Underwater Image Enhancement Based on Color Correction and Fusion

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Abstract: For underwater images quality of those pictures are terribly low in comparison to traditional images. These images suffer from quality degradation, color cast, low brightness and degraded visibility because to absorption of light and scattering of light within the water. To beat these affects we proposed an effective underwater image enhancement to improve the standard of pictures in underwater and color correction is done. So, enhancement of underwater images is vital for images which are captured underwater. In our method we will take single image, which does not require any specialized hardware or knowledge about underwater conditions or scene structure. Our model consists of color correction, fusion of images. Firstly, color correction is done using white balance algorithm and after that gamma correction and sharpening of images are estimated for white balanced image. Then weights of fusion process are estimated and thereby normalizing the weights.Then, fusing of images is processed using Gaussian and Laplacian pyramids to construct the images that are more appropriate, perceivable and understandable for the human and machine perception. So as to guide the priority of underwater image enhancement, sufficient evaluations are conducted to discuss the impacts like color correction and fusion. Compared to different ways our proposed underwater image enhancement method can achieve higher accuracy and higher information retention.

KEYWORDS: Image enhancement, underwater, white-balancing, image fusion.

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INTRODUCTION

Underwater image enhancement technique is employed to improve the quality of standard which results in clear and correct visibility of images that may be used for the various researches like, analysis of monuments in submerged water, marine applications, scene understanding, computer vision, underwater surveillance, image and video compression and transmission.

When media is acquired in the air that's while capturing images within the air due to variations in the amount of light, poor illumination and weather conditions the light that is reaching the camera is severely scattered by the atmosphere that ends up in changes in the image contrast and visibility. So, the images are degraded. In comparison to air the quality of degradation is additional in underwater image acquisition. In underwater, red light is having more wavelength when compared to green and blue colors so the red light attenuates quicker, as result underwater images typically seems as green bluish colors. The image distortion is because of light scattering and color change which lowers visibility and contrast of captured images. To enhance the visibility and for higher quality of experience we proposed an effective methodology for the enhancement of images that relies on color correction and fusion of images. The above methods improve the quality of underwater images and improves the brightness and contrast for better quality of experience.

STRUCTURE OF PAPER

The paper is organized as follows: In Section 1, the introduction of the paper is provided along with the structure, important terms, objectives and overall description. InSection 2 we discussed literature survey. In Section 3 we discussed related work. In Section 4 methodology of basic image processing is discussed. In Section 5 detailed information of proposed system is discussed. Section 6gives the results and evaluation. Section 7 gives the conclusion of the entire process.

OBJECTIVES

The main objective of underwater image enhancement based on color correction and fusion is to restore and enhance the visibility of degraded images. We have conducted the experiments on following objectives. To access the inputs from white balance, to calculate weight maps for fusion process and to access the fusion process and overall performance of the proposed underwater image enhancement method.

LITERATURE SURVEY

Many methods have been proposed to measure and enhance the perceived standard of quality. B. L. McGlamery [1] proposed a computer model in which it allows the image components of camera system to be computed. The light which is received by the camera was decomposed into three parts. They are the light reflected from an object, the forward scattered portion and the backward scattered light. Ghani and Ashidi Mat Isa [2] proposed underwater image quality enhancement through integrated color model with Rayleigh distribution. This technique increases the contrast and reduces the noise. In this method mapping of image histogram according to Rayleigh distribution is employed. Trucco and Olmos [3] projected self-tuning underwater image restoration method. During this the optimal values of the filter parameters are estimated automatically for every image by optimizing the standard supported international distinction value.

In this paper we proposed an effective methodology for the enhancement of images that is based oncolor correction and fusing of images.

RELATED WORK

Underwater images are mainly enhanced by two types of techniques. They are Image based methods and the Physics based methods.

Image Based Methods:

An Image based methods work on modifying the pixel values of images to improve the brightness, contrast of hazed images. In Spatial Domain Method [4] image processing methods operates directly on pixel values. They modify the pixel values depending on the original pixel value that is point process or local process. Other traditional image enhancement methods like Histogram Equalization, Contrast limited adaptive histogram equalization, White balance can also improve visibility, brightness and contrast. Histogram Equalization[5] is a method to process images in order to adjust the contrast of an image by modifying the intensity distribution of histogram. The objective of this

technique is to give linear trend to the cumulative probability function associated to image. The processing of histogram equalization relies on use of cumulative probability function. The cumulative probability function is cumulative sum of all probabilities lying in its domain. But these techniques are less effective.

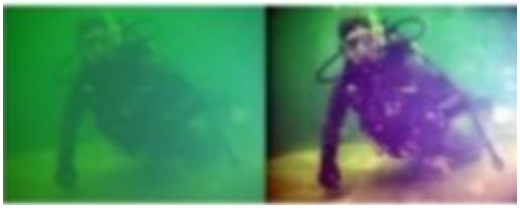

Figure 1: Image based methods output

Physics Based Methods:

The Physics based methods restore the underwater images by considering basic physics of light propagation and theory of underwater imaging. We have to consider basic physics of light propagation in the water medium. The restoration process deduces the parameters of physical model then recovers the underwater images. Due to the similarities between underwater images and hazy images which is caused by light degradation and scattering of light Kaiming He, Jian Sun [6] used Dark channel prior method for removing haze from input image. The dark channel prior is primarily based on statistics of outdoor haze free images. In most of non-sky patches at least one-color channel has very low intensity at some pixels called dark pixels. These dark pixels offer the estimation of haze transmission. This method is physically acceptable and work well in dense haze. However, these ways show restricted improvement.

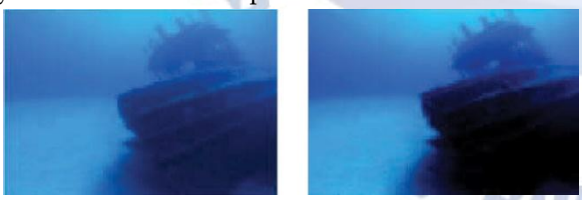

Figure 2: Physics based methods output

METHODOLOGY

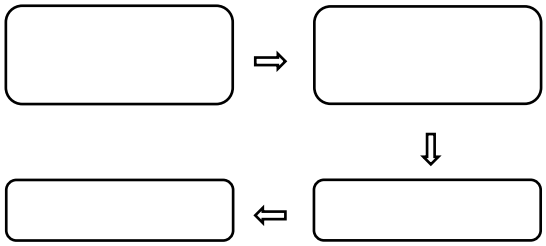

Figure3: Basic Image Processing Steps

Image Acquisition:

Input images are captured from the underwater through camera. These captured images are in the form of RGB image which consists of red, green, blue region. The captured images then undergo pre-processing stage. As a consequence, this algorithm chooses the in-focus areas from each and every enter image through picking the finest value for each and every pixel which results in particularly targeted output.

Pre-processing:

The pre-processing stages in image process consists of varied number of processing that depends per theinput image. The aim of pre-processing associate improvement of the image information that suppresses undesired distortions or enhances some image features relevant for additional process and analysis task. This method reduces the noise that is present within the image.

Detection:

The detection process which includes the enhancement of image which is taken as input image. In the proposed work enhancement is carried out usingcolor correction and fusing of images. Using these techniques high quality of images can be achieved and brightness and contrast can be increased.

Fusion:

Image fusion is defined as process of collecting all the important information from multiple images and combining them to result in a single image. The single output image is more informative and accurate than any of the single source image and it consists of all the necessary information.

PROPOSED METHOD

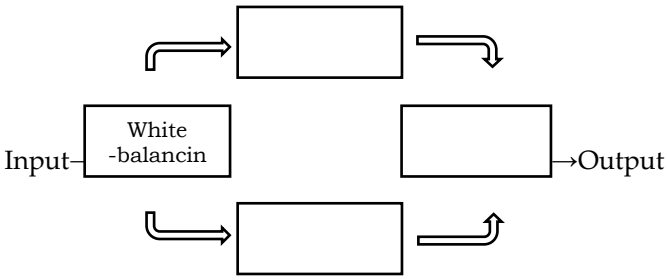

Figure 4: Block diagram for proposed method

Our proposed method basically works on R-G-B color space, aiming not only to recover the underlying scene radiance but also improves the contrast, color and visibility. The block diagram for our proposed methodology is shown in Figure 2. First color correction is done and two inputs are derived from white balance image which are gamma corrected image and sharpened image. Then these are given as inputs to the fusion process and finally dehazed image is obtained.

As depicted in Figure 2, our image enhancement approach adopts a two-step strategy, combining white balancing and image fusion, to improve underwater images without restoring to the explicit inversion of the optical model. In our approach white balancing aims to compensating for the color cast caused by the selective absorption of colors with depth, while image fusion is used to improve the edges and details of the pictures and to overcome the loss of contrast which results from the process of back scattering.

We will briefly revise those approaches and explain how they inspired us in the derivation of our novel approach proposed for underwater scenes. Most of those methods make a specific assumption to estimate the color of the light source, and then achieve color constancy by dividing each color channel by its corresponding normalized light source intensity. Among those methods, the gray world algorithm assumes that the average reflectance in the scene is achromatic. Hence, the illuminant color distribution is simply estimated by averaging each channel independently.

The max RGB assumes that the maximum response in each is channel is caused by a white patch, and consequently estimates the color of the light source by employing the maximum response of the different color channels.

White-Balance

In our methodology, white balancing aims at compensation for the color cast resulted by the selective absorption of colors with depth. White balancing aims at improving the image aspect, mainly by removing the unwanted color castings because of varied illumination or medium attenuation properties. In underwater, the color of images which are taken highly depends on the depth, as the depth increases the images appears as green-bluish colors which are needed to be corrected. As the light penetrates the water, the attenuation process affects selectively the wavelength spectrum, thus affecting the intensity and the appearance of colored surface. Since the scattering attenuates the colors which are having longer wavelengths when compared to the shorter wavelengths, the color perception is affected as we go down in deeper water.

We have considered the large spectrum of existing white balancing methods, and have identified a number of solutions that are both effective and suited toward problem. Firstly, we will transform the RGB color space to YCbCr color space. Next, we will calculate the average values of Cb, Cr, calculate the mean square error of Cb, Cr. Find the candidate reference white point. If meeting the following requirements then the point is candidate reference white point. Then we will sort the candidate reference white point set with descend value of Y.Then we will get the 10% points of the candidate reference white point set, which is closer to the white region, as reference white point set. After we will get the reference white points of RGB, then the average values of the reference white points of RGB. Then we will calculate the maximum Y value of the source image. After that we will calculate white balance gain and white balance correction is done.

Figure5: Input image

Figure 6: White balance image

Inputs For Fusion Process:

Since the color correction is vital in underwater, we tend to first apply our white balancing technique to the initial image. This step aims at enhancing the image look by discarding unwanted color casts caused by numerous illuminants. In water deeper than thirty feet,

white balancing suffers from noticeable effects since the absorbed colors are tough to be recovered. As a result, to induce our initial input we tend to perform a gamma correction of the white balanced image version.

Gamma correction aims at correcting the global contrast and has relevancy since, in general, white balanced underwater pictures tend to look too bright. This correction will increase the difference between darker/lighter regions at the price of a loss details within the beneath or over exposed regions.

To compensate for this loss, we tend to derived a second input that corresponds to a sharpened version of the white balanced image. Therefore, we tend to follow the unsharp masking principle, within the scene that we blend a blurred or unsharp (here Gaussian filtered) version of the image with the image to sharpen. The standard formula for unsharp masking defines the sharpened image S.

$$S = I + \beta (I - G * I)$$

where I is that the image to sharpen (in our case the white balance image), G * I denotes the Gaussian filtered version of I, and β is the parameter. A small β value fails to sharpen the image, but a too large β value results in over saturated regions, with brighter highlights and darker shadows.

Figure 7: Gamma corrected image

Figure 8: Sharpened image

Weights For Fusion Process:

The weight maps are used during blending in such a way that pixels with a high weight value are more represented in the final dehazed image. They are thus defined based on a number of local image quality or saliency metrics.

Laplacian Contrast Weight (WL):

This estimates the global contrast by computing the absolute value of a Laplacian filter applied on each input luminance channel. This straight forward indicator was used in different applications such as tone mapping and extending depth of field since it assigns high values to edges and texture. For the underwater dehazing task, however, this weight is not sufficient to recover the contrast, mainly because it cannot distinguish much between the ramp and flat regions. To overcome this problem, we introduce another contrast assessment metric.

Saliency Weight (WS):

This aims at accentuation the salient objects that lose their prominence within the underwater scene. Saliency maps tends to favor highlighted areas (regions with high brightness values). To beat this limitation, we have a tendency to introduce further weight map supported the observation that saturation decreases within the highlighted regions.

Exposedness Weight for Saturation Weight (WE):

This enables the fusion algorithm to adapt to chromatic information by advantaging highly saturated regions. This weight is simply computed by

$$WE1 = \exp(-(R1 - aver).^2 / (2 * sigma ^ 2)$$

Where, sigma = 0.25 aver = 0.5

To reducethe overall complexity of the fusion process, we have observed that, when using the two inputs proposed in this paper, the exposedness weight map tends to amplify some aircrafts, such as ramp edges of our second input, and to edges the benefit derived from the gamma corrected image in terms of image contrast. Originally, in an exposure fusion context, the exposedness weight map had been introduced to reduce the weight of pixels that are beneath or over-exposed. In our case, since the gamma corrected input tends to exploit the whole dynamic range, the use of exposedness weight map tends to penalize it in favor of the sharpened image, thereby including some sharpening aircrafts and missing some contrasts enhancements.

Figure 9: Saliency1

Figure 10: Saliency 2

Figure 11: Saturation 1

Figure 12: Saturation 2

These weight maps are merged in a single weight map which is normalized weights. Normalized weights are obtained by dividing the weight of each pixel in each map by the sum of the weights of the same pixel over all maps.

Normalized weights can be calculated by

$$W1 = (WL1 + WS1 + WE1) / (WL1 + WS1 + WE1 + WL2 + WS2 + WE2)$$

$$W2 = (WL2 + WS2 + WE2) / (WL1 + WS1 + WE1 + WL2 + WS2 + WE2)$$

Where, WL = Laplacian Contrast Weight

WS = Saliency Weight

WE = Exposedness Weight for Saturation

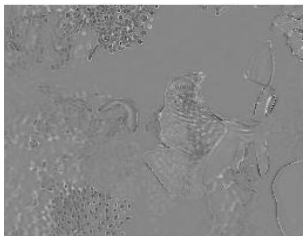

Figure 13: Normalized weight-1

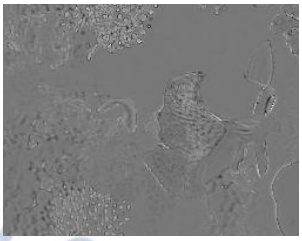

Figure 14: Normalized weight-2

Multi Scale Fusion:

In our approach we tend to designed on the multi-scale fusion principles to propose a single image underwater dehazing solution. Image fusion has shown utility in several applications such as image compositing, multispectral video enhancement, defogging and HDR imaging. Here we, aim for a straightforward and quick approach that's able to increase the scene visibility in an exceedingly wide selection of underwater videos and pictures. Similarly, our framework builds on a group of inputs and weight maps derived from a single original image. In distinction to existing strategies, however, those ones are specifically chosen so as to require the most effective out of the white-balancing methods.

This multi-scale fusion significantly differs from previous fusion based underwater dehazing approaches. To derive the inputs from the original image, our algorithm did assume the backscattering component. This assumption is generally valid for underwater scenes decently illuminated by the result section. In distinction, this paper does not rely on the optical model and proposed an alternative definition of inputs and weights to deal with severely degraded scenes.

The first level in image fusion method is decomposition of input image and therefore the output image of the entire method has got to be obtained by applying reconstruction method. Variety of image decomposition and reconstruction techniques are projected and classified. Pyramid representation is applied to decompose the input image into multiscale

representation that provides a series of residual images and one approximate image.

The multiscale representation is relying on Laplacian pyramid. The pyramid representation decomposes a picture into sum of bandpass images. Every level of the pyramid will filter the input image employing a low pass Gaussian G and decimates the filtered image by a factor of two in both directions. It then subtracts from the input image an up sampled version of the low pass image there by approximating the Laplacian and uses the decimated low pass image as for the input for the following level of the pyramid.

Using G_l to denote a sequence of l lowpass filtering and decimation, followed by l up sampling operations, we have a tendency to outline N levels L_l of the pyramid as follows:

$$I(x) = I(x) - G_1\{I(x)\} + G_1\{I(x)\}$$

$$\Rightarrow L_1\{I(x)\} + G_1\{I(x)\}$$

$$I(x) = L_1\{I(x)\} + G_1\{I(x)\} - G_2\{I(x)\} + G_2\{I(x)\}$$

$$= L_1\{I(x)\} + L_2\{I(x)\} + G_2\{I(x)\}$$

$$=.....$$

$$= \sum_{l=1}^{N} L1\{I(X)\}$$

In the above equation L_l and G_l represents l^{th} level of the Laplacian and Gaussian pyramids respectively.

The dehazed output is obtained by summing all the fused contribution of all levels after appropriate up sampling.

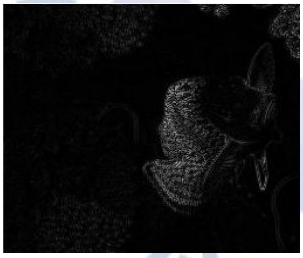

Figure 15: Laplacian image

Figure 16: Output image

RESULTS AND EVALUATION

In this section, to ensure the fairness of each evaluation, all the underwater images under test are pre-processed setting the same resolution of 256×256 pixels. All methods are implemented on a Windows 10 personal computer and performed in MATLAB R2016a software. We performed white balancing approach and fusion process and finally obtained dehazed image.

Performance Metrics analysis:

1. PSNR and MSE:

The PSNR computes the peak signal to noise ratio in decibels, between two pictures. This ratio is employed as a top-quality measurement between the first and a compressed image. The higher the PSNR, the higher the standard compression quality. The mean square error MSE and peak signal to noise ratio are used to compare image compression quality. The MSE represents the cumulative square error between the compressed and the original image, whereas PSNR represents a measure of the peak error. The least is the value of MSE, the smaller the error.

To evaluate the PSNR, it first calculates the mean-squared error using the subsequent equation:

$$MSE = \sum [I_1(m, n) - I_2(m, n)]^2 / M*N$$

Where, M is the number of rows and N is the number of columns in the input image.

Then it computes the PSNR using the following equation

$$PSNR = 10\log_{10}(R^2/MSE)$$

Where, R represents the maximum fluctuation in the input.

2. Correlation Coefficient:

Correlation is that the method of moving the guide or sub-image round the image area and computing the worth of C there in area. This involves multiplying every pixel within the guide by the image pixel that it overlaps then summing the results over all the pixels of the guide. This parameter offers the amount of information restored back when applying any processing algorithms on images.

3. SSIM:

The structural similarity index may be a sensory activity metric that quantifies image quality degradation caused by process like information compression or by losses in data transmission. SSIM really measures the perceptual difference between the two similar pictures. It cannot choose that which of the two is best, that has got to be inferred from knowing

which is that the original and which has been subjected to additional processing like data compression and image enhancement.

4. Entropy:

The entropy or average information of an image is measure of the degree of randomness in the image. The entropy is beneficial within the context of image coding. It is a lower limit for the typical coding length in bits per pixel which may be realized by an optimum coding scheme with none loss of data.

S. No	Parameter	Output Image value
1	PSNR	9.2498
2	Elapsed Time	35.628
3	Entropy	5.02665

Table 1: Performance Metrics of Image Based Method

S. No	Parameter	Output Image value
1	PSNR	19.16
2	SSIM	0.6512
3	Entropy	5.2808
4	Correlation Coefficient (Accuracy)	0.9832(98%)

Table 2: Performance Metrics of Proposed Method

As we can see in table 1 and table 2 performance metrics are more accurate in proposed method when compared to image based methods.

Figure 17: Input image

Figure 18: Output image

CONCLUSION

We proposed an alternative methodology to enhance underwater images. Our strategy works on the fusion principle and it doesn't require extra information other than the single original image. The planned approach is able to enhance a wide range of underwater images with high accuracy, being able to recover important faded features and edges.

We have proposed an underwater image enhancement method including underwater image restoration based on color correction using white balancing and fusion process. Our proposed method can produce better results in processing various underwater images. We evaluated the performance of the proposed underwater image dehazing with other techniques with performance metrics like, PSNR, SSIM, entropy and correlation coefficient.

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