AN EFFECTIVE APPROACH USING THE PRINCIPLE OF FUSION TO DEHAZE THE UNDERWATER IMAGE

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Abstract : The underwater images are usually degraded due to the medium scattering and absorption. An effective technique based on multiscale fusion to enhance and dehaze such images has been introduced in the paper. The two images derived from white-balancing and color compensating of the original image are processed for the fusion. The associated weight maps of derived images are defined for transition of color contrast and edges to the output image. The multiscale fusion technique removes the artifacts in the low frequency components of the reconstructed image due to sharp weight map transitions. PCQI and UCIQE are used to evaluate the quality of the underwater image which proves that the proposed algorithm improves the accuracy of various image processing applications. The evaluated results also reveal that the algorithm is reasonably independent of the camera settings**.**

***IndexTerms* -** Underwater image, gamma correction, fusion, white-balance, weight maps**.**

I. INTRODUCTION

Marine animals, fishes, strange shipwrecks and landscape are unusual attractions of underwater environment. Underwater imaging along with underwater photography has been an important source of interest in present technology and research area [1]. Inspection of underwater infrastructures, detection of manmade objects, cables, marine archeology and biology research, and control of underwater vehicles are the main interest areas of underwater surroundings.

Underwater images suffer from poor visibility. It is mainly from the attenuation of the propagated light. Absorption and scattering effects of light also add bad effects on underwater images. Light energy reduces by absorption and scattering causes changes in the direction of light propagation. These effects result in foggy manifestation and contrast deprivation. Therefore; distant objects become steamy. It has been noticed practically that images of the objects under sea water at a distance of more than 10 meters are unperceivable. The colors of these objects are faded because their composing wavelengths are cut according to the depth of water. To enhance the visibilit of poor or faded images of underwater objects, several methods and techniques are implemented previously. Traditional enhancing techniques such as gamma correction and histogram equalization are strongly limited for enhancing the quality of underwater images as well as reducing their practical applicability [2, 3].

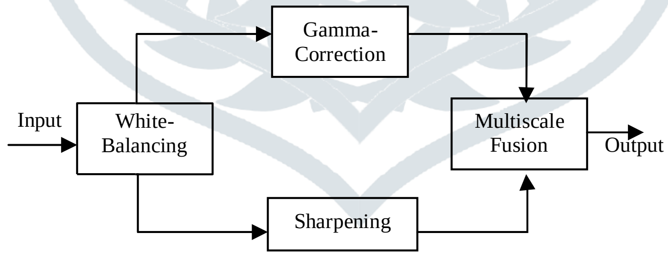

Fig. 1 Block diagram of dehazing techmnique of underwater image

The paper introduces an advanced approach of dehazing and enhancing the underwater images captured by means of a conventional camera. The proposed approach is based on the fusion of multiple inputs described by the block diagram as shown in Fig. 1. The white balancing of original underwater image removes the color cast induced by underwater light scattering, so as to produce a natural appearance of the sub-sea images. By independently employing a fusion process at every scale level, the possible artifacts due to the sharp transitions of the weight maps are minimized. Multi-scale fusion is motivated by the human visual system, which is very sensitive to sharp transitions appearing in smooth image patterns, while being much less sensitive to variations/artifacts occurring on edges and textures (masking phenomenon) [4]. An artifact-free blending is an outcome of the multi-scale fusion process.

The structure of the paper is as follows. Section II describes the detailed overview about the underwater image dehazing technique used in the paper for implementation. The technique consists of three core steps: (i) inputs derivation from the white balanced underwater image, (ii) weight maps definition, and (iii) multi-scale fusion of the inputs and weight maps.

Section III presents the results and outcomes of the underwater image dehazing technique based on multiscale fusion strategy along with quantitative assessments. The paper is concluded in Section IV.

II. METHODOLOGY FOR UNDERWATER DEHAZING TECHNIQUE

2.1 White-Balancing of underwater image

In underwater, the color perception is greatly correlated with the depth, and a problem of the green-bluish appearance in the image needs rectification. As the scattering attenuates more in case of the long wavelengths, the color perception is affected if going down in deeper water [5]. Additionally, the attenuation and the loss of color depend on the net distance between the viewer and the sight. Therefore, the primary aim of white-balancing is improving the target (original) image by removing the undesired color casts due to distance or attenuation properties as shown in Fig. 2.

2.2 Gamma Correction of White-Balanced Image (Input 1)

It has been observed that white balancing of underwater image (for the image captured in water deeper than 30 ft) tends to appear too bright as few absorbed colors are not possible to recover. Hence, a gamma correction of the white balanced image, as shown in Fig. 3, has been introduced to get the first input. The main role of gamma correction is to correct the global contrast but increases the difference between darker/lighter regions at the cost of a loss of details in the under-/over-exposed regions.

2.3 Sharpening of White-Balanced Image (Input 2)

To compensate for the loss of details resulted from gamma correction, a sharpened version of the white balanced image is also obtained which is considered as second input. The unsharp masking principle has been utilized by mixing of an unsharped (or blurred) version of the image with the white-balanced image to sharpen. The sharpened image *S* is expressed as

$$S = I + \beta\,(I - G * I) \quad (1)$$

where *I* is the white-balanced image to sharpen, $G * I$ denotes the Gaussian filtered version of *I*, and β is a parameter whose value is set as 0.5.

It is observed that a small value of β fails to sharpen *I*, and a too large value of β results in over-saturated regions, with brighter highlights and darker shadows. To avoid this problem, the normalized unsharp masking process is opted. The new sharpened image *S* is defined as:

$$S = (I + \mathcal{N}\{I - G * I\})/2, \quad (2)$$

Where, $\mathcal{N}\{.\}$ denotes the linear normalization operator (histogram stretching). This operator does not require any parameter tuning and results in effective sharpening of the image. This operator shifts and scales all the color pixel intensities of an image with a unique shifting and scaling factor defined so that the set of transformed pixel values cover the entire available dynamic range [6].

The second input mainly helps in reducing the degradation caused by scattering as shown in Fig. 4. Since the difference between white balanced image and its Gaussian filtered image is a high pass signal that approximates the opposite of Laplacian, this operation is less suitable to enlarge the high frequency noise, thereby generating undesired artifacts in the second input [6]. These artifacts can be minimized by the multi-scale fusion process.

2.4 Weights for the Fusion Process

During the step of blending, the weight maps are used in order to highlight those pixel values which have high weights in the final image (Fig. 6). Three weight maps are defined as follows:

i. *Laplacian contrast weight (WL):* It estimates the global contrast by computing the absolute value of a Laplacian filter applied on each input luminance channel. But it has a disadvantage in case of underwater dehazing task. It is not sufficient to recover the contrast as it distinguishes very little between a ramp and flat regions. Therefore, an additional weight map has been introduced to tackle with the problem.

ii. *Saliency weight (WS):* It aims at emphasizing the salient objects that lose their importance in the underwater scene. To measure the saliency level, we have employed the saliency estimator of Achantay et al. [7]. However, the saliency map tends to support highlighted areas (regions with high luminance values). To overcome this limitation, an additional weight map is also used. It is based on the observation that saturation decreases in the highlighted regions.

iii. *Saturation weight (W_{Sat}):* It's purpose is to enhance the saturated regions, thereby, enabling the fusion algorithm to adapt to chromatic information. The saturation weight map is computed for each input I_k as

$$W_{Sat} = \sqrt{1/3\,[(R_k - L_k)^2 + (G_k - L_k)^2 + (B_k - L_k)^2]} \quad (3)$$

Equation (3) is computed as the deviation for every pixel location between the R_k, G_k and B_k color channels and the luminance L_k of the kth input.

For each input *k*, the three weight maps are combined in a single weight map using the equation (4). The normalized weight maps $\overline{W_k}$ are computed for each input as

$$\overline{W}_k = \frac{W_k + s}{\sum_{k=1}^{K} W_k + K.s} \quad (4)$$

Fig. 2 White-balalnced image of underwater image.

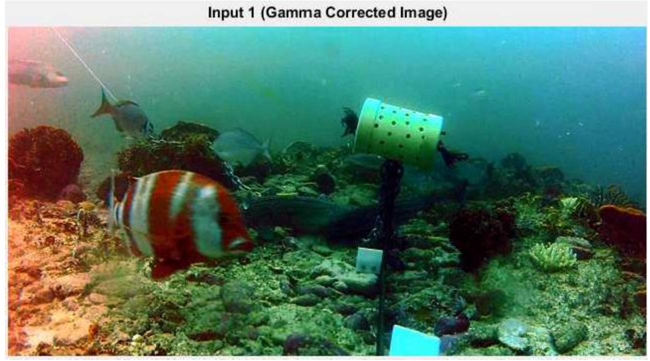

Fig. 3 Gamma Corrected image (input 1) of white-balanced image.

Fig. 4 Sharpened version image (input 2) of white-balanced image.

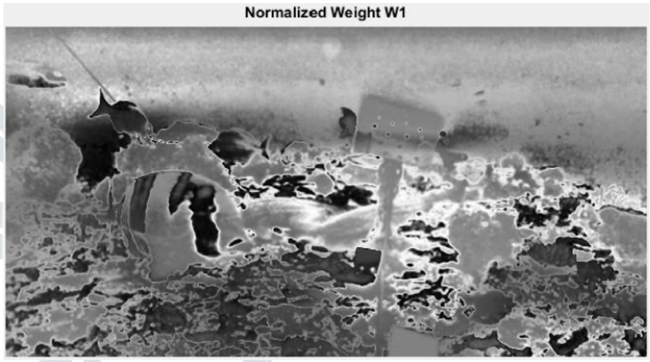

Fig. 5 Normalized weight of input 1.

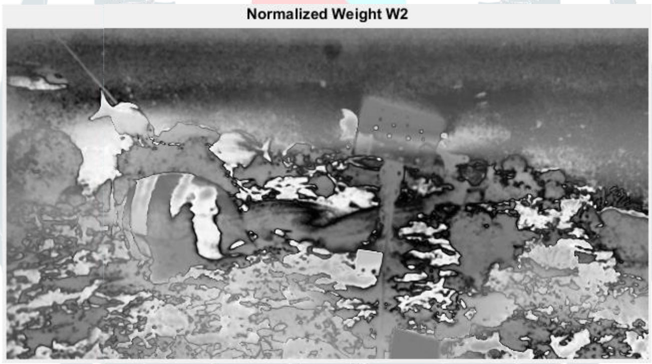

Fig. 6 Normalized weight of input 2.

where, ε is a small regularization term that ensures that each input contributes to the output and k is the index of the inputs. Here, ε = 0.1 and K = 2 for the implementation, W_k is the aggregated weight map of W_L, W_S and W_{Sat} and K is the Number of the aggregated maps.

The normalized weights of corresponding weights for two inputs are shown in Fig. 5 and Fig. 6.

In the previous work of dehazing technique of underwater image [8], the exposedness weight map has been utilized in order to reduce the overall complexity of the fusion process but some sharpening artifacts has been observed along with missing some contrast enhancements. Hence, the three weight maps i.e. Laplacian contrast weight, Saliency weight and Saturation weight are used in the proposed paper.

2.5 Multi-Scale Fusion Process

According to naive fusion process [9], the reconstructed image R(x) at every pixel location x can be obtained as

$$R(x) = \sum_{k=1}^{K} \overline{W}_k(x) I_k(x) \quad (5)$$

where I_k denotes the input

The approach has a disadvantage of introducing uninvited halos (circles of white or colored light around few pixels). Therefore, this limitation is overcome by employing multi-scale linear [7] or non-linear filters [8].

The multi-scale decomposition is based on Laplacian pyramid [9] which decomposes an image into a sum of band-pass images. Each level of the pyramid filters the input image using a low-pass Gaussian kernel G, and decimates the filtered image by a factor of 2 in both directions. Next, it subtracts an up-sampled version of the low-pass image from the input, thereby approximating the Laplacian, and uses the decimated low-pass image as the input for the successive level of the pyramid. The N-levels L_l of the pyramid can be defined as follows:

$$\begin{aligned} I(x) &= I(x) - G_1\{I(x)\} + G_1\{I(x)\} = L_1\{I(x)\} + G_1\{I(x)\} \\ &= L_1\{I(x)\} + G_1\{I(x)\} - G_2\{I(x)\} + G_2\{I(x)\} \\ &= L_1\{I(x)\} + L_2\{I(x)\} + G_2\{I(x)\} = \dots\dots\dots \\ &= \sum_{S=1}^{N} L_S\{I(x)\} \end{aligned} \tag{6}$$

where, G_l denotes a sequence of l low-pass filtering and the decimation, followed by l up-sampling operations. In the equation (6), L_l and G_l represent the lth level of the Laplacian and Gaussian pyramid, respectively.

For an efficient implementation of multi-scale fusion strategy [8] [9], each source input I_k is decomposed into a Laplacian pyramid [9] while the normalized weight maps $\overline{W}_k$are decomposed using a Gaussian pyramid. Both pyramids have the same number of levels, and the mixing of the Laplacian inputs with the Gaussian normalized weights is performed independently at each level l:

$$R_S(x) = \sum_{k=1}^{K} G_S\{\overline{W_k}(x)\} L_S\{I_k(x)\} \tag{7}$$

where l denotes the pyramid levels and k refers to the number of input images. The number of levels N depends on the image size, and has a direct impact on the visual quality of the blended image. The dehazed output is obtained by summing the fused contribution of all levels, after appropriate up-sampling.

III. Results and Discussion

T In this section, a comprehensive validation of the proposed dehazing technique has been performed through MATLAB R2014b as represented in Fig. 7 and then compared with the existing particular underwater image processing techniques [8, 9]. Since in general the color is captured differently by various cameras, it is demonstrated that white-balancing is robust to the camera settings [Reference].

The proposed approach has been tested for underwater image obtained from the source [12] as well as for underwater images (not presented in the paper) captured by

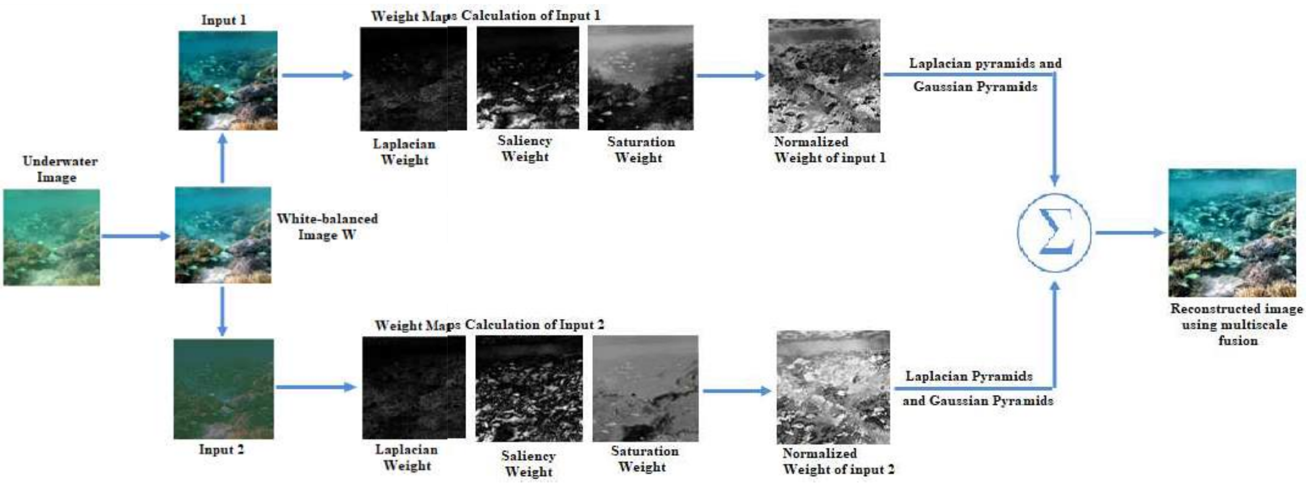

Fig.7 Block Diagram of Dehazing Technique of underwater image.Block Diagram of Dehazing Technique of underwater image.

Fig. 8 Underwater image from the source [13].

Fig. 9 Final reconstructed image using multiscale fusion.

means of different cameras and setups. Fig. 8 is the image file in JPEG format of 329 x 640 size used for dehazing processing and the reconstructed image using the multiscale fusion is shown in Fig. 9. Table 3.1 provides the associated quantitative evaluation of two different images [12], using two recent metrics: PCQI [10] and UCIQE [11] for the selected underwater image from the source. PCQI is a general-purpose image contrast metric while the UCIQE is dedicated to underwater image assessment. UCIQE metric was designed specifically to quantify the non-uniform color cast, blurring, and low-contrast that characterize underwater images.

Table 3.1: Quantitative Evaluation of Underwater Image

Image from Source [12]	Reconstructed Image after fusion	PCQI	UCIQE
		1.3161	0.9275
		1.2834	0.8593

IV. Conclusion

In the paper, an alternative approach to dehaze underwater images has been presented. The technique is based on the principle of multiscale fusion of two different inputs derived from white-balanced underwater image. A pair of inputs is introduced to enhance the color contrast and the edge sharpness of the white-balanced image respectively, and the weight maps are defined to preserve the qualities and reject the defaults of those inputs. By performing the extensive experiments and quantitative evaluation, it is clear that the proposed dehazing technique is capable of enhancing underwater images with greater accuracy.

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