Edge Aware Turbidity Restoration of Single Shallow Coastal Water Image

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Abstract. The blur and low contrast of underwater images are indicative of the high noise, intense scattering and ultimately the low quality of such images. Image Enhancement and Restoration are imperative pre processing steps for single images from shallow coastal areas. Pre processing of underwater images is hence a prerequisite to processes like classification, object detection and computer vision. The paper presents an effective edge aware restoration models that goals turbid water images. The dark channel based restoration method with a rolling guidance filter gives a more edge aware restored and denoised version of the heavily blurred, low contrast shallow coastal image. This is evident from the subjective and objective projections. Moreover the edge preserving nature projects 13.05% and 5.53% more than UHP (which is in close) in terms of number of edges and UCIQE scores in comparisons with promising algorithms over the decade.

1. Introduction
Light propagation through water due to dissolved particles result in absorption and scattering effects termed as the internal optical property (IOP) of water. This introduces effects in the process of underwater imaging [1]. The reduced visibility and color cast produced due to reduced competence to extract valued features from underwater images [2]. Underwater images possess a contrast degraded appearance due to haze the scattering of light rays. The color tone variation due to change in the percentage of light absorption for varied wavelengths and its restricted range. Insufficient lighting leading to reduced brightness in the underwater images. All these necessitate formulating an efficient enhancement method. The restoration methods functioned based on the physical imaging process and estimated the parameters of the imaging model from the observation for prior assumptions. Absorption and scattering of light by suspended particles were the major issues for the degradation underwater images. The various prior-based techniques executed involved: The Dark channel prior (DCP)[3] considered the darkest portion from among the three channels to remove the haze. This method was not effective for brightest points and shadows. The underwater dark channel prior (UDCP) [4] does not consider the attenuation in the red channel. The Maximum Intensity Prior (MIP) [5] estimated a brighter estimation of the Backlight that the ground truth. The Underwater Light Attenuation Prior (ULAP) [6] used the difference between the maximum intensities of Green-Blue channel and that of the Red channel for one pixel of the underwater image. But they had lower accuracy in Backlight estimation and also could not handle artificially illuminated regions. The Underwater Image
Restoration Based on Image Blurriness and Light Absorption (IBLA) [7] estimated the color cast and transmission depth using the blurriness and light absorption but this had high computational complexity. For a variant of the DCP the restoration by an automatic red channel method (ARCR) [8] proposed to compensate for the attenuation of the red channel but proved to have the red tint of the restored image for images from great depths. Restoration works for single image involves the image color restoration using Haze lines (UHP) [9] which gave over saturated results for shallow water and images with heavy sediments. The single image restoration of [10] estimated the aitlight and depth of the scene by computing the disparity concerning the observed intensity and the background light and the work also projects color distortion for images with strong color casts. These priors estimated the enveloping light and transmission distance between camera and object integrated as the image restoration posing the image formation model (IFM). The conclusions from the observations of the models for real time data ( likening to the ones stated in this paper) projected that underwater image restoration methods proved to possess the final restored images not very clear (retained some haze and color cast) and also needed an increase in contrast. 

Image enhancement is the process of improving the quality and information content of an image as it is found not suitable for human perception as well as for further processing like classification and computer vision. Common methods consist of contrast enhancement, spatial filtering and density slicing. These adjustments could be implemented on the spatial or transform domain. The spatial domain methods include Histogram Equalization (HE) [11] and Contrast Limited Adaptive Histogram Equalization (CLAHE) [12] worked to enhance the image contrast. The HE amplified the noises in the images and also gave an enhanced the red tint whereas the CLAHE computed using both RGB and HSV formats improved image quality by reducing noise and artifacts. The Retinex method (RX) [13] simulated the human visual perception aimed to correct color cast. Methods like the Integrated Color Model (ICM) [14] and Unsupervised Color Correction method (UCM) [15] used HSI color space and proposed to distribute the saturation and intensity components which led to under- and over-saturated images. The image quality enhancement using the arrangement of dual-intensity images and Rayleigh-stretching (Rayleigh) [16] masks certain minute local details of information of the enhanced images. The transform domain utilized the physical properties to map image pixels into a specific domain to implement the adjustments. The Fourier and wavelets [17, 18] were the commonly used transform domain methods. Though the transform-domain methods served to improve image clarity, it also resulted in amplification of noise and color distortion. The complications of enhancement techniques include highlight noise, raise artifacts, and produce color distortions for the real time turbid data and could hardly result in high quality images. Thus a comprehensive work to incorporate both the restoration and enhancement scheme to process the image was undertaken. The contributions are:

- Introducing the rolling guidance filter in the restoration of DCP which settles for reduction in unwanted textures and noise.
- Encapsulates the properties of shallow coastal regions and mainly focuses for datasets from the same with heavy blurring effect.

The remainder of this paper is structured as follows. Section 2 outlines the DCP based underwater imaging model. Section 3, describes the proposed edge aware restoration cum enhancement model. The optical natures of coastal turbid areas are recorded and the proposed model in Section 4. Relative trials are presented in Section 5. Finally, the closing remarks in Section 6.

2. Existing Work

The inverse attenuation process of underwater image restoration is projected when light rays passess in water. The DCP based restoration and the underwater imaging model are elaborated in this section.

2.1 Jaffe-McGlamery Model

The Jaffé-McGlamery underwater imaging model [19] portrays the total light from an image that ranges the camera is given by:
\[ I_{cl(obj)}(i,j) = I_{cl(res)}(i,j) + t_{cl}(i,j) + (1 - t_{cl}(i,j))B_{cl}^{\infty}(i,j) \]  

(1)

where \( I_{cl(obj)}(i,j) \) is the observed intensity at point \((i,j)\) of the image, \( c_l \) refers to the color channel RGB, \( c_l = \{ R, G, B \} \). \( I_{cl(res)}(i,j) \) represents the scene radiance, \( B_{cl}^{\infty}(i,j) \) the global atmospheric light and \( t_{cl}(i,j) \) the transmission medium through which the light reaches the camera is defined as:

\[ t_{cl}(i,j) = e^{-\alpha_d d(i,j)} \]  

(2)

where \( d(i,j) \) is the space between the object and imaging device and \( \alpha \) the attenuation coefficient. For underwater conditions, \( \alpha_d \) is the totality of the wavelength \( \lambda \) dependent absorption coefficient \( x_d \) and the scattering coefficient \( y_d \) given as

\[ \alpha_d = x_d + y_d \]  

(3)

The restored image \( I_{cl(res)}(i,j) \) is obtained from \( I_{cl(obj)}(i,j) \), \( t_{cl}(i,j) \) and \( B_{cl}^{\infty}(i,j) \) as

\[ I_{cl(res)}(i,j) = \frac{I_{cl(obj)}(i,j) - B_{cl}^{\infty}(i,j)}{t_{cl}(i,j)} + B_{cl}^{\infty}(i,j) \]  

(4)

the transmission map estimation based on DCP is given (9). This can be elaborated by compensating for the attenuation of the red channel and hence represented with the final version to include the inversion formula as:

\[ I_{res}^{R}(i,j) = \frac{I_{cl(obj)}^{R}(i,j) - B_{cl}^{\infty}(i,j)}{\max(t_{R}^{c}(x),0.1)} + (1 - B_{cl}^{\infty}(i,j))B_{cl}^{\infty}(i,j) \]  

(5)

\[ I_{res}^{G}(i,j) = \frac{I_{cl(obj)}^{G}(i,j) - B_{cl}^{\infty}(i,j)}{\max(t_{G}^{c}(x),0.1)} + (1 - B_{cl}^{\infty}(i,j))B_{cl}^{\infty}(i,j) \]  

(6)

\[ I_{res}^{B}(i,j) = \frac{I_{cl(obj)}^{B}(i,j) - B_{cl}^{\infty}(i,j)}{\max(t_{B}^{c}(x),0.1)} + (1 - B_{cl}^{\infty}(i,j))B_{cl}^{\infty}(i,j) \]  

(7)

2.2 Image Restoration for Underwater Environment

Placed on the DCP [3], the dark channel (\( D_{ch} \)) of a color underwater image \( I_{cl(obj)}(i,j) \) is calculated by minimizing in local patches \( \Omega(i,j) \) over the three channels \( c_l = \{ R, G, B \} \). The estimated backlight and hence the transmission map are related using DCP as:

\[ I_{dark}(x,y) = \min_{x \in D_{ch}(x,y)} \min_{c_l \in \{ R, G, B \}} (I_{cl(obj)}(i,j)) \]  

(8)

\[ t_{cl}(i,j) = 1 - \min_{y \in \Omega(i,j)} \min_{c_l \in \{ R, G, B \}} \frac{I_{cl}(m,n)}{\tilde{B}_{cl}(m,n)} \]  

(9)

Where \( \tilde{t}_{cl}(i,j) \) and \( \tilde{B}_{cl}(m,n) \) are the transmission estimation and backlight estimation respectively of the DCP applied image on the original image \( I_{cl(obj)}(i,j) \). The original image is regarded as
where the dark pixel is considered in a patch of \( \Omega(i,j) \) in all the color channels.

3. Edge Aware Underwater Image Restoration

The DCP based edge aware underwater image restoration algorithm is formulated by determining of veiling light using [9]. A rolling guidance filter [20] implemented along with the DCP based image restoration and is as shown in Figure 1.

![Flowchart of the proposed edge aware underwater restoration model](image)

The edge aware restoration is achieved using a bilateral filtering of the DCP image. The edge-preserving, and noise-reducing smoothing property of the non-linear bilateral filter is exploited for this operation. Here the adjoining pixel replaces the weighted average of intensity values of the intensity of each pixel. As applying bilateral filter guidance creates smoothly curved edges [20], the bilateral filter performs better in guidance with the guided filter for the haze removal.

The bilateral filters are.

\[
I_{BF(i,j)} = \frac{1}{Wp} \sum_{(i,j)\in\Omega} I_{(i,j)} \sigma_r \left( \| I_{(i,j)} - I_{(i,j)} \| \right) \sigma_s \left( \| (i,j) - (i,j) \| \right)
\]

where the normalization term \( Wp \) is as

\[
W_p = \sum_{(i,j)\in\Omega} \sigma_r \left( \| I_{(i,j)} - I_{(i,j)} \| \right) \sigma_s \left( \| (i,j) - (i,j) \| \right)
\]

Here the \( I_{BF(i,j)} \) is the image after Bilateral filtering, \( I_{(i,j)} \) is the image to be filtered. The current pixel coordinates to be filtered is given by \((i,j)\), \( \Omega \) is a window centered in \((i,j)\) where \((i,j) \) is another pixel coordinate in \( \Omega \). \( \sigma_r \) is the value that defines the range weight of the bilateral filter and \( \sigma_s \) the spatial
weight also known as the filtering scale of the bilateral filter. The result of edge aware restoration is depicted in Figure 3. The method proposed proved to restore underwater images and focused on shallow coastal regions with heavy suspended matter and color cast. The rolling guidance using the bilateral filter proves to denoise as well as preserving the edges by reducing unwanted textures present in the image. This proves to be effective for computer vision applications. a simple gamma correction is incorporated finally in order to increase the contrast of the resultant images.

4. Shallow Coastal Underwater Image Data
The presence of organic and inorganic constituents in the water body has consequences on the underwater visibility. The coastal areas possess exclusive optical features. The data collection method, location and dataset used is the one elaborated and analyzed in [24]. The images are graded by the Jerlov water types [25] as C5. The images are calculated to possess a very less underwater color image quality evaluation (UCIQE[27]) index of between 12-20. The coloring of the waters of the original image in the data is bluish green. The resolution of the images is 960x540 and is of jpeg type.

5. Experimental Results and Quality Evaluation
The proposed method was validated on coastal shallow water images. The image data presented here has a sample of two from the collected real time dataset [24] with divers and another from a standard image [8]. For the resolution of the images mentioned above the patch size for both the dark channel and bilateral filter is set as 11X11. All the experiments were carried out on a system with Intel Processor i5 @250 GHz and 4GB RAM.

5.1 Subjective Inspection
The proposed method was from a subjective point of view in Figure 2 compared with other relevant lead methods put forth over the decade such as DCP [3], RX [13], ARCR [8] and UHP [9]. The images appear without haze. Unlike the DCP with low contrast, the ARCR that has more haze and the RX has change of natural color, the proposed has retained the naturalness and reduced haze. Though the results obtained are subjectively similar to the UHP method, they have significant differences on the visibility restoration in Figure 3 on a human perception point of view. The Figure 3 input column does not display most of the edges of the input image. The UHP though having most edges displayed are not effectively centered on the object and has edges from the waters as well. For higher level applications like object detection, the proposed method projects visible edges restored centered on the object. The other methods and Input images’ visibility are not as much as that of the proposed method.

| Input Image | DCP | RX | ARCR | UHP | PROPOSED |
|-------------|-----|----|------|-----|----------|
| ![Input Image](image1) | ![DCP](image2) | ![RX](image3) | ![ARCR](image4) | ![UHP](image5) | ![PROPOSED](image6) |

**Figure 2.** Subjective comparison of proposed restoration model with other models
Figure 3. Subjective comparison of visibility restoration of proposed restoration model with other models

5.2 Objective Inspection

The Visibility Restoration of Objects [28] calculates the number of edges. By computing the coefficients $e$ and $r$, the measure of new visible edges that a method restores is calculated. The term $e$ is calculated using an expression as:

$$e = \frac{n_r - n_0}{n_0}$$

(13)

where $n_0$ is the total number of edges on the image data and $n_r$ on the final restored image. This calculates the number of edges that are invisible in the original input image (Io) but found in the final restored image (Ir). The $r$ value is calculated by the original image $r_i$, expressed as

$$r = \frac{1}{n_r} \sum \log(r_i)$$

(14)

This assesses the capacity of the method to replace edges that are invisible in the input expressed as:

$$r = \frac{VL_r}{VL_o}$$

(15)

where $VL_r$ is the restored image visibility and $VL_o$ the original image visibility. A higher value observed from table I. shows that more edges are restored using the proposed method.

| Table 1. Comparison of Number of Visible Edges restored |
|-----------------------------------------------|
| Input Image | Input | DCP | RX | ARCR | UHP | PROPOSED |
|--------------|-------|-----|----|------|-----|----------|
|              | 2794  | 64465 | 53135 | 26408 | 115811 | 142975 |
|              | 258   | 64793 | 29766 | 24360 | 126585 | 103673 |
|              | 26851 | 65872 | 38446 | 20857 | 79684  | 117487 |

Percentage Increase 13.05% more than UHP

The UCIQE [27] is a measure of the overall quality of an image in terms of contrast, color and sharpness. It is expressed as

$$UCIQE = C_1X\sigma + C_2Xcon_i + C_3X\mu$$

(16)

Here $C_1$, $C_2$, $C_3$ are weighted coefficients, $\sigma_i$ is the chroma obtained using standard deviation, $con_i$ takes the contrast and $\mu_i$ considers average saturation. These enumerate the color veiling, low-contrast
and blurring that the mainly describe the underwater images. The higher values for this metric from table II indicate the quality of the image. Both the objective metrics are of no reference type.

| Table 2. Comparison of Number of UCIQE Values |
|-----------------------------------------------|
| Input Image | Input | DCP | RX | ARCR | UHP | PROPOSED |
| 18.0417 | 31.8178 | 32.0246 | 32.5713 | 33.1924 | 33.9919 |
| 16.6665 | 31.8263 | 29.5110 | 31.5570 | 31.3741 | 32.2064 |
| 20.7442 | 36.7448 | 33.7115 | 37.1220 | 34.0842 | 37.912 |

**Percentage Increase** 5.53% more than UHP

6. Conclusion
The proposed turbidity restoration model for shallow coastal waters has proved best both on a subjective and objective basis and is evident from the figures and tables. The method has proved to possess better edge based dehazing than the standard methods. This is evident with the UCIQE values showing a higher score indicating better contrast and hence reduced noise. The metric has shown robustness for edge restoration with 13.05% more edges than the UHP which is the second best amongst the methods considered. The simple gamma correction proves ineffective for areas in the image with low lighting but still shows 5.53% more than UHP which scores next best in UCIQE compared to the other methods considered. The method needs a better enhancement scheme to be incorporated along with the restoration model for a better subjective view. The proposed model also has a better denoised final output with its rolling filter adopted along with the restoration model.

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References
[1] Kjerstad I. Underwater Imaging and the effect of inherent optical properties on image quality (Master's thesis, Institutt for biologi).
[2] Li C, Quo J, Pang Y, Chen S, Wang J. Single underwater image restoration by blue-green channels dehazing and red channel correction. 2016 In2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) Mar 20 (pp. 1731-1735).
[3] He K, Sun J, Tang X. Single image haze removal using dark channel prior. 2010 IEEE transactions on pattern analysis and machine intelligence. Sep 9;33(12):2341-53.
[4] Peng YT, Cosman PC. 2017 Underwater image restoration based on image blurriness and light absorption. IEEE transactions on image processing. Feb 2;26(4):1579-94.
[5] Carlevaris-Bianco N, Mohan A, Eustice RM. 2010 Initial results in underwater single image dehazing. InOceans Mts/IEEE Sep 20 (pp. 1-8).
[6] Song W, Wang Y, Huang D, Tjondronegoro D. 2018 A rapid scene depth estimation model based on underwater light attenuation prior for underwater image restoration. InPacific Rim Conference on Multimedia Sep 21 (pp. 678-688). Springer, Cham.
[7] Peng YT, Cosman PC. 2017 Underwater image restoration based on image blurriness and light absorption. IEEE transactions on image processing. Feb 2;26(4):1579-94.
[8] Galdran A, Pardo D, Picón A, Alvarez-Gila A. 2015 Automatic red-channel underwater image restoration. Journal of Visual Communication and Image Representation. Jan 1;26:132-45.
[9] Berman D, Levy D, Avidan S, Treibitz T. 2020 Underwater single image color restoration using haze-lines and a new quantitative dataset. *IEEE transactions on pattern analysis and machine intelligence*. Mar 2.

[10] Peng YT, Cao K, Cosman PC. 2018 Generalization of the dark channel prior for single image restoration. *IEEE Transactions on Image Processing*. Mar 7;27(6):2856-68.

[11] Hummel R. 1975 Image enhancement by histogram transformation. Unknown. Sep.

[12] Stimper V, Bauer S, Ernstorfer R, Schölkopf B, Xian RP. 2019 Multidimensional contrast limited adaptive histogram equalization. *IEEE Access*. Nov 11;7:165437-47.

[13] Fu X, Zhuang P, Huang Y, Liao Y, Zhang XP, Ding X. 2014 A retinex-based enhancing approach for single underwater image. In2014 *IEEE International Conference on Image Processing (ICIP)* Oct 27 (pp. 4572-4576).

[14] Iqbal K, Salam RA, Osman A, Talib AZ. 2007 Underwater Image Enhancement Using an Integrated Colour Model. *IAENG International Journal of computer science*. Dec 1;34(2).

[15] Iqbal K, Odetayo M, James A, Salam RA, Talib AZ. 2010 Enhancing the low quality images using unsupervised colour correction method. In2010 *IEEE International Conference on Systems, Man and Cybernetics* Oct 10 (pp. 1703-1709).

[16] Ghani AS, Isa NA. 2014 Underwater image quality enhancement through composition of dual-intensity images and Rayleigh-stretching. *SpringerPlus*. Dec;3(1):1-4.

[17] Asmare MH, Asirvadam VS, Hani AF. 2015 Image enhancement based on contourlet transform. *Signal, Image and Video Processing*. Oct;9(7):1679-90.

[18] Vasamsetti S, Mittal N, Neelapu BC, Sardana HK. 2017 Wavelet based perspective on variational enhancement technique for underwater imagery. *Ocean Engineering*. Sep 1;141:88-100.

[19] Emberton S, Chittka L, Cavallaro A. Hierarchical rank-based veiling light estimation for underwater dehazing.

[20] Zhang Q, Shen X, Xu L, Jia J. 2014 Rolling guidance filter. In*European conference on computer vision* Sep 6 (pp. 815-830). Springer, Cham.

[21] Khoury J. Model and quality assessment of single image dehazing (*Doctoral dissertation*, Université de Bourgogne Franche-Comté).

[22] Levis A, Schechner YY, Davis AB. 2017 Multiple-scattering microphysics tomography. In*Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 6740-6749).

[23] Jackson T, Bouman HA, Sathyendranath S, Devred E. 2011 Regional-scale changes in diatom distribution in the Humboldt upwelling system as revealed by remote sensing: implications for fisheries. *ICES Journal of Marine Science*. Mar 1;68(4):729-36.

[24] Cecilia SM, Murugan SS, Padmapriya N. 2019 Analysis of Various Dehazing Algorithms for Underwater Images. In2019 *International Symposium on Ocean Technology (SYMPOIL)* Dec 11 (pp. 98-105). IEEE.

[25] Jerlov NG. Marine optics. Elsevier; 1976.

[26] Ancuti CO, Ancuti C, De Vleeschouwer C, Bekkaert P. 2017 Color balance and fusion for underwater image enhancement. *IEEE Transactions on image processing* Oct 5;27(1):379-93.

[27] Yang M, Sowmya A. 2015 An underwater color image quality evaluation metric. *IEEE Transactions on Image Processing*. Oct 19;24(12):6062-71.

[28] Hautiere N, Tarel JP, Aubert D, Dumont E. 2008 Blind contrast enhancement assessment by gradient ratioing at visible edges. *Image Analysis & Stereology*. 27(2):87-95.