# Structure and color based comparison of halftone images

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# Abstract

A combined similarity metric for analysis of image quality is presented, which allows comparisons of halftone images based on their color difference and structure similarity. Color comparison is based on the I\*color metric [2], which was developed in the context of photographic image persistence. Structure similarity SSIM [1], initially designed for quality estimation in the context of image and video coding, characterizes the achromatic channel and refers to average luminance, average gradient and covariance (i.e. structure) calculated within a pre-defined neighborhood of each pixel. The two images to be compared must be given in terms of XYZ. After color opponent processing, they are spatially filtered according to the viewing distance with a spatial human visual observer model (HVOM), that takes different blurring of achromatic and chromatic channels into account (CSF's for AC1C2). In contrast to the original SSIM approach, CIELAB L\* or the A channel of the AC1C2 color space (see [3]) are used for the achromatic channel to already account for the non-linearity of luminance perception. Several examples of image comparison of simulated halftone prints are presented.

## Introduction

A quantitative similarity comparison of halftone printed pictorial images is challenging due to their discrete structure as a result of the printing method, due to the changes that printouts undergo in different applications (drying, fading etc.) and due to viewing circumstances (viewing distance etc.). A manifold of comparison methods and combinations of these methods with different weighting factors have been proposed for various applications over the last decades, spanning from global image quality measures [6] to image-wise comparison, most of them being based on a pixel-wise or histogram comparison.

Continuous work of CIE [8, 9] resulted in improved color appearance distance metrics for comparably color patches, and the most recent one, CIE  $\Delta$ E2000, is widely used and generally accepted as a standard providing satisfactory results for many practical needs, like color rendering benchmarks. Detail rendition aspects are addressed by spatial extension of CIELAB or more sophisticated multi-scale observer models. These methods were applied to benchmark image compression algorithms and virtual rendering. When it comes to halftone image comparisons, color differences are usually computed on the color palette of each image [4]. The drawback of CIE  $\Delta$ E2000 is given by its applicability to small changes in color and tone reproduction only. In certain applications, however, there is a need of quantifying more pronounced color changes, even falsely encoded colors. The paper of McCormick-Goodhart et al. [2] offers an interesting and more extensive debate on this problem in the context of image permanence for photographs. The authors propose a computational model for estimating 'the retained image appearance' of photographs, called I\* model. That paper also stresses the importance of a metric that directly provides results on specific images rather than being tied to a certain test target, like a predefined array of color patches. Also, the authors argue that the color information in an image (hue and chroma) is supplemental to the black-and-white information (lightness and contrast), and they therefore design the I\* model to analyze hue and chroma information separately from lightness and contrast information. I\*<sub>BW</sub> accounts for changes in achromatic contrast and luminance expressed in L\*, while the I\*<sub>color</sub> metric accounts for changes in chroma and hue. The result of the two analyses can be combined in an overall "figure of merit", that combines the two with a weight.

Wang et al. [1] have presented a method for the estimation of similarity between images with focus on the achromatic channel, the structure similarity metric SSIM: it measures similarity of images in terms of luminance, gradient and structure. This method is a full-reference quality assessment method, initially designed for quality estimation in the context of image and video coding. The main advantage of SSIM over  $I^*_{BW}$  is the introduction of structure information and a more flexible use of the pixel neighborhood.

In this paper we propose a combination of the  $I^*_{color}$  difference metric and the SSIM structure similarity metrics (achromatic channel), to which a human visual observer model can be added to obtain perceived image difference maps, that together depict the most relevant dimensions of image appearance, namely color, luminance, contrast and structure. With the individual difference maps and similarity scores at hands, still correlation with psychophysical scores need to be worked out, either using average difference measures or other percentiles to resemble "peak-picking" [7].

# **Similarity metrics**

## I\*color difference model

The  $I_{color}^*$  difference metric by McCormick-Goodhart et al. [2] aims at full tonal scale evaluation of image differences in the context of retained image appearance estimation. The color metric is based on the hue and chroma of the image, and a similarity value of 1 is obtained when no change has occurred. Changes in chroma bring the I\* values closer to 0. Negative values indicate falsely encoded colors, when also the hue has changed considerably (a hue shift of more than 60 degrees). The LCH space is divided in 7 color sectors, six fundamental ones obtained by dividing the color space in 60 degree sectors, and the seventh one covering the so-called 'gray sector', which denotes picture elements with a chroma less than or equal to 9.5. The I\* color metric at a given pixel is defined by the following computation:

$$I^* = 1 - \frac{(\Delta a * b *) - \varepsilon}{(C_i^*)}, \text{ for } C_i^* > 9.5$$

$$I^* = 1 - \frac{(\Delta a * b *) - \varepsilon}{9.5}$$
, for  $C^*_i \le 9.5$ 

where

$$\Delta a * b^* = \sqrt{(\Delta a)^2 + (\Delta b)^2}, \quad C *_i = \sqrt{(a_i)^2 + (b_i)^2}$$

The term  $\varepsilon$  compensates for small numerical errors in the course of experimental color measurement (typically 0.5), ensuring I\* equals 1 for identical colors. C\*<sub>i</sub> refers to the "initial" chroma (the reference image).  $\Delta a$  and  $\Delta b$  are the differences between the a\* and b\* values of the compared pixels.

# Structural Similarity (SSIM)

In their paper [1], the authors Wang et al. argue that pointbased metrics do not account for the structure (correlation) of the signal, whereas a measure of structural information change can provide an improved figure of merit for perceived image distortion.

Structural information in an image is analyzed in terms of *local* luminance, contrast and structure. Local computation takes into consideration that luminance and contrast can vary across the image. The three similarity dimensions are then combined in an overall similarity measure. With x and y representing the input signals under comparison, the computation of the luminance l, contrast c and structure s similarity measures is based on the following formulas:

$$l(x, y) = \frac{2\mu_x \mu_y + C_1}{\mu_x^2 + \mu_x^2 + C_1}, \qquad C_1 = (K_1 L)^2$$

$$c(x, y) = \frac{2\sigma_x \sigma_y + C_1}{\sigma_x^2 + \sigma_x^2 + C_1}, \qquad C_1 = (K_1 L)^2$$

$$s(x, y) = \frac{\sigma_{xy} + C_2}{\sigma_x \sigma_y + C_2}, \qquad C_2 = \frac{C_1}{2}$$

$$SSIM(x, y) = l(x, y) \cdot c(x, y) \cdot s(x, y),$$

where L is the range of values in the image, K<sub>1</sub> is a constant, and

$$\mu_{x} = \sum_{i=1}^{N} x_{i}, \ \sigma_{x} = \left(\sum_{i=1}^{N} (x_{i} - \mu_{x})^{2}\right)^{\frac{1}{2}}$$
$$\sigma_{xy} = \sum_{i=1}^{N} (x_{i} - \mu_{x})(y_{i} - \mu_{y})$$

The local statistics in terms of  $\mu_x$ ,  $\sigma_x$ ,  $\sigma_{xy}$  are computed within a local square window of adjustable size, which moves pixel-bypixel over the entire image. At each step the SSIM index is computed within such a window and allocated to the central pixel of the window in the resulting difference map. The overall SSIM index is the average of all the local indices.

# **Experimental Results**

#### Test images

Test images have been generated by a virtual image chain based simulation of Inkjet printing systems (multi-level halftoning), currently under development at Agfa-Gevaert [5]. For image comparison we present several examples of simulated halftone prints for a virtual printing process with the following settings: 4 inks (CMYK), one printhead per ink with 180 nozzles, no shingling, resolution 720 dpi, up to 4 levels per dot, where the smallest drop has 4 pl ink. The output of the simulation is an over-sampled image in terms of XYZ in which each ink dot is represented by a matrix of 9x9 pixels. Therefore, the physical size of the simulated print represents 9.22 mm only. The reference image marks the ideal printing process, i.e. no deviations from the intended settings. The images for comparison were obtained by the same print settings as before, except for one modification each. The resulting images are shown in Figure 1.



Figure 1. Simulated inkjet printouts. Upper row: the reference image (left) and a cropped region of it (right). Middle row: the printout with magenta bleed (left) and a cropped region of it. Lower row: Less ink load (left) and the printout with nozzle faults.

Three parameter variations were chosen with respect to the reference image, namely the following three cases:

- <u>Nozzle Faults</u>: 15% of the nozzles show systematic dot displacements in the range of 7 to 28 μm resulting in banding.
- 2. <u>Magenta Bleed</u>: (humidity-induced) bleed of Magenta ink, i.e. the ink dots get larger, while preserving their initial volume.
- 3. <u>Less ink</u>: the concentration of ink is reduced with 25% for all inks (equivalent to image fading)

# Results

The two images to be compared must be given in terms of XYZ. The difference maps obtained by applying the SSIM and the  $I_{color}^*$  metric are presented in Figure 2. Larger differences are indicated by darker pixels, whereas white indicates high similarity in the image difference maps. The SSIM index and the average  $I_{color}^*$  index for the three comparisons are shown in Table 1. In Figure 2 only the combined SSIM image difference map (the product of luminance, gradient and covariance) is shown. It should also be noted that the authors [1,2] correlated differently the two metrics to psychophysical scales.

SSIM is applied on the L\* channel with the following settings (for details refer to [1]): the local window is a Gaussian window of size 11x11, the values range L is set to 100, and  $K_1$  is 0.05. L and  $K_1$  tune the similarity metrics to fit the characteristics of the input signals. This means that the two parameters have different values when applied on images represented in different color spaces.

Case 1: Banding due to nozzle faults. We notice that the SSIM map correctly identifies the 'structural' source of the distortion, by highlighting the ink dots displacement as a result of the systematic nozzle faults. The  $I^*_{color}$  difference map also catches the region where the distortions occur, but the banding artifact is to a large extend camouflaged by the image content, whereas the SSIM map more clearly shows the structural image difference as perceived.

Case 2: Distortions due to bleeding of the magenta ink. The two metrics highlight distortions complementary: SSIM identifies structural changes due to changes of intensity and dot diameter of magenta dots, especially in areas where they are printed isolated. In neutral areas that are printed as combination of CMY individual dot changes are found less prominent by SSIM. I\*<sub>color</sub> on the other hand reports mainly changes in the colored areas, whereas less differences are found in the lighter areas. The two maps turn out to deliver complementary difference information in this case.

Case 3: Distortions due to less ink load. In this case both metrics provide similar results, basically indicating the darker regions as the place where ink fading has stronger effects.

Irrespective of the different psychophysical scales employed in  $I^*_{color}$  and SSIM, the two methods report different ranking of the image distortions for the three cases, which corresponds to the different effects that the distortions have on the achromatic and color channels of the simulated prints, respectively.

The individual difference maps of SSIM, namely the luminance, contrast and structure difference maps, can also provide a clue on the nature of the changes indicated by SSIM. Figure 4 shows an example of such difference maps, in the test Case 3 (ink fading). We notice that the maps indicate that the main changes caused in the case of less ink are in luminance (increased luminance due to less ink load) and in structure (due to smaller ink drops), whereas contrast changes are minimal.

## SSIM comparison after HVOM spatial blurring

Structural comparison of halftone images can be applied on a magnified (microscopic) view of the printouts, where the halftone structure is distinguishable, or on the spatially blurred version of the image that simulates the human perception at a given viewing distance, and where the halftone structure is no longer visible. Thus, one can choose for a kind of "technical image comparison" mode (without HVOM) or for a "perceived image comparison" mode, in which HVOM filtering is included in order to focus comparison on the perceived structure of the printout.

The HVOM method employed in our computations is a refined version of s-CIELAB [9, 3], with XYZ for each (sub-)pixel as input. After color opponent processing, the two input images are spatially filtered according to the viewing distance (30 cm) and to the linear CSF for achromatic and chromatic channels (different CSF's for AC<sub>1</sub>C<sub>2</sub>). For SSIM computation only the filtered achromatic channel (A) of the compared images was used, where the value range setting of L has been set to 50 (instead of 100, the setting for the L\* channel).



Figure 2. Difference maps wrt the reference image. Left: SSIM maps; Right: I\* maps. Upper row: Printout with nozzle faults; Middle row: Printout with magenta bleed; Lower row: Printout with less ink

Table1. Experiment	al results: SSIM and I*,	<sub>color</sub> similarity indices

Comparison	SSIM index	Average I* <sub>color</sub>
	0.952	0.848
Nozzle faults		
	0.984	0.775
25% less ink		
	0.993	0.866
Magenta bleed		

The image of the test-case "nozzle faults" is presented in Figure 3. Next to it we see the SSIM difference map with respect to the HVOM filtered reference image. The overall SSIM index in this case is 0.998. As expected, the similarity to the filtered reference image is higher than when all details in the halftone image where taken into account (Case 1 in the previous section).



Figure 3. HVOM filtered image with nozzle faults (left) and the SSIM difference map obtained by comparing to the reference image after filtering



Figure 4. SSIM individual difference maps for Case 3 (less ink). Upper row: Luminance differences (left), Contrast differences (right); Lower row: Structure differences (left) and combined SSIM differences (right).

# Conclusions

A new combination of image difference metrics for imagewise comparison of halftone images has been identified, which is based on a weighted combination of achromatic differences in terms of luminance, gradient and co-variance (structure) and of differences in hue and chroma (color). The corresponding metrics have been introduced in the context of quality estimation for image compression (SSIM) and image permanence ( $I^*_{color}$ ), respectively. For determining the weight of each image quality dimension in the combined metrics, a correlation with psychophysical scores on various images will have to be worked out.

We assume that structure and detail perception is mostly governed by achromatic (brightness and contrast) information, whereas color perception within an image is less influenced by the neighborhood of pixels. Otherwise, a straightforward extension of SSIM to color seems feasible, e.g. the value, gradient and structure of color in terms of C and H, with as drawback a considerable increase of the image quality dimensions. Alternatively, there might only be the need to introduce color structure, in addition to  $I^*_{color}$ , as 5<sup>th</sup> dimension in order to account for color noise.

Following the experimental approach of the authors of SSIM in [1], one can consider the use of the combined similarity metric for halftone images as a print quality prediction tool. This requires first a step of psychophysical tests aiming at correlating the scale of similarity indices to the quality scale. Quality can then be expressed either as function of technical parameters (so correlation is done to the technical mode of comparison), or as function of human perception (where the metrics are used after applying a HVOM filtering on the images).

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## References

- Z. Wang, A.C. Bovik, H.R. Sheikh, E.P. Simoncelli, "Image Quality Assessment: From Error Visibility to Structural Similarity", IEEE Transactions on Image Processing, pg. 143, (2004).
- [2] M. McCormick-Goodhart, H. Wilhelm, D. Shklyarov, "A 'Retained Image Appearance' Metric For Full Tonal Scale, Colorimetric Evaluation Of Photographic Image Stability", Proc. IS&T NIP20, pg. 680, (2004).
- [3] C. Marchessoux, J, Jung, "Extension of s-cielab for a virtual image chain", to appear in IS&T ICIS06, (2006).
- [4] J. Uroz, M.R. Luo, J. Morovic, "Perception of colour differences between printed images", in Colour Science: Exploiting digital media, John Wiley & Sons, Ltd, (2002).
- [5] J. Jung, R. Geelen, D. Vandenbroucke, "The virtual image chain: a powerful tool for the evaluation of the perceived image quality as a function of imaging system parameters", Proc. IS&T/PICS, pg. 128. (2001).
- [6] C. J. Bartleson, "The combined influence of sharpness and graininess on the quality of colour prints", Jour. Photog. Science 30:33 (1982)
- [7] P. G. Engeldrum, "A framework for image quality models", Jour. Imag. Sci. & Tech. 39:312 (1995)
- [8] M. D. Fairchild, Color Appearance Models, Addison-Wesley, Reading, MA. ISBN 0-201-63464-3. (1998)
- [9] G.M. Johnson, M.D. Fairchild, "A top down description of S-CIELAB and CIEDE2000", Color Research and Application, 28(6), pg. 425, (2003).

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Florica Mindru received her MS in Computer Science in 1997 from the Technical University of Cluj-Napoca, Romania. In 2003 she obtained a PhD in Applied Engineering - Computer Vision at the Katholieke Universiteit Leuven (KULeuven), Belgium. In 2003 she received a 9 moths European postdoctoral fellowship at the Fraunhofer Institute of Applied Research, at the Institute for Media Communication (IMK) in Bonn, Germany. Since 2004 she works at the R&D Division of Agfa-Gevaert, Belgium, on a virtual image chain based simulation project for Inkjet systems.