# Local Gray Component Replacement Using Image Analysis

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## Abstract

*In printing, ink is one of the most important cost factors, which accounts for approximately 25-30% of the cost per page; therefore, reducing ink consumption is of great interest. The traditional approach to this problem is to modify the ICC profile to increase the use of black ink instead of the combination of cyan, yellow, and magenta; this approach is known as the gray component replacement (GCR). While this strategy reduces ink consumption, it often results in visually grainy images in otherwise smooth regions, and is therefore of limited use or even unacceptable for many applications, such as photoprinting.*

*In this work, we propose a novel, context sensitive and spatially variant GCR method, which yields ink consumption figures that are similar to an aggressive GCR, but in contrast produces perfectly acceptable print quality results. Our approach is based on the visual masking effect: image areas with high activity level, such as high contrast textures, mask the increased graininess, and other inaccuracies such as (small) color shifts. Therefore, we propose to dynamically vary the amount of gray replacement across the image as a function of the local "activity" of the image. In lighter, smoother regions, less aggressive GCR is applied, and the image quality is preserved, while in more active regions where the change is not visible, more aggressive GCR is applied.*

*The performance of the proposed method is tested on images randomly chosen from several photo collections. The initial results indicate about 15% reduction in overall ink consumption with perfectly acceptable print quality.*

## Introduction

Currently, the main approach to reducing ink consumption and keeping good color reproduction is building optimized ICC profiles (e.g., [1]); that task is performed by highly qualified color scientists. In that approach, a reduction of ink consumption is achieved by increasing the use of black ink (K) instead of the combination of cyan, yellow, and magenta (CMY). This strategy is known as the gray component replacement (GCR). However, that method is quite limited since, when used aggressively for lower ink consumption, GCR causes grainy appearance of images, and is therefore unacceptable for many applications such as photoprinting.

## The proposed approach

We take an alternative approach to the problem of reduction of ink consumption that can be combined with an optimized ICC profile. Figure 1 outlines the main steps of the proposed approach. We explain these steps in details in the next section. For now, we concentrate on the main idea of our approach.

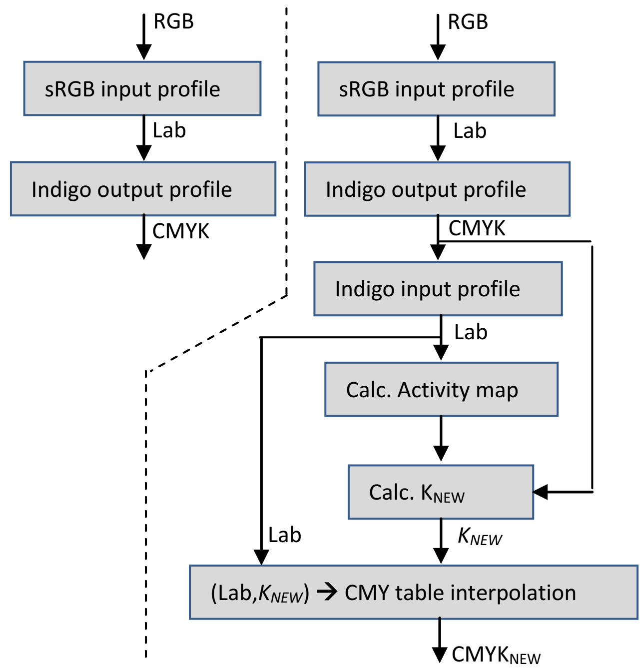


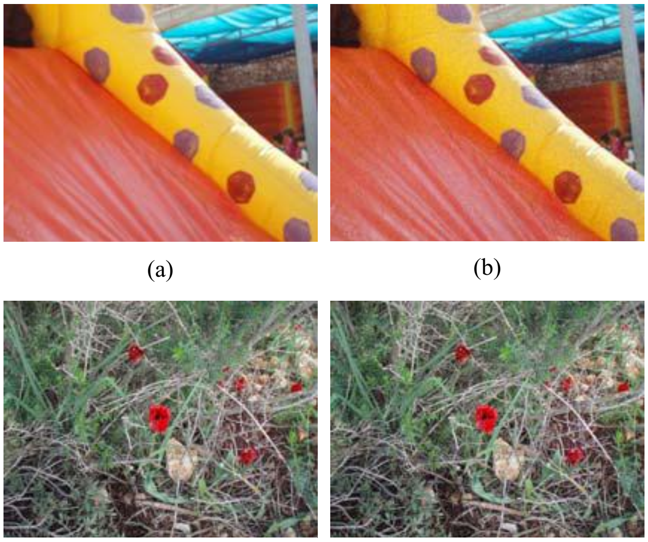

***Fig.1.*** *Color Conversion: traditional (left), proposed (right)*

Our approach is based on the visual masking effect: image areas with high activity level, such as various textures, mask the increased graininess and other print inaccuracies, such as color shifts and others. The masking idea is widely used in watermarking (see for example [2]-[4]), where one embeds watermarks in the areas of the image where they are perceptually invisible. Although the masking idea behind our approach is similar, our goal is quite different. In order to illustrate the masking phenomenon, we show the four images in Figure 2. Images 2(a) and 2(c) are the originals, and images 2(b) and 2(c) are the corresponding images with a same amount of additive random noise. Clearly, the $L_2$ distance between 2(a) and 2(b), and the $L_2$ distance between 2(c) and 2(d) is the same. However, visual differences are much more noticeable between 2(a) and 2(b), as the original image is smoother, than between 2(c) and 2(d), where the original image contains various textures.

Therefore, our approach is as follows: We first analyze a given image, and estimate the map of local activity. Then we vary the aggressiveness of the ink replacement (GCR) in a pixel-wise manner, according to the estimated local activity strength.

The rest of the paper is organized as follows. We first compare the traditional Color Conversion scheme to the proposed Color Conversion scheme that incorporates the idea of the masking



(a) (b)

(c) (d)

***Figure 2.*** *Illustration of the masking effect. Identical noises are added to (a) and (c). The noise is more visible in (b) which is smooth as compared to (d); the noise is masked by the intrinsic image features in (d).*

effect. We then get into details of the main steps of the proposed scheme, and finally show results of experiments we conducted.

## *Color conversion guided by image analysis*

The traditional color conversion steps are depicted in the left side of Figure 1. The main steps of the proposed color conversion scheme that incorporates the idea of masking effect are depicted in the right side of Figure 1. The first two steps in both schemes are identical: First, a sRGB image is converted to Lab space, and then the ICC profile of a specific printer is applied to transfer the Lab image values to CMYK values. As described previously, the ICC profile would generally be optimized for print quality, or it may already be optimized for lower ink consumption. In fact, these two steps perform perceptual color conversion, the gamut mapping from RGB to the device CMYK. The rest of the steps are done colorimetrically, aiming at the best match to the device CMYK color.

In particular, the following steps are unique to our scheme. First, we apply the printer input profile to transfer back to the in-gamut image Lab values. We use these values to estimate the local level of image activity $A(i,j)$ for each pixel $(i,j)$, as described in the following section. Given this value of activity, we calculate a new value of K.

If the particular pixel is in a smooth image area, the corresponding activity value will be very low or even zero. In this case, the original K will be preserved, and therefore there will be no increased graininess in this particular area. If, in contrast, a local activity value is high, this indicates that there are intrinsic image features, such as various textures, which are high frequency variations. The addition to the original K will be somewhat proportional to this local activity value.

The last step of the scheme, the color search, computes the new CMY values. In particular, given the newly calculated K value and the Lab image values for pixel $(i,j)$, we look for the new CMY values, which along with KNEW, yield the closest match to the original Lab value. The details of the search algorithm are described below.

## *Perceptual local activity*

There are several possible choices for the calculation of local activity; one of the simplest measures would be based on the image block variance, or some thresholded version of it. More sophisticated methods such as [5], characterize textures as fine scale details, usually with some periodicity and oscillatory nature. In [6], the authors propose Total Variation model of textures and edges.

While these methods are theoretically sound, they are not always well supported by the visual experiments, and do not take into account human visual system (HVS) properties and considerations. In turn, many compression schemes, such as cosine or wavelet transform based ones, exploit the HVS properties (see for example [7] and [8], and the references therein). In JPEG compression, small quantization steps are set for low-frequency DCT components, whereas large steps are set for high-frequency components. It is this insight that drives our approach of calculating the local activity measure. In particular, we first calculate the discrete cosine transform of overlapping image blocks of size 4x4. We found that using this block size gives similar activity values to the ones obtained using the 8x8 block size, but is much less computationally intensive. We then multiply the resulting DCT coefficients by an HVS weighting matrix which is calculated using widely available JPEG quantization tables; the weights are proportional to the quantization step sizes. The resulting local activity measure for pixel $(i,j)$ is calculated as the square root energy of the weighted local DCT coefficients of block $B(i,j)$ with the center-pixel coordinates $(i,j)$, excluding the DC component, and divided by the local mean lightness value $C_1[B(i,j)]$. In math notation,

$$A(i,j)=\frac{\sqrt{\sum_{m=2}^{M}\left(W_m\cdot C_m\left\{\psi_{\delta_{CSF}}\left[B(i,j)\right]\right\}\right)^2}}{C_1\left\{\psi_{\delta_{CSF}}\left[B(i,j)\right]\right\}} \qquad (1)$$

where $C_m$ are block DCT coefficients, and $W_m$ are the JPEG quantization table weights. Further, function $\psi$ is the image detail-removing operation applied to each block $B[(i,j)]$.

This operation effectively zeroes out the image details in the block that are below a threshold $\delta$. This threshold is calculated using the Contrast Sensitivity Function (CSF). The rationale behind this operation is as follows. If an image has large number of pixels but the print size is small, then the activity on a 'pixel level' will not be perceived, and otherwise active area will look relatively smooth. In this case, it is desirable that the corresponding activity is adaptive to reflect this phenomenon. Clearly, the perceived activity strength is dependent on the print resolution and on the number of pixels in an image. These two factors determine the physical pixel size. Given this pixel size and a standard viewing distance, we use the well-known CSF curve to calculate the minimal contrast required to perceive differences between neighboring pixels. The resulting perceptual activity is therefore

***Figure 3.*** *Original image (upper), and the corresponding Activity map (lower).*

adaptively adjusted to a given printing resolution and a given image size.

An example of such activity map is presented in Figure 3. The bright areas in the map correspond to high activity in the image. In these areas, more aggressive ink replacement (higher black ink usage) will not influence the perceived quality of the print because of the masking effect.

The estimated local activity value determines the new amount of black ink. In order to evaluate the amount of black ink that can be added without visually noticeable grain and color shift, we conducted the following experiment. We printed 6 pages, each containing 10x15 patches of the same color (Lab specification). On one axis, the patches vary in the amount of printed black (K), while on the other axis, the pages varies in the level of activity (noise of various types with gradually increasing variance). Our purpose was to achieve a formula for the new values of K ($K_{NEW}$) that will, on the one hand, assure optimal quality, and on the other hand, achieve the minimal ink consumption. The resulting formula which was derived experimentally is:

$$K_{NEW}(i,j) = 100 \cdot \left(K(i,j)/100\right)^{\max[0.3,1-F\cdot A(i,j)]} \quad (2)$$

where $K(i,j)$ is the initial black ink amount for pixel $(i,j)$ determined by a given ICC profile, $K_{NEW}$ is the new, higher value of black ink to be used, and $F$ is the ink replacement strength (i.e., the GCR aggressiveness factor; higher value corresponds to higher black ink consumption).

### *Color search algorithm*

Given the new black ink amount $K_{NEW}$, the color search algorithm – the {Lab, $K_{NEW}$}-to-CMY module in Figure 1 – calculates the new CMY values that, along with $K_{NEW}$ yield the closest match to the original Lab values. In order to do that, we calculate the conversion table from {Lab, K} to CMY by using the device ICC profile. In particular, we use the colorimetric A2B1 tag to create the printer characterization data (the so-called forward model). We then perform the color search by the following iterative steps:

1) At each iteration $n$, starting from $n$=0, given $K_{NEW}$ and the current CMY$_n$, we calculate the new Lab$_{n+1}$ values using the forward model
2) We compare the original Lab to Lab$_n$ by calculating ΔE distance. If ΔE is smaller than a predefined threshold, then we finish the iterations. If not, we proceed with iterations as follows.
3) At each iteration step, we perform the following sub-steps. We change each one of C, M, and Y values at a time, with the increments up and down from the current value. We calculate the corresponding ΔE, and replace the particular color to a new value only if ΔE has decreased.

We found the above algorithm converges to (nearly) the same CMY values regardless of its starting point, as long as it is selected sufficiently close to the initial CMY values. Therefore, we use these initial CMY values as our starting point in the first iteration. This search algorithm ensures the color preservation property of the method.

## Experimental results

We tested the performance of the proposed method on several sets of images randomly chosen from various image banks. We set 6 levels of the ink replacement strength $F$; each level corresponds to different amount of black ink used instead of CMY inks.

We have conducted an experiment with 59 different images having various resolutions, and containing various amounts of active areas. We measured the consumed ink amount for images with original and modified CMYK values as follows. The coverage values of all separations were transformed through a job LUT and a machine LUT of a particular printer (we used an HP Indigo Press), and translated into ink weights. The savings in each separation were computed as the difference in weight between original and modified CMYK's, divided by the total weight of ink consumed by the original CMYK. In particular, the per-pixel ink consumption values were averaged over the whole image, yielding the Average Ink Consumption Per Image (AICPI). The saving amount for each separation $Q$ = C, M, Y, K in percentage from the original usage is calculated as:

$$S_Q = \frac{\left(AICPI\left(Q_{orig}\right) - AICPI\left(Q_{NEW}\right)\right)}{\sum_{Q=C,M,Y,K} AICPI\left(Q_{orig}\right)} \quad (3)$$

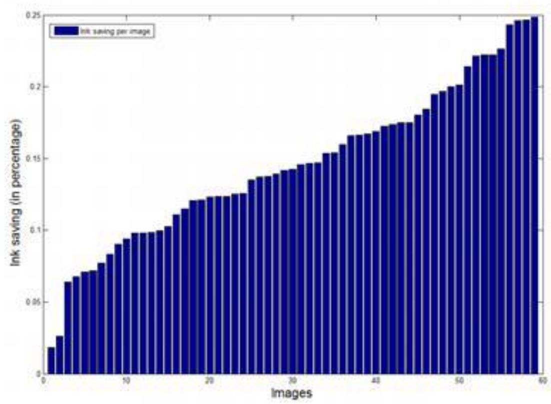



***Figure 4.*** *Total ink consumption reduction percentages (divided by 100) for the 59 tested images.*

The total ink consumption reduction percentage, achieved using the proposed approach is calculated as:

$$S_{total} = \sum_{Q=C,M,Y,K} S_Q . \qquad (4)$$

### *Real images*

The resulting total ink consumption reduction percentages for the 59 tested images are presented in Figure 4 and Figure 5. In Figure 4, the values are sorted in the ascending order. The leftmost (smallest) bar corresponds to the lowest total ink consumption reduction percentage of 2%. The rightmost (highest) bar corresponds to the largest total ink consumption reduction percentage of 25%. The two corresponding images are shown in Figure 6. As expected, smooth image (left) yields the lowest ink consumption reduction, while more active image (right) yields substantially greater ink consumption reduction.

Figure 5 shows the corresponding actual differences of the ink consumption per pixel for each separation (in micro grams), calculated for each of the test images. As can be seen, the black consumption for all images was increased (reflected by negative savings), while the cyan, magenta and yellow consumption was reduced. The sum of these differences resulted in the total savings of inks (blue dots).

Figure 7 shows total ink consumption relative to its original consumption, as a function of *F*, the GCR aggressiveness; the restraining factor of 0.3 in (1) restricts higher ink consumption reduction for larger values of *F*. This explains relatively small additional gain in saving for *F*=25 and *F*=30 compared to *F*=20.

A committee of 3 color experts performed visual comparison of the ink-replaced prints and the standard ICC profile prints, and found that the print quality of 95% of the prints in the test was perfectly acceptable up to the aggressiveness level of *F*=20. This further proves the effectiveness of the proposed method

## Summary

In this work we proposed a novel approach to the reduction of ink consumption. It is based on the visual masking effect: image areas with high activity level, such as high contrast textures, mask the increased graininess and other inaccuracies such as (small) color shifts. We dynamically vary the amount of gray replacement

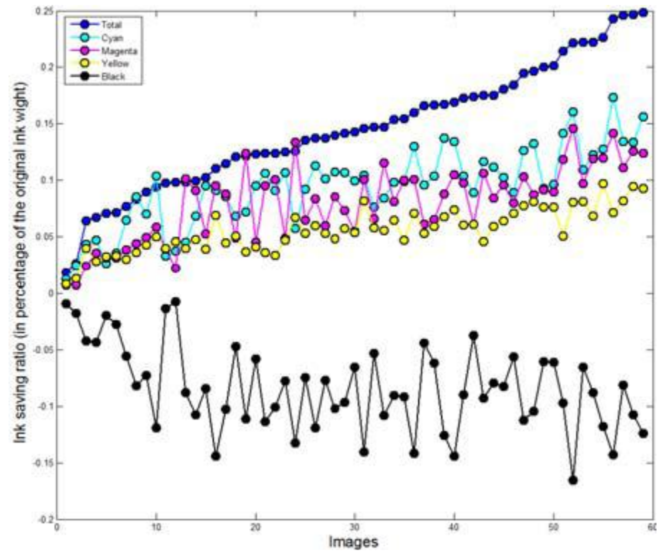



***Figure 5****. Total ink consumption per pixel (blue dots), and consumption per pixel for each separation (in nano grams).*

strength across the image as a function of the local "activity" of the image. In lighter, smoother regions, less aggressive GCR is applied, and the image quality is preserved, while in more active regions where the change is not visible, more aggressive GCR is applied.

The local pixel-wise activity measure is calculated as the square root energy of the weighted local DCT coefficients, with weights derived from the HVS-motivated standard quantization table. Furthermore, the map strength is adaptively adjusted to print resolution and to actual image size (in pixels), according to the CSF curve.

The performance of the proposed method was tested on images randomly chosen from various photo collections. The initial results indicate about 15% overall ink consumption reduction with perfectly acceptable print quality.

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*Figure 6*. Two images from the test with the lowest (left) and the highest (right) ink consumption reduction values.

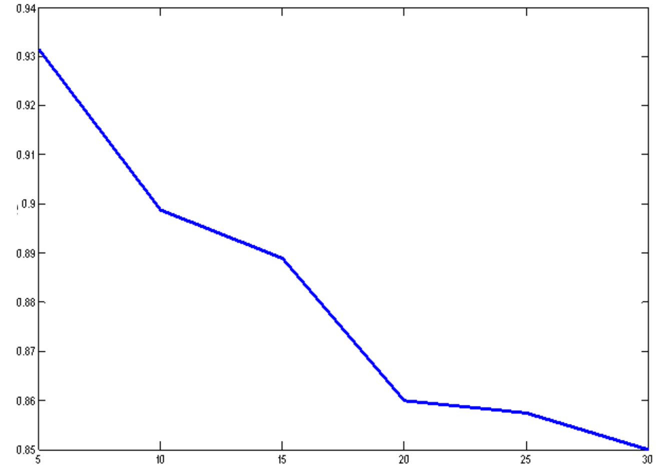


***Figure 7.*** *Total ink consumption relative to the original consumption as a function of F, the GCR aggressiveness parameter (average over 59 tested images)*

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## Author Biography

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*Michal Aharon received her B. Sc. (summa cum laude), M.Sc. (cum laude), and PhD degrees in Computer Science from the Technion-Israel institute of Technology, Haifa, Israel, in 2001, 2004, and 2007, respectively. Both the M.Sc and PhD dissertations are in the field of image and signal processing, concentrating on dimensionality reduction and sparse representation of signals. Michal worked at HP Labs Israel from 2006 to 2011, when she joined Yahoo! Labs in Haifa, Israel.*

*Carl Staelin received his PhD in Computer Science from Princeton University in 1991 in high performance file system design. His research interests include automatic image enhancement and processing, digital commercial printing, performance analysis, document and information management, and high performance storage systems. Until 2011 he worked as the Chief Technologist for Hewlett-Packard Laboratories Israel. He led a team developing system software for commercial printers, such as the HP SmartStream Photo Enhancement Server. Before that, he led a group which developed the HP Document system based in part on the Multivalent document framework from U.C. Berkeley. He is also a co-developer of the popular lmbench micro-benchmark suite. Previously he worked on the first HP AutoRAID product, and while working for HP at U.C. Berkeley he worked on the 4.4BSD LFS port, the HighLight hierarchical storage file system, the Mariposa distributed database, and the NOW project. Carl joined Google Labs in Haifa, Israel, in 2011.*

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