Image Graininess via Flatbed Scanner and Image Segmentation

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Abstract

Granularity is one of the most important visual artifacts to evaluate the performance of an imaging system, including a printer. At present, granularity-measuring techniques can only be applied on patches with uniform color. However, human can easily perceive graininess on any image; Hence, in this paper, we propose an algorithm to quantify image graininess. First, a flatbed scanner is adopted for its capability to capture large image area. A short-time Fourier transform technique is devised to accurately remove color screen halftone signal without any prior knowledge of the adopted screen signals. At last, users can pinpoint the area of interest to measure color graininess based on CIEDE-2000.

Introduction

Granularity is one of the most important visual artifacts to evaluate the performance of an imaging system such as a printer, and there have been significant amount of effort and success to quantify the perceived graininess objectively. In general, granularity can be described as high frequency aperiodic reflection density fluctuation. For example, ISO13660 international industrial standard has defined a procedure to measure achromatic granularity on a gray patch.[1] Other researchers have proposed to incorporate the human visual sensitivity function to measure achromatic granularity.[2] With the rapid prevalence of color printing systems, the demand for measuring chromatic granularity becomes ever increasing. Unlike the achromatic case where it is sufficient to quantify various visual attributes in a unidimensional basis, i.e. *reflection density*, a general color granularity algorithm needs to summarize the perceived graininess on an image in, at least, a three dimensional space. We recently proposed to measure color noise in the visually uniform CIEDE2000 color difference space.[3,4]

The aforementioned algorithms share one limitation: they can only be applied on patches with uniform intended color, which exists primarily in graphics, but not in ordinary images. Hence, we will propose an algorithm in this paper to extend the current color granularity techniques to be applicable to ordinary printed color images. It has been shown that it is essential to remove all screen signals without affecting inherent image noise before measuring granularity to achieve satisfactory correlation against visual response.[2] As a result, the requirement for a screen-removal algorithm is the ability to first precisely identifying present color screen halftone signals, and then removing them. In the case of a scanned patch with uniform color, this can be translated to designing one two-dimensional filter for each color channel of which frequency response is zero at the identified halftone frequencies as well as the associated strong harmonics, and is one elsewhere. This two-dimensional filter design problem is known to be very difficult. This problem becomes more complicated when a scanned ordinary image is involved because the color screen signal becomes space variant. Our previously proposed screen-removal algorithm based on log-frequency thresholding principle can only be applied on uniform color patches[4]; Hence, in this paper, we will extend this technique to be applicable to any scanned images based on *short-time Fourier transform*.[5] When users obtain the descreened image, they can pinpoint the area of interest to measure color granularity. An area of the image is segmented based on the perceived color similarity and spatial distance with respect to the selected pixel. Since we are dealing with ordinary images, it is most probable that we will obtain an area with irregular shape. As a result, it is very difficult to extend the granularity metrics based on *Fast Fourier Transform* (*FFT*). We suggest to first cluster the segmented area into a predefined number of centroids, $\{C_i \mid i = 1 \sim N\}$, and compute the standard deviation of color variation, $\{\sigma_i \mid i = 1 \sim N\}$, near each centroid. The color variation is quantified via *CIEdE2000*. The estimated color noise can be estimated as the mean of σ_i denoted as $E\{\sigma_i\}$. We can then estimate the perceived color graininess as suggested in Ref. [4]. At last, we will test the proposed algorithm on several images.

Proposed Algorithm

A prerequisite step before adopting a flatbed scanner as measuring equipment is to calibrate it to perform closely as a colorimetric device, of which accuracy is constrained by metamerism.[6] The discrepancy between two equipments becomes more pronounced when more than three colorants are used during the printing process. However, it is the color difference, i.e. color gradient, that is critical in measuring color granularity. We demonstrated that the color mapping function $f_{map}:\{r,g,b\}\rightarrow\{L^*,a^*,b^*\}$ is roughly a smooth quadratic function.[4] Hence, it is reasonable to assume that the color gradient in a neighborhood in *CIELab* space is very similar. As result, we can further assume that the estimated color variation is valid although the actual color might be slightly off. The scanner calibration algorithm is explained in Ref. [4].

Space Variant Color Screen Removal

Halftone screen removal algorithms generally can be classified into two categories: low-pass/band-pass filtering and halftone signal detection/subtraction. Unlike the usual applications needed descreening for scanned image segmentation, classification or visualization, where the only requirement is to produce visually similar images, because image granularity is the inherent high frequency noise, any successful granularity measuring algorithm needs to precisely identify and remove the existing halftone screen signals without affecting inherent image noise. Moreover, it has to be able to achieve this objective adaptively with respect to all possible halftone screen signals, their harmonics as well as combinations. This essentially eliminates the low-pass/band-pass filtering approaches because of the difficulty of designing such two-dimensional filters. As a result, we can reformulate the problem of removing space variant color halftone screen signals as a problem of sparse signal representation. This generally can be classified into two approaches: *wavelet transform* and *short-time Fourier transform* (*STFT*).[5] Because halftone screen signals exhibit strong peaks in the frequency domain, *Fourier* basis should be a natural candidate. We propose to adopt the *STFT* approach to accommodate the space variant characteristics of halftone screen signals on regular images. Let the scanned image be $I_o(x,y|r,g,b)$, and the task becomes to derive an overcomplete signal basis, B_o. The halftone signals, $i_b(x,y\}$, is the signal in $I_o(x,y|r,g,b)$ spanned by B_o. Then, the descreened image, $I_d(x,y|r,g,b\}$, is the residual image as explained by Eq. (1):

$$I_d(x,y|r,g,b\}= I_o(x,y|r,g,b)-P(I_o(x,y|r,g,b)) = I_o - i_b, \quad (1)$$

where P is an operator projecting an image onto B_o.

There are two conflicting parameters in building B_o based on *STFT*: spatial and frequency resolution. To reduce the computational complexity of simultaneously optimizing both parameters, we will first estimate an appropriate window size to reliably identify screen frequencies. Then, we will adopt Fourier transform via using overlapping blocks to avoid border effect. Let's assume that most of halftone screen signals and their harmonics reside in spatial frequency ranges from 50 to 300*dpi*, and a digitized sinusoid with signal length approximately 10*cycles* or more will exhibit well-defined peaks after applying *FFT*. Scanning resolution of 600*dpi* is minimal to avoid aliasing artifacts based on the *Nyquist* sampling principle. As a result, we propose to set the scanner resolution to be 800*dpi* by providing 100*dpi* margin to the highest halftone screen frequency. Furthermore, the block size should be approximately 10×(800/50)=160 *pixels*. Thus, we select the overlapping block width to be 128 *pixels* (~4 *mm*) to reach the compromise between the spatial and frequency resolution demand.

Let the scanned image $I(x,y|r,g,b)$ be decomposed into three components: the actual image, $I_o(x,y|r,g,b)$, the halftone screen image, $I_s(x,y|r,g,b)$, and the imaging noise, $I_g(x,y|r,g,b)$. $I_g(x,y|r,g,b)$ contains color granularity, mottle and other artifacts, which could come from the original imaging process as well as the printing process. We can formulate the problem of halftone screen signal removal as a binary hypotheses decision problem. Let $\mathbf{H_0}$ and $\mathbf{H_1}$ be the two hypotheses:

$$\boldsymbol{H_0}: I(x,y|r,g,b) = I_o(x,y|r,g,b)+I_g(x,y|r,g,b)$$

$$\boldsymbol{H_1}: I(x,y|r,g,b) = I_o(x,y|r,g,b)+I_s(x,y|r,g,b)+I_g(x,y|r,g,b).$$

In general, I_o and I_s are much stronger than I_g, which is the signal that we intend to measure, and I_o+I_g is common in $\mathbf{H_0}$ and $\mathbf{H_1}$. Thus, it is preferable to first subtract I_o from I before increase the signal-to-noise (*S/N*) ratio. The difference between using color patches and actual images is that a color patch I_o can be reliably estimated as the overall mean, i.e. $\underline{I}_o \sim \mathbf{E}\{I_o(x,y|r,g,b)\}$. This conclusion can't be reached with respect to ordinary images without prior knowledge of the original imaging process. As a result, it is not possible to separate the estimated color granularity between the original imaging process from the printing process. Nonetheless, we can still compare the perceived graininess difference among various printing processes using the same original image $I_o(x,y|r,g,b)$. Based on the assumed frequency range of possible halftone screen signals, I_o can be estimated via FIR low-pass filters or nonlinear filters to better preserve image edge information such as color sigma filter.[7] Because we only need to subtract the majority portion of I_o to facilitate the following halftone removing algorithm, a simple FIR Gaussian lowpass filter with stopband frequency begin slightly higher than 50*dpi* is adopted to remove I_s and obtain $I_h = I - \underline{I}_o$.

Transform to the spatial frequency domain, and the updated $\underline{\mathbf{H}}_0$ and $\underline{\mathbf{H}}_1$ can be expressed as:

$$\underline{\boldsymbol{H}}_0: I_h(w_x,w_y|r,g,b) = I_g(w_x,w_y|r,g,b)$$

$$\underline{\boldsymbol{H}}_1: I_h(w_x,w_y|r,g,b) = I_s(w_x,w_y|r,g,b)+I_g(w_x,w_y|r,g,b).$$

Let's assume that the logarithm of the magnitude of $I_g(w_x,w_y)$, $log||I_g(w_x,w_y)||$, in the null hypothesis $\underline{\mathbf{H}}_0$ is composed of two separable signals: a slow-varying two dimensional signal, S_g, and a white Gaussian noise signal, $N(0,\sigma)$. Note that there exist constraints when a real signal is transformed to the frequency domain, such as *Conjugate symmetry*:

$$I(w_x,w_y) = (I(-w_x,-w_y))^*. \quad (2)$$

We first devise a two dimensional spline functional while satisfying equation (2) to estimate S_g. As a result, by taking the logarithm and subtracting S_g from $log||I_h(w_x,w_y|r,g,b)||$, the two hypotheses $\underline{\mathbf{H}}_0$ and $\underline{\mathbf{H}}_1$ can be modified as below:

$$\underline{\boldsymbol{H'}}_0: N(0,\sigma) \quad (3)$$

$$\underline{\boldsymbol{H'}}_1: N(0,\sigma)+logI_s(w_x,w_y|r,g,b). \quad (4)$$

Thus, it is obvious that we can first estimate σ, and apply the hard-thresholding technique to recover $I_s(x,y|r,g,b)$.[8] Let

$$\underline{I}_n(w_x,w_y|r,g,b) =log||I_h(w_x,w_y|r,g,b)||-S_g. \quad (5)$$

Assume $\underline{I}_n$ as a random field with distribution $N(0,\sigma_{r,g,b})$, and $\sigma_{r,g,b}$ can be estimated via a Maximum Likelihood method. Define threshold values $\delta_{r,g,b} = 3\sigma_{r,g,b}$, and we can readily deduce that the probability of *Type-**I*** error is less than *0.2%*.

Figure 1 shows a example of one image block, and Figure 2 illustrates that our assumption of $\underline{I}_n$ being normal distributions is reasonable. As a result, the halftone screen signal $I_s(w_x,w_y|r,g,b)$ can be estimated via following hard-thresholding algorithm:

$$I_s(x,y|r,g,b) = 0, \qquad if\ \underline{I}_n(w_x,w_y|r,g,b)\le\delta \quad (6)$$

$$I_s(x,y|r,g,b) = I_h(w_x,w_y|r,g,b),\ if\ \underline{I}_n(w_x,w_y|r,g,b)>\delta \quad (7)$$

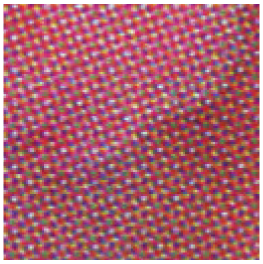

Figure 1. Example of Image Block

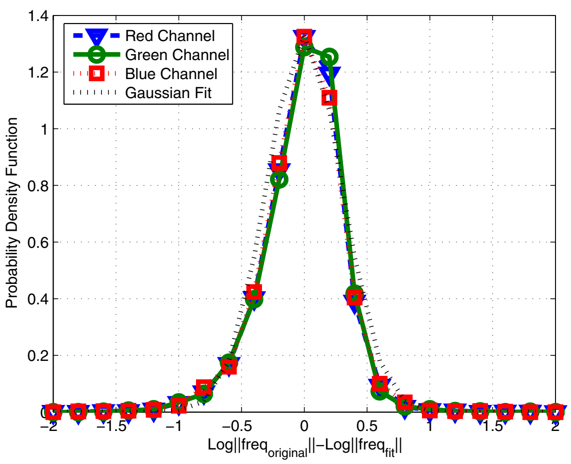

Figure 2. I_n Distribution and Gaussian Fit

Interactive Image Granularity Sampling

Besides the inherent noise from the imaging process, color granularity is due to the variation of the dot size, shape and relative location. Hence, image granularity should be measured in an area with slight color variation. This, in turn, suggests that scanned images need to be segmented into non-overlapping regions before estimating color granularity. Moreover, regions with high frequency image structures should be avoided because of the visual masking effect on perceived graininess by those image structures. The challenge of measuring color granularity in a whole image is the high computational complexity in blind image segmentation. Recognizing that observers usually pay their attention to only several locations within an image, we propose an interactive image granularity-sampling algorithm based on human interference. The algorithm is separated into four steps:

1. Manually identify points of interest, $\{ p_i | i = 1 \dots L\}$.
2. Extract a connected region, R_i, associated with each p_i where $dE2000(x_i,p_i) < \alpha$, $\forall\, x_i \in R_i$. Currently, we set $\alpha = 9$.
3. Exclude the border of R_i, and limit the size of R_i to be no larger than $(12.7)^2$ mm^2 with relative distance to p_i.
4. Adopt k-means clustering algorithm to uniformly sample R_i at 100 points, $\{c_i | i = 1 \dots 100\}$.

Step 3 and 4 are derived from the current international standard (*ISO/IEC13660*) on measuring gray granularity.[1] At last, we transform the descreened *RGB* image onto *CIELab* space via the color mapping function derived from the scanner calibration procedure. A small window centered at each c_i with width 40 *pixels* (1.27 *mm*) is extracted, and the color granularity at the point of interest p_i is measured as the average of the standard deviation of color variations at $\{c_i | i = 1 \dots 100\}$ as explained in Ref. [4]. Figure 3 shows a descreened image where each dot denotes one sampling point. It demonstrates that the proposed algorithm distributes sampling centroids fairly uniformly in an irregular region and it successfully avoids pronounced inherent image structures.

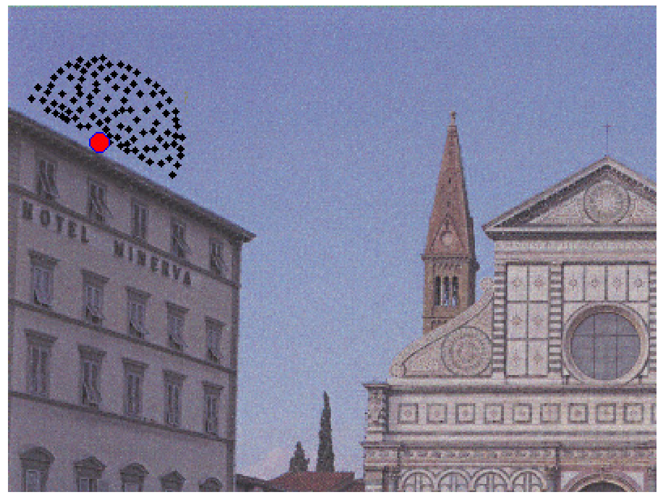

Figure 3. Interactive Granularity Sampling

Experiment Result

The main difference of removing halftone screen signals between from regular images and from single color patches is the space variant characteristics of the halftone screen signals. Hence, we propose to adopt *STFT* to reach a compromise between precisely removing halftone screen signals and quickly adapting to local image content variations. Consequently, we should first compare this algorithm with that based on *Fourier transform* (*FT*) as explained in Ref. [4] on single color patches. A black patch with 60% tint and the corresponding two descreened images based on *FT* and *STFT* are shown in the following:

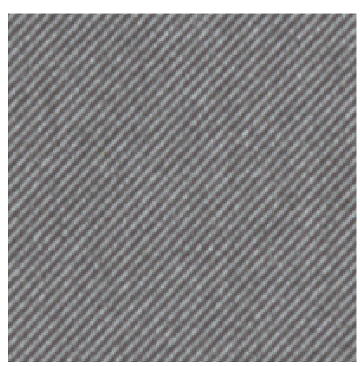

Figure 4. Black Patch with 60% Tint

Figures 5 and 6 show that both algorithms can reliably remove halftone screen signals on a color patch, and it is very difficult to perceive the difference between Figure 5 and 6. To show the relative numerical changes, we can easily calculate the *50th* and *95th* percentile points of code value fluctuations within Figure 5 to be –*0.34* and *13.09* respectively while the corresponding percentile points of code value difference between Figure 5 and 6 are only *0* and *3*.

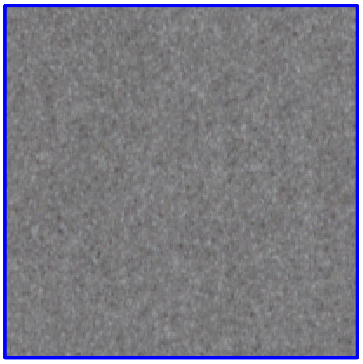

Figure 5. Descreened Patch via FT approach

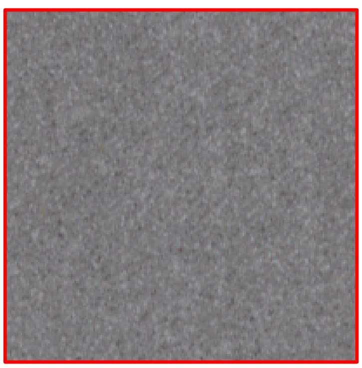

Figure 6. Descreened Patch via STFT approach

The *50th* percentile point being *0* indicates that more than half of the pixels between two figures are exactly the same. Furthermore, to evaluate how much this code value difference affects the computed color granularity, we adopt both descreening algorithms to seven color patches with 60% tint, including cyan, magenta, yellow, black, red, green and blue. They show that *STFT* algorithm creates color patches with slightly higher computed color granularity than *FT* algorithm with average offset being *0.06* and maximum *0.11*. To put this difference in perspective, the average dynamic range of computed color granularity on a color patch using *FT* algorithm is also *0.06*. We can, therefore, deduce that we can ignore the difference between the *FT* and *STFT* algorithm.

Figure 7 and 8 illustrates the effectiveness of our proposed STFT algorithm on removing image color halftone screen signals. Figure 7 is the original scanned image which contains at least three different color screen combinations, and Figure 8 shows that our algorithm successfully remove those color screen signals without degrade the inherent image content. For example, unlike the low-pass filter approach, edges and fine details are well preserved. Note that we can still perceive slight reminiscence of color screen signals along the edges as well as within fine details. This is the compromise we made to select one window block size in the *STFT* color screen-removing algorithm to reduce the computational complexity. However, we can argue that a large image area is necessary to compute the corresponding color granularity. That is, image regions with fine details and edges are not suitable for computing granularity. Thus, this limitation will not affect our objective to measure image graininess.

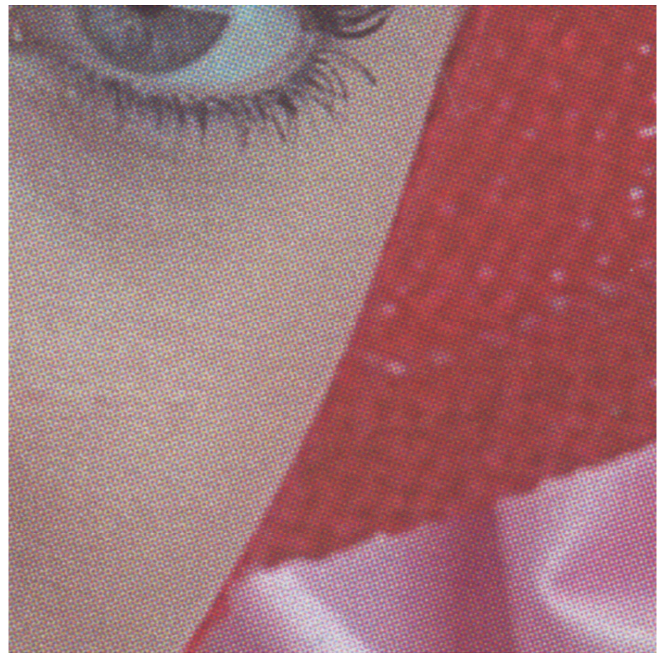

Figure 7. Original scanned image

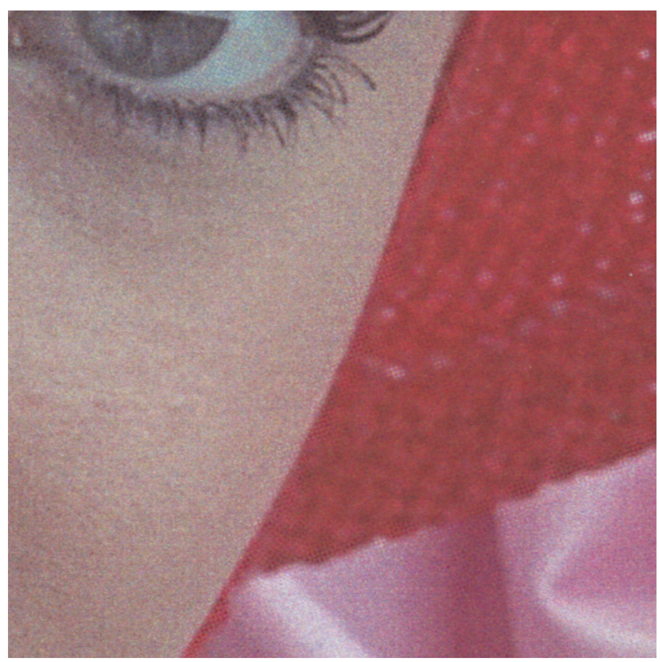

Figure 8. Descreened Image via the STFT algorithm

Although measuring granularity on uniform color patches is an effective approach to assess the performance of a printing system, there sill exists situations where measuring granularity on real images are needed. For example, the performance of two *ICC* profiles is best evaluated on real images because the computed granularity on primary colorants is unchanged. We select a test image as shown in Figure 9, and print it via two versions of *ICC* profiles. A quick survey shows that the *profile-A* results in higher perceived graininess than *profile-B* in all four tested regions: (1) arm, (2) lower-left tree, (3) forehead and (4) background tree, which are denoted in Figure 9. The computed granularity using our proposed algorithm is listed in Table 1.

Table 1 shows that the proposed algorithm successfully match the rank order of human observation.

Table 1: Granularity in 4 Areas of Interest

	Area 1	Area 2	Area 3	Area 4
Profile A	10.58	6.75	8.62	4.98
Profile B	5.86	4.60	5.57	4.47

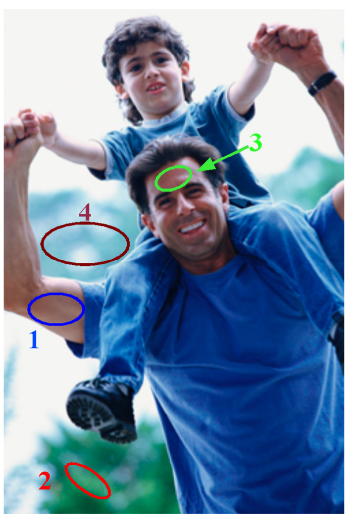

Figure 9. Test Image

Conclusion and Future Works

We have described an algorithm to quantify color granularity on regular images, and it consists two steps: removing space variant color halftone screen signals based on *STFT*, and interactive image granularity sampling technique. The proposed algorithm is shown to produce similar results on uniform color patches when compared with the *FT* approach we suggested in Ref. [4]. We then successfully measure color granularity and correlate with human observation in rank order on four areas of interest in an image. In the future, we plan to conduct psychophysical experiments on perceived graininess on regular images to obtain a more detailed and precise perceptual transformation from objective measurements.

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