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Underwater Image Enhancement

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Abstract
Underwater image enhancement and reconstruction is a challenging task and has gained priority in recent years, as the human eye cannot clearly perceive underwater images. The image acquisition systems fail to capture images with significant detail when used at greater depths underwater, such equipment is also expensive. Thus, with the use of image processing algorithms it is possible to reconstruct and enhance the image quality in the absence of reliable and costly image acquisitionare good source of information which explores the idea about sea creatures. Low contrast, color distortion and poor visual appearance are the major issues that an underwater image has to undergo. Such problems were caused by dispersion and due to the presence of underwater organisms. Here we introduce an improved method for underwater image enhancement based on the fusion method that is capable to restore accurately underwater images

Keywords: underwater images, AHE technique, BBHE technique, Gamma correction, CLAHE technique, Image enhancement algorithms, histogram

Introduction

Similar to light traveling in the air, the underwater light propagation suffers from scattering and absorption. Nonetheless, the magnitude of absorption and scattering is enormous. While the light attenuation coefficients in the air are measured in inverse kilometers for an underwater environment it is in inverse meters. Such severe degradation of light poses serious challenges for imaging sensors to capture the information of the underwater area of interest. Unlike air, water is only trans- parent to the visible part of the electromagnetic spectrum and opaque to all other wavelengths. Furthermore, the constituent wavelengths of the visible spectrum are absorbed in different rates with longer wavelengths are absorbed more rapidly. The decay of light energy in water is truly remarkable. In the crystal clears waters of the middle oceans less than 1% of light energy remain by the depth of 150m. Hence the visibility degradation is such that the object is harder to see beyond the 20m range and in turbid coastal waters the visibility falls below the 5m mark. Also, no natural light from sun reaches below 1km of sea.

Hence, the amount of light with in water is always less than the amount of light over the surface of water. Therefore, images obtained under water generally have low visual quality. The scarcity of light under water is usually because of two unavoidable facts. One, the light under water is loses its true intensity, and second the chances for scattering of light within water is quite high. The immediate impact of this insufficient amount of light is the color distortion and illumination of the underwater scene visibility. Two of the most deteriorating effect on under- water image quality are the absorption of light energy and

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random path change of the light beams and at travel in water medium filled with suspended particles. The part of light energy which enters the water is rapidly absorbed and converted into other forms of energy like heat which in returns makes the water molecules get energized and become warmer and tend to evaporate.

Unlike conventional imaging taken above sea in open air, underwater photography shows a strong dominance of bluish and greenish colors. On the other hand, the strong attenuation of light in the water with respect to the air and a greater diffusion of the incident light have the consequence of considerably reducing the visibility. Thus, objects at distant distances from the acquisition system or the observer but also at medium distances, or even relatively short in some cases, are hardly visible and poorly contrasted with respect to their environment. In addition, in the presence of particles suspended in water (sand, plankton, algae, etc.), the incident light is reflected by these particles and forms a kind of in- homogeneous mist that adds to the scene observed. This turbidity of the water, most often white, also affects the visibility but also the color dynamics of the objects contained in the image by tarnishing or veiling them. On the water. The other hand, the formation of an underwater image is highly dependent on the nature of the water in which it was acquired. Natural waters can have very varied constitutions in terms of plants or minerals dissolved or suspended in behavior of the propagation of light in such a medium is strongly governed by this factor.

.Bukatahave established a first approximation in a classification according to the total concentration of chlorophyll-based pigments including phytoplankton. A second component corresponding to Dissolved Organic Matter, or yellow substance, was added later improving the model. From optical measurements and chemical measurements, spectral attenuation curves for different concentrations were obtained. An attenuation model was then established by regression of these data, making it possible to define a function expressing the attenuation coefficient directly from the concentration.

Although this algorithm does produce good results for most of the cases, it does suffer from over compensation of the color and sometime distort the contrast in a negative way. Different variations of this techniques exists and there is room for improvement. Specifically, improving the color degradation part of the method can make use of the linear function proposed by. Thus, combining the color improvement algorithm with the image fusion principle could improve the overall quality of the enhanced image even more.

Software based underwater image enhancement techniques are usually work by controlling some aspect of the mathematical model of underwater to compensate for the degrading effects introduced by the water's light absorption and the presence of organic and inorganic particles in water. Current state of the art method for underwater image restoration are typically designed for a single image input as using multiple images for the processing usually require more computational resources and may not be suitable for the real-time applications.

Underwater diffusion involves polarization effects. The method exploits these effects to compensate for the degradation of visibility. Considering a light source illuminating the particles of the line of sight, an incidence plane is formed by a ray coming from the source and the line of sight. The backscattered light is partially polarized perpendicularly to this plane. For this reason, typical natural backscattering in the underwater environment is partially horizontally polarized.

In order to measure the different polarization components, the scene is acquired through a polarizing filter. Since backscattering is polarized, its intensity depends on the orientation of the filter around the optical axis. There are two orthogonal orientations for which the transmittance of the backscattered light reaches maximum values

Bmax and Bmin. Thus, there are two linear polarization components.

When the polarizer is mounted, the intensity of each pixel in the image depends on a cosine function of the orientation angle. Similar to backscattering, there are two intensity extremes, and the visibility enhancement algorithm compensates for the haze effect caused by the broadcast.

From the local characteristics of the image a global regularity is measured. This regularity is called “total variation” and is calculated as the sum of the local gradients of the image. In the case of an additive noise, the image observed. The image noise is made by looking for the image. TV is used as a term of regularization which allows to penalize the big variations and to allow the discontinuities along the sufficiently regular outlines. The denoising force is controlled and the larger it is, the smaller the total variation of the resulting image.

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The Bayes formula expresses the posterior distribution of having an image in there is a random noise. Denoising is maximizing this probability. The probability is known and plays the role of a normalization constant, and is the likelihood and is determined from the model of data formation. The maximum likelihood (ML) estimate consists of looking for the value of that maximizes the likelihood. For reasons of simplicity, it is preferable to estimate the log of this product of probabilities. In general, the maximization is done by looking for image which satisfies the probability density in the case of a Gaussian noise. The Maximum a posteriori (MAP) estimation has the advantage of being able to take into account the prior. the image which maximizes, which gives, by applying the logarithmic function to the Bayes formula .

The purpose of this type of approach is to modify the histogram of the image by assigning new values to the pixels of the input image. The histogram of images witlow contrast occupies a small portion of the intensity range. The goal of equalization is to spread the histogram over a larger beach. For this, from the histogram of the image, the approach calculates the cumulative histogram and applies it (after normalization) to the image in order to spread its histogram uniformly over the entire range of dynamics There are also other functions such as logarithmic, exponential, power and others to obtain a histogram with a certain shape. Histogram equalization often gives better results when applied locally.

He, Sun, and Tang [27] used the dark channel prior algorithm to remove haze from single image and concluded that this method improves the quality of colour images. The study proposed a simpler implementation to transfer colour information to neighboring pixels. For this it applied a simple morphological closure to the transmittance map obtained. The results showed that in places that do not contain colors there is a zero intensity that corresponds to the “Dark Channel”. Note that no smoothing was performed, hence the artifacts generated on the contours. The defect of this method is that it applies only to images containing everywhere colors.

In many cases, the histogram of the image covers a broad dynamic. In this case a local histogram equalization is necessary to bring out the contrasts of the different parts of the image. For this, the image is scanned with a small window and the equalization principle described above is applied to each window separately. Then, in order to eliminate the generated block effects, due to the difference of the histograms between neighboring blocks, a bi-linear interpolation is used. This method is called Contrast Limited Adaptive Histogram Equalization (CLAHE). The defect of this type of method is the over-amelioration of contrasts: it brings out false details. Because of the local character of the method, it requires more processing time than a global equation.

METHODOLOGY:

It should be noted that the system can be generalized to any domain but for run-time purposes, we choose to utilize

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spatial filter or frequency domain filters. For hardware implementation. it would make sense to utilize spatial filter kernel structures. since these architectures can be easily established using hardware description language (HDL) in digital hardware such as FPGAs.

i. PDE

The proposed scheme can be realized in the frequency or spatial domain [30] as shown in:

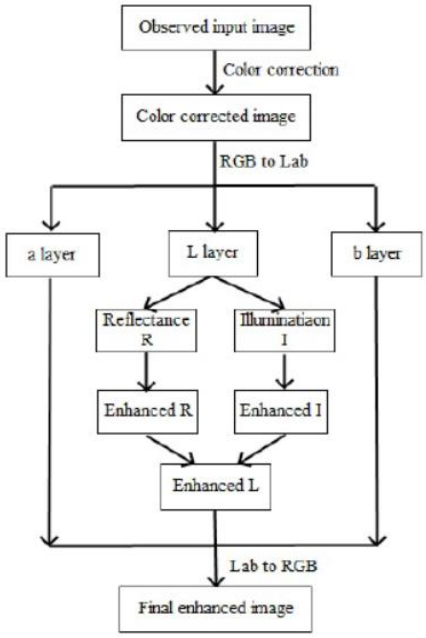
$$I_e(x.y) = \Psi\{I_{HPF}(x.y)\} + \gamma\{I_{LPF}(x. y)\}$$

Where Ψ{ } and γ{ } are amplification and attenuation functions for the high-pass, IHPF(x,y) and low-pass, ILPF(x,y) images respectively [30] and Ie(x,y) is the enhanced image. In previous work, we used the following expression to obtain the enhanced output image:

$$Ie(x,y) = IHPF(x,y) + \sqrt{ILPF(x,y)}$$

The PDE-based formulation can then be realized after derivation as:

$$\frac{\partial I(x,y,t)}{\partial t} = \lambda(-\nabla 2\ I(x,y,t) + [D-1]1-k\{I(x,y,t)\}k + \nabla 2I(x,y,t)\}k - I(x,y,t)) + \frac{\beta(I(x,y,t)-\mu}{\sigma}$$



The flow chart of the proposed algorithm

ii. Image Acquisition

The process of acquiring or capturing the images through image sensors such as camera. We generally capture the image using a camera or some type of sensors which acquire the data of the image.

iii. Change of color space

As we have seen from section 1.2, YCbCr and LAB color spaces are more desirable for performing image enhancement operations on the image (AHE and CLAHE). In this step, we convert the lo contrast degraded underwater image which is in RGB color space into YCbCr and LAB space.

iv. Separation of the channels

In this step, we split the converted image into its constituent channels. That is YCbCr space into Y,Cb,Cr channels and LAB space into L,A,B channels. The reason behind this step is that, the Y (brightness) and L (luminance) channels are majorly, if not alone responsible for the contrast of the image. By performing AHE and CLAHE on these channels, we aim at enhancing the overall image the model becomes too closely fit to the training data and performs bit poor on new and unseen data. It can be achieved by applying various transformations such as image rotating, flipping, cropping, zooming to the existing data. In proposed methodology, augmentation techniques like: rescaling, rotation range, height and width shift ranges were used.

V. Histogram Equilization

In this step we do histogram equalization (for AHE, BBHE and CLAHE), in order to increase the contrast of the image. Histogram equalization for BBHE has been implemented (5.1.3) and for the other two, we have used MATLAB's image processing toolbox function called adaptive histogram equalization.

Retinex:Retinexisthecombination ofthewordsRetinexandcortex.Themethodisbasedontheobservationthatthehumanvisualsystemperceivesthecontrastandcolourofanobjectrelativelyinthesamewayunderdifferentilluminationconditions.Thisisnotthecaseforcamerasensorsbecausetheintensityvalueofapixeldependsstronglyonthephotonflux.Theobjectiveistobuild,fromagivenimage, a new image illuminated by a constant white light .Retinex has a scale that applies a non linear operation to the logarithmic input image. There is also., Multi Scale Retinex (MSR) which as the name suggests, a combination of severalretinex(usually3)madeatdifferent scales(differentsizes).Experimentally,it has been shown that a uniform weighting gives good results. The last step of the algorithm is normalization which brings the result back to the definition interval of the image using an affine operation. The retinex algorithm is simple and automatic but requires a large signal-to-noise ratio to obtain a satisfactory result. On the other hand, in order to improve the processing time and to be able to process large images more quickly, it is customary to replace the convolution in the spatial domain by a multiplication in the frequency domain. In the following, we tackle an other problem which is the white balance.

Post processing for fuzz and under exposure: After computing R and I with a few iterations, a post-processing based on histogram is adopted to address the fuzz and under-exposure problem. Since the reflectance R. which contains details and edges ion, is fuzzed and attenuated by suspended particles" affection in the water, contrast limited adaptive histogram equalization (CLAHE) is adopted to obtain the enhanced reflectance Renhanced. This operation can enhance details and edges effectively mean-while avoids noise amplification. To address the problem of under-exposure, a slight improved histogram specification is worked on the illumination I. The enhanced illumination should be bright enough to improve exposure and lighten dark regions: meanwhile the lightness order

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and naturalness should be preserved. According tothe experimental results, the shape of arc tangent performs well: I' = arctan(I).

Inspired by the Bi-log Transformation. the number of the gray intensity is utilized as a weight to generate a weighted histogram. This operation takes both the numbers of pixels and gray values into consideration and can well preserve the naturalness. According to the definition of the Cumulative Density Functions (CDF). the CDF of I' is:

$$C(z) = \frac{\sum_{i=0}^{z} I'(i) \,.\, n(i)}{\sum_{i=0}^{\max(z)} I'(i) \,.\, n(i)}$$

where z is the zthgray level of I, max(z) is the maximum gray level of I, n is the number of the zthgray level. In order to lighten dark regions and preserve naturalness to avoid over-enhancement, we constrain the region of specified histogram in [15,230]. The CDF of the specified histogram is defined:

$$Cf(t) = \frac{\sum_{i=0}^{t} s(i)}{\sum_{i=0}^{230} s(i)}$$

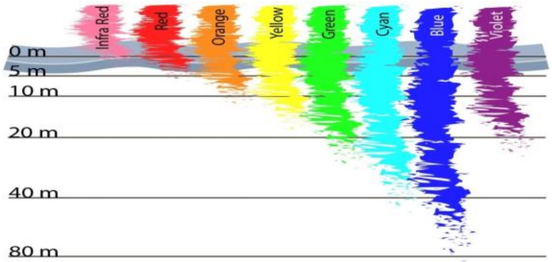
where s(t) = arctan(t — 15),t € [0,230]. The enhanced illumination $I_{enahneed}$can be obtained by

$$L_{enhanced} = Cf^{-1}(C(I)).$$

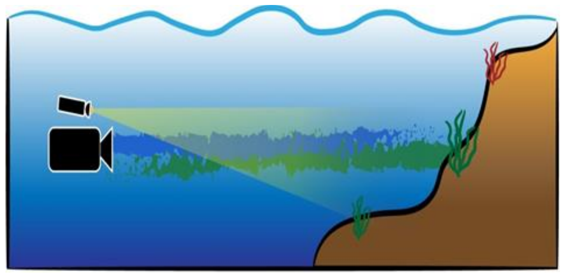
Finally, we combine the enhanced R and I together to obtain the enhanced L layer:

$$L_{enhanced} = R_{enahneed} * I_{enahneed}.$$

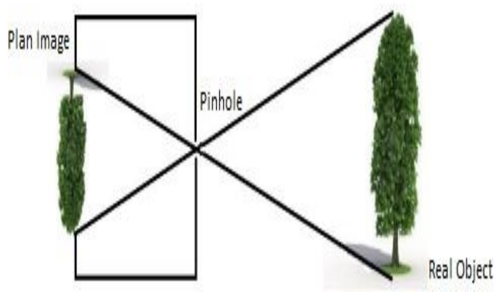
Then the new Lab color space is transformed into RGB to acquire the final enhanced color image.



Attenuation of light under water



Light Propagation from object to camera



Pinhole principal

RESULTS

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR is most commonly used to measure the quality reconstruction.of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs, PSNR is an approximation to human perception of reconstruction quality. Although a higher PSNR generally indicates that the reconstruction is of higher quality, in some cases it may not. One has to be extremely careful with the range of validity of this metric; it isconclusively valid when it is used to compare results from the same codec (or codec type) andsame content.PSNR is most easily defined via the mean square error (MSE). Given a noise-free m×nmono chrome image I and its noisy approximation K, MSE is defined. Here, MAXI is the maximum possible pixel value of the image The entropy of a system as defined by Shannon gives a measure of uncertainty about the images' actual structure. Shannon's function is based on the concept that the information gain from an event is inversely related to its probability of occurrence. Several authors have used Shannon's concept for image processing and pattern recognition problems. Many used Shannon's concept to define the entropy of an image assuming that an image is entirely represented by its gray level histogram only. As a result, segmentation algorithms using Shannon's function resulted in an unappealing result, same entropy and threshold values for different images with identical histogram.

Shannon defined the entropy of an n-state system as

$$H=-\sum_{i=1}^{n} p_i \log p_i$$

III. DICUSSION / LIMITATIONS

In this test. two up-to-date approaches 2][3] are referenced to make a comparison. It is obviously that method [2] observed image as shown in Fig. 3 (b) uses the dark channel prior and base removal algorithm [7] 10 restore the degraded image. while in some extremely conditions, such as serious color distortion and ambient light is very dark. this algorithm docs not work well. Method [3] uses image fusion technology enhance underwater images and obtain a good result as shown in Fig. While in some regions has a slight over-enhancement. Such as the five-pointed star on the statue. This due to the method [3] blends different filter to enhance corresponding deals which to consider the balance of the objective facts and subjective perception. The result, which is shown in fig 3 has a similar visual quality with [3] meanwhile the global naturalness is preserved better. This is because the proposed method. which based on the human vision system not only enhances details but also adjusts the illumination to make subjective visual perception comfortable. In addition. the proposed approach can enhance other kinds of degraded image. such as sandstorm image. Since the sandstorm has the similar environment with underwater both of them have suspended particles in the medium light is absorbed and catered, images appear color distortion and fuzz. Fig. 4 shows the experimental result of 4 sandstorm image.

IV. CONCLUSION

The enhancement of underwater images is a challenge in itself, because of the various factors affecting the acquired image. The use of various image enhancement techniques like AHE, GC, BBHE and CLAHE can be used to improve the visual appearance of the acquired images. The choice of the technique plays a vital role in image enhancement. The effects of noise, blurring, limited visibility on an image can therefore be reduced. In the future we would like to work on building an algorithm which helps to reconstruct images taken under other liquids, wherein the amount of wavelength absorbed by the liquid is different when compared to water. Also, from our research conducted, we conclude that AHE and CLAHE techniques performed relatively better than Gamma Correction and BBHE methods. A new retinex-based enhancing approach for single underwater image is proposed in this paper. Reflectance and illumination from single color corrected underwater image are decomposed to address the fuzz and under-exposure. A novel variational retinex model is built and an alternating direction optimization algorithm is introduced to make the decomposition.

A simple and yet effective post-processing is adopted to enhance degraded images after decomposing. Experimental results demonstrate that enhanced images have the property of color correction, brightness, naturalness preservation and well sharpness. Moreover, it is shown that the proposed new approach can enhance other kinds of degraded image.

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