

Predicting the Performance of a Spatial Gamut Mapping Algorithm

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Abstract

Gamut mapping algorithms are currently being developed to take advantage of the spatial information in an image to improve the utilization of the destination gamut. These algorithms try to preserve the spatial information between neighboring pixels in the image, such as edges and gradients, without sacrificing global contrast. Experiments have shown that such algorithms can result in significantly improved reproduction of some images compared with non-spatial methods. However, due to the spatial processing of images, they introduce unwanted artefacts when used on certain types of images. In this paper we perform basic image analysis to predict whether a spatial algorithm is likely to perform better or worse than a good, non-spatial algorithm. Our approach starts by detecting the relative amount of areas in the image that are made up of uniformly colored pixels, as well as the amount of areas that contain details in out-of-gamut areas. A weighted difference is computed from these numbers, and we show that the result has a high correlation with the observed performance of the spatial algorithm in a previous psychophysical experiment.

Introduction and background

When an image is reproduced by a device, the colors that can be used are limited by the characteristics of the device. The color gamut of a device is the range of colors that the device can reproduce. When an image is to be reproduced on another device, it is necessary to apply a gamut mapping algorithm (GMA) to compensate for the differences in their color gamuts. These algorithms use a gamut boundary descriptor (GBD) to represent the extent of the color gamuts. The GMA must transform the image so that all the colors are within the destination gamut, while trying to give a reproduction that is pleasant to look at and as accurate (close to the original) as possible. The algorithms need to find a good balance between maintaining global and local contrast in the images, so that details are still visible in the reproduction and the images don't appear to be too bland.

The performance of gamut mapping algorithms has been the focus of extensive research. Morovic and Luo have made a survey of the various point-based algorithms [1, 2] available at the time. They divided the basic algorithms into two major groups, gamut clipping and gamut compression algorithms. The clipping algorithms do not change colors that are on the inside of the destination gamut, while the colors that are on the outside are moved onto the gamut surface. There is a wide variety of such algorithms, differentiated by the direction in which they move the colors. Hue-preserving minimum delta E (HPMINDE) clipping performs all movement in the hue plane of the color that should be clipped, and the color is moved to the position on the gamut surface that is closest to the source color. A different clipping algorithm moves colors towards the color space center, while other variants clip towards the point on the lightness axis with the same lightness as the cusp of the destination gamut (the cusp being

the point on the gamut with the same hue and the most extreme chroma).

Compression algorithms differ from clipping algorithms in that they also change at least some of the colors that are on the inside of the destination gamut. In order to achieve this, they typically utilize the source gamut as well as the destination gamut. The parts of the source gamut that need to be mapped can then be compressed, e.g., by using a knee function that leaves colors close to the color space center unchanged, but uses a percentage of the available gamut to linearly compress extreme colors. Different compression approaches have been proposed, usually by changing the compression type to a non-linear step. A further improvement is the use of the image gamut instead of the source device gamut to limit the amount of compression necessary [1].

The concept of image-dependent algorithms has later been expanded to utilize the spatial information in the image. When people are asked to judge the quality of image reproductions, the amount of details present in the reproduction is well known to be an important factor [3, 4]. Spatial GMAs try to balance the two contradictory goals of maintaining color accuracy and local detail. The concept was introduced by Meyer and Barth [5], and further work on this subject has been done by several researchers [6, 7, 8, 9, 10].

Kolås and Farup [11] introduced a spatial GMA that uses an edge-preserving filter to process an image containing the clipping distances of the original image pixels. The reproduction image is then created as a convex combination of the original pixel colors and grey, using the distance image as weights. Due to the properties of the filter (decreasing, edge preserving), the resulting image is guaranteed to be within the destination gamut while attempting to preserve edges.

Farup et al. [12] proposed an algorithm based on a multi-scale image representation, which performs gamut mapping of the scaled images at increasing dimensions. In accordance with [13] we will refer to this as the Gatta algorithm.

Motivation

There are two main reasons why printer drivers and color management systems do not employ spatial algorithms when processing images:

- * The algorithms give a particularly poor result when they are used on certain types of images
- * They are slower than conventional methods, since they have to adapt to the image content

While spatial algorithms by their nature add some complexity to the calculations, there are several spatial algorithms that could process images relatively fast using an optimized implementation. However, while spatial algorithms show better performance on some images, this is negated by their poor performance on other images. The spatial algorithms introduce artefacts, some of which can be seen in the experimental images in

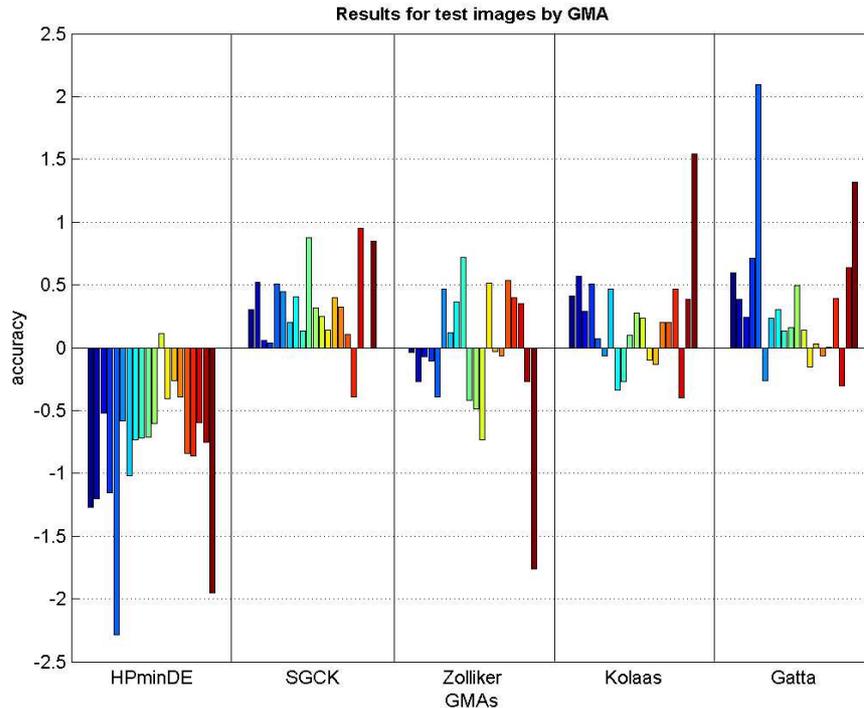


Figure 1. GMA score per image. Figure courtesy of Fabienne Dugay.

this paper. Farup et al. [12] investigate some of these effects, and show that they still constitute a serious impediment to the general use of spatial GMAs.

We knew that an experiment had previously been performed by Fabienne Dugay [13, 14], in which several point based and spatial GMAs had been compared. Three spatial and two point-based GMAs were used on 20 different images. The resulting images were then used in a ranking experiment on paper, as well as a pair comparison experiment on screen. 20 observers participated, and were asked to judge the accuracy of the reproductions. This is one of the few psychophysical experiments that have been performed for gamut mapped images that involve relatively many images and observers, since this is a very time-consuming procedure. One of the conclusions [14] was that the choice of images had a great impact on the result, since the algorithms showed significantly different performance on the images used in the experiment. Figure 1 illustrates the performance of the GMAs on each separate image.

In particular, the Zolliker [15] spatial GMA performed either very well or very poorly for the individual images. After the experiment, some issues were discovered regarding the implementation of this algorithm. Because of this, we will disregard the Zolliker algorithm in the following discussion. The two other spatial GMAs, Kolås [11] and Gatta [12], display similar tendencies in their performance on the various images. They have superior performance on source images containing a lot of detail in the dark areas of the images. By taking advantage of the spatial image information, the global contrast of the image is better while details are preserved. The clipping algorithm used maintains global contrast, but the loss of all detail in out-of-gamut image areas is not preferred by the observers.

Method and experiment

We constructed an image based on previous experience with spatial GMAs and their properties. The image in Figure 2 is a document containing both computer generated graphics and two captured images that were a part of the psychophysical experiment. The spatial algorithms perform better than point-based algorithms when used on these images separately, but the other parts of the document cause problems. Several artefacts are introduced into the image by the spatial GMAs, including a halo around the star. Figure 3 illustrates this problem, and a person trying to reproduce this document will complain that the halo has changed the appearance of the star into a sun with spikes.

We start by suggesting a method to determine which parts of the image contain features that have proven to be difficult for spatial algorithms. Identifying the large, uniform areas in the image that have been created using a computer is necessary to avoid applying a spatial algorithm to areas of this type. The Gatta algorithm, similarly to other spatial GMAs, often introduces spatial artefacts when used on such areas. We introduce a novel approach to detecting this problem. First, every square consisting of 4 pixels in the image is inspected. If a pixel belongs to such an area where the colors of the four pixels are almost equal, the pixel value is set to black. We define almost equal as no pixel may have a larger RGB difference from the average color than 1. Otherwise, the pixel value is set to white.

Figure 4 is the result of performing this operation on the image. To create completely filled areas and reduce the amount of noise in this black and white image, a mathematical morphology [16] technique known as dilation is applied. This removes most of the small patches of two by two equal pixels in otherwise non-uniform areas. Afterwards, we count the number of pixels in connected areas of pixels which are either black or white. If the number of pixels in such an area is small, the pixel values are inverted. Equation 1 shows the sequence of the operations,

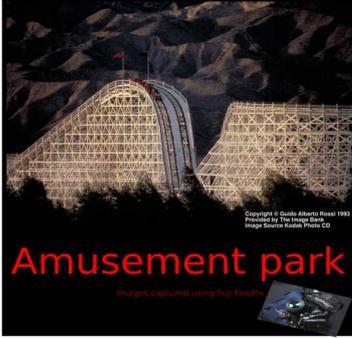


Figure 2. Our test image

where *Block* is the initial block detection, and *Inv* refers to the conditional inversion of small areas of connected pixels.

$$I_{uniform} = Inv(Dilate(Block(I_{original}))) \quad (1)$$

The result of applying this algorithm to our constructed image is shown in Figure 5. The areas of the two natural images has for the most parts been correctly identified. The amusement park image has several large areas of pixels which have been clipped to black, but are mistakenly identified by the algorithm as computer generated graphics. However, while these areas are not generated on a computer, they still represent parts of the image which cause problems for spatial algorithms. As such, the inclusion of these areas with the computer generated graphics can be considered a benefit when trying to choose a GMA for this image. Whether the uniform areas consist of colors that are on the inside of the gamut is largely irrelevant, since the spatial algorithms have a tendency to change the color of pixels even when they are within the gamut. After the uniform areas have been detected, we compute the relative amount of uniform pixels $A_{uniform}$ by counting the number of white pixels and dividing by the count of total pixels in the image in Equation 2.

$$A_{uniform} = C_{white}(I_{uniform})/C(I_{original}) \quad (2)$$

As suggested by Dugay [14], the Gatta algorithm seems to perform better on images with a lot of detail in dark areas. Having looked at the destination gamut, it seems reasonable that the good performance on details in dark areas is explained by the poor ability of the printer to reproduce dark colors. We therefore extend this hypothesis to claim that the spatial algorithms perform better on images where there is a lot of detail in heavily out-of-gamut areas. This seems plausible, since this is one of the main motivations for extending GMAs to the spatial domain. Our approach to identify such areas combines a threshold operation with a high-pass filter.

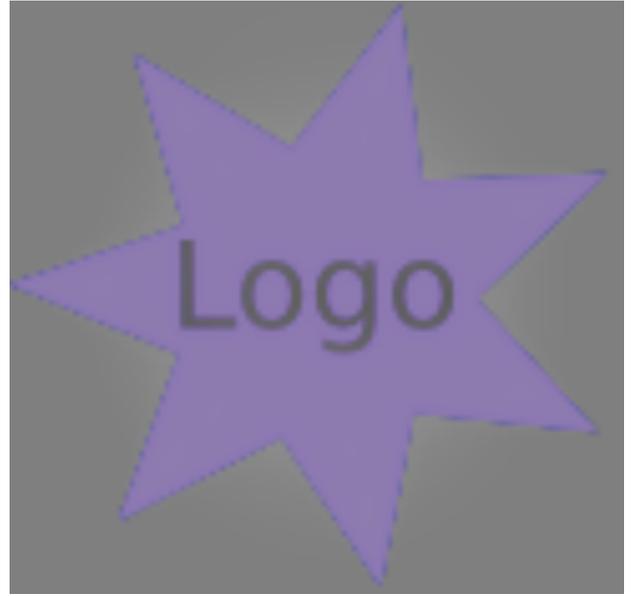


Figure 3. Artefacts introduced by the Gatta GMA. The star suffers from a halo effect.

We first compute the difference between the original image and a reproduction that has been clipped to the device gamut. All pixels that have had their values changed by the clipping algorithm are out-of-gamut, and we use a thresholding operation on the difference image to set such pixels to white.

$$I_{oog} = Threshold(Clip(I_{original} - I_{original})) \quad (3)$$

We define details to be high-frequency information in the image. After experimenting with different edge detection and high-pass filters, we decided to use a Gaussian filter with radius 5 and subtract the original image to detect areas containing such details.

$$I_{high-pass} = Gaussian(I_{original}) - I_{original} \quad (4)$$

The high-pass filtered image is then used to process the thresholded image, setting each pixel which is not near a detail (pixel distance larger than 5) to black. The remaining white areas are then per our definition out-of-gamut areas containing details. Our choice of radius is based on our training data, and will probably vary with the resolution of the device used to reproduce the image, as well as the viewing distance.

$$I_{oogd} = Threshold(I_{oog}, I_{high-pass}) \quad (5)$$

Finally, the amount of out-of-gamut pixels with details nearby is computed relative to the total number of pixels.

$$A_{oogd} = C_{white}(I_{oogd})/C(I_{original}) \quad (6)$$

We will now suggest an overall method for predicting the performance of a spatial GMA based on the image content. Due to the problems with the Zolliker images explained in the previous section, we will concentrate on the Gatta and Kolås algorithms. Calculating the correlation between the score of the two algorithms on the images shows that they behave very similarly. However, the Gatta algorithm performs better on average than the Kolås algorithm, therefore we will choose Gatta as our spatial GMA. Our findings are also relevant for the Kolås algorithm.

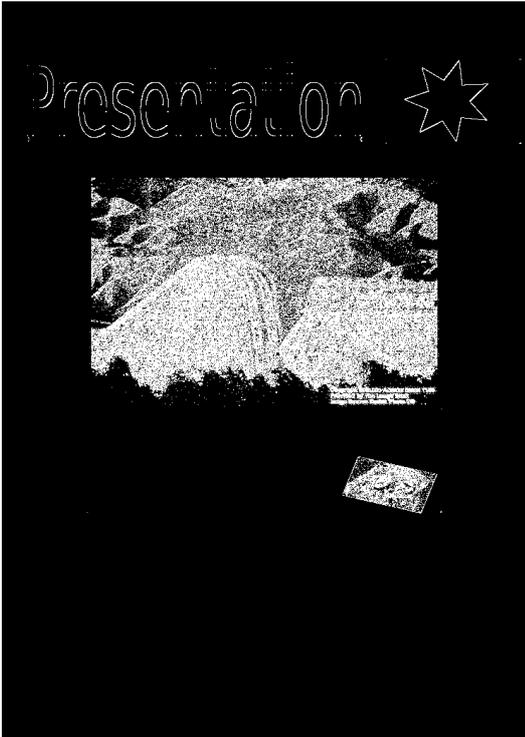


Figure 4. Blocks of pixels with uniform color have been detected.

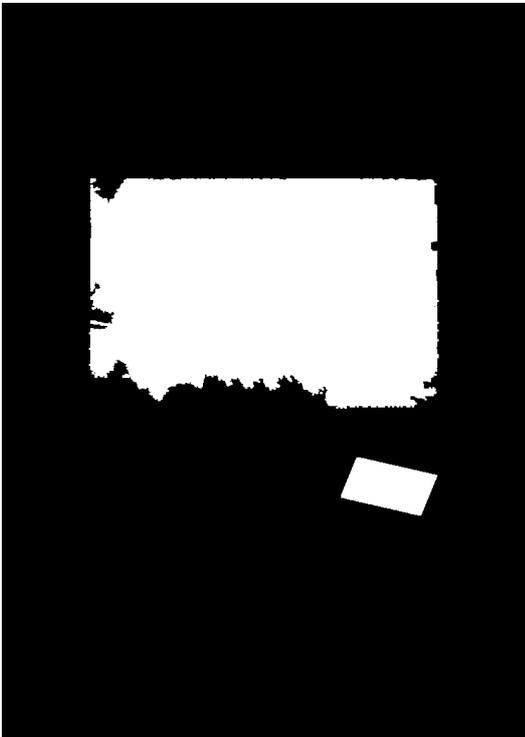


Figure 5. Further processing leaves only the areas of the two images.

We propose that the general performance of the algorithm depends on the relative amount of the two previously specified types of areas in the image. Our two approaches are combined into a single model in order to try to predict whether a spatial algorithm should be applied to an image. We create a predictor for the performance of the spatial GMAs by detecting the two different types of pixel areas in the image and computing a weighted sum as follows in Equation 7. Here, the predicted performance P_{pred} is the weighted sum of the relative pixel area with uniform color and the relative area with uniform color in the image. Our model gives a good fit with the observed performance using $w = 1.27$.

$$P_{pred} = A_{ogd} - w * A_{uniform} \quad (7)$$

Further analysis shows that there is a strong correlation between this predictor and the Z-score of the Gatta algorithm for the 20 images used in the experiment. A correlation ρ of 0.89 has been calculated. More importantly, the images where the Gatta algorithm performs quite well or poorly can generally be identified. The predictor fails for one of the images in the experiment, because the Gatta algorithm performs well on an image which contains a large area of uniform color. This exception can probably be explained by the small gradient values surrounding this area, since the halo artefacts mostly occur when the uniform areas are surrounded by sharp edges. Taking this into account, an even better fit with the Z-score could be achieved.

Conclusions and future work

The previous psychophysical experiment suggested that spatial GMAs perform poorly on content where there are large uniform areas, in particular synthetically generated images, due to the generation of visual artefacts. Spatial GMAs do improve the mapping of images that have a lot of detail in areas that are outside the destination gamut. We have successfully exploited these suppositions to create a model that with some accuracy is able to predict the performance of a spatial GMA. This makes the practical application of such algorithms more feasible.

The correlation between our suggested model and the Z-score of the Gatta algorithm can be further improved by adding some detection of whether the uniform areas in the images are surrounded by hard edges or gradients. This could be done by using an edge detection filter, and using erosion/dilation to get some overlap between the edge and the uniform area. If there is no overlap between the edges and the borders of the area, you can assume that there is a gradual transition. The area could then be processed by a spatial algorithm and still give a good visual result. A new psychophysical experiment is also desired to verify the model on independent test data.

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