FreqPatchNet: A Dual-Domain Patch-Wise Fusion Network for Robust Phase Correction in Underwater Image Reconstruction

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ABSTRACT

This paper presents FreqPatchNet, a novel patch-wise dual-domain Convolutional Neural Network (CNN) designed to correct phase distortions in underwater images. The model uses bispectral frequency features and local CNN regression to reconstruct clean images from distorted inputs. Evaluated using Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE), FreqPatchNet achieves a maximum PSNR of 35.6 dB and a lowest MSE of 0.28 at 10% distortion. A comparative analysis with state-of-the-art methods shows the superior performance of the proposed model in structural similarity. Real-world tests confirm its potential for underwater robotics and vision applications.

Keywords-underwater image enhancement; phase distortion correction; bispectrum features; patch-wise convolutional neural network; FreqPatchNet; frequency domain analysis; deep learning; SSIM; PSNR; MSE; image reconstruction; sinusoidal attack modeling; underwater robotics; UCIQE; UIQM

I. INTRODUCTION

Underwater imaging presents a unique set of challenges due to the complex optical properties of aquatic environments. As light propagates through water, it undergoes scattering, absorption, and wave-induced phase distortions, which significantly degrade image quality. These distortions reduce both spatial and spectral fidelity, making it difficult to extract accurate visual information from underwater scenes. This poses a critical issue for applications such as marine biology, underwater archaeology, and Autonomous Underwater Vehicles (AUVs), where image clarity is essential for interpretation and navigation. One of the most significant sources of distortion is the dynamic wave movement, which alters the phase of light and leads to blurred, warped, and geometrically inconsistent images. Unlike terrestrial photography, where light travels through a relatively homogeneous medium, underwater imaging must contend with constantly changing refractive indices and uneven surfaces that make traditional image enhancement methods insufficient.

Traditional techniques, such as Fourier-based phase reconstruction, have been used to address these problems, but often fail under nonlinear and dynamic underwater conditions. These methods assume global uniformity and do not adapt well to localized distortions, particularly those caused by waves and depth variations. To overcome these shortcomings, researchers have turned to deep learning, which has shown remarkable success in a variety of low-light and image restoration tasks. Although many of these approaches, such as contrast enhancement and dehazing, primarily focus on improving color and visibility, they often neglect the correction of structural phase errors, which are critical for accurate shape reconstruction and object detection. In response to this gap, this study proposes FreqPatchNet, a patch-wise dual-domain Convolutional Neural Network (CNN) that leverages bispectrum features in the frequency domain to learn and correct local phase distortions. This architecture is specifically designed to capture localized phase anomalies caused by underwater wave dynamics. The model is trained using a synthetic distortion framework based on sinusoidal attack modeling, mimicking real-world underwater disturbances and allowing it to generalize well to real conditions.

Phase distortion affects critical underwater operations where the shape, structure, and orientation of objects are vital. For instance:

- In marine biology, blurred images can lead to misidentification of species or incorrect analysis of morphology.
- In search-and-rescue operations, phase distortion can make it difficult to detect submerged objects or bodies.
- In underwater robotics, distorted inputs degrade the performance of navigation algorithms, increasing the risk of operational failure.

Accurate phase correction ensures that images preserve structural integrity, improving the efficiency of downstream computer vision tasks such as segmentation, object tracking, and recognition.

A. Deep Learning for Underwater Image Enhancement

Numerous deep learning models have been proposed for underwater image enhancement, each addressing unique difficulties in underwater environments. DBFNet [1] presents a dual-branch fusion strategy that combines wavelet domain processing and triple-color channel learning to effectively improve color fidelity and structural detail, although it faces difficulties in turbid waters and extremely bright lighting. DIMN [2] uses a Multi-Information Enhancement Module to address uneven color attenuation by improving spatial awareness and sharpness through transformer and attention mechanisms; however, scalability may be hampered by its high computational demands. LANet [3] uses a multiscale fusion and adaptive attention approach with perceptual loss optimization, which performs well but has limitations in highly dynamic or particulate-heavy environments and requires a large amount of labeled data. A grid-based CNN with feature-level attention [4] further improves degraded regions through synergistic pooling and attention mapping, although it is still restricted to single-image input and has uncertain generalization across a variety of underwater scenes. A deep residual CycleGAN framework was combined with VDSR [5] using synthetic data and improved loss functions, showing better color correction; however, it runs the risk of overfitting and does not provide a thorough analysis of training efficiency. LAFFNet [6] is a lightweight architecture for real-time autonomous applications, but it may perform poorly in highly complex scenarios. However, it reduces the parameters by 94% through adaptive fusion and channel attention. UICoE-Net [7] uses Siamese encoder-decoders to exploit mutual correlations between paired images, effectively enhancing similar underwater scenes, but it requires paired inputs and has limited exploration in dissimilar or unstructured conditions. UWCNN [8] and UWIE-Net [9] are based on a parallel combination of a denoising Deep CNN and use synthesized datasets and underwater scene priors to improve underwater videos in a lightweight manner without the need for explicit imaging model estimation. However, these models may not perform well in harsh environments and are highly dependent on dataset diversity.

B. Feature Fusion in Deep Architectures

Recent advances in underwater image enhancement and broader vision applications have led to the development of several deep learning architectures to address challenges such as color distortion, low contrast, and detail degradation. The dual-domain feature aggregation transformer network in [10] improves information capture by integrating spatial and frequency domain cues, although its real-time applicability may be limited due to computational overhead. Similarly, HDAGAN [11] leverages high-dimensional attention mechanisms with generative adversarial training to correct chromatic aberration and blurriness, but faces challenges in processing time and generalization across diverse underwater scenes. The study in [12] focused on deep learning in medical imaging (MRI), but underscored the importance of automated enhancement and noise correction concepts transferable to underwater scenarios. A broader review of deep learning trends [13] highlighted key architectures, such as CNNs, and their applications across domains, although it may underrepresent emerging non-CNN models. WPFNet [14] introduces a multi-branch architecture that combines wavelet, residual attention, and transformer modules to enhance both color and fine details in underwater images, but has longer processing times and possible artifact generation. A fusion adversarial network [15] emphasized performance on real underwater benchmarks with complex loss design, although its generalization beyond specific datasets is uncertain. In a related domain, IGT [16] offered a cross-modal detection approach using RGB and thermal data for autonomous driving, showing how illumination guidance can enhance feature fusion, although challenges persist in diverse lighting and adverse environments. Finally, a Vision Transformer-based underwater restoration framework [17] utilized spectral domain regularization to enhance detail recovery, achieving strong results but potentially limiting real-time use due to architectural complexity and frequency-domain processing constraints.

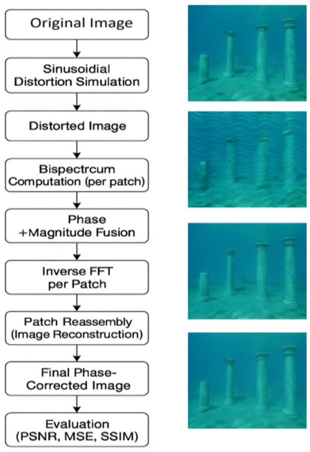

Fig. 1. System architecture.

II. PROPOSED METHOD

FreqPatchNet utilizes a patch-wise CNN architecture, shown in Figure 1, to combine spatial and frequency-domain (bispectral) features to restore phase information in distorted underwater images. The first step is to use sinusoidal patterns to simulate phase distortions. Distorted images are split into overlapping patches, and those that are not very good are thrown away based on how similar their structures are. Valid patches go through a bispectrum transformation, and a CNN makes predictions about local phase corrections. These corrections are added to the original phase and averaged magnitudes to make a new version of the frequency representation. Inverse FFT is then used to rebuild the corrected image, which gives an output that is phase-corrected. PSNR, MSE, and SSIM are used to evaluate the quality improvement. The overall method has five main steps: simulating distortion, extracting patches, analyzing the bispectrum, correcting the image with a CNN, and reconstructing the image.

A. Sinusoidal Distortion Modeling

Synthetic sinusoidal attacks are introduced to model the phase distortions that happen when waves move underwater. This method works by changing the brightness of pixels according to (1), making it look like natural aquatic wave interference.

$$D(x,y) = A.\sin\left(\frac{2\pi x}{\lambda} + \varphi\right) \quad (1)$$

where $D(x,y)$ is the distorted value at pixel x,y, A is the amplitude (set to 10), λ is the wavelength (10 pixels), φ is a random phase shift, and x is the horizontal pixel coordinate. The sinusoidal distortion function is used in horizontal, vertical, and both directions at levels of 10%, 20%, and 30%, respectively. This setup allows testing how well the model works with different amounts of phase distortion.

Figure 2 shows how simulated sinusoidal distortions affect an architectural image to show how waves look underwater. The top-left image shows the original one without any changes. Rows show changes made horizontally, vertically, and in both directions. Each row shows more and more warping of the image, going from 10% to 30% distortion. Arches and columns, which are important structural elements, bend in a way that makes it clear how phase distortions change with direction and intensity. This shows how important they are for underwater imaging.

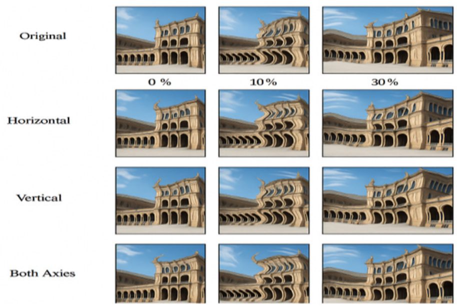

Fig. 2. Simulated sinusoidal distortion effects.

B. Patch-Based Data Preparation

Original and distorted images are cut into patches that are either 32×32 or 64×64 pixels. SSIM is used to eliminate patches that have lost a lot of quality, and each remaining patch is processed to obtain bispectral features that retain phase information.

C. Bispectrum-Based Feature Extraction

Bispectrum is better for correcting distortion because it captures third-order statistics and non-linear phase coupling, unlike the traditional Fourier spectrum that loses phase details. Let $P(x,y)$ be a patch. The 2D Fourier transform is:

$$F(u,v) = \sum_x \sum_y P(x,y).e^{-j2\pi\left(\frac{ux+vy}{N}\right)} \quad (2)$$

The bispectrum $B(u_1, u_2)$ is calculated as:

$$B(u_1, u_2) = F(u_1). F(u_2). F^*(u_1 + u_2) \quad (3)$$

where F^* is the complex conjugate, and u_1 and u_2 are frequency components.

CNN input channels focus on these bispectral features. Figure 3 shows how to extract patches and compute the bispectrum for analyzing underwater images. It starts with a raw input image that is split into overlapping patches. A 2D Fourier transform is used on each patch to change spatial data in the frequency domain. Then, a frequency spectrum is obtained, and the bispectrum is calculated, which gives a multidimensional tensor. This bispectral tensor captures relationships between higher-order frequencies, giving it many useful features that are necessary for accurate phase correction.

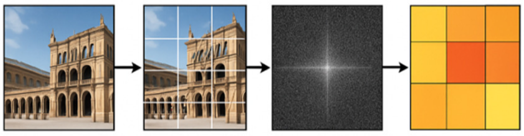

Fig. 3. Patch extraction and bispectrum computation workflow.

D. CNN-Based Phase Correction Network

The CNN gets the extracted bispectrum features and uses them to do real-valued regression on the phase correction for each patch. Table I shows the structure of the network. The predicted phase correction is represented as:

$$\Delta\phi_i(u, v) = CNN(B_i(u, v)) \quad (4)$$

where B_i is the bispectral representation of patch i, and $\Delta\phi_i$ is the phase correction for patch i.

TABLE I. PARAMETERS USED FOR CNN-BASED PHASE CORRECTION NETWORK

Layer	Parameters	Output Shape
Input	(32, 32, 3)	32×32×3
Conv2D + ReLU	32 filters, 3x3 kernel	30×30×32
MaxPooling	2×2	15×15×32
Conv2D + ReLU	64 filters, 3x3 kernel	13×13×64
MaxPooling	2×2	6×6×64
Conv2D + ReLU	64 filters, 3x3 kernel	4×4×64
Flatten	—	1024
Dense + ReLU	64 units	64
Output (Linear)	1 unit	1 (phase correction)

E. Image Reconstruction

The corrected frequency representation of each patch is reconstructed using:

- Compute corrected phase as:

$$\phi'_i(u, v) = \phi_i(u, v) + \Delta\phi_i(u, v) \quad (5)$$

- Estimate magnitude by averaging across the ensemble:

$$|F_{avg}(u, v)| = \sqrt{\frac{1}{N}\sum_{i=1}^{N}|F_{avg}(u, v)|^2} \quad (6)$$

- Construct a corrected Fourier representation:

$$\bar{F}_i(u, v) = |F_{avg}(u, v)|. e^{j\phi'_i(u,v)} \quad (7)$$

- Apply the inverse Fourier transform:

$$\bar{P}_i(x, y) = \mathcal{F}^{-1}[\bar{F}_i(u, v)] \quad (8)$$

- Reconstruct the whole image by:

$$I(x, y) = \sum_{i,j} \bar{P}_{i,j}(x - i.s, y - j.s) \quad (9)$$

where s is the patch stride.

Figure 4 shows the whole deep learning process for phase correction and image reconstruction. The process starts with input patches that are distorted by wave-like sinusoidal waves. A CNN makes predictions about local phase corrections, which are then added to the original magnitude data to make a corrected frequency representation. Then, the Inverse Fast Fourier Transform (IFFT) changes them back to the spatial domain to make a clean, restored image. The figure shows how learned phase corrections can fix distortions in underwater images and make them clearer again.

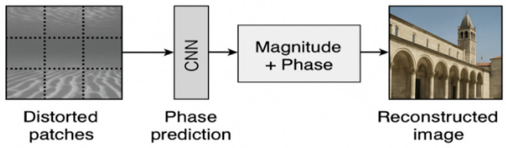

Fig. 4. Overall phase correction and reconstruction pipeline.

F. Loss Function

The Mean Squared Error (MSE) between the predicted and ground-truth corrected patches is used to train the model:

$$\mathcal{L}_{MSE} = \frac{1}{N}\sum_{k=1}^{N}(T_k - \hat{T}_k) \quad (10)$$

where T_k is the ground truth pixel value, $\hat{T}_k$ is the predicted output pixel value, N is the total pixels in the patch.

III. RESULTS AND DISCUSSION

The proposed FreqPatchNet model was tested by looking at both synthetic distortion scenarios and real-time underwater emulation.

A. Training Setup and Parameters

The model was trained on a synthetically distorted dataset made using sinusoidal phase attacks at different levels of distortion to ensure that it would work in a wide range of situations. The training dataset had 20 standard images that were distorted in six different ways, such as with horizontal, vertical, and combined sinusoidal attacks at 10%, 20%, and 30% severity levels. This gave a total of 120 distorted images, which were then split into 1,080 overlapping patches so that training could be done in specific areas. The dataset was split into 80% for training, 10% for validation, and 10% for testing. The Adam optimizer was used to train the model for 50 epochs with a learning rate of 0.001. These parameters were chosen to strike a balance between fast convergence and low overfitting, especially since patch-wise learning is localized.

B. Quantitative Analysis

The model's strength was tested by putting it through different levels of sinusoidal distortion. In addition, the Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) were used to examine how well the reconstruction worked.

TABLE II. COMPARATIVE EVALUATION

Attack level	Max PSNR (dB)	Avg PSNR (dB)	Min MSE
10%	35.6	34.0	0.28
20%	32.4	31.1	0.35
30%	30.2	29.4	0.42

The model achieved its best performance at 10% distortion, indicating high fidelity in mild-to-moderate wave distortions. The decline in PSNR with increased distortion levels is gradual, reflecting the model's resilience against more severe perturbations. Figure 5 shows how PSNR changes when the distortion level is 10%, 20%, or 30%, indicating both the highest and lowest PSNR values. The values decrease noticeably as distortion increases. This trend shows that the model works best when there is only a little distortion (10%). It also shows that it can handle more phase distortion without losing performance.

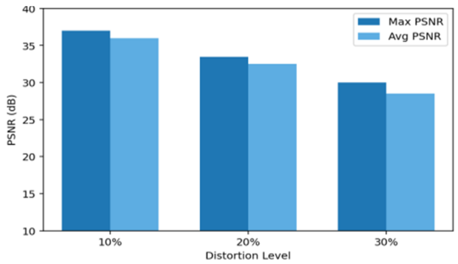

Fig. 5. PSNR vs. distortion level.

Figure 6 shows that MSE increases steadily as the distortion levels increase to 10%, 20%, and 30%. As the distortion worsens, the MSE values increase from 0.28 to 0.42. The smooth, upward trend shows that model accuracy will steadily drop as phase distortion gets worse.

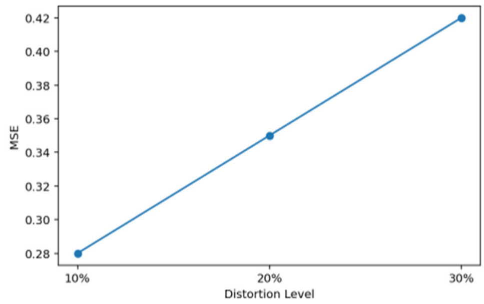

Fig. 6. MSE vs. distortion level.

C. Comparative Evaluation with Existing Methods

To ensure fairness and reproducibility, the proposed model was compared with benchmark models, such as DBFNet [1], DIMN [2], LANet [3], and a multi-scale attention CNN [4], on the same synthetic underwater distortion dataset.

This dataset comprises 20 high-resolution images that were artificially distorted using sinusoidal wave modeling at three levels: 10%, 20%, and 30%. These images, which range in size from 512×512 pixels to 1024×1024 pixels, offer a variety of visual content that is typical of underwater settings. This synthetic dataset allows controlled evaluation of phase distortion correction and visual restoration across multiple models. When pre-trained weights were not publicly available, the models were reimplemented based on their publicly released architectures and trained under identical conditions on the synthetic dataset to ensure comparability. FreqPatchNet achieved the highest SSIM (0.877), demonstrating superior preservation of structural details, which is crucial for identifying and deciphering underwater objects.

TABLE III. COMPARATIVE EVALUATION

Method	PSNR	SSIM	UCIQE	UIQM
DBFNet [1]	21.12	0.812	7.845	3.587
DIMN [2]	22.34	0.856	8.127	3.922
LANet [3]	20.89	0.838	7.659	3.768
Multiscale CNN [4]	19.36	0.873	5.468	4.196
FreqPatchNet	19.37	0.877	4.899	3.975

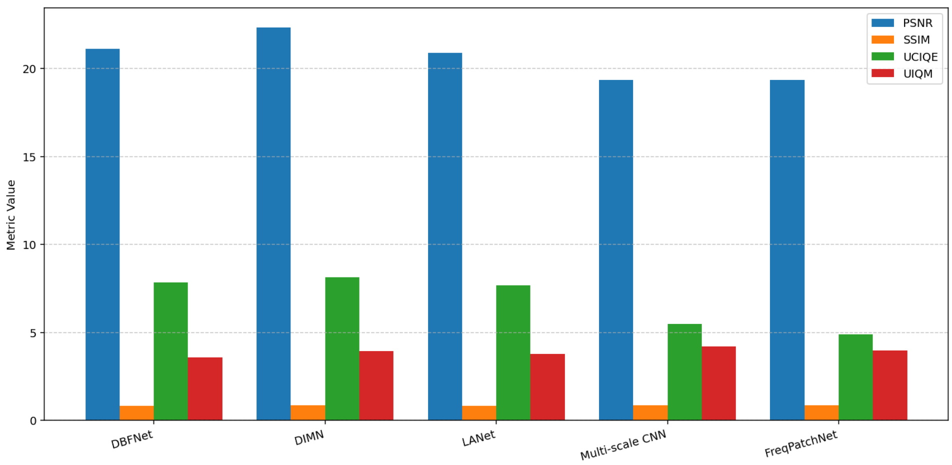

Fig. 7. Comparative structural and visual metrics.

DIMN and DBFNet achieved higher PSNR and UCIQE values, but they may introduce artificial enhancement through post-processing and rely more heavily on color correction techniques. FreqPatchNet focuses on phase distortion correction to preserve a balance between structural fidelity and visual realism. FreqPatchNet was superior in terms of SSIM, showing its efficacy in maintaining structural consistency, although DIMN led in PSNR and UCIQE, and multiscale CNN achieved the highest UIQM. Therefore, it is well-suited when shape and structural accuracy are crucial, such as in marine biology, underwater robotics, and object detection.

D. Real-Time Validation on Captured Data

A 2MP USB webcam captured real-world distorted images subjected to wave disturbances and phase distortion, to examine the practical applicability of FreqPatchNet. Figure 8 shows how FreqPatchNet works in real-world underwater situations, showing the original image (ground truth), the distorted underwater image with wave-induced phase noise, and the phase-corrected output, where edges, details, and text have been clearly restored. Therefore, the proposed model can generalize beyond synthetic data and effectively reverse real-world aquatic distortions in real-world situations.

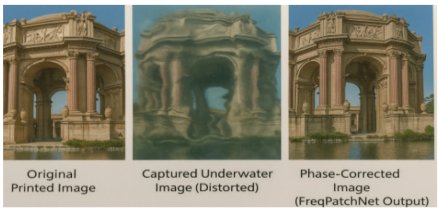

Fig. 8. Real-time validation output.

IV. CONCLUSION

FreqPatchNet is a patch-wise dual-domain CNN to solve the important problem of phase distortion in underwater images. FreqPatchNet differs from traditional methods that focus only on restoring color or adjusting contrast, focusing directly on phase anomalies caused by wave dynamics, which are a major cause of structural damage in underwater environments. The model uses bispectral frequency-domain features to find non-linear phase relationships and a localized CNN to make small corrections at the patch level. Test results with different amounts of synthetic distortion showed a high PSNR and a low MSE. The system worked best with mild (10%) to moderate (20%) distortion. FreqPatchNet was better at SSIM compared to other methods [1-4], showing that it can get back important object-level detail without having to rely on post-processing or contrast exaggeration. Real-world tests with images that were physically distorted while being taken underwater showed that the FreqPatchNet is both useful and strong. Although it had to work within certain computational limits, the model produced outputs that were structurally consistent and easy to see. Future work will focus on adding diverse underwater scenes to the training dataset, examining transformer-based architectures, and making the system handle real-time video streams so that it can be used for autonomous underwater navigation and marine monitoring.

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