View Reviews

Paper ID
19

Paper Title
Diving Deep: Comparative Analysis and Design of Neural Network Based Algorithm Selection for Underwater Image Processing

Track Name
SCIA2025

Reviewer #1

Questions

1. Confirm that you have read and understood the Review Guidelines and Rules (https://scia2025.org/review/).
Agreement accepted

2. Please describe the contribution of the paper. Just a few lines.
The authors investigate underwater images. They summarize 6 existing works, reimplement them and evaluate restoration results on 6 metrics They create a supervised classification model built with standard neural networks to automate the algorithm selection process.

3. List the main strengths of the paper. Please provide details to support your statements (whats and hows).
+ overview of underwater imaging methods.
+ overview of their strengths
+ coupling it to 6 metrics
+ comparing results and selecting a method

4. List the main weaknesses of the paper. Please provide details to support your statements (whats and hows), and provide references to prior work.
- the paper is in between a state of the art overview (what, when how) and a novel method. As a results, it lacks enough contribution for each component.
- the 6 methods seem to be selected randomly. (why these?)
- start of section 2 and the second half contain the same information.
- as the authors write "Each algorithm is designed to eliminate specific distortion in an image." So knowing the distortion to be eliminated, the algorithm is given.
- data set imbalance: good discussion, but at the same time it undermines the contribution.
- The final contributoin is unclear, contradicting "This work establishes a solid foundation for advancements in underwater image processing, marking a significant step toward fully automated solutions for managing image distortions in aquatic

settings."
- "This article introduces an approach to automatically identify the optimal image-processing algorithm customized to the type of distortion." I then expect a thorough experiment with RoC curves etc. etc. for newly unseen images. This is missing.

5. Rate the paper on a scale from 1 to 5 (1 reject and 5 accept). For example: Strong reject - paper with trivial/already known results, technical flaws, wrong evaluations, and unaddressed ethical considerations. Weak reject - fair paper with limited technical contributions, weaknesses that slightly weigh over merits. Borderline - good paper with an equal amount of merits and weaknesses. Only use it if necessary. Weak accept - strong paper with novel ideas, strong evaluation/methods, few weaknesses. Strong accept - award-worthy paper with a research breakthrough, flawless evaluation/resources.

weak reject

6. Reviewer confidence. Based on your answers and your overall experience, how would you rate your confidence in your review?

Highly confident

Reviewer #2

Questions

1. Confirm that you have read and understood the Review Guidelines and Rules (https://scia2025.org/review/).

Agreement accepted

2. Please describe the contribution of the paper. Just a few lines.

The paper introduces a method for the automatic selection of the most appropriate image-processing algorithm for underwater images that are subject to various distortions. This approach seeks to reduce human involvement in the selection process by assessing images through quality metrics and utilizing a supervised neural network model. The study incorporates six enhancement algorithms, evaluating and ranking their performance based on empirical data. This ultimately facilitates automated decisio

3. List the main strengths of the paper. Please provide details to support your statements (whats and hows).

This paper introduces an empirical methodology for automating the selection of underwater image enhancement algorithms through the use of neural networks. It evaluates six popular underwater image enhancement algorithms. It examines their performance using six quality metrics, which include both reference-based metrics (PSNR, SSIM) and non-reference-based metrics (UIQM, BRISQUE, NIQE). The evaluation ensures a comparison of the algorithms' performances. A supervised classification model is developed using a neural network based on EfficientNet-B7, harnessing deep learning to enhance the accuracy of algorithm selection. This methodology offers scalability and adaptability for various underwater environments. The dataset comprises 4,173 images sourced from various origins, including UIEB, EUVP, and real-world images captured by a Chasing Dory underwater drone, thereby improving the generalizability of the proposed model. The paper also addresses the challenge of dataset imbalance, particularly the prevalence of certain algorithms in the selection process. Strategies such as white-balanced training images, transfer learning, and k-fold cross-validation are employed to mitigate overfitting and enhance classification accuracy.

4. List the main weaknesses of the paper. Please provide details to support your statements (whats and hows), and provide references to prior work.

The paper presents a notable issue of dataset imbalance, as certain algorithms (e.g., Fusion and Auto Red-Channel Restoration) disproportionately dominate the selection process. This dominance can potentially introduce bias into the trained neural network, compromising the model's ability to generalize effectively across a diverse range of underwater images. Despite utilizing EfficientNet-B7 and transfer learning techniques, the final test accuracy remains relatively low at 30.83%, indicating that the neural network struggles to classify the most suitable enhancement algorithm for specific images. This limitation detracts from the practical applicability of the proposed approach.

Furthermore, the emphasis is primarily on six classical image processing algorithms, raising the question of why only six are considered. This approach overlooks advanced deep learning enhancement techniques, such as Generative Adversarial Networks (GANs) and transformer-based models, which have demonstrated superior performance in underwater image restoration. Notably, Ren et al. (2025) introduced the UIEVUS method for various underwater scenes in their paper "UIEVUS: An underwater image enhancement method for various underwater scenes" published in Signal Processing: Image Communication (vol. 135, art. no. 117264, DOI: 10.1016/j.image.2025.117264). Additionally, Tang et al. (2023) explored underwater image enhancement using a transformer-based diffusion model with non-uniform sampling, as presented in the proceedings of the 31st ACM International Conference on Multimedia (pp. 5419 - 5427, DOI: 10.1145/3581783.3612378). Given the advancements in deep learning, the complete disregard for these approaches in the paper is not warranted.

The neural network model used in the paper determines the most appropriate enhancement algorithm based on computed quality metrics; however, the absence of an interpretability framework limits transparency by failing to elucidate the rationale behind specific algorithm selections. This lack of mechanism constrains trust in the model's decision-making process. Furthermore, while the paper acknowledges computational constraints and evaluates processing times, it does not assess the approach's performance in a real-time underwater imaging context. Although it identifies instances where certain algorithms perform well for specific distortions, it fails to propose a robust solution to address these inconsistencies, relying instead on a ranking-based selection process without incorporating adaptive decision strategies.

Lastly, the paper exclusively examines neural networks without conducting a comparative analysis with alternative classification methods, such as support vector machines (SVMs) or decision trees. Including such comparisons could yield valuable insights into the effectiveness of different machine-learning approaches for this task.

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weak reject

6. Reviewer confidence. Based on your answers and your overall experience, how would you rate your confidence in your review?

Highly confident

Reviewer #3

Questions

1. Confirm that you have read and understood the Review Guidelines and Rules (https://scia2025.org/review/).

Agreement accepted

2. Please describe the contribution of the paper. Just a few lines.

The paper considers the problem of underwater image distortion correction. The idea is to have a collection of different distortion-correction methods, and then train a neural network to predict which method would perform the best on a given a image.

3. List the main strengths of the paper. Please provide details to support your statements (whats and hows).

The motivation and problem setup is interesting, and the paper provides good arguments for why having different distortion corrections methods for different images might be required.

4. List the main weaknesses of the paper. Please provide details to support your statements (whats and hows), and provide references to prior work.

The paper has somewhat limited technical contribution, as all the methods are previous work, and the contributions are mainly in designing the training setup for the classifier.

For generating the ground truth labels for the training data the paper propose to consider six image-based metrics, where the rankings are combined in the end. The selection and weighting of these metrics seem arbitrary and it is not clear why this would be a good choice. It would be more natural to consider some downstream task, e.g. if you want to run some object detection or semantic segmentation on the restored image, then selecting the method based on metrics for this task would be more meaningful.

The writing and exposition in the paper could also be improved. For example, it is not entirely clear what is being shown in Table 1, 2 and 3. Is this for a single example?

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weak reject

6. Reviewer confidence. Based on your answers and your overall experience, how would you rate your confidence in your review?

Confident but not absolutely certain