Effects of Contrast Adjustment on Visual Gloss of Natural Textures

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ABSTRACT

We propose a novel subband-based S-curve transformation for increasing the perceived contrast of images, and use it to explore the relation between perceived gloss and perceived contrast of natural textures. The proposed transformation makes minimal assumptions on lighting conditions and does not require prior knowledge of surface geometry. Through a series of subjective experiments with both complex real-world textures and synthesized Lambertian surfaces, we show that there is a strong and robust correlation between perceived contrast and perceived gloss, regardless of the composition of the texture. We also show that contrast modification of an image with near-frontal illumination can compensate for the change in perceived gloss due to an oblique illumination (of the same texture at the same viewing angle).

Keywords: Gloss perception, local band-limited contrast, natural texture, relief height

1 INTRODUCTION

Visual texture can be characterized by a wide range of attributes that provide important cues for material perception, such as color composition, gloss, roughness, sharpness, and regularity. The focus of this paper is on visual gloss, which is a fundamental attribute that describes the appearance of the surface of an object. Materials like paper, metal, and plastics can be perceptually distinguished based on their characteristic gloss. Thus, we can effortlessly tell the difference between paper and foil and between a metal and a plastic ball. In addition, when walking or driving, we are able to judge whether the road ahead is wet and slippery.

Visual texture in general, and visual gloss in particular, depend on surface geometry and material (intrinsic properties) as well as illumination and viewing angle (extrinsic factors). The human visual system (HVS) can easily estimate surface gloss. However, how it accomplishes this is still an open problem, and so is the derivation of objective psychophysically-based metrics for estimating perceived gloss.

One hypothesis for understanding the process by which the HVS estimates gloss is that it solves an inverse optics problem[1,2] to separate the effects of geometry, material, and lighting. However, this is a complex and ill-conditioned problem that requires supplementary assumptions about the observed objects. Moreover, it requires a lot of time and computation, which makes it unlikely in light of the limited computational resources of the brain and the need to respond quickly to situations that are critical for survival. An alternative hypothesis, known as the ecological approach, is that the brain relies on image statistics to account for the joint effects of the various intrinsic and extrinsic factors that affect texture appearance. This is the approach taken by Motoyoshi *et al.*,[3] who proposed that, under certain conditions, the skewness of the luminance histogram is positively correlated with the perceived gloss. This relatively simple skewness hypothesis was challenged by Anderson and Kim,[4] who

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pointed out that the effect of histogram skewness on gloss perception was highly restricted to the specific stimuli and the specific illumination fields. They argued that the perceived surface gloss can be affected by its 3D shape and the illumination field, which could not be determined from simple photometric histogram statistics. Thus, there is still no full explanation of how the HVS perceives surface gloss, and no objective measures of perceived gloss that work across image content and across lighting/viewing conditions.

An intrinsic material property that has been found to have a significant effect on perceived gloss is surface relief height.[5] Ho *et al.*[5] found that within a certain degree of "bumpiness," increasing the stretch of relief height in viewing direction can change the surface gloss from matte to glossy. The relations among geometrical relief height, skewness, and perceived gloss were further explored by Wijntjes and Pont[6] for synthetically generated Lambertian surfaces. To accomplish their goal, they introduced a simple λ-curve transformation, which effectively manipulates the relief height, and thus has an impact on skewness and gloss perception. They found that, for near-frontal illumination, skewness positively correlates with the degree of surface relief stretch, and hence with perceived gloss. However, such correlation collapses in oblique lighting directions. Therefore, since it is affected by changes in illumination, the skewness hypothesis cannot provide reliable diagnostic information about perceived gloss.

Rather than relying on simple photometric statistics when there is little structural and contextual information about the texture surface, there is general agreement that the HVS relies on context-related image attributes in gloss perception. Recent studies by Marlow and Anderson[7,8] demonstrated that, for synthesized static 3D surfaces, judgments of perceptual gloss depend on heuristically determined weighted combinations of image cues: specular coverage, contrast, and sharpness of specular reflections. However, their experimental results are based on synthesized 3D stimuli with given reflectance functions. When the surface reflectance is more complex, as is typically the case in real-life surfaces, it is difficult to determine the appropriate combination of such cues. Moreover, for images of real objects, estimating and manipulating such cues is a challenging unsolved problem in its own right.

The goal of this paper is to study the perception of gloss in natural textures with minimal assumptions on lighting conditions and without prior knowledge of surface geometry. In contrast to previous studies, which either assume a tightly controlled experimental environment,[3] or rely exclusively on synthetic data to isolate image attributes that affect the perception of gloss,[6–8] we consider a perceptual attribute that is closely related to gloss: image contrast. Thus, our goal becomes the exploration of the relationship between the perceived gloss and the perceived contrast of natural textures. However, rather than manipulating the contrast of specular reflections as in Ref. 7, 8, we propose a transformation that manipulates the overall contrast. As such, it can be applied to any image, including natural textures and synthesized Lambertian surfaces, without prior knowledge of surface geometry. The proposed transformation leverages the work of Haun and Peli[9] on the overall perceived contrast of natural images.

In the remainder of this paper, Section 2 proposes a novel subband-based transformation for perceived contrast enhancement. Section 3 describes the subjective experiments. Section 4 presents the experimental results and Section 5 summarizes the conclusions.

2 CONTRAST MODIFICATION VIA SUBBAND DOMAIN S-CURVE TRANSFORMATION

To explore the relationship between perceived gloss and perceived contrast, we manipulate the texture contrast by applying a transformation to each of the frequency bands and then combine the results.

2.1 Perceived Contrast Analysis

The contrast sensitivity function (CSF) provides the threshold for contrast perception as a function of spatial frequency. The CSF can also be used to predict contrast sensitivities for low-contrast stimuli, but cannot predict sensitivities well above threshold.[10,11] Moreover, the CSF predicts the sensitivities of sinusoidal gratings. For complex images, Peli[12] introduced the concept of local band-limited contrast, that is, the contrast at a particular spatial location and spatial frequency band. For images of natural scenes, the overall perceived contrast is determined by the interaction of contrasts at different spatial frequency bands;[9] Haun and Peli[9] proposed a model that computes the weighted average of the contrast in different frequency bands. They showed that spatial frequencies around the peak of the CSF contribute most to the overall experience of image contrast, while low and high spatial frequencies contribute less.

Peli[12] and Haun and Peli[9] used raised-cosine log filters to obtain a radial subband decomposition. The local band-limited contrast at band k is defined as the ratio of the image filtered by a raised-cosine log filter $G_k(f)$ to the mean of the local luminance. The filter for the k^{th} subband is defined as follows:

$$G_k(f) = \begin{cases} 0.5 + 0.5\cos(\pi \log_2 f - \pi k), & \text{if } 2^{k-1} < f < 2^{k+1} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

where f is the radial spatial frequency. Note that the k^{th} filter is centered around 2^k cycles/picture and has one octave bandwidth. The filters are circularly symmetric, and constitute a perfect reconstruction filter bank.

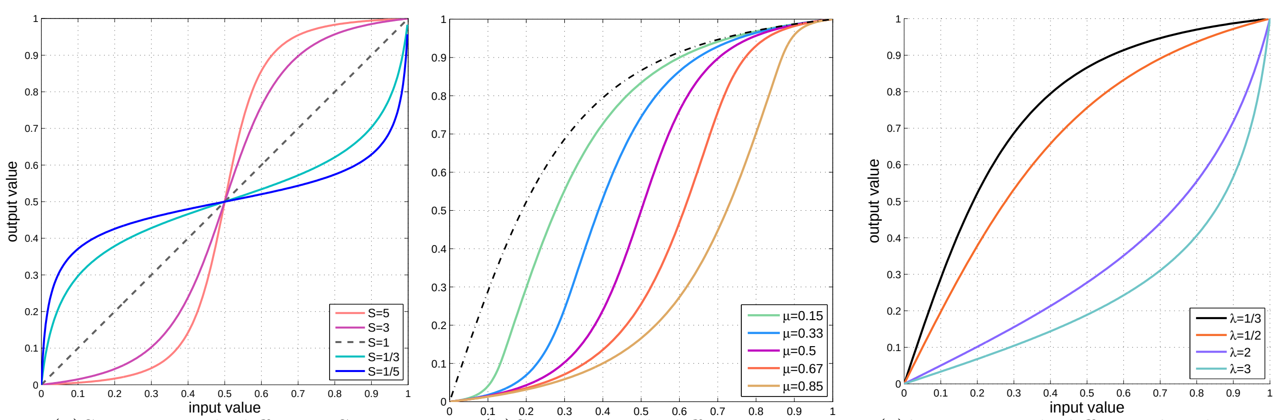
2.2 Subband Domain S-Curve Transformation

To modify the texture contrast, we first decompose the input image into different frequency bands using Peli's raised-cosine log-spaced filter bank.[12] In our experiment, a 256×256 image is divided into eight bands. The first seven one-octave bands are defined by filters $G_k(f)$ with central spatial frequencies at 1, 2, 4, 8, 16, 32, 64 cycles/picture. The eighth band is the residual at frequencies larger than 128 cycles/picture, i.e., $G_7(f) = 1$ for $f \geq 128$. Then each subband image is transformed using the S-curve transformation given in (2) below.

The S-curve transformation is inspired by the λ-curve $\left(Y = \sqrt{\frac{X^2}{X^2+\lambda^2(1-X^2)}}\right)$ transformation in Ref. 6, which was derived from the analysis of the effect of a relief stretch on the pixel luminance of a Lambertian surface under perpendicular illumination in the direction of observation. Figure 1(c) plots several λ curves, where the value of λ represents the degree of stretch of the relief height of the 3D surface.

If X and Y are input and output grayscale values of a (subband) image, taking values in the interval of $[0, 1]$, the S-transformation is defined as follows:

$$Y = \mu - \frac{(\mu - X)}{\sqrt{\alpha^2(\mu - X)^2(1 - 1/S^2) + 1/S^2}}, \tag{2}$$

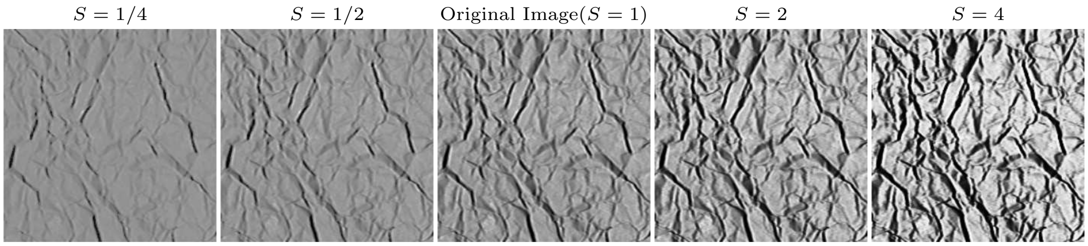


(a)S-curves with different S values ($\mu = 0.5$)

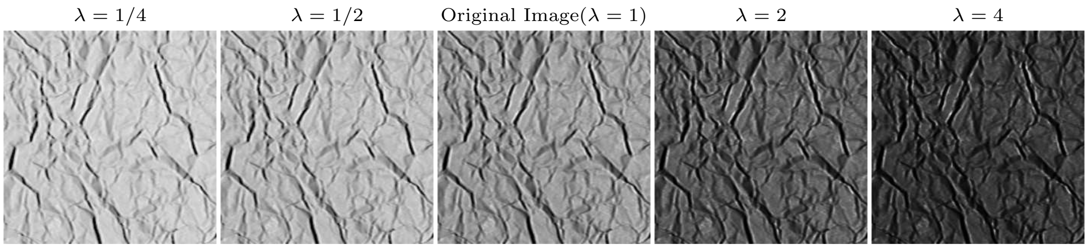
(b)S-curves with different μ values ($S = 3$)

(c)λ-curves with different λ values

Figure 1: Examples of S-curves in (a) and (b) and λ-curves in (c)



(a) Subband S-curve transformed images



(b) λ-curve transformed images

Figure 2: Subband S-curve and λ-curve transformations for CUReT #28

where μ represents the mean value of X, and α and S are parameters that control the shape of the S-curve. The parameter α is given by

$$\alpha = \begin{cases} \frac{1}{1-\mu}, & \text{if } X > \mu \\ \frac{1}{\mu}, & \text{if } X \leq \mu \end{cases}.$$

while S is the slope at the point where $X = \mu$ of the S-curve, and as such, takes values in the interval of $(0, \infty)$.

Figure 1(a) shows several S-curves with different values of S. If $S > 1$, the root-mean-square (RMS) contrast of the output will increase; if $0 < S < 1$, the RMS contrast of the output will decrease. When $S = 1$, the curve is a straight line that leaves the original grayscale values unchanged. The S-curve is centered at μ so that the mean values of X and Y remain the same. Actually, when $\mu \to 0$ and $S \geq 1$, the S-curve approaches a λ-curve as proposed in Ref. 6 with value of $\lambda = 1/S$. For example, the dash-dotted line in Figure 1(b) is plotted with $S = 3$ and $\mu \to 0$, which approaches the $\lambda = 1/3$ plotted in Figure 1(c). As mentioned, the value of μ is determined by the mean of input values, therefore the only free parameter of S-curve that can be controlled externally is the slope S.

Given the eight subband images, to enhance the perceived contrast, we apply S-transformations with high S values to the subbands centered on 1 to 6 cycles/picture, and S-transformations with low S values to the subbands centered far away from the peak range of CSF curve. In the remainder of this paper, we will refer to the subband domain S-curve transformation as the *sub-S-curve* transformation. The detailed parameter settings will be stated in Section 3. Figure 2 shows images transformed by sub-S-curves for different S values and λ-curves for different λ values. Note that the sub-S-curve transformation with S values in the range of 1/4 to 4 results in obvious contrast changes that appear to be increasing with the value of S. The effect of λ-curve transformation on contrast is not as pronounced, and does not appear to be monotonic with λ. However, the value of λ is strongly correlated with the skewness of the illumination histogram. In Figure 2(b) skewness decreases as λ increases from left to right.

3 EXPERIMENTS

In this section, we present two subjective experiments that we carried out to study the relation between perceived contrast and perceived gloss. The goal of the first experiment was to find the effects of the sub-S-curve transformation and the λ-transformation on perceived contrast and perceived gloss, and indirectly, to study the effect of

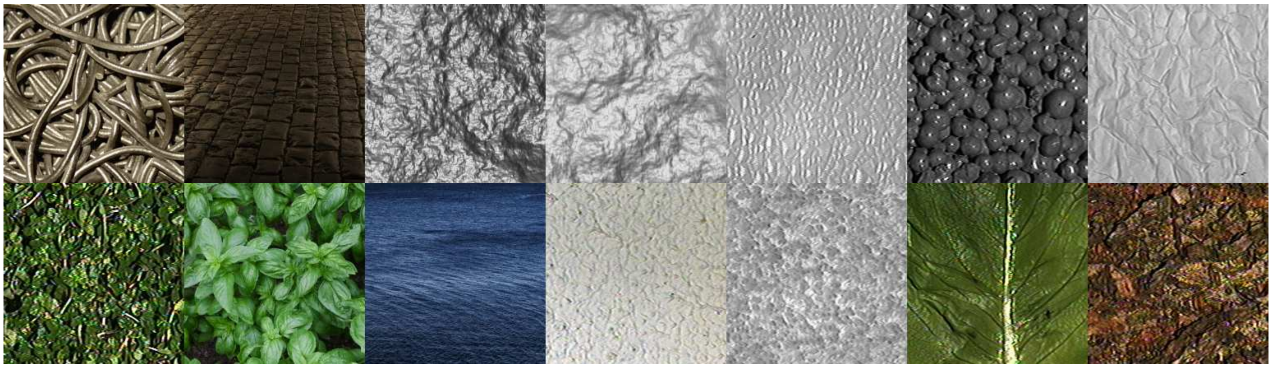


Figure 3: Examples of original texture samples

perceived contrast on perceived gloss. The second experiment considered the influence of (actual) illumination direction on perceived gloss with the goal of determining whether the sub-S-curve transformation can be used to compensate for the change in illumination.

3.1 Apparatus

The experiments were conducted using a calibrated LCD screen with gamma correction and 1920×1080 resolution. The viewing distance was approximately 60 cm, so that a 256×256 pixel image subtended an angle of 9.39 degrees. Thus, the spatial frequency bands of the image decomposition were centered at 0.11, 0.21, 0.43, 0.85, 1.7, 3.4, 6.8 cycles/degree.

3.2 Texture Stimuli

The stimuli used in these experiments consisted of both natural textures and synthesized Lambertian surfaces, all cropped to size 256×256 pixels. The natural texture images were obtained from the CUReT database[13,14] and the Corbis website (`http://www.corbis.com`). Figure 3 shows some examples of the stimuli. To generate the Lambertian surface stimuli, we rendered Brownian random surfaces which approximately have $1/f$ falloff in their amplitude spectra, as in Ref. 6, using the same settings.

Both the CUReT and the Lambertian stimuli contain textures captured from both near-frontal illumination and oblique illumination angles. For each of the CUReT texture samples we used stimuli that correspond to two different illuminations, at polar angles of 0.196 and 0.589 radians, and the same frontal viewing direction, with polar angles of 0.589 radians and azimuthal angle of 3.14 radians. Each Lambertian surface was separately rendered assuming a collimated light source with polar angle of 0 and 50 degrees.

The stimuli contained both grayscale and color textures. For each original image in the **first experiment**, we applied both the sub-S-curve transformation and the λ-curve transformation. The transformations for the color textures were carried out in CIELAB color space. For sub-S-curve transformation we used six different values for S: 0.2, 0.33, 0.67, 1.5, 2.5, 5. We also used six parameter values for λ in λ-curve transformation: 0.67, 0.8, 1.2, 1.5, 2, 2.5.

As we discussed in Section 2.2, for sub-S-curve transformation, the frequency bands centered between 1 and 6 cycles/degree were modified with higher S values (the range of values mentioned in the previous paragraph), while the frequency bands outside the range of 1 and 6 cycles/degree were modified with lower S values (the same range of values decreased by a factor of 2).

3.3 Procedure

The **first experiment** consisted of two sessions. In each trial of the first session, the subjects were presented with seven texture images and were instructed to arrange the images, from left to right, in order of decreasing gloss. The graphical user interface is shown in Figure 4. The definition of “gloss” was left to the subjects, unless they asked, in which case they were told that “gloss” is “the shiny and smooth region of a surface.” The seven stimuli in each trial of the first session consisted of an original texture and six sub-S-curve transformed (or λ-curve transformed) textures in random order. The same type of transformation was used for all of the images in a trial but the type selection was random from trial to trial.

The setup, stimuli, and transformations for the second session were the same as the first, except that the subjects were asked to arrange the images in order of decreasing contrast. Again, the definition of “contrast” was left to the subjects, unless they asked, in which case they were told that “contrast” is “the amount of difference you see between two colors or two grayscale values”.

The goal of the **second experiment** was to consider the influence of (actual) illumination direction on perceived

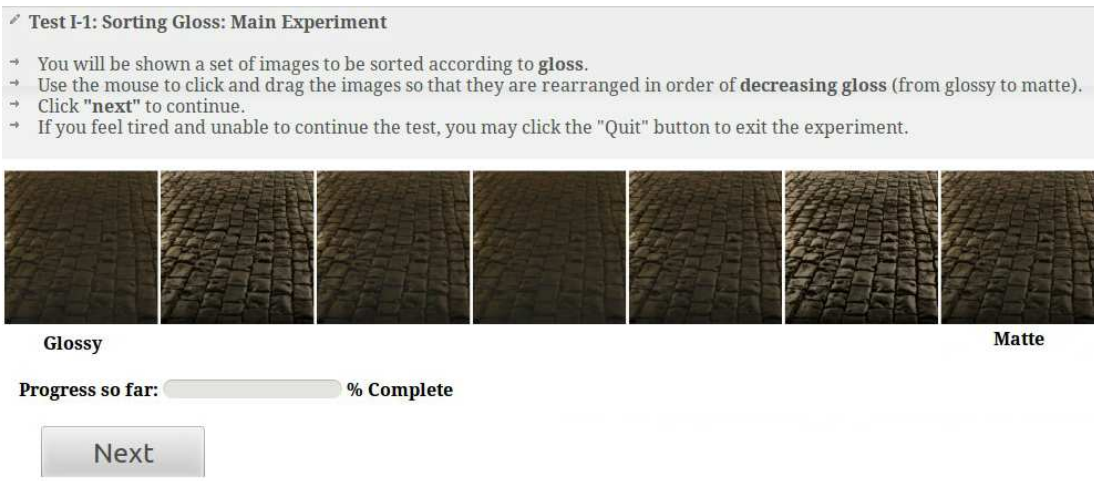


Figure 4: Graphical user interface used in Experiment 1

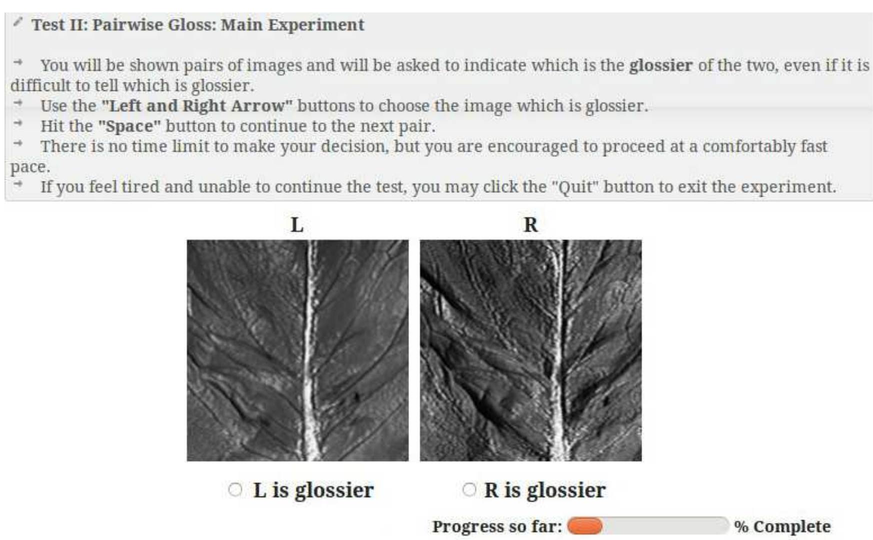


Figure 5: Graphical user interface used in Experiment 2

gloss and to find out whether the S-transformation can be used to compensate for the change in illumination. For this test we used a two-alternative forced-choice experimental setup. In each trial of the experiment, the subject was presented with a pair of images side by side and asked to select the one that is "glossier" using keyboard shortcuts. The graphical user interface is shown in Figure 5. The pair of images in each trial consisted of an original texture in oblique illumination direction and a sub-S-curve transformed version of the same texture in near-frontal illumination. The positions of original and modified images were selected randomly in each trial to eliminate response biases.

In order to eliminate biases due to changes in parameter values for the same image from trial to trial, we randomized the order of the texture samples in consecutive trials.

In both experiments there were no time limits for carrying out the experiment but the participants were encouraged to proceed at a comfortable fast pace. A progress bar was shown at the bottom of the screen. To familiarize the subjects with the experimental setup, each experiment was preceded by a training session.

3.4 Subjects

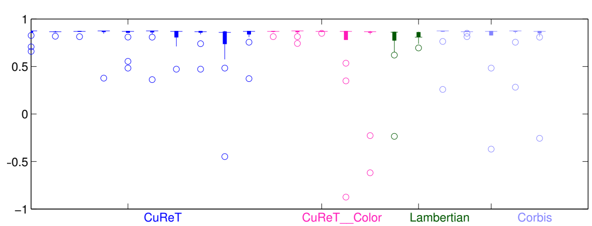
Twenty subjects, 15 male and 5 female, with normal or corrected-to-normal vision, participated in these experiments. There was no financial compensation for participation in the experiments. Participation was voluntary. Before the test, all participants were asked to read and sign a consent form.

4 RESULTS AND DISCUSSION

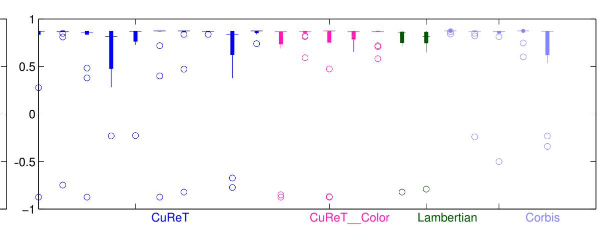
4.1 Experiment 1: Effects of Sub-S-curve and λ-curve transformations on perceived contrast and gloss

By exploring the effects of the two luminance transformations on the perceived contrast and gloss, the first experiment investigated the relationship between perceived contrast and perceived gloss.

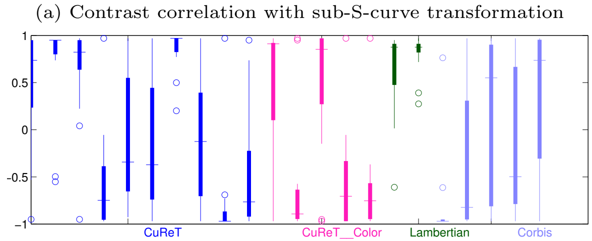
Figure 9 illustrates the subjective gloss and contrast ranking results separately for each of the texture samples under the sub-S-curve and λ-curve transformations. For each texture sample, we calculated the Pearson correlation coefficient between the perceived contrast ranking results and the parameter values of each transformation(S in S-curve, λ in λ-curve), and between the perceived gloss ranking results and the parameter values of each transformation, as shown in Figure 6. As can be seen in Figure 9(a), increasing the slope of the sub-S-curve results



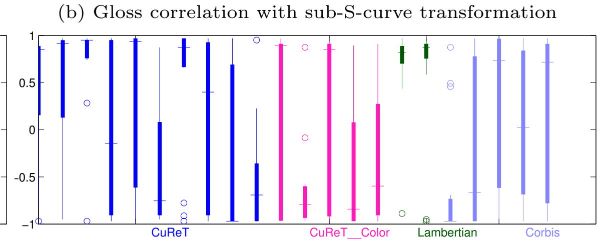
(a) Contrast correlation with sub-S-curve transformation



(b) Gloss correlation with sub-S-curve transformation



(c) Contrast correlation with λ-curve transformation



(d) Gloss correlation with λ-curve transformation

Figure 6: Pearson correlation analysis

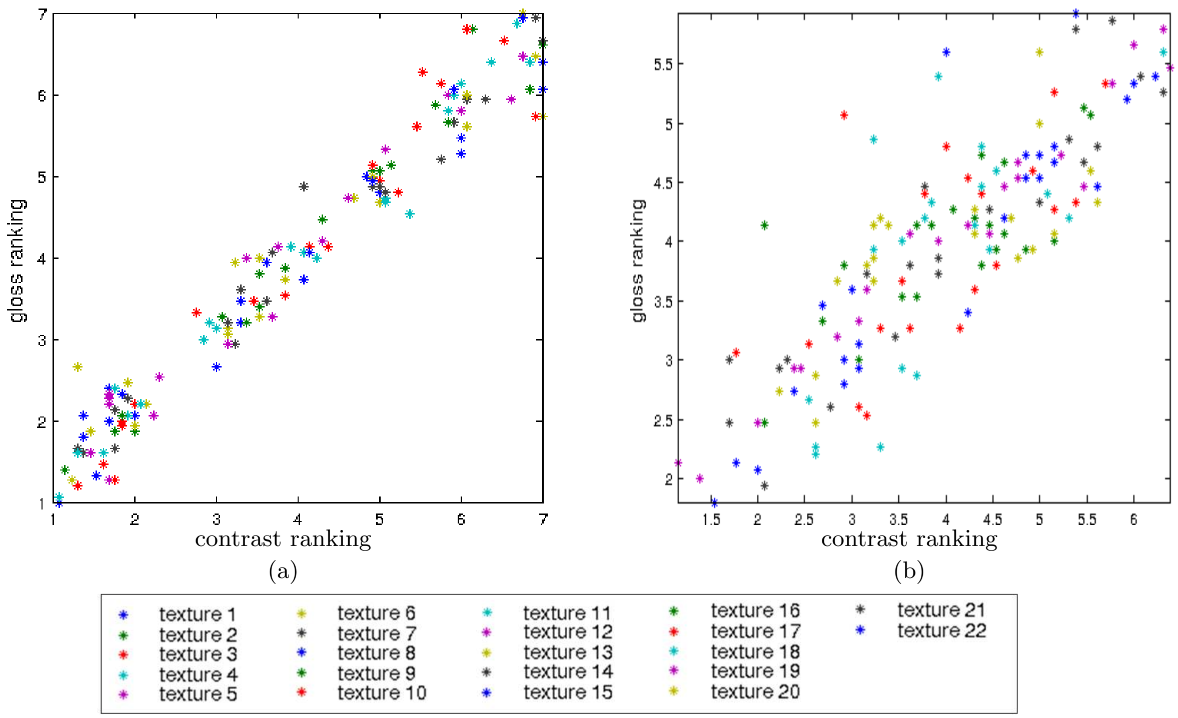


Figure 7: (a) Contrast and Gloss Ranking Relation in sub-S-curve transformation. (b) Contrast and Gloss Ranking Relation in λ-curve transformation.

in an increase of perceived contrast and gloss for almost all types of texture samples. The Pearson correlation coefficients have average values close to 1 and small variances, which indicates that the sub-S-curve effectively manipulates the overall perception of contrast. Similar results hold for the case of perceived gloss as can be concluded from Figure 6(b).

In contrast, the Pearson coefficients that correspond to the λ-curve transformations, shown in Figures 6(c) and 6(d), varied from -1 to 1 for the various textures, with large variances. We conclude that the λ-curve does not have a consistent effect on the perception of gloss and contrast on most natural textures, except for the Lambertian surfaces. The positive correlation between perceived gloss and λ value for the two Lambertian surfaces in near-frontal illumination is in line with the findings of Wijntjes and Pont on Lambertian surface renderings. However, such correlation does not always apply for complex natural scenes.

Figure 7 plots the relation between the rankings of perceived gloss and perceived contrast for the different texture samples, for each of the two transformations. Figure 7(a) shows that under sub-S-curve transformation, the rankings of gloss and contrast align close to the diagonal for almost all the types of textures involved in the experiment, which indicates a robust and strong correlation between perceived contrast and perceived gloss for arbitrary types of texture. We conclude that an increase in perceived contrast increases the perception of gloss, regardless of the structure or content of the texture.

In comparison with Figure 7(a), the points in Figure 7(b) are more randomly scattered. However, this does not necessarily indicate a weaker correlation between perceived contrast and perceived gloss. This is because the λ-curve does not have a consistent effect on the perceived contrast of the input image. Thus, in most cases, the transformed textures do not exhibit clear contrast variations. When the differences in perceived contrast are small, the differences in perceived gloss are also small, which explains the divergence in the rankings of perceived contrast and perceived gloss. Indeed, the comparison of Figures 7(a) and 7(b) can be deceiving because they show rankings with no indication of the strength of the perceived differences.

Table 1: Probability that frontal-illuminated texture with modified contrast (transformed by sub-S-curve with slope S) was chosen as glossier than the oblique-illuminated texture

Texture	$S=1$	$S=1.5$	$S=2.5$	Texture	$S=1$	$S=1.5$	$S=2.5$
CUReT_03	0.15	0.32	0.59	CUReT_35	0.83	0.90	0.98
CUReT_04	0.52	0.82	0.96	CUReT_53	0.05	0.19	0.59
CUReT_10	0.62	0.78	0.81	CUReT_58	0.24	0.42	0.62
CUReT_23	0.42	0.79	0.88	Lambertian_09	0.25	0.28	0.48
CUReT_28	0.34	0.68	0.90	Lambertian_11	0.33	0.53	0.62

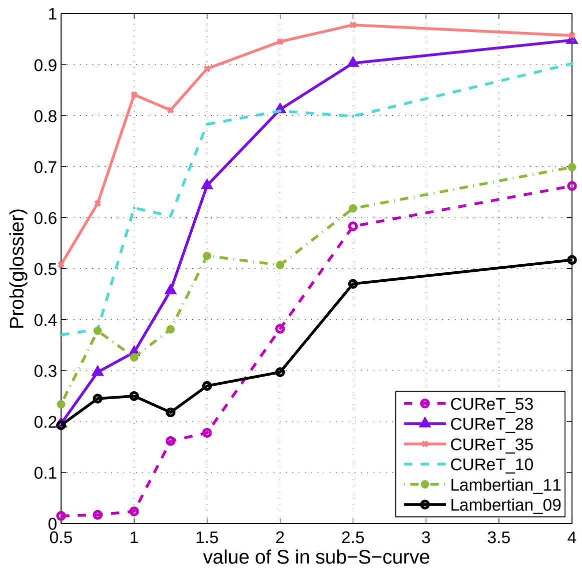


Figure 8: Probability that frontal-illuminated texture with modified contrast (transformed by sub-S-curve with slope S) was chosen as glossier than the oblique-illuminated texture

4.2 Experiment 2: Gloss matching with contrast manipulation

The goal of the second experiment was to determine whether the S-transformation can be used to compensate for a change in perceived gloss due to a change in illumination.

Table 1 shows the probability that the frontal-illuminated texture was chosen as glossier than the oblique-illuminated texture when the contrast of frontal-illuminated texture was modified with different values of slope S of the sub-S-curve transformation.

It can be readily seen that, as the slope of sub-S-curve transformation increases, so does the probability of choosing the frontal illuminated texture rather than the oblique illuminated texture. Figure 8 shows how the probabilities change with the slope of the sub-S-curve for some of the textures in the second experiment. The slope increase represents an increase in perceived contrast. When the probability reaches 0.5, the perceived gloss difference between two conditions (different illumination directions, sub-S-curve compensation) is considered indistinguishable. The nearly monotonically increasing curves suggest that the perceived contrast enhancement via sub-S-curve transformation can compensate for the perceived gloss difference due to a change in illumination direction.

5 CONCLUSIONS

Determining the image attributes that affect the perception of gloss in natural texture images remains a challenging problem for image analysis and psychophysics. Here we have focused on an easier but highly relevant problem. We proposed a novel subband-based S-curve transformation for increasing the perceived contrast of natural textures, and showed that it results in increased perception of gloss. The proposed transformation makes minimal assumptions on lighting conditions and does not require prior knowledge of surface geometry. We thus showed that there is a strong and robust correlation between perceived contrast and perceived gloss, regardless of the composition of the texture. We also found that contrast modification of an image with near-frontal illumination can compensate for the change in perceived gloss due to an oblique illumination (of the same texture at the same viewing angle).

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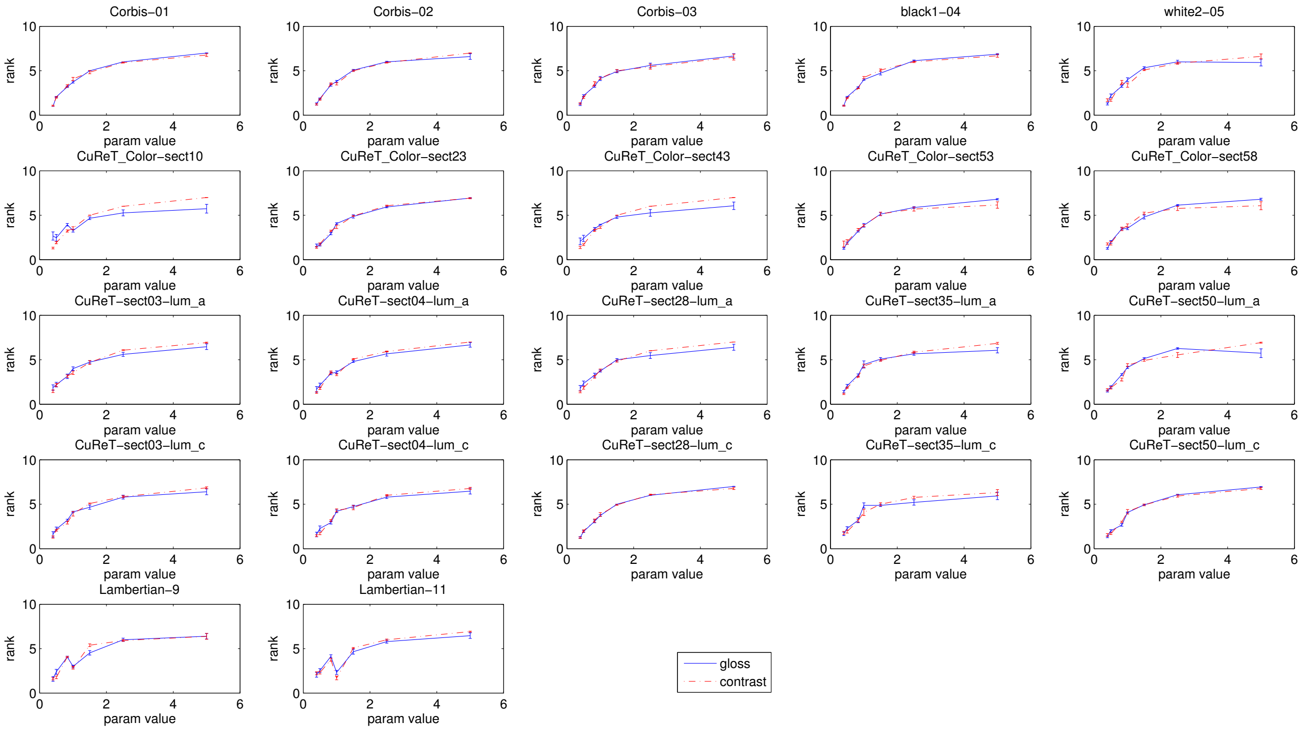
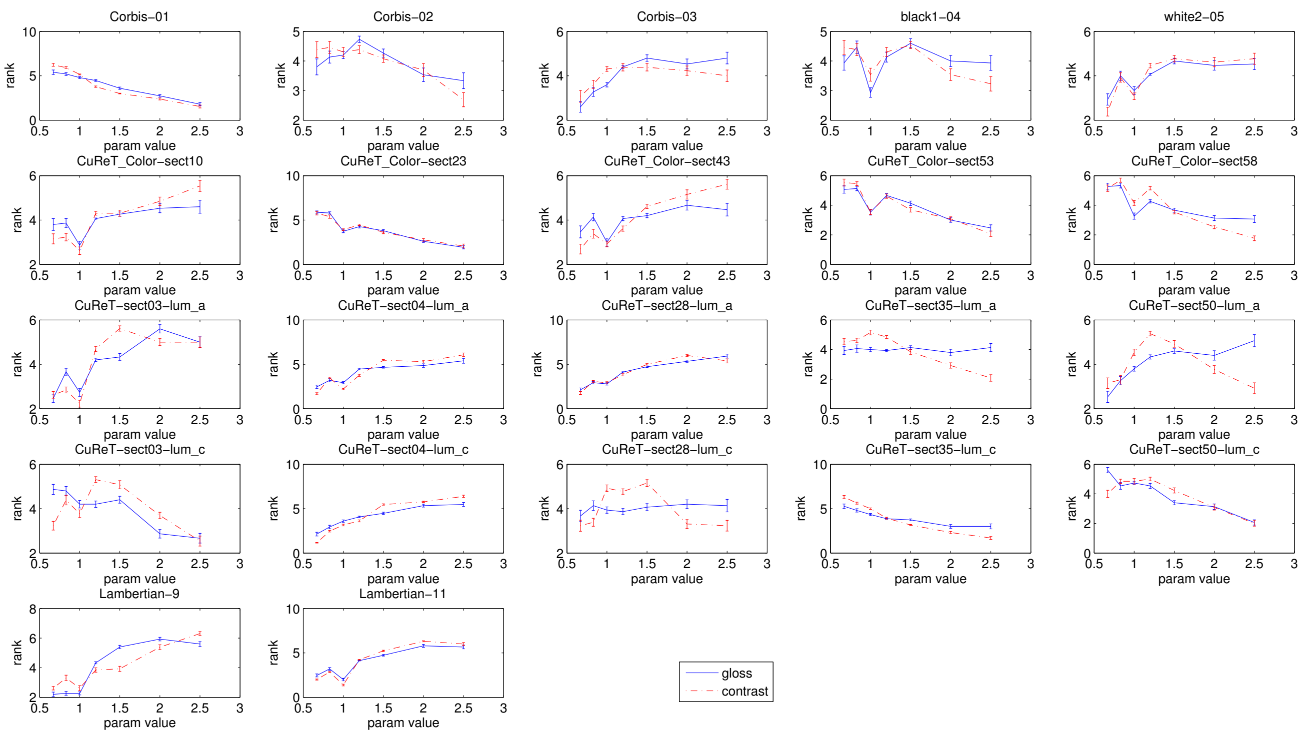


(a) Plots of contrast and gloss ranking results with different S values of sub-S-curve



(b) Plots of contrast and gloss ranking results with different λ values of λ-curve

Figure 9: Comparisons of two transformations on the performance of contrast and gloss of all texture samples