Appendix

A. EXPERIMENTAL DETAILS

In this section, we present the experimental setup for each method. Our aim is to ensure consistency with the official settings for each baseline model while introducing the GT-mean loss to demonstrate its effectiveness. To ensure fair comparisons, both the baseline models and the ones using GT-mean loss were trained under identical hardware and software environments, minimizing the effects of randomness.

Uformer. Both the baseline and the GT-mean loss variant were trained following the experimental setup for motion deblurring in [3], selected Uformer-T as the backbone model. The Charbonnier loss used in the baseline was extended to GT-mean loss for the variant.

MIRNet. Both the baseline and the GT-mean loss variant were trained according to the settings used for the denoising task in [6]. In the GT-mean loss variant, the Charbonnier loss was replaced with the GT-mean loss.

RetinexFormer. For both the baseline and the GT-mean loss variant, we followed the training settings for LOL datasets in [1]. The L_1 loss used in the baseline was extended to GT-mean loss in the variant.

Restormer. The baseline and the GT-mean loss variant were both trained following the motion deblurring settings described in [7]. The L_1 loss in the baseline was extended to GT-mean loss in the variant.

LLFormer. Both the baseline and the GT-mean loss variant were trained according to the settings for the LOLv1 dataset described in [2]. The Smooth L_1 loss used in the baseline was extended to GT-mean loss for the variant.

SNR-Aware. The baseline and the GT-mean loss variant were both trained using the settings for for LOL datasets outlined in [4]. The Charbonnier loss and perceptual loss used in the baseline were extended to GT-mean loss in the variant.

CID-Net. Both the baseline and the GT-mean loss variant were trained using the LOLv1 settings described in [5]. In the GT-mean loss variant, the Charbonnier loss, edge loss, and perceptual loss were extended to GT-mean loss.

In summary, for each method, the original loss functions were extended to GT-mean loss, and all models were trained using consistent settings to ensure a fair comparison.

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