Light Stage Super-Resolution: Continuous High-Frequency Relighting

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[1]UC San Diego, [2]MIT, [3]Google, [4]Google Research

Overview

Overview

Portrait Acquisition

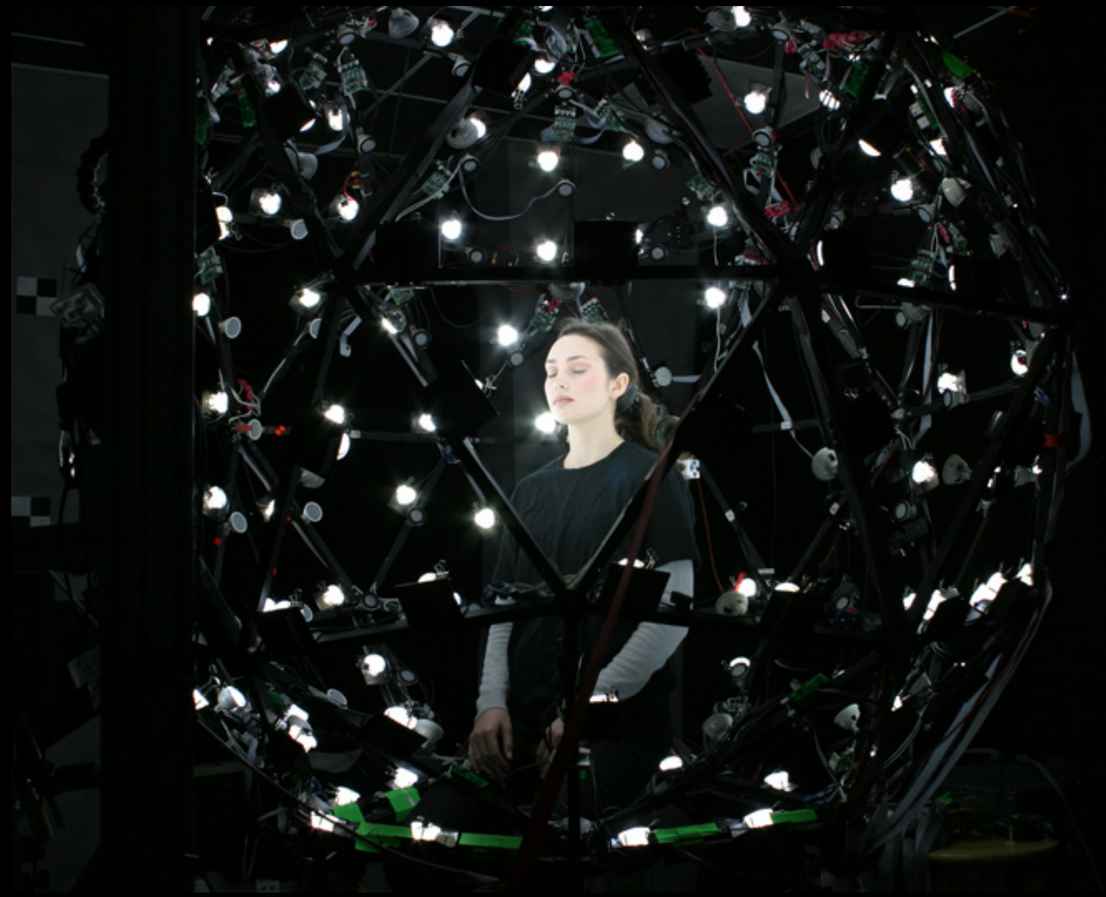
Overview

Portrait Acquisition

change lighting

Overview

Light Stage



change lighting

Overview

One-Light-At-a-Time scans (OLAT)

change lighting

Overview

- Light Stage:
  - Capture one-light-at-a-time (OLAT) image set with ~300 LEDs

Overview

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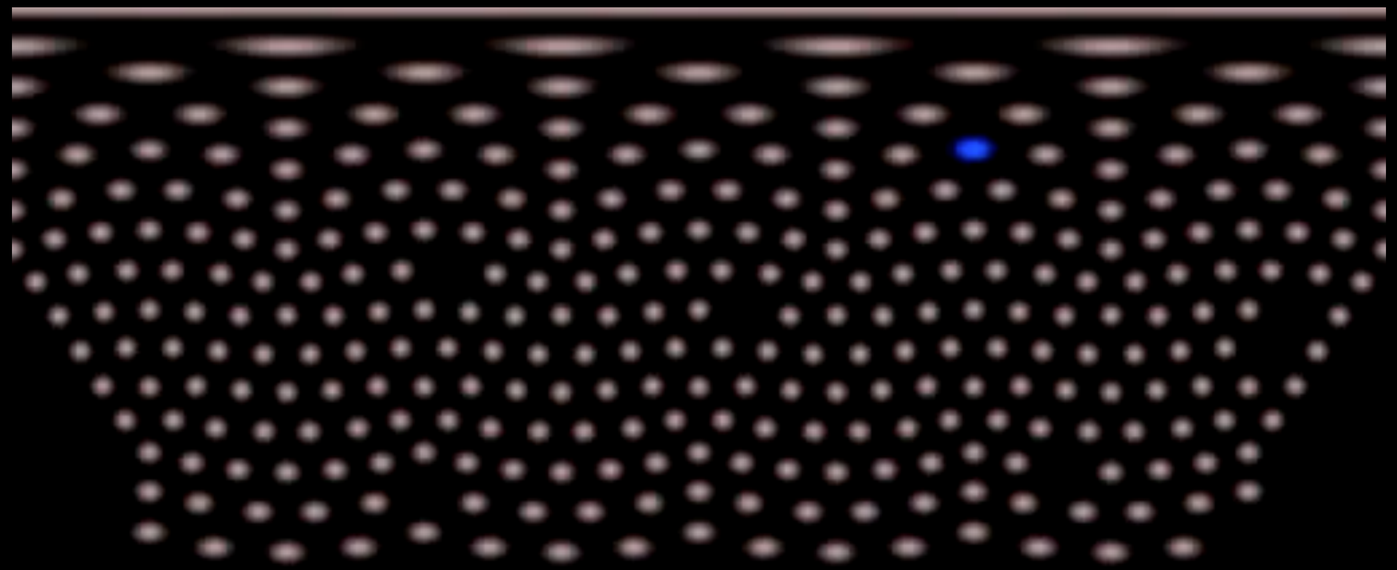
  - Capture one-light-at-a-time (OLAT) image set with ~300 LEDs



Lights on Light Stage

Captured Image

Overview

Overview

captured images under adjacent LEDs

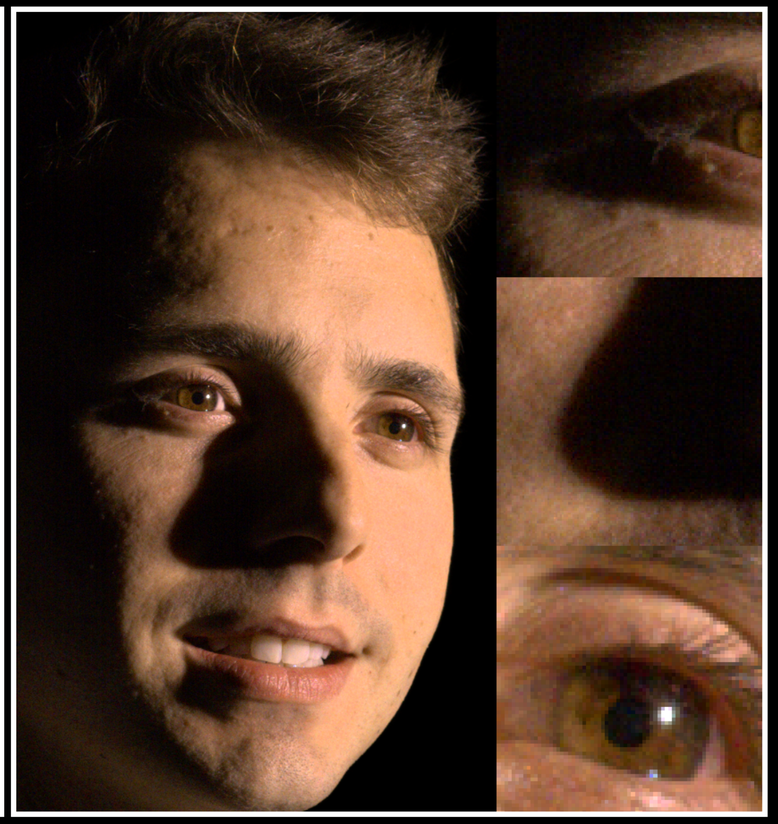
Overview

captured images under adjacent LEDs

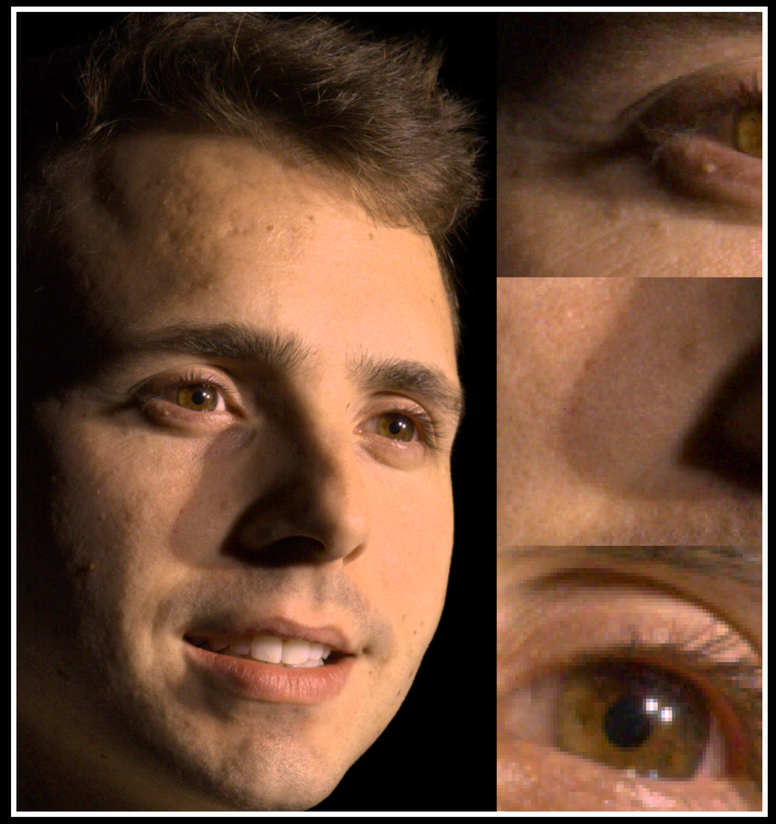
relit image

Overview

- Light samples still too sparse to capture all frequency



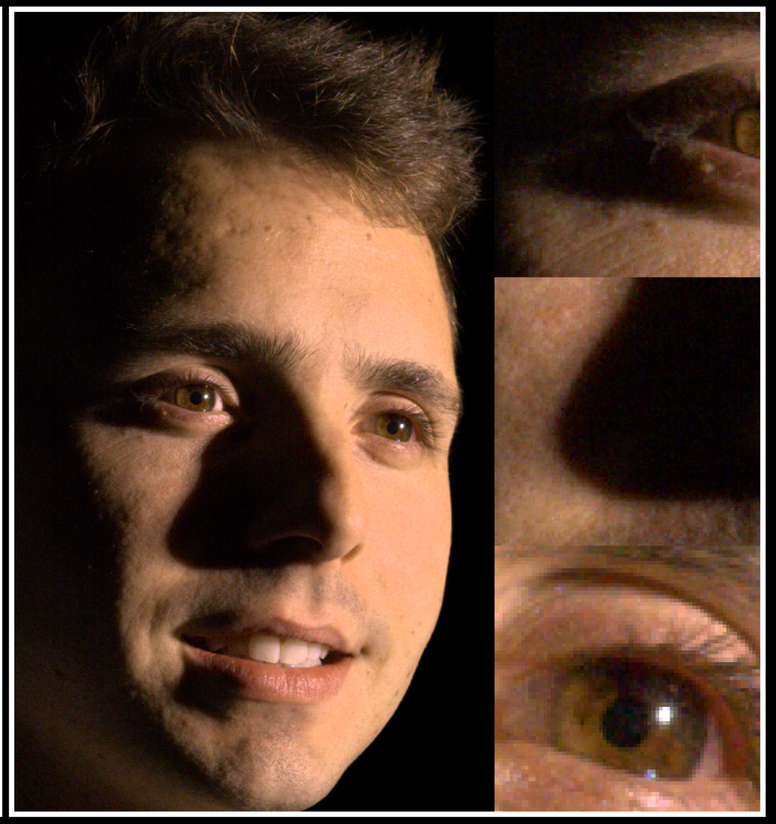
captured images under adjacent LEDs



relit image

Overview

- Light samples still too sparse to capture all frequency
- Goal: super-sample the LEDs on the light stage



captured images under adjacent LEDs

our result

Previous work

Previous work

- Single image portrait relighting

(a) Input image and estimated lighting

(b) Rendered images from our method under three novel illuminations

Sun, Tiancheng, et al. “Single Image Portrait Relighting." SIGGRAPH 2019

Previous work

- Single image portrait relighting

Portrait relighting under natural illumination

(a) Input image and estimated lighting

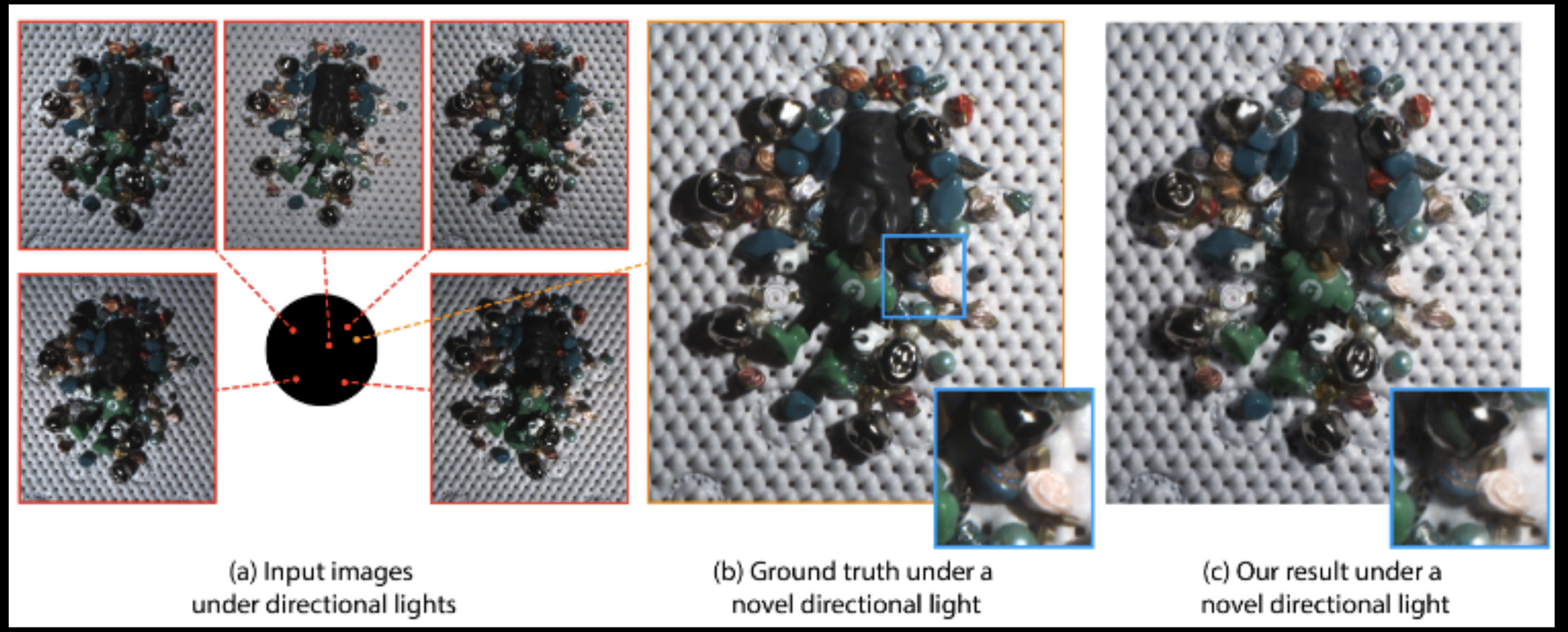
(b) Rendered images from our method under three novel illuminations

Sun, Tiancheng, et al. “Single Image Portrait Relighting." SIGGRAPH 2019

Previous work

Previous work

- Deep image-based relighting

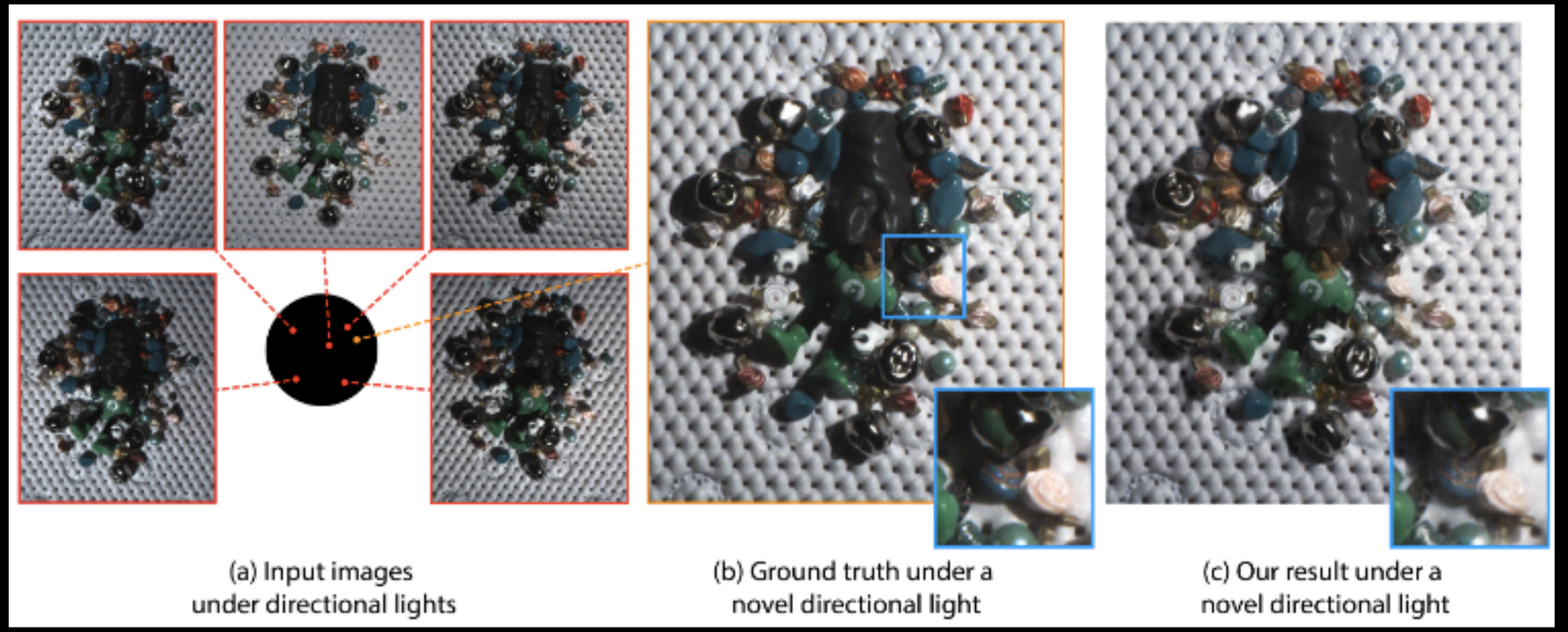


Xu, Zexiang, et al. "Deep image-based relighting from optimal sparse samples." SIGGRAPH 2018

Previous work

- Deep image-based relighting

capture 5 images and do relighting via neural network



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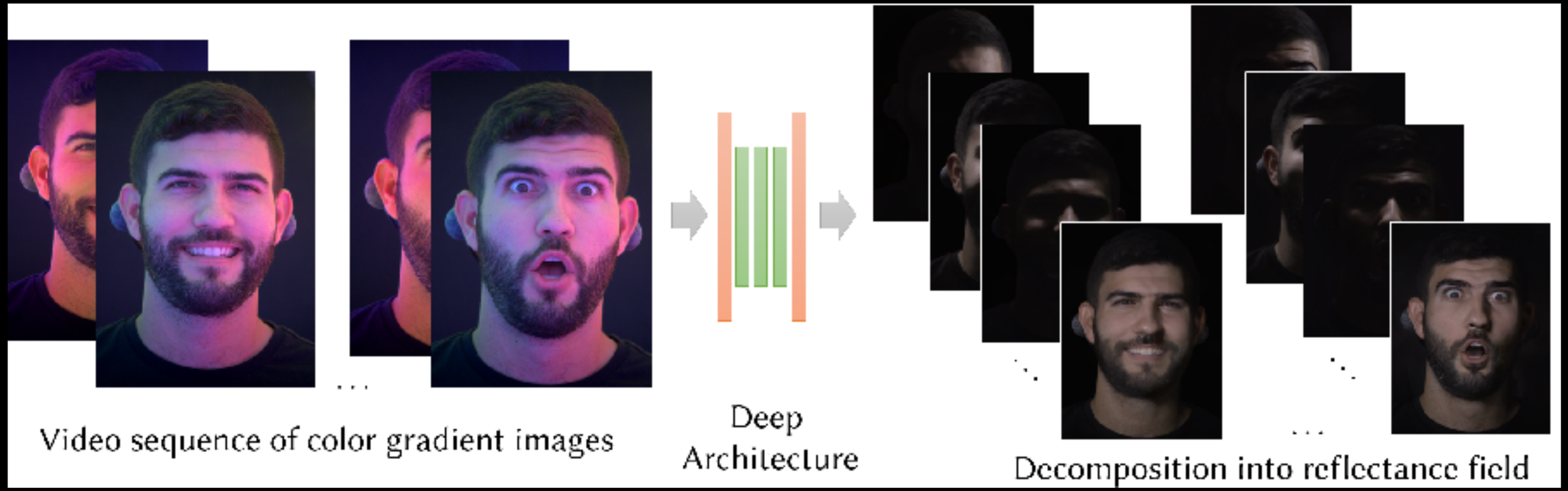
Previous work

Previous work

- Deep reflectance field

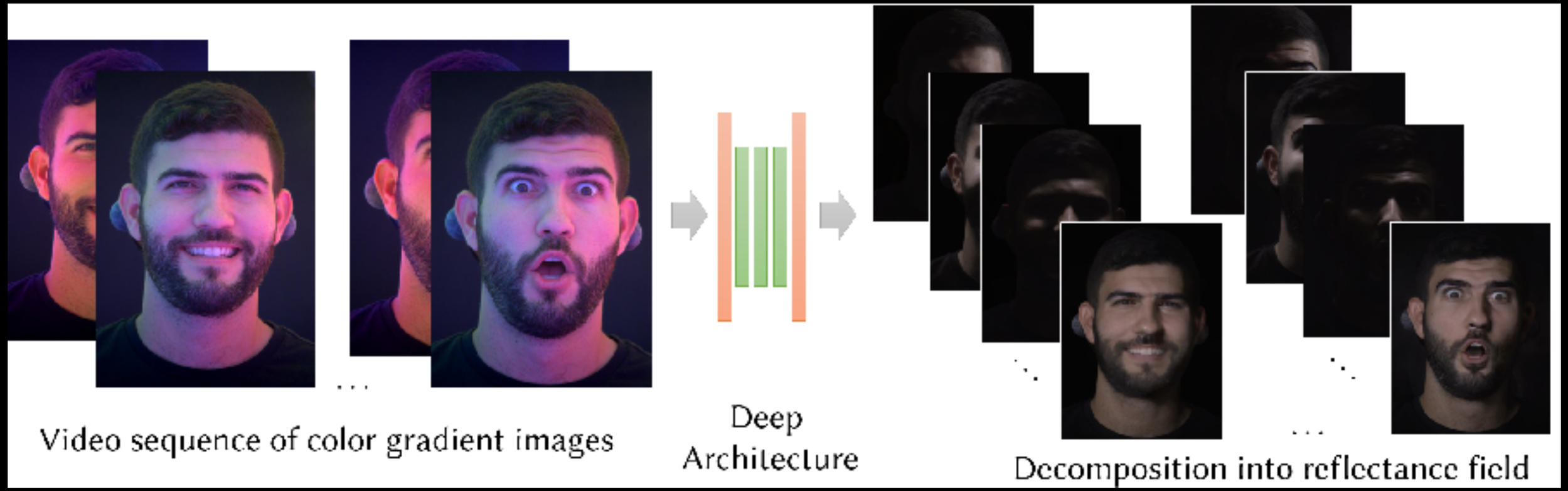


Meka, Abhimitra, et al. "Deep reflectance fields: high-quality facial reflectance field inference from color gradient illumination." SIGGRAPH 2019

Previous work

- Deep reflectance field

Predict point light relit images from two special lighting



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Overview

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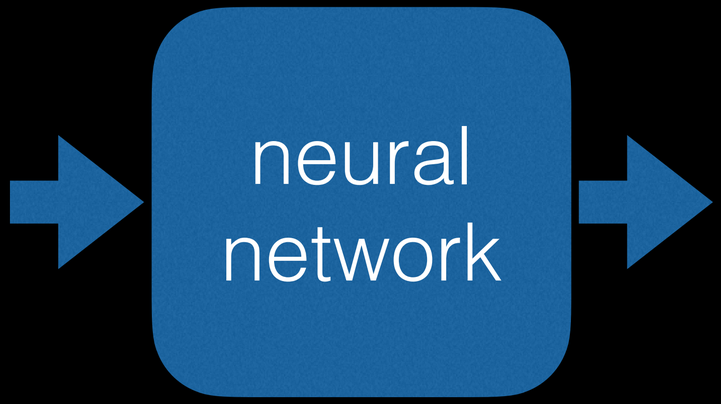
OLAT data

Overview

OLAT data



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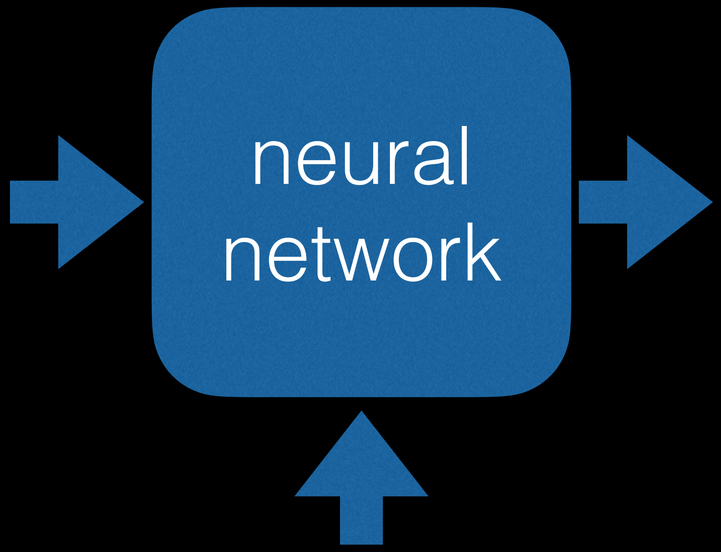
OLAT data



light direction

Overview

OLAT data

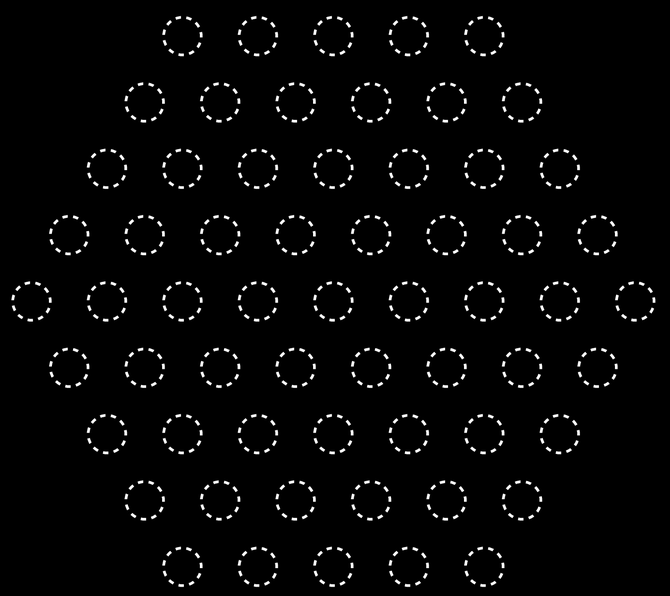
neural network

light direction

relit under arbitrary light direction

Method

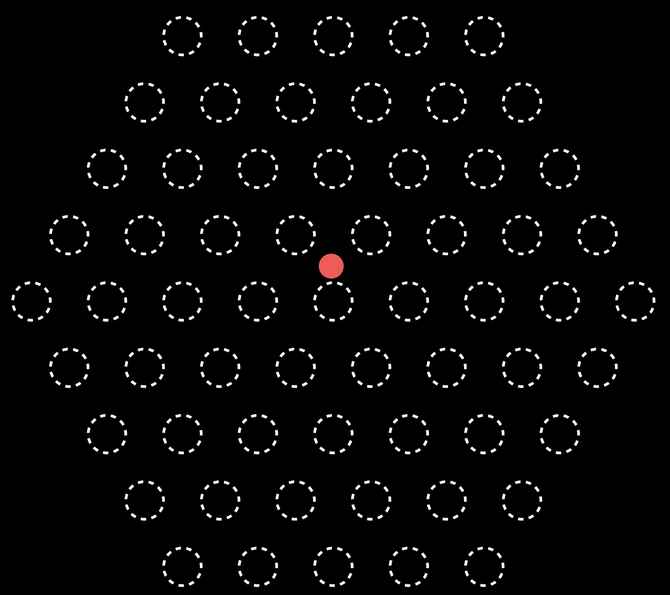
Method



Lights on Light Stage

Method

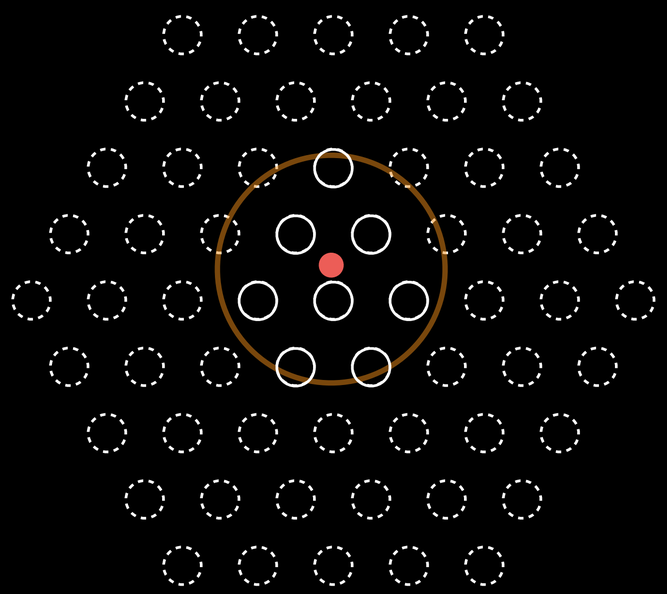
- Query light



Lights on Light Stage

Method

- Query light
- Neighbor lights

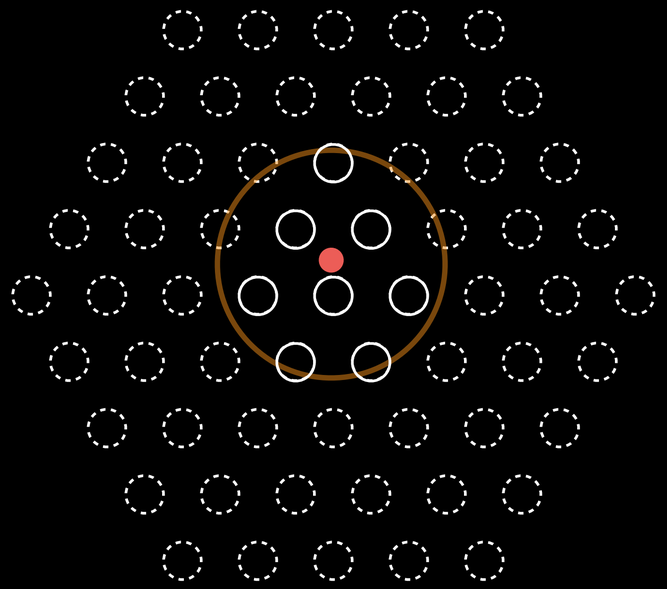


Lights on Light Stage

Method

neighbor captured images
(light ID and weight at bottom corner)

- Query light
- Neighbor lights



Lights on Light Stage

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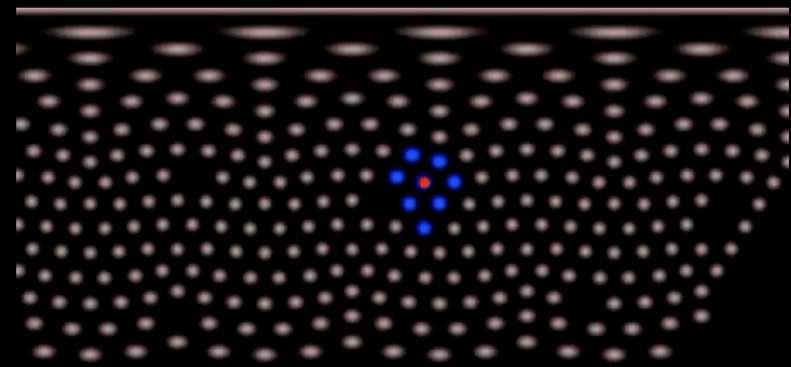
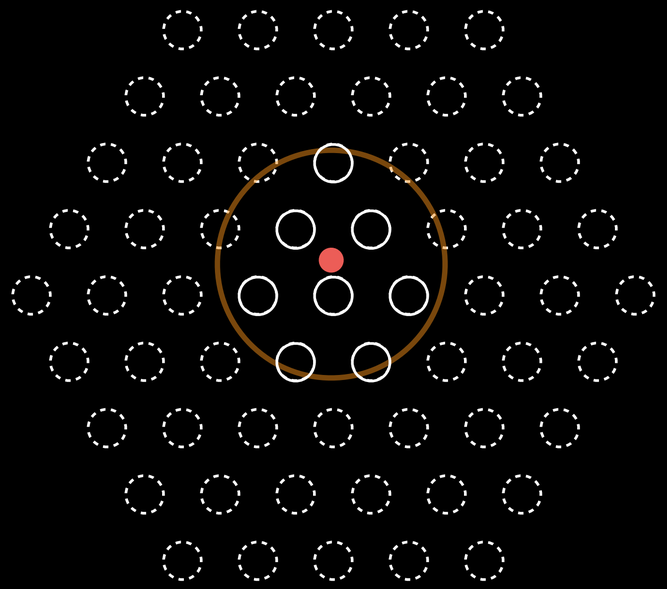
neighbor captured images
(light ID and weight at bottom corner)

light direction



Query light

Neighbor lights



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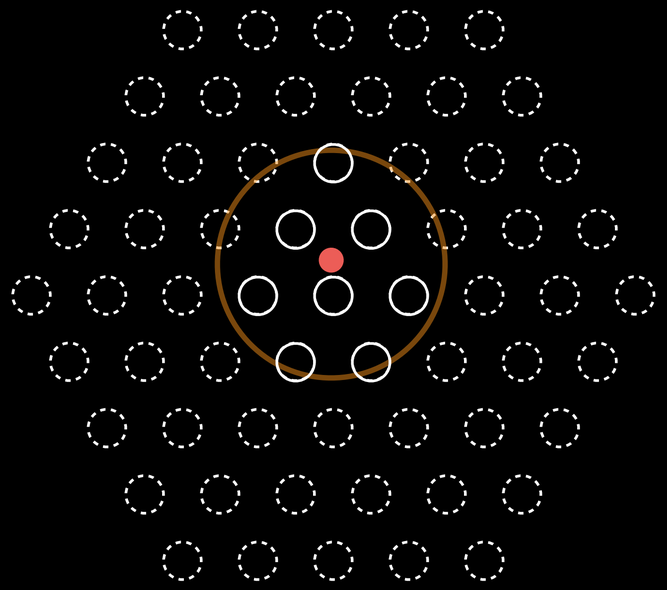
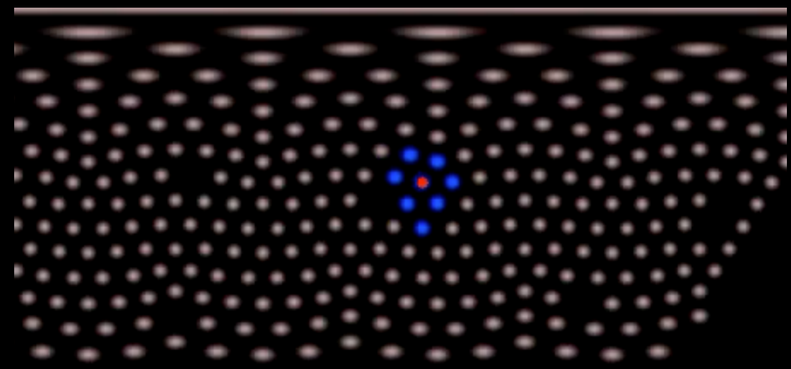
Query light

Neighbor lights



Lights on Light Stage



Neural Network

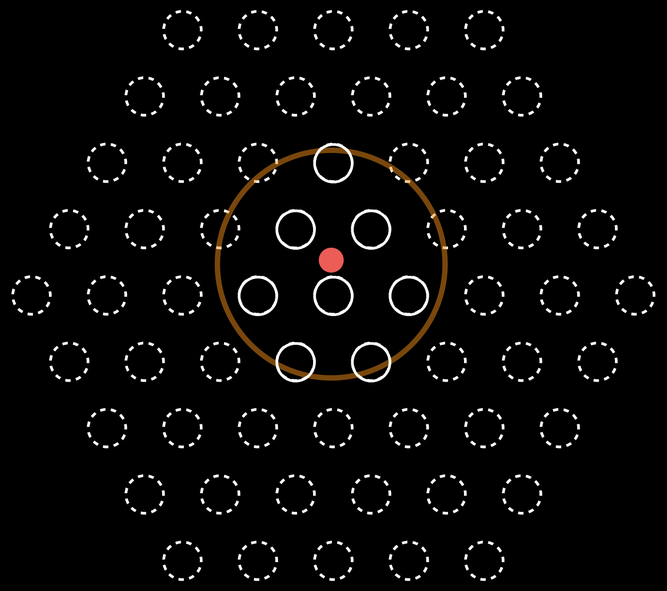
Method

neighbor captured images
(light ID and weight at bottom corner)

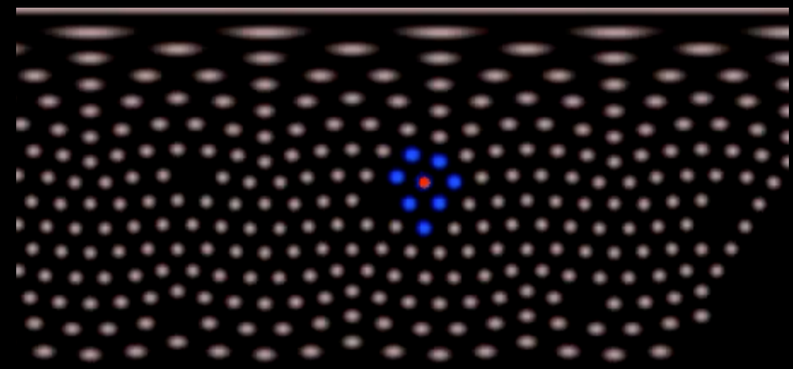
light direction

Query light

Neighbor lights



Lights on Light Stage



Neural Network

predicted image

Method

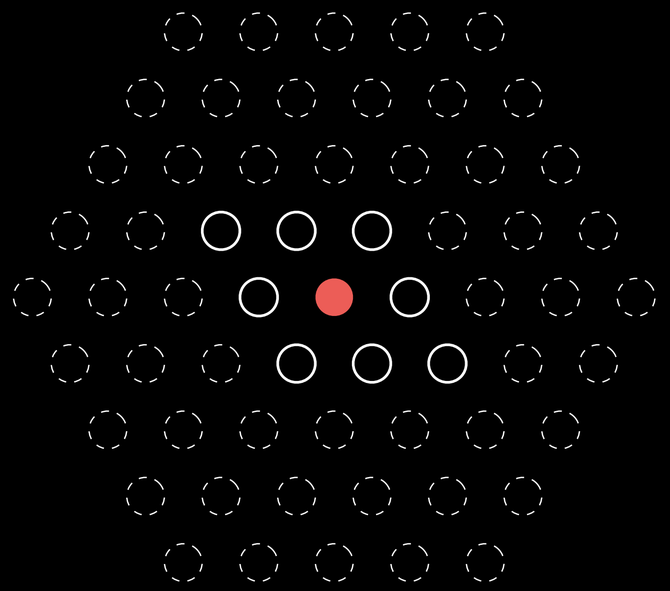
Method

- Input light selection

Method

- Input light selection

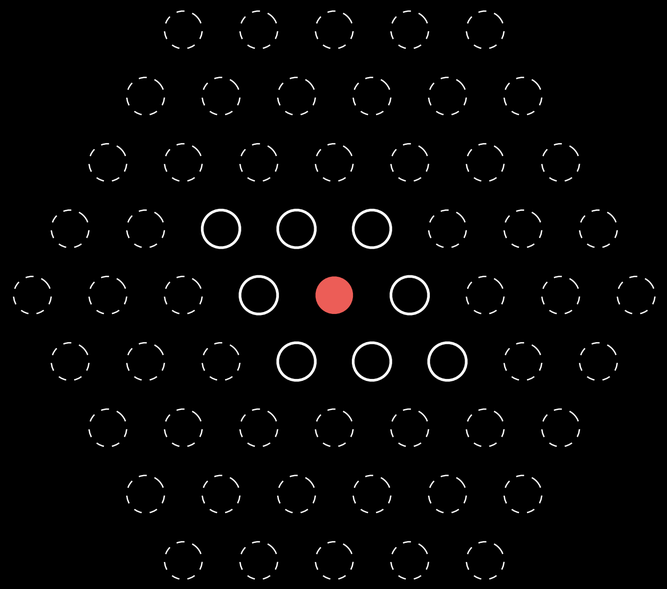
Training



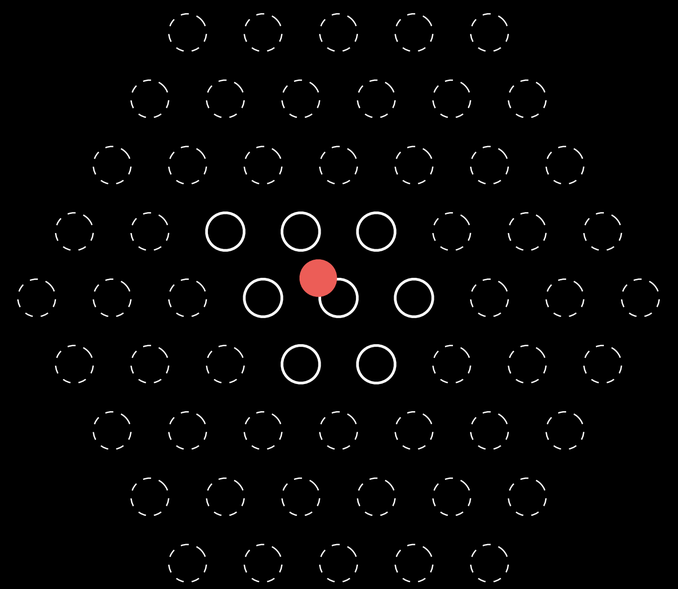
Method

- Input light selection

Training



Testing



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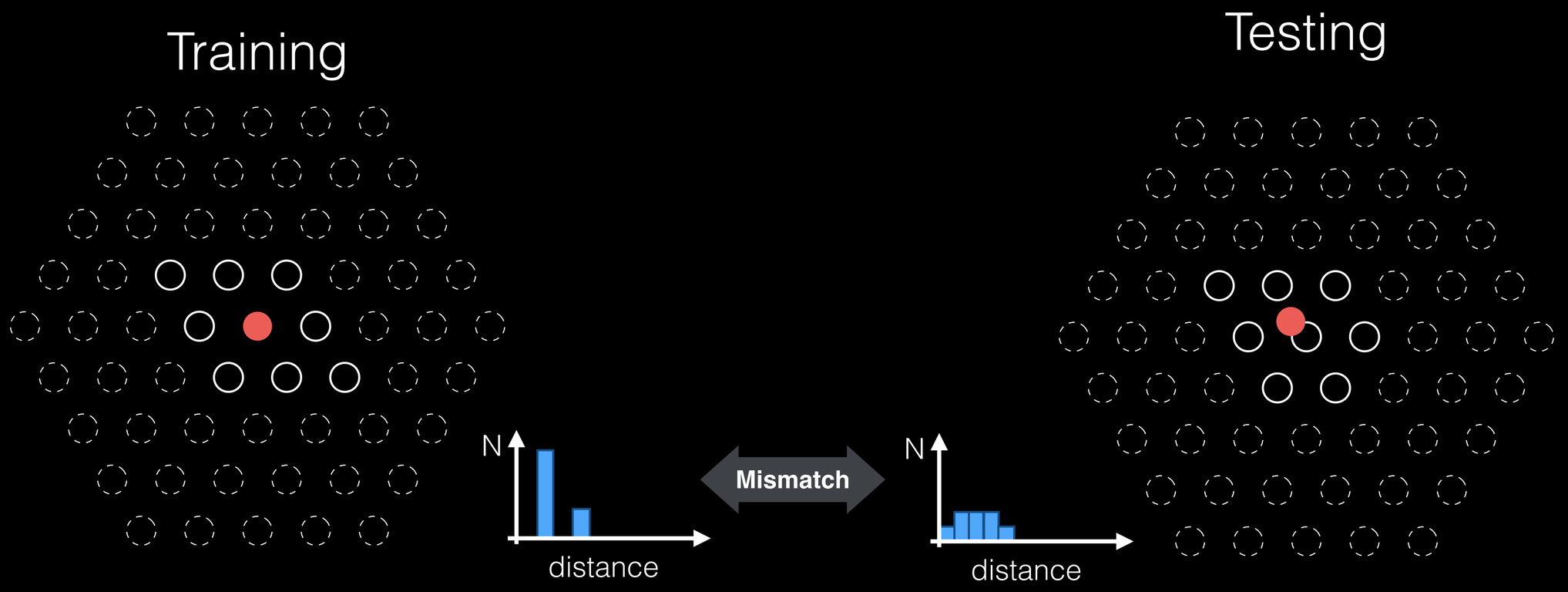
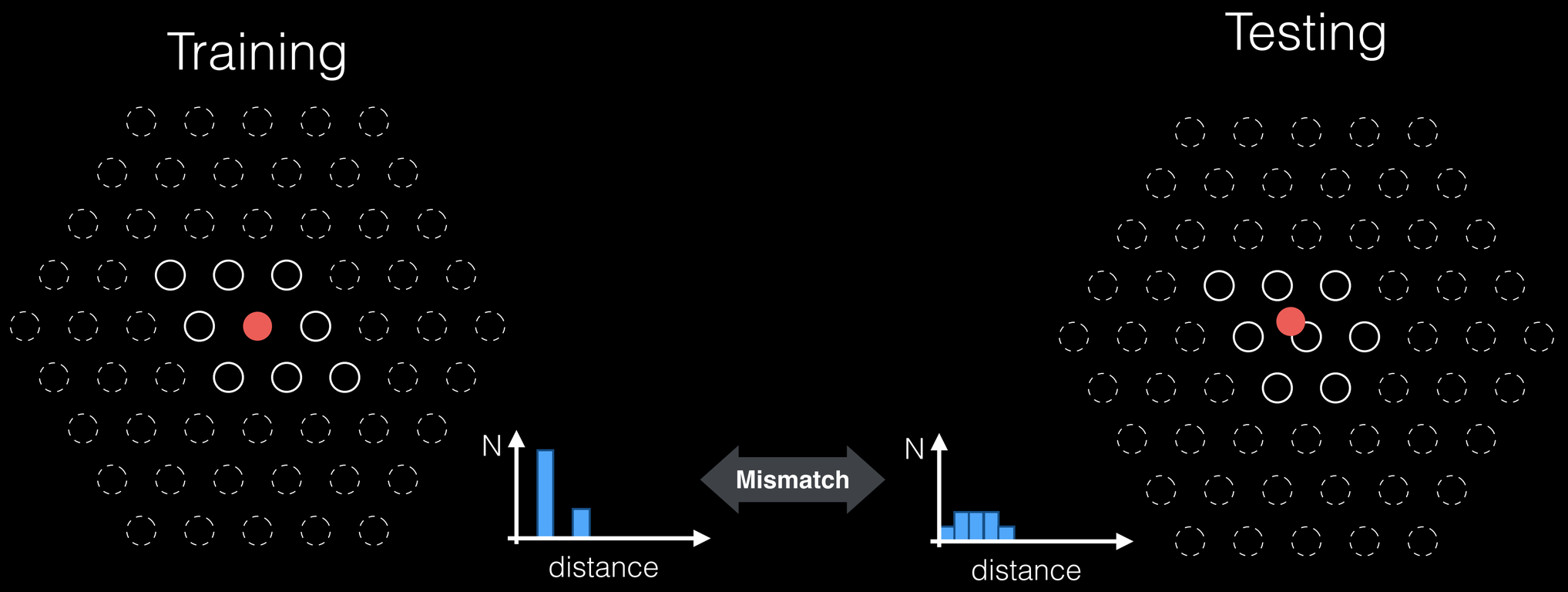


Method

- Input light selection: Dropout during training



Method

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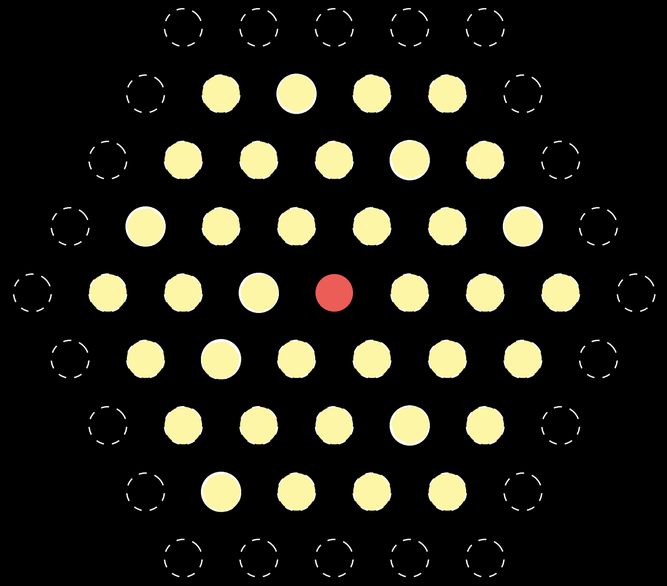
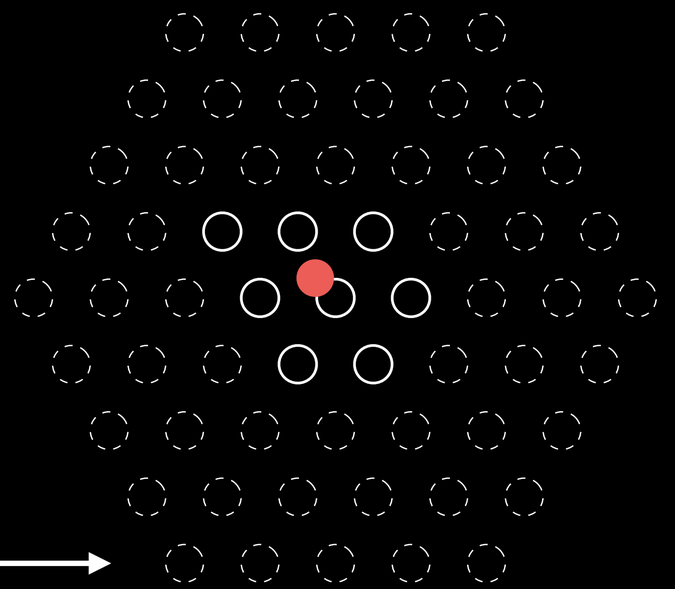
Training



Testing



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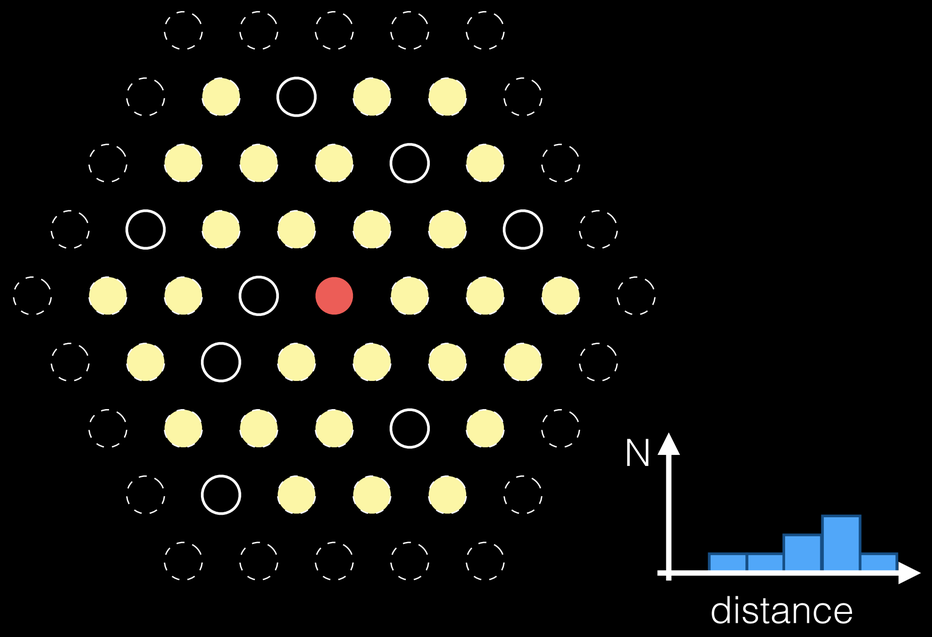
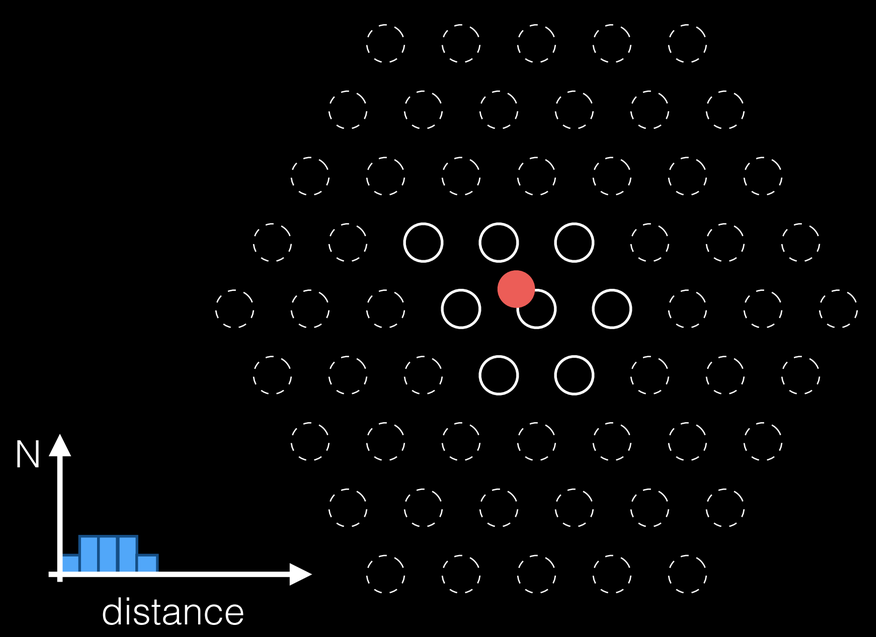


Testing



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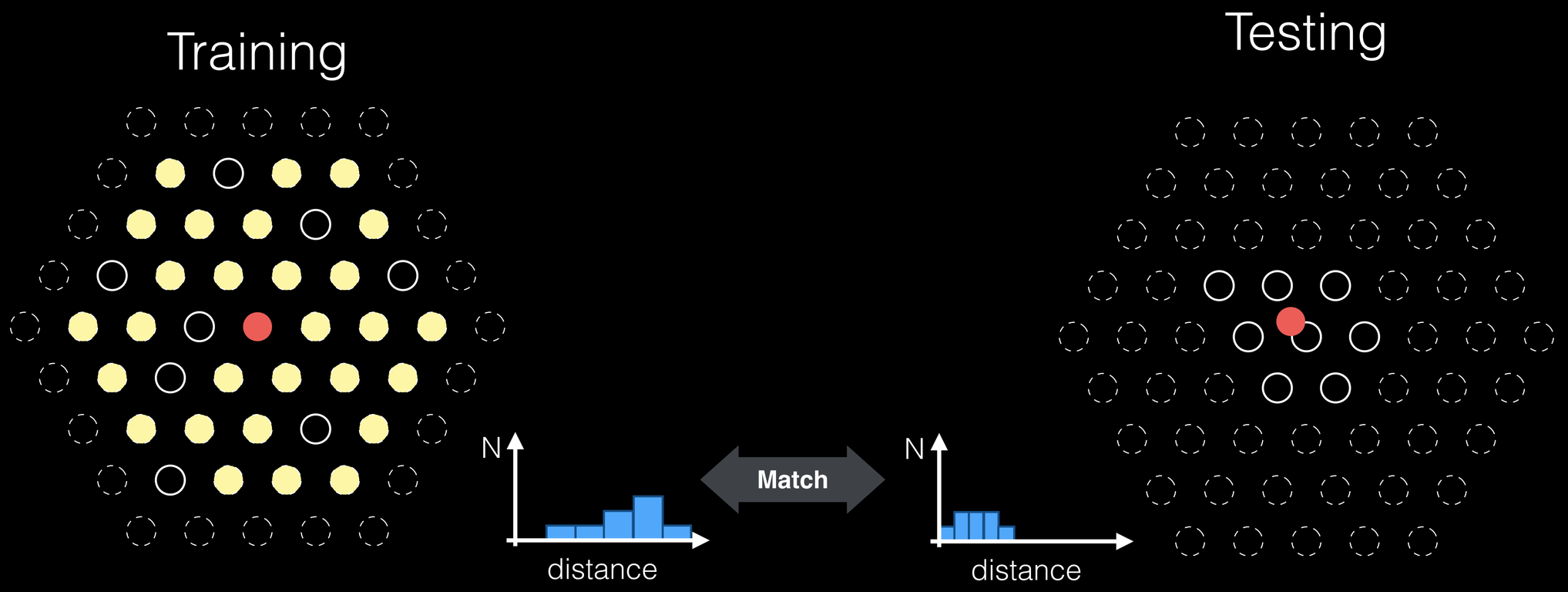

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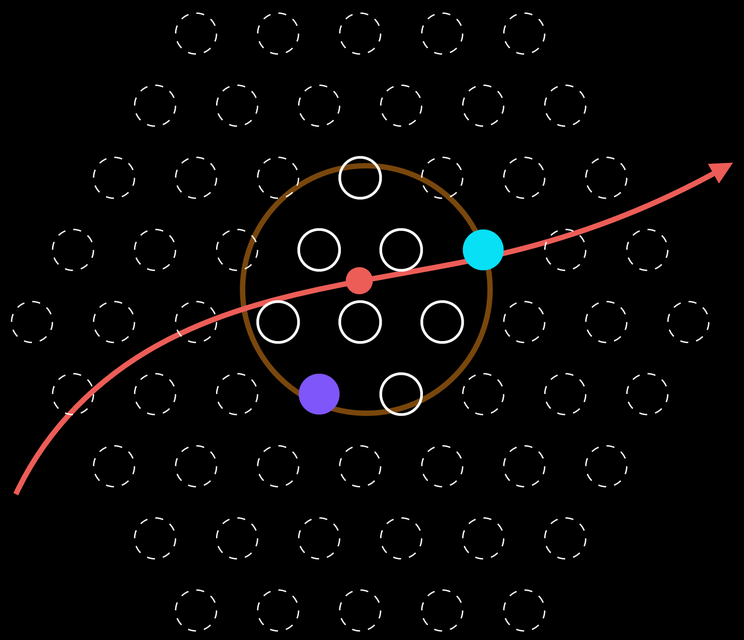
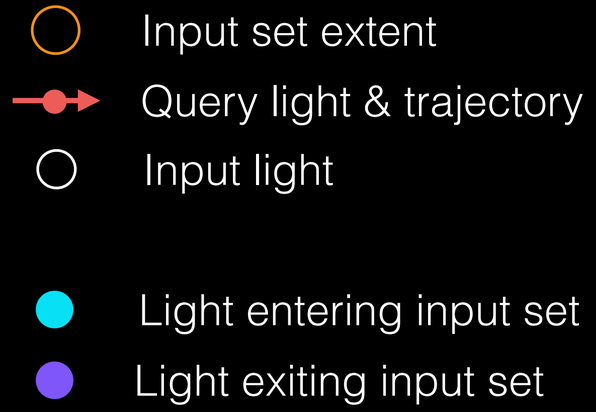
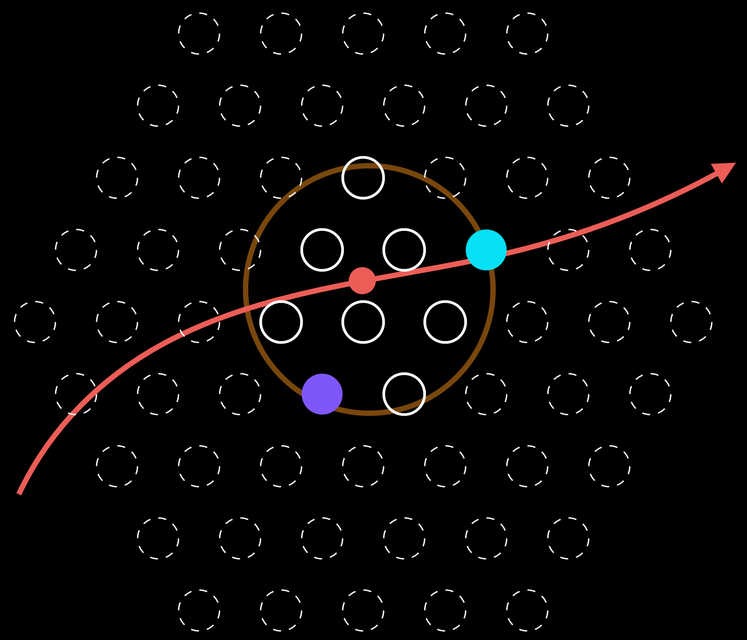
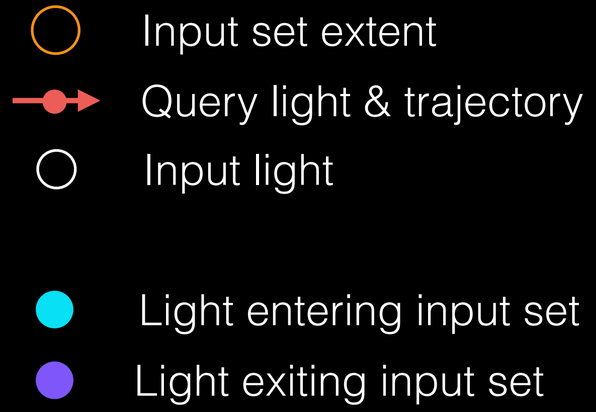



Input set extent
Query light & trajectory
Input light
Light entering input set
Light exiting input set

Method

- Alias-Free Pooling





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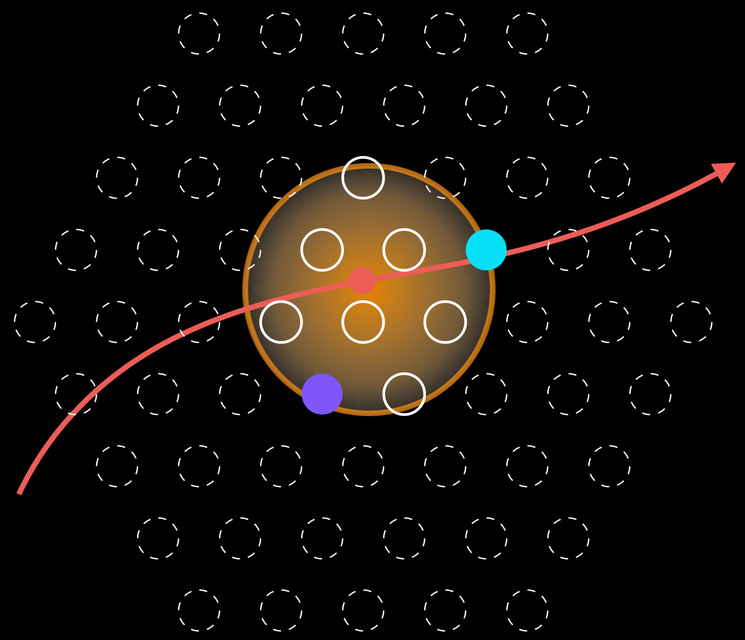

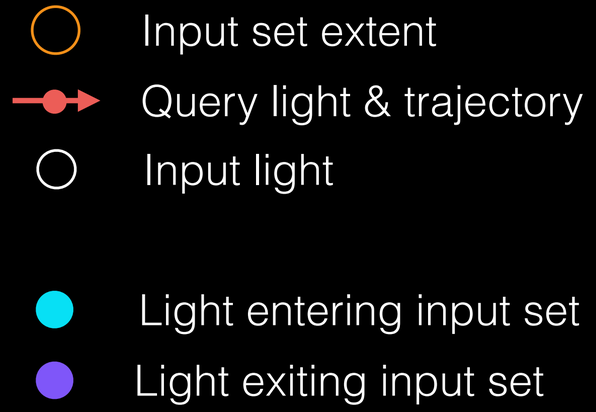

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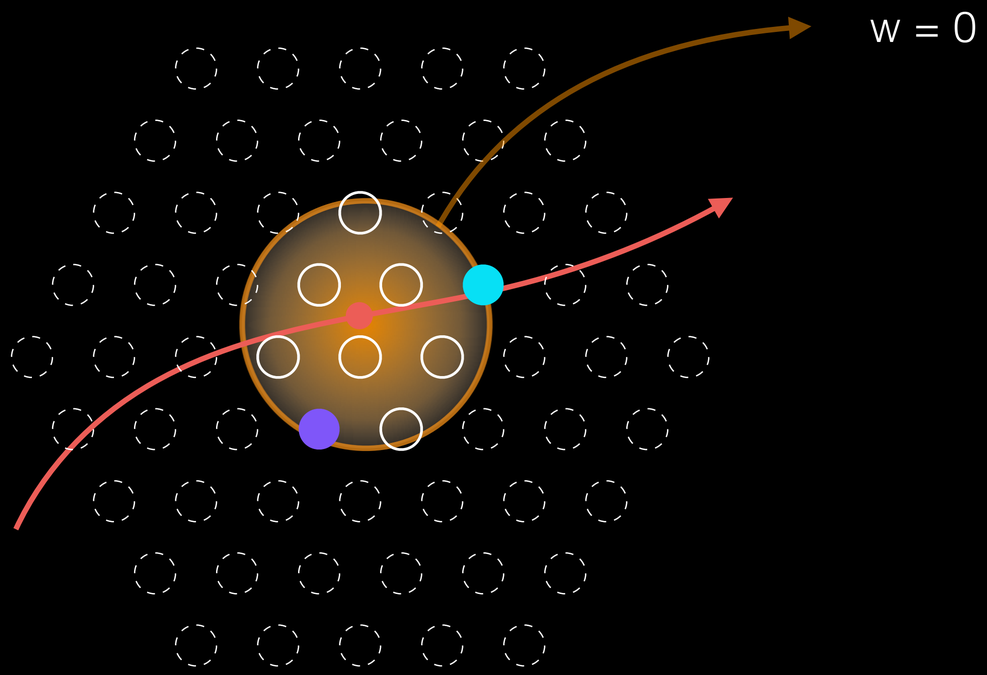


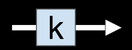
Input set extent
Query light & trajectory
Input light

Light entering input set
Light exiting input set

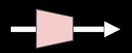
Method

Input or label with c channels and n images (or 1 image)

Activations with c channels and n images (or 1 image)



(k x k) Conv Layer



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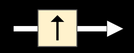
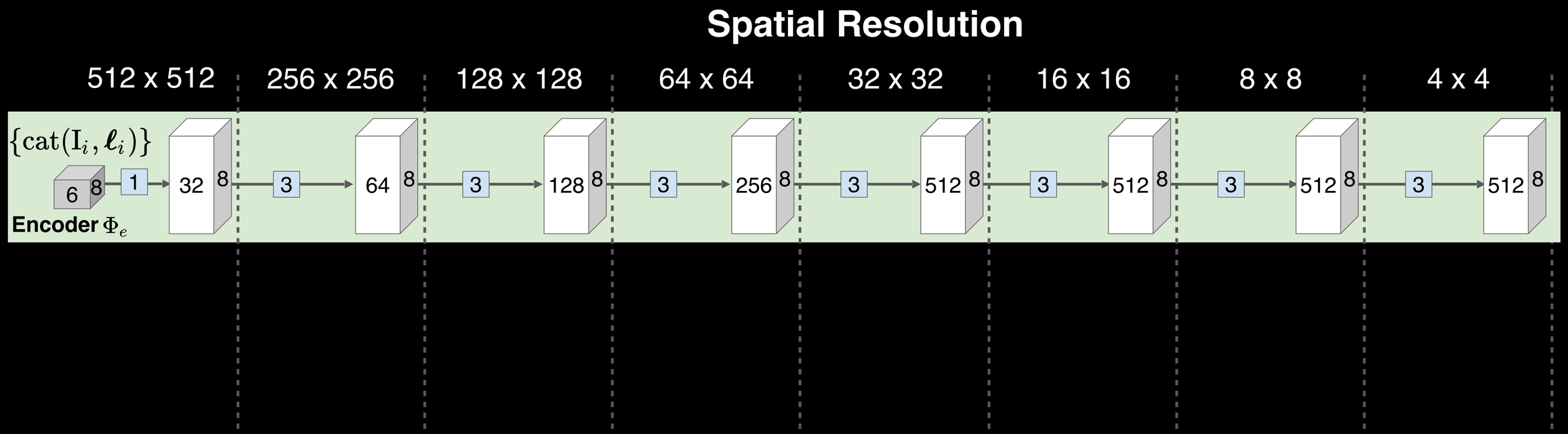


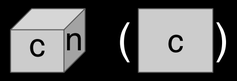
2x bilinear upsampling

Concatenation

Loss

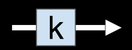
Method





Input or label with c channels and n images (or 1 image)

Activations with c channels and n images (or 1 image)



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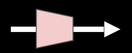

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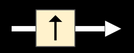

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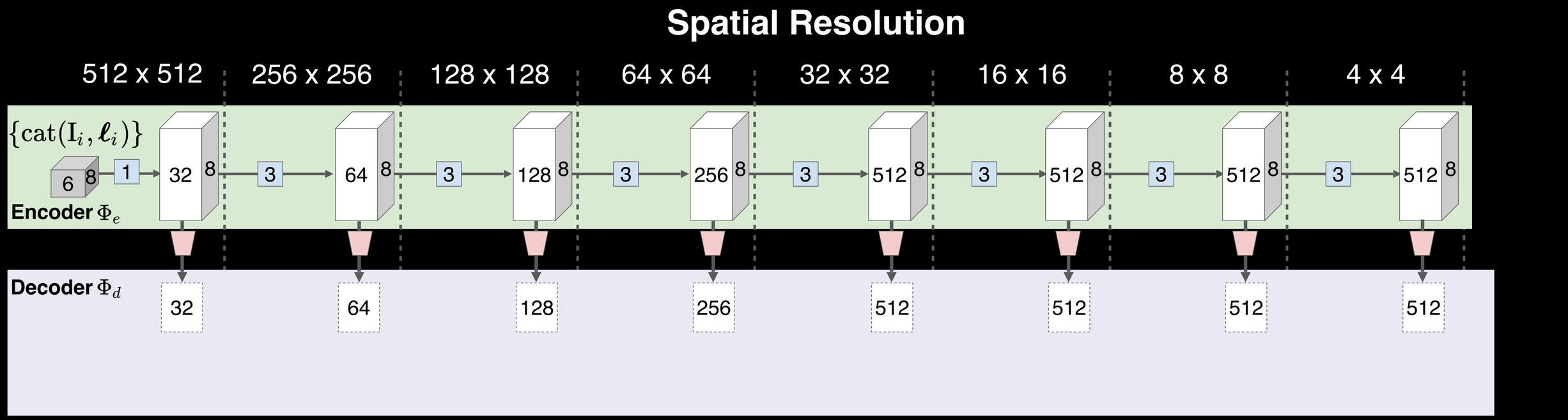

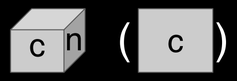

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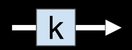

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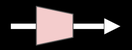

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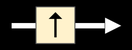

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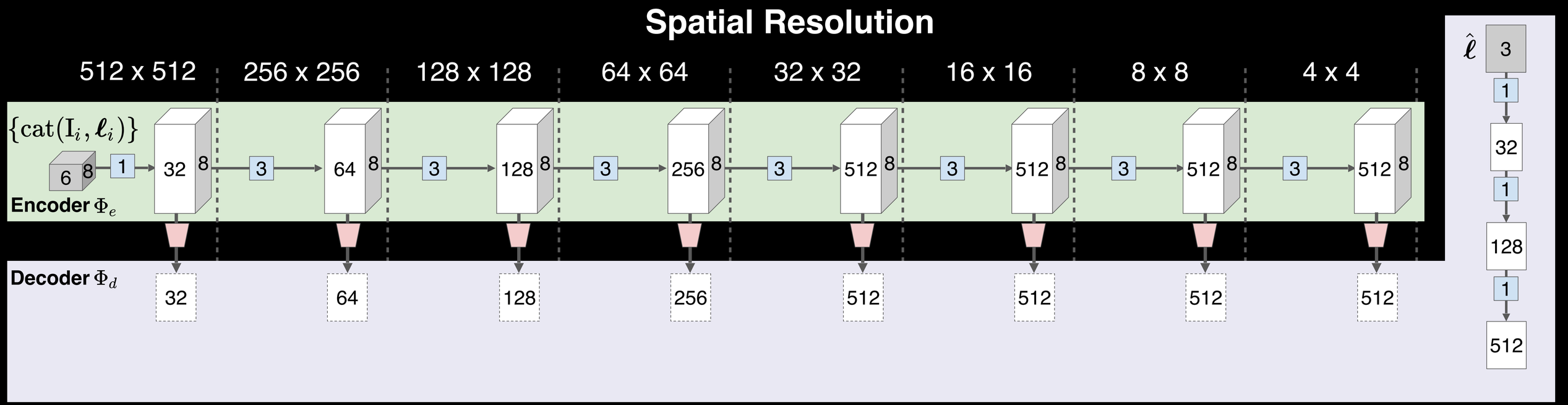
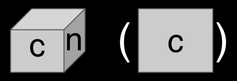
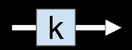
Method



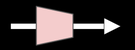


Input or label with c channels and n images (or 1 image)

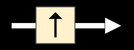
Activations with c channels and n images (or 1 image)



(k x k) Conv Layer



Alias-Free Pooling

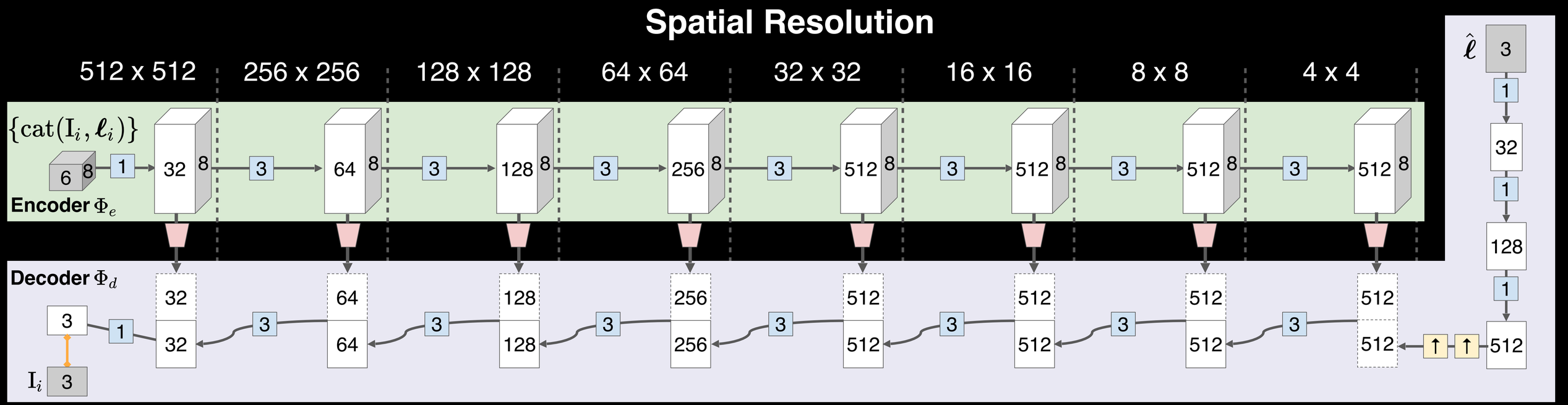


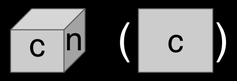
2x bilinear upsampling

Concatenation

Loss

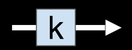
Method



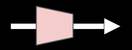


Input or label with c channels and n images (or 1 image)

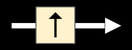
Activations with c channels and n images (or 1 image)



(k x k) Conv Layer



Alias-Free Pooling



2x bilinear upsampling

Concatenation

Loss

Method

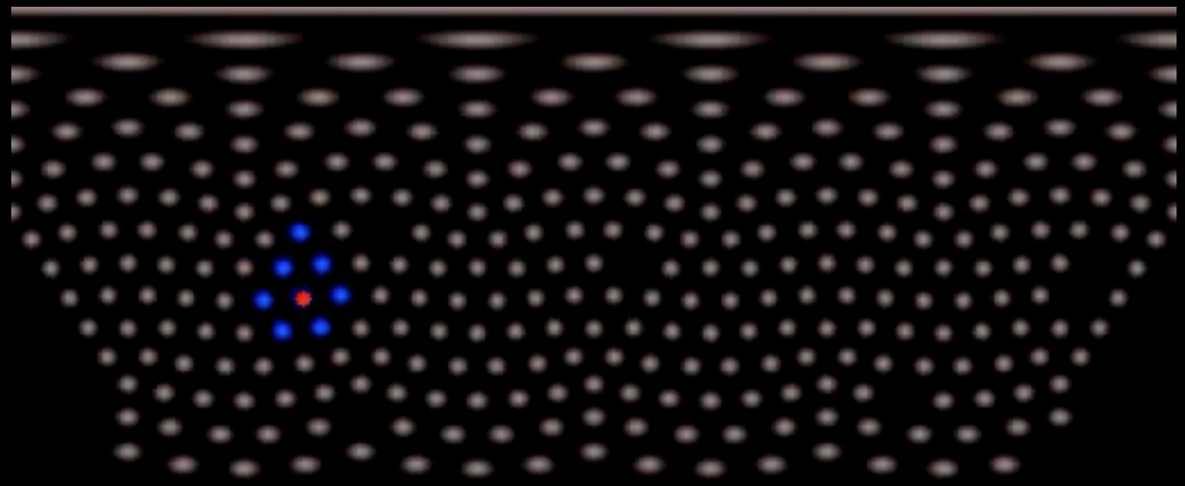
- Training
  - Trained on 16 different OLAT image sets
  - Supervise the output with L1 loss
  - Train the network progressively

Results

Ours

Input images

Lights on Light Stage



Results

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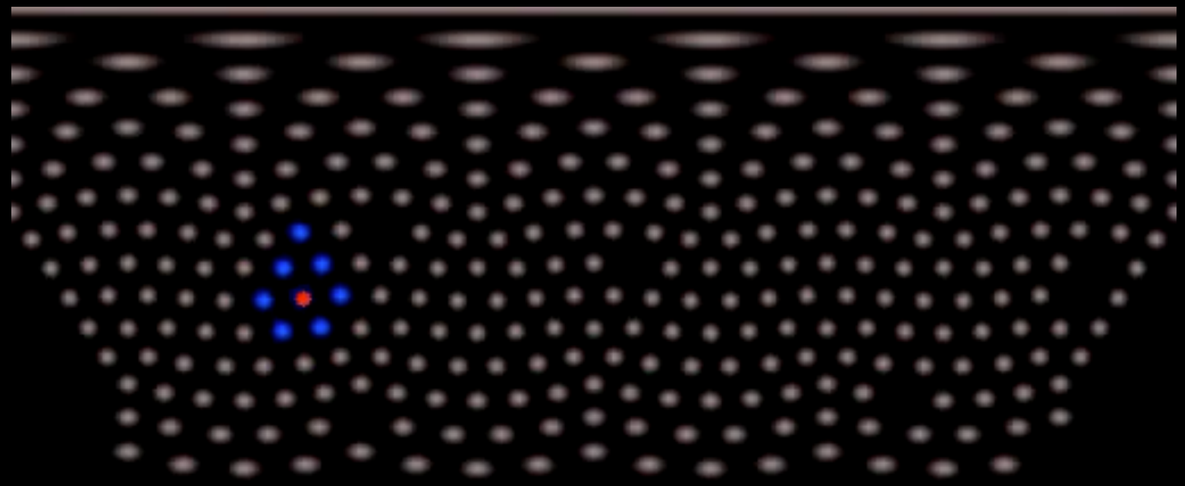
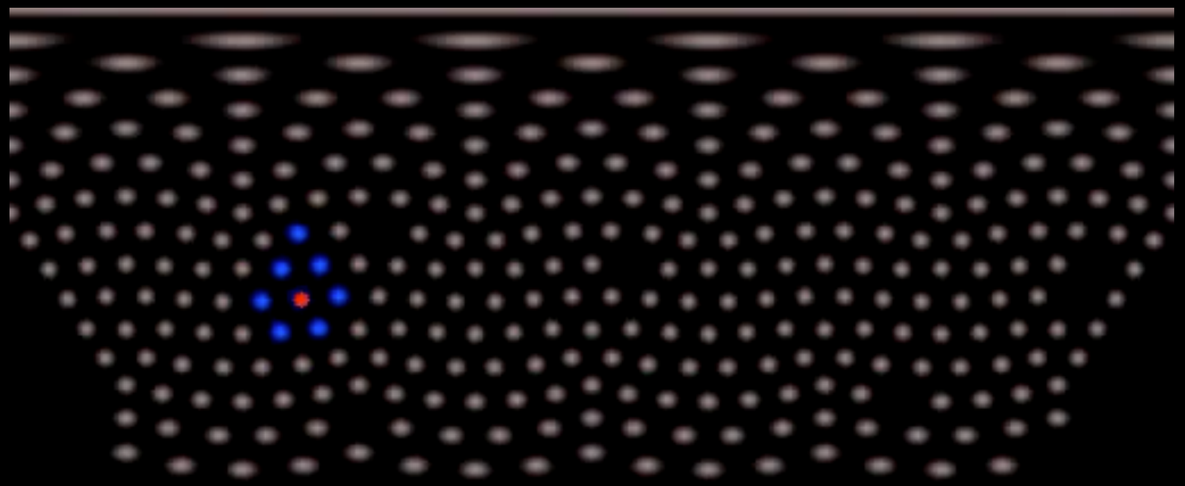


Input images

Lights on Light Stage

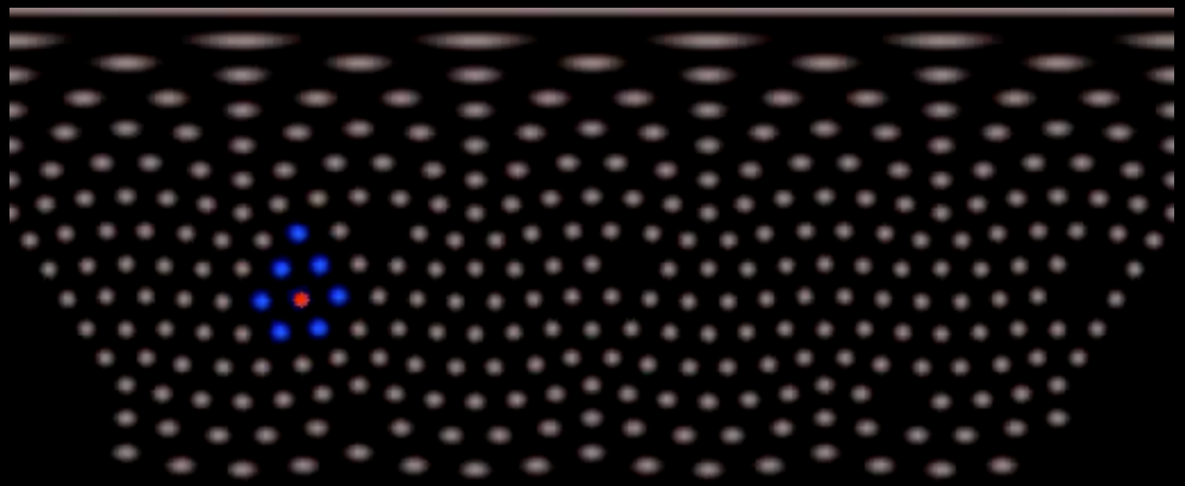


Ours

Ours w/ ave-pooling (flickering)

Input images

Lights on Light Stage



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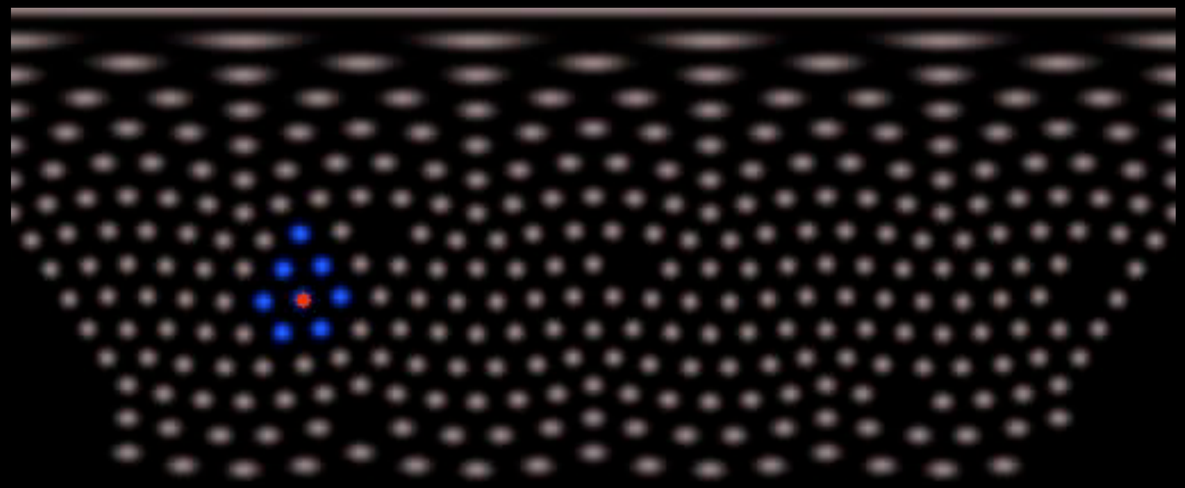

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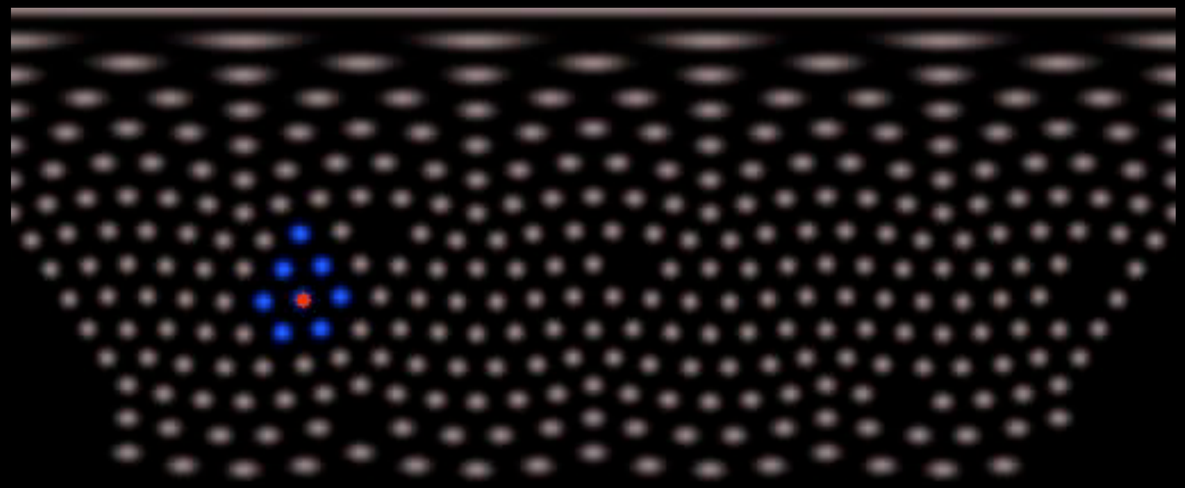

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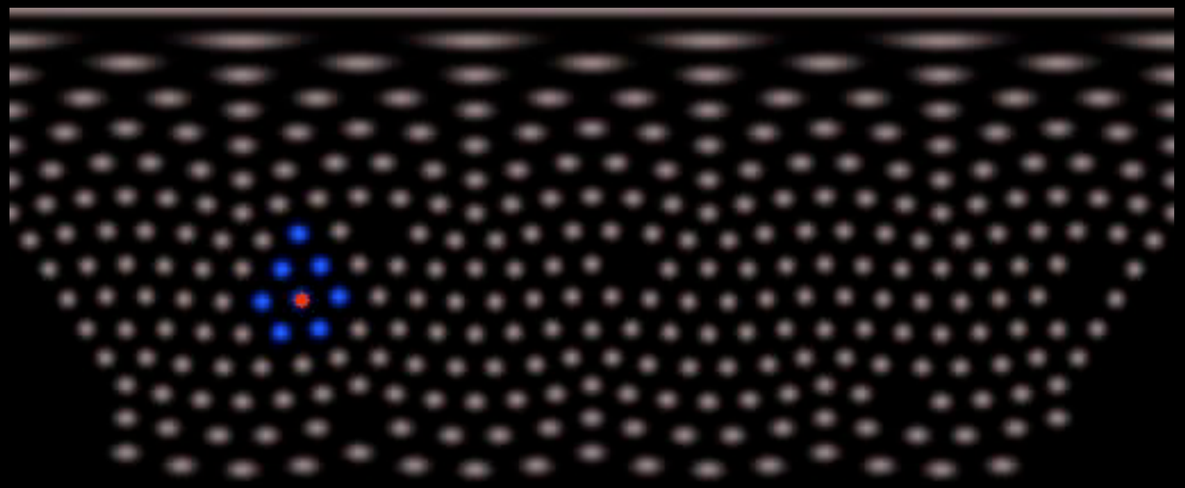
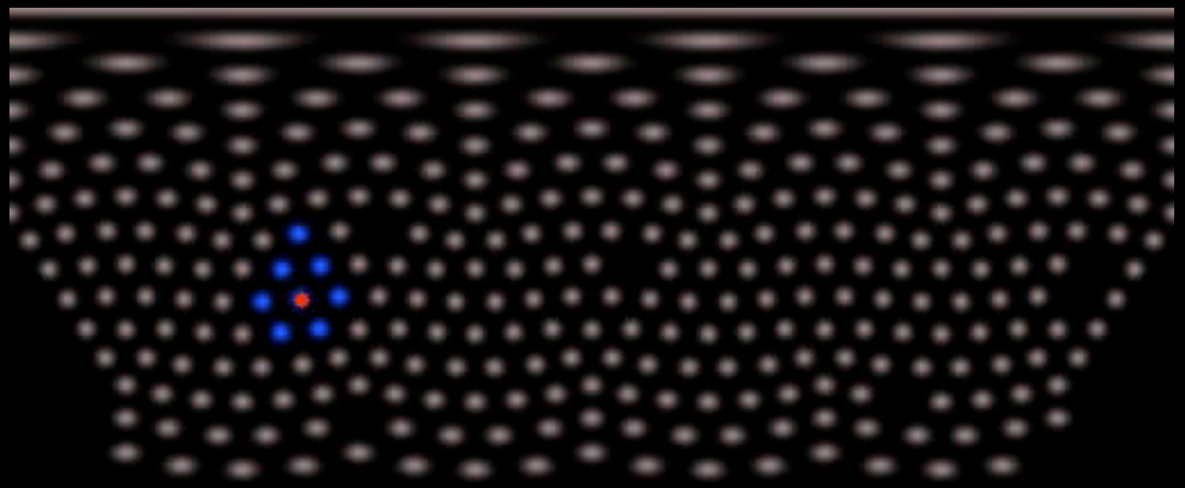


Ours

Xu et al.[2018] w/ adaptive sampling **(ghosting)**

Input images

Lights on Light Stage



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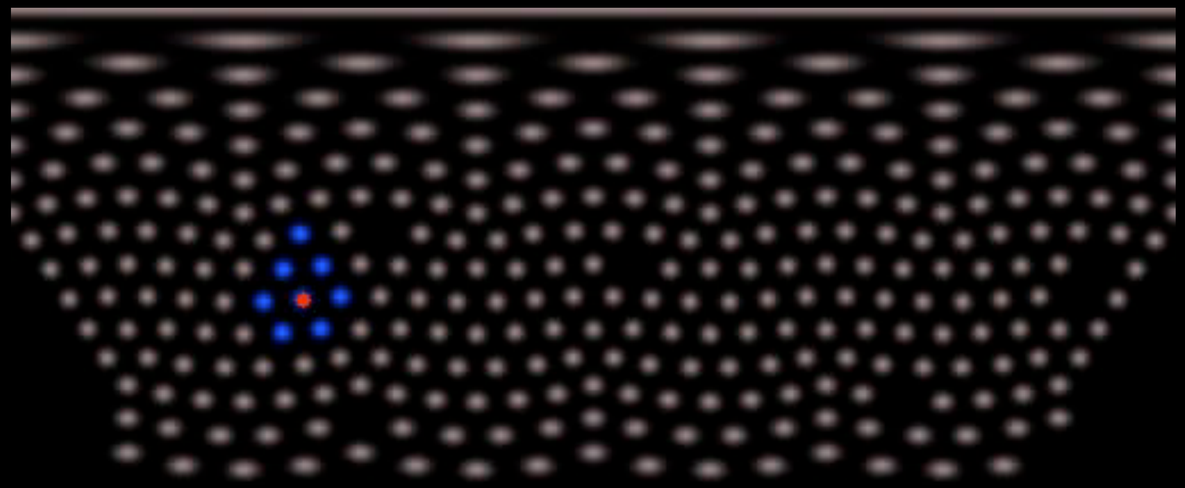

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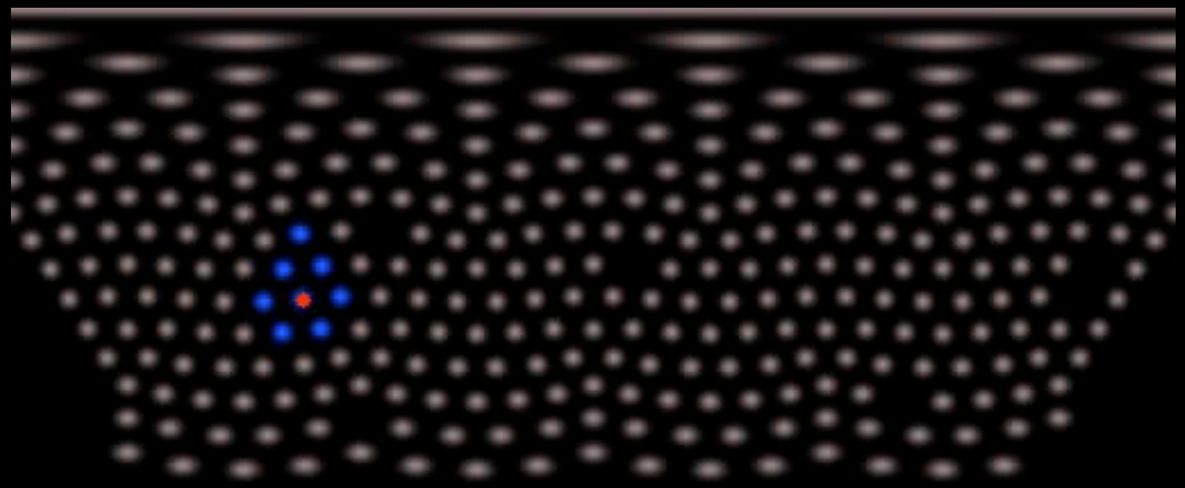

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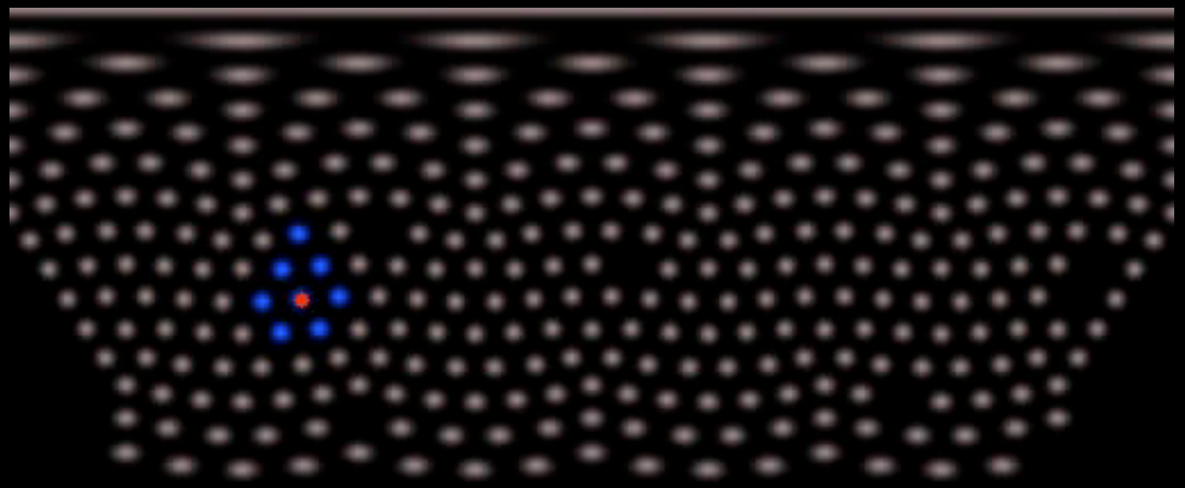
Lights on Light Stage

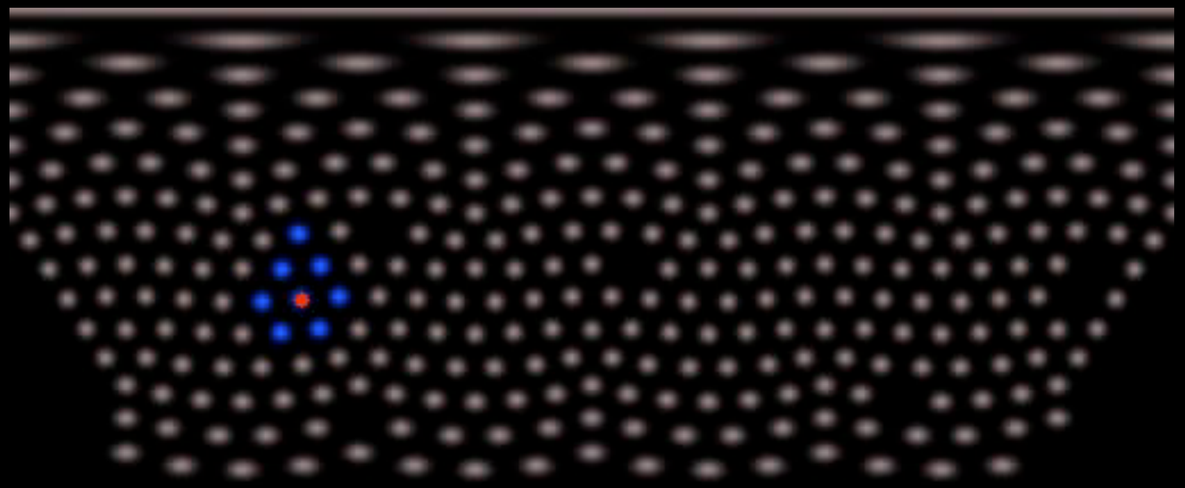


Ours

Meka et al.[2019] **(blurry)**

Input images

Lights on Light Stage

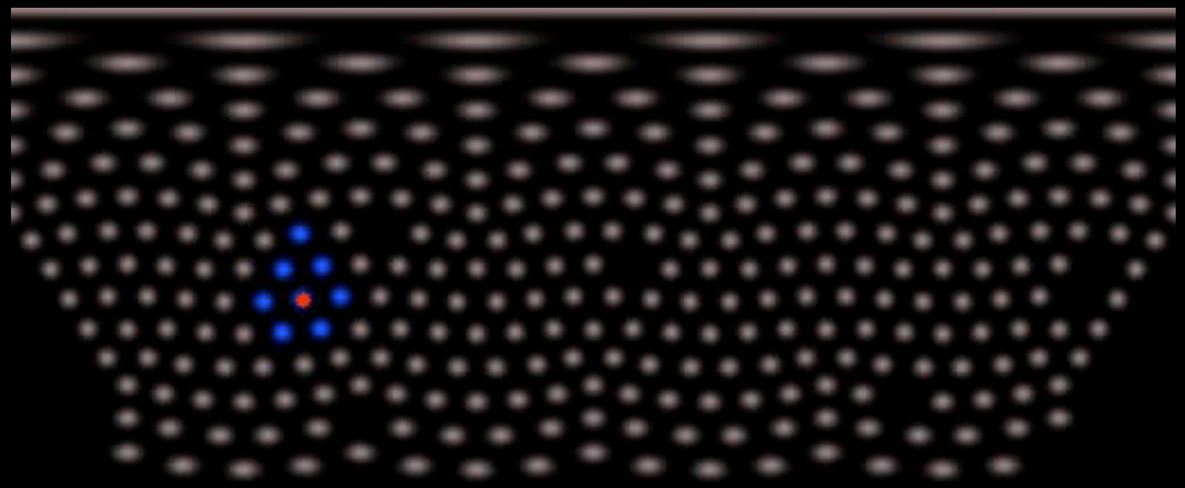


Ours

Meka et al.[2019] **(blurry)**

Input images

Lights on Light Stage

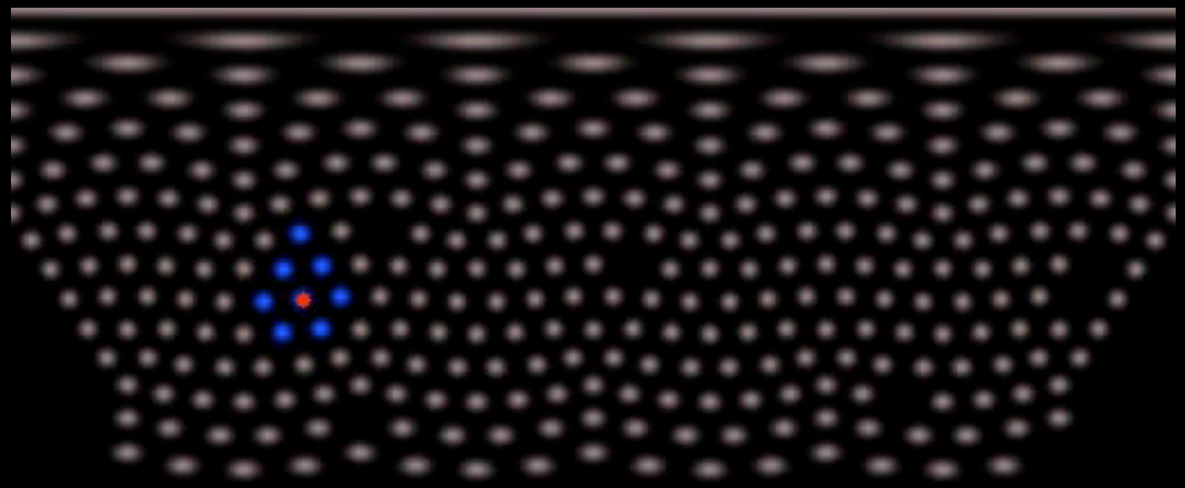


Ours

Meka et al.[2019] **(blurry)**

Input images

Lights on Light Stage

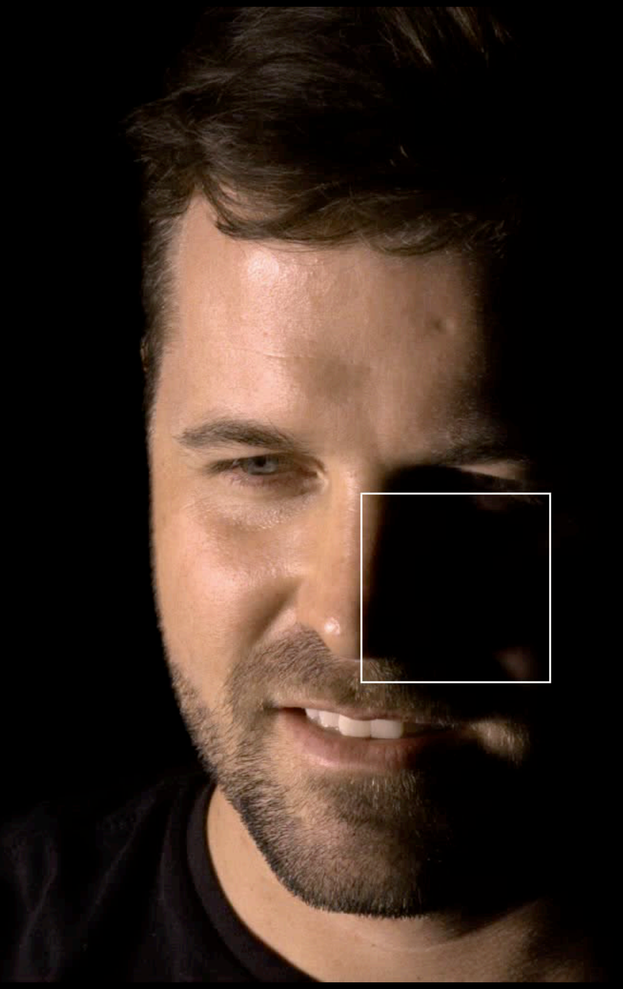


Ours

Meka et al.[2019] **(blurry)**

Different number of lights on the light stage

n=302



n=302

n=250

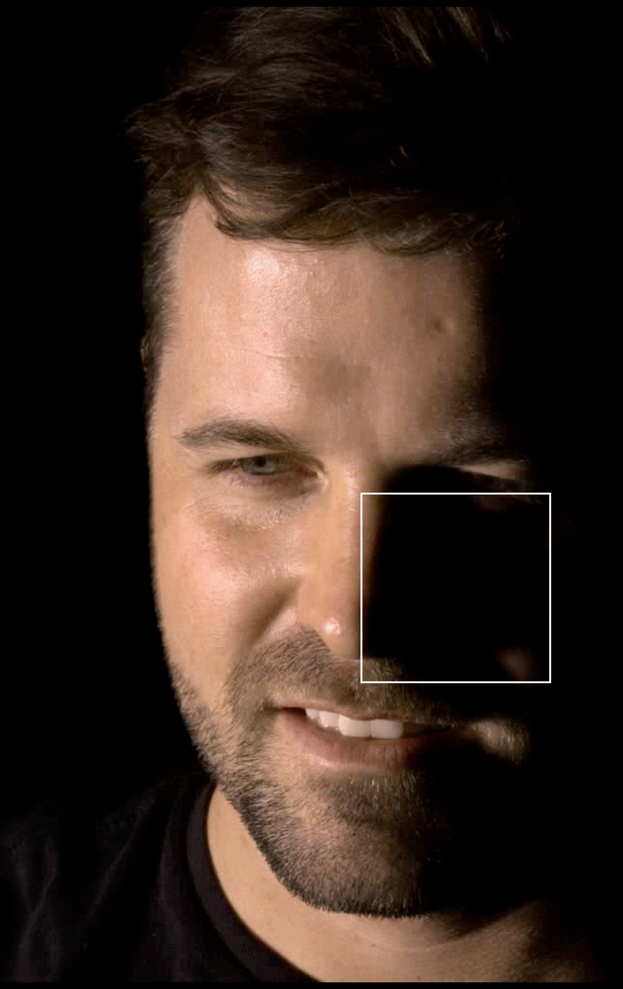
n=200

n=150

n=100

Different number of lights on the light stage

n=302



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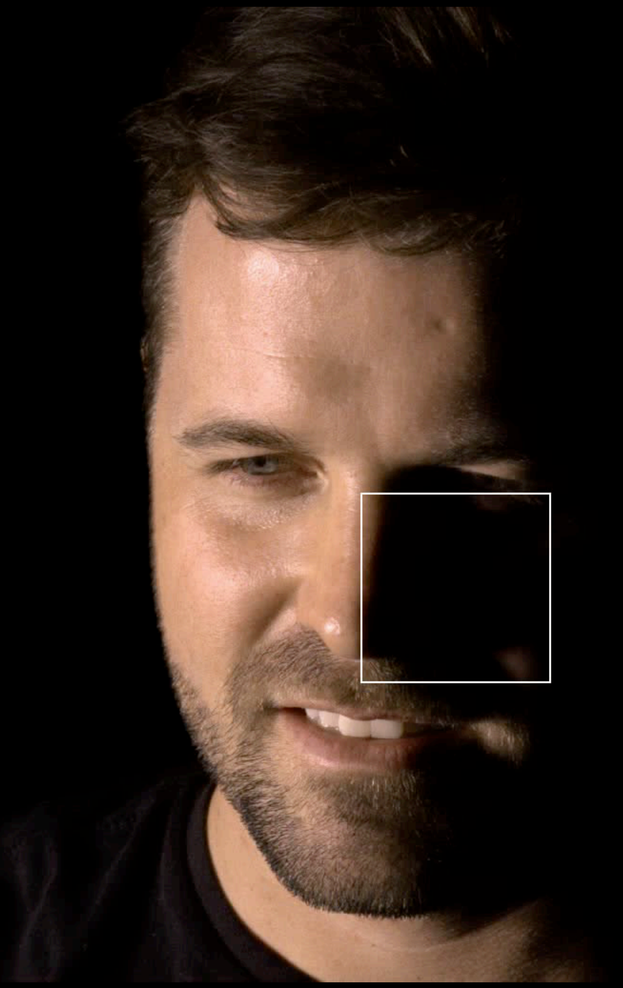


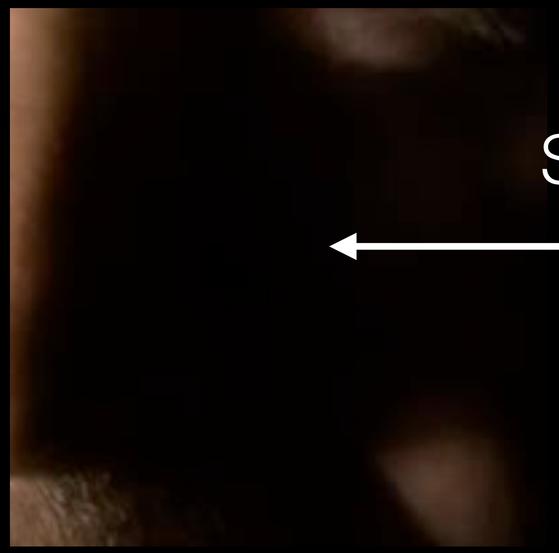
n=302

n=302

n=250

n=200

n=150

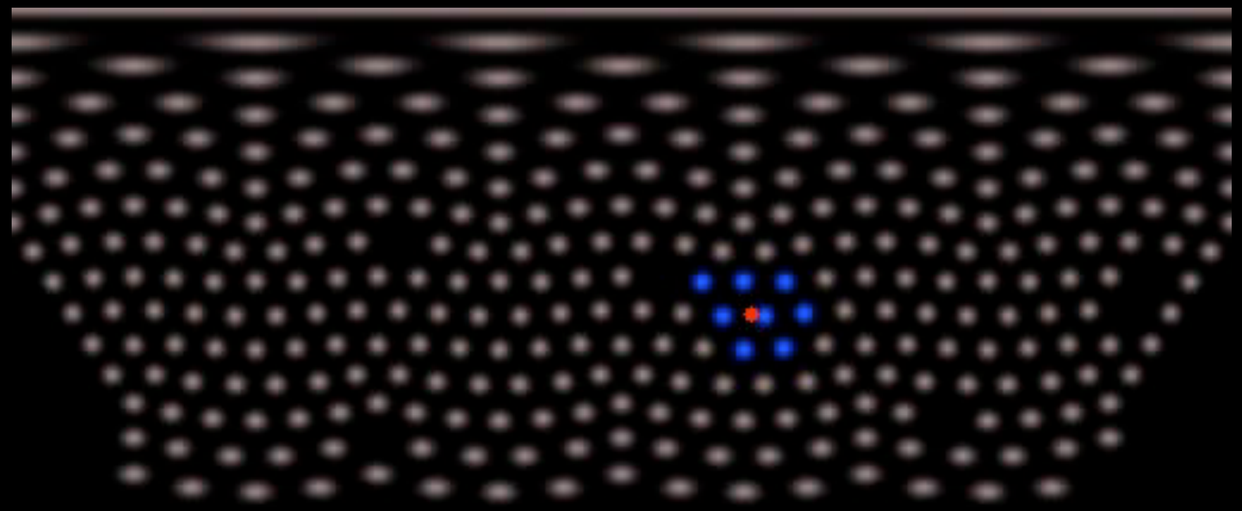


n=100

Work well on n >= 150
Small ghosting at n = 100

Results: Applications

- Precise directional light relighting

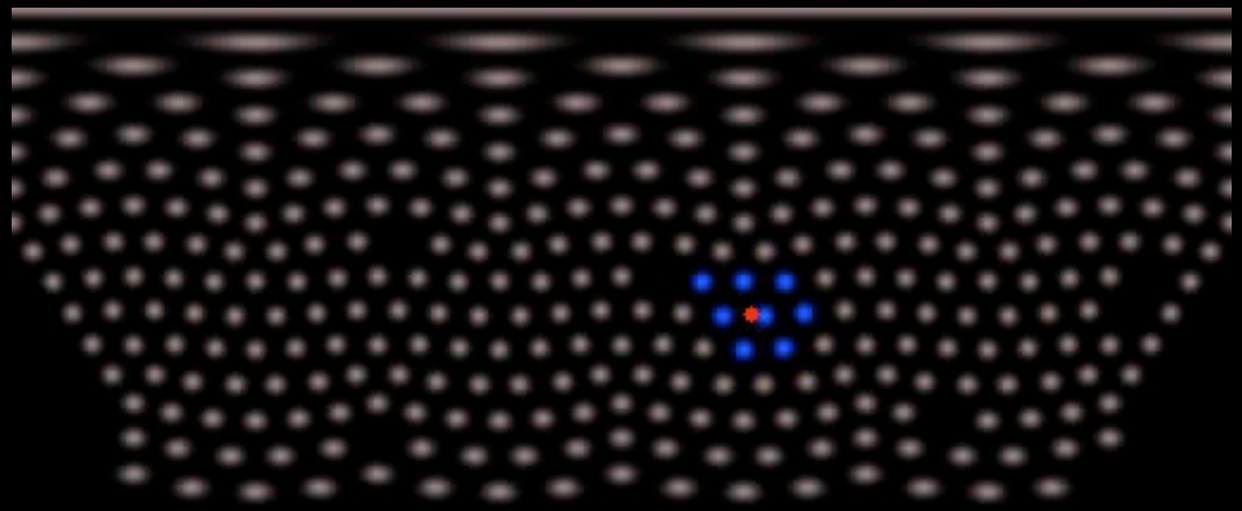


Lights on Light Stage

Ours

Results: Applications

- Precise directional light relighting



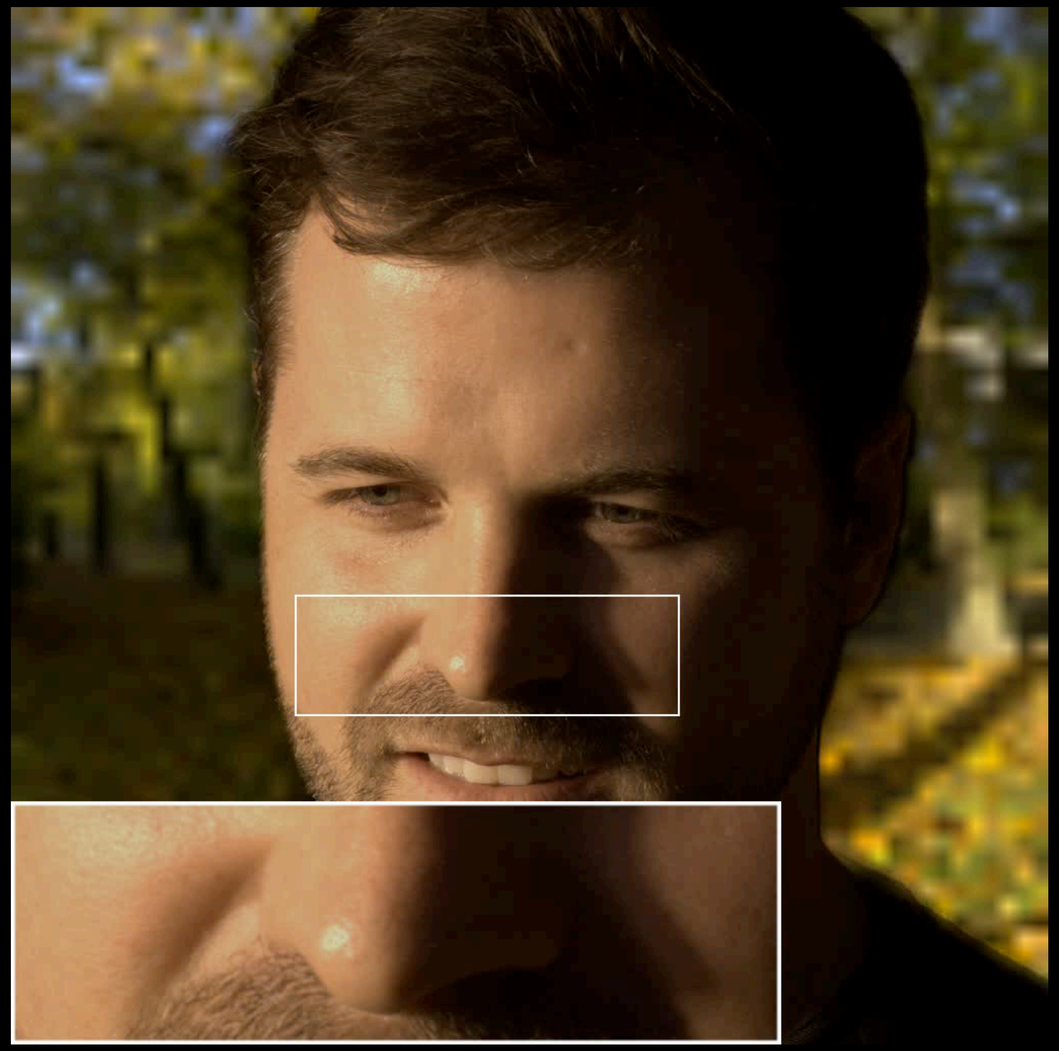
Lights on Light Stage

Ours

Results: Applications

- High-frequency Environment Map Relighting

Ours

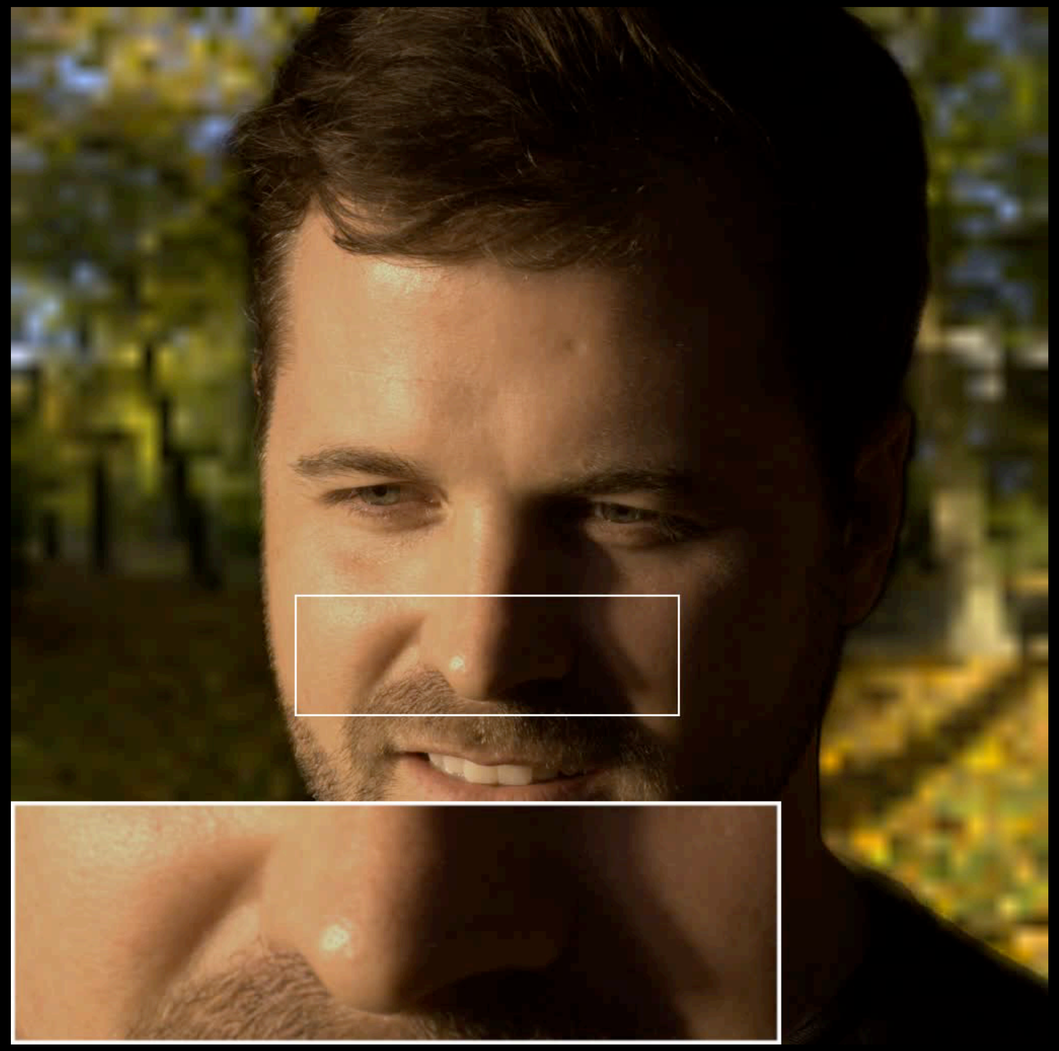


Linear Blend

Results: Applications

- High-frequency Environment Map Relighting

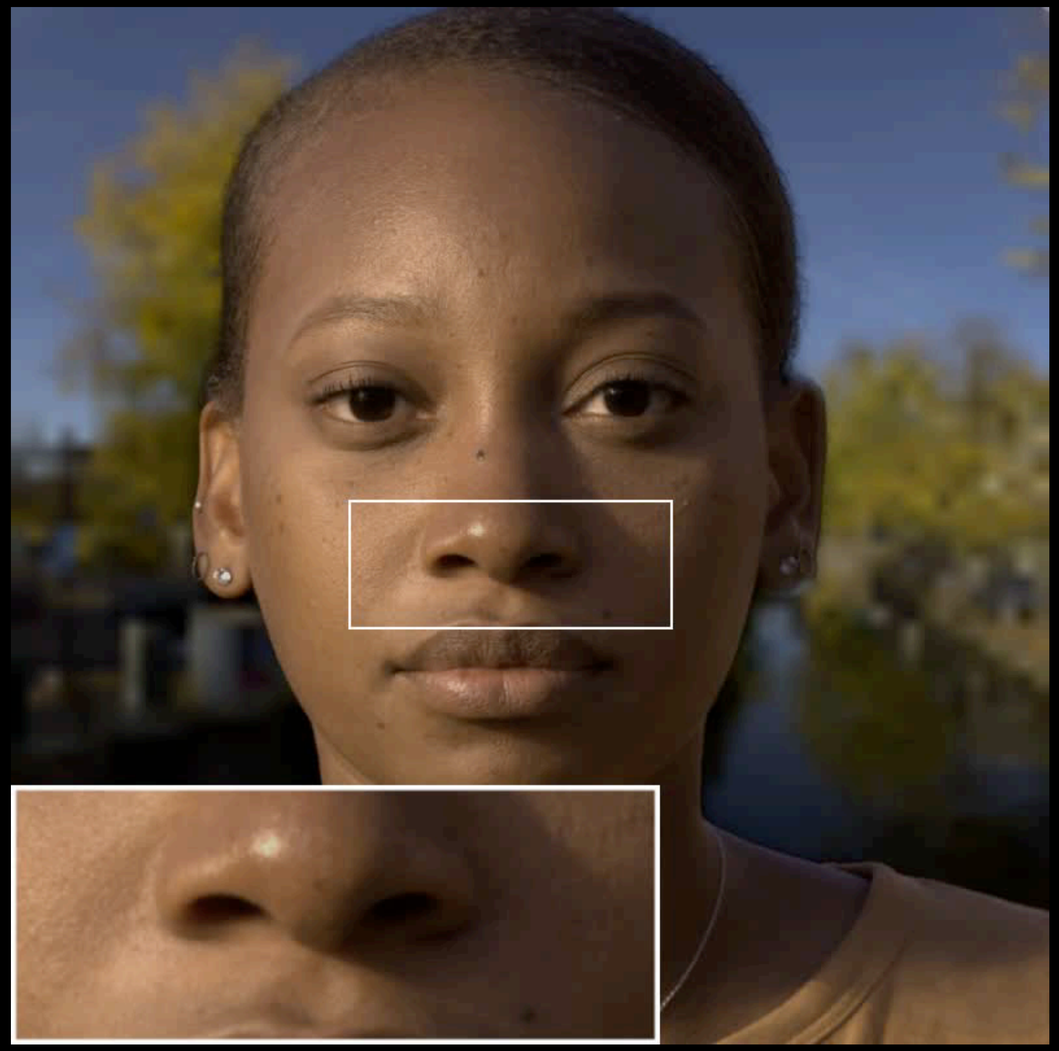
Ours



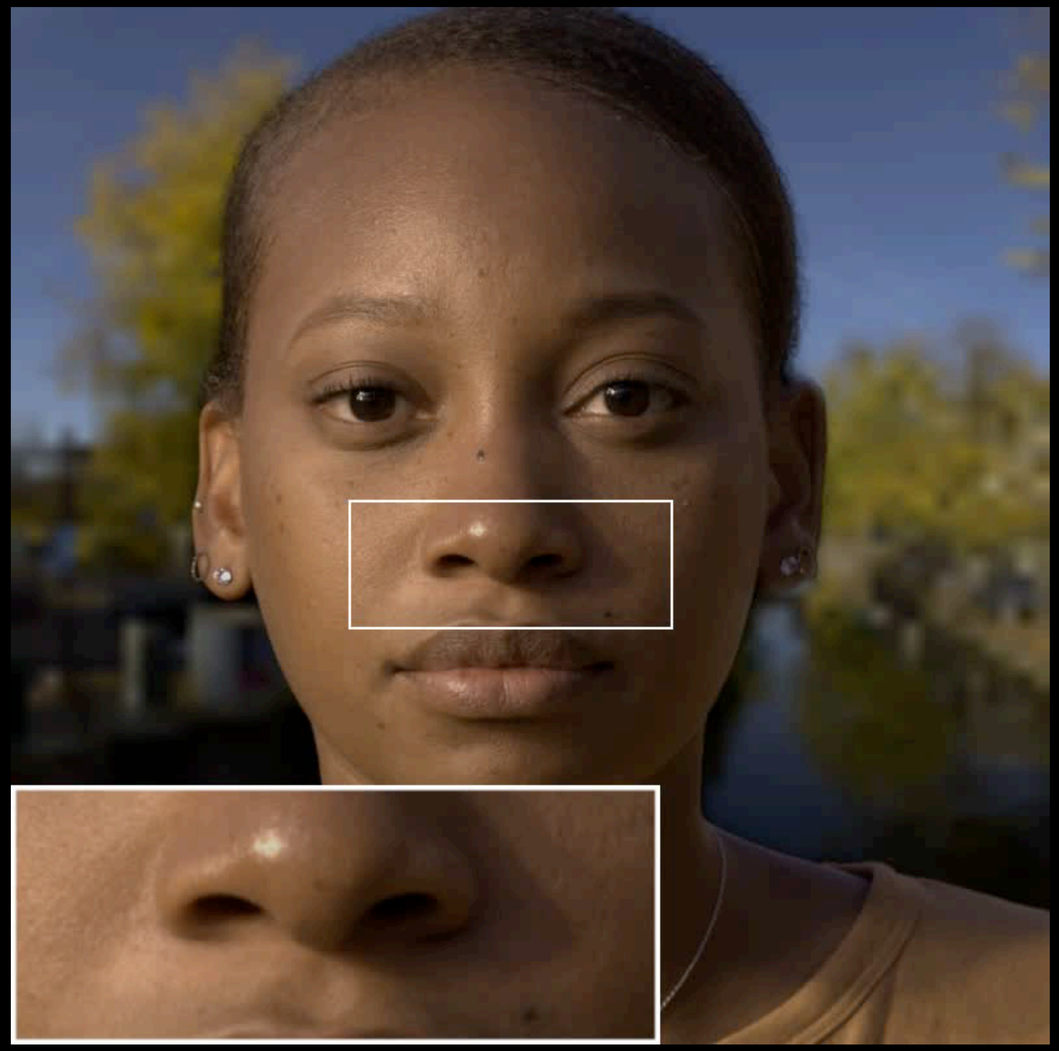
Linear Blend

Results: Applications

- High-frequency Environment Map Relighting



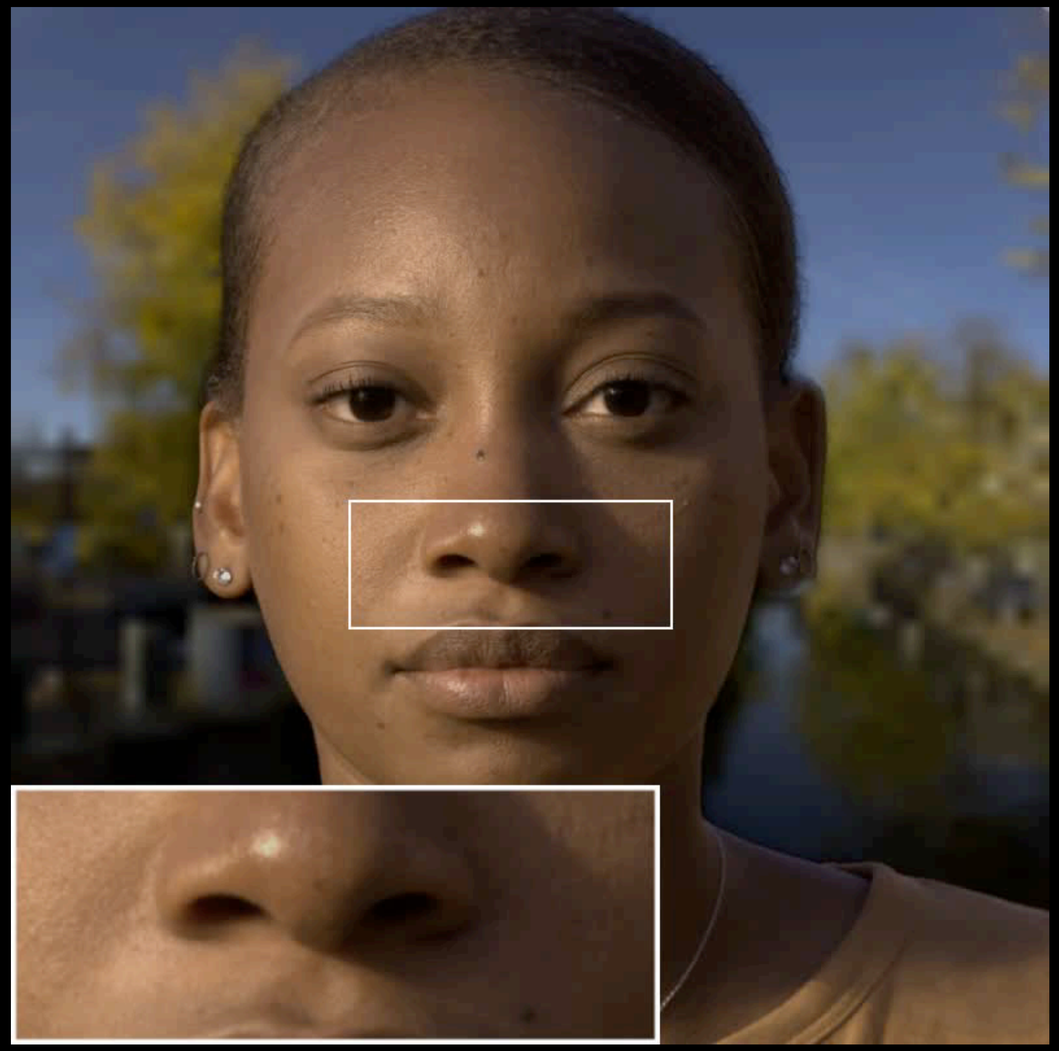
Ours



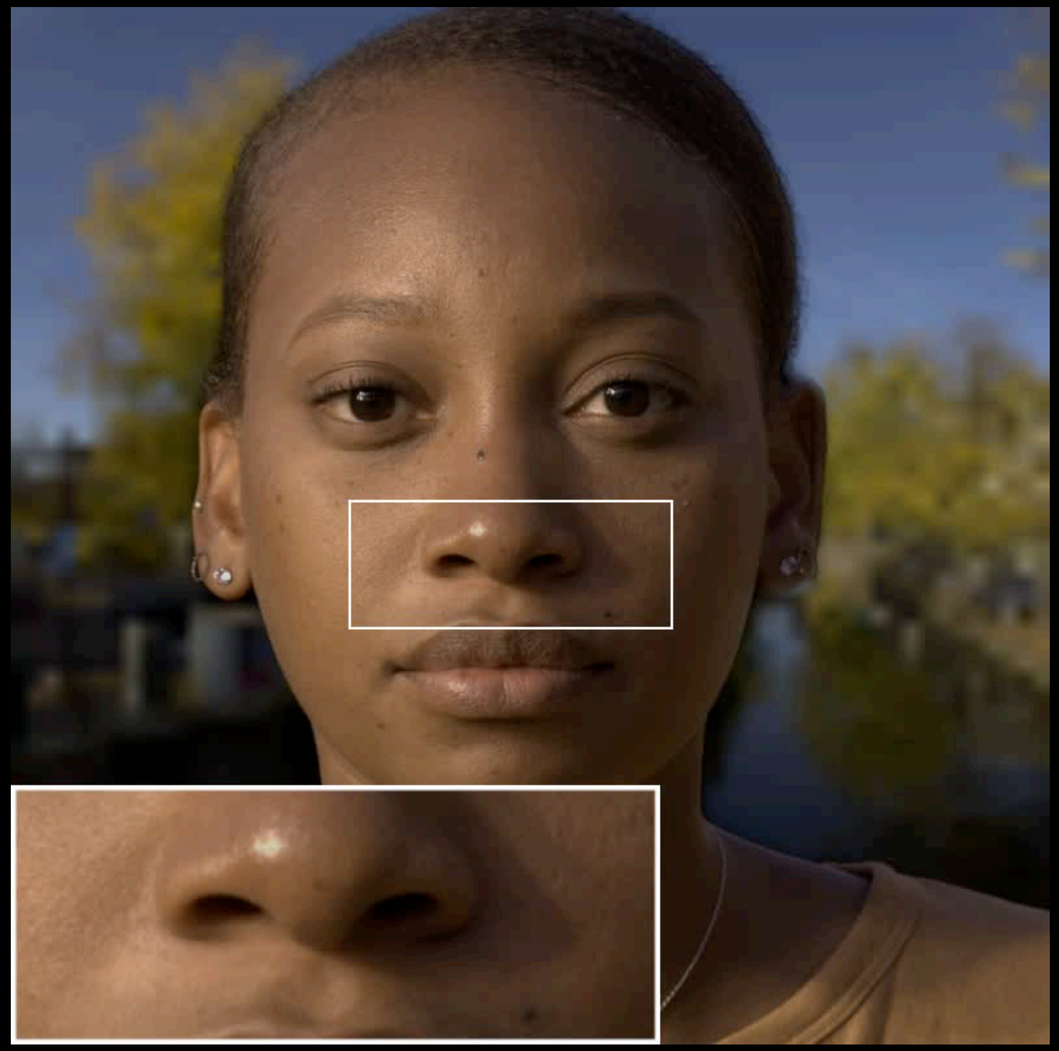
Linear Blend

Results: Applications

- High-frequency Environment Map Relighting



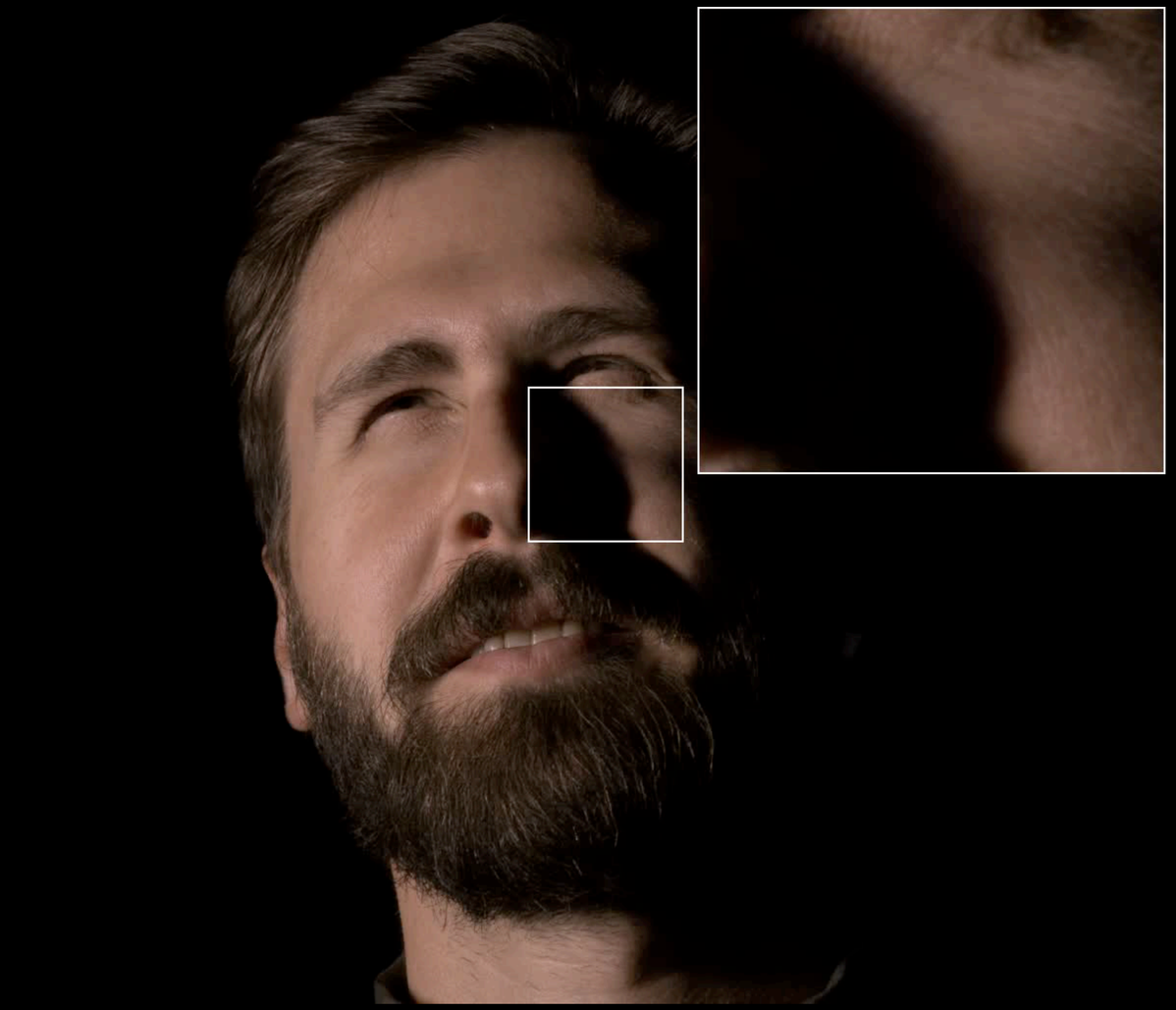
Ours



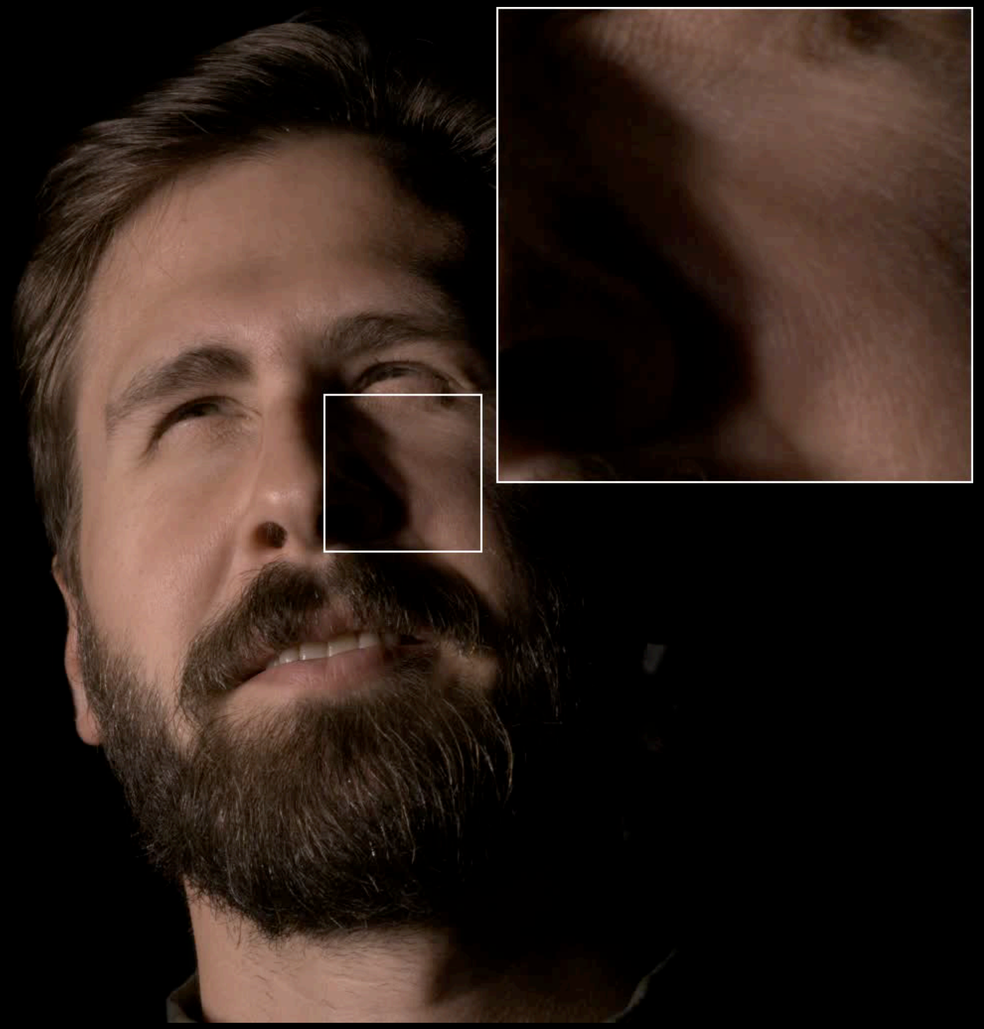
Linear Blend

Results: Applications

- Shadow softness control



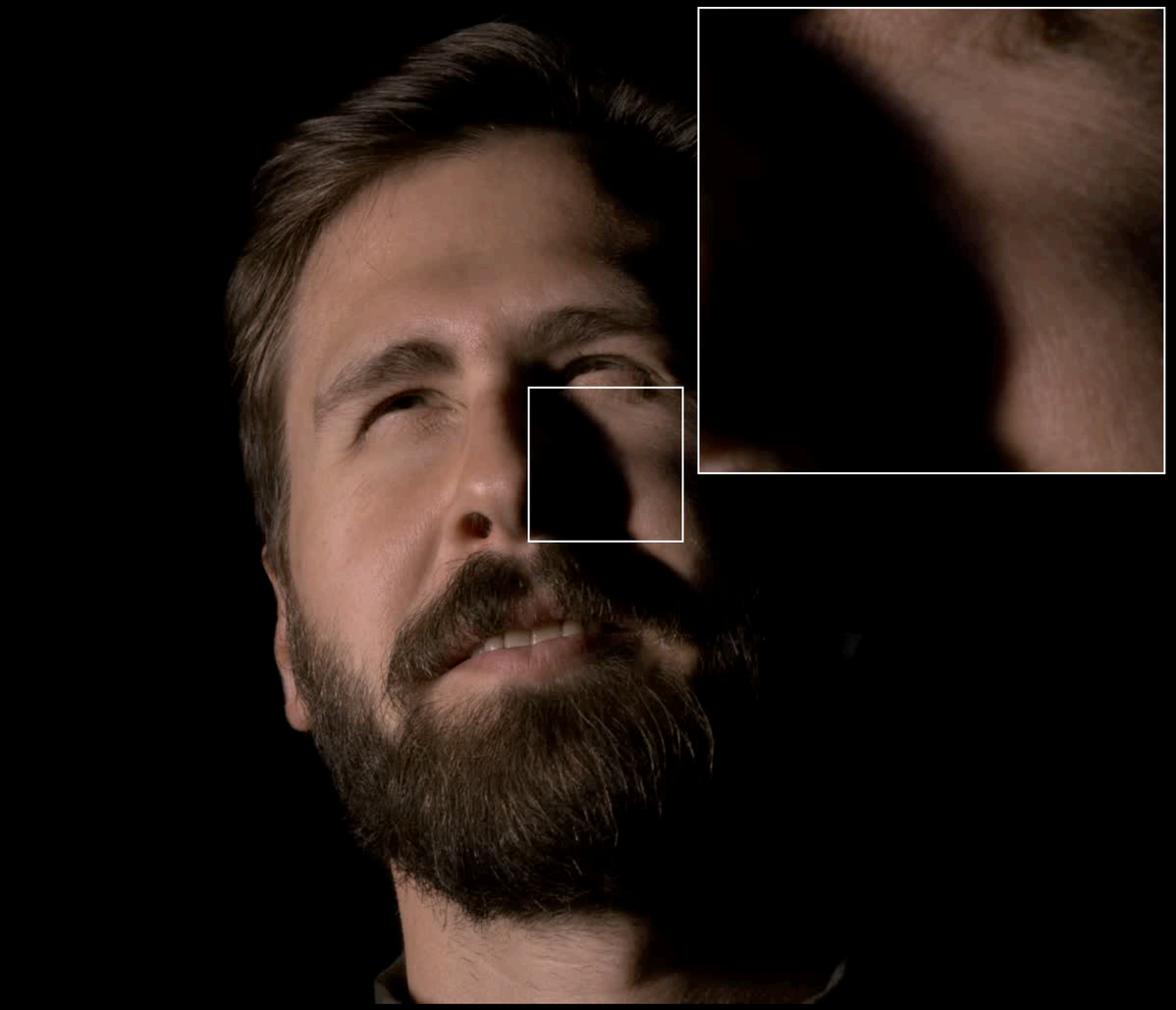
Ours



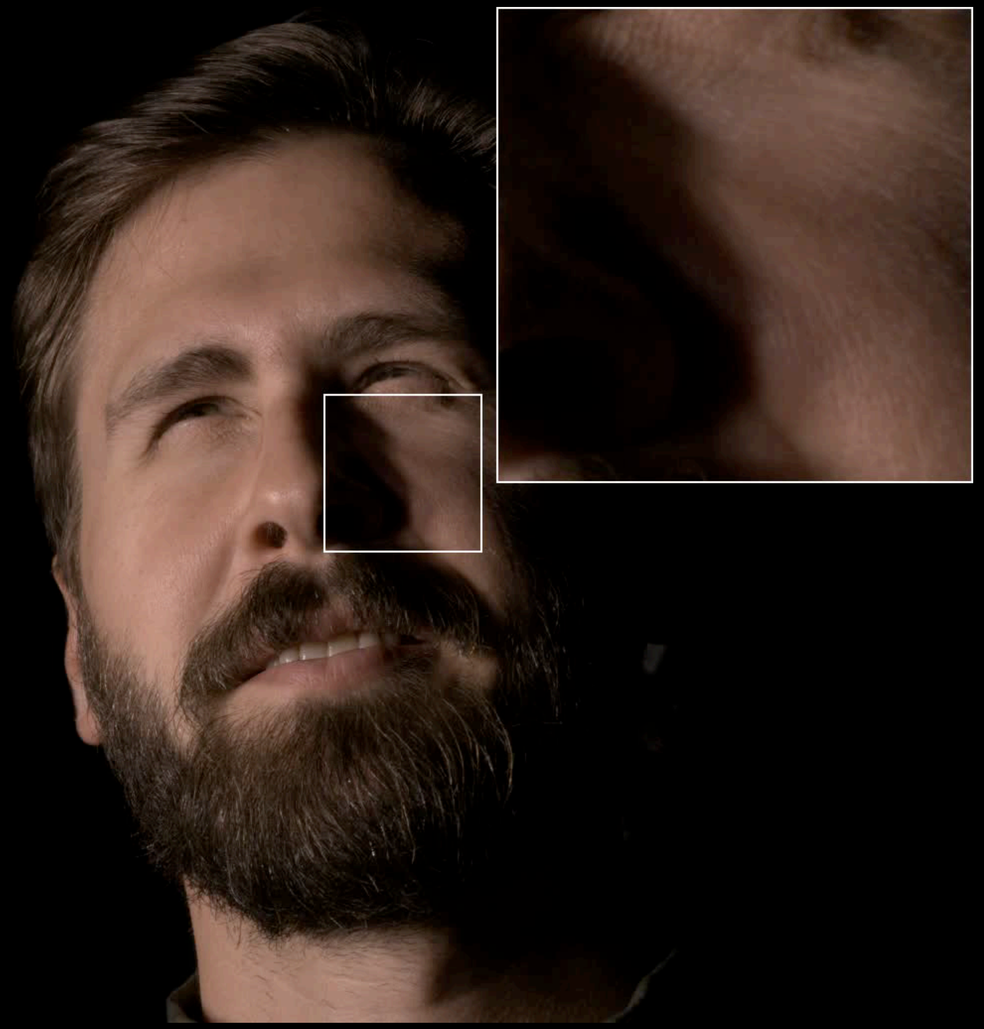
Linear Blend

Results: Applications

- Shadow softness control



Ours



Linear Blend

Conclusion

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- Super-resolves the lighting pattern on the light stage.

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- Two key techniques:

Conclusion

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  - “Dropout” on input neighbours;

Conclusion

- Super-resolves the lighting pattern on the light stage.
- Two key techniques:
  - “Dropout” on input neighbours;
  - Alias-free weighting on network activations.

Acknowledgement

Acknowledgement

- This work was funded in part by
  - Google Fellowship
  - NSF grants 1617234, 1703957
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  - Ronald L. Graham Chair
  - UC San Diego Center for Visual Computing.
- Thanks to all anonymous volunters in the dataset.
- Thanks to all anonymous reviewers for the valuable feedback.

Light Stage Super-Resolution: Continuous High-Frequency Relighting

Light Stage Super-Resolution: Continuous High-Frequency Relighting