Underwater Image Restoration and Object Detection

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Abstract

Underwater environments present unique challenges for imaging due to factors such as light attenuation, scattering, and colour distortion. This research combines advanced CNN models like CBAM(convolutional Block Attention Mod-ule) and VGG16 with state-of-the-art object detection methods of CNN like YOLO or RCNN to enhance the visual quality of underwater images and to detect the objects based on an accuracy rate. Leveraging the various capabilities of the VGG16 model, pretrained on extensive datasets, the system efficiently restores degraded underwater images by capturing and learning intricate features. Integrating the CBAM model enhances this process by selectively attending to salient features while suppressing irrelevant ones, thereby refining the restoration results. Additionally, the combined architecture facilitates object detection within the restored images, enabling the identification and localization of submerged objects with high accuracy. Currently the work presents short review on the existing methods of underwater image restoration and a suggests method employing the CBAM(convolutional Block Attention Mod-ule) and VGG16 to overcome the prevailing challenges in underwater object detection. In future, the research aims to present a website that would be more useful for the students , researchers and the underwater explorers.

Keywords: Convolutional Neural Networks (CNNs), VGG 16, Underwater Object Detection, Image Restoration

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1. Introduction

Underwater image restoration and object detection play pivotal roles in advancing the capabilities of underwater computer vision systems. The under-water environment introduces unique challenges, including light attenuation, scattering, and colour distortion, which collectively degrade image quality [6]. Addressing these challenges is essential for ap-plications ranging from marine biology studies to underwater archaeology and environmental monitoring. Image restoration techniques aim to mitigate the adverse effects of attenuation, haze, and colour shifts, enhancing visibility and overall image quality[7]. These methods often involve dehazing algorithms, colour correction, and contrast enhancement to improve the interpretability of underwater scenes. We use prominent CNN based models like VGG-16 and CBIM and combines them for the final model and is used for the restoration process [8-12]. Simultaneously, object detection in underwater environments is crucial for identifying and analysing marine life, archaeological artifacts, or underwater structures. Overcoming the complexities of underwater imaging not only facilitates scientific exploration but also enhances the performance of autonomous underwater vehicles and robotics in tasks such as underwater surveillance and exploration[13]. The integration of the image restoration and object detection components results in a com-prehensive solution for underwater image analysis. Our framework not only enhances the visual perception of underwater scenes but also provides a robust platform for detecting and identifying sub-merged objects. The applications of this integrated approach span a range of domains, including marine biology, underwater archaeology, and surveillance[14-15].

2. Literature Survey

The literature on underwater image restoration and object detection reflects a growing interest in addressing the unique challenges posed by the underwater environment. Several studies have focused on developing advanced techniques to enhance the quality of underwater images, making them suitable for accurate object detection. Below are the literature reviews that are referred for the better implementation of the project.

2.1 A Survey of Restoration and Enhancement for Underwater Images

The underwater environment significantly degrades the quality of captured images due to factors like light scattering and absorption. This survey paper explores the various techniques used to restore and enhance underwater images. These techniques are broadly classified into two categories: spatial domain and frequency domain methods. Spatial domain methods directly manipulate the pixels of the image for improvements, while frequency domain methods transform the image into another domain (like a frequency spectrum) for processing and then transform it back. The paper highlights the challenges faced in underwater image restoration, including color distortion, blurred details, and the dominance of blue or green hues. Various restorative techniques are then reviewed, including filtering methods to remove noise and improve contrast and color correction methods to achieve natural-looking colors. Enhancement techniques like histogram equalization and unsharp masking are also explored to improve the overall visual quality. The authors emphasize the recent advancements in deep learning approaches for underwater image restoration. These data-driven methods are achieving superior results compared to traditional techniques. Finally, the paper discusses the evaluation methodologies used to assess the performance of restoration and enhancement algorithms and explores publicly available datasets for training and testing these methods [1].

2.2 Underwater Image Restoration: A State-of-the-Art Review

Underwater images suffer from significant quality issues like poor contrast and color cast due to light scattering and absorption in water. This paper reviews methods for restoring underwater images. The authors explore both traditional and computer vision techniques. They delve into the challenges of underwater image restoration, explaining why it's an inherently difficult problem. Different approaches are explored, along with the conditions they are suited for. The paper also discusses how the performance of these restoration techniques is measured. By comparing various methods, the authors identify the strengths and weaknesses of current underwater image restoration technology. They conclude by highlighting promising areas for future research in this field [2] .

2.3 Periodic Integration-based Polarization Differential Imaging for Underwater Image Restoration

The research paper proposes a new method for improving underwater image quality, specifically addressing challenges like inconsistent polarization detection and noise. This method, called periodic integration-based polarization differential imaging (PDI), utilizes a series of polarization images captured at different polarization angles throughout a complete light intensity cycle. Traditionally, PDI systems rely on just one or two pairs of images with orthogonal polarizations. This new approach integrates multiple polarization images. By stacking these images, the method approximates the total intensity of polarized light across various polarization directions. Finally, a calculation determines the degree of polarization for each pixel, resulting in a clear, restored image. The researchers compared this new method to existing PDI techniques using one or two image pairs. Their findings, based on both qualitative and quantitative analysis, demonstrate that the periodic integration method offers superior performance in enhancing underwater image textures and suppressing noise. This improvement paves the way for clearer underwater images in various applications like ocean exploration and underwater rescue missions [3].

2.4 Review of Underwater Image Restoration Algorithms

Underwater images are plagued by poor quality due to factors like scattering and absorption of light. This paper reviews the various algorithms designed to restore these underwater images. The core idea behind these restoration techniques is to recover the original scene by taking into account the distortions caused by the underwater environment. There are two main categories of restoration methods: those that rely on an image formation model (IFM) and those that don't. IFM-based methods attempt to mathematically model the way light travels underwater to estimate the original scene. Non-IFM-based methods focus on correcting the image directly using techniques like color correction, contrast enhancement, and haze removal. The paper highlights the challenges of underwater image restoration due to the unpredictable nature of underwater environments. It emphasizes the need for algorithms that can handle these variations while maintaining important image details. The authors also call for future research to address the shortcomings of existing methods [4] .

2.5 Intelligent Underwater Object Detection and Image Restoration for Autonomous Underwater Vehicles

The research paper discusses an approach to enhance underwater image quality and object detection for autonomous underwater vehicles (AUVs). Underwater environments pose challenges for image clarity due to factors like limited light and scattering. This two-stage system addresses these issues. First, it tackles image restoration by automatically identifying key areas (regions of interest) within the image. Redundant data is filtered out, leaving a more manageable dataset. Next, the system performs object detection on this reference image. The authors propose a method specially designed for underwater object detection, considering the unique challenges of the environment. This approach tackles issues like small object detection and cluttered backgrounds that traditional methods struggle with. Overall, the system offers a comprehensive solution for AUVs to improve their visual perception underwater, leading to better object recognition and mission execution [5].

3 System Development

3.1 System Architecture

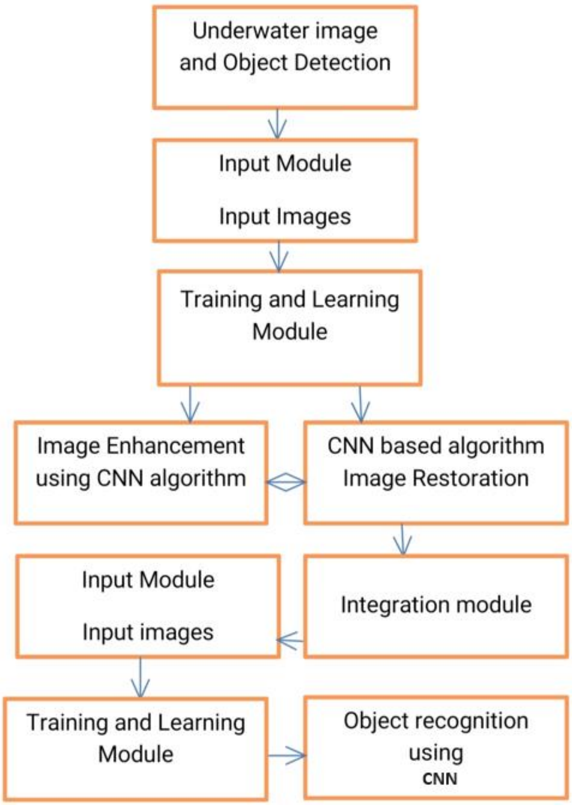

Figure .1 System Architecture

The block diagram (shown in Figure .1) of a system uses a convolutional neural network (CNN) for object detection in underwater images. Here's a breakdown of the system:

1. **Input Module**: This module takes underwater images as input.
2. **Training and Learning Module**: This module trains a CNN-based algorithm on the input images. Here, image enhancement is performed using a CNN algorithm for image restoration.
3. **Integration Module**: This module combines the restored image and the output from the CNN-based algorithm for object recognition.
4. **Object Recognition**: This module uses the CNN to recognize objects in the image.

The system takes underwater images as input, trains a CNN to recognize objects in those images, and then uses the trained CNN to recognize objects in new underwater images.

4. Methodology

This paper combines two predefined CNN (Convolutional Neural Network) models, namely CBAM (Convolutional Block Attention Module) and VGG16, respectively. The output of the project, which is an enhanced and detected image, is obtained through the integration of both of these models.

4.1 CBAM

The Convolutional Block Attention Module (CBAM) is a powerful tool in image processing, particularly within convolutional neural networks (CNNs). It enhances feature representation by integrating both spatial and channel attention mechanisms. The spatial attention mechanism recalibrates feature maps across spatial dimensions to focus on informative regions, while the channel attention mechanism adaptively weights feature maps along the channel dimension to emphasize relevant features. By dynamically adjusting future responses, CBAM enables CNNs to attend to important image regions and channels, enhancing their capability in tasks such as object detection, segmentation, and classification, ultimately leading to improved performance and robustness in various computer vision applications.

4.2 VGG-16

In the process of underwater image restoration, the VGG-16 model stands out as a powerful tool. Its deep architecture, pretrained on vast datasets, allows it to effectively capture and learn intricate features within underwater images. By leveraging its convolutional layers, the VGG16 model can accurately identify and rectify distortions and degradations commonly found in underwater photography, thereby enhancing image clarity and quality. Moreover, when integrated with the CBAM (Convolutional Block Attention Module) model, the restoration process gains an additional layer of sophistication. The CBAM model enhances the VGG16's performance by selectively attending to important features and suppressing irrelevant ones, thus refining the restoration process further. This integration empowers the system to achieve remarkable results in restoring underwater images, making it invaluable for various underwater imaging applications, from marine research to underwater archaeology.

4.2.1 Architecture

The "16" in VGG-16 refers to the fact that it has 16 layers that have weights. The architecture consists of: 13 convolutional layers: used for extracting features from the images. These layers use a 3x3 receptive field (i.e., the size of the filter) and a stride of 1 pixel. The convolutional layers are followed by activation functions (ReLU). 3 fully connected layers: The neural layers use the features extracted by the convolutional layers to classify the images into their respective categories. The first two have 4096 channels each, and the third performs a 1000-way ILSVRC classification and thus contains 1000 channels (one for each class). 5 Max-pooling layers: placed periodically between convolutional layers to reduce the spatial size of the representation, thus reducing the number of parameters and computation in the network. These use a 2x2 receptive field and a stride of 2 pixels.

4.3 Advantages

- Enhanced restoration of degraded underwater im-ages.
- Improved object detection accuracy in underwater environments.
- Selective feature attention improves image quality and object localization.
- Robust performance leveraging pretrained VGG16model and CBAM integration
.• Potential for diverse applications in marine research and underwater exploration.

4.4 Disadvantages

- High computational resource requirements for training and inference
.• Limited performance in extreme underwater conditions with high turbidity or low visibility.
- Dependency on large, labelled datasets for effective model training
.• Potential challenges in generalization to diverse underwater environments.
- Difficulty in fine-tuning models for specific underwater imaging tasks due to domain-specific nuances.

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- Interpretability issues with complex deep learning architectures, hindering user understanding of model decisions

5 Conclusion

In conclusion, the integration of underwater image restoration and object detection represents a significant advancement in underwater computer vision. The unique challenges posed by the aquatic environment, including colour distortion, reduced visibility, and light attenuation, necessitate sophisticated image restoration techniques. Colour correction, contrast enhancement, and dehazing algorithms contribute to the enhancement of visual quality, providing a crucial foundation for subsequent object detection tasks. Deep learning, particularly convolutional neural networks, has demonstrated remarkable success in underwater object detection, leveraging features such as texture, colour, and local characteristics. The synergy between image restoration and object detection not only enhances the overall interpretability of underwater scenes but also facilitates more accurate analysis and decision-making in aquatic environments. As technology continues to advance, these integrated approaches hold promise for applications ranging from marine research to underwater surveillance and exploration.

5.1 Future Scope

At present, we have developed a website on the project 'Underwater Image Restoration and Object Detection'. This website can be used by various researchers, students, underwater explorers, etc. Our method of image enhancement and restoration can be integrated into various devices and has various future scopes. Also, the future scope of the project on underwater image restoration and object detection utilizing CBAM and VGG16 models is promising and expansive. Further advancements in deep learning techniques and model architecture could lead to even more precise and restoration of underwater images, enabling clearer visualization of submerged environments. Integration with emerging technologies such as underwater drones or autonomous underwater vehicles (AUVs) could extend the applicability of the system to real-time underwater monitoring and surveillance tasks, aiding in marine conservation efforts and underwater resource management. Moreover, continued research into domain adaptation and transfer learning could enhance the adaptability of the system to different underwater conditions and environments, making it more versatile and widely applicable. Collaborations with marine biologists, oceanographers, and underwater archaeologists could also lead to the development of specialized tools tailored to specific underwater research needs, further expanding the project's impact and relevance in the field of underwater exploration and conservation.

References

[1] Zhang, Weidong, Lili Dong, Xipeng Pan, Peiyu Zou, Li Qin, and Wenhai Xu. "A survey of restoration and enhancement for underwater images." IEEE Access 7 (2019): 182259-182279.

[2] Sheezan Fayaz, Shabir A Parah, GJ Qureshi, andVijaya Kumar. Underwater image restoration: Astate-of-the-art review. IET Image Processing, 15(2):269–285, 2021.

[3] Jiajie Wang, Minjie Wan, Guohua Gu, Weixian Qian,Kan Ren, Qinyan Huang, and Qian Chen. Periodicintegration-based polarization differential imagingfor underwater image restoration. Optics and Lasersin Engineering, 149:106785, 2022.

[4] Jarina Raihan A, Pg Emeroylariffion Abas, andLiyanage C. De Silva. Review of underwater im-age restoration algorithms. IET Image Processing,13(10):1587–1596, 2019.

[5] Sheezan Fayaz, Shabir A Parah, GJ Qureshi, JaimeLloret, Javier Del Ser, and Khan Muhammad. Intelli-gent underwater object detection and image restora-tion for autonomous underwater vehicles. IEEETransactions on Vehicular Technology, 2023.

[6] Ming Zhou, Bo Li, Jue Wang, and Kailun Fu. Alightweight object detection framework for under-water imagery with joint image restoration and colortransformation. Journal of King Saud University-Computer and Information Sciences, 35(9):101749,2023.

[7] Xingyu Chen, Yue Lu, Zhengxing Wu, Junzhi Yu,and Li Wen. Reveal of domain effect: How visualrestoration contributes to object detection in aquaticscenes. arXiv preprint arXiv:2003.01913, 2020.

[8] Tengyue Li, Shenghui Rong, Wenfeng Zhao, LongChen, Yongbin Liu, Huiyu Zhou, and Bo He. Un-derwater image enhancement using adaptive colorrestoration and dehazing. Optics Express, 30(4):6216–6235, 2022.

[9] Min Han, Zhiyu Lyu, Tie Qiu, and Meiling Xu. Areview on intelligence dehazing and color restorationfor underwater images. IEEE Transactions on Sys-tems, Man, and Cybernetics: Systems, 50(5):1820–1832, 2018.

[10] Prasen Sharma, Ira Bisht, and Arijit Sur. Wavelength-based attributed deep neural network for underwaterimage restoration. ACM Transactions on MultimediaComputing, Communications and Applications, 19(1):1–23, 2023.

[11] Xiaowen Cai, Nanfeng Jiang, Weiling Chen, JinsongHu, and Tiesong Zhao. Cure-net: A cascaded deepnetwork for underwater image enhancement. IEEEJournal of Oceanic Engineering, 2023.

[12] Guojia Hou, Xin Zhao, Zhenkuan Pan, Huan Yang,Lu Tan, and Jingming Li. Benchmarking underwa-ter image enhancement and restoration, and beyond.IEEE Access, 8:122078–122091, 2020.

[13] Muwei Jian, Xiangyu Liu, Hanjiang Luo, XiangweiLu, Hui Yu, and Junyu Dong. Underwater image pro-cessing and analysis: A review. Signal Processing:Image Communication, 91:116088, 2021.

[14] Nan Wang, Yabin Zhou, Fenglei Han, Haitao Zhu,and Jingzheng Yao. Uwgan: Underwater gan forreal-world underwater color restoration and dehaz-ing. arXiv preprint arXiv:1912.10269, 2019.

[15] Keyan Wang, Yan Hu, Jun Chen, Xianyun Wu,Xi Zhao, and Yunsong Li. Underwater image restora-tion based on a parallel convolutional neural network.Remote sensing, 11(13):1591, 2019.