

MicroUniformity: An Image Quality Metric For Measuring Noise

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Abstract

An overview of a new metric for measuring perceived uniformity of hardcopy, color prints is presented. We discuss the algorithm, and present examples of how the metric can be applied to a wide range of non-uniformity problems.

Introduction

Uniformity is one of the most important attributes of image quality of output from color printers or copiers, and present a challenge to all printing technologies. There is a vast range of different “looks” of non-uniformities, both for a given technology and between different technologies, which makes it difficult to establish measurement techniques which correlate to human visual perception of uniformity and that can be used to compare different technologies.

In the DAC system for characterizing image quality,¹ uniformity is segmented into two attributes: MacroUniformity and MicroUniformity. MicroUniformity is loosely defined as characterizing any non-uniformities which are visible even in very “busy” images that contain only small regions of nominally uniform color. More rigorously, DAC MicroUniformity can be defined to consider those non-uniformities which are visible even when the image is viewed through a mask with a 6mm diameter aperture. With this definition, MicroUniformity considers, among others, the following types of issues:

- What is commonly referred to as graininess, for example as seen in photographs due to the film grain, or as seen in electrophotographic prints and caused by process noise, especially during development.
- The “noisy-looking” pattern resulting from stochastic screens, seen most commonly from ink-jet printers.
- The periodic, cluster-dot screen seen in most lithographic, electrophotographic and other printing technologies.
- High frequency moire pattern seen where halftone screens of two or more separations beat against each other.
- High frequency periodic bands, for example caused by motion quality deficiencies.
- Non-periodic, high-frequency, streaks, for example caused by misdirected jets in an ink-jet printer.

From a measurement point of view, there are several challenges. For purposes of benchmarking it is often necessary to measure and compare print samples that exhibit different types of MicroUniformity, for example a comparison between samples where the main contribution to MicroUniformity is the pattern from stochastic screening with samples that are dominated by periodic screens and process noise. To compare such print samples it is necessary to use technology-independent Appearance Metrics² as opposed to technology specific Diagnostic Metrics. For example, a metric that describes uniformity in terms of dot size and shape regularity would not work at all.

Another challenge comes from applications for product development teams. When a specification for MicroUniformity has been determined, partly based on benchmarking, a product development team needs to track that measure and improve the product performance to reach the goal level. However, during product development you are often faced with a multitude of print quality defects, all of which are being worked on at the same time. This means that one print quality defect can potentially contaminate the measurements of another print quality attribute. For example, in the case of ink jet, there may be problems with paper advance motion quality that causes streaks, which in turn make it difficult to measure the obtainable MicroUniformity quality level corresponding to various ink formulations. Another example of a similar problem, taken from electrophotography, is the need to measure process noise in the presence of halftone screens. With a commonly used graininess³ measurement technique, based on Wiener spectrum estimates, the halftone screen, if it is coarse, can dominate the graininess measure.

Several techniques have been developed in the past to address some of these problems. In the case where data from a slit-scanning micro densitometer is used to estimate the Wiener spectrum, peaks caused by a single halftone screen can be eliminated in two ways. Through signal processing of the spectrum,⁴ or through an “aperture filtering technique” used during the data acquisition.⁵ In the case of aperture filtering, the width of the scanning slit is set equal to the period of the halftone screen, thus effectively filtering out the halftone frequency. However, this technique has severe limitations in that it can only be applied to images with a single halftone screen, and in particular not to images with several rotated dot screens.

In this paper we report on development of a new image quality metric to address many of the issues described above.

Measurement Environment

Many of the technical issues with measuring uniformity as described above, can be overcome in a straightforward manner if an imaging scientist is allowed to do manipulation and analysis on an image by image basis. The requirements to this work was, that the method be suitable not only for research purposes, but also for fully automated, production environments. The metric has been developed as a module within the IQAF⁶ image quality analysis system, and is used with image input from drum scanners as well as flatbed scanners. The IQAF system takes care of calibrating the images, scanned either in RGB mode, or in a channel that is complementary to the color being measured, such that the analysis can be defined in terms of images represented in CIE Lab or other visual color space.

Algorithm

The main advantages of the method lies in its capabilities to separate the spatial structure into different components. This separation can be performed both for gray scale images, representing CIE Lab L*, and for full color images. We will here report only on the analysis of the luminance part of a color image, since the luminance variations are visually most significant for MicroUniformity.

The algorithm operates on an image representing photopic reflectance. The image has typically been scanned at 600dpi sampling. The following steps are taken.

First, a Fast Fourier Transform (FFT) of the image is calculated, and a binary mask in frequency space is generated, which classifies each pixel in the Fourier image as belonging either to the "structured image" or to the "unstructured image." This classification is done based on a statistical analysis of the Fourier image. At each spatial frequency the average and standard deviation of the Fourier amplitude is calculated, taken over a narrow frequency band, and over all orientations. Those pixels where the amplitude exceeds the average (at that frequency) by more than a certain, fixed number of standard deviations are marked as belonging to the structured image. Pixels corresponding to frequencies below a certain threshold are all marked as belonging to the unstructured image, since there is not sufficient statistical information to reliably make a proper classification.

Secondly, the original photopic reflectance image is processed through a model of human perception of luminance variations at a viewing distance of 40cm. This is done via a kernel operation in real space where, to gain computational advantage, the kernel is represented as a sum of Gaussians. If necessary, this kernel is modified depending on the image input device used to capture the image, such that devices with more limited resolving power use a kernel that blur the image to a correspondingly lesser degree.

Thirdly, the visually processed image is separated into two components. Its FFT is calculated and split using the binary mask, and then each part is transformed back into real space. The resulting real space images are denoted "structured" and "unstructured," respectively. These two images are then further processed independently, to yield information on the different types of non-uniformities in the image.

For example, to calculate a measure equivalent to the previously mentioned metric for graininess, the unstructured image is passed through a high-pass filter, in order to filter out such variations as mottle, and the standard deviation of the resulting image is calculated. Based on visual scaling experiments a "density-factor" has been determined, and the standard deviation multiplied by the density-factor is taken as a measure of graininess.

The structured image can be analyzed similarly, to provide information on the perceptible non-uniformities in this category.

Examples

The section gives examples from ink jet and electrophotographic printers. In each case three images are shown: The original scanned image, the unstructured image, and the structured image. To better ensure a reproduction of the details of interest the images have been contrast enhanced. However, each of the three images within one set, have been enhanced by the same amount.

Notice that the exact same algorithm were applied to all the images.

Streaks in Ink Jet Print Sample

The images in Figure 1 show processing of an ink jet print sample that shows both horizontal streaks as well as two-dimensional random density fluctuations.

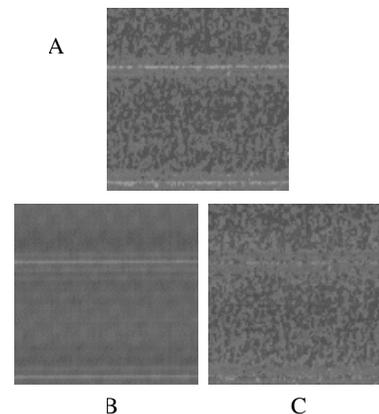


Figure 1. (A) Original scan of ink jet sample showing both streaks and two-dimensional noise. (B) The image component classified as "structured" shows the horizontal streaks. (C) The image component classified as "unstructured" shows the random variation.

A noise measure applied to the image in Figure 1C will correctly quantify the two-dimensional random fluctuations, without being influenced by the horizontal streaks.

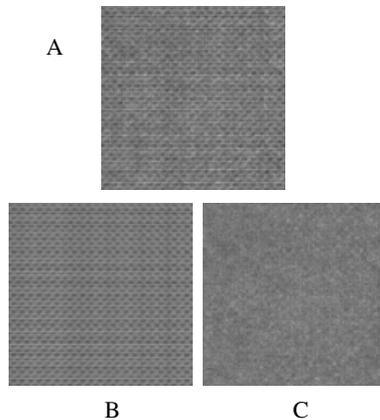


Figure 2. (A) Original scan of a halftone image from an electrophotographic printer, showing a strong screen, vertical streaks, and two-dimensional noise. (B) The image component classified as “structured” contains both the screen and the vertical streaks. (C) The image component classified as “unstructured” contains the random variation.

Screen in Electrophotographic Images

The images in Figure 2 are from an electrophotographic printer. The original image contained several rotated dot screens, and showed weak vertical streaks. Figure 2 (B) and (C) show an excellent separation of the periodic screen from the random fluctuations.

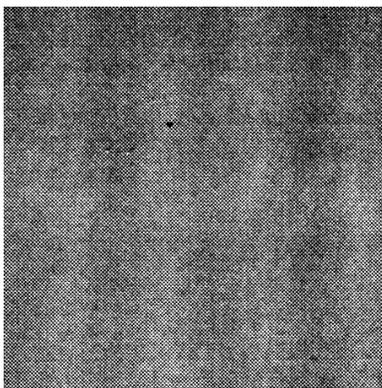


Figure 3. Original scan of a halftone image from an electrophotographic printer showing, halftone screen, banding, streaks and two-dimensional noise.

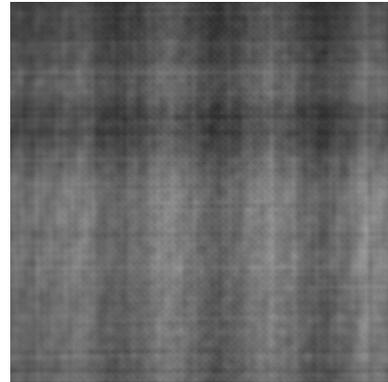


Figure 4. The structured image corresponding to Figure 3, after processing with a visual filter. This shows bands, streaks, and remnants of the halftone screen.

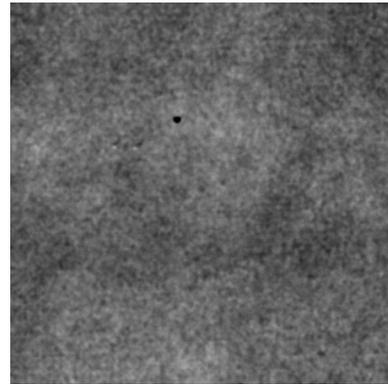


Figure 5. The unstructured image corresponding to Figure 3, after processing with a visual filter. This random two-dimensional fluctuations, as well as low frequency mottle.

Banding and Noise in Electrophotographic Images

The image in Figure 3 represents the original scan of a print sample from an electrophotographic printer. It shows a relatively high-frequency screen, vertical periodic bands, horizontal streaks, as well as random two-dimensional noise.

In Figure 4 is shown the corresponding structured image, after it has been processed through a visual filter. This image shows bands, streaks, and, due to the visual filter, only remnants of the screen. The unstructured, visually filtered image is shown in Figure 5. By further processing of the unstructured image, separate measures for high-frequency (graininess) and lower-frequency (mottle) variations can easily be obtained.

Conclusion

An image processing technique has been described, which allows an image to be separated into two components, representing different aspects of image quality. To obtain an overall measure of MicroUniformity it is important that such a separation is performed, since human observers have a different emotional response to the different types of variations—even if the variations on a physical scale have the same amplitude.

References

1. Edul N. Dalal, D. René Rasmussen, Fumio Nakaya, Peter A. Crean and Masaaki Sato, Evaluating the Overall Image Quality of Hardcopy Output, *Proc. PICS*, pg. 169 (1998).
2. D. René Rasmussen, Peter A. Crean, Fumio Nakaya, Masaaki Sato and Edul N. Dalal, Image Quality Metrics: Applications and Requirements, *Proc. PICS*, pg. 174 (1998).
3. R. P. Dooley and R. Shaw, *J. Appl. Photogr. Eng.*, **5**, 190 (1979).
4. Theodore Bouk and Norman Burningham, *IS&T's Eighth International Congress on Advances in Non-Impact Printing Technologies*, pg. 506 (1992).
5. Martin S. Maltz, Richard Bigelow and Kristen Natale, Half-tone image noise measuring techniques, *IS&T's Ninth*

International Congress on Advances in Non-Impact Printing Technologies, (1993).

6. D. René Rasmussen, Bimal Mishra and Michael Mongeon, Using drum and flatbed scanners for color image quality measurements, *Proc. PICS*, (2000).

Biography

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Bimal Mishra is a research member in the Color Science and Image Quality Area at the Wilson Center for Research and Technology in Webster, New York. His current responsibilities include development and implementation of image quality evaluation algorithms. He has a Ph.D. from Columbia University. His thesis was on the application of Brownian motion to visco-elastic liquid simulation. Prior to coming to Xerox, he worked as a visiting researcher at the Courant Institute of Mathematical Sciences in New York.