Enhancement of Underwater Images in Low-to-High Turbidity Rivers

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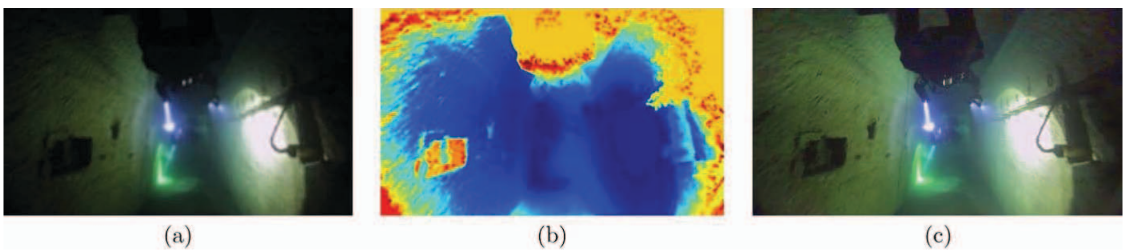

Fig. 1. Teasing result of our method: source image (a); saturation map (b); saturation map is used to enhance the contrast based on the worst saturated part of image corrections in illumination and in color, that will produce our result (c).

***Abstract*—The demand for efficient enhancement methods of underwater images of the rivers in the Amazon region is increasing. However, most of those in the region present moderate turbidity and low luminosity. This work aims to improve these images by non-linear filtering techniques, which promote the minimization of light interaction characteristics with the environment, loss of the contrast and colors. The proposed method is compared with two others techniques that requires a unique image as input. The results of the proposed method is promising, with better visual quality considering a wide range of experiments with simulation data and real outdoor scenes.**

***Keywords*-Underwater Images; Image Enhancement; Degraded Images.**

I. Introduction

Several factors intervene in a negative way on the visual quality of outdoor images. In aerial environments, there is mist, fog, rain, smoke and hail, while in underwater environments, degrating factors arising mainly from the properties and the way light interacts with the environment, leading to difficulties in accessing and understanding the information contained in the image [1], [2], [3].

The underwater images are typically less defined that most of the images acquired in the atmosphere, as they are subject to a strong negative influence of the environment as particulate matter, air bubbles and in addition to several other problems involving the propagation of light in the liquid medium, as well to produce light reflections and low lighting.

Mitigating the impact of negative factors becomes, therefore, a necessary requirement for applications such as automated guided systems of ground and aerial vehicles, recognition of outdoor objects and air or underwater remote sensing, including also automatic tracking systems for low visibility environments.

The degradation of visual quality of the images promoted by these phenomenons is modeled as a function that relates the density of suspended particles with the distance from the camera to the scene. Thus, the visibility depends on the extension of spreading of the luminance caused by these particles in the phenomenon [4]. To promote the development of an enhancement images system that improves visibility in poor conditions means mitigate the effects caused by this spreading.

Adding to this, one has the negative influence due to the problem of non-uniformity of illumination on the scene. This factor is directly related to the intensity of light that is captured by the sensor through the camera lens, creating overexposed (lighter), and underexposed (darker) regions. In any case, it is not easy to see and interpret the information contained in these regions [5].

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Contributions: This paper discusses the problem of the enhancement of images acquired from scenes immersed in an underwater environment, more specifically, in rivers from the Amazon basin with either low or medium turbidity levels and low luminosity. The proposed method uses a combination non-linear techniques of Digital Image Processing to treat and mitigate the impact of degrading factors typical of such environment.

A. Related work

In underwater images one observes, on one hand, regions that have higher values of color saturation and luminosity as a strong indication of objects located closer to the camera sensor. And, on the other hand, lower values indicate regions with more distant objects. This is directly related to the fact that the image formation process quickly degrades with distance [6].

Any attempt to enhance images neglecting the depth of the scene can compromise the quality of the achieved improvement. In this context, the saturation map proposed in [6] is used to estimate the regions where the enhancement process is more or less challenging. It allows to remove regions/objects that are farther away from the camera or low-quality of lightning and opacity of colors that may corrupt the automatic adjustment. This is valid not only for light (intensity), but also for color saturation.

The problem of non-uniformity of lightning is treated using the homomorphic filtering [7], [8]. More specific, the authors applied the high-pass Butterworth filter proposed in [5] for treatment of the frequencies reflectance and luminance.

The contrast enhancement step aims to improve the image details, such as texture and color of the objects present in the scene. It is based on a deeper analysis of the histogram of the intensities before and after the application of homomorphic filtering. In this scenario, we realized that even after a better occupation of the gray levels and distribution of lightning, contrast enhancement in general was not satisfactory. This is due to low-quality images and/or light, feature artifacts compression and regions with underexposed information. Thus, noised present in dark areas are maximized. These issues were also observed in [5], [9], [10].

To minimize the effects of this loss of contrast, we seek to recover the quality of opaque colors and keep the information of the borders. To do so, we use contrast expansion techniques as proposed in [5], [11], [12], [13]. These studies showed good results by applying contrast expansion algorithms in channels S and V in the HSV color space and each of the RGB channels. Besides, one may also workout the color contrast equalization, by minimizing the predominance of certain colors; like in water rivers with a loamy and black-red tones. In our work, the contrast expansion algorithms are applied separately in regions considered satisfactory, and excluded the poor quality ones according to the estimated saturation map.

B. Technique overview

This study aims to develop an automatic enhancement method comprised of four steps to achieve the improvement of a single degraded input image, as can be seen in Fig. 2. Further details of each step are explained in the following sections.

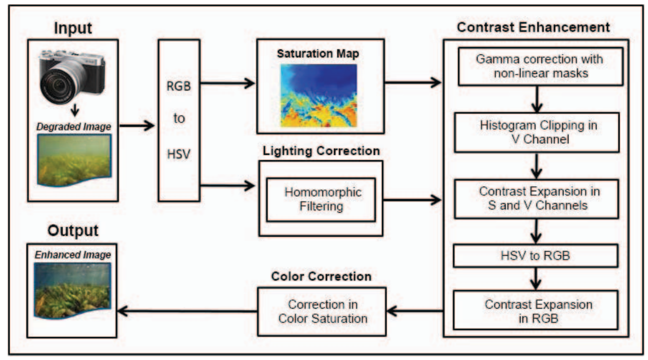


Fig. 2. Flowchart of the proposed method.

II. Technical background

In this section, we detail the steps of the proposed method. Starting with the Saturation Map to the Color Saturation Correction.

A. Saturation Map

Conventional image processing algorithms are not suitable for underwater image enhancement due to space variant degradation in the image formation process. If such characteristic is neglected, and depending on the range encompassed by the scene, measured from the farthest visible point, the enhancement process will certainly fail either for the closest or the farthest observed scene points.

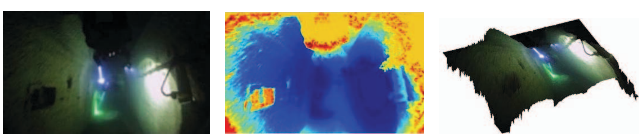
Since we assume that only a single input image is provided to our restoration system, and considering the lack of information about the medium parameters and the acquisition system, even a rough approximation of the distance map is a very difficult task to accomplish. However, by observing the behavior of the values related to the saturation and luminance of a point of interest as it moves away from the camera, and using this information in the image formation model, we observe that it is possible to estimate a map that indicates the regions where the restoration process should be applied either more or less aggressively. We call this the *saturation map* and its computation is described next.

The procedure is based on the image model of Equation 1, proposed by [14], where L_d is the luminance of the input signal related to the d distance between the point at (x_o, y_o) and the optical center of the camera, L_0 is the original image radiance, c is the attenuation coeficient, β is a proportionality constant that depends on the wavelength of the light, as described in [14].

$$L_d(x_o, y_o) = L_0(x_o, y_o)\mathrm{e}^{-cd} + \beta(1 - \mathrm{e}^{-cd}). \qquad (1)$$

The saturation map is calculated in order to obtain a rough approximation to the cd term of Equation 1. Thus, the original image radiance, L_0, is approximated by a histogram equalization of the underwater image luminance, L, and an approximation of the L_∞ term is obtained through observing pixels from the underwater image with both low saturation and luminance values. Hence, this is achieved by looking at the darkest pixels (low luminance) that were contaminated by the backscattering effect and, therefore, have low chromatic purity (low saturation). After these approximations are performed, the saturation map, $\mu(x, y)$, can be directly estimated by the cd term of Equation 1.

This saturation map was first proposed in [6]. The idea behind the saturation map is to indicate where the enhancement should be more or less intensified. In the Fig. 3-(b), the saturation map is illustrated where the red colors are related to closest points and blue ones are the fartest. The Fig. 3-(c) shows the same map of saturation, however, represented as a rough approximation of the tridimensional view of the scene.



(a) (b) (c)

Fig. 3. Saturation map. (b) and (c) are estimated maps from the image (a). The image (c) shows a 3D view of the saturation map.

This map is used for contrast enhancement step and is obtained using only the information of saturation and luminosity image as shown in 1, adapted from [6].

Algorithm 1 Saturation Map

Require: Degraded image in HSV colorspace (IdegHSV)

1: Apply contrast expansion function, $E_{contrast}$, in the luminosity area of the IdegHSV to obtain an approximation $\mathcal{L}_0 = E_{contrast}(I_{lum})$
2: Calculate the saturation I_{sat} and luminosity I_{lum} thresholds of the image IdegHSV
3: Detect the positions (i, j) of IdegHSV that have saturation and luminosity less than the calculated threshold
4: Make *mapCompCromatica*(x, y) receive the located positions (i, j)
5: Estimate $\mathcal{L}_\infty = \overline{[\mathcal{L}_{0_{lum}}(i, j) - I_{lum}(i, j)]}$
6: $\mu(x, y) \leftarrow \ln(\mathcal{L}_0 - \mathcal{L}_\infty) - \ln(L - \mathcal{L}_\infty)$
7: Locate the group of regions W, where the map $\mu(x, y)$ have indeterminate values
8: Review the map $\mu(x, y)$ with the values found in the neighborhood of the regions in W
9: **return** Normalize $\mu(x, y)$ and *mapCompCromatica*(x, y)

where $\mathcal{L}_0$ and $\mathcal{L}_\infty$ are approximations of L_0 and L_∞, $\mu(x, y)$ is the normalized saturation map and *mapCompCromatica*(x, y) is the chromatic compensation map containing regions with poor lighting and color saturation.

B. Lighting Correction

The second step aims to correct the non-uniformity of illumination commonly present in our working environments. This step makes the lighting becomes as more homogeneous as possible over the scene, allowing the information to became perceivable in both underexposed overexposed areas.

According to [15], the homomorphic filtering is a technique to transform an image from a two-dimensional Cartesian plane into another coordinate system, so that the enhancement image operations become easier to apply. In the problem at hand, the process is used to enhance images with bad lighting conditions. As explained in [16], the ideal situation would be to generate the original set of objects in an image without having to take into account the impact of lighting on the objects. Unfortunately that cannot be disregarded, or all images would be dark and featureless.

The Equation 2 is the function that describes mathematically how to deal with this issue [17].

$$f(x, y) = i(x, y) \cdot r(x, y) \quad (2)$$

where $f(x, y)$ is the captured image, $i(x, y)$ lighting and $r(x, y)$ the reflectance of the objects in the scene. Now we must consider that the lighting in underwater scenes tends to vary relatively slowly through an image. The reflectance is characterized by abrupt changes, especially at borders (edges). This means that illumination are dominant on low frequency components, and reflectance on middle and high frequency, and a high-pass filter can reduce the issue. Therefore, it is necessary to convert the image to the frequency domain where the operations will be simplified. in the paper we use the Fast Fourier Transform, as shown in Equation 3.

$$\Im\{f(x, y)\} \neq \Im\{i(x, y)\} \cdot \Im\{r(x, y)\} \quad (3)$$

In accordance with [16], [17] and [18], the process to obtain the correction of the image is performed in five steps.

Step 1: Applies to the logarithm of the original image in gray scale (or in the V channel of HSV color space, if it is color).
Step 2: Applies to the Fast Fourier Transform.
Step 3: Adds the high-pass Butterworth filter.
Step 4: Returns to the space domain with the inverse of Fourier Transform.
Step 5: Finally, the exponential is applied to the image to reverse the effects of the logarithm of Step 1. Thus getting the filtered image.

This filtered image is the input of the next step. If the intensities are high, additional improvement can be achieved by a simple thresholding filter, as in [19].

In this work, we used the Cooley-Tukey algorithm [20] implementation version of the Fast Fourier Transform (FFT). The filtering of the high-pass Butterworth was used to obtain a clearer image, attenuating low-frequency components without affecting the high-frequency information in the

Fourier. Equation 4 represent the expression of a high-pass filter in concerned.

$$H(u,v) = \frac{1}{1 + [D_0/D(u,v)]^{2n}} \quad (4)$$

where n is the degree of transform, D_0 is a constant that determines the cut-off frequency of the pass filter and $D(u,v)$ is the distance between a point (u,v) in the frequency domain to the center of the spectrum. The $D(u,v)$ can be obtained with Equation 5.

$$D(u,v) = \sqrt{[(u - P/2)^2 + (v - Q/2)^2]} \quad (5)$$

where P and Q are the sizes of the extremity of the image in the frequency domain.

C. Contrast Enhancement

The contrast enhancement step is initiated specifically aiming to recover details in the dark areas of pictures, as well as prevent the loss of information due to excessive brightness. This happens because its histogram is not limited to a global area of the image. To do so, ImgV_HF is applied, already processed with homomorphic filtering and a correction filter that uses non-linear masks using as a foundation a saturation map, as seen in 2 below.

Algorithm 2 Correction step of underexposed and overexposed regions

Require: $\mu(x,y)$, ImgV_HF, H and S channels of IdegHSV and *mapCompCromatica*(x,y)

1: Obtain in $\mu(x,y)$ an average distance in the regions with best saturation of the IdegHSV based on *mapCompCromatica*(x,y)
2: **for each** pixel p_i of the IdegHSV **do**
3: Obtain in $\mu(x,y)$ the average distance of 8-neighborhood of the pixel p_i
4: Estimate the ideal distance that p_i could have based on an average of the distance from the best regions of saturation obtained in line 1
5: Calculate the exponential value ^{exp} of the gamma filter correction
6: Make ImgV_HF_Corrected receive the result of the application of the *power*$(ImgV\_HF)^{exp}$ filter
7: **end for**
8: **return** ImgV_HF_Corrected

where ImgV_HF_Corrected represents an image with correction of underexposed and overexposed areas.

The next step intends to make use of the contrast expansion technique, considering the better color saturation and brightness regions identified in the saturation map, as suggested by [6] in their chromatic compensation map.

First, the expansion filter is submitted in S and V channels of the HSV color space. Then, the image converts to RGB and applied in each of the channels for stretching the dynamic range of image intensities in order to make the colors become brighter and dark colors become darker. This, in fact, promotes a better quality, lengthening the histogram so that the dynamic range is completely filled, as can be verified in the paper by [5]. This dynamic range is the interval between the minimum and maximum intensity value obtained after applying the threshold.

It is possible, after applying the contrast expansion filters, that some noises can be maximized. To avoid this, a contrast threshold is applied. This threshold is used to eliminate the effect of extreme values and improve intrinsic details in the image maintaining the contrast ratio. However, the values of the output pixels are redistributed in the range [0, 255], as observed in the work of [5], [10], [21].

To determine the contrast limit, and therefore, the amount of intensities that will be cut, we consider those containing saturated levels present at the ends of the histogram, specifically those that are distributed outside of the 97% range. This percentage value was obtained after the execution of numerous experiments, which resulted the best cut indicative.

D. Color Saturation Correction

This step allows minimizing the alteration of saturation of the colors between the input and output images in order that they stay more vivid, making it as close as possible the actual colors as well as those that have not been degraded.

Underwater images that suffer degradations originated from nature usually have opaque or turbid colors. To recuperate them and complete the processing chain, we apply a formula suggested by [21], used in [9] and [5]. The transformations promoted by the Equation 6 are applied to each RGB channel model producing new R', G'and B'values obtained as:

$$\begin{aligned} R' &= \frac{1}{2}\left[\frac{V'}{V}(R+V) + R - V\right] \\ G' &= \frac{1}{2}\left[\frac{V'}{V}(G+V) + G - V\right] \\ B' &= \frac{1}{2}\left[\frac{V'}{V}(B+V) + B - V\right] \end{aligned} \quad (6)$$

where V' is the lighting intensity value obtained in the non-uniformity of illumination and contrast enhancement with histogram cut correction steps, as observed in the previous sections. The values related to V, R, G and B are obtained from the input image.

III. Experiments

A. Evaluation Methodology

The experiments were simulated on a personal computer with Intel Core I7 2.3GHz processor, 8GB of RAM. The development environment used was MATLAB® r2015a. The proposed method was applied to twenty color images presenting degradations resulting from different natural anomalies that negatively affects in both the atmospheric environment and underwater. The tests were submitted in both environments in order to demonstrate to the reader the adaptability capacity, development and quality improvement that the method can achieve despite the types or number of issues treated in the image.

The test images have distinct visibility distances and rates of turbidity. They are classified into different scenarios, being scenes that present issues of non-uniformity of illumination and atmosphere and underwater issues. For each classification, four images have been selected and subjected to each of the three methods of evaluation. Details of the images that are beyond the visibility limit are not considered as regions to be recovered. The proposed method is submitted in HSV and RGB color spaces in various channels, as shown in Fig. 2.

The evaluation of image quality was performed primarily in a subjective manner starting from the observer's point of view. In each trial experiments, a pair of images is available for viewing for each of the 50 volunteer evaluators. Each pair of images consists of two versions of the same scene and a random appraiser was invited to respond, subjectively indicating which image was his favorite. Each version of a scene has been compared with all the other versions of the same scene, representing 40 pairs of images (20 images x 2 combinations). In total, two thousand experiments were performed as shown in Table I.

TABLE I
QUANTITATIVE EXPERIMENTS.

Environment of the Image	Quantity of Images	Combination of Pair of images	Quantity of Pair of Images	Quantity of Experi-ments
Illumination	4	2	8	400
Atmosphere	4	2	8	400
Subaquatic	12	2	24	1200
Total of Experiments				2000

In addition to the subjective evaluation technique presented above, another methodology was used to objectively assess the numerical data gathered to enable the measurement of quality indexes. Thus, three metrics gathered from the literature were applied to all images in order to estimate the brightness and contrast: Entropy (H), Absolute Mean Brightness Error (AMBE) and Measure of Enhancement (EME).

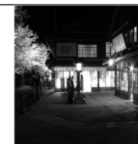
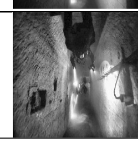
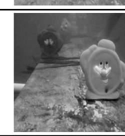
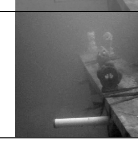
B. Condition of Assessment

To perform the psychovisual evaluation, the images were shown on an interface based on desktop applications. The 14" LED monitor of an Asus notebook with a resolution of 1366x768 pixels corresponding to 111.94 dpi and a refresh rate of 60 Hz was used in the tests. The lighting was composed of typical office lights and the ambient light levels were kept constant among the numerous sessions. The distance between the observer and the monitor was about 60 cm. All the original scenes used were re-dimensioning and sub-sampled to fit in a box comprised of 600x600 pixels.

IV. RESULTS AND DISCUSSION

The results obtained after performing the luminosity correction step are shown in Table II. The images are displayed in gray scale in order to allow for the identification of regions witch present improvements in both atmospheric lighting distribution and underwater.

TABLE II
COMPARATIVE CHART OF IMAGES WITH IMPROVED LIGHTING.

Atmospheric Images			
Original Images			
Images with Illumination Correction			
Subaquatic Images			
Original Images			
Images with Illumination Correction			

By analyzing the original images, the presence of areas with overexposure and underexposure in the intensity of illumination can be noted. It was also noted that the use of holomorphic filter combined with the correction of underexposed and overexposed areas using non-linear masks produced satisfactory results, specifically on the enhancement of images that had underexposed areas with presence of many dark pixels. On the other hand, areas that before were overexposed with occurrence of multiple light pixels and without information have been improved. The method shows stability when correcting images with issues occurring in both the atmosphere, as in underwater mediums.

The third step of the proposed method aims to adjust the brightness and enhance the contrast. Fig. 4 shows, in a gray scale image, the result obtained after performing the lighting improvement and contrast correction steps.

It is noticed that in Fig. 4-(a) because of the low light in the scene, much of the visual information is too dark for human vision. By utilizing the homomorphic filter in combination with the Butterworth filter, the details were slightly improved in Fig. 4-(b). However, there is light saturation of overexposed and underexposed regions present in the center and around the image, respectively. In Fig. 4-(c), the result of Fig. 4-(b) was applied in a filter using non-linear masks to make luminance become more evenly distributed in the scene and finally

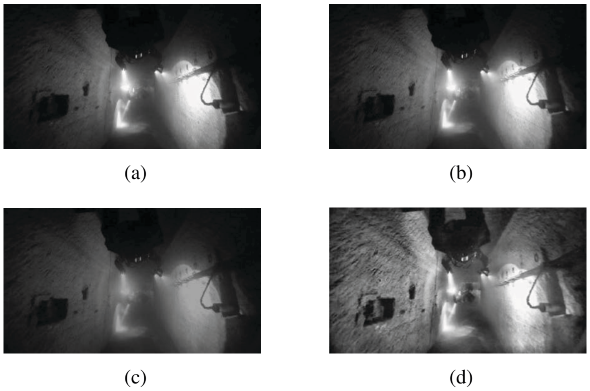
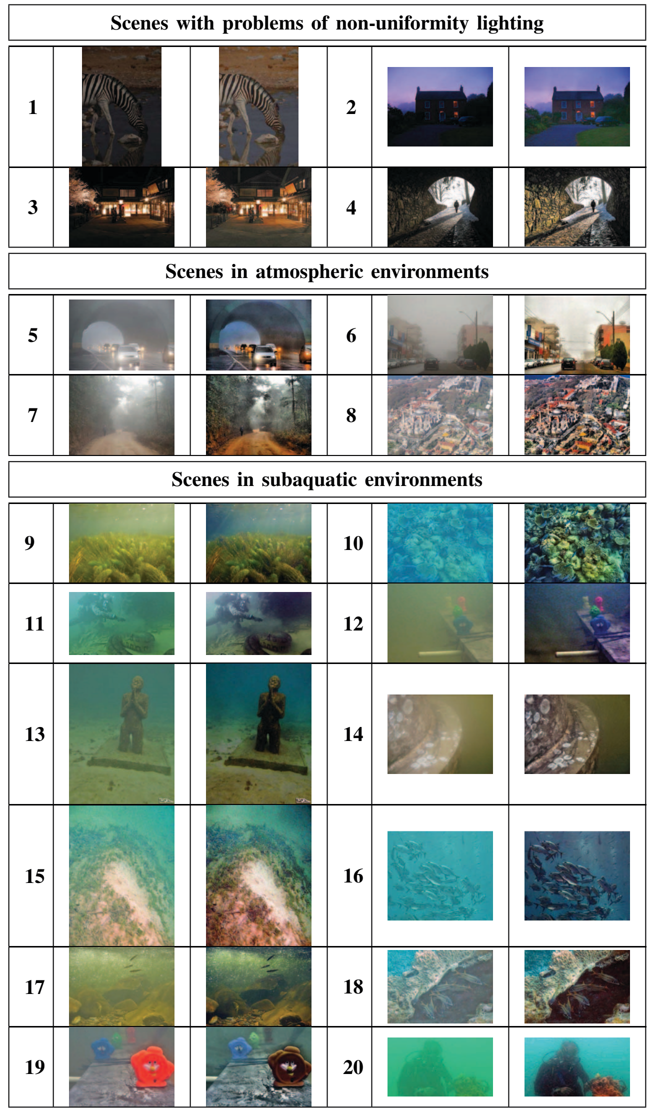


Fig. 4. (a) Original image with low light; (b) image with homomorphic filtering, (c) image with underexposed and overexposed areas correction filter and (d) contrast enhancement image.

TABLE III
COMPARATIVE CHART OF THE IMAGES BEFORE AND AFTER IMPLEMENTATION OF THE PROPOSED IMPROVEMENT METHOD.



in Fig. 4-(d), we note that the contrast was brought back, turning visible areas of the image that suffered degradation.

Table III presents the results obtained in three different scenarios in which the tests were submitted. Pairs of images before (left side) and after (right side) the application of the proposed method are shown. From a subjective evaluation, we can see significant improvements in all scenarios, whether in environments with severe lighting issues or in environments with problems arising from natural phenomenon, both in the atmosphere and in underwater environments with low and high levels of turbidity.

Table IV presents a comparative chart of images enhanced by the evaluated methods. We can see that the method of [9] does not present good results for underwater images, since it is not intended to treat the problems of lighting and opacity inherent in participatory environments, while other methods have better improvements from the point of view of subjective evaluation. This proves the importance and the need to treat the problems in a separately and sequentially way, which actually occurred in the proposed method.

The index score of preference was recorded for each methods and environments submitted to the test. The total score is 2000, corresponding to 100% of the votes. The proposed method scored 60.75% of the points, achieving first place. The other two methods, [12] positioned second place marking preferably 20% and [9] with 19.25% in third. In Table V the data of the subjective evaluation is shown.

When considering the quantitative score obtained by the proposed method shown in Table III, that is, the total of 1.215 (60.75%), Table VI describes in detail the satisfaction index (QoS) of the evaluators. The representative voting scenario shows that the method has high satisfaction among evaluators who chose this method as the best enhancement of quality.

The measure of the quality of an enhancement applied to an image after an improvement process is usually very difficult to accomplish. Until now, subjective criteria was applied to assess improvement in images. Literature can be found concerning objective metrics that aim to estimate the brightness and contrast of an image such as entropy (H), absolute mean brightness error (AMBE) and measure of enhancement (EME).

Table VII shows the average values of objective metrics obtained in each of the images enhanced by each evaluation method. It is possible to note that in all the metrics, the proposed method score was greater because it showed higher values. The results of objective evaluation are close the subjective evaluation scores.

Despite of the higher averages showing that the proposed method represents the best method, case-by-case analysis is deemed necessary since high values rates are not necessarily correspondent of better quality in terms of increasing the brightness and contrast [9].

In light of the results, let us examine the values of these

TABLE IV
COMPARISON TABLE OF THE IMAGES OF THE PROPOSED METHOD WITH THE EVALUATED METHODS.

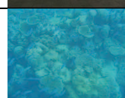
#	Iqbal *et al.*	Schettini *et al.*	Proposed
3			
4			
11			
12			
13			
16			
17			
19			

TABLE V
AVERAGE SCORE OPINIONS IN THE SUBJECTIVE EVALUATION.

Measure Methods	Punctuation x Environment				
	Luminosity without uniformity	Atmosphere	Subaquatic	Total	%
Proposed Method	204	206	805	1215	60,75
Schettini *et al.* [9]	191	194	0	385	19,25
Iqbal *et al.* [12]	5	0	395	400	20,00

metrics for image 8 of Table III. The H values indicates better occupation of all intensity levels on the histogram. This is associated with a visually pleasing image, considering the positive reasonably balanced conditions of image acquisition. The values of this metric for that image are $7.6334, 8.4562, 7.7634$ and 7.3561, respectively representing the result of the original image, the proposed method, Schettini *et al.* [9] and Iqbal *et al.* [12]. It is noteworthy that in this case, the highest value of Entropy represents, in fact, a reasonable pleasant picture. However, there are cases where this is not always what happens. [9] found similar behaviors in the study.

TABLE VI
SATISFACTION INDEX FOR THE PROPOSED METHOD.

MOS*	Quality	Deterioration	Quantity of votes	%
5	Excelent	Unperceptible	667	54.9
4	Good	Perceptible but not annoying	531	43.7
3	Reasonable	Lightly annoying	17	1.4
2	Degraded	Annoying	0	0
1	Terrible	Very annoying	0	0

* Mean Opinion Score

TABLE VII
AVERAGE VALUES OF OBJECTIVE METRICS BY THE EVALUATION METHOD.

Method	Metrics		
	H	AMBE	EME
Proposed	8.2689	31.2134	17.3873
Schettini *et al.* [9]	6.6156	27.6452	4.5683
Iqbal *et al.* [12]	7.1799	28.3863	10.9801

The AMBE represents the average distance from the original brightness, i.e., the difference of the average level of intensity in the new and original gray scale image. In an enhancement procedure, it is not always ideal to preserve the original brightness of the scene, considering the lighting uniformity problems must be fixed.

[9] state that preserving the original brightness does not mean always preserving the natural appearance of the image. He adds that, if the original images are strongly underexposed and/or overexposed, a high AMBE value is expected, indicating that the quality can be improved. In one hand, as an example, we have resulting images from the steps of corrected luminosity improving the contrast showing in the images 1, 2, 3 and 4 of Table III, more specifically, the image 3, which shows a AMBE value of $52,47$. On the other hand, in the case of correctly exposed images or pictures obtained in dark scenes (night), it is expected that our method does not significantly alter the average brightness. See other values of this metric for image 2 of Table III with such feature (proposed method = 19.39, Schettini = 20.46 and Iqbal = 34.38).

EME brings an average contrast in the image dividing it into blocks, which do not overlap. This definition is measured based on minimum and maximum intensity values at each block and the average of them. For analysis of this metric, high values should indicate regions with high local contrast, while values close to zero should correspond to homogeneous regions. If the improvement method introduces noise in such homogeneous regions, a higher value of EME will be obtained, and possibly not correspond to a better image quality. As an example, see the values of this metric in image 12 of Table III (proposed method = 8.1763, Schettini = 1.9832, Iqbal = 5.7634). In this scenario, we can see that our method was the one that presented the highest value, due mainly to the third step of the proposed method, which also adjust the highlights of the contrast and brightness, improving the enhancement of suspended particles issues in the participatory environment. On the other hand, this high value does not necessarily represent a negative factor that might compromise, circumstantially, the quality of the improvement obtained, given the quality of the results exposed by each method in the comparison Table III.

V. Conclusion

This paper presents a method: enhancement of degraded underwater images by natural phenomena that allows the improvement of visibility from a single input image without using any information from its model's formation. The improvement of visual quality of distant objects present in the scene is desired. Based on the images enhanced by the proposed method, it can be noted that most of the intensity of the xenobiotic phenomenon is minimized, promoting a better contrast enhancement, brightness and invigoration of colors when compared with other techniques. It is considered that the method is promising for presenting good results with low computational cost and useful for application in various systems that work in atmospheric and underwater environments.

When comparing the proposed method with other well-known solutions, we noticed a proper increase in dynamic range in both regions: low and high luminosity of an image, preventing the loss of quality due to artifacts, desaturation, low luminance and grayish appearance. The Mean Opinion Score (MOS) was used to evaluate the performance of different methods of contrast correction for color images. The highest score was achieved by the proposed method. The proposed method stood out on both subjective and objective evaluations and proved to be stable for satisfactory attempt on three different scenarios. The most significant improvement was achieved in underwater environment images, being the deciding factor that granted this method the highest score.

Despite the good results obtained, it should be noted that in environments with very high levels of turbidity (up to 10 cm visibility) or with very low luminosity, the method could not obtain satisfactory results, meaning the objects present at the scene were not visible. The enhanced images in this scenario presented only the intensity of the predominant color in the image, in other words, increasing the clay color and/or dark red, the characteristic colors of the soil of the beds of Amazonian rivers: Solimões and Negro Rivers respectively.

Additional improvements may be obtained from using an optimization process to estimate the parameter values from the image formation model, such as: mitigation and diffusion coefficients characterizing the turbidity of the scene and depth-first search of an object on the image, despite that the process would not only perform an enhancement , but would restore the image.

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