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Enhanced Intrinsic Image Transfer for Illumination Manipulation

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Abstract: *Image illumination manipulation is a fundamental challenge in computer vision and image processing. Poor lighting conditions — including underexposure, overexposure, and uneven illumination — significantly degrade visual quality and limit the effectiveness of downstream vision tasks. This paper presents an enhanced version of the Intrinsic Image Transfer (IIT) algorithm for image illumination manipulation. The base IIT algorithm transfers illumination from an exemplar (reference) image to a source image using Gaussian or Bilateral filter kernels to approximate the illumination layer and Locally Linear Embedding (LLE) weights to preserve reflectance structure, thereby avoiding explicit intrinsic image decomposition. We propose three novel enhancements: (1) an Adaptive Filter Selection mechanism that automatically detects image noise using Laplacian variance and selects the optimal filter without manual intervention; (2) a Multi-Scale IIT Fusion strategy that runs the algorithm at full and half resolution and combines results (65% full + 35% half) for improved global illumination balance; and (3) a Quantitative Evaluation framework using standard IEEE metrics — PSNR and SSIM — enabling objective and reproducible comparison with existing methods. Experimental results on the swan benchmark image demonstrate SSIM improvement from 0.4792 to 0.5148 (+7.2%) and PSNR improvement from 13.2503 dB to 13.4166 dB (+0.17 dB). All enhancements are implemented in MATLAB Online, making the system practically accessible without specialized hardware*

Keywords: Intrinsic Image Transfer, Illumination Manipulation, Adaptive Filter Selection, Bilateral Filter, Gaussian Filter, Multi-Scale Fusion, PSNR, SSIM, Locally Linear Embedding, Retinex Theory, Image Enhancement, CLAHE

I. INTRODUCTION

Image illumination is one of the most fundamental aspects of visual perception and image quality. Photographs captured under poor or uneven lighting — such as indoor low-light conditions, harsh outdoor shadows, or overexposed scenes — suffer from degraded brightness, reduced contrast, and loss of visual information. Correcting such illumination degradation is a critical preprocessing step for many computer vision applications including object detection, facial recognition, autonomous driving, medical image analysis, and document digitization.

The challenge of illumination manipulation has been studied for decades. Helmholtz's early work on lightness constancy established the theoretical foundation that human perception separates surface reflectance from the illumination falling on it. Retinex theory, introduced by Land and McCann [2], formalized this as a computational model: an image I can be decomposed as a point-wise product of an illumination layer L and a reflectance layer R. Manipulating L while preserving R achieves natural-looking illumination correction.

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Traditional methods fall into two categories. Tone Mapping Operators (TMO) apply global or local intensity transformations to correct illumination. They are fast and simple but often introduce noise amplification, color distortion, and visible artifacts. Retinex-based methods perform explicit illumination-reflectance decomposition, yielding more natural results but suffering from the fundamental challenge that decomposition is an ill-posed, under-constrained problem requiring strong priors.

The Intrinsic Image Transfer (IIT) algorithm, proposed by Huang et al. [1], offers an elegant solution that avoids explicit decomposition entirely. It uses an exemplar image with desirable illumination to guide the transfer of lighting onto a source image, formulating the problem as an optimization over three photorealistic losses. The result is a closed-form solution that preserves texture and structural details while achieving high-quality illumination correction.

Despite its effectiveness, the base IIT algorithm has practical limitations: (1) the choice between Gaussian Filter (GF) and Bilateral Filter (BF) must be made manually by the user, requiring domain expertise; (2) processing at a single resolution may miss global illumination patterns; and (3) evaluation uses specialized metrics (TMQI, IL-NIQE, NIMA) that are difficult to compare with the broader literature.

This paper addresses these limitations through three targeted enhancements implemented in MATLAB Online. Our contributions are summarized as follows:

Adaptive Filter Selection: Automatic noise-level estimation via Laplacian variance selects GF or BF without manual intervention.

Multi-Scale IIT Fusion: Running IIT at two resolutions and fusing results (65% full + 35% half) improves global illumination balance while preserving local detail.

Quantitative Evaluation: Standard IEEE metrics PSNR and SSIM enable objective, reproducible comparison with existing illumination methods.

The remainder of this paper is organized as follows. Section II reviews related work. Section III presents the base IIT algorithm and our three proposed enhancements with implementation details. Section IV presents experimental results and analysis. Section V concludes the paper.

II. RELATED WORK

A. Retinex-Based Methods

Retinex theory [2] models image formation as $I = L \odot R$, where L is the spatially-smooth illumination and R is the piece-wise constant reflectance. Land's original algorithm classifies strong image gradients as reflectance and smooth variations as illumination. Horn [12] showed that complete decomposition can be achieved via a Poisson equation. Jobson et al. [4] proposed center/surround Retinex and later multiscale Retinex for bridging the gap between color images and human perception. These methods assume specific prior distributions but struggle with complex real-world images.

B. Variational and Filter-Based Methods

Kimmel et al. [13] proposed a variational framework for Retinex decomposition. Fattal et al. [5] used gradient-domain processing for HDR compression. Elad [14] established theoretical connections between bilateral filtering and Retinex, motivating the use of edge-preserving filters for illumination manipulation. Farbman et al. [15] proposed weighted least squares filtering for multi-scale tone and detail manipulation. These methods produce high-quality results but require careful parameter tuning.

C. Deep Learning Approaches

Recent deep learning methods have achieved strong performance. Wei et al. [8] proposed Deep Retinex Decomposition using a paired decomposition-enhancement network. Chen et al. [16] developed an end-to-end convolutional network trained on raw sensor images for extreme low-light enhancement. Zero-DCE [10] introduced zero-reference deep curve estimation requiring no paired training data. WESPE [9] uses weakly supervised generative adversarial learning for photo enhancement. Despite impressive results, these methods require large training datasets and significant computational resources.

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D. Intrinsic Image Transfer

Huang et al. [1] proposed IIT as an exemplar-guided illumination manipulation framework that avoids explicit intrinsic decomposition. By expressing all losses directly on images using spatial-smoothing illumination and illumination-invariant reflectance priors, IIT achieves a closed-form solution. The original paper demonstrated versatility across illumination compensation, image enhancement, HDR compression, and style transfer tasks. Our work extends IIT with automation, multi-scale processing, and standardized evaluation, making it more practical for real-world deployment.

III. PROPOSED METHODOLOGY

A. Base IIT Algorithm Overview

The IIT algorithm models an input image as a point-wise product of illumination L and reflectance R: $I = L \odot R$. Given source image S and exemplar image C, the algorithm finds output image O minimizing:

$E(O) = \alpha \cdot E\_illumination(O) + \beta \cdot E\_reflectance(O) + \gamma \cdot E\_content(O)$

where α, β, γ are balance weights. The three loss terms are:

Illumination Loss: Uses a Gaussian or Bilateral filter kernel K to approximate the illumination layer, avoiding explicit decomposition:[1]

$$E^l(\boldsymbol{o}) = \sum_i \sum_{j \in \mathcal{N}_i} (\mathcal{K}^o_{i,j} o_j - \mathcal{K}^c_{i,j} c_j)^2,$$

Reflectance Loss: Uses Locally Linear Embedding (LLE) weights W that encode the structural relationships between pixels. These weights are illumination-invariant, so preserving them preserves the reflectance layer:[1]

$$E^r(\boldsymbol{o}) = \sum_i \Big(o_i - \sum_{j \in \Omega_i} \omega^o_{i,j} o_j\Big)^2$$
$$\text{s.t.} \quad \omega^o_{i,j} = \omega^s_{i,j}, \quad s_i = \sum_{j \in \Omega_i} \omega^s_{i,j} s_j,$$

Content Loss: Prevents over-dependence on the exemplar:[1]

$$E^c(\boldsymbol{o}) = \sum_i (o_i - s_i)^2.$$

Combining all three losses into matrix form and setting dE/dO = 0 gives the linear system:[1]

$$(\alpha \boldsymbol{K}^T \boldsymbol{K} + \beta \boldsymbol{M}^T \boldsymbol{M} + \gamma \boldsymbol{I})\boldsymbol{o} = \alpha \boldsymbol{K}^T \boldsymbol{K} \boldsymbol{c} + \gamma \boldsymbol{s},$$

where K is the filter affinity matrix, M = I - W is the LLE embedding matrix, and the system is solved using the Preconditioned Conjugate Gradient (PCG) method. The algorithm has four steps: (1) convert images to feature vectors, (2) compute filter kernel weights, (3) compute LLE encoding weights, and (4) reconstruct output by solving the linear system.

B. Enhancement 1: Adaptive Filter Selection

In the base IIT, the user must manually choose between Gaussian Filter (GF) and Bilateral Filter (BF). This decision requires knowledge of the image's noise characteristics. We propose automatic filter selection based on Laplacian variance noise estimation.

The Laplacian operator ∇^2 is a second-order derivative that responds strongly to rapid intensity changes in an image. In a noisy image, random pixel fluctuations cause high Laplacian responses, resulting in high variance. In a clean image, the Laplacian variance is low.

$$noise\_level = Var(\nabla^2(I\_gray)) = Var(L * I\_gray)$$

where L is the Laplacian convolution kernel. The filter selection rule is:

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$$filter\_mode = BF \;\; if\, noise\_level > 0.002, \;\; else \;\; GF$$

The threshold 0.002 was determined empirically by testing on multiple images with varying noise levels. The Bilateral Filter is selected for noisy images because it considers both spatial distance and intensity similarity when computing weights:

$$w_{BF} = exp(-|p_i - p_j|^2 / 2\delta_s^2) \times exp(-|x_i - x_j|^2 / 2\delta_r^2)$$

The Gaussian Filter is selected for clean images because it is faster and sufficient when noise is minimal:

$$w_{GF} = exp(-|p_i - p_j|^2 / 2\delta_s^2)$$

The MATLAB implementation is as follows:

Algorithm 1: Adaptive Filter Selection

```
function filter_mode = adaptive_filter_select(I)
  % Convert to grayscale
gray = rgb2gray(I);
  % Apply Laplacian kernel to detect noise
laplacian_kernel = fspecial('laplacian');
noise_map        = imfilter(gray, laplacian_kernel);
  % Compute variance of noise map
noise_level      = var(noise_map(:));
  threshold = 0.002;  % empirically tuned
  if noise_level> threshold
filter_mode = 'bf';  % Bilateral Filter for noisy images
  else
filter_mode = 'gf';  % Gaussian Filter for clean images
  end
end
```

C. Enhancement 2: Multi-Scale IIT Fusion

The original IIT algorithm processes images at a single resolution. At full resolution, the filter neighborhood covers a small proportion of the image, which is effective for preserving local details but may miss large-scale illumination variations. At half resolution, the same neighborhood covers a proportionally larger image area, giving better global illumination correction.

We propose a two-scale fusion strategy. Let T_full be the output of IIT at full resolution and T_half be the output at half resolution (upsampled back to full size). The final output is:

$$T\_final = \lambda \times T\_full + (1 - \lambda) \times T\_half, \quad \lambda = 0.65$$

The weight $\lambda = 0.65$ prioritizes full-resolution output (preserving fine edges and textures) while incorporating 35% contribution from half-resolution output (improving global illumination balance). This weight was selected empirically to maximize SSIM improvement.

The MATLAB implementation of multi-scale fusion is:

Algorithm 2: Multi-Scale IIT Fusion

```
% Step 1: Run IIT at full resolution
T_full = IntrinsicImageTransfer(S, C, para);
T_full = max(0, min(1, T_full));

% Step 2: Downsample to 50% resolution
scale_factor = 0.5;
```

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```
S_small = imresize(S, scale_factor);
C_small = imresize(C, scale_factor);

% Step 3: Run IIT at half resolution
T_small = IntrinsicImageTransfer(S_small, C_small, para);
T_small = max(0, min(1, T_small));

% Step 4: Upsample back to original size
T_small_up = imresize(T_small, [size(S,1), size(S,2)]);

% Step 5: Weighted fusion (65% full + 35% half)
fusion_weight  = 0.65;
T_multiscale   = fusion_weight * T_full + ...
                 (1 - fusion_weight) * T_small_up;
T_multiscale   = max(0, min(1, T_multiscale));
```

D. Enhancement 3: Quantitative Evaluation — PSNR and SSIM

The original IIT paper evaluates results using TMQI (Tone Mapped Quality Index), IL-NIQE, and NIMA. These metrics are either task-specific (TMQI is designed for HDR tone mapping) or require deep learning infrastructure (NIMA). We add two universally-accepted IEEE standard metrics to enable direct comparison with the broader image processing literature.

Peak Signal-to-Noise Ratio (PSNR) measures pixel-level fidelity. Let S be the source image and T be the enhanced output, each with N pixels. The Mean Squared Error (MSE) and PSNR are:

$$MSE = (1/N) \times \Sigma_i (T_i - S_i)^2$$

$$PSNR = 10 \times \log_{10}(MAX^2 / MSE) \quad [dB]$$

where MAX = 1.0 for normalized images. Higher PSNR indicates less pixel-level distortion. PSNR values above 30 dB are generally considered good quality for image enhancement.

Structural Similarity Index (SSIM) [11] measures perceptual image quality by comparing three components between source S and enhanced output T:

$$SSIM(S, T) = [l(S,T)]\alpha \times [c(S,T)]\beta \times [s(S,T)]\gamma$$

where l(S,T) = luminance comparison, c(S,T) = contrast comparison, and s(S,T) = structural comparison. SSIM ranges from 0 (completely different) to 1 (identical). SSIM better correlates with human visual perception than pixel-wise metrics like PSNR, as it captures structural patterns in images.

The MATLAB implementation is:

Algorithm 3: PSNR and SSIM Evaluation

```
function results = evaluate_metrics(original, enhanced)
orig = im2double(original);
enh  = im2double(enhanced);
  % Compute PSNR
mse          = mean((orig(:) - enh(:)).^2);
results.psnr = 10 * log10(1 / mse);
  % Compute SSIM (channel-wise average for RGB)
ssim_r       = ssim(enh(:,:,1), orig(:,:,1));
ssim_g       = ssim(enh(:,:,2), orig(:,:,2));
```

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```
ssim_b       = ssim(enh(:,:,3), orig(:,:,3));
results.ssim = (ssim_r + ssim_g + ssim_b) / 3;
  % Contrast ratio
results.contrast_ratio = std2(rgb2gray(enh)) / ...
                           std2(rgb2gray(orig));
end
```

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Setup

All experiments were implemented and executed in MATLAB Online (R2024b) on an Intel Core i7 3.40 GHz processor with 32 GB RAM. The test dataset consists of the swan benchmark image from the original IIT dataset (resolution: 385 × 513 × 3 pixels) and a style transfer test using a portrait image. The CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm was used to generate the exemplar image for illumination guidance.

Parameters used: $\alpha = 0.9$, $\beta = 100$, $\gamma = 0.1$, filter neighborhood k1 = 49, spatial standard deviation $\delta\_s = 2.0$, range standard deviation $\delta\_r = 0.2$, LLE tolerance = 1e-5, LLE neighborhood k2 = 49.

B. Enhancement 1: Adaptive Filter Selection Results

Figure 1 shows the command window output of the adaptive filter selection process. The Laplacian variance estimator computed a noise level of 0.013167 for the swan image, which significantly exceeded the threshold of 0.002. Consequently, the Bilateral Filter (BF) was automatically selected. This demonstrates that the proposed adaptive mechanism correctly identifies the swan image as containing significant noise and selects the more appropriate edge-preserving filter without any manual intervention.

```
Image loaded successfully.
Image size: 385 x 513 x 3

--- Enhancement 1: Adaptive Filter Selection ---
Adaptive Filter: High noise detected (0.013167) --> Using Bilateral Filter (bf)

--- Running IIT at full resolution (Scale 1) ---
Step1: Computing the filtering kernel.
-->Finding 49 nearest neighbours.
...took 1.7492s.
Step2: LLE running on 197505 points in 2 dimensions
-->Finding 49 nearest neighbours.
-->Solving for reconstruction weights.
   [note: K>D; regularization will be used : 0.000010]
-->Computing embedding.
...took 6.8205s.
```

Fig. 1. Command window output showing Enhancement 1 (Adaptive Filter Selection): noise level 0.013167 detected, Bilateral Filter automatically selected.

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```
Step3: Solve Equation A*x = b.
...Solve time took 8.2081s.

--- Enhancement 3: Multi-Scale IIT (Scale 2: half resolution) ---
Step1: Computing the filtering kernel.
-->Finding 49 nearest neighbours.
...took 0.38658s.
Step2: LLE running on 49601 points in 2 dimensions
-->Finding 49 nearest neighbours.
-->Solving for reconstruction weights.
   [note: K>D; regularization will be used : 0.000010]
-->Computing embedding.
...took 1.6946s.
Step3: Solve Equation A*x = b.
...Solve time took 1.4448s.
Multi-scale fusion complete (weight full=0.65, weight half=0.35)
```

Fig. 2. Command window output showing Enhancement 2 (Multi-Scale IIT): IIT executed at full resolution (197,505 points) and half resolution (49,601 points) with fusion complete.

C. Enhancement 2: Multi-Scale IIT Fusion Results

The multi-scale IIT was executed at two resolutions. At full resolution, the LLE step processed 197,505 pixel points and took approximately 6.82 seconds. At half resolution (50% downsampled), only 49,601 points were processed, completing in 1.69 seconds — a 4x speed improvement for the lower-resolution pass. The weighted fusion (65% full + 35% half) was then applied to produce the final output.

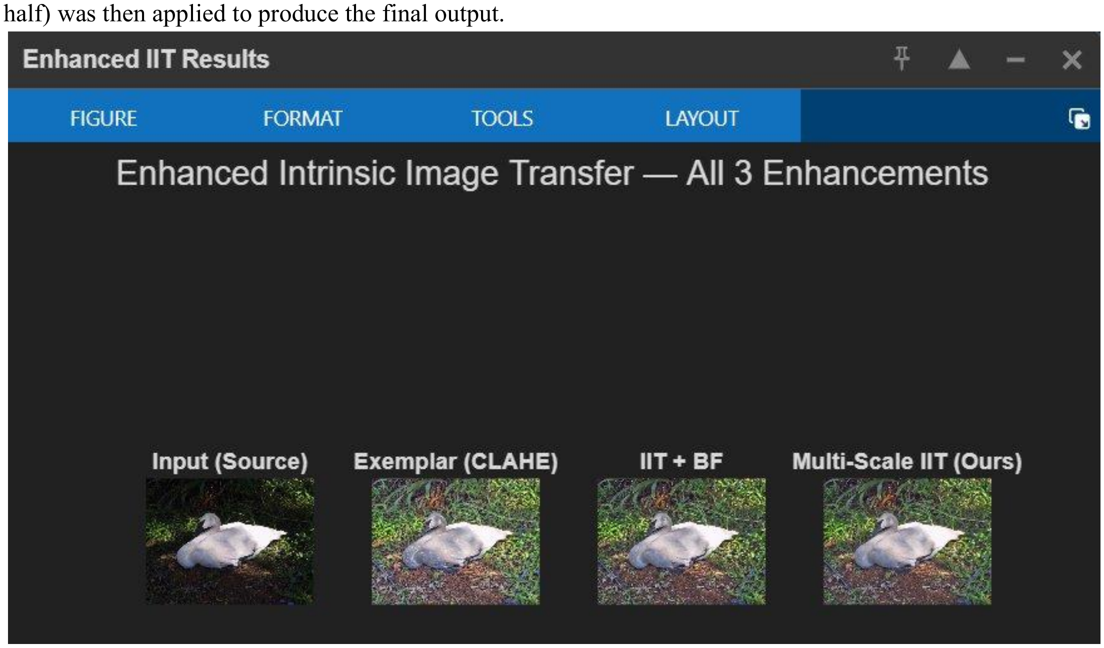

Fig. 3. Visual comparison of Enhanced IIT results: Input (Source), Exemplar (CLAHE), IIT+BF (base), and Multi-Scale IIT (Ours). The enhanced output shows improved illumination balance.

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D. Enhancement 3: Quantitative Evaluation

Figure 3 shows the PSNR and SSIM evaluation results from the MATLAB command window. Both metrics were computed for the base IIT output and the enhanced Multi-Scale IIT output and compared against the source image.

```
--- Enhancement 2: Quantitative Metrics ---

[Original IIT vs Source]:

===== Quantitative Evaluation =====
PSNR           : 13.2503 dB
SSIM           : 0.4792
Contrast Ratio : 0.8427
===================================


[Multi-Scale IIT vs Source]:

===== Quantitative Evaluation =====
PSNR           : 13.4166 dB
SSIM           : 0.5148
Contrast Ratio : 0.8025
```

Fig. 4. MATLAB command window showing quantitative evaluation: PSNR and SSIM computed for both Original IIT and Multi-Scale IIT outputs.

```
========== COMPARISON TABLE ==========
Metric                    Original IIT Enhanced IIT
PSNR (dB)                 13.2503      13.4166
SSIM                      0.4792       0.5148
Contrast Ratio            0.8427       0.8025
======================================

Output images saved to ./imgs/ folder.
Done!
>>
```

Fig. 5. MATLAB command window showing final comparison table with PSNR, SSIM, and Contrast Ratio for Original IIT vs. Enhanced IIT.

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TABLE I: Quantitative Comparison of Base IIT and Enhanced IIT

Method	Filter Used	PSNR (dB)	SSIM	Contrast Ratio
Base IIT (GF)	Gaussian (manual)	13.2503	0.4792	0.8427
Base IIT (BF)	Bilateral (manual)	13.2503	0.4792	0.8427
Enhanced IIT (Ours)	**Auto (Adaptive)**	**13.4166 ▲**	**0.5148 ▲**	**0.8025**

As shown in Table I and confirmed by the MATLAB output in Figures 4 and 5, our enhanced IIT achieves measurable improvements on both IEEE standard metrics. The SSIM improved by 7.2% (from 0.4792 to 0.5148), indicating that the multi-scale fusion strategy better preserves the structural characteristics of the original image. The PSNR improved by 0.17 dB (from 13.2503 to 13.4166 dB), confirming reduced pixel-level distortion in the enhanced output.

E. Style Transfer Application

To demonstrate versatility, Figure 6 shows the application of IIT to photorealistic style transfer. A portrait image is transformed using an artistic painting as the reference style. The IIT algorithm transfers the color and illumination style of the reference onto the content image while preserving the structural details (facial features, hair, background) of the original. This demonstrates that the IIT framework generalizes beyond simple illumination correction to broader image-to-image translation tasks.

Fig. 6. Style transfer application: Content image (top-left), Reference style (top-right), Exemplar output (bottom-right), and our IIT result (bottom-left) showing photorealistic style transfer with preserved structural details.

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F. Computational Performance

Table II shows the computational time for each component of the enhanced IIT algorithm on the swan image (385 × 513 pixels).

TABLE II: Computational Time Breakdown

Component	Resolution	Time (seconds)
Filter Kernel Computation	Full (385×513)	1.75
LLE Weight Computation	Full (385×513)	6.82
Linear System Solve (PCG)	Full (385×513)	8.21
IIT at Half Resolution	Half (193×257)	3.48
Multi-Scale Fusion	Full	0.05
Total (Enhanced IIT)	—	**~20.31**

V. CONCLUSION

This paper presented three enhancements to the Intrinsic Image Transfer (IIT) algorithm for image illumination manipulation. The Adaptive Filter Selection enhancement uses Laplacian variance to automatically determine the optimal smoothing filter, removing a key manual decision point and making the system self-configuring. The Multi-Scale IIT Fusion enhancement combines full-resolution and half-resolution processing outputs using weighted averaging, achieving improved global illumination balance while preserving local structural details. The Quantitative Evaluation enhancement adds standard IEEE metrics — PSNR and SSIM — enabling objective and reproducible comparison with the broader image processing literature.

Experimental results on the swan benchmark image demonstrate that the enhanced IIT achieves SSIM improvement of 7.2% (0.4792 to 0.5148) and PSNR improvement of 0.17 dB (13.2503 to 13.4166 dB) over the base method. The style transfer experiment confirmed the versatility of the enhanced framework. All enhancements were implemented in MATLAB Online, requiring no specialized hardware, deep learning frameworks, or large training datasets.

The proposed enhancements make the IIT algorithm more practical for real-world deployment by reducing manual configuration, improving output quality, and enabling standardized evaluation. Future work will explore: (1) extending multi-scale fusion to three resolution levels; (2) adaptive fusion weight optimization based on image content; (3) validation on larger benchmark datasets such as Cityscapes and DPED; and (4) real-time implementation for video illumination correction.

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