



Restoring and Enhancing Degraded Underwater Images to Detect the Corrosion: A Survey

Anjali Puri, Prof. Satish Todmal

PG Student, JSPM's Imperior College of Engineering and Research Pune, India

Professor, Dept of Computer Engineering, JSPM's Imperior College of Engineering and Research Pune, India

ABSTRACT: The visibility of scene was compensated by the object-camera distance to recover the colors of the background and objects. Subsequently, by analyzing the physical property of the point spread function, we developed a simple but efficient low-pass filter to deblur degraded underwater images. A wide variety of underwater images with different scenarios were used for the experiments. A new method for subsea pipeline corrosion estimation by using color information of corroded pipe. As precursor steps, an image restoration and enhancement algorithm are developed for degraded underwater images. The developed algorithm minimizes blurring effects and enhances color and contrast of the images. The enhanced colors in the imaging data help in corrosion estimation process. The image restoration and enhancement algorithm are tested on both experimentally collected as well as publicly available hazy underwater images. A reasonable accuracy is achieved in corrosion estimation that helped to distinguish between corroded and non-corroded surface areas of corroded pipes. The qualitative and quantitative analyses show promising results that encourage to integrate the proposed method into a robotic system that can be used for real-time underwater pipeline corrosion inspection activity. Underwater image degradation, surveys the state-of-the-art intelligence algorithms like deep learning methods in underwater image dehazing and restoration, demonstrates the performance of underwater image dehazing and color restoration with different methods, introduces an underwater image color evaluation metric, and provides an overview of the major underwater image applications.

I. INTRODUCTION

Underwater imaging is widely used in scientific research and technology such as marine biology and archaeology. Generally, captured underwater images are degraded by scattering and absorption. Scattering means a change of direction of light after collision with suspended particles, which causes the blurring and low contrast of images. Absorption means light absorbed by suspended particles which depends on the wavelength of each light beam. The light with shorter wavelength (i.e., green and blue light) travels longer in water. As a result, underwater images generally have predominantly green-blue hue. Contrast loss and color deviation are main consequences of underwater degradation processes, which bring difficulties to further processing. Hence, there is great significance to restore degraded underwater images.

Our purpose in this paper is to explore underwater image restoration techniques with CNN. The contributions of this work are summarized as follows:

- 1) We propose a new underwater restoration algorithm using CNN which improves the image contrast and color cast. A new network for estimating transmission which can preserve fine spatial structures and edges features is proposed. And we also introduce a robust global ambient light estimation method based on CNN.
- 2) To improve the performance of the networks, we design a new underwater images synthetic method which can simulate underwater images captured in various underwater environments.

Optical images captured in underwater environment scenes, normally, lack of visual quality. Those environments have generally large numbers of suspended particles in the medium that causes "haziness" on the captured image, here called turbidity. When the light rays propagate on underwater environment, it interacts with the suspended particles being both scattered and absorbed. These phenomena reduce the amount of image information culminating into a degraded version of the scene signal. Underwater images are important on many applications such as: 3D reconstruction of scenes [1], coral image classification [2] [3] or robot navigation [4] [5]. However, frequently the raw data is not sufficient to sustain those applications. Thus, image processing algorithms are often used to increase the general quality of underwater images [6]. To recover general image visibility on underwater images, general enhancing methods can be used, e.g, contrast stretching, white balance, etc. However, besides producing some visually satisfying results, the enhancement methods do not invest into recovering the non-degraded signal properties. An alternative to this is the restoration methods. These methods are designed to recover the degraded image by removing the degradation relying on a physical model of image formation. Independently of the method used to process underwater images, image quality evaluation is a hard matter. This matter makes the development of better restoration algorithms a hard task,



since there is unknown way to accurately compare restoration algorithms. Usually one can evaluate the quality of images depending on the amount of the original, nondegraded, signal information [7]. This can be divided into three categories i. evaluation based on a noise free version of the image, ii. evaluation based on some statistical information of the noise free image, iii. evaluation based on just the degraded image. Underwater restoration algorithms can only fall on the third category of image evaluation. This happens since the degraded underwater image do not have the reference image, i.e. the same underwater image without degradation, as a way to compare.

Motivations

Challenges associated with obtaining visibility of objects at long or short distances have been difficult to overcome due to the absorptive and scattering nature of seawater. Mitigating these effects has been the focus of the underwater imaging community for decades, but recent advances in hardware, software and algorithmic methods has led to improvements in several application areas. For example, advancements such as:

- Affordable, high quality cameras support a suite of fast, inexpensive specialized image processing software and hardware add-ons.
- Digital holographic cameras record interference fringes directly onto solid state sensors (i.e., mega pixel charge coupled devices) to produce time resolved, 3-D views
- High repetition rate, moderate power lasers and advanced detector designs enhance performance of two-dimensional (2-D) and three-dimensional (3-D) imaging systems.

II. LITERATURE SURVEY

In the criterion, the corrosion rate can be calculated using any industrially accepted internal corrosion prediction model (ICPM), such as the Norsok model [1]. However, the results of the respective ICPMs may deviate from the realistic corrosion rates when the internal environmental parameters of the inspection segments are not within the scope of the prediction model. Then, the selected excavation points based on the ICPM's results may not provide an effective means for identifying areas that are "above average" in terms of weight loss.

The internal corrosion rate of wet gas gathering pipelines is influenced by the fluid composition, temperature, pressure, flow velocity and many other factors [2]. It is difficult to develop a theoretical model that is capable of describing the relationship between all of these factors and the associated corrosion rates. However, a variety of methods can be used to predict future data based on the historical data of the system; these methods include the statistical prediction method, artificial neural networks (ANNs) and fuzzy logic methods [3].

A red-dark channel prior was defined and derived to estimate the background light and the transmission. The visibility of scene was compensated by the object-camera distance to recover the colors of the background and objects. Subsequently, by analyzing the physical property of the point spread function, we developed a simple but efficient low-pass filter to deblur degraded underwater images. A wide variety of underwater images with different scenarios were used for the experiments. The experimental results indicated that the proposed algorithm effectively recovered underwater images while eliminating the influence of absorption and scattering.[1]

The reason for underwater image degradation, surveys the state-of-the-art intelligence algorithms like deep learning methods in underwater image dehazing and restoration, demonstrates the performance of underwater image dehazing and color restoration with different methods, introduces an underwater image color evaluation metric, and provides an overview of the major underwater image applications. The underwater environment, which contains numerous biological resources and energy, is one of the central components necessary to maintain the sustainable development of human beings. People often use video or images to obtain valuable information when studying the underwater environment. The enhancement of underwater image contrast is a widely used technique for color correction. The development of contrast enhancement has attracted much attention in recent years.[2] The deals with the application of side scan sonar (SSS) for inspection of underwater lengthy objects (cables and pipelines). The autonomous underwater vehicle using are suggested for this purposes. The problem of acoustic images processing for detection of communication lines on a sea-bottom and underwater robot control task are solved. Real cable recognition results and pipeline tracking modeling experiments are discussed. Manned or tethered devices using in this case is limited due to their small radius of action and necessity of support vessel (that increase the cost of inspection works). Processing results of a real SSS-images (received by AUV during cable inspection) and pipeline-tracking modeling experiments allow to conclude that these methods can be used in acoustic vision movement control systems of underwater robot for inspection of underwater communications.[3]

The developments in visual and hydro acoustic tracking are discussed, as are theoretical and practical concerns. This review also describes methods and tools for detection of the transmission lines laid on a seabed. Finally, it highlights



the need to construct a simple reliable system to estimate the position and burial depth of subsea transmission lines. Subsea cables have to be periodically maintained and checked for movement in terms of their position and burial depth. This task is difficult because of the dynamic environment of the sea floor, which can cause changes in position, depth, visibility and access to the utilities. With technological progress, the task of visual inspection can now be performed with an ROV controlled by an operator on the surface. They suggested that before the image processing is performed, the initial, predicted localization and direction of the cable should be estimated [4].

Introduced two vision-based corrosion detection algorithms that have been developed within the context of the European project MINOAS. Both algorithms are based on the idea of combining weak classifiers for obtaining a good global performance. After assessing their performance, the misclassification percentages obtained for both algorithms result to be not null. These results can be explained by analyzing the kind of misclassifications and the areas where they appear.

On the one hand, the FN percentages are not zero because the detectors tend to label as corrosion the center of the corroded area, while the borders are usually not totally labeled. On the other hand, the FP percentages are neither null due to the presence of different structures in the image that are misclassified as defects[5].

Describes a methodology for automatic analysis of the inner surface of pipelines by means of digital image processing (DIP). The whole platform consists of an inspection mobile robot that carries a Line-Laser and a CCTV camera to recognize defects of the inner pipeline structure that is not easily accessible for human inspectors. A simple algorithm is presented that is able to detect cracks in the inner surface of the pipes with approximately 80 percent accuracy in final result, representing the main purpose of vision systems and the use of DIP technique. Pipe inspection is not a new topic in academic and industry fields. Many diverse methods have been proposed but inspecting an environment not accessible for direct human observation is still a topic of interest[6].

A novel systematic approach to enhance underwater images by a dehazing algorithm, to compensate the attenuation discrepancy along the propagation path, and to take the influence of the possible presence of an artificial light source into consideration. Once the depth map, i.e., distances between the objects and the camera, is estimated, the foreground and background within a scene are segmented. The light intensities of foreground and background are compared to determine whether an artificial light source is employed during the image capturing process. After compensating the effect of artificial light, the haze phenomenon and discrepancy in wavelength attenuation along the underwater propagation path to camera are corrected. Next, the water depth in the image scene is estimated according to the residual energy ratios of different color channels existing in the background light. Based on the amount of attenuation corresponding to each light wavelength, color change compensation is conducted to restore color balance. The performance of the proposed algorithm for wavelength compensation and image dehazing (WCID) is evaluated both objectively and subjectively by utilizing ground-truth color patches and video downloaded from the Youtube website[7].

III.DISCUSSION

A-network: As mentioned before, most of the conventional ambient light estimation methods select pixels with infinite depth to estimate ambient light. But the selection is often limited by camera angle and interfered by some special pixels. To address these issues and improve the robustness of the estimation, we proposed a new global ambient light estimation method based on CNN by learning the mapping between underwater images and their corresponding ambient light.

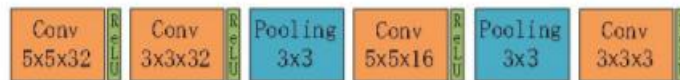


Figure 1 : CNN build layer

The illustration of the A-network architecture is given in Fig.2. It consists of mainly of two operations: convolution and max-pooling. The input of the A-network is an underwater image after downsampling. And the output is global ambient light, which size is the same as a pixel value. We use three convolution layers to extract features, and two max-pooling layers to overcome local sensitivity and to reduce the resolution of feature maps. The last layer is also a convolution layer for non-linear regression. In addition, we add the widely used ReLU layer after every convolution layer to avoid problems of slow convergence and local minima during the training phase. The major difference between our algorithm and the method proposed by Shin et al. (2016) lies in the following two aspects. Firstly, we estimate three channel values of the ambient light at the same time by our A-network, instead of one by one like Shin et al. (2016), which reduces the number of parameters. Secondly, considering that the depth information is helpful to ambient



light estimation, we adopt the lower resolution underwater images which generated by depth map and underwater optical model as the training samples of our network, rather than small local patches which lack of global transmission information. In this way, we can get a more accurate estimate because of a better training set. Moreover, because the image details are not important when we estimate global ambient light. So, we reduce the size of A-network training images to improve the training speed.

IV.CONCLUSION

This paper presented a novel dataset of real time underwater images where it is possible to access the reference image, i.e. the same underwater images with no degradation was acquired and put available. The proposed dataset created possibility for a novel evaluation on underwater restoration/enhancement algorithms. With this, we compared some of the most popular image restoration/enhancement methods on their capacity to approximate a turbid image with the clean image. As a future work we believe that restoration methods should consider different turbidity conditions as a way to propose priors. For that, we think that learning approaches can be the most suited since is hard to design multiple priors by hand. Finally, the dataset and methodology proposed in this work can be useful not only to evaluate image restoration methods, but also to test any vision algorithms that are sensitive to turbidity on underwater vision applications.

REFERENCES

- [1] Gao, Y.; Liu, Y.; Ma, Y.; Cheng, X.; Yang, J. Application of the differentiation process into the correlation-based leak detection in urban pipeline networks. *Mech. Syst. Signal Process.* 2018, 112, 251–264.
- [2] Yin, S.; Weng, Y.; Song, Z.; Cheng, B.; Gu, H.; Wang, H.; Yao, J. Mass transfer characteristics of pipeline leak-before-break in a nuclear power station. *Appl. Therm. Eng.* 2018, 142, 194–202.
- [3] Scott, S.L.; Barrufet, M.A. Worldwide Assessment of Industry Leak Detection Capabilities for Single & Multiphase Pipelines. Offshore Technology Research Center College Station. 2003. Available online: <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.118.6455&rep=rep1&type=pdf> (accessed on 17 December 2018)
- [4] Khan A, Ali SS, Anwer A, Adil SH, Mériaudeau F. Subsea Pipeline Corrosion Estimation by Restoring and Enhancing Degraded Underwater Images. *IEEE Access.* 2018 Jul 13;6:40585-601.
- [5] Rankin A, Ivanov T, Brennan S. Evaluating the performance of unmanned ground vehicle water detection. In *Proceedings of the 10th Performance Metrics for Intelligent Systems Workshop 2010 Sep 28* (pp. 305-311).
- [6] L. Developments in sonar technologies and their applications. In *2013 IEEE International Underwater Technology Symposium (UT) 2013 Mar 5* (pp. 1-8). IEEE.
- [7] Szyrowski T, Sharma SK, Sutton R, Kennedy GA. Developments in subsea power and telecommunication cables detection: Part 1-Visual and hydroacoustic tracking. *Underwater Technology.* 2013 Jul 1;31(3).
- [8] Bonnin-Pascual F, Ortiz A. On the use of robots and vision technologies for the inspection of vessels: A survey on recent advances. *Ocean Engineering.* 2019 Oct 15;190:106420.
- [9] Motamedi M, Faramarzi F, Duran O. New concept for corrosion inspection of urban pipeline networks by digital image processing. In *IECON 2012-38th Annual Conference on IEEE Industrial Electronics Society 2012 Oct 25* (pp. 1551-1556). IEEE.
- [10] Zheng L, Shi H, Sun S. Underwater image enhancement algorithm based on CLAHE and USM. In *2016 IEEE International Conference on Information and Automation (ICIA) 2016 Aug 1* (pp. 585-590). IEEE.