# Color Difference Evaluation Model on Partly Changed Complex Images

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#### Abstract

Since there has been a strong demand from industry to have an efficient way of managing color image quality presented in different media, by specifically investigating partly changed complex images, this article proposed a revision to existing CIE color difference model which cannot give a proper color difference assessment on partly changed complex images. The key method applied is to find out weight coefficients of color attributes such as lightness, hue and chroma in color difference prediction.

Keywords: color diffirence, partly changed complex image, evaluation model

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#### 1. Introduction

Nowadays color image reproduction is very common in daily life. A perfect reproduction should produce an image identical to the original one. Practically, however, this is rarely the case due to factors affecting the final image of reproduction, e.g. device gamut, media gamut, system noise, system error, etc. Hence, the reproduced image may look quite different from the original one. To decide whether the difference is noticeable or acceptable is usually judged by experienced people. However, for massive reproduction, this becomes unpractical. Therefore, there has been a strong demand from industry to have a metric that can quantify the difference automatically by powerful computer system [1, 2].

Lots of effort have been done in the past decade [3], however, the images used in those studies were mostly systematically rendered, i.e. all pixels in an image were varied via a mathematical function on a particular color attribute such as lightness, chroma, hue or their combination. The intents were to establish perceptibility thresholds on different media and to test the performances of color-difference formulae. Available research outcome demonstrated the failure of conventional formula in predicting color differences for two images having only part of the image being different. Additionally in many experiments, the observers started to report difference between two images when only part of the difference became obvious while the rest still look similar. These results suggest that investigation of partly changed images may be important as well as systematically changed ones. This article is to design an experiment to investigate partly changed images and attempts to propose an initial model that can fits the experimental result. Further more this model would be tested by using the systematically changed images for compatibility.

### 2. Methods

In the experiment, resources employed include HP p1130 Monitor, UNIX workstation, Photometer PR650, Matlab or C/C++ and 14 human observers. Three main stages comprised the experiment, which can be described as device simulation, subjective evaluation and difference metrics modelling. The following section presents each stage in more details.

## 2.1. Device Simulation

Device simulation or device characterization model enables us to test our understanding of the devices, predict their output, and optimize their design. As far as this experiment is concerned, we only investigate CRT display characterization model [4], which

covers gamma function, spectral power distribution of phosphors, and pixel point-spread function.

Considering two CRT models available, GOG and PLCC [4], two independent testing sets are carefully chosen for their evaluation. The results by mean $\angle E^*ab$  between actual value and its prediction using GOG and PLCC models are listed in Table 1; Figure 1 is its corresponding graphical representation.

As far as this experiment is concerned, accuracy is the main priority for representing the transformation between image pixel RGB values and its corresponding tristimulus values. Although GOG model has the advantages of easy to implement and few measurements, PLCC model requires large number of measurements but yields better accuracy. As seen obviously from Figure1, mean  $\angle E^*$  ab for PLCC all below one unit, nearly half the value of GOG model. So PLCC model is justified to choose for this experiment.



		GOG	PLUU
∠Eab	EvenSpaced	1.46	0.87
	Random	1.55	0.68
	Average	1.51	0.77



Figure 1. Plots of Mean ∠E\*ab from Evaluating GOG and PLCC Models

#### 2.2. Subjective Evaluation

Following characterization of the CRT display, subjective evaluation is conducted, whose goal is to find the perceptibility threshold for each "area change ratio" among partly changed images. Psychophysical judgments (detection, discrimination and preference) are made under controlled viewing conditions (fixed lighting, viewing distances, etc) to generate highly reliable and repeatable data [5].

Regarding partly changed complex images, two images compared differ in color only for a small part. This experiment is designated change of individual object (CIO) in an image, which differentiates from earlier studies investigating change of entire image (CEI). Four images shown in Figure 2 are investigated. Since other images were conducted in a similar manner, image1\_threegirl is taken as an example for the following statements of explanation, analysis and conclusion.



Figure 2. Four Test Images used in the Experiment



Figure 3. Example of Choice for Objects in image1\_threegirl

The procedure for rendering partly changed image in this experiment is explained as follows:

Firstly, choose important individual objects in an image which are to be changed, the wider the area change ratio spread out among objects, the more accurate final result would be. In Figure 3 six objects (area change ratio range from 2% to 6%) were isolated individually using Photoshop, which include three girls' skin, top addresses and blanket plus grass as a whole (area change ratio about 19%).

Secondly, select mapping functions shown in Figure 4 to transform a particular color dimension for each object in the original image, such as CIELAB L\*, C\* or h. Each time, only one perceptual color attribute's value was modified in one object.



Figure 4. Transfer Functions used in CIO Experiment

The mapping functions listed in Figure 4 approximate typical variations in color reproduction such as contrast, gain, gamma control and color shift, which are also used in CEI experiment.





Figure 5. Work Flow for Partly Changed Images Rendering

It is critical to estimate the two extreme levels when rendering desired images: One is that more than half percent of the observers CANNOT see the difference; The other is that more than half percent of the observers CAN detect the difference. Estimation for the two extreme levels is tested by a group of observers till the pinpoint levels are found. Thus the perceptual threshold for each object is narrowed down within the above two levels to find out. Choice of the in-between levels can be evenly spaced between the above two extreme levels.

Thirdly, render partly changed images by means of C/C++ program [6]. Work flow of image rendering procedure is illustrated in Figure 5, where color appearance model referring to CIELAB color space, the forward CRT model referring to CRT characterization model PLCC which uses three look-up tables relating digital counts and radiometric scalars for each channel, CIE specification are obtained through a linear transformation between radiometric scalars and tristimulus values.

The psychophysical judgments were conducted on a HP p1130 monitor in a dark room. Before each observer's observation, device calibration was adjusted to ensure the monitor perform in a predefined way (adopted white point, contrast, brightness, etc) in which conditions CRT display characterization was developed [7]. A pair of images was presented side by side each time on monitor and the original image is randomly positioned on left or right to minimize the negative effect of monitor's spatial uniformity. Observers were asked to judge whether they could see a difference or not between two images, and the object exhibiting difference was spotted for validity following the detection of difference.

#### 3. Results and Analysis

Objective in the following work is to determine functions between threshold  $\angle E$  and area change ratio, the following gives its explanation: Firstly, relationship between object mean  $\angle E$  and color attribute [L, C, h] is proved to be linear according to deduced Equation (1):

$\Delta E^* ab = \sqrt{\Delta L^2 + \Delta C^2 + \Delta h^2}$	
$\Delta E^* ab = \Delta L  (when \ \Delta C = \Delta h = 0)$	(1)
$\Delta E^* ab = \Delta C  (when \ \Delta L = \Delta h = 0)$	
$\Delta E^* ab = \Delta h  (when \ \Delta L = \Delta C = 0)$	

Therefore, function (denoted by f) associating color attribute [L, C or h] and difference detection ratio by observers can transformed to function (denoted by f') relating object mean $\angle E$  and difference detection ratio by observers. Which can be simplified as f{x, y}  $\rightarrow$  f'{X, y}, where x stands for one color attribute [L, C or h], X equals to object mean $\angle E$ , y represents difference detection ratio by observers.

Secondly, by fitting the result data sets through mathematical tools, function f' can be obtained. In succession, value of threshold  $\angle E$  for each area change ratio is fixed on by setting y equals to 0.5. Finally, function regarding threshold  $\angle E$  and corresponding area change ratio using result data sets from the above four images is illustrated in Figure 6.





In Figure 6 it is apparent that the lightness difference (denoted by blue points) is less noticeable than chroma and hue differences (denoted by yellow and red points respectively) when evaluate image difference on partly changed complex images. In addition, the correlation between area change ratio and corresponding threshold object mean  $\angle E$  is currently still low, the reasons for that may be explained as follows:

One is that threshold  $\angle E$  also depends on factors such as which object, its position and how large area was selected, etc. Therefore, more factors need to be taken into consideration to maximize the correlation between image threshold  $\angle E$  and area change ratio; Another problem is that whether the experiment result is image dependent, in other words, can it be generalized to other type of images? Therefore different type of images need to be investigated to see whether the further results obtained show agreement with earlier ones, that is the function curve between image threshold  $\angle E$  and area change ratio; Finally, the four images used in the experiment are of the same size and image size is also a factor affecting image difference. Thereby, whether the image size will have an influence on the experimental result is still an open question.

In a word, the objective is to combine all counting factors to get the right function F illustrated in Figure 7, which relating image threshold  $\angle E$  and area change ratio.



Figure 7. Function Curve Relating Threshold *L* and Area Change Ratio

### 4. Conclusion

Since color difference is the main difference between images, so CIELAB formula was adopted for revising through adding weight coefficients derived from this experiment on color attribute [L,C or h]. In Equation (2) below, if the  $\angle E^*ab\_CIO$  is great than one unit, image difference should be noticeable, where weight coefficient (Lw, Lw, hw) can be obtained through function Y = F (X) in Figure 7.

$$\Delta E^* ab \_ CIO = \sqrt{\frac{\Delta L^2}{Lw} + \frac{\Delta C^2}{Cw} + \frac{\Delta h^2}{hw}}$$
(2)

Our ultimate goal is to identify the visual signals that annoy our viewing customers and minimize their visibility. Device simulations enable us to isolate source of a visual signal. Psychophysical evaluation enables us to assess role of the signal plays in subjective judgments of image quality. Eventually, difference metrics help us to quantify or measure the magnitude of the signal.

Furthermore, it would be interesting to test S-CIELAB [8] using the CIO experiment data sets and what are the prediction results from S-CIELAB for evaluating image difference on partly changed complex images would be.

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