



KLE Technological
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**School
of
Electronics and Communication Engineering**

**Mini Project Report
on
Learning Based Estimation of Attenuation
Coefficient Towards Restoration of
Underwater Images**

By:

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SCHOOL OF ELECTRONICS AND COMMUNICATION
ENGINEERING

CERTIFICATE

This is to certify that project entitled “**Learning Based Estimation of Attenuation Coefficient Towards Restoration of Underwater Images** ” is a bonafide work carried out by the student team of ”**Tejashwini Kulkarni(01FE18BEC242), Megha Somaradder(01fe18bec079), Akshata Vernekar(01FE18BEC018), Swathi V(01FE18BEC194)**” . The project report has been approved as it satisfies the requirements with respect to the mini project work prescribed by the university curriculum for BE (V Semester) in School of Electronics and Communication Engineering of KLE Technological University for the academic year 2020-2021.

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-The project team

ABSTRACT

When the light penetrates the surface of ocean there are many physical and chemical reactions occurs due to which water attenuates light in wavelength dependent manner and because of this reason we obtain color degraded and distorted images. Underwater images are of great importance in applications like marine and military so there is need to restore degraded images to extract the information from the images. Many traditional methods are used to restore these images but there are many drawbacks to these methods so in this project we make use of learning based estimation to find out the attenuation coefficients that will help in underwater image restoration.

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Chapter 1

Introduction to estimating attenuation coefficient

When light penetrates into the ocean, water attenuates light in a wavelength dependent manner, due to which ocean gets its color and optical properties. Because of these wavelength dependent process underwater image suffer from color degradation. Underwater images are useful in applications like marine military so there is a need to restore these underwater images.

1.1 Motivation

- The traditional methods present so far for underwater image restoration will perform better up to some extent but these will not resolve issues like amplification of noise, color distortion and artificial artifacts.
- With the help of revised image formation that makes use of optical measurements to restore underwater images we are able to estimate attenuation coefficients which are used for underwater image restoration.
- By making the estimation learning based we can generalise restoration for different water types.

1.2 Objectives

- Proposing a learning based approach to predict the attenuation coefficients for a given underwater image.
- Estimating attenuation coefficient via learning based approach that can be generalised for different water types.

1.3 Literature survey

I. What is The Space of Attenuation Coefficients in Underwater Computer Vision?[1]

Water attenuates light in wavelength dependent manner giving the ocean its color and optical properties. These wavelength dependent processes gives underwater image low contrast and color distortion. In order to reconstruct underwater image we need the knowledge of wide band attenuation coefficient per color channel. Image intensity at each pixel is sum of direct transmitted at back scattered light. Considering the direct transmitted light equation and assuming attenuation coefficient is constant per color channel and substituting the dependencies such as reflectance, illumination irradiance, we obtain attenuation coefficient a weak function of wavelength. This is contradictory to common image formation model. The errors obtained from ignoring these dependencies are shown with the help of graphs.

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

where

β_c : wideband attenuation coefficient

$S_c(\lambda)$: spectral response of the camera

$\rho(\lambda)$: Reflectance spectrum

$I(\lambda)$: Illustration irradiance

II. A Revised Underwater Image Formation Model[2]

In the previous paper the back scattered light was ignored and considered that for both direct and back transmitted light the attenuation coefficient remains same but in reality they both are different. A common wide band attenuation coefficient cannot be used for both direct and back scattered signal. Hence, the attenuation coefficient for back scattering was derived and validated by conducting real world experiments. A revised Image Formation Model was proposed that has different attenuation coefficients for both direct and back scattered light.

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

where

I_c : Image with attenuation signal

J_c : unattenuated image

β_c^D : attenuation coefficient for direct transmitted signal

β_c^B : attenuation coefficient for back scattered signal

B_c^∞ : wideband veiling light

V_D and V_B : Vector representation coefficient of dependencies

III. Sea-thru: A Method For Removing Water From Underwater Images [3]

This paper involves the work done in previous two papers. The attenuation coefficients for direct and back-scattered light are calculated and substituted in the revised image formation model to get the restored image. The results achieved by this method are better than considering the same coefficient for direct transmitted signal and back-scattered signal to reconstruct the underwater

image.

IV. Underwater Image Restoration using Deep Networks to Estimate Background Light and Scene Depth

$$I^c(x) = J^c(x)t^c(x) + B^c(1 - t^c(x)), c \in \{r, g, b\}$$

where

$I^c(x)$:Image Intensity at each pixel $J^c(x)$:scene radiance $t^c(x)$:transmission map

Images captured underwater will suffer from color distortion and low contrast because of wavelength dependent attenuation of light. Underwater image is modeled as sum of clear image and background light. This paper proposes the deep neural network structures to estimate background light and scene depth which helps in underwater image restoration.

1.4 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.

1.5 Project Planning

Gantt chart is a project management tool which helps in planning and scheduling of projects of all sizes and useful for simplifying complex projects.

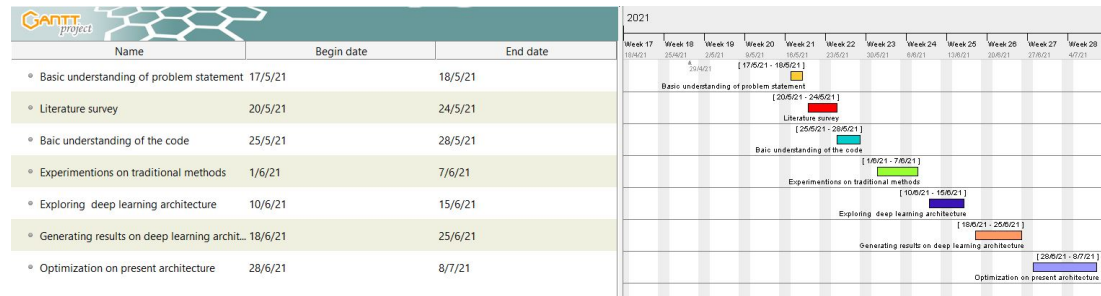


Figure 1.1: Gantt chart

1.6 Organization of the report

In Chapter 1 which is the current chapter, we give brief description about our project topic, Estimation of attenuation coefficient towards underwater image restoration, motivation for choosing the topic, the literature survey done by the team, formation of problem statement, project planning and applications related to topic. In Chapter 2, we describe the proposed system

design, a block diagram of the system, alternate solutions available for learning Based Estimation of Attenuation Coefficients towards Restoration of Underwater images, and the final design of our project. In Chapter 3 we describe the implementation details, algorithm of the proposed model, flow of the designed. In Chapter 4, we discuss about the optimizations for estimating of attenuation coefficient, and various techniques available for it, and the optimization techniques used in the algorithm. In Chapter 5, we discuss on the results of attenuation coefficient. Finally we conclude the project in Chapter 6, with conclusions and the future scope of the project.

Chapter 2

System design: Estimating Attenuation Coefficient

This chapter is about system design in which, design alternatives and final design are included.

2.1 Functional block diagram for estimating attenuation coefficient

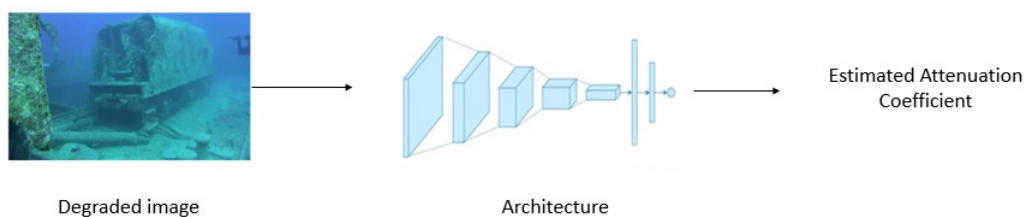


Figure 2.1: Block diagram for estimating attenuation coefficients

2.2 Design alternatives for learning based model

The two design alternatives are

I. Underwater Inherent Optical Properties Estimation Using a Depth Aided Neural Network
A novel depth aided deep neural network is proposed to predict the inherent optical properties from noisy underwater images. The depth information is given as an aided input to the feed forward layer.

II. Underwater Image Restoration using Deep Networks to Estimate Background Light and Scene Depth
Underwater image can be modeled as combination of clear image and background light, with

the relative amounts of each determined by the camera. This paper proposes the deep neural network architecture to estimate attenuation coefficients towards underwater image restoration.

2.3 Final design chosen for estimating attenuation coefficient

The final design we choose was Underwater Image Restoration using Deep Networks to Estimate Background Light and Scene Depth since the first design has the drawback with the generation of data set which was not feasible in all cases and also the result obtained from second design are more efficient compared to first.

The parameters for the design chosen are as follows:

- Learning rate : 0.001
- Batch size : 4
- Number of epochs : 25
- Optimizer : Adagrad

Chapter 3

Implementation details of estimating attenuation coefficient

In this chapter we provide implementation details that include final system architecture, algorithm, flowchart and the block diagram of the proposed data.

3.1 Specifications and final system architecture

This paper involves the estimation of attenuation coefficients via learning based approach. By making use of revised underwater image formation model, we determine the value of background light as our attenuation coefficient. with the help of these attenuation coefficients we are able to restore underwater images.

Architecture: In order to estimate the background light, 5 layer convolutional neural network is implemented. The first 3 layers are convolution layers with kernel size of 5×5 , 5×5 , and 3×3 after performing convolution for each layer 2×2 pooling and normalisation is done the next 2 layers are fully connected layers and the final output is background light per color channel. The results are compared with actual value with the mean square error and the model is built.

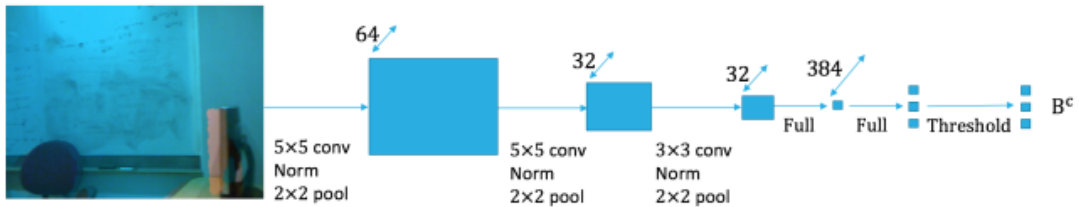


Figure 3.1: Network Architecture for Background Light Estimation

3.2 Algorithm

Result: Attenuation coefficient B^c

for *Each image in the dataset* **do**

 Read the image. Perform convolution twice with 5×5 kernel, normalise it and do max pooling.

 Perform convolution with 3×3 kernel, normalise it and do max pooling.

 Apply 2 fully connected layers to obtain attenuation coefficient per color channel.

 calculate mean square error between actual and predicted attenuation coefficient values.

end

3.3 Flowchart

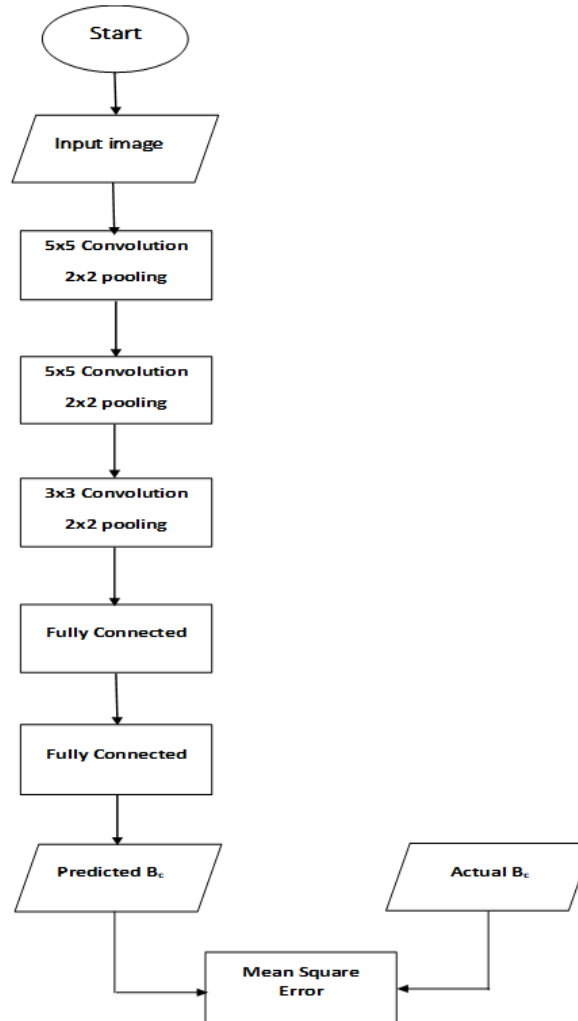


Figure 3.2: Working flowchart of proposed system

Chapter 4

Results and discussions

Here, we discuss about the different tasks which were carried out during the project. The results are mentioned in tables.

4.1 Experimental setup



(a) Ground truth



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

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.

An example of the generated dataset is shown in fig. 4.1 and 4.2.

The model is trained for 25 epochs with a dropout of 0.5. Mean square error is used to evaluate the performance of the model and the result is mentioned in table 4.1.

When an additional convolutional layer was added to the model and was trained, the results obtained are mentioned in table 4.2.

Training loss	0.182
Testing loss	0.161
Training accuracy	47.33
Testing accuracy	48.50

Table 4.1: Result for standard model

Training loss	0.07
Testing loss	0.06
Training accuracy	47.33
Testing accuracy	49.50

Table 4.2: Result after adding extra convoltional layer

Chapter 5

Conclusions and future scope

5.1 Conclusion

A model to predict backscattered light for a given underwater image. We use convolutional neural network to achieve this. This model is generalised for all Jerlov types and depths ranging from 1m to 20m. The model takes the synthetic underwater images as input and the a tensor containing backscattered light values for different channels is given as output.

5.2 Future scope

- Improving the accuracies of the model.
- Validation of the predicted backscattered light values by restoring underwater images.

Bibliography

- [1] 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
- [2] D. Akkaynak and T. Treibitz. A revised underwater image formation model. In Proc. IEEE CVPR, 2018.
- [3] D. Akkaynak, T. Treibitz, T. Shlesinger and D. Iluz Sea-thru: A Method For Removing Water From Underwater Images In Proc. IEEE CVPR, 2019
- [4] Chen, Liang-Chieh, et al. "Semantic image segmentation with deep convolutional nets and fully connected crfs." arXiv preprint arXiv: 1412.7062(2014).