A Fusion Based Approach for Underwater Image Restoration

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Abstract
Enhancing underwater images is crucial for marine exploration, robotics, and surveillance, as underwater environments often cause poor contrast, color distortion, and noise due to light absorption and scattering. This paper proposes a fusion-based approach integrating dehazing, denoising, fusion, and edge sharpening for effective underwater image restoration. The dehazing module reduces blue-green intensity while preserving details, with gamma correction enhancing visibility in dark regions, the denoising stage removes noise using a deep learning-based CNN, and the fusion process integrates the dehazed and denoised images to produce a visually refined output with improved clarity. Finally, edge sharpening preserves fine details for better interpretability. The system has been tested on images from the EUVP Dataset, covering various underwater conditions. Experimental results show that the proposed method significantly improves visibility, contrast, and edge details while maintaining natural colors making it a promising solution for real-world applications.

Keywords:
Physics-based Correction, Exposure Fusion, Dehazing, Denoising.

1. INTRODUCTION

Underwater image enhancement is crucial for applications like marine exploration, underwater robotics, and surveillance. Due to the absorption and scattering of light, underwater images often suffer from low contrast, color distortion, and haze, making accurate image processing challenging. The presence of suspended particles such as minerals, salt, and plankton introduces additional challenges, requiring specialized enhancement methods to restore image clarity [5]. Many approaches have been developed to tackle these issues, including physical model-based methods, non-physical model-based methods, and data-driven techniques.

Physical model-based methods estimate transmission properties to reverse the underwater imaging model. The underwater dark channel prior (UDCP) improves the DCP method to better adapt to underwater scenes, but it only considers the blue and green channels, ignoring red channel information, which affects color restoration [4]. Non-physical model-based techniques, such as contrast enhancement and histogram equalization, adjust pixel intensities to enhance image quality, but they may introduce artificial distortions [4]. Fusion techniques integrate contrast enhancement, white balancing, and different weighting mechanisms [2]. Although the fusion technique in [3] improves contrast and visibility, it does not compute depth information prior to restoration, which may limit performance in extreme underwater conditions.

To address these limitations, this paper proposes a fusion-based underwater image restoration system integrating dehazing, denoising, fusion, and edge sharpening techniques. To counteract haze, a dehazing technique is employed in our approach, which selectively reduces the intensity of blue and green channels while preserving image details. Additionally, gamma correction is used to enhance visibility in darker regions, further contributing to haze removal. The denoising stage applies a CNN-based approach to eliminate noise. The fusion module combines the outputs of these stages using exposure fusion algorithm to enhance image clarity while preserving essential details. Finally, edge sharpening is applied to further improve image interpretability.

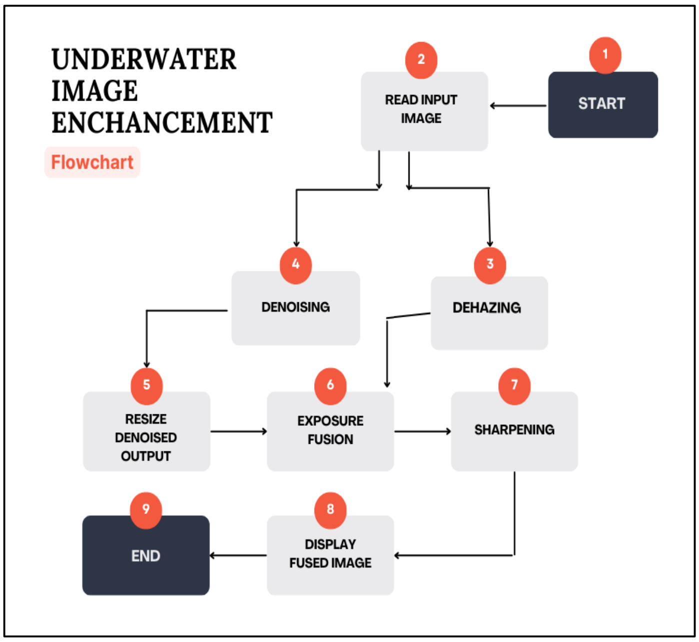

Fig.1. Block Diagram of the proposed system

The CNN model was trained for 11 epochs, achieving a training loss of 0.0079, a validation loss of 0.007979, and a test loss of 0.0081, ensuring effective noise reduction while maintaining structural details. The proposed system has been tested on images from the EUVP Dataset under varying underwater conditions.

The rest of the paper is organized as follows: Section 2 describes the proposed methodology. Section 3 presents the experimental results and discussion. Finally, Section 4 concludes the study and suggests potential future directions.

2. PROPOSED METHODOLOGY

To effectively enhance underwater images, a multi-stage approach is necessary to tackle different types of distortions. The proposed system consists of four key stages: dehazing, denoising, fusion, and edge sharpening. Each stage addresses a specific challenge—removing color distortion, reducing noise, integrating enhancements, and refining details. The following subsections describe these steps in detail.

2.1. DEHAZING

Underwater images often exhibit a strong blue-green color cast due to selective light absorption and scattering, reducing visibility and distorting natural colors. This effect becomes more pronounced with increasing depth, as longer wavelengths (red and orange) are absorbed first, leaving blue and green as the dominant colors.

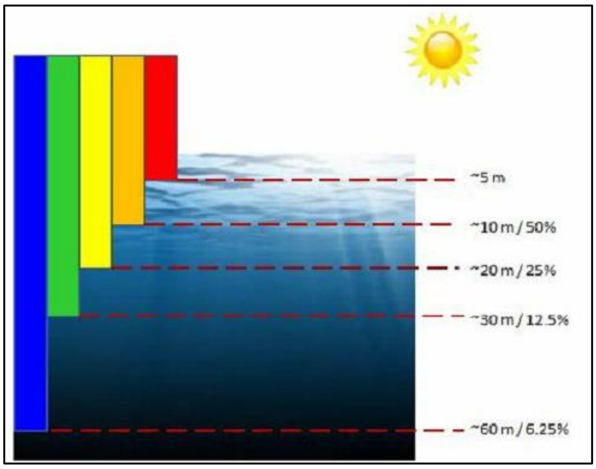

Fig.2. Absorption of Light by Water

To address this, our dehazing module selectively reduces the intensity of blue and green channels while preserving image details. The input image is first converted to a float format and split into Blue (B), Green (G), and Red (R) channels. The intensity of the blue and green channels is then proportionally reduced, ensuring better color balance while maintaining structural integrity.

Since underwater images often contain dark regions due to light attenuation, gamma correction is additionally applied to non-linearly adjust brightness and contrast. This transformation helps in enhancing visibility by brightening shadowed areas without overexposing well-lit regions.

2.2. DENOISING

Underwater images often contain high levels of noise due to low-light conditions, sensor limitations, and scattering effects. Traditional denoising methods, such as Gaussian and bilateral filtering, often result in loss of fine details. To address this, a CNN-based deep learning model is trained to remove noise while preserving important image structures.

2.2.1. Dataset & Preprocessing

The model was trained on 6,850 underwater images collected from the EUVP dataset. The dataset was split into:

- Training Set: 60%
- Validation Set: 20%
- Test Set: 20%

Each image was resized to 128×128 pixels and normalized for efficient training.

2.2.2. Supervised Learning & Ground Truth

To effectively remove noise, the CNN-based denoising model follows a supervised learning approach. The model is trained using paired noisy and clean images from the EUVP dataset, where:

- Input: Noisy underwater images
- Ground Truth: Corresponding clean images

During training, the model continuously compares its output with the ground truth images and updates its parameters to minimize pixel-wise differences using MSE loss. This process enables the network to learn complex noise patterns and restore high-quality images with minimal artifacts.

2.2.3. Loss Function & Optimization

The Mean Squared Error (MSE) loss function was used to measure pixel-wise differences between the noisy and clean images. The model was optimized using the Adam optimizer with a learning rate of 0.001.

Training was conducted for 11 epochs until convergence, with the final loss values recorded as:

- Train Loss: 0.0079
- Validation Loss: 0.007979
- Test Loss: 0.0081

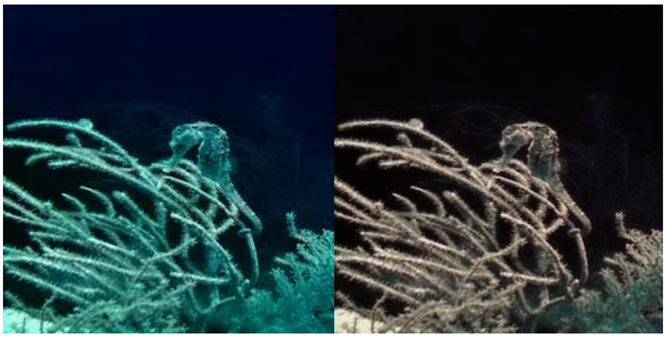

Fig.3. Original & Denoised Image using CNN

2.3. FUSION

After dehazing and denoising, the enhanced images are combined using a fusion technique to integrate the strengths of both processes while preserving essential image details. The fusion module ensures that the final output maintains high visibility, natural colors, and structural integrity.

2.3.1. Exposure Fusion Technique

The fusion process is based on exposure fusion, where the dehazed and denoised images are blended using pixel-wise weighting mechanisms to create a visually refined output with improved clarity. Before fusion, gamma correction is applied to both images to enhance contrast and improve visibility. The fusion method employs a weighted blending approach, where the dehazed image contributes 40% and the denoised image contributes 60% to the final output. This ensures that denoising has a stronger influence, effectively reducing residual noise while maintaining important image details.

Mathematically, the fused image F(x, y) is computed as:

$$F(x, y) = 0.4 * D_{dehazed}(x, y) + 0.6 * D_{denoised}(x, y) \quad (1)$$

Where:

- $D_{dehazed}(x,y)$ is the dehazed image
- $D_{denoised}(x,y)$ is the denoised image

This weighting approach prioritizes noise reduction, ensuring the final image retains clarity while minimizing unwanted distortions.

2.4. EDGE SHARPENING

After dehazing, denoising, and fusion, the enhanced image may still appear slightly smooth due to the blending process. To restore fine details, an edge sharpening technique is applied, improving the sharpness of edges and textures while maintaining a natural appearance.

2.4.1. Sharpening Technique

The sharpening process is implemented using a Laplacian-based convolution kernel, which enhances edges by emphasizing intensity differences between neighboring pixels. This technique helps restore fine details that may be lost during dehazing, denoising, and fusion. By preserving structural clarity without introducing unwanted artifacts, edge sharpening ensures that important features remain distinguishable. Additionally, it improves the interpretability of objects in underwater images, making them more suitable for applications such as marine exploration and object recognition.

Mathematically, the sharpening filter S(x,y)S(x,y)S(x,y) is computed as:

$$S(x,y) = I * (x,y) + k * L(x,y) \quad (2)$$

Where:

- I(x,y) is the **input image (fused image)**
- L(x,y) is the Laplacian-filtered image
- k is a scaling factor (typically set to 1 for balanced sharpening)

3. EXPERIMENTAL RESULTS & DISCUSSION

3.1. QUALITATIVE ANALYSIS

The effectiveness of the proposed method was evaluated visually by comparing the original underwater images with the processed outputs.

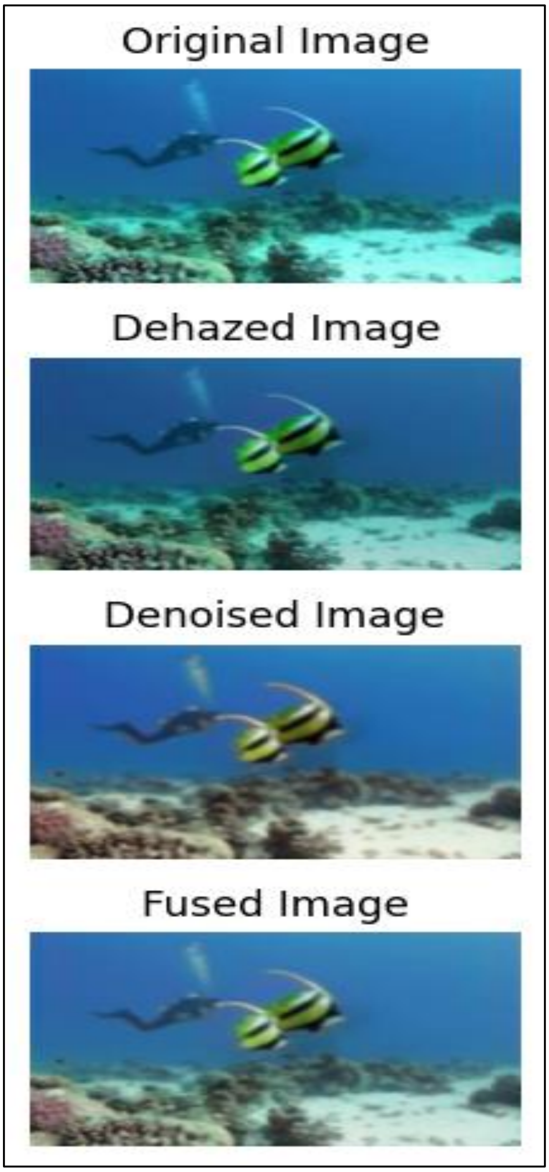

Fig.4. Results of the system

From the visual analysis, the fused images demonstrated improved clarity and enhanced perceptual quality compared to the original underwater images. The method effectively reduced haze and noise while preserving the structural details. Additionally, color distortions present in the input images were significantly mitigated, leading to more realistic underwater scene restoration.

The results highlight the advantages of the fusion-based approach in underwater image enhancement. Unlike traditional single-step methods, the integration of dehazing and CNN-based denoising allows for better preservation of fine details and overall image clarity. The color restoration component ensures that the final output remains natural without excessive enhancement.

3.2. LIMITATION & FUTURE WORKS

One limitation observed here is that, when the input image has an excessive blue or green tint, the denoising process tends to remove color details, leading to partial loss of natural color variations. This effect is more noticeable in images with strong wavelength attenuation, where essential color information is already limited. Further refinements, such as adaptive denoising techniques or post-processing color correction, could help mitigate this issue.

Fig.5. Images showing the loss of natural colours during denoising

Overall, the proposed method demonstrates a promising approach for underwater image enhancement, effectively reducing haze and noise while improving perceptual quality.

4. CONCLUSION

This work presented an underwater image enhancement approach that integrates dehazing, denoising using a CNN model, and a fusion technique to improve image clarity while preserving essential details. The results demonstrate that the proposed method effectively reduces noise and enhances visibility in underwater images. However, limitations were observed in cases where the input had excessive blue or green tint, leading to a loss of color details after denoising.

Despite these challenges, the approach holds significant potential for applications in marine exploration, underwater robotics, and scientific research where clear underwater imagery is crucial. Future work can focus on improving color preservation techniques, incorporating adaptive denoising strategies, or exploring real-time processing for practical deployments.

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