

Printer-Specific Automatic Enhancement of Photographic Color Images

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Abstract

This paper discusses the advantages of printer-specific color image enhancement. A study of algorithms used for automatic global color adjustment revealed that to achieve optimum results, a knowledge of output device properties is required. Particularly important printer characteristics were the size and shape of the color gamut. Simple examples illustrating this observation are given. In addition, a research project where automatic image enhancement software was developed exclusively for a selected large-format ink jet printer is described.

The main aim of the automatic image enhancement was to adjust overall contrast and gray balance in an optimum way. To achieve this, a multilayer feedforward neural network was trained to define adjustment parameters for color prints. The input of the neural network consisted of statistical properties of RGB images. The target data (desired output) were defined visually by selecting the best print from pictures enhanced with different adjustment variable combinations. After training, the neural network was capable of finding optimum or nearly optimum adjustment parameters for photographic pictures. In practice, the automatic adjustment software was capable of significantly improving image quality in slightly more than half the cases. For the rest of the pictures no statistically significant change in visually assessed quality was observed. Most images falling into this category originally had good contrast.

Introduction

The primary purpose of this introduction is to discuss and verify the need for output device-specific image enhancement. The discussion is restricted to global color adjustments (thus excluding all spatial adjustments).

General automatic color image enhancement algorithm can be defined using the simple Formula (1).

$$COLOR_{output} = f(COLOR_{input}, I\_FEATURES_i) \qquad (1)$$

$i = 1...n$; n = the number of image features used.

The adjustment function f has two (multidimensional) variables: the original color ($COLOR_{input}$) and the feature vector characterizing the image ($I\_FEATURES_i$). This function calculates a new color ($COLOR_{output}$) for every pixel of the original image. For monochrome image adjustment the COLOR variable has only one dimension, but it normally has three (e.g. CIE L*,a*,b*)[1].

The assumption that optimal automatic color adjustment is subject to output device properties implies that no function (f) exists that would work optimally regardless of output device. Moreover, it must be presumed that the output colors given by Formula (1) cannot be completely successfully converted for another output device with empirically defined look-up tables, ICC profiles[2], or any other image independent conversion. The resulting colors should not give an optimum result if the other output device had significantly different properties. In other words, if Formula (1) gives optimum colors ($COLOR_{output1}$) for an output device and these colors can, using simple Formula (2), be converted into other colors ($COLOR_{output2}$) giving optimum output for another output device, printer-specific color image enhancement is not needed. But if this cannot be done, the opposite is true.

$$COLOR_{output2} = g(COLOR_{output1}) \qquad (2)$$

Formulae (1) and (2) can be combined into formula (3):

$$COLOR_{output2} = g(f(COLOR_{input}, I\_FEATURES_i)) \qquad (3)$$

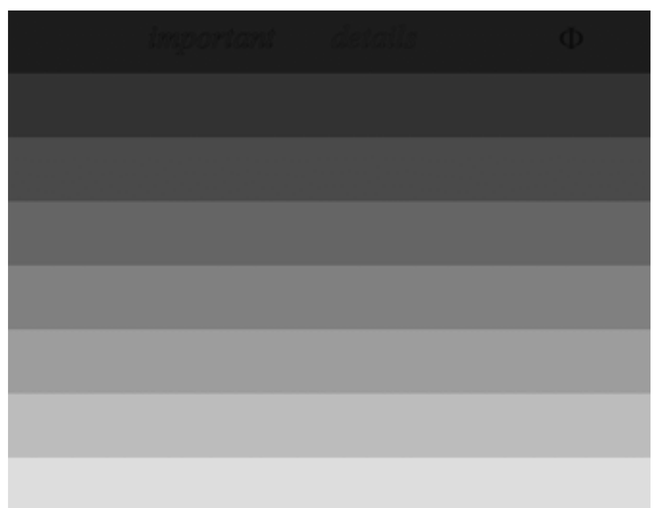

Figure 1. A simple test image (all parts of the original tonal range are of equal importance).

In practice, if (interactively adjusted and visually assessed) optimum color reproductions having different (output) dynamic range are compared, examples can be found where image properties affect adjustment needs differently depending on color gamut characteristics. Such images were discovered among photographic pictures but the example given here illustrates this phenomenon with a simple monochrome test image. If the image in Figure 1 is printed with two different printers having different tonal ranges, good results may be attained through linear reduction of CIELAB L* (lightness) values. This implies, however, that all parts of the original tonal range are at least of approximately equal importance.[3]

This is illustrated in Figures 2 and 3. Specifically this implies that the darkest tones ("details" at the top of the image) are as important as other tones.

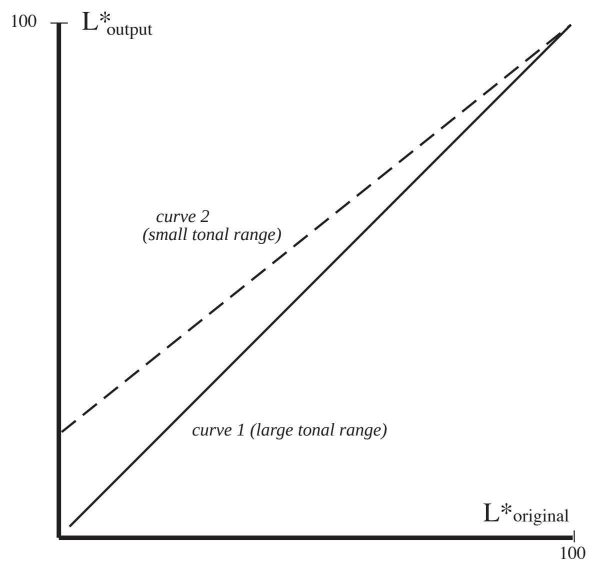

Figure 2. Examples of optimum tone rendering curves (original: Fig. 1.).

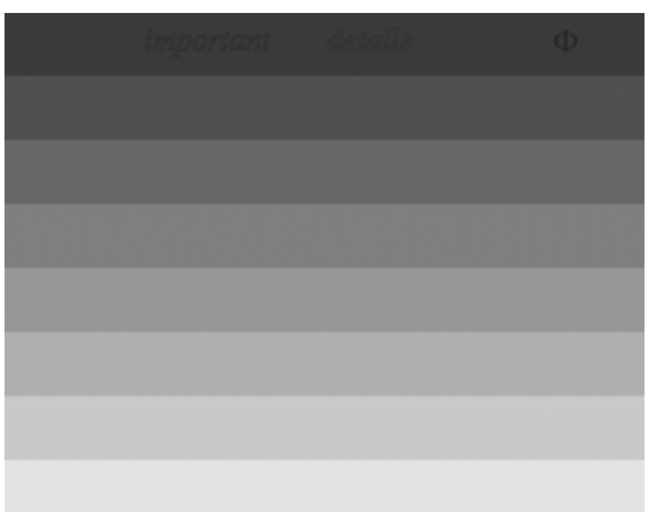

Figure 3.Result of linear lightness reduction. (curve 2 in Fig. 2)

If this is not the case, the unimportant details can be sacrificed and the limited attainable tonal range used more effectively as illustrated in Figures 4, 5 and 6.

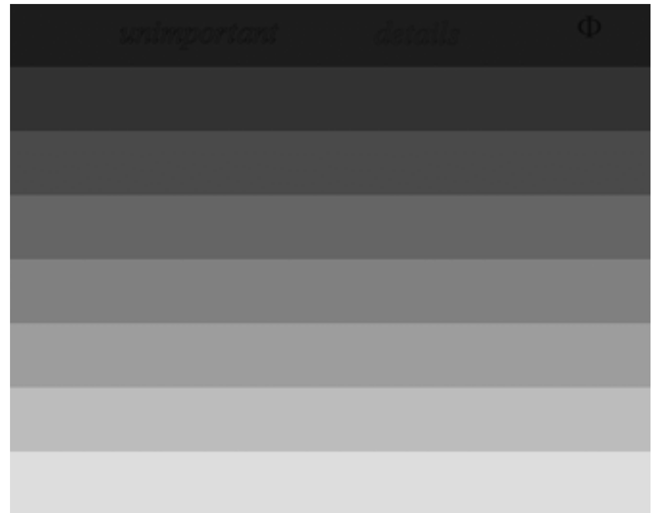

Figure 4. Another simple test image (unimportant dark tones).

However, this trade-off is not needed if the output device has a large tonal range (Fig. 4 and 5, curve 1 (original tones are unchanged)).

All in all, the smaller the reproducible color gamut is, the more critical and difficult image enhancement becomes. A small gamut increases the possibility that some important details cannot be distinguished because of poor contrast. Unfortunately, the possibilities for increasing contrast in desired color areas are also usually poor.

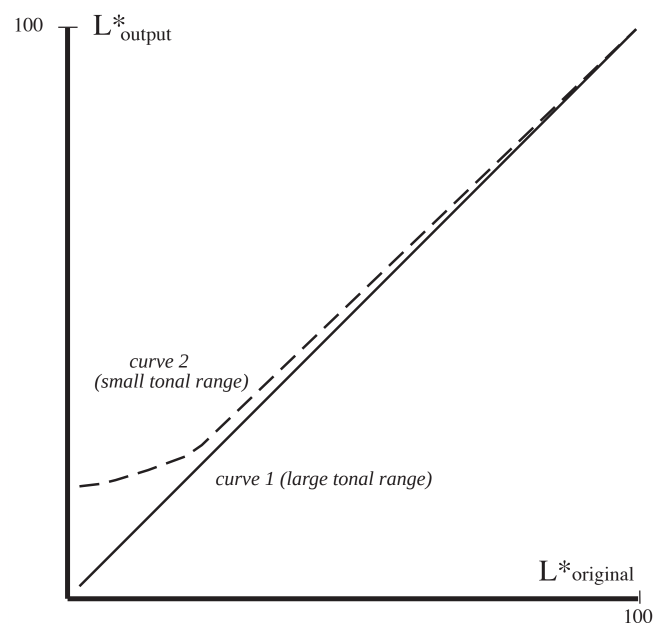

Figure 5. Examples of optimum tone rendering curves (original: Fig. 4.).

In practice, optimum image quality is far too demanding an aim for current automatic image enhancement algorithms. However, significant quality improvement was attained in a research project where a printer-specific image enhancement algorithm was developed. The goal of this study was to train an artificial neural network to select color adjustment parameters yielding the best visual quality for the selected HP printer. Unlike previous applications developed at the Helsinki University of Technology[4], these parameters were based solely on a simple RGB color model. Another difference was that no empirical heuristic algorithms were used in addition to the neural network.

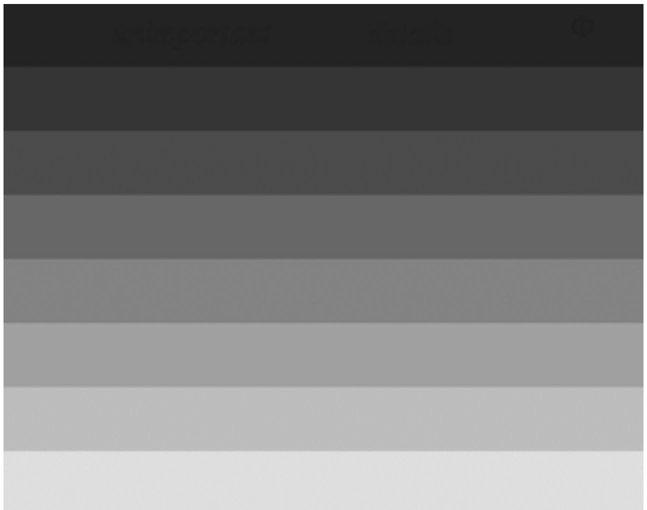

Figure 6. Result of non-linear lightness reduction. (curve 2 in Fig. 5)

Printer Configuration and Calibration

All test, pretest and training pictures were printed with an HP DesignJet 755 CM large format ink jet printer on high gloss white film (roll). The opportunity to use large media format was a very important practical factor allowing all simultaneously compared pictures to be printed on the same sheet.

From various options, we elected to print the color pictures as RGB images from Windows Photoshop (4.0). Printing was independent from monitor (and all other) settings, and all colors were printed with CMY inks (without black) taking their values from the simplest possible equations (4).

$$\begin{aligned} C &= 1 - R \\ M &= 1 - G \\ Y &= 1 - B \end{aligned} \tag{4}$$

To attain good color stability only ink cartridges (and media) of the same lot number were used. The printer was tested every time an ink cartridge was changed and if any significant change was detected in gray balance or contrast, the ink cartridge set was rejected.

Adjustment Variables

Only two variables, gamma and RGB contrast, were used to define the shapes of R, G and B tone rendering curves. Gamma is simply the exponent used to calculate new values for R, G and B. RGB contrast adjusts R, G and B components separately using curves with a linear mid-tone section and Bezier-curve-fitted "tails" which affect the darkest and lightest output tones. Besides overall image contrast, RGB contrast also affects various other image properties, including gray balance.

Before searching the optimum gamma and RGB contrast values, pretests were carried out in order to optimize the RGB contrast adjustment for the printer. With a small set of test images values were selected for the constants affecting the range and smoothness of Bezier curve fitting as well as the ratio between gray component contrast and gray balance change potential. In addition pretests were needed to establish suitable scales for gamma and RGB contrast values. Relative gamma was scaled from 0.4 to 1.6 and RGB contrast from 0.0 to 1.0. For both variables a change of 0.1 units caused, for most images, a small but visually significant change in image properties. For practical reasons, however, the test images were printed using a 0.2 interval for both variables. Nevertheless the visually optimum gamma / RGB contrast combinations were estimated with an accuracy of 0.1 units.

Neural Network

Before training the neural network, appropriate data had to be gathered with visual tests and statistical image analysis. In practice the target data had to be known first because the knowledge of desired output was required before different input features and neural network structures could be tested.

The training set of test prints consisted of 414 different images. For each of these images the optimum adjustment variables (i.e. the two outputs of the net) were selected with the help of a large combination print consisting of 42 small, differently adjusted variations of the same original.

A multilayer feedforward neural network was trained with an improved version of backpropagation called Levenberg-Marquardt optimization. Different network structures were evaluated using a test image set (not used in training, of course). The tested input features included variables based on RGB, lightness and saturation histograms and skin probability tables. In practice, however, a remarkable reduction of input features proved possible without sacrificing network performance. Thus the final network became quite simple. The selected 12 input features were based solely on RGB and saturation histograms. There was only one hidden layer with five neurons in it.

Results of Color Measurements and Visual Tests

The white reference and lighting CIE D50 was used in the color measurements and visual tests. CIELAB color values were measured with a Minolta CM-1000 spectrophotometer.

The spatial color variation within a sheet proved to be small but the temporal color variation during the tests did not. Particularly the changing of ink cartridges regularly caused drastic color changes. However, even with the same cartridges (and media) large color shifts were noticed. For example color differences exceeding 10 ΔE^* units were not rare between (theoretically similar) dark and mid-tone gray patches printed at different times. This was true for most saturated colors too.

Very selective use of ink cartridges did help, but did not solve the problem completely. For example, the average chroma C* of the reference gray tone included in the 414 test prints used for training of the neural network was 1.9 with a standard deviation of 0.5. For lightness component L* the average was 70.1 and standard deviation 1.1.

All visual tests needed for training and testing the neural network were made by the author. The performance of the final adjustment software was, however, evaluated by 14 test persons. When differently adjusted images were compared they were placed apart against a gray background. This gray served as a visual reference primarily guiding the assessment of gray balance. Some further rules were also applied in order to obtain consistent results. It was assumed that with no contrast enhancement at certain gamma values the color balance is correct unless there is an obvious reason to believe that it is not. Even though this rule is ambiguous, it greatly affected the results. The aim was not simply to find the gamma/RGB contrast combination which gives the most pleasing impression but also, to a certain extent, to retain the original color balance.

First the performance of the neural network was evaluated with a test image set of differently adjusted images. The selections made by the author were compared with the output of the net. In less than 15 % of all cases both gamma and RGB-contrast values given by the net matched precisely those preferred in the visual tests (with a $\pm$ 0.05 accuracy). Various reasons may have led to this result, including the inconsistency of the printed colors and the visual evaluations themselves. However, even though the desired $\pm$ 0.05 accuracy was not attained, this does not mean that the adjustment algorithm is not viable. In fact it was designed not to be too sensitive to any small inexactitude of its parameters. Thus the best way to assess the results of this study was to compare images printed with and without automatic color adjustment. This type of visual test showed that automatic image enhancement was capable of significantly improving slightly more than half of the test images. For all the rest of the images statistical (non-parametric) tests were not able to show significant differences between unchanged and adjusted prints. In most cases the reason was that the adjustment algorithm did not change, or only slightly chanced those images which originally had good contrast. Moreover, the software was able to recognize if an image had been manipulated with global color enhancement measures (either by the program itself or some other software). As with image enhancement this algorithm was primarily based on color histogram analysis. If any significant former enhancement was noticed, the images were usually kept unchanged.

Computational Efficiency

Since all adjustments at the final stage were based solely on three separate RGB curves, it proved possible to work out an effective algorithm. As an example, the Windows version of the automatic color adjustment software was capable of processing one megabyte of image data in 0.1 - 0.2 seconds with a Pentium Pro PC. This includes image analysis, all neural network calculations, calculation of the RGB curves (including Bezier curve fitting) and the actual adjustment of RGB values.

Future Work

The experimental results showed that the automatic color adjustment software is fast and also works quite well qualitatively. This approach might, however, yield even better results if the unpredictable color variation of the printer could be reduced. Moreover, automatic color adjustment should (and will) be tested in conjunction with different color management systems and printer profiles.

References

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