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Depth-Based Underwater Image Restoration Using Blur Map and Channel Priors

NAYUDU DHANA LAKSHMI[1], MULUPURI NAGA SRUTHI[2], MEDIKONDA ANIL KUMAR[3], VEMPARALA PAVANA KRISHNA[4], DR BHASHYAM KRISHNA MOHAN[5]
[1, 2, 3, 4, 5]*Department of Information Technology*, *R.V.R. & J.C. College of Engineering*
Guntur, India

Abstract-* *Underwater images often suffer from degradation due to light absorption and scattering, resulting in reduced contrast, color distortion, and loss of details. Traditional restoration methods such as Dark Channel Prior (DCP) are designed for atmospheric haze and perform poorly in underwater environments. In this paper, a depth estimation based underwater image restoration method is proposed using blur map analysis, red channel prior, and maximum intensity prior. The blur map captures scattering effects, while channel priors assist in estimating scene depth. The estimated depth is used to compute the transmission map, followed by background light estimation and image recovery to obtain the enhanced image. Experimental results demonstrate improved visual clarity and detail visibility. Performance evaluation using entropy and Underwater Image Quality Measure (UIQM) indicates that the proposed method effectively enhances underwater image quality compared to the existing DCP-based approach.

Index Terms-* *Underwater Image Enhancement, Depth Estimation, Blur Map, Channel Priors, Transmission Map, Underwater Image Quality Measure (UIQM)

I. INTRODUCTION

Underwater imaging is widely used in marine exploration, underwater robotics, oceanographic research, and environmental monitoring. However, images captured in underwater environments often suffer from severe degradation due to the physical properties of water. When light propagates through water, it undergoes absorption and scattering. Absorption reduces the intensity of light, particularly affecting longer wavelengths such as red light, while scattering causes blurring and reduces image contrast.

These effects result in several visual distortions, including low contrast, color imbalance, reduced visibility, and blurred structures. Consequently, underwater images often lose important visual information, making interpretation difficult for both human observers and computer vision systems.

The degradation of underwater images is commonly modeled using the following imaging formation model: $I(x)=J(x)t(x)+A(1t(x))$ where:

- $I(x)$ represents the observed underwater image
- $J(x)$ represents the scene radiance (true image)
- $t(x)$ represents the transmission map
- A represents the background light
- x represents the pixel location

The transmission map $t(x)$ describes the portion of light that reaches the camera. Accurate estimation of depth and transmission is critical for restoring degraded underwater images.

A. Limitations of Existing Methods

Several image restoration techniques have been proposed to improve the quality of degraded images. Among them, the Dark Channel Prior (DCP) method has been widely used for haze removal in atmospheric images. The DCP approach assumes that in most non-sky regions of a haze-free image, at least one color channel contains very low intensity values within a local neighborhood.

Although the DCP method performs well in atmospheric conditions, it does not always produce satisfactory results in underwater environments. The main limitation arises from the fact that underwater light propagation differs significantly from atmospheric haze. In underwater scenes, light attenuation is wavelength dependent, and red light is absorbed much more rapidly than green and blue light. As a result, directly applying DCP to underwater images may lead to inaccurate

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transmission estimation, color distortion, and halo artifacts near object boundaries.

Therefore, more specialized approaches are required to handle the unique characteristics of underwater image degradation.

B. Proposed Method

To overcome the limitations of existing underwater image restoration methods, a depth estimation based enhancement approach is proposed. The proposed method utilizes multiple visual cues to estimate scene depth and improve the restoration of underwater images.

First, a blur map is estimated using the Laplacian operator to capture scattering effects present in underwater images. Regions affected by strong scattering tend to exhibit reduced edge intensity and appear more blurred. Therefore, blur information provides useful cues for estimating the degradation level in underwater scenes.

Next, channel priors are used to estimate depth information. The red channel prior is based on the physical property that red wavelengths are absorbed rapidly in underwater environments, causing the red channel intensity to decrease with increasing depth. In addition, the maximum intensity prior is used to obtain additional depth cues based on the brightest pixel values in the image.

These cues are combined to estimate the depth map of the underwater scene. The depth estimation can be expressed as d(x) = theta b(theta a MIP(x) + (1-theta a)R(x)) + (1-theta b)B(x)

- d(x) represents the estimated depth map
- MIP(x)represents the maximum intensity prior
- R(x) represents the red channel prior
- B(x) represents the blur map
- theta a ,theta b are weighting parameters

Using the estimated depth map, the transmission map is computed based on the underwater light attenuation model:

t(x)=e power(beta d(x)) where beta represents the attenuation coefficient.

The background light is then estimated from the brightest pixels of the degraded image. Finally, the restored underwater image is obtained using the image recovery model based on the estimated transmission map and background light.

By integrating blur information with channel priors, the proposed method improves depth estimation accuracy and enhances the visibility and detail of underwater images compared with traditional restoration methods.

II. RELATED WORK

A. Dark Channel Prior (DCP)

The Dark Channel Prior (DCP) method was originally proposed for atmospheric haze removal and has been widely applied to degraded images. The key idea behind DCP is that in most non-sky regions of haze-free images, at least one color channel has very low intensity within a local neighborhood. The dark channel of an image can be defined as:

D*dark*(*x*) = *miny*(*x*)(*mincr,g,bIc*(*y*)) where

- Ic(y) represents the pixel intensity in color channel ccc
- Omega(x) represents a local patch centered at pixel xxx

Using this prior, the transmission map can be estimated and the degraded image can be restored. Although DCP performs effectively in atmospheric haze conditions, its assumptions do not always hold in underwater environments due to wavelength-dependent light attenuation.

B. Red Channel Prior

The Red Channel Prior was specifically developed for underwater image restoration by exploiting the physical property of light absorption in water. In underwater environments, red wavelengths are absorbed more rapidly compared to green and blue wavelengths. As a result, the red channel intensity decreases significantly with increasing depth.

This characteristic can be used to estimate scene depth and restore underwater images. The red channel prior can be expressed as:

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R(x) = 1 minus ($I_r(x)/255$*where*
I _r(x) represents the red channel intensity at pixel xxx

C. Fusion-Based Enhancement Methods

Fusion-based approaches enhance underwater images by combining multiple enhanced versions of the same image. Typically, different preprocessing techniques such as white balancing, contrast enhancement, and sharpening are applied to generate several candidate images. These images are then fused using weight maps that emphasize contrast, saliency, and exposedness.

Although fusion-based methods can improve visual appearance, they do not explicitly model the physical process of underwater light propagation. As a result, they may fail to accurately restore scene radiance.

D. Limitations of Existing Methods

Despite the progress made by existing methods, several limitations remain. The DCP method does not consider wavelength-dependent light absorption, which often leads to color distortion in underwater images. Red channel prior methods rely on a single cue and may not provide accurate depth estimation in complex scenes. Similarly, fusion-based techniques mainly focus on visual enhancement rather than physical restoration.

To address these limitations, this paper proposes a depth estimation based underwater image restoration method that combines blur map analysis with channel priors to improve transmission estimation and image restoration.

III. PROPOSED METHOD

The proposed underwater image restoration method estimates scene depth using multiple visual cues including blur information, red channel prior, and maximum intensity prior. These cues are combined to estimate the depth map of the underwater scene. The estimated depth is then used to compute the transmission map, which models underwater light attenuation. Finally, the restored image is obtained using a physical image recovery model.

The overall framework of the proposed method consists of the following stages:

1) Blur map estimation
2) Red channel prior estimation
3) Maximum intensity prior estimation
4) Depth map estimation
5) Transmission map estimation
6) Background light estimation
7) Image recovery

A. Blur Map Estimation

Blur information provides an important cue for estimating the degradation level in underwater images. Due to scattering effects caused by suspended particles in water, distant objects tend to appear more blurred compared to objects closer to the camera. Therefore, blur estimation can be used as an indicator of scene depth in underwater environments.
In the proposed method, the blur map is computed using the Laplacian operator applied to the grayscale version of the input image. The Laplacian operator detects edge information by measuring the second-order derivative of pixel intensity. Regions with strong edges produce higher Laplacian responses, whereas blurred regions exhibit weaker responses. To reduce noise and obtain a smoother blur representation, Gaussian filtering is applied to the absolute Laplacian response.

.

B(x) = Gaussian(mod(Laplacian(I(x)))) where

- I(x)represents the input image
- B(x) represents the estimated blur map The resulting blur map provides useful information about the spatial distribution of scattering effects in the underwater scene. Pixels with higher blur values generally correspond to regions that are farther from the camera and affected by stronger scattering. This information is later used as one of the cues for depth estimation.

B. Red Channel Prior

The red channel prior is based on the physical property of wavelength-dependent light absorption in underwater environments. In water, longer wavelengths such as red light are absorbed more rapidly compared to shorter wavelengths like blue and green. As a result, the red channel intensity decreases significantly as the distance between the object and the camera increases.

By exploiting this property, the red channel can be used as a useful indicator of scene depth. Regions with lower red channel intensity typically correspond to areas that are farther away in the underwater scene. Therefore, the red channel prior provides important information for estimating the degradation level caused by light absorption.

In the proposed method, the red channel prior is computed by normalizing the red channel intensity of the input image. This normalized value is used to represent the attenuation of red light in the underwater environment. The resulting red channel prior contributes to the depth estimation process by highlighting regions with strong color attenuation.

The red channel prior can therefore be used as a depth cue and is defined as: R(x) = 1 minus $I_r(x)/255$
where
Ir(x) is the red channel intensity at pixel xxx
Higher values of R(x) indicate regions that are likely to be farther from the camera.

C. Maximum Intensity Prior

The maximum intensity prior is another cue used to estimate the relative depth of objects in underwater images. It is based on the observation that pixels with higher intensity values are generally less affected by light attenuation and are therefore likely to be closer to the camera.

In the proposed approach, the maximum intensity prior is computed by selecting the maximum value among the three color channels (red, green, and blue) for each pixel. This operation captures the brightest channel information and helps identify regions with higher illumination.

The maximum intensity prior complements the information provided by the red channel prior and blur map. By combining these cues, the proposed method achieves more reliable depth estimation compared with approaches that rely on a single prior. The integration of multiple cues improves the robustness of the restoration process and leads to enhanced visibility in the final restored image.

The maximum intensity prior is defined as: MIP(x) = 1 minus max(I(x)) / 255 where max(I(x))max(I(x))max(I(x)) represents the maximum intensity among the RGB channels.

D. Depth Map Estimation

The depth map represents the relative distance of objects in the underwater scene from the imaging camera. Accurate depth estimation is important for modeling the degradation caused by underwater light absorption and scattering. In the proposed method, the depth map is estimated by combining multiple visual cues including the blur map, red channel prior, and maximum intensity prior.

The blur map captures scattering effects that increase with distance, while the red channel prior reflects the rapid attenuation of red wavelengths in underwater environments. The maximum intensity prior provides additional information about pixel brightness that is less affected by attenuation. By integrating these cues, a more reliable estimation of scene depth can be achieved.
d(x) = theta b(theta a MIP(x) + (1-theta a)R(x)) + (1-theta b)B(x)
where

- d(x)represents the estimated depth map

This multi-cue approach improves depth estimation accuracy compared with methods that rely on a single prior.

E. Transmission Map Estimation

The transmission map represents the portion of light that reaches the camera after traveling through the underwater medium. It plays an important role in the restoration process because it models the attenuation of light caused by absorption and scattering in water.

In underwater imaging, the transmission is commonly modeled using an exponential attenuation function based on the estimated scene depth. This model describes how the intensity of light decreases as the distance between the object and the camera increases.
t(x) = $e minus beta d(x)$ where

- t(x) is the transmission map
- beta represents the attenuation coefficient.

The transmission map describes the amount of light that reaches the camera from the scene.

F. Background Light Estimation

Background light represents the ambient light scattered by water particles in the underwater environment. It plays a significant role in the underwater image formation process because a portion of the captured light does not originate directly from the scene objects but from scattered environmental illumination. Accurate estimation of background light is therefore essential for recovering the true scene radiance.

In underwater images, background light is typically estimated from the brightest regions of the degraded image, since these regions are more likely to be influenced by scattered ambient light. In the proposed method, the background light is computed by selecting a small percentage of pixels with the highest intensity values. These pixels are assumed to correspond to areas where the influence of background illumination is dominant.

The background light value is estimated by calculating the average intensity of the selected brightest pixels. This estimated value is then used in the image recovery model to compensate for the scattered light component present in the underwater image.

Let A denote the estimated background light of the scene. This parameter is later incorporated into the image restoration model to recover the enhanced underwater image. Accurate estimation of background light helps improve the effectiveness of the restoration process and contributes to better visibility and contrast in the final restored image.

G. Image Recovery Model

The final restored image is obtained using the underwater image formation model. J(x) = (I(x) minus A) / t(x) + A where

- J(x) represents the restored image
- I(x) represents the degraded image
- A represents the background light • t(x) represents the transmission map.

The recovered image exhibits improved visibility, enhanced contrast, and better color balance.

H. Flowchart

The overall workflow of the proposed underwater image restoration method is illustrated in Fig. 1. The process begins with the input underwater image, which typically suffers from degradation caused by light absorption and scattering in the underwater environment. These effects reduce image contrast and distort color information.

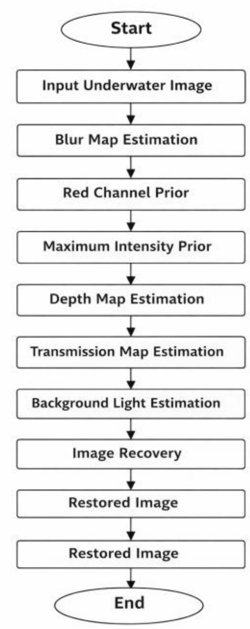

Fig. 1. Flowchart of the proposed underwater image restoration method.

Initially, a blur map is estimated using the Laplacian operator to identify regions affected by scattering and blurring. Blur information provides important cues for estimating the relative depth of objects in underwater scenes. Next, the red channel prior and maximum intensity prior are computed from the input image. The red channel prior exploits the rapid attenuation of red wavelengths in underwater environments, while the maximum intensity prior provides additional information about pixel intensity distribution.

These cues are then combined to estimate the depth map of the underwater scene. The depth map represents the relative distance of scene objects from the camera. Based on the estimated depth map, the transmission map is computed using the exponential attenuation model, which describes how light intensity decreases as it propagates through water.

Subsequently, the background light is estimated from the brightest pixels in the degraded image. Finally, the restored underwater image is obtained using the image recovery model, which utilizes the estimated transmission map and background light to enhance image visibility and structural details.

I. Proposed Algorithm

Input: Underwater image I(x)
Output: Restored image J(x)

1) Read input underwater image I(x).
2) Convert the image to grayscale and compute the blur map B(x)using the Laplacian operator. B(x) = Gaussian(mod(Laplacian(I(x)))) where
- I(x)I(x)I(x) represents the input image
- B(x)B(x)B(x) represents the blur map.
3) Compute the red channel prior R(x)R(x)R(x) from the red channel intensity.

R(x) = 1 minus $I_r(x)/255$

4) Compute the maximum intensity prior MIP(x) from the maximum RGB channel value.

MIP(x) = 1 minus max(I(x)) / 255

5) Estimate the depth map d(x) by combining blur map, red channel prior, and maximum intensity prior.

d(x) = theta b(theta a MIP(x) + (1-theta a)R(x)) + (1theta b)B(x)

6) Compute the transmission map t(x) using the exponential attenuation model. t(x) = e*minusbetad*(*x*)
7) Estimate the background light A from the brightest pixels of the image.
8) Recover the restored image J(x) using the image recovery model.

J(x) = (I(x) minus A) / t(x) + A

9) Output the enhanced underwater image J(x).

IV. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

This section presents the experimental evaluation of the proposed underwater image restoration method. The performance of the proposed method is analyzed using both visual inspection and quantitative metrics. The proposed approach is compared with the existing Dark Channel Prior (DCP) based method to demonstrate its effectiveness in enhancing underwater images.

The experiments were conducted using underwater images captured in different conditions exhibiting common degradations such as low contrast, color distortion, and blurring caused by light absorption and scattering. The proposed method was implemented using Python with image processing libraries for performing blur estimation, depth estimation, and image restoration.

The evaluation is carried out using entropy and Underwater Image Quality Measure (UIQM), which are commonly used metrics for assessing underwater image enhancement performance.

A. Entropy

Entropy is a statistical measure that represents the amount of information present in an image. Higher entropy values indicate richer details and improved distribution of pixel intensities in the restored image.
H = minus segma p(i) log p(i) where

- p(i) represents the probability of pixel intensity iii
- H represents the entropy value.
- A higher entropy value generally indicates better information content in the enhanced image.

B. Underwater Image Quality Measure (UIQM)

UIQM is a no-reference metric specifically designed for evaluating the quality of underwater images. It considers three important visual properties of underwater images:

- colorfulness
- sharpness
- contrast

The UIQM metric is defined as:
UIQM = c1 × UICM + c2 × UISM + c3 × UIConM
where

- UICM measures underwater image colorfulness
- UISM measures image sharpness
- UIConM measures image contrast
- c1,c2,c3 are weighting coefficients.

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Higher UIQM values indicate better visual quality of underwater images.

The quantitative evaluation results are presented in Table 1. The proposed method generally achieves higher entropy values compared with the existing Dark Channel Prior method, indicating improved information content and better preservation of image details. The UIQM values demonstrate competitive underwater visual quality across different test images. In several cases, the proposed method also achieves higher UIQM scores, showing its effectiveness in enhancing underwater image contrast and visibility.

C. Results Comparison

The performance of the proposed method is compared with the existing Dark Channel Prior based restoration method using entropy and UIQM metrics.

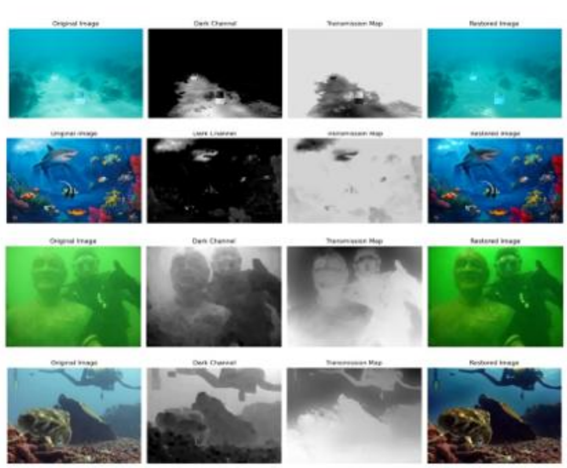

Fig. 2. Visual results obtained using the existing Dark Channel Prior (DCP) method for multiple underwater images. Each row shows (a) original underwater image, (b) dark channel map, (c) estimated transmission map, and (d) restored image obtained using the DCP-based restoration approach.

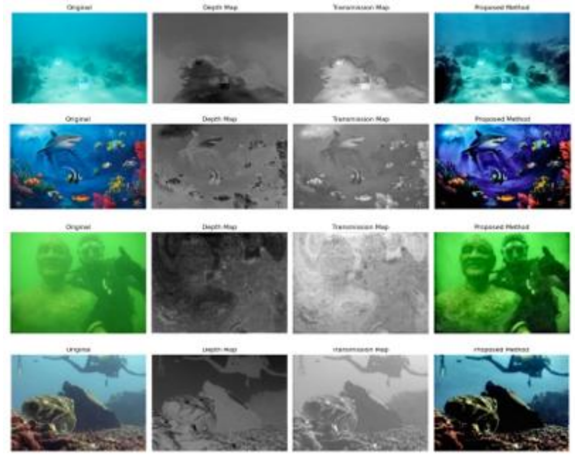

Fig. 3. Visual results obtained using the proposed underwater image restoration method for multiple test images. Each row shows (a) original underwater image, (b) estimated depth map, (c) transmission map, and (d) restored image produced by the proposed method.

TABLE I
PERFORMANCE METRICS

Image	Performance Metrics		
	Method	Entropy	UIQM
image1	DCP	6.74	11.71
	Proposed	7.10	11.90
image2	DCP	6.77	12.19
	Proposed	7.46	12.63
image3	DCP	6.36	12.15
	Proposed	7.11	12.83
image4	DCP	6.35	12.54
	Proposed	7.46	12.63

The results show that the proposed method improves entropy values, indicating better preservation of image details and information content. Although the UIQM value of the proposed method is slightly lower than that of the DCP method, the proposed method provides visually clearer and more natural restoration results in underwater images. The quantitative evaluation results are presented in Table 1. The proposed method generally achieves higher entropy values compared with the existing Dark Channel Prior method, indicating improved information content and better preservation of image details. The UIQM values demonstrate competitive underwater visual quality across different test images. In several cases, the proposed method also achieves higher UIQM scores, showing its effectiveness in enhancing underwater image contrast and visibility.

D. Visual Results

The visual results of the existing Dark Channel Prior (DCP) method and the proposed method are presented in this section. Underwater images often suffer from low contrast and color distortion due to light absorption and scattering. The DCP method enhances visibility by estimating the transmission map based on dark channel information. However, it may introduce color imbalance in some regions. The proposed method improves image restoration by estimating scene depth using blur map analysis and channel priors. The visual comparison results demonstrate that the proposed method provides clearer structures and improved contrast in underwater images.

From the visual results fig.2, it can be observed that the DCP method enhances the visibility of underwater images by estimating the transmission map and recovering the scene radiance. However, due to the unique characteristics of underwater light propagation, the restored images may still exhibit color imbalance or insufficient enhancement in certain regions. These limitations motivate the need for improved underwater image restoration techniques. However, underwater environments exhibit wavelength-dependent light absorption and scattering, which are different from atmospheric haze conditions. As a result, the DCP method may not fully address the color distortion and scattering effects present in underwater images. In some cases, the restored images may still exhibit color imbalance or limited contrast enhancement.

These limitations indicate that the conventional DCP-based approach may not always produce optimal results for underwater image restoration.

The visual results of the proposed underwater image restoration method are illustrated in Fig. 3. Each row presents the intermediate processing stages and the final restored image for different underwater scenes. The depth map is estimated using blur information together with channel priors, which provides useful cues about the distance of objects in the underwater environment. Based on the estimated depth map, the transmission map is computed using the exponential attenuation model to represent the amount of light reaching the camera.

Using the estimated transmission map and background light, the degraded underwater image is restored using the image recovery model. Compared with the existing DCP method, the proposed method produces clearer structures and improves the visibility of underwater objects. The restored images exhibit improved contrast and enhanced structural details, demonstrating the effectiveness of the proposed depth estimation framework for underwater image restoration.

V. CONCLUSION

A depth estimation based underwater image restoration method is presented to improve the visibility and quality of degraded underwater images. Underwater images often suffer from significant degradation due to light absorption and scattering, resulting in reduced contrast, color distortion, and loss of important visual details. Traditional restoration techniques such as the Dark Channel Prior method are mainly designed for atmospheric haze removal and may not effectively address the unique characteristics of underwater environments.

The proposed approach integrates blur map analysis with channel priors for improved depth estimation. The blur map captures scattering effects present in underwater images, while the red channel prior and maximum intensity prior provide additional cues for estimating scene depth. The estimated depth map is used to compute the transmission map based on the underwater light attenuation model. Using the estimated transmission and background light, the degraded underwater image is restored through the image recovery model.

Experimental results demonstrate that the proposed method improves underwater image visibility and enhances structural details. Quantitative evaluation using entropy and Underwater Image Quality Measure (UIQM) indicates improved information content and competitive visual quality compared with the existing Dark Channel Prior based restoration method. The visual comparisons further confirm that the proposed approach produces clearer and more enhanced underwater images.

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