Dehazing using Non-Local Regularization with Iso-Depth Neighbor-Fields

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Single Image Dehazing

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Input

Output (ours)

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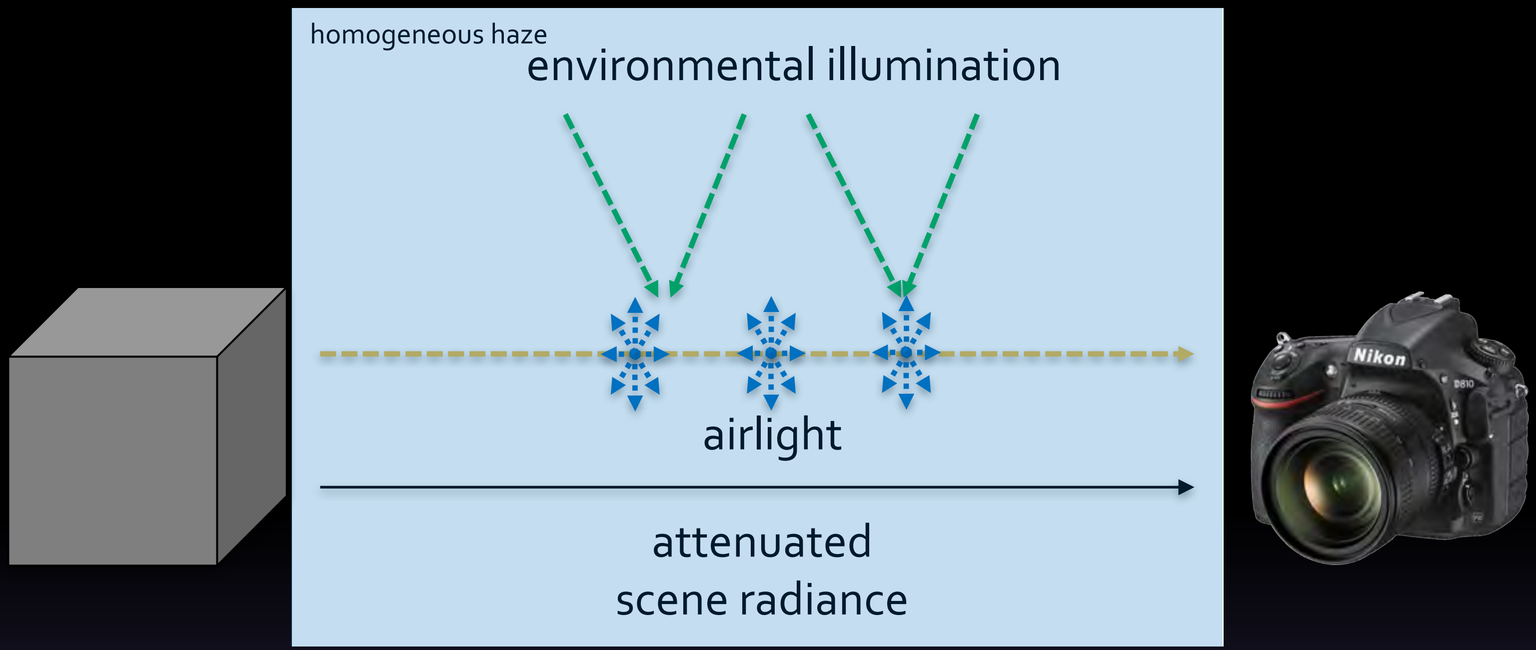
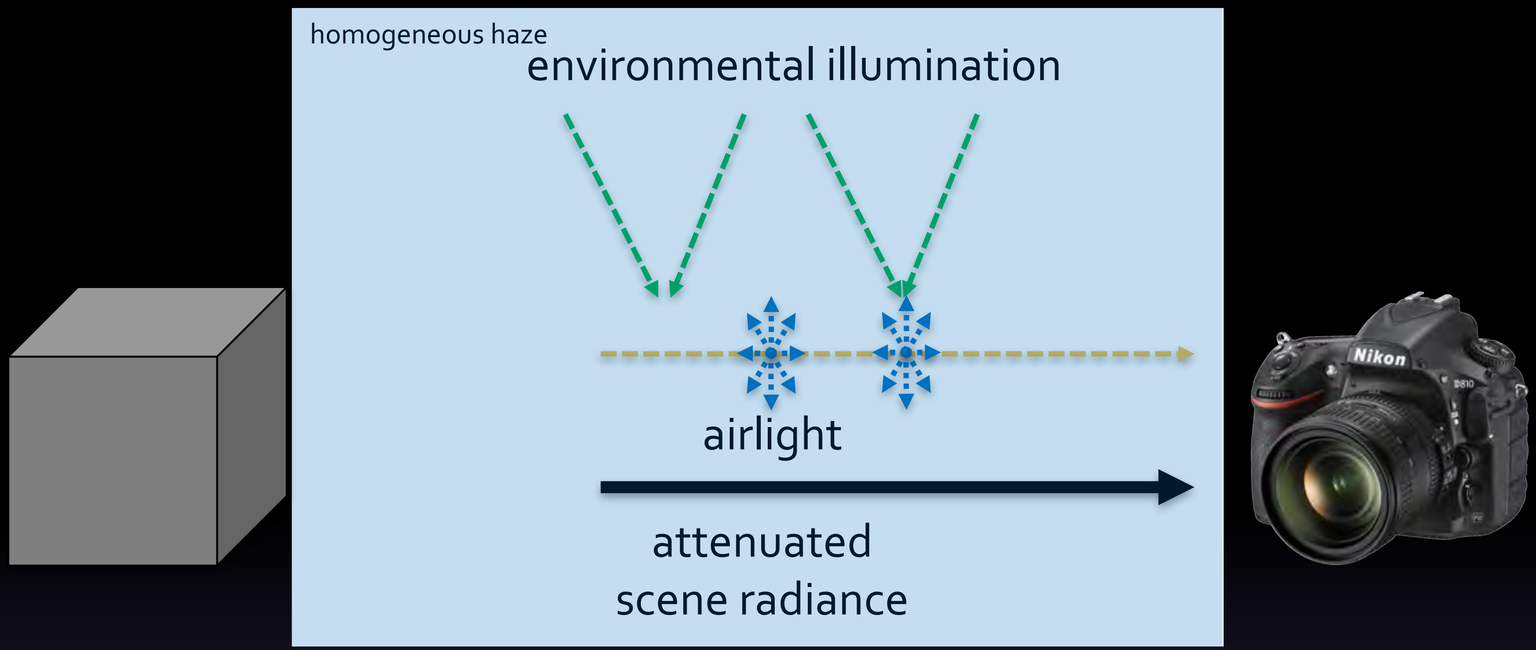
Haze Formation Model

Haze Formation Model

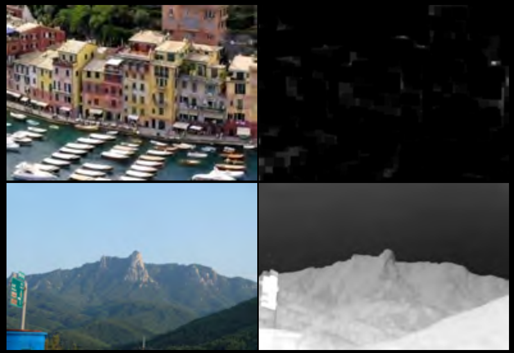


Depth-Dependency on Airlight

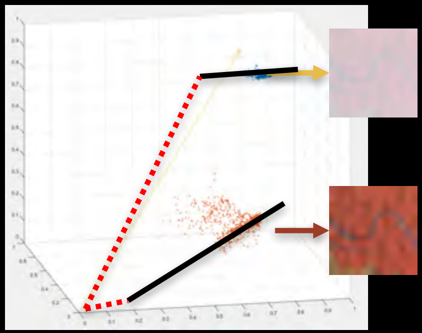


- The amount of scattering depends on the depth of an object.

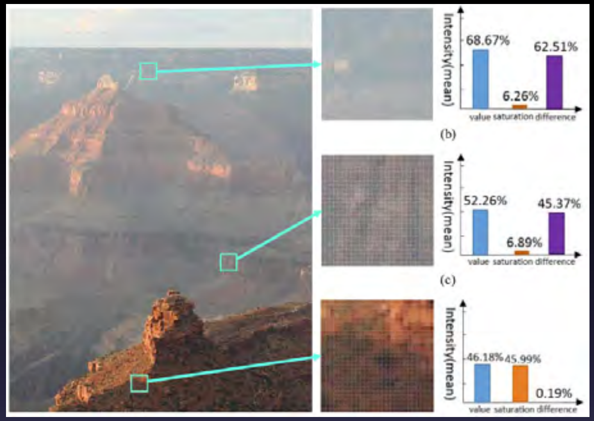
Related Work: Haze Estimation



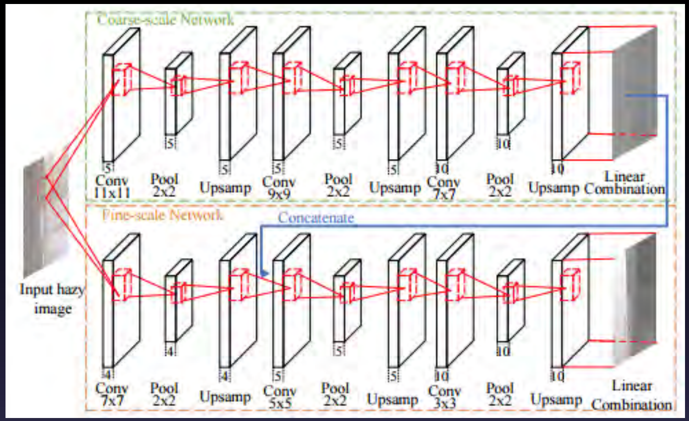
Dark channel prior
[He et al. 2009]



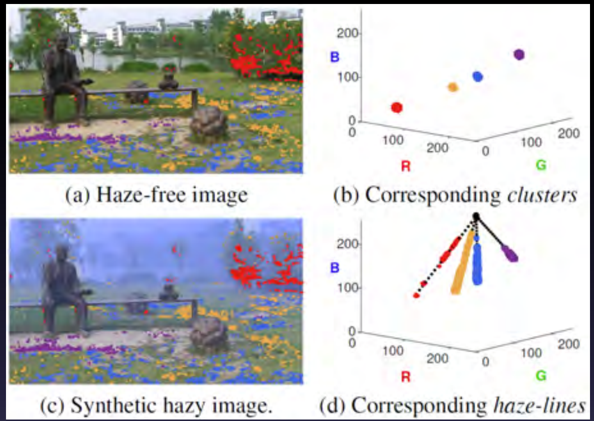
Color-line prior
[Fattal 2014]



Color attenuation prior
[Zhu et al. 2015]

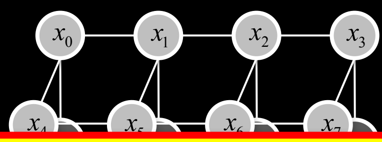


CNN
[Ren et al. 2016]

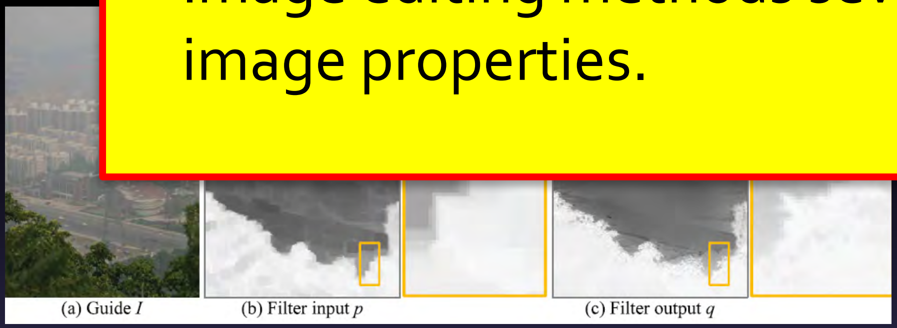


Non-local haze-line prior
[Berman et al. 2016]

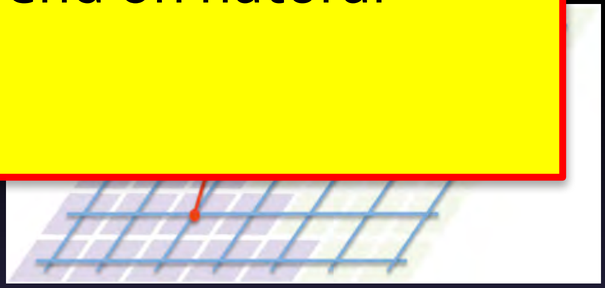
Related Work: Haze Regularization



- MRF-based methods do not use **depth-implied non-local information**.
- Image editing methods severely depend on natural image properties.



Guided filtering
[He et al. 2013]



Augmented GMRF
[Fattal 2014]

Key Insight

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- There is no method that depth-inferred information is used for regularization.

- We employ **depth cue in regularization** to achieve high-quality scene recovery.

HAZE ESTIMATION

Dehazing Model

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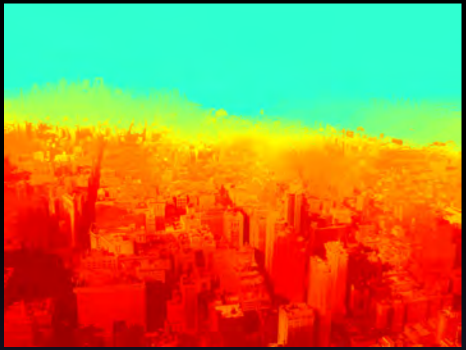
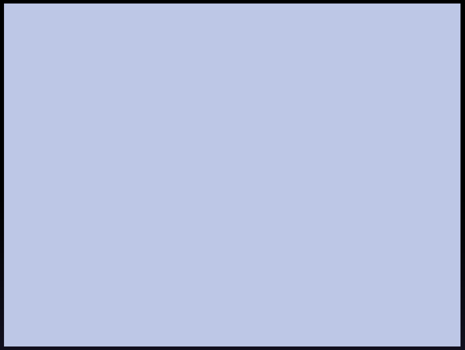
Haze formation model $\underbrace{I(\mathbf{x})}_{\text{hazy image}} = \underbrace{t(\mathbf{x})J(\mathbf{x})}_{\text{attenuated scene radiance}} + \underbrace{(1-t(\mathbf{x}))A}_{\text{airlight}}$

$I(\mathbf{x})$



$t(\mathbf{x})$



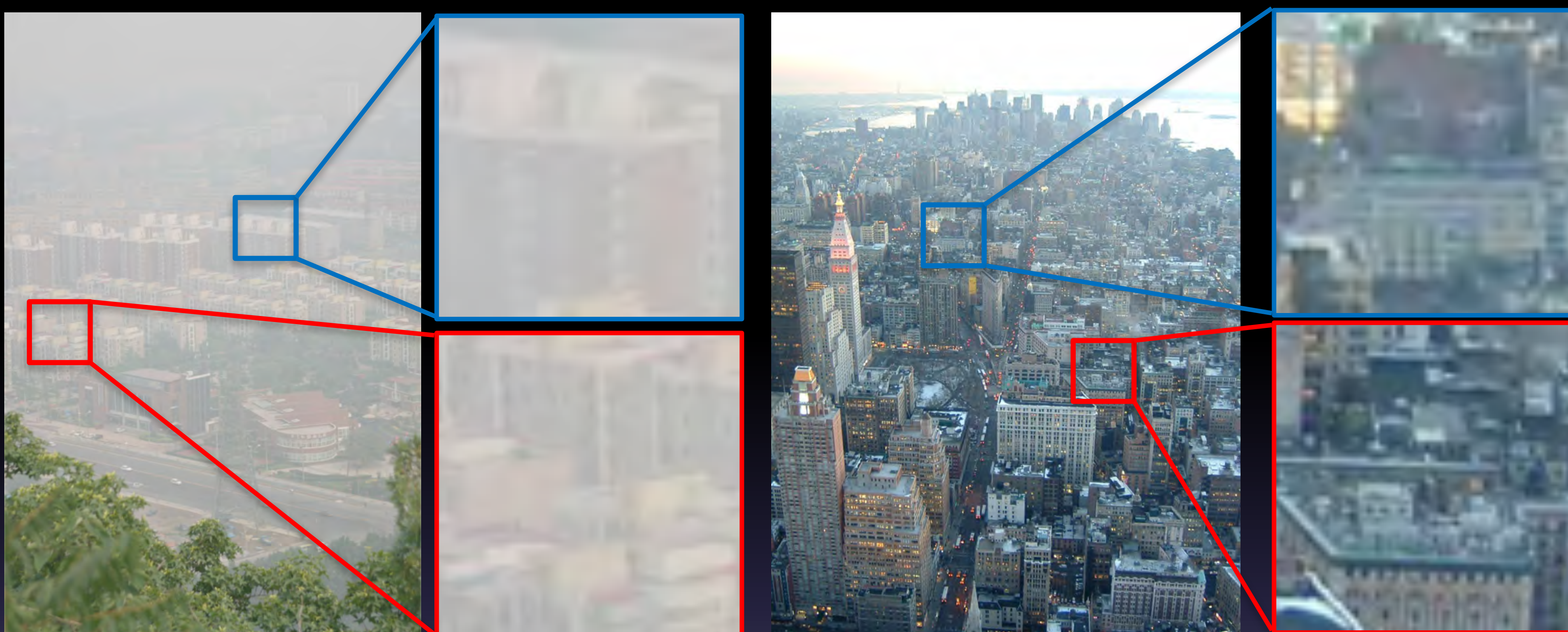
A

$J(\mathbf{x})$

Properties of Transmission

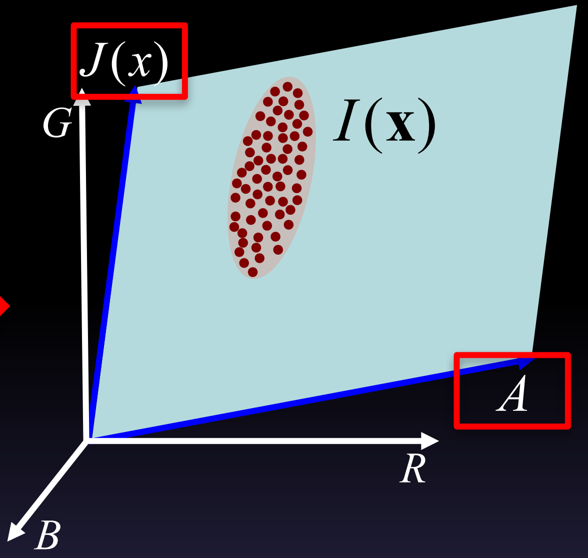
$$I(\mathbf{x}) = t(\mathbf{x})J(\mathbf{x}) + (1 - t(\mathbf{x}))A$$

- Haze does not change largely within a local region.
- Transmission values are piecewise smooth.



Problem Formulation

$$\underbrace{I(\mathbf{x})}_{\text{hazy image}} = \underbrace{t(\mathbf{x})J(\mathbf{x})}_{\text{attenuated scene radiance}} + \underbrace{(1-t(\mathbf{x}))A}_{\text{airlight}}$$



Atmospheric Light Estimation

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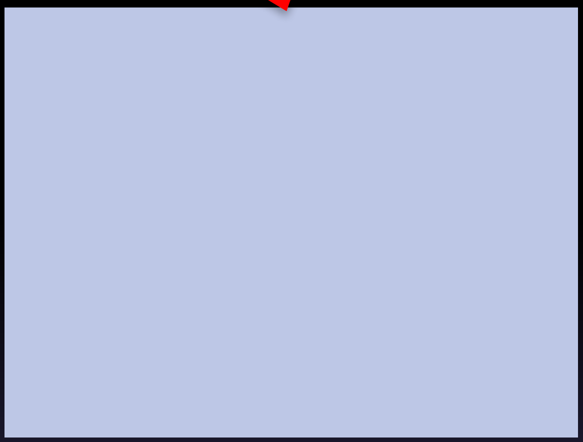
$$I(\mathbf{x}) = t(\mathbf{x})J(\mathbf{x}) + (1 - t(\mathbf{x}))\underline{A}$$

input

dark channel



atmospheric light map

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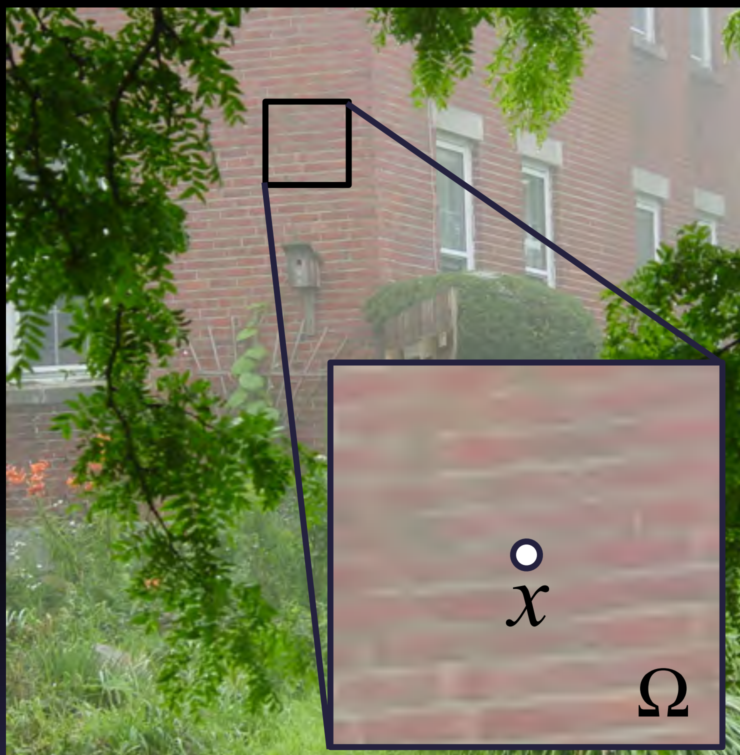
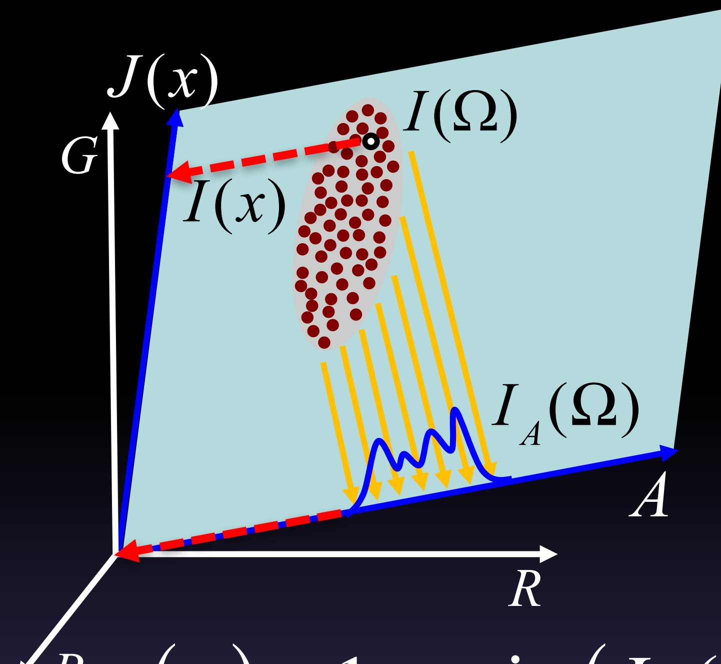
Transmission Estimation in a Linear Subspace

$$I(\mathbf{x}) = t(\mathbf{x})J(\mathbf{x}) + \underline{(1 - t(\mathbf{x}))A}$$





$$t(x) = 1 - \min\left(I_A(\Omega)\right) / A$$

Outlier Rejection: Color Ambiguity

- Ambiguous to separate haze.

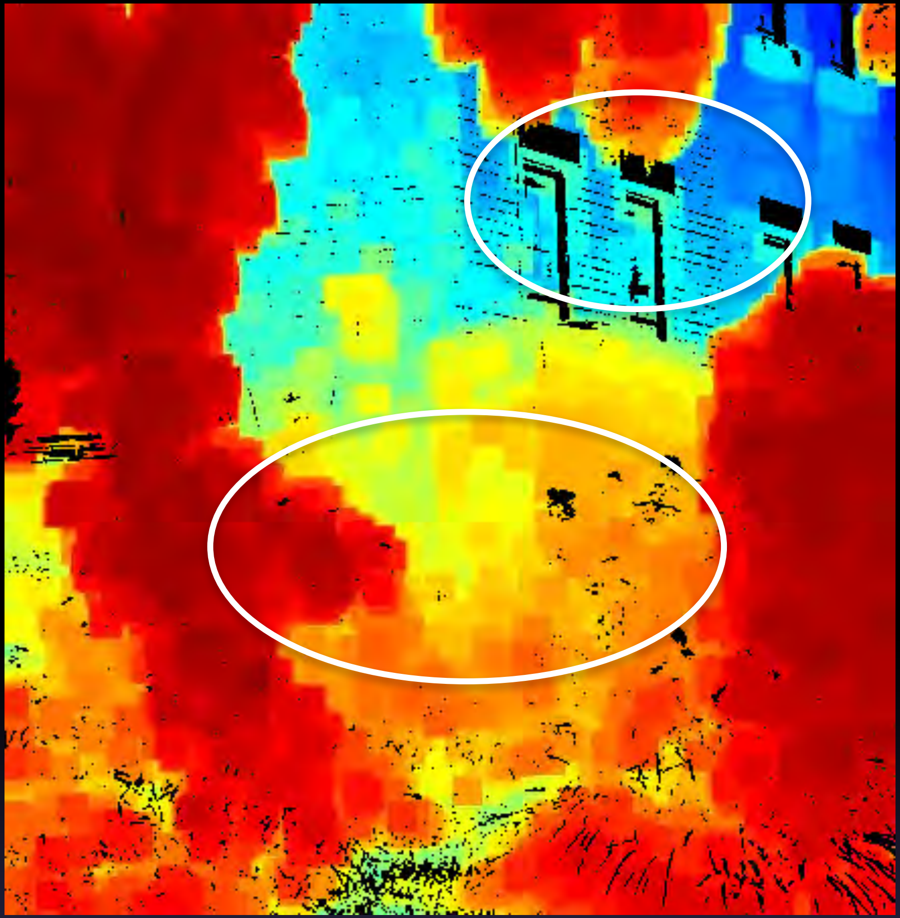
$$\angle\big(I(\mathbf{x}), A\big) < 0.2\ rad$$

Outlier Rejection: Saturation

- Higher luminance than atmospheric vector.

$$lum\left(I\left(\mathbf{x}\right)\right) > lum\left(A\right)$$

Initial Estimate

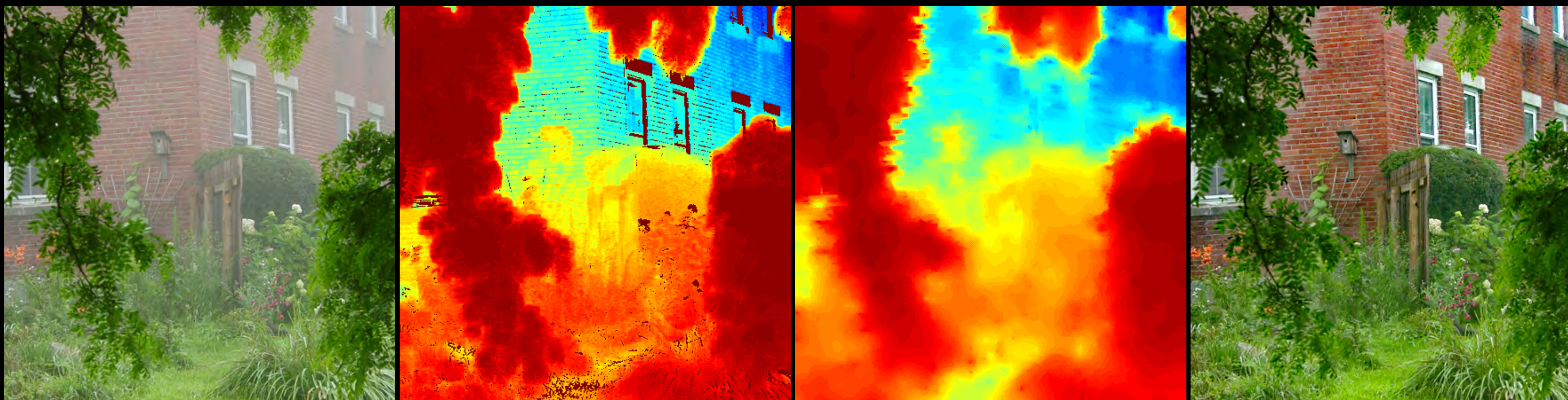


- Outliers
- Blocky artifacts

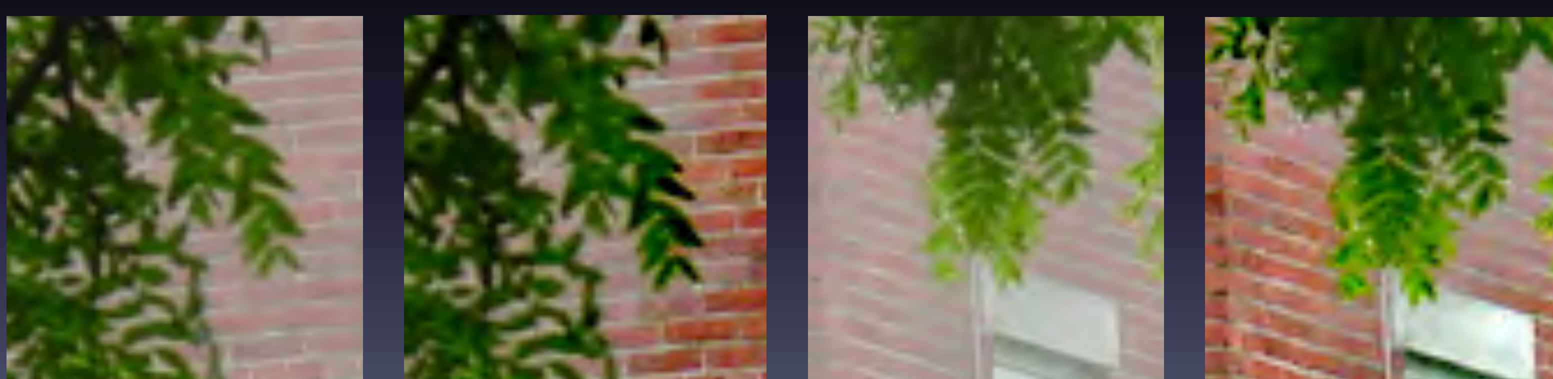
HAZE REGULARIZATION

Regularization with Traditional MRFs

input	initial estimate	regularized with grid MRFs	dehazed



- Blurry artifacts where there is an abrupt change in depths



Traditional Grid MRF Estimation

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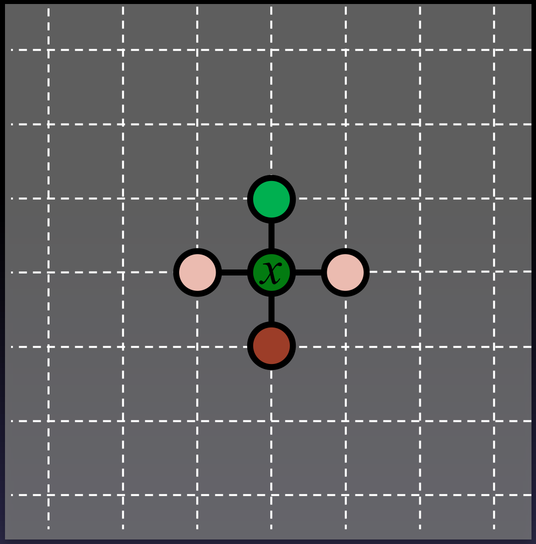
$$E(t) = \sum_x \left\{ \underline{E_{\text{data}}\left(t(x)\right)} + \sum_{y \in N_x} \underline{E_{\text{smooth}}\left(t(x), t(y)\right)} \right\}$$



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Inaccurate Propagation

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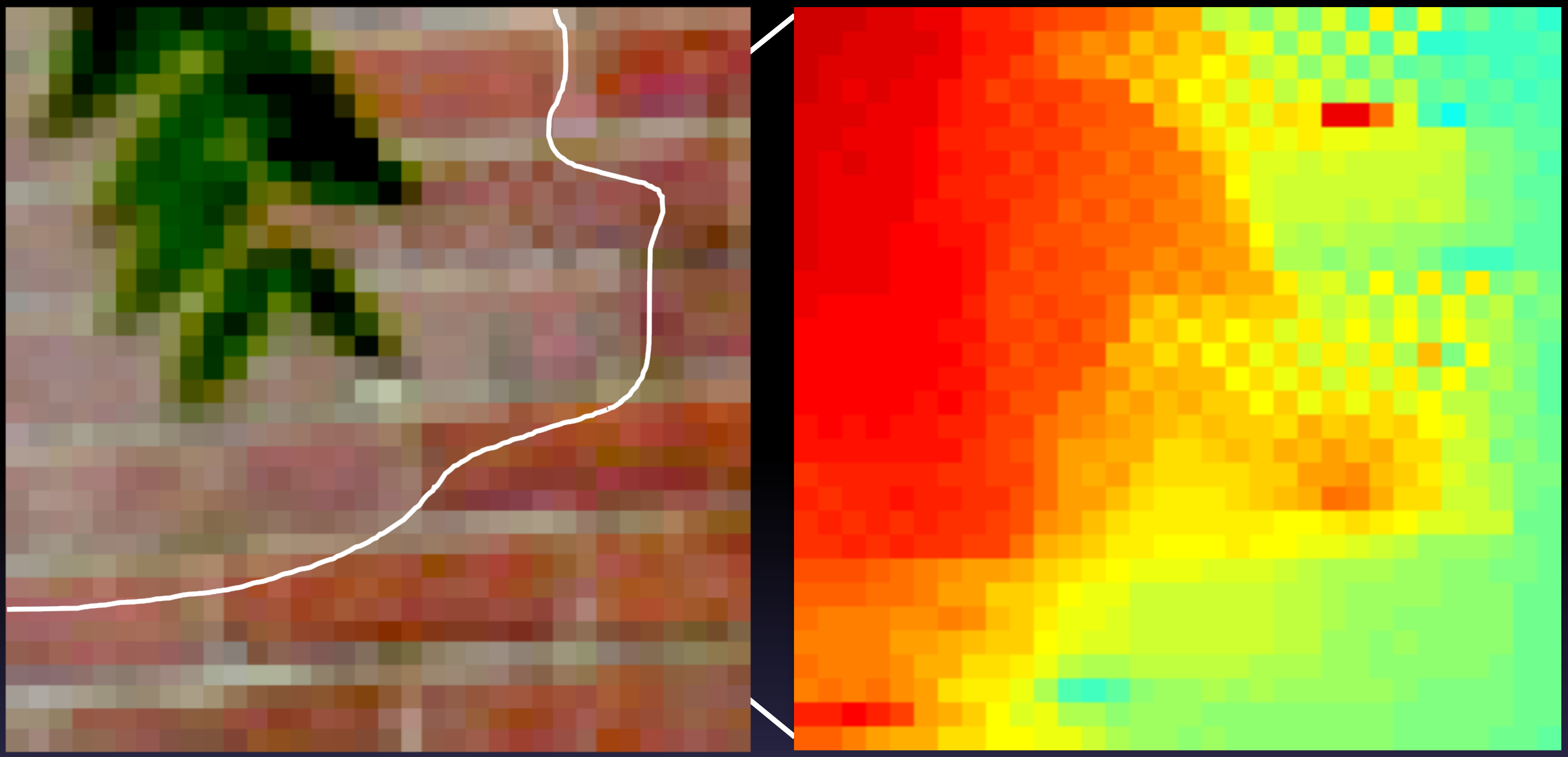

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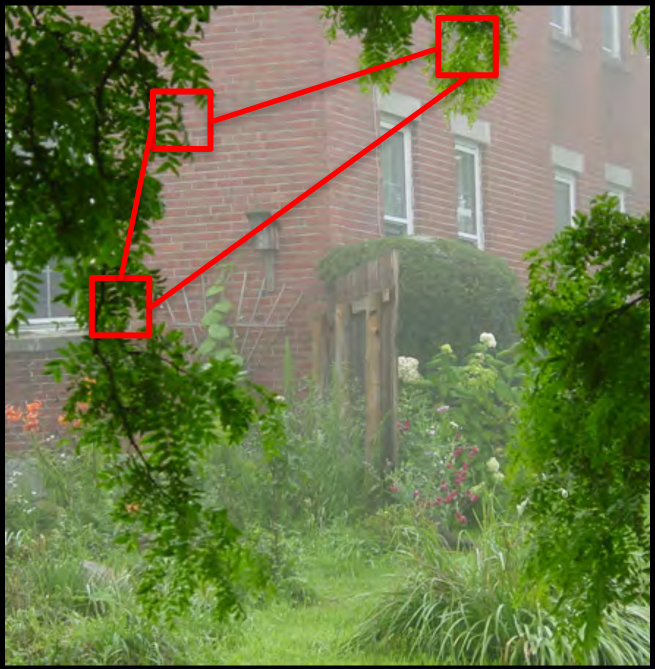
PatchMatch Algorithm



$$\mathrm{dist}(s_1, s_2) = \sqrt{\sum_{i,j} (\mathrm{R}_1(i,j) - \mathrm{R}_2(i,j))^2 + (\mathrm{G}_1(i,j) - \mathrm{G}_2(i,j))^2 + (\mathrm{B}_1(i,j) - \mathrm{B}_2(i,j))^2}$$

- Finds similar patches with Euclidean distance.

PatchMatch Algorithm

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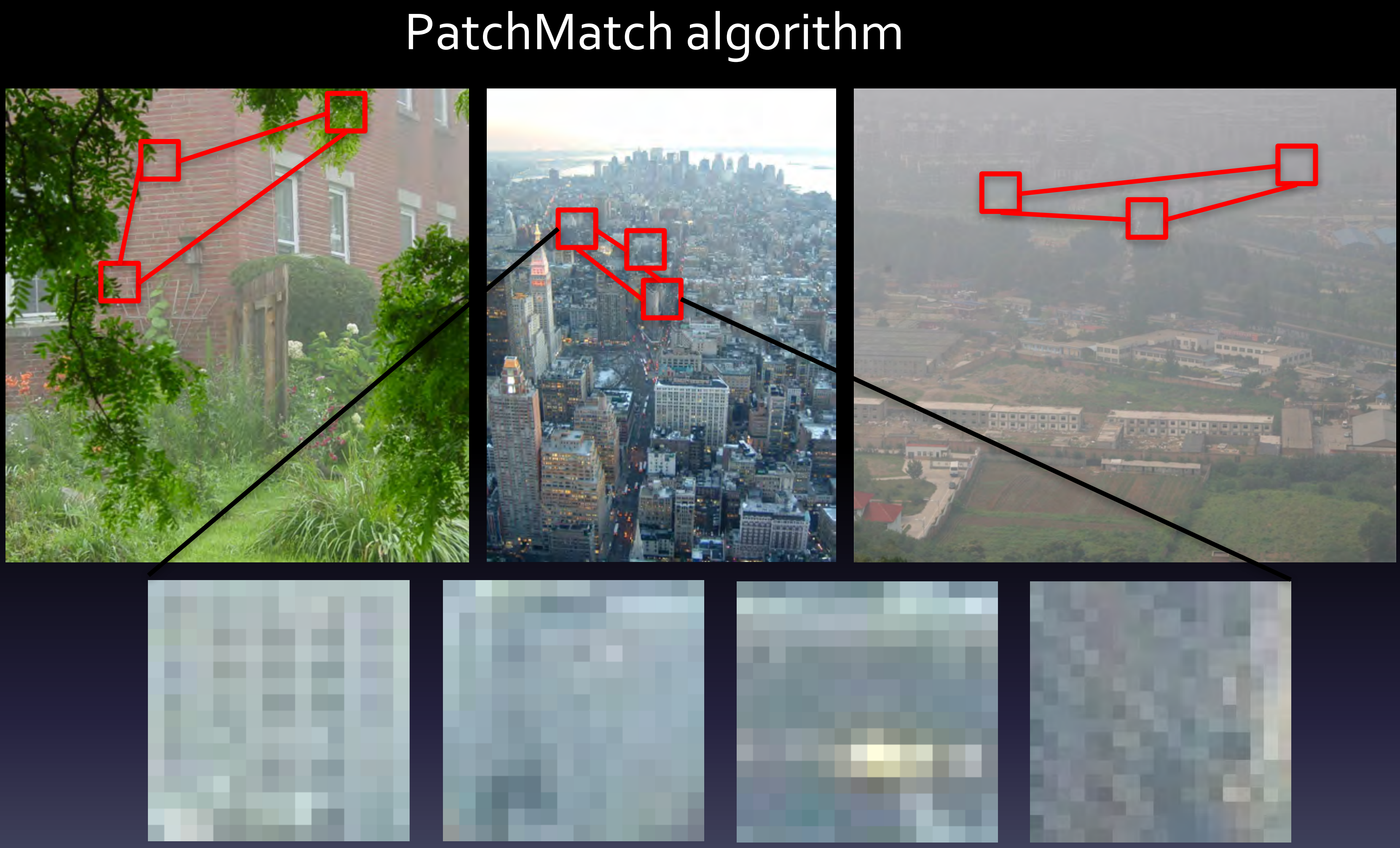
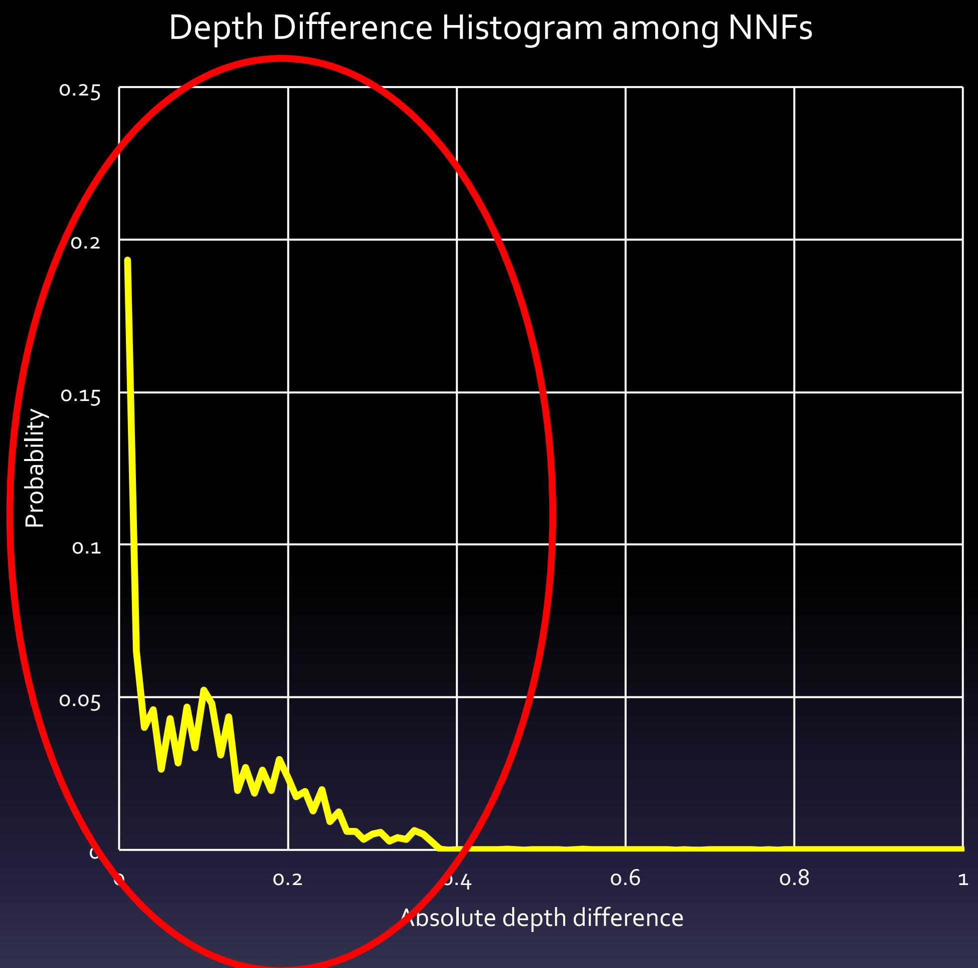


PatchMatch Algorithm

- Haze is more dominant than scene radiance.
- Haze is proportional to depth.
- NNF associates iso-depth pixels.

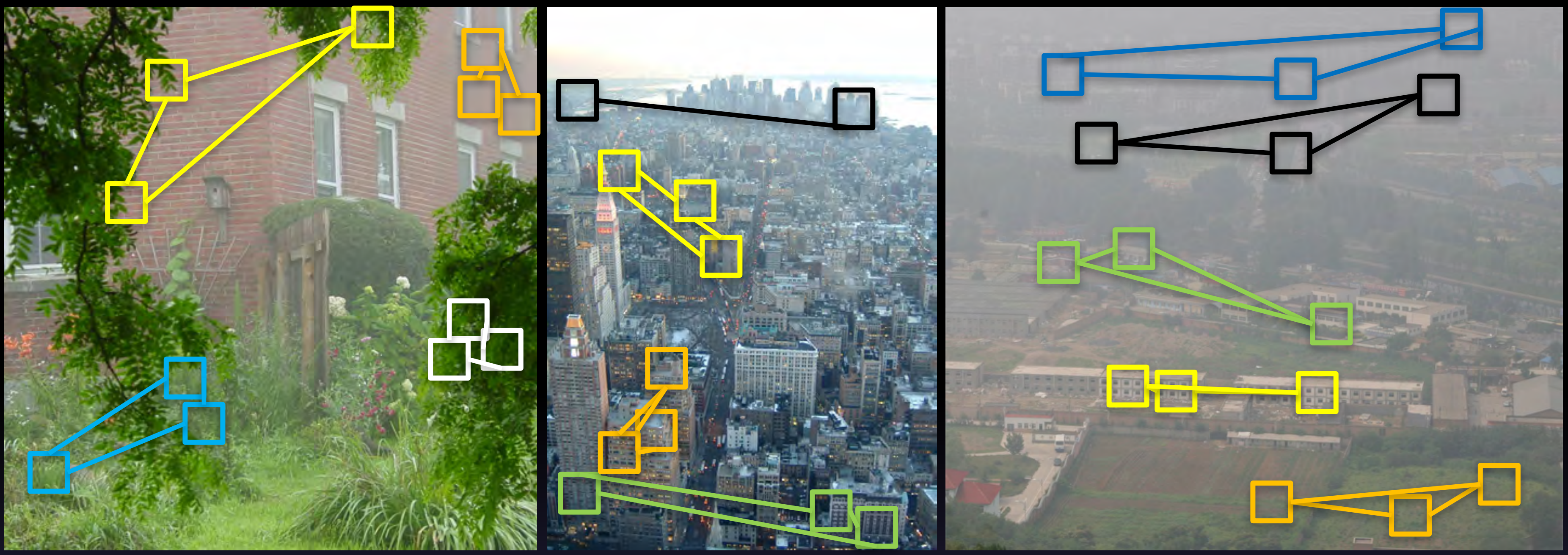
Iso-Depth NNFs



% of (difference < 0.2) = 86%

Our Novel Insight for Regularization

Iso-depth neighbor-fields



- We use our novel information for regularization.

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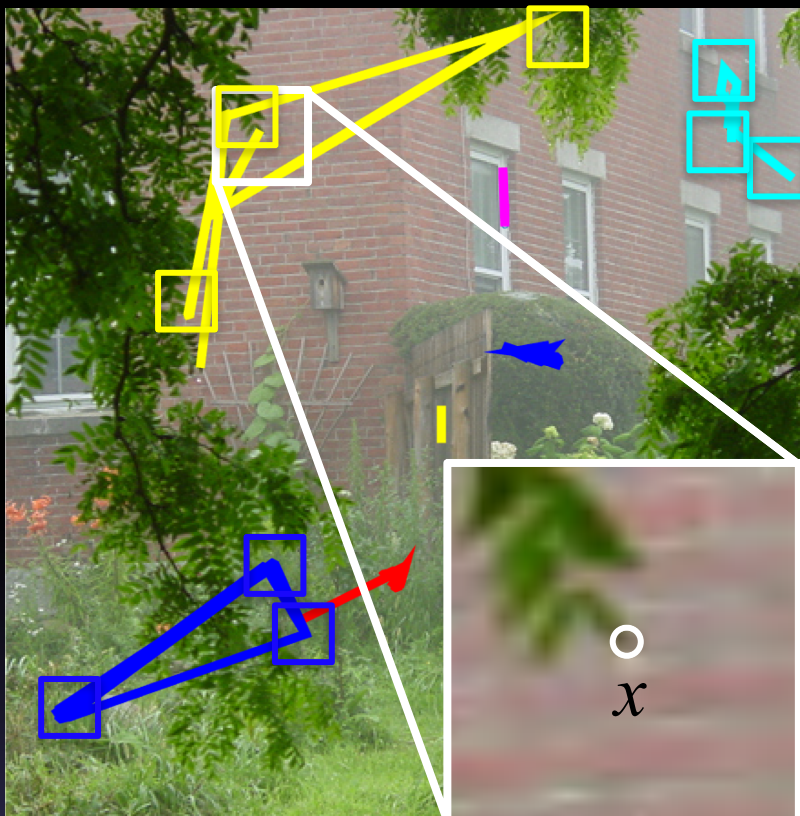
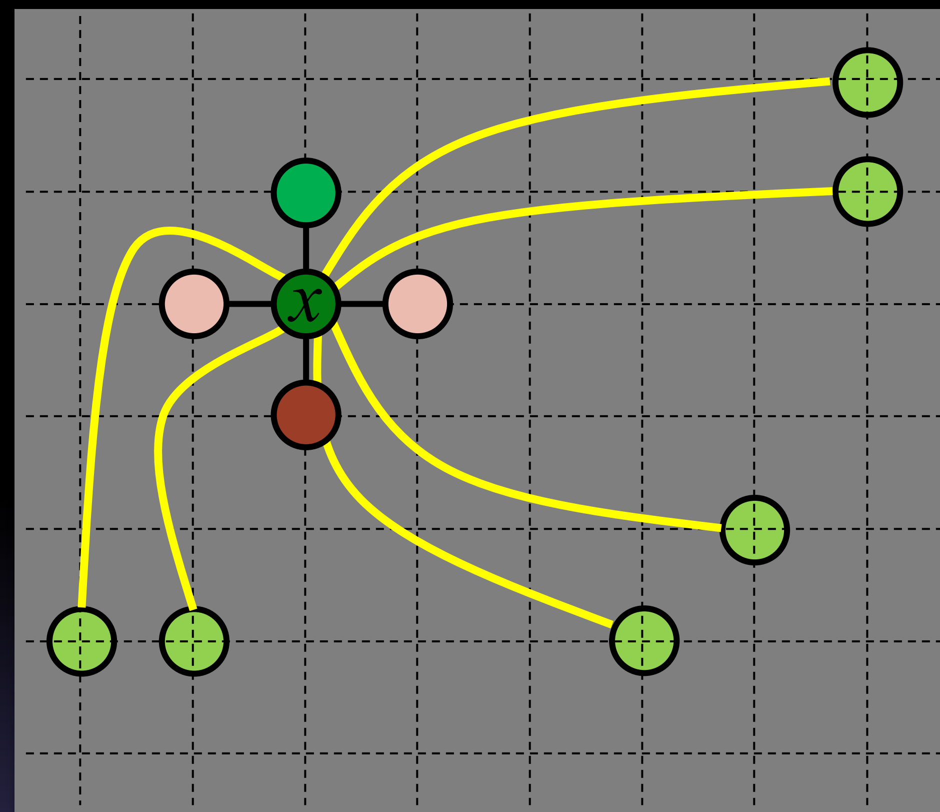
Our MRF with Iso-Depth Neighbor-Fields





Our MRF with NNFs Estimation

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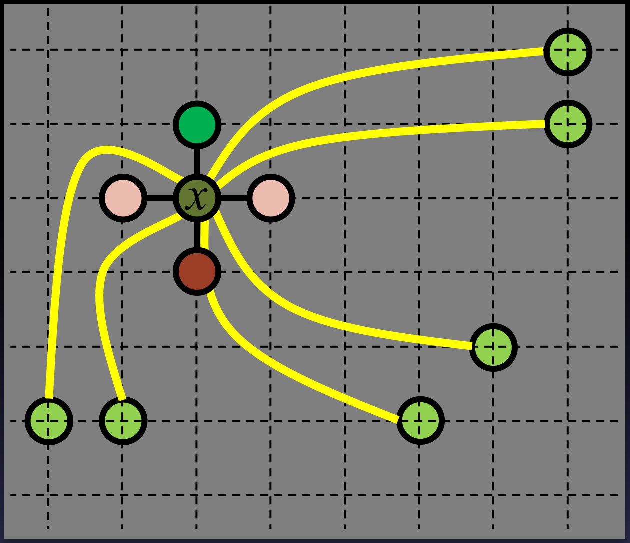
$$E(t) = \sum_{x} \left\{ \underline{E_{\text{data}}\left(t(x)\right)} + \sum_{y \in N_x} \underline{E_{\text{smooth}}\left(t(x), t(y)\right)} \right\}$$



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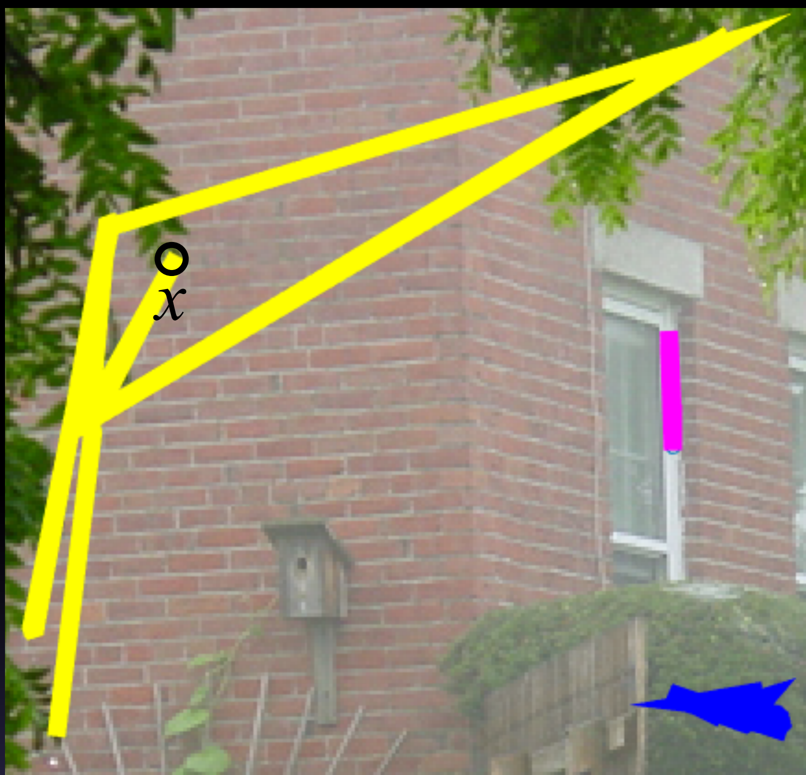
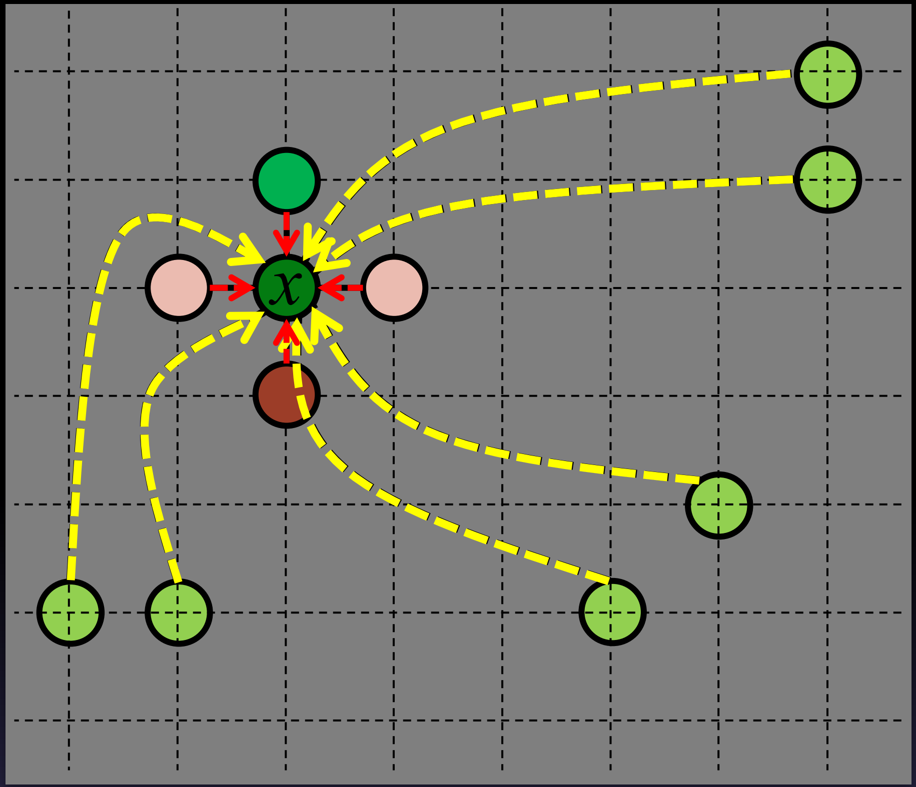
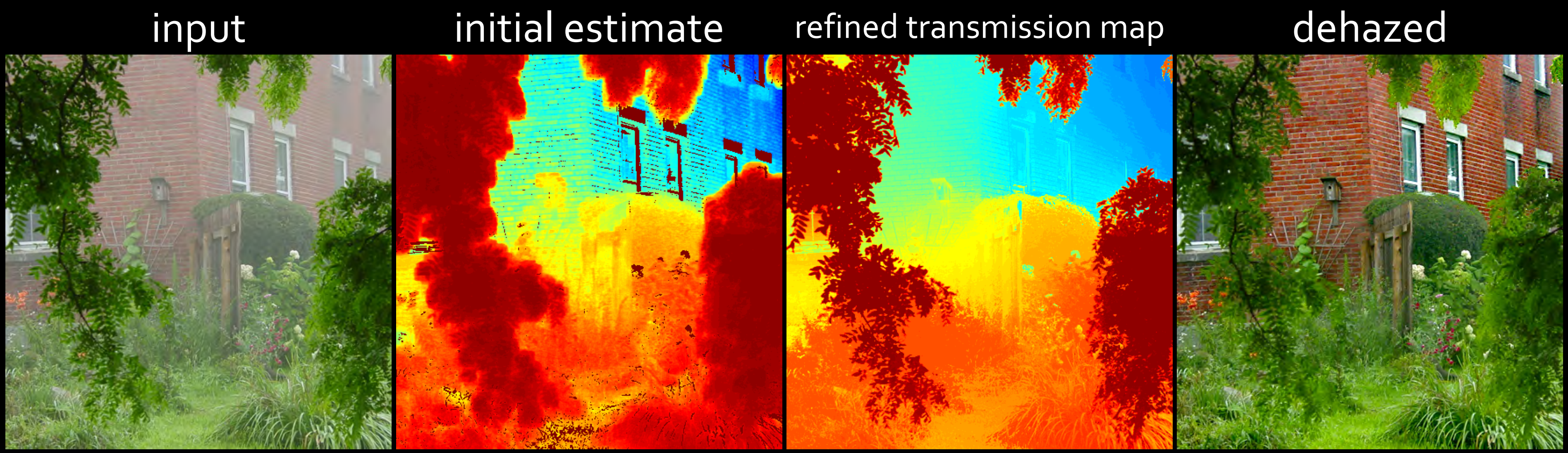
Our NNF-MRF Propagation



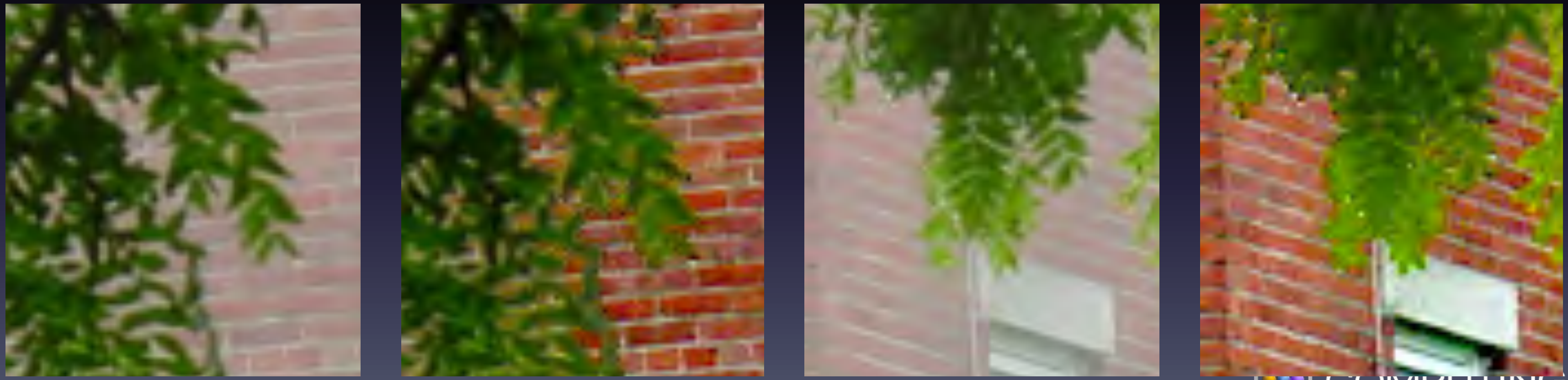


- Neighbors associated by NNFs are in similar depths.

Regularization with Our NNF-MRF



- Sharp edge-discontinuities are preserved.



RESULTS

Grid MRFs vs. Ours

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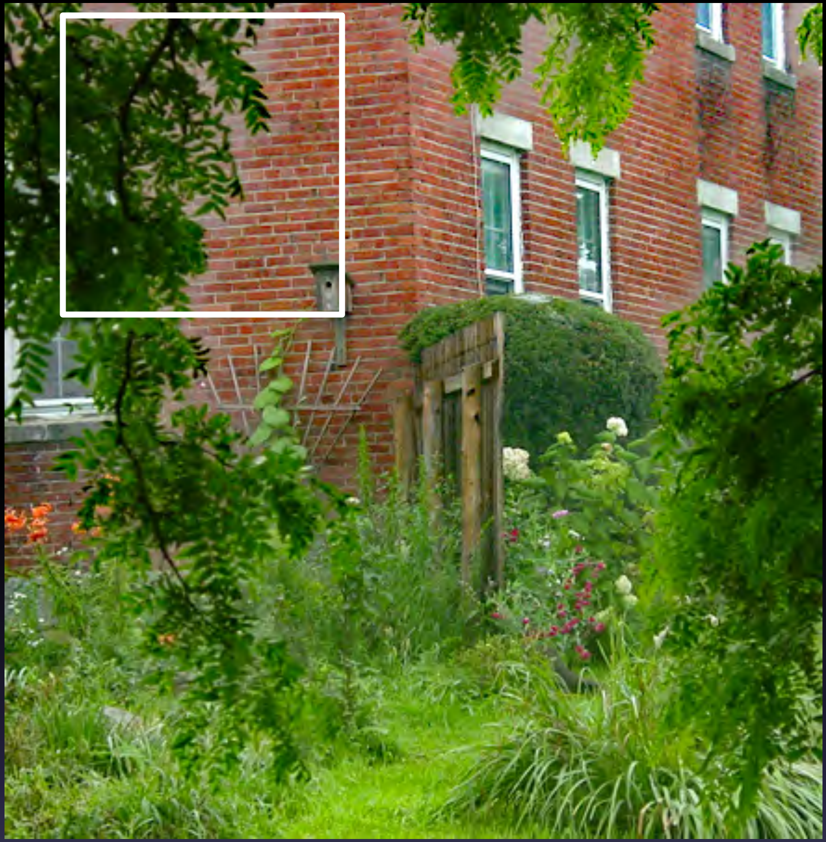
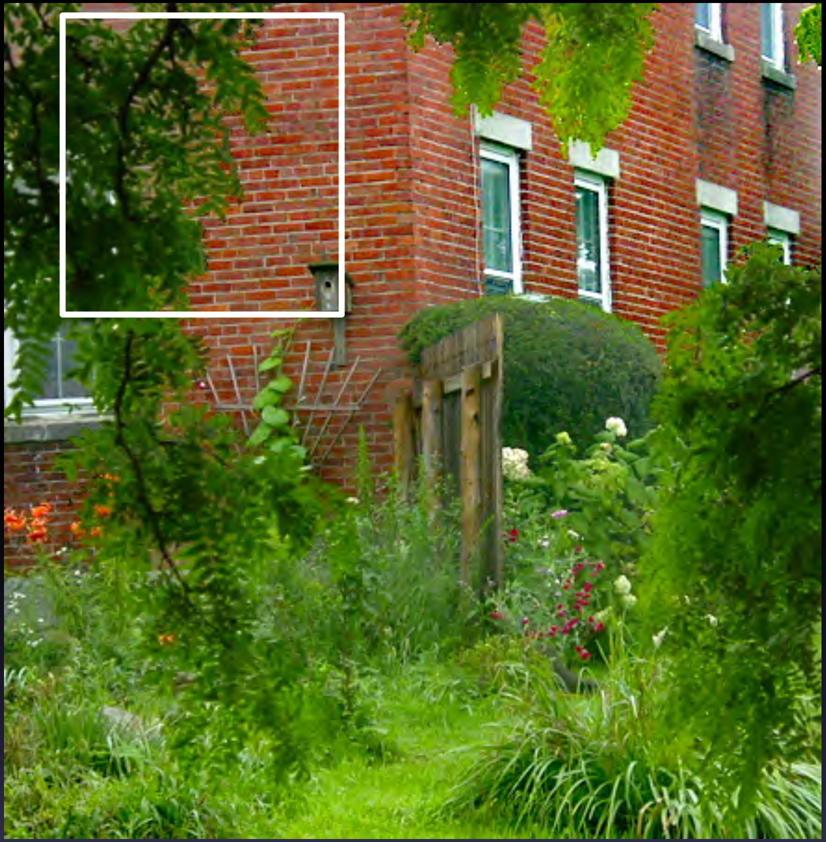
Dehazing with traditional grid MRFs



Dehazing with our NNF-MRFs



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Grid MRFs vs. Ours

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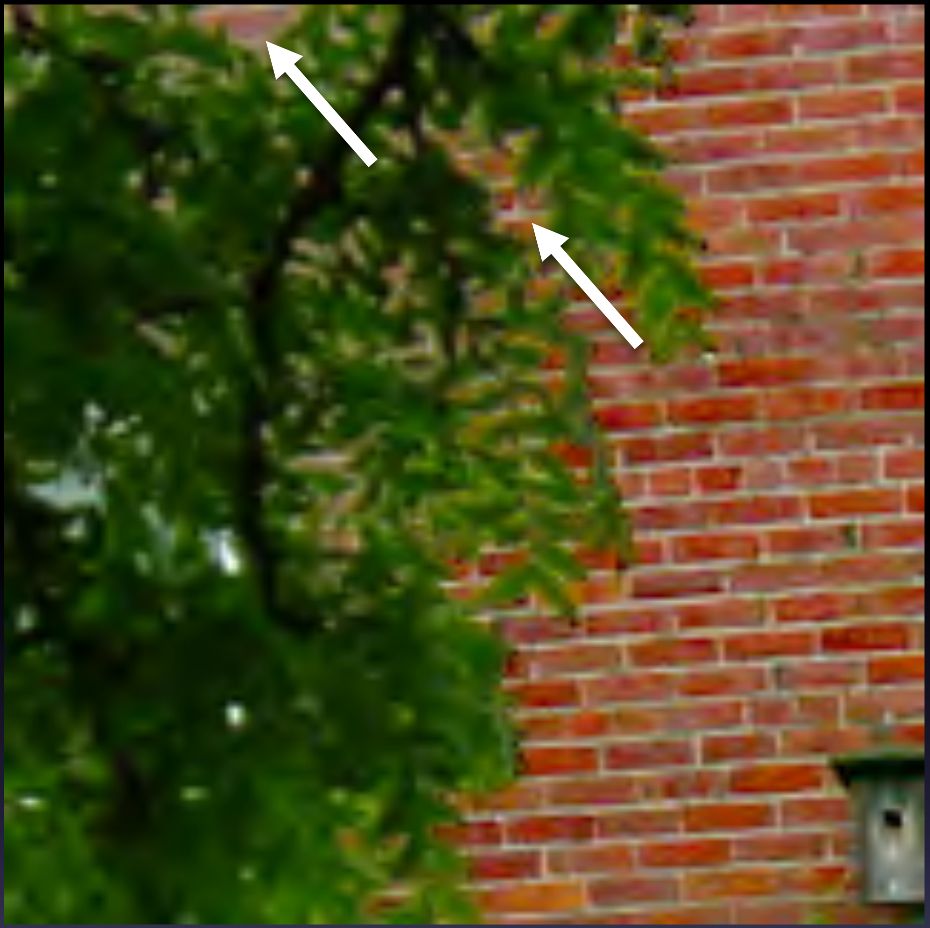

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Image Editing Methods vs. Ours

original

guided filter

matting Laplacian

ours

Image Editing Methods vs. Ours

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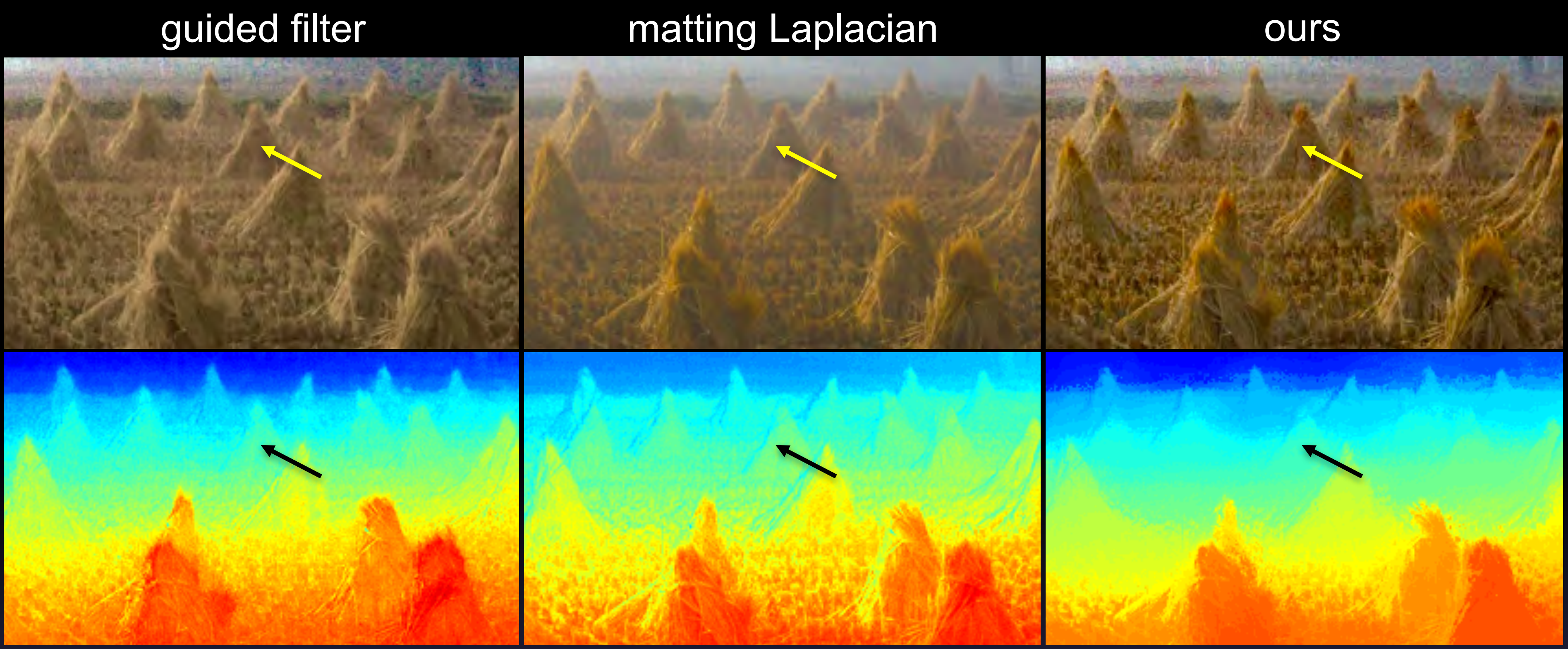

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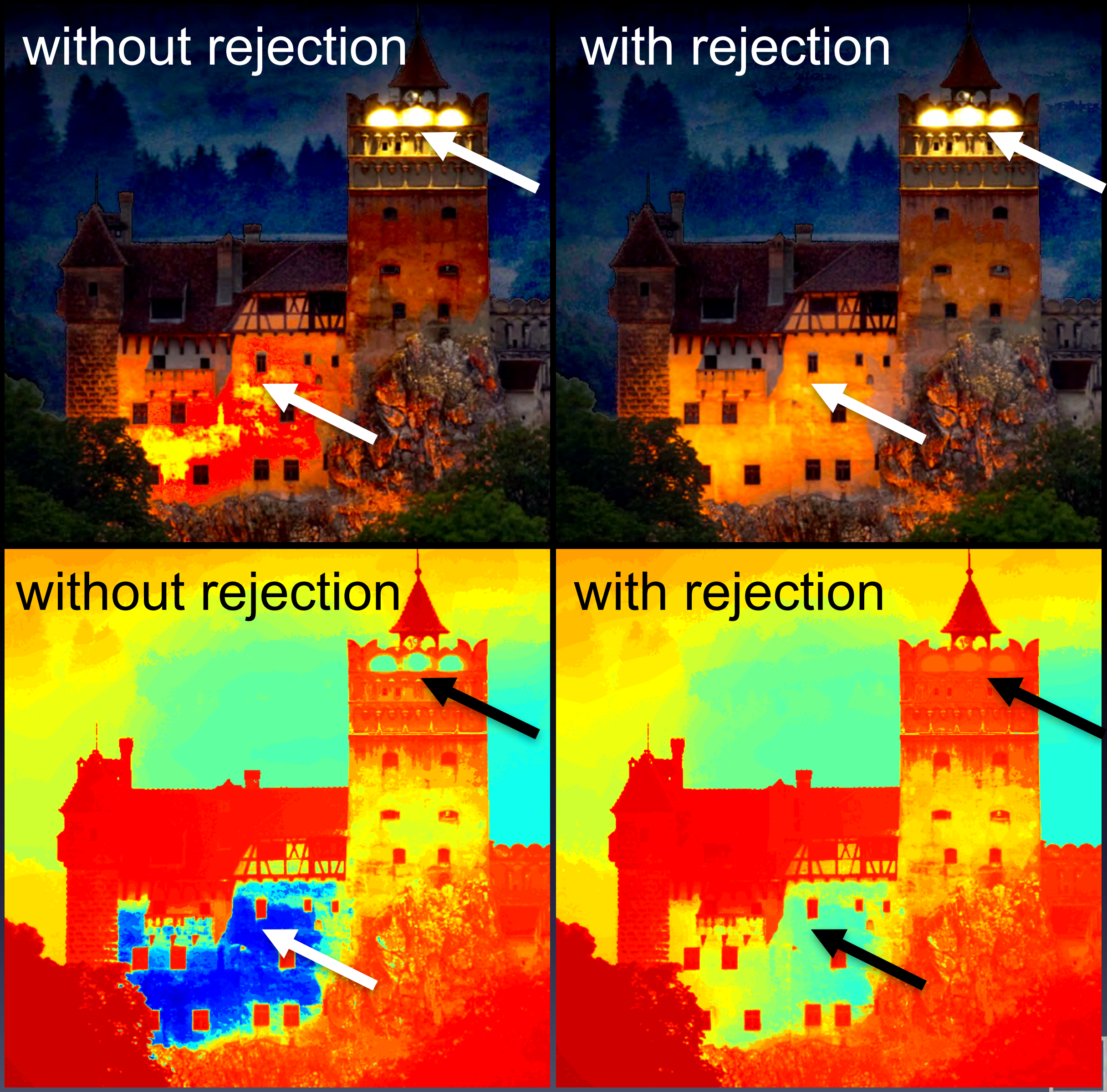
Impact of Angle Outlier Rejection

input | without rejection | with rejection

Impact of Saturated Outlier Rejection



VISUAL COMPUTING Lab

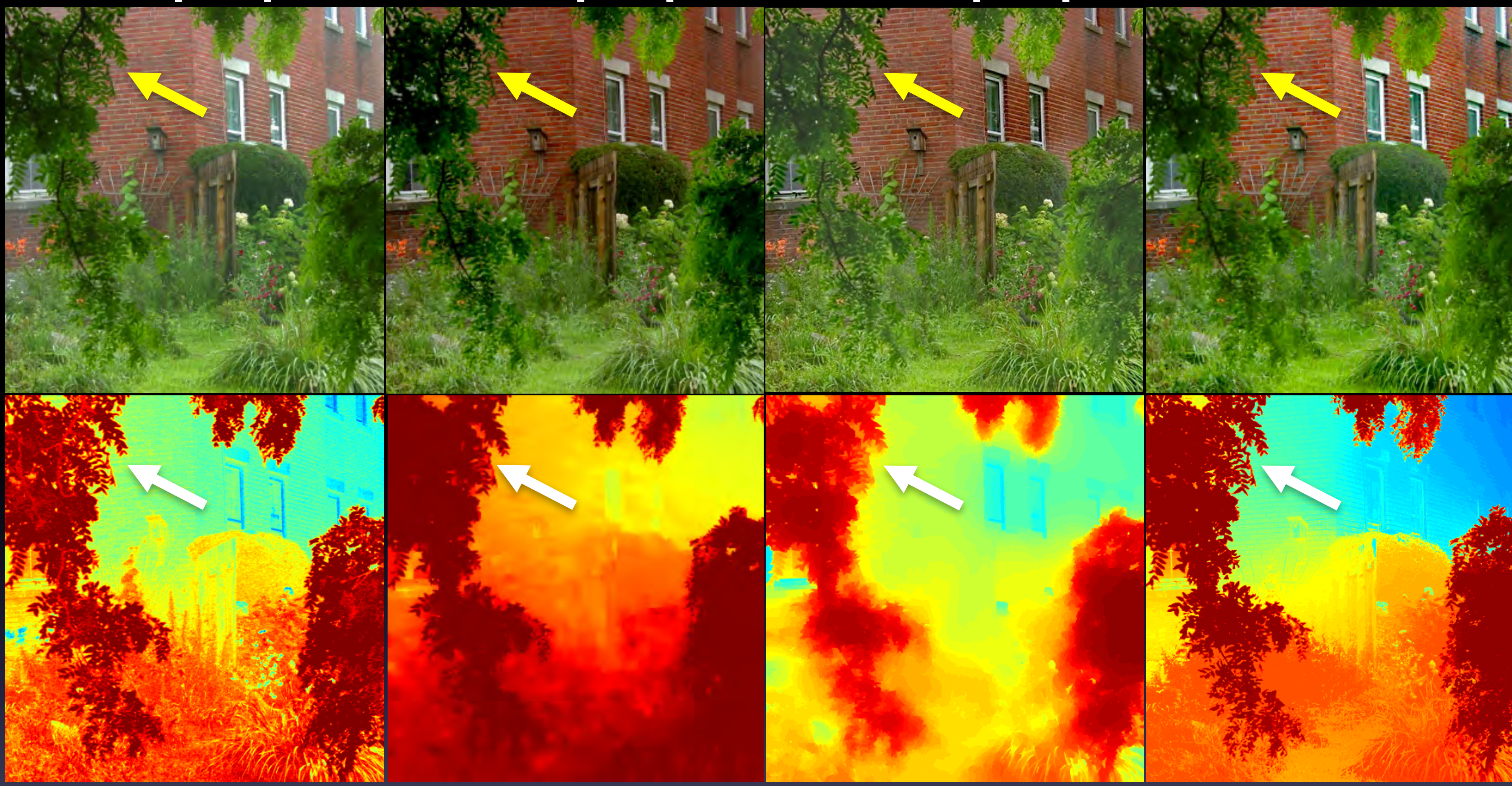
Qualitative Comparison

input

He [2009] | Fattal [2014] | Berman [2016] | ours

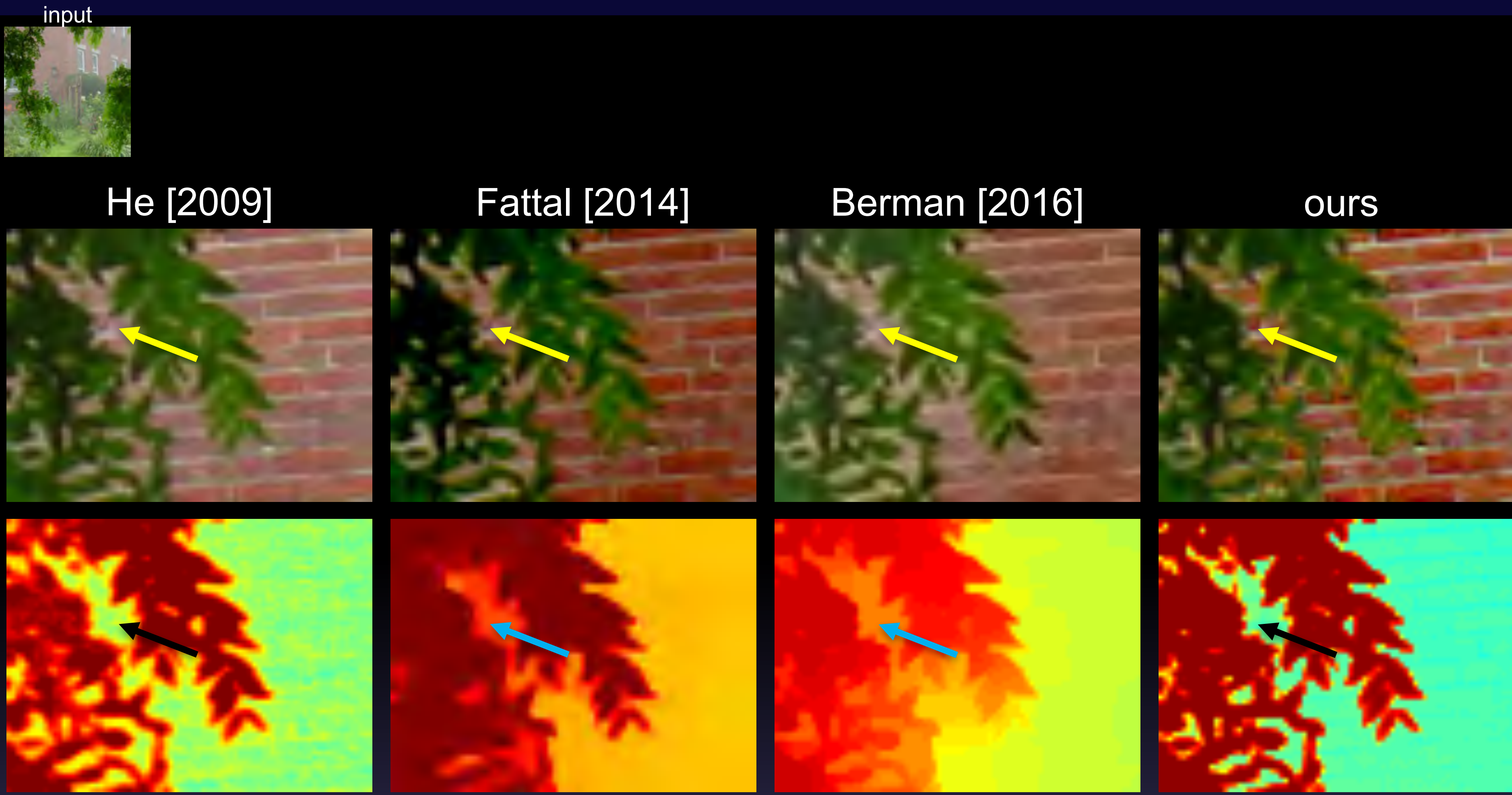
image

transmission



Qualitative Comparison

KAIST



Qualitative Comparison

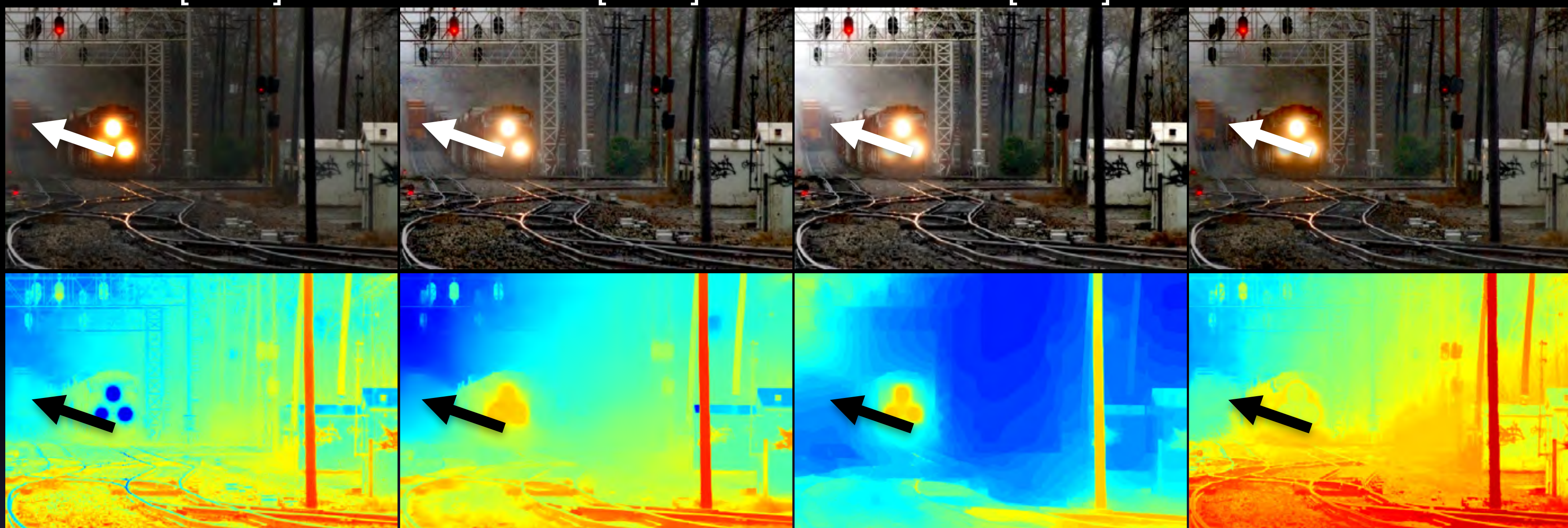
KAIST

input

He [2009] | Fattal [2014] | Berman [2016] | ours

image

transmission



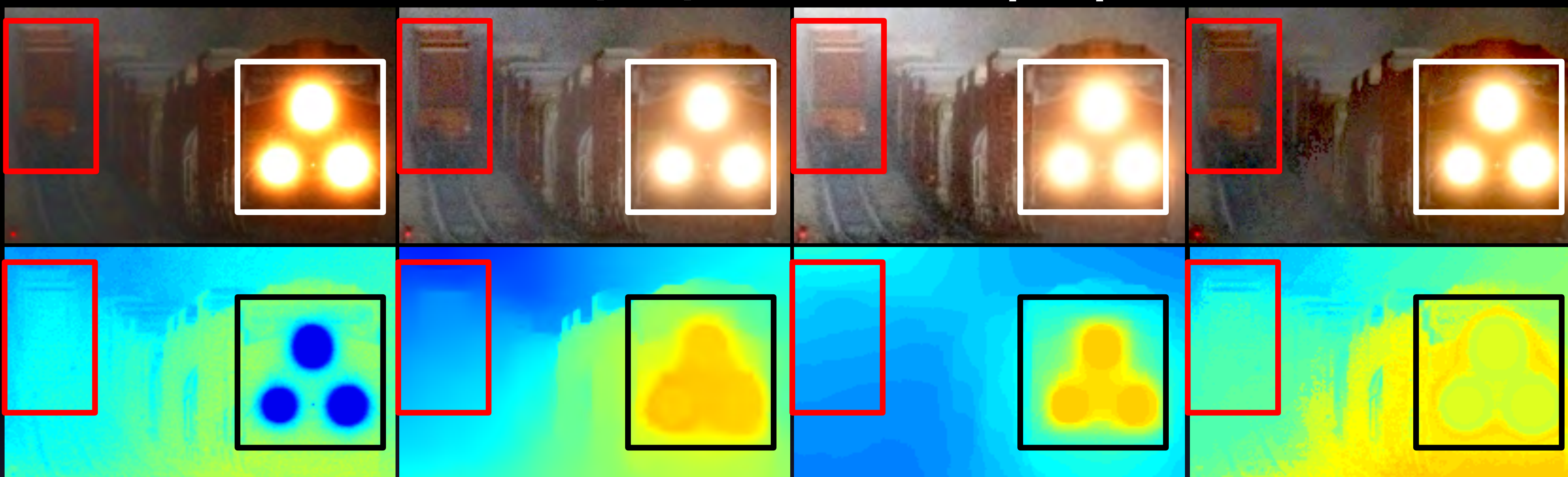
VISUAL COMPUTING Lab

Qualitative Comparison

KAIST

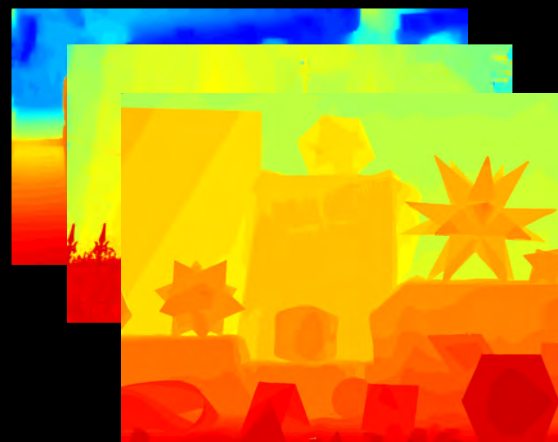
input

He [2009] | Fattal [2014] | Berman [2016] | ours



Quantitative Comparison (Datasets)

Ground truth
haze-free images

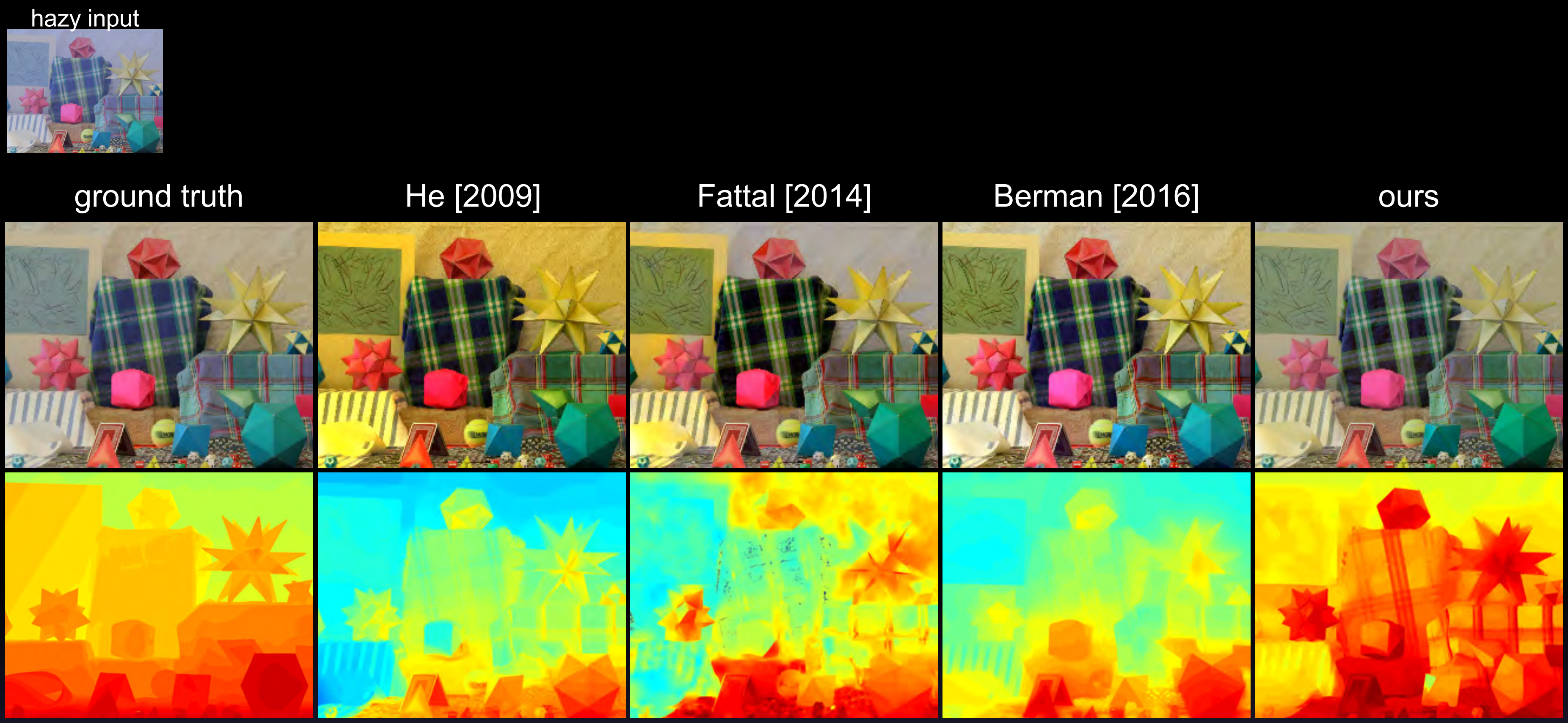


Ground truth
depth maps

Synthetic
hazy image

Datasets from Scharstein and Szeliski [2002], Zhang et al. [2009], and Kim et al. [2013]

Quantitative Comparison

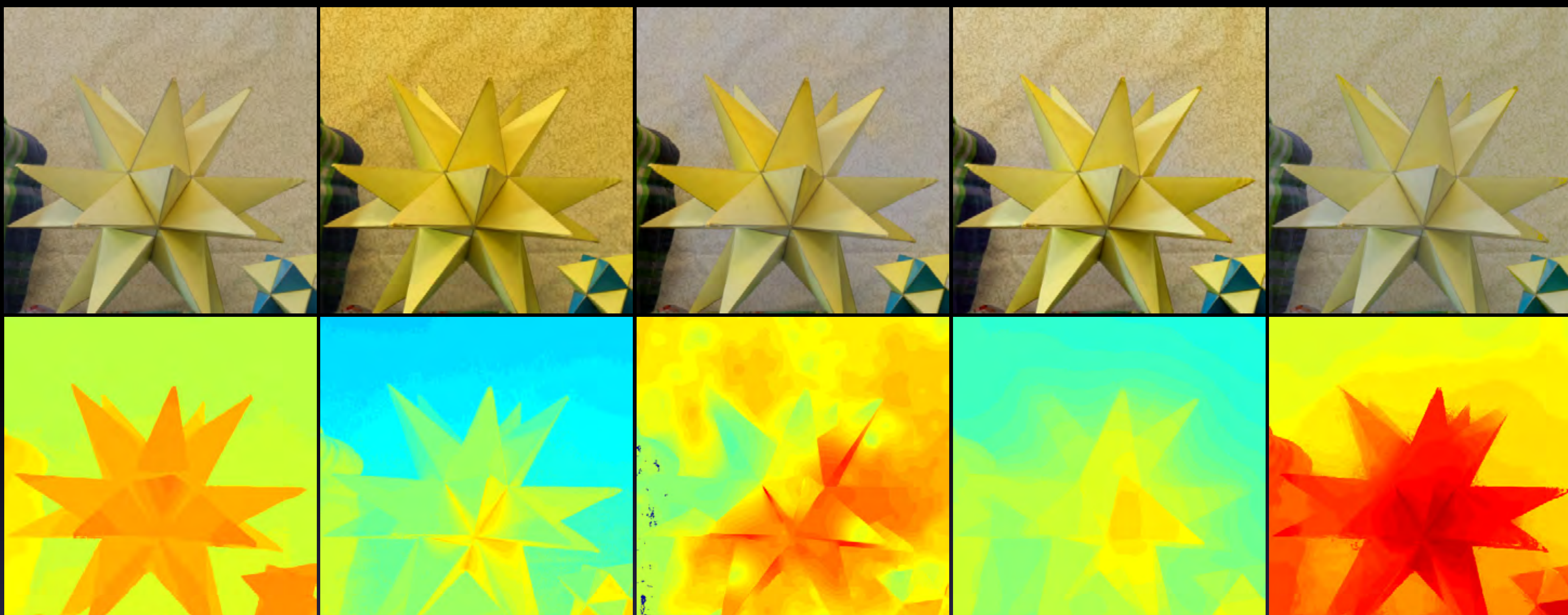


Quantitative Comparison

KAIST

hazy input

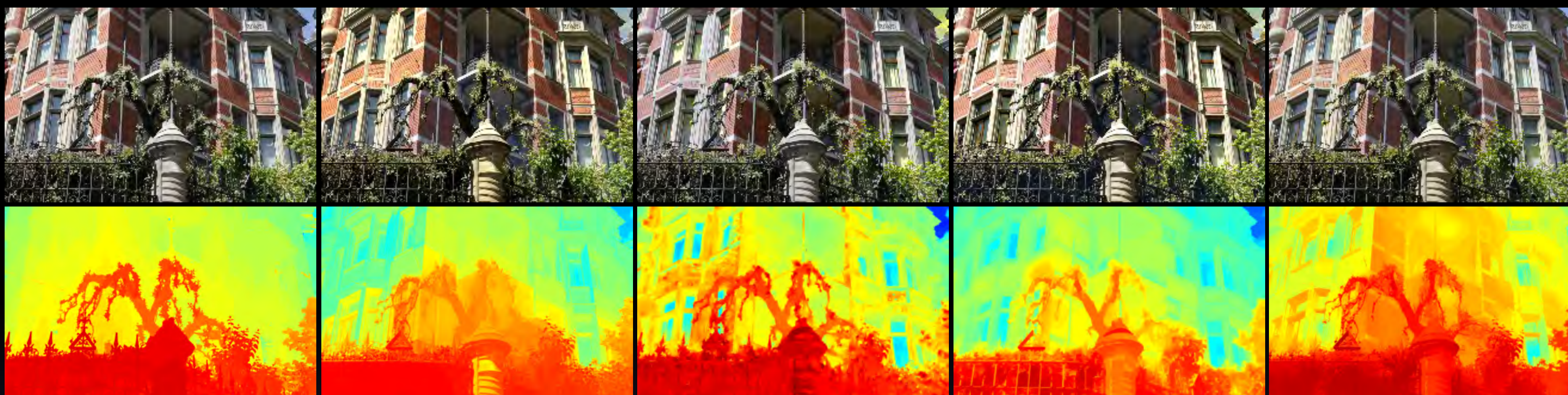
ground truth | He [2009] | Fattal [2014] | Berman [2016] | ours



Quantitative Comparison

hazy input

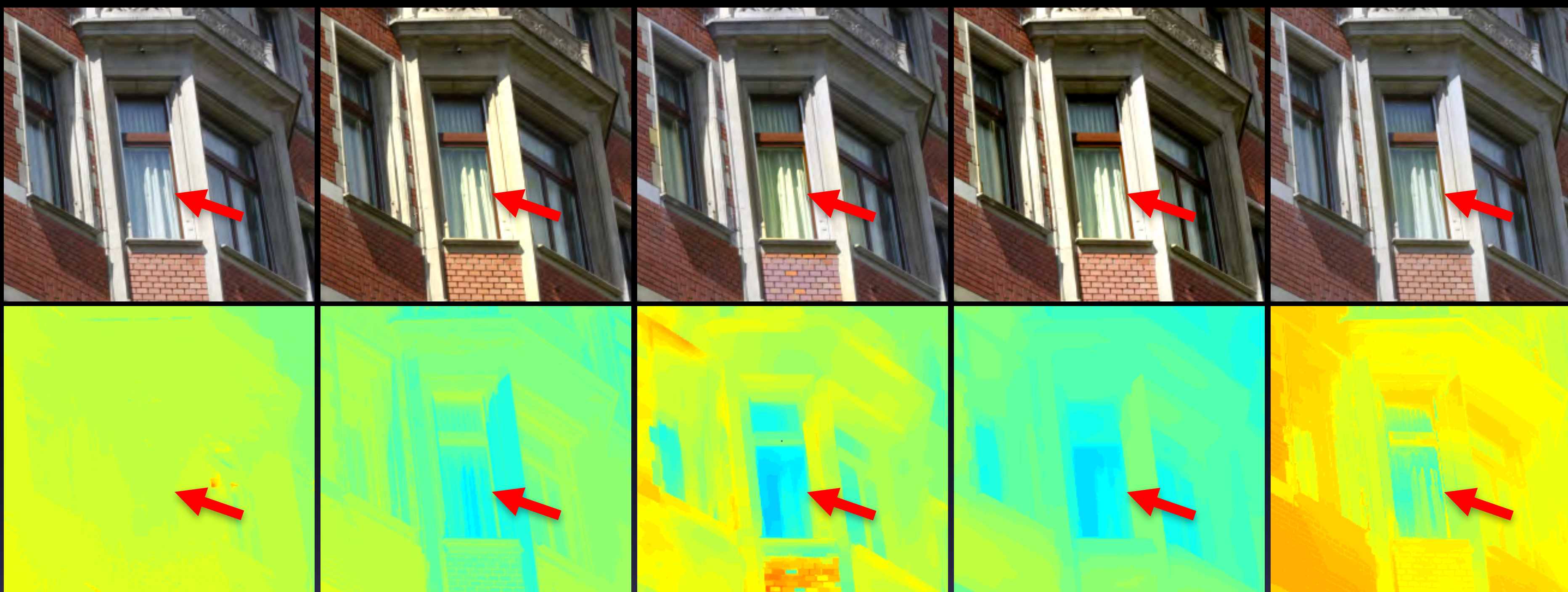
ground truth | He [2009] | Fattal [2014] | Berman [2016] | ours



Quantitative Comparison

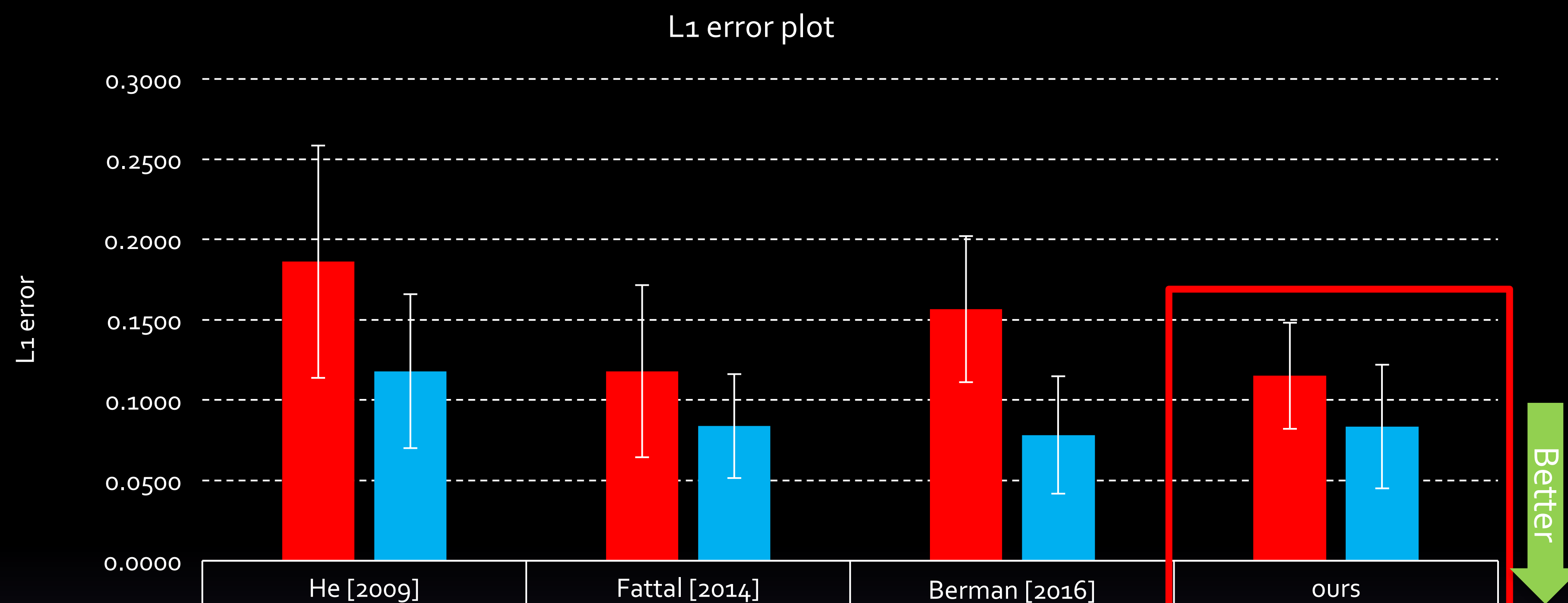
hazy input

ground truth | He [2009] | Fattal [2014] | Berman [2016] | ours



Quantitative Comparison (Error Plots)

KAIST



	He [2009]	Fattal [2014]	Berman [2016]	ours
dehazed	0.1862	0.1180	0.1567	0.1152
transmission	0.1181	0.0839	0.0783	0.0836

dehazed transmission

- Best performance in dehazed images.
- Strongly competitive in transmission maps.

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Conclusion

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- A simple but powerful marginalization-based transmission estimation method.

- A **non-local regularization** method with the **novel iso-depth prior** that enables to yield a more accurate transmission map.

- Outperforms state-of-the-art methods both qualitatively and quantitatively.

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Acknowledgements

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THANK YOU