# Color Channel Transfer for Image Dehazing

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***Abstract*—In this letter we introduce a simple but effective concept, Color Channel Transfer (CCT), that is able to substantially improve the performance of various dehazing techniques. CCT is motivated by a key observation: in scattering media the information from at least one color channel presents high attenuation. To compensate for the loss of information in one color channel, CCT employs a color-transfer strategy and operates in a color opponent space that helps to compensate automatically the chromatic loss. The reference is computed by combining the details and saliency of the initial image with uniform gray image that assures a balanced chromatic distribution. The extensive qualitative and quantitative experiments demonstrate the utility of CCT as a pre-processing step for various dehazing problems such as day-time dehazing, night-time dehazing and underwater image dehazing.**

***Index Terms*—color transfer, dehazing, underwater, image enhancement**

## I. Introduction

Due to the scattering and absorption the propagated light is significantly attenuated in hazy and underwater media and as a result the recorded images are characterized by poor contrast, low illumination, color shifting and noise. While the absorption substantially reduces the light energy, the scattering changes the directions of the propagated light, making distant objects to have a hazy appearance.

Restoring the visibility of such images is an ill-posed problem. The optical model of Koschmieder [1] (similar to the simplified underwater optical model [2]) requires estimating two unknowns: the airlight (backscattering in underwater) and the transmission map (related to the depth of the scene). Single image dehazing is a well studied topic in image processing with many solutions introduced in the last decade [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13]. For day-time hazy scenes, He et al. [6] introduce the Dark Channel Prior (DCP), a simple but effective solution to estimate the transmission map. This prior has been at the source of many dehazing and underwater restoration techniques. Night-time hazy scenes add the problem of artificial illumination, which tends to introduce additionally glowing artifacts. To address this issue, several dedicated dehazing methods [14], [15], [16], [17], [18], [19] have been introduced recently. Pei and Lee [14] adopt a color transfer strategy in addition to DCP to estimate haze thickness and airlight [6]. Li et al. [16] also employs the DCP to estimate the transmission map but extend the optical model to incorporate the atmospheric point spread function for modeling the glowing effect. More recently, Ren et al. [20] extends the fusion-based approach of Ancuti et al. [8] by constructing and end-to-end trainable neural network that consists of an encoder that captures the context of the derived input images and a decoder that estimates the contribution of each input to the final result.

In parallel, underwater image restoration [21], [22], [23], [24], [25], [26], [27], [28], [29] followed the trend introduced by outdoor dehazing methods. Chiang and Chen [21] uses the DCP to segment the foreground and the background regions in underwater. Drews-Jr et al. [23] introduce Underwater Dark Channel Prior (UDCP), an underwater specific prior directly derived from DCP.

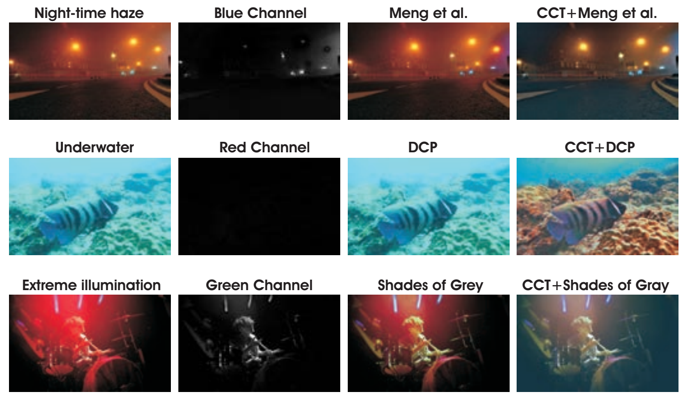


Fig. 1. *First column shows three examples of challenging images with one color channel highly attenuated (2nd column). Employing the well known DCP [6] and Meng et al. [30] but also Shades of Gray color constancy method [31] does not solve the problem (3rd column). However, applying our operator (CCT) as a pre-processing step to the same techniques, results in competitive results. Please refer to Figure 2 for additional comparative results.*

Analyzing a large dataset of night-time hazy and underwater images (+2000) we observed that one of the color channels is often highly attenuated. The loss of information is mostly due to selective attenuation and scattering (Rayleigh). This can be easily noticed in underwater scenes where the larger wavelength are absorbed first making the red components to disappear at only few meters deep.

To mitigate the limitations of existing dehazing methods in front of such strong attenuation of one channel, this letter introduces a novel concept named *Color Channel Transfer* (CCT). Our operator builds on color-transfer [32], an operation that changes the dominant illumination of a target image by transferring the selected color characteristics of a source reference image. To compensate for the loss of information in one color channel, CCT operates in the opponent color space, and derives the reference image directly from the input image, using a saliency and a detail map to adjust opponent color variations in the component affected by the strongly attenuated channel. CCT operator extends the recent work of Ancuti et al. [26], that compensates for the red channel attenuated in underwater scenes. In contrast to [26] that depends on manual parameter adjustment, CCT is the first work that demonstrates a general automatic solution for various dehazing applications.

In our extensive qualitative and quantitative experiments, CCT operator has shown high robustness and demonstrates its utility as a pre-processing step for various local and global dehazing techniques in applications such as day-time dehazing, night-time dehazing and underwater image restoration (see Fig. 1). Our study reveals that appropriates color compensation considerably improves the existing dehazing techniques.

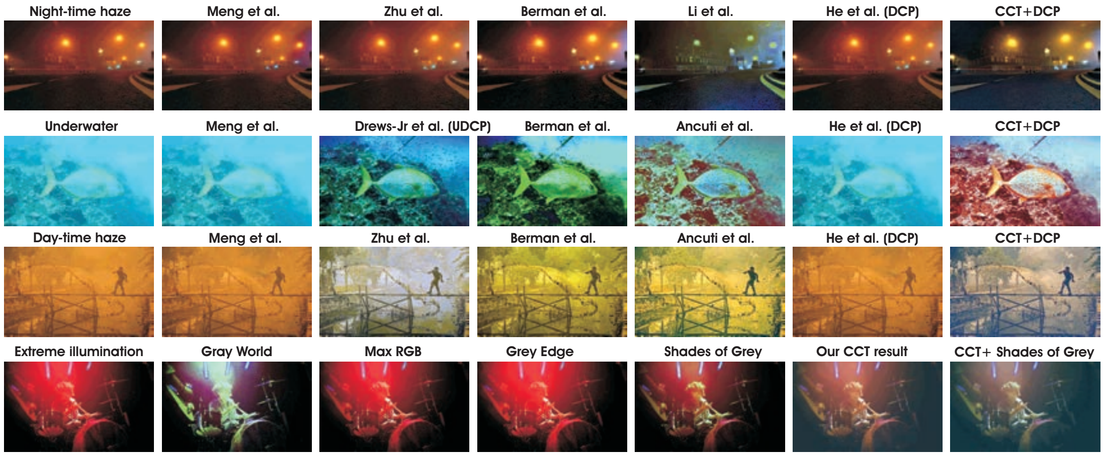


Fig. 2. *Global and local airlight/backscattering estimation techniques fail in many cases to restore the visibility of hazy scenes. Applied as a pre-processing step (here shown only for DCP [6]) our CCT operator appears to considerably enhance the visibility for various hazy scenes but also for challenging extreme illumination scenes (bottom row).*

## II. Color Channel Transfer Approach

### *A. Motivation: Color Channel Attenuation*

We built our approach on the following observation: images taken in extreme conditions (e.g. underwater, night-time haze and artificial illumination) contain highly attenuated information in at least one color channel. To consolidate this observation from a statistical point of view, we gathered a large database of images (+2000 images) taken in such adversarial conditions that most conventional, typically DCP-based, dehazing approaches fail in enhancing them. Fig. 3 presents the statistics of the most attenuated channel for those images.

From a physical perspective, the loss of information for such images is mostly due to selective attenuation, scattering (Rayleigh), or lack of color band in artificial illumination. The scattering and attenuation phenomena depend on the optical characteristics of the medium. For instance, in underwater, it is well known that the radiations with lower frequency (larger wavelength) are absorbed first, which means that the red components disappear after 5-6 m, orange after 7-8 m, yellow after 10-15 m, and green around 21 m. At deeper depth, the underwater scenes have a blue (green-blue) appearance. Similarly, atmospheric scattering influences the visible spectrum as a function of the wavelength. Shorter wavelengths (associated with blue color) are more scattered than longer wavelengths (associated with red color). A well-known consequence of the atmospheric scattering is the blue color of the sky. Regarding illumination, the light chromaticism/spectrum has a great uncontrollable impact over the entire scene (due to multiplication effect).

To deal with this problem, we propose a novel operation named Color Channel Transfer (CCT) that aims at transferring information from significant channels towards attenuated ones. Our operator builds on the color-transfer paradigm [32], which is a well-known operation that changes the dominant illumination of a target image by transferring the selected color characteristics of a source reference image. Our operator is specific in that it derives the source reference image directly from the initial image, and can be used as a general pre-processing step for challenging applications such as image dehazing and underwater image enhancement. It is indeed well-known that the strong color attenuation, inherent to severe observation conditions, cannot be solved by traditional color constancy solutions (e.g MaxRGB, Gray-world, Gray edge, Shades of Gray). Interestingly, our work demonstrates that those same traditional color constancy solutions become able to generate pleasing results when CCT is applied as a pre-processing step. In other words, CCT is shown to considerably improve the color appearance of the results when it is employed as a pre-processing step for several well-known image dehazing techniques.

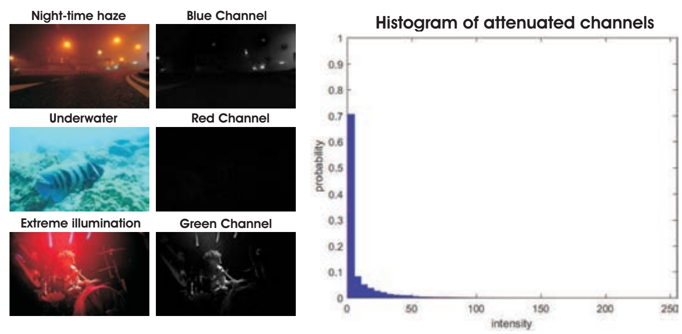


Fig. 3. *Right: the distribution of the attenuated color channels over our collected +2000 images. Left: three examples of images with their most attenuated color channel (shown in the second column).*

### *B. Optical Model for Image Dehazing*

The image dehazing and underwater image enhancement techniques rely on the simplified optical model of Koschmieders [1] that is very similar with the simplified McGlamery [2] (underwater) image formation model. The simplified underwater optical model is expressed as:

$$\begin{aligned}\mathbf{I}(x) &= \mathbf{J}(x)e^{-\eta\mathbf{d}(x)} + B_\infty(1 - e^{-\eta\mathbf{d}(x)}) \\ &= \mathbf{J}(x)\mathbf{t}(x) + B_\infty(1 - \mathbf{t}(x))\end{aligned} \tag{1}$$

where $\mathbf{I}(x)$ represents the radiance of the scene (input hazy image), $\mathbf{J}(x)$ is the radiance of the scene (that needs to be recovered) at each image coordinate $x$, $\mathbf{d}(x)$ is the distance between the sensor and the scene, and $\eta$ is the attenuation coefficient. The exponential term $e^{-\eta\mathbf{d}(x)}$ is called transmission $\mathbf{t}(x)$ and $B_\infty$ is a color vector known as the *back-scattered light* in underwater, or *airlight* in day time or night-time dehazing (and marked as $A_\infty$). To solve the optical model and recover the radiance of the scene, $\mathbf{J}(x)$, two unknowns have to be estimated: the transmission $\mathbf{t}(x)$, which is related to the depth map of the underwater scene, and the back-scattered light $B_\infty$ or airlight ($A_\infty$), which might be local, i.e. depend on x, in presence of artificial illumination.

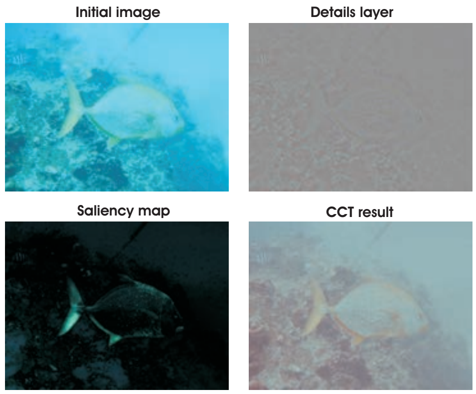


Fig. 4. *The color channel transfer (CCT) operation takes as reference a combination (see text) of the details layer and the saliency information from the original image (see Fig. 5, Fig. 6 and Fig. 7 for CCT + conventional dehazing method).*

It is worth noting that, since the attenuation is achromatic, the model defined by Eq.1 fails to capture the attenuation of colors (e.g. in underwater environment). In the next section, we explain how the images can be pre-processed to compensate for a color-dependent attenuation, thereby facilitating the algorithms to be effective for considered applications (e.g. day-time, night-time and underwater).

### *C. Color Channel Transfer Approach*

As already mentioned, our algorithm extends the concept of red channel attenuation compensation [26] for underwater images. [26] relies on the color-opponent concept, and the attenuated red channel is partially recovered from the opponent green channel information. Following a similar principle, our work introduces a general solution to automatically reduce all types of attenuation. We employ the color transfer paradigm [32]. The goal of image transfer is to borrow the characteristics of the reference image and to manipulate the input values in order to transfer these characteristics. One of the most important utility of the color transfer has been to enhance photo-consistency [32], [33], [34], [35].


Fig. 5. ***Night-time image dehazing.*** *The results of DCP applied on the images pre-processed by our CCT operator are comparable and even better than the results yielded by the local dehazing techniques of Ancuti et al. [17] and Berman et al. [36].*

Here, the color transfer is implemented to align the global mean value and the standard deviation of the reference and source images. In practice, the transfer is implemented in opponent color space, so as to transfer information between pairs of opponent colors (blue-yellow or red-green) when aligning the global features of source and reference images.

We tested the validity of our implementation for the CIE L$*$a$*$b$*$ color space, but also for the l$\alpha\beta$ color space developed by Ruderman et al. [37] which is employed in the original manuscript of Reinhard et al. [32]. We observed that employing the CIE L$*$a$*$b$*$ color space yields more natural outputs.

The color transfer works in three simple steps. First, it subtracts the mean value of the initial image. Second, it rescales the image based on the ratio between input and reference standard deviations. Finally, it adds the new mean of the reference image. Mathematically, color transfer can be expressed in the CIE L$*$a$*$b$*$ color space as:

$$\begin{aligned}
I_{L*}(x) &= \left[I_{L*}(x) - \bar{I}_{L*}\right].\sigma_r^{L*}/\sigma_s^{L*} + \bar{I}_{L*}^r \\
I_{a*}(x) &= \left[I_{a*}(x) - \bar{I}_{a*}\right].\sigma_r^{a*}/\sigma_s^{a*} + \bar{I}_{a*}^r \\
I_{b*}(x) &= \left[I_{b*}(x) - \bar{I}_{b*}\right].\sigma_r^{b*}/\sigma_s^{b*} + \bar{I}_{b*}^r
\end{aligned} \tag{2}$$

where $\bar{I}_{L*}$ , $\bar{I}_{a*}$,$\bar{I}_{b*}$ are the mean values for each channel L$*$,a$*$,b$*$ of the source image, respectively $\bar{I}_{L*}^r$, $\bar{I}_{a*}^r$ and $\bar{I}_{b*}^r$ represents the mean values for each channel L$*$,a$*$,b$*$ of the reference image. The parameters $\sigma_r^{L*}$, $\sigma_r^{a*}$ and $\sigma_r^{b*}$ are the standard deviation of the reference image, and $\sigma_s^{L*}$,$\sigma_s^{a*}$ and $\sigma_s^{b*}$ are the standard deviation of source. This formulation is similarly implemented in the l$\alpha\beta$ color space of Ruderman et al. [37].

The advantage of formulating the color transfer in an opponent color space is that the color loss can be compensated automatically, without requiring to estimate the chromatic loss direction. This is possible because, in the color-opponent spaces, red-green and blue-yellow chromatic information are mixed, while in RGB color space each channel is independent. Modifying the mean value of opponent colors with a suitable reference image induces a transfer between the color channels sharing the opponent axes. In other words, regularizing through transfer- the red-green (blue-yellow) opponent color helps in compensating a strong attenuation of either red or green (blue).

During transfer, both the mean and variance are modified. When working in the RGB space, in this case it would mainly amplify noise when the channel is fully attenuated. In contrast, when working in the opponent color space, bringing back the mean towards zero transfers colors between the two opponent colors of a channel, and aligning the standard deviation adjust their intensity.

The main challenge of this algorithm is to build a reference that effectively remove the unwanted color cast, and in turn tends to compensate the attenuated color channel. As suggested in the literature [32], the color cast can be partially removed using a simple gray reference. However, this solution tends to result in images with dull colors. It also appears to fail in completely removing unwanted color casts due to attenuation, and might even introduce undesired color casts in scenes captured without color channel attenuation. As a result we cannot simply consider as a reference image only the mean value (0.5). Hence, in this work we propose to adapt the reference image so that it includes the color variations induced by the salient regions and the details of the original input.

We propose a different reference to solve this problem. Our reference $R(x)$ image (computed in RGB) is automatically computed by the expression:

$$R(x) = G(x) + D(x) + S(x)I(x) \tag{3}$$

where $G(x)$ is a uniform gray image (50%), $D(x)$ is the details layer of the original input and $S(x)$ is the saliency of the input

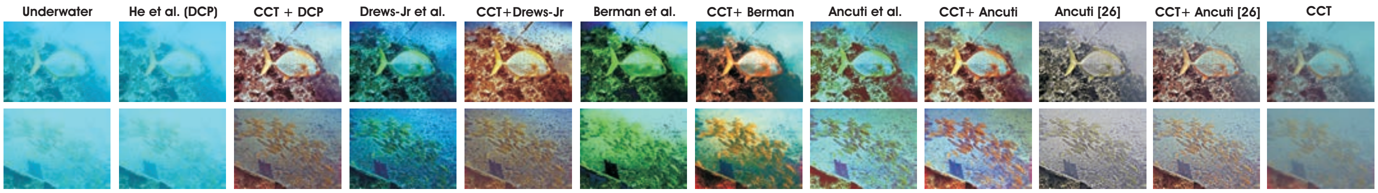


Fig. 6. ***Underwater image dehazing.*** *CCT ensures a robust compensation of the lost information and improves considerably the visibility when applied as a pre-processing step for both global [6], [38] and local [39], [17] back-scattering estimation approaches. Moreover, CCT also improves the recent technique of Ancuti et al. [26].*

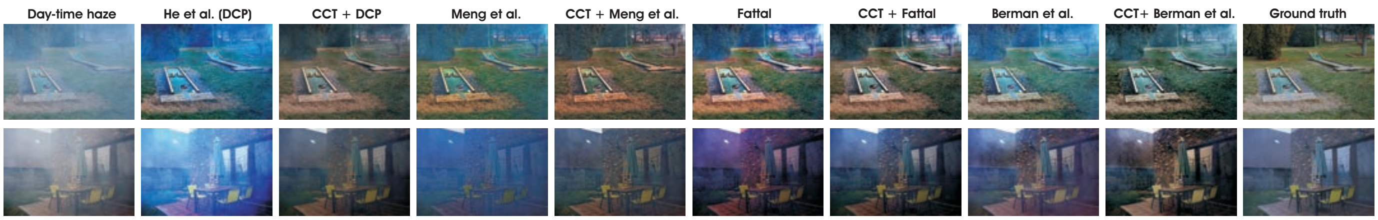


Fig. 7. ***Day-time image dehazing.*** *We employ four specialized single image dehazing techniques [6], [30], [40], [36] on the original hazy images of the O-Haze [41] dataset and also on the same images that have been pre-processed with CCT. We observe that CCT helps to improve the visibility for all the considered techniques. Quantitative results over the entire O-Haze dataset are summarized in Table I.*

| | **He et al.** | **CCT+ He et al.** | **Meng et al.** | **CCT+ Meng et al.** | **Fattal** | **CCT+Fattal** | **Berman et al.** | **CCT+Berman** |
|---|---|---|---|---|---|---|---|---|
| **CIEde00** | 20.745 | 13.985 | 16.968 | 15.636 | 19.854 | 17.754 | 17.088 | 17.388 |
| **PSNR** | 6.586 | 18.031 | 17.443 | 17.541 | 15.639 | 15.701 | 16.61 | 16.725 |

TABLE I

***Quantitative evaluation of day-time dehazing.*** *We processed all 45 images from the O-Haze [41] dataset. This table presents the average values of the PSNR and CIEde00 indexes, over the entire O-Haze dataset. As can be observed, applying CCT, as a pre-processing step for the specialized dehazing methods of He et al. (DCP) [6], Meng et al. [30], Fattal [40] and Berman et al. [36] yields better results in terms of color and structure.*

image $I(x)$. Employing input image $I$ is related to the grey world assumption since in the opponent color space, for natural images, the mean value for luminance is close to 0.5, and the one for opponent color channels is relatively close to zero. To compute the salience map $S(x)$ of the input image $I(x)$ we employ the effective technique of Achanta et al. [42]. Adding the product between saliency and initial image introduces a bias towards dominant colors, thereby helping in recovering initial colors. The details layer $D(x)$ is obtained by subtracting from the image the Gaussian blurred version from the input image. Injecting details $D$ (which is a priori zero mean, and thus only impacts the standard deviation) helps in adapting the reference standard deviation to the scene one.

## III. Experimental Results and Discussion

This section demonstrates the utility of our new operator (CCT) in the context of several dehazing applications. More exactly, we present comparative results for applications such as day-time and night-time image dehazing and underwater image enhancement.

To validate our operator for the night-time dehazing, we considered 130+ images of the night-time dehazing dataset introduced by Li et al. [16] (see Fig. 1, Fig. 2 and Fig. 5 and also the supplementary material). Since for night-time dehazing there is no specialized quality metric, we build our assessment based on qualitative visual comparisons. As can be seen, the results of DCP [6] applied on the images pre-processed by CCT operator are comparable and even better than the results yielded by the local dehazing techniques of Ancuti et al. [17] and Berman et al. [36]. In Fig. 5 it can be noticed that local airlight estimation solutions are not able to solve the problem of channel attenuation (see for instance the specialized night-time dehazing methods of Li et al. [16] and Zhang et al. [15] that generate undesired color appearance).

In Fig. 6 we present several comparative results for underwater image dehazing. As can be seen, CCT ensures a robust compensation of the missing color and therefore it improves considerably the visibility when applied as a pre-processing step for both global [6], [38] and local [39], [17] back-scattering estimation approaches. Additionally, CCT also improves the recent technique of Ancuti et al. [26].

Moreover, we apply CCT on the recent outdoor image dehazing dataset O-Haze [41] (used in the first dehazing challenge- NTIRE 2018 [43]), which contains 45 real hazy and haze-free ground-truth images. We employ four specialized single image dehazing techniques [6], [30], [40], [36] on the original hazy images and also on the images that have been pre-processed with CCT. Figure 7 demonstrates qualitatively the improved enhancement when CCT is employed. In Table I we summarize the overall quantitative results over the entire O-Haze dataset. Using the ground-truth images we compute PSNR and CIEDE2000 [44] indexes.

## IV. Conclusions

We introduce a new operator (CCT) that is based on a statistic observation of various hazy scenes. Our extensive validation shows the utility of CCT as a pre-processing step for various dehazing problems such as day-time dehazing, night-time dehazing and underwater image dehazing. Despite of its simplicity both in principle and implementation, our operator CCT is quite effective and generic.

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