Image/Video Restoration Problems:

Brief Review

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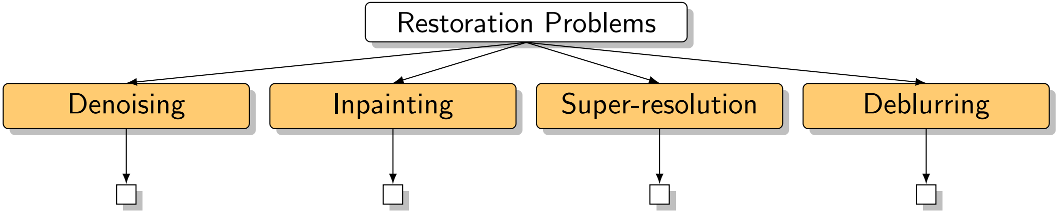
Video Computing Group

Types of Restoration Problems



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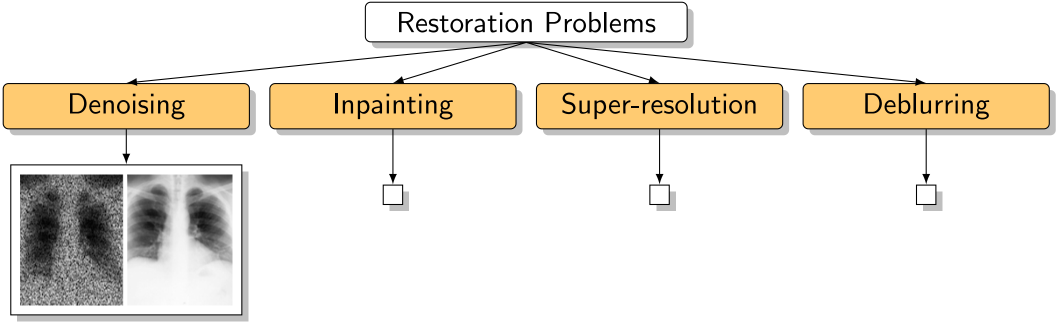
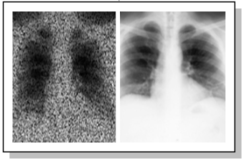


Types of Restoration Problems

- Restoration Problems
  - Denoising
  - Inpainting
  - Super-resolution
  - Deblurring



Types of Restoration Problems

Restoration Problems

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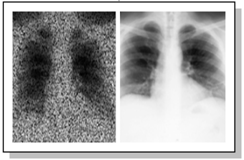
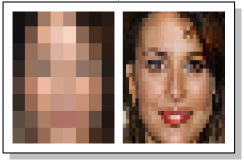


- Inpainting

- Super-resolution



- Deblurring

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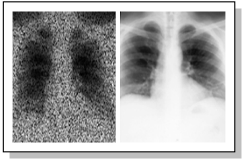
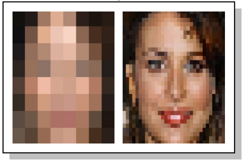


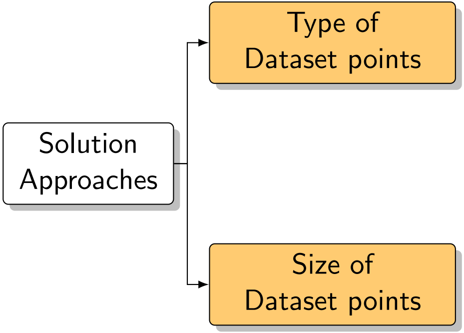
- Inpainting

- Super-resolution



- Deblurring

Categorisation of Approaches



[1] Dmitry Ulyanov et al. "Deep image prior". *CVPR*. 2018.

[2] Reinhard Heckel et al. "Deep Decoder: Concise Image Representations from Untrained Non-convolutional Networks". *ICLR*. 2019.

[3] Alexander Krull et al. "Noise2void-learning denoising from single noisy images". *CVPR*. 2019.

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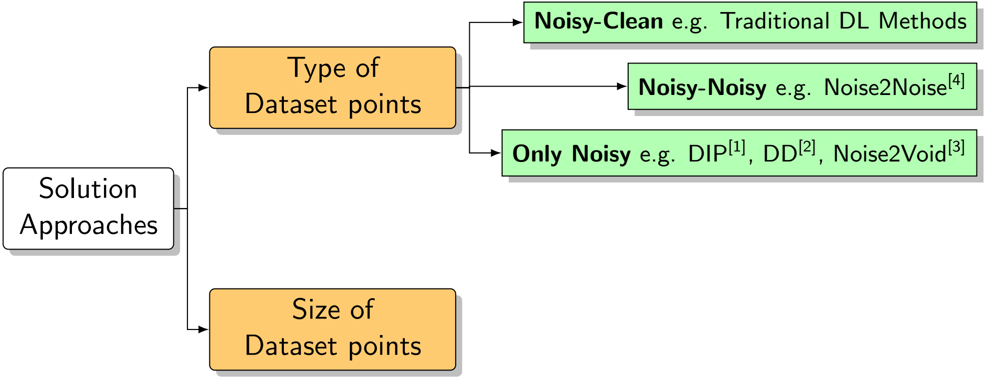

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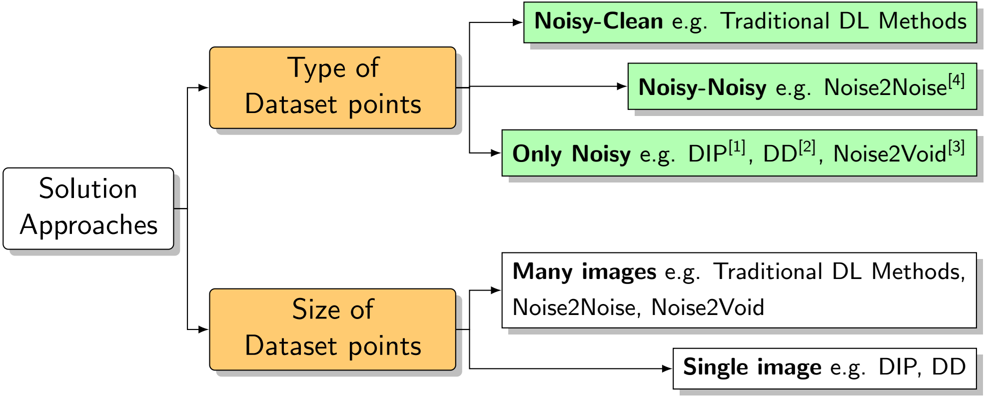

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Quick Overview of Loss Layers[5][6]

1. ℓ_2 norm
2. ℓ_1 norm
3. Structural SIMilarity Index (SSIM)
4. Perceptual Loss

- x : Reconstructed image
- y : Target image
- P : Patch of image
- N : # of pixels in P

Features of this loss function:

- $$\mathcal{L}^{\ell_2}(P) = \frac{1}{N} \sum_{p \in P} \|x(p) - y(p)\|_2$$
- ☺ Convex and differentiable–very convenient properties for optimization problems.
- ☹ Assumes (a) white Gaussian noise (b) impact of noise is independent of local characteristics. Results in blurry artifacts.

[5] Hang Zhao et al. "Loss functions for neural networks for image processing". *arXiv preprint arXiv:1511.08861* (2015).

[6] Justin Johnson et al. "Perceptual losses for real-time style transfer and super-resolution". *ECCV*. 2016.

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Features of this loss function:

- $$\mathcal{L}^{\ell_1}(P) = \frac{1}{N} \sum_{p \in P} |x(p) - y(p)|$$
- ☺ Retains more color information and brightness information compared to ℓ_2.
- ☹ Non-differentiable at 0: Set $\texttt{sign}(0) = 0$.

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Features of this loss function:

- $$\mathcal{L}^{\text{SSIM}}(P) = \frac{1}{N}\sum_{p \in P} 1 - \text{SSIM}(p), \quad \text{SSIM}(p) = \left(\frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}\right)\left(\frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}\right)$$
- $\mu_{(\cdot)}$ and $\sigma_{(\cdot)}$ are computed with a Gaussian filter.
- ☺ Preserves high frequency details.

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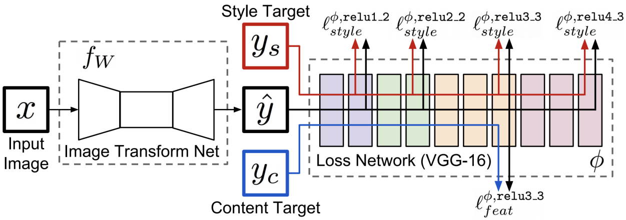

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Paper Overview:

I. Deep Decoder: Concise Image Representations from Untrained Non-convolutional Networks[2] (ICLR' 19)

II. Noise2Void-Learning Denoising from Single Noisy Images[3] (CVPR' 19)

III. Unconstrained Foreground Object Search[7] (ICCV' 19)

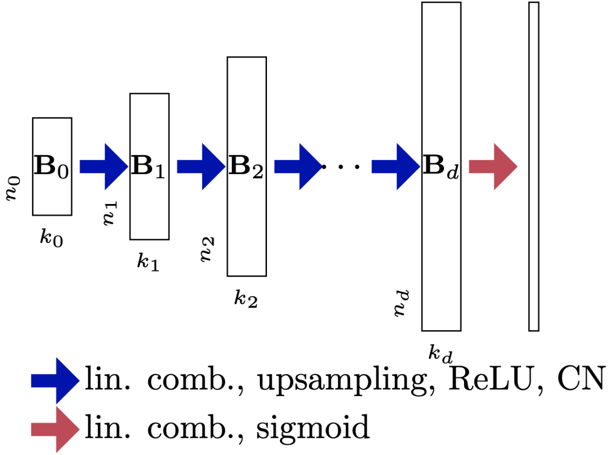
[2] Reinhard Heckel et al. "Deep Decoder: Concise Image Representations from Untrained Non-convolutional Networks". *ICLR*. 2019.

[3] Alexander Krull et al. "Noise2void-learning denoising from single noisy images". *CVPR*. 2019.

[7] Yinan Zhao et al. "Unconstrained Foreground Object Search". *ICCV*. 2019.

Paper Overview:

I. Deep Decoder: Concise Image Representations from Untrained Non-convolutional Networks (ICLR' 19)



Paper Overview:

I. Deep Decoder: Concise Image Representations from Untrained Non-convolutional Networks (ICLR' 19)

Deep Image Prior

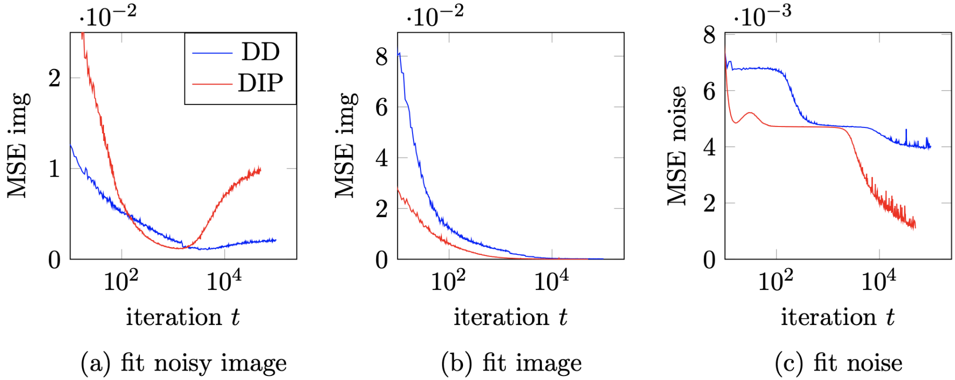
- Convolutional Network
- Over-parameterized
- Requires stopping criterion

Deep Decoder

- Non-Convolutional Network
- Under-parameterized
- Doesn't require stopping criterion

Paper Overview:

I. Deep Decoder: Concise Image Representations from Untrained Non-convolutional Networks (ICLR' 19)

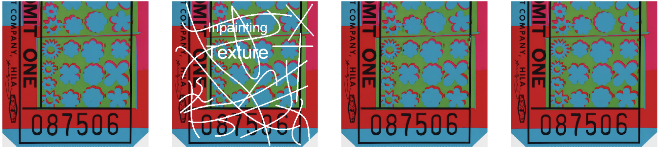


Paper Overview:

I. Deep Decoder: Concise Image Representations from Untrained Non-convolutional Networks (ICLR' 19)

original image	noisy image 19.1dB	DD 29.6dB	DIP 29.2dB	BM3D 28.6dB

(a) Denoising Result

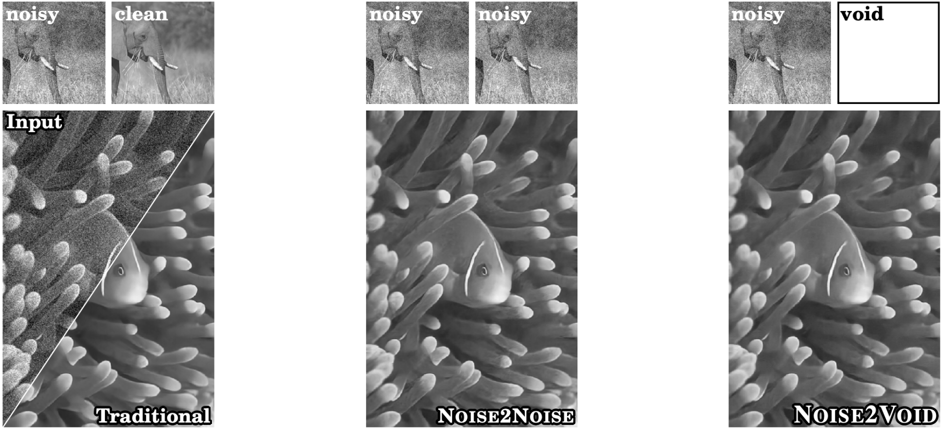


original image	noisy image 12.9dB	DD 33.6dB	DIP 35dB

(b) Inpainting Result

Paper Overview:

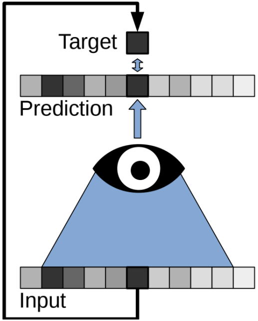
II. Noise2Void-Learning Denoising from Single Noisy Images (CVPR' 19)



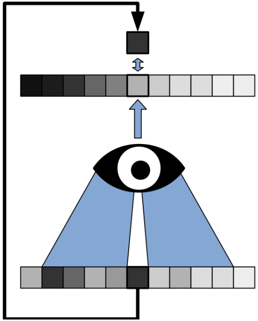
(a) Traditional Method (b) Noise2Noise (c) Noise2Void

Paper Overview:

II. Noise2Void-Learning Denoising from Single Noisy Images (CVPR' 19)



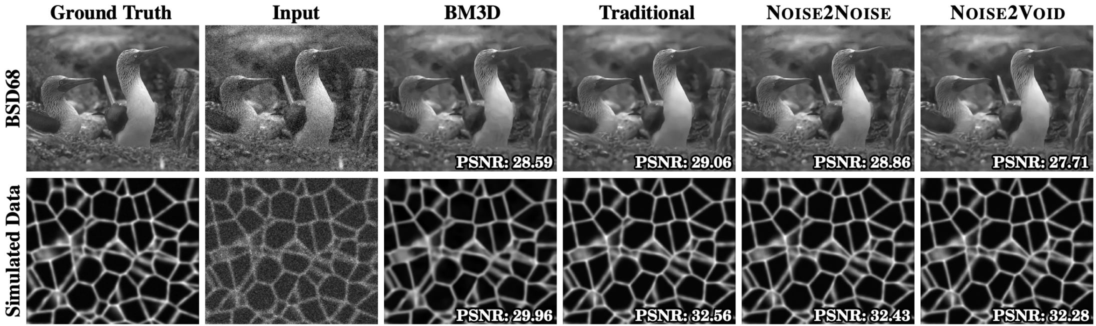
(a) Conventional Convolution



(b) Blind-spot convolution

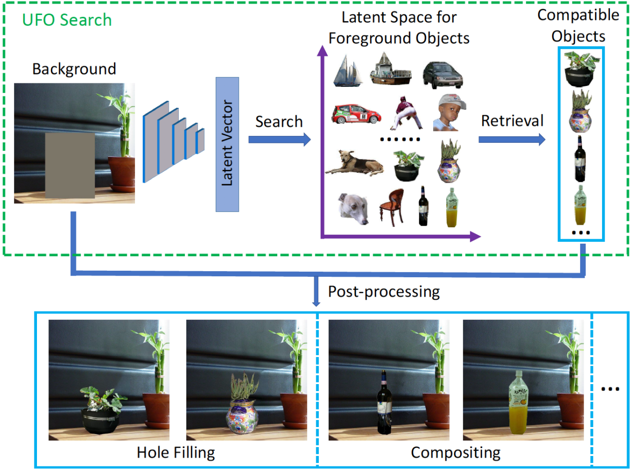
Paper Overview:

II. Noise2Void-Learning Denoising from Single Noisy Images (CVPR' 19)



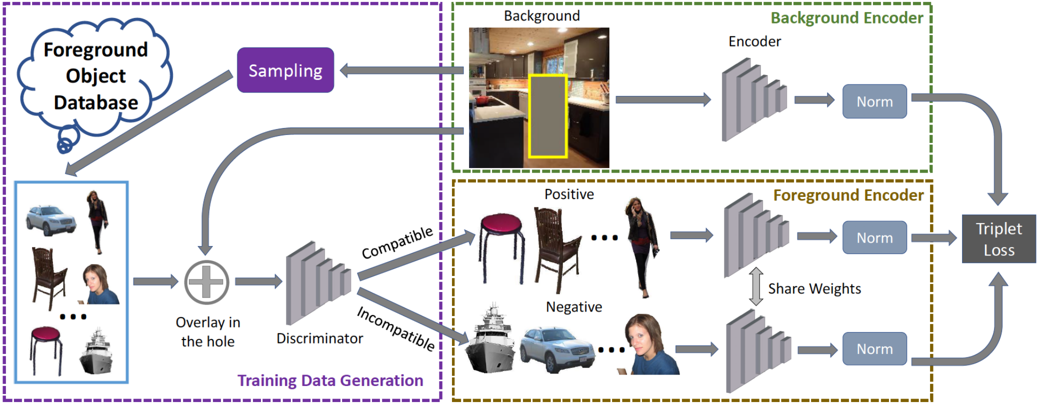
Paper Overview:

III. Unconstrained Foreground Object Search (ICCV' 19)



Paper Overview:

III. Unconstrained Foreground Object Search (ICCV' 19)



Paper Overview:

III. Unconstrained Foreground Object Search (ICCV' 19)

Paper Overview:

III. Unconstrained Foreground Object Search (ICCV' 19)

No Training

Regression

No D

D Only

UFO

Paper Overview:

IV. DAVID: Dual-Attentional Video Deblurring[8] (WACV' 19)

IIV. Reblur2Deblur: Deblurring Videos via Self-Supervised Learning[9] (ICCP' 19)

[8] Junru Wu et al. "DAVID: Dual-Attentional Video Deblurring". *WACV*. 2020.

[9] Huaijin Chen et al. "Reblur2deblur: Deblurring videos via self-supervised learning". *ICCP*. 2018.

Paper Overview:

IV. DAVID: Dual-Attentional Video Deblurring (WACV' 19)

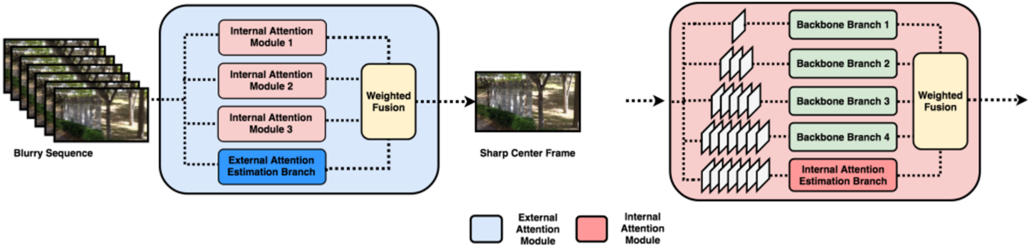


Figure 2. The overview of the proposed DAVID framework. Left: the structure of the external attention module. Right: the structure of the internal attention module. Each internal attention module is designed for a specific blur level. Each backbone branch in the same internal attention module works on a specific temporal scale.

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IV. DAVID: Dual-Attentional Video Deblurring (WACV' 19)

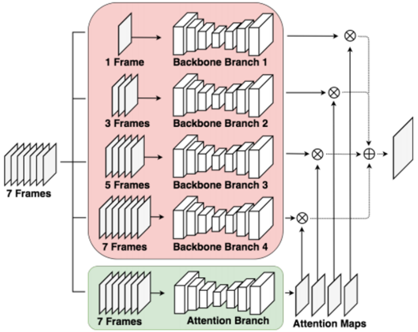

Figure 4. An internal-attentional module for DAVID.

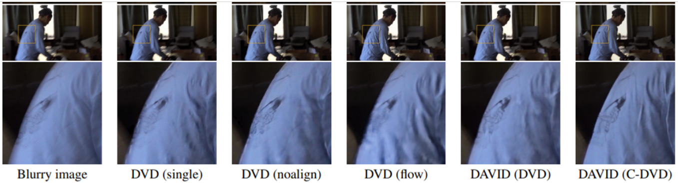

Figure 6. Visual result comparison on real blurry videos. The second and fourth rows depict enlarged local areas of the first and third rows, respectively, where blur artifacts could be most easily observed and compared around the boundary of the front fender (second row), and the texture on clothes (fourth row).

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Paper Overview:

V. Reblur2Deblur: Deblurring Videos via Self-Supervised Learning (ICCP' 19)

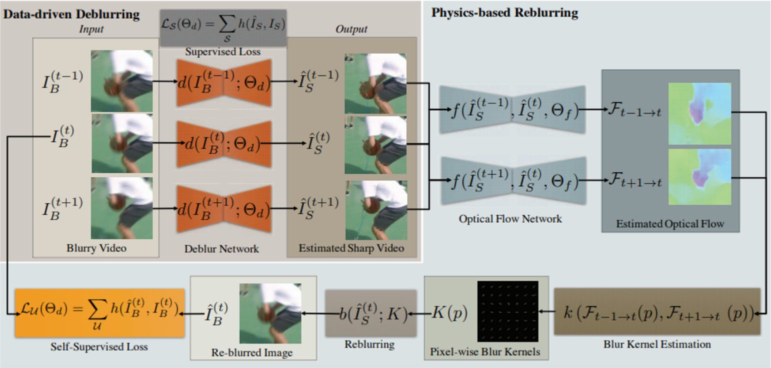

Figure 2. **System Overview**. Our proposed deblurring framework takes three consecutive blurry images as inputs. We first deblur each input image through the deblur network. After that, we compute the optical flow between the three recovered sharp images. We then estimate the per-pixel blur kernel and reconstruct the blurry input — this "reblurring" step offers an additional training signal for self-supervised learning to improve the deblur network and remove image artifacts.

Paper Overview:

V. Reblur2Deblur: Deblurring Videos via Self-Supervised Learning (ICCP' 19)

(a) Input (b) DVD [22] (c) DeblurGAN [13] (d) Proposed (e) Ground Truth

Figure 1. We propose a novel method for video motion deblur with self-supervised learning. Compared to prior method such as DVD [25] and DeblurGAN [13], we enforce a physics-based blur formation model during Deep Neural Network (DNN) learning, which effectively reduces image artifacts and improves generalization ability of DNN-based video deblurring.

Thank You!