Enhancement of Degraded Images by Natural Phenomena

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Abstract: The efficiency of environmental monitoring through imagery data is strongly dependent on the quality of the acquired information, despite weather conditions or other uncontrolled degradation factor. This article describes a series of combined techniques of image enhancement to partially recover information "lost" due to unfavorable operational conditions or natural phenomena, such as: fog, rainstorms, underwater dust (green dust), poor illumination, etc. We based our approach on a process known as homomorphic filtering, which is intrinsically related to the transformation from the spatial to the frequency domains, directly involving the Fourier Transforms, followed by specific enhancement techniques, such as Clipping and Stretching. Although, the use of these techniques separately, without the proper adaptation and coupling, can result in damaging even more the image, the authors developed an efficient sequence of enhanced filtering able to recover most of the affected information. Moreover, the proposed methodology proved to be generally applicable to a large class of images in poor conditions, with a performance comparable to the methodology used as benchmarks.

1 INTRODUCTION

The use of algorithms for image enhancement has been a subject of study for decades. For the specific application of environmental monitoring and surveillance, the advent of software focused on image manipulation for mitigating the effects of natural phenomena drawn the attention from academic, commercial and military research.

Therefore, the removal of the negative effects promoted by phenomena like fog, rain, water, lack or poor illumination, among others, becomes a necessary requirement for a sort of applications. Autonomous navigation of ground and aerial systems, outdoor air or underwater remote sensing, automatic object recognition, and active perception, are just a few examples of situations where outdoor imagery plays a critical role in a successful application.

Studies on the area of image enhancement indicate that in many working environments, several factors influence negatively in scene visualization, such as those present in the aerial environment, where there are mist, fog, rain, smoke and hail (Oakley and Satherley, 1998), (Liu et al., 2010) and (Tan et al., 2007). These phenomena are mostly characterized by the presence of aerosols and/or tiny water particles suspended in air. Depending on its density they, in one hand, may compromise considerably the original characteristics of color and contrast of the images and, on the other, hamper the ability of the observer to perceive and interpret the information contained therein.

The degradation of the visual quality of the images fostered by these phenomena is modeled as a function of density of particles in suspension along the distance from the camera to the scene. The quality index of visibility depends on the extension of the scattering caused by these particles in the phenomenon (Agarwal et al., 2013). Thereby, to development a system to enhance the visibility of acquired images in bad weather implies to mitigate the effects caused by this scattering. Additionally, the non-uniformity of scene illumination as captured by the camera sensor negatively influences the image quality. Due to the automatic camera adjustments, the overexposing of one region, besides saturates that region to white, also results in underexposing other

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region, darkening part of the image. Therefore, factors such as low natural illumination, lack of equipment accessories (lens, flashes and filters), poor capturing devices and inexperienced users deeply affect the quality of the acquired image.

Researchers have devoted considerable efforts to improve the acquired images independently to the operational conditions of the data acquisition. In the present work, the authors conduct a study of the problem and propose a method to perform automatic enhancement of the input (images or video) through the use of filters with no prior knowledge of the environment. In short, the contribution of this paper is an effective combination of enhancement techniques that besides recovering information and improve contrast, cleanses the image from noise. Comparison evaluation showed that the proposed technique outperforms similar methods.

This work follows a very standard organization. Section 2 shows a short description of correlated works and contributions. On section 3, the authors summarize the proposed method, and on section 4, they describe the methodology and the evaluation conditions of the experiments. Section 5 presents the comparisons to others available in the literature and discussions about the performance of the proposed methodology. A psychovisual test, Mean Opinion Score or MOS (Schettini et al., 2010), is performed to measure the quality of correction. Finally, Section 6 concludes the paper.

2 RELATED WORKS

The image enhancement methods in the literature can be classified into two main categories, based on the physical model of the image formation and based on the enhancement of the image using subjective and objective criteria to produce a visually pleasing image (Gonzalez and Woods, 2010).

The work of Zhai et al. (2007) provided an overlapped modification of histogram equalization on sub-block to improve images affected by the phenomenon of fog.

Panetta et al. (2008) proposed an algorithm for image enhancement with variable illumination to enhance the local contrast, and also to keep the details of the edges. These authors also proposed an algorithm of multi-histogram equalization in the HSV color space to segment the image, allowing a rapid and efficient correction of non-uniform illumination.

The work of (Iqbal et al., 2007) developed a model that improves the techniques and methods of perception of underwater images based on slide stretching applied both in the RGB as the HSV color spaces.

Kalia (Kalia et al., 2011), investigated different pre-image processing techniques that can affect or improve the performance of the SURF (Speed-Up Robust Features) detector, and proposed a new method named IACE (Image Adaptive Contrast Enhancement). They modified the technique of contrast enhancement, adjusting it according to the statistics of image intensity levels. Equation (1) enables the estimation of the change in intensity levels P_{out} according to the intensities of the levels P_{in} of the image to be enhanced.

$$P_{out}(x,y) = \left(\frac{P_{in}(x,y) - c}{d - c}\right).(b - a) \qquad (1)$$

Where a is the lower possible intensity level of the image. b is its corresponding counterpart. c is the lowest level of the threshold intensity of the original image for which the number of pixels in the image is less than 4% and, d is the intensity level of the upper threshold for which the cumulative number of pixels is greater than 96%. These thresholds are used to eliminate the effect of outliers, improving the intrinsic details of image while maintaining the contrast ratio. However, the values of P_{out} should be in the range [0, 255].

The results of this algorithm are very promising. The relative performance of IACE method is better than the method proposed by (Iqbal et al., 2007), in terms of time needed to process improvement and complete matching image. The contributions of studies (Kalia et al., 2011) and (Iqbal et al., 2007) occurs in the sense of making use of contrast stretching algorithms both in RGB and HSV, besides the results indicate prosperity by applying thresholds at the end of the stretching intensities.

At last, (Schettini et al., 2010), proposed a method for image enhancement based on a location-dependent exponential image correction. The technique aims to correct images that have both underexposed and overexposed regions simultaneously. To avoid artifacts, the bilateral filter is used as a mask in the exponential correction. Depending on the characteristics of the image (driven by histogram analysis), an automatic step of tuning parameters is introduced, followed by stretching, trimming, treatment and preservation of color saturation. His contribution is on the use of cropping and stretching, as well as the correction of color saturation stage.

3 PROPOSED METHOD

3.1 Basic Block-Diagram

The authors proposed a three-step improvement method, depicted in the block-diagram of Figure 1. The method is applied to the input image converted into HSV color space, due to the fact that the human eye maximizes the perception of color of objects in the scene.

The first step corrects the non-uniformity of the illumination, making it as more homogeneous as possible throughout the scene. This step works on the information present in both underexposed and overexposed regions. The second step involves contrast enhancement, intended to enhance image details. Finally, the third step minimizes color saturation changes between the input and output images, to vivid them as close as possible to the actual colors. The following sections explain in details each step.

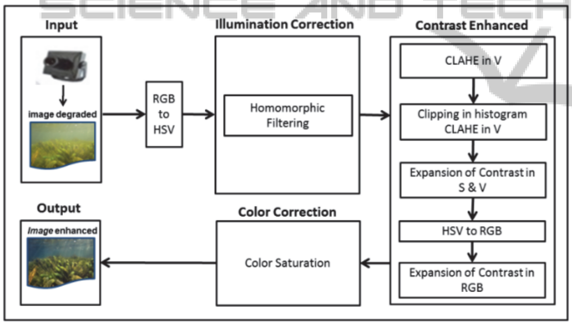


Figure 1: Block diagram of the proposed method.

3.2 Illumination Correction, Fast Fourier Transform and High Pass Filtering

As explained by (Padmavathi et al., 2010), the formation of images can modeled as the product matrix generated by the intensity of illumination and reflectance of objects in the scene, that is:

$$f(x,y) = i(x,y) \cdot r(x,y) \tag{2}$$

where $f(x,y)$ represents the captured image, $i(x,y)$ the illumination and $r(x,y)$ the reflectance of the objects in the scene. One needs to consider that illumination tends to vary slower (low frequency), throughout the image when compared to the reflectance, characterized by abrupt changes, especially in the edges (high frequency). Therefore, by suppressing lower frequency components, while reinforcing medium and high frequencies, one would address the issue. However, the necessary Fourier transform is a non-linear operation, and any attempt of filtering will include both illumination and reflectance matrices. According to eq. (3):

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

According to (Delac, 2006), (Gonzalez and Woods, 2010) and (Padmavathi et al., 2010), there are five steps to obtain the corrected image.

Step 1: Apply the logarithm operator to linearize the process on grayscale (HSV if color) image (eq. (4).

$$z(x,y) = \log[f(x,y)] = \log[i(x,y)] + \log[r(x,y)] \tag{4}$$

Step 2: Apply Fast Fourier Transform, as in eq. (5).

$$\begin{aligned} \Im\{z(x,y)\} &= \Im\{\log[i(x,y)]\} + \Im\{\log[r(x,y)]\} \\ &\to Z(u,v) \\ &= I(u,v) + R(u,v) \end{aligned} \tag{5}$$

Step 3: Filtering by a Butterworth high-pass filter. If $Z(u,v)$ is processed with a high-pass filter $H(u,v)$, we obtain eq. (6).

$$\begin{aligned} S(u,v) &= H(u,v) \cdot Z(u,v) \\ &= H(u,v) \cdot I(u,v) \\ &+ H(u,v) \cdot R(u,v) \end{aligned} \tag{6}$$

Where $S(u,v)$ is the result of image on frequency domain with the high-pass filter.

Step 4: Apply the Inverse Fourier Transform to go back to the spatial domain (eq. (7)).

$$\begin{aligned} &\Im^{-1}\{S(u,v)\} = \\ &= s(x,y) = i'(x,y) + r'(x,y) \end{aligned} \tag{7}$$

Assuming:

$$i'(x,y) = \Im^{-1}\{H(u,v)I(u,v)\} \tag{8}$$

In addition:

$$r'(x,y) = \Im^{-1}\{H(u,v)R(u,v)\} \tag{9}$$

Step 5: Apply the exponent ial operator in all image to revert the effects of logarithm on step 1. Since $z(x,y)$ is constructed as the log $f(x,y)$, the inverse of $s(x,y)$ leads to the desired result on eq. (10):

$$\begin{aligned} g(x,y) = e^{[s(u,v)]} &\to e^{[i'(x,y)+r'(x,y)]} \\ &\therefore e^{i'(x,y)} e^{r'(x,y)} \end{aligned} \tag{10}$$

The $g(x,y)$ represents the homomorphic filtered image of $f(x,y)$. If the intensities are high, a second or third additional enhancement technique can be applied (Toth, 2011).

In this work, we used the Cooley-Tukey (Diniz et al., 2014) implementation of the Fast Fourier Transform at Step 2. The overall code complexity of this step is equal to $O(nlgn)$ (Weeks, 2012).

Butterworth high-pass filtering was used to obtain a sharper image, by attenuating low frequency components without affecting the high-frequency information in the Fourier. The eq. (12) shows the filter expression:

$$H(u,v) = \frac{1}{1 + [D_0/D(u,v)]^{2n}} \tag{11}$$

Where $\boldsymbol{n}$ is the degree of transform, constant D_0 is the threshold of the filter, and $D(u,v)$ is the distance from point (u,v) to the center of the frequency spectrum, given by:

$$D(u,v) = \sqrt{[(u - P/2)^2 + (v - Q/2)^2]} \tag{12}$$

Where $P \times Q$ is the size of input image in frequency domain (in that case, $Z(u,v)$ of eq. (5)).

3.3 Contrast Enhanced (CLAHE, Clipping and Stretching)

This step involves contrast improvement, and is intended to retrieve image details emerged from a deeper analysis of the histogram intensities before and after application of homomorphic filtering. In this scenario, we realized that even after a better occupation of gray levels, improving overall contrast is not satisfactory, since low-quality images have compression artifacts and noise in darker areas are maximized. These negative characteristics were also perceived in (Schettini et al., 2010) and (Kalia et al., 2011).

The contrast enhancement is divided into sub-steps. First, it transforms the model RGB to HSV and then applies the technique of Contrast Limited Adaptive Histogram Equalization (CLAHE) in channel V. Its use aims to facilitate the recovery of details in dark areas of pictures, as well as prevent the loss of information due to excessive gloss, because its histogram is not limited to a particular region.

We noticed that CLAHE promote the maximization of noises. To avoid this, we also applied a contrast threshold to eliminate the effect of extreme values and improve the intrinsic image details, while maintaining the contrast ratio. However, the output pixel values are redistributed in the range [0, 255], also reported by (Sakaue et al., 1995, Kalia et al., 2011). This practice significantly improve the picture quality, but, increases the complexity of the method to $O(2n)$ or $O(n)$.

To determine the contrast threshold that will be used to limit the intensities, we will consider the saturation levels at the ends of the histogram, more specifically, those distributed outside the interval of 97%. This percentage is experimentally obtained, and proved to be the best threshold indicator after several trials.

At last, the contrast enhancement step uses the technique of contrast stretching on both S and V channels in HSV color space. After that, we used the same technique on RGB color space to stretch the dynamic range of the image intensities. The intension is to provide brighter colors and make dark colors even darker. This procedure provides a gain in quality, i.e., to stretch the histogram so that the full dynamic range be better distributed along the same range. This dynamic range is the range between the minimum and maximum intensity value obtained after applying the threshold.

3.4 Color Saturation

As already mentioned, images that suffer from degradation due to environmental phenomena generally have turbid or opaque colors. To retrieve them and finalize the processing chain, we applied the same formula suggested by Sakaue (Sakaue et al., 1995) and used in (Schettini et al., 2010). This idea seeks to minimize the color variation between the input image and the output. The transformations are applied to each RGB channel model producing new values R', G' e B' obtained as:

$$\begin{aligned} R' &= \frac{1}{2}\left[\frac{V'}{V}(R+V) + R - V\right] \\ G' &= \frac{1}{2}\left[\frac{V'}{V}(G+V) + G - V\right] \\ B' &= \frac{1}{2}\left[\frac{V'}{V}(B+V) + B - V\right] \end{aligned} \tag{13}$$

where *V'* is the value of the intensity of illumination obtained after the illumination correction and contrast enhancement with histogram clipping, as discussed earlier. The values corresponding to V, R, G e B are obtained in the input image.

4 EXPERIMENTS

4.1 Evaluation Methodology

The experiments were implemented in C++ and OpenCV library set, and simulated on a two-core @ 2.5GHz personal computer with 8GB RAM. The proposed method was applied in twelve color images that show degradations resulting from various natural anomalies that Nature can adversely promote in the atmosphere or underwater. The images have different sight distances and different rates of turbidity. They are classified into different scenarios, including scenes that present problem of non-uniformity of illumination, problems in the atmosphere, and problems in underwater environments. For such classification, four images were selected and submitted to each of the three methods in evaluation. Details of the images that are beyond the limits of visibility are not considered as regions to be reclaimed. The proposed method is subjected to the color space RGB and HSV in various channels, as was shown in Figure 1.

The assessment of image quality is performed subjectively from the point of view of the observer. In each trial of the experiments, a pair of images is available for viewing each of the 30 volunteer evaluators. This pair of images consists of two versions of the same scene and an evaluator was randomly invited to respond subjectively indicating which image was his favorite. Each version of a scene was compared with all other versions of the same scene, representing 24 pairs (12 images with 2 combinations each). Overall, 720 trials were conducted and the results are explained in Chapter 5.

4.2 Evaluation Conditions

To perform the psychovisual evaluation, the images were judged to be shown in an interface based desktop applications. We adopted an LED monitor of a 14'' notebook with resolution of 1366 x 768 pixels corresponding to 111.94 dpi. The refresh rate is 60 Hz. The lighting is typical of office and the ambient light levels were kept constant between numerous sessions. The distance between the observer and the monitor was about 60cm. All original scenes used were subsampled and scaled to fit a square 600 x 600 pixels.

5 RESULTS

We submitted the images to the proposed methodology and, then, compared the results obtained with others techniques. Figure 2, shows the result when running the steps of illumination correction and contrast enhancement.

We noticed that in (a), due to low light in the scene, many information were "hidden" from a typical human eye. Through the homomorphic filter, many details appear in (b), however, one ca note a slight saturation in overexposed region of the background image. In (c), the result of (b) was combined with techniques CLAHE, Clipping and stretching to make the light become better distributed

Figure 2: In (a) original image under low light; In (b) image with simple homomorphic filter and (c) image with the proposed correction method to non-standard lighting, consisting of homomorphic filtering, CLAHE, Clipping and Stretching.

in the scene and the edges more prominent. Despite the image (c) apparently be better, the complexity of the operation is still high (in $O(n)$), but it is a major advances compared with $O(n^2)$. A future work will be to reduce this complexity to $O(nlgn)$.

Table 1 presents the results obtained of three different scenarios in pairs of images, original (left side) and after the application of the proposed method (right side). From a subjective evaluation, we find significant improvements in all scenarios, whether in environments with serious illumination issues or in environments with issues arising from acts of nature, and both in atmosphere and in underwater environments, with low and high turbidity.

Table 1: Comparison between before and after the proposed method applied.

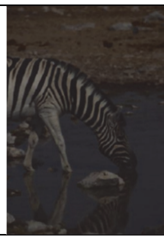
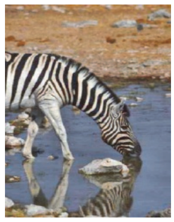
Fig.	Original	Proposed Method
Images with poor illumination		
1		
2		
3		

Table 1: Comparison between before and after the proposed method applied (Cont.).

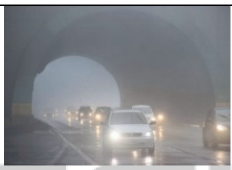
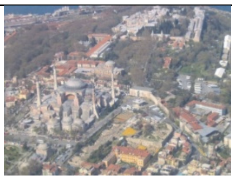
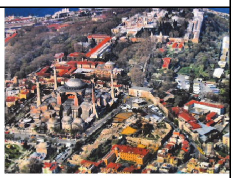
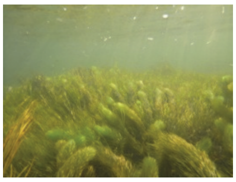
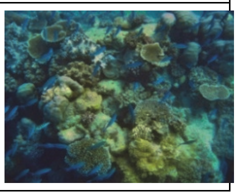
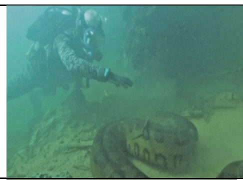
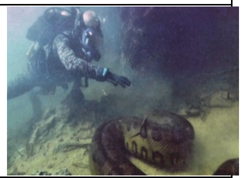
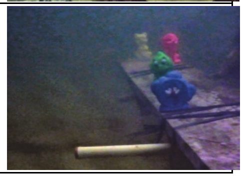
Fig.	Original	Proposed Method
Images with poor illumination		
4		
Foggy images		
5		
6		
7		
8		
Underwater images		
9		
10		

Table 1: Comparison between before and after the proposed method applied (Cont.).

Fig.	Original	Proposed Method
Underwater images		
11		
12		

In order to compare with others techniques, we first conducted a psychovisual experiment in which viewers were asked to choose the better perceived picture of a pair. Based on the preferences of viewers, we obtained an average score of opinions. The content preference score is calculated for each method, including the original scene (Identity). The highest score goes to 100. First place got 51.25 points, corresponding to the proposed method. Regarding the other two methods, the technique of (Schettini et al., 2010) is on second place with 25.41 points and the model of (Iqbal et al., 2007) with 22.5 point, on third position. Table 2 shows the results.

Table 2: Average Opinion Score (MOS) experiment.

Method (Result Image)	Preference Score	%
Identity	6	0.834
Proposed	369	51.251
Schettini et al.	183	25.417
Iqbal et al.	162	22.523

One may realized that each method has a better performance in specific aspects. When considering the correction factor of uniformity of illumination, the algorithm of (Iqbal et al., 2007) is the one with the lowest score, however, it gets good recovery in underwater imagery. The algorithm of (Schettini et al., 2010), in short, have as good results as the our proposed method, however, it does not promote good outcomes for underwater images, being the determining factor of its second place rank, as presented in Table 2. This scenario determines that applying algorithms in contrast saturation and brightness of channels HSV color space, as well as in each of RGB channels, promotes not only the improvement of the contrast, but also makes color recovering feasible.

Measuring the quality enhancement applied to an image after enhancement process is often very difficult to accomplish. So far applies to subjective evaluation criteria of improvement in the image. In literature some objective metrics that aim at estimating the brightness and contrast of the image, such as Entropy (H), Absolute Mean Brightness Error (AMBE) and Enhancement Measure (EME). The use of the values of these metrics need certain care, since it does not necessarily correlate improved quality in terms of contrast enhancement (Schettini et al., 2010).

Analyzing the values of these metrics for image 8 of Table 1, the values of H indicate better occupation of all intensity levels in the histogram. This is associated with a visually pleasing image, positive considering the balanced conditions of image acquisition. The values of this metric for that image are 6.9384, 7.6334, 6.8803 and 7.3561. Representing the result of the original image, the proposed method, the method of (Schettini et al., 2010) and of (Iqbal et al. 2007), respectively. It is noteworthy that in this case, the highest value of Entropy in fact represented a nice image. However, it does not always happen in other cases. Analogous behavior is found in the study of (Schettini et al., 2010).

The AMBE is the average distance from the original brightness, i.e., the difference in the average intensity level of the gray scale, and new original image. In a procedure improvement, if not always aims to preserve the original brightness of the scene, given the problems of uniformity of illumination. (Schettini et al., 2010) states that preserve the original brightness does not always mean preserve the natural appearance of the image. Additionally, the original images are strongly underexposed and/or overexposed, we expect a high value AMBE, indicating that the quality could be improved. For example, the steps resulting from the applied illumination correction and contrast enhancement of the image 1, shown in Table 1, obtains a correction value AMBE equals to 49.52. On the other hand, in a correct exposure images or pictures obtained in dark scenes (overnight), it is expected that our method does not significantly alter the average brightness. The metric values for image 2 of Table 1 with this characteristic are, the proposed method equals 19.39, AMBE (Schettini et al, 2010) equal to 20.46 and AMBE (Iqbal et al, 2007) equal to 34.38.

The EME approximates an average contrast in the image by dividing the image into no overlapping blocks, defining a measure based on minimum and maximum intensity values in each block and averaging them. By this metric, high values should indicate regions with high local contrast, while values close to zero, should correspond to homogeneous regions. If improvement method introduces noise in such homogeneous regions, a higher value of EME will be obtained, and possibly not correspond to an improvement in image quality. As an example, the values of this metric in image 10 of Table 1: Proposed Method = 9.2414, Schettini method = 1.7403 and Iqbal method = 5.4655. In this scenario values, on the one hand, we can see that our method was the one with the highest value; this is due mainly to the use of CLAHE. Moreover, this value is not necessarily as a negative factor which might compromise the quality of the circumstantially improvement obtained.

6 CONCLUSIONS

This article presents a method of enhancement of images degraded by natural phenomena which allows the improvement of visibility from a single input image without using any information of their training model. The goal is to improve the visual quality of distant objects on the scene. From the results, one can notice that most of the intensity of degrading phenomena are minimized, providing a better contrast enhancement, brightness and color brightening compared to other techniques. The authors found the methodology promising for showing good results with low computational cost and useful for their application in various systems working in outdoor or submerged environments.

When we compared the proposed solution with other well-known method in the literature, we find a correct increased dynamic range in both regions of low and high brightness of an image, preventing the common 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 contrast correction methods of color images. The proposed method reached the highest scores.

The method adequately performed in all three different scenarios, especially when compared to others. Its performance with images of underwater environments, where the method achieved the higher points, was especially interesting. However, in future works, we intend to improve the algorithm optimizing the parameter estimation values from the model of image formation, such as attenuation and diffusion coefficients that characterize the turbidity of scene and depth of a given object in image.

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