Color transfer between high-dynamic-range images

Hristina Hristova, Rémi Cozot, Olivier Le Meur, and Kadi Bouatouch

IRISA, University of Rennes 1, 263 Avenue du General Leclerc, 35000, Rennes, France

ABSTRACT

Color transfer methods alter the look of a source image with regards to a reference image. So far, the proposed color transfer methods have been limited to low-dynamic-range (LDR) images. Unlike LDR images, which are display-dependent, high-dynamic-range (HDR) images contain real physical values of the world luminance and are able to capture high luminance variations and finest details of real world scenes. Therefore, there exists a strong discrepancy between the two types of images. In this paper, we bridge the gap between the color transfer domain and the HDR imagery by introducing HDR extensions to LDR color transfer methods. We tackle the main issues of applying a color transfer between two HDR images. First, to address the nature of light and color distributions in the context of HDR imagery, we carry out modifications of traditional color spaces. Furthermore, we ensure high precision in the quantization of the dynamic range for histogram computations. As image clustering (based on light and colors) proved to be an important aspect of color transfer, we analyze it and adapt it to the HDR domain. Our framework has been applied to several state-of-the-art color transfer methods. Qualitative experiments have shown that results obtained with the proposed adaptation approach exhibit less artifacts and are visually more pleasing than results obtained when straightforwardly applying existing color transfer methods to HDR images.

Keywords: HDR Images, Color Transfer

1. INTRODUCTION

High-dynamic-range (HDR) imagery uses a set of techniques to reproduce natural light in real-world scenes. HDR images are representative of the human visual perception. They contain real physical values of the world luminance and therefore, capture high luminance variations, from extreme shade to direct sunlight. As a result, details in shadows and highlights of HDR images are well-preserved.

Low-dynamic-range (LDR) devices are unable to display the range of light of real-world scenes. To this end, tone mapping operators are applied to fit the large luminance variations of HDR images to the displayable range. Nevertheless, this type of compression results in loss of details and may cause the appearance of structural artifacts. As the plausibility of the tone mapped image cannot be guaranteed, any possible modifications to HDR images need to be handled directly in the HDR domain.

The objective of this paper is to carry out a transfer of color and light between two HDR images. In the context of the LDR domain, color transfer methods offer a number of solutions to example-based transfer of features between pairs of images. Color transfer domain aims at modifying the light and color distributions of an input image with regards to a reference image. However, the direct application of color transfer methods to the HDR domain is limited. Therefore, in this paper, we extend state-of-the-art LDR color transfer methods to HDR images by introducing series of adaptation techniques. The paper focuses mainly on the extension of a novel local method for style transfer. This method is composed of general steps which (independently or as a combination) are incorporated in the framework of state-of-the-art color transfer methods. To this end, the adaptation techniques, developed to extend the first method to HDR images, serve as a basis for generalizing the extension to a wider class of color transfer methods. Furthermore, experiments show that results obtained with the proposed adaptation techniques exhibit less artifacts and are visually more pleasing than results obtained

Further author information: (Send correspondence to H. Hristova)

H. Hristova: E-mail: hristina.hristova@irisa.fr

R. Cozot: E-mail: remi.cozot@irisa.fr

O. Le Meur: olivier.lemeur@irisa.fr

K. Bouatouch: kadi.bouatouch@irisa.fr

when straightforwardly applying existing color transfer methods to HDR images. To our best knowledge, this paper introduces the first attempt to bridge the gap between the color transfer and the HDR domains.

The paper is organized as follows. Section 2 outlines state-of-the-art color transfer methods and discusses the main drawbacks of applying them to HDR images. Extensions to the HDR domain of state-of-the-art color transfer methods are proposed in Section 3, followed by results and evaluation. Finally, Section 4 concludes the paper.

2. BACKGROUND AND RELATED WORK

The present section outlines exiting state-of-the-art color transfer methods and discusses the drawbacks of applying them directly (without any modifications) to the HDR domain.

2.1 Color transfer methods in LDR domain

Recently, many interesting solutions and applications to digital image stylization have been introduced to the color transfer domain. However, the existing methods in this domain have been focusing on LDR images. Color transfer methods aim at building a mapping between the light and color distributions of the input and reference images either by introducing statistically-based transformation models or by seeking content-based correspondences between pairs of images.[1]

Naive histogram matching is a non-parametric method which tries to borrow the thorough look of an image by matching the shape of an input histogram to that of a target histogram. Put differently, the method aims to reproduce the reference colors and light by matching the cumulative density functions of both images.

Furthermore, Reinhard et al.[2] introduce the first parametric color transfer method. It is specially designed for natural scenes. The color mapping is built under the assumption that the input/reference light and color distributions can be fitted by a multivariate Gaussian distribution. The color transformation is carried out in $l\alpha\beta$ color space by using diagonal covariance matrix the diagonal elements of which correspond to the reference-to-input standard deviation ratios.

Similarly to Reinhard et al.,[2] Pitié et al.[3] also adopt the multivariate Gaussian law. Their color mapping is built as a closed-form solution to Monge-Kantorovich optimization problem.[4] Unlike Reinhard et al.,[2] Pitié et al.'s method takes into account the dependencies between the channels of CIE Lab color space by using non-diagonal covariance matrix in the transformation.

Unlike the two latter methods which rely on a global homogeneous transformation, there exist methods performing the transformation locally between pairs of image clusters.

Tai et al.[5] apply a 3D Expectation-Maximization algorithm to cluster the input and reference images. The mapping function between the clusters is based on the luminance channel of $l\alpha\beta$ color space. Finally, Reinhard's color grading method[2] is adopted to carry out the color transfer between each pair of corresponding input/reference clusters.

Furthermore, Bonneel et al.[6] present a luminance-based clustering approach. Their method clusters both input and reference images into three luminance bands. On one hand, Pitié's color transformation[3] is used to carry out the color transfer on the a and b channels of CIE Lab color space for each two corresponding clusters. On the other hand, histogram matching is applied to the luminance channel to reproduce the reference luminance.

Finally, Hristova et al.[7] have recently introduced a new local approach for style transfer based on four mapping policies. The authors aim to properly transfer the reference style features by detecting the main features in both input and reference images. The mapping policies in their method are based upon photographic techniques and equally consider both light and color features. More details on this method will be given in Section 3.

Apart from the color transfer domain, one more topic is advocated in this paper, namely chromatic adaptation transform. It has applications in the fields of white balancing and color transfer, as discussed in the following subsection.

2.2 Chromatic adaptation transform

Chromatic adaptation transform (CAT) aims at adapting the colors of an image to a given illuminant. CAT has been used as a white balancing step in many algorithms[8–10] for the purpose of adapting the colors of an image to a well-known illuminant (D65, D50, etc.).

Furthermore, Frigo et al.[11] apply CAT algorithm iteratively. They start using CAT in the context of color transfer. Instead of adapting the colors of an image to a well-known illuminant, they use a global estimation of both the input and reference white points by assuming Gray World.[12]

In addition to that, Hristova et al.[7] adopt CAT in their color grading method. Similarly to Frigo et al.,[11] Hristova et al. compute a global reference white point. Nevertheless, they apply CAT locally to each pixel of the input image. The input white point is computed pixel-wisely by applying a low-pass Gaussian filter to the input image.

The two latter approaches yield plausible results in the LDR domain, but they may exhibit some problems if directly applied to HDR domain due to the dynamic range of the HDR images.

Finally, Fairchild et al.[8,9] apply CAT to HDR images. The chromatic transform in iCAM algorithm is performed locally on the pixels of the input image. However, the transform serves only to adapt the input white point to D65 illuminant for further conversion to IPT color space (rather than being used for the purpose of image stylization).

2.3 Why do LDR color transfer methods need to be extended to HDR images?

The state-of-the-art color transfer methods have so far been limited to LDR images. However, color transfer methods cannot be directly applied to the HDR domain due to several restrictions, as discussed hereafter.

To carry out a color transfer, state-of-the-art methods adopt a number of color spaces. For instance, Reinhard et al.[2] have introduced $l\alpha\beta$ to predict light and colors of natural LDR images. The color space $l\alpha\beta$ is derived as a linear transformation of CIE XYZ. The color space CIE XYZ uses imaginary primaries such that values in a low-dynamic range interval (usually [0, 1]) cover the visible gamut. Therefore, values much greater than the upper bound of this low-dynamic range interval have to be accommodated as well to include the desired high-dynamic range of HDR images.

Furthermore, CIE Lab color space is widely used in a variety of color transfer methods. Reinhard et al.[13] have conducted experiments showing that CIE Lab is the best color space for carrying out a color transfer. However, CIE Lab is limited to color stimuli with luminance levels from zero to perfect diffuse white. This means that CIE Lab predicts the color trend for luminance levels below and around the display white point. Therefore, the applicability of CIE Lab to HDR images is uncertain.

Moreover, global color transfer methods model the light and color distributions with multivariate Gaussian distribution assuming that the parametric model can account for the luminance variations in the image. However, a unique multivariate Gaussian distribution can hardly fit the large luminance range of HDR images and be representative of it. In general, the multivariate Gaussian assumption does not hold in the LDR domain as well. Therefore, to handle this issue, local LDR color transfer methods cluster images into Gaussian clusters.[5–7] Luminance is often used to carry out the clustering process and the mapping between the clusters.[6,7] Thanks to the low dynamics of LDR images, luminance is often approximated with lightness and vice versa. Nevertheless, in the context of HDR imagery, absolute luminance (measured in cd/m^2), relative luminance (relative to the perfect diffuse white) and lightness need to be distinguished and accommodated properly in the color transfer methods. To this end, new strategies for carrying out the clustering and the mappings between the clusters in the HDR domain have to be developed.

The next section presents an extension of Hristova et al.'s local color transfer method[7] to HDR images. The method introduces a solution to style transfer between two LDR images. Independently or as a combination, the steps of the method are integrated in the frameworks of state-of-the-art color transfer methods. Therefore, the adaptation of Hristova et al.'s method to HDR images underlies the adaptation generalization for other color transfer methods.

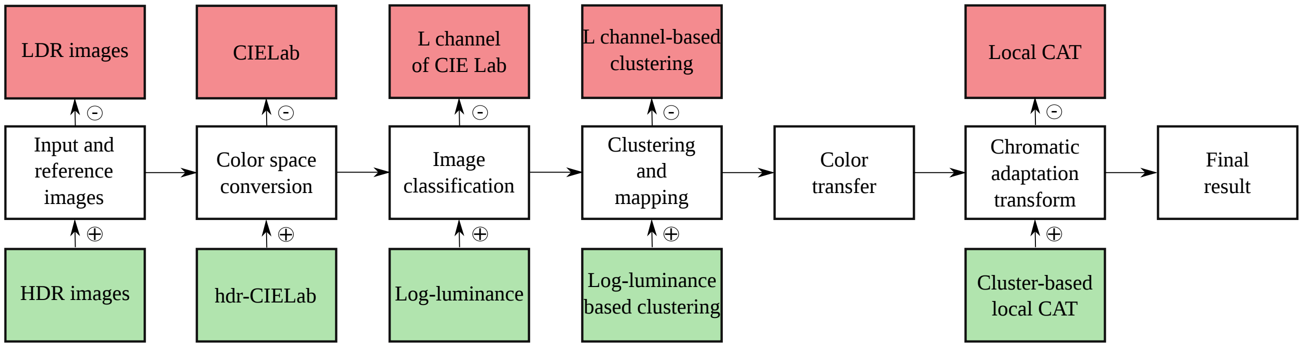

Figure 1. Hristova et al.'s framework, consisting of several steps (displayed in the middle boxes). Red boxes display the parts of the algorithm which are replaced by modifications in the extended to HDR images method. The modifications themselves are shown in green boxes.

3. ADAPTING A COLOR TRANSFER METHOD TO HDR IMAGES

We analyze and propose an adaptation of Hristova et al.'s method[7] to the HDR domain. First, we introduce the steps of the method and then, we focus on their extension to HDR images by taking into account the main drawbacks, discussed in the previous section.

3.1 Style-aware color transfer[7]

The framework of Hristova et al.'s style transfer method[7] is illustrated in Figure 1. Before performing any color grading operations, the method classifies and clusters both input and reference images. The image classification algorithm detects the main features of the input and reference images. Two features, light and colors, are considered. They define two types of images, light-based style images and colors-based style images, as illustrated in Figure 2. The classification is carried out in CIE Lch color space and it boils down to finding significant peaks in the hue histogram of the set of non-gray image pixels.

Once both input and reference images are classified according to the main features, they are separated into Gaussian clusters using Gaussian mixture models. The clustering is performed either on the luminance histogram or on the luminance-hue distributions (depending on the image type).

Furthermore, four mapping policies are applied to properly map the obtained input and reference clusters. Similarly to Bonneel et al.,[6] Hristova et al. apply luminance-based mapping to map the clusters of two light-based style images. The other three mapping policies jointly consider the luminance and the hue of the input and reference images to design a mapping strategy based on widely used photographic techniques.

Hristova et al. apply Pitié's color transformation[3] to the a and b channels of CIE Lab color space. Unlike Bonneel et al.,[6] local chromatic adaptation transform is adopted as a final step of the algorithm to preserve naturalism in the result and to reduce the transfer of false colors. Local CAT is performed pixel-wisely on the pixels of the input image. A global reference white point is computed by assuming Gray World.[12] Moreover, the input illuminant is computed in the form of "white" image by performing Gaussian low-pass filter.

For more information regarding the method, refer to Hristova et al.'s paper.[7]

3.2 Extension to the HDR domain

Hristova et al.'s method is adapted to HDR images on several stages. Each stage refers to modifications to a step in the framework of the method. Figure 1 illustrates the proposed modifications for extension of the method to HDR images.

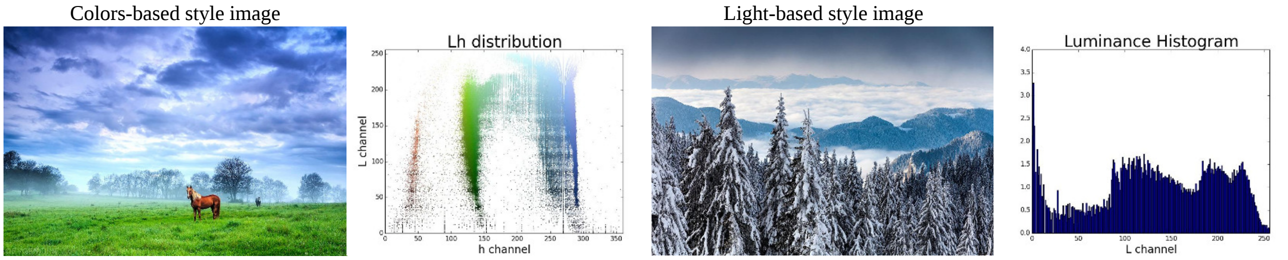

Figure 2. A colors-based style image and its luminance-hue distribution with well-defined color clusters (on the left). A light-based style image and its luminance histogram, identifying the presence of shadows, midtones and highlights in the image (on the right).

3.2.1 Color space conversion

Hristova et al.'s method is carried out in CIE Lab color space which offers a good representation of the lightness and the chroma of LDR images. However, for luminance values far beyond the perfect diffuse white, CIE Lab is no longer able to reproduce well the image color gamut. To address this issue, we follow the recommendations of Fairchild et al.[14] and we replace the cubic root function of the L channel of CIE Lab color space with Michaelis-Menten function[14] (denoted as f(y)) as follows:

$$f(y) = 247\frac{y^{\epsilon}}{y^{\epsilon} + 2^{\epsilon}} + 0.02 \tag{1}$$

where y denotes the relative luminance (obtained by scaling the absolute luminance by the perfect diffuse white) ranging from 0 to 4, and ϵ is equal to 0.58.

The chroma channels a and b are then computed by replacing the cubic root function in their standard formulas with Equation 1 and scaling them by 1/100. That is how we obtain the per-channel equations of hdr-CIELab color space[14] as an extension of CIE Lab in the HDR domain. The color space hdr-CIELab is specially developed to predict the color trend above the diffuse white for images with high dynamic range.

3.2.2 Image classification

Once a good prediction of the color gamut of HDR images it ensured, we carry out the classification step of Hristova et al.'s method. Apart from the detection of the main features in images, the classification algorithm determines the number of clusters which will be passed to the clustering step. For colors-based style images, the number of color clusters is derived from their hue histogram. In the context of HDR imagery, the hue is computed as a transformation of the a and b channels of hdr-CIELab color space. To this end, the classification system of the method will properly determine the number of significant color clusters in HDR images. Moreover, as the detection of light and color features in images consists in determining the number of significant color clusters, the proposed modification of CIE Lab ensures that both input and reference images will be correctly classified.

Regarding the number of luminance clusters in light-based style images, they correspond to the number of significant peaks in the luminance histogram. Instead of using the luminance histogram in the extension of the method to HDR images, we adopt log-luminance histogram. An explanation, justifying this choice, will be given hereafter.

3.2.3 Clustering and mapping

The clustering step of the method partitions both images into Gaussian clusters. The clustering is performed using either the luminance histogram or the luminance-hue distributions. As we approximate the luminance with the lightness in the LDR domain, the L channel of CIE Lab color space is used to cluster the images. However, in the context of HDR imagery, the L channel of hdr-CIELab refers to the lightness (the relative luminance). Therefore, instead of adopting the L channel (Equation 1) for carrying out the clustering in the HDR domain, we use the logarithmic transformation of the absolute luminance.

As illustrated in Equation 1, the L channel of hdr-CIELab is a function of the relative luminance, which is obtained by scaling the absolute luminance (in cd/m^2) by the diffuse white. On the other hand, the logarithmic function of the absolute luminance is a good approximation of the brightness.[15] Moreover, as a monotonic transformation, the logarithmic transformation preserves the locations of the minima and the maxima in the histogram of absolute luminance. To this end, we can use the logarithmic approximation of the brightness in the place of the L channel in both clustering approaches (luminance-based and luminance-hue-based).

In a similar manner, log-luminance histogram is adopted for the purposes of finding the number of luminance clusters during the classification process. Moreover, it is then used to map the reference to the input clusters after the image clustering.

Once we carry out all the described adaptation operations, we perform the color transformation between each pair of corresponding clusters. The transformation is given as a closed-form solution to Monge-Kantorovich optimization problem. The mapping between the input and reference images is linear and therefore, no additional modifications are required regarding the color transformation.

Finally, the last step of Hristova et al.'s method, namely local CAT, has been replaced by a new cluster-based method for chromatic adaptation transform, which can be either integrated in a color transfer framework or applied as a standalone color grading technique. This method is described in the following subsection.

3.2.4 Cluster-based local CAT

CAT algorithm adapts the colors of a given image to a reference illuminant, which usually is one of well-known white points: D65, D50, etc. CAT is often carried out in LMS color space as follows:

$$D = F\left[1 - \left(\frac{1}{3.6}\right)e^{\left(-\frac{(L_A-42)}{92}\right)}\right] \tag{2}$$

$$L_c = \left(L_{W_r}\frac{D}{L_{W_i}} + (1-D)\right)L \tag{3}$$

$$M_c = \left(M_{W_r}\frac{D}{M_{W_i}} + (1-D)\right)M \tag{4}$$

$$S_c = \left(S_{W_r}\frac{D}{S_{W_i}} + (1-D)\right)S \tag{5}$$

where (L, M, S) are the values of pixels in LMS color space, $(L_{W_i}, M_{W_i}, S_{W_i})$ and $(L_{W_r}, M_{W_r}, S_{W_r})$ are respectively the input and reference white points, and (L_c, M_c, S_c) are the illuminant adapted values in LMS color space. Factor D varies from 0 to 1. It strongly depends on the adaptation luminance L_A, computed as 20% of the adaptation white, and the surrounding factor F.[8,9] In addition, iCAM algorithm[8] introduces a scaling of factor D by 0.3 to reduce the de-saturation of the rendered image.

To adapt the colors of an HDR image to a well-known illuminant, we can compute an estimation of the reference white point. However, due to the high luminance range of HDR images, one global white point may not be representative enough of the illuminant of the scene. To tacke this issue, we have designed a cluster-based local CAT algorithm. We propose a partitioning into regions of the range of HDR images with regards to their luminance values. We estimate several local reference white points from the luminance values of several regions of the reference image.

The number of regions resulting from the partitioning of each image depends on its luminance range. We build the luminance histogram of a given image in the log-domain (for elaboration on the choice of the log-domain, refer to Subsection 3.2). The number of peaks in the log-luminance histogram corresponds to the number of the differently illuminated regions in an image as illustrated in Figure 3.

The image partitioning is carried out in the log-domain, according to the log-luminance histogram. Two parameters are considered for finding the peaks of the log-luminance histogram: the minimum histogram peak value s_{min} and the minimum distance between two peaks d_{min}. The number of bins in the log-luminance

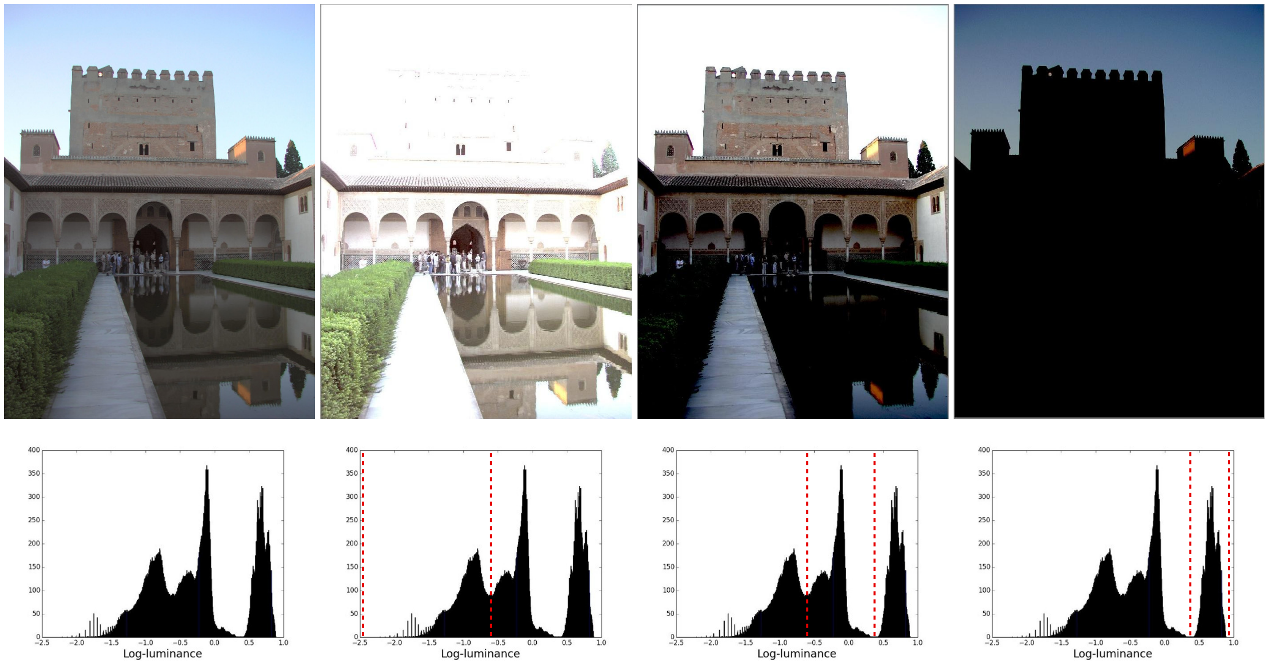

Figure 3. An HDR image and its three regions, corresponding to the peaks of its log-luminance histogram (we use Reinhard et al.'s mapping operator[15] to display the HDR image and its regions). Two red dashed lines define the region limits in the log-luminance histogram.

histogram is set to $32r$ (r is the range of the log-luminance histogram[16]). For the values of s_{min} and d_{min}, we follow the recommendations of Boitard et al.[16] and set them respectively to $\frac{nm}{32r}$ (where n and m are the two image dimensions) and 0.65.

Once the minima between each two peaks are defined, they are set as limits between the regions. Each image region consists of pixels with three coordinates (X, Y, Z), for which *log(Y)* lies within the limits of the region. To make a smooth transition between the different regions after the chromatic adaptation, overlapping between them is performed. All of the pixels with log-luminance values within a small offset δ from a given limit, are considered as overlapping pixels. The value δ is given in the log-domain and it is set to 1. Each overlapping pixel is assigned two weights, measuring the belonging of the pixel to each of two image regions. The weight of an overlapping pixel for a given region is derived as follows (as proposed in Boitard et al.'s method[16]):

$$\omega = e^{-\frac{(log(Y)-log(l))^2}{2\sigma^2}}, \ \sigma = \frac{\delta}{2\sqrt{2log(3)}} \tag{6}$$

where Y is the luminance of the pixel and l stands for the limit of the given region.

Moreover, the white point of each reference image region is computed in the following way (as in Boitard et al.'s method[16]):

$$X_{Wr} = e^{\frac{1}{s_j}\sum_{i=1}^{s_j} log(X_r+\delta_1)}, \ Y_{Wr} = e^{\frac{1}{s_j}\sum_{i=1}^{s_j} log(Y_r+\delta_1)}, \ Z_{Wr} = e^{\frac{1}{s_j}\sum_{i=1}^{s_j} log(Z_r+\delta_1)} \tag{7}$$

where s_j is the size of region j and δ_1 a small offset.[16]

Once the reference white points are computed, they are mapped to the input regions. We define the center value of an input region as the maximum *log(Y)* value within the limits of the region. The reference white point, the *log(Y)* value of which is the closest to the center value of an input region, is mapped to that input region.

The chromatic adaptation transform illustrated in Equations 3, 4 and 5 is performed locally by considering an estimation of the input white point for each pixel in the input image. Unlike Kuang et al.,[8] the estimation of

Input | Result in 7 iterations | Result in 20 iterations | Reference

Figure 4. Results from applying cluster-based CAT algorithm. For this pair of input/reference images, CAT algorithm converges in 20 iterations. After the first 7 steps, the input image is already adapted to the reference illuminant. However, there is still a cast of the greenish input illuminant which is removed by the time the algorithm converges.

the input white point is managed by performing a low-pass Gaussian filter with a size equal to the sum of both input image dimensions.

To sum up, the proposed CAT algorithm is performed locally to each pixel of the input image by considering the local reference white point mapped to the input region to which the pixel belongs (Equation 7). The process is iterative and it is repeated until convergence. The convergence criterion is as follows:

$$\Delta = \frac{||I_W^k - I_W^{k-1}||_F}{||I_W^{k-1}||_F} \tag{8}$$

where $||.||_F$ is the Frobenuis norm, I_W refer to the input "white image" and k is the number of the current iteration. The iteration process stops when Δ gets lower than 10^{-3}. Usually, the number of iterations does not exceed 20. Figure 4 illustrates how the result of applying cluster-based local CAT changes over the iterations.

3.3 RESULTS

Several experiments have been conducted to test the effectiveness of the proposed extension of Hristova et al.'s method.

3.3.1 Protocol

We apply independently the color transformation and the local CAT algorithm to show their impact on the color transfer (for both Hristova et al.'s method and its extension). Then, we carry out the HDR extension method (by applying local CAT after the color grading) and compare the obtained results with results of a direct application to HDR images of Hristova et al.'s method. The tone mapping operator by Reinhard et al.[15] is used to display the results in Figure 5.

Moreover, we use a set of ten image pairs to obtain 10 HDR image results for both Hristova et al.'s method[7] (directly applied to HDR images) and its HDR extension. To evaluate the effectiveness of the proposed extension, an objective evaluation has been carried out. The evaluation is performed on the ten image pairs for both the extended and the original methods as explained in the following subsection.

3.3.2 Objective evaluation

As there is no objective metrics to evaluate the match in the color palette of two HDR images, the evaluation of the results is carried out in the LDR domain after tone mapping. To evaluate how successful a color transfer is and whether it introduces structural artifacts to the final result, we use two complimentary metrics, Bhattacharya coefficient[17] and SSIM[18] respectively (as proposed in Hristova et al.'s paper[7]). On one hand, we apply SSIM on the tone-mapped result and the tone-mapped input image to measure the degree of artifacts in the final result. On the other hand, we apply Bhattacharya coefficient to evaluate how close the color and light distributions of the tone-mapped result are to those of the tone-mapped reference image. As the displayed result strongly depends on the tone mapping operator, two tone mapping operators, Reinhard et al.'s[15] and Durand et al.'s,[19] are used in the evaluation. Figure 6 presents the Box-and-Whisker plots of both SSIM and Bhattacharya coefficient for each of two methods (the original method and its HDR extension) and for each of two tone mapping operators.

Figure 5. Results obtained by applying Hristova et al.'s method[7] (without any modifications) and its extension to HDR images. From left to right: results of applying the color transformation without the local CAT as a final step; results of applying local CAT in iterative manner (without color transformation); result of applying both color transformation and local CAT. All images are displayed using the tone mapping operator by Reinhard et al.[15]

The results obtained with the HDR extension preserve the structure of the input image. Conversely, if we apply the original LDR method directly to HDR images, the degree of artifacts (measured by SSIM), caused by the color transfer, increases. This analysis holds for both tone-mapping operators[15,19] and moreover, it is supported by the results in Figure 5. The loss of structural details as well as the presence of artifacts (both caused by the direct application of Hristova et al.'s method) are visible in images *(d)* and *(f)*. Even more, they are clearly noticeable on an HDR display as well. Unlike the original color transfer method,[7] the proposed HDR extension succeeds in preserving the structural details of the input image as results *(a)* and *(b)* show.

Furthermore, the results obtained with the HDR extension of Hristova et al.'s method have significantly higher Bhattacharya coefficients than the results obtained with the direct application of the method to HDR images (for both tone mapping operators). In comparison to the colors of image *(d)* in Figure 5, the color palette of image *(a)* gets much closer to that of the reference image. Finally, by applying the cluster-based local CAT,

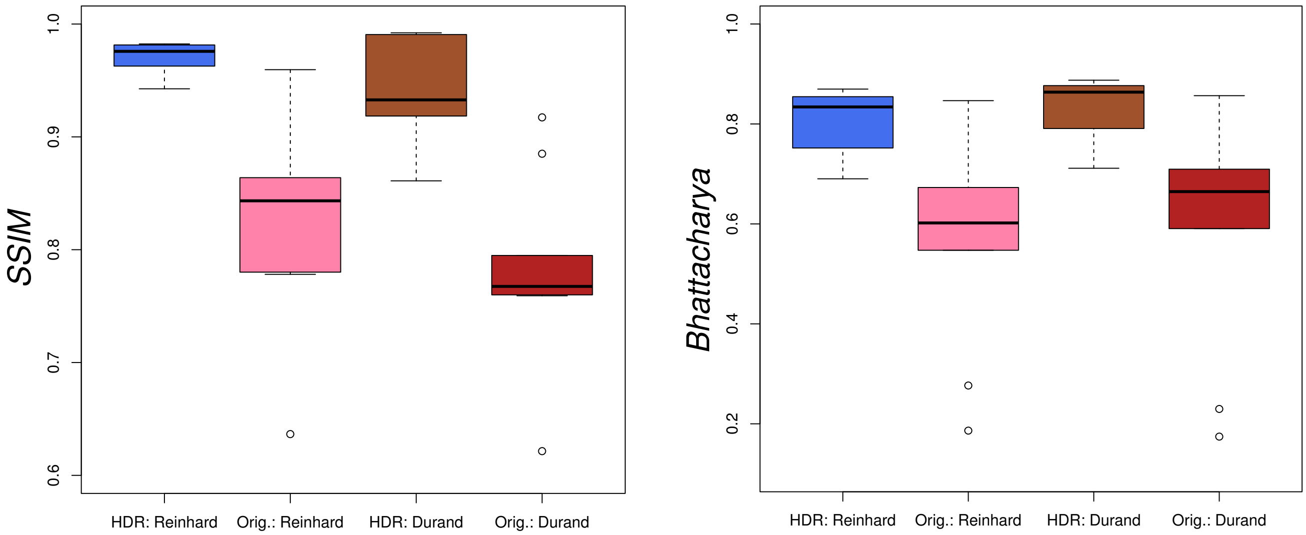

Figure 6. Box-and-Whisker plots of both SSIM and Bhattacharya coefficient for results obtained by using Hristova et al.'s original method and its HDR extension.

we adapt the colors of image *(a)* to the reference illuminant for a better representation of the reference light and color distributions.

3.4 Is the proposed extension applicable to state-of-the-art color transfer methods?

In the previous section we detailed and analyzed the extension of Hristova et al.'s local color transfer method[7] to the HDR domain. The proposed modifications serve as a basis for extending state-of-the-art color transfer methods to HDR images. Depending on the method, we recommend different types of modifications as shown in Table 1.

Table 1. General modifications for adapting color transfer methods to HDR images. Column *LDR domain* displays the steps of the method which are modified as shown in column *HDR domain*.

Method	**LDR domain**	**HDR domain**
Reinhard et al.[2]	Global method	Local method (Tai et al.[5])
Pitié et al.[3]	CIE Lab	hdr-CIELab
Bonneel et al.[6]	Luminance-based clustering	Log-luminance-based clustering
Tai et al.[5]	$l\alpha\beta$	$l\alpha\beta$-extended

First, Reinhard et al.'s transformation is build upon the assumption that the image color and light distributions can be fitted by a multivariate Gaussian distribution. This assumption does not hold in the HDR domain due to the high luminance variations. Therefore, there is a need to use more than one parametric Gaussian model to compute the luminance distribution of HDR images. Consequently, to enhance the effect of the color transfer, we propose to carry out Reinhard et al.'s method[2] in a cluster-based manner. We can either adopt luminance-based clustering or use Tai et al.'s color transfer method[5] in the extension of Reinhard's method to the HDR domain. In both cases, an extension to $l\alpha\beta$ color space is recommended for accommodating the high luminance range of HDR images.

Furthermore, following the modifications, presented in Subsection 3.2, we replace CIE Lab color space with its HDR extension (hdr-CIELab) in both Pitié et al.'s[3] and Bonneel et al.'s[6] methods. Like in the proposed extension to Hristova et al.'s method, we recommend the clustering step of Bonneel et al.'s method to be carried out on the logarithmic transformation of the absolute luminance rather than on the L channel of hdr-CIELab.

Figure 7 shows results of a color transfer with and without the proposed modifications (using state-of-the-art color transfer methods). As hdr-CIELab predicts better than CIE Lab the color gamut of HDR images, the reference color palette is well transferred to the result for both Pitie et al.'s and Bonneel et al.'s extended methods. Furthermore, if we apply Bonneel et al.'s color grading method directly to HDR images, visible artifacts are observed. On the other hand, if we carry out the proposed modifications (regarding CIE Lab color space and the clustering step) to the former method, the degree of artifacts is lessened. This is a result of the more precise log-luminance-based clustering. Finally, as expected, Tai et al.'s method accounts for the high luminance range in HDR images and therefore, it yields more plausible results than Reinhard et al.'s method when applied to HDR images.

4. CONCLUSION

In this paper, we have presented extensions to state-of-the-art color transfer methods to HDR images. The extensions include modifications of traditional color spaces as well as of the clustering and the mapping steps in local methods. Moreover, we have introduced a novel cluster-based chromatic adaptation transform which could be used as a standalone color grading method. Experiments have proved that when applied, the extensions of the methods yield more plausible results than the results obtained with the direct application of the LDR methods to HDR images. However, there is a room for improvements. Our experiments have shown the need to create a more precise color mapping between two HDR images. Moreover, this paper introduced modifications to already existing color transfer methods to improve their applicability to the HDR domain. The development of a special color transformation between HDR images is an interesting direction for further improvement in the future. To this end, we consider that this paper is an important first step towards bridging the gap between the color transfer domain and the HDR domain.

ACKNOWLEDGMENTS

REFERENCES

[1] Faridul, H. S., Pouli, T., Chamaret, C., Stauder, J., Trémeau, A., Reinhard, E., et al., "A survey of color mapping and its applications," in [*Eurographics 2014-State of the Art Reports*], 43–67, The Eurographics Association (2014).

[2] Reinhard, E., Adhikhmin, M., Gooch, B., and Shirley, P., "Color transfer between images," *Computer Graphics and Applications, IEEE* **21**(5), 34–41 (2001).

[3] Pitié, F., Kokaram, A. C., and Dahyot, R., "Automated colour grading using colour distribution transfer," *Computer Vision and Image Understanding* **107**(1), 123–137 (2007).

[4] Evans, L. C., "Partial differential equations and monge-kantorovich mass transfer," *Current developments in mathematics* **1999**, 65–126 (1997).

[5] Tai, Y.-W., Jia, J., and Tang, C.-K., "Local color transfer via probabilistic segmentation by expectation-maximization," in [*Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*], **1**, 747–754, IEEE (2005).

[6] Bonneel, N., Sunkavalli, K., Paris, S., and Pfister, H., "Example-based video color grading," *ACM Transactions on Graphics (Proceedings of SIGGRAPH 2013)* **32**(4), 2 (2013).

[7] Hristova, H., Le Meur, O., Cozot, R., and Bouatouch, K., "Style-aware robust color transfer," *EXPRESSIVE International Symposium on Computational Aesthetics in Graphics, Visualization, and Imaging* (2015).

[8] Kuang, J., Johnson, G. M., and Fairchild, M. D., "icam06: A refined image appearance model for hdr image rendering," *Journal of Visual Communication and Image Representation* **18**(5), 406–414 (2007).

[9] Fairchild, M. D. and Johnson, G. M., "icam framework for image appearance, differences, and quality," *Journal of Electronic Imaging* **13**(1), 126–138 (2004).

[10] Nguyen, R., Kim, S., and Brown, M., "Illuminant aware gamut-based color transfer," in [*Computer Graphics Forum*], **33**(7), 319–328, Wiley Online Library (2014).

[11] Frigo, O., Sabater, N., Demoulin, V., and Pierre, H., "Optimal transportation for example-guided color transfer," *12th Asian Conference on Computer Vision (ACCV)* (2014).

[12] Huo, J., Chang, Y., Wang, J., and Wei, X., "Robust automatic white balance algorithm using gray color points in images.," *IEEE Trans. Consumer Electronics* **52**(2), 541–546 (2006).

[13] Reinhard, E. and Pouli, T., "Colour spaces for colour transfer," in [*Computational Color Imaging*], 1–15, Springer (2011).

[14] Fairchild, M. D. and Chen, P.-H., "Brightness, lightness, and specifying color in high-dynamic-range scenes and images," in [*IS&T/SPIE Electronic Imaging*], 78670O–78670O, International Society for Optics and Photonics (2011).

[15] Reinhard, E., Stark, M., Shirley, P., and Ferwerda, J., "Photographic tone reproduction for digital images," in [*ACM Transactions on Graphics (TOG)*], **21**(3), 267–276, ACM (2002).

[16] Boitard, R., Cozot, R., Thoreau, D., and Bouatouch, K., "Zonal brightness coherency for video tone mapping," *Signal Processing: Image Communication* **29**(2), 229–246 (2014).

[17] Bhattacharyya, A., "On a measure of divergence between two multinomial populations," *Sankhyā: The Indian Journal of Statistics* , 401–406 (1946).

[18] Wang, Z., Bovik, A. C., Sheikh, H. R., and Simoncelli, E. P., "Image quality assessment: from error visibility to structural similarity," *Image Processing, IEEE Transactions on* **13**(4), 600–612 (2004).

[19] Durand, F. and Dorsey, J., "Fast bilateral filtering for the display of high-dynamic-range images," *ACM transactions on graphics (TOG)* **21**(3), 257–266 (2002).

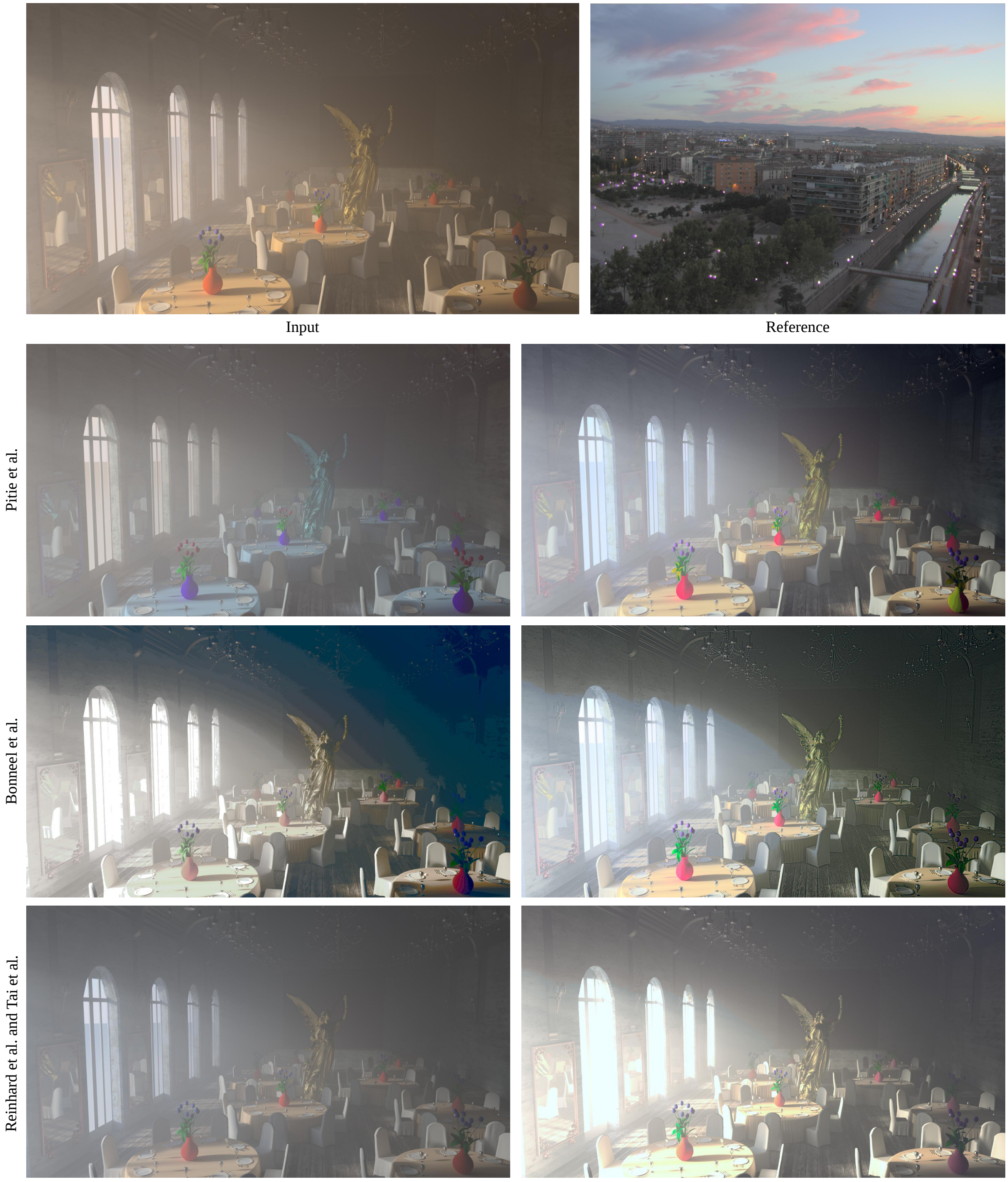

Figure 7. Results, obtained by applying state-of-the-art color transfer methods (directly, without any modifications) and results obtained with their extensions to HDR images. Reinhard et al.'s tone mapping operator[15] is used to display the images.