Considering saliency in a perception inspired gamut reduction algorithm

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Abstract

Gamut reduction transforms the colors of an input image within the range of a target device. A good gamut reduction algorithm will preserve the experience felt by the viewer of the original image. Saliency algorithms predict the image regions where an observer first focuses. Therefore, there exists a connection between both concepts since modifying the saliency of the image will modify the viewer's experience. However, very little attention has been given to relate saliency and gamut mapping. In this paper we propose to modify a recent gamut reduction algorithm proposed by Zamir et al. *[32] in order to better respect the saliency of the original image in the reproduced one. Our results show that the proposed approach presents a gamut-mapped image whose saliency map is closer to that of the original image with a minor loss in the accuracy of perceptual reproduction.*

Introduction

Gamut reduction deals with the problem of modifying the gamut of an input image to make it fit into a smaller destination gamut. This problem occurs frequently both in the printing industry where images must be carefully mapped to those colors that are reproducible by the different inks and in the cinema industry where cinema footage needs to be passed through a gamut reduction method in order to be displayed on a television screen [5], [15].

There exist a huge number of gamut reduction algorithms in the literature and we refer the reader to the book of Morovič [23] for a detailed explanation of them. Gamut reduction algorihms are usually divided into two classes: global (or non-local, non-adaptative) and local (or adaptative). Global methods [10], [14], [31], [25] involve point-to-point mapping of colors (usually through a predefined lookup table) from source to target gamut. The standard global method is the Hue Preserving Minimum ΔE (HPMINDE) proposed by Murch and Taylor [25] where the point to point mapping is done through lines of constant hue. Local or adaptative methods have been recently been on track thanks to two important properties they share with human perception: first, they better preserve the color gradient between two out-of-gamut colors instead of mapping them to the same in-gamut color and second, two out-of-gamut colors with identical lightness and chromaticity map to two different in-gamut colors depending on their spatial context in the image. Some examples of local gamut reduction algorithms are the ones presented in [1], [4], [16], [22], [24], [33], [20], [21], [11], [17], and [2]. Recently, Zamir *et al.* [32] presented a local method that is based on a perceptually based contrast reduction of the colors.

Image saliency predicts the attentional gaze of observers viewing a scene [26], [30]. It has been used as a cue to aid in the performance of both image processing and computer vision applications such as color to gray conversion [12], [3], image detail visibility [28], and motion-compensated frame interpolation [13]. In a domain closer to that of gamut mapping, it has been used to decide whether a black point compensation algorithm is needed when printing an image [18]. However, despite the fact that the gamut reduction goal is to emulate the experience felt by the viewer in the original image, there is a limited amount of research relating saliency and gamut mapping. One exception is Chen and Beghadi [8] who considered saliency in their Image Gamut Boundary Reduction (IGBR) algorithm. IGBR was proposed as a pre-process for gamut mapping algorithms. The idea is that the gamut boundary in the non-salient regions can be reduced without losing any discriminative power. Saliency models have also been suggested as gamut-mapping artifact detectors by Raja *et al.* [29] and Cao *et al.* [7].

The goal of this paper is to bring saliency one step closer to gamut mapping by introducing it in the gamut reduction process. In particular, the hypothesis of our work is that it is possible to modify the recent work by Zamir *et al.* [32] to better represent the saliency of the original image without a noticiable loss of the image reproduction quality.

The paper is organized as follows. In the next section we will recap the method presented by Zamir *et al.* After that, we will explain how saliency can be inserted into their method. This explanation is followed by the results and conclusions.

Perception based gamut reduction

Zamir *et al.* [32] adapted the perceptually-inspired image energy functional defined in Bertalmío *et al.* [6] to perform gamut reduction. With their modifications, the image energy functional is defined as

$$E(I) = \frac{\alpha}{2}\sum_x (I(x)-\mu)^2 - \frac{\gamma}{2}\sum_x\sum_y w(x,y)|I(x)-I(y)| + \frac{\beta}{2}\sum_x (I(x)-I_0(x))^2, \quad (1)$$

where α and β are constant and positive weights, γ is a constant and real weight, I is a color channel $(R,G$ or $B)$, $w(x,y)$ is a normalized Gaussian kernel of standard deviation σ, I_0 is the original image, and μ is the mean average of the original image, and $I(x)$ and $I(y)$ are two intensity levels at pixel locations x and y respectively.

The resulting evolution equation for the previous functional can be expressed as

$$I^{k+1}(x) = \frac{I^k(x) + \Delta t\left(\alpha\mu + \beta I_0(x) + \frac{\gamma}{2}R_{I^k}(x)\right)}{1+\Delta t(\alpha+\beta)} \quad (2)$$

where the initial condition is $I^{k=0}(x) = I_0(x)$. The function $R_{I^k}(x)$ indicates the contrast function:

$$R_{I^k}(x) = \frac{\sum_{y\in\mathfrak{I}} w(x,y)s\left(I^k(x) - I^k(y)\right)}{\sum_{y\in\mathfrak{I}} w(x,y)} \tag{3}$$

where x is a fixed image pixel and y varies across the image domain $\mathfrak{I}$. The slope function $s()$ is a regularized approximation to the sign function, which appears as it is the derivative of the absolute value function in the second term of the functional; in [6] they choose for $s()$ a polynomial of degree 7.

Zamir *et al.* show that by considering a negative value of the γ parameter, i.e., by considering the second term of the functional to represent contrast reduction, the gamut of the image decreases. Furthermore, the smaller the value of γ, the smaller the gamut of the resulting image. Based on these two facts, they propose an iterative method for gamut reduction in terms of the γ coefficient. At each iteration authors run Eq. (2) for some particular α, β, and γ until they reach the steady state. At iteration 1, they set $\beta = 1$, $\alpha = 0$, and $\gamma = 0$, and therefore the original image is obtained as the steady state. They select the pixels that are inside the destination gamut for the final image and leave them untouched for the following iterations. After that, they move to iteration 2, where they decrease γ (for example, setting $\gamma = -0.05$) and increase α in relation to γ by $\frac{|\gamma|}{20}$. They run again Eq. (2) until steady state, and then check whether any of the colors that were outside the gamut in the previous iteration have been moved inside the destination gamut. If this is the case, they select them for the final image and leave them untouched for the following iterations. They keep iterating by decreasing γ (and increasing α accordingly) until all the out-of-gamut colors come inside the destination gamut.

Therefore, they obtain a map of the γ values used at each pixel accounting for the amount of contrast reduction that is necessary at that pixel. The main goal of this paper is to adapt this map of to better represent the saliency presented in the original image.

Considering saliency in the perception inspired gamut reduction algorithm

To start with, let us shed some light into Zamir *et al* method [32]. Smaller values of γ will lead to a smaller gamut in the output image and to a bigger reduction of the contrast. As the above mentioned method follows an iterative approach on the γ parameter that may result on a large difference of the contrast reduction performed in a region in comparison to the one performed in the surrounding ones. This fact will affect the saliency of the mapped image since contrast is known to be an important cue for human saliency, and therefore, saliency in the regions where a small value of γ has been used might be lost.

The idea pursued in this paper is to modify Zamir *et al.* method to obtain a gamut-mapped image with a saliency map closer to that of the original image. To this end, our idea is to reduce the difference in the gamma values between the regions where saliency has been lost, and their surrounds. Increasing the γ value will take us out of the target gamut, therefore, our approach will decrease the γ value of the surrounding areas. Our method is divided into three parts: detection of the regions where saliency has been lost, creation of the new γ values map, and combination of the initial gamut-mapped image (obtained using Zamir *et al.* method) and the one obtained by the new map. Figure 1 presents

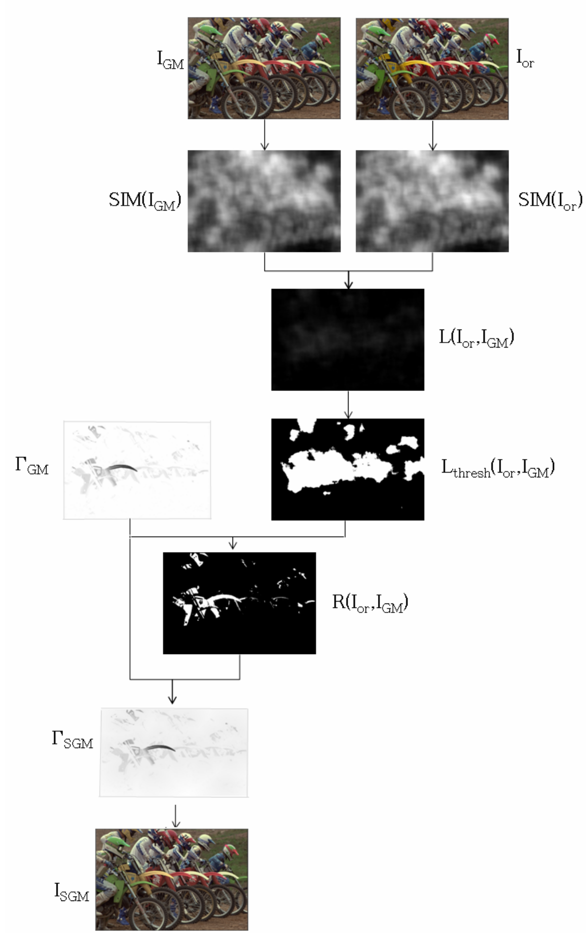

Figure 1: Workflow of our method. From the original image and the gamut mapped one by Zamir *et al.* [32] method we obtain their saliency maps and the difference between them. We binarize this image and we combine it with the maps obtained by Zamir *et al.* obtaining the set of interesting regions. Then, we compute the new map and we apply the functional of Equation (2) for generating a new gamut-mapped image.

the workflow of our approach which is carefully explained in the following subsections.

Detecting the regions where saliency has been lost

In this paper we will use the SIM saliency method presented by Murray *et al.* [26]. Let us call I_{or} the original image and I_{GM} the gamut-mapped image by Zamir *et al.*. We can obtain the amount of saliency that has been lost in each pixel by

$$L(I_{GM}, I_{or})(x) = \begin{cases} \frac{SIM(I_{or})(x)}{max(SIM(I_{or}))} - \frac{SIM(I_{GM})(x)}{max(SIM(I_{or}))} \\ \quad \text{if } SIM(I_{or})(x) > SIM(I_{GM})(x) \\ 0 \quad \text{otherwise} \end{cases} \tag{4}$$

In order to obtain binary regions to work with, we perform a thresholding operation on $L(I_{GM}, I_{or})$ and obtain

$$L_{thres}(I_{GM}, I_{or})(x) = \begin{cases} 1 & \text{if } L(I_{GM}, I_{or})(x) > \varepsilon_1 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where ε_1 is a real number. Let us denote as Γ_{GM} the map of the γ values for the I_{GM} image. As we said previously, we are interested in those regions where saliency has been lost due to a large difference between their gamma values and the gamma values of their surrounds. Therefore, to refine those regions given by L_{thres} we compute a new map $R()$ as

$$R(I_{GM},I_{or})(x) = \begin{cases} 1 & \text{if } L_{thres}(I_{GM},I_{or})(x)\cdot|\Gamma_{GM}(x)| > \varepsilon_2 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

where ε_2 is a real number. In other words, we select only those regions where the value of γ is small enough so that the surrounds can be decreased.

The map $R()$ is already defining those regions we want to handle. However, we need to be sure that the contours of the regions are consistent with the original image data. To that end, we fill in the map $R(I_{GM},I_{or})$ with the adjacent pixels that have a similar γ value.

Creating the new γ map

Our goal here is to reduce the difference in the γ values between the regions where saliency has been lost and their surrounds. But, at the same time, we do not want to sacrifice reproduction accuracy to a great extent. Therefore, our method takes into account the distance of each pixel from a region of interest. By taking this into consideration, our new map Γ_{SGM} is defined as

$$\Gamma_{SGM}(x) = \begin{cases} \Gamma_{GM}(x)+\tau\cdot(1-d(x,R))\cdot max(R(I_{GM},I_{or})\cdot\Gamma_{GM}) & \text{if } R(x)=0 \\ \Gamma_{GM}(x)+\frac{\tau}{2}\cdot max(R(I_{GM},I_{or})\cdot\Gamma_{GM}) & elsewhere \end{cases} \quad (7)$$

where $d(x,R)$ is the distance between the pixel x and its closest region of interest in R (that is, the closest pixel with a $R=1$) and τ is a real number between 0 and 1 that controls the decrease in the surrounding pixels.

Then, from the new map Γ_{SGM} we can run Equation(2) for each of the values and obtain a new gamut mapped image I_{SGM}.

Combining the mapped images

Let us note here that the image I_{SGM} obtained by the map Γ_{SGM} will have a saliency closer to the original image in our regions of interest, but may lose some saliency in other regions. Thus, the last step of our algorithm combines both I_{GM} and I_{SGM}. Our final image is then defined as

$$I_{final}(x) = \begin{cases} I_{SGM}(x) & \text{if } SIM(I_{SGM})(x) > SIM(I_{GM})(x) \\ I_{GM}(x) & \text{otherwise} \end{cases} \quad (8)$$

Results

We ran our algorithm on a set of 17 still images presented in Figure 2. We considered different values of τ and selected the image that presents a saliency closer to that of the original image. We have defined $d(x,R)$ as the normalization between 0 and 1 of the Euclidean distance in the pixel domain. ε_1 is obtained by using Otsu's method [27], while ε_2 is defined as the value given by the Otsu's method divided by 4.

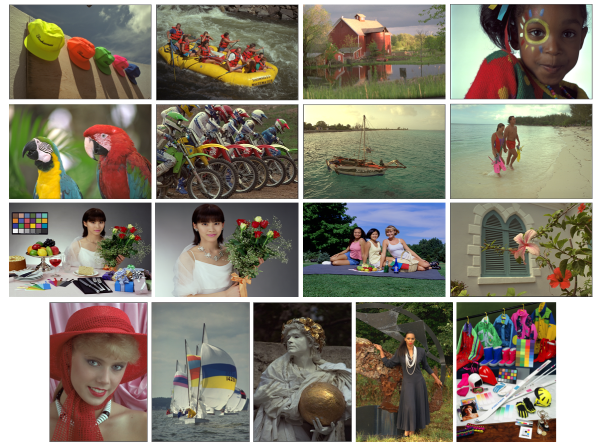

Figure 2: Images used for our experiment. The first 3 images of row 3 and the fifth image of row 4 are from CIE [9]. Rest of the images are courtesy of Kodak.

In order to measure the performance of our method we have defined a measure of saliency difference. This measure compares the saliency of a gamut mapped image to the saliency of the original image as follows

$$S(I_{GM},I_{or}) = \sum_x |(SIM(I_{or})(x)) - (SIM(I_{GM})(x))| \quad (9)$$

Based on this formula, we compare our method to the one of Zamir *et al.* [32]. Results are presented in Table 1. We can see that there is only one image where our method fails to improve the saliency difference. In counterpart, our method achieves a remarkable improvement of more than 10% in 4 of the images.

Image	Zamir *et al.* [32] (units=10^6)	Proposed (units=10^6)	Improve (%)
Caps	3.02	2.67	11.77
Raft	2.63	2.59	1.71
Barn	2.03	1.98	2.61
Girl	1.10	1.06	3.51
Birds	2.56	2.53	1.22
Motorbikes	3.24	2.79	14.20
Boat	1.58	1.55	1.67
Beach	0.77	0.67	13.22
Party	8.20	8.14	0.81
Portrait	7.85	7.37	6.17
Picnic	10.90	9.29	15.27
Window	4.02	3.95	1.86
Woman with Hat	3.32	3.27	1.49
Sailing Boats	0.84	0.84	0
Statue	3.08	2.98	3.32
Model	5.76	5.70	1.09
Ski	2.88	2.62	8.99

Table 1: Saliency difference error versus the original image for both the original Zamir *et al.* method and our modification.

Once it is proven that our approach does reduce the saliency difference with respect to the original image, a new question arises: does this improvement come at the cost of bad imaqe quality reproduction? To answer this question, we use the Color Image Difference (CID) metric [19]. The CID metric was specially devised for objectively evaluating gamut reduction algorithms. It is based on estimating the perceptual differences given by the changes, from one image to the other, in features such as hue, lightness, chroma, contrast, and structure.

Results of the CID metric in the form of mean, median and root mean squared error (RMSE) for the 17 images are presented in Table 2. In this Table we compare our approach to the Zamir *et al.* [32] method as well as to other state-of-art-methods: HPMIMDE [25], the Alsam and Farup method [2], and the Lau *et al.* method [2]. Results for our approach are slightly poorer than those obtained by the Zamir *et al.* method, but they are still better than the results presented by all the other methods. In other words, we achieve better salient reproduction at the expense of a slight loss in image quality, but this loss is affordable since none of the other state-of-the-art methods outperforms our proposed approach.

Method	Mean	Median	RMSE
Proposed	0.0414	0.0299	0.0576
Zamir *et al.* [32]	0.0360	0.0280	0.0485
HPMINDE [25]	0.0674	0.0514	0.0873
Alsam and Farup [2]	0.0472	0.0398	0.0627
Lau *et al.* [17]	0.0665	0.0695	0.0807

Table 2: CID error for our new approach and four state of the art methods.

Conclusions

In this paper we have proposed a modification to the gamut reduction algorithm recently published by Zamir *et al.* [32] in order to obtain a gamut-mapped image that is closer in terms of its saliency to the original image. To this end, we have modified the amount of contrast reduction applied by Zamir *et al.* in the adjacent regions to those where saliency was lost.

Our results show that by following our proposed approach, an image with a closer saliency to that of the original image is obtained. This improvement of saliency comes at the expense of a slight decrease in the quality of the reproduced image, although this slight loss is acceptable since our method competes with the state-of-the-art methods in terms of overall image quality.

Further work might take two directions. First, to study how our approach adapts to other image saliency methods. Second, to study the possibility of segmenting the original image in order to perform a local coefficient modification.

References

[1] A. Alsam and I. Farup. Colour gamut mapping as a constrained variational problem. In *Proc. of 16th Scandinavian Conference on Image Analysis*, pages 109–118, 2009.

[2] A. Alsam and I. Farup. Spatial colour gamut mapping by orthogonal projection of gradients onto constant hue lines. In *Proc. of 8th International Symposium on Visual Computing*, pages 556–565, 2012.

[3] C. O. Ancuti, C. Ancuti, and P. Bekaert. Enhancing by saliency-guided decolorization. In *CVPR*, pages 257–264. IEEE, 2011.

[4] R. Bala, R. Dequeiroz, R. Eschbach, and W. Wu. Gamut mapping to preserve spatial luminance variations. *Journal of Imaging Science and Technology*, 45:122–128, 2001.

[5] D. Bankston. The color-space conundrum, part one. *American Cinematographer*, page 6, 2005.

[6] M. Bertalmío, V. Caselles, E. Provenzi, and A. Rizzi. Perceptual color correction through variational techniques. *IEEE Transactions on Image Processing*, 16(4):1058–1072, 2007.

[7] G. Cao, M. Pedersen, and Z. Baranczuk. Saliency models as gamut-mapping artifact detectors. In *5th European Conference on Colour in Graphics, Imaging, and Vision (CGIV)*, pages 437–443, Joensuu, Finland, June 2010.

[8] S. Chen and A. Beghdadi. Improve gamut mapping of color management system by perceptual quality-oriented analysis. In *EUVIP*, pages 12–17. IEEE, 2011.

[9] CIE. Guidelines for the evaluation of gamut mapping algorithms. Technical report, 2004.

[10] F. Ebner and M. D. Fairchild. Gamut mapping from below: Finding minimum perceptual distances for colors outside the gamut volume. *Color Research and Application*, 22:402–413, 1997.

[11] I. Farup, C. Gatta, and A. Rizzi. A multiscale framework for spatial gamut mapping. *IEEE Transactions on Image Processing*, 16(10):2423–2435, 2007.

[12] A. A. Gooch, S. C. Olsen, J. Tumblin, and B. Gooch. Color2gray: salience-preserving color removal. *ACM Trans. Graph.*, 24(3):634–639, 2005.

[13] N. Jacobson and T. Q. Nguyen. Video processing with scale-aware saliency: Application to frame rate up-conversion. In *ICASSP*, pages 1313–1316. IEEE, 2011.

[14] N. Katoh, M. Ito, and S. Ohno. Three-dimensional gamut mapping using various color difference formulae and color spaces. *Journal of Electronic Imaging*, 8(4):365–379, 1999.

[15] G. Kennel. *Color and mastering for digital cinema: digital cinema industry handbook series*. Taylor & Francis US, 2007.

[16] R. Kimmel, D. Shaked, M. Elad, and I. Sobel. Space-dependent color gamut mapping: A variational approach. *IEEE Transactions on Image Processing*, 14:796–803, 2005.

[17] C. Lau, W. Heidrich, and R. Mantiuk. Cluster-based color space optimizations. In *Proc. of IEEE International Conference on Computer Vision*, ICCV '11, pages 1172–1179, 2011.

[18] A. Lindner, N. Bonnier, and S. Ssstrunk. Saliency driven black point compensation. In *Proc. SPIE*, volume 7866, pages 786609–786609–9, 2011.

[19] I. Lissner, J. Preiss, P. Urban, M. S. Lichtenauer, and P. Zolliker. Image-difference prediction: From grayscale to color. *IEEE Transactions on Image Processing*, 22(2):435–446, 2013.

[20] J. J. McCann. Lessons learned from mondrians applied to real images and color gamuts. In *Proc. of Color Imaging Conference*, pages 1–8, 1999.

[21] J. J. McCann. A spatial colour gamut calculation to optimize colour appearance. In *Colour Image Science: Exploiting Digital Media*, pages 213–233, 2002.

[22] J. Meyer and B. Barth. Color gamut matching for hard copy. In *Proc. of SID Digest*, pages 86–89, 1989.

[23] J. Morovič. *Color gamut mapping*, volume 10. Wiley, 2008.

[24] J. Morovič and Y. Wang. A multi-resolution, full-colour spatial gamut mapping algorithm. In *Proc. of Color Imaging Conference*, pages 282–287, 2003.

[25] G. M. Murch and J. M. Taylor. Color in computer graphics: Manipulating and matching color. *Eurographics Seminar: Advances in Computer Graphics V*, pages 41–47, 1989.

[26] N. Murray, M. Vanrell, X. Otazu, and C. A. Prraga. Low-level spatiochromatic grouping for saliency estimation. *IEEE Trans. Pattern Anal. Mach. Intell.*, 35(11):2810–2816, 2013.

[27] N. Otsu. A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man and Cybernetics*, (1):62–66.

[28] M. Pedersen, X. Liu, and I. Farup. Improved simulation of image detail visibility using the non-subsampled contourlet transform. In *Color and Imaging Conference (CIC)*, pages 191–196, Albuquerque, NM, USA, Nov 2013. IS&T and SID.

[29] K. B. Raja and M. Pedersen. Artifact detection in gamut mapped images using saliency. In *Colour and Visual Computing Symposium (CVCS)*. IEEE, Sept 2013.

[30] H. J. Seo and P. Milanfar. Static and space-time visual saliency detection by self-resemblance. *Journal of Vision*, 20(9):15.1–17, 2009.

[31] M. C. Stone, W. B. Cowan, and J. C. Beatty. Color gamut mapping and the printing of digital color images. *ACM Transactions on Graphics*, 7(4):249–292, 1988.

[32] S. Zamir, J. Vazquez-Corral, and M. Bertalmio. Gamut mapping in cinematography through perceptually-based contrast modification. *Selected Topics in Signal Processing, IEEE Journal of*, 8(3):1–1, 2014.

[33] P. Zolliker and K. Simon. Retaining local image information in gamut mapping algorithms. *IEEE Transactions on Image Processing*, 16(3):664–672, 2007.