**An Intelligent Approach of Underwater Image Co-Enhancement using Correlation Feature Matching with Enhanced Meta-Heuristic Optimization-aided Transformer UNet**

**Introduction**

Underwater image enhancement is a specialized field of research and application aimed at improving the quality of images captured in the challenging underwater environment [9]. The underwater setting poses unique challenges, such as light attenuation, color distortion, and backscatter caused by suspended particles, which can significantly degrade the quality of captured images [10]. The repercussions of these challenges include diminished visibility, low contrast, and inaccuracies in color representation [11]. This specialized field has gained increasing significance across various disciplines, including marine biology, oceanography, underwater archaeology, environmental monitoring, and underwater surveillance. In these fields, high-quality underwater images are essential for researchers, scientists, and professionals to gain a precise understanding of the submerged world and to extract meaningful insights from the captured visual data [12]. Underwater image enhancement is a field of research and technology aimed at improving the quality of images captured in underwater environments. Unlike terrestrial photography, underwater imaging faces unique challenges due to the distinct characteristics of water, such as absorption, scattering, and attenuation of light [13]. These factors result in degraded image quality, reduced contrast, and color distortion [14]. The need for underwater image enhancement arises in various applications, including marine biology, oceanography, underwater archaeology, and underwater surveillance. Researchers and engineers in this field employ a variety of techniques and technologies to address the specific challenges posed by the underwater environment, ultimately aiming to enhance visibility, contrast, and color fidelity in underwater images [15].

The underwater environment presents formidable obstacles for imaging systems. Light attenuation, where light diminishes as it travels through water, is a primary challenge [16]. These results in reduced visibility and challenges in capturing clear and detailed images. Additionally, suspended particles in the water cause backscatter; further complicating image quality by scattering light in multiple directions [17]. Color distortion is another critical issue underwater. The absorption and scattering of light in water can alter the colors of objects, leading to inaccurate color representation in images [18]. The combination of these factors often results in images with low contrast and reduced overall clarity. The significance of underwater image enhancement techniques lies in their ability to overcome these challenges. By employing various methods, researchers and engineers can enhance the quality of underwater images, producing clearer and more accurate representations of the underwater world [19]. In conclusion, the field of underwater image enhancement plays a vital role in overcoming the challenges associated with capturing high-quality images in the underwater environment. The application of dehazing algorithms, color correction techniques, contrast enhancement processes, image fusion approaches, and machine learning algorithms collectively contributes to producing clearer, more accurate representations of the underwater world [20]. These advancements have profound implications for research, exploration, and practical applications in various underwater disciplines.

Deep learning techniques have emerged as powerful tools for addressing the challenges of underwater image enhancement. Leveraging neural networks and advanced learning algorithms, deep learning models can automatically learn complex mappings between degraded underwater images and their enhanced counterparts [21]. CNNs have proven to be highly effective in various computer vision tasks, including image enhancement. They consist of layers of convolution filters that automatically learn hierarchical features from input images [22]. GANs consist of a generator and a discriminator network trained simultaneously through adversarial training [23]. GANs have been applied to UIE by generating realistic-looking underwater images from degraded ones. Autoencoders are neural network architectures designed to encode input data into a compact representation and then decode it back to the original form. ResNets address the challenge of training very deep neural networks [24]. They introduce skip connections, allowing information to flow more easily through the network. These deep learning techniques are often implemented in conjunction with traditional image processing methods to create hybrid approaches that capitalize on the strengths of both paradigms. The application of deep learning in underwater image enhancement continues to evolve, with ongoing research efforts aimed at developing more robust and efficient models to improve underwater image quality for various applications [25].

**Related works**

In 2023, Zhao and Yuan [1] have recommended the Residual Dense Block (RDB) and Contrastive Regularization (CR) techniques. By leveraging the local and global feature fusion of RDB and the contrastive learning of CR, our model effectively extracted multi-level features from the original images, adaptively preserves hierarchical features, and achieved high-quality underwater image deblurring through learning from the original images. Experimental results demonstrated that our model outperformed other comparative algorithms in terms of subjective visual quality and objective evaluation metrics across four datasets.

In 2021, J. Hu *et al.* [2] have suggested a novel two-branch deep neural network for Underwater Image Enhancement (UIE), which was capable of separately removing color cast and enhancing image contrast by fully leveraging useful properties of the HSV color space in disentangling chrominance and intensity. Specifically, the input underwater image was first converted into the HSV color space and disentangled into HS and V channels to serve as the input of the two branches, respectively. Then, the color cast removal branch enhanced the H and S channels with generative adversarial network architecture while the contrast enhancement branch enhances the V channel via a traditional Convolutional Neural Network (CNN).

In 2022, Qi Qi *et al.* [3] have proposed an Underwater Image Co-enhancement Network (UICoE-Net) based on an encoder-decoder Siamese architecture. For joint learning introduced correlation feature matching units into the multiple layers of our Siamese encoder-decoder structure in order to communicate the mutual correlation of the two branches. Extensive experiments using the Underwater Image Enhancement Benchmark (UIEB), Underwater Image Co-enhancement Dataset (UICoD) collected from an underwater video dataset with ground-truth reference and Stereo Quantitative Underwater Image Dataset (SQUID) dataset demonstrated the effectiveness of our method.

In 2023, Y. Zhang *et al.* [4] have proposed an underwater image enhancement framework based on transfer learning, which consists of a domain transformation module and an image enhancement module. The two modules, respectively, perform color correction and image enhancement, effectively transferring in-air image dehazing to underwater image enhancement. To maintain the physical properties of an underwater image, embedded the physical model into the domain transformation module this ensures that the transformed image complies with the physical model. To effectively remove the color deviation, a coarse-grained similarity calculation is added to the domain transformation module to improve the model performance.

In 2022, Wen-Hui *et al.* [5] have recommended an unsupervised deep learning framework, called Underwater Loop Enhancement Network (ULENet), to improve the quality of turbid underwater images. First propose an underwater dataset construction scheme and construct the dataset on which the network proposed above was trained. The underwater dataset contains images of three different scenes: lake and reservoir scene data (no label), pool scene data (weakly correlated label), and laboratory scene data (strongly correlated label). Then propose a loop enhancement structure that uses the approximate candidates as labels and improves the visual quality of the image through the iterative training process. To formulate a new underwater visual perception loss function that evaluates the perceptual image quality based on its color, contrast, saturation and clarity.

In 2023, Qiong *et al.* [6] have proposed a Weak-Strong Dual Supervised Generative Adversarial Network (WSDS-GAN) for UIE. During the first weakly supervised learning phase, unpaired images, consisting of degraded underwater images and clear in-air images, was used to train the model with the goal of recovering color, brightness, and content. In the second strongly supervised learning phase, a limited number of paired images are fed into the model to further train the image detail recovery generator.

In 2022, Wenming *et al.* [7] have proposed the rapid development of deep learning and powerful feature learning capabilities have been widely used in underwater image enhancement tasks, but current research still has problems such as loss of local details and oversaturation. Aiming at the above problems, this paper proposed an underwater image enhancement method combining dual color space and contrast learning, including RGB color space and Lab color space. The RGB color space was used for color correction and artifact removal, and the Lab color space was used to enhance saturation and detail texture. The contrastive learning of positive and negative samples makes the generated image closer to the clear underwater image and deviates from the real underwater image.

In 2023, Dandan *et al.* [8] have recommended an embarrassingly-efficient two-stream UIE approach to improve both the enhancement quality of underwater images. One stream was the Significant Region Refinement (SRR) that stacks channel attention optimized residual groups to improve the image illumination and resolve the color casting problem, and the other was the Global Appearance Adjustment (GAA) that relied on several dense blocks to enhance the global image sharpness. The final output was derived by intelligently weighing contributions from the SRR and GAA branches.

**Problem Statement**

The significance of enhancing underwater images extends beyond scientific research, encompassing applications in marine biology, archaeology, environmental monitoring, and various industries like oil and gas exploration. Features and challenges of existing techniques is shown in Table I. RDB [1] promotes the reuse of features through skip connections, allowing the network to retain and reuse important information from previous layers but the dense connections in RDB may increase computational cost and memory requirements, especially for deeper networks. CNN [2] excels at capturing spatial hierarchies, allowing them to be highly effective for tasks like image recognition but it automatically learns hierarchical representations of features from raw input data. UIEB [3] typically requires a fixed-size input, which can be a limitation when dealing with inputs of varying dimensions but it may have limitations in representing the diversity of real-world underwater scenarios, potentially leading to biased evaluations. Deep Transfer Learning [4] allows models trained on one task to leverage their knowledge for improved performance on a related task but it may suffer when there is a significant difference between the source and target domains. ULENet [5] is designed specifically for underwater image enhancement, ensuring that the model is tailored to the characteristics of underwater images but it may be optimized for specific underwater conditions and may not generalize well to diverse underwater environments. WSDS-GAN [6] leverages both weak and strong supervision signals, allowing the model to benefit from different levels of labeled information but it can be challenging to train and may suffer from issues like mode collapse or training instability. Deep Learning [7] automatically learn hierarchical representations of features from raw data, eliminating the need for manual feature engineering but it often requires substantial computational resources, limiting accessibility for some researchers. DNN [8] can be applied to a wide range of tasks, including image recognition, natural language processing, and more but can be challenging to interpret, making it difficult to understand their decision-making process. These challenges helps to develop better deep learning based underwater image enhancement model.

**Table 1:** Features and challenges of deep learning based underwater image enhancement model

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| --- | --- | --- | --- |
| **Author [citation]** | **Methodology** | **Features** | **Challenges** |
| H. Zhao and H. Yuan *et al.* [1] | RDB | * It promotes the reuse of features through skip connections, allowing the network to retain and reuse important information from previous layers. | * The dense connections in RDB may increase computational cost and memory requirements, especially for deeper networks. |
| J. Hu *et al.* [2] | CNN | * It excels at capturing spatial hierarchies, allowing them to be highly effective for tasks like image recognition. | * It automatically learns hierarchical representations of features from raw input data. |
| Qi Qi *et al.* [3] | UIEB | * It typically requires a fixed-size input, which can be a limitation when dealing with inputs of varying dimensions. | * It may have limitations in representing the diversity of real-world underwater scenarios, potentially leading to biased evaluations. |
| Y. Zhang *et al.* [4] | Deep Transfer Learning | * It allows models trained on one task to leverage their knowledge for improved performance on a related task. | * It may suffer when there is a significant difference between the source and target domains. |
| Wen-Hui *et al.* [5] | ULENet | * It is designed specifically for underwater image enhancement, ensuring that the model is tailored to the characteristics of underwater images. | * It may be optimized for specific underwater conditions and may not generalize well to diverse underwater environments. |
| Qiong *et al.* [6] | WSDS-GAN | * It leverages both weak and strong supervision signals, allowing the model to benefit from different levels of labelled information. | * It can be challenging to train and may suffer from issues like mode collapse or training instability. |
| Wenming *et al.* [7] | Deep Learning | * It automatically learns hierarchical representations of features from raw data, eliminating the need for manual feature engineering. | * It often requires substantial computational resources, limiting accessibility for some researchers. |
| Dandan *et al.* [8] | DNN | * It can be applied to a wide range of tasks, including image recognition, natural language processing, and more. | * It can be challenging to interpret, making it difficult to understand their decision-making process. |

**Research Methodology**

The realm beneath the water's surface remains an intriguing and challenging environment for exploration and observation. Underwater imaging plays a pivotal role in unlocking the mysteries of the deep, offering insights into marine ecosystems, geological formations, and the vast diversity of aquatic life. However, capturing clear and vibrant images in underwater conditions poses unique challenges due to factors such as light attenuation, color distortion, and particle scattering. The primary advantage of underwater image enhancement is the enhancement of visibility in challenging aquatic environments. By mitigating the effects of light attenuation and water turbidity, enhanced images provide clearer views of underwater scenes, allowing for better observation and analysis. On other hand underwater environments often lead to color distortion due to the absorption and scattering of light. Despite enhancement efforts, achieving true color representation can be challenging, impacting the accuracy of underwater imagery. Image enhancement processes can introduce artifacts or noise, reducing the overall quality of the enhanced images. Striking a balance between removing distortions and preserving important details is a continual challenge in this field. To reduce these kinds of issues, an adaptive deep learning-based co-enhancing underwater image is proposed using heuristic approaches. In the initial phase, the images will be aggregated from the online sources. Further, the image will be fed to the correlation feature matching module. Here, the feature matching will be done by the Adaptive Trans-Unet (ATUNet), and the correlation feature matching performance of the ATUNet will be strengthened by tuning the parameter using the Improved Red Kite Optimization Algorithm (IKOA) [26]. At last, the experimental validation will be performed on the suggested co-enhancing underwater image model to prove the effectiveness of the suggested model. The structural view of the deep learning based co-enhancing underwater image framework is offered in Figure 1.

Correlation feature matching using ATUNet

Final outcome

Gathered Image

IRKOA

**Figure 1:** Diagrammatic representation of proposed co-enhancing underwater image Model

**Expected Outcome**

The proposed deep learning based co-enhancing underwater image framework will be developed in Python, and the experimental analysis will be carried out. Here, the performance of the proposed model will be compared over the conventional models.

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