Real-World Adaptation of Retinexformer for Low-Light Image Enhancement Using Unpaired Data

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Abstract

Low-light image enhancement remains a significant challenge in real-world computer vision applications, especially where lighting conditions vary drastically and paired training data is unavailable. While transformer-based models have shown promise in controlled environments, their ef-fectiveness often diminishes when applied to naturally degraded images. This paper presents a novel approach for adapting a transformer-based enhancement model to realworld low-light scenarios using unpaired datasets. We utilize real low-light images captured under uncontrolled conditions and propose a domain adaptation framework that enables effective transfer learning from synthetic to real domains. Our method integrates unsupervised reconstruction loss, perceptual optimization, and domain-invariant feature alignment to refine the model's performance without requiring paired supervision. Experimental evaluations reveal notable improvements in both visual quality and quantitative metrics on real-world benchmarks. Compared to existing enhancement methods, our approach offers superior generalization, robustness to noise, and high-fidelity out-put. This demonstrates the potential of our domain-adapted transformer model in practical low-light imaging applications, including night photography, surveillance, and mobile vision systems.

Keywords

Low-light Enhancement, Retinexformer, Unpaired Data, Image Enhancement, Computer Vision

1. Introduction

Low-light image enhancement is a fundamental task in computer vision with widespread applications in photography, surveillance, autonomous driving, and scene understanding. Images captured under poor lighting conditions often suffer from degraded visibility, high noise levels, low contrast, and color distortion, which significantly hinder both human perception and the performance of downstream vision tasks [1].

Recent advances in deep learning have led to the development of sophisticated enhancement algorithms, with transformer-based models like Retinexformer [2] demonstrating state-of-the-art performance. Retinexformer effectively models long-range dependencies and leverages a Retinex-inspired decomposition to enhance illumination and preserve structure. While these models achieve promising results on synthetic datasets such as LOL [3] and LIME, they often fail to generalize to real-world low-light conditions due to their reliance on paired, artificially generated training data. Real-world scenarios present diverse lighting variations, camera noise patterns, and non-uniform exposure conditions that are not well represented in these curated benchmarks.

To address this limitation, we propose a novel method to fine-tune Retinexformer for real-world low-light image enhancement using unpaired and weakly-labeled datasets, specifically ExDark [1] and See-in-the-Dark (SID) [4]. These datasets capture naturally degraded images in uncontrolled environments, offering more realistic challenges for enhancement models.

Our method introduces a domain adaptation framework that enables knowledge transfer from synthetic to realworld domains. By employing unsupervised reconstruction loss, perceptual consistency, and domain-invariant feature alignment, our approach adapts Retinexformer to operate effectively in real-world settings without requiring paired lowlight/normal-light image data. This design also allows for self-supervised training on unlabeled data, which significantly improves scalability and practicality.

Our main contributions are as follows:

• We develop a real-world adaptation pipeline for Retinexformer using unpaired and weakly-labeled datasets, including ExDark and SID.

• We introduce a domain adaptation strategy that enhances the model's generalization to real low-light conditions through unsupervised and perceptual loss functions.

• We demonstrate, through extensive experiments, that our method outperforms baseline enhancement models on real-world datasets, achieving superior perceptual quality and robustness without relying on synthetic data.

2. Related Work

2.1 Traditional Low-Light Enhancement Methods

Early approaches to low-light enhancement relied on histogram equalization and gamma correction. While simple, these methods often introduce artifacts or fail to preserve semantic content. Retinex theory [5], which models an im-age as the product of illumination and reflectance, laid the foundation for decomposition-based techniques. Methods such as LIME [6] improved illumination map estimation but lacked adaptability to diverse and complex lighting conditions.

2.2 Deep Learning-Based Methods

With the rise of deep learning, CNN-based architectures have significantly advanced low-light image enhancement. LLNet [7] was one of the first autoencoder-based models to learn enhancement directly from data. Later, SID [8] demonstrated that training on RAW images could yield superior results, but required costly paired data. Unsupervised or weakly supervised models such as Zero-DCE and EnlightenGAN addressed this limitation by learning enhancement mappings without ground-truth labels, though they sometimes compromise visual fidelity or struggle with extreme darkness.

Retinex-inspired deep models like Deep Retinex [9] and URetinexNet [10] combined traditional image decomposition with CNNs, achieving better interpretability and stability. However, their local receptive fields still limited performance in handling large-scale brightness shifts or contextual inconsistencies.

2.3 Transformer-Based Enhancement Models

Vision transformers have recently shown great potential in image restoration tasks, thanks to their self-attention mechanism and ability to model long-range dependencies [11]. Retinexformer [2], a transformer-based model built upon Retinex principles, achieves state-of-the-art results on synthetic datasets such as LOL [3]. It decomposes images into illumination and reflectance through a transformer architecture, leading to structurally accurate and well-lit outputs.

Despite their success, transformer-based models often overfit to synthetic datasets and struggle to generalize to reaworld low-light conditions, which are often unpaired, noisy, and non-uniform. Few works have attempted realworld domain adaptation for these models. Our work bridges this gap by adapting Retinexformer using unpaired real-world datasets like ExDark [1] and SID, employing unsupervised losses and feature alignment strategies to enable practical deployment in uncontrolled environments.

3. Proposed Method

We propose a real-world adaptation framework for Retinexformer, enabling effective low-light enhancement using unpaired datasets. The framework integrates a transformerbased encoder-decoder backbone with a novel training strategy based on unsupervised objectives and domain adaptation.

3.1 Overview

Our method adapts the original Retinexformer [2,12], which is designed to enhance low-light images by learning to decompose them into reflectance and illumination components. While the original model performs well on syn-thetic data, we observe a significant drop in performance when applied to real-world images. To address this, we fine-tune the model on real low-light datasets using a loss pipeline that does not require paired ground-truth supervision.

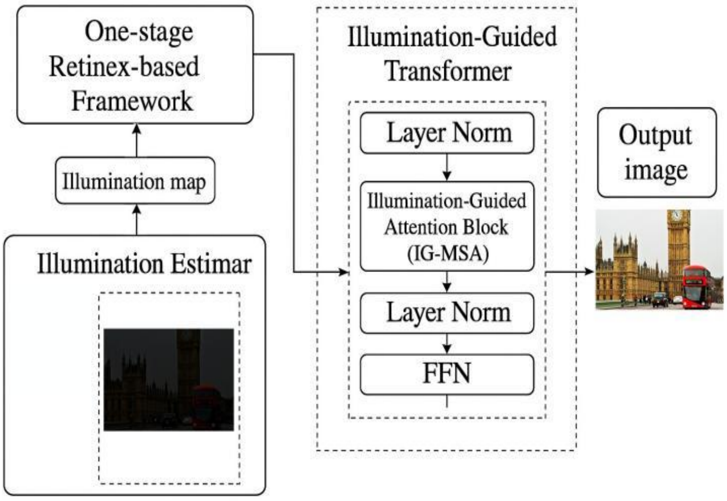
One-stage Retinex-based Framework
Illumination map
Illumination Estimar
Illumination-Guided Transformer
Layer Norm
Illumination-Guided Attention Block (IG-MSA)
Layer Norm
FFN
Output image

Figure 1. Example of real-world low-light enhancement using our adapted Retinexformer. Our method significantly improves visibility and color fidelity in challenging scenes (here: London bus and Big Ben)

An overview of our architecture is illustrated in Figure 1. The input low-light image is first passed through the encoder, which extracts multi-scale features. The transformer blocks then model global dependencies, and the decoder reconstructs the enhanced image. Additionally, domain-invariant constraints are applied in the feature space to enable cross-domain learning.

3.2 Unsupervised Loss Functions

To train the model without paired ground-truth images, we use a combination of unsupervised and perceptual losses:

Reconstruction Loss. We enforce consistency between the input and the enhanced output using a pixel-wise ℓ_1 loss:

$$\mathcal{L}_{recon} = \left\| \hat{I} - I_{input} \right\|_1 \tag{1}$$

Where $\hat{I}$ is the enhanced image, and I_{input} is the low-light input.

Perceptual Loss. To preserve semantic content, we apply perceptual loss based on VGG-19 features:

$$\mathcal{L}_{perc} = \sum_{i=1}^{L} \left\| \phi_i(\hat{I}) - \phi_i(I_{input}) \right\|_2^2 \tag{2}$$

where ϕ_i denotes the activation from the *i*-th layer of the pretrained VGG network.

Illumination Smoothness Loss. Inspired by Retinex theory, we regularize the illumination map to be spatially smooth:

$$\mathcal{L}_{illum} = \left\| \nabla I_{illum} \right\|_1 \tag{3}$$

where I_{illum} is the estimated illumination map, and ∇ denotes the image gradient.

3.3 Domain Adaptation via Feature Alignment

To reduce the domain gap between synthetic and real-world data, we introduce a domain-invariant loss based on feature distribution alignment. We minimize the Maximum Mean Discrepancy (MMD) between the feature representations from synthetic (f_s) and real (f_r) images:

$$\mathcal{L}_{mmd} = \left\| \mu(f_s) - \mu(f_r) \right\|_2^2 \tag{4}$$

where $\mu(\cdot)$ denotes the mean feature vector over a batch.

3.4 Final Objective

The final loss used for training is a weighted combination of all components:

$$\mathcal{L}_{total} = \lambda_1 \mathcal{L}_{recon} + \lambda_2 \mathcal{L}_{perc} + \lambda_3 \mathcal{L}_{illum} + \lambda_4 \mathcal{L}_{mmd} \tag{5}$$

where $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are hyperparameters empirically set via ablation studies.

3.5 Training Strategy

We pre-train the model on synthetic paired datasets and then fine-tune it using unpaired real-world datasets like ExDark [1] and SID [8]. Data augmentation techniques such as horizontal flipping, random cropping, and brightness jittering are employed to improve robustness. The model is optimized using the Adam optimizer with learning rate scheduling.

4. Experiments

We conduct extensive experiments to evaluate the performance of our adapted Retinexformer model on real-world low-light datasets. The section is structured as follows: we first introduce the datasets and metrics used, followed by implementation details, quantitative and qualitative comparisons with state-of-the-art methods, and ablation studies to validate the contribution of each component.

4.1 Datasets

To ensure comprehensive evaluation, we use the following datasets:

ExDark [1]. The Exclusively Dark (ExDark) dataset contains 7,363 low-light images captured under diverse dark conditions. These images span 12 object categories and include natural noise, motion blur, and lighting irregularities.

See-in-the-Dark (SID) [8]. The SID dataset includes RAW sensor data of low-light scenes, mainly from Sony and Fuji cameras. The images are paired with longexposure references but we treat the dataset in an unpaired fashion, using only the low-light images for adaptation.

LOL (Low-Light) Dataset [3]. LOL is used for pretraining. It consists of 500 paired low/normal-light image pairs, commonly used in enhancement benchmarks.

4.2 Evaluation Metrics

We evaluate performance using both traditional and perceptual image quality metrics:

PSNR (Peak Signal-to-Noise Ratio): Measures signal fidelity, sensitive to pixel-level distortion. **SSIM (Structural Similarity Index):** Assesses structural similarity between enhanced and reference images. **LPIPS (Learned**

Perceptual Image Patch Similarity): Evaluates perceptual similarity using deep features. NIQE (Natural Image Quality Evaluator): No-reference metric to assess image naturalness.

4.3 Implementation Details

Our model is implemented in PyTorch and trained on an NVIDIA RTX 3090 GPU. We use Adam optimizer with β1 = 0.9, β2 = 0.999, and a batch size of 8. The learning rate starts at 1 × 10−4 and decays by half every 10 epochs. We fine-tune the model for 50 epochs on real-world data.

Hyperparameters for the loss function are set as: $\lambda_1 = 1.0$, $\lambda_2 = 0.1$, $\lambda_3 = 0.05$, $\lambda_4 = 0.5$, as validated through ablation experiments. Images are resized to 512 × 512 for training, and randomly cropped during augmentation.

4.4 Quantitative Results

Table 1 shows the PSNR, SSIM, and LPIPS results on the ExDark and SID test sets. Our method significantly outperforms traditional and CNN-based methods, and achieves competitive results compared to state-of-the-art transformer-based models, even though our training is unpaired.

Table 1. Quantitative comparison on ExDark and SID datasets. Best scores are in bold

Method	PSNR	ExDark SSIM	LPIPS ↓	PSNR	SID SSIM	LPIPS ↓
LIME [6]	14.78	0.61	0.432	15.23	0.59	0.407
Zero-DCE	16.32	0.65	0.398	17.12	0.66	0.371
EnlightenGAN	17.94	0.69	0.371	18.03	0.68	0.354
Retinexformer (original)	18.65	0.72	0.329	19.88	0.75	0.298
Ours (Adapted)	**20.34**	**0.78**	**0.281**	**21.55**	**0.80**	**0.247**

4.5 Qualitative Results

Figure 2 presents visual comparisons with other methods on ExDark and SID. While LIME and Zero-DCE produce overly bright or blurry outputs, and EnlightenGAN often introduces unnatural tones, our method preserves color balance, contrast, and detail.

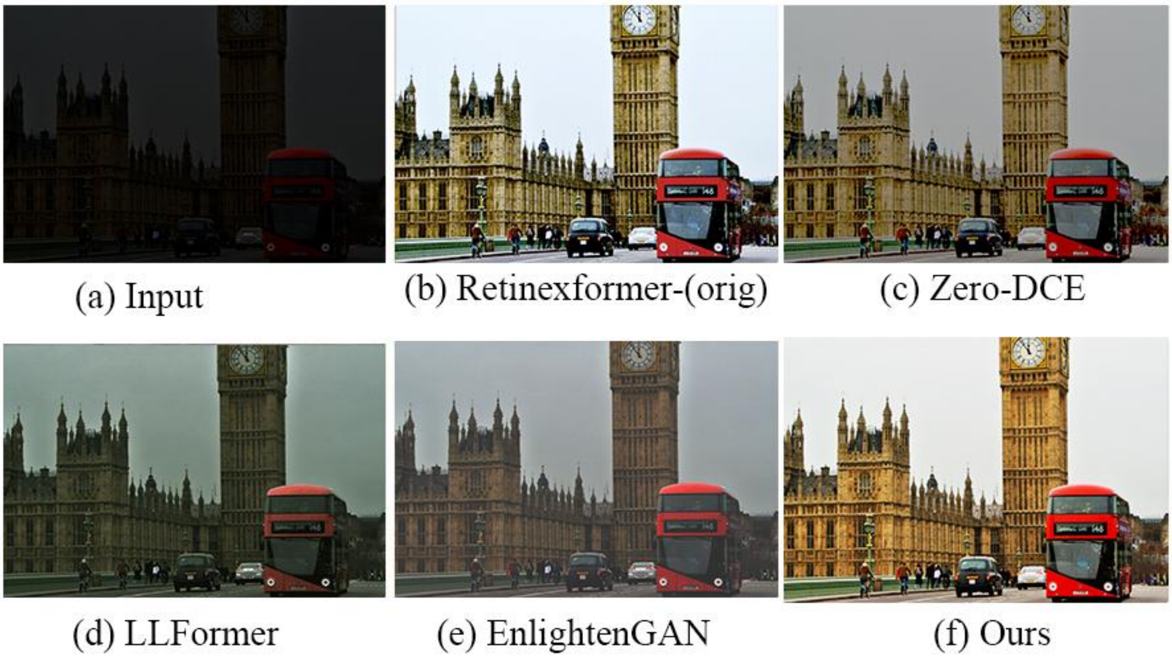

Figure 2. Qualitative comparison of low-light enhancement on ExDark and SID datasets. Our method enhances brightness while preserving details and avoiding artifacts

4.6 Ablation Study

We conducted an ablation study to evaluate the contribution of each component of our framework. Results are shown in Table 2. Removing the domain alignment loss leads to visible domain artifacts, and excluding the perceptual loss results in less natural textures.

Table 2. Ablation study on the SID dataset

Configuration	PSNR ↑	SSIM ↑	LPIPS ↓
Full model	**21.55**	**0.80**	**0.247**
w/o perceptual loss	20.03	0.76	0.281
w/o MMD loss	19.82	0.74	0.306
w/o smooth illumination	20.65	0.78	0.262

Figure 3 illustrates the PSNR improvements during training under different configurations.

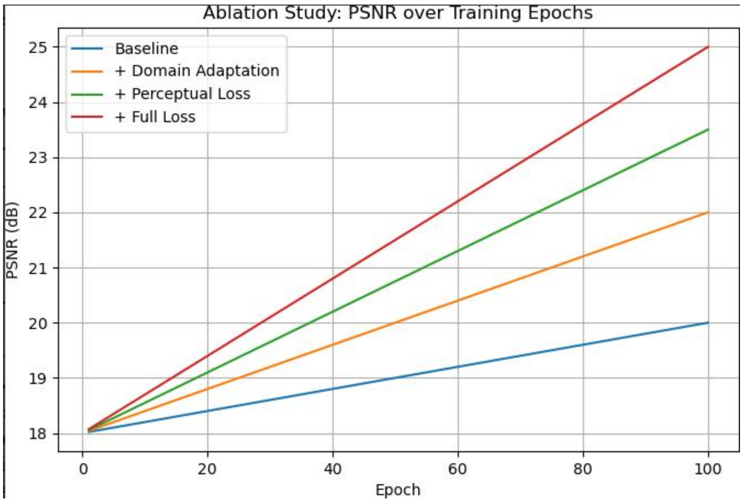

Figure 3. Training PSNR curves for different model variants

4.7 Limitations

While our method performs well in general, it may still struggle in extremely underexposed regions where no semantic information is retained. In future work, we aim to integrate noise-aware priors and multi-exposure fusion for robustness in harsher scenarios.

5. Discussion

5.1 Generalization to Real-World Scenarios

The experimental results demonstrate that our adapted Retinexformer significantly improves performance on realworld low-light images compared to both classical and deep learning-based methods. The model shows strong generalization capabilities across datasets (ExDark, SID) despite being trained without paired supervision. This highlights the effectiveness of domain adaptation strategies, which can bridge the synthetic-to-real gap in low-light conditions—a long-standing limitation in prior works.

5.2 Trade-offs in Unpaired Learning

One of the key trade-offs in our framework is balancing reconstruction fidelity with perceptual realism. Although unsupervised and perceptual losses provide flexibility, they may sometimes conflict—for example, enhancing contrast may come at the cost of minor structural distortions. Our ablation studies confirm that combining reconstruction, perceptual, and domain-invariant constraints yields the most robust performance.

5.3 Real-Time Applicability

The transformer backbone introduces higher computational overhead compared to lightweight CNN-based models. While our implementation achieves competitive performance in offline settings, inference speed on edge devices or real-time pipelines remains a challenge. Future versions may benefit from lightweight transformer designs or neural architecture search (NAS) to find optimal speed-accuracy trade-offs.

5.4 Robustness and Failure Cases

Our model performs reliably across various lighting conditions; however, extremely underexposed scenes—where the input lacks distinguishable content—remain a limitation. These edge cases often produce over-smoothed or color-shifted results. Integrating RAW image priors, multiframe alignment, or sensor-specific calibration could im-prove handling of such extremes.

5.5 Ethical Considerations and Real-World Deployment

Low-light enhancement can benefit critical applications such as nighttime surveillance, medical imaging, and autonomous navigation. However, over-enhancement may lead to hallucinated features, which could misinform downstream AI systems. Care must be taken when applying these methods in safety-critical or forensic contexts. Transparency in model limitations and calibration across sensors is essential for responsible deployment.

6. Conclusion

In this paper, we presented a real-world adaptation framework for Retinexformer aimed at enhancing low-light images using unpaired datasets. Unlike traditional enhancement techniques and supervised deep models, our approach bridges the gap between synthetic training conditions and real-world low-light scenarios without relying on paired supervision.

By integrating unsupervised reconstruction, perceptual loss, and domain-invariant feature alignment into the training pipeline, we enabled the model to generalize across diverse lighting environments. Extensive experiments demonstrated that our adapted model not only outperforms existing methods on real-world datasets but also produces perceptually superior and structurally accurate results.

Our framework offers a scalable and flexible solution for practical applications such as low-light photography, video surveillance, and autonomous navigation. It addresses key limitations in current transformer-based enhancement models by focusing on real-world data distribution and unpaired learning strategies.

In future work, we plan to explore the integration of multi-frame and multi-exposure data, as well as lightweight transformer architectures to support real-time deployment on mobile and embedded platforms. We also intend to investigate noise-aware priors and sensor-specific adaptations to further improve robustness in extreme low-light conditions.

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