

Good Image Priors for Non-blind Deconvolution: Generic vs Specific

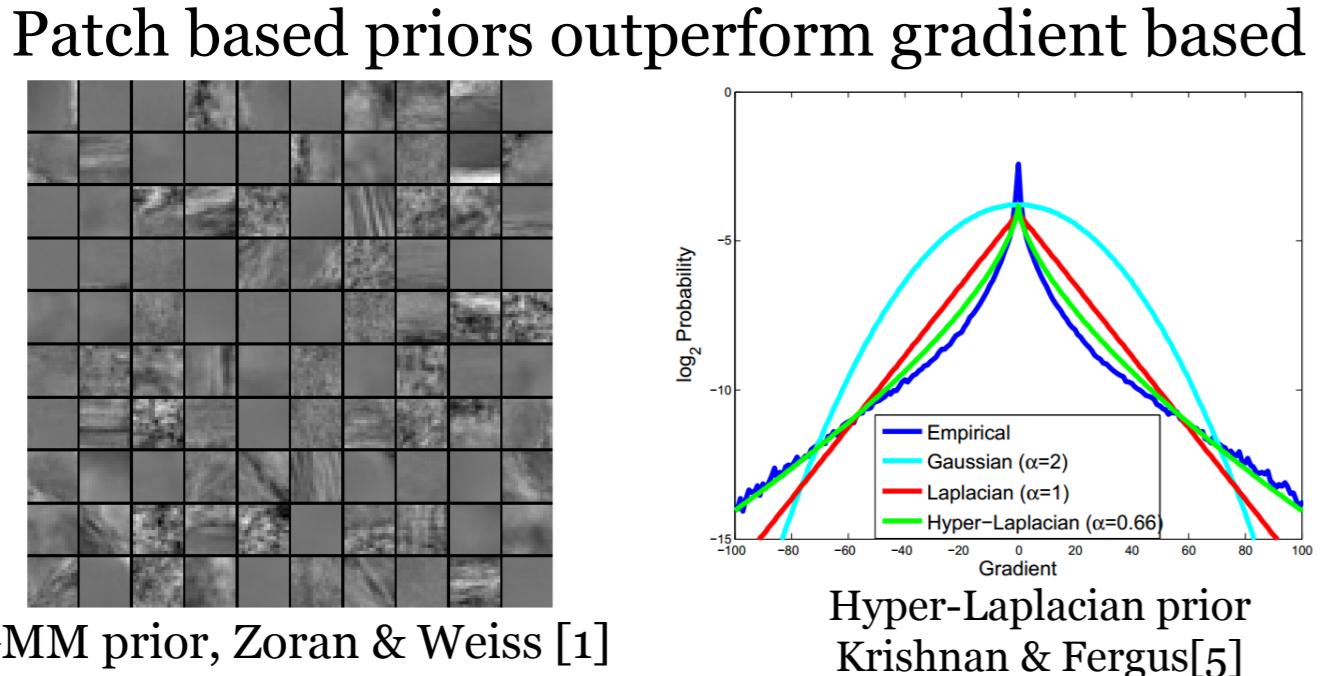
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Background

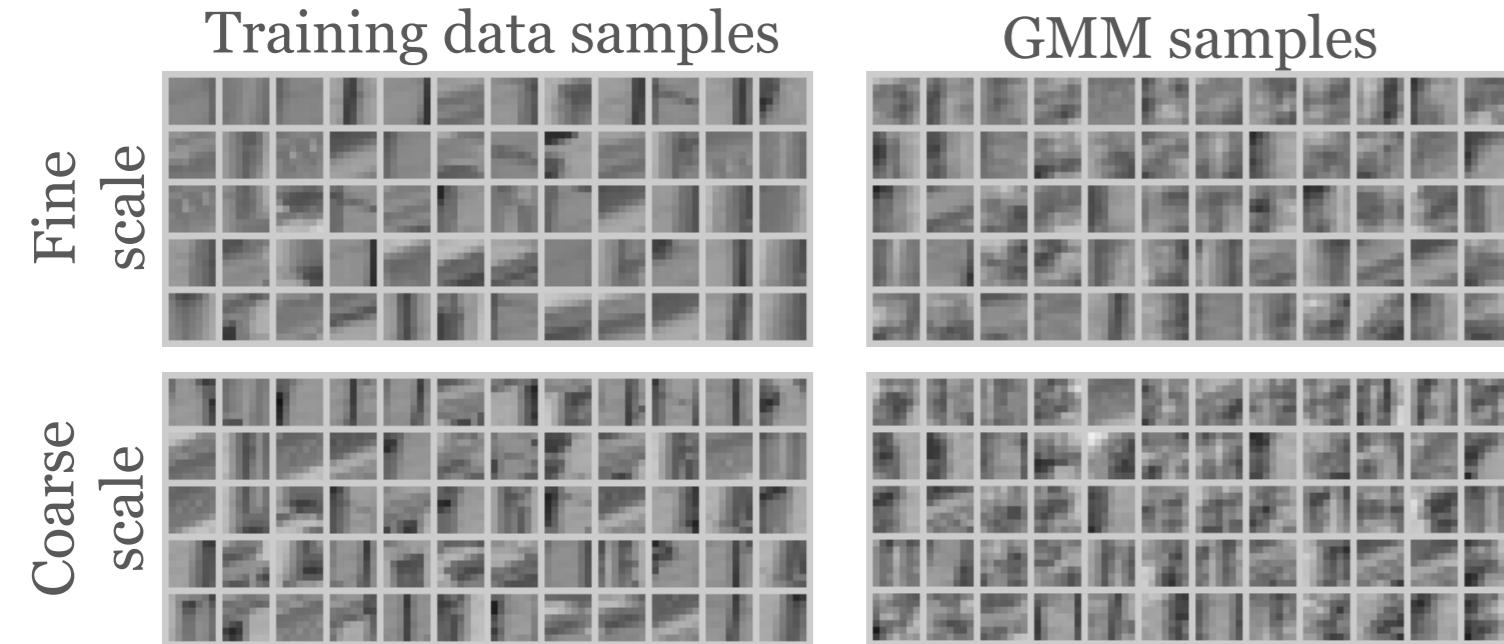


Motivation

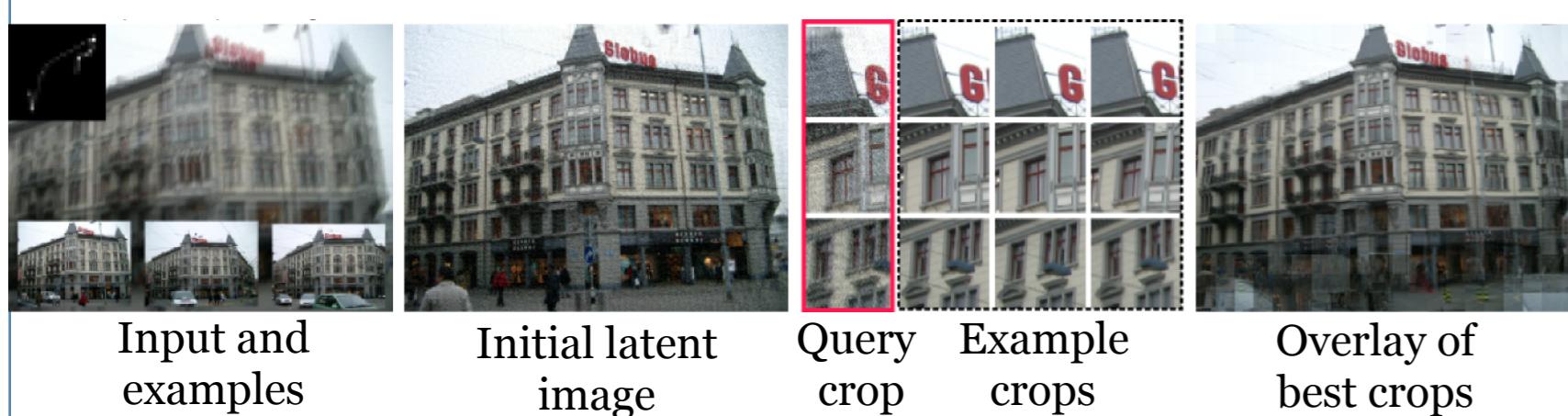
- Generic image priors **do not** benefit from having relevant training images
- Relevant example images are abundant, e.g. personal albums, Flickr, Google image search

Our Method

1. Multi-scale patch model



2. Training local prior models



3. Iterative optimization

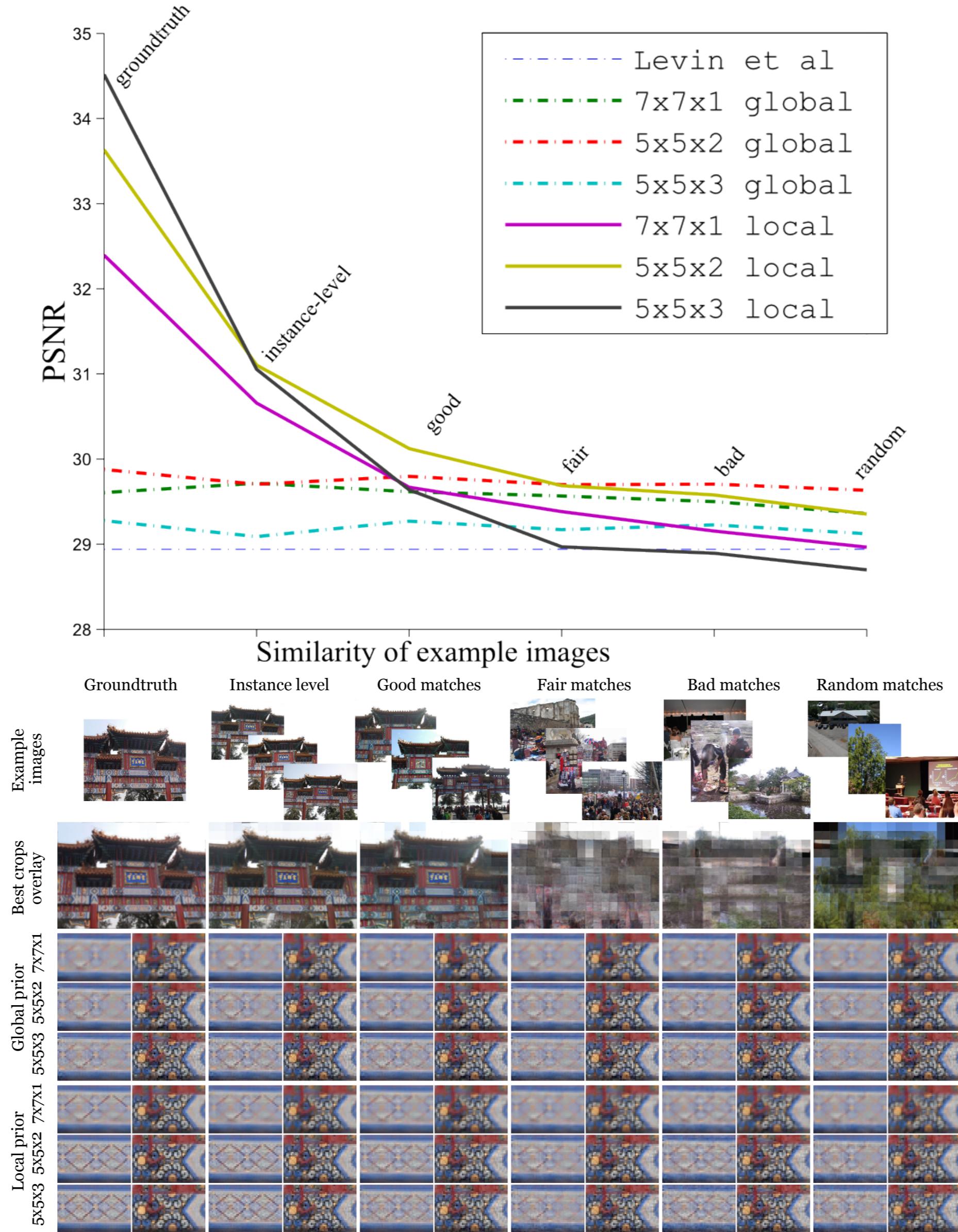
$$c_{p,\beta}(\mathbf{x}, \{\mathbf{z}^i\} | \mathbf{y}) = \frac{\lambda}{2} \|\mathbf{Ax} - \mathbf{y}\|^2 + \sum_i \frac{\beta}{2} ((\mathbf{x}^i - \mathbf{z}^i)^T \Sigma_{noise}^{-1} (\mathbf{x}^i - \mathbf{z}^i)) - \log p(\mathbf{z}^i)$$

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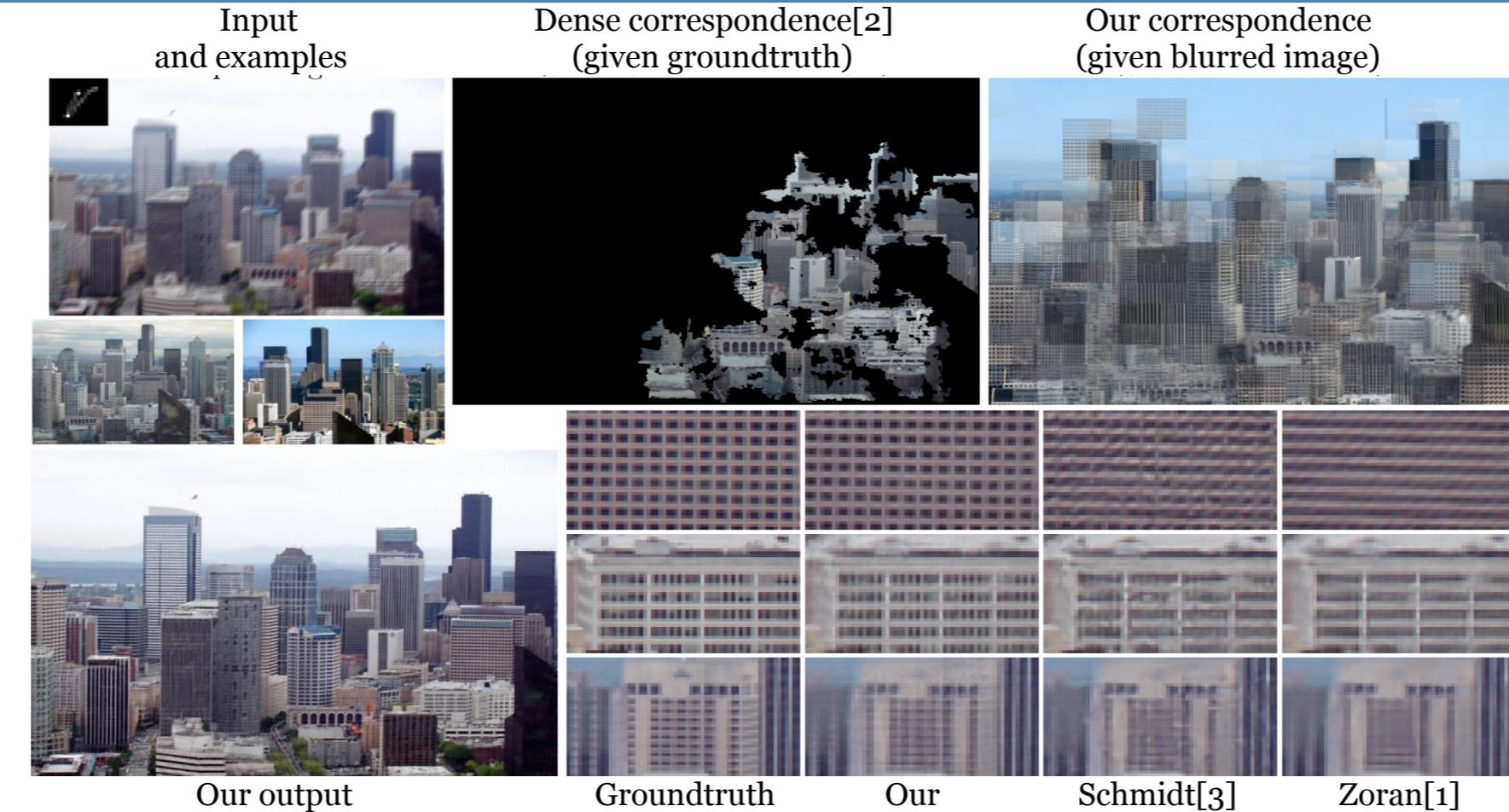
data term patch similarity term prior term

X-step: update image Z-step: update patches

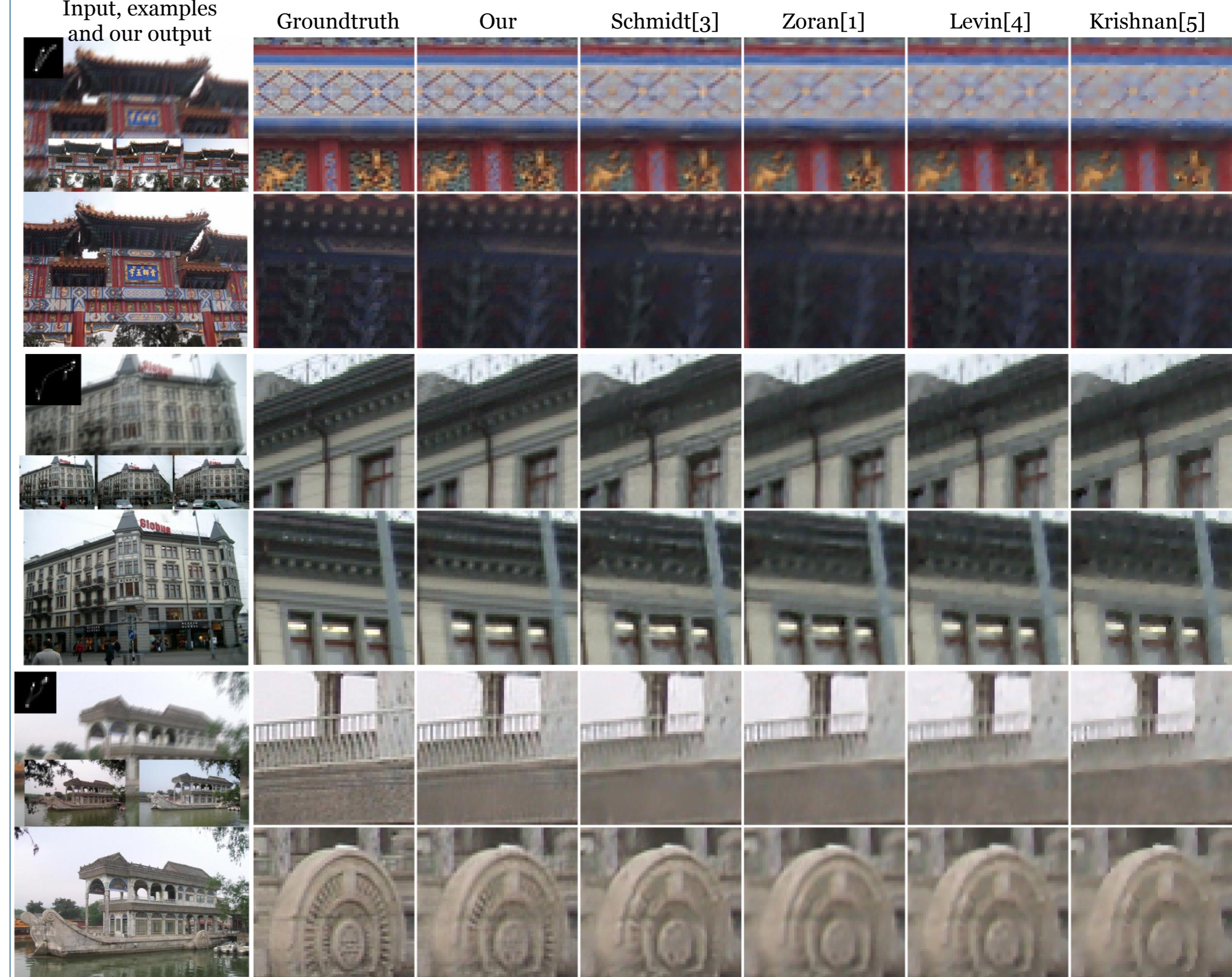
Baseline Comparisons



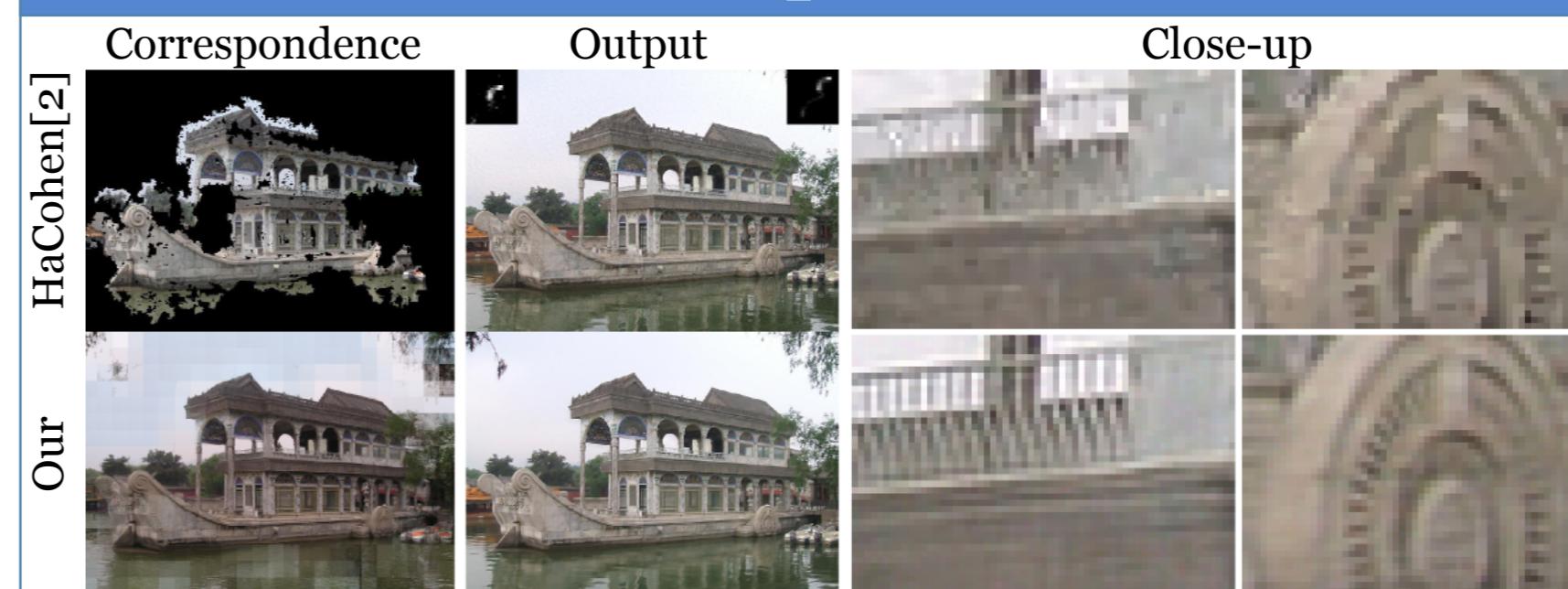
Comparing against leading methods



Results: vs generic methods



Results: vs example-based methods



Conclusions

- Global training insensitive to relevance of example images.
- Multi-scale prior recovers more image details.
- Local training + multi-scale prior yields best performance.

References

- From learning models of natural image patches to whole image restoration. Zoran, D., Weiss, Y. ICCV 2011
- Deblurring by example using dense correspondence. HaCohen, Y., Shechtman, E., Lischinski, D. ICCV 2013
- Discriminative nonblind deblurring. Schmidt, U., Rother, C., Nowozin, S., Jancsary, J., Roth, S. CVPR 2013
- Image and depth from a conventional camera with a coded aperture. Levin, A., Fergus, R., Durand, F., Freeman, W.T.. ACM ToG 2007
- Fast image deconvolution using hyper-laplacian priors. Krishnan, D., Fergus, R. NIPS 2009