COLOR TRANSFER FOR UNDERWATER DEHAZING AND DEPTH ESTIMATION

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ABSTRACT

Imaging in the underwater environment suffers from color degradation and poor visibility since the light spectrum is selectively absorbed and scattered by water and floating particles. In this paper we introduce a simple but effective underwater dehazing approach that builds on an original color transfer strategy to align the color statistics of a hazy input to the ones of a reference image, also captured underwater, but with neglectable water attenuation. As an original specificity, our proposed color transfer approach is designed to promote the preservation of salient regions, as well as of the details obtained by subtracting from the input an edge-preserving smoothed version of itself. The color-transferred input is then restored by inverting a simplified version of the McGlamery underwater image formation model, using the conventional Dark Channel Prior to estimate the transmission map and the back-scattered light parameter involved in the model. We demonstrate that our color transfer step is crucial for a good transmission estimation but mostly for underwater dehazing where other specialized techniques fail. Extensive qualitative and quantitative results demonstrate the effectiveness of the proposed approach to estimate the transmission, including for cases where traditional specialized techniques fail, and to improve the image quality.

***Index Terms*—** underwater visibility enhancement, color transfer, color constancy, depth estimation

I. INTRODUCTION

Underwater visual inspection is a key component for many scientific and industrial applications, including but not restricted to the inspection of oil pipes or platforms, underwater man-made constructions, non-destructive testing (NDT) performed underwater for naval structures. Underwater images are however affected by significant visibility degradation due to strong light scattering.

The techniques that enhance the visibility of underwater images can be grouped in methods that employ multiple input images, and methods that are based only on a single input image. From the first group, the most representative ones are the polarization techniques [1], [2], which process several images that are captured with different orientations of a camera-mounted polarizer. In general these techniques are impractical, especially for dynamic underwater imaging. More recently, several single-image based underwater enhancing techniques have been introduced [3], [4], [5], [6], [7], [8], [9], [10]. Most of these techniques have been inspired by the single image outdoor dehazing approaches [11], [12], [13], [14], [15], [16], [17], assuming a high similarity between the optical model of underwater and outdoor hazy scenes. However,

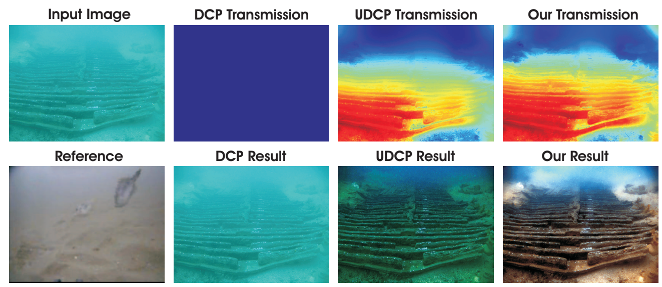

Fig. 1. *By transferring the color of the reference image to the input underwater image (shown on the first column), we can estimate the transmission and enhance the visibility of the underwater scene (shown on the last colum). The second and third columns show the estimated transmissions and the enhanced results obtained by the He et al. [13] (DCP) and Drews-Jr et al. [7] (UDCP). As can be observed, even if the transmission is relatively well estimated by UDCP, the level of enhancement is significantly better for our approach.*

this assumption is generally not valid since the attenuation of the color spectrum is less homogeneous under water than in outdoor environments. In particular, the well known Dark Channel Prior (DCP) [11], [13] has shown important limitations to estimate the transmission in underwater scenes [7], and has been adapted for underwater by various techniques [4], [6], [8]. However, even if the transmission is relatively well estimated by those methods, the restoration of the scene radiance based on the inversion of the image formation model still introduces undesired color artifacts, mainly due to the selective attenuation of the light spectrum in underwater (e.g. red color channel is highly attenuated with the depth)(see Fig. 1).

To circumvent this problem, in this paper, we introduce an effective pre-processing step building on a color transfer, a well-known strategy to enhance photo-consistency of the input images [18], [19]. To the best of our knowledge, we are the first that employ color transfer for underwater dehazing and depth estimation. The reference images from which the color is transferred have to be characterized by a proper, weakly attenuated, color spectrum. They are typically obtained from numerous underwater studies (e.g. underwater vehicles (UV) acquiring images at different depths during a 2D mapping survey), or even from outdoor scenes corresponding to similar environments than those observed underwater (e.g. sand, rocks). We built on the well-known color transfer method of Reinhard et al. [20] but adapt it for underwater scenes. Basically we propose to blend the original information of the reference with the salient regions and the edge-exclusive details of the input image. This helps in reducing the level of artifacts in the output image but also in preserving the input details that might be lost by applying the standard color transfer procedure. We then restore the color-transferred image by inverting the conventional simplified version of the simplified underwater image formation model of McGlamery [21]. As a worthwhile contribution, our experimental results demonstrate that the transmission and the back-scattered light are accurately estimated by employing the Dark Channel Prior [13] on the color-transferred image. This is a major outcome of our study, since the dark channel prior was generally considered as being only relevant for outdoor scenes in previous literature. Additionally, our extensive qualitative and quantitative experiments demonstrate that the image radiance of the underwater scene can be enhanced significantly.

II. UNDERWATER DEHAZING BY COLOR TRANSFER

Many existing underwater image restoration techniques assumes the McGlamery [21] image formation model. The simplified underwater optical model is expressed as:

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

where I is the total radiance of the scene that reaches the imaging sensor, $J(x)$ is the radiance of the scene at each image coordinate x, d is the distance between the observer and the scene, and η is the attenuation coefficient. The exponential term $e^{-\eta d(x)}$ is also known as the transmission $t(x)$ and B_∞ is a color vector known as the *back-scattered light*. To recover the radiance of the scene, $J(x)$, we have to estimate the two unknowns of the simplified underwater optical model: the back-scattered light B_∞, and the transmission $t(x)$ that is related to the depth map of the underwater scene.

It is worth noting that the model defined by Eq.1 fails to capture the non-homogeneous attenuation of colors in the underwater environment. In the next section, we explain how the underwater image can be pre-processed to mitigate this color-dependent attenuation, thereby making the simplified image formation model applicable to underwater scenes.

Despite of numerous recent efforts, existing single-image underwater techniques exhibit significant limitations in the presence of strong spectrum attenuation. This attenuation is hindering both the transmission estimation and the correct scene color recovery. Since underwater mediums suffer from significant loss of color information, we define a color transfer pre-processing step to transfer this missing information from available reference underwater images. The color transfer step is motivated by the fact that there are many reference images taken in good visibility conditions.

Our technique consists of two main steps. First, the underwater image color is enhanced based on our proposed underwater color transfer procedure. Second, the Dark Channel Prior (DCP) [13] is used to estimate the two unknown image formation model parameters (transmission $t(x)$ and back-scattered light B_∞).

II-A. Color Transfer in Underwater Imaging

Color transfer is a well-known image processing method that manipulates the color values of an input image so that the output image shares the appearance of a reference image. One of the most important utility of the color transfer has been to enhance photo-consistency [20], [23], [18], [19]. In underwater imaging, the color transfer is motivated by two observations: first the transmission derived from DCP is highly influenced by the color channel attenuation. Secondly, even if the transmission is relatively well estimated, the restored radiance of the scene J after solving the optical model equation 1 may present undesired color artifacts. This is due to the fact that the attenuated information (especially for the red channel in underwater) cannot be recovered. This problem is illustrated in Fig. 2. Common existing white-balance solutions such as gray-world [24], max-RGB [25], shades-of-gray [26] or grey-edge [27], due to their linear-stretching operation, will amplify the color noise of the red channel.

In this work, we extend the simple and fast color transfer method of Reihard et al. [20]. Other more advanced color transfer approaches could be employed as well. As observed in previous work [28] the color transfer problem shares similarities to the problem of color constancy and white-balancing in that they both also manipulate the mean value of the processed image [29]. However, the advantage of [20] (extremely important in underwater imaging) with respect to the gray-world is that it uses the color-opponent space, and therefore can reconstruct strongly the attenuated red channel from the opponent channel.

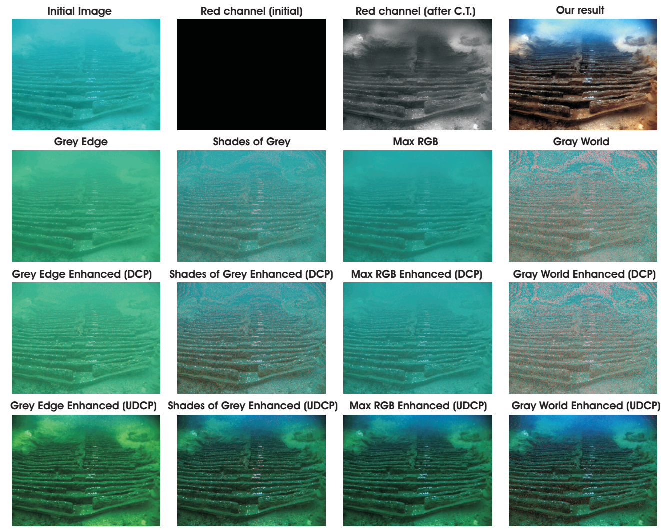

Fig. 2. *Top row from left to right: initial underwater image with highly attenuated red channel, original red channel and red channel after our color transfer procedure, our final enhanced result. Second row: results after applying different white balance methods. Third row: employing the dark channel (DCP) [13] method for the above color corrected images versions fail. Bottom row: even when using the underwater Dark Channel Prior (UDCP) [7], the color distortions are not properly corrected.*

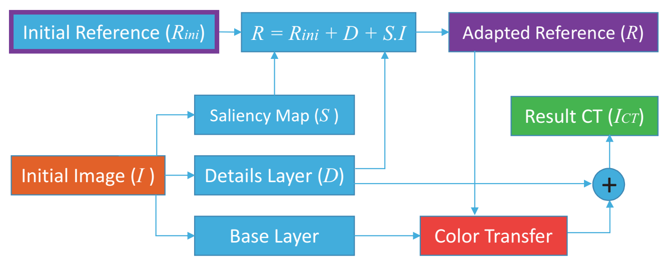

Fig. 3. *Overview of our color transfer strategy.*

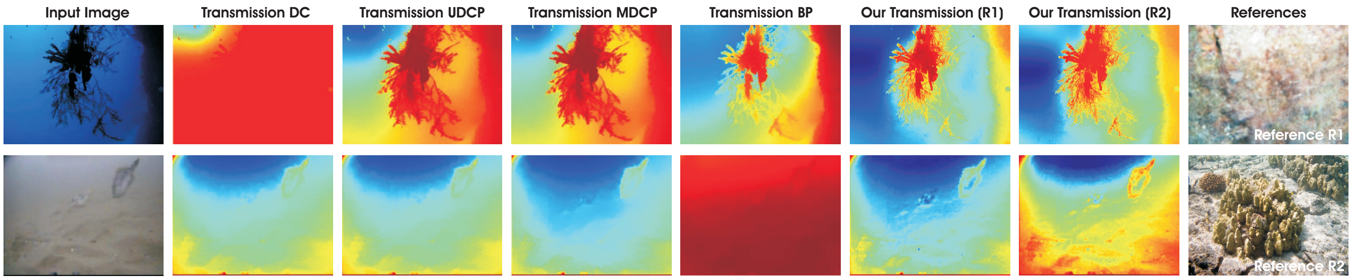

Fig. 4. *Estimated transmission maps generated by different specialized underwater techniques (DCP [13], UDCP [7], MDCP [22], BP [4]) and our approach with two different reference images.*

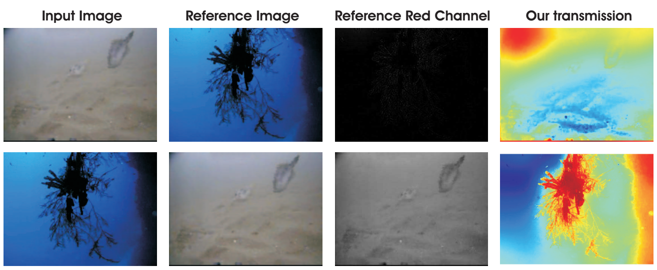

Fig. 5. *Our method requires a reference image with a good distribution of all the color channels. The first row shows a failure case, where the reference image has a strong attenuated red channel. In the second row, when the reference image satisfies this basic condition, our method performs well.*

In [20], the image color correction is performed in the Ruderman et al. [30] perception-based $l\alpha\beta$ color opponent color space. The RGB to $l\alpha\beta$ conversion is presented in details in [31]. The RGB signals are first converted to XYZ tristimulus values and then to LMS space. The LMS values are then logarithmically compressed to reduce skew in the data before applying a decorelative linear transform. In the resulting $l\alpha\beta$ color space, the l axis is the achromatic channel, and the α and β channels correspond to chromatic yellow-blue and red-green opponent channels. Once moved to $l\alpha\beta$ space, the color transfer in [20] shifts and scales the pixel values of the source image to match the mean and standard deviation of the reference image.

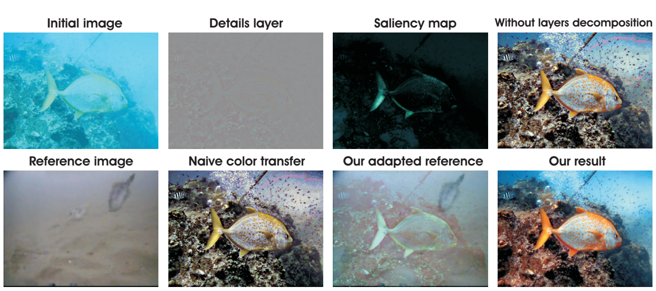

Fig. 6. *Adapting our reference image based on the details and saliency map of the original input image. Compared with the naive color transfer procedure (that employs directly the initial reference) and the strategy that does not employ layer decomposition (top row, right column) our result shows better visibility with less color distortion and grain effects.*

The color transfer step is effective in manipulating the global image appearance since it affects its global mean value. However, it tends to introduce artifacts such as grain effects and loss of details [32] (see Fig. 7). Therefore, we adapt the original color transfer procedure of Reihard et al. [20].

Firstly, as summarized in Fig.3), guided filtering [33] is considered to split the input image into a base and a detail layer. As defined in [33], the base layer consists in an edge-preserving smoothed version of the input, while the details are computed by subtracting the base layer from the input. Color transfer is applied only to the base layer. The detail layer is then added to the output of the color transfer procedure. This step ensures that the output details are well-preserved after the transfer procedure.

As a second difference if compared to [20], we adapt the reference image so that it includes the color variations induced by the salient regions and the details of the original input. Considering the salience map S of the input image I, computed based on the technique of Achanta et al. [34], and its detail layer D, our adapted reference image R is obtained by simply summing up the initial reference image R_{ini} with the detail layer and the information of the salient regions (see Fig.6):

$$R(x) = R_{ini}(x) + D(x) + S(x)I(x) \tag{2}$$

This step, besides reducing the level of artifacts, ensures a better consistency of the results when slightly different references are selected (see Fig.7). Such consistency is for example desired when processing videos with a single reference image. To shift the enhanced image towards natural underwater colors, the reference image should preferably consists in images captured underwater, but for which the water attenuation is reduced (see Fig.7).

II-B. Transmission and back-scattering estimation

The output of the color transfer step, denoted $I_{CT}(x)$ is restored by inverting the image formation model defined by Eq. 1. Formally, when $\Omega(x)$ defines a local patch centered in x, the Dark Channel Prior [13] states that $\min_{y\in\Omega(x)}\left(\min_{c\in r,g,b} J^c/{B_\infty}^c\right) \approx 0$ for all x. As a consequence, the large values of the dark channel $DC(x)$, defined as $DC(x) = min_{y\in\Omega(x)}(min_{c\in r,g,b} I^c_{CT}(y))$, correspond to locations x where $t(x)$ is close to 0, and where $I_{CT}(x) \approx B_\infty$. Hence, based on the image formation model (1), we can estimate the transmission as:

$$t(x) = 1 - \min_{y\in\Omega(x)}\left(\min_{c\in r,g,b} I^c_{CT}(y)/{B_\infty}^c\right) \tag{3}$$

For estimating the back-scattered light we use the same proce-

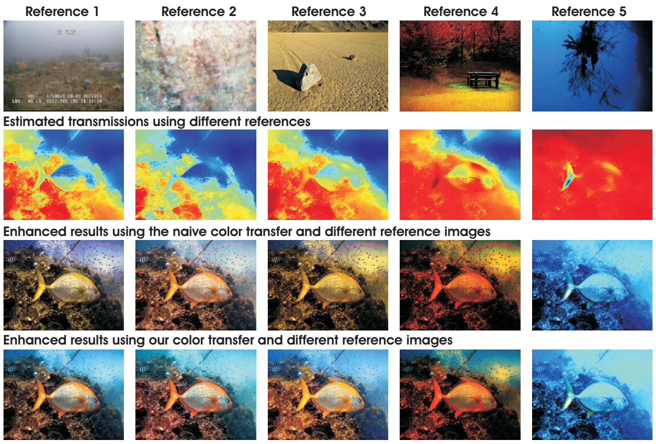

Fig. 7. *Our approach perform well for reference images (not necessary to be an underwater image) that have good distribution of all color channels (the input image is shown in Fig. 6). As discussed and shown in Fig.5, when the red channel of the reference image is highly attenuated (last column example), our approach shows limitations in estimating the transmission and enhancing the input. In addition, the third row shows that the results when using the original color transfer of [20] introduce grain effects and loss of details.*

dure as in He et al. [13]:

$$B_\infty = I_{CT}(y*),\ with$$
$$y* = \underset{y|DC(y)>DC^{99.9}}{\textbf{arg max}} \left(I^r_{CT}(y) + I^g_{CT}(y) + I^b_{CT}(y) \right) \quad (4)$$

where $y*$ denotes the location of the brightest pixel among those pixels whose dark channel value lies above the 99.9^{th} percentile $DC^{99.9}$, while r, g, b refer to the red, green and blue color components, respectively.

III. Discussion and Results

Our color transfer-based technique has been tested on various underwater scenes. The influence of the reference image is important to recover the original color spectrum of the underwater scene. Fig.7 shows how various reference images can influence the enhanced image and the estimated transmission. From our experiments, as expected, the best results are obtained using underwater images taken in good illumination conditions, where the water attenuation is reduced. Interestingly the method is still valid for images that are not taken underwater, as long as their content is reasonably representative of underwater scenes (e.g. sand).

In Fig.4 we present some comparative results of transmission estimation, and show that our method is better than the specialized underwater techniques of [13], [22], [7], [4]. Fig.8 shows a comparison of the enhanced images yielded by the DCP [13] and DCP-derived techniques of [4], [22], [7], [4]. For quantitative evaluation, we use two recent metrics: PCQI [35] and UCIQUE [36]. PCQI is a general blind measure that is used to evaluate the image contrast while UCIQUE metric is a recent metric dedicated to underwater image assessment (the larger the metrics, the better the quality).

Table I shows the average values of PCQI and UCIQUE of the results generated with the methods of [13], [4], [22], [7] and our approach when applied to 20 images (only 3 are shown in Fig.4; for all the results please refer to https://drive.google.com/file/d/0B01A5GB7NRpna0RDVkNBaGpGN2s/view?usp=sharing). For all those results, we used Reference 1, shown in Fig.7. Compared with DCP-derived techniques our approach generally yields to better transmission estimates and enhanced image quality.

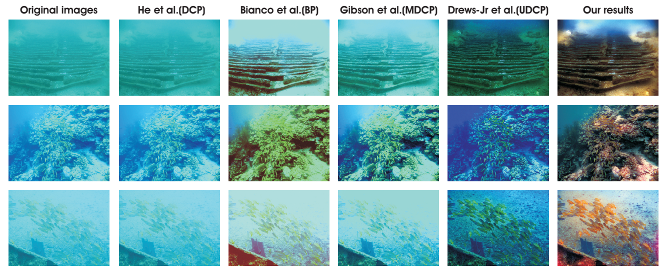

Fig. 8. *Comparison to (DCP) [11], (BP) [4], (MDCP) Gibson et al.[22] and UDCP [7].*

	DCP	BP	MDCP	UDCP	Our method
UCIQUE	0.4503	0.6118	0.5541	0.5913	0.6698
PCQI	0.9975	1.0483	1.0530	1.0150	1.1022

Table I. *Average values of UCIQUE and PCQI of the results shown in https://drive.google.com/file/d/0B01A5GB7NRpna0RDVkNBaGpGN2s/view?usp=sharing.*

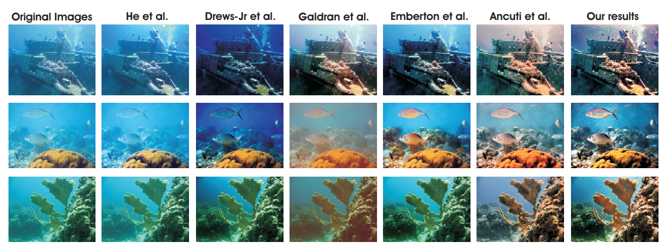

Fig. 9. *Comparison to He et al. [11] and to several recent specialized underwater techniques, including Drews-Jr et al. [7], Galdran et al. [8], Emberton et al. [9] and Ancuti et al. [3].*

	He et al.	Drews-Jr.	Galdran	Emberton	Ancuti et al.	Our method
UCIQUE	0.5624	0.5707	0.5823	0.6259	0.6471	0.6725
PCQI	0.9455	0.7801	0.8438	0.9781	1.0876	1.1065

Table II. *Average values of UCIQUE and PCQI of the results shown in https://drive.google.com/file/d/0B01A5GB7NRpndG5lQ3ZzRmRRUGs/view?usp=sharing.*

Additionally, in Fig.9 we show several comparative results. Table II presents the average values of UCIQUE and PCQI measures when applied on the 10 image results shown in https://drive.google.com/file/d/0B01A5GB7NRpndG5lQ3ZzRmRRUGs/view?usp=sharing. Visually, but also quantitatively, our color-transfer based approach is able to yield comparative results with the specialized techniques of Emberton et al. [9] and Ancuti et al. [3] and even better outputs compared with the others analyzed techniques.

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