Clean Images are Hard to Reblur:
Exploiting the Ill-Posed Inverse Task for Dynamic Scene Deblurring

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ICLR

INTRO & BACKGROUND

Dynamic Scene Deblurring

Dynamic scenes contain various motion blurs:
moving objects, camera shake, depth variation, etc.

Blurry image (B) — Deblurring model $\mathcal{M}_{\mathrm{D}}$ — Deblurred image (L)

$$L = \mathcal{M}_{\mathrm{D}}(B)$$

How can we better optimize deblurring models?

Related Works: Loss Functions

Basic Optimization — L1 or MSE Loss

Compute L1 distance between output/target

$$L = \mathcal{M}_{\mathrm{D}}(B;\theta_{\mathrm{D}}) \longrightarrow \min_{\theta_{\mathrm{D}}} ||L - S||$$

θ_D: model parameters, S: sharp image

- Focuses on PSNR, color correctness [Tao et al., CVPR 2018]
- Tends to predict blurry solution [Gao et al., CVPR 2019]

Supervised Perception — VGG Loss

Compute feature distance between output/target

$$\min_{\theta_{\mathrm{D}}} ||L - S|| + \lambda ||\mathrm{VGG}(L) - VGG(S)||$$

- Uses visual recognition feature [Johnson et al., ECCV 2016]
- Better than L1, still not perfect [Kupyn et al., CVPR 2018; 2019]

Unsupervised Perception — Adversarial Loss

Joint optimization with L/S discriminator

$$\min_{\theta_{\mathrm{D}}} ||L - S|| + \lambda \mathcal{L}_{\mathrm{adv}}$$

- Tends to produce sharper texture [Nah et al., CVPR 2017]
- Artifacts are also introduced [Kupyn et al., CVPR 2018; 2019] [Zhang et al., CVPR 2020]

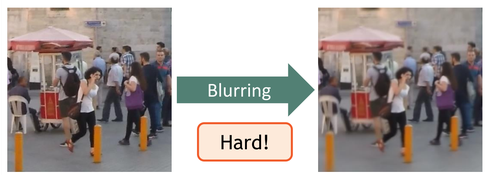
PROPOSED METHOD

Question We can remove motion blur from learning.
But can we also reconstruct true blur from a sharp image?

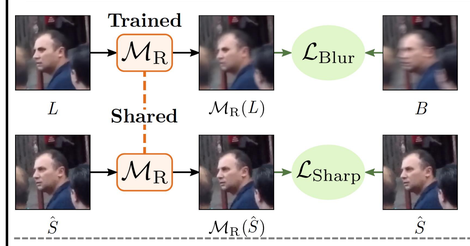
Observation: Clean Images are Hard to Reblur

Reblurring is Easy
Find the remaining blur information
Amplify to reconstruct the blur

Blurring is Hard
Find true motion among infinitely many possibilities

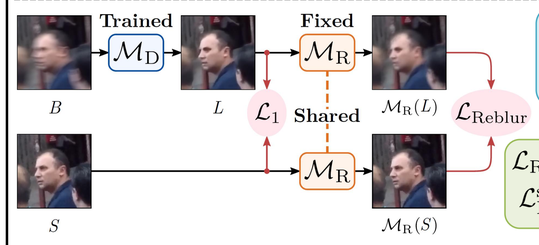


Supervised/Self-Supervised Reblurring Loss



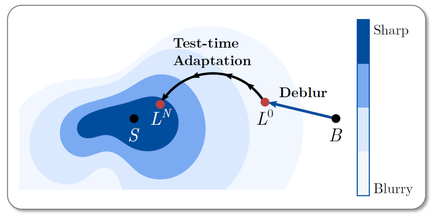
Train Reblurring Module
Find the remaining blur information
Amplify to reconstruct the blur

$$\mathcal{L}_{\mathrm{Blur}} = \|\mathcal{M}_{\mathrm{R}}(L) - B\|$$
$$\mathcal{L}_{\mathrm{Sharp}} = \|\mathcal{M}_{\mathrm{R}}(\hat{S}) - \hat{S}\|$$



Train Deblurring Module
Try to deblur image well
By making it hard to reblur

$$\mathcal{L}_{\mathrm{Reblur}} = \|\mathcal{M}_{\mathrm{R}}(L) - \mathcal{M}_{\mathrm{R}}(S)\|$$
$$\mathcal{L}^{\mathrm{self}}_{\mathrm{Reblur}} = \|\mathcal{M}_{\mathrm{R}}(L) - L\|$$

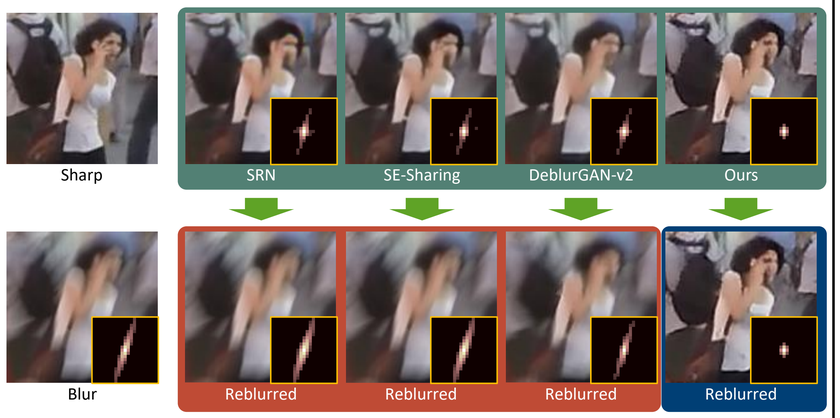


Self-supervised Adaptation

$L^0 = \mathcal{M}_{\mathrm{D}}(B)$.
for $i = 0 \ldots N-1$ **do**
  $L^i_* = \mathcal{M}_{\mathrm{D}}(B)$.
  $\mathcal{L}^{\mathrm{self}}_{\mathrm{reblur}} = \|\mathcal{M}_{\mathrm{R}}(\mathcal{M}_{\mathrm{D}}(B)) - L^i_*\|$.
  Update θ_{D} by $\nabla_{\theta_{\mathrm{D}}}\mathcal{L}^{\mathrm{self}}_{\mathrm{Reblur}}$ and μ.
$L^N = \mathcal{M}_{\mathrm{D}}(B)$.

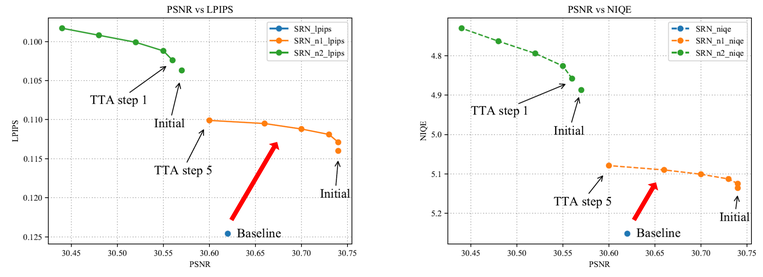
EXPERIMENTS

Qualitative Comparison w/ SoTA



Ablation: Reblurring Loss, Test-Time Adaptation

Perception-Distortion Trade-Off



Supervised Reblurring Loss improves PSNR vs LPIPS, NIQE trade-off
Self-Supervised Reblurring Loss puts more weight on perceptual quality