Underwater Image Enhancement Using Fusion Process

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***Abstract*—This paper describes an efficient method to enhance underwater images. It uses a process known as fusion process which will work according to the fusion principle. This method proposes a single image approach from which two images are derived. First input is the white balanced and noise corrected version of the degraded image and second input is theadaptive histogram equalized output of the first input. These inputs are weighted by specific maps and finally multi scale fusion of weight measures and inputs.**

***Keywords*—Underwater image enhancement; Input assignment; White balancing; Weight maps assignment; Image fusion**

I. INTRODUCTION

Underwater imaging is a difficult task due to the physical properties of such environments.Underwater images get blurred due to poor visibility conditions and effects like “absorption of light”, “reflection of light”, “bending of light, “denser medium (800 times denser than air)”, and “scattering of light” etc. These are the important factors which cause the degradation of underwater images. Therefore these images have restricted visibility, non-uniform lighting, low-contrast, diminished colors and blurring of image features. Some of these effects are even observed when external lighting is used.

Scattering and color change are two major problems of distortion for imaging, especially in underwater environment. Scattering is caused by large suspended particles, like fog or turbid water. Color change corresponds to the varying degrees of attenuation encountered by light traveling in the water with different wavelengths. Capturing images underwater is difficult, mostly due to attenuation caused by light that is reflected from a surface and is deflected and scattered by particles, and absorption substantially reduces the light energy. The random attenuation of the light is mainly cause of the haze appearance while the fraction of the light scattered back from the water degrades the scene contrast. The colors are also faded due to the characteristicsbecause wavelengths are cut according to the water depth.

Underwater image enhancement techniques provide a way to improve the object identification in underwater environment. There are lots of researches started for the improvement of image quality, but limited work has been done in the area of underwater images. Enhancement methods have been proposed in the literature to improve image quality, compensate attenuation effects, enhance contrast, adjust colors, suppress noise and blur, while preserving and possibly even enhancing edges.

The existing research shows that underwater images raise new challenges and impose significant problems due to light absorption and scattering effects of the light and inherent structure less environment. Exploring, understanding and investigating underwater activities of images are gaining importance for the last few years. Today, scientists are keen to explore the mysterious underwater world. However, the area is still lacking in image processing analysis techniques and methods that could be used to improve the quality of underwater images.

Relevance of Underwater Image Enhancement

There are many fields which needs underwater image enhancement. Some of them are listed below

- Submarine operations
- Military operations
- Underwater engineering
- Underwater communication
- Underwater navigation and control
- Archeology
- Marine biology
- Diving science and tools
- Inspection of underwater things etc…

This paper introduces a new single image enhancement approach based on image fusion strategy. A process called fusion process is applying here which will work according to the fusion principle. This method proposes a single image approach from which two images are derived. First input is the white balanced and noise corrected version of the degraded image and second input is the adaptive histogram equalized output of the first input. These inputs are weighted by specific maps and finally multi scale fusion of weight measures and inputs.

With trivial modifications, we tried to apply changes in the white balancing algorithm by changing the value in the “Minkowski p norm” factor to give best result than existing method. Also we applied a gamma factor and gain factor to get better result. We applied a median filter for noise correction after white balancing process and finally adaptive histogram equalization. The enhanced images are attempted to reach reduced noise level, better exposedness of the dark regions, improved global contrast while the finest details and edges are enhanced significantly.

II. ENHANCING STRATEGY

This paper proposes a fusion-based strategy that can enhance underwater image with high efficiency, low complexity. The method includes three important steps: First, how to produce appropriate inputs. Second, choose effective weight maps. Finally we have to integrate inputs and weight maps. This paper proposes an approach that is able to enhance underwater images based on a single image.Fusion based approach does not require multiple images, deriving the inputs and the weights only from the original degraded image. We aim for a straightforward and computationally inexpensive process that is able to perform effectively on hardware. Since the degradation process of underwater scenes is both multiplicative and additive, traditional enhancing techniques like white balance, color correction, histogram equalization shown strong limitations for such a task. Instead of directly filtering the input image, this method developed a fusion-based scheme driven by the intrinsic properties of the original image. Intrinsic properties are represented by weighted maps. The success of the fusion techniques is highly dependent on the choice of the inputs and the weights.

In this work the degraded image is firstly white balanced in order to remove the unwanted colors while producing a natural appearance of the sub-sea images. This partially restored version is then further enhanced by suppressing some of the undesired noise. The second input is derived by applying histogram equalization to this filtered version. Fusion based enhancement process is driven by several weight maps. The weight maps of our algorithm assess several image qualities that specify the spatial pixel relationships. These weights assign higher values to pixels to properly depict the desired image qualities. Finally, this process is designed in a multi-resolution fashion that is robust to artifacts.

This work proposes an alternative single image based solution built on the multi-scale fusion principles. It aims for a simple and fast approach that is able to increase the visibility of a wide variation of underwater videos and images. This framework chooses specific inputs and weights carefully in order to overcome the limitation of such environments. This enhancing strategy consists of three main steps: inputs assignment, defining weight measures and fusion of the inputs and weight measures.

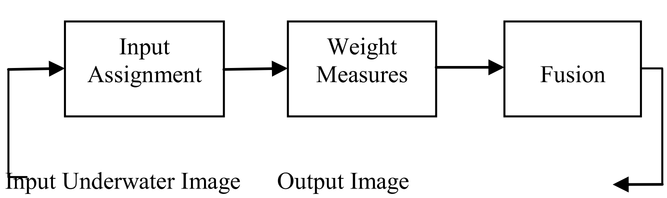

Fig.1 Block diagram for Fusion Process

A. *Input Assignment*

This paper introduces a new single image enhancement approach based on image fusion strategy. Different from most of the existing fusion methods this fusion technique processes only a single degraded image. The general idea of image fusion is that the processed result, combines several input images by preserving only the most significant features of them. Thus the resulting image has the best effect with good image features. In this single-based image approach two inputs of the fusion process are derived from the original degraded image. This work aims for a fast and simple technique that works generally. First input is the white balanced and noise corrected version of the degraded image and second input is the adaptive histogram equalized output of the first input. Thus, it consists of two stages. They are,

- Stage – I [First input]
  - White balancing of input
  - Noise corrected version of white balanced input
- Stage – II [Second input]
  - Apply Adaptive histogram equalization to first input

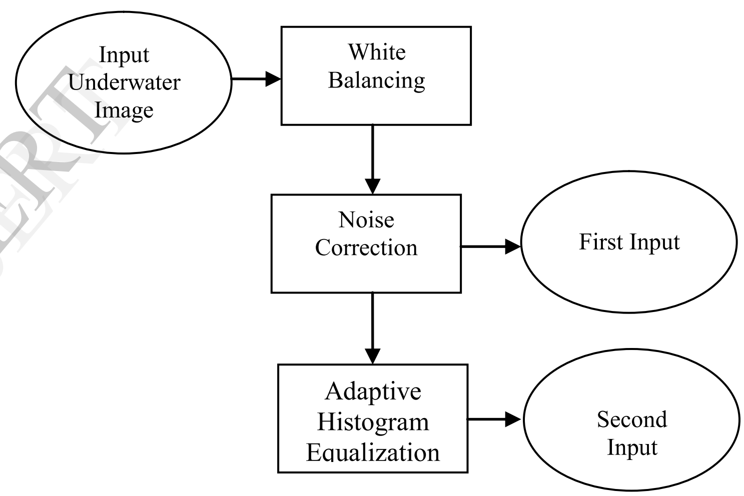

Fig.2 Block Diagram for Input Assignment

1. First Input

a. White Balancing

White balancing is an important processing step that enhances the image appearance by discarding unwanted color casts, due to various illuminants. In water deeper than 30 feet, white balancing suffers from noticeable effects since the absorbed colors are difficult to be restored. White balancing is also known as color constancy. The physical color, that is, humanly perceived color of any object generally depends on two factors; one is the incident light and the other one is surface property, which offers information of reflected light from the surface of the object. Therefore, the same object shot under different lighting conditions often show completely different colors. Fortunately, human eyes have an ability to perceive relatively constant in color under different external irradiation conditions. This is called Color Constancy [16].Color constancy refers to a stable psychological tendency in perception even if the lighting circumstances are changed. Simply, that is, the surface of the same object under different lighting conditions will produce different appearance, and the mechanism of the human body is not able to distinguish between the different surface reflectance caused by changes in illumination. Many algorithms are developed for color constancy or white balancing.

b. Algorithms for White Balancing

Many estimation algorithms have been proposed and can be broadly classified into two categories, either statistical or physics-based. Physics-based approaches are popular which usually require a learning procedure to get information for estimating illumination. While statistical-based approaches are relatively simpler in processing with low complexity, which means, they use low-level image features. However, both of these two approaches can be conducted under certain assumptions.

In [16], Dian Liu systematically summarizes review of existing algorithms, as well as their theoretical foundations and characteristics. The author analyses their mechanisms and discuss their corresponding strengths and weaknesses and also present a comparison analysis with proper criteria defined, both in definition and performance, among three basic color constancy algorithms, namely, Gray World, Max RGB and Shades of Grey. They are explained below.

- **The Gray World**

The Gray World algorithm is one of the oldest and the simplest color constancy algorithms which gives the assumption that, the average value of the R, G, and B components of the image should average to a common gray value. This implies that any deviation of the average color away from grey is caused by the effects of the light source.

- **Max RGB**

It is defined as if there is a white patch in the imaging scene of an image, the maximum value of each channel of the RGB-format image will appear in the white patch. Thus, under the assumption of the presence of white patch, the max values of each R, G, B channel of the image is the illumination color, therefore it is also known as max-RGB algorithm.

- **Shades of Grey**

The Gray World and the Max-RGB algorithm are two different general color constancy algorithm based on Minkowski norm. Gray World and Max-RGB algorithms will respectively return the relatively satisfying results if the average scene color is approximating grey or the maximum is white, but we need to make trade-off between them. To avoid problems with the above two algorithms, Finlayson and Trezzi [17] has given a mathematical answer and all the methods are analyzing with the help of a function known as “Minkowski- p norm”

$$e_i = [1/N\ (\sum p_i)^p]^{1/p}$$

The Minkowski-norm is the normalized result forms the estimated illumination vector. It computes a weighted average of the pixel values, assigning higher weights to pixels with higher intensities. It is notable that, for p= 1, the equation is equal to the assumption of Gray World, and for p= infinity, it is equal to compute the maximum value and that is color constancy by Max-RGB. Besides, through repeated experiments, when 1<p<infinity, Finlayson [17] get an approximately accurate value, that is, when p=6, Shades of Grey algorithm performs the best estimation results.

In this work, the illumination is estimated by the value ‘μ’ that is computed from the average of the scene ‘μ_{ref}’ and adjusted by the parameter ‘λ’ :

$$\mu_i = 0.5 + \lambda\mu_{ref}$$

The average color ‘μ_{ref}’is used to estimate the illuminant color and can be obtained based on Minkowski norm when p = 1.This method assigns a value 0.2 for ‘λ’ and observed that this value yields visually pleasing results.Despite of its simplicity, white balance strategy is able to remove effectively the color cast but also to recover the white and gray shades of the image, while producing a natural appearance of the output.

c. Comparison Analysis of Algorithms

From the comparison of the above three algorithms [16], we can say that Shades of Grey gives best resolution than the Gray World and Max RGB. Also Shades of Grey dominates the first place with the shortest time among all test images while the time consumed by algorithm Gray World and Max RGB are high. So Shades of Grey algorithm shows obvious advantages in time saving. Thus Shades of Gray algorithm is adopting in this method.

d. Modification of White balancing process with Gain constants and Gamma factor

White balancing process is modified with addition of gamma factor and gain factor. All of the algorithms estimate the R, G and B components of the illumination vector. The image is then correctedby adding gain factors and Gamma factors as mentioned in [20]. Gain factor is nothing but a constant. Gamma factor for each illumination channel can be calculated with the help of the below equations.

$$I = [I_R\ I_G\ I_B]^T$$

Gamma factors each channel. $\Gamma_i = \max(I)/I_i,\ I \in \{R, G, B\}$

2.Second Input

In this fusion framework, the second input is computed from the noise-free and color corrected version of the original image. This input is designed in order to reduce the degradation due to scattering. For getting the noise free input we used a median filter and to obtain an image with high contrast and for getting pixel values equally distributed, the median filtered image undergoes adaptive histogram equalization.

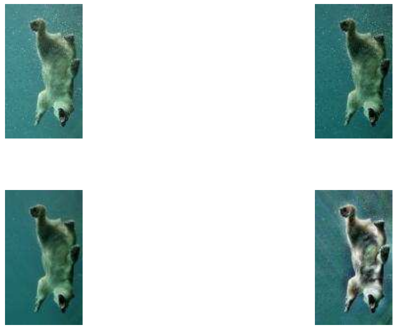

Fig.3 Input Assignemnt applied foran underwater image; Top line images are the degraded input image and the modified white balanced image; bottom line images are the noise corrected image(First Input);and the adaptive histogram equalised result of the first input(second input)

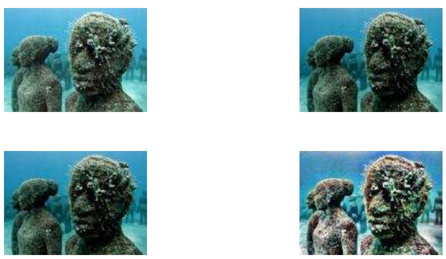

Fig.4 Input Assignemnt applied for an underwater image; Top line images are the degraded input image and the modified white balanced image; bottom line images are the noise corrected image(First Input);and the adaptive histogram equalised result of the first input(second input)

B. Weights of the Fusion Process

The design of the weight measures is an important task in fusion process for getting the desired appearance of the restored output. Weight maps assess several image qualities. Image quality specifies the spatial pixel relationships. These weight maps assign higher values to pixels to properly depict the desired image qualities. Itdoes not introduce artifacts. Higher pixel values will appear in the final image.Image restoration is tightly correlated with the color appearance, and as a result the measurable values such as salient features, local and global contrast or exposedness are difficult to integrate by naive per pixel blending, without risking to introduce artifacts. Therefore many weight measures are available to get the image more noise free and smoothened. Laplacian and local contrast weights are used in this approach.

- **Laplacian Contrast Weight (W_L)**

This weight is dealing with the global contrast. So in order to find the global contrast, first of all we have to apply a Laplacian filter on each input luminancechannel and then compute the absolute value of the filter result. It has the merit of assigning high values to edges and texture. But for the underwater restoration task, this weight is not sufficient to recover the contrast, mainly because it cannot distinguish between a ramp and flat regions. To avoid this problem, we searched for an additional contrast measurement that independently assesses the local distribution.

Fig.5 Top line images are the first and second input; bottom line images are the Laplacian Weight applied to each input

Fig.6 Top line images are the first and second input; bottom line images are the Laplacian Weight applied to each input

- **Local Contrast Weight (W_{LC})**

Apart from Laplacian Contrast Weight, Local Contrast Weight deals with the relation betweeneach pixel and its neighborhoods average. The main impactof this measure is to strengthen the local contrast appearance because it advantages the transitions mainly in thehighlighted and shadowed parts of the second input. The(W_{LC}) is computed as the standard deviation between pixelluminance level and the local average of its surrounding region:

$$\mathbf{W_{LC}(x, y) = I^k - I^k_{whc}}$$

Where'$\mathbf{I^k}$' represents the luminance channel of the input andthe '$\mathbf{I^k_{whc}}$' represents the low-passed version of it. For the low pass filtered version of the luminance channel, we are applying the Gaussian low pass filter.

Fig.7 Top line images are the first and second input; bottom line images are the Local Contrast Weight applied to each input

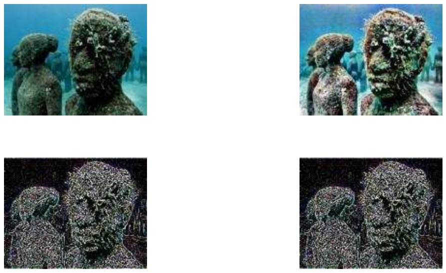

Fig.8 Top line images are the first and second input; bottom line images are the Local Contrast Weight applied to each input

C. Image Fusion

In final step, we have adopted a multi-scale image fusion[15]. In the fusion process, the inputs are weighted by specific computed maps in order to conserve the most significant detected features. In our case, each input is decomposed into a pyramid by applying the Laplacian operator to different scales. Similarly, for each normalized weight map, a Gaussian pyramid is computed. The enhanced image version R(x, y) is obtained by fusingthe defined inputs with the weight measures at everypixel location (x, y):

$$\mathbf{R(x, y) = \sum_{k=1}^{K} W^{k} (x, y)\, I^{k} (x, y)}$$

Where I^k symbolizes the input (where k=2 as we have two inputs) that is weighted by the normalized weight maps W^k. The normalized weights $W^k$are obtained by normalizing each weight measures over all k.

III. SIMULATION RESULTS

The enhanced underwater images by fusion process are shown below.

Fig. 9 First image is the input image and second image is the final result with Gain constant = 150; p = 10

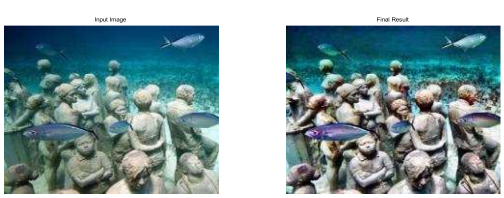

Fig. 10 First image is the input image and second image is the final result with Gain constant = 5; p = 11

Fig. 11 First image is the input image and second image is the final result with Gain constant = 5; p = 12

Fig. 12 First image is the input image and second image is the final result with Gain constant = 150; p = 12

IV. CONCLUSION

Forimplementing first block of Fusion process, we should consider different processes such as white balancing of the original image, noise correction of white balanced image, and histogram equalization of noise free white balanced image. From the comparison of the three algorithms for white balancing, we can say that Shades of Grey gives best resolution than Gray World and Max RGB. Also Shades of Grey dominates the first place with the shortest time among all test images while the time consumption of Gray Worldand Max RGB are high. So Shades of Grey algorithm shows obvious advantages in time saving. Thus Shades of Gray algorithm has adopted for White Balancing in this method. Shades of Grey algorithm is modified with addition of gain factor and gamma factor. Resulting white enhanced image has got better visibility compared with those obtained for other recent methods. White balanced image is then noise corrected with median filter and applied adaptive histogram equalization to that noise free result. After the input assignment process we measured different weights for first and second inputs. Finally we have done the Laplacian pyramid decomposition to get the enhanced underwater image.

Thus Fusion process is modified in the white balancing algorithm by changing the value in the Minkowski p norm factor, and then we added agamma factor and gain factor to give best result than the existingmethods.

V. FUTURE WORKS

We applied a median filter for noise correction. So we are planning to change the filter for noise correction and also in adaptive histogram equalizationafter white balancing process.

Also we are planning to apply changesin the weight measures as so many weight measures are available. Finally the whole system is planning to implement with hardware. If a better algorithm is obtained in the long run, this method can be subjected to adaptation.

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