Underwater Image Hyper-Resolution Using MLDRG

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Abstract—**Turbidity, light absorption, sediment, and other environmental factors greatly hinder imaging in the underwater setting and degrade image quality. Standard procedures such as white balance and histogram equalization do not improve the visuals. In this work, we propose a deep learning framework for hyper-resolution underwater images and design a Multi-Level Degradation Restoration Generator (MLDRG) framework specifically to denoise and correct color distortion for underwater imagery. To improve the texture and resolution further, the model also incorporates a High-Frequency Learning Module (HFLM). The proposed model also demonstrates good transferability after being trained on a global underwater image dataset. The evaluation of the model with the PSNR and SSIM metrics, along with the modified Clarity Index, exhibited the advanced performance of the proposed technique against traditional techniques in color reproduction, resolution boost, structure retention, and other aspects. The work demonstrates further development of underwater imaging systems for possible use in marine studies, navigation robotics, and submerged vehicle systems. The primary focus of the research is writing advanced techniques for the Global Maritime Systems Dataset Underwater images, applying deep learning, hyper-resolution and image enhancement using MLDRG and HFLM.**

Index Terms—**Underwater Imaging, Deep Learning, Hyper-Resolution, MLDRG, HFLM, Image Restoration, PSNR, SSIM, Global Marine Dataset, Image Enhancement.**

I. INTRODUCTION

Underwater imaging is essential to many applications including marine biology, environmental monitoring, autonomous underwater vehicles (AUVs), and subsea exploration. However, taking quality underwater images remains a considerable challenge due to the scattering, absorption and turbid media causing color shift, low contrast and reduced resolution, especially at depth or in turbid environments. Due to this limitation, the quality of the visual data collected in these applications is greatly diminished, and decision-making based on visual analysis, is hindered..

Classical enhancement techniques, such as white balance correction, histogram equalization and contrast stretching, frequently do not adequately correct complex, nonlinear deterioration in underwater environments, and they typically work in a vacuum, correcting colors or contrast, but not resolution or textural detail. Deep learning methods, particularly generative models, present a fine alternative to enhance underwater imagery by learning from data and reconstructing, more reasonably and meaningfully, underwater imagery.

To address these issues, we propose a deep learning enhancement framework which contains a Multi-Level Degradation Restoration Generator (MLDRG), in addition to a High-Frequency Learning Module (HFLM), specifically tested on the global underwater datasets. Our architecture makes use of both channel attention and self-attention blocks to focus on informative features by adaptively downweighting unimportant features based on local and global dependencies within the image. The proposed model outperforms other benchmark models as highlighted by the PSNR, SSIM, and a modified form of the Clarity Index suitable for underwater display, indicating its ability to recover an underwater image with high fidelity, detail-rich visuals.

A. MOTIVATION

Underwater imaging is adversely affected by several factors that introduce visual impairments like light scattering, turbidity, and distortion of colors that produce unclear and inaccurate images. These visual impairments limit underwater exploration, research in marine biology, and autonomous navigation tasks.

Traditional image enhancement techniques often perform poorly, particularly with the variations of water conditions. To overcome the limitations of traditional enhancements, our research examines a deep learning approach that uses channel attention and self-attention to identify and enhance important features and textures in the image. This has enabled our models to produce high-resolution underwater images that have better representation and visual fidelity, regardless of the geographical location of the dataset used for training and testing.

B. Research Objectives

The primary objectives of this study include:

a. Develop a deep learning-based system that will improve the resolution and quality of underwater images.
b. Incorporate channel attention and self-attention mechanisms to focus on informative features and improve texture restoration..
c. Evaluate the model's performance concerning conventional and up-to-date underwater image enhancement strategies.

II. LITERATURE REVIEW

Underwater image enhancement and super-resolution have been thriving research areas and addressed challenges such as color distortion, noise and low-resolution images. Types of approaches observed in the literature range from image-processing-based to deep-learning-based.

A. Underwater Image Restoration and Enhancement

Historically, underwater image restoration techniques have focused on restoring clarity by attempting to improve image quality disrupted by color imbalance or noise. Simple restoration techniques, such as white balance corrections, histogram equalization, and contrast-limited adaptive histogram equalization (CLAHE), produced modest enhancements to underwater image quality, but could only do so much for complex and transformative distortions presented in turbid waters like those found along the Indian coastline. For example, the dark channel prior (He et al., 2011) and the red channel method (Galdran et al., 2015) methods proved useful for improving color, but produced artifacts in the presence of significant turbidity.

B. Single Image Super-resolution (SISR)

Super-resolution techniques attempt to upscale low-resolution images while retaining detail. The interpolation-based methods, such as bicubic interpolation and Lanczos filtering (Keys, 1982; Duchon, 1979), were first attempts but often produced images with blurry edges. Deep learning has produced methods like SRCNN (Dong et al., 2016) and SRGAN (Ledig et al., 2017), which produced state-of-the-art results by learning end-to-end mappings between low- and high-resolution images. ESRGAN (Wang et al., 2018) did improve perceptual quality, however it was primarily made for terrestrial images, leaving a void in underwater applications.

C. Simultaneous Restoration and Super-resolution

Only a few studies have considered simultaneous restoration and super-resolution of underwater images. Cheng et al. (2018) used color restoration and super-resolution, but only used vanilla preprocessing and did not examine recovery under complex degradation. SESR (Islam et al., 2020a) describes an adversarial pipeline to facilitate enhanced resolution, but also has artifacts in heavily turbid environments.

D. Gaps in the Literature

Current methodologies have some limitations in Indian coastal waters due to the environmental context, like high sediment load, seasonal monsoons, and variability in water quality. Current methodologies are often too generic to be informative or don't represent the environmental conditions and degradation characteristics of the region.

The HGF simultaneously encompasses restorative and super-resolution steps in a single pipeline, which performs well across different degradation conditions.

III. PROPOSED SYSTEM

The Hyper-resolution Generative Framework (HGF) is a deep learning-based system for improving underwater images that suffer from turbidity,

suspended particles, low contrast, and light absorbance. These impairments often affect the ability of underwater visuals to be seen clearly. The limitations of classical adjustments for images in water--i.e., histogram equalization and white balance--can lead to temperamental approaches to existing waterscape photography.
To tackle these issues, HGF utilizes a two-stage enhancement pipeline that combines restoration and resolution enhancement, producing realistic and high-quality underwater images.

A. MLDRG for Image Restoration
The Multi-Level Degradation Restoration Generator (MLDRG) removes distortion such as color cast and haze. The model consists of residual blocks that allow for preserving structure, channel attention that allows the model to focus on areas of importance, and self-attention to give the model access to global relationships. The basic innovation of the model is the use of multi-scale extraction to give the model more versatility with different types of distortion.

B. HFLM for Detail Enhancement
The High-Frequency Learning Module(HFLM) enhances texture, edges, and fine details that are often submerged. The High-Frequency Learning Module features a residual learning approach to recover sharp features, focusing on fine detail recovery. This recovery is very important for precision tasks, such as object detection or habitat inspection.

C. Training and Inference Pipeline
The model is trained on normalized, paired low-quality images using L1 loss. After training, it enhances new images, and is measured using PSNR.

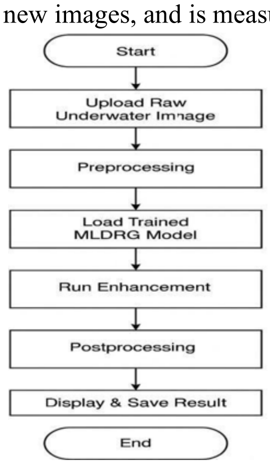

Fig: User Flow Diagram

IV. METHODOLOGY

The proposed image enhancement system utilizes a modular deep learning pipeline designed to restore and enhance underwater images using a series of components. The proposed system contains two main steps: restoration activities that employ MLDRG and enhancement activities that use HFLM..

A. Data Preparation
A set of low-quality underwater images and their associated high-quality references have been collected. These images are resized, normalized, and converted to tensors. This allows for consistency and compatibility with the training of deep neural networks..

B. Preprocessing
In this phase, the collected images are prepared for training. The images are resized to uniform resolution, normalized to standard value ranges, and converted into tensors to accommodate deep learning models. Additionally, data augmentations, such as random cropping and random rotation, may be applied to improve the model's ability to generalize across different target image conditions

C. Model Training
In this phase, the model is trained using paired low-quality and high-quality images. The model architecture includes several key blocks to enhance performance:

- Residual Blocks: These blocks learn identity mappings to preserve important image information. This alleviates problems with vanishing gradients while maintaining features downstream in deeper layers.
- Channel Attention Blocks: These blocks dynamically emphasize the most informative feature channels. This allows the model to focus on important visual detail and de-emphasize not-very-informative visual detail, improving the model's explicatory ability in visually focusing on objects of importance.
- Self-Attention Blocks: These blocks are used to capture long-range dependencies between far-off pixels, allowing the network to learn the image at a global level. In doing so, this projects the overall consistency of the image even if there is

structural inconsistency in the global image.

- Multi-Scale Feature Extraction: The model analyzes the image at different scales, enabling it to adapt to distortions of varying sizes and complexities. This block helps the model deal with both fine-grained and larger-scale distortions.

The training process consists of passing the low-quality images through these blocks to get improved outputs and comparing them with the high-quality reference images. A loss function (e.g., L1 Loss) computes an error between the generated and reference images. The model's weights are adjusted iteratively, relying on performance metrics such as PSNR to judge the improvement and help guide the optimization process.

D. Flask Integration

After the model has been trained and evaluated, it is deployed in a Flask web app for real-time image enhancement. There is a lot of potential for deploying this type of solution in web-based approaches where users can upload a low-quality underwater image and then the trained model processes it and returns the enhanced outputs. The Flask application is the user interface for the user to interact with the model easily, providing them access to the benefits of the model with little technical knowledge in implementation.

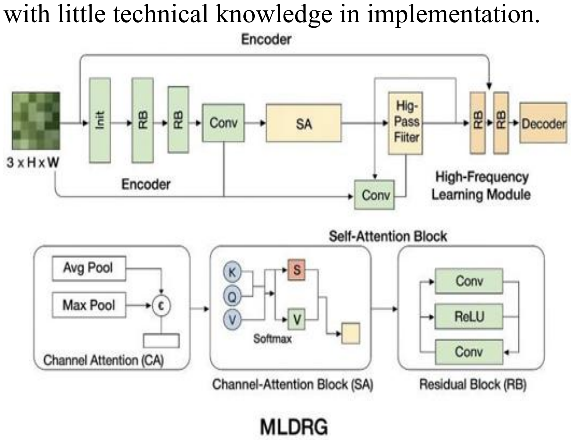

Fig: Architecture

V. RESULTS & DISCUSSION

The performance of the proposed Hyper-resolution Generative Framework (HGF) to enhance underwater images was tested on several datasets. Testing within the HGF showed significant improvements in restoring underwater images affected by turbidity, an overall low contrast, and other typical distortions. The results and discussions are listed below:

1. Peak Signal-to-Noise Ratio (PSNR): 21.26 dB
2. Structural Similarity Index Measure (SSIM): 0.773
3. Underwater Image Quality Measure (UIQM): 0.341
4. UCIQE (Underwater Color Image Quality Evaluation): 0.656

The Hyper-resolution Generative Framework (HGF), has indicated good promise and is suitable for real-world underwater image-enhancement applications. By leveraging the power of MLDRG for restoration, then applying HFLM to achieve super-resolution, the quality of restored images was good enough for marine monitoring, exploration of resources, and autonomous vehicle navigation.

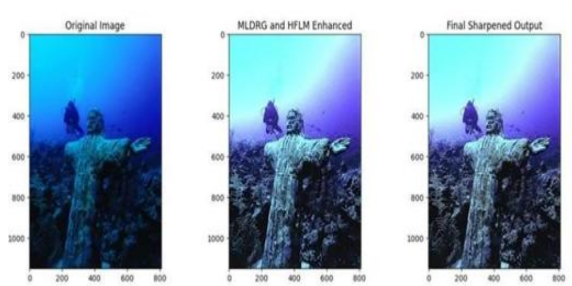

Fig: Sample Tests

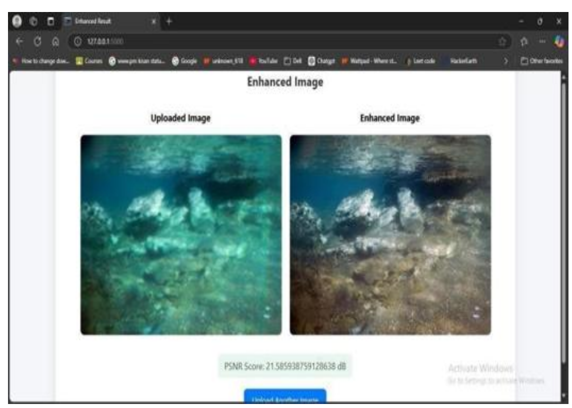

Fig: Enhanced Images with Score

VI. CONCLUSION & FUTURE SCOPE

The Hyper-resolution Generative Framework (HGF) enhances underwater images affected by turbidity, depth, and light attenuation. It uses the MLDRG to restore noisy, discolored images and HFLM to boost

resolution. Tested under various conditions, HGF outperforms previous methods in clarity, color, and resolution. Its nine-fold usability spans marine research, disaster monitoring, and underwater exploration using autonomous vehicles and industrial tools. Future advancements aim to improve user experience through evolving imaging technologies.
Future enhancements include integration of:

- Real-Time Deployment: Facilitate real-time improvement in underwater vehicles and drones for more rapid decision making.
- Low-Power Edge Computing: Optimize for deployment on edge devices that are in remote underwater environments.
- Integration with 3D Imaging: Add depth and 3D visualization capabilities for a more thorough underwater exploration.

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