Learning Based Estimation of Attenuation Coefficient Towards Restoration of Underwater Images

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Introduction to Underwater Image Restoration

- When light penetrates the ocean, it attenuates in a wavelength-dependent manner, giving ocean it's color and optical properties.
- Due to these wavelength-dependent processes, underwater images suffer from reduced contrast and other degradations.

Figure: 1. Underwater Image and its Restoration

Motivation for Estimation of Attenuation Coefficients

- The existing traditional methods for underwater image restoration requires the knowledge of underwater imaging and do not solve the issue of amplification of noise, color distortion and artificial artifacts.
- The **Image Formation Model** makes use of ocean optical measurements for restoration of underwater image.
- By making use of **Leaning Based Technique**, we can generalise the estimation of coefficients for different water types.

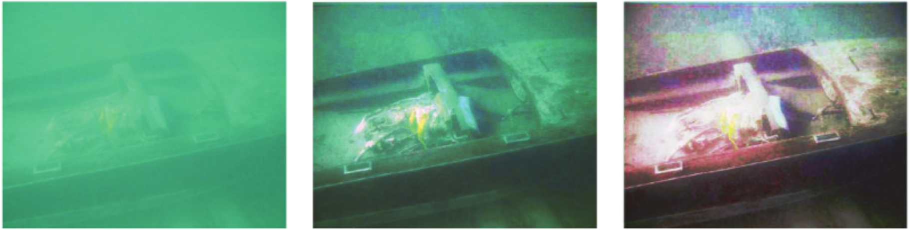

Figure: 2. Traditional Methods for Underwater Image Restoration

What is the Space of Attenuation Coefficients in Underwater Computer Vision? (Derya Akkaynak et al. CVPR 2017)

Description:

- Based on the Image Formation Model, wide band attenuation coefficient is considered by ignoring the effect of backscattered light.
- Derivation of wideband attenuation coefficient shows that attenuation coefficient depends on scene properties in addition to water properties and it is proved using in-situ experiment.

$$\beta_c = ln\left[\frac{\int S_c(\lambda)\rho(\lambda)E(\lambda)e^{-\beta(\lambda)(z)}d\lambda}{\int S_c(\lambda)\rho(\lambda)E(\lambda)e^{-\beta(\lambda)(z+\Delta d)}d\lambda}\right]/\Delta z$$

Literature Survey

A Revised Underwater Image Formation Model (Derya Akkaynak et al. CVPR 2018)

Description:

- A common wideband attenuation coefficient cannot be used for both direct and backscattered signal.
- Hence, the attenuation coefficient for backscattering was derived and validated by conducting real world experiments.

$$I_c = J_c e^{-\beta_c^D(v_D).z} + B_c^{\infty}(1 - e^{-\beta_c^B(v_B).z})$$

Sea-thru: A Method For Removing Water From Underwater Images (Derya Akkaynak et al. CVPR 2019)

Description:

- This paper involves the works done in previous two papers.
- The attenuation coefficients for direct and backscattered light are calculated and substituted in the revised image formation model to get the restored image.

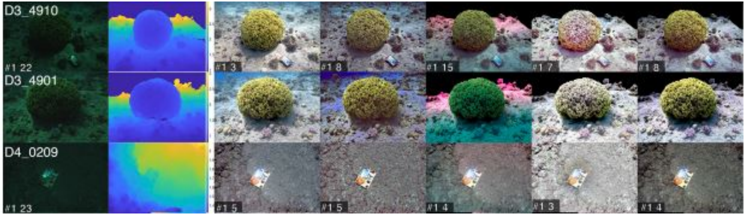

Figure: 5. Underwater Image Restoration Using See-Thru Model

Literature Survey

Underwater Image Restoration using Deep Networks to Estimate Background Light and Scene Depth (Keming Cao et al. SSI AI 2018)

Description:

- Learning based estimation is employed in order to estimate the attenuation coefficient such as background light and scene depth.
- BL is estimated using CNN with max pooling and normalisation followed by fully connected layers.
- The predicted value of BL is compared with actual value and MSE loss is minimised to obtain the better results.

Results

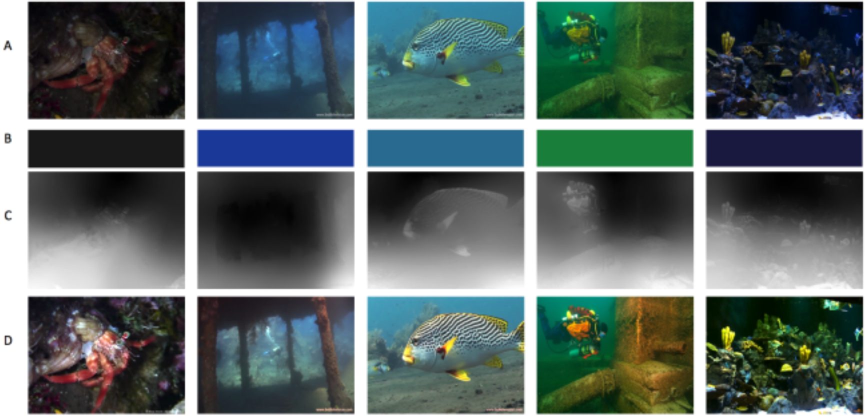

Figure: 6. Restoration of underwater images based on the proposed method. A: Original underwater image. B: Estimated BL. C: Estimated transmission map. D: Restored images

List of Formulae Used

- Image Formation Model:

$$I_c = J_c e^{-\beta_c^D(v_D).z} + B_c^{\infty}(1 - e^{-\beta_c^B(v_B).z})$$

- Direct Transmission Signal Attenuation Coefficient:

$$\beta_c^D = ln\left[\frac{\int S_c(\lambda)\rho(\lambda)E(\lambda)e^{-\beta(\lambda)(z)}d\lambda}{\int S_c(\lambda)\rho(\lambda)E(\lambda)e^{-\beta(\lambda)(z+\Delta d)}d\lambda}\right] / \Delta z$$

- Backscattered Signal Attenuation Coefficient:

$$\beta_c^B = -ln\left[1 - \frac{\int S_c(\lambda)B^{\infty}(\lambda)(1 - e^{-\beta(\lambda)(z)})d\lambda}{\int S_c(\lambda)B^{\infty}(\lambda)d\lambda}\right] / z$$

List of Formulae Continued

- Veiling Light:

$$B^{\infty}(\lambda) = \frac{b(\lambda)E(\lambda)}{\beta(\lambda)}$$

$$B_c^{\infty} = \int S_c(\lambda)B^{\infty}(\lambda)$$

Problem Statement and Objectives

Problem Statement

With the help of attenuation coefficient measured per color channel and at certain depth, estimate the attenuation coefficients, make this estimation learning based in order to generalise underwater image restoration to different water types.

Objectives

- We propose a learning based approach to predict the attenuation coefficients for a given underwater image.
- We propose a learning based approach which predicts attenuation coefficients irrespective of water type.

Approach

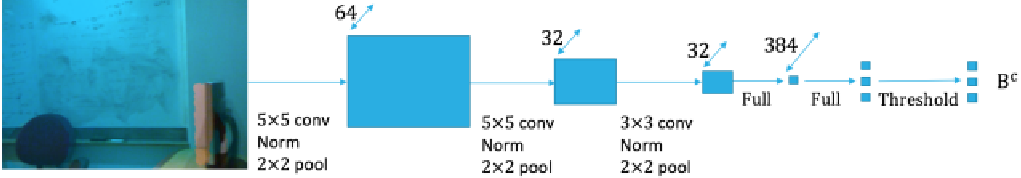

Figure: 7. Network Architecture for BL Estimation.

Dataset Description

Synthetic Underwater image dataset is generated for depths ranging from 0-20meters and different Jerlov classes using NYU Depth dataset. The generated dataset contains 19567 images,in which 19000 images are used for training and 567 images for testing.

(a) Ground truth

(b) Synthetically generated image for Jerlov type 7 at 7m

Experimental Results

The model was trained with a dropout of 0.5. Mean square error is used to evaluate the performance of the model and the result are mentioned in table 1.1. When an additional convolutional layer was added to the model and was trained the results obtained are on table 1.2.

1	Training loss	0.182
2	Testing loss	0.161
3	Training accuracy	47.33
4	Testing accuracy	48.50

Table: Results for the standard mode

Experimental Results

1	Training loss	0.07
2	Testing loss	0.06
3	Training accuracy	47.33
4	Testing accuracy	49.50

Table: Results after adding extra convolution layer

bibliography

- D. Akkaynak, T. Treibitz, T. Shlesinger, R. Tamir, Y. Loya, and D. Iluz. What is the space of attenuation coefficients in underwater computer vision? In Proc. IEEE CVPR, 2017
- D. Akkaynak and T. Treibitz. A revised underwater image formation model. In Proc. IEEE CVPR, 2018.
- D. Akkaynak, T. Treibitz, T. Shlesinger and D. Iluz Sea-thru: A Method For Removing Water From Underwater Images In Proc. IEEE CVPR, 2019
- Zhibin Yu, Yubo Wang, Haiyong Zheng, Nan Wang, Zhaorui Gu. Underwater Inherent Optical Properties Estimation Using a Depth Aided Deep Neural Network