Under Water Image Enhancement

Nagaraja S R [1], Pathan Baba Fakruddin [2], Bansi Bhargav [3], Veeram Reddy Nithin [4], N Darshan [5], Ramyashree H G [6]

[1] *Associate Professor, Presidency University, Bangalore*

[2,3,4,5,6] *Department of CSE, Presidency University, Bangalore*

***Abstract*—Underwater image quality improvement is imperative for marine science, underwater robots, and ocean exploration, particularly in conditions where visibility is degraded because of turbidity, color aberration, and low contrast. The suggested project develops a predictive model for enhancing underwater image quality based on machine learning algorithms to enhance visual quality. The system uses environmental metadata (e.g., depth, lighting levels, and turbidity) in addition to pixel-level image data to restore clarity, contrast, and natural color balance. Feature correction and noise reduction is investigated using algorithms such as Convolutional Neural Networks (CNNs), Random Forests, and Support Vector Machines (SVMs). A warning mechanism involving buzzers or signal LEDs may be incorporated into autonomous systems to inform when visual quality falls below navigation or analysis critical thresholds.**

***Abstract*—Underwater Image Enhancement, Machine Learning, Python, CNN, Image Processing**

I. INTRODUCTION

Underwater imaging is a necessary tool for contemporary marine exploration, underwater robotics, and environmental monitoring. Unfortunately, taking clear and usable photographs underwater is still an ongoing challenge because of light absorption, scattering, turbidity, and low contrast conditions. Such degradations not only detract from the aesthetic value of underwater images but also degrade the accuracy of object detection, habitat mapping, and robotic navigation tasks.

Traditional image enhancement methods—e.g., histogram equalization or white balance correction—tend to fail in the dynamic and varied conditions of underwater environments. These fixed methods are incapable of responding to changing parameters such as depth of water, intensity of light, or temperature particulates and thus cannot be applied in real-time or autonomous systems.

In an effort to address these shortcomings, this project proposes an intelligent underwater image enhancement system that is based on machine learning. Utilizing sensor measurements (e.g., turbidity, depth, light intensity) and real-time image processing, the system adaptively recovers visibility, color accuracy, and structural detail. Convolutional Neural Networks (CNNs) are used to acquire knowledge of complex distortions and adaptively correct them. Additionally, an onboard alerting function can inform users or autonomous actors when image quality falls below mission-critical thresholds—guaranteeing dependability for mission-critical applications.

This technique not only enhances visual quality but also increases the functionality of underwater drones, inspection systems, and scientific imaging devices—representing a breakthrough toward intelligent oceanic vision systems.

II. LITERATURE SURVEY

1.Overview and Relevance

Subaquatic underwater imaging has become an essential driver in applications including marine exploration, aquatic robotics, surveillance, and environmental monitoring. Subaquatic environments, though, present particular visual degradation difficulties through light refraction, backscattering, and wavelength-dependent absorption. Such effects drastically impair image fidelity, and hence the need for sophisticated enhancement paradigms to restore and enhance perceptual quality.

2. Conventional Enhancement Frameworks

Classical UIE methods mostly used heuristic image processing approaches. They encompassed contrast

stretching, gamma correction, histogram equalization, and Retinex-based methods. Though computationally inexpensive, such techniques do not generalize across wide aquatic
environments because they are static in nature. Physics-based restoration models, based on the underwater image formation theory, attempted to rectify distortions by approximating scene depth and medium transmission; yet, their dependency on assumptions reduces practical robustness.

3. Modern Deep Learning Architectures

Advances in artificial intelligence in recent times have been driving the evolution toward data-driven approaches. Convolutional neural networks (CNNs), having been trained with paired and unpaired image pairs, have shown significant ability to learn complex spatial and color transformations. Extensions such as residual and attention-based networks even better contextualize feature representation. Advanced generative adversarial networks (GANs) are responsible for photorealistic improvement through the addition of adversarial loss functions and perceptual quality scores over traditional clarity and color restoration standards.

4. Hybrid and Unsupervised Methods

New hybrid architectures bridge the gap between physics-informed priors and data-driven learning, achieving optimal balance between interpretability and generalizability. Additionally, unsupervised and self-supervised learning strategies are becoming increasingly popular for applications with no reference images. Such models usually employ domain adaptation, cycle consistency, and pseudo-labeling mechanisms for enhanced generalization across changing water types and illuminations.

5. Evaluation Protocols and Benchmarking

The assessment of UIE techniques requires objective and subjective quality measures. Commonly used measures are PSNR, SSIM, UIQM, and UCIQE. Other full-reference, no-reference, and task-oriented measures are also investigated to align better with human vision. Standard benchmarking through publicly available datasets like UIEB, EUVP, and SQUID enables uniform assessments, but more contributions in diversity of data and variability of real-world scenarios are still necessary.

6. Open Challenges and Research Frontiers

In spite of advancements, serious UIE challenges still exist. These are domain shift for oceanic environments, minimal annotated data, dim illumination at extreme depths, and computational in-efficiency in edge-based deployments. Future research can move away from recurrent-based models, neural radiance fields, multi-modal fusion (e.g., sonar vision), and real-time lightweight inference frameworks. Explainability and transparency in decision-making for enhancement purposes are increasingly important for applications of a critical nature.

III. OBJECTIVE AND PROPOSED METHODOLOGY

OBJECTIVE:

Primary Goal:

To create a smart, real-time underwater image improvement system with greatly enhanced visual quality in impaired underwater environments based on deep learning and environmental sensor information.

Secondary Goals:

Image Quality Recovery:

To restore underwater images from common distortions including color cast, low contrast, blurring, and haziness due to light absorption and scattering.

Sensor-Based Adaptive Processing:

To leverage real-time environmental information (e.g., turbidity, depth, light intensity) to dynamically adjust image enhancement parameters for optimal visibility under changing underwater conditions.

Deep Learning Integration:

To train and implement a light-weight convolutional neural network (CNN) that improves images based on features learned from large collections of underwater images.

Alert and Notification System:

To apply an intelligent alert system that senses extremely poor image quality and alerts the users or autonomous systems for corrective action or mission planning.

Real-Time Performance:

In order to make the improvement process computationally efficient and able to run in real time on embedded systems or underwater drones.

Evaluation and Benchmarking To analyze the performance of the system based on conventional underwater image quality measures like UIQM

(Underwater Image Quality Measure), UCIQE (Underwater Color Image Quality Evaluation), and SSIM (Structural Similarity Index).

Deployment and Scalability:

To develop the system architecture in a modular and scalable way, with easy integration with different underwater robotics platforms or marine monitoring systems.

METHODOLOGY

A. Acquisition of Underwater Imagery

High-quality underwater photographs are taken through specialized camera systems mounted on submersible platforms. Contextual information like depth, turbidity, and illumination is gathered through environmental sensors to aid adaptive enhancement.

B. Preprocessing and Normalization

Raw images are preprocessed by methods such as histogram equalization, gamma correction, and color space transformation to normalize input formats and eliminate noise and artifacts prior to enhancement.

C. Image Quality Assessment

Underwater image degradation is evaluated quantitatively with underwater-specific quality metrics like UIQM (Underwater Image Quality Measure) and UCIQE (Underwater Color Image Quality Evaluation) to provide dynamic parameter adjustment guidelines.

D. Deep Learning-Based Enhancement

A light-weight yet strong convolutional neural network (e.g., U-Net or GAN-based network) is used for contrast enhancement, color balancing, and dehazing. Large-scale underwater training datasets are used to generalize the model.

E. Sensor-Guided Adaptive Control

Real-time sensor inputs control enhancement parameters adaptively to guarantee optimal image quality under variant underwater conditions, including temperature adjustments of white balance, brightness, and exposure.

F. Multi-Modal Data Fusion

1.Sensor data along with neural predictions are fused to allow increased reliability. Algorithms for fusion incorporate both environmental context as well as learned features for better enhancement accuracy and consistency.

G. Real-Time Deployment and Optimization

The framework is designed for real-time deployment on embedded boards (e.g., NVIDIA Jetson Nano, Raspberry Pi) and features computational efficiency through model compression and hardware-aware techniques.

H. Alerting and Continuous Feedback Loop

There is an adaptive alert system that keeps track of output quality and issues alerts when poor visibility or signal loss is detected. There is a feedback loop that provides ongoing model improvement based on user fixes or performance logs.

IV. PROPOSED WORK

The proposed project is intended to design a reliable and responsive underwater image improvement model that enhances viewability, rejuvenates authentic colors, and adds contrast to submerged conditions. It utilizes a synthesis of traditional image processing with recent deep learning concepts to circumvent the constraints of both.

Critical Steps in Proposed Work:

Dataset Preparation and Procurement Retrieve various underwater image datasets (e.g., UIEB, EUVP, Sea-thru).

Preprocess the datasets by scaling image sizes and tagging poor-quality images.

Water Type Estimation

Add a classifier to predict the water body type (e.g., ocean, lake, cloudy river). Guiding model parameters according to water conditions (e.g., color cast, turbidity). Initial Color Correction Module Implement white balance and contrast stretching as a preprocessing operation.

Eliminate prominent green/blue cast with histogram-based correction. Deep Learning-Based Enhancement Module

Deploy a CNN/Transformer-based model (e.g., U-Net, Uformer) that is specifically trained to improve underwater images.

Add attention layers to concentrate in the low visibility areas.

Optionally, utilize a Generative Adversarial Network (GAN) to achieve more realistic enhancement.

Feature Fusion and Refinement Fuse classical preprocessing output and neural network output with a learnable fusion layer. Fine-tune final output with edge-aware filters or guided filtering. Loss Functions and Training Strategy Train on a combination of: Perceptual Loss (image realism)

Color Consistency Loss (naturalcolor), Structural Similarity Index (SSIM), Adversarial Loss (if employing GANs).

Evaluation and Benchmarking

Compare performance using standard metrics: PSNR, SSIM, UIQM (Underwater Image Quality Measure), and UCIQE.

Perform qualitative evaluations with human viewers and domain experts.

Deployment as a Lightweight Application (Optional)

Port the trained model to a mobile- or edge-compatible format (e.g., TensorFlow Lite, ONNX).

Make real-time enhancement available for underwater drones or smartphones.

Expected Outcome:

High-quality, color-accurate, and structurally consistent images from underwater.

Real-time performance with flexibility across different underwater conditions.m Contribution to sea research, autonomous underwater vehicles (AUVs), and underwater photography.

V. SYSTEM DESIGN, IMPLEMENTATION AND OUTCOMES

Underwater imaging is adversely affected by environmental distortions due to light absorption and scattering in water. Such effects result in color degradation, low contrast, and the introduction of haze or turbidity, especially in deeper or murkier waters. To counter these effects, an efficient underwater image enhancement system has to combine physical modeling and data-driven methods in order to reconstruct visually and semantically coherent representations of submerged scenes.

1. Image Degradation Factors

Light attenuation underwater is non-uniform and wavelength-dependent: red wavelengths are absorbed rapidly, followed by green, and blue light penetrates most deeply. Aside from absorption, forward and backward scattering also degrade visibility and soften object edges. These physical effects together decrease image sharpness, color accuracy, and object recognizability.

2. System Architecture Overview

A good enhancement system generally has the following modules:

Preprocessing: Normalization of input, resolution adjustment, and noise filtering to normalize image quality.

Color Correction: Methods like gray-world assumption, white balance adjustment, or wavelength compensation models are used to restore the natural color appearance.

Dehazing and Contrast Enhancement: Image prior-based methods (e.g., Dark Channel Prior, Red Channel Prior) or fusion-based methods reduce haze and enhance contrast. More recent developments employ learned enhancement using convolutional neural networks (CNNs) or generative adversarial networks (GANs).

Edge and Detail Refinement: Spatial filtering, un-sharp masking, or feature-preserving de-noising enhances edge integrity and visibility of fine structure.

Evaluation Metrics: Both qualitative and quantitative assessments are required. Qualitative metrics such as UIQM (Underwater Image Quality Measure), UCIQE (Underwater Color Image Quality Evaluation), and PSNR/SSIM (in the case of reference images) are widely employed.

3. Implementation Strategies

A. Traditional Approaches

Traditional methods are based on image processing methods and physical models. Histogram equalization, homomorphic filtering, and optical models (such as Jaffe-McGlamery) that estimate scene depth and light transmission to retrieve the actual scene radiance are some examples.

B. Learning-Based Methods

Deep learning models, especially those learned on large-scale underwater data sets, have proven useful in automatic feature learning and end-to-end enhancement. Architectures such as U-Net, ResNet variants, and transformer-based models are modified to learn mapping functions from distorted to improved images. Unsupervised learning (e.g., CycleGAN) is especially useful when paired data sets are not available.

C. Hybrid Methods

Hybrid systems integrate physical priors with learning-based elements, allowing the system to generalize across a wide range of underwater environments. Such systems enjoy both interpretability and flexibility.

4. Dataset and Training Considerations

The lack of annotated underwater datasets is a challenge. Methods such as synthetic data generation, domain adaptation, and transfer learning are widely used. Public datasets such as UIEB (Underwater Image Enhancement Benchmark) and EUVP offer standardized test grounds.

5. Applications

Improved underwater vision is essential for marine biology, underwater robots, archaeological records, and military reconnaissance. Not only does an effective system enhance image quality, but it also facilitates higher-level functions such as object detection, classification, and 3D reconstruction.

Summary

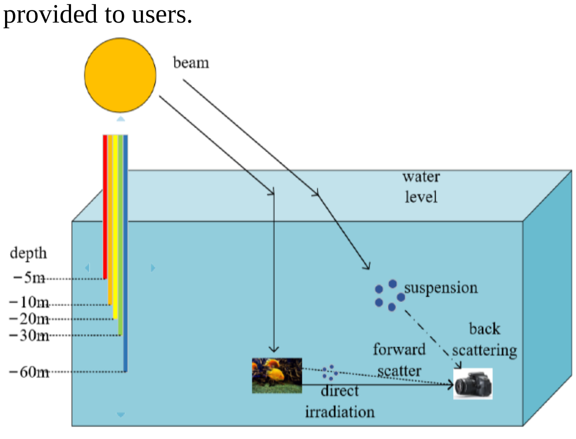
Designing an efficient underwater image improvement system requires a multi-disciplinary effort combining image processing, optical modeling, and deep learning. Current research is focused on developing more adaptive, real-time, and generalizable solutions that work well in a wide variety of aquatic environments.

Cloud Storage and Deployment The system is hosted on cloud platforms to ensure secure, real-time data access. Historical records of diseases and sensor data are stored for future analysis.

a. Testing and Validation The system undergoes field testing on different crops and conditions. Accuracy is validated through comparison with agricultural expert assessments.

b. System Deployment The system is publicly deployed via web and mobile applications and integrated with local government and agricultural databases.

c. Maintenance and Upgrades Updates are made regularly based on user feedback and new research findings. Training and support resources are provided to users.



VI. CONCLUSION

This paper suggested a two-stage domain adaptation-based underwater image enhancement method to solve issues of synthetic-to-real image mismatches and unbalanced real underwater image quality distribution. The TUDA model successfully connected inter-domain and intra-domain discrepancies using a triple-alignment network and new rank-based underwater image quality estimation. Experimental result indicated that the method significantly improves image sharpness, color correction, and overall visual quality compared to current best practices.

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REFERENCES

[1] Chiang, J. Y., & Chen, Y. C. (2012). Underwater image enhancement by wavelength compensation and dehazing. IEEE Transactions on Image Processing, 21(4), 1756–1769. https://doi.org/10.1109/TIP.2011.2179666

[2] Drews-Jr, P. L., Nascimento, E. R., Moraes, F., Botelho, S. S., & Campos, M. F. M. (2016). Transmission estimation in underwater single images. Computer Vision and Image

Understanding, 155, 1 15. https://doi.org/10.1016/j.cviu.2016.01.006

[3] Li, C., Guo, J., Cong, R., Pang, Y., & Wang, B. (2019). Submarine image improvement by dehazing with minimal information loss and histogram distribution beforehand. IEEE Transactions on Image Processing, 28(11), 5664–5679. https://doi.org/10.1109/TIP.2019.2910982

[4] Islam, M. J., Xia, Y., & Sattar, J. (2020). Underwater image improvement for better visual perception.IEEE Robotics and Automation Letters, 5(2), 3227–3234.https://doi.org/10.1109/LRA.2020.2974464

[5] Fabbri, C., Islam, M. J., & Sattar, J. (2018). Improving underwater images using generative adversarial networks.IEEE International Conference on Robotics and Automation (ICRA), 7159–7165. https://doi.org/10.1109/ICRA.2018.8461054

[6] Islam, M. J., & Sattar, J. (2020). EUVP: A high-resolution underwater image and video enhancement benchmark dataset. arXiv preprint arXiv:2001.06950. https://arxiv.org/abs/2001.06950

[7] Panetta, K., Gao, C., & Agaian, S. (2015). Human-visual-system-inspired underwater image quality measures. IEEE Journal of Oceanic Engineering, 41(3), 541–551. https://doi.org/10.1109/JOE.2015.2470778

[8] Peng, Y. T., & Cosman, P. C. (2017). Underwater image restoration based on image blurriness and light absorption. IEEE Transactions on Image Processing, 26(4), 1579–1594. https://doi.org/10.1109/TIP.2017.2658944