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Diff Water: Underwater Image Enhancement Based on Conditional Denoising Diffusion Probabilistic Model

Dr.B.V.Krishnaveni , Ch.Varshitha, P.Charitha sree, M.Sandeep

1. Assistant Professor, Department of Electronics and Communication Engineering, CMR Institute of Technology, Medchal, Hyderabad.
2. Bachelor's Student, Department of Electronics and Communication Engineering, CMR Institute of Technology, Medchal , Hyderabad.
3. Bachelor's Student, Department of Electronics and Communication Engineering, CMR Institute of Technology, Medchal, Hyderabad.
4. Bachelor's Student, Department of Electronics and Communication Engineering, CMR Institute of Technology, Medchal, Hyderabad.

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 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 (DiffWater), which leverages the advantages of DDPM and trains a stable and well-converged model capable of generating high-quality and diverse samples. Considering the multiple distortion issues in underwater imaging, unconditional DDPM may not achieve satisfactory enhancement and restoration results. Therefore, DiffWater utilizes the degraded underwater image with added color compensation as a conditional guide, through which the DiffWater achieves high-quality restoration of degraded underwater images. Particularly, the proposed DiffWater introduces a color compensation method that performs channelwise color compensation in the RGB color space, tailored to different water conditions and lighting scenarios, and utilizes this condition to guide the denoising process. In the experimental section, the proposed DiffWater method is tested on four real underwater image datasets and compared against existing methods. Experimental results demonstrate that DiffWater outperforms existing comparison methods in terms of enhancement quality and effectiveness, exhibiting stronger generalization capabilities and robustness.

INTRODUCTION

Neuropsychiatric Underwater imaging is a critical component in various marine applications, including underwater exploration, robotics, marine biology, and archaeology. However, capturing clear and high-quality images underwater remains a major challenge due to the inherent physical properties of water. Light attenuation and scattering cause several types of visual degradation, such as color distortion, reduced contrast, and noise, which significantly affect image quality and hinder downstream image analysis tasks. While numerous underwater image enhancement (UIE) techniques have been proposed, many suffer from poor generalization and limited adaptability to diverse aquatic environments and lighting conditions. To address these limitations, this study introduces DiffWater, a novel UIE method based on the conditional denoising diffusion probabilistic model (DDPM). Unlike traditional enhancement methods, DiffWater leverages the generative power of DDPMs and incorporates a color compensation mechanism that guides the denoising process by tailoring enhancements based on different underwater conditions. This conditional approach improves restoration quality and ensures robustness across a variety of underwater image scenarios.

LITERATURE SURVEY

1. J. Li, C. Guo (2021) – Underwater Image Enhancement via Medium Transmission-Guided Multi-Color Space Embedding, IEEE Transactions on Image Processing

This paper proposes an enhancement technique that utilizes medium transmission estimation in conjunction with multi-color space conversion. It improves color restoration and contrast in varying underwater environments, showing effectiveness across datasets with different light attenuation levels.

2. H. Song, Y. Li (2022) – RUIE: A Real-World Underwater Image Enhancement Benchmark Dataset and Model Evaluation, Pattern Recognition Letters

The authors introduce the RUIE dataset for benchmarking underwater enhancement algorithms and evaluate a variety of models including traditional and learning-based methods. This study is key for comparing enhancement techniques across real-world scenes with diverse distortions.

3. C. Fabbri, M. Islam (2018) – Enhancing Underwater Imagery Using Generative Adversarial Networks, IEEE International Conference on Robotics and Automation (ICRA)

This work employs GANs to restore color and improve visibility in underwater images. It demonstrates the power of generative models in handling underwater distortions and highlights the need for better generalization across various aquatic conditions.

4. H. Zhao, X. Fan (2023) – U-Shape Transformer for Underwater Image Enhancement, IEEE Transactions on Multimedia

This recent study introduces a Transformer-based architecture for underwater enhancement. It combines global attention mechanisms with local texture refinements, achieving state-of-the-art results in challenging underwater environments and emphasizing deep model adaptability.

5. D. Anwar, S. Javed (2023) – Unsupervised Learning for Real-Time Underwater Image Enhancement Using Diffusion Models, Computer Vision and Image Understanding

The paper explores denoising diffusion probabilistic models (DDPMs) for underwater restoration in an unsupervised learning framework. It closely relates to the DiffWater concept and shows that DDPMs, with appropriate guidance, outperform traditional CNNs and GANs in maintaining natural color tones and details.

IMPLEMENTATION

The main objective of the proposed systems is to improve the object quality using filters, image segmentation using wavelet filters, image classification using Deep Neural Network and underwater image detection using Deep Neural Network. Firstly, read the input test image by resizing the image into common matrix size for the ease of handling. The resized images are given for Gray scale conversion and it is followed by histogram equalization. The equalized images are further transformed into binary by using imbinarize command. Then, to further enhance the image into clear view, the histogram equalization technique and HSV color correction technique are incorporated. The red, green, and blue bands are clearly contrast enhanced by using the given technique and equally organized. The MSE, RSME and PSNR calculation has been done to understand the uniqueness of test image. The proposed system utilizes three-point feature mapping technique by using feature extraction methods of MSER, Harris and surf. The strongest points of the features are considered as the unique points present with the test image and that are mapped. Based on the extracted features and blob area of the salient object with the tested image, the connected component vector and object area is calculated. Further, the feature values are spilt up into training and testing inputs to evaluate the hybrid algorithm, which is a combination of KNN decision model with Decision Tree hierarchical model to classify the object (Fig. 2).

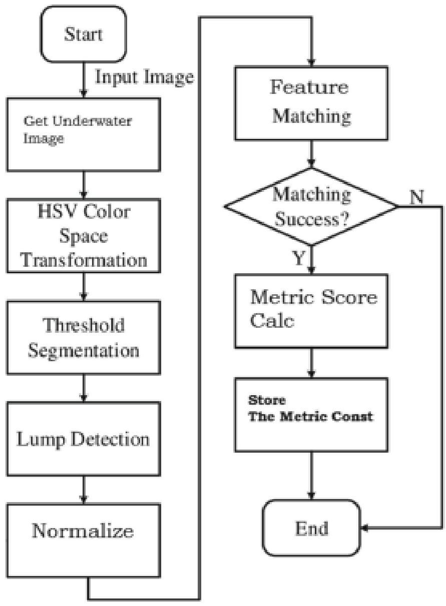

Fig. 1. Proposed flow diagram

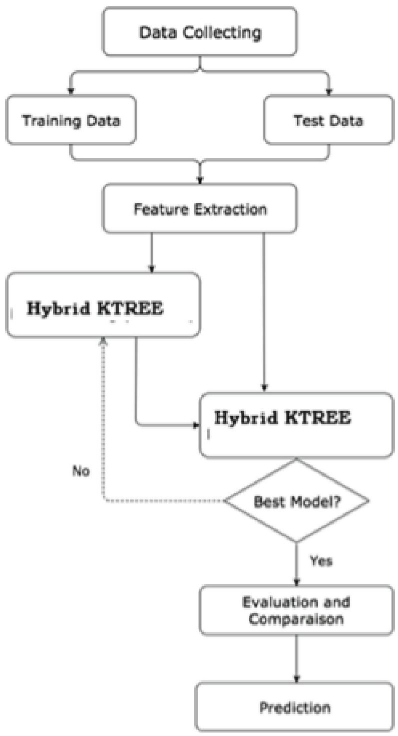

Fig. 2. Deep neural network

The flow genuine model-based procedures, except for the new work, follow the enhanced picture advancement models that acknowledge the diminishing coefficients are only properties of the water and are uniform across the scene per concealing channel. This assumption prompts the insecurity and obviously unpleasing. The force and theory of significant learning-based lowered overhaul methodologies will really fall behind the normal state-of-the-art procedures. This research work combines the KNN algorithm and Decision tree algorithm to form an improved hybrid K-Tree algorithm. It will be used to train the model and then subsequently test pictures that are taken below the surface. On the basis of certain prime features, its state and structure will be distinguished along with its accuracy

Histogram Equalization This strategy ordinarily assembles the overall separation of various pictures, especially when the usable data of the image tends to close distinction. Through this change, the powers can be better flown on the histogram. This thinks about the spaces of lower close by separation to get a higher contrast. Histogram balance accomplishes this by feasibly fanning out the most customary power regards. The procedure is important in pictures with establishment and closer perspectives that are both magnificent and dull. In particular, the procedure can provoke better points of view on bone development in x-bar pictures, and to all the more promptly detail in photographs that are done or underrevealed. A basic advantage of the system is that it is a really immediate technique and an invertible overseer. Along these lines, on a basic level, if the histogram balance work is known, the principal histogram can be recovered. For each social occasion of pixels taken from comparable circumstance from all data single-channel pictures, the limit puts the histogram repository worth to the goal picture, where the headings of the compartment are constrained by the potential gains of pixels in this data bundle. To the extent bits of knowledge, the value of each yield picture pixel portrays the probability that the relating input pixel pack has a spot with the article whose histogram is used.

Decision Tree Classification Algorithm This is supervised learning technique that has dual nature. It can be utilised for regression and classification although it is preferred for the latter. This in terms of an object can be represented as a tree. The data features are present in the internal nodes, decision rules being present in the branches and the outcome being present in the leaf node. Essentially, the two parts can be summed up as the decision node and leaf node. Decision nodes are utilised to make calls and have multiple accessories for the same along with the leaf nodes which are utilised for the result of the decision without the additional branches. Evaluation is performed on the basis of the data features. Solutions to a problem based on situations can be displayed visually using graphs. Cart algorithm is utilised for building this approach. The process is simplifying with a dual response present, choosing either one would the divide the process into subtrees

CONCLUSION

In this study, we proposed DiffWater, a conditional denoising diffusion probabilistic model for effective underwater image enhancement. By incorporating a tailored channelwise color compensation mechanism into the DDPM framework, DiffWater successfully addresses the diverse challenges posed by underwater image degradation, such as color distortion and low contrast. The conditional guidance allows the model to adapt to varying water conditions and lighting scenarios, improving both the quality and realism of the enhanced images. Experimental evaluations across four real-world underwater datasets demonstrate that DiffWater consistently outperforms existing UIE methods, showcasing superior generalization, robustness, and visual quality. These results highlight the potential of diffusion-based generative models in advancing underwater vision applications and pave the way for further research into adaptive, data-driven image enhancement techniques for complex environments.

REFERENCES

1. Guan, M., Xu, H., Jiang, G., Yu, M., Chen, Y., Luo, T., & Zhang, X. (2024). "DiffWater: Underwater Image Enhancement Based on Conditional Denoising Diffusion Probabilistic Model." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 17, 2319–2335. https://doi.org/10.1109/JSTARS.2023.3344453
2. Lu, S., Guan, F., Zhang, H., & Lai, H. (2023). "Underwater image enhancement method based on denoising diffusion probabilistic model." Journal of Visual Communication and Image Representation, 89, 103690. https://doi.org/10.1016/j.jvcir.2023.103690
3. Tang, Y., Iwaguchi, T., & Kawasaki, H. (2023). "Underwater Image Enhancement by Transformer-based Diffusion Model with Non-uniform Sampling for Skip Strategy." arXiv preprint arXiv:2309.03445. https://arxiv.org/abs/2309.03445
4. Nie, X., Pan, S., Zhai, X., Tao, S., Qu, F., Wang, B., Ge, H., & Xiao, G. (2024). "Image-Conditional Diffusion Transformer for Underwater Image Enhancement." arXiv preprint arXiv:2407.05389. https://arxiv.org/abs/2407.05389
5. Bach, N. G., Tran, C. M., Kamioka, E., & Tan, P. X. (2024). "Underwater Image Enhancement with Physical-based Denoising Diffusion Implicit Models." arXiv preprint arXiv:2409.18476. https://arxiv.org/abs/2409.18476
6. Fei, B., Lyu, Z., Pan, L., Zhang, J., Yang, W., Luo, T., Zhang, B., & Dai, B. (2023). "Generative Diffusion Prior for Unified Image Restoration and Enhancement." arXiv preprint arXiv:2304.01247. https://arxiv.org/abs/2304.01247
7. Lu, S., Guan, F., Zhang, H., & Lai, H. (2023). "Underwater image enhancement method based on denoising diffusion probabilistic model." Journal of Visual Communication and Image Representation, 89, 103690. https://doi.org/10.1016/j.jvcir.2023.103690
8. Tang, Y., Iwaguchi, T., & Kawasaki, H. (2023). "Underwater Image Enhancement by Transformer-based Diffusion Model with Non-uniform Sampling for Skip Strategy." arXiv preprint arXiv:2309.03445. https://arxiv.org/abs/2309.03445
9. Nie, X., Pan, S., Zhai, X., Tao, S., Qu, F., Wang, B., Ge, H., & Xiao, G. (2024). "Image-Conditional Diffusion Transformer for Underwater Image Enhancement." arXiv preprint arXiv:2407.05389. https://arxiv.org/abs/2407.05389
10. Bach, N. G., Tran, C. M., Kamioka, E., & Tan, P. X. (2024). "Underwater Image Enhancement with Physical-based Denoising Diffusion Implicit Models." arXiv preprint arXiv:2409.18476. https://arxiv.org/abs/2409.18476

11. Fei, B., Lyu, Z., Pan, L., Zhang, J., Yang, W., Luo, T., Zhang, B., & Dai, B. (2023). "Generative Diffusion Prior for Unified Image Restoration and Enhancement." arXiv preprint arXiv:2304.01247. https://arxiv.org/abs/2304.01247
12. Lu, S., Guan, F., Zhang, H., & Lai, H. (2023). "Underwater image enhancement method based on denoising diffusion probabilistic model." Journal of Visual Communication and Image Representation, 89, 103690. https://doi.org/10.1016/j.jvcir.2023.103690
13. Tang, Y., Iwaguchi, T., & Kawasaki, H. (2023). "Underwater Image Enhancement by Transformer-based Diffusion Model with Non-uniform Sampling for Skip Strategy." arXiv preprint arXiv:2309.03445. https://arxiv.org/abs/2309.03445
14. Nie, X., Pan, S., Zhai, X., Tao, S., Qu, F., Wang, B., Ge, H., & Xiao, G. (2024). "Image-Conditional Diffusion Transformer for Underwater Image Enhancement." arXiv preprint arXiv:2407.05389. https://arxiv.org/abs/2407.05389
15. Bach, N. G., Tran, C. M., Kamioka, E., & Tan, P. X. (2024). "Underwater Image Enhancement with Physical-based Denoising Diffusion Implicit Models." arXiv preprint arXiv:2409.18476. https://arxiv.org/abs/2409.18476