Perceptual Color Granularity Metric via Scanner

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Abstract

Perceived graininess is one of the most important image artifact attributes to describe the image quality of a printing system. Although a international standard, *ISO13660*, defines the perceived graininess on a monochrome image, rapid prevalence of color printing systems in recent years significantly increases the demand for a color granularity metric which correlates with visual assessment in the color space. We propose to adopt flatbed scanners to efficiently capture high-frequency color noise. The perceived noise is then mapped to the visually uniform *CIEDE2000* color difference space. Consequently, a psychophysical experiment will be conducted to evaluate the perceived grain on patches with various colorants. At last, we will propose a color granularity metric to best describe the obtained color grain perception.

Introduction

Perceived graininess is one of the most important image artifact attributes to describe the image quality of a printing system. The granularity on monochrome (black and white) images is defined in the *ISO13660* international standard as the aperiodic density fluctuation with spatial frequency being over 0.4 cycle/mm [1]. Nonetheless, rapid prevalence of color printing systems in recent years significantly increases the demand for a color granularity metric which correlates with visual assessment in the color space. The current color granularity metrics are either extensions from the monochrome granularity metric by converting to the optical reflectance density space or measuring noise separately in the transformed *CIELAB* space. We propose to adopt flatbed scanners to efficiently capture high-frequency color noise. The perceived noise is then mapped to the visually uniform *CIEDE2000* color difference space [2]. Note that the color mapping function from a scanner *RGB* to *CIELAB* space can only achieve metameric match and colorant dependent, we first need to devise an algorithm to adaptively generate such mapping functions to achieve general applicability.

Flatbed scanners have been adopted to measure image artifacts such as granularity, mottle and streak for their capability to efficiently capture large areas of images [3, 4]. However, unlike spectrophotometers, the reported *RGB* values are device dependent and visually nonuniform with respect to the perceived color difference. Moreover, researchers often compress scanner color outputs to an appropriate optical density axis, and extend the existing artifact measurements to each color respectively. This method becomes inefficient when the type of colorants increases. Hence, we devise a progressive color mapping algorithm which consists of global transformation $G_{L^*a^*b^*}(r, g, b)$ and local transformation $g_{L^*a^*b^*}(r, g, b)$ to project to the *CIELAB* color space [5]. The global regression provides the overall transformation and the local mapping adjustment corrects the residual mapping error. We will verify in the following section that this technique is able to create an accurate mapping function from the device *RGB* to the *CIELAB* color space.

One difficulty found to adopt flatbed scanners to measure image artifacts is the signal contamination by screen signals [6]. This difficulty is even more severe when applying the *ISO13360* granularity measurement on halftone images because both signal resides in the high frequency domain. Thus, it is necessary to remove the screen signal before applying any granularity metric [7]. Note that any screen removal algorithm should not affect the inherent granularity signal. That is, the proposed algorithm needs to adaptively remove the detected screen frequency components while keeps the frequency response being one in the rest frequency domain. We will propose a robust noise measuring algorithm to achieve this requirement in the third section.

At last, a psychophysical experiment is conducted to correlated between the visual response and the objective image noise measurement. Because extensive researches have been done to identify how the visual response changes when the optical density of printed patches increase, we design our experiment to investigate how the visual response changes by varying printed colorants but fix colorant coverage percentage.

Scanner Calibration

It is well known that most of the color flatbed scanners are not colorimetric device, therefore, the accuracy of the devised color mapping function, $M(r, g, b) \rightarrow (L^*a^*b^*)$, is constrained to achieve only metameric equivalence. However, because the proposed color granularity measurement will be applied on a patch with intended uniform color $C \equiv (\bar{L}^*, \bar{a}^*, \bar{b}^*)$, we can still assume that the behavior of the *CIEDE2000* is very similar within the neighborhood of C. As a result, flatbed scanners should be applicable to measure color granularity in spite of their inherent color mapping inaccuracy.

The scanner calibration can be separated into two steps: locating patches on a scanned target and generating a color mapping function $M(r, g, b)$. Assuming having the *LAB* measurement of the intended target, we need to first locate center of each patch on the scanned target and obtain the corresponding device *RGB* value. We propose a patch identification algorithm as following:

1. Scan the printed target with paper background surrounding the target.
2. Project the scanned image horizontally and vertically, and approximately locate the four outside corners of the target as well as the skew angle of the scanned target.
3. Extract vertical and horizontal strips within the identified target and pinpoint the top, bottom, and right three border positions.
4. Identify the anchor point as the topleft corner of the first patch.
5. Assume the prior knowledge of the layout of the target, and the center of each patch can be computed.
6. Crop a 31×31 block centered at each patch centroid and take the device *RGB* value as the mean value of these pixels.

Figure 1 to 4 demonstrate that the proposed algorithm successfully identifies the centroids of all patches on four selected targets issued by *INCITS W1.1* standardization committee [4].

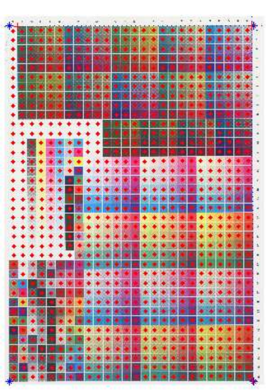

Figure 1: *IT8/73 928 Target*

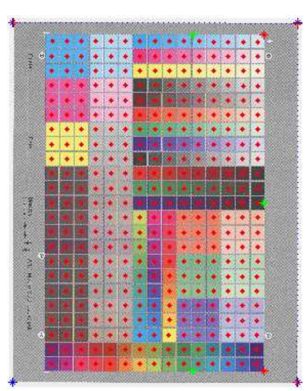

Figure 2: *W1.1 Test V3*

After obtaining the device *RGB* values for every patch, we can create a mapping function $M(r, g, b) \rightarrow (L^* a^* b^*)$ by a progressive color mapping algorithm which consists a

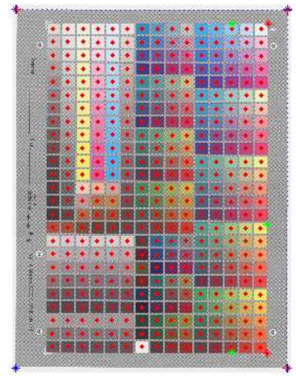

Figure 3: *W1.1 CMYK V9*

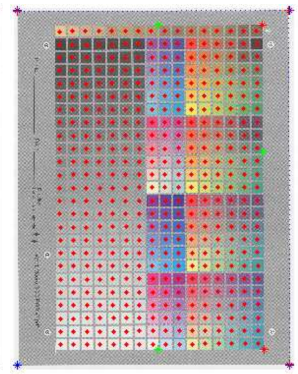

Figure 4: *W1.1 RGB V3*

global function regression and residual mapping error reduction via functionals with finite support [5]. It is essential to achieve a good compromise between mapping accuracy and smoothness to avoid color contouring artifact. A degree-two polynomial is selected to achieve global color mapping approximation because it is the polynomial with lowest degree to achieve satisfactory accuracy. The *W1.1 CMYK V9* target is adopted as the training set and the *W1.1 RGB V3* and *W1.1 Test V3* targets are used as test sets, which are used to check if the designed color mapping function overfits the training data set so that large mapping errors occur in the untrained device *RGB* domain. The mapping accuracy is summarized in Figures 5 and 6. The median and $90th$ percentile point of the mapping error in ΔE_{2000} for the training set is 0.67 and 2.40 respectively. Furthermore, the median mapping errors for two test targets are 2.08 and 1.03, and the $90th$ percentile points are 5.19 and 3.19. Larger mapping error for the *W1.1 RGB V3* target can be contributed to the dense sampling in the neutral region. The smoothness of the color mapping function can be seen from Figure 7 to 10, where Figure 7 contains smooth variation in the device *RGB* space. Note that the hexagon target also contains pixels whose *RGB* values exceed the domain achievable by actual print scans. That is used to check the extrapolation mapping smoothness. It shows in Figure 8, 9 and 10 that there exists no mapping contour and inversion.

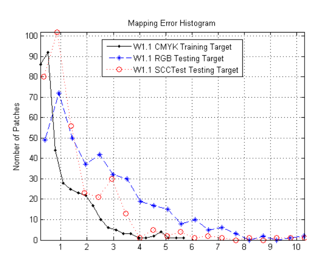

Figure 5: *Training and Testing Error in* ΔE *2000*

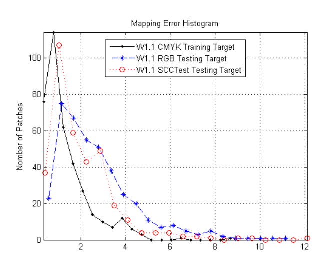

Figure 6: *Training and Testing Error in* ΔE *76*

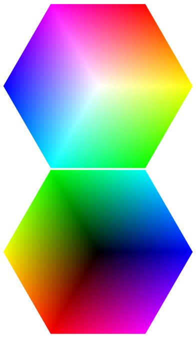

Figure 7: *RGB Hexagon*

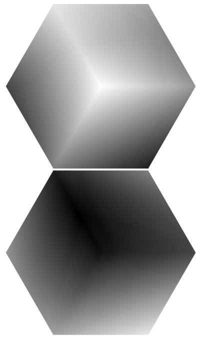

Figure 8: *Estimated L^**

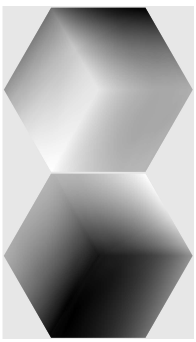

Figure 9: *Estimated a^**

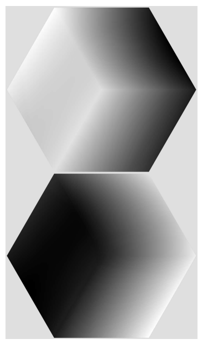

Figure 10: *Estimated b^**

Robust Noise Measurement

For screen halftone images, it is essential to remove screen signal before estimating granularity [7]. However, to minimize the screening removal affecting granularity, the frequency response of the descreening algorithm should be one except on the screen frequency and its harmonics; Moreover, this algorithm needs to be adaptive to all possible screens appearing on scanned images. Designing a two dimensional filter under constraints noted above is known to be very difficult. Because our objective is to measure color granularity of a printing system, we can relax the requirement of the screen removal algorithm such that it only needs to be applicable on color patches with uniform intended color.

Let the scanned image $I(x,y)$ is composed of $I_o + I_s(x,y)+I_g(x,y)$, where I_o is the intended color, $I_s(x,y)$ is the two dimensional screen signal, and $I_g(x,y)$ is the signal containing color granularity. We can treat I_o as a slow varying signal with mean value $\bar{I}$ because of the inherent nonuniformity of a printing system. Thus, we can approximate I_o by a two dimensional spline functional S_o. In the frequency domain, $I_s^f(f_x,f_y)$ consists of a set of δ functions centered at the screen frequencies and their harmonics W_s. Let's assume that $\log(\|I_g^f(f_x,f_y)\|)$ can be decomposed into two parts: a slow varying two dimensional signal in the frequency domain, S_g^f, and a white gaussian noise signal $N(0,\sigma_f)$. To remove $I_s(x,y)$ from $I(x,y)$, we first subtract S_o from $I(x,y)$, denoted as

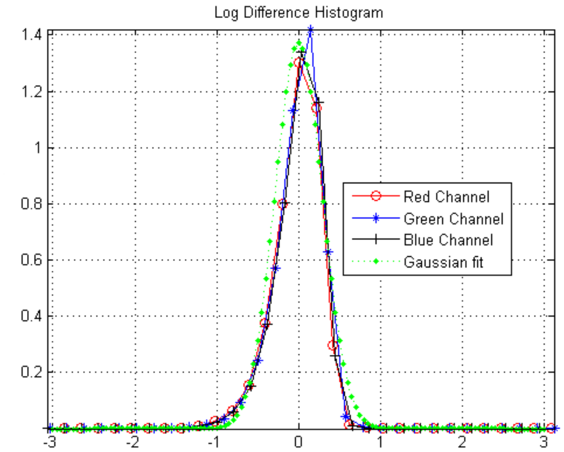

Figure 11: *Histogram of* log *Difference*

$I_h(x,y)$, and then take *2D FFT* on $I_h(x,y)$ resulting in $I_h^f(f_x,f_y)$. Secondly, denote

$$\begin{aligned} & \log(\|I_h^f(f_x,f_y)\|) - S_g^f = \psi_f(f_x,f_y) \\ = \; & \log(\|I_s^f(f_x,f_y)+I_g^f(f_x,f_y)\|) - S_g^f = N(0,\sigma_f) \end{aligned}$$

$\forall (f_x,f_y)\cap W_s = \emptyset$. Figure 11 demonstrates that the distributions of $\psi_f(f_x,f_y)$ from the *Red*, *Green* and *Blue* channel can be well fitted by a *Gaussian* random process with zero mean and $\sigma_f = 0.29$. Based on this assumption, it is possible to estimate the screen signal $I_s(x,y)$ via thresholding [8]. Note that, since $I_s(x,y)$ is a real signal, its *2D FFT*, $I_s^f(f_x,f_y)$, is a periodic function with period 2π, and must satisfy the following constraint:

$$\begin{aligned} \|I_s^f(f_x,f_y)\| &= \|I_s^f(-f_x,f_y)\| = \|I_s^f(f_x,-f_y)\| \\ &= \|I_s^f(-f_x,-f_y)\|. \end{aligned} \tag{1}$$

As a result, we devise a thresholding approach in the *log* frequency space to achieve descreening. Let the threshold $\delta = c\sigma_f$, and define a hypothesis H_0 that the signal belongs to $N(0,\sigma_f)$. Currently, we define $c=5$, and this, in turns, suggests the type **I** error is less than 3×10^{-7}. Define $\Omega = ([0,\pi),[0,\pi))$, and the estimated screen signal $\log \bar{I}_s^f(f_x,f_y)$ can be devised as following:

$$\log \bar{I}_s^f(f_x,f_y) = 0 \quad if \;\; \psi_f(f_x,f_y) < \delta \tag{2}$$
$$\log \bar{I}_s^f(f_x,f_y) = \psi_f(f_x,f_y) \quad if \;\; \psi_f(f_x,f_y) \geq \delta \tag{3}$$

where $(f_x,f_y)\in\Omega$. For all $(f_x,f_y)\cap\Omega=\emptyset$, $\log \bar{I}_s^f(f_x,f_y)$ is reconstructed based on Equation 1. Figure 12 and 13 show the original scanned color patch and the descreened color patch by subtracting the estimated $\bar{I}_s(x,y)$ from each channel, and demonstrate that our proposed algorithm successfully remove screen from the scanned image. We have successfully tested our algorithm on samples with screen frequency ranging from 130 to 200 *DPI* and their overprints. In the future, we will extend our algorithm to include samples generated by error diffusion or blue noise mask.

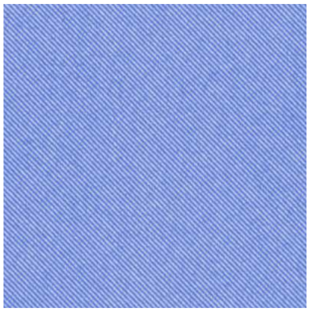

Figure 12: Original Color Patch

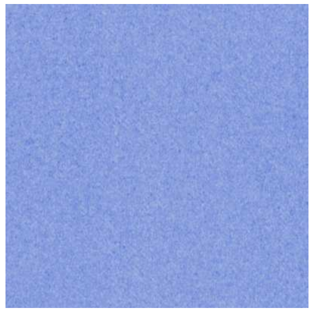

Figure 13: Descreened Color Patch

We can assume that $I_{ds}(x,y) = I(x,y) - \bar{I}_s(x,y) \approx I_o + I_g(x,y)$, where $I_g(x,y)$ is a stochastic two dimensional signal with zero mean. Thus, we can estimate I_o as $E\{I_{ds}(x,y)\}$, and then apply the $RGB \rightarrow LAB$ mapping function derived before to obtain the predicted *CIELAB* value for the scanned patch, denoted as I_o^{lab}. Moreover, the same mapping function is also applied on $I_{ds}(x,y)$ and results in $I_{ds}^{lab}(x,y)$. Therefore, a routine computing the *CIEDE2000* between I_o^{lab} and $I_{ds}^{lab}(x,y)$ can be applied and project the scanned image from three dimensional device *RGB* color space to a one dimensional visually uniform color difference space. To maintain the zero mean property of $I_g(x,y)$, a separating plane in the *CIELAB* space is created which contains I_o^{lab} and normal vector $\overrightarrow{I_o^{lab}}/\|\overrightarrow{I_o^{lab}}\|$. Opposite signs are assigned to each ΔE measurement when the predicted LAB value on each pixel falls into different regions separated by this plane, and we denote the obtained image as $G(x,y)$.

Psychophysical Experiment

In this experiment, we focus on samples with very similar colorant percentage coverage but varying colorants. Seven popular colorants are selected, and they are: cyan, magenta, yellow, black, red, green and blue. Approximately 60% colorant coverage is applied on every color patch. The experiment was conducted under the standard graphic art viewing environment with *D50* diffused lighting condition. Each observer is asked to evaluate all twenty one pairs of patches. The observer first decides the rank order of each pair based on the perceived grain, and then represents the perceived grain difference by a nonnegative number. Seven observers from the IQ and software group participated in this experiment.

Among the tested patches, observers have agreement on most pairs of color patches regarding the order of the perceived graininess. Denote this set of data as Λ. Thus, we can first estimate the average perceived graininess difference in Λ by assuming the observers' response obeys the lognormal distribution [9]. Assuming that individual response is linearly correlated to the average visual response, we can then adjust the remaining visual numerical response $\bar{\Lambda}$ individually. The average response in $\bar{\Lambda}$ is computed as the arithmetic mean of all normalized numerical responses. As a result, the average dissimilarity matrix D can be constructed based on the average perceived graininess difference on all pairs of patches. We adopt the classical multidimensional scaling technique to analyze D [10], and find that, although the average dissimilarity matrix D can be represented in a two dimensional plane, the first axis accounts for approximately 80% of the data distribution. Considering the variability of the visual experiment, we only use the first axis for the following correlation analysis, and extend to the second axis when we obtain more data in the future.

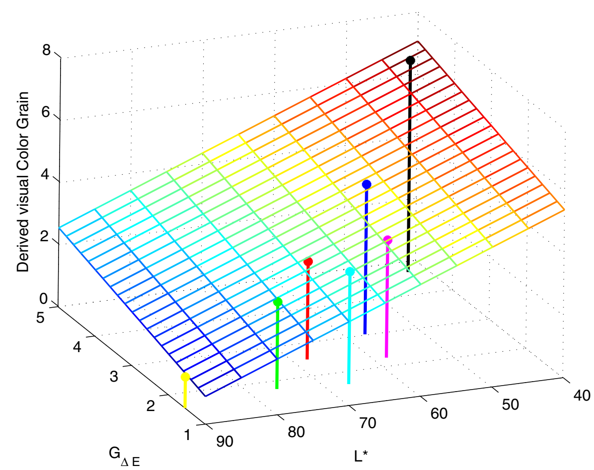

Figure 14: Color Grain Correlation Map

We propose a granularity metric based on *ISO13660* where $G(x,y)$ is first divided into nonoverlapping blocks with size $1.27mm \times 1.27mm$. Let σ_i represents the standard deviation of each block, we can derive a granularity metric $G_{\Delta E} = \sqrt{E\{\sigma_i^2\}}$. Note that the color grain is the perceived high frequency noise inside a color patch. Hence, the brightness of that color patch might affect the perceived amount of high frequency noise according to the *Weber's Law*, which asserts that change of stimuli should be proportional to the stimuli to achieve the same perceived amount of variation, that is, $\Delta I/I = C$ [11]. Therefore, we propose to linearly correlate the derived visual color grain rating with the estimated L^* and $G_{\Delta E}$, and the result is shown in Figure 14. The R^2 statistics for the linear regression above is 96.5% indicating a good fit, and the obtained linear relationship is listed as following:

$$V_{ColorGrain} = U(8.6 + 0.4G_{\Delta E} - 0.1L^*) \qquad (4)$$

where $V_{ColorGrain}$ represents the predicted perceived color graininess, and $U(x)$ is a step function, $(U(x) = 0,\ if\ x < 0)$, to prevent $V_{ColorGrain}$ becomes negative. Equation 4 shows that the perceived color graininess increases proportional to the measured high frequency noise but decreases when the *Luminance* of the color patch increases consisting with the *Weber's Law*. Note that the perceived graininess should reduce to zero when $G_{\Delta E} = 0$. That is to say, $V_{ColorGrain} = 0$ along the *Luminance*. To correct this deficiency, we will include samples with very little amount of density variations of various colorants in the future experiment to extend the current linear model to a nonlinear model with the constraint noted above.

Conclusion and Future Works

We propose a color granularity algorithm based on flatbed scanners. First, an algorithm locating automatically the patch positions is proposed and tested, and a progressive color mapping algorithm is designed to achieve satisfactory color mapping accuracy and smoothness. We then devise a robust screen removal algorithm to preprocess the scanned image to obtain robust color granularity measurement. Based on the psychophysical experiment, we find that the perceived color graininess is linearly correlated with the high frequency noise measurement, $G_{\Delta E}$, and the patch luminance, L^*. In the future, we plan to extend our experiment to include samples with the same colorant but different coverage percentage and various amounts of high frequency spatial noise, and propose a nonlinear model to satisfy the constraint noted in the previous section.

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Biographies

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