AN ADVANCED VISIBILITY RESTORATION TECHNIQUE FOR UNDERWATER IMAGES

Sidharth Gautam, Tapan Kumar Gandhi, B.K. Panigrahi

Department of Electrical Engineering, IIT Delhi, India

ABSTRACT

Images captured in underwater (UW) are often disturbed with several kind of degradation such as low visibility, non-uniform color cast, haze, and blurriness. To date, most UW image restoration methods have ignored the effects of sensor blur and noise. Therefore, in this paper, we propose a novel three stage algorithm for visibility recovery in UW images by considering both sensor blur and noise. In the first stage, blind deconvolution is used for the estimation of an unknown point spread function (PSF). In the second stage, a new prior called weighted median channel prior (WMCP) is used for the estimation of scene depth and background light. In the third stage, a color balancing (CB) module is adopted to minimize the effect of non-uniform color cast. Experimental results manifest that the proposed algorithm is effective and has the character of visibility improvement, and color correction than previous state-of-the-art methods.

Index Terms— Underwater image correction, visibility restoration, image dehazing, visibility enhancement.

1. INTRODUCTION

Underwater (UW) image restoration has received a great deal of interest in both consumer and computer vision applications used for the exploration of deep ocean in the search of natural resources, fauna monitoring and ocean mapping. However, due to poor lightening condition and limited capability of optical imaging device, capturing clear underwater images is a challenging task. In underwater, when images are captured by optical devices, light after reflecting from an object is scattered and absorbed, before it reaches the camera. This is due to the fact that water acts as efficient mirror and a sponge. In UW, the scattered rays cause blurring of image features, whereas, absorption hinder lights path to deeper water and limits the visibility. Poorer visibility, in turn affects the contrast and clarity of shots. Hence both the scattering and absorption properties of water play their role collectively, to degrade an image.

From past few decades, several attempts have been made to restore single underwater images. Initial work on UW image restoration are simply based on the contrast enhancement. The restoration process proposed by Bazeille *et al.* [1] used a series of independent filters to reduce the underwater perturbations. However, using too many filters on one image are often results in unnatural looking. Thus, a considerable research is directed toward the knowledge of the scattering phenomena and design of optical model. In recent years, significant progress has been directed towards restoration of single underwater images, using the traditional 'atmospheric scattering model' [2]. In [3], Schechner *et al.* try to restore visibility in underwater images by capturing multiple images of the same scene through the use of a polarized camera. In contrast, L.Chao *et al.* [4], J.Chiang *et al.* [5], and S. Serikawa *et al.* [6] used dark channel prior (DCP) [7] to remove the haze effects from single UW images. Furthermore, P.Drews *et al.* [8] used a modified version of DCP called UDCP, which consider the blue and green channel for estimating the transmission in UW. Similarly, Galdran *et. al.* [9] proposed a red channel variant of DCP to recover the lost contrast in underwater images. Carlevaris-Bianco *et al.* [10] tackled the problem by employing a maximum intensity prior (MIP) which takes into account the intensity attenuation difference among the three color channels to estimate the scene-depth. Chong-Yi Li *et al.* [11] proposed a method based on the principle of minimum information loss and histogram distribution prior to dehaze UW images. Ancuti *et al.* [12] used the fusion principle to enhance the visual quality of UW images. Yan-Tsung Peng *et al.* [15] fused image blurriness and light absorption to restore UW images. Methods [2]-[15] can achieve good results, but in UW scenario, these strategies are not useful as there is a significant difference in physical process between UW imaging and outdoor imaging. Actually, water is many times denser than air, and is capable of holding matter in suspension, which makes it hard to identify and visualize things after few feet. Therefore, it is not convenient to use the 'atmospheric scattering model' for the restoration of UW images. In general, all the previous established methods have ignore the problem of sensor blur and noise in UW imaging.

In this paper, we propose a novel approach that can take both sensor blur and noise into account, while restoring UW images. However, to the best of our knowledge, a visibility restoration algorithm considering both blur and noise has not appeared in the literature to date. The rest of this paper is as follows: In section II, a brief background of atmospheric scattering model is presented. In section III, we introduce our approach in detail. Finally, section IV present experimental results, and concluding remarks are provided in section V.

2. BACKGROUND

2.1 Haze image formation model

The atmospheric scattering model used for representing haze images in computer vision is expressed as [2] - [15]:

$$I(x) = J(x)t(x) + a_{ir}\big(1 - t(x)\big) \quad (1)$$
$$t(x) = e^{-\beta d(x)} \quad (2)$$

where, $x \in (u, v)$ represent a pixel location, $I(x)$ is the intensity of observed hazy image, $J(x)$ is the real scene radiance, which is aimed to be recovered. $t(x)$ is the medium transmission, a_{ir} is the global background light, β is the atmospheric attenuation coefficient, and $d(x)$ is the scene depth. On putting the value of $t(x)$ in Eq. (1)

$$I(x) = J(x)e^{-\beta d(x)} + a_{ir}\big(1 - e^{-\beta d(x)}\big) \quad (3)$$

In Eq. (3), $J(x)e^{-\beta d(x)}$ is called '*direct attenuation'* which exponentially reduce the scene radiance in proportional to the scene depth, and $a_{ir}(1 - e^{-\beta d(x)})$ is called the '*background-light'* which fades the color and adds whiteness in the scene. Intuitively, the image received by the observer is the combination of the attenuated version of underlying scene radiance with an additive background-light. Since $I(x)$ is known, the ultimate goal of dehazing is to recover $J(x)$, as:

$$J(x) = \frac{I(x) - a_{ir}}{e^{-\beta d(x)}} + a_{ir} \quad (4)$$

The restoration of scene radiance $J(x)$, is a highly ill-posed problem, because it requires us to recover a_{ir} and $d(x)$, from only a single input image $I(x)$. In literature, there are several methods for estimation of background-light and scene depth, but they all are based on haze imaging model under atmospheric imaging conditions. But, water is many times denser than air and capable of holding matter in suspension through which we have to take our underwater photographs. Therefore, it is not convenient to use the above described model for the restoration of UW images.

3. PROPOSED METHODOLOGY

In this paper, the restoration technique are oriented toward mathematically modeling the degradations in underwater, by considering both blur and noise into account.

3.1 Haze image formation in turbid medium

By taking into account, both the sensor blur and noise the UW image formation model can be expressed as:

$$G(x) = \big[J(x)t(x) + a_{ir}\big(1 - t(x)\big)\big] \otimes h(x) + n(x) \quad (5)$$
$$G(x) = [I(x)] \otimes h(x) + n(x) \quad (6)$$

where, $G(x)$ is an observed UW image, $h(x)$ is a point spread function (PSF), which models the blurring of UW images, $n(x)$ is an additive noise. The other parameters are the same as Eq. (1). Our goal is to recover the scene radiance $J(x)$ from $G(x)$, but the success of restoring $J(x)$ depends upon precise estimation of $h(x)$. In UW, blur are caused by several reasons such as relative motion between camera and the object [16], improper focusing [17], and water turbidity [18]. Since in UW, exact source of blurring is unknown, therefore, to overcome this problem, we proposed a new model, which has the capability of handling underwater degradations. Based on this model, a three-stage algorithm is proposed to restore visibility of UW images. The flowchart of the proposed methodology is shown in Fig.1. In the first stage, blind deconvolution algorithm [19] proposed by Krishnan *et al.* is used for the estimation of unknown PSF. In the second stage, a new prior called weighted median channel prior (WMCP) is used for the estimation of a_{ir} and $d(x)$. In the third stage, a color balancing (CB) module is adopted to minimize the effect of color cast in UW mages.

3.2 Blind deconvolution algorithm

In this paper, we use a normalized sparsity measure to deconvolute an UW image. For the given UW image $G(x)$, we use a set of discrete filters $\nabla_m = [1, -1]$ and $\nabla_n = [1, -1]^T$ to generate a high frequency image $z(x) = [\nabla_m G,\ \nabla_n G]^1$. The cost function for spatially-invariant blurring is given by:-

$$\min_{m,h} \lambda \|m \otimes h - z\|_2^2 + \frac{\|m\|_1}{\|m\|_2} + \psi\|h\|_1 \quad (7)$$

where, m is an unknown sharp image in the high frequency space, h is the unknown PSF subject to the constraint that $h \geq 0$, $\sum_i h_i = 1$ (where, h_i are individual element), λ and ψ are the scalar weights which control the relative strength of the PSF and image regularization terms. The solution of Eq. (7) can be found by alternatively solving:

$$\min_{m} \lambda \|m \otimes h - z\|_2^2 + \frac{\|m\|_1}{\|m\|_2} \quad (8)$$

and

$$\min_{h} \lambda \|m \otimes h - z\|_2^2 + \psi\|h\|_1 \quad (9)$$

where, Eq. (8) and Eq. (9) can be solved efficiently by iterative shrinkage thresholding algorithm (ISTA) [20] and iterative re-weighted least squares algorithm (IRLS) [21], respectively. Once the PSF, $h(x)$ for the finest level has been estimated, we can recover $I(x)$ from $G(x)$ by solving:-

$$\min_{h} \lambda \|I \otimes h - G\|_2^2 + \|\nabla_m G\|_\alpha + \|\nabla_n G\|_\alpha \quad (10)$$

where, $\lambda = 3000$, $\alpha = 0.8$, $\nabla_m = [1, -1]$, $\nabla_n = [1, -1]^T$ for all results.

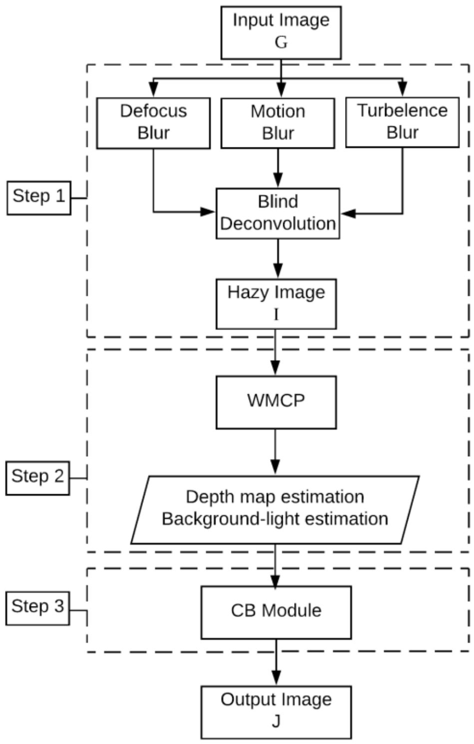

Figure 1. A three-stage flowchart of the proposed method.

3.3 Weighted Median Channel Prior (WMCP)

A scene-depth estimation based on the utilization of weighted median operator is used in the proposed method. The proposed WMCP is different from conventional unweighted techniques [4]-[9], which treat each neighbor pixel equally. The motivation behind choosing weighted technique is that it has the edge preserving capability which helps to retain most of the edge information while estimating scene-depth. In WMCP, first for each pixel, the lowest value from all color channels is chosen. Then, the median pixel value is chosen within the neighborhoods (Ω) after associating it with a weight function $w(x,y)$. Mathematically, the weighted median channel prior (WMCP) for an input image $I(x)$ can be expressed as:

$$d(x) = \underset{x \epsilon \Omega(u,v)}{\mathrm{med}} \left(w(x,y) \times \underset{c \in (\mathrm{r,g,b})}{min} \left(I^c(x) \right) \right) \quad (11)$$

where, $\Omega(u,v)$ represent an image local-patch, min is a minimum filter, med is a median filter, and $w(x,y)$ are the weights between the color-vectors of the neighboring pixels:

$$w(x,y) = e^{-\|I(x)-I(y)\|^2/2\sigma^2} \quad (12)$$

where, σ^2 represents the variance of weights in a patch size (Ω).

3.4 Estimation of background-light (a_{ir})

Generally, in an UW image, the influence of background-light is higher in the region of deeper depth, and lower in the region of shallower depth. Since the background-light contribution increase along with the increase in scene-depth, we can estimate (a_{ir}) by considering the pixel intensity of deepest region in the depth map by using:

$$a_{ir} = \frac{I^C(x)}{|R|} \left\{ \underset{x \in R_{0.1\%}}{argmax} \left(d(x) \right) \right\}, c \in (\mathrm{r,g,b}) \quad (13)$$

Where, R is the deepest region in $d(x)$ and $R_{0.1\%}$ be the set of position of those pixels in $d(x)$. Then, among these pixels, the pixel corresponding to highest intensity in the input image $I(x)$ are chosen to provide the estimate of (a_{ir}).

3.5 CB Module

UW images usually exhibit serious color change problems due to water's greatest absorption to light. In UW, colors associated to different wavelength have different attenuation rates (red channel loses its intensity fastest, while the green and blue keep their intensity longer) thus resulting in serious color cast. To solve this problem, we make use of gray world assumption [22] to determine whether or not the average intensity of the each color channel are equal. The average intensities of the red, green and blue channels are given by:

$$avg_c = \frac{\sum_{u=1}^{M} \sum_{v=1}^{N} I^c(x)}{(M \times N)}, \quad \text{for } c \in \{r,g,b\} \quad (14)$$

Where, $(M \times N)$ denote the size of the input image. The average intensity for each color channel avg_c is then used to calculate the color difference value, $cdv^C(x)$ as:

$$cdv^C(x) = avg_r - avg_c, \quad \text{for } c \in \{r,g,b\} \quad (15)$$

Eq. (15) provide an estimate of illumination by computing the mean of each color channel of the input image.

3.6 Image recovery

Once the depth-map of the scene has been obtained, we can obtain the transmission-map easily according to Eq. (2) by using $\beta = 0.7$. Finally, the scene radiance $J(x)$ is given by:

$$J^c(x) = \frac{I^c(x) - \left(a_{ir}^c - cdv^c(x) \right)}{\min\{\max\{t(x),0.1\},0.9\}} + \left(a_{ir}^c - cdv^c(x) \right) \quad (16)$$

Where, $cdv^c(x)$ denotes the color difference for each color channel. In other words, the offset for each channel caused by water is subtracted before the recovery of scene radiance. For avoiding instability, we also restrict the value of the transmission-map $t(x)$ between 0.1 and 0.9.

4. EVALUATION AND RESULT

In this paper, all experimental images are processed by MATLAB R2017b on a PC with Intel(R) Core(TM) i5-4260U CPU@ 1.40GHZ, 4.00GB RAM. The parameters λ, α, ∇_m ∇_n, β, and Ω are fixed as 3000, 0.8, $[1,-1]$, $[1,-1]^T$, 0.7 and 15 respectively, in our experiment.

Figure 2. shows our restoration result for few color distorted, blurry, under-exposed UW images. As we can observe, the restoration result produced by our approach has the character of detailed improvement by blur reduction, color correction, and lightening dark regions.

(a)

(b)

Figure 2. Our restoration result. (a) Real UW images synthesized with defocus blur [16], motion blur [17] and turbulence blur [18], respectively. (b) Our method. (Best viewed on high-resolution display with zoom-in.)

(a)

(b)

(c)

(d)

(e)

Figure 3. Qualitative comparison with other state-of-the-art methods. (a) Real-UW images (b) WCID method [5] (c) MIL-HDP method [11] (d) Ancuti method [12] (e) our proposed method. (Best viewed on high-resolution display with zoom-in.)

Figure 3. shows the qualitative comparison of proposed method with other state-of-art methods including WCID [5], MIL-HDP [11] and Ancuti [12]. It is observed that the restored images in Fig. 3(e) has more vivid colors, sharpness and contrast than the original images. The advantage of proposed approach is especially apparent in the dark and blurry regions. While, in these regions the result of WCID [5], MIL-HDP [11], and Ancuti [12] are dark, and fuzzy.

Table 1. RESTORATION EFFICACY OF THE COMPARED METHODS OBTAINED VIA $\boldsymbol{UICM}$, $\boldsymbol{UISM}$, $\boldsymbol{UIConM}$ & $\boldsymbol{UIQM}$

Image	Metric	WCID [5]	MIL-HDP [11]	Ancuti [12]	Ours
Diver	$UICM$	-97.8201	-53.5234	-13.8934	**-0.0459**
	$UISM$	6.2180	6.5442	6.7779	**6.8744**
	$UIConM$	0.3161	0.5970	0.7860	**0.6610**
	$UIQM$	0.2078	2.5576	4.4199	**4.3920**
Fish1	$UICM$	-1.0193	-7.1973	-1.6485	**-1.4933**
	$UISM$	7.2232	7.1903	7.2260	**7.1401**
	$UIConM$	0.7572	0.8175	0.6169	**0.7877**
	$UIQM$	4.8115	4.8431	4.2930	**4.8826**
Fish2	$UICM$	-6.8803	-23.5528	**-5.4640**	-7.7628
	$UISM$	6.1751	7.0106	**7.5245**	7.0990
	$UIConM$	0.6485	0.7729	**0.7954**	0.7082
	$UIQM$	3.9481	4.1694	**4.9117**	4.4096

To quantitatively evaluate the restoration efficacy of each method, we adopted underwater image quality measures $(UIQM)$, namely, the underwater image colorfulness measure $(UICM)$, the underwater image sharpness measure $(UISM)$, and the underwater image contrast measure $(UIConM)$ [23]. Specifically, the $UICM$ measures the image colorfulness, $UISM$ is the attribute related to the preservation of fine detail and edges, $UIConM$ measure the image contrast. The $UIQM$ measure the overall image quality by collectively using $UICM, UISM$, and $UIConM$. Generally a higher value of $UIQM$ corresponds to an image with better quality. The restoration results are summarizes in Table 1. According to this table, the visual appeal of proposed method is significant and unveil great details.

5. CONCLUSION

In this paper, we refine the atmospheric scattering model and propose a new imaging model, for underwater images by taking both sensor blur and noise into account. Based on this new model, a three-stage algorithm is proposed to restore visibility in UW images. In the first stage, blind deconvolution algorithm is used for the estimation of unknown PSF. In the second stage, a new prior called weighted median channel prior (WMCP) is used for the estimation of scene depth and background light. In the third stage, a color balancing (CB) module is adopted to minimize the effect of non-uniform color cast. Experimental results on a variety of underwater images manifest that the proposed algorithm is effective, based on both the visual effect and quantitative assessment.

6. REFERENCES

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