Perceptually inspired gamut mapping between any gamuts with any intersection

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ABSTRACT

Gamut mapping transforms the color of an input image within the range of a target device. A huge amount of research has been devoted to two subproblems that arise from this general one: gamut reduction and gamut extension. Gamut reduction algorithms convert the input image to a new gamut that fits inside the one of the image , i.e. the gamuts' intersection is equal to the target gamut, while gamut extension algorithms convert the input image to a gamut that embodies the original image gamut, i.e. the gamuts' intersection is equal to the source gamut. In contrast to the two aforementioned cases, very little attention has been paid to the most general problem, where the intersection of source and target gamut is not equal to one of the two gamuts. In this paper we address this most general problem of gamut mapping between any two gamuts presenting any possible intersection. To deal with this problem we unify the gamut extension and gamut reduction algorithms presented in Zamir –et al- (Zamir 2014), which are based in the perceptually inspired variational framework of Bertalmío –et al- (Bertalmío 2007) that presents three competing terms; an attachment to the original data, a term for not-modifying the per-channel image mean (i.e. not modifying the white point), and a contrast enhancement term. In particular, in this paper we show how by defining a smooth transition on the contrast enhancement parameter over the chromaticity diagram we can simultaneously reduce the input gamut in some chromatic areas while increasing it in some other without introducing neither color artifacts nor halos.

1. INTRODUCTION

Gamut mapping is defined as the modification of the gamut of an input image to make it fit into a destination gamut. This problem is usually divided into two sub-problems that are treated separately: gamut reduction and gamut extension. The former is when the destination gamut is smaller than of the original image. This situation occurs 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 (Kennel 2007). Conversely, gamut extension is devoted to the case where the destination gamut is bigger. This is currently needed for state-of-the-art cinema projectors which are able to display a wider variety of color than those obtained by cameras.

There exist a huge number of gamut reduction algorithms and just a few gamut extension algorithms in the literature and we refer the reader to the book of Morovic (Morovic 2008) for a detailed explanation of them. Gamut reduction algorihms are usually divided into two classes: global (or non-local, non-adaptive) and local (or adaptive). Global methods involve point-to-point mapping of colors from source to target gamut. In contrast, local methods share two important properties of human perception: i), they better preserve the

color gradient between two out-of-gamut colors instead of mapping them to the same in-gamut color and ii), 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. Recently, Zamir -et al- (Zamir 2014) presented a local method that is based on a perceptually based contrast reduction of the colors. This method was also modified to take into consideration the saliency of the original image (Vazquez-Corral 2014). Regarding gamut extension, the simplest method consists of simply taking any GRA and use the one-to-one mapping in the reverse direction to perform gamut extension, as Morovic comments in his book. Other methods that exist in the literature are (Kang 2003, Kim 2004, Laird 2009). Recently, Zamir -et al- showed how that by modifying the contrast parameter on their reduction method, a gamut expansion method was obtained (Zamir 2014, Zamir 2015).

In this work we do not focus on any of these two particular problems, but in the most general one: the case where the intersection between the two gamuts is not one of them (this intersection is the destination gamut in case of the reduction, and the image gamut in case of the extension). In particular, we explain how we can introduced some locality in the algorithms of Zamir -et al- in order to simultaneously perform reduction on those parts of the original image that exceed the destination gamut whilst performing extension on those parts of the image that are in the surface of the image gamut but far from the destination gamut. In particular, we will show the ability of this method to harmonize different images.

The paper is organized as follows. In the next section we explain the Zamir -et al- methodology. Later on, we explain how we introduce locality which allows us to extend or reduce each of the parts of the image. Results are presented in section 4. Finally in section 5 we sum up the conclusion of this work.

2. ZAMIR –ET AL- METHOD

Zamir –et al- (Zamir 2014) method is a modification of the perceptually-inspired image energy functional defined in Bertalmío -et al- (Bertalmio 2007). In particular, the image energy functional considered is Zamir –et al- is

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

(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, 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

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

(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. 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 (Bertalmio 2007) they choose for s() a polynomial of degree 7.

Zamir –et al- presented the importance of the weighting parameter of the contrast term (γ) for the gamut mapping problem. In particular, they showed that for γ smaller than 0, the gamut of the image was reduced, while for γ bigger than 0, the gamut of the image was extended. Moreover, they also showed that the smaller the value of γ, the smaller the gamut of the resulting image.

Zamir –et al- therefore chose a set of γ values smaller than 0 for creating a gamut reduction algorithm and a set of γ values bigger than 0 for creating a gamut extension algorithm. They, however, did not try study the case of selecting both negative and positive values of the γ parameter for the same image, in order to obtain a more general gamut mapping algorithm. This problem is the one we are tackling in this paper. In the next section we explain how given an input image and a target gamut (coming from a different image or from a display) a local γ value for each image pixel can be obtained, allowing the method to perform reduction in some parts of the image and extension in the others.

3. LOCAL CONTRAST COEFFICIENTS

To start with let us shed some light in the situation we will face. Let us call Y_1 the gamut of the image to modify and Y_2 the gamut we want to obtain. When plotting these gamuts in the chromaticity diagram three different regions will be presented. The first region will be the one where both gamuts intersect, and we denote it as Φ. The second region will present those colors in the input image that are not presented in the destination gamut. We call this region Ψ. Finally, the last region, that will call Ω, will be formed by the colors present in the destination gamut that are not present in the input image. Therefore, our goal is to reduce section Ψ while at the same time increasing section Φ to cover the section Ω. In other words, we want to reduce those colors presented only in the input image, while at the same time, expanding colors of the input image presented in the destination gamut to cover the full destination gamut. An illustration of the aforementioned procedure can be found in Figure 1.

Mathematically, we will proceed as follows to obtain the γ value corresponding to each chromatic color. First, we erode the region Φ to obtain the core region of the intersection between the two gamuts.

$$\Phi_{er} = \Phi \oplus D_\tau \tag{4}$$

where D_τ is a disk of radius τ.

Then, we define those points where we want to perform a bigger reduction, i.e., the points of section Ψ that are at a further distance of Φ, and we will give them a value that depends on the minima gamma we consider (γ_{min}). In particular, if we call Γ the map of the
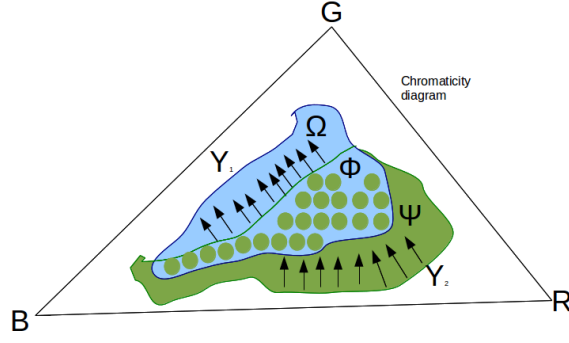
Figure 1: Explanation of the different regions found in our problem. See first paragraph of section 3 for details.

different gammas presented in the chromaticity diagram, and we call z any point presented in the chromaticity diagram, we obtain

$$\Gamma(z) = \left\{ \gamma_{min} \cdot \frac{d(z, \Phi_{er})}{\max_{\hat{z} \in \Psi}(d(\hat{z}, \Phi_{er}))} \right\} \; if \; z \in \Psi \, and \; \frac{d(z, \Phi_{er})}{\max_{\hat{z} \in \Psi}(d(\hat{z}, \Phi_{er}))} < \delta_1 \quad (5)$$

where all the values obtained will be negative.

Later, we look for the points in Φ that are in the border with respect to Ω. These points are the ones where we want to perform a bigger expansion to cover the region Ω. Their value will be based on the maxima gamma we consider (γ_{max}).

$$\Gamma(z) = \left\{ \gamma_{max} \cdot \left(1 - \frac{d(z, \Omega)}{\max_{\hat{z} \in \Phi}(d(\hat{z}, \Omega))} \right) \right\} \; if \; z \in \Phi \; and \; \frac{d(z, \Omega)}{min_{\hat{z} \in \Phi}(d(\hat{z}, \Omega))} < \delta_2$$

$$(6)$$

where all the values obtained will be positive.

Finally, we look for the points we want to keep static when performing our method.

$$\Gamma(z) = 0 \; if \; z \in \Phi_{er} \qquad (7)$$

Once all these different values have been defined in the matrix Γ, all the rest of the values are obtained by interpolation. Finally, for each pixel of the input image, its gamma value is obtained by searching its correspondence in Γ.

4. RESULTS

Figure 2 shows a result of our method. In the upper row of the figure we show the input image (left), the image from where we obtain the reference gamut (right) and the result of our method (center). In the bottom row we present: i) left: the gamut intersection between the images, where the red region represents Φ, the yellow region represents Ψ, and the blue region Ω represent, ii) center: the map of Γ, and iii) an image with the gammas used at each pixel. We would like to fix the reader attention both in the sky and in the sand, where our method is able to match the colors of the original image to those of the reference one. The parameters used in this image are $\delta_1=0.25$, $\delta_2=2$, $\sigma=3$, $\gamma_{max}=0.3$, and $\gamma_{min}=-0.75$.
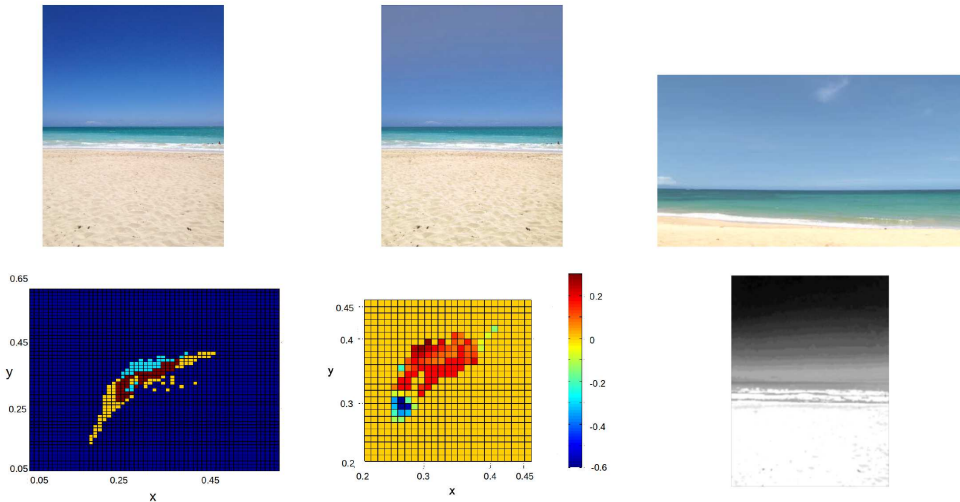
Figure 2: Results of our method. Upper row: Input image (left), Reference image (right) and our result (center). Bottom row: the gamut intersection between the images, where the red represents Φ, yellow represents Ψ, and blue represents Ω (left), the map of Γ, (center) and the gammas at each pixel (right).

More results are presented in Figure 3, where we show the input image (left), the reference image from where the gamut is obtained (right), and our result (center). Again, we want to notice our ability to match the original image to look closer to the reference image. In thefirst case, we see how the white color has tent to the yellow of the reference image, while the blue has got the electric tone of the tub. In the second image, the orangish background has been moved towards the red of the reference image. Finally, in the last one, blue of the sky has been modified as there have been also modified other regions of the input image to look greener.

5. CONCLUSIONS

In this work we have presented a modification of Zamir –et al- algorithms in order to perform full gamut mapping, i.e., to being able to simultaneously reduce gamut of colors in some parts of the image while extending the colors in some other parts. The results presented are promising. Some future lines to improve our results may be the consideration of the full 3D gamut (a first attempt is presented in Figure 4) and the search of further applications such as semantic transfer.

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Figure 3: Results of our method. Left: original image. Right: reference image. Center: Our result

Figure 4: Example of the 3D case for our method. Left: original image. Right: reference image. Center: Our result

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