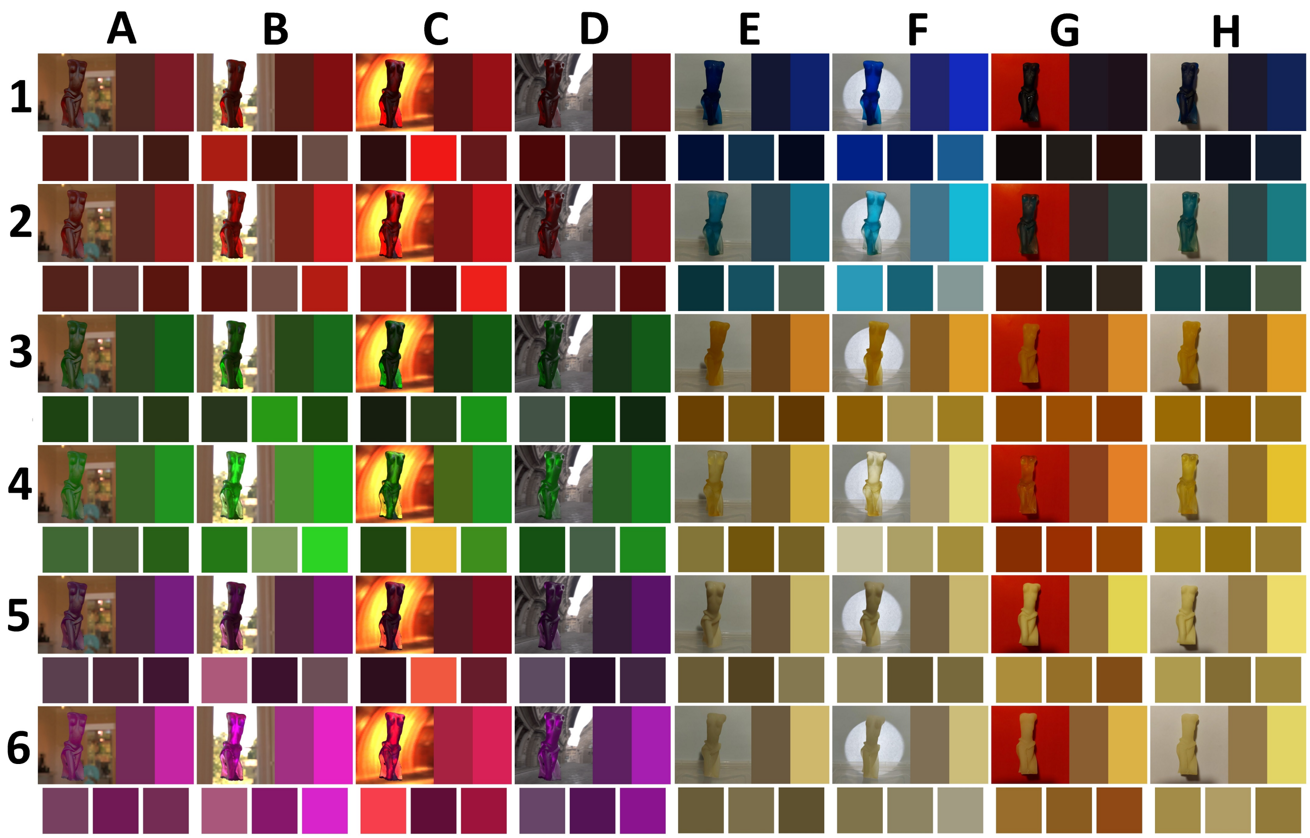

Figure 5: Each block shows the following: the image of the translucent object (top left), the average color of the object (top middle), the color picked by observers in the color matching experiments (top right), and the three-color palette of K-means centroids in the bottom half. The illumination varies among columns. Besides, columns A-D show synthetic images, while columns E-H show photographs of real objects. Each row shows two materials in four different conditions each (A-D in a given row is one material; E-H another material).

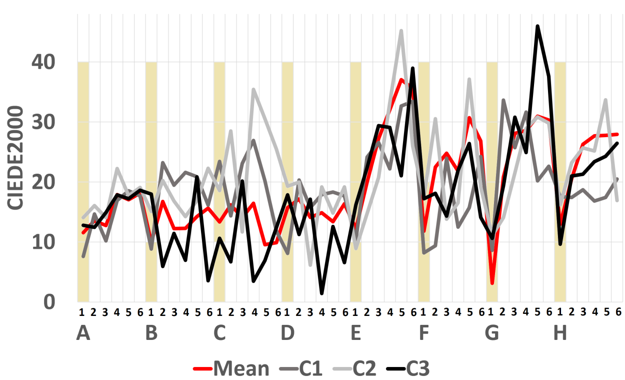

Figure 6: CIEDE2000 color difference between matched color, on the one hand, and pixel-wise average or cluster-centroids, on the other hand. Grayscale curves correspond to 3 different cluster centroids, while the red curve corresponds to the average. The images are grouped by the lighting conditions, and the alphanumeric labels correspond to their coordinates in Fig. 5.

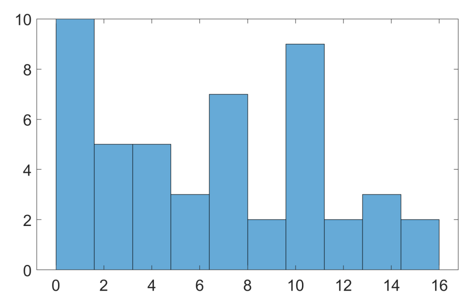

Figure 7: The histogram of discrepancies in CIEDE2000 color difference between matched color and the average, and between matched color and the closest K-means centroid. If the average is the closest one, the discrepancy is 0.

jects are lit from behind, their color difference is larger. This has significant implications, because color difference measurements on sample materials under controlled laboratory conditions is unlikely to generalize to other conditions. The lower the opacity, the larger is the dependence on the conditions.

In this work, we provide more thorough analysis of the experiment. In particular, we analyze the correlations between perceived (ΔV) and calculated (ΔE) color differences and explore whether perceived color differences between translucent objects can be predicted by calculating traditional color difference metrics from images without first matching objects to a single uniform color, which would be highly impractical in many applications. In [8], we argue that traditional color difference metrics are developed for small color differences and suggest using metrics that are specifically tailored for large color differences, since the average colors of translucent objects usually have very high calculated color differences. Abasi *et al.* [22] studied color difference metrics for very large color differences. They concluded that a hybrid model, which incorporates Euclidean distance in chroma and hue, and the cityblock distance for lightness differences, performs best for such scenarios. They refer to the metric as HyAB (*Hy* stands for hybrid) and calculate it as:

$$HyAB = |\Delta L_1^* - \Delta L_2^*| + \sqrt{[(a_1^* - a_2^*)^2 + (b_1^* - b_2^*)^2)]} \quad (1)$$

They also studied completely cityblock-distance-based metric cbLAB:

$$cbLAB = |\Delta L_1^* - \Delta L_2^*| + |a_1^* - a_2^*| + |b_1^* - b_2^*| \quad (2)$$

In addition to HyAB, and cbLAB, we also calculated CIE76, CIEDE2000, and achromatic difference ΔL*, since the reference is achromatic. The color difference was found between the average colors of the two objects. Afterward, we calculated correlation between ΔV and ΔE values, which ranged between 0.75 and 0.90 and did not substantially differ among the four metrics, ΔL* having the lowest correlation. With a simple linear model, calculated ΔE values explained 75% of variation in ΔV (R^2=0.75). Afterward, we calculated STRESS – the Standardized Residual Sum of Squares metric, as proposed by [23] and implemented in [24]. STRESS is normalized in 0-100 range, with 0 meaning the perfect agreement. Among the four metrics, CIEDE2000 produced the lowest STRESS value (38), while it was 47, 49, 49, and 62 for CIELAB, HyAB, cbLAB, and ΔL*, respectively. Interestingly, achromatic difference was the worst correlate of the ΔV, even though the reference scale was achromatic.

Fig. 10 shows a plot of ΔV as a function of ΔE. We can see the linear relationship between the two – ΔV increases as the ΔE increases. However, the STRESS value is lower for high ΔE cases than it is for low ΔE ones, when analyzed separately.

It is not clear exactly what single color should be input to the color difference formula to reliably estimate perceived differences. The previous sections demonstrated that average color itself is a poor predictor of what humans consider the color of the translucent object. Therefore, instead of calculating color differences between average colors, we conducted clustering for each individual image and generated a palette of three dominant colors per object. As shown in Fig. 5, not all colors of the palette are close to what humans pick as the most representative color. Therefore, we calculated color differences among all possible combinations of the palette colors (3×3=9 comparisons per pair). If we have 9 options for ΔE per comparison, many of them will be indeed irrelevant and far from what humans would pick. For 36 comparisons, there are 9^{36} combinations of ΔEs, which is, indeed, infeasible to test exhaustively. However, we calculated STRESS for 100 million random combinations and got comparable STRESS values to that of average color differences. Indeed, when fewer comparisons are made, likelihood of better ΔE combinations increases. We tested STRESS for 100 million random combinations, but this time for 10 random comparisons only (9^{36} vs 9^{10}) and identified cases with STRESS value as low as 8. This indicates that if properly conditioned and carefully chosen, K-means color palettes may provide more reasonable color differences than the simple pixel-wise average. Interestingly, a greedy approach, always selecting the palette colors with the largest sum of L* and C* yielded a rather high STRESS value of 55.

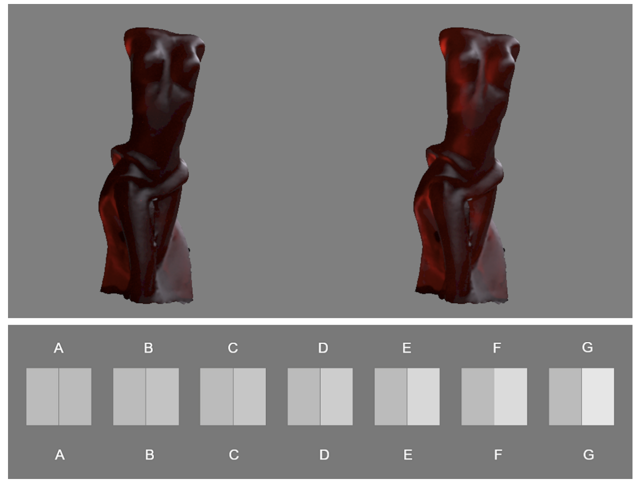

Figure 8: A sample comparison of two translucent objects used in the psychophysical experiment, and the grayscale reference. The task was to compare the color differences and pick the grayscale pair, which best matches the color difference between the translucent objects. The grayscale patches were measured on a calibrated display using a spectroradiometer. The color differences between a reference and test patches were ensured to increase in linear steps. Reproduced from [8].

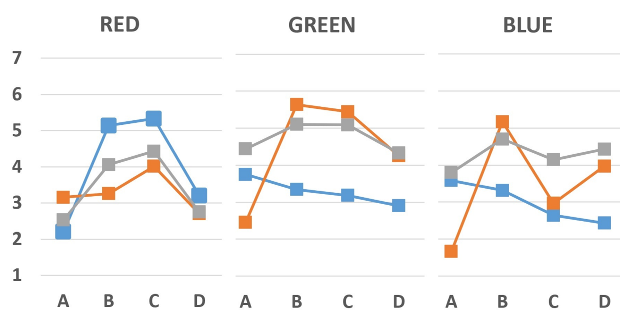

Figure 9: Perceived color differences for red, green, and blue objects. Scenes A, B, C, and D correspond to different illumination conditions. Namely, Bernhard Vogl's light probe *At the Window* illuminating the object from front (A) and back (B), and Paul Debevec's *The Grace Cathedral* (also mostly back-lit) (C) and *The Uffizi Gallery* (ambient diffuse light) (D), respectively. Blue curve corresponds to comparisons between the objects with medium and high opacity; Orange – between the medium and low opacity; and gray – between high and low opacity. Reproduced from [8].

Conclusion

3D translucent objects are a vivid example of limitations that the traditional point color measurements suffer from. Their colors highly vary among different parts of the object and depend on many external factors that make their measurement and communication a difficult task. In this paper, we followed up previous literature and demonstrated that in comparison with the global spatial average color, observers usually overestimate lightness and chroma, when they are asked to pick a single color for the entire object. Hue is invariant in most cases except for transmissive objects on a chromatic background. Average colors are often biased by large but less salient regions that observers pay less attention to. Therefore, K-means clustering provides a promising method for extracting dominant colors, some of which can be a better cor-

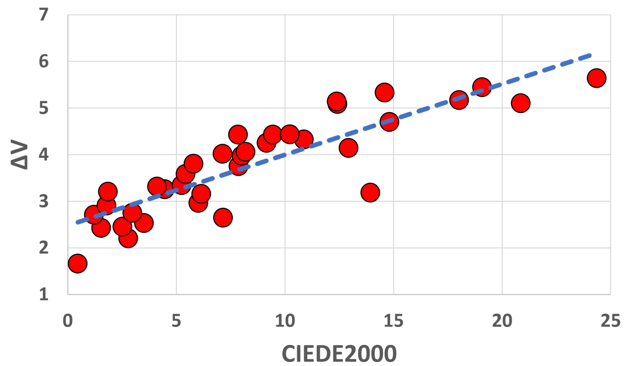

Figure 10: ΔV as a function of CIEDE2000 color differences. Blue line corresponds to a linear fit.

relate of the single most representative color. Color difference between objects' average colors is highly correlated with perceived magnitude of color differences between two translucent objects. However, clustering methods may help to capture more accurate computational correlate of perceived color differences.

Many unanswered questions remain for future works. It is not clear whether aiming for single color representation, which we usually do in daily lives for color naming, is the best approach. A set of multiple local averages may be more robust and consistent descriptors of translucent objects. Image saliency and eye tracking research may reveal some of such regions. Whether objective optical properties or rendering parameters, such as absorption and scattering coefficients, can be universal predictors of matched color in different scenes also merits future research. Color differences are highly dependent on lighting conditions, which is a substantial challenge for industrial applications. Two translucent samples may exhibit translucency-induced metamerism: they may match in color in the laboratory but look noticeably different in other environments. Traditional color difference metrics provide only limited information about color differences between translucent objects. Very large color differences that are usually exhibited by translucent objects as well as multiple parametric factors (such as lighting direction) need to be taken into consideration. The follow up works should explore methods to quantify and model the impact of lighting and object geometry on perception of color and translucency. While this work is limited to a single but a complex shape, it is important to investigate whether these observations generalize to other objects – such as simpler spheres and cubes or those with even more complex geometries.

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