Effective Single Underwater Image Enhancement by Fusion

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***Abstract*—Due to the absorption and scattering, the clarity and the observation of the depth of field of the image which is obtained by underwater photoelectric imaging will be reduced. This paper introduces a new single image enhancement approach based on image fusion strategy. The method first applies the white balance and global contrast enhancement technologies to the original image respectively, then taking these two adapted versions of the original image as inputs that are weighted by specific maps .We obtain the enhanced results by computing the weight sum of the two inputs in a per-pixel fashion. Since we do not employ deconvolution (computationally expensive), the algorithm reduce the execution time and can effectively enhance the underwater image. The experimental results demonstrate that our method can obtain good visual quality.**

***Index Terms*—underwater image enhancement, image fusion, white balance, saliency map**

I. INTRODUCTION

Poor visibility under water is a major problem for oceanic applications of computer vision [1-2]. In order to understand the underwater world better, we often using photovoltaic systems to objects under water for imaging [3]. Actually, underwater scenes are usually veiled by the light interaction with the medium: absorption and scattering of the light induce poor contrast, low luminosity and restricted visibility. And turbider the water is, greater the proportion of scattering part is. Thus the data acquired under the sea often suffer of large defaults and have to be preprocessed before any analysis or understanding. In order to get the quality enhancement image, we will compensate for the effect of the attenuation and restore color balance between physical and images. In the literature, a few approaches have been proposed to enhance the underwater image based on physics-based methods. Using the polarization imaging to improve the visibility of underwater color images which are obtained through natural lighting [4-6], automatic underwater image pre-processing [7], underwater image enhancement by attenuation inversion with quaternions [8], underwater image enhancement using an integrated color model [9], comparison and validation of point spread models for imaging in natural waters [10], retinex enhancement algorithm [11] and so on.

This paper proposes a fusion-based strategy [12] 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. The last, to effectively integration inputs and weight maps . Now the background information and related algorithms are introduced briefly .The rest of this paper is organized as follows. In section 2, we give the optical model for underwater images. Then, The outline of our algorithm is presented in Section 3. In section 4 the proposed method illustrates detailedly. and, the simulation results show in section 5.Finally, the conclusions are provided .The following chapters will introduce these detailedly.

II. UNDERWATER MODEL

Due to the absorption and scattering, the light crossing the water is attenuated and dispersed. Based on the common and popular optical model [13], the captured image can be modeled as two components: the direct reflection of light from the object and the reflection from the particles of the medium. The model is described as follow:

$$I(x) = J(x)T(x) + B(1 - T(x)) \quad (1)$$

Where x is a point in the underwater scene, $T(x)$ is the image captured by the camera, $J(x)$ is the scene radiance at point x. B is the homogeneous background light. $T(x)$ is the residual energy ratio of after reflecting from point x in the underwater scene and reaching the camera. Assuming a homogeneous medium, the transmission T is determined as $T(x) = e^{(-\beta\, d(x))}$ with β being the

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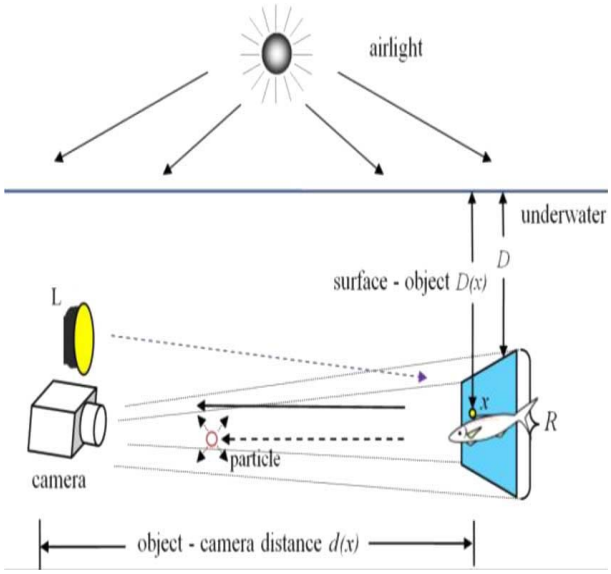


Figure 1. Natural light enters from air to an underwater scene point . The light reflected propagates distance to the camera. The radiance perceived by the camera is the sum of two components: the background light formed by multi-scattering and the direct transmission of reflected light.

mediu mattenuation coeffcient due to the scattering while *d* represents the distance between the observer and the considered surface.

The direct attenuation term *J(x)T(x)* describes the decay of scene radiance in the water [14],and the second part *B(1-T(x))* is the background light formed by multi-scattering . These will cause the color deviation, we use white as a benchmaek and restore color offset.And then emhance the contrast , increasing the performance of the details.Such a hypothesis is the oretically able to achieve our desired results.

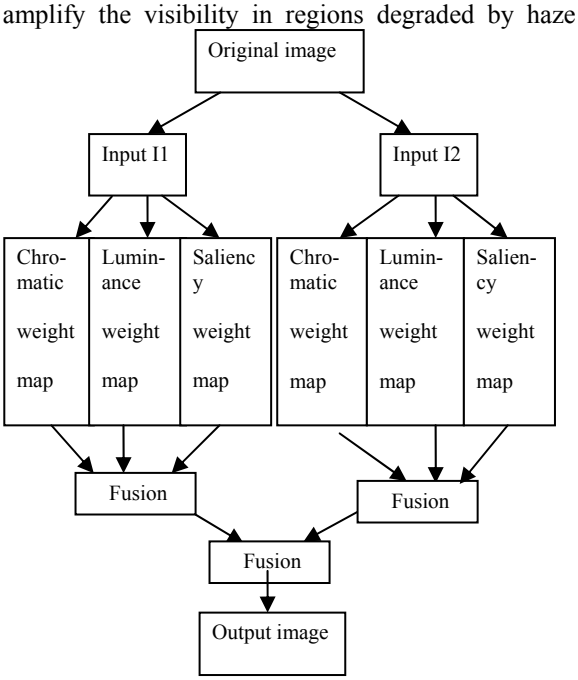
III. ALGORITHM FRAMEWORK

The poor quality of the underwater image mainly manifests in two aspects: One is the light attenuation, the countermeasure we should take is increasing the contrast; the other is the color change, we need to white balance the original underwater image to recover the distorted color to normal .Therefore, this paper propose the processing according to the two factors. The algorithm that putting forward in this paper employs a fusion-based strategy to recover the single underwater image. Image fusion has a wide applicability (e.g. remote sensing, medical imaging, microscopic imaging, robotics) and the main idea is to combine several images into a single one, keeping only the most significant features of them. By choosing appropriate weight maps and inputs, our fusion-based method is able to effectively enhance underwater images. The outline of our algorithm is showing in figure 2:

A. Inputs

Due to the different wavelengths of light, light absorption and scattering cause part of the light of shorter wavelength scattering, and the rest light of other length wavelenth will cross the medium. This will inevitably lead to the offset of the color. Simultaneously, Light absorption will make the light intensity weaker .Therefore, we need white balance to restore the natural light. White balance refers to no matter in any kind of the light source, it can revert the white objects to white in images. For the color cast while taking pictures under certain light source, it will be compensated through the strengthening of the complementary color. White balance is an indicator which can describe the accuracy of the white color which is generate by mixing three primary colors red (R), green (G), blue (B) .So we use the white color as the standard to restore color offset. The brightness value of images will be normalized and compressed within the range of [0,1]. This step can effectively reduce the significant difference between the brightness values and prepare for the next step of image enhancement. As a result, we get the first input image I1.

The global contrast of the image become weaker after the attenuation of the light. In order to get a clear image, we will be bound to improving a global contrast of the source image .Hereon, we use histogram stretching to increase the contrast. This operation has the effect to amplify the visibility in regions degraded by haze but



Figuer 2. The outline of our algorithm

yielding some degradation in the rest of the image. A similar effect may be obtained by general contrast enhancing operators (e.g. gamma correction) that also amplify the visibility in the hazy parts while destroying

the details in the rest of the image. However, this degradation is solved by employing proper weight maps (please refer to the next subsection and Figure 3).

B. Weight Maps

White balance and enhancing the contrast are preliminary process to the image in RGB space. Actually the RGB model is not well adapted to explain the color for the human visual. In order to describe the saturation, hue and contrast of images better while observe color objects, we use the luminance weight map、chromatic weight map and saliency weight map to measure and extract more details of the input image. Then integrated into one image, we can get more accurate results. The following are the instruction of three weight maps.

Chromatic weight map controls the saturation gain in the output image. Chroma is the purity of the color, it is used to describe the saturation of the image, the higher saturation is, the more vivid the color is. To obtain this map, for every pixel is computed the distance between its saturation value S and the maximum of the saturation range using a Gauss curve:

$$d = exp\left(-\frac{(S - S_{max})^2}{2\sigma^2} \right) \quad (2)$$

The standard deviation σ =0.3. Thus, weights close to zero are assigned to the pixels with smaller saturation while the most saturated pixels have weights close to one. This weight map is motivated by the fact that in general humans prefer increased saturation, being desirable that more saturated areas to be better depicted in the underwater image.

Luminance weight map manages the luminance gain in the output image. This map computes the standard deviation between every R, G and B color channels and each pixel luminance L of the input. The two input images are converted from RGB space to HSV space, for the component of V is the component of luminance. This weight map plays a role of balancing the brightness.

Saliency weight map identifes the degree of conspicuousness with respect to the neighborhood regions. The main information of the image is concentrated in only a small number of critical areas. The people's attention usually focused on the sudden change in the area of the image or the contour of the

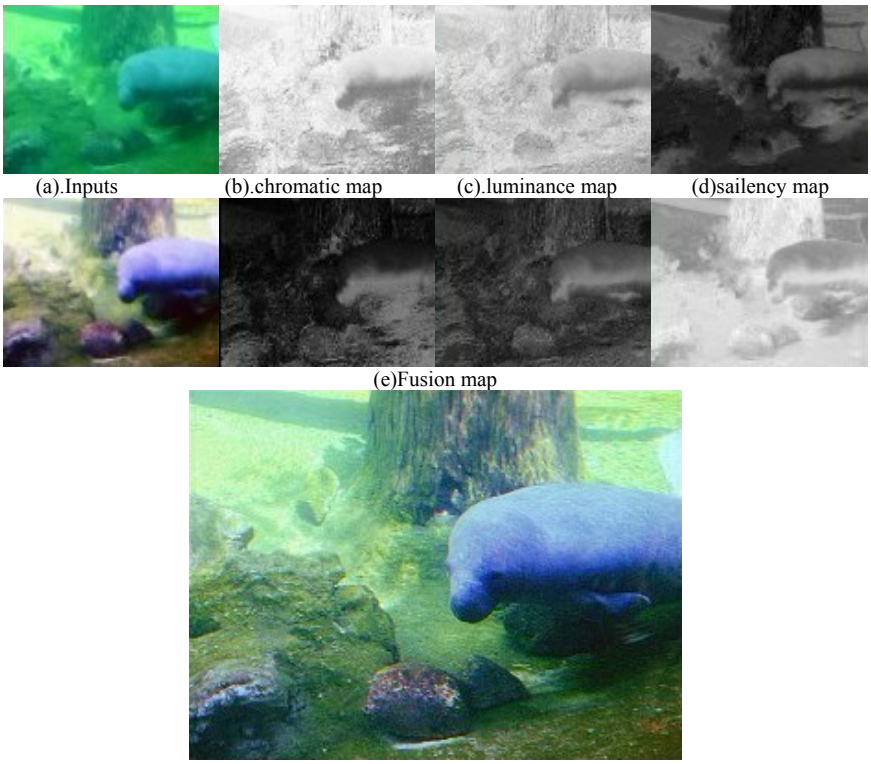


Figure 3 .(a) The two inputs.(b)(c)and (d)are the three weight maps corresponding to the inputs.(e) Our result.

image with the biggest curvature, and these will be reflect by the saliency map. This map reflects the contrast between a particular region and its adjacent areas. If the area's contrast become more obvious, it will be easier to attract people's attention, and it will have greater significance. Different with the method in enhancing the global contrast which was mentioned previously, saliency map can make the edge of the original image to be highlighted. After extracting the contours of the local area. we increase its corresponding weight value, so as to

achieve the result of image contrast enhanced. Beforehand, we use saliency algorithm of Achanta et al[16]. Here, we use a newer method [17] to generate Saliency map. They propose a regional contrast based saliency extraction algorithm, which simultaneously evaluates global contrast differences and spatial coherence. The proposed algorithm is simple, efficient, and yields full resolution saliency maps. This algorithm consistently outperformed existing saliency detection methods, yielding higher precision and better recall rates, when evaluated using one of the largest publicly available data sets.This algorithm can produce the full-resolution map. It is better than the previous method.The example for the three weight maps show in Figure 3.

C. Image Fusion

Final step, we have adopted a multi-scale image fusion [18]. In the fusion process, the inputs are weighted by specific computed maps in order to conserve the most significant detected features. our approach is simply blending the inputs weighted by several maps. Our strategy combines the input information in a per-pixel fashion minimizing the loss of the image structure. After we got the two input maps ,we extract the three weight maps for each input image,they are wL_1, wL_2 （luminance weight map）, wC_1 , wC_2 （chromatic weight map）and wS_1 , wS_2 （saliency weight map）.In order to facilitate the subsequent weighted fusion. Each weight map must be normalized first. And the normalized value of the illuminace map of the input I1:

$$NwL\_1 = wL\_1 / (wL\_1 + wL\_2) \quad (3)$$

$$NwL\_2 = wL\_2 / (wL\_1 + wL\_2) \quad (4)$$

By analogy,the normalized value of other maps of I_1 is NwC_1, NwS_1 .We use the same method to get the values for I_2.

The follow step is the linear integration of the three weighted value. We use W to express the final weight which is calculated as following:

$$W_i = a * NwL\_i + b * NwC\_i + c * NwS\_i \quad (5)$$

In the formula,a,b and c,are the three weighted value of the coefficient.

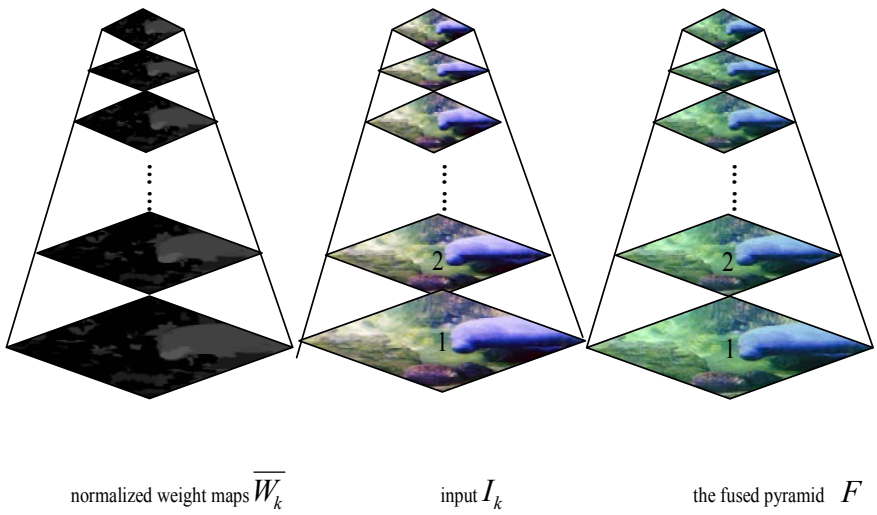
In our experiments, the value of a,b,c are all set to 1.

The output image can be described as:

$$F^{(i,j)} = \sum_k m_k * W_k^{(i,j)} I_k^{(i,j)} \quad (6)$$

In the foemula, m_k are the coefficient of the two input images I_1 and I_2,

Each pixel (*i, j*) of the output *F* is computed by summing the inputs *Ik* weighted by corresponding normalized weight maps $\overline{W_k}$ .In our case, each input is



Figuer 4 . Pyramid Model

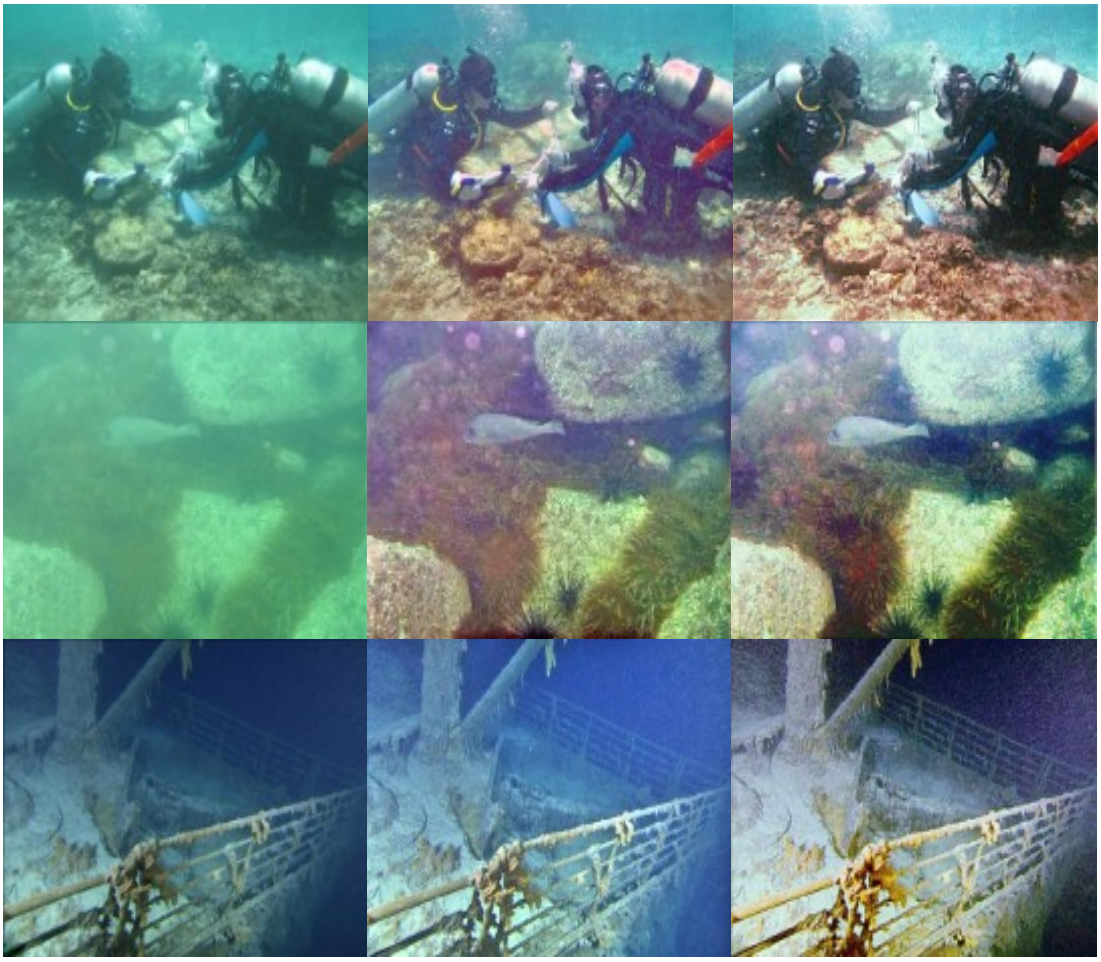
decomposed into a pyramid by applying Laplacian operator at different scales. Similarly, for each normalized weight map $\overline{W}$ a Gaussian pyramid is computed. Considering that both the Gaussian and

Laplacian pyramids[15] have the same number of level, the mixing between the Laplacian inputs and Gaussian normalized weights is performed at each level independently yielding the fused pyramid:

$$F_l^{(i,j)} = \sum_k G_l\{\overline{W_k}^{(i,j)}\} L_l\{I_k^{(i,j)}\} \quad (7)$$

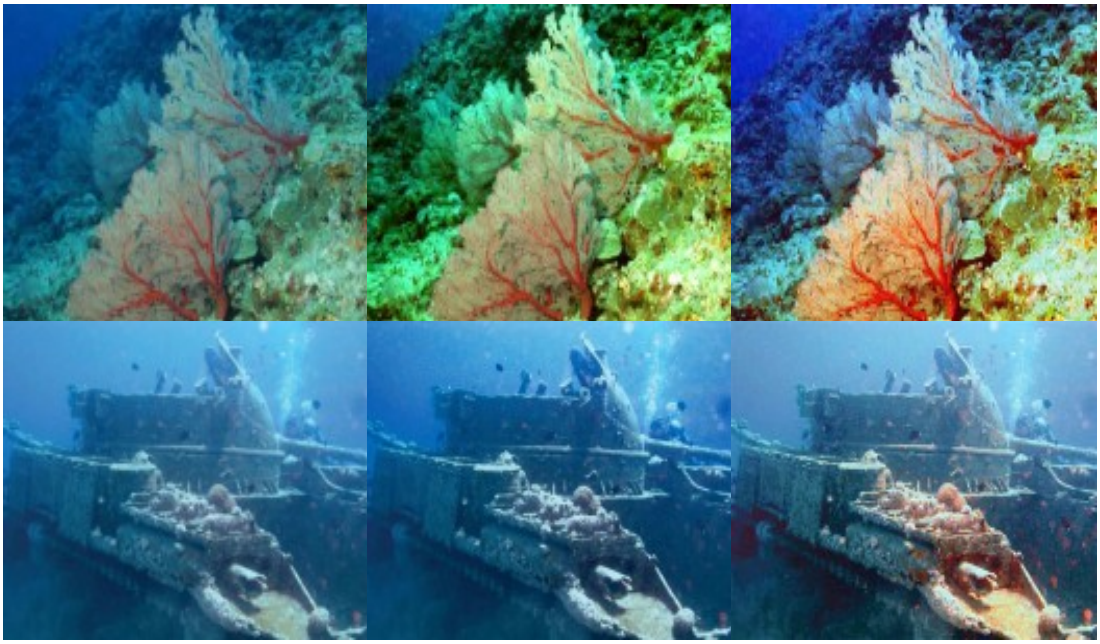
where l represents the number of the pyramid levels and $L\{I\}$ is the Laplacian version of the input I while $G\{\overline{W}\}$ represents the Gaussian version of the normalized weight map of the $\overline{W}$. This step is performed successively for each pyramid layer, in a bottom-up manner. The final output image $J$is obtained by summing the fussed contribution of all inputs. Through low-pass filtering and down-sample process we can generated Gaussian pyramid . Pyramid model shows in figure 4.

The first level of $\overline{W_k}$ is original version,then we get the up layer by sampling after low-pass filter from the layer below it[19].Finally,fusing the two weighted inputs to yield the fused pyramid F.For pyramid F,to expand the top level to the same size of the next level and plus the next level,the result obtained by accumaluting them in turn until the return to the size of the first level., then we get the final enhanced underwater image.



(a). Original (b). literature[11] (c). Our results

Figure 5 . The comparison of underwater images



(a).Original (b).literature[20] (c).Our results

Figure 6. The comparison of underwater images

(a).Original (b).literature[13] (c).Our results

Figure 7. The comparison of underwater images

IV. Experimental Results And Analysis

To illustrate the performance of our method, we use three group of test images, shown in Fig5-7. Comparing the image quality for three enhancement methods. We can obvious that our method can effectively enhance the underwater image. The first group is the contrastive experiments with the literature[11], this methord reduce scattering of water and increase true characteristic of underwater objects by MSR calculations for luminance channel of color underwater image. Comparison results show in figure 5.

Seen by the group of comparison images in Figure 5, whether the degree of bright color or the display of details, our result is more satisfactory. The literature [11] employs deconvolution, and we compute the weight sum of the two inputs in a per-pixel fashion, computational efficiency is more efficient.

The literature[20] empolys underwater image enhancement based on dark channel prior.The methord firstly use the median filter to estimate depth map,then combine the black channel to build the scene image,finally they employ the color enhancement. However,this methord exist estimation error. And it will result in the deviation of the color fidelity.Through the Fig 6 we can see that the color fidelity can be maximize saved under the premise of enhancing the underwater

image.

The water depth in the image scene is estimated according to the residual energy ratios of different color channels existing in the background light in the literature[13]. There must be exist estimation error. Through the Fig 7 we can see that the results of this paper demonstrate more realistic colors and sharper details. Overall, our algorithm can highlight details, without causing color distortion. And various contrastive experiments verify the effectiveness of our algorithm. The results obtain better visual effects. In addition, the proposed algorithm has a distinct advantage in computational efficiency. Besides, this method requires less computing resource and is well suitable for implementing on the surveillance and underwater navigation in real time. Even thought the method performs generally well, as the previous methods, a limitation of this algorithm is when the images are characterized by non-homogenous mediun in the water.

V.CONCLUSION

In this paper, we propose an efficient and low complexity underwater image enhancement method. The proposed approach contains two mainly procedures, the direct reflection of light from the object and the reflection from the particles of the medium.We have shown that by choosing appropriate weight maps and inputs, the fusion strategy can be used to effectively underwanter images. Our technique has been tested for a large data set of underwater images. The method is faster than existing single image enhanced strategies yielding accurate results and the color contrast of the object in underwater. The experimental results show that the proposed approach can effectively enhance the underwater image. To future work we would like to test our method for videos.

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