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Blurring Impairs Translucency Perception

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Abstract

Translucency and factors impacting its perception is not yet fully understood. Various studies have examined the correlation between physical material properties and perceived translucency. Furthermore, the concept of translucency constancy has been introduced. However, to the best of our knowledge, no study has been conducted to identify how image quality impacts perceived translucency. In this study, we address to one particular image quality attribute - blurriness. We quantified blur with objective image quality metric and conducted psychometric scaling experiments to identify how blurring impacts the perceived degree of translucency. The analysis of the results show some indications that blur impairs translucency perception.

Introduction & Background

Translucency is among the least studied appearance attributes [1]. No single agreed definition of translucency exists. According to Eugene [1], "translucency occurs between the extremes of complete transparency and complete opacity... 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"; while Gerbino [2], defines distinction between transparency and translucency as "transparent substances, unlike translucent ones, transmit light without diffusing it."

The most extensive survey of the image cues affecting translucency perception has been carried out by Fleming and Bülthoff [3]. They review a broad range of the factors affecting the perceived translucency, like specular highlights, color, object scale, image contrast and illumination direction.

Furthermore, the study by Xiao *et al.* [4] concludes that perceived degree of translucency depends strongly on the illumination direction, phase function used in rendering (i.e. a probability distribution over directions, which describes the angular distribution of scattered light), and object geometric properties. In the same paper, they introduce the concept of translucency constancy, i.e. an ability of human beings "to estimate translucency in a consistent way across different shapes and lighting conditions."

It has been illustrated that the background and the pattern seen through the translucent material can also have dramatic impact on translucency perception [5].

In computer vision, translucency perception is often considered within the broader problem of material identification [6, 7, 8, 9]. Even though image quality has been considered an important factor for identification tasks in other fields, e.g. biometrics [10, 11], references to image quality as one of the factors impacting material identification and object appearance, is limited. Motoyoshi [12] argues that blurring non-specular regions, while keeping the specular highlights intact, increases the perceived degree of translucency, but blurring the whole image is not mentioned in the paper.

An interesting study has been conducted by Sharan *et al.*[9], where the authors demonstrated that blurring impairs material categorization. They tried to study the role of surface properties, like color, texture and gloss, in material categorization. They created a database using images from Flickr image sharing website[1] and sorted the images into nine material categories. The authors conducted psychophysical experiments, where observers had to categorize the materials. Afterwards, they introduced different degradation in the images, which they believed removed or decreased the role of the different surface properties (e.g. they used grayscale images to remove the role of color), conducted another material categorization experiment with the degraded images and compared the categorization accuracy with that of the original experiment. In order to remove high spatial information and impair texture recognition, the authors blurred the images and demonstrated that blurring the images decreased categorization accuracy from original 91% to 75.5%.

Sharan *et al.*[9] did not explicitly refer to image quality, but the authors obviously degraded the quality of the images when they blurred them. Blurring the images impairs not only texture recognition, but also makes surface geometry, shadings and highlights more ambiguous, because the luminance histogram is shrunk and the high contrast areas get smoother, as demonstrated by Motoyoshi[12]. The fact that blurring the images decreases material categorization accuracy on the one hand, and degrades the cues that are demonstrated to be correlated with translucency perception [3, 4, 12], on the other hand, we found it interesting to investigate further, how image quality, in terms of blurriness, impacts perceived degree of translucency.

The key research question is the following:"can blur of the image impact perceived degree of translucency?"

However, dilemma was whether to blur the whole image, or just the object. Therefore, as mentioned above, two different experiments were held with different stimuli: one with the images with the whole scene and context, and another one with the translucent objects cropped and displayed on neutral gray backgrounds. Hence, another research question arouse:"do blurred objects seen in the blurred scene demonstrate higher degree of translucency constancy than blurred objects seen in isolation?"

There are two major points that motivated us study the correlation between blur and translucency perception: first of all, in broader perspective, we are interested how different translucency perception is between the people with impaired and normal vision. Secondly, we want to identify how image quality impacts the perception of appearance attributes - translucency, in this case, and whether there is any threshold, when the quality becomes not acceptable when addressing the images of the translucent objects. In contrast with full scene images, isolated object images look unnatural. However, in non-blurred versions of them, we still have

[1] https://www.flickr.com

enough cues to consider the objects translucent. In the broader perspective, we want to identify, what are those cues, when they vanish and when a translucent object becomes a non-translucent blob.

To the best of our knowledge, no study has been conducted to examine the impact the blurriness of the image has on perceived degree of translucency of the materials. The aim of the study is to identify, and if possible, quantify, the impact blurriness of the image has on perceived translucency. The subsequent chapters are organized as follows: in Research Methodology & Experimental Setup chapter, we will discuss the approach applied to the problem. Afterwards, we will illustrate and discuss the results in Results & Discussions and finally, draw the conclusions from the latter and define directions for the future work.

Research Methodology & Experimental Setup

Design of the Experiments

The psychometric experiments were conducted using QuickEval web-based tool[13] . The experiments were held in two parts: one for the whole-scene images, and another one for the isolated objects. As mentioned above, full-scene experiments included the original images and blurred versions of them, while in isolated-object experiments, the translucent objects were cropped from the original images (and blurred versions of them), and placed on the neutral gray background, in order to remove scene and contextual information. Both experiments were pairwise comparisons [14], where the observers were shown two images and were given the following instruction: "Select the object with higher degree of translucency, i.e. transmitting higher amount of light." Additional oral instructions given, if needed. The experiment was conducted in forced-choice regime, where the observer necessarily had to select either object of the pair. The same pair was displayed twice in a flipped order. No reference image was displayed separately. Three different versions of each image were used in each of the experiments: original, moderately blurred and highly blurred. This totals to nine images within each experiment. All the images were compared against each other - hence, considering that the pairs were shown in a flipped order as well, 72 comparisons and about 10 minutes were needed for each of the experiments.

The observers could recognize the objects shown in isolated object experiments on the gray background were simply cropped from the full-scene images that they had already seen in full-scene image experiments. In order to discard the effect of this issue, we used different triplets of the images for full-scene and isolated object experiments. All the observers completed the experiments in the following order: 1. Full Scene Image-based experiment. 2. Isolated Object Image-based experiment.

Stimuli

We used the Flickr Material Database created by Sharal *et al.*[9] As the focus of this research is translucency, we used the images from the single category "Glass". Six different images were selected in total - three for full-scene image experiments, and three for isolated object image experiments. All images were RGB color images, provided in JPEG format and with resolution of 512×384 pixels. In order to avoid confusion among observers, only images with a single translucent object were selected.

The images were randomly selected from the database (with the constraint of including just single translucent object). "Moderate" and "High" Gaussian blur was applied to each of the images, with standard deviation of 5 and 25 respectively (with default kernel size of MATLAB *imgaussfilt* function [15]). The examples of the blurred images are illustrated on Figures 1 - 6. We understand that the number of images is low. However, we focused on the number of observers, rather than the number of images, as according to Sharma [16] *"given the amount of time necessary to perform these experiments,it is often more desirable to have a larger number of observers."*

Display

The experiments were conducted in controlled conditions. The images were displayed on EIZO CG246 display, with 1920x1200 resolution and 59 Hz refresh rate. The display was calibrated according to the following parameters: Gamut: sRGB; Gamma: 2.20; Brightness: 80 cd/m^2; Black point: 0.19 cd/m^2; White Point: 6502K, with the following x,y coordinates: (0.3127,0.3293); Contrast Ratio: 412:1;

The experiment was held under dim ambient illumination. The illumination was 27 lux in front of the keyboard and the color temperature of the ambient illumination was 4450K. The distance to the screen was approximately 50 centimeters.

Observers

20 observers, 12 males and 8 females, with normal, or corrected-to-normal vision voluntarily participated in the experiment. Average age of the observers was 28.1 years. The observers had technical background, but were naïve to translucency studies.

Analysis of the Collected Data

Collected subjective evaluation data was analyzed in the following way: first of all, Z-scores and their 95% confidence intervals [14] were used to illustrate the responses of the observers. Furthermore, binomial sign tests were conducted to examine the significance of the difference between the observations [17, 18]. The raw data, as well as the p-values out of the binomial sign tests are reported below.

On the other hand, objective metric was used to quantify the degradation of the image quality. Namely, Structural Similarity (**SSIM**) - Full Reference image quality metric [19] - where the original image was considered a reference, with SSIM score of 1, while the SSIM score was found for two blurred images. 1 is considered best score (full similarity), while 0 is the worst case (no similarity). SSIM is one of the metrics used to measure Gaussian blur degradations [20]. It's worth mentioning that metrics, like BRISQUE, or blur-specific [21, 22], CPBD [23] and JNBM [24] failed to adequately quantify very high amount of blur.

Finally, Pearson's Linear Correlation Coefficients were found between the objective image quality assessment metric and the mean z-scores obtained for each of the psychometric scaling experiments.

Results & Discussion

Image Quality

SSIM metric reflects the changes in the image quality and the score has a decreasing tendency as the image is blurred. Please, refer to the Figure 7.

Figure 1. *"Glass" full-scene image: Original (left), moderately blurred (middle), and highly blurred (right)*

Figure 2. *"Horse" full-scene image: Original (left), moderately blurred (middle), and highly blurred (right)*

Figure 3. *"Pot" full-scene image: Original (left), moderately blurred (middle), and highly blurred (right)*

Figure 4. *"Scull" isolated object image: Original (left), moderately blurred (middle), and highly blurred (right)*

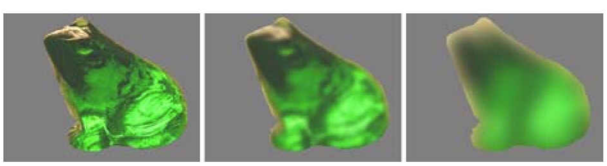

Figure 5. *"Frog" isolated object image: Original (left), moderately blurred (middle), and highly blurred (right)*

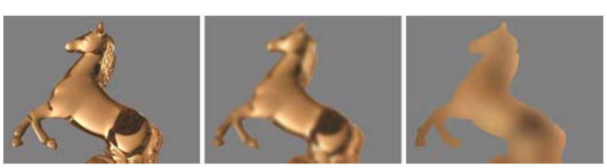

Figure 6. *"Horse" isolated object image: Original (left), moderately blurred (middle), and highly blurred (right)*

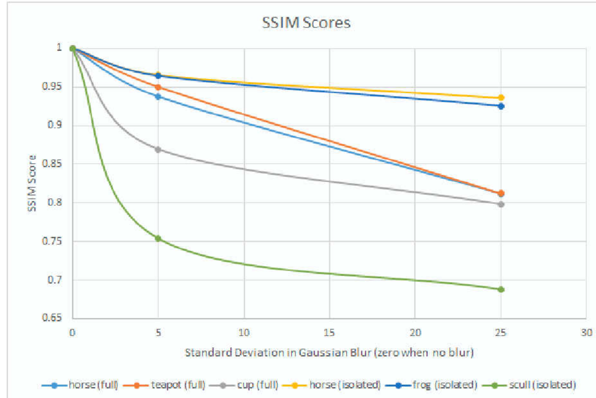

Figure 7. *SSIM score as a function of the amount of blur*

Psychometric Scaling Experiments

Z-scores of the psychometric scaling experiments are illustrated on Figure 8 and Figure 9. Figure 8 summarizes the z-scores of the three full-scene images with three different degrees of blurriness. As we can see on the figure, mean z-score for the undistorted image is always higher than that of its blurred versions. For all three images, there is no overlap of the confidence intervals between more blurred and less blurred versions of a particular scene (although there is a substantial overlap between 95% confidence intervals for different images (Cup, Horse, and Teapot)). Considering this clear separation, we can conclude that perceived degree of translucency decreases for a given object when the image is blurred. This is logical and intuitive for the images with high amount of blur, as high blur removes all the cues necessary for translucency perception (highlights, shades, background that is seen through, surface geometrical properties) and transforms the translucent object into a nearly homogeneous patch. On the other hand, when blur is moderate, translucency perception is impaired less dramatically in comparison with the original. Therefore, we can conclude that translucency perception impairment is correlated with the amount of degradation introduced.

Figure 9 illustrates z-scores for three isolated object images with three different degrees of blurriness, when the objects are seen in isolation on the neutral gray background. The trend remains the same as in case of the full-scene images: mean z-scores, i.e. perceived degree of translucency decreases, as the blurriness increases. However, in contrast with the full-scene images, the gap between mean z-scores, as well as between the confidence intervals of the different versions of the same image is less than that of full-scene images.

This is opposite to our expectation that access to the full-scene context might lead to higher translucency constancy. Whether impact of the full-scene information is statistically significant, needs further examination with larger dataset. As the images used for the two experiments are different, they are not directly comparable. The reason for the difference can be content of the image and characteristics of the objects, rather than the lack of access to the full context information. However, one of the explanations for this indication is that cropped objects, in contrast with the objects in blurred full-scene images, still stand out from the homogeneous background, considering that the edges are clear,

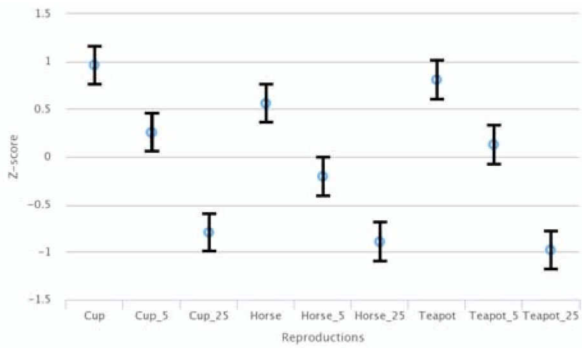

Figure 8. *Translucency z-scores for each of the examined full-scene images. The number after image name indicates the standard deviation of the Gaussian blur. The error bars and the blue circles show 95% confidence interval and the mean z-scores respectively. Same variance assumed for all the samples.*

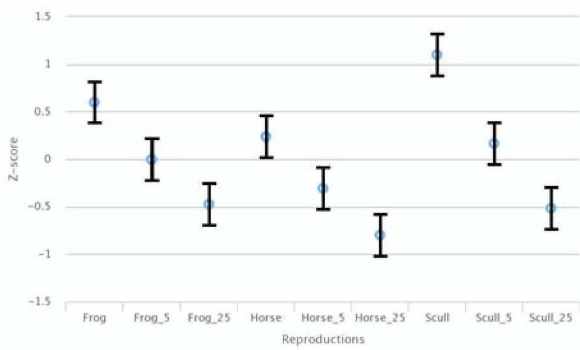

Figure 9. *Z-scores for each of the examined Isolated Object images. Same variance assumed for all the samples.*

evoking a perception of the object as a hole transmitting light. Besides, the highlights, texture other translucency cues might be more apparent when observing on the homogeneous background. This can be a topic for further investigation.

Pearson's Linear Correlation

The fact that image quality distortion is correlated with impairment of translucency perception, means that image quality assessment is important while working on quantification of perceived translucency and image quality metrics could be used to predict the extent to which translucency constancy could hold. In order to further examine this hypothesis, Pearson's Linear Correlation coefficients between SSIM values and mean z-scores were found. For Full-scene images, the correlation coefficient was significantly high - equal to 0.91. On the other hand, SSIM values and z-scores for Isolated Object images demonstrated little correlation, as the coefficient was equal to 0.36.

This can be explained with the fact, that the large area covered with neutral gray background in the isolated object images, leads to high structural similarity even for highly blurred images, while as we have already seen, blur significantly decreases mean z-scores for those kind of images (refer to Figure 10). Therefore, we found SSIM values from cropped objects only, disregarding gray background in the SSIM pooling step. However, correlation coefficient between new SSIM values and mean z-scores increased insignificantly - up to 0.42. The reason for this could be the content of the images: as shown on Figure 10, the scull has very complex shape and fine details that lead to higher structural dissimilarity when blurred. Hence, need for further investigation with larger and more diverse dataset, as well as for the application specific image quality metric arises and should be considered in the future work.

Figure 10. *The Quality Maps for moderately (left) and highly (right) blurred "Scull" (top) and "Glass" (bottom) images. Lighter areas mean higher similarity, darker areas mean less similarity with the original.*

In this particular case, we could have found correlation between z-scores and the amount of blur introduced (standard deviation of the Gaussian blur function) avoiding objective image quality metrics. In this case, high correlation has been demonstrated even for isolated images. However, in real-life situations information about the distortion might not be available. This is the primary reason, why it is very important to have objective metrics that quantify the amount of degradation and correlate well with the perceived degree of translucency.

Sign Tests

In order to further substantiate the credibility of our findings, we studied the raw data and conducted binomial sign tests on them. The raw data can be found in Tables 1 and 2, for full-scene - and isolated object images, respectively. The number in the cell signifies the number of the observers, which considered the object of the corresponding row more translucent than the object of the corresponding column. The names of the objects without numbers represent the original images, while the names with the numbers signify the blurred images with the number signifying the standard deviation of the Gaussian blur. The number of responses for each pair sums up to 40, as there were 20 observers and each pair was shown twice, in a flipped order. In order to compensate the problem of multiple comparisons, we applied Bonferroni[25] correction to our data.

As we observe for full-scene images, objects with high amount of blur are mostly significantly less translucent, except for the cases, when compared against other highly blurred images. Moderately blurred images are also significantly less translucent than the original ones. Refer to Table 1. The results are color-coded: if object in the corresponding row is significantly more translucent than the object in the corresponding column, the cell is green; if it is significantly less translucent, the cell is red; while

Table 1. The raw data of the observer responses for full-scene images. Raw p-values obtained from the binomial sign tests are given in the parentheses. Green cell: object in the corresponding row is significantly more translucent than the object in the corresponding column; Red cell: object in the corresponding row is significantly less translucent than the object in the corresponding column; White cell: no statistically significant difference.

	Cup	Cup_5	Cup_25	Horse	Horse_5	Horse_25	Teapot	Teapot_5	Teapot_25
Cup		34(8.36e-06)	34(8.36e-06)	29 (0.0064)	35(1.38e-06)	36(1.86e-07)	17 (0.4295)	35(1.38e-06)	35(1.38e-06)
Cup_5	6 (8.36e-06)		35(1.38e-06)	16 (0.2681)	26 (0.0806)	35(1.38e-06)	14 (0.0806)	18 (0.6358)	36(1.86e-07)
Cup_25	6 (8.36e-06)	5 (1.38e-06)		7 (4.23e-05)	11 (0.0064)	18 (0.6358)	7 (4.23e-05)	7 (4.23e-05)	16 (0.2681)
Horse	11 (0.0064)	24 (0.2681)	33(4.23e-05)		34(8.36e-06)	35(1.38e-06)	11 (0.0064)	33(4.23e-05)	36(1.86e-07)
Horse_5	5 (1.38e-06)	14 (0.0806)	29 (0.0064)	6 (8.36e-06)		33(4.23e-05)	8 (0.0001)	11 (0.0064)	33(4.23e-05)
Horse_25	4 (1.86e-07)	5 (1.38e-06)	22 (0.6358)	5 (1.38e-06)	7 (4.23e-05)		6 (8.36e-06)	5 (1.38e-06)	22 (0.6358)
Teapot	23 (0.4295)	26 (0.0806)	33(4.23e-05)	29 (0.0064)	32 (0.0001)	34(8.36e-06)		33(4.23e-05)	36(1.86e-07)
Teapot_5	5 (1.38e-06)	22 (0.6358)	33(4.23e-05)	7 (4.23e-05)	29 (0.0064)	35(1.38e-06)	7 (4.23e-05)		37(1.95e-08)
Teapot_25	5 (1.38e-06)	4 (1.86e-07)	24 (0.2681)	4 (1.86e-07)	7 (4.23e-05)	18 (0.6358)	4 (1.86e-07)	3 (1.95e-08)	

Table 2. The raw data of the observer responses for isolated object images. Raw p-values obtained from the binomial sign tests are given in the parentheses. Green cell: object in the corresponding row is significantly more translucent than the object in the corresponding column; Red cell: object in the corresponding row is significantly less translucent than the object in the corresponding column; White cell: no statistically significant difference.

	Frog	Frog_5	Frog_25	Horse	Horse_5	Horse_25	Scull	Scull_5	Scull_25
Frog		36(1.86e-07)	35(1.38e-06)	19 (0.8746)	34(8.36e-06)	35(1.38e-06)	6 (8.36e-06)	29 (0.0064)	30 (0.0022)
Frog_5	4 (1.86E-07)		35(1.38e-06)	14 (0.0806)	25 (0.1538)	33(4.23e-05)	5 (1.38e-06)	17 (0.4295)	29 (0.0064)
Frog_25	5 (1.38e-06)	5 (1.38e-06)		12 (0.0165)	18 (0.6358)	30 (0.0022)	5 (1.38e-06)	10 (0.0022)	25 (0.1538)
Horse	21 (0.8746)	26 (0.0806)	28 (0.0165)		30 (0.0022)	29 (0.0064)	10 (0.0022)	21 (0.8746)	25 (0.1538)
Horse_5	6 (8.36e-06)	15 (0.1538)	22 (0.6358)	10 (0.0022)		29 (0.0064)	5 (1.38e-06)	18 (0.6358)	22 (0.6358)
Horse_25	5 (1.38e-06)	7 (4.23e-05)	10 (0.0022)	11 (0.0064)	11 (0.0064)		4 (1.86e-07)	9 (0.0006)	13 (0.0384)
Scull	34(8.36e-06)	35(1.38e-06)	35(1.38e-06)	30 (0.0022)	35(1.38e-06)	36(1.86e-07)		34(8.36e-06)	36(1.86e-07)
Scull_5	11 (0.0064)	23 (0.4295)	30 (0.0022)	19 (0.8746)	22 (0.6358)	31 (0.0006)	6 (8.36e-06)		36(1.86e-07)
Scull_25	10 (0.0022)	11 (0.0064)	15 (0.1538)	15 (0.1538)	18 (0.6358)	27 (0.0384)	4 (1.86e-07)	4 (1.86e-07)	

white cells signify no statistically significant difference. The rows of the original images (Cup, Horse, and Teapot) are composed of 16 green, 8 white, and 0 red cells. The number of green cells decreases down to 8 for moderately blurred image rows, while there are 7 red, and 9 white cells. Finally, the rows corresponding highly blurred images are composed of just 17 red and 7 white cells. There is a clear trend that less blurry versions are considered more translucent by the observers.

On the other hand, difference is not significant in many cases when judging cropped objects. The original image rows are composed of 11 green cells, and 7 out of them is accounted for the "Scull" image that is considered the most translucent one among the nine images.

Besides, the amount of blur does not make significant difference between the versions of the Horse image. It is very interesting that this object at some extent demonstrates translucency constancy. One of the reasons for this could be the dark texture that can be perceived as being inside the object and that is present even on the blurred image.

Furthermore, highly blurred version of the Scull is significantly different only from other less blurry images of the Scull. Considering this, we could hypothesize that the impact of blur on the perception of very translucent objects is limited. However, the observers might be biased with their knowledge about the original Scull image - relying on that information regardless the appearance of the actual blurred version. Another reason could be that the Scull is achromatic with a lot of specularities that as has been demonstrated by another study [26] might also significantly impact translucency perception.

It is also worth mentioning that many differences might become more significant, if the experiment is conducted with higher number of observes. Example of this is illustrated on Table 3.

Table 3. P-values decrease, when the number of observers increases, but the portion of the observers with similar response remains the same.

Number of observers with similar responses	P-values
15 out of 20	0.04138947
30 out of 40	0.002221434
45 out of 60	0.000134514
60 out of 80	8.58E-06
75 out of 100	9.58E-07

Conclusion and Future Work

To summarize, we have introduced different amount of Gaussian blur to the Flickr Material Database images. Afterwards, the blurriness were quantified by objective image quality assessment metric and psychometric scaling experiments were conducted to determine, how introduction of blur impairs perception of translucency.

The data analysis has shown that for given images, blur significantly impairs translucency perception and the degree of impairment is correlated with the amount of image degradation.

We have also demonstrated that for full-scene images, SSIM objective image quality assessment has significant correlation with the perceived degree of translucency, while introduction of homogeneous background in isolated images, decreases this correlation. As examined image quality metrics, like BRISQUE, CPBD, and JNBM failed to adequately quantify high amount of blur, needs for more application specific metric arise.

Furthermore, there are some indications that the effect of blur is more dramatic when full scene is blurred. We hypothesize that cropped blurred images with sharp edges are unnatural and might evoke the perception of the object as a hole transmitting the light. Besides, the translucency cues might be more apparent on the homogeneous background. This can be a topic of the further study comparing appearance of identical objects in those two setups.

In order to model the impact of blur on translucency perception and identify the limits of translucency constancy, larger number of images, as well as smaller steps in blurriness variation are needed in the future study. More diverse database will also help figure out the fundamental reasons why blur impairs translucency perception and what are the cues people use for translucency assessment.

Finally, we were limited just to a single type of image distortion in this paper. In further study, we will examine how distortions other than blur, e.g noise, or compression artifacts, impact translucency perception and translucency constancy.

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