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PRIDNet based Image Denoising for Underwater Images

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Abstract— Underwater image enhancement has become a popular research topic due to its importance in aquatic robotics and marine engineering. However, the underwater images frequently experience signal-dependent speckle noise when transmitting and acquiring data, which can limit certain applications such as detection, object tracking. In the recent years, the existing underwater image enhancement algorithms efficiency has been analysed and evaluated on a small number of carefully chosen real-world images or synthetic datasets. As such, it is challenging to predict how these algorithms might function with images acquired in the wild under various circumstances. This paper introduces a new solution for noise removal from underwater images called Pyramid Real Image Noise Removal Network (PRIDNet) with patches.PRIDNet is a three-level network design using image patches. The tests were carried out on a dataset of actual noisy images demonstrate that, in terms of quantitative metrics, our proposed denoising model reduction performs better with the exixting denoisers. We determine the effectiveness and constraints of existing algorithms using benchmark assessments and the suggested model, offering valuable information for further studies on underwater image enhancement.

Keywords- Underwater Image enhancement, PRIDNet, Noise removal,Patch based denoising

I. INTRODUCTION

In recent years, image processing and underwater vision have given significant attention to underwater image improvement [10]. Images taken may contain random variations in brightness or colour information, which is known as image noise. It is an image signal degradation brought on by outside factors. Image noise is the result of random fluctuations in the brightness or color information of captured images. It occurs when the image signal is degraded by external factors. Enhancing the underwater image clarity and quality is quite challenging due to the intricate varying lighting conditions and the habitat of the ocean. Generally, underwater images suffer from degradation caused by absorption and scattering, which are both wavelengths dependent. These factors include both forward and backward scattering. Moreover, marine snow may intensify scattering effects and add noise, which further lowers the contrast and visibility. In the real-world domains of biological oceanography and archaeology the photos and videos of underwater areas play an important role. Although many researchers have worked on underwater image enhancement, there is still a lack of comprehensive study and insightful analysis as the publicly accessible real-world underwater image dataset are only limited. Additionally, for many types of water bodies, it is difficult capture an original underwater picture scene and its equivalent ground truth image. In contrast to recent deep learning models that have demonstrated unique achievement on high-level and low-level visual quality images, the efficiency of the algorithms diminishes because of the insufficient number of images in the dataset available for underwater images [1]. Though the deep learning methods for image denoising has given a good performance efficiency for handling the noisy data, a few more challenges and issues is needed to be resolved.

Firstly, a problem with many convolutional neural networks (CNN) based denoising techniques is that they treat all feature channels identically, without considering how significant each feature channel is in obtaining distinct types of noise in various parts of a noisy image. It is crucial to assign more weight to feature channels that capture more significant noise to improve denoising performance.

Second issue is that there is a limitation of existing denoising methods is their fixed receptive fields, which may not capture diverse information effectively. For example, traditional methods such as BM3D rely on searching for similar blocks throughout the entire image, while deep learning-based methods with fixed receptive fields can only capture limited spatial context. This can make it difficult to capture complex patterns or long-range dependencies in the image. Contextual information can be especially helpful when dealing with high levels of noise in images and receptive fields of varying sizes can aid in the exploitation of hierarchical spatial characteristics.

Thirdly, the existing methods for aggregating multi-scale features in image denoising often combine them through element wise summation or concatenation. This does not consider scale-wise features like the spatial and channel specificity. As a result, features with different scales are treated indiscriminately, leading to suboptimal performance. Thus, there is a need for more adaptive approaches to effectively utilize multi-scale features in image denoising.

The proposed work aims to build a method for effectively denoise the underwater images by identifying the appropriate parameters for training the images. The objective is to achieve high accuracy and produce high-quality noise-free images, surpassing the performance of other filters. Though the procedure requires a considerable amount of time, our goal is to produce images that are as near to the actual data as possible. There are two key constraints that need to be considered while addressing this problem:

(1) Reducing the distinction between the clean underwater image and the denoised image

(2) No time constraint on the denoising process. The research aims to develop effective and efficient methods for removing noise from underwater images, which could have practical applications in underwater imaging for scientific research, environmental monitoring, and industrial inspections.

II. LITERATURE SURVEY

Liu, J. Et al. [2]propose a method to develop a generalized energy minimization model using a weighted l2-l0 norm to eliminate mixed noise types like Gaussian impulse noise, Gaussian-Gaussian mixture, and impulse noise from images. This model is based on the Maximum Likelihood Estimation (MLE) framework. To solve the mixed distribution MLE problem, the K-SVD denoising algorithm was modified and utilized. Therefore, this approach presents a novel solution to the problem of removing mixed noise from images.

Tang, X., Et al. [3] proposed method for Synthetic Aperture Radar (SAR) image despeckling is based on a neural network model. The intensity features of image patches are fed to this model by employing a series of historical SAR images from a specific region of interest. After training, the model can determine the weights and thresholds adaptively needed for image despeckling using a neural network approach. This method makes use of the multilayer perceptron (MLP) neural network model. Based on the obtained results, it can be concluded that the MLP model has successfully reduced noise while maintaining the edges of images.

Jin, L., Et al. [4] has presented a framework to improve the recognition of fish species in underwater images, which involves an improved median filter to reduce the noise in the images. A pretrained CNN with fine tuning on the preprocessed data of ImageNet dataset has been employed to find the classification performance. The proposed method employs the Improved Median Filter and CNN algorithms and contributes to the advancement of deep learning in underwater image recognition research, especially for cases with limited sample images.

Lu, Y. Et al. [5] suggested a way to directly quantify speckle noise which is granular in nature and affects the sonar images. The sonar images are dynamically transformed to the logarithmic domain. Using deep learning algorithms, the image quality if sonar images can be improvised. The method entails estimating the speckle noise using a convolutional neural network, which can then be utilized to compute the sharp image using the image degradation model. In the logarithmic domain, the proposed neural network has proven to be capable of precisely estimating the speckle noise.

Ma, C., Et al. [6] explored the use of a technique known as Gradient Generation Adversarial Network (GGAN) to improve severely distorted underwater images. They have utilized deep learning techniques for real-time communication and have combined the gradient difference damage and retrieved the underwater images without blurring from the physical layer. In order to remotely control underwater robots, recommended method incorporates high-resolution data compression.

Sun, X., Et al. [7] has done a work with deep learning model called a "deep pixel-to-pixel mesh". This network helps to enhance the picturesque quality of the underwater image dataset. The model uses an encoder-decoder framework which reduces the noise by filtering with the encoder framework and the decoder is used for decision making to identify the missing content and restore the pixels from the images. The process is data driven and adaptable regardless of the physical environment.

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Mi, Z., Et al. [8] presented a method to optimise underwater images quality for suitable real-world applications. The method divides the input image into two levels: a reflecting layer and an illumination layer allowing manipulation of distinct data on their respective layers. Next, a multi-scale processing methodology is applied to perform contrast improvement and colour restoration to the reflectance layer. High control flexibility is provided by the suggested approach, which significantly increases the clarity of images taken underwater.

Huang, Y., Et al. [9] developed an adaptive dictionary learning method based on the wavelet transform and K-SVD dictionary learning methodology, which is based on the multi-resolution features. This method can provide better performance in speckle noise removal and edge detail conservation compared to several traditional methods. The proposed method inherits the features of wavelet analysis and has the various characteristic like dictionary learning.

Wang, Y., Et al. [10] presented a complete underwater image enhancement system using the UIE-Net network, which is based on the Convolution Neural Network architecture. The two objectives that UIE-Net is trained on are haze removal and hue correction. The network jointly develops an effective depiction of features for each task by using this dual training strategy.

Li, C., Et al. [11] has done his work on a benchmark dataset for underwater image enrichment and used it to train a CNN-based network called Water-Net as a baseline. The findings of the baseline analyses and the proposed Water-Net show the advantages and disadvantages of the current underwater image enhancement algorithms, which may direct further study in this area.

Moghimi, et al. [12] investigates several cutting-edge methods and algorithms to enhance underwater images, in addition to the outcomes of hardware and software. The performance of the algorithms is evaluated from multiple perspectives. The PSO algorithm and contrast stretching are among the techniques used. Additionally, the investigation showed many approaches to deal with image transfer issues.

Zhuang, P., Et al. [13] suggested a Bayesian Retinex algorithm to enhance an underwater image using multiple previous resolutions for albedo and illumination. The algorithm begins by correcting colour casts and restoring naturalness. Next, a maximum a posteriori formulation is generated from the color correction image using a multi-order gradient before reflection and illumination to improve the underwater image quality.

Wang, Y., Et al. [1] provides an overview of the methodologies for the preservation and enhancement of underwater images, dividing them into two categories: image enhancement (based on non-physical models) and image reconstruction (based on physical models). It gives a comprehensive study of methods for underwater image preservation and enhancement.

Zhang, W., Et al. [14] present research on restoration methods examining both non-IFM and IFM-based methods is presented. A comparative empirical analysis of the advanced method is conducted, taking into account the IFM-based method's prior-based prediction algorithms. Evaluation based on content and objective analysis demonstrates the shortcomings of current methods and offers suggestions for future research in this area.

Anwar, S., Et al. [15] aims to achieve two main objectives. First, it aims to provide a comparative and detailed survey on deep learning-based techniques for enhancing underwater images, covering various aspects such as algorithms and open issues. Second, it aims to perform a quantitative and quality-based comparison of deep learning algorithms on different datasets, which has not been extensively explored before. The evaluation metrics are developed for evaluating underwater image properties.

III. RELATIVE WORK & PERFORMANCE METRICS

A. Dataset

There are many real-world datasets available for underwater images such as the Fish4Knowlwdge dataset, MARIS dataset, Haze-line dataset, SUN dataset and Sea-thru dataset. The Fish4Knowledge dataset can be used for identifying and detecting underwater entities. The SUN dataset can be employed for detecting objects and identification of images. The MARIS dataset can be used for underwater monitoring radioactivity in the marine habitat. The Haze-line database, consists of marine images in TIFF files, camera calibration files, and distance maps and the Sea-thru dataset, which has 1100 underwater images with range maps. However, the currently available datasets frequently lack adequate data and features with only a handful of scenes, identical content, and few deteriorated features.

Furthermore, there are challenges and complexities involved in obtaining true underwater images and their corresponding ground truth images of the same scene. The data may not be practically used as it may result in low-quality ground truth images or reference results due to a variety of water, lighting conditions, and expensive and logistically demanding imaging devices. The EUVP dataset, available in the paper "Enhancing Underwater Visual Perception: A Comprehensive Benchmark for Underwater Image Enhancement" published in IEEE Xplore, is a dataset specifically designed for research on enhancing and recovering of underwater images. The dataset consists of a collection of underwater images captured in various aquatic environments, such as coral reefs, open ocean, and shallow water.

The EUVP dataset contains both raw and processed underwater images, where the processed images have been enhanced using techniques such as contrast and brightness adjustment, denoising, and color correction. This provides researchers with a comprehensive dataset for evaluating and comparing various image enhancement algorithms.

B. Physical model-based methods

The visibility of noisy underwater images has been increased with several approaches that are proposed in recent years. These methods can be categorized into four main groups. The underwater image enhancement refers to techniques that use mathematical models for image formation and to improve the underwater images' visual quality. These methods are based on the physical processes that govern light propagation and image formation in underwater environments.

Radiative transfer models, which replicate the intricate relationships between light, water, and particles, are a particular kind of physical model-based technique for improving underwater images. These models can be used to estimate the inherent optical properties of water and to correct for color shifts and contrast loss caused by scattering and absorption. Other physical model-based methods include the use of polarization filters to remove glare and increase contrast, and the use of structured light illumination to improve image quality and recover 3D geometry. Physical model-based methods have the advantage of being based on sound physical principles, which can provide accurate estimates of underwater image formation. However, they often require accurate knowledge of environmental parameters such as water composition and light conditions, which can be difficult to obtain in practice [16]. Additionally, physical models can be computationally expensive and may not be applicable to all underwater environments.

C . Non-physical model-based methods

For improvising the image quality of underwater images, we can reference the techniques that do not rely on mathematical models of underwater image formation. Instead, these methods often use statistical approaches or machine learning algorithms to learn the relationship between degraded and enhanced image pairs. To train the model these techniques may require a larger set of data with many images.

Non-physical model-based techniques for improving underwater images include convolutional neural networks (CNNs), generative adversarial networks (GANs), and autoencoders, based on deep learning models. These models show impressive results in improvising the visual quality of underwater images by learning the mapping between degraded and enhanced image pairs. Further non-physical model-based techniques include image fusion methods, which create a single high-quality image by fusing together several images of the same scene captured under various conditions. These methods handle a many underwater conditions without the need for accurate physical models. However, these models require vast training data and can be computationally expensive.

D. Supplementary information-based methods

For enhancing the quality of underwater images refer to the techniques that use additional information to improve the visual quality of underwater images. These methods aim to correct the color cast and restore the true colors of the underwater scene. Depth information is used to remove the scattering-induced haze and provide a more accurate estimation of the scene's geometry. Examples of supplementary information-based methods include color correction using a color chart, depth-based image enhancement, and multi-modal image fusion. These methods are often combined with traditional image processing techniques or deep learning-based approaches to enhance the efficiency of the underwater image enhancement algorithm.

E. Data-driven methods for underwater images

Data-driven methods boosts the graphical features of corrupted images by taking several images into consideration. These methods often rely on machine learning algorithms to learn the underlying relationship between degraded and enhanced image pairs. Convolutional neural networks (CNNs) and generative adversarial networks (GANs) are two instances of data-driven deep learning methods for boosting underwater images. By learning the mapping between pairs of improved and corrupted images, these approaches enhance the visual representation of underwater images. These techniques often use statistical methods and machine learning algorithms to fuse the images in a way that maximizes the information content while minimizing artifacts.

Data-driven methods have the advantage of being able to handle a wide range of underwater conditions and are often more effective than traditional image processing techniques. However, these methods also require a large set of data for processing, which could be expensive.

F. Performance Metrics

Underwater images can be assessed using a variety of metrics depending on their intended purpose. These are a few standard reference measurements that are often used to assess underwater image quality:

Peak Signal-to-Noise Ratio (PSNR): The Peak-Signal-to-Noise Ratio calculates the ratio between the maximum signal level and the noise level in the image. It is often used in underwater imaging applications to assess the quality of compressed or reconstructed images.

Structural Similarity Index (SSIM): This metric measures the similarity between two images in terms of their

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structure, luminance, and contrast. It is commonly used to evaluate the quality of underwater images where subtle details and textures are important.

Mean Squared Error (MSE): MSE is the average squared difference between the pixel values in two images. It is frequently used in image processing applications to assess the quality of denoising, filtering, and compression algorithms.

Entropy: This metric measures the amount of randomness or uncertainty in an image. It's helpful in evaluating the quality of underwater images where preserving fine details and textures is important.

Color Fidelity Index (CFI): This metric measures the accuracy of the colors in an image compared to a reference image. It's commonly used in underwater photography and videography applications where color accuracy is critical.

Visual Quality Metrics (VQM): This family of metrics assesses the perceptual quality of an image by simulating human visual perception. They are often used to evaluate the quality of underwater images in applications where human perception is the ultimate judge of quality.

These metrics can be used individually or in combination to evaluate the quality of underwater images depending on their specific purpose or application.

IV. PROPOSED METHOD

In the proposed methodology we have proposed a pyramid real image denoising network (PRIDNet) with patches to remove real world noise from underwater photos, addressing various difficulties. In addition, we will contrast the outcomes with a few cutting-edge denoising algorithms that are employed to remove noise from images.

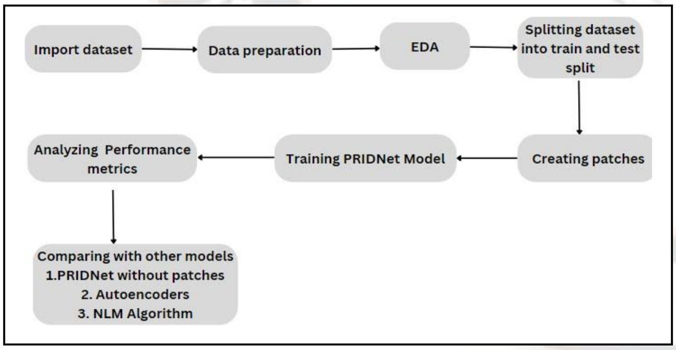

Figure 1. Flow Diagram of the Proposed System.

A. *Creating Patches*

Creating patches in images can be a useful technique for better noise reduction in certain cases. When an image is large, it may be difficult to apply noise reduction techniques to the entire image at once. In such cases, dividing the image into smaller patches can make it easier to apply noise reduction techniques more effectively. For instance, if an image contains a lot of high-frequency noise, such as salt-and-pepper noise, applying a simple median filter or Gaussian filter to the entire image may blur out important details. However, by dividing the image into smaller patches, noise reduction techniques can be applied more selectively to areas with high noise levels, while preserving important details in other areas.

In addition, dividing an image into patches can also make it easier to parallelize noise reduction algorithms, which can speed up processing time and improve overall efficiency. Overall, creating patches in images can be a useful technique for better noise reduction, particularly when dealing with large or complex images that may contain high levels of noise.

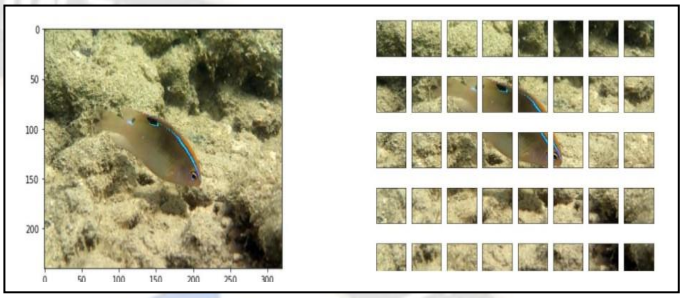

Figure 2. Patches created with Underwater Image

The noisy image patches contain a substantial amount of noise, which is what we are attempting to eliminate. We must shrink each image to a constant size in order to maintain a fixed number of patches for each image. In order to make patches with a 256 x 256 patch size, we will scale all the photos to a set size of 1024 by 1024. We will utilize these train and test image patches for modeling after constructing patches.

B. *Network Architecture*

PRIDNet is an advanced deep learning model created to address the challenge of removing noise from underwater images, through image restoration. To increase accuracy and efficacy, the model is trained on a large dataset of underwater images with different levels of noise employing a deep convolutional neural network architecture. The proposed PRIDNet with patches network has three levels such as evaluating the noise in the image, denoising with multi-scaling, and then fusing the features. The three levels do not depend on each other and can operate on input images of different sizes. The output of the first level which is the noise evaluation process is given as the input to the multi-scale denoiser and the output of the denoiser is given as the input for feature fusion.

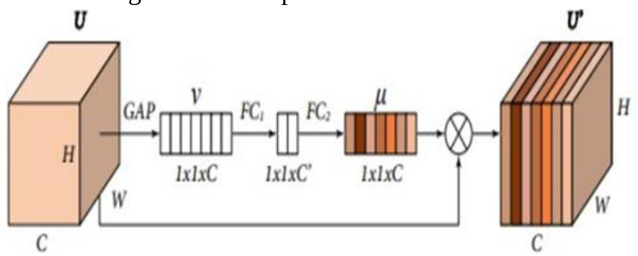

Figure 3. Channel Attention Channel

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C. Noise Estimation Stage

This phase of the process involves extracting distinctive characteristics from noisy input images, which serves as an approximation of the noise level. Our approach employs a simple five-layer fully convolutional subnetwork that does not use pooling or batch normalization, and uses ReLU activation after each convolution. Except for the last layer, which contains one or three feature channels, each convolutional layer includes 32 feature channels with a 3x3 filter size. Before the last phase, we introduce a channel attention module to modify the connections between feature channels.

The input feature maps are represented as $U \in R\ H \times W \times C$. Utilizing the attention channel weights μ = [μ1, μ2 ,..., μ_c] ∈R_(1)×1×C, the input feature maps are recalibrated and rescaled. The global features are initially extracted from the input feature map U and through global average pooling (GAP) the channel descriptor $v \in\ R_1\ \times 1 \times C$ is generated. There are two channels in the middle layer and there are two fully connected layers (FC). The formula for the above phenomenon is

$$\mu = Sigmoid\ (F\,{}^{\circ}C_2\ (RELU(F{}^{\circ}C_1))) \qquad (1)$$

The output of the channel attention is given as $U_0 \in R_H \times W \times C$ and is obtained by the formula given in Eq (2)

$$U_0\ = U\,{}^{\circ}\mu \qquad (2)$$

Where ° is the channel-wise multiplication of scalar calibration weight μ_i, i = 1, 2, ...C and Ui ∈ $R_H\ \times W$.

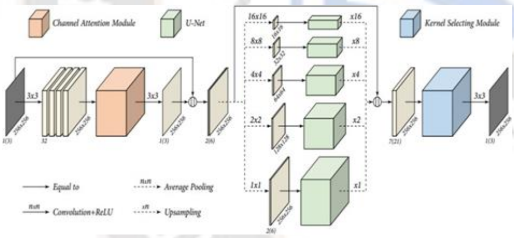

Figure 4. Five Layer Pyramid

D. Multi-scale Denoising Stage

Pyramid pooling is a popular concept utilized in various areas such as scene parsing and image compression. Image denoisers have not exploited this type of pooling beforehand. This is because the actual receptive field of CNN is smaller than the other layers because the global data cannot be obtained in the feature extraction phase. The full image may contain similar content and same type of blocks through which we can build a five-level pyramid model. The branches can acquire and notably scale-different receptive fields that efficiently capture actual, regional, and global data after down sampling the input feature maps through five concurrent paths. 1x1, 2x2, 4x4, 8x8, and 16x16 are the configurations that are available for the pooling kernels.

Each pooled feature passes into a U-Net, which comprises of deep encoding-decoding layers and skip connections, during the denoising phase. For noise removal, this architecture leverages the advantages of consecutive up- and down-sampling. Each U-Net's output feature will be combined after being upsampled to the same size using bilinear interpolation. This enables information from various dimensions and levels of abstraction to be efficiently captured and fused by the network.

E. Last stage: Feature fusion stage

Varying kernel sizes can be chosen for each channel inside the concatenated multi-scale outputs in our proposed model. It operates on the feature maps $U\ \in\ R_H\ \times W \times C$. Three parallel convolutions with kernel sizes of three, five, and seven are applied to the feature maps resulting in feature maps $U_0\ \in\ R_H\ \times W \times C$, $U_{00}\ \in\ R_H\ \times W \times C$, and $U_{000}\ \in\ R_H\ \times W \times C$. We first use element-wise summation to integrate data from all branches.

$$U =\ U_0 + U_{00} + U_{000} \qquad (3)$$

Then, the channel attention module's operations—a GAP and two FCs—are applied to shrink and increase U, respectively, but finally, there is no Sigmoid. The outputs are of the form α_0 ∈ R 1×1×C, β_0 ∈ R 1×1×C, and γ_0 ∈ R 1×1×C and are given to the softmax layer in a channel wise manner in the manner of gating mechanism.

$$kc = ek_0ce\alpha_0c + e\beta_0c + e\gamma_0c\,.\,k = \alpha, \beta, \gamma \qquad (4)$$

where the soft attention vector U_0, U_{00} and U_{000} are indicated by α, β and γ respectively. α_c is indicated as the c^{th} element of α, β_c is the c^{th} element of β and γ_c is the c^{th} element of γ. To compute the final output feature maps V, different kernels and their attention weights are combined as in equation (5)

$$V_c =\ \alpha_c\,.\,U_0 +\ \beta_c\,.\,U_{00} + \gamma_c\,.\,U_{000} \qquad (5)$$

where V = [V1, V2 ,..., Vc], Vc ∈ R H×W, and α, β, and γ must fulfil αc + βc + γc = 1. To compress the dimension to 1 or 3 for feature fusion, we employ a 1 × 1 convolutional layer at the end.

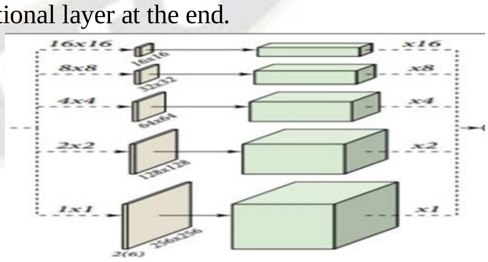

Figure 5. Kernel Selection Module

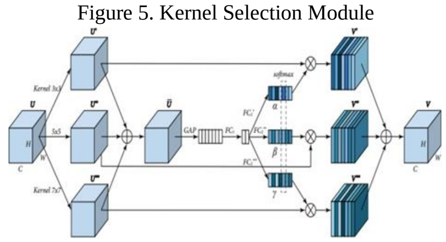

Figure 6. PRIDNet network architecture

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Results and analysis

A full-reference evaluation of the image quality using two widely-used measures, namely PSNR and SSIM.

TABLE I. PSNR VALUES OBTAINED WITH AND WITHOUT PATCHES

S.NO			
	PEAK SIGNAL TO NOISE RATIO (PSNR)	***Without Patches***	***With Patches***
1	Original average ground truth-noisy images	20.219	22.076
2	Predicted average ground truth - predicted images	21.003	25.154

TABLE II. SSIM VALUES OBTAINED WITH AND WITHOUT PATCHES

S.NO			
	STRUCTURED SIMILARITY INDEX (SSIM)	***Without Patches***	***With Patches***
1	Original average ground truth-noisy images	0.713	0.730
2	Predicted average ground truth	0.653	0.721

From the obtained results patch-based underwater image denoising is more efficient in comparison to the traditional image denoising i.e., without creating patches for the underwater images. As patch-based underwater image denoising is a more effective method compared to traditional image denoising methods that do not involve patch creation.

The results of our model i.e., PRIDNet with patches is also compared with some of the state of the arts. They are baseline PRIDNet model, Autoencoders and NLM filter.

TABLE III. PSNR OF PRIDNET WITH PATCHES ON DATASET IS BEING COMPARED WITH OTHER DENOISING TECHNIQUES

S.NO	**PSNR VALUES WITH PRIDNet/Autoencoders/NLM Algorithm**				
	Image Type	***PSNR With PRIDNet and Without Patches***	***PSNR With PRIDNet and With Patches***	***PSNR with Auto-encoder***	***PSNR with NLM Algorithm***
1	Original average ground truth-noisy images	20.219	22.076	22.076	17.918
2	Predicted average ground truth -predicted images	21.003	25.154	7.359	20.141

TABLE IV. SSIM OF PRIDNET WITH PATCHES ON DATASET IS BEING COMPARED WITH OTHER DENOISING TECHNIQUES

S.NO	**SSIM VALUES WITH PRIDNet/Autoencoders**			
	Image Type	***SSIM With PRIDNet and Without Patches***	***SSIM With PRIDNet and With Patches***	***SSIM with Auto-encoder***
1	Original average ground truth-noisy images	0.713	0.730	0.751
2	Predicted average ground truth -predicted images	0.653	0.720	0.063

We cannot find SSIM for the Non-local Means (NLM) filter because, it is a non-linear and non-local algorithm without a closed-form solution for its output, therefore it cannot be directly applied to it he.

Autoencoders suffer from edge distortion. also introduce some kind of different color artifacts to the denoised image that can be seen clearly [17]. NLM faces problems of losing crucial details and structures and suffers from over-smoothing. The NLM filter is a non-linear filter that uses a weighted average of neighboring pixels to denoise an image. However, the filter can sometimes over smooth the image, which can lead to a loss of important details and structures. This implies that the PRIDNet with patches approach is a promising solution to enhance underwater image quality, which could result in more accurate image analysis and better visual outcomes [18].

Quantitative results indicate that the proposed PRIDNet with patches is effective. The results of image denoising that are shown by the various methods PRIDNet without patches still contain some noise. This suggests that there might be room for further improvement in the denoising performance of PRIDNet or the chosen set of noisy underwater images might be too challenging for the algorithm.

V. CONCLUSION

The unregulated nature of the ocean environment makes underwater image enhancement particularly denoising, a very challenging undertaking. Significant results have been obtained on improvising the quality of underwater images. Dataset acquisition can be challenging and expensive in the underwater domain. Additionally, underwater images acquired with cameras can cause backscattering because particles in the water scatter light towards the camera distorts the image quality.

We utilized an extensive dataset for underwater image enhancement which has enough real-world images with their noisy references [19]. The underwater image enhancement algorithms available were applied on this dataset and its effectiveness were analysed with which our proposed model was compared and investigated. Through quantitative evaluations, we found that no single method completely and consistently outperforms all others.

We can expand the dataset in future work to include more difficult underwater images and underwater films as well. Nonetheless, improving underwater image does benefit from the high image quality of several reference images. We can also optimize the image capture of underwater image dataset using external strobes or LED lights which may lower back scattering and enhance the visual representation.

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