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Color Image Distortion Assessment based on Synthetic Ground Truth Recovery

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Abstract

Color distortion is one of the serious problem that can appear in color image. Despite various image quality evaluation methods have been studied over the past decades, the color distortion-related assessment method is available only in situations where the ground truth is essential. Here, this paper proposes a comprehensive quantitative method for measuring color distortion that may occur in color image. Our method can objectively evaluate a practical color distortion (which may occurred in natural scenes) that cannot be evaluated by previous methods. To achieve this, we first designed a test chart. The image taken with this chart can reproduce two types of color distortion, false color and decolorization. Our proposed evaluation algorithm can assess the level of color distortion quantitatively. It is confirmed that our experimental results were well matched with human subjective evaluation results.

Introduction

With the high growth of the industrial technologies related to digital camera, users can experience superb image quality that has never been seen before. Each device that constitutes a digital camera, such as lens, CMOS image sensor, and digital image processor, improves image quality through the state-of-the-art technologies. The thickness of the mobile camera module is getting thinner, and the resolution of the image sensor increases. Further, advanced image processing gives us an unbelievable image quality. However, image quality degradation during the image acquisition still remains as an inevitable problem.

Efforts to assess image quality objectively have been made considerably over the years. Even though the image quality standards that define essential image quality evaluations, such as resolution, noise, and texture have been published, but color distortion is still challenging [1]. Color is one of the salient features that attract human visual attention, and contains very important information when humans perceive objects. If color distortion occurs in the area of color, people tend to feel very strange. Therefore, there is a need for a quantitative assessment method of the color distortion occurring in an image. However, it is difficult to evaluate as a simple evaluation method due to a complex and unknown black boxes, such as image sensor and digital image processor. It is also ambiguous to set the level of absolute color accuracy because individual tastes vary decisively. Therefore, it is necessary to develop a new metric that can evaluate color distortion.

Color distortion is one of the remarkably noticeable distortions in color image. We define the color distortion significantly as two categories, false color and decolorization, as shown in Fig. 1. False color means incorrectly estimated color pixel. Traditionally, the demosaic process of converting from Bayer to RGB is the main cause of color distortion [2]. Up-to-date Color Filter Array(CFA), such as Tetra and Nona of high-resolution image sensor over millions of pixel, can cause much more serious color distortion. False color can be suppressed by image post-processing. At this time, if the color is excessively removed, the original color can be removed together and a side effect called decolorization may occur. Decolorization refers to a phenomenon in which the original color is removed and transferred to gray-axis. These two color distortions stand in a trade-off relationship with each other, and are considered as the most important evaluation for color distortion.

In order to evaluate color distortion, the previous studies mainly proposed a method of calculating an error between the reference and target images in a specific color space. *Chen et al.* expressed the false color as Mean Absolute Error (MAE) between the original and target image in RGB color space [3]. *Alleysson et al.* measured the false color with Mean Square Error (MSE) between the two of them [4]. Color difference ΔE in CIE-Lab color space is the most widely used method for evaluating a color error. Since the distance between the two color points located in CIE-Lab color space correlates to perceptually uniform difference, it represents the human perception property. CIE has continuously improved color error models that close to the subjective evaluation results by applying HVS, such as CIE76, CIE94, and CIEDE2000 [5]. Despite these methods enable quantification of color differences that humans can detect, in order to evaluate the target, it is necessary to secure a distortion-free reference image. In addition, research for decolorization assessment has not yet been actively conducted.

In this study, we present a comprehensive method for measuring two representative color distortion. Inspired by previous studies, we propose a new design of chart that can reproduce color distortion as well as measure color distortion in CIE-Lab color space. We focus on estimating the synthetic ground truth through the priori information on the chart without referring to the distortion-free reference image.

The remainder of this paper is organized as follows. In the *Design Concept of Test Chart* Section, we describe a design concept of test chart that can reproduce color distortion. Then, in *Objective Assessment for Color Distortions* Section, we present a method for measuring color distortion on images taken with the designed chart. In the *Experimental results* Section, we show the validation of our proposed method and finally present a conclusion and future works.

(a) False color (b) Decolorization

Figure 1. Examples of color distortion in natural scene: Left side in each image has no distortion and right side is distorted.

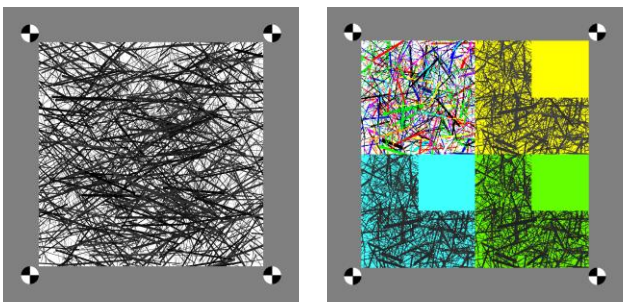
Design Concept of Test Chart

Beyond the previous studies, we considered a method of measuring the color distortion without a distortion-free reference. It should reproduce the color distortions in a laboratory and expand the evaluation spectrum as much as possible, enabling it to make everyone evaluate the imaging devices, such as mobile camera, DSLR, and image sensor.

Fig. 2 shows the charts for measuring two types of color distortion, false color and decolorization. We established two assumptions as follows:

(1) The chart for measuring false color has only gray scale value. It consists of only luminance Y channel.

(2) In a chart for decolorization, the background is filled with a specific color.



(a) False color (b) Decolorization

Figure 2. Test charts for color distortion assessment

The foreground of the proposed charts consists only of gray-level lines. As shown in Fig 2a, a chart for false color evaluation has gray-level lines in both background and foreground, so all pixels should always be distributed on gray-axis in an ideal environment. Conversely, this means that when false color occurs, chrominance, not luminance, occurs, so it is suitable for false color evaluation. Unlike the chart for false color, the decolorization chart in Fig 2b is filled with a specific color on the background. They consists of three representative colors: yellow, green, and cyan. This is because three colors may have high luminance in sRGB color gamut. These assumptions provide a priori to the object's original color information so that help us estimating an undistorted image. In addition, many lines overlap each other, so it is possible to evaluate various frequency components. In fact, both charts have statistical frequency components similar to that of the natural scene, so they can represent the color distortion of the natural scene.

The proposed charts comprise a variety of gray-level lines that follow the random distribution with the length, phase, thickness, location, and intensity of the line as random variables. Chart configuration can be changed by adjusting the range of these random variables. For example, if you want to focus on evaluating high frequency components, you can set a range of random variables so that the random lines are configured very closely. We recommend the following parameters' range in Table 1.

Table 1. Chart parameters (chart full size = 1024 x 1024 [pixels])

Name	Random distribution	Range	Remarks
Line length	Uniform	[400, 800]	
Line phase	Uniform	[0, pi]	
Line thickness	Exponential	[1, 4]	$f(x;\lambda) = \lambda e^{-\lambda x}$, $\lambda = 0.5$
Position(x,y)	Uniform	[0, 1023]	
Intensity level	Uniform	[0, 63] @8bit	

Objective assessment for color distortions

In previous section, we addressed a design concept of test chart. Under a limited and controllable environment, you can acquire an image of the imaging devices to evaluate color distortion. As a next step, an objective assessment is performed on this captured image through an evaluation procedure of false color and decolorization described in this section.

False color

As mentioned earlier, the false color chart in Fig. 2a has only gray components. If there is no color distortion, no color components should appear in the captured image. However, the post-processed image may not be a perfect gray one. In the whole process of image acquisition, color components may exist locally and globally due to the physical characteristics of the camera or digital image processing. Therefore, calculating the absolute color components would result in an incorrect false color evaluation.

Fig. 3 illustrates an overall process for measuring the false color. Considering the local and global color component, the color reference level $\hat{a}$ and $\hat{b}$ is estimated as the result of curve fitting of the color components, a (Red-Green) and b (Blue-Yellow) in CIE-Lab color space in Eq. 1,

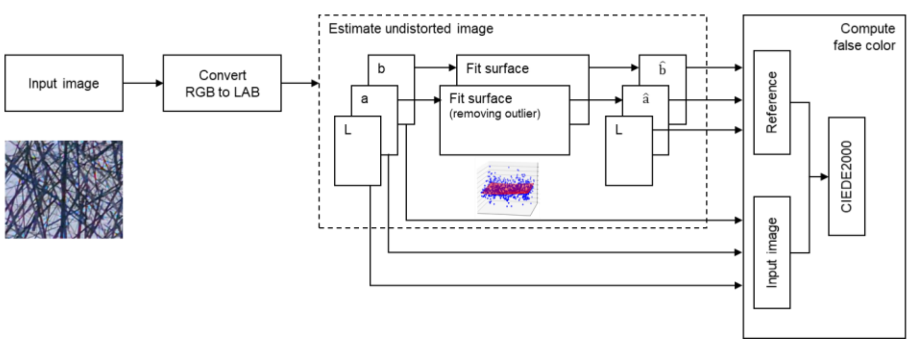
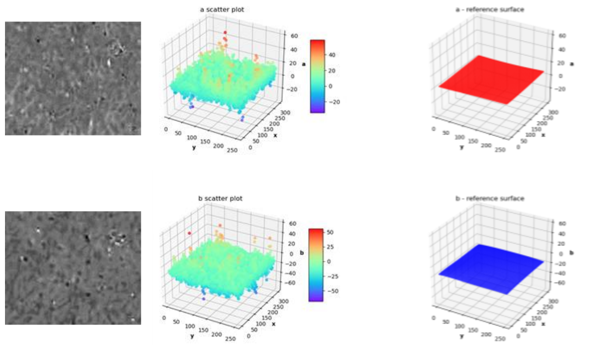


Figure 3. Proposed flow chart for false color assessment



(a) a/b color channel (b) Estimated ground truth

Figure 4. Un-distorted ground truth estimation by surface fitting : Upper row (a channel), Lower row (b channel)

$$\underset{w}{\operatorname{argmin}} \sum_{(x,y)\in I} |c(x,y) - f(x,y;\boldsymbol{w})|^2, \tag{1}$$

, where $c(x,y)$ means the color components $a(x,y)$ and $b(x,y)$, and model curve f is a polynomial surface with coefficient $\boldsymbol{w}$. We find the polynomial surface fitting result by least square error. Curve fitting is a representative method widely used to estimate a mathematical model in a distribution of numerous data samples. Consistent with our purpose, distortion-free and false color pixels are mixed so that it can be a good solution to estimate a reference without false color. An outlier elimination process may be required to increase the reliability and accuracy of curve fitting result. If the false color pixels are more dominant than normal color pixels, the accuracy of the reference estimation result may be inferior. To solve this problem, the process of calculating the surface fitting is iteratively performed after elimination of outliers for minimizing fit error. Fig. 4 shows the distribution and fitting result of a and b color channel. The result of fitting means a color level corresponding to ground truth with no color distortion. Then, only false color pixels would have a large difference from this recovered ground truth. The numerical results of false color can be calculated by chrominance ΔC and hue ΔH from CIEDE2000 [6] in Eq. 2 and the more the false color distortion, the higher the value.

$$\text{False color} = \sum_{(x,y)\in I} \Delta CH\big([a,b],[\hat{a},\hat{b}]\big), \tag{2}$$

, where $\Delta CH = \sqrt{(\Delta C)^2 + (\Delta H)^2 + R_T(\Delta C)(\Delta H)}$.

Decolorization

The decolorization chart consists of a flat area and high-frequency content with complex patterns, as shown in Fig. 2b. Compared to the false color chart in Fig. 2a, the background is filled with a specific color. The flat color area on the decolorization chart is used to estimate the original color without color distortion, and the remaining line pattern area is used to measure the decolorization distortion of complex patterns. If the decolorization distortion occurs, the color components in the background are lost depending on the distortion level.

Fig. 5 shows the overall process of measuring decolorization distortion. It is composed of two processes, a process of estimating the original color component, and a process of recovering the original image. It is possible to simply calculate the decolorization using a full-reference method with the chart information a_{ref} and b_{ref} in Eq. 3,

$$\Delta C = \sqrt{a^2 + b^2} - \sqrt{a_{ref}^2 + b_{ref}^2} \tag{3}$$

However, regardless of the decoloriztion, if the color transition occurs during the image post-processing, such as color correction matrix or white balance, this difference in Eq. 3 cannot accurately measure the decolorization that has disappeared from the original image. So, we consider the sRGB color gamut and a luminance information of the input image to estimate the undistorted color.

Fig. 6 describes the process of transition to the reference chart through color information of the flat area in the input image. It is assumed that the luminance of the decolorized pixels remains unchanged. This may be reasonable, because the luminance of the pixel does not usually change to not affect the brightness of the image when the color components are removed to attenuate the false color. First, we measure the luminance, chrominance and hue in a flat area. It is then projected to the outermost point of the sRGB color gamut for the fixed luminance and hue in the CIE-Lab color space. A cyan circle in Fig. 6. is the projected point and means the probable maximum chrominance of the input image. This

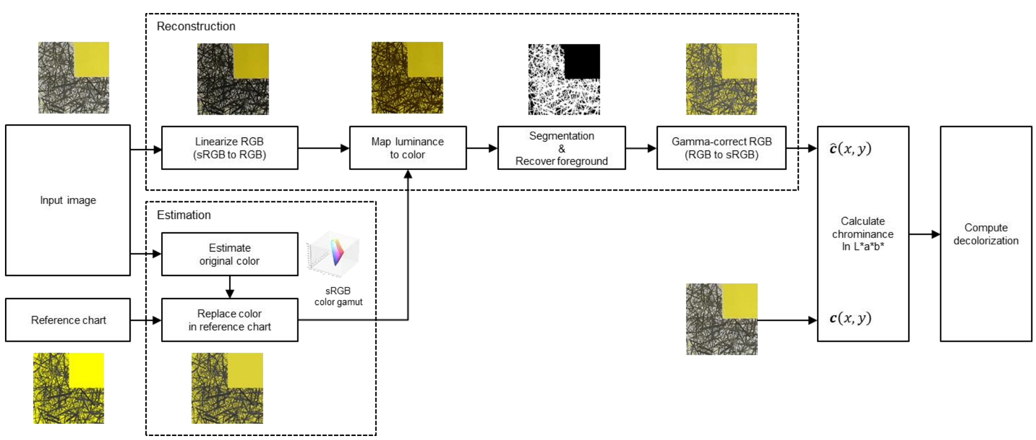


Figure 5. Proposed flow chart for decolorization evaluation

chrominance replaces the original reference chart and is used in the subsequent reconstruction process. Next, based on color-transformed reference chart, the color is reconstructed depending on the luminance of the input image by in-painting technique. We used in-painting method proposed by Welsh et al.[7]. Finally, only the background area is filled with reconstructed color pixels after the image segmentation process. The decolorization can be evaluated as how much the recovered color component is preserved compared to the original color component. Finally, it is calculated as the chrominance ratio between the input image and the reconstructed image in Eq. 4. If the color is perfectly preserved, the evaluation result is close to 1.

$$\text{Decolorization} = \frac{\text{distorted chroma}}{\text{reconstructed chroma}} = \frac{\sum_{(x,y)\in \boldsymbol{I}} \boldsymbol{c}(x,y)}{\sum_{(x,y)\in \boldsymbol{I}} \hat{\boldsymbol{c}}(x,y)}, \quad (4)$$

, where $\boldsymbol{c}(x,y) = \sqrt{\boldsymbol{a}(x,y)^2 + \boldsymbol{b}(x,y)^2}$.

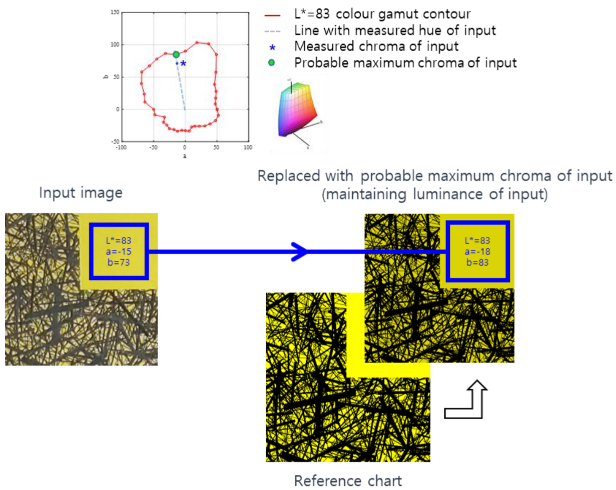


Figure 6. Process of transition to the reference chart through color information of the flat area in the input image.

Experimental results

Fig. 7 shows the experimental results of false color and decolorization applied to three different levels of color distortion. The image pairs in upper and lower rows are obtained within an identical image. We evaluated cameras equipped with ISP modules with difference color distortion levels for each column. These images contain contents that took the chart we propose.

Fig. 7a-c shows that the more severe the false color (a to c), the higher the result value, which means that there are more false colors. On the other hand, in Fig. 7d-f, the more severe the decolorization (f to d), the lower the value, which means that the color is closer to the original chart. These results were confirmed to be well consistent with the human's subjective evaluation results.

We obtained the natural scene acquired in the same environment as in Fig. 7. Fig. 8a-c are glittery sponge images with a prominent false color distortion, and d-f are flower images containing a lot of vivid colors, and decolorization distortion is well shown. Their results show that they are well matched with the qualitative and quantitative results of Fig. 7.

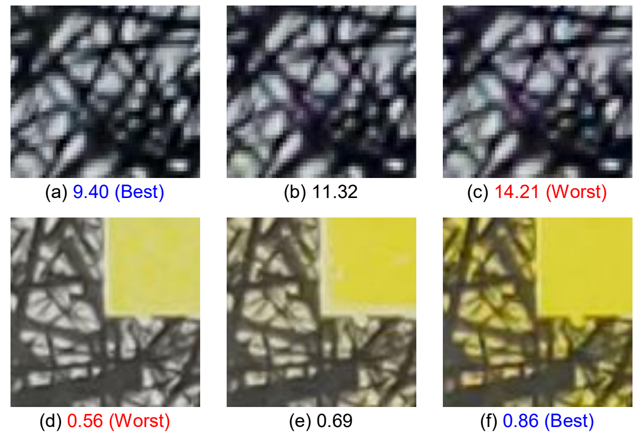


Figure 7. Quantitative evaluation results for color distortion: a-c (false color), d-f (decolorization)

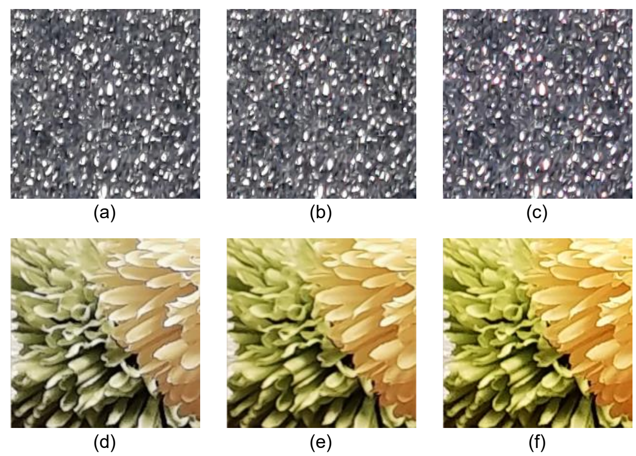


Figure 8. Natural scene acquired in the same environment as the image captured in Fig.7: a-c (Glittery sponge), d-f (Flowers)

Conclusion and future work

In this study, we proposed a comprehensive method to evaluate the two types of color distortion, false color and decolorization. We focused on how to reproduce effectively and assess quantitatively the color distortion. Compared to standard methods based on full-reference based method, our method can design a newly chart and measure the color distortion by estimating distortion-free. Anyone can easily generate a chart for color distortion measurement. Moreover, our evaluation algorithm can secure compatibility and scalability by estimating the distortion-free ground truth.

As a result of evaluating a series of color distortion images, we have shown that the quantitative results fit well with subjective evaluation. Therefore, our proposal is particularly attractive in evaluating the color distortion of imaging devices.

In the near future, we plan to improve the disadvantage that a prior information on the chart is still required and find a way to directly assess the natural scenes.

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