COLOR RESTORATION METHOD FOR UNDERWATER IMAGES

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ABSTRACT

Light scattering and color distortions are two major issues with underwater imaging. Scattering occurs due to turbidity of the medium and color distortions are caused by differential attenuation of wavelengths as a function of depth. As a result, underwater images taken in a turbid medium have low contrast, color cast, and color loss. The main objective of this work is color restoration of underwater images i.e, produce its equivalent image as seen outside of the water surface. As a first step, we account for low contrast by employing dark channel prior based dehazing. These images are then color corrected by learning a mapping function between a pair of color chart images, one taken inside water and another taken outside . Color restoration results are given on several images to validate the efficacy of the proposed methodology.

Keyword:- *Color mapping, Dehazing, White balancing.*

1. INTRODUCTION

Understanding and investigating underwater activities using images has been gaining popularity over the past few years. Classical image processing tools fail in underwater scenarios due to variations in optical properties of water such as light scattering and color distortions. Water being dense, light gets attenuated and scatters more as compared to its transport in air. These effects are directly responsible for image degradations in the form of blur, contrast loss, color cast and color loss.

Scattering is usually caused either due to suspended particles or due to turbidity in the medium. This induces color cast and haze to the captured images. Attenuation occurs due to absorption of light rays, as they travel through a medium. Different wavelengths of light get attenuated differently in water and hence the light reflected from the object inside water has different attenuation factors across the visible spectrum. Red undergoes severe attenuation followed by green, while blue is the least attenuated and penetrates the most. The net result is color loss. True color plays a very important role while analyzing specimens found in water. In this paper, it is initiated to mitigate the effect of color cast and haze, and proceed to develop an approach for color correction which compensates for color loss in underwater images. Methods has been developed in the literature that are specifically tailored to handle underwater degradations. In the literature, three types of approaches are prevalent for color correction of underwater images captured in turbid scenarios. These methods are enhancement based, dehazing based and sensor based.

Images captured in haze or fog experience severe contrast loss and color loss. Based on the nature of water and particulates in water, the light gets scattered and results in color cast. Hence, modeling of color cast can be done akin to atmospheric haze and the dark channel prior has been advocated for restoring the images. Most of the ocean expeditions are performed by using remotely operated vehicles which are fitted with depth sensors. True color correction can be done only if only we know the absolute depth. Hence, approaches that employ depth sensors are more accurate than enhancement. Hence, a proposal of framework for restoration of colors in turbid underwater imagery was done by proposing a learning based technique in which a mapping between a pair of images for a reference depth was learnt. The image pair consists of a color chart taken under the water surface and its corresponding pair taken outside water surface. Visibility loss due to turbidity is accounted for by dehazing using dark channel prior. The dehazed image is further color corrected using the learned mapping. The main contributions of the proposal are as follows a color correction of underwater images taken in turbid medium was performed. In the post correction, the recovered colors resemble their equivalent outside the water surface, the above can be achieved by learning a color mapping between colors of a color chart taken inside and outside water. The mapping is learned for a reference depth. Atlast , the color corrected image is white balanced.

2. FORMATION OF HAZY IMAGE

Haze is traditionally an atmospheric phenomenon where dust, smoke and other dry particles obscure the clarity of the image. The World Meteorological Organization manual of codes includes a classification of horizontal obscuration into categories fog ,ice-fog, snow dust.

A hazy image formed can be mathematically modeled as follows

$$I(x)=J(x)e^{-\beta d(x)} + A(1-e^{-\beta d(x)}) \tag{1}$$

where x represents the image coordinates, I is the observed hazy image, J is the haze-free image, A is the global atmospheric light, β is the scattering coefficient of the atmosphere, and d is the scene depth. Here, $e^{-\beta d}$ is often represented as the transmission map and is given by

$$t(x)=e^{-\beta d(x)} \tag{2}$$

In clear weather conditions, we have $\beta \approx 0$, and thus $I \approx J$. However, β becomes non-negligible for many hazy images. The first term of Eq. (1), J(x)t(x) decreases as the scene depth increases. In contrast, the second term of Eq. (1), $A(1-t(x))$,increases as the scene depth increases. Since the goal of image dehazing is to recover J from I, once A and t are estimated from I, J can be arithmetically obtained as

$$J(x)=I(x)-At(x)+A.J(x) \tag{3}$$

However, the estimation of A and t is non-trivial. In particular, since t varies spatially according to the scene depth, the number of unknowns is equivalent to the number of image pixels. Thus, a direct estimation of t from I is prohibitive without any prior knowledge.

3. COMPUTE DARK CHANNEL PRIOR(DCP)

According to the empirical investigation of the characteristic of haze-free outdoor images, it is found that there are dark pixels whose intensity values are very close to zero for at least one color channel within an image patch. Based on this observation, a dark channel is defined as follows:

$$J_{dark}(x)=\min_{y\in\Omega(x)}(\min_{c\in\{r,g,b\}} J_c(y)) \tag{4}$$

where J_c is an intensity for a color channel $c \in \{r, g, b\}$ of the RGB image and $\Omega(x)$ is a local patch centered at pixel x. According to Eq. (1), the minimum value among the three color channels and all pixels in $\Omega(x)$ is chosen as the dark channel $J_{dark}(x)$.The dark channel prior is based on the following observation on haze-free outdoor images: in most of the non-sky patches, that at least one color channel has very low intensity at some pixels. In other words, the minimum intensity in such a patch should has a very low value. The same idea is then followed in under water images .The assumptions made in DCP are valid for underwater images as well i.e.,at least one color channel has pixel intensity close to zero.DCP has been widely used in dehazing of underwater images too.

Based on the above observation, the pixel value at the dark channel can be approximated as follows:

$$J_{dark} \approx 0. \tag{5}$$

$$I(x)=J(x)t(x)+A(1-t(x)), \tag{6}$$

$$\min_{y\in\Omega(x)} \frac{Ic(y)}{Ac} = \tilde{t}(x)\left(\min_{y\in\Omega(x)} \frac{Jc(y)}{Ac}\right) + (1-\tilde{t}(x)) \tag{7}$$

Here the transmission in the local patch $\Omega(x)$ is assumed to be constant and is represented as $\tilde{t}(x)$. Then, the min operator of the three color channels can be applied to Eq. (7) as follows:

$$\mathrm{Min}_{y\in\Omega(x)}\left(\min_c \frac{Ic(y)}{Ac}\right) = \tilde{t}(x)\min_{y\in\Omega(x)}\left(\min_c \frac{Jc(y)}{Ac}\right) + (1-\tilde{t}(x)) \tag{8}$$

According to the DCP approximation of Eq. (6), $\tilde{t}(x)$ can be represented as,

$$\tilde{t}(x) = 1 - \min_{y\in\Omega(x)}\left(\min_c \frac{Ic(y)}{Ac}\right) \tag{9}$$

The homogeneous background light refers to the brightest pixel intensity in the image. But this might go wrong in the presence of shining surface in the observed image. Hence, the input hazy image is first subjected to local minima operation in local patches and the background light is defined as the maximum intensity among all the local minima.

$$A_c = \max_{x\in I} \min_{y\in\Omega(x)} Ic(y) \tag{10}$$

The transmission map $\tilde{t}(x)$ defined in Eq. (9) is obtained from the DCP. If the DCP is not exploited, then the equ(9) can be rewritten as,

$$\tilde{t}(x) = 1 - \min_{y\in\Omega(x)}\left(\min_c \frac{Ic(y)}{Ac}\right) + \tilde{t}(x) \cdot \min_{y\in\Omega(x)}\left(\min_c \frac{Jc(y)}{Ac}\right) \tag{11}$$

As it has been observed earlier, the pixel value of the dark channel, $J_{dark}(x)$, is highly likely zero, and so is $(J/A)_{dark}(x)$. However, if $(J/A)_{dark}(x)$ is not close to zero, the transmission map obtained as Eq. (9) can be under-estimated since the positive offset in Eq. (11) is always neglected .

In the original DCP-based dehazing method, it is mentioned that the image may look unnatural if the haze is removed thoroughly. A constant ω $(0 < \omega < 1)$ is thus used to retain a small amount of haze:

$$\tilde{t}(x) = 1 - \omega \min_{y\in\Omega(x)}\left(\min_c \frac{Ic(y)}{Ac}\right) \tag{12}$$

However, that a better visibility in the dehazed image can be achieved with Eq. (9) because it inadvertently compensate for the under-estimation of $\tilde{t}(x)$ by multiplying ω. The directly recovered scene radiance J is prone to noise certain amount of haze are preserved in very dense haze regions. The final scene radiance J(x) is recovered by:

$$J(x) = I(x) - A\max(t(x), t0) + A. \tag{13}$$

A typical value of t_0 is 0.1.Since the scene radiance is usually not as bright as the atmospheric light, the image after haze removal looks dim. So, the exposure of J(x) has been increased for display.

4. COLOR MAPPING

Color mapping is a function that maps the colors of one i.e., source image to the colors of another (target) image. A color mapping may be referred to as the algorithm that results in the mapping function or the algorithm that transforms the image colors. Color mapping is also sometimes called color transfer or, when grayscale images are involved, brightness transfer function (BTF). The goal of color mapping is to map the colors from a source to the target image. A scene imaged under different situations will show the color variations depending on the surrounding illumination as well as the characteristics of the imaging device used. A mapping function f can be found in such situations that maps the colors from a standard color chart to the required reference colors but these functions are illuminant to cameras.

In the system there employed a color mapping to map from a dehazed image in the underwater to that of its equivalent taken outside the water surface. This mapping is specific for an object to water surface D. We learn this mapping for a color chart pair taken inside and outside the water surface. A color map is matrix of values between 0 and 1 that define the colors for graphics objects such as surface, image, and patch objects. MATLAB draws the objects by mapping data values to colors in the color map. Color maps can be any length, but must be three columns wide. Thus, each row in the matrix defines one color using an RGB triplet. An RGB triplet is a three-element row vector whose elements specify the intensities of the red, green, and blue components of the color. The intensities must be in the range [0,1]. A value of 0 indicates no color and a value of 1 indicates full intensity.

The mapping can be written as a transform T which when applied on the RGB value from input will give the corresponding RGB value of the reference image. For linear mapping, the dimension of T turns out to be 3 x 3. Hence our transform matrix is a 3 x n matrix. The transform is learned using M corresponding pixels from the color charts taken under the two conditions described earlier. Let the reference image pixel intensity be collected in a matrix $R_{3 \times M}$ and its corresponding intensity with its higher orders from the source image be collected in the matrix $S_{n \times M}$

The mapping can be written as

$$R_{3 \times M} = T_{3 \times n} S_{n \times M} \tag{14}$$

5. WHITE BALANCE

White balancing is used to remove unrealistic color casts from the captured images. It works with the assumption that there is at least one white point in the captured image. There are different methods of white balancing such as gray world, shades of gray, white patch algorithm etc. Here, used the gray world algorithm which assumes that average reflectance of a scene is gray. It works by equalizing the means of all the color channels. It keeps the green channel as reference and multiplies the means of other channels with a gain factor such that all the means become equal. Let R_m, G_m and B_m be the means of the three color channels. Then the white balanced image is given by the following set of equations,

$$R_w(x,y)=\frac{Gm}{Rm}R(x,y) \tag{15}$$

$$G_w(x,y)=G(x,y) \tag{16}$$

$$B_w(x,y)=\frac{Gm}{Bm}B(x,y) \tag{17}$$

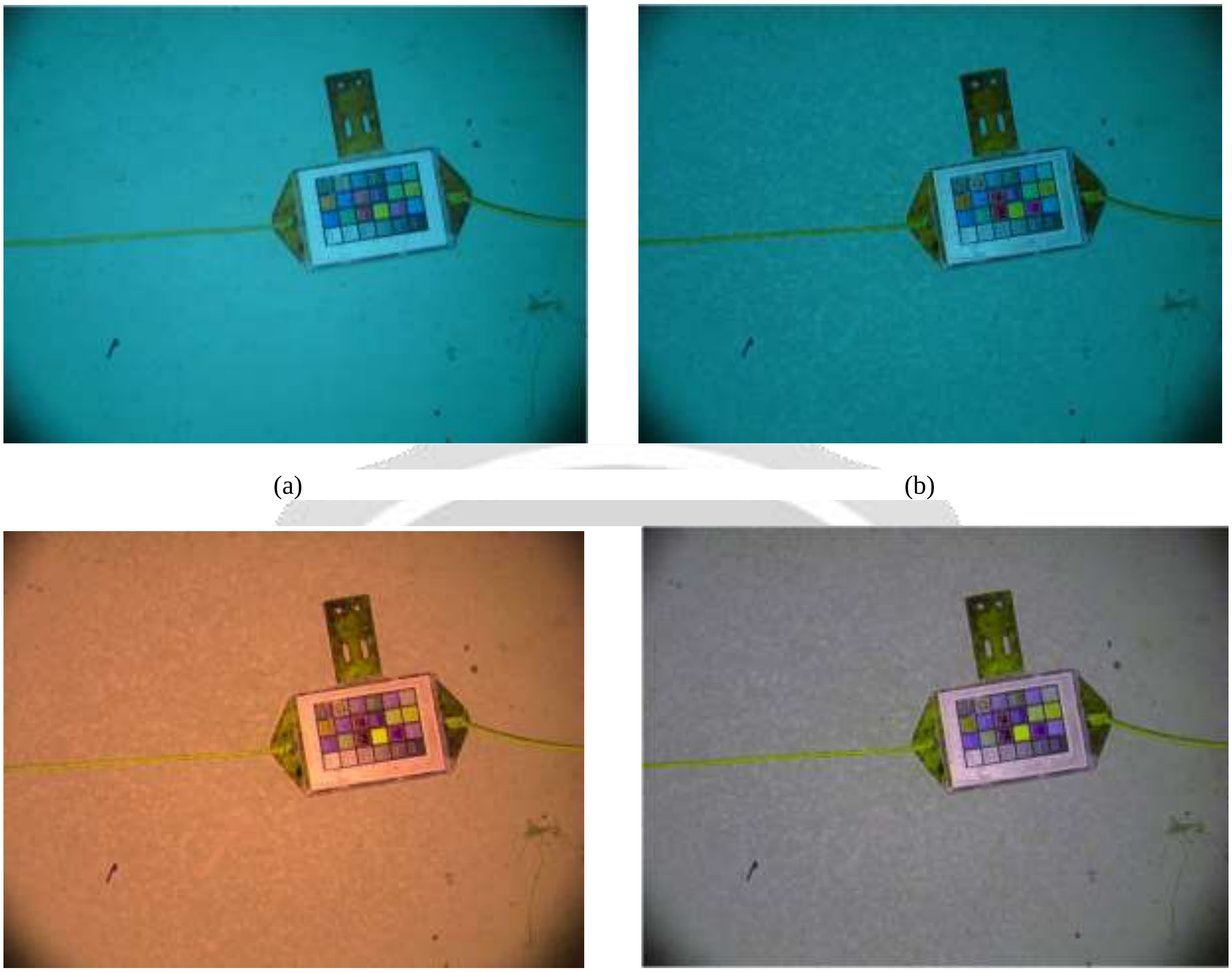
Table 1: Quantitative analysis (PSNR in dB).

Image	Input	Our result	DWB
1	16.03	23.68	18.9
2	16.1	20.01	17.8
3	15.47	19.1	16.4

where DWB refers to the result of Direct White Balancing of the input hazy image.

6. RESULTS AND DISCUSSION

The following are the results of the Color Restoration method for Underwater images using dehazing and color mapping.,

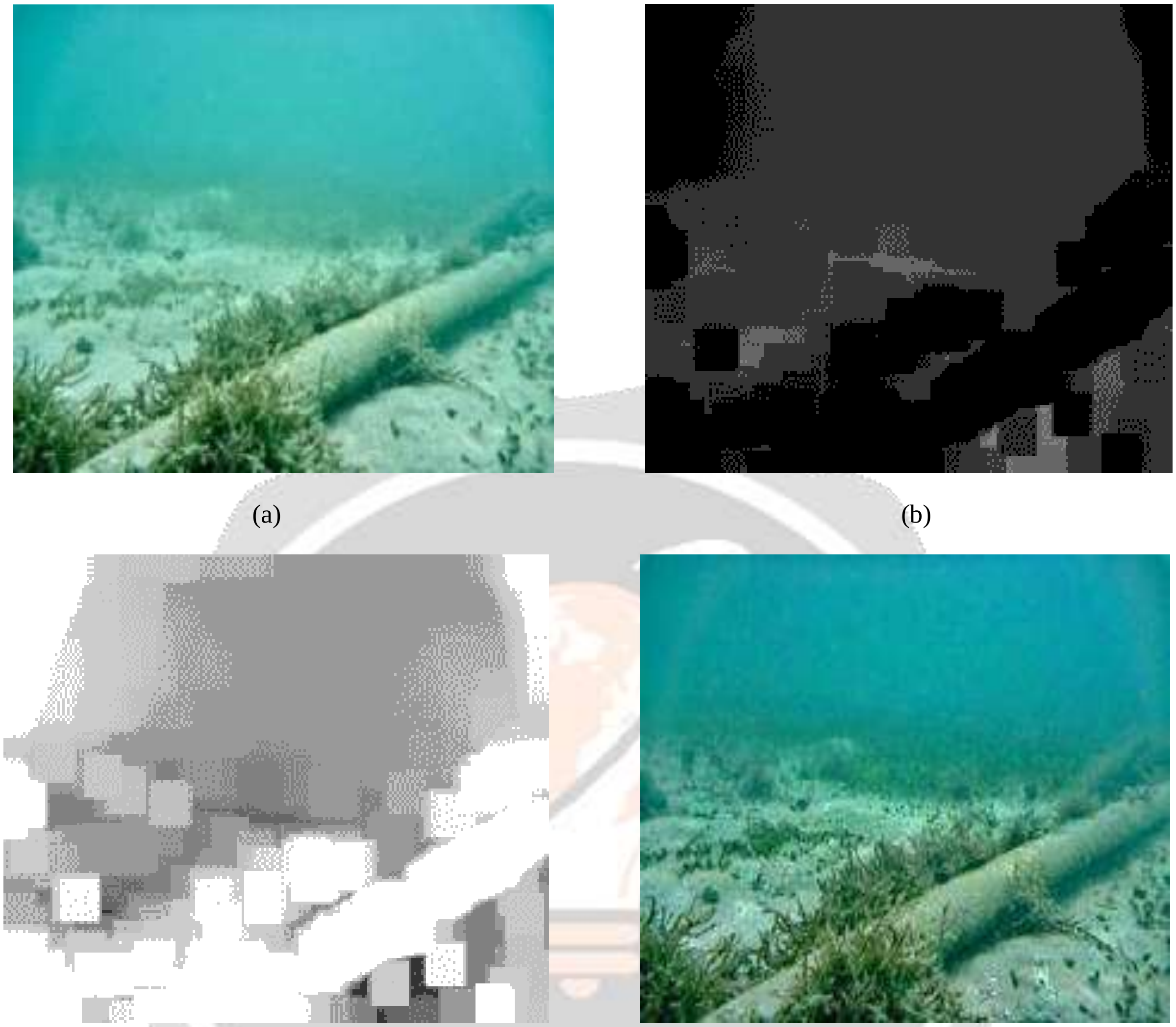


(a) (b)

(c) (d)

Fig- 6: (a) Input color chart image (b)Dehazed image (c) Color mapped image (d) Final output after white balancing.

The color chart image taken at the air medium is taken as the reference image and it is compared with the color chart image taken at underwater. By using this pair of images a transform function T is formed. This transform function is applied to the input image and the color mapped image is obtained. In Fig 6 (c) the unrealistic color present in the image is removed in Fig 6 (d) using white balancing. The dehazed image have sharp details than than the input hazy image. The hazy image contains significant color distortion by abnormal conditions in the underwater and thus the dehazing of the image is done to perform the color correction. The haziness present in the image is removed using the dark channel prior based dehazing method. Then the image is color mapped and then white balanced and the final color restored image is obtained.



(a) (b)

(c) (d)

Fig- 6.1: (a) Input image (b) Dark channel image (c) Transmission map (d) Dehazed image

The dark channel is first constructed from the input image. The transmission map is then obtained from the dark channel. The atmospheric light A is estimated in order to obtain the transmission map. To achieve a better visibility in the dehazed image, a compensation technique called transmission map is inadvertently exploited. The transmission map will appear opposite of dark channel. The dehazed image have sharp details than the input hazy image. The hazy image contains significant color distortion by abnormal conditions in the underwater and thus the dehazing of the image is done to perform the color correction. The haziness present in the image is removed using the dark channel prior based dehazing method. Then the image is color mapped and then white balanced and the final color restored image as shown in fig 6.2 is obtained.

Fig- 6.2: Final ouput after color mapping and white balancing.

6. CONCLUSIONS

In order to reduce the issues which have been faced in underwater imaging, thus proposed here a scheme for color restoration of underwater images taken in turbid medium. Turbidity leads to haziness in the captured images along with color loss. Here, employed the idea of color mapping and mapped the colors of an underwater image to its equivalent as seen from outside the water surface. The mapping is learned only once for reference depth. We also accounted for haze by using the dark channel prior. The quantitative results were provided on example.

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