Project Proposal: Implementation and Extension of Deep Retinex Decomposition for Low-Light Image Enhancement

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Motivation & Problem

Low-light images suffer from low contrast, detail loss, and noise amplification, degrading both human perception and downstream vision tasks. Traditional enhancement (HE/CLAHE) and hand-crafted Retinex variants improve visibility but often introduce haloing, color shifts, or require scene-specific tuning. *Deep Retinex Decomposition for Low-Light Enhancement* (Wei *et al.*, BMVC 2018) proposes a data-driven Retinex formulation (Retinex-Net) that jointly decomposes an image into reflectance (R) and illumination (I), adjusts I, and denoises R. This project will (i) reproduce Retinex-Net faithfully with clear image-processing emphasis on the decomposition and smoothness priors, and (ii) extend it with classical, edge-preserving image-processing modules to strengthen interpretability and robustness.

Technical Approach

Retinex model. For source image S, $S = R \circ I$ (element-wise product). We implement two subnetworks:

- **Decom-Net** to obtain (R, I) using only key priors: (a) reflectance consistency across paired low/normal-light images and (b) structure-aware smoothness of I.
- **Enhance-Net** (encoder–decoder with skips) to brighten I while preserving global consistency and local contrast; reconstruction $\hat{S} = \hat{R} \circ \hat{I}$.

Losses (image-processing centric).

$$\mathcal{L}_{\text{recon}} = \sum_{i \in \{\text{low,normal}\}} \sum_{j \in \{\text{low,normal}\}} \lambda_{ij} \, \|R_i \circ I_j - S_j\|_1, \tag{1}$$

$$\mathcal{L}_{\text{ir}} = \|R_{\text{low}} - R_{\text{normal}}\|_1, \tag{2}$$

$$\mathcal{L}_{\text{is}} = \sum_i \Big(\|\nabla_h I_i \circ e^{-\lambda_g |\nabla_h R_i|}\|_1 + \|\nabla_v I_i \circ e^{-\lambda_g |\nabla_v R_i|}\|_1 \Big), \tag{3}$$

$$\mathcal{L}_{\text{enh}} = \|R_{\text{low}} \circ \hat{I} - S_{\text{normal}}\|_1 + \mathcal{L}_{\text{is}}(\hat{I}, R_{\text{low}}). \tag{4}$$

This emphasizes an *edge-aware* (structure-preserving) TV prior on I driven by R, a core image-processing contribution.

Planned Extensions (Image Processing Focus)

E1. Edge-preserving denoising on R. Evaluate BM3D, bilateral filter, guided filter, and wavelet shrinkage on $\hat{R}$ with illumination-aware strength (stronger in darker regions).
E2. Alternative structure-aware smoothness for I. Replace $e^{-\lambda_g|\nabla R|}$ with guidance from (i) guided filter weights, (ii) anisotropic diffusion conductance, or (iii) bilateral weights to study artifact suppression vs. structure retention.
E3. Photometric post-adjustments. Gamma curve on $\hat{I}$ and local contrast (DoG/unsharp mask) on $\hat{R}$ to control global brightness vs. micro-contrast.

Datasets & Evaluation

Data. LOL paired dataset (500 real pairs) for supervised constraints; optional synthetic augmentation following the paper's RAW-to-low-light protocol.
Baselines. HE, CLAHE, LIME; DeHz/NPE (if time permits).
Metrics. PSNR/SSIM (paired), NIQE/BRISQUE (no-reference), LPIPS (perceptual), and runtime. Visual assessment: artifacts (haloing/ringing), color fidelity, noise, edge sharpness.
Ablations. (i) Remove $\mathcal{L}_{\text{is}}$, (ii) swap I-smoothness variants (E2), (iii) denoiser choices (E1), (iv) multi-scale concat on/off in Enhance-Net.

Expected Outcomes

(i) High-quality enhancement with reduced artifacts and better interpretability via explicit (R, I); (ii) evidence that *edge-aware* I-smoothness and *illumination-aware* denoising on R materially improve quality; (iii) clear guidance for when classical image processing complements learned decomposition.

References

1. C. Wei, W. Wang, W. Yang, J. Liu. "Deep Retinex Decomposition for Low-Light Enhancement." *BMVC*, 2018.
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