

Today's Image Capturing Needs: Going beyond Color Management

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Abstract

One of the main concerns in both desktop and pre-press environments is reliable color reproduction. This problem is addressed by the color management systems which are aiming at the production of so-called facsimile color. In order to use color management systems, one should know very well what the color space of the digital representation of the source image is. If this knowledge is not available, the CMS work-flows cannot be followed and more intelligent adaptive color correction techniques are required.

Even if the source of the images and the scanning equipment is well-known, people often want to reproduce their originals "better". In order to produce more appealing images, so-called color editing is required. This kind of editing includes range adjustments, tonal adjustments, saturation enhancement, global and selective color transformations etc. In order to increase productivity, these color corrections should be carried out automatically.

The main goal of automatic color correction techniques thus consists of bringing the original images (the source of which might not be known) into a well-known calibrated RGB space such that the reproduction of the images is appealing to the viewer. In order to achieve these goals, the images have to be analyzed and reference points have to be detected.

This paper is organized as follows. In the first section, we will introduce a general purpose model for automatic image correction. The general techniques exposed in that section will be illustrated by several case studies in the following sections. In the first case study, we will introduce an automatic tonal correction which has been used in the newspaper business for black and white images. The second case study will briefly describe adaptive techniques which have been used in order to convert negatives to a well-calibrated positive RGB space. The complexity of this technique is relatively low since it only involves a global color correction through the indication of a neutral point (which is equivalent to the specification of a global cast). In the third case study, we will deal with the general problem of automatic image correction of color images from unknown sources. In the last section, we will summarize the obtained results and indicate topics for future research.

A generic approach to automatic image correction

First, we will introduce a formal model that defines a general framework for automatic image correction. Both spatial image corrections (such as unsharp masking, de-screening, noise removal etc.) as well as color corrections (such as tonal corrections, selective color corrections) or a combination (such as the correction of colored patterns) can be considered. Basically, any automatic image correction scheme can be split up in 4 steps. The first step is the most difficult one and deals with the general problem analysis. Following steps deal with image correction as such.

Step 1: problem analysis by studying a test set of images

First, the problem needs to be defined. Often, this is done based on a number of images $(I_n)_{n:1..K}$ to be corrected and the manually corrected images $(I'_n)_{n:1..K}$. A classification of the test set can be realized by studying both the original set and the corrected set. This classification can be formalized by a set of parameters $(\alpha_n)_{n:1..L}$ which can be calculated for each source image. The parameter set can be used to derive a set of M corrections $(\Gamma_n)_{n:1..M}$ such that for each image I_n in the test set :

$$\bigcirc_{i=1}^{M} \Gamma_i(I_n) \cong I'_n$$

The idea, of course, is that the composition of the transformations should produce good results on arbitrary images as well. The problem is to find a number of characterizing parameters which contain enough information to classify the images and to generate good transformations. There is no general method to describe how to define those parameters. There is a danger in both using too many parameters as well as in using not enough of them. The extreme cases are either using the empty set of parameters or taking all input pixels into consideration. Clearly none of these approaches makes much sense. If only color (non-spatial) corrections are to be applied, using a down-sampled version of an input image might turn out to be useful. Other characterizing parameters are f.i.:

- one-dimensional histograms
- multi-dimensional histograms
- frequency analysis (using either classical FFT techniques, windowed FFT techniques or multi-resolution analysis)
- filtered versions of a complete image or smaller regions etc.

Also parameters that are special to the problems to be addressed can be used. We hereby think, e.g., of parameters such as the hue of the lightest and darkest point, average colors of regions of interest showing skin, snow, grass, sky etc.

The type of the corrections to be applied in order to generate the output images can be determined either automatically from the corrected test set or by discussing the applied corrections with the skilled scanner operator. In the past, we have been doing experiments to determine the parameters of well-defined parameterized transformations automatically using neural networks. The learning set consists of K elements (one for each image) mapping the analysis parameters $(\propto_n)_{n:1..L}$ to the parameterized representation of the transforms $(\Gamma_n)_{n:1..M}$.

$$\begin{array}{ccc} I_n & \longrightarrow & I'_n \\ & \Downarrow & \\ \alpha_1(I_n) \;\cdots\; \alpha_L(I_n) & \rightarrow & \Gamma_1(I_n) \;\cdots\; \Gamma_M(I_n) \end{array}$$

Although reasonable results were obtained at that time, often better results can be obtained using classical methods from numerical analysis based on linear and non-linear regression techniques [4,5].

The following steps (2,3 and 4) describe how a particular image will be transformed.

Step 2: detection of well-known parameters

Now, we need to calculate the characterizing set of parameters as described above. In this step, we basically determine which class(es) the given image belongs to. Often, heuristic techniques (based on fuzzy logic) are applied; rule-based systems or Prolog-based search engines can be used in this context as well.

Step 3: generating color transforms based on these parameters

This step calculates the image transforms based on the characterizing set of parameters as returned in Step 2. Now, the image correction can be applied to the source image.

Step 4: learning mode

The user is able to request small adjustments to the (automatically) proposed image transforms. The modified parameters are then fed back to the algorithm and used later on. We advise an additional option to enable/disable the learning mode.

We now present a few case studies that illustrate our approach.

Case study 1: tonal correction of black/white images for the newspaper business

In contrast with the traditional offset presses, the newspaper printing has specific constraints and, therefore, special gamut mapping techniques are required in order to produce good reproductions. In particular, the total ink limit constraints are very important and should be used as a driving force behind the gamut mapping. Although the solutions to this problem are far from trivial, they already have been studied in the past.

Often, skilled scanner operators apply subtle tonal changes on top of the color management transforms described above. These tonal changes appear to depend heavily on the type of the original. In order to get a better feeling of what kind of corrections usually are applied, we asked an experienced scanner operator to collect a number of representative grey-scale images and to correct those images. This experiment resulted in a database of images and their corrected versions. It turned out that the corrections could be reduced to a global remapping of the intensity values. Most often, a small contrast enhancement or reduction was applied together with some corrections in the highlights or shadows. More sophisticated spatial filters to create local contrast changes (such as dodging) were not considered.

The test set that we got back from our skilled scanner operator consists of 30 images some of which:

- are tonally good;
- are overexposed;
- are underexposed;
- have flat shadow parts;
- have a high contrast in the shadows;
- have a low contrast in the highlights;
- have a too high contrast in the highlights;
- have flat mid-tones;
- have too much contrast in the mid-tones;
- etc.

All of the images in the test set have one or more of the characterics listed above. Most of the items in the list can be derived by looking at the histogram or cumulative distribution function (CDF). By plotting all CDF's in a diagram, we get a fairly good idea of what types of originals we can expect. Most of the CDF's are positioned in a kind of hysteresis shape.

In figure 1, we show a few CDF curves and how they can be interpreted. The horizontal axis represents the dot percentages; the vertical axis represents the accumulated frequency percentages. The curves can be interpreted as follows :

•curve 1 is the CDF of an image which will be perceived as overall too dark;

•curve 2 is the CDF of an image with no mid-tones;

•curve 3 is the CDF of an image with a uniform histogram;

•curve 4 is the CDF of an image which has enhanced mid-tones at the cost of little highlight and shadow areas; and,

•curve 5 is the CDF of an image which will be perceived as overall too light.

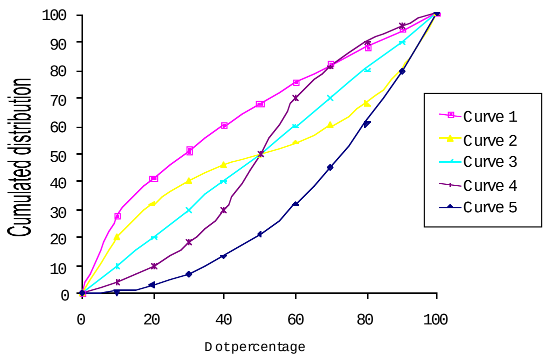

Figure 1: CDF sample curves

A straightforward method to improve the CDF would be to apply a so-called histogram equalization (as pointed out in [1]). It turns out that, although the tonally compressed areas come out much better after histogram equalization, the result often looks artificial and is unacceptable. Therefore, we propose to use the test set created by the skilled operator. After careful investigation of the test set, the test images can be divided in 5 different families:

- Family CO, containing 5 images : underexposed images without contrast problems;
- Family CH, containing 10 images : overexposed images without contrast problems;
- Family CN, containing 5 images : images with normal exposure;
- Family CL , containing 9 images : images with contrast problems (usually located near the mid-tones); and,
- Family CU, containing 1 image : images with extremely high contrast and lacking mid-tones.

The families were derived by analyzing the problem and looking at the proposed correction. After averaging the curves proposed by the expert user, following corrections could be derived for each family:

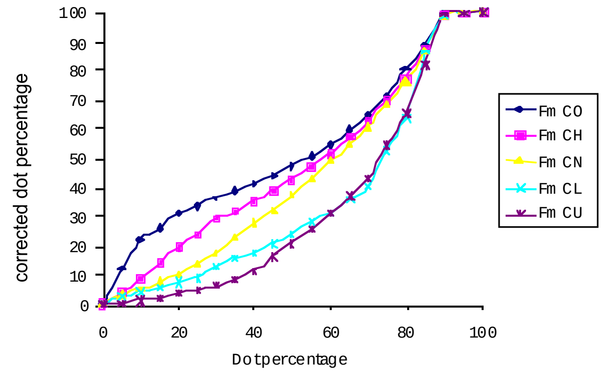

Figure 2: Corrrection for the different families

We now are ready to start with the actual correction of any given image. First of all, we determine the family to which the image belongs. This is done by means of a distance function Δ. Good results can be obtained by using a sum of squares of differences in a limited number of points.

If F denotes the set of families f, CDF(f) the cumulative distribution function of f, Fm(f) the proposed correction as in Figure 2, and Δ a distance function in a function space as described previously, then the tonal correction TF to be applied on an image g can be calculated as follows:

$$TF(g) = \frac{\sum_{f \in F} \frac{Fm(f)}{\Delta(CDF(f), CDF(g))}}{\sum_{f \in F} \frac{1}{\Delta(CDF(f), CDF(g))}}$$

Additional spatial corrections can be carried out to sharpen the images; the parameters for these USM filters can also be determined automatically but are not covered in this article.

Case study 2: adaptive color corrections for negative to positive conversion

The problem of scanning negative film and converting the negative signal into a well-known positive RGB space has been addressed extensively in the past [8,10,11,12]. The main problem consists of calculating appropriate inversion tables in order to convert from negative to positive; these inversion curves are based on the characteristic film curves of the negative film as perceived by the scanner as shown in Figure 3 (see also [9]). It turns out, however, that the characteristic film curves do not only depend on the type of film, but can vary from batch to batch and are also heavily influenced by the development of the negative film. On top of these problems, the circumstances under which the picture was taken also influence the final result (shutter speed, opening, type of camera, light conditions etc.).

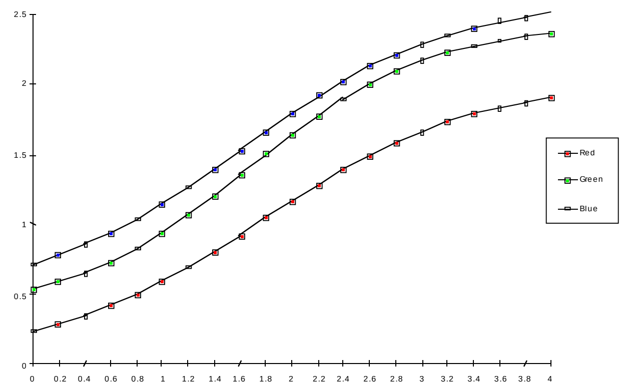

Figure 3: characteristic curves of Agfa HDC 100 film as seen by Agfa's DuoScan

The above arguments suggest that it is almost impossible to take all these parameters into account. We can, however, get a reasonable idea of the characteristic curves of a particular negative film by considering a test wedge (made on the same type of film, captured by the same scanner) and use these curves as a basis to determine future corrections. In figure 3, the characteristic film curves of an Agfa HDC 100 film[1] are shown as measured by the Agfa DuoScan[2]. The X-axis contains the exposing intensities on a logarithmic scale; the Y-axis contains the densities of the developed negative wedge in DuoScan scanner space. In order to get rid of measuring errors, we use a parameterized curve (as described in [6]); the parameters of these curves are determined in a least square sense [4,5].

The adaptive corrections to these curves need to be obtained by analyzing the actual negative film strip and the specific picture on this strip which we want to scan and convert. The corrections we have in mind here are defined as corrections on the characteristic film curves and are thus inherently global. Local or so-called selective color corrections will not be considered but better results can be obtained by applying additional multi-dimensional color corrections on the inverted image to produce more reliable color (see [11,12]). In the traditional photo-finishing labs, however, the only parameters that can be influenced to generate the print on photo paper are the exposure parameters of the light-source in red, green and blue (which are, of course, global corrections).

These global correction parameters can be specified as red, green and blue densities in the scanner input space. The meaning of this density triplet is that a density point of the negative film should be mapped to a neutral point of a given intensity in the inverted (positive) space. As such, the density triplet influences both tonal and color balance.

The color balance correction is based on a statistical analysis of our film strip and involves the calculation of a histogram of the near-neutrals. This information is combined with statistical information on the average characteristic film curves of a representative set of various films (of different vendors). All these data are weighted and result in the so-called TFS curves[3] which define the adapted characteristic film curves for this specific film.

Now the frame to be converted is analyzed further in order to get rid of local color casts due to, e.g., the illumination or other environmental parameters (such as flash-light). The final correction is obtained as a weighted average of the general mean densities, the densities of the near-neutrals and the TFS curve.

The last parameter to be determined is related to the dynamic range and indicates a mid-tone neutral. Parameters which are taken into account to determine this mid-point are:

- the minimum density of the frame;
- the maximum densities of concentric zones to find out where the *main* object of the frame resides;
- the densities of particular areas of interest showing skin, white areas (skiing), etc.;
- corrections based on the classification of scenes (portrait, landscape, ...)
- the orientation of the frame;
- …

The algorithm above thus results in three densities which are used to calculate the inversion curves. Basically, these densities will translate the characteristic curves horizontally such that said densities (on Y axis) originate from a triplet with equal values, i.e., neutral light (on the X axis). The dynamic range of the selected frame (exposure latitude) is also taken into account when calculating the inversion curves. For further detail, we refer to [8].

The user has the option to specify small changes to the proposed parameters. In Agfa's FotoLook 3.0[4] scanning software, this can be done by picking a color cast in a hue/saturation color-wheel. The proposed changes can be stored in a database and be used later on to influence the system's behavior.

Summarizing, we conclude that we basically follow the same work-flow as described in the first section:

- Step 1: general problem analysis;
- Step 2: analysis of the original (the film strip and one specific frame on this strip), resulting in a histogram of near neutrals and many other parameters resulting in three characterizing parameters;
- Step 3: calculation of the color correction based on the three parameters; and,
- Step 4: small corrections to characterizing parameters suggested by user and learning facility.

Case study 3: automatic correction of color images from an unknown source

The general problem of automatic image correction of images from unknown sources is very complex. The complexity is not only caused by the inherent, technical problems related to the recognition of objects, patterns etc. but also stems from the fact that the proposed corrections will always be very subjective. In this section, we will not cover our solution to automatic image correction in detail but we will rather outline some ideas we have been pursuing and which seem of fundamental importance. In particular, we will summarize the corrections we have been using for image improvement in general and some of the indicators that allowed the determination of the parameters for the transformations.

Global color corrections:

Global corrections can be defined as color corrections which are applied to one or more color components independently of each other. They can be implemented using one-dimensional tonal LUT's (look-up tables). The most important global color corrections are:

- **dynamic range adjustments:** often, the digital image is not using its full range of values. This suggests that the dynamic range should be stretched to the allowed values. This should be carried out carefully, however, based on a classification the original. Otherwise, very saturated colors or pastel tints might be ruined.
- **tonal corrections:** a more general tonal correction is needed if the original appears to be overall too light or too dark. One way to determine this is to study the CDF as discussed in Case 1. This method can be improved by also taking into consideration the spatial activity in certain areas, the main idea being that a spatially active area often needs tonal enhancement.
- **color cast removal**: for color cast removal, analogous techniques to Case 2 can be used.

Local color corrections:

Sometimes, particular areas in the color space require further enhancement. In order to determine such color corrections (which are also known as selective color corrections), we need to detect reference objects in the original. This detection will be based on both spatial and color content. Areas which are considered to be very important are, e.g., areas containing skin, sky, meadows etc.

The correction then consists of mapping the color of the detected area to a configurable color using a selective color transformation. The learning facilities (cf. Step 4 above) consist of both influencing the detection of the special categories as well as the determination of the target colors.

Spatial corrections:

On top of color corrections, spatial corrections might be needed for further enhancement. We hereby think of:

- sharpening;
- noise removal and removal of other artifacts (such as artifacts from lossy compression schemes);
- scratch removal;
- dodging;
- …

This type of correction requires a study of the spatial characteristics of the image by means of Fourier or wavelet analysis [3].

To conclude, I would like to emphasize that the obtained results must be interpreted in a standard color space that has been determined up front. The classifying parameters as well as the proposed corrections depend on the choice of this exchange space. Candidates for such a space are monitor spaces having a specific gamma value. The chromaticities of of this space should be wide enough to span a reasonable gamut. Preferably, it should be specified as an ICC profile (cf. [2]). Once the images are in this exchange space, standard CMS techniques can be used to transform the images from this space to any other space.

Conclusions

In this document, we described a global approach to automatic image correction. Although substantial results have been reached so far, it is obvious that the general problem of correcting colored images automatically will never have a completely satisfying solution and therefore will need on-going attention and improvements. The main technique which has been introduced here is essentially based on a statistical analysis of a test set of images using a number of parameters which describe important features allowing to make some kind of classification. After the analysis of the test set, a relationship is established between the classifying parameters and the corrections proposed by an experienced user. In operational mode, the algorithm will calculate the image specific parameters and come up with a correction as proposed by the expert. In addition, the end-user will be able to apply minor changes to the proposed corrections; the system will learn about the subjective changes proposed by a particular user and will correct its future behavior accordingly.

The inference engine which establishes a relationship between the input parameters and image correction is essentially a rule-based system. It might be worthwhile to study the usability of other formalisms to establish this relationship such as, .e.g, neural networks or Prolog-based engines.

The quality of the obtained results is heavily dependent on the classifying parameters. Much of the future work will be concentrated on trying to come up with new classifying parameters and more sophisticated corrections. For spatial corrections, we can make use of wavelets and the associated multi-resolution analysis; for color corrections, further analysis of 3-D histograms can give better insight in what type of original scene we are dealing with. An even more advanced solution might be based on a 5-dimensional spatial/color analysis; this is, e.g., necessary to deal with colored patterns of cloth.

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[1] Agfa HDC 100 is a registered trademark of Agfa-Gevaert N.V.

[2] Agfa DuoScan is a registered trademark of Agfa-Gevaert N.V.

[3] TFS stands for Total Film Scanning and refers to the fact that, in order to determine the correction parameters for a particular frame of the negative film roll, the entire strip (i.e., the total film) is scanned first. TFS is a registered trademark of Agfa-Gevaert N.V.

[4] Agfa FotoLook 3.0 is a registered trademark of Agfa-Gevaert N.V.