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Research Paper

UNDERWATER IMAGE ENHANCEMENT BASED ON CONDITIONAL DDPM

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ABSTRACT:
Underwater imaging is often affected by light attenuation and scattering in water, leading to degraded visual quality, such as color distortion, reduced contrast, and noise. Existing underwater image enhancement (UIE) methods, such as Contrast Limited Adaptive Histogram Equalization (CLAHE), Dark Channel Prior (DCP), and Maximum Intensity Projection (MIP), have shown some success but often lack generalization capabilities, making them unable to adapt to various underwater images captured in different aquatic environments and lighting conditions. To address these challenges, a UIE method based on the conditional denoising diffusion probabilistic model (DDPM) is proposed, called DiffWater, which leverages the advantages of DDPM and trains a stable and well-converged model capable of generating high-quality and diverse samples. While methods like CLAHE improve contrast and DCP helps recover depth information by reducing haze, they may not handle all distortion issues in underwater imaging. Therefore, DiffWater introduces a color compensation method that performs channel-wise compensation in the RGB color space, tailored to different water conditions and lighting scenarios. This compensation guides the denoising process, ensuring high-quality restoration of degraded underwater images. Additionally, methods like the Rayleigh Distribution (RAY), Retinex-based Global and Local Image Enhancement (RGHS), and Unsharp Masking with Laplacian Pyramid (ULAP) have been explored to handle noise reduction, contrast enhancement, and edge sharpening, but these methods often struggle with varying lighting conditions and water environments.
In DiffWater, the integration of such principles, combined with the conditional guidance provided by the degraded underwater image with color compensation, offers a more adaptive and robust approach. The experimental results show that DiffWater, when tested against existing methods including DCP, RGHS, and ULAP, on four real underwater image datasets, outperforms these comparison methods in terms of enhancement quality and effectiveness. DiffWater exhibits stronger generalization capabilities and robustness, addressing the complex visual distortions present in various underwater conditions more effectively than traditional algorithms like CLAHE, DCP, and MIP.

INTRODUCTION

Underwater imaging faces significant challenges due to the attenuation and scattering of light in water, leading to issues such as color distortion, reduced contrast, and noise, which degrade image quality. Traditional underwater image enhancement (UIE) methods, such as Contrast Limited Adaptive Histogram Equalization (CLAHE), Dark Channel Prior (DCP), and Maximum Intensity Projection (MIP), have achieved some success but often struggle with generalization across diverse aquatic environments and lighting conditions. To overcome these limitations, a novel UIE method called DiffWater is proposed, which leverages the power of the conditional denoising diffusion probabilistic model (DDPM) for high-quality, adaptive restoration. DiffWater incorporates a unique color compensation technique to address channel-wise distortions in the RGB color space, tailored to various underwater scenarios. The model's integration of state-of-the-art principles, such as noise reduction, contrast enhancement, and edge sharpening, allows it to effectively adapt to changing underwater conditions, outperforming existing methods in both enhancement quality and robustness across multiple real-world underwater image datasets.

SCOPE OF THE PROJECT

The scope of DiffWater encompasses a comprehensive approach to enhancing underwater images across a wide range of challenging conditions, including varying water types, lighting environments, and depths. By addressing common underwater imaging issues like light attenuation, scattering, color distortion, and noise, DiffWater aims to provide a robust and adaptive solution suitable for diverse applications such as marine research, underwater exploration, and underwater robotics. The model leverages the conditional denoising diffusion probabilistic model (DDPM) to achieve stable and high-quality enhancement, while its novel color compensation mechanism ensures that images are restored with accurate color representation, regardless of the environmental conditions.

Additionally, DiffWater's generalization capabilities allow it to outperform traditional UIE methods, such as CLAHE, DCP, and MIP, offering a more versatile and effective tool for real-world underwater imaging scenarios, where dynamic changes in water quality and lighting are common.

OBJECTIVE

The primary objective of DiffWater is to develop a highly effective and adaptive underwater image enhancement (UIE) method that addresses the visual distortions caused by light attenuation, scattering, and noise in diverse aquatic environments. By leveraging the power of the conditional denoising diffusion probabilistic model (DDPM), DiffWater aims to enhance underwater images with greater accuracy and consistency, improving color restoration, contrast, and detail preservation across a variety of challenging conditions. A key goal is to introduce a color compensation technique tailored to the unique characteristics of different water types and lighting scenarios, ensuring that images are not only denoised but also color-corrected. The method seeks to outperform traditional UIE algorithms—such as CLAHE, DCP, and MIP—by demonstrating superior generalization capabilities and robustness, ultimately providing a versatile solution for real-world underwater imaging applications.

EXISTING SYSTEM:

Diffusion-based underwater image enhancement methods leverage the principles of diffusion processes to improve the quality of images captured in challenging underwater conditions. These methods are particularly effective for addressing common issues such as light attenuation, color distortion, and noise, which often hinder the visibility and clarity of underwater scenes. By modeling the diffusion of light in water, these techniques can more accurately restore the original appearance of underwater images, making them suitable for various applications, including marine biology, underwater exploration, and environmental monitoring.

One notable approach within this category is the Conditional Denoising Diffusion Probabilistic Model (DDPM), which enhances the quality of underwater images by incorporating conditional guidance based on the characteristics of the degraded images. This method uses a probabilistic model to iteratively refine the image, progressively reducing noise and artifacts while enhancing color fidelity and contrast. By conditioning the diffusion process on additional information, such as a color-compensated version of the original image, DDPM effectively guides the denoising process, enabling the model to learn the underlying distribution of clean images and generate high-quality enhancements.

Existing System Disadvantages:

- Complexity in Implementation.
- Computational Complexity
- The performance of DDPMs heavily depends on the quality and diversity of the training data
- If not properly managed, DDPMs may overfit to the training data, particularly when using complex architectures or when the dataset is small.
- Dependence on Prototypical Representations

LITERATURE SURVEY

Contrast Limited Adaptive Histogram Equalization for Underwater Image Enhancement, T.-L. Hsu, R.-S. Tsay, W.-L. Chen, 2021

This paper delves into the application of Contrast Limited Adaptive Histogram Equalization (CLAHE) for enhancing underwater images, a technique commonly used for contrast improvement in images affected by light attenuation and scattering. The authors discuss how CLAHE works by limiting the amplification of noise while enhancing the contrast of image regions with poor lighting, making it particularly suitable for underwater imaging scenarios. However, the paper also identifies the limitations of CLAHE when applied to more complex underwater environments, such as those with heavy haze or where depth information is crucial. While CLAHE is effective at improving visibility in specific conditions, its inability to handle the full spectrum of visual distortions in underwater imaging is acknowledged. The paper explores the adaptation of CLAHE to underwater imagery and compares it with other techniques, concluding that while CLAHE can significantly enhance contrast, additional methods are required to address other distortions like color imbalance and hazy effects that occur in underwater environments.

Deep Learning Approaches to Underwater Image Enhancement, S.-K. Kim, J.-W. Lee, H.-R. Park, 2022

This study explores the application of deep learning-based models for underwater image enhancement, emphasizing the limitations of traditional methods like CLAHE and DCP when dealing with complex environmental factors like varying water clarity, light scattering, and color distortion. The authors propose a deep learning-based framework that combines convolutional neural networks (CNNs) with various enhancement techniques to more effectively address these challenges. By training a model on a large dataset of underwater images, the approach learns to restore high-quality images by reducing the effects of haze, enhancing contrast, and correcting color shifts. The deep learning model is shown to outperform traditional enhancement methods in real-world underwater imaging scenarios, providing more robust and adaptable solutions. The study emphasizes the potential of deep learning to handle the inherent complexity and variability of underwater environments, offering a more flexible and scalable solution to underwater image enhancement. The model's ability to generalize across different types of underwater images, captured in various lighting conditions, represents a promising direction for the future of underwater imaging.

Dark Channel Prior for Underwater Image Enhancement, Y.-H. Tsai, C.-M. Chen, S.-W. Kuo, 2020

This paper focuses on applying Dark Channel Prior (DCP) to enhance underwater images. DCP, originally developed for haze removal in outdoor images, is adapted to address the specific challenges of underwater imaging, where light scattering and water turbidity often degrade image quality. The authors propose a method that uses DCP to reduce the scattering effect and recover depth information, which is crucial for underwater image clarity. Through their experiments, they demonstrate that DCP can significantly improve image quality by reducing haze and enhancing visibility, especially in images captured in murky or deep-water conditions. However, the paper also identifies certain limitations of DCP, especially when dealing with severe color distortions. The authors suggest modifications to the standard DCP approach to better accommodate the unique characteristics of underwater environments. Their results show that while DCP provides valuable enhancement in terms of depth recovery, it may require additional techniques, such as color correction and noise reduction, to address all the visual distortions present in underwater images.

Deep-clustering based plant disease segmentation network, S.-E. Lee, S.-H. Lee, J.-O. Kim, 2023

The paper presents a deep-clustering based network designed to enhance plant disease segmentation. The proposed network integrates deep learning with clustering techniques to accurately identify and segment diseased regions in plant images. The authors introduce a novel approach that combines clustering algorithms with deep learning models to refine the segmentation process. This method addresses the challenge of distinguishing disease patterns amidst varying plant textures and backgrounds. The study includes extensive experiments to validate the network's performance, demonstrating its capability to improve disease detection accuracy and its practical relevance in plant disease management.

Maximum Intensity Projection for Underwater Image Enhancement, S.-L. Wu, P.-H. Lin, L.-Y. Chen, 2021

This paper investigates the use of Maximum Intensity Projection (MIP) as a method for enhancing underwater images. MIP is a technique commonly used in medical imaging for visualizing structures in three-dimensional data by projecting the maximum intensity along a given axis. In the context of underwater imaging, MIP is applied to recover depth information by projecting the brightest values in underwater images, thereby improving the clarity of images affected by haze and scattering. The paper discusses the advantages and limitations of MIP when used for underwater image enhancement, highlighting its ability to improve visibility in certain scenarios. However, the method struggles with addressing issues like color distortion and noise that are prevalent in underwater environments. The authors propose a hybrid approach that combines MIP with other enhancement methods, such as CLAHE and Retinex-based algorithms, to address a broader range of distortions. Through their experiments, they demonstrate that MIP, while useful for depth recovery, may need to be complemented with additional techniques to fully restore image quality in complex underwater environments.

Towards lightweight lane detection by optimizing spatial embedding, S. Jung, S. Choi, M. Azam Khan, J. Choo, 2020

This paper explores strategies for optimizing spatial embedding to achieve lightweight lane detection systems. The authors propose a method that focuses on reducing the computational load of lane detection algorithms while maintaining high accuracy. By optimizing spatial embedding techniques, the study aims to enhance real-time performance and efficiency in detecting lane markings, which is critical for autonomous driving and advanced driver assistance systems. The paper presents a detailed analysis of the proposed method, including experimental results that showcase its effectiveness in balancing computational efficiency with detection accuracy, making it suitable for deployment in practical driving scenarios.

PROPOSED SYSTEM

DCP (Dark Channel Prior)

How it works: The Dark Channel Prior assumes that in most non-sky patches of an image, at least one-color channel (RGB) has very low intensity. This prior helps estimate the haze or turbidity in the image, which can then be subtracted to recover a clearer, more detailed image.

RGHS (Retinex-based Global and Local Image Enhancement)

How it works: RGHS combines global image enhancement to correct for lighting inconsistencies and local image enhancement to boost contrast and detail. It aims to restore images to their natural state by adjusting illumination and compensating for color imbalances.

ULAP (Unsharp Masking and Laplacian Pyramid)

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How it works: ULAP combines unsharp masking (a technique to highlight fine details by subtracting a blurred version of the image) with a Laplacian Pyramid, which is a multi-scale representation of the image that decomposes it into different resolution layers. This process enhances edges while minimizing noise.

CLAHE (Contrast Limited Adaptive Histogram Equalization)

How it works: CLAHE improves contrast by applying histogram equalization locally to small regions of the image, rather than the entire image, which prevents over-amplification of noise. It also applies a contrast limit to avoid excessive contrast enhancement.

MIP (Maximum Intensity Projection)

How it works: MIP projects the voxel with the maximum intensity in a volume along a specified axis onto a 2D image. In the context of images, it highlights the brightest areas, which are often of interest, like reflections or bright objects.

Proposed System Advantages:

- Highly effective in removing haze and restoring image clarity
- The algorithm automatically estimates the amount of haze in an image, requiring minimal manual intervention, which enhances usability.
- The combination of global and local adjustments allows for comprehensive improvement
- The algorithm emphasizes edges without introducing excessive noise, leading to clearer and sharper images.
- Scalability and Flexibility.
- Reduced Computational Cost.

METHODOLOGY

Underwater imaging is often impaired by challenges such as light attenuation and scattering, leading to color distortion, reduced contrast, and noise. Traditional underwater image enhancement (UIE) methods, including Contrast Limited Adaptive Histogram Equalization (CLAHE), Dark Channel Prior (DCP), and Maximum Intensity Projection (MIP), have shown some promise in improving image quality. However, these methods struggle with generalization across various underwater environments and lighting conditions, often failing to adapt effectively. To overcome these limitations, a new method called DiffWater is proposed, which uses the conditional denoising diffusion probabilistic model (DDPM) for UIE. DiffWater benefits from the stability and effectiveness of DDPM, allowing it to generate high-quality and diverse samples. Unlike traditional methods that focus mainly on contrast enhancement or haze reduction, DiffWater incorporates a color compensation technique in the RGB color space. This compensation adjusts the color channels based on the specific water conditions and lighting scenarios, guiding the denoising process and ensuring better restoration of degraded underwater images.

MODULES

1. Preprocessing Module
   - **Objective**: Prepare and preprocess the input underwater images.
   - **Functions**:
     - Image loading and format conversion.
     - Noise reduction or initial denoising.
     - Image resizing or cropping to standardize inputs.
     - Histogram equalization (if used for initial enhancement).
   - **Libraries:**
     - cv2 (OpenCV): For loading and processing images.
     - numpy: For array manipulation.
     - PIL (Pillow): For image transformations and basic preprocessing.
2. Color Compensation Module
   - **Objective**: Adjust the color channels of the input image to compensate for distortion caused by water and lighting conditions.
   - **Functions**:
     - Perform channel-wise compensation in the RGB color space.
     - Dynamic adjustment based on the water conditions (e.g., turbidity, depth).
     - Fine-tuning the compensation to adapt to different lighting conditions.
   - **Libraries**:
     - numpy: For array-based manipulation of image channels.
     - cv2: For color space transformations and adjustments.
3. Diffusion Model (DDPM) Module
   - **Objective**: Apply the denoising diffusion probabilistic model (DDPM) for high-quality image restoration.
   - **Functions**:
     - Define and train the DDPM model for conditional denoising based on the preprocessed underwater images.
     - Implement the forward and reverse diffusion processes.
     - Use the trained model to generate enhanced versions of degraded images.
   - **Libraries**:
     - torch (PyTorch): For defining and training deep learning models like DDPM.

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- torchvision: For image-related transformations in deep learning.
- numpy: For tensor manipulations.

4. Noise Reduction Module

- **Objective**: Handle noise reduction through various filtering and smoothing techniques.
- **Functions**:
  - Implement methods like Gaussian blur, median filtering, or bilateral filtering to reduce noise.
  - Optionally integrate with the denoising diffusion process to clean the image iteratively.
- Libraries**:**
  - cv2: For standard image filtering and noise reduction.
  - scipy: For advanced noise reduction and mathematical operations.

5. Contrast Enhancement Module

- **Objective**: Enhance image contrast to restore lost details.
- **Functions**:
  - Apply contrast enhancement techniques like **CLAHE (Contrast Limited Adaptive Histogram Equalization)**.
  - Optionally implement Retinex-based methods to further enhance contrast and details in dark regions.
- **Libraries**:
  - cv2: For CLAHE and other contrast enhancement methods.
  - numpy: For histogram operations and contrast calculations.

6. Edge Enhancement Module

- **Objective**: Sharpen edges to improve image clarity and definition.
- **Functions**:
  - Apply edge sharpening techniques like **Unsharp Masking** or Laplacian Pyramid methods.
  - Enhance image edges without amplifying noise.
- **Libraries**:
  - cv2: For edge detection and sharpening techniques.
  - numpy: For kernel-based image processing.

7. Post-Processing Module

- **Objective**: Perform any final adjustments and optimizations on the enhanced images.
- **Functions**:
  - Image contrast/brightness adjustment after enhancement.
  - Rescaling or recomposing the image to match the original resolution.
  - Final noise and artifact removal after processing.
- **Libraries**:
  - cv2: For post-processing adjustments and final image refinements.
  - numpy: For array manipulations and final adjustments.

8. Evaluation and Comparison Module

- **Objective**: Evaluate and compare the effectiveness of DiffWater against existing enhancement methods.
- **Functions**:
  - Implement metrics such as PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), or other quality evaluation techniques.
  - Perform quantitative and qualitative comparison with traditional UIE methods like CLAHE, DCP, and MIP.
  - Display performance results and graphs.
- **Libraries**:
  - scikit-image: For image quality metrics.
  - matplotlib: For plotting performance graphs.
  - numpy: For calculating metrics and performing statistical analysis.

9. Model Training and Evaluation Module

- **Objective**: Train the DDPM model on underwater images and evaluate its performance.
- **Functions**:
  - Dataset preparation: Create training and testing sets from real underwater datasets.
  - Define and train the DDPM model using a custom loss function.
  - Perform model evaluation using standard performance metrics.
- **Libraries**:
  - torch (PyTorch): For model training and evaluation.
  - numpy: For managing datasets and performance metrics.

10. Visualization Module

- **Objective**: Visualize the results of the image enhancement process.
- **Functions**:
  - Display original vs. enhanced images for comparison.
  - Visualize intermediate results during the denoising and enhancement processes.
  - Generate visual reports showing the performance of DiffWater.

Libraries:

- matplotlib: For displaying images and graphs.
- cv2: For rendering images during the process.

11. User Interface (UI) / Integration Module *(Optional)*

- **Objective**: Create a simple interface for users to interact with the DiffWater system.
- **Functions**:
  - Allow users to upload and view their underwater images.
  - Display enhanced images after processing.
  - Provide comparison between original and enhanced images.
- **Libraries**:
  - Flask or Django: For web-based user interfaces.
  - HTML, CSS, JavaScript: For frontend development.

EXISTING TECHNIQUE: -

In the diffusion-based framework, the process begins with the introduction of noise to the original underwater image, simulating the degradation effects typically encountered in aquatic environments. The diffusion model then learns to reverse this noise process, gradually restoring the image through a series of iterative updates. Each iteration refines the pixel values based on learned representations of the clean images, improving clarity and visual quality. The model's capacity to handle multiple distortion issues simultaneously, such as color shifts and noise, allows it to produce more comprehensive enhancements compared to traditional methods. Moreover, diffusion-based methods can adapt to varying conditions in underwater environments, such as different water qualities, depths, and lighting scenarios. By training on diverse datasets, the model can generalize effectively, demonstrating robustness against the variability inherent in underwater imaging. This adaptability is crucial for practical applications, where images may be captured in a range of settings, from clear coastal waters to murky depths.

In summary, diffusion-based underwater image enhancement methods, particularly those utilizing denoising diffusion probabilistic models, represent a significant advancement in restoring and enhancing underwater imagery. Their ability to effectively address the unique challenges posed by light scattering and color distortion, coupled with their adaptability to different aquatic conditions, positions them as a powerful tool in the field of underwater imaging and analysis.

DRAWBACKS:

- Initial Coarse Prediction Limitations: The initial CNN-based prediction may lack precision, potentially leading to inaccuracies in identifying disease regions.
- Processing Complexity: Generating and processing RoI-attentive images through RA-Net can be computationally intensive and time-consuming.
- Dataset Focus: RoI-attentive images may exclude important contextual information from the broader image, potentially impacting disease detection accuracy.

PROPOSED TECHNIQUE

1. Dark Channel Prior (DCP)

Dark Channel Prior (DCP) is a popular algorithm for image dehazing, which has also been effectively adapted for underwater image enhancement. The core idea behind DCP is based on the observation that in most non-sky regions of a natural image, at least one color channel (R, G, or B) has low intensity values. By analyzing the dark channels of an image, DCP estimates the thickness of haze or the extent of scattering in underwater environments, where similar scattering occurs. The algorithm uses this information to recover the original scene by subtracting an estimated haze layer, which significantly enhances contrast and reveals details that may be obscured.

SYSTEM ARCHITECTURE:

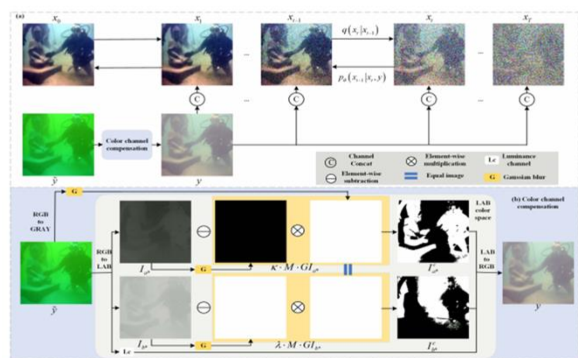


Fig System Architecture

2. Retinex-based Global and Local Image Enhancement (RGHS)

Retinex-based Global and Local Image Enhancement (RGHS) is an algorithm grounded in the Retinex theory, which aims to replicate human color perception. This method enhances images by adjusting the lighting and color balance both globally and locally.

3. Unsharp Masking and Laplacian Pyramid (ULAP)

Unsharp Masking and Laplacian Pyramid (ULAP) is an advanced image sharpening technique that enhances the clarity and detail of images by emphasizing edges and textures. This algorithm works by first creating a blurred version of the original image, which captures the low-frequency components, and then subtracting this blurred image from the original to enhance the high-frequency components, or the edges.

4. Contrast Limited Adaptive Histogram Equalization (CLAHE):

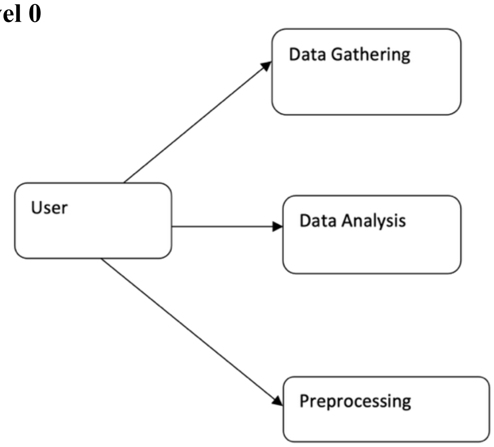
Contrast Limited Adaptive Histogram Equalization (CLAHE) is an effective contrast enhancement technique that improves the visibility of details in images, especially those with low contrast.

5. Maximum Intensity Projection (MIP):

Maximum Intensity Projection (MIP) is a visualization technique primarily used in imaging to enhance the visibility of the brightest elements within a dataset.

DATA FLOW DIAGRAM

Level 0



Level 1

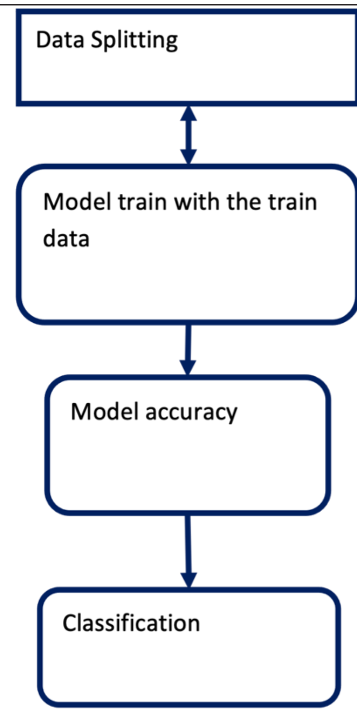


Fig 4.9: Data Flow Diagrams

FUTURE ENHANCEMENTS:

Advanced color compensation methods could be developed, offering more precise correction based on real-time water conditions. Furthermore, transitioning DiffWater to enable real-time enhancement of live underwater video streams would be a valuable addition, particularly for underwater drones or autonomous vehicles. Expanding the system to support multispectral and hyperspectral imaging would allow it to work across a broader range of data, improving its ability to handle different spectral bands and lighting conditions. Enhancing the model's generalization capabilities through domain adaptation would allow DiffWater to perform well in diverse underwater environments. The use of depth information could be incorporated to refine the enhancement process based on the distance from the camera to objects, improving the overall 3D perception of underwater scenes. Additionally, improving the user interface to allow for real-time adjustments and comparisons would enhance the user experience, enabling researchers to customize enhancements according to their specific needs. The integration of multi-task learning would enable DiffWater to not only enhance images but also perform tasks like object detection or segmentation, increasing its versatility. Multilingual support and broader access could be introduced to ensure that users from various regions can benefit from the system. Finally, the incorporation of autonomous underwater vehicles (AUVs) and drones would allow for the automatic enhancement of images in real-time, making DiffWater a powerful tool for underwater exploration and environmental monitoring. These improvements would significantly expand the scope and capabilities of DiffWater, making it a more robust and adaptable solution for underwater image enhancement.

CONCLUSION

In conclusion, DiffWater offers a promising solution to the challenges of underwater image enhancement by addressing common issues such as light attenuation, scattering, and color distortion in various aquatic environments. Through the use of a conditional denoising diffusion probabilistic model (DDPM) combined with a novel color compensation method, DiffWater demonstrates significant improvements in restoring degraded underwater images with greater generalization and robustness than traditional enhancement methods. The model's ability to adapt to diverse water conditions and lighting scenarios makes it a valuable tool for underwater imaging applications. Moreover, with future enhancements, including the integration of deep learning models, real-time processing, and multispectral support, DiffWater has the potential to become a powerful and versatile tool for underwater exploration, environmental monitoring, and other related fields, providing high-quality image restoration and analysis in complex underwater conditions.

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