Subjective Rules on the Perception and Modeling of Image Contrast

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Abstract

When evaluating image contrast, the present work found that total impression formed from global and local appearances played an important role. Vividness, clearness and colorfulness were addressed by observers on account of the global appearance generated from an entire image. For the local appearance created from particular areas in an image, four factors were considered: reproduction of detail, distinguishability of objects, either or both lightness- and colorfulness-difference, and colorfulness of objects. To determine changes in perceived contrast arising from variations in the local and global appearances, pixel-based color differences at different image resolutions were selected as image contrast correlate. It was demonstrated that this approach was reasonable in the prediction of perceived contrast changes for images rendered in lightness, chroma or sharpness domain.

Introduction

In the display industry, contrast is generally specified in terms of the contrast ratio computed using the Michelson contrast, Eq. (1), and checker-boards composed of alternating black and white areas [1].

$$C = (L_{\max} - L_{\min}) / (L_{\max} + L_{\min}) \quad (1)$$

where L_{max} and L_{min} are the maximum and minimum luminance values for a display considered.

The computed contrast ratio, e.g. 5,000 : 1, indicates the luminance difference between two points of extreme brightness and darkness in an image seen on a display. Image contrast is likely, in retail outlets, to be perceived as different for two representations of the same image on two similar displays, although the two displays have the same computed contrast-ratio. This indicates that the contrast ratio may not be representative of the perceived image contrast that is experienced while watching e.g. a broadcast baseball game. Further, display customers are recommended to experience image contrast using their own eyes, rather than to be dependent on specifications provided by display producers [2]. If this is the current situation, it is required to establish the visual factors influencing the perceptual responses to image contrast. The present work investigated such factors.

Images are composed of spatial components of broadband-frequency. Human contrast sensitivity to sinusoidal modulations in luminance is highly dependent on spatial frequency [3]. Peli [4] took this nature into account for modeling image contrast and proposed the concept of local band-limited contrast. Bex [5] measured the contribution of different spatial frequencies to the supra-threshold contrast of natural images, resulting in 0.5 – 4 cpd of spatial frequency range to be most significant in the perception of image contrast.

Images are also composed of a few or many elements representing different objects and components of scenes. For example, an achromatic image containing people against a building is viewed on a display. To recognize the main elements such as the people or to see detail of people's hair, relative luminance variations in the hair or between the people and building are necessary. Further, the perception of image contrast arises from these relative luminance variations. Considering this aspect, image contrast was determined by calculating the standard-deviation of the luminance values of all pixels in an image [6]. Matković [7] used the average of luminance differences between neighboring pixels, instead of standard-deviation, to define local image contrast. The local contrasts computed at various resolutions were then combined with different weights, in order to obtain a measure of the global image contrast for the image.

All above studies [4-7] used achromatic images as target stimuli to propose methods for computing image contrast, and to evaluate the effect of different spatial frequencies on image contrast. However, images normally seen on displays usually contain chromatic contents. Calabria and Fairchild [8] found significant perceived image-contrast differences between full color images and their corresponding achromatic versions, suggesting that the previously proposed image-contrast models need to be extended to include information regarding their chromatic contents. Thus, they developed models using image statistics associated with image lightness, chroma, and sharpness information [9].

The present work attempted to establish important criteria that influence the perception of contrast when observers assessed the contrast of a series of complex color images reproduced on a large display. An image contrast model was then developed using parameters that were responsible for contrast variations caused by changes in the key criteria revealed in the results of the psychophysical experiment.

Psychophysical Experimental Setting

Twelve observers were asked to assess image contrast using a 9-point qualitative category scale. Eight color images (five natural scenes, two portraits and one fruits) were manipulated to produce variations by separately rendering the lightness, chroma and sharpness. These manipulated images were used as the stimuli in the assessment and were displayed on a 42-inch Samsung Plasma Display Panel. *RGB* values of each pixel in a test image were converted to *XYZ* tristimulus values using a 3D-LUT and tetrahedral interpolation. The *XYZ* values were again converted to lightness (*J*) and chroma (*C*) values using the CIECAM02 color appearance model [10]. Eleven manipulations in the *J* channel were performed: four linear, three sigmoid, three inverse-sigmoid functions and the local color correction method [11]. Chromatic transfer functions used included four linear functions, one sigmoid and one inverse-sigmoid functions. A sharpness change was created by manipulating J in its frequency domain. Five methods were applied to increase sharpness: four high-frequency emphasis filters and enhancing frequency ranges where human contrast sensitivities are highest. The resulting 22 manipulated images may look darker than, sharper than, or have different contrast or colorfulness to the original image. A total of 2208 observations was made: 8 images × 23 manipulations including the original image × 12 observers.

Subjective Rules on the Perception of Image Contrast

The 12 observers were told to assess the contrast of manipulated versions of the eight original images. Afterwards, they were asked what kind of rules they had used in making their assessments and which parts in each of the eight test images they paid closest attention to. Observers looked at the test images not just globally or locally but together, i.e. the total impression formed from several image-appearance attributes played an important role in the perception of image contrast. If appearances formed from particular areas in the images were considered in the assessment of image contrast, these were named local appearance; whereas if they were formed from the whole image, these were named global appearance. The rules applied by all the observers can be summarized as follows, separated into local and global appearances.

Local Appearance

(1) Reproduction of detail (shadow-detail and object-detail).
(2) Distinguishability of objects (how well some objects in an image can be distinguished).
(3) Considering either lightness-difference (dark parts look darker and light parts look lighter) or colorfulness-difference (low-chroma parts look less chromatic and high-chroma parts look more chromatic, or difference between two different objects), or considering both of these.
(4) Colorfulness of objects.

Global Appearance

The following three terms were often mentioned by observers to express their own rules applied to judge image contrast based on the impression formed from an entire image.
(1) Vividness
(2) Clearness
(3) Colorfulness

Amongst the eight test images, six were used for developing the image-contrast model, and two images, 'Sheep' and 'Park', were used for evaluating the model performance in the following section. Figure 1 shows these testing and training images. Table 1 describes the particular areas in 'Harbor', 'Fruits' and 'Kids' images at which the observers looked using one of the above local appearances (1) – (4), when they assessed image contrast.

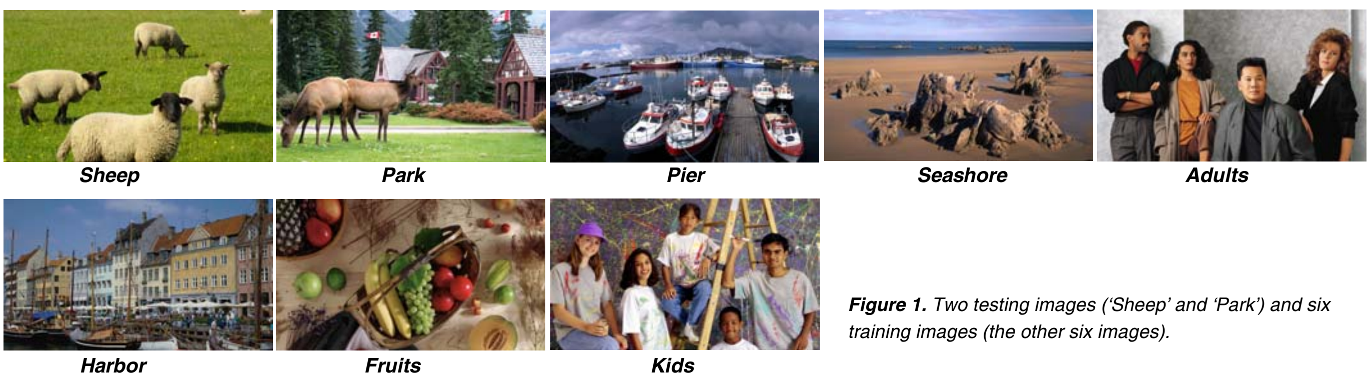


Figure 1. *Two testing images ('Sheep' and 'Park') and six training images (the other six images).*

Table 1: Particular areas in 'Harbor', 'Fruits', and 'Kids' images to which the observers gave attention in the assessment of image contrast. These areas are described according to (1) – (4) local appearances.

	Harbor	Fruits	Kids
(1)	Shadow-detail in dark areas in the sea. Detail in the red roof.	Shadow-detail of the bottom areas in the basket located in the top left. Fruit-detail, especially grape.	Hair-detail of the kids.
(2)	Window frames in the yellow house. Rigging in the boats.	Individual fruits in the basket.	Eye lines of the kids.
(3)	Lightness difference between white and dark areas in the boats, and between dark sea and light sky. Colorfulness difference between the houses.	Lightness difference between the light grape and dark areas in the basket. Colorfulness difference between the fruits and the table.	Lightness difference between the light faces and dark hairs in the kids. Lightness and Colorfulness differences between the kids' faces and the wall behind them.
(4)		Red plums	

Modeling Image Contrast

Pixel-based color differences at eight resolutions

The previous section showed that the observers estimated image contrast using their own rules composed of global and four local appearances. These appearances can evoke a common perceptual effect on an image: when these appearances increase, differences in chroma and lightness either within one object or between adjacent objects in the image become larger. The mean of the color differences computed between neighboring pixels in an image was therefore chosen as an image metric for modeling image contrast. In order to take into account both local and global differences corresponding to both the local and global appearances, pixel-based color differences were calculated at eight different image resolutions. This approach to modeling image contrast is similar to that of Matković [7] in which pixel-based luminance differences were used to rate the contrast of achromatic images containing different contents.

The pixel resolution of the display studied was 1024 (H) × 768 (V) and the experimental viewing distance was 2 m. The maximum spatial frequency that observers could detect was 19.224 cpd (cycles per degree of visual angle) horizontally and 25.631 cpd vertically at this distance. In the frequency domain, this equates to a limit of 31.957 cpd. For the image at half the original resolution (512×384), four neighboring pixels (2×2) from the 1024×768 image were treated as one new pixel. The color of this new pixel was simply the average of the four neighboring pixels. In the same manner, the 256×192 image was generated from the 512×384 image, and so on for the other sub-sampled images. Table 2 introduces the resulting eight image-resolutions at each of which pixel-based color difference was computed. In the second row, the values correspond to the frequency domain maxima.

Table 2: Eight different resolutions at which pixel-based color difference was computed.

Pixel Resolution	Maximum Frequency (cpd)	**Pixel Resolution**	Maximum Frequency (cpd)
1024×768	31.957	**64×48**	1.997
512×384	15.979	**32×24**	0.999
256×192	7.989	**16×12**	0.499
128×96	3.995	**8×6**	0.250

In calculating color difference, three color spaces, CIECAM02, CAM02-UCS and CIELAB, were used [10,12]. Eqns. (2), (3) and (4) describe three color-difference equations in the three color spaces. Two weighting parameters (K_L = 1 and 2) were applied to the lightness difference so as to control the contribution of lightness difference in the total color difference.

$$\Delta E_{CIECAM02} = \sqrt{(\Delta J / K_L)^2 + \Delta a_C{}^2 + \Delta b_C{}^2} \qquad (2)$$

$$\Delta E_{CAM02-UCS} = \sqrt{(\Delta J' / K_L)^2 + \Delta a'_M{}^2 + \Delta b'_M{}^2} \qquad (3)$$

$$\Delta E_{CIELAB} = \sqrt{(\Delta L^* / K_L)^2 + \Delta a^{*2} + \Delta b^{*2}} \qquad (4)$$

The color differences between a pixel and its surrounding pixels were calculated and averaged at each pixel. The color difference value at each pixel was averaged over all pixels in an image, giving a pixel-based color difference for the image. The pixel-based color difference was computed for each training image × 23 manipulations including the original version. The category-scaling data given from the observers were converted into equal-interval scale values using Case V of Thurstone's law of comparative judgments.

All the pixel-based color-difference values and the scale values were re-calculated on a relative scale by dividing those of each of the original image and 22 manipulated images by those of the original image. The ratio was therefore unity for the original image but greater than or less than unity for the 22 manipulated images. These ratios were image independent, and thus were averaged over the six training images for each of the original image and 22 manipulated images, resulting in 23 pixel-based color-difference ratios and 23 scale-value ratios of perceived image contrast. The computation was repeated at the eight image resolutions and in the three color spaces (CIECAM02, CAM02-UCS and CIELAB).

Correlations between pixel-based color-difference ratios and scale-value ratios

Pearson correlation coefficients were calculated between the 23 scale-value ratios and 23 pixel-based color-difference ratios at each of the eight image resolutions. The three color spaces (CIECAM02, CAM02-UCS and CIELAB) and two weighting parameters (K_L =1 and 2) were used in the computation of color difference. Figure 2 plots the correlation coefficients computed between the 23 pixel-based color-difference ratios in CAM02-UCS with K_L=1 and the 23 scale-value ratios, against the eight image resolutions. The results calculated using CIECAM02 and CIELAB are not presented in Figure 2, because the general trends were not significantly affected by the different color space and K_L values. In Figure 2, the data points are shown differently for three independent data sets corresponding to the three image-manipulation methods, and for one combined data set considering all manipulations together. Among the correlation coefficients calculated using the data of all manipulations (▲ in Figure 2), the highest coefficient is found at 256×192 resolution. The correlation coefficients are about 0.90 at all image resolutions for the images altered in the chroma (○) or lightness (■) domains.

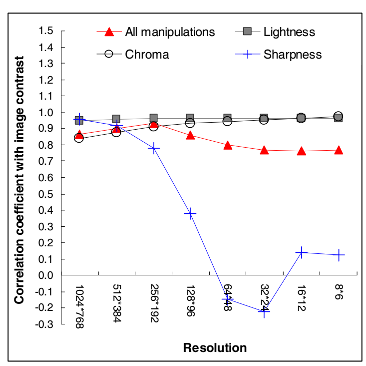


Figure 2. *The eight correlation coefficients at the eight image resolutions. The data are shown with respect to the different manipulations methods.*

For the correlation coefficients calculated using the data of images manipulated in the sharpness domain (+), the highest coefficient is seen at the 1024×768 resolution. The variation of pixel-based color differences calculated in resolutions of 64×48 – 8×6 do not seem to match the changes of perceived image contrast, i.e. coefficients at these resolutions are close to zero. As image sharpness increases, the visibility of detail in images increases due to larger color differences between neighboring pixels in the edge areas of the images. This leads to an increase in image contrast. Therefore, it can be thought that the increased image contrast due to enhanced visibility of detail is not predicted by the pixel-based color differences at low image resolutions (< 256×192).

The above result suggests that the pixel-based color differences from up to eight different resolution images need to be combined with different weights to model image contrast. The image contrast model will then be able to predict variations of the perceived contrast of the images that are visually different in all or each of the three domains, lightness, chroma and sharpness.

New image contrast model

The image contrast model was developed by combining all or some of the pixel-based color-difference ratios at the eight different resolution images with optimized weights. This is expressed in Eq. (5). The values of the eight weights, w_1 – w_8, were optimized in order to give the least difference between the experimental image contrast and the image contrast predicted by Eq. (5).

$$y = w_1 \times PBCDR_{(31.957)} + w_2 \times PBCDR_{(15.979)} + w_3 \times PBCDR_{(7.989)} + w_4 \times PBCDR_{(3.995)} + w_5 \times PBCDR_{(1.997)} + w_6 \times PBCDR_{(0.999)} + w_7 \times PBCDR_{(0.499)} + w_8 \times PBCDR_{(0.250)} \quad (5)$$

where j is the maximum frequency achievable at each of the eight image resolutions (see Table 2), $PBCDR_j$ is pixel-based color-difference ratio at j, and y is the predicted perceived image-contrast ratio.

Table 3 gives the optimized weights for seven image contrast models that were derived using seven different combinations of $PBCDR_j$ in CAM02-UCS with K_L=1. Those derived using the calculated results in CIELAB and CIECAM02 are not described here, but the evaluation of all the developed models will be given in the following section. In the top three models in Table 3, the smallest weights are seen for the color differences computed in the three lowest resolution images among the eight. This implies that the pixel-based color differences calculated for the images whose resolutions are greater than 32×24 (0.999 cpd) will be sufficient for modeling image contrast.

Performance of the image contrast model

The coefficient of variation, *CV*, was used to compute observer variations in the psychophysical experiment and to evaluate the developed-model performance. The mean CV values for intra- and inter-observer agreement were similar with a value of 18, indicating that observers performed similarly within an observer and between observers in the assessment of image contrast.

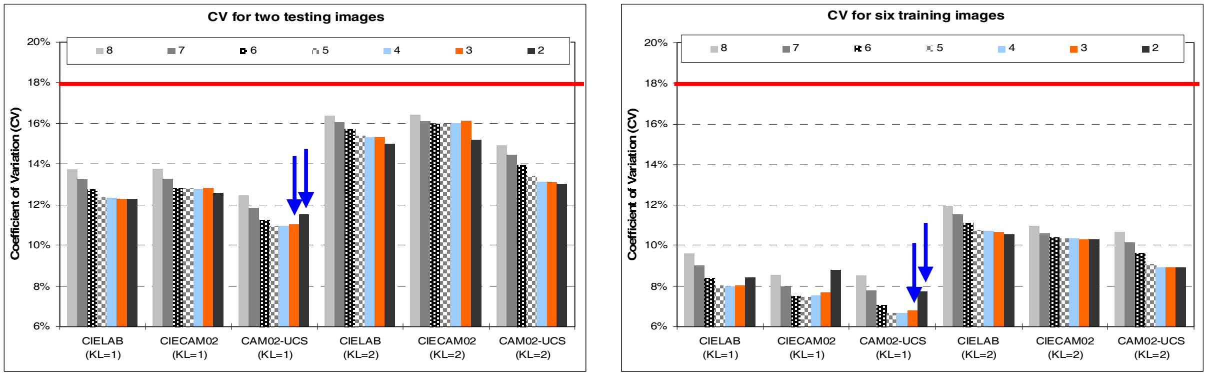
For the six training and two testing images, perceived image contrast was predicted using all the developed models: seven combinations of color-difference data calculated from the images at eight different resolutions × CIELAB, CIECAM02 and CAM02-UCS × K_L =1 and 2. The coefficient of variation, CV, was then calculated between the predicted and experimental image-contrast data. Figures 3(a) and 3(b) show the resulting CV values, respectively, for the two testing and six training images, with respect to the three color spaces and the two weighting parameters. The CV value corresponding to the observer variation is indicated by a red line in the figures. In each group, seven bars indicate the number of different resolution images from each of which pixel-based color difference was calculated to derive the image contrast model. For example, the CV value of the light grey bar expresses the performance of the model developed using the color-difference data obtained from all eight different resolution images.

The main tendencies for both training and test images are summarized as follows.

- Overall, the pixel-based color differences computed with K_L=1 have better agreement with the scale values of observer-judged contrast than those calculated with K_L=2, i.e. smaller CV values for K_L=1 than those for K_L=2. This suggests that there is no need to give smaller weight to the lightness difference in a total color difference when pixel-based color difference is used as a correlate of image contrast.

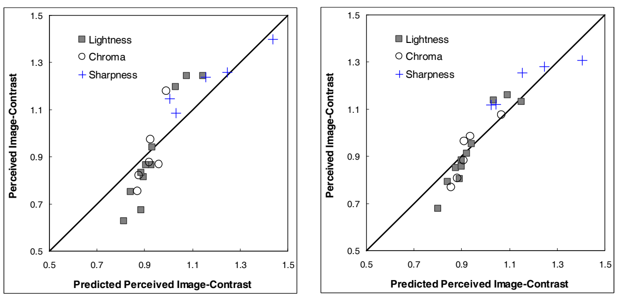
Table 3. Optimized weights for seven image contrast models derived using seven different combinations of color-difference data calculated from the eight different resolution images (in CAM02-UCS with K_L=1).

Image resolution (Max. frequency)	1024×768 (31.957)	512×384 (15.979)	256×192 (7.989)	128×96 (3.995)	64×48 (1.997)	32×24 (0.999)	16×12 (0.499)	8×6 (0.250)
Weights	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8
Model 1	0.08	0.14	0.18	0.19	0.18	0.14	0.08	0.0001
Model 2	0.11	0.18	0.22	0.22	0.18	0.11	0.0001	
Model 3	0.14	0.22	0.25	0.22	0.14	0.0001		
Model 4	0.18	0.28	0.28	0.20	0.02			
Model 5	0.19	0.28	0.29	0.21				
Model 6	0.14	0.33	0.50					
Model 7	0.001	0.95						



(a) (b)

Figure 3. *Comparison of the CV values calculated between the experimental image-contrast data and the image contrast predicted by all the developed models* ***(a)*** *for the two testing images and* ***(b)*** *for the six training images.*



(a) (b)

Figure 4. *Plot of the experimental image-contrast data against the predicted image-contrast data for* ***(a)*** *the two testing images and* ***(b)*** *the six training images.*

- The smallest CV values for both training and testing images are found for CAM02-UCS with K_L=1.
- All the CV values are smaller than the mean CV value for the observer variations (18), suggesting perceived image contrast can be well predicted by any of the image contrast models developed in the three color spaces with the two weighting parameters.
- Thus, it is demonstrated that the pixel-based color difference computed at different resolutions could successfully model image contrast for images varied in lightness, chroma and sharpness domains.
- Considering simplicity and performance, the two models (orange and black) indicated by blue arrows are recommended. These models were derived using the color-difference data that were calculated from the three highest resolution images, i.e. 1024×768, 512×384 and 256×192 (32 cpd, 16 cpd and 8 cpd), in CAM02-UCS with K_L=1.

Figures 4(a) and 4(b) show comparisons between the observer-judged contrast data and the predictions made by the model (orange in Figure 3), for the testing and training images, respectively. The data points are shown using three different symbols for the three image-manipulation domains. A 45° line representing a perfect agreement between the experimental and predicted data is also given. As all data points are located close to the 45° line, it can be concluded that this model successfully predicts image contrast variations arising either from changes in image lightness, chroma and sharpness.

Relationship between the optimized eight weights and the contrast sensitivities

The contrast sensitivities at the eight image resolutions were calculated using Barten's contrast sensitivity function [13] in which 44.9 cd·m^{-2} – the average luminance of the eight test mages – and 26.3° – the angular size of the display studied at 2 m viewing distance – were used as input parameters. These were compared with the eight optimized weights of the image contrast model built in CAM02-UCS with K_L=1 (see Table 3). Figure 5 compares these eight weights with the calculated contrast sensitivities at the eight image resolutions (the maximum frequency achievable at that resolution is given in parentheses).

The maximum weight is seen between the resolutions of 64×48 (2 cpd) and 256×192 (8 cpd). Human eyes are, however, most sensitive to spatial frequencies of 4 cpd. The contrast sensitivity suddenly drops after 4 cpd whereas the weight gradually decreases. The weights are much higher than the contrast sensitivities at 8, 16 and 32 cpd. In other words, the contrast sensitivity function under-estimates the importance of high-frequency information in images. The cause of this deviation is thought to be due to the difference in experimental conditions where achromatic sinusoidal patterns were used to measure eye

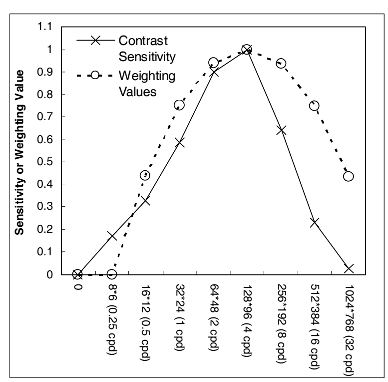


Figure 5. *The comparison of contrast sensitivities with the values of the weights at the eight image resolutions.*

contrast sensitivity, while complex color images were used to establish contributions (weights) of various spatial-frequency components to the perceived image contrast.

Limitations of the developed image-contrast model

The developed image-contrast model is for general display development use, e.g. evaluating an existing model against a new type of display in terms of image contrast. If the predicted image-contrast ratio is 1.2, this indicates that an image presented on the new display may appear to have 20 % more contrast than that on the existing one.

In the first sub-section (*Pixel-Based Color Differences at Eight Resolutions*), which used pixel-based color differences and scale values, converting this original data onto a relative scale requires only the original image (rather than any of the 22 manipulations) as a denominator. The manipulated images may look darker, sharper, or have different contrast or colorfulness compared with the original image due to the rendering process. Therefore, the developed image-contrast model is limited to being used on displays for which the previous criteria are met. Certainly there are other appearance-comparison cases and these can be considered by using each of the manipulated images as a denominator in the conversion of the original data onto a relative scale. The purpose of this work was, however, to verify some specific approaches applied to determining image contrast. A comprehensive image-contrast model will be introduced elsewhere, which will be applicable to the majority of cases involving the industrial comparison of displays having different characteristics.

Conclusions

The subjective rules governing the perceptual responses for evaluating image contrast were established from the observers' judgments against the eight natural images and their 22 manipulations in lightness, chroma and sharpness dimensions. Globally, vividness, clearness and colorfulness appearances were important. Locally, four criteria were addressed: reproduction of detail, distinguishability of objects from their surrounding area, considering either or both lightness-difference and colorfulness-difference, and the colorfulness of objects. The observers evaluated image contrast based on both global and local appearances. These established rules can be used to enhance image contrast.

All or some of the pixel-based color differences calculated from eight image resolutions were selected as a correlate of image contrast, since this factor can take into account image contrast changes arising from variations in the above global and local appearances. The color differences were calculated in three color spaces, CIELAB, CIECAM02 and CAM02-UCS using two weighting parameters controlling the contribution of lightness difference to total color difference. Image contrast models were developed from the optimized six functions relating the pixel-based color differences (three color spaces × two weighting parameters) to the scale values of observer-judged contrast. The highest correlation with the observer-judged contrast was found from the color differences computed in CAM02-UCS space and with equal contributions of lightness, chroma and hue differences. The deviation between the judged contrast data and those predicted by all six models was, however, smaller than the typical observer variation. This indicates that combined pixel-based color difference at different image resolutions is suitable for use in estimating visual image contrast.

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