Adding Local Contrast to Global Gamut Mapping Algorithms

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Abstract

This paper deals with the potential of spatial gamut mapping methods as a complement to global gamut mapping algorithms. The main goal is to recover the original local contrast between neighboring pixels in addition to the usual optimization of preserving lightness, saturation and global contrast. As a typical representative for such a spatial mapping concept, we study unsharp masking applied to an image of the difference of the original and the result of a given gamut mapping algorithm. Thereby an edge preserving smoothing algorithm is used to avoid halo artefacts. In our psychophysical experiments every considered gamut mapping algorithm shows a significant gain in preference by our local contrast approach. The presented method can be seen as an additional feature towards an image-to-device gamut mapping design.

Introduction

The adaption of a specified color image to device limitations is fundamental for digital color reproduction. For this process – called gamut mapping – a wide variety of techniques were proposed. An overview of the work in this field was summarized by Morovic [1]. Recently, in order to improve the comparability of the different approaches, the technical committee of CIE worked out and published corresponding guidelines [2]. We are particularly interested in combining different gamut mapping concepts in a modular way and determining the visual gain induced by specific components.

At first we would like to setup our notation. The term 'gamut mapping' is used in a general sense, and means the adaption of a specified color image to device limitation. In a more restricted sense, 'gamut mapping' is often understood as a point-to-point mapping of color vectors from a source to a device gamut. In this paper we prefer the term 'global gamut mapping' for this interpretation. 'Global gamut mapping' again can be categorized in 'device-to-device' and 'image-to-device' techniques, depending on whether an image independent source gamut is used or not. In addition, the term 'spatial gamut mapping' is used for strategies where the color mapping depends on the spatial neighborhood of a pixel and is not only covered by a global color transformation.

Most of todays gamut mapping algorithms are 'global' and 'device-to-device' in this sense [3, 4, 5, 6], in particular in connection with ICC color management. But recently 'image-to-device' concepts begin to emerge [7, 8, 9, 10]. The basic idea is to determine the shape and size of the source gamut by image statistics. Although these algorithms are still 'global', they are generally expected to perform better in color rendering. However these algorithms can not take spatial neighborhood effects into account, because they are restricted to point-to-point color transformations. A further class of gamut mapping algorithms use spatial gamut mapping techniques [11, 12, 13, 14]. For such algorithms, two identically colored pixels might map to different colors in the output image depending on their local neighborhood. Local techniques of this kind are well-established for image rendering of high dynamic range images [15, 16, 17, 18]. This operation, known as 'tone mapping' provides in fact the same functionality for image rendering as 'gamut mapping' does for the image reproduction process. The theoretical foundation of local techniques is the Retinex theory [19]. Its potential for an application to gamut mapping was shown with experiments using Mondrian-type images [13]. The results question the use of minimal overall colorimetric distance as a sole metric to design and judge gamut mapping algorithms and indicate a high potential for improvements using spatial methods for gamut mapping algorithms. The modeling of dodging and burning of images is a further approach to deal with local contrast in high dynamic images. This can be realized by constructing an image mask and combining it with the orignal image [20].

The method presented here is designed as a component among others within a gamut mapping concept. Special attention has been taken to avoid halo artefacts. A major challenge is the optimal balance between global and local contrast preservation. Although our approach is related to the Retinex theory, we do not explicitly describe a corresponding visual model. Instead, we developed a robust algorithm designed for the multitude of images in a typical color management work-flow. The component structure allows the subsequent improvement of existing global gamut mappings, including 'image-to-device' solutions.

The paper is organized as follows. In the next section the methodology of the used spatial mapping is described. In the following section the results of a psycho-visual experiment are presented evaluating the gain in preference if spatial gamut mapping is added to known gamut mapping algorithms. The last section gives concluding remarks.

Methodology

Basic Model

At first we introduce a simple model for a spatial gamut mapping method. The basic idea is to recover the local contrast of the original image as good as possible. We use an unsharp masking technique to accomplish this task. It is assumed that the working color space is visually approximately equidistant, such as CIELAB, MLab or DIN6164. In contrast to other applications using spatial gamut mapping, we apply the masking to all three coordinates and not only to the luminance coordinate. We assume that the image is already rendered for a specific color space within its gamut, such as sRGB. All image enhancement, such as color balance, tone mapping, sharpening are made. The task we want to accomplish is to map the image into a different, usually smaller gamut.

Let I_O be an original image, and I_M the mapped image, then we understand I_M as function of I_O:

$$I_M = GMA_x(I_O) \tag{1}$$

Thereby GMA_x may be any gamut mapping algorithm, usually a global one. In a first step a smoothed difference image I_S is calculated by the convolution of the difference image I_D with a

Gaussian smoothing filter F.

$$I_D = I_O - I_M \tag{2}$$

$$I_S = I_D * F \tag{3}$$

with

$$F(dx) = e^{-((dx/dX_{ref})^2)/2} \tag{4}$$

The width of the Gaussian dX_{ref} is a parameter of the method. We call it *reference spatial distance*. Its size determines the range of the unsharp masking operation. The variable dx means the spatial distance within the image. Next a correction image I_C is calculated by taking the difference of I_D and the smoothed image I_S:

$$I_C = I_D - I_S \tag{5}$$

The correction image I_C is then added to the mapped image I_M to get the contrast recovered image I_E:

$$I_E = I_M + wI_C \tag{6}$$

Thereby w stands for an arbitrary weight parameter, in particular a value of $w = 1$ means full recovery of local contrast.

To obtain the final image I_{EM}, a re-mapping into the destination gamut is needed, because some of the colors close to the gamut border may have moved out of gamut in the contrast recovery step. Here a clipping algorithm such as HPMinDE is appropriate.

$$I_{EM} = GMA_{HPMinDE}(I_E) \tag{7}$$

Some basic features are visualized on a simple one-dimensional intensity image as shown in Fig. 1. It consist of a gradual sweep from minimum to maximum and a five step wedge from maximum to minimum intensity, superimposed with a statistical noise, representing the local contrast. The values have to be mapped from the interval $[0,100]$ to $[0,50]$. A nonlinear compression is used for the mapping conserving values close to zero and strongly compressing values close to the maximum. The reference spatial distance dX_{ref} is 1% of the image size. The main features of the unsharp masking method are nicely visualized. Color regions which are unchanged by the mapping are not altered by the method as can be seen in the correction image. This is the case in the image in Fig. 1 with color values close to zero. Overall we see a good recovery of the local contrast. In the contrast recovered image the statistical variations again have the size of the original image. An exception are values close to the gamut boundary, where the last step again clipped the values which would lie outside of the allowed interval. With the unsharp masking method we also introduced an artefact, namely halo effects on sharp edges. This can be disturbing and has to be avoided. This effect is small as long as the reference spatial length is short, but for maximizing the visual gain in contrast recovery, larger reference spatial length are needed. In the following we will introduce a method to avoid halo artefacts.

Extended Model

The global filter F is replaced by an edge conserving smoothing. The smoothed image I_S with pixels C_S^i is calculated as a weighted sum over all pixels C_D^j of the difference image I_D:

$$C_S^i = \sum_j (C_D^j F(|x^i - x^j|, |c^i - c^j|)) / \sum_j (F(|x^i - x^j|, |c^i - c^j|)) \tag{8}$$

where x^i is the spatial position if the pixel i in the image and c^i its color value. The filter function F is defined as

$$F(dx, dc) = e^{-((dx/dX_{ref})^2 + (dc/dC_{ref})^2)/2} \tag{9}$$

Here we introduce a second parameter, the *reference color distance* dC_{ref}. The proposed edge preserving smoothing algorithm is in fact a normalized Gaussian smoothing in a five dimensional position-color space where the positional distances are scaled by dX_{ref} and the color distance by dC_{ref}. A similar combination of spatial and color distances in the filter function to avoid halo artefacts was proposed by DiCarlo and Wandell for their robust tone reproduction operators [16]. The effect of halo suppression is shown in Fig. 2 using $dC_{ref} = 5$. This can be best seen in the correction image and the contrast recovered image where the artefacts at the sharp edges have vanished compared to Fig. 1

In all we have three parameters dX_{ref}, dC_{ref} and the weighting parameter w. For full contrast recovery $w = 1$ is used. For images mapped to a small gamut with a low global contrast, full recovery may not be visually pleasing. Here the weighting factor can be set to a smaller value. For the choice of dX_{ref} we have to consider the spatial range of the unmasking operation. Very small values will recover only very fine structures of the image. This mainly influences the perceived sharpness of the image. Values in the range of the image will basically try to recover the entire original image, but then too many colors have to be mapped again in the last mapping step. The selection of dC_{ref} is directly related to the definition of ΔE as just noticeable color difference. Because we want to retain small color differences dC_{ref} should be substantially larger than 1. On the other side colors further apart than $\Delta E = 50$ can be considered as large and should not contribute to the smoothing filter. We found that dX_{ref} values in the range of $2-5\%$ of the image diagonal and dC_{ref} values in the range of $\Delta E = 10-25$ give good performance.

Psychophysical Tests

Psycho-visual Tests: As far as applicable, the test procedure was done following the CIE-guidelines [2]. All pair comparisons have been performed on an LCD screen (EIZO cg220). The background of the screen was set to neutral gray. Behind the

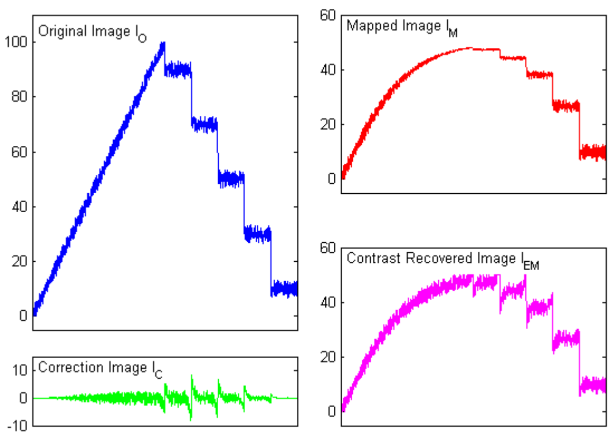

Figure 1. Effect of contrast recovery for a one dimensional monochrome image. Original image (top left), Mapped image (top right), Unsharp masked image (bottom right) and difference image (bottom left)

Figure 3. *Psycho-visual tests: First test set of 8 images*

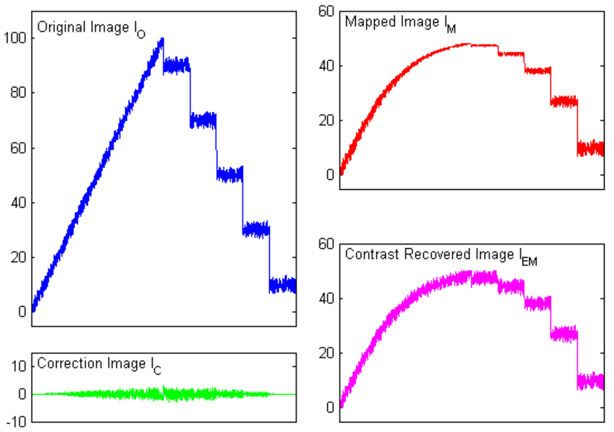

Figure 2. Effect of contrast recovery for a one dimensional monochrome image using an edge preserving smoothing. Original image (top left), Mapped image (top right), Unsharp masked image (bottom right) and difference image (bottom left).

screen and in the back of the observer dark gray and black paper backgrounds respectively were used. For the psycho-visual test two sets of test images were used: A first, traditional test set of 8 test images four of them ISO test images and the SKI image recommended by the CIE guidelines (see Fig. 3) and 8 sets, each containing 8 images from a newspaper agency [21].

The original image and two mappings thereof were shown simultaneously on the screen, the original in the middle of the screen and the two mappings left and right of the original. All images had a constant height of 10.5 cm. The observing person had to select the mapped image which he or she judged to be the better representation of the original image. If both mappings were judged to have equal quality, the original image had to be selected. The observers were members of the staff of our institute. They were instructed and trained for tests doing a test with 3 different GMAs applied to 2 images. Every observer had passed the "Ishihara test" and the "Farnsworth-Munsell Hue test" with at least average discrimination. Each pair of different mappings was shown equally often with exchanged positions to eliminate preference effects of left or right position. All pairs were presented in random order.

Results and Discussion

Application to different gamut mapping algorithms

We applied the method to different gamut mapping algorithms. The method parameters were $dX_{ref} = 4\%$ of the image diagonal, $dC_{ref} = 20$ and $w = 1$. The results presented here are on four algorithms covering the whole range from linear compression to clipping. As a representative algorithm for linear compression we choose simultaneous compression of lightness and chroma towards the middle gray of the destination gamut. We call this algorithm LComp. As clipping algorithm we used minimum distance clipping (HPMinDE) one of the proposed algorithms in the CIE guidelines [2]. Furthermore we used two sophisticated algorithms with nonlinear compression, one is the smooth gamut deformation algorithm (SGDA) [22] and the other SGCK [2] the second CIE-recommendation. For all our experiments we used the sRGB to newspaper printing work-flow as application having an especially small destination gamut [23].

In general an improvement in perceived image quality was achieved on the vast majority of the images with all investigated algorithms. Fig. 4 shows sample images for the three algorithms LComp, SGDA and HPMinDE. A significant improvement can be seen for all three algorithms. Most noticeable is the recovery of the background structure of the MUSICIAN image.

Halo artifacts

Unsharp masking methods are known to produce halo on smooth color regions close to large edges. Artificial images such as test images with color patches are especially prone to disturbing effects. Fig .5 shows typical halo effects and their suppression by the proposed method for two sample images, the Gretag-Macbeth color chart and the ISO-test image CAFE. In the color chart the halo effect is especially disturbing and its suppression is almost complete. Only in one dark gray patch a trace of halo is remaining. In the CAFE image the halo effect is most pronounced in the sky region close to the buildings.

Psychophysical Tests

The following algorithms were compared: SGCK and HPMinDE, SGDA and LComp. The results of the test set is shown in Fig. 6. It summarizes the judgments of 21 persons on a total of 5376 pair comparisons. The accuracy scores shown, were calculated from the z-score matrix as described by [3].

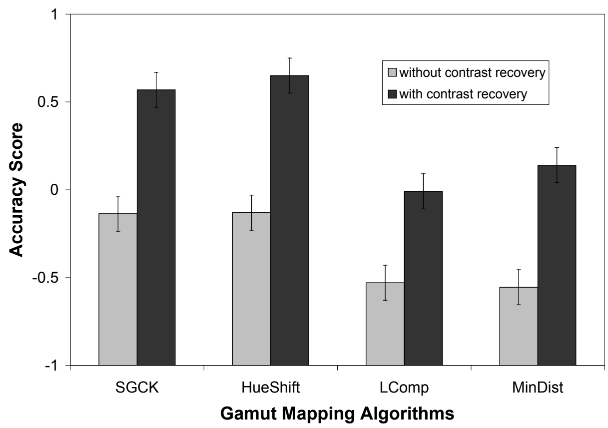

Figure 6. Psycho-visual tests: Results using 72 test images and 21 observers. Left light bars show result for original mapping algorithm, the right dark bar the result after applied contrast recovery

The difference between the initial gamut mapping algorithms are as expected from other published psychophysical tests [22, 3]. The performance of LCusp (linear compression) and HPMinDE (clipping) is significantly poorer than those of the

Figure 4. Effect of contrast recovery for three GMAs: LComp (left), SGDA (middle) and HPMINDE (right) on the example of the MUSICIAN image. The top row shows the mapped image I_M and bottom row the contrast recovered image I_{Me}.

more sophisticated algorithms SGCK and SGDA. The most surprising result is the large gain if contrast recovery is applied. The gain is larger then the differences between the initial algorithms. All algorithms gain, but to a different level. LCusp gains less then the other three. For this algorithm which tries to keep local contrast on the cost of saturation, it is not surprising, that the gain for additional contrast recovery is not as pronounced as for the algorithms which primarily optimize saturation and lightness.

Conclusion

We have presented that spatial methods can successfully be added to existing gamut mapping algorithms with a substantial gain in perceived image quality. The use of a content based adaptive filter allows to prevent halo artifacts. The presented method can be seen as a sample component within a modern gamut mapping design, combining global gamut mapping techniques with spatial filtering and image-to-device gamut mapping. We are convinced, that the potential for improvements ist not exploited with the presented method. In fact there remains a vast field to find the best combination of original gamut mapping algorithm and contrast recovery. This could be one path towards a 'universal gamut mapping algorithm' as a combination of nonlinear compression, spatial methods and image dependent gamut source gamuts.

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Figure 5. Effect of edge preserving smoothing to avoid halos: mapped image I_M (left), image I_{EM} using conventional unsharp masking (middle), I_{EM} using edge preserving smoothing

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