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EFFICEINT IMAGE ENHANCMENT USING WCID ALGORITHM WITH UNDER WATER IMAGES

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***Abstract*— —** Light scattering and color change are two major sources of distortion for underwater photography. Light scattering is caused by light incident on objects reflected and deflected multiple times by particles present in the water before reaching the camera. This in turn lowers the visibility and contrast of the image captured. color change corresponds to the varying degrees of attenuation encountered by light traveling in the water with different wavelengths, rendering ambient underwater environments dominated by a bluish tone. wavelength compensation and image dehazing (WCID) algorithm to improve the visibility of under water images. The performance of the algorithm for wavelength compensation and image dehazing (WCID) is evaluated both objectively and subjectively. Acquiring clear images in underwater environments is an important issue in ocean engineering . The quality of underwater images plays a pivotal role in scientific missions such as monitoring sea life, taking census of populations, and assessing geological or biological environments. Capturing images underwater is challenging, mostly due to haze caused by light that is reflected from a surface and is deflected and scattered by water particles, and color change due to varying degrees of light attenuation for different wavelengths . Light scattering and color change result in contrast loss and color deviation in images acquired underwater. WCID algorithm for enhance the under water images with good resolution and visibility .

Keywords – *dehazing algorithm, WCID, artifical light, underwater propagation*

I INTRODUCTION

Acquiring clear images in underwater environments is an important issue in ocean engineering [1], [2]. The quality of underwater images plays a pivotal role in scientific missions such as monitoring sea life, taking census of populations, and assessing geological or biological environments. Capturing images underwater is challenging, mostly due to haze caused by light that is reflected from a surface and is deflected and scattered by water particles, and color change due to varying degrees of light attenuation for different wavelengths [3]–[5]. Light scattering and color change result in contrast loss and color deviation in images acquired underwater. For example, in Fig. 1, the haze in the school of Carangid, the diver,and the reef at the back is attributed to light scattering, whereas color change is the reason for the bluish tone appearing in the brown coral reef at the bottom and the yellow fish in the upper-right corner.

Haze is caused by suspended particles such as sand, minerals, and plankton that exist in lakes, oceans, and rivers. As light reflected from objects propagates toward the camera, a portion of the light meets these suspended particles. This in turn absorbs and scatters the light beam, as illustrated in Fig. 2. In the absence of blackbody radiation [6], the multiscattering process along the course of propagation further disperses the beam into homogeneous background light.

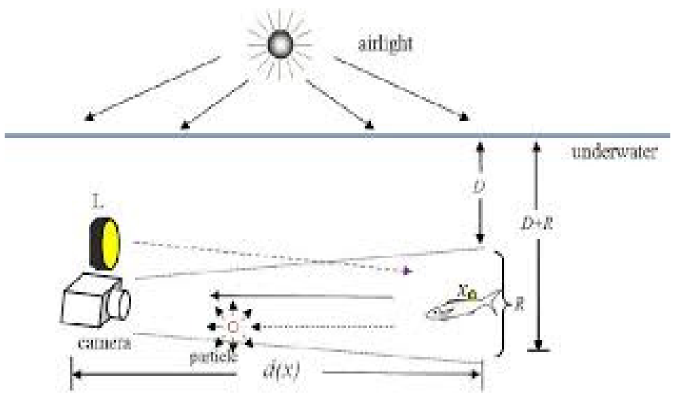

Fig: 1 Basic Image Restoration with under water data

Conventionally, the processing of underwater images focusessolely on compensating either light scattering or color change distortion. Techniques targeting on removal of light scattering distortion include exploiting the polarization effects to compensate for visibility degradation [7], using image

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dehazing to restore the clarity of the underwater images [8], and combining point spread functions and a modulation transfer function to reduce the blurring effect [9]. Although the aforementioned approaches can enhance scene contrast and increase visibility, distortion caused by the disparity in wavelength attenuation, i.e., color change, remains intact. On the other hand, color-change correction techniques estimate underwater environmental parameters by performing color registration with consideration of light attenuation [10], employing histogram equalization in both RGB and HSI color spaces to balance the luminance distributions of color [11], and dynamically mixing the illumination of an object in a distance-dependent way by using a controllable multicolor light source to compensate color loss [12].

Fig: 2 Basic Under water Image

Despite the improved color balance, these methods are ineffective in removing the image blurriness caused by light scattering. A systematic approach is needed to take all the factors concerning light scattering, color change, and possible presence of artificial light source into consideration.

II RELATED WORK

Poor visibility in bad weather is a major problem for many applications of computer vision. Most automatic systems for surveillance, intelligent vehicles, outdoor object recognition, etc., assume that the input images have clear visibility. Unfortunately, this is not always true in many situations, therefore enhancing visibility is an inevitable task. Optically, poor visibility in bad weather is due to the substantial presence of atmospheric particles that have significant size and distribution in the participatingmedium. Light from the atmosphere and light reflected from an object are absorbed and scattered by those particles, causing the visibility of a scene to be degraded. In the literature, a few approaches have been proposed. The first approach is to use polarizing filters. The main idea of this approach is to exploit two or more images of the same scene that have different degrees of polarization (DOP), which are obtained by rotating a polarizing filter attached to the camera. The common drawback of the methods in this approach is that they cannot be applied to dynamic scenes for which the changes are more rapid than the filter rotation in finding the maximum and minimum DOP.

The second approach is to use multiple images taken from bad weather scenes . The basic idea of this approach is to exploit the differences of two ormore images of the same scene that have different properties of the participating medium. While the methods in this approach can significantly enhance visibility, unfortunately their requirements render them unable to deliver the results immediately (have to wait until the properties of the medium change) for scenes that have never been encountered before. Moreover, like the first approach, they also cannot handle dynamic scenes.

The third approach is to use a single image and demand the approximated 3D geometrical model of the input scene. Compared with the previous two approaches, this approach resolves the requirements of multiple images; however, their demand of the approximated 3D geometrical models is problematic, since the structure of the real world (both natural scenes and man-made scenes) are significantly varied. In addition, the method of Narasimhan et al. is not intended to be automatic, it neeeds user interactions. To solve the problems, we introduce an automated method that only requires a single input image. Unlike the existing methods that use a single image, the proposed method does not require the geometrical information of the input image, nor any user interactions. The method is based on two basic observations: first, images with enhanced visibility (or clear-day images) have more contrast than images plagued by bad weather; second, airlight whose variation mainly depends on the distance of objects to the viewer, tends to be smooth. Relying on these two observations, we develop a cost function in the framework ofMarkov random fields (MRFs), which can be efficiently optimized by various techniques, such as graph-cuts or belief propagation. The method is applicable for both color and gray images. A brief overview of the method is as follows. Given an input image, we first estimate the atmospheric light, from hich we can obtain the light chromaticity. Using the light chromaticity, we remove the light color of the input image. Subsequently, we compute the data cost and smoothness cost for every pixel. The data cost is computed from the contrast of a small patch cropped from the image.

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The smoothness cost is computed fromthe difference or distance of the labels of two neighboring pixels, where the labels are identical to the airlight values. These data and smoothness costs build up complete MRFs that can be optimized using the existing inference methods, producing the estimated values of the airlight. Based on the estimated airlight, finally we compute the direct attenuation that represents the scene with enhanced visibility. Note that, in this paper, we do not intend to fully recover the scene's original colors or albedo. Our goal is to solely enhance the contrast of an input image so that the image visibility is improved. Very recently, Fattal independently developed a method that solely requires a single input image. The method uses a local window-based operation and a graphical model. However, unlike our proposed method, it attempts to separate uncorrelated fields, namely, the object shading and the particle attenuation.

Underwater vision is plagued by poor visibility conditions . According to, most computer vision methods (e.g., those based on stereo triangulation or on structure from motion) cannot be employed directly underwater. This is due to the particularly challenging environmental conditions that complicate image matching and analysis. It is important to alleviate these visibility problems since underwater imaging is widely used in scientific research and technology. Computer vision methods are being used in this mode of imaging for various applications such as mine detection, inspection of underwater power and telecommunication cables, pipelines, nuclear reactors, and columns of offshore platforms . Underwater computer vision is used commercially to help swimming pool lifeguards . As in conventional computer vision, algorithms are sought for navigation and control of submerged robots. In addition, underwater imaging is used for research in marine biology, archaeology, and mapping. Moreover, underwater photography is becoming more accessible to a widerWhat makes underwater imaging so problematic? To understand the challenge, consider Fig. 1. which shows an underwater archaeological site about 2.5-m deep. It is easy to see that visibility degradation effects vary as distances to objects increase. Since objects in the field of view (FOV) are at different distances from the camera, the causes for image degradation are spatially varying. This situation is analogous to open-air vision in bad weather (fog or haze) described in earlier works . Contrary to this fact, traditional image enhancement tools, e.g., high pass filtering and histogram equalization, are typically spatially invariant. Since they do not model the spatially varying distance dependencies, traditional methods are of limited utility in countering visibility problems, as has been demonstrated in past experiments as well as in this paper.

In earlier works, we develop a physics-based approach for recovery of visibility when imaging underwater scenes in natural illumination. Since it is based on the models of image formation, the approach automatically accounts for dependencies on object distance and estimates a distance map of the scene as a by-product. The approach is fast and relies on raw images taken through different states of a polarizing filter.1 These raw images have slight photometric differences with respect to one another. The differences serve as initial cues for our algorithm factoring out turbidity effects. It is interesting to note that marine animals use polarization for improved vision . To demonstrate the approach, we built an underwater polarization imaging system composed of both custom and off-theshelf components (the considerations for selecting the components are described). We used the method by experimenting in public the sea. Significant improvements of contrast and color are obtained. The recovered range maps indicate that the visibility range has been approximately doubled by the approach

In earlier work a self-tuning image restoration filter based on a simplified version of the Jaffe–McGlamery underwater image formation model. *Image restoration* is, for our purposes, the problem of *recoveringa degraded image using quantitative criteria*, i.e., given a model of the degradation and/or of the original image formation. Notice that *image enhancement* usually indicates the same problem but using qualitative or subjective criteria, i.e., nothing is known of the noise or of the image. Restoration techniques appear in the image processing literature under various names in different contexts, including recovery, reconstruction, deblurring, denoizing, deconvolution. and are good introductions, and and recent reviews. Underwater, efficient restoration could improve visualization in real-time and offline inspection of mission videos [5], as well as lead to better results in quantitative image analysis, e.g., automatic classification .

Well-known causes of image degradation underwater include turbidity, particulate matters in the water column, and the interaction between light and medium as light travels through water. All these phenomena are negligible when imaging in air, where the only important effects are due to light sources, surfaces (reflectance characteristics) and sensor properties .

Consequently, using full image formation models to design restoration algorithms is more complex in water than in air. In addition, the values of the model parameters relating to water properties, e.g., attenuation and scattering coefficients, are known only approximately in practice. Given that degradations affect the vast majority of underwater images,

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one would expect image restoration to feature in many underwater image processing systems. Instead, very few algorithms reported incorporate restoration or explicit imaging models (on this point, see Trucco and Plakas's critical survey of recent subsea video tracking systems [10]).Work addressing image formation in subsea image processing include Li *et al.*, who present a detailed photogrammetric model; Eustice *et al.*, who adopt enhancement heuristics (e.g., histogram equalization to detect shadows) in a mosaicing system for flow measurement and seafloor mapping; Negahdaripour [13] devises a generalized model to decouple the different changes induced by illumination and motion on image intensities. Liu *et al.* report wavelet-based algorithms for enhancement, detection and tracking in satellite imagery. Model complexity and uncertainty on parameter values are probably two important reasons discouraging the inclusion of image formation models in image processing algorithms.

In earlier proposes the design of an image restoration filter tackling the two problems above. First, we devise a simplified version of the well-known, complete underwater image formation model by Jaffe and McGlamery. Our simplifications make a simple design possible. The underlying assumptions point to diffuse illumination and limited backscatter as the ideal imaging conditions for the restoration filter, and experiments indicate good performance even in the presence of significant turbidity. Second, approximate parameter values are used only to initialize the filter; optimal values are estimated by optimizing a quality criterion based on a global contrast measure, guaranteeing that each image is processed by an individually tuned filter. We also give a concise account of the Jaffe–McGlamery model. The structure of the paper is as follows. then reviews the Jaffe–McGlamery model. Next works describes and motivates the simplification of the general model, and uses the results to derive our self-tuning restoration algorithm. Finallay describes briefly the results of our qualitative and quantitative tests. In clear images in underwater environments is an important issue in ocean engineering . The quality of underwater images plays a pivotal role in scientific missions such as monitoring sea life, taking census of populations, and assessing geological or biological environments. Capturing images underwater is challenging, mostly due to haze caused by light that is reflected from a surface and is deflected and scattered by water particles, and color change due to varying degrees of light attenuation for different wavelengths. Light scattering and color change result in contrast loss and color deviation in images acquired underwater. For example, in Fig. 1, the haze in the school of Carangid, the diver, and the reef at the back is attributed to light scattering, whereas color change is the reason for the bluish tone appearing in the brown coral reef at the bottom and the yellow fish in the upper-right corner.

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The algorithm for wavelength compensation and image dehazing (WCID) proposed in this paper combines techniques of WCID to remove distortions caused by light scattering and color change. Dark-channel prior [13], an existing scene-depth derivation method, is used first to estimate the distances of the scene objects to the camera. The low intensities in the dark channel are mainly due to three factors: 1) shadows, e.g., the hadows of creatures, plankton, plants, or rocks in seabed images; 2) colorful objects or surfaces, e.g., green plants, red or yellow sands, and colorful rocks/minerals, deficient in certain color channels; and 3) dark objects or surfaces, e.g., dark creatures and stone . Based on the depth map derived, the foreground and background areas within the image are segmented. The light intensities of foreground and background are then compared to determine whether an artificial light source is employed during the image acquiring process. If an artificial light source is detected, the luminance introduced by the auxiliary lighting is removed

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from the foreground area to avoid overcompensation in the stages followed. Next, the dehazing algorithm and wavelength compensation are utilized to remove the haze effect and color change along the underwater propagation path to the camera. The residual energy ratio among different color channels in the background light is employed to estimate the water depth within an underwater scene. Energy compensation for each color channel is carried out subsequently to adjust the- bluish tone to a natural color.With WCID, expensive optical instruments or stereo image pairs are no longer required.

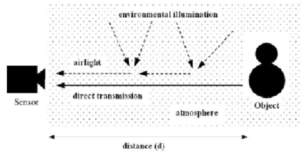

Figure 2. *The pictorial description of the optical model*

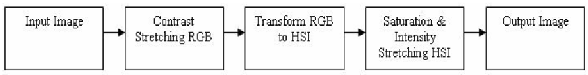

Figure 3: Methodology for Underwater Image Enhancement

Fig 3 : Existing and Previous method of image sensing with under water

IV PROPOSED WORK IMPLEMENTATION

The background light in an underwater image can be used to approximate the true in-scattering term in the full radiative transport equation to achieve the following simplified hazy image formation model:

$$I_\lambda(x) = J_\lambda(x)\cdot t_\lambda(x) + (1 - t_\lambda(x))\cdot B_\lambda, \lambda \in \{\text{red, green, blue}\} \qquad (1)$$

where is a point in the underwater scene, is the image captured by the camera, is the scene radiance at point , is the residual energy ratio of after reflecting from point in the underwater scene and reaching the camera, is the homogeneous background light, and is the light wavelength. Note that the residual energy ratio is a function of both wavelength and the object–camera distance . summarizes the overall effects for both light scattering and color change suffered by light with wavelength traveling the underwater distance . The direct attenuation term describes the decay of scene radiance in the water [16]. The residual energy ratio can be represented alternatively as the energy of a light beam with wavelength before and after traveling distance within the water and , respectively, as follows:

$$t_\lambda(x) = \frac{E_\lambda^{\text{residual}}(x)}{E_\lambda^{\text{initial}}(x)} = 10^{-\beta(\lambda)d(x)} = \text{Nrer}(\lambda)^{d(x)} \qquad (2)$$

Where the normalized residual energy ratio Nrer corresponds to the ratio of residual to initial energy for every unit of distance propagated and is the medium extinction coefficient [15]. The normalized residual energy ratio Nrer depends on the light wavelength transmitted [17], as illustrated in Fig. 3, where red light possesses longer wavelength and lower frequency and thereby attenuates faster than the blue counterpart. This results in the bluish tone prevalent in underwater images.

Other than the wavelength of light transmitted, the normalized residual energy ratio Nrer is also affected by water salinity and concentration of phytoplankton [17]. In light of this observation, oceanic water is further classified into three categories. Type-I waters represent extremely clear oceanic waters. Most clear coastal waters with a higher level of attenuation

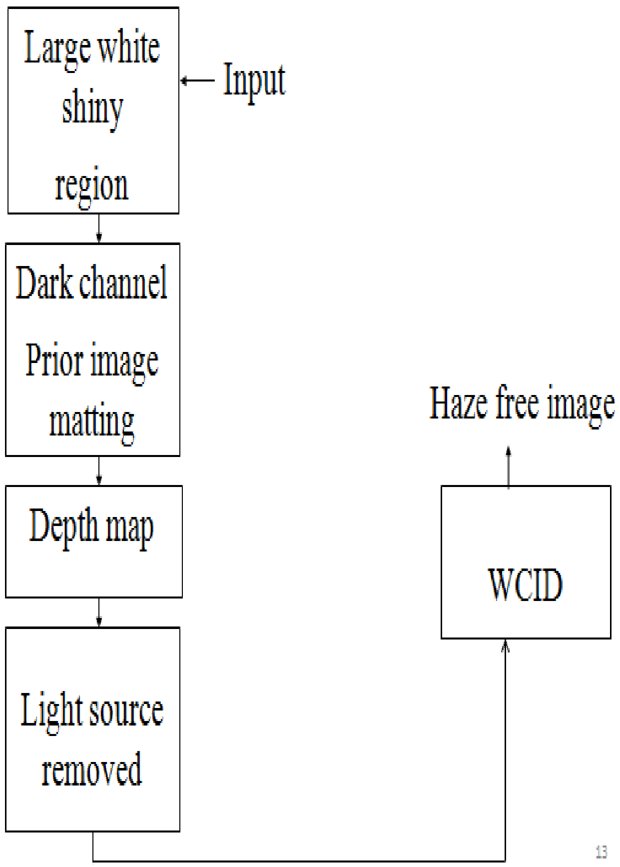

Fig: 4 Proposed working model diagram

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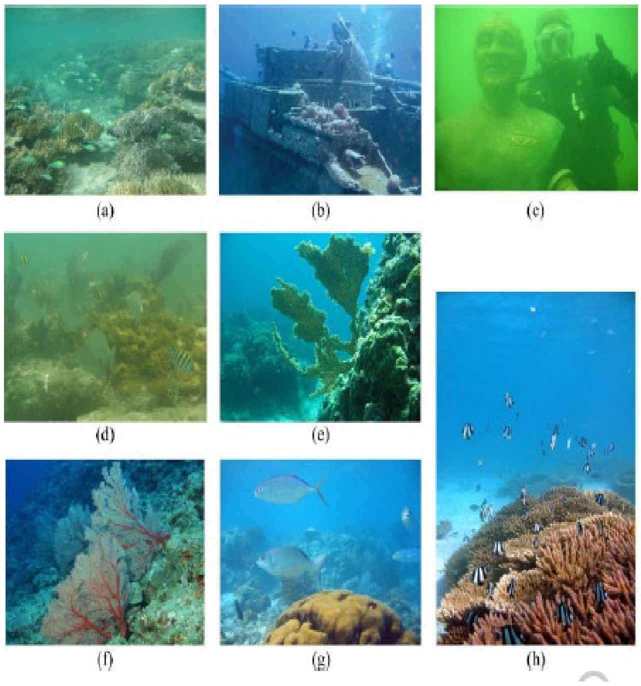

Fig: 5 Various resultants for under water image

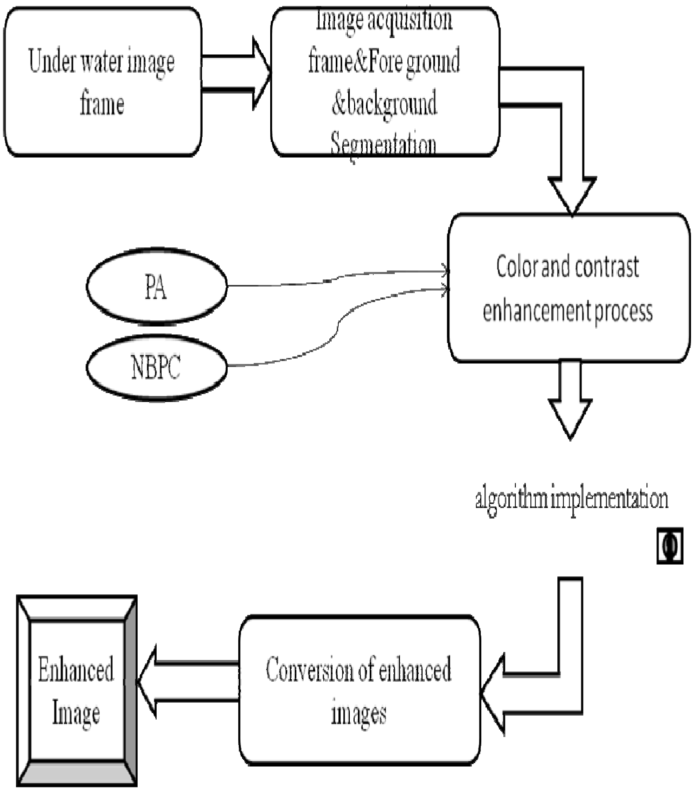

Fig: 7 Under Water Image Enhancement using NBPC and WCID

VI. EXPERIMENTAL RESULTS

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Input Image

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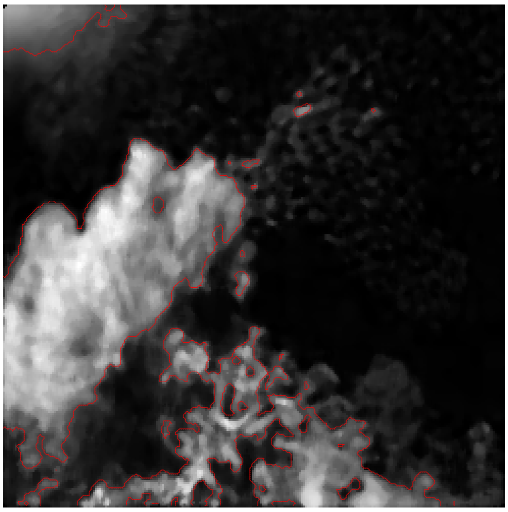
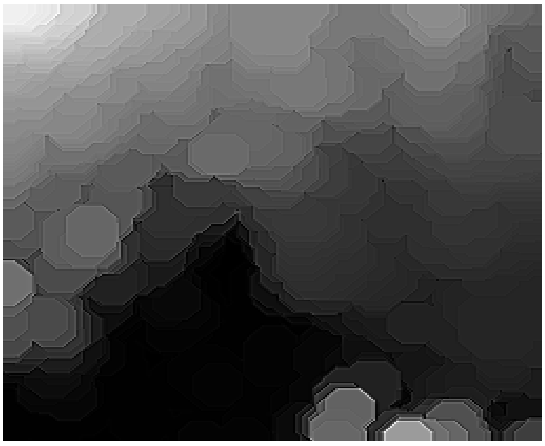
Large White Shiny Region



Depth Map



Depth Map after Image Matting

Image obtained after applying WCID

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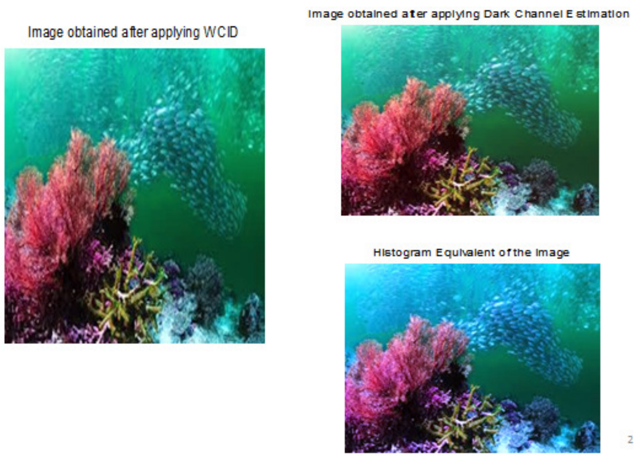
COMPARISION OUTPUT



V CONCLUSION

The WCID algorithm proposed in this paper can effectively restore image color balance and remove haze.The experimental results demonstrate superior haze removing and color balancing capabilities of the proposed WCID over traditional dehazing and histogram equalization methods.Image can be refined by focusing only under water and the objects on it.Both Image rendering and Visibility enhancement based on Koschmieder's Law. A new PA algorithm is used

REFERENCES

[1] K. Lebart, C. Smith, E. Trucco, and D. M. Lane, "Automatic indexing of underwater survey video: algorithm and benchmarking method," *IEEE J. Ocean. Eng.*, vol. 28, no. 4, pp. 673–686, Oct. 2003.

[2] J. Yuh and M. West, "Underwater robotics," *Adv. Robot.*, vol. 15, no. 5, pp. 609–639, 2001.

[3] J. R. Zaneveld and W. Pegau, "Robust underwater visibility parameter," *Opt. Exp.*, vol. 11, no. 23, pp. 2997–3009, 2003.

[4] E. Trucco and A. T. Olmos-Antillon, "Self-tuning underwater image restoration," *IEEE J. Ocean. Eng.*, vol. 31, no. 2, pp. 511–519, Apr. 2006.

[5] J. S. Jaffe, "Computer modeling and the design of optimal underwater imaging systems," *IEEE J. Ocean. Eng.*, vol. 15, no. 2, pp. 101–111, Apr. 1990.

[6] M. C.W. van Rossum and T. M. Nieuwenhuizen, "Multiple scattering of classical waves: Microscopy, mesoscopy and diffusion," *Rev. Modern Phys.*, vol. 71, no. 1, pp. 313–371, Jan. 1999.

[7] Y. Y. Schechner and N. Karpel, "Recovery of underwater visibility and structure by polarization analysis," *IEEE J. Ocean. Eng.*, vol. 30, no. 3, pp. 570–587, Jul. 2005.

[8] L. Chao and M. Wang, "Removal of water scattering," in *Proc. Int. Conf. Comput. Eng. Technol.*, 2010, vol. 2, pp. 35–39.

[9] W.Hou,D. J.Gray,A.D.Weidemann,G. R. Fournier, and J. L. Forand, "Automated underwater image restoration and retrieval of related optical properties," in *Proc. IGARSS*, 2007, vol. 1, pp. 1889–1892.

[10] A. Yamashita, M. Fujii, and T. Kaneko, "Color registration of underwater image for underwater sensing with consideration of light attenuation," in *Proc. Int. Conf. Robot. Autom.*, 2007, pp. 4570–4575.

[11] K. Iqbal, R. Abdul Salam, A. Osman, and A. Zawawi Talib, "Underwater image enhancement using an integrated color model," *Int. J.Comput. Sci.*, vol. 34, no. 2, pp. 2–12, 2007.

[12] I. Vasilescu, C. Detwiler, and D. Rus, "Color-accurate underwater imaging using perceptual adaptive illumination," in *Proc. Robot. Sci. Syst.*, Zaragoza, Spain, 2010.

[13] K. He, J. Sun, and X. Tang, "Single image haze removal using Dark Channel Prior," in *Proc. IEEE CVPR*, 2009, vol. 1, pp. 1956–196

[14] S. Shwartz, E. Namer, and Y. Y. Schechner, "Blind haze separation," in *Proc. IEEE CVPR*, 2006, vol. 2, pp. 1984–1991.

[15] J. T. Houghton*, The Physics of Atmospheres*, 2nd ed. Cambridge, U.K.: Cambridge Univ. Press, 2001, ch. 2.

[16] W. N. McFarland, "Light in the sea—Correlations with behaviors of fishes and invertebrates," *Amer. Sci. Zoology*, vol. 26, no. 2, pp. 389–401, 1986.

[17] S. Q. Duntley, "Light in the sea," *J. Opt. Soc. Amer.*, vol. 53, no. 2, pp. 214–233, 1963.

[18] L. A. Torres-Méndez and G. Dudek, "Color correction of underwater images for aquatic robot inspection," in *Proc. EMMCVPR*, 2005, vol. 3757, Lecture Notes in Computer Science, pp. 60–73.

[19] N. G. Jerlov, *Optical Oceanography*. Amsterdam, The Netherlands: Elsevier, 1968.

[20] R. Tan, "Visibility in bad weather from a single image," in *Proc. IEEE CVPR*, 2008, vol. 1, pp. 1–8.

[21] R. Fattal, "Single image dehazing," in *Proc. Int. Conf. Comput. Graph. Interact. Tech.*, 2008, pp. 1–9.

[22] A. Levin, D. Lischinski, and Y.Weiss, "A closed form solution to natural image matting," in *Proc. IEEE CVPR*, 2006, vol. 1, pp. 61–68.

[23] Y. Y. Schechner and N. Karpel, "Clean Underwater Vision," in *Proc. IEEE CVPR*, 2004, vol. 1, pp. 536–543.

[24] N. Carlevaris-Bianco, A. Mohan, and R. M. Eustice, "Initial results in underwater single image dehazing," in *Proc. IEEE OCEANS*, 2010, pp. 1–8.

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Available online at www.ijarmate.com

International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE)
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[25] C. Perer and H. Richard, "Improved Single Image Dehazing Using Geometry," in *Proc. IEEE DICTA*, 2009, pp. 103–110.

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