The Role of Background Blur and Contrast in Perceived Translucency of See-through Filters

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Abstract

Translucency is an appearance attribute, which primarily results from subsurface scattering of light. The visual perception of translucency has gained attention in the past two decades. However, the studies mostly address thick and complex 3D objects that completely occlude the background. On the other hand, the perception of transparency of flat and thin see-through filters has been studied more extensively. Despite this, perception of translucency in see-through filters that do not completely occlude the background remains understudied. In this work, we manipulated the sharpness and contrast of black-and-white checkerboard patterns to simulate the impression of see-through filters. Afterward, we conducted paired-comparison psychophysical experiments to measure how the amount of background blur and contrast relates to perceived translucency. We found that while both blur and contrast affect translucency, the relationship is neither monotonic, nor straightforward.

Introduction

Translucency is a significant attribute of objects' appearance [1]. More specifically, it is *"the property of a specimen by which it transmits light diffusely without permitting a clear view of objects beyond the specimen and not in contact with it"* [2]. Visual perception of translucency has attracted attention in the last two decades after computer graphics enabled realistic simulation of subsurface light transport [3, 4]. The majority of the works study complex 3D objects made from highly scattering materials that completely occlude the background – such as jade statues, soap bars, wax figures, glass of milk etc. [4, 5, 6] (see a review on translucency perception in [7]).

Perception of transparency is relatively well-studied and modeled. Transparency is *"the degree of regular transmission, thus the property of a material by which objects may be seen clearly through a sheet of it"* [2]. The primary distinction between *transparency* and *translucency* is subsurface scattering, or lack thereof – *"transparent substances, unlike translucent ones, transmit light without diffusing it"* [8]. However, the two can co-exist in the same object. *"If it is possible to see an object through a material, then that material is said to be transparent. If it is possible to see only a "blurred" image through the material (due to some diffusion effect), then it has a certain degree of transparency and we can speak about translucency"* [9].

The central problem in transparency perception is separation of different spatial layers from the pixel intensities, which is proposedly possible thanks to geometric and colorimetric regularities between the parts of the background seen in a plain view and through a transparent object [10, 11, 12]. Different models of perceptual transparency have been proposed, usually based on thin flat filters. Metelli [13, 14, 15] proposed an episcotister model, where the intensities of an achromatic opaque background and a rotating disc with a missing sector add up. This model was later extended to chromatic stimuli as well [16]. Subsequent works proposed filter models that have two fundamental components – subtractive component that models light's absorption and attenuation through the medium, and an additive component to account for reflection from the surface [10, 11, 12]. While the light attenuation causes the background to be seen darker, the reflection increases the mean lightness of the filter area, both of them affecting the contrast of the background. If earlier works claimed that the perceived transmittance is explained by the comparison of luminance differences in the plain view and filter areas, Singh and Anderson demonstrated that Michelson contrast explains it better [12]. This means that darker objects appear more transmissive than lighter ones with the same optical transmittance due to larger Michelson contrast [12, 17].

The overwhelming majority of these studies have assumed direct transmission without any subsurface scattering and hence, no blurring of the edges. See-through filters, however, can look translucent [12, 17, 18, 19]. Human observers, when possible, attend to background distortions to judge translucency [18], and the human visual system (HVS) is actually more sensitive to translucency and subsurface scattering differences between the two objects when the background is visible rather than when it is completely occluded [19]. Faul and Ekroll [11] noticed that while directional reflectance component is perceived as gloss, reflection of uniform diffuse illumination can be mistaken for subsurface scattering, and decrease in contrast alone – without blurring the edges – can evoke perception of translucency. This was also illustrated in Figure 1 in [7], where the authors suggested that the additive component makes a stronger impression of translucency than absorbing-attenuating component. However, these phenomena were not studied experimentally.

The exception is a study by Singh and Anderson [17], which addressed transparent filters that scatter light. The authors studied how background blur affects perceived transmittance while the Michelson contrast is fixed. They demonstrated that although Michelson contrast is a reliable predictor of perceived transmittance when there is no blur, background blur contributes to perceived transmittance independent of the Michelson contrast; and this cannot be fully attributed to the fact that blur decreases perceived contrast. It is worth noting that in this study authors studied transmittance, which they define as *"the degree to which a transparent layer lets light through from underlying surfaces. Highly transmissive surfaces let a large proportion of the light through; highly opaque surfaces let very little light through"*. This is primarily presented as a transparency-opacity continuum without explicit place for perceived translucency.

In this work, we investigate how background blur and contrast affect perceived translucency. Furthermore, we explore whether contrast reduction alone without any blur can produce translucent look, and whether there is a difference between absorption-attenuation and additive component scenarios of contrast reduction. Finally, we also compare the chromatic and achromatic cases.

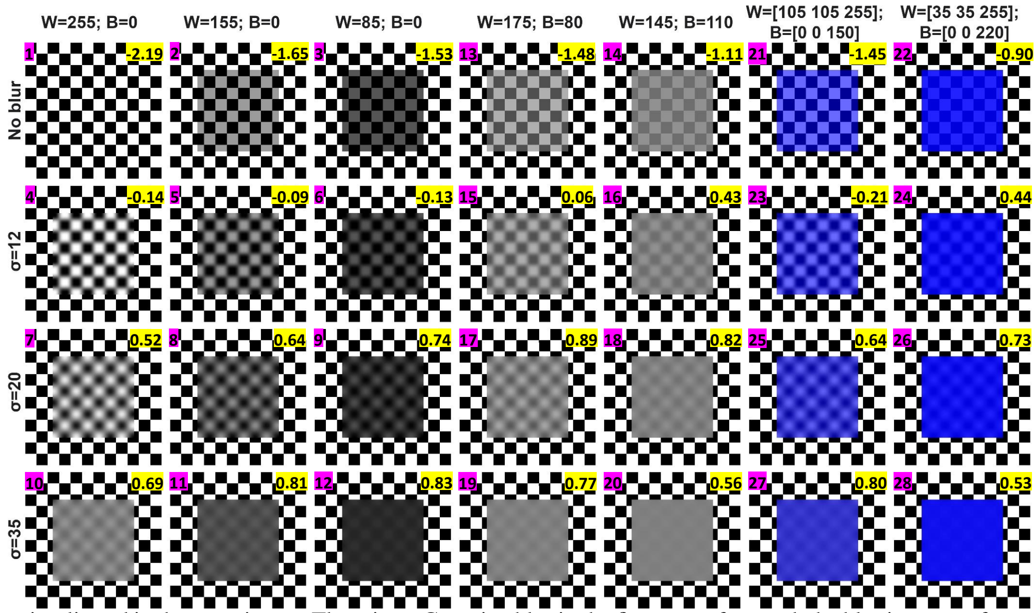

Figure 1: The stimuli used in the experiment. There is no Gaussian blur in the first row; afterward, the blur increases from top to bottom, with σ=12, 20, and 35, respectively. The first column has no manipulation other than blur. The columns 2-3, 4-5, and 6-7 are *absorbing*, *scattering*, and *chromatic scattering* cases, respectively, with contrast decreasing from left to right in each case. The numbers on top of each column specify the intensity or an RGB triplet (chromatic case) for non-blurred white (W) and black (B) patches. The number in magenta box (not shown in the experiment) is a label to identify a stimulus in subsequent plots; respective Z-score is shown in yellow.

Methodology

Experimental Protocol

We conducted a forced-choice pair-wise comparison experiment [20], where observers were shown pairs of stimuli, and they were instructed to select the one that depicted a more translucent filter. As explained in [21], the concept of *more translucent* needs a clear reference, otherwise, it can be interpreted both as *less transparent*, as well as *less opaque*. Because the corpus included the former reference (perfectly transparent filter – a checkerboard with no manipulations), we used *"more translucent and less transparent"* formulation. Before starting the experiment, we tested observer's visual acuity and color vision with Snellen and Ishihara tests, respectively. Additionally, they were given above-mentioned definitions of *transparency*, *translucency*, and *opacity* from [2, 8, 9]. To check the impact of instructions on their performance, a group of 6 observers were given additional clarification on the transparency-translucency-opacity continuum illustrated with the bell-shaped curve proposed in [21].

We used 28 stimuli, where each was compared with all others twice (in a flipped order) in a random sequence, producing 756 comparisons that took each observer approximately 35 to 45 minutes to complete. The time to answer was not limited. The experiment was hosted on the QuickEval platform [22] and conducted in controlled conditions in a dark room, where the only light source was the display. The patches were displayed on BenQ SW321 monitor, with 3840×2160 px and 60Hz refresh rate. The display was calibrated as follows: Gamut: sRGB; Gamma: 2.2; Brightness: $80\frac{cd}{m^2}$; White point: D65; Black point: 0.19 units. The distance between the screen and the observer was 50 cm. Images were displayed on a gray background separated with a 15 px gap. The delay between trials was 200 milliseconds.

Stimuli

The stimuli were created by manipulating a black-and-white checkerboard texture of 799×799 px resolution, where part of the texture remained intact, while blurring and/or contrast manipulations were applied in a center of the image – creating the impression of a see-through filter. Each image was 14.65 cm in both dimensions and occupied 16.67° of the field-of-view (FoV), i.e. 1.39° of the FoV per square of a checkerboard. According to the *transmittance-anchoring principle* [23], the area with the largest contrast is considered the plain view of the background, and the one with less contrast - a transparent overlay. Three levels of Gaussian blur and three types of contrast manipulation were applied with two levels each. Gaussian blur was used to be consistent with [12]. The stimuli with no Gaussian blur and no contrast manipulation were also included. We used 28 stimuli in total: 4 (levels of blur) × [3 (types of contrast) × 2 (levels of contrast) + 1 (intact contrast)]. Blur also affects contrast, but here *contrast manipulation* means change in the checkerboard patch intensities without blurring their edges.

The Gaussian blur was applied using MATLAB's *imgaussfilt()* function [24], with a default kernel size and standard deviation σ equal to 12, 20, and 35. Although each σ step was not necessarily perceptually equal, we made sure that the blur differences among all levels were clearly noticeable. In the first type of contrast manipulation, we kept the intensity of the black patches to 0, and decreased the contrast by making white patches darker. As demonstrated in [7], this simulates the filter that absorbs light and darkens the background (*absorbing filter*). In the second type of the contrast manipulation, we simultaneously made white patches darker and black patches lighter. As proposed in [7], introduction of the additional energy in the black pixels seen through the filter evokes impression of scattering or reflection (*scattering filter*). Finally, the third type of contrast manipulation was similar to the *scattering filter*, but the intensity was decreased only for the red and green channels of the white patches, and increased only in the blue channel of the black ones, to produce bluish chromatic filters (*chromatic scattering filter*). We conducted a pilot study with red, green, and blue primaries. To avoid excessively long experiments, we finally picked one chromatic color. Since a similar phenomenon was already demonstrated for red in [7] and several observers pointed out that blue is the hue they associate most with the concept of translucency, we decided to focus on blue. Whether the perceptual trends vary among hues is an interesting topic for future research. All stimuli with respective parameters are shown in Figure 1.

Observers

15 observers, 8 female and 7 male, with an average age of 30.71 years, took part in the experiment. All of them had normal or corrected-to-normal visual acuity and normal color vision. While the majority had knowledge in color science, none of them were familiar with the translucency perception research.

Analysis and Discussion

The result of the psychophysical experiments is illustrated as Z-scores and their respective 95% confidence intervals in Figure 2. It shows that blur has a significant impact and is a major factor in filters' translucency. However, there is a noticeable diminishing returns and even negative returns effect when blur is too high, as the filters start to appear opaque. Besides, contrast alone without introducing additional blur impacts translucency. However, this effect is significant only when there is no blur, or when σ=12 – only for scattering and chromatic scattering cases. While in low blur scenarios decrease in contrast increases translucency, the opposite is the case for highly blurred filters (see filters 17-20 and 27-28 in Figure 1). These are the aggregate results for all 15 observers. As mentioned previously, we studied the impact of definitions and instructions. While they had negligible impact on most of the filters, it turned out that the instructions are critical in specific cases with high σ. When *less transparent* was provided as a sole reference, decrease in contrast was still increasing translucency – as it was further away from transparency (e.g. filter 18 had higher mean Z-score than filter 17; filter 20 than filter 19; filter 26 than filter 25); however, the opposite was true for another group, which saw the bell-shaped curve hypothesis with transparency and opacity as the references on the two opposing ends; in their case, the decrease in contrast for highly blurred filters decreased translucency as the filter was perceived more opaque. This demonstrates the importance of instructions and definitions. While this conclusion needs to be taken with care due to low number of observers and high variance in each group, this point deserves rigorous study in the future. Finally, the filters with absorbing and scattering ways of contrast reduction yield different luminance range and Michelson contrast. When they are used as predictors for a Z-score separately in each case, the slope is steeper for the scattering one, which may be an indication that the latter has stronger effect. However, to get a deeper insight, future work should use more stimuli, where contrast will be equal between absorbing and scattering cases.

The data shows that contrast and blur manipulation can induce significant differences in perceived translucency. However, the exact calculations that the HVS relies on remain unclear. There is no agreement on quantitative contrast metrics. Luminance range and Michelson contrast [13, 12, 17] have been proposed for this purpose. In order to calculate contrast metrics, we first normalized RGB values in the range of 0-1, linearized them and then converted linearized RGB to L relative luminance values (in the range of 0-1, where 1 means $80\frac{cd}{m^2}$ (white) and 0 means $0.19\frac{cd}{m^2}$ (black)). For each filter region, we calculated the following metrics previously proposed in the literature [12, 17, 25, 26, 27, 28]: mean difference between non-linear RGB values of black and white squares in no blur versions of a filter; luminance range ($L_{\max} - L_{\min}$); mean luminance L_{avg}; standard deviation of luminances; Contrast ratio ($\frac{L_{\max}+0.05}{L_{\min}+0.05}$, 0.05 is added to avoid division by zero); Michelson contrast ($\frac{L_{\max}-L_{\min}}{L_{\max}+L_{\min}}$); Weber contrast ($\frac{L_{\max}-L_{\min}}{L_{\min}}$); King-Smith and Kulikowsi (KSK) contrast ($\frac{L_{\max}-L_{\text{avg}}}{L_{\text{avg}}}$); and RMS variation of luminance values (RMS). We also tested more sophisticated perceptual contrast metrics proposed by Peli [27] and Simone *et al.* [29], but they did not distinguish different levels in our stimuli and were excluded from further analysis. Due to *transmittance-anchoring principle* [23], each of these metrics where divided by the value of the same metric for the intact checkerboard pattern seen in a plain view. Finally we studied whether these metrics are linearly correlated with the Z-scores. The results are summarized in Table 1 (marked in yellow). None of these metrics show high correlation except standard deviation of the luminance values, which is negatively correlated with translucency - lower standard deviation means more translucent, but as we have seen in Z-scores, this is true only to a limited extent. Blur in our dataset has considerably stronger effect on translucency than contrast manipulation alone. The reason why all these contrast metrics are poorly correlated with Z-scores is the fact that they do not adequately capture blur; e.g., the filters with the same contrast manipulation and different blur level can have nearly identical luminance range and Michelson contrast, because blur may not affect the minimum and the maximum values in the entire filter. However, if we consider each blur level separately, the correlation increases for Michelson contrast to -0.87 -0.95 -0.56 -0.76, for each level of σ, respectively. We fit a simple linear model with Michelson contrast as a predictor and Z-score as a dependent variable (Figure 3). Michelson contrast can to some extent explain the variation in observers' responses when σ is fixed.

This means that we need to quantify blur in addition to contrast metrics. Although blur itself impacts contrast, we showed that these contrast metrics alone cannot fully capture the effect of blur. Singh and Anderson [17] use the standard deviation of the Gaussian (σ) as a measure of blur. There is no universal way to quantify perceived blur, and it remains a topic of research in image quality [33]. Therefore, we also quantify blur with σ. In addition to that, we explored whether no reference image quality metrics that are designed to capture blur (BRISQUE [30], NIQE [31], PIQE [32], JNBM [33], CPBD [34]) and full-reference image quality metrics (PSNR, SSIM [35]), where the intact checkerboard pattern is a reference, could be of any use. Table 1 (blue rows) shows that σ is positively and significantly correlated with translucency, while SSIM also showed relatively high correlation. Although PIQE and CPBD show very high correlation too, they need to be taken with care, because they take identical values for several different stimuli and essentially group high blur and low blur – i.e. high Z-score and low Z-score – filters into two distinct clusters. Image quality metrics usually suffer from biases for very high degrees of blur [33].

Figure 3 shows Z-score as a function of σ, which explains 71% of the overall variation in Z-scores. However, we can see that there is more variation remaining in Z-score values for each σ level, which, as mentioned previously, can be quantified by Michelson contrast. Therefore, we ran multiple linear regression to check whether σ and Michelson contrast as two predictor variables could adequately predict a Z-score. The fitting resulted in a model with $R^2 = 0.72$, F-statistic$= 21.04$, and p-value< 0.01. While there are indications that blur and Michelson contrast are significantly correlated with the degree of perceived translucency, there is a considerable amount of variation that remains unexplained. Ferzli and Karam [33] showed that the amount of σ needed to produce just noticeable blur differs among different contrast levels. We also tried a model with an interaction term, which slightly increased R^2 to 0.79.

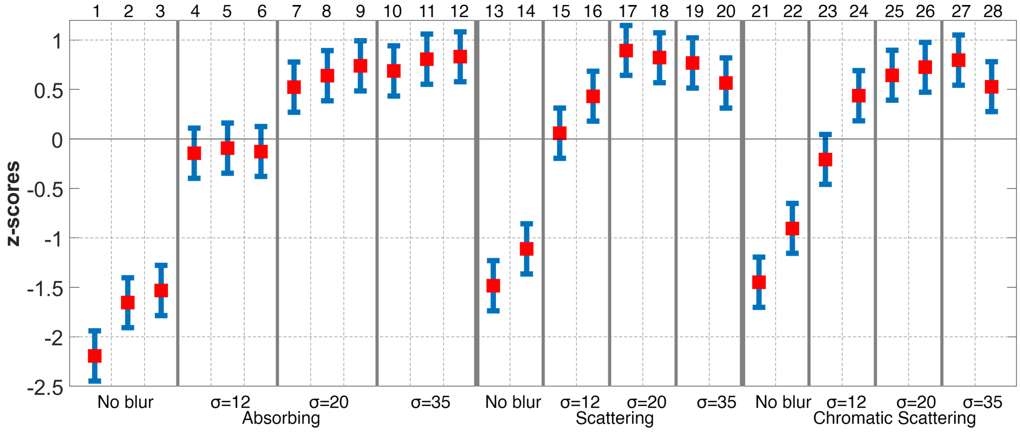

Figure 2: Z-scores for all 28 stimuli. The higher the Z-score, the more translucent the stimulus. Red squares and blue whiskers mark mean Z-scores and 95% confidence intervals, respectively (equal variance is assumed for all stimuli). The numbers on top of the figure correspond to the stimuli number in Figure 1. The stimuli are grouped by Gaussian blur level and contrast manipulation type (*absorbing*, *scattering*, *chromatic scattering*) from left to right, respectively. The plot illustrates that manipulating contrast alone affects perceived translucency when blur is low, while its role decreases for the stimuli with high blur. Gaussian blur itself significantly affects perceived translucency, but this relationship is not monotonic, and highly blurred filters may appear opaque not translucent.

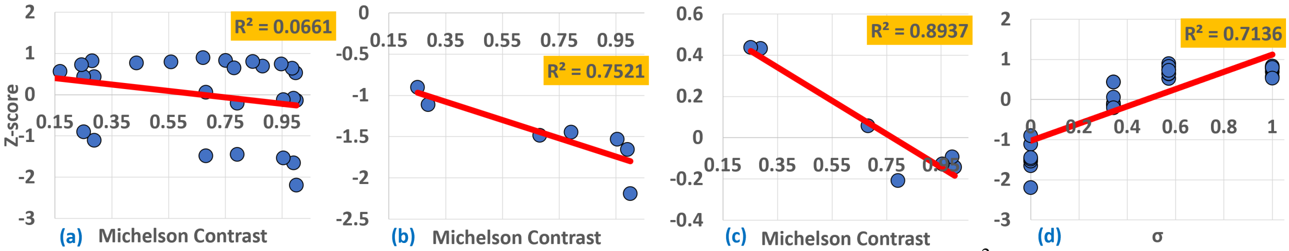

Figure 3: Z-score as a function of Michelson contrast (a-c) and σ (d). The number in the orange box is R^2 of the linear fitting. Michelson contrast cannot explain Z-score variation when stimuli with different levels of blur are considered (a); The correlation is larger if the level of blur is fixed (subplot (b) and (c) correspond to no blur and σ=12 scenarios, respectively). This needs to be taken with care. In future works more even sampling is needed in the Michelson Contrast space to evaluate the linearity. σ alone can explain 71% of the variation in the data, but it is apparent that for low σ, there are still significant differences in translucency within each level of σ.

Singh and Anderson [17] found that not only Michelson contrast, but also blur affects perceived transmittance. Our findings are consistent with this and can be extended to translucency. Blur in our case seems to be the major cue to translucency, while contrast to some extent explains variations among the filters with the same degree of blur. Their study also mentions that observers usually overestimate transmittance of filters that make background darker, while underestimate that for filters that make background lighter. Similar indications are found in our study too; this question merits a further study with more stimuli. To judge translucency, observers seemingly use yet unknown combination of contrast and blur (which itself is an additional source of contrast reduction). The mathematical metrics proposed in the literature do not fully explain the variation in their responses. Which contrast and blur metrics are best to predict perceived translucency remains an open question for future research.

Conclusion

In this study we investigated how contrast and blur affect perceived translucency of flat see-through filters. The contrast was manipulated by changing pixel intensities in black and white patches of the checkerboard texture, while keeping the edges intact, and Gaussian filter was applied to introduce blur. We made several important observations: firstly, blurring sharp edges increases perceived translucency, but this is characterized by diminishing or even negative returns effect – for large amounts of blur, the filter becomes too homogeneous where background is not well discernible anymore, the filter appears opaque and translucency decreases; secondly, manipulation of contrast alone (keeping the edges intact) can affect translucency when the filter is not too blurry; furthermore, there are indications that filters that lighten black part of the background and darken white part of it may appear more translucent than those that only darken the white; and finally, the filters with high blur and low contrast may be interpreted in two different ways that depends on the a priori instructions and definitions of translucency given to observers.

Table 1: Pearson's and Spearman's correlation coefficients between Z-scores and measures of contrast (yellow) and blur (blue).

	Pearson	p-value	Spearman	p-value
Pixel Diff.	-0.31	0.11	-0.37	0.05
Range	-0.25	0.20	-0.25	0.20
L_{avg}	-0.33	0.08	-0.25	0.20
Stdev	-0.57	<0.01	-0.58	<0.01
Ratio	-0.27	0.16	-0.29	0.14
Michelson	-0.26	0.19	-0.33	0.09
Weber	-0.33	0.08	-0.33	0.09
KSK	0.14	0.47	0.04	0.84
RMS	-0.57	<0.01	-0.58	<0.01
σ	0.84	<0.01	0.88	<0.01
BRISQUE	-0.56	<0.01	-0.79	<0.01
NIQE	0.09	0.64	0.16	0.42
PIQE	0.93	<0.01	0.76	<0.01
JNBM	-0.17	0.38	-0.05	0.78
CPBD	-0.92	<0.01	-0.75	<0.01
SSIM	-0.79	<0.01	-0.60	<0.01
PSNR	-0.19	0.35	-0.35	0.06

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