Video Reconstruction From a Single Blurry Image

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Deep Learning Course (05107-25501)

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Motion Blur

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Rapid Dynamics

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- Caused by:
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  - Camera motion at the time of the acquisition.

Rapid Dynamics

Camera Motion

Motion Deblurring

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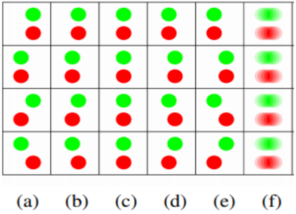
Blurry Input Sharp Output

Single Frame Deblurring Example

Deblurring Challenges

Deblurring Challenges

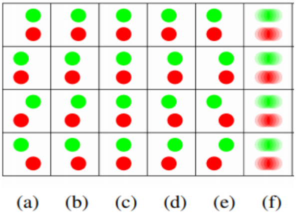
- Ambiguity.



Ambiguity

Deblurring Challenges

- Ambiguity.
- Unknown Blur kernel, generally shift-variant.



Ambiguity

Shift-Variant Kernel

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Blur Model Approximation

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- Blurry image $\approx$ mean of subsequent sharp frames:

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$$y = g(\frac{1}{T}\int_0^T \tilde{x}(t)dt) \approx g(\frac{1}{N}\sum_{i=1}^{N} x[i])$$

  - y: Blurry frame
  - g: Camera's CRF
  - T: Exposure time (blurry frame).
  - $\tilde{x}(t)$: Instantaneous irradiance.
  - $x[i]$: Sharp frame (captured at $\frac{N}{T}$ FPS).

Dataset Manipulation

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- REDS (REalistic and Dynamic Scenes [1]) dataset (30K frames, 720x1280, 120FPS).

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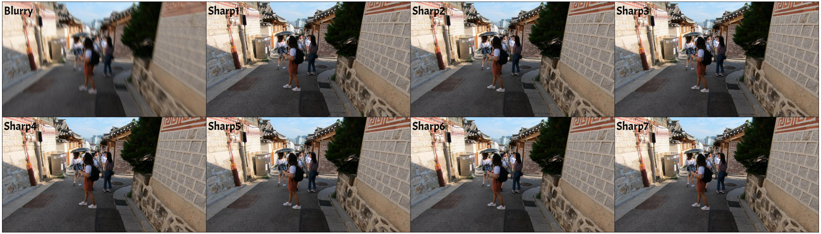

Gradual Learning

Gradual Learning

- Jin et al. [2]: 7 separate FCNs (1 CNN per restored sharp frame).

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- 1. $\hat{x}_4 = \phi_4(y)$
  2. $\hat{x}_3, \hat{x}_5 = \phi_3(\hat{x}_4, y),\ \phi_5(\hat{x}_3, \hat{x}_4, y)$
  3. $\hat{x}_i, \hat{x}_{8-i} = \phi_i(\hat{x}_{i+1}, \hat{x}_{i+2}, y),\ \phi_{8-i}(\hat{x}_{7-i}, \hat{x}_{6-i}, y), i \in 1, 2$

Computational Imaging

Computational Imaging

- Elmalem et al. [3]: Dynamically changing spatial phase-mask.

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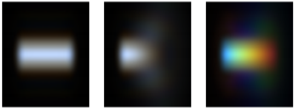
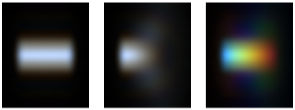
- Color coded PSF - direction and magnitude.



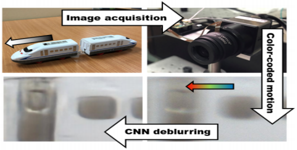
Blur PSF Simulation

Computational Imaging

- Elmalem et al. [3]: Dynamically changing spatial phase-mask.
- Color coded PSF - direction and magnitude.
- FCN post-processing.



Blur PSF Simulation



Motion Deblurring Procedure

Methods Fusion

Methods Fusion

- Goals:
  1. Simulate phase-masked blur on REDS dataset.
  2. Re-train Video-from-Image network with simulated data.

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- Goals:
  1. Simulate phase-masked blur on REDS dataset.
  2. Re-train Video-from-Image network with simulated data.
- Challenges:
  1. Generate blur simulations (standard and phase-masked).
  2. Implement training routine.
  3. Optimize hyper-parameters.
  4. Re-train network with standard and phase-masked blurred dataset.

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- **Input**: The blurry input frame.

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- **Re-trained (Standard)**: After re-training with standard-blur simulated dataset.
- **Re-trained (Masked)**: After re-training with phase-masked simulated dataset.

Image Quality Metrics

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- Diminished average accuracy in re-trained networks.

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Network	PSNR	SSIM
Pre-Trained	24.946	0.749
Re-trained (Standard)	24.602	0.72
Re-trained (Masked)	24.168	0.691

Qualitative Impression

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- Superior deblurring in re-trained networks (in most cases).

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- Superior deblurring in re-trained networks (in most cases).
- Masked re-training outperforms the standard (in some cases, ROIs).

Middle-Frame Reconstruction

Full Image

Middle-Frame Reconstruction

Zoomed In

Middle-Frame Reconstruction

Full Image

Middle-Frame Reconstruction

Zoomed In

Video Reconstruction

- Temporally-consistent feet and faces
- Sharp tiger stripes

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Questions

Questions?

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References

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