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Unsupervised Image Translation for Underwater Image Enhancement

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Abstract: ***Underwater images are often degraded due to the absorption and scattering of light, leading to color distortion, reduced contrast, and blurriness. Enhancing these images is vital for improving visibility in marine applications such as underwater robotics, oceanographic surveys, and archaeological studies. In this paper, we propose a novel unsupervised image translation approach for underwater image enhancement using a Cycle-Consistent Generative Adversarial Network (CycleGAN). Unlike supervised models, our method requires no paired data, addressing a major limitation in underwater datasets. We enhance the baseline CycleGAN framework by introducing perceptual loss and structural similarity index (SSIM) loss to preserve semantic and structural details. Experimental results on multiple underwater datasets demonstrate significant improvement in image quality, outperforming several state-of-the-art methods both quantitatively and qualitatively.***

Keywords: Underwater image enhancement, CycleGAN, unsupervised learning, generative adversarial networks, image translation, perceptual loss, SSIM

1. Introduction

Underwater imaging plays a crucial role in numerous scientific and industrial domains. However, image degradation caused by the selective attenuation of light wavelengths and forward/ backward scattering poses significant challenges. The resulting images often suffer from haze-like effects, color casts, and loss of detail. Traditional image enhancement techniques, including histogram equalization and white-balancing, fail to generalize across different underwater conditions.

Recent advances in deep learning, particularly with Generative Adversarial Networks (GANs), have shown promise in image restoration and translation tasks. However, most models rely on paired training data, which are scarce or infeasible to obtain in underwater environments. To address this, we explore an unsupervised CycleGAN-based framework that performs domain translation from degraded to clean underwater images without requiring paired samples.

Contributions of this paper include: An unsupervised deep learning model based on CycleGAN for underwater image enhancement. - Integration of perceptual loss and SSIM loss into the training objective to preserve image content and structure. Extensive evaluations on benchmark underwater datasets with improved visual quality and objective metrics.

2. Related Work

2.1 Traditional Approaches

Early methods for underwater image enhancement were based on histogram equalization, white balance, and dehazing techniques. Examples include the Retinex model and the dark channel prior adapted for underwater scenarios. While simple and fast, these methods often fail under diverse lighting and turbidity conditions.

2.2 Supervised Deep Learning

Supervised CNN-based models such as Water-Net and U-Net variants require ground-truth clean images for training. Such paired datasets are difficult to collect in real-world underwater environments, limiting their scalability.

2.3 Unsupervised Learning

CycleGAN enables unpaired image translation and has been used in several vision tasks. Recent studies have applied GANs to underwater enhancement using synthetic datasets or by translating between domains. Our method builds upon CycleGAN and improves its performance for underwater scenarios by incorporating perceptual and SSIM losses.

3. Proposed Method

3.1 Overview

Let X denote the domain of degraded underwater images, and Y denote the domain of high-quality underwater images. The goal is to learn two mappings: - $G : X \to Y$, translating degraded to enhanced - $F : Y \to X$, inverse mapping

Two discriminators D_Y and D_X ensure adversarial training, where D_Y distinguishes real vs. generated images in domain Y, and vice versa.

3.2 Loss functions Adversarial Loss

$$L_{GAN}(G, D_Y, X, Y) = \mathbb{E}_{y\sim Y}[\log D_Y(y)] + \mathbb{E}_{x\sim X}[\log(1 - D_Y(G(x)))]$$

Cycle Consistency Loss:

$$L_{cyc}(G, F) = E_{x\sim X}[\|F(G(x)) - x\|_1] + E_{y\sim Y}[\|G(F(y)) - y\|_1]$$

Perceptual Loss:

$$L_{perc}(x, y) = \sum_i \|\phi_i(x) - \phi_i(y)\|_2^2$$

Where ϕ_i denotes the feature map from the i^{th} layer of a pretrained VGG network.

SSIM Loss:

$$L_{ssim}(x, y) = 1 - SSIM(x, y)$$

Final Loss:

$$L_{total} = L_{GAN} + \lambda_{cyc}L_{cyc} + \lambda_{perc}L_{perc} + \lambda_{ssim}L_{ssim}$$

3.3 Network Architecture

We use ResNet-9 based generators and PatchGAN discriminators. Residual blocks preserve semantic structure, and instance normalization is used to stabilize training. Skip connections ensure low-level details are retained.

3.4 Training Setup

Optimizer: Adam ($\beta_1 = 0.5$, $\beta_2 = 0.999$) - Learning rate: 0.0002 - Batch size: 1 - Epochs: 200 - Framework: PyTorch - Data augmentation: random cropping, horizontal flipping, color jittering

4. Experiments and Results

4.1 Datasets - EUVP

Contains paired and unpaired underwater images with varying quality. - UIEB: Unpaired dataset with real-world degraded images and reference images. - U45: Challenging dataset with poor visibility and noise.

4.2 Evaluation Metrics

PSNR (Peak Signal-to-Noise Ratio) - SSIM (Structural Similarity Index) – UCIQE (Underwater Color Image Quality Evaluation) - UIQM (Underwater Image Quality Measure)

4.3 Results

Quantitative comparisons show our model achieves higher PSNR and SSIM values than Water- Net, UGAN, and histogram equalization. Table 1 summarizes the results.

Table 1: Quantitative Comparison

Method	PSNR ↑	SSIM ↑	UIQM ↑	UCIQE ↑
HE	15.2	0.61	2.8	44.5
Water-Net	22.5	0.75	4.1	53.2
UGAN	21.0	0.70	4.0	51.0
Ours	24.3	0.80	4.6	55.8

4.4 Visual Results

Figure 1 shows side-by-side comparisons of enhanced images by different methods. Our results exhibit better color balance, detail recovery, and contrast.

5. Conclusion and Future Work

We proposed an unsupervised deep learning model for underwater image enhancement using CycleGAN with perceptual and SSIM losses. The model improves visual quality without requiring paired training data. Experiments demonstrate its superiority over existing methods. Future work includes extending the model to real-time processing and 3D scene understanding for underwater SLAM and reconstruction.

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