International Journal of Engineering & Technology, 7 (4.38) (2018) 944-949

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper



An Underwater Image Enhancement via Wavelet domain Gradient Guided Filter

Chrispin Jiji, Nagaraj Ramrao

Department of ECE, The Oxford College of Engineering, Bangalore, India
chrispinjij@gmail.com, nagarajramrao@gmail.com

Abstract

Pictures confined in underneath are often yield limited visibility and low dissimilarity due to haze in undersea. Existing approaches enhance pictures but frequently undergo noise issue; this paper presents a hybrid method for solving mage enhancing difficulty in frequency domain. Firstly, we propose locally adaptive Non locally robust regularization to deblur the image. The deblurred image has small gray-level rate in any color channel. Secondly we used an open dim channel scheme to increase visibility in low-intensity rate. Thirdly, gradient guided filter to enhance the details. Later, we use the soft-thresholding process to decrease noise in high-intensity rate to advance texture information. Finally, image is well enhanced via wavelet domain gradient guided filter. The projected technique intends to raise perceptual visibility, keep extra texture information as well lower noise effect. The performance evaluations prove that projected scheme give up better results by existing methods.

Keywords: *Underwater image enhancement, Dehazing, Wavelet domain Gradient guided filter*.

1. Introduction

Acquiring clear descriptions in ocean environment is a significant problem in oceanography engineering [1]. The key challenges that ocean imaging suffer from severe degradation due to scattering by impurity and organisms in water. The underwater image quality plays an essential task for examining survey of undersea populations, ocean mines, shipwrecks, coral reefs, telecommunication cables and evaluating biological surroundings. Acquiring ocean descriptions is tough typically owing to haze causes light reflections, scatterers by element underneath and color alteration owing towards wavelength reduction [2] results blur, partial visibility and color variation. The element such as sand, minerals and plankton also results haze. The reflected beam from substance propagates to camera absorb and scatterers the ray. The multi-scattering process in [3] dissolves the ray keen on homogeneous surroundings of illumination. Usually processing underneath descriptions focuses to balance both scatterers or color deformation. The elimination of scatterers deformation contain polarization property balance visibility [4] to enhance undersea descriptions [5] and joining point spread and modulation transfer function decreases causes of blur [6]. Image enhancement based scheme do not acquire causes of degradation but mainly improve dissimilarity details as well as visual property. Recently lots of researchers have widened preprocessing schemes for enhancing undersea descriptions. Traditional schemes increase perceptual eminence but failed to balance adaptive degradation. To undertake these issue a few researchers added more information for haze reduction. As scatters were indefinite task of depth was frequently under constrained. Although this method is mainly for improving haze visibility and generate exciting outcome but fail to support color because enhanced imagery does not always enclose maximum dissimilarity. In modern day's major development of haze elimination employ reasonable priors or assumptions to exploit local dissimilarity for enhancement.

In this paper, we use hybrid undersea image enhancement method to enhance image via wavelet domain gradient guided filter. Our contributions are five-fold: (1) locally adaptive non locally robust regularization for deblurring the image; (2) use open dim channel model to improve visibility efficiently; (3) gradient guided filter to enhance details; (4) exploit soft thresholding for noise removal; and (5) projected approach boost perceptual visibility as well as details, but decrease noise effect. Tentative outcome prove that the projected scheme removes blur, advance visibility, enhance details and remove noise more faithfully with state-of-the-art process.

The paper is organized as follows. Section 2 provide a review of prior art. Section 3 includes details of projected method. Section 4 presents tentative outcome and analysis. The last section concludes our paper.

2. Previous Art

In this section conventional dehazing methods are summarized with wavelet domain gradient guided filter. Image enhancement methods not necessary for solving substantial type of degradation, but relatively enhance the picture from human visual perception. Histogram equalization [6] represents a basic algorithm to solve small dissimilarity imagery. It compresses brightness to get more uniform exposure characteristics but causes "halo" and brilliance distortion. The contrast limited adaptive histogram equalization [7] scheme remove fog effects, but lead to noise amplification in some hazy imagery. Multi-scale Retinex [8] is to boost dissimilarity and brilliance, but lead to halo phenomena in some sharp boundary or cause whole picture too bright. Homomorphic filtering [9] based light model practiced foggy color imagery and

Copyright © 2018 Authors. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

achieved good enhancement but cannot enhance a foggy image with dense fog or inhomogeneous fog. High Boost Filtering [10] enhances an image by amplifying high-frequency part to improve visibility and boundary but causes color distortion and noise amplification. To undertake this difficulty, prior details are added to increase intensity.

In recent years, [11] uses DCP priors invalid when picture appearance inherently alike airlight or true hazy picture. Later, [12, 13] employ empirical study on local patches in improved descriptions enclosed small albedo rate in any RGB channel. Later, uses soft-mating method for decreasing haze consequence. Soon after, [14] established boundary restraint taking place in transmission purpose, since [15] offered new color alteration for obtaining consistent diffusion but under-estimate whole picture. Differently, [16] initially decompose high-excellence imagery into dissimilar spatial levels for eliminating haze but difficulty in choosing decomposition stage. Presently, [17] used wavelet transform to get better contrast, but fail to maintain true texture facts. Despite this significant development are unacceptable for noisy imagery.
The wavelet structure in [18] takes care of the difficulty in frequency field, uses [19] for maintaining edges but undergo halo artifacts as confined linear form cannot signify image well near some edges. Later [20] introduces gradient GF by including a boundary-aware constraint into previous GF for avoiding halo artifacts but it fail to conserve boundaries. Recently, [21] introduced gradient domain filter to enhance undersea deblurred descriptions. The scheme leads to most visual excellence near the boundaries than existing schemes.

3. Proposed Methodology

The hybrid approach for recovering true picture from blurry and noise descriptions are exposed in Figure 1. The primary phase is to create blur with numerical form, added by Gaussian white noise to produce blurred & noisy picture. For color imageries, y component after iterations eliminate blur. In deblurred image few pels have little intensity in any one RGB channel, so [18] uses open dim channel process to increase visibility, soft thresholding to denoise the image and guided filter (GF) to preserve boundaries. But GF can't correspond to image fine close to a few boundaries. So we proposed Gradient guided filter (GGF) by incorporating a boundary-aware restraint into GF to preserve the edges better. Finally the image is well enhanced via the wavelet domain gradient guided filter. Tentative results with proposed approach shows eminence metric values related towards earlier methods.

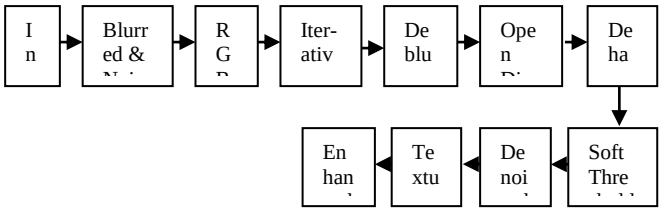


Figure 1: Block diagram of Proposed Methodology

3.1 Image Deblurring

In modern days, there has been an emergent concern for learning sparse representation [22, 23]. The major purpose is to learn dictionary using compacted sub-dictionaries are grouped into several groups. While every group contains several areas with alike pattern, a compacted sub-dictionary learned from each group. Mainly, we employ principal component analysis (PCA) method to train sub-dictionaries. To code image patch, top sub-dictionary that is generally relevant is selected; whole image can be more accurately reconstructed. For low complexity, we can compute the remoteness among two patches as follows:

$$dist(b_r, b_c) = \exp\left(-\frac{\|b_r - b_c\|_2^2}{h}\right) \tag{1}$$

where b_i and b_j represent patch position and h denotes balance factor for managing bias. The spatially adaptive regularization is considered as follows.

$$\hat{\alpha} = \arg\min\left\{\|B - H\phi\alpha\|_2^2 + \sum_{r=1}^{N}\sum_{c=1}^{m}\lambda_{r,c}|\alpha_{r,c}|\right\} \tag{2}$$

where $\lambda_{r,c}$ signify regularization factor for the r^{th} coefficient c^{th} column in dictionary.
Now let us consider local regularization term is characterized in vector model as

$$J_L(D) = \sum_{r=1}^{N}\left\|(I - W_1)D_r\right\|_2^2 = \left\|(I - W_1)\phi\alpha\right\|_2^2 \tag{3}$$

The nonlocal constraint is denoted in a vector model as

$$J_{NL}(D) = \sum_{r=1}^{N}\left\|(I - W)D_r\right\|_2^2 = \left\|(I - W)\phi\alpha\right\|_2^2 \tag{4}$$

Combining (2), (3) and (4), novel regularization term computed as

$$\hat{\alpha} = \arg\min\left\{\|B - H\phi\alpha\|_2^2 + \sum_{r=1}^{N}\sum_{c=1}^{m}\lambda_{r,c}|\alpha_{r,c}| + \gamma\|(I - W_1)\phi\alpha\|_2^2 + \eta\|(I - W_2)\phi\alpha\|_2^2\right\} \tag{5}$$

where a new regularization parameter γ is stable controlling AR regularization and η provides stability among local variation and nonlocal robustness. Later [24] employed these methods for deblurring underwater images.

3.2 Image Dehazing:

For visibility advancement, [13] give dim channel prior (DCP) technique to estimate scene depth. The enhanced representation has low gray level in one RGB model, tends to overrate haze thickness, which cannot handle particularly bright region. In most cases, best possible global underwater radiance is little dim than brightest pels. Further creating least operator as

$$o^{dark}(d) = \underset{B,b\in\Omega_d}{open}\left(\min_c\left\{\frac{I^c(b)}{U^c}, \frac{\tilde{I}^c}{\tilde{U}^c}\right\}\right) \tag{6}$$

where $\tilde{I}^c = 1 - I^c$ denotes inverse picture and $\tilde{U}^c = 1 - U^c$. For ease, the enhanced transmission inference process called open dark channel module (ODCM) is crucial to smooth by a boundary conserving filter. From ODCM, top 0.1 percent high intensity pel was chosen as global radiance. In [18], transmission is stable, often has a tendency to over-estimate haze thickness. To deal with this issue, we include inherent edge restraint and morphological open function for accurately estimating transmission map as

$$\tilde{t}(D)=1-\underset{J,b\in\Omega_D}{open}\left(\min_{c}\left\{\frac{I^c(b)}{U^c},\frac{\tilde{I^c}(b)}{\tilde{U^c}(b)}\right\}\right) \quad (7)$$

To preserve boundaries [19] used guided filter which assume linear relation among filtered and the guided image, though experience halo since do not indicate fine picture close to boundaries. This paper projected a gradient guided filter through primary-order boundary-aware constraint to conserve boundaries better than GF and generate enhanced imagery. A novel boundary-aware weighting defines by

$$\hat{\Gamma}_G(p^1)=\frac{1}{N}\sum_{p=1}^{N}\frac{\chi(p^1)+\varepsilon}{\chi(p)+\varepsilon} \quad (8)$$

where $\chi(p^1)$ is denoted as $\sigma_{G,1}(p^1)\sigma_{G,\varsigma_1}(p^1)$, ς_1 represents window dimension of the filter. The ultimate rate of $\hat{Z}(p)$ represents

$$\hat{Z}(p)=\bar{a}_p\,G(p)-\bar{b}_p \quad (9)$$

where $\bar{a}_p$ and $\bar{b}_p$ signifies average rate of a_{p^1} and b_{p^1} in the window, denoted as

$$\bar{a}_p=\frac{1}{\left|\Omega_{\varsigma_1}(p)\right|}\sum_{p^1\in\Omega_{\varsigma_1}(p)}a_{p^1}\quad;\quad \bar{b}_p=\frac{1}{\left|\Omega_{\varsigma_1}(p)\right|}\sum_{p^1\in\Omega_{\varsigma_1}(p)}b_{p^1} \quad (10)$$

The best possible standards of a_{p^1} and b_{p^1} signifies

$$a_{p^1}=\frac{\mu_{G\square X,\varsigma_1}(p^1)-\mu_{G,\varsigma_1}(p^1)\mu_{X,\varsigma_1}(p^1)+\frac{\lambda}{\hat{\Gamma}_G(p^1)}\left(1-\frac{1}{1+e^{\eta\left(\chi(p^1)-\mu_{\chi,\infty}\right)}}\right)}{\sigma^2_{G,\varsigma_1}(p^1)+\frac{\lambda}{\hat{\Gamma}_G(p^1)}} \quad (11)$$

$$b_{p^1}=\mu_{X,\varsigma_1}(p^1)-a_{p^1}\mu_{G,\varsigma_1}(p^1) \quad (12)$$

$\mu_{\chi,\infty}$ shown average rate of complete $\chi(p)$. η represents, $\eta=\frac{4}{\left(\mu_{\chi,\infty}-\min\chi(p)\right)}$. Consequently, boundaries improved well in proposed filter than the GF.

3.3. Image Denoising

Extremely, earlier dehazing approaches undergo noise in high frequency part, eliminated using soft-thresholding function as

$$S_\tau(D)=sign(D).\left(|D|-\tau\right) \quad (13)$$

where τ denotes threshold value and in general expected using median of first level decompositions. The degradaded imagery $I(D)=J(D)t(D)+U\left(1-t(D)\right)$, to find texture details through gradients. Using gradient form:

$$\nabla I_\Omega(D)=t_\Omega.\nabla J_\Omega(D) \quad (14)$$

where Ω denotes confined patch with small dimension. The high-band component, i.e., horizontal, vertical and diagonal information in gradients as

$$\nabla I_\Omega=\left\{\partial_d I_\Omega,\partial_b I_\Omega,\partial_b\partial_d I_\Omega\right\}=t_\Omega.\left\{\partial_d J_\Omega,\partial_b J_\Omega,\partial_b\partial_d J_\Omega\right\} \quad (15)$$

$$\begin{cases}\partial_d I_\Omega=t_\Omega.\partial_d J_\Omega & \text{horizontal}\\ \partial_b I_\Omega=t_\Omega.\partial_b J_\Omega & \text{vertical}\\ \partial_b\partial_d I_\Omega=t_\Omega.\partial_b\partial_d J_\Omega & \text{diagonal}\end{cases} \quad (16)$$

Using these gradients, wavelet coefficients are associated among low and high-frequency component adaptively.

3.4. Wavelet Transform Enhancement

The aim of dehazing is to get better scene radiance via the following equation:

$$J^c(d)=\frac{\left(I^c(d)-U^c\right)}{\max\left(t(d),t_0\right)}+U^c \quad (17)$$

Where t_0 a lower is bound developed to confine transmission and its typical rate is 0.1.

4. Results and Discussion

We conducted experiments to evaluate the effectiveness of our projected scheme. Primary module focus on deblur images by LANLR method to improve picture quality. Next module portraits dehazing process to improve visibility. Later module presents denoising to decrease noise in high-frequency parts. Finals part is to give quantitative evaluation of images acquired in undersea images.

4.1. Underwater Deblurring Evaluation

As displayed in Figure 2, matlab projected blur to create blurred imagery. Additive gaussian white noise by standard deviations of 1.414 is then added to blurred picture. To prove the effectiveness of deblurring we initially employ adaptive sparse domain to reconstruct but it create over smoothed outcome and a few ringing artefact around boundaries. Next used locally adaptive scheme for advancing quality and regularized smoothness but fail to develop local statistics. Later established non locally robust scheme to further improve quality of reconstructed imagery. The tentative results illustrated that proposed LANL approach outperforms many existing methods both visually and qualitatively

4.2 Underwater Dehazing Evaluation

As displayed in Figure 3, DCP underestimate the diffusion task tends to over-saturation. To compare this, projected scheme employs edge restraint and morphological filter for increasing imagery. As in Figure 4, an over-saturated result in [14], tend to undervalue the diffusion task. Over-saturated artifacts as well exposed in [15] while it try to get better image using edge restraint to restore bright colour and limiting over-saturation. Meanwhile [19] used GF for regularized transmission to smoothness and regularly transmit few texture information but decrease dissimilarity at far area. Similarly [18] removes haze control as well as noise contact concurrently but cannot conserve boundaries. Therefore, our pro-

jected approach better preserves the edges mainly suitable for enhancing undersea descriptions.

4.3 Underwater Denoising Evaluation

The DCP method was extremely perceptive to noise and underestimated. The major cause confined space by noise shall create entire space dim. As a result our projected technique is not sensitive to noise and expected diffusion map is mainly for proficient haze removal. The noise is gradually weakened by wavelet levels so noises in low-frequency resolve diffusion evaluation. The morphological filter is good to get rid of noise. However [18] selected wavelets decomposition to boost visibility in low-frequency whereas noise minimizing noise in high-frequency component adaptively; thus enhances picture clear enough. Therefore the proposed approaches further reduce noise as well improve texture information as in Figure 4. Tentative experimentation has exposed its excellent performance.

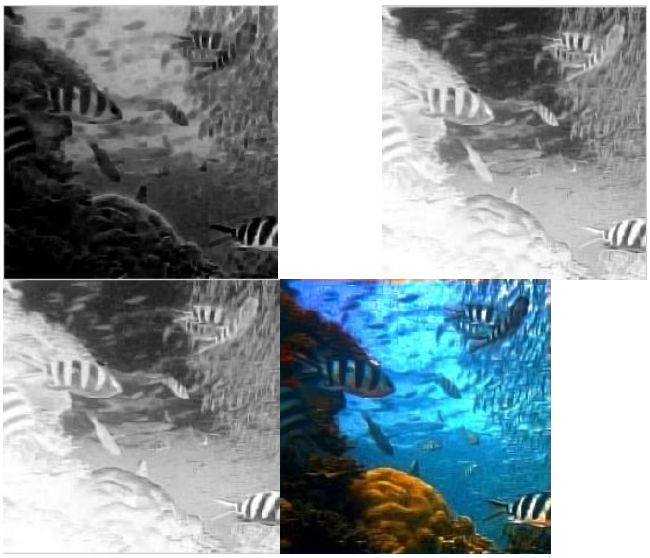
4.4 Quantitative comparison

As shown in Table 1, decomposition level 2 proved enhanced outcome among other levels. So we choose level 2 in all experimentation. Though, window dimension predetermined by 8×8 for every illustration shown in Table 2. Generally, haze frequently decrease visible boundaries and texture details. The quantitative metrics showed in Table 3 namely PSNR, RMSE, SSIM, e, $\bar{r}$ and σ, for dehazing undersea imagery. Higher PSNR, SSIM and lesser RMSE show improved quality of image. The descriptor e correspond to the rate of boundaries recently perceptible in enhancement; the $\bar{r}$ express the average gradient at perceptible boundaries; and σ convey the gain of pels which happen to entirely black or totally white subsequent to enhancement. Following, higher e and $\bar{r}$ show additional texture information thus generate improved enhancement result, whereas lesser σ signifies fewer data loss.

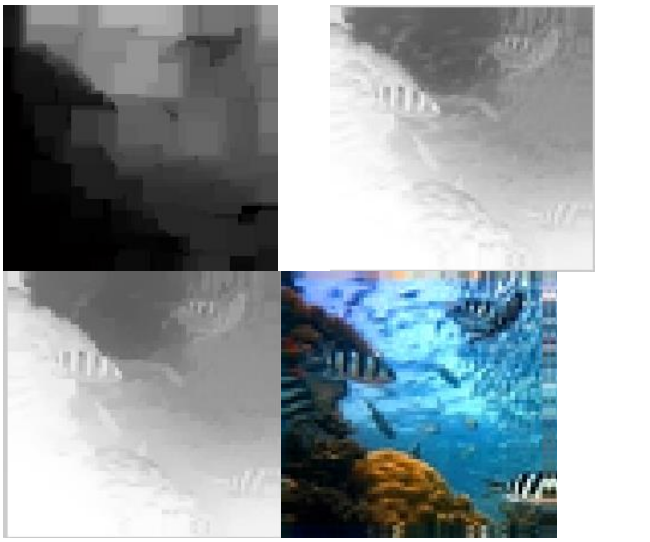


a)Blurred imag b) ASDS c)LAR d)LANL

Figure 2: Image deblurring results



a) Dark channel b)Transmission c) Gradient Guided Filter d) Radiance



e) Dark channel f) Transmission g) Gradien Guided Filter h) Refined radiance

Figure 3: Image dehazing results obtained by DCP and ODCM



a) Kai 11 **b) Gaof 13** **c) Kai 13**



d) Zhu 15 **e) Xin 17** **f) ours**

Figure 4: **Comparison of state_of _the_art methods**

Table 1: **Proposed method with different levels**

Ours	**PSNR**	**RMSE**	**SSIM**
level 0	66.307	0.123	0.9978
level 2	**67.777**	**0.104**	**0.9985**
level 4	66.392	0.122	0.9981

Table 2: The PSNR, RMSE and SSIM values of proposed method with various patch sizes

Methods	**2X2**	**4X4**	**8X8**	**16X16**
Xin 17	68.704 0.093 0.9987	68.297 0.090 0.9986	67.932 0.102 0.9985	67.777 0.104 0.9985
Ours	**68.706** **0.093** **0.9987**	**68.300** **0.090** **0.9986**	**67.935** **0.102** **0.9985**	**67.781** **0.104** **0.9985**

Table 3: Quantitative metrics of Proposed Method

Methods	**PSNR**	**RMSE**	**SSIM**	**e**	**σ**	**r**
Kai 11	63.154	0.177	0.9958	0.3854	0.3143	1.2966
Gaof 13	66.108	0.126	0.9981	0.0362	0.4852	1.3846
Kai 13	63.664	0.167	0.9961	0.2120	0.8850	1.2343
Zhu 15	65.776	0.131	0.9977	0.064	0.317	0.966
Xin 17	67.777	0.104	0.9985	0.0259	0.1846	1.2042
Ours	**67.781**	**0.104**	**0.9985**	**0.0242**	**0.1831**	1.2044

5. Conclusion

A hybrid underwater image enhancement via wavelet domain gradient guided filter is presented. The locally adaptive Non locally robust regularization for deblurring the image, which has small gray level in one RGB channel. Accordingly, open dim channel module offered to advance visibility and gradient guided filter for enhancing details. Although, projected technique established to remove haze and noise impact simultaneously. Finally, image is well enhanced via wavelet domain gradient guided filter. The projected process intends to boost perceptual appearance, however maintain extra texture information as well as diminish noise cause. Experimental results demonstrated that the projected schemes do better than various state-of-the-art processes both visually and qualitatively.

References

[1] Lebart K, Smit, Trucc and Lan, 2003. "Automatic indexing of Underwater Survey Video: Algorithm and Benchmarking Method," IEEE Jrnl. Ocean Engg,

[2] Trucco E and Olmo, 2006. "Self-tuning Underwater Image Restoration," IEEE Jrn. Oceanc. Enggn

[3] V Rossu and M. Nieuwe, 1999 "Multiple Scattering of classical waves: Microscopy, Mesoscopy and Diffusion," Revw of .Moden Phycs

[4] Schec and Karp, 2005. "Recovery of underwater visibility and structure by polarization analysis," IEEE Journ. Oceani. EnginL. Chao and M. Wang, 2010 "Removal of water scattering," Proceed. Intrn. Confr. Comptr. Enggn. Techn\

[5] Hou,D. Gry, Weidem,Fournr, and Forad, 2007. "Automated Underwater image restoration and Retrieval of related Optical properties," Procd. IGARSS

[6] ZhuH, Chan, La, 1999. Image contrast enhancement by constrained local histogram equalization. Comput. Visn & Imge understandg.

[7] Xui Z, Li M and Jia, 2009 "Fog removal from color images using contrast limited adaptive Histogram Equalization," IEEE Intr Congs on Img & Sign Procsge.

[8] Rahmn Z, J. Jobs and A. Woodel, 1996 "Multi-scale retinex for Colour Image Enhancement," in Proce. IEEE Intrn. Conf. Img Proceng.

[9] Seow M and K. Asar, 2007 "Ratio rule and homomophic filter for enhancement of digital color image," NeurocomptG.

[10] Gonzalz and Wood E, Digital Image Processing. Uppr Sadle Rivr, Prentce-hal
[11] Taral, JP, Hat N 2009. Fast Visibility Restoration from a single Color or Gray level image. Procee of IEEE Internl. Confr. on Comptr Visn.
[12] Kai H, Jia S, Tang Xiao Ta, 2009. Single image haze removal using dark channel prior. Proceedings IEEE Internl Confern Comptr Visn & Pattn
[13] Kai H, Jia S, Tang Xiao Ta, 2011. Single image Haze removal using Dark Channel Prior. IEEE Transcn. Patten Analy. Machn. Intellg.
[14] Gaof M., Wag Y, Dun J, Xiag S, Pa C, 2013. Efficient image Dehazing with boundary constraint and contextual Regularization. Proceedgs of IEEE Inter Conf Compter Visin
[15] Fattal R, 2014. Dehazing using Color-Lines. ACM Transct. Grph.
[16] Zhu Q, J Ma, LShao,2015. Fast single image Haze Removal algorithm using Color attenuation prior. IEEE Tran. Imge Processng.
[17] Rong Z, JunW, 2014. Improved Wavelet Transform algorithm for single image dehazing. Opti- Int.rn Jnrl. Ligt Electrn Opts.
[18] X Liu, H Zhg, Yiu Cg, Yuan T, 2017. Efficient single image Dehazing and denoising: An Efficient Multi-scale correlated Wavelet approach. Comptr Vis& Imge Understg
[19] Kai H, Jia S, Tang Xia, 2013. Guided Image Filtering. IEEE Tra. Patrn Analy. Machn. Intelgn.
[20] Fe Ko, Weih Chn, Chanun We, Zheno Li, 2015. Gradient Domain Guided Image Filtering. IEEE Transa on Imag Procs
[21] Chrispin J, Nagaraj R, 2018. Enhancement of Underwater Deblurred Images using Gradient Guided Filter. IEEE Inter Confer on RTEICT.
[22] Weisheng Da, Zha, Guan Shia, Xian W,2012 “Image reconstruction with locally adaptive sparsity and nonlocal robust regularization”, Sigl Procsg: Imge Commucn
[23] Weishg D, Le Z, Gua S, Xi W, 2011. "Image Deblurring and Super resolution by Adaptive Sparse Domain Selection and Adaptive Regularization", IEEE Transac on Imag Proceg.
[24] Chrispin Jiji, Vivek M. 2017. “Underwater Turbidity Removal through ill-posed Optimization with Sparse Modeling” IEEE Intern Confrn. on PCSI