HYBRID TECHNIQUE FOR IMPROVING UNDERWATER IMAGE

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ABSTRACT

As light attenuate when disseminating in water, descriptions confined beneath water is generally corrupted towards varying degrees. An acquired image underneath water gets degraded due to optical properties of light in water. First, we describe optical behaviour of light in ocean due to which acquired images gets degraded. However, due to degradation of observed picture, conventional forms are not correct enough for faithful reconstruction. So, to improve the perception, we intend a Non-Locally Centralized Method (NLCM) for deblurring underwater descriptions. Later by considering characteristic of light propagation, we propose Gradient Guided Filter (GGF) method for improving the visibility of picture details. Finally, the image is well enhanced by Hybrid technique called Non-locally centralized gradient guided filter (NLCM-GGF). Tentative outcome demonstrates that proposed technique produces improved results than several conventional techniques together in quality metrics and visual evaluation.

KEYWORDS

Underwater Image Processing, Deblurring, Edge preserving filters.

1. INTRODUCTION

Light always acts a significant task in oceanic explorer. Light transmission in sea is the base of ocular studies for describing light transmission procedure. Underwater image analysis attracts an increased level of attention as well as support of ocean application such as undersea exploration; see life in undersea, ocean rescue in Lebart *et al.* (2003) and species identification in Strachan (1993). Thus, it has been a challenging task to restore as well enhance underwater images reasons the variation in ocular property underneath. The main effect of degradation processes causes turbid, decreases visibility along with color distortion owing to ocular property. In particular, for severe absorption of light, confined picture is under exposed. In the meantime, altered wavelength of light has diverse absorbing characteristic in Seibert (1963), attained picture has cruel color distortion. Larger wavelength determines poorer attenuation in transmission medium. Shorter wavelength travel further, because of these undersea descriptions subject to blue or green color in Torres-Méndez and Dudek (2005). The water turbidity in Huimin *et al.* (2015) and organic element suspended on medium yields a hard restoration problem, since overall technique becomes highly dependent on environmental conditions.

Numerous works encompass to undertake those problems. For past decades, an extensive study has performed to build up a variety of reconstruction methods in Bertero and Boccacci (1998), and Chan *et al.* (2005). Based on ill-posed nature, several methods are widely employed to improve the restored picture. For effective process, it is very important to model earlier facts of natural descriptions. The classic models, such as quadratic Tikhonov as well as TV model in Oliveira, Bioucas-Dias, and Figueiredo (2009) are effective to decrease noise artefacts however have a tendency to over-smooth the descriptions based on piecewise steady statement. As a substitute, in modern era sparsity model in Daubechies, Defrise, and De Mol (2004) and Dong *et al*. (2011) shows the potential outcome for different reconstruction issues in Mairal, Elad, and Sapiro (2008) and Mairal *et al.* (2009).

In this paper, we intend hybrid technique for improving underwater image. Our contributions are two-fold: (1) Non-Locally Centralized Method (NLCM) for deblurring the images; (2) Gradient Guided Filter (GGF) method for enhancing the images. Finally, the proposed NLCM-GGF method better improve its quality than conventional technique.

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Tentative result shows that projected technique performs better than many conventional techniques together in quality metrics and visual evaluation. In the rest of the paper, we present short outline of earlier art and describe optical properties of light under water in section 2. Section 3 describes proposed hybrid technique. Section 4 describes tentative result; finally, section 5 brings to a close note.

2. MATERIALS AND METHODS

A variety of techniques has projected for getting better ocular excellence of degraded undersea descriptions, roughly classified into deblurring and enhancement process. Deblurring undersea picture is an ill-posed problem. As an essential issue in undersea description, reconstructions have widely considered in earlier years in Banham and Katsag (1997) and Bioucas-Dias and Figueiredo (2007). The ill-posed nature of IR is normally not exceptional. Past facts of typical descriptions employed to regularize such issues in reconstruction. The main model is total variation (TV) which lack flexibility for characterizing local picture structures but often generates over-smoothed results. To well keep up the picture boundaries, several methods have developed for improving TV model in Lysaker and Tai (2006), Beck and Teboulle (2009) and Chantas *et al.* (2010). The autoregressive (AR) modelling in Wu, Zhang, and Wang (2009) closely computes a primary representation which gives improved results than TV model to restore boundary formation, but have a tendency to generate ghost artefact.

In Buades, Coll, and Morel (2005) training-based adaptive scheme learns a better-quality learning pictures, to increase its accuracy. In modern era non-local (NL) in Kindermann, Osher, and Jones (2005) and Zhang *et al.* (2010) process has led a hopeful effect in several reconstruction schemes. The plan of NL process is straightforward: patch that contain related pattern be spatially distant and so we bring together in the image. In Dong *et al.* (2011) and Jiji and Vivek (2017), the edges are sharper than all the other process but there shows some ringing noise around edges and with different patches for reconstructing the images in Jiji and Ramrao (2017). With this aim, centralized NL method exploits NL redundancy to lower SCN noise.

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The NCSR method in Dong *et al*. (2013), use NL self-similarity for gaining fine approximation of sparse code coefficients, later integrate attained picture to those approximation. It is also characterized by training online sub-dictionaries by choosing most excellent online sub-dictionary for every patch. It employs Iterative Shrinkage-Threshold (IST) for solving l-norm trouble produced by model. Although the method achieved good, but never considers the statistical picture formation, therefore undergo artefact near boundaries.

Enhancement method does not rely on any picture formation, and enhances imagery by modifying scene pixel values. In Farbman *et al.* (2008) fine points in true description will smooth while keep boundaries to subtract smooth picture from true description for generating detailed picture. The mixture of range and domain filter in Tomasi and Manduchi (1998) keeps boundaries sharper, but experience gradient problems next to few boundaries. To avoid gradient reversal artifacts in He, Sun, and Tang (2013), picture elements in a window consider the structure of guidance image, but fail to signify close to a few boundaries. The boundary responsive factor in Li *et al.* (2015) lowers halo artifact which makes the edges better, but they cannot keep up edges well in some cases. The factors in Kou *et al.* (2015) signify the descriptions more correctly next to boundaries and keep up good boundaries. The work in Jiji and Ramrao (2019) is the extensive version primarily existed to improve the undersea imagery.

Here, we describe a hybrid technique for improving undersea descriptions which built upon the idea of NLCM exploit regulation limit determines the geometrical formation of image. A new method is particularly functional on boundaries of restored representation, so known as NLCM based Gradient guided filter (NLCM-GGF). Experimental results proved that the projected scheme gives much enhancement in both quality metrics and visual excellence than conventional technique.

2.1. OPTICAL PROPERTIES IN WATER

This section describes the behaviour of beam in undersea. Beam propagates in water medium is same as in air. Absorption denotes power reduction and scattering refers to deflection of propagation path. In underwater environment, beam also undergoes diffraction as well as refraction due to its wavelength and refractive index of water. Lambert-Beer empirical law states that the ocular property decay underneath material via exponential dependence:

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$$E_r = E_o e^{-cd} \tag{1}$$

where c denotes overall attenuation coefficient, d denotes the distance from an object. This model further decomposes in a form that openly expressed as

$$E_r = E_o e^{-ad} e^{-bd} \tag{2}$$

In order to deal with these effects another property volume scattering $B(\theta)$ as:

$$f = \frac{1}{2\pi}\int_0^{\pi} B(\theta)\sin(\theta)\,d\theta \tag{3}$$

The angle θ be integrated to get total scattering f. It theoretically considers all contributions coming from all directions. Modelling the backward scatter is more complicated than the forward one because it requires explicit volume scattering function. Four quantities a, b, c, $B(\theta)$ represents an ocular property of underneath medium. This resulting form used to predict ocular behaviour of light underneath.

For scattering, absorption as well as other optical properties always strictly related to specific medium composition. This fact justifies variability that we meet in dealing with them. Therefore, to concern picture arrangement process itself, direct, back-scattered as well as forward-scattered beam forms three additive total irradiance mechanisms, which mathematically expressed as:

$$E_T = E_D + E_B + E_F \tag{4}$$

Where light received by camera consists of three components: (i) object reflect beam with scattering, (ii) object reflect beam without scattering, (iii) back scatter part. For further details in Jaffe (1990) crucial quantities E_D, E_B and E_F as well analytical formulas that discussed in deep with definition of an expression for each part of whole irradiance.

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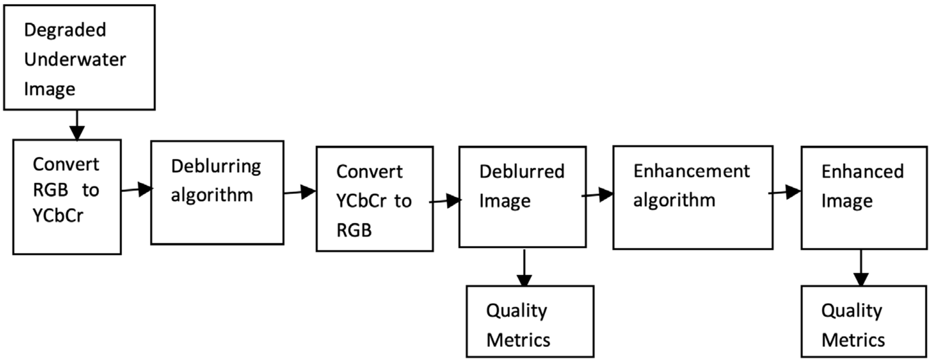

Figure 1. Block diagram of Proposed Method.
Source: own elaboration.

3. PROPOSED METHOD

The optical behaviour of beam in water will degrade the obtained pictures taken from underwater. In order to solve these issues, we intend a Hybrid technique that is able to deblur and enhance the underwater images depicted in Figure 1. Our hybrid approach consists of two main steps. In the first step, the Non-locally centralized method used for deblurring the scene. It mainly improves sparse restoration and suppresses the sparse coding noise. The main feature is to train online sub-dictionaries and choosing online sub-dictionary to each patch, using IST method for solving l1-minimization trouble created using such models. But it generates some ringing artefacts around the restored boundaries. In the second step, we introduce a Gradient guided filter (GGF) to improve edge sharpness. Finally, the output is well enhanced through Non-Locally Centralized Method via Gradient Guided Filter (NLCM-GGF). Experimental results proved that the projected scheme gives much enhancement in both quality metrics and visual excellence than conventional technique.

3.1. DEBLURRING ALGORITHM

The deblurring algorithm as depicted in Figure 2, blurred & noisy description *(b)* attained with blurring an ideal picture *(r)* with point spread function *(H)*, then imposing noise *(n)*, corresponding mathematical formula expressed as follows:

$$b = Hr + n \tag{5}$$

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In fact, some unknown quantities higher than known quantities; this problem becomes an ill-posed problem, which needs some other priori information.

To recover the reconstruction, first b is sparsely coded to solve minimization problem as:

$$\alpha_y = \arg\min\left\{\|b - H\phi\alpha\|_2^2 + \lambda\|\alpha\|_1\right\} \tag{6}$$

Conversely, reconstructing α_r from b is the very difficult task. For faithful reconstruction, we used in Dong *et al*. (2013) to reduce sparse coded image. The sparse coding noise stage represents

$$n_\alpha = \alpha_b - \alpha_r \tag{7}$$

By reducing n_α we can get better output. To suppress n_α, improve α_b, we propose the following model:

$$\alpha_b = \arg\min\left\{\|r - \phi\alpha\|_2^2 + \lambda\|\alpha_i\|_1 + \gamma\|\alpha_i - \beta_i\|_p\right\} \tag{8}$$

where β_i signify fine evaluation of α_i, γ signify regularize constraint and p will be 1 or 2.

To select dictionary, we cluster the patches by K-means clustering, then uses PCA in each cluster to find the sub dictionary. To code each patch, we enforce that particular patch by keeping sub-dictionaries as zero.

Hence sparse coding model as:

$$\alpha_b = \arg\min\left\{\|r - \phi\alpha\|_2^2 + \gamma\sum_i\|\alpha_i - \beta_i\|_p\right\} \tag{9}$$

Where β_i represents mass, average related by NL like patches

$$\beta_i = \sum_{t\in\Omega_i} m_{i,t}\alpha_{i,t} \tag{10}$$

where $m_{i,t}$ denotes weight. Related to NL means, we set weights as:

$$m_{i,t} = \frac{1}{w}\exp\left(-\left\|\hat{r}_i - \hat{r}_{i,t}\right\|_2^2 / h\right) \tag{11}$$

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where $\hat{r}_i$ and $\hat{r}_{i,t}$ denotes estimation of patch r_i and $r_{i,t}$ h represents predestined scalar and w denotes normalization part.

For each iteration, sparse vector represents:

$$\alpha_b^{(l)} = \arg\min \left\{ \left\| r - \phi\alpha \right\|_2^2 + \gamma \sum_i \left\| \alpha_i - \beta_i^{(l)} \right\|_p \right\} \tag{12}$$

For IST process, learning patches updated by present description of reconstruction and update PCA bases as well as by repeating neighbourhood choice with reorganized learning information. For every iteration by updating learning set with PCA bases, current test patch updated by $y = \{y_j\} = \left\{ \hat{r}_j \right\}_{j=1}^{M}$. The restored representation is then updated as $\hat{r}^{(l)} = \phi \circ \alpha_b^{(l)}$

3.2. GRADIENT GUIDED FILTER (GGF)

The deblurred output better reconstruct the image but it generates a few ring artefacts around the restored boundaries. With this aim, a Gradient guided filter (GGF) in Kou *et al.* (2015) is to improve edge sharpness. The filtered as well as guidance pictures are same for detailed output. The projected method gives an edge-preserved smooth picture. The difference among input with output gives detail layer, which is mainly for strengthening the output. In an edge, $a_{d'}$ denotes

$$a_{d'} = \frac{\sigma_{g,\xi_1}^2\left(d'\right) + \dfrac{\lambda}{\hat{\Gamma}\left(d'\right)}}{\sigma_{g,\xi_1}^2\left(d'\right) + \dfrac{\lambda}{\hat{\Gamma}\left(d'\right)}} \tag{13}$$

The rate of $a_{d'}$ is nearer to 1 if pixel $a_{d'}$ is in boundary, such that sharp boundaries are good in projected method than conventional technique.

In flat area, $a_{d'}$ is usually 0 and $\hat{\Gamma}(d')$ is smaller than 1 denoted as:

$$a_{d'} = \frac{\sigma_{g,\xi_1}^2\left(d'\right)}{\sigma_{g,\xi_1}^2\left(d'\right) + \dfrac{\lambda}{\hat{\Gamma}\left(d'\right)}} \tag{14}$$

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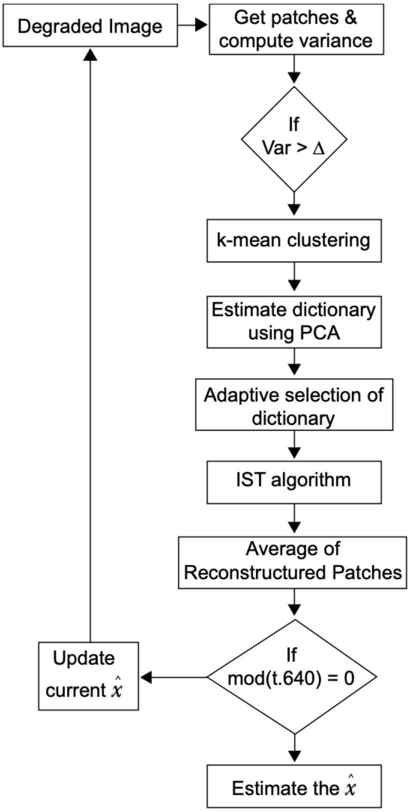

Figure 2. Flowchart of Deblurring algorithm.
Source: own elaboration.

In an edge, larger λ chooses for projected method than existing because choice will not affect edges. This means that projected method smooth flat area better than existing technique.

For these two cases the weighing function $\hat{\Gamma}(d')$ denoted as:

$$\hat{\Gamma}\left(d'\right) = \frac{1}{N}\sum_{d=1}^{N}\frac{\sigma^2_{g,\xi_1}\left(d'\right)+\varepsilon}{\sigma^2_{g,\xi_1}\left(d\right)+\varepsilon} \tag{15}$$

Where ξ_1 signify filter window dimension. The projected method is sharper by way of increasing of λ. Though, it has fewer artefacts even by larger λ. So, we used larger λ in projected method exclusive of halo artefacts.

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3.3. ENHANCEMENT METHOD

After the process of NLCM and GGF, we joined both to improved eminence of representation. For better reconstruction we employed NLCM method which generate sharper boundaries and restore best descriptions, but it produces some ringing artefacts around the reconstructed edges. To avoid these effects, deblurred output takes advantage of GGF for edge-preservation. The projected NLCM-GGF offer enhanced outcome than existing techniques for both evaluation metrics and visual perception.

4. RESULTS

Our projected scheme compared by various conventional reconstruction methods: ASDSARNL in Dong *et al.* (2011), NCSR in Dong *et al.* (2013) and DCFGGF in Jiji and Ramrao (2019). Our method also combines with BF, GF, WGF and GGF. Consequently, it is obligatory for comparing different edge filters to better keep edges. Here we carried out performance of various techniques, image evaluations.

4.1. Subjective Performance Comparison

Various methods of reconstruction include: ASDSARNL in Dong *et al.* (2011), NCSM in Dong *et al.* (2013), DCFGGF in Jiji and Ramrao (2019), NLCM-BF, NLCM-GF, NLCM-WF and NLCM-GGF.

To make sure the fairness of each assessment system, all test underwater images are pre-processed at size 256×256 pixels and processed by evaluated schemes with default parameters. The results in Dong *et al.* (2011) generate better visual excellence and evaluation metrics, though lesser patch dimension produces few artefacts in smooth areas. The results in Dong *et al.* (2013) much outperform Dong *et al.* (2011), produce sharper boundaries and further restore its quality. The projected smoothing layer in Figure 3 yields improved results than conventional schemes. Similarly, detail enhancement in Figure 4 is also much clearer and better than conventional schemes but there exhibit fewer edges in WGF than others. In Figure 5 we present hybrid result of existing and projected means.

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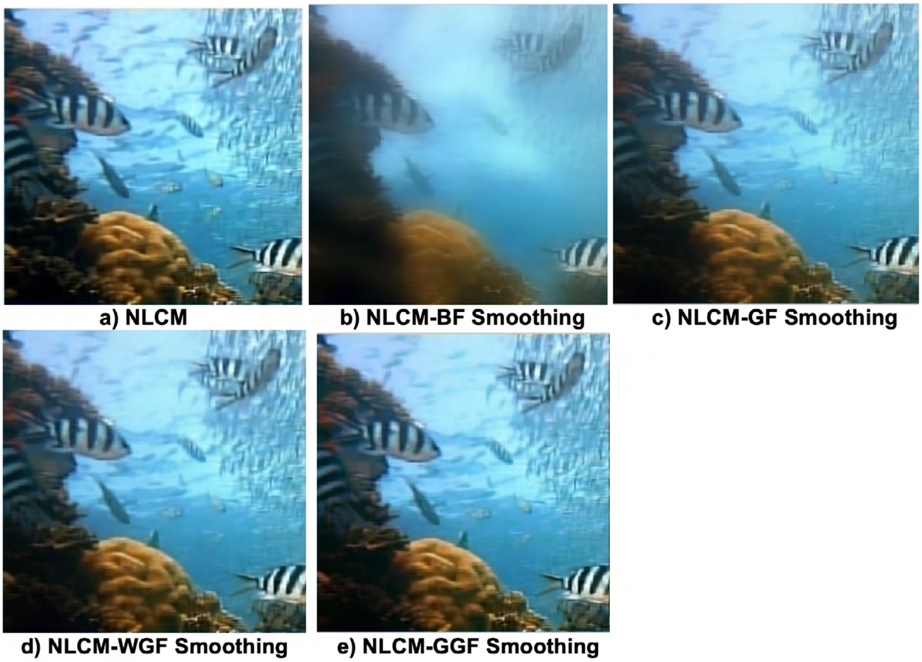

Figure 3. Edge smoothing results of Existing and Proposed Method.
Source: own elaboration.

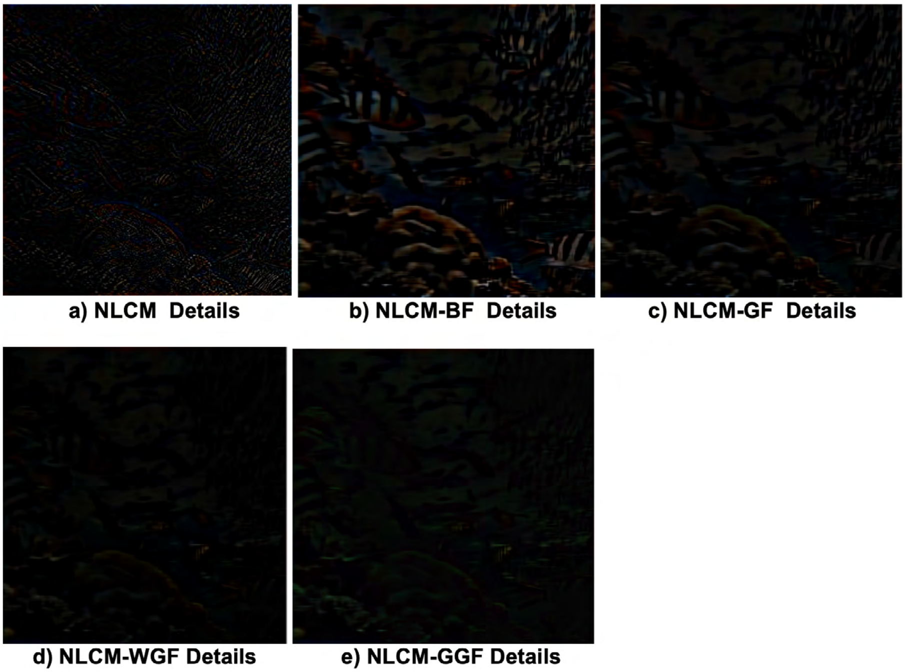

Figure 4. Detail Enhancement results of Existing and Proposed Method.
Source: own elaboration.

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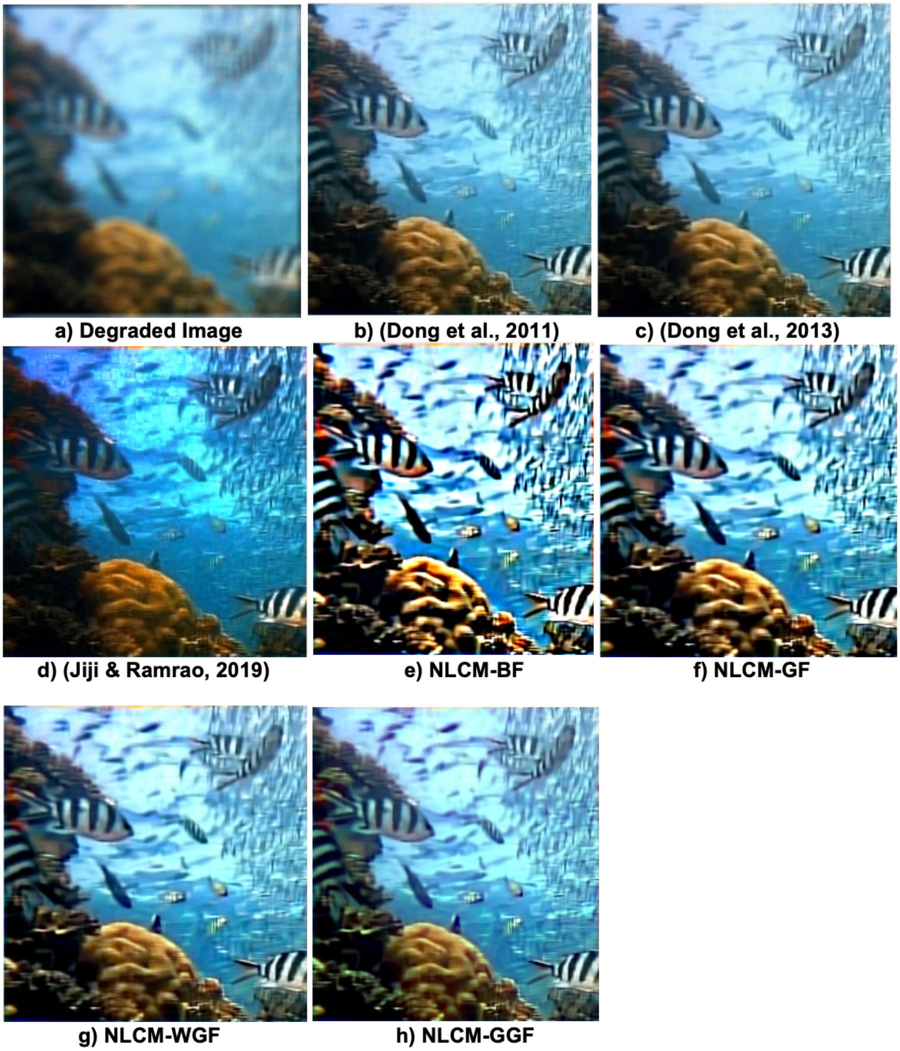

Figure 5. Enhancing performance evaluation of Underwater Imagery.
Source: own elaboration.

We observed that proposed process results much improved and enhanced details than conventional process.

4.2. OBJECTIVE PERFORMANCE COMPARISON

Image quality usually affected through imaging equipment, instrument noise, imaging conditions, image processing and other factors. Image Quality Assessment (IQA) is often

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separated into subjective qualitative assessment. Gray mean rate of picture reflects integral intensity and expressed as:

$$Mean = \frac{1}{RC}\sum_{r=1}^{R}\sum_{c=1}^{C} O(r,c) \tag{16}$$

Standard deviation reflects high frequency part that relates picture contrast. Higher values give better contrast.

$$SD = \frac{1}{RC}\sum_{r=1}^{R}\sum_{c=1}^{C}\{O(r,c), Mean\}^2 \tag{17}$$

Mean gradient reflects speed of changes in minor details of picture; it can represent description of grain transform and quantity of clearness well.

$$AG = \frac{1}{RC}\sum_{r=1}^{R}\sum_{c=1}^{C}\sqrt{\frac{\left[O(r,c)-O(r+1,c)\right]^2+\left[O(r,c)-O(r,c)+1\right]^2}{2}} \tag{18}$$

Entropy interprets as average uncertainty of data. When applied to images, it represents abundance data observed in picture. Higher entropy gives more uniform contrast

$$Entropy = -\sum_{r=1}^{L} P(O_r)\log_2 P(O_r) \tag{19}$$

Mean Square averages squared intensity differences of among distorted and reference representation as

$$RMSE = \sqrt{\frac{1}{RC}\sum_{r=1}^{R}\sum_{c=1}^{C}\left[O(r,c)-O'(r,c)\right]} \tag{20}$$

where *R*, *C* denotes row and column, $O(r,c)$ remains original with $O'(r,c)$ denotes deblurred picture. Peak SNR (PSNR) signify a key meant for signal alteration.

$$Peak\ SNR = 10\log\frac{O_{\max}^2}{MSE} \tag{21}$$

Where O_{max} represents maximum gray rate. Higher PSNR value represents lesser distortion. Generally, ocular view in Wang and Yuan (2017) and Wang *et al.* (2004) particularly adapted to extract picture information, thus process image excellence by three mechanism specifically; luminance $l(I,O)$, contrast $C(I,O)$, structure comparison $S(I,O)$. Thus, similarity computation represents

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$$S(r,c) = F\left(l(I,O), C(I,O), S(I,O)\right) \tag{22}$$

The similarity of two images has a rate among [0, 1]. When it is close to 1, two descriptions are more similar.

In Yang and Sowmya (2015) underwater color image quality evaluation (UCIQE) represents contrast, chroma and saturation expressed as:

$$UCIQE = c_1\sigma_c + c_2 con_l + c_3\mu_c \tag{23}$$

Where σ_c, con_l and μ_c represent standard deviation, contrast and mean, c_1, c_2, c_3 represent these three weights. Higher UCIQE metrics have improved results than conventional schemes. Similar to UCIQE, undersea image quality measure (UIQM) in Panetta, Gao, and Agaian (2016) constructed linear combination of UI colorfulness metric (UICM), UI sharpness metric (UISM) and UI contrast metric (UIConM). Thus, larger UCIQE and UIQM, improved undersea color image quality will be.

$$UIQM = \alpha UICM + \beta UISM + \gamma UIConM \tag{24}$$

Where α, β, γ signifies weight coefficients to organize each measure as well as balance their rates. Higher UICM value indicates improved color of undersea descriptions. Table 1 shows assessment metrics of conventional and projected technique.

Table 1. Comparison of quality metric with existing and proposed methods.

Methods / Quality metrics	DEBLURRED IMAGE		ENHANCED IMAGE				
	(Dong *et al.*, 2011)	(Dong *et al.*, 2013)	(Jiji & Ramrao, 2019)	NLCM-BF	NLCM-GF	NLCM-WGF	NLCM-GGF
Mean	127.34	127.36	96.639	126.81	126.73	127.22	127.29
SD	71.236	71.153	67.783	94.869	86.831	77.084	74.339
AG	9.226	8.065	10.194	23.761	18.507	12.988	11.681
Entropy	7.933	7.941	7.541	6.351	6.984	7.536	7.619
PSNR	24.10	26.231	65.843	66.916	70.956	72.255	72.417
RMSE	13.717	0.752	0.139	0.115	0.072	0.062	0.061
SSIM	0.619	12.443	0.9977	0.9990	0.9997	0.9998	0.9998
UICM	-45.558	-45.555	-62.107	-33.899	-39.299	-43.522	-44.177

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UIConM	0.736	0.728	0.785	0.305	0.583	0.701	0.681
UISM	6.906	7.007	7.105	7.827	7.289	7.057	7.073
UIQM	3.389	3.388	3.155	2.449	3.131	3.364	3.278
UCIQE	32.073	32.112	35.233	35.597	33.729	32.548	32.423

Source: own elaboration.

5. CONCLUSIONS

An acquired image underneath water gets degraded due to optical properties of light in water. However, due to degradation of observed picture, conventional forms are not correct enough for faithful reconstruction. In this paper, we proposed a hybrid technique for improving undersea descriptions. First, we used a Non locally centralized (NLCM) method for deblurring underwater descriptions, later gradient guided filter algorithm to improve the visibility of picture details and finally a Hybrid technique called non-locally centralized gradient guided filter (NLCM-GGF) gives improved results. Experimental results of proposed technique perform better than many conventional techniques together in quality metrics and visual evaluation. Nevertheless, when the illumination is very uneven, enhancement limits the local dark region, and it requires further research.

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