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Underwater Image De-hazing using Weight Map Fusion with Gamma Correlation

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Abstract- Underwater images are degraded due to scatters and absorption, resulting in low contrast and color distortion. In this article, a novel self-similarity-based method for de-scattering and super resolution (SR) of underwater images is proposed. The traditional approach of preprocessing the image using a de-scattering algorithm, followed by application of a SR method, has the limitation that most of the high-frequency information is lost during de-scattering. The super-resolved images have a reasonable noise level after de-scattering and demonstrate visually more pleasing results than conventional approaches. Furthermore, numerical metrics demonstrate that the proposed algorithm shows a consistent improvement and that edges are significantly enhanced. Underwater images are difficult to process because of low contrast and color distortion. The in-water light propagation model was proposed several years ago but is relatively complicated to be used in reality. An effective technique to enhance the images captured underwater and degraded due to the medium scattering and absorption. Our method is a single image approach that does not require specialized hardware or knowledge about the underwater conditions or scene structure. It builds on the blending of two images that are directly derived from a color compensated and white-balanced version of the original degraded image. The two images to fusion, as well as their associated weight maps, are defined to promote the transfer of edges and color contrast to the output image. To avoid that the sharp weight map transitions create artifacts in the low frequency components of the reconstructed image, we also adapt a multi-scale fusion strategy. By applying color moment and fusion techniques for improve quality of underwater images. The proposed methodology implement on MATLAB R2013a. Quality of underwater image can be determined on basis of PCQI, UCIQE and UIQM. The methodology Weight Map Fusion with Gamma Correlation (WMFGC) enables to explore image quality parameters for reduced haze level of underwater images. The experimental result shows that the average value of PCQI, UCIQE and UIQM is improve by 5.18%., 2.62% and 6.17% respectively.

Keywords: Image De-hazing, Super resolution, PCQI, UCIQE, UIQM and WMFGC.

1. INTRODUCTION

In order to deal with underwater image processing, we have to consider first of all the basic physics of the light propagation in the water medium. Physical properties of the medium cause degradation effects not present in normal images taken in air. Underwater images are essentially characterized by their poor visibility because light is exponentially attenuated as it travels in the water and the scenes result poorly contrasted and hazy. Light attenuation limits the visibility distance at about twenty meters in clear water and five meters or less in turbid water. The light attenuation process is caused by absorption (which removes light energy) and scattering (which changes the direction of light path). The absorption and scattering processes of the light in water influence the overall performance of underwater imaging systems. Forward scattering (randomly deviated light on its way from an object to the camera) generally leads to blurring of the image features. On the other hand, backward scattering (the fraction of the light reflected by the water towards the camera before it actually reaches the objects in the scene) generally limits the contrast of the images, generating a characteristic veil that superimposes itself on the image and hides the scene. Absorption and scattering effects are due not only to the water itself but also to other components such as dissolved organic matter or small observable floating particles. The presence of the floating particles known as “marine snow” (highly variable in kind and concentration) increase absorption and scattering effects. The visibility range can be increased with artificial lighting but these sources not only suffer from the difficulties described before (scattering and absorption), but in addition tend to illuminate the scene in a non uniform fashion, producing a bright spot in the center of the image with a poorly illuminated area surrounding it. Finally, as the amount of light is reduced when we go deeper, colors drop off one by one depending on their wavelengths. The blue color travels the longest in the water due to its shortest wavelength, making the underwater images to be dominated essentially by blue color. In summary, the images we are interested on can suffer of one or more of the following problems: limited range visibility, low contrast, non uniform lighting, blurring, bright artifacts, color diminished (bluish appearance) and noise. Therefore, application of standard computer vision techniques to underwater imaging requires dealing first with these added problems.

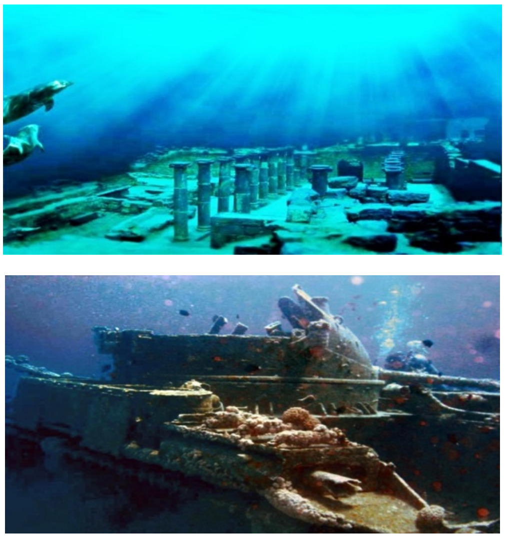

Figure 1: Underwater Images

2. BACKGROUND

We introduce an effective technique to enhance the images captured underwater and degraded due to the medium scattering and absorption. Our method is a single image approach that does not require specialized hardware or knowledge about the underwater conditions or scene structure. It builds on the blending of two images that are directly derived from a color compensated and white-balanced version of the original degraded image. Our validation also proves that our algorithm is reasonably independent of the camera settings, and improves the accuracy of several image processing applications, such as image segmentation and keypoint matching.(Codruta O. Ancuti, Cosmin Ancuti, Christophe De Vleeschouwer and Philippe Bekaert; 2018)

Underwater images are difficult to process because of low contrast and color distortion. The in-water light propagation model was proposed several years ago but is relatively complicated to be used in reality. In this paper, the full underwater light propagation model is simplified to be used as the transmission model. On the basis of this model, we propose a new method, called maximum attenuation identification, to derive the depth map from degraded underwater images. At the same time, regional background estimation is implemented to ensure optimal performance. Experiments on three groups of images, namely, natural underwater scene, calibration board, and color map board, are conducted. (Nan Wang, Haiyong Zheng and Bing Zheng; 2017)

Underwater images are degraded due to scatters and absorption, resulting in low contrast and color distortion. In this article, a novel self-similarity-based method for descattering and super resolution (SR) of underwater images is proposed. The traditional approach of preprocessing the image using a descattering algorithm, followed by application of a SR method, has the limitation that most of the high-frequency information is lost during descattering. (Huimin Lu, Yujie Li, Shota Nakashima, Hyongseop Kim and Seiichi Serikawa; 2017)

Underwater exploration has become an active research area over the past few decades. The image enhancement is one of the challenges for that computer vision based underwater researches because of the degradation of the images in the underwater environment. The scattering and absorption are the main causes in the underwater environment to make the images decrease their visibility, for example, blurry, low contrast, and reducing visual ranges. (Shu Zhang, Ting Wang, Junyu Dong and Hui Yu; 2017)

Self-similarity based super-resolution (SR) algorithms are able to produce visually pleasing results without extensive training on external databases. Such algorithms exploit the statistical prior that patches in a natural image tend to recur within and across scales of the same image. However, the internal dictionary obtained from the given image may not always be sufficiently expressive to cover the textural appearance variations in the scene. In this paper, we extend self-similarity based SR to overcome this drawback. We expand the internal patch search space by allowing geometric variations. (Jia-Bin Huang, Abhishek Singh, and Narendra Ahuja; 2015)

3. PROBLEM IDENTIFICATION

The identified problem in existing work is as follows:

1. During recognize deep underwater image, contrast quality index becomes low.

2. The comparable performance of underwater image with natural image is more differentiation.

3. Color and sharpness of underwater images with natural images have more differentiation.

4. METHODOLOGY

The method is Weight Map Fusion with Gamma Correlation (WMPGC), which is described through following point.

Step 1: Select underwater image I.

Step 2: Split image I into R, G and B components and double each components of an image and obtain mean value of their components.

Step 3: Now obtain white balance image through recombination of these channels.

Step 4: To obtain our first input, we perform a gamma correction of the white balanced image version.

Step 5: To obtain our second input that corresponds to a sharpened version of the white balanced image.

Step 6: For obtain fusion process, construct weight map through following weight map. They are thus defined based on a number of local image quality or saliency metrics.

Weight map calculation is done by following matrics-

A. Laplacian contrast weight (WL): It estimates the global contrast by computing the absolute value of a Laplacian filter applied on luminanace channel and Guassian filter applied on chrominance channel.

B. Saliency weight (Ws): Aims at emphasizing the salient objects that lose their prominence in the underwater scene. The saliency map tends to favor highlighted areas (regions with high luminance values). To overcome this limitation, Obtain saliency weight of an image.

C. Saturation weight (W_{Sat}): It enables the fusion algorithm to adapt to chromatic information by advantaging highly saturated regions.

Step 7: Now obtain normalized form of weight map. Given the normalized weight maps, the reconstructed image R(x) could typically be obtained by fusing the defined inputs with the weight measures at every pixel location (x):

where I_k denotes the input (k is the index of the inputs k = 2 in our case) that is weighted by the normalized weight maps W_K .

Step 8: Obtain Laplacian pyramids of different ROI of based input image and also obtain Gaussian pyramids of different ROI of normalized weight map image.

Step 9: Now fused Laplacian pyramids of input image and Gaussian pyramids of normalized image.

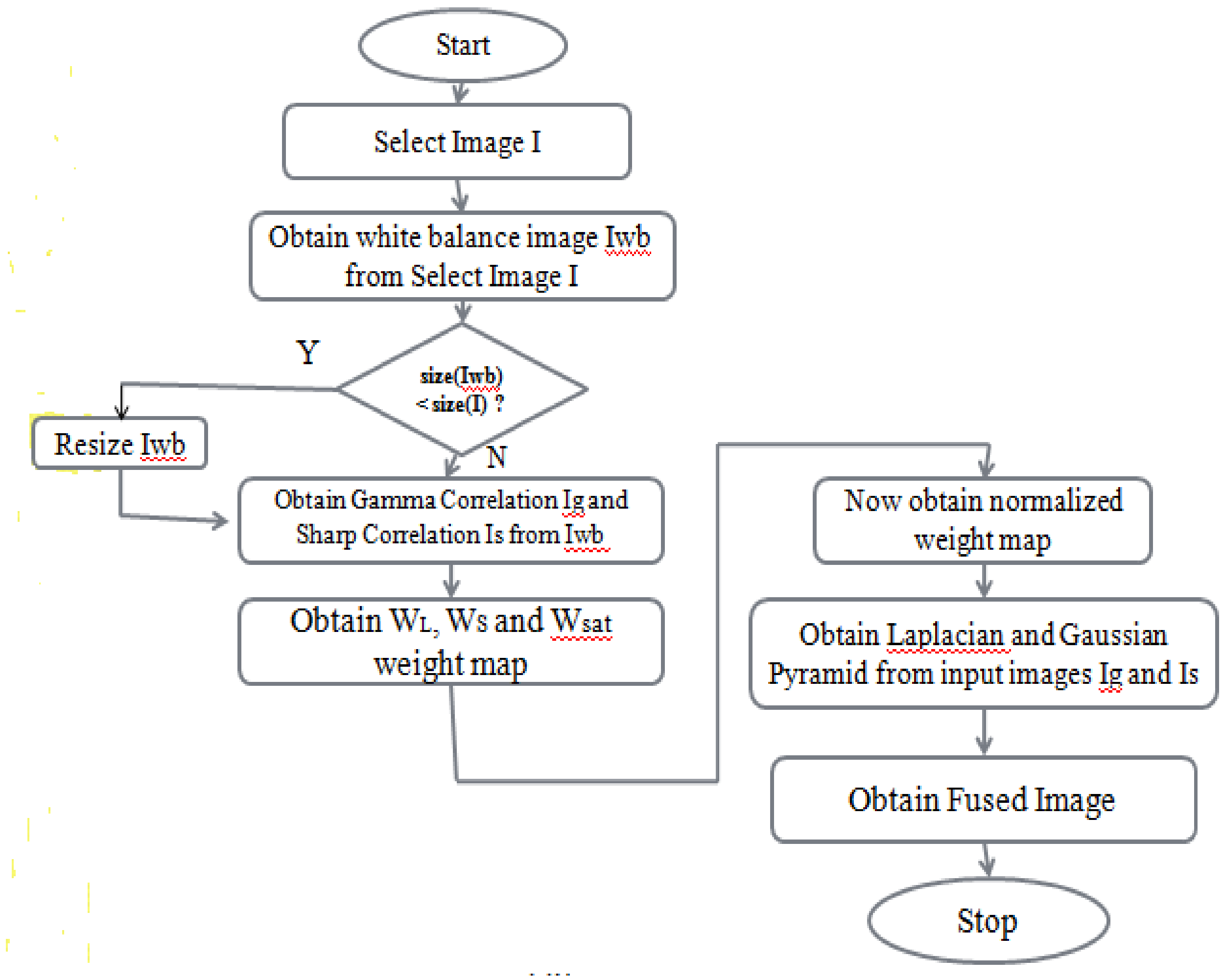

Figure 2: Flowchart of WMFGC

5. RESULTS AND ANALYSIS

The experimental works start with MATLAB R2013a version. Firstly, assume original grayscale image. For this purpose imread() function has been used, then show the image in figure window with figure command. For showing image in figure window, we have to use imshow() function, then following output has been generated.

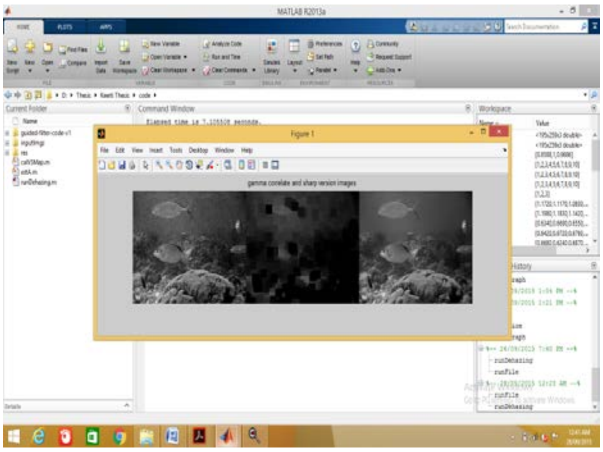

Figure 3: Source image with gamma correlation

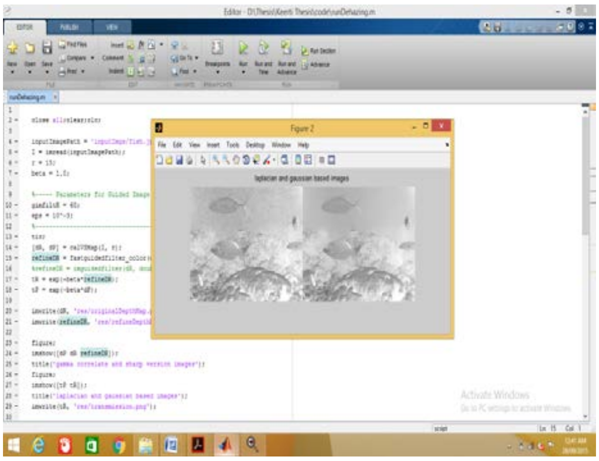

Figure 4: Laplacian and Gaussian based Source images and sharp version images

In above snapshot, take fish image in form of gamma and sharp version form then appy laplacian and Gaussian filter to that image. After evaluate saturate weight find out normalized form of an Now finally obtain the underwater dehazed image which is as follows image, which is below:

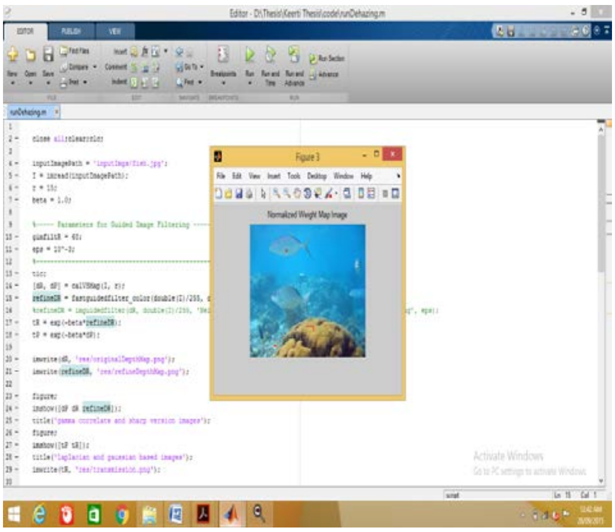

Figure 5: Normalized form of weight map

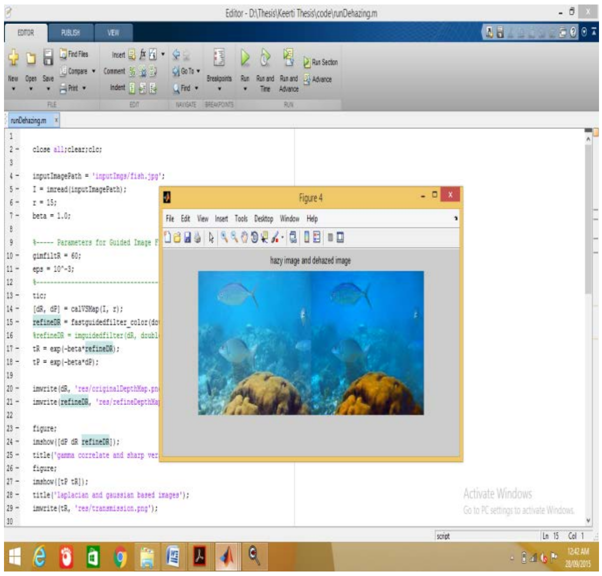

Figure 6: Obtain de-hazed image

Analysis performs on the basis of some underwater images. These source images are listed below

Table 1: Underwater Image De-hazing Evaluation

Image	MSF[1]	WMFGC
Shipwreck	0.634	0.642
Fish	0.669	0.672
Reef1	0.655	0.676
Reef2	0.718	0.722
Reef3	0.705	0.711
Galdran1	0.643	0.652
Galdran9	0.667	0.671
Ancuti1	0.588	0.591
Ancuti2	0.59	0.652
Ancuti3	0.652	0.692

Table 2: Underwater Image Dehazing Evaluation based on based on PCQI UCIQE

Image	MSF[1]	WMFGC
Shipwreck	1.172	1.198
Fish	1.117	1.183
Reef1	1.083	1.142
Reef2	1.075	1.132
Reef3	1.276	1.308
Galdran1	1.152	1.187
Galdran9	1.192	1.223
Ancuti1	1.022	1.089
Ancuti2	0.914	1.065
Ancuti3	1.207	1.264

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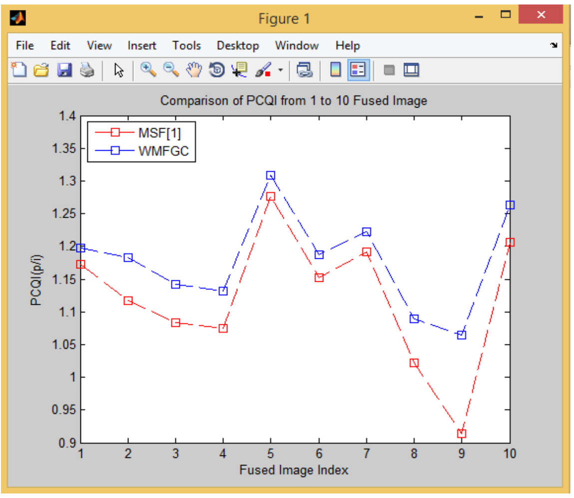

Figure 7: Analysis of Patch-based Contrast Quality

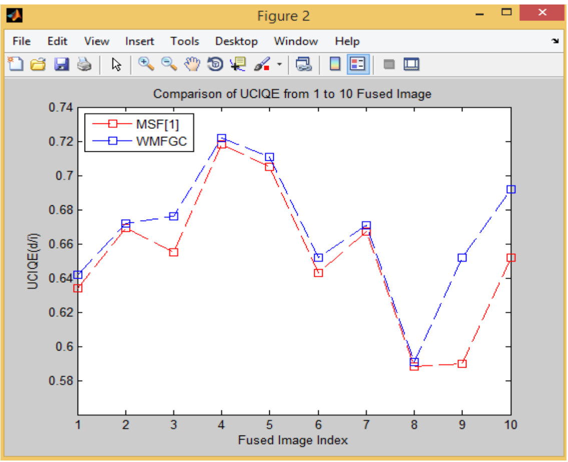

Figure 8: Analysis of UCIQE between MSF[1] and Index between MSF[1] and WMFGC (Proposed) WMFGC (Proposed)

In above figure, image index shows the source fused images and PCQI evaluate on the basis of patch per inch level in image. The value of PCQI become increase for WMFGC(proposed) as compare then MSF[1]. Hence quality index improve as compare than MSCFC[1].

In above figure, image index shows the source fused images and UCIQE evaluate on the basis of patch per inch level in image. The value of UCIQE become increase for WMFGC(proposed) as compare then MSF[1]. Hence differentiation with natural images may reduce.

Table 3: Underwater Image De-hazing Evaluation based on UIQM

Image	MSF[1]	WMFGC
Shipwreck	0.668	0.711
Fish	0.624	0.686
Reef1	0.687	0.724
Reef2	0.781	0.812
Reef3	0.766	0.798
Galdran1	0.68	0.742
Galdran9	0.663	0.721
Ancuti1	0.507	0.531
Ancuti2	0.687	0.715
Ancuti3	0.651	0.684

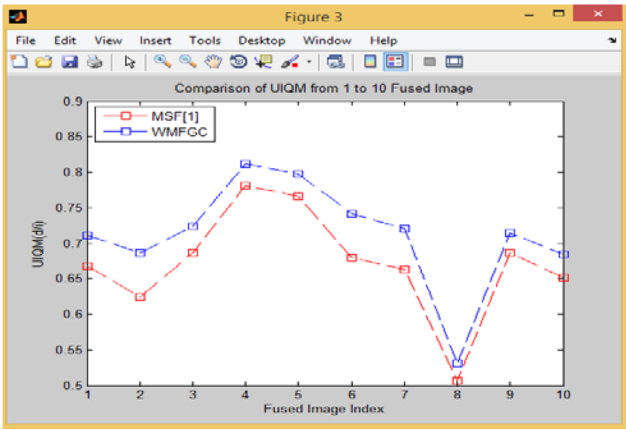

Figure 8: Analysis of Underwater Image Quality Measure between MSF[1] and WMFGC (Proposed)

In above figure, image index shows the source fused images and UIQM evaluate on the basis of patch per inch level in image. The value of UIQM become increase for WMFGC(proposed) as compare then MSF[1]. Hence color and sharpness may improve as compare than MSF[1].

Table 4: Underwater Image Dehazing Evaluation based on PCQI, UCIQE and UIQM

Performance Parameters	MSF[1]	WMFGC
PCQI	1.121	1.1791
UCIQE	0.651	0.6681
UIQM	0.671	0.7124

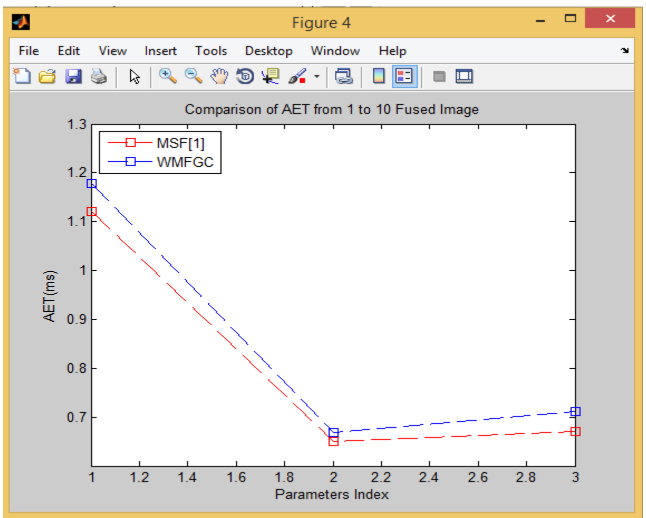

Figure 9: Analysis of Average PCQI, UCIQE and UIQM in between of MSF[1] and WMFGC (Proposed)

6. CONCLUSIONS AND FUTURE WORK

WMFGC approach is extensively to enhance quality of underwater videos and images. Our strategy builds on the fusion principle and does not require additional information than the single original image. This approach is able to enhance a wide range of underwater images with high accuracy.

1. The average value of PCQI is improved by 5.18%.

2. The average value of UCIQE is improved by 2.62%.

3. The average value of UIQM is improved by 6.17%.

4. Therefore results of WMFGC provide more improved significantly results as compare than Multi Scale Fusion[1].

This work will extend with image segmentation techniques for enhance luminance and chrominance channel. We can use various color models for enhancing visibility of underwater images. Underwater image de-hazing can be improves through various transform method like cosine transform, wavelet transform and feature transform etc.

7. REFERENCES

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