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## UNDERWATER IMAGE RESTORATION AND ENHANCEMENT USING HYBRID ALGORITHM

Sarojini J<sup>1</sup>, Mano Andrew M<sup>2</sup>, Vanisri R<sup>3</sup>, Aravindkumaran S<sup>4</sup>

<sup>1</sup> UG - Biomedical Engineering, Rajiv Gandhi College of Engineering And Technology, Kirumampakkam, puducherry

<sup>2</sup> UG - Biomedical Engineering, Rajiv Gandhi College of Engineering And Technology, Kirumampakkam, puducherry

<sup>3</sup> UG - Biomedical Engineering, Rajiv Gandhi College of Engineering And Technology, Kirumampakkam, puducherry

<sup>4</sup> Assistant Professor, Biomedical Engineering,  
Rajiv Gandhi College of Engineering And Technology, Kirumampakkam, puducherry

### ABSTRACT :

Underwater image restoration and enhancement using a Hybrid algorithm to evaluate the undersea activities like underwater vehicles to carry optical imaging systems for recording. The captured images and videos frequently suffered from two displeasing problems: 1. Color distortion; 2. Poor visibility. Those factors are the most notorious threats in underwater imaging systems because the light is exponentially attenuated while penetrating through water and the strength of attenuation is color dependent. Under these inferences, an effective single underwater image restoration, and enhancement framework-based Sea-thru algorithm has been proposed for image restoration, depth estimation, and transmission compensation to enhance the image. To address the consequences of scattering and absorption, a new restoration algorithm outperformed by the state-of-the-art method both qualitatively and quantitatively. A wide variety of underwater images with various scenarios were exploited to assess the restoration performance of the proposed algorithm. The proposed underwater image restoration technique is a promising result for undersea activities that required high-quality images. Sea-thru method estimates backscatter using the dark pixels and machine learning algorithms, to create exciting opportunities for future underwater image exploration and conservation.

### I. INTRODUCTION

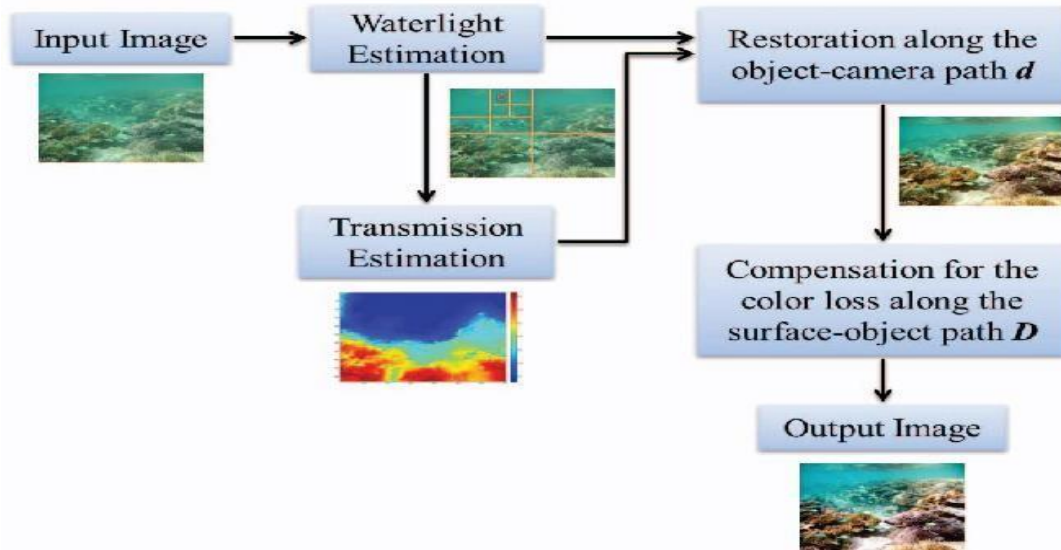
Underwater image restoration and enhancement by using a hybrid algorithm is a new method with high reliability compared to other underwater restoration methods. Light scattering by particles causes the underwater image to seriously degrade, and light absorption dulls the colors. Therefore, the goal of underwater enhancement is to restore color and improve visibility by removing any unwanted effects from the imaging process. The restoration capabilities of the suggested approach were evaluated using a wide range of underwater photos from varied settings. The experimental outcomes were examined using a variety of evaluation indicators. It was claimed that this new restoration algorithm performed better both qualitatively and numerically than numerous state-of-the-art techniques. Additionally, examples of possible applications for autopilot and three-dimensional visualization were shown. In this study, we discuss the state-of-the-art in underwater image processing and categorize the methods into two groups: picture enhancement and restoration. We describe the model hypothesis and categorization of these two approaches and compare their benefits, drawbacks, and relevant scenarios.

### II. EXISTING WORK

Image restoration and depth estimation are ambiguous tasks since there are typically fewer constraints available than there are variables that are unknown. Imposing additional constraints that are based on some a priori knowledge about the scene is one of the approaches in computer vision that is most frequently used to address these issues. MS is limited by the extent to which the prior is valid. Some of the most widely used

priors in image processing are smoothness, sparsity, and symmetry. We used a simplified model that accounts for the three main factors that contribute to image degradation: absorption, scattering, and backscattering. In this study, we describe a restoration technique that uses statistical priors of the scene and is based on a physical model of light propagation.

- Estimation of background light
- SDCP
- Transmission optimization and radiation recovery
- Deconvolution of the PSF
- Components of transmission and color



**Fig 1. Block diagram of Depth Estimation and Transmission Compensation**

### 1) BACKGROUND LIGHT ESTIMATION

We start by estimating the ambient light. According to the properties of undersea environments. Due to light fading and/or the presence of planktonic algae, the predominant color in the majority of underwater photographs is a green to blue hue. Accordingly, we define a disparity map as

$$M(x) = \max(S(x, D, G), S(x, D, B) - S(x, D, R))$$

Here,  $M(x)$  is the maximum value of the red channel  $S(x, D, R)$  and the green channel  $S(x, D, G)$  and the blue channel  $S(x, D, B)$ . It shows the difference in strength between the historical past mild is then expected with the aid of averaging the depth values that have the maximum full-size disparities primarily based on

$$M(x) \text{ calculated with } B() = \text{mean}(S(x, D,))$$

### 2) SDCP (Submerged Dark Channel Prior)

The DCP was established on the basis of the observation that most local patches in haze-free images contain some pixels whose intensity value is quite small in at least one RGB color channel. When applied to the signal in our scenario, it can be expressed mathematically as,

$$SDCP(x, D, ) = R, G, B \min_y(x)$$

$$(S(y, D,)) 0$$

where  $R, G, B$  represent the color channel index and  $x$  represents the local patch. Using air as the medium, statistics of outdoor haze-free photographs served as the foundation for the DCP. As can be seen from the standpoint of optical image creation models in water, this does not apply to underwater images. We found that the intensity in the red channel was easily reduced due to the light attenuation in water by contrasting the high visibility features with the poor visibility properties in a range of underwater photographs. The deeper the depth ( $D$ ), the thinner the red channel intensity. A new SDCP

is solely presented to handle this phenomenon while utilizing the DCP paradigm on underwater photos.

### 3) RADIANCE RECOVERY AND TRANSMISSION REFINEMENT

With the constraint of constant local patches, the transmission map  $t(x)$  is estimated. This inevitably produces the mosaic effect, which more or less hampers the subsequent processing, depending on the patch size. Fortunately, the guided image filtering technique provides a convenient and efficient mechanism to refine the transmission map by the guidance of the input image  $ET(x, y)$ . The guided filter is appropriate for structure-transferring, feathering, matting, and dehazing and can be utilized as an edge-preserving smoothing operator. Readers are kindly asked to consult the original study for more information. When compared to  $t(x)$ , the refined transmission map, denoted as  $t(x)$ , reveals fine features in accordance with the scene. Replace  $t(x)$  with and rearrange the terms to get

$$ET(x, D) = B(x) + t(x) S(x, D)$$

To avoid the effect of overexposure when  $t(x)$  approaches zero, a lower bound  $t_l$  of the transmission is introduced to recover the radiance using  $S(x, D) = ET(x, D) - B(x) / (1 - t_l)$  (26) where  $t_l$  is a tiny number, with a value suggested to be less than 0.5 in most cases. The recovered radiance of the input image is based on This image approximately represents the signal after the removal of the backscattered effect.

### 4) PSF DECONVOLUTION

To expand on this, The PSF in (6) is modelled as  $g(x) = [e^{-Ax} - e^{-Bx}]$  to resolve  $(S(x, D))$  due to the edge-blurring effect.  $f^{-1} [e^{-Bx} f]$

is the inverse Fourier transform, and  $f$  is the radial frequency, where  $A$  and  $B$  are empirical constants. A low-pass filter with varying blurring effects in each color channel is basically what the PSF represents. Take the Fourier transform on both sides. We have represented the Fourier transform. If we treat the inner Fourier transform result in the outer bracket as a coefficient, we can simplify it.

Because the color dependent Fourier transform is assumed to be constant and serves as a scaling function for the low-pass filter, it greatly simplifies the subsequent processing. The low-pass filter's edge blurring effect is also a good way to fully characterize the forward scattered effect. The blind deconvolution method is then used to obtain  $E_d(x, D)$  in the spatial domain. Where  $E_d(x, D)$  is the direct radiance without any scattering.

### 5) COLOR AND TRANSMISSION COMPONENTS

Assume further that there is no dispersion and that the vertical absorption entirely attenuates the object's energy. To estimate both the depth  $D$  and the air light  $EA(\lambda)$ , we exploit the Nelder–Mead method to minimize the discrepancy between the air light after penetration and the detected ambient light using  $\min_{\lambda \in \{R, G, B\}}$

$$e^{-D/2} E_{\text{intact}}(D) - EA(\lambda)$$

After the minimization procedure, the estimated depth is obtained and denoted as  $D$ .

Once the depth has been determined, each channel's attenuation is used to make up for lost energy and correct color distortion.

$$E_{\text{intact}}(D) e^{-D} = E_{\text{intact}}$$

where  $E_{\text{intact}}$  is the desired recovered radiance, in contrast to the input image.

### DEMERITS OF THE EXISTING WORK

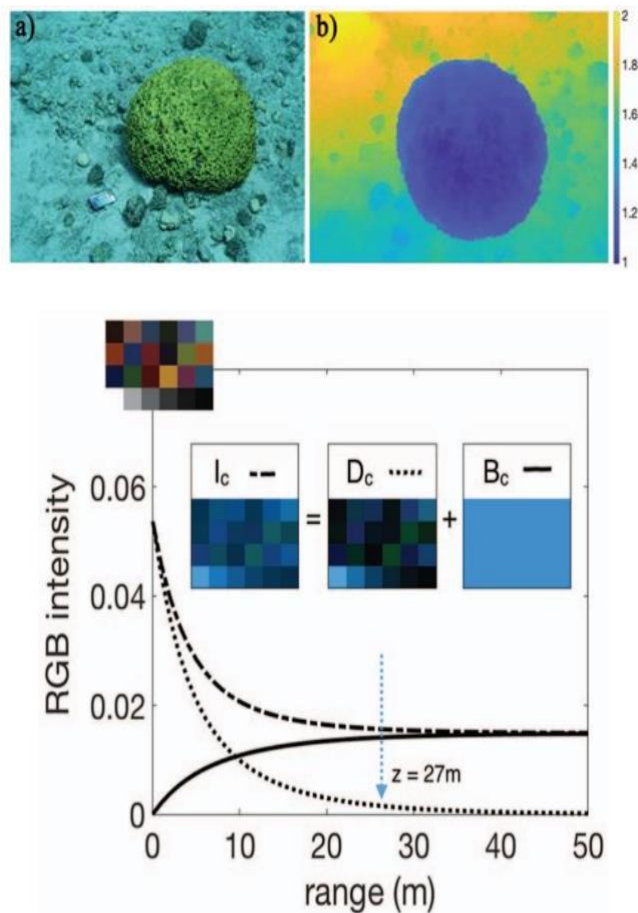
This scheme can restore the image to some extent, depending on the light homogeneity. In the scenarios of severely inhomogeneous light, the restoration is challenging and this algorithm can fail. Another issue for real-time processing is the time complexity of this algorithm, which can be dramatically reduced by parallel computing techniques such as the graphics processing unit architecture

### CNN based ED PRELUDE

The Aim of this paper is to develop a more robust and effective underwater image restoration framework that can resolve the dilemmas of poor contrast & inhomogeneity simultaneously.

### III. PROPOSED WORK

Robust recuperation of misplaced colorations in underwater pix stays a tough problem. We these days confirmed that this turned into partially because of the conventional use of an atmospheric picture formation version for underwater pix and proposed a bodily correct version. The revised version confirmed: 1) the attenuation coefficient of the sign isn't uniform throughout the scene however relies upon on item variety and reflectance, 2) the coefficient governing the boom in backscatter with distance differs from the sign attenuation coefficient. Here, we gift the primary approach that recovers color with our revised version, the usage of RGBD pix. The Sea- via approach estimates backscatter the usage of the darkish pixels and their recognized variety information. Then use the spatially variable lighting estimates to get a distance-dependent attenuation factor. Using over 1,100 images of two visually different bodies of water we provide, we show that the method using the revised model is superior to the method using the atmospheric model. Consistent water removal opens up large underwater datasets to powerful computer vision and machine learning algorithms, opening up exciting possibilities for the future of underwater exploration and conservation.



**Fig 2. Underwater image formation**

The previous work has inhomogeneity problem, in our work we are going to include sea-thru computer vision algorithm which removes the water from the underwater image. After the removal of water, the depth estimation algorithm is applied which encounters the inhomogeneity problem and produces an efficient output.

Introducing the Sea-Thru method. This outlines how to estimate these parameters to improve scene recovery. See-through method removes water from underwater images. Best viewed online for color and details. Large image datasets like ImageNet have been instrumental in igniting the artificial

intelligence boom, which fueled many important discoveries in science and industry in the last two decades. However, underwater areas that are not lacking large image datasets do not benefit from the full power of computer vision and machine learning methods that made these discoveries possible. This is because water obscures many computationally intensive features of the scene. Underwater photography is equivalent to photography taken in the air, but is covered with a dark fog and exposed to a light source whose white point and intensity change with distance. It is difficult to train learning-based methods for different optical conditions that represent the global ocean, because calibrated underwater datasets are expensive and logistically difficult. Existing methods that attempt to reverse the degradation due to water are either unstable, too sensitive, or only work for short object ranges. Therefore, analysis of large underwater datasets often requires costly manual work.

On average, human experts spend more than two hours identifying and counting fish in an hour's video. The Sea-thru method aims to consistently remove water from underwater images, so large datasets can be analyzed with increased efficiency. It functions as follows: given an RGBD image, it predicts backscatter by using the known range map and drawing inspiration from the Dark Channel Prior (DCP) established for haze. Next, it uses an optimization framework to estimate the range-dependent attenuation coefficient using an illumination map obtained using local space average color as input. We demonstrate that the 2-term exponential may be used to simulate the distance-dependent attenuation coefficient, considerably reducing the number of unknowns in the optimization step.

a) A 3D model created from 68 photographs b) Range map  $z$  for image a

#### IV. METHODOLOGY

The distance between the camera and scene along the line-of-sight  $z$ , depth at which the photo was taken  $d$ , the reflectance of each object in the scene  $\rho$ , and the spectral response of the camera  $S_c$ . These parameters are rarely, if ever, known at the time an underwater photo is taken. We showed that  $\beta D c$  was most strongly governed by  $z$ , and  $\beta B c$  was most affected by the optical water type and illumination  $E$ . Therefore, we tailor the Sea-thru method to tackle these specific dependencies. Since the coefficients vary with imaging angle and exposure, we assume that they generally cannot be transferred across images, even those taken sequentially with the same camera, and we estimate the relevant parameters for a given image from that image only.

It was assumed that the scattering coefficient is constant over the camera sensitivity range in each color channel, resulting in a coefficient per wavelength. This approach was then widely used to adverse weather and then modified for usage in an underwater environment. This model was further simplified to include a single attenuation coefficient that is uniform across all color channels coordinator. As a result, the BS can be made to transmit enough coded packets without the coordinator's assistance, ensuring that all of the group's users can successfully decode the data. In other words, for delay sensitive groups a coordinator selection can be tuned such that users can be served at once by the BS, without any delay caused by the coordinator's assistance.

On the other side, a coordinator of a group that is tolerant of delays can be the user with the best channel conditions. Various methods for the selection of appropriate coordinators based on the channel state information (CSI) of users have been discussed in [10]. The selection of coordinators, however, is outside the purview of this study. Modeled as zero-mean, independent, but not identically distributed complex Gaussian random variables with variances of  $21$  and  $22$ , respectively, the gains  $h_{i1}$  and  $h_{i2}$  of the channels between the  $i$ th antenna of the BS and the two coordinators of the multicast groups. The quasi-static nature of the channel implies that the value of  $h_{iu}$  remains constant for the duration of a transmitted frame of symbols but changes independently from frame to frame.

#### MERITS OF THE PROPOSED WORK

- It ultimately overcomes the inhomogeneity problem which are faced in the previous works.
- Producing an efficient output with high entropy factor

- Time consumption is less.

Edge detailing are perfect comparing with the previous works.

**SUMMARY**

The proposed system primarily focuses on the restoration and enhancement of the underwater images which can be used effectively to meet the future needs of research and educational purposes. From that perspective, this work comprehensively surveys the recent progress of underwater imaging techniques, reviewing the physical and also the quality measuring parameters. Taking its strength from an image formation model derived for the ocean, Hybrid algorithm offers a glimpse into the underwater world without skewed color and contrast enhanced images.

**IV.RESULTS AND SIMULATION PARAMETERS**

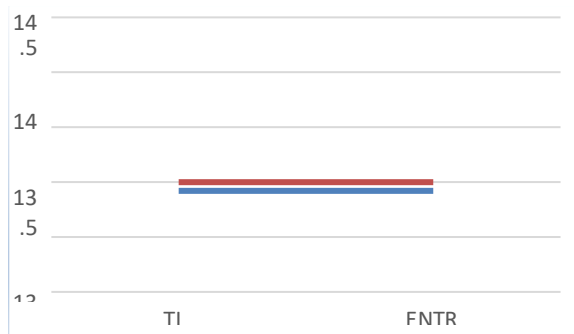
The performance of the proposed system is done through PyCharm and simulations are done accordingly. With fixed values to the differential values. Entropy, which counts the number of times an image has changed, reveals the degree of unpredictability in an image. Using the entropy is useful here when coding images limits the average coding length in a pixel to only a fraction of the previous values and enables operators without compromising the quality of data in the image. PyCharm provides smart code complexion, code inspections, on the fly error highlighting and quick fixes along with automated codes refactoring and rich navigation abilities.

The entropy of an image is calculated by calculating at each pixel position (i, j)

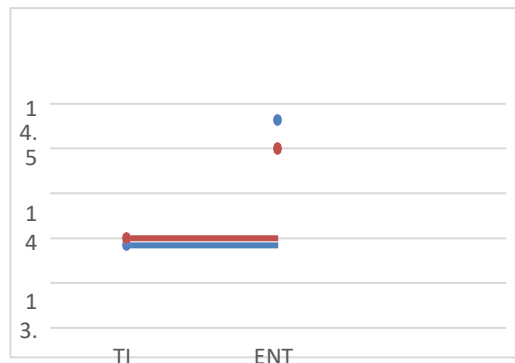
| Parameters         | Values                           |
|--------------------|----------------------------------|
| Entropy (Existing) | 15.529(Accurate)<br>16(Absolute) |
| Entropy (Proposed) | 14.312(Accurate)<br>14(Absolute) |
| Time (Existing)    | 14.831(Accurate)<br>15(Absolute) |
| Time (Proposed)    | 12.921(Accurate)<br>13(Absolute) |

Graphical representation of DE and CC algorithm

- PROPOSED WORK
- EXISTING WORK



### Graphical Representation of algorithm



### V. CONCLUSION

Simulation results confirmed the validity of the theoretical expressions, which can be used to verify that the output generated was convincing. As recovering these intricate dependencies is extremely challenging, deep nets should perform better than the estimation methods we used. Since ground-truth cannot be attained for this environment, their training has to be conducted with carefully designed simulations based on the correct image formation models. Careful simulations can also help with another challenge that arose in this work; the evaluation of results. Thus, can significantly improve the overall performance of the algorithm.

### SCOPE FOR FUTURE WORK

Superior performance of the algorithm results in terms of reducing the cost and increasing the performance parameters of the work. The first stage in deducing scene geometry from 2D photos is depth estimate. Monocular depth estimation has as its only input a single RGB image, and the objective is to forecast the depth value of each pixel or infer depth information. A new field of study is underwater imaging. Due to dispersion and absorption, the underwater image is degraded. To overcome these issues, the acquired images are adjusted using color balance and then corrected using white balance.

### IMAGE RESTORATION

The process of restoring an image from a degraded copy—typically a blurry and noisy image—is known as image restoration. An important issue in image processing is picture restoration, which also serves as a test case for more complicated inverse issues.

### IMAGE ENHANCEMENT

Before processing, original data is improved for quality and information content through the process of image enhancement. Common techniques include FCC, spatial filtering, density slicing, and contrast augmentation. It effectively eliminates blurring, is mostly similar to the Weiner filter, and solves the inverse filter issue. Blind and non-blind deconvolution are the two categories used for image restoration.

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