Compressive Image Recovery using Recurrent Generative Model

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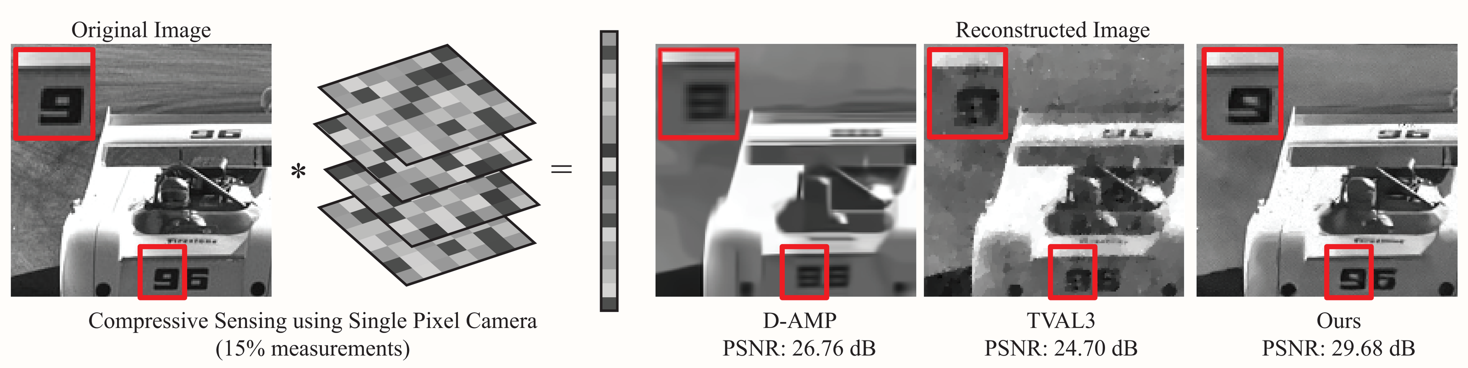
Highlights

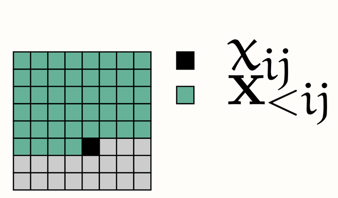


- Reconstruction of signals from compressively sensed measurements is an **ill-posed** problem.
- We propose to use the **deep generative model**, RIDE, as an image prior to model long-term dependencies for reconstructing compressively sensed images.
- We use **backpropagation** to inputs while doing gradient ascent for **MAP inference**.
- Using this **data-driven global prior** provides superior results than the prior methods TVAL3 and D-AMP.

Background

- Joint distribution over image $\mathbf{x}$ can be factorized as,

$$p(\mathbf{x}) = \prod_{ij} p(x_{ij} | \mathbf{x}_{<ij})$$



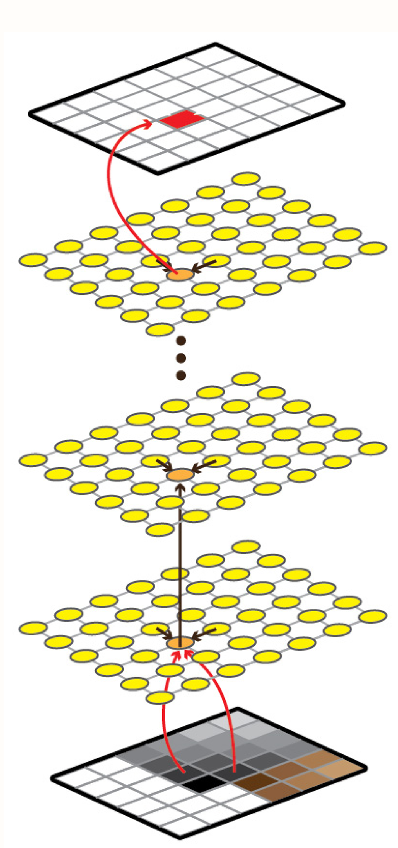
- Spatial LSTMs summarize the entire causal context - long-term dependencies.

$$\mathbf{h}_{ij} = f(\mathbf{x}_{<ij}, \mathbf{h}_{i-1,j}, \mathbf{h}_{i,j-1})$$

- Each factor is modelled by conditional Gaussian Scale Mixtures.

$$p(\mathbf{x}) = \prod_{ij} p(x_{ij} | \mathbf{h}_{ij}, \theta)$$

$$p(x_{ij} | \mathbf{h}_{ij}, \theta) = \sum_{c,s} p(c, s | \mathbf{h}_{ij}, \theta) p(x_{ij} | \mathbf{h}_{ij}, c, s, \theta)$$



RIDE by Theis et al, 2015

MAP Inference via Backpropagation

- Here, we use Maximum-A-Posteriori principle to find the desired image as,

$$\hat{\mathbf{x}} = \arg\max_{\mathbf{x}} p(\mathbf{x})\, p(\mathbf{y}|\mathbf{x})$$
$$\hat{\mathbf{x}} = \arg\max_{\mathbf{x}} p(\mathbf{x}) \quad \text{s.t.} \quad \mathbf{y} = \Phi\mathbf{x}$$

- Projected gradient method: Each gradient update is projected back on to the affine solution space for $\mathbf{y} = \phi\mathbf{x}$

$$\hat{\mathbf{x}}_k = \mathbf{x}_{k-1} + \eta \nabla_{\mathbf{x}_{k-1}} p(\mathbf{x})$$
$$\mathbf{x}_k = \hat{\mathbf{x}}_k - \Phi^T \left(\Phi\Phi^T\right)^{-1} (\Phi\hat{\mathbf{x}}_k - \mathbf{y})$$

Results

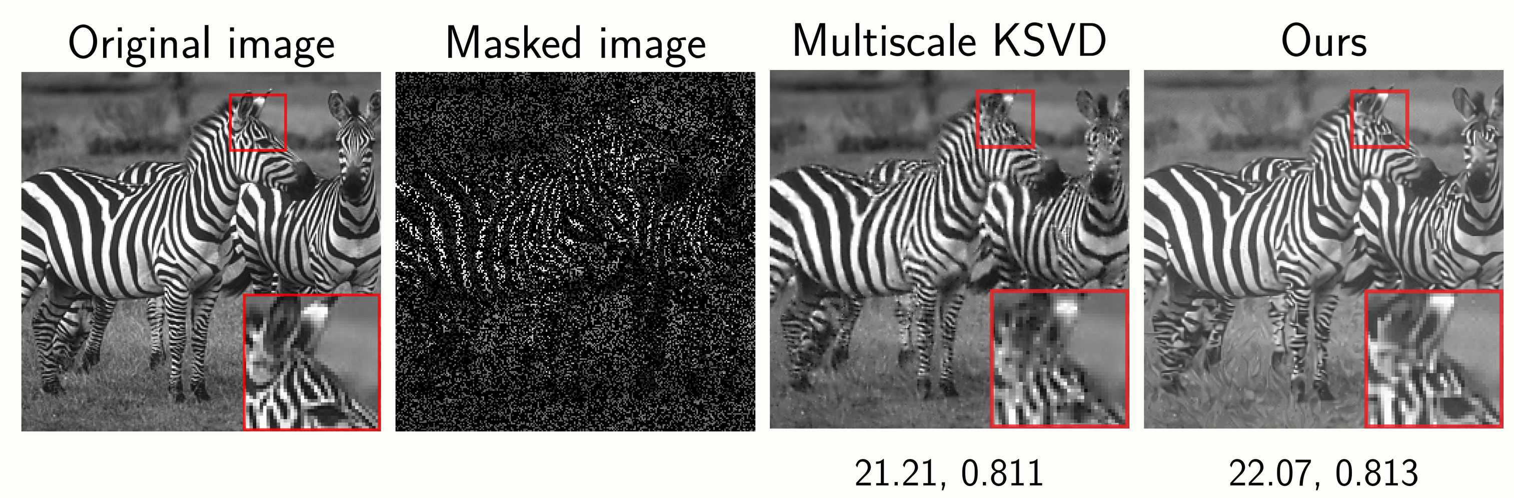
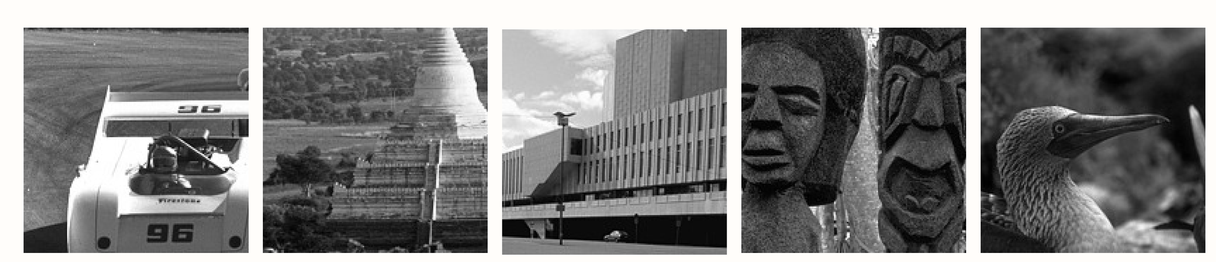


Figure 1 : Inpainting comparisons: We compare our approach with the multiscale dictionary learning approach (KSVD). Our method is able to recover the sharp edges better.



Method	M.R. = 40% PSNR	M.R. = 40% SSIM	M.R. = 30% PSNR	M.R. = 30% SSIM	M.R. = 25% PSNR	M.R. = 25% SSIM	M.R. = 15% PSNR	M.R. = 15% SSIM
TVAL3	29.70	0.833	28.68	0.793	27.73	0.759	25.58	0.670
D-AMP	32.54	0.848	29.95	0.800	28.26	0.760	24.02	0.615
Ours	**33.71**	**0.903**	**31.91**	**0.862**	**30.71**	**0.830**	**27.11**	**0.704**

Table 1 : Average quality of CS reconstructions at different measurement rates for the selected images(160x160). Our method outperforms the existing global prior based methods in most of the cases.

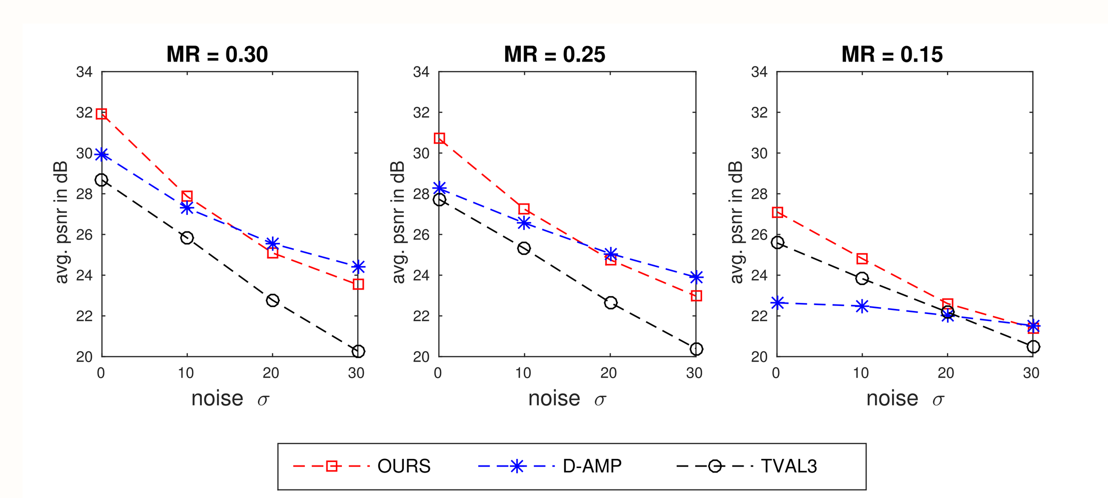


Figure 2 : Reconstructions from noisy measurements at different σ.

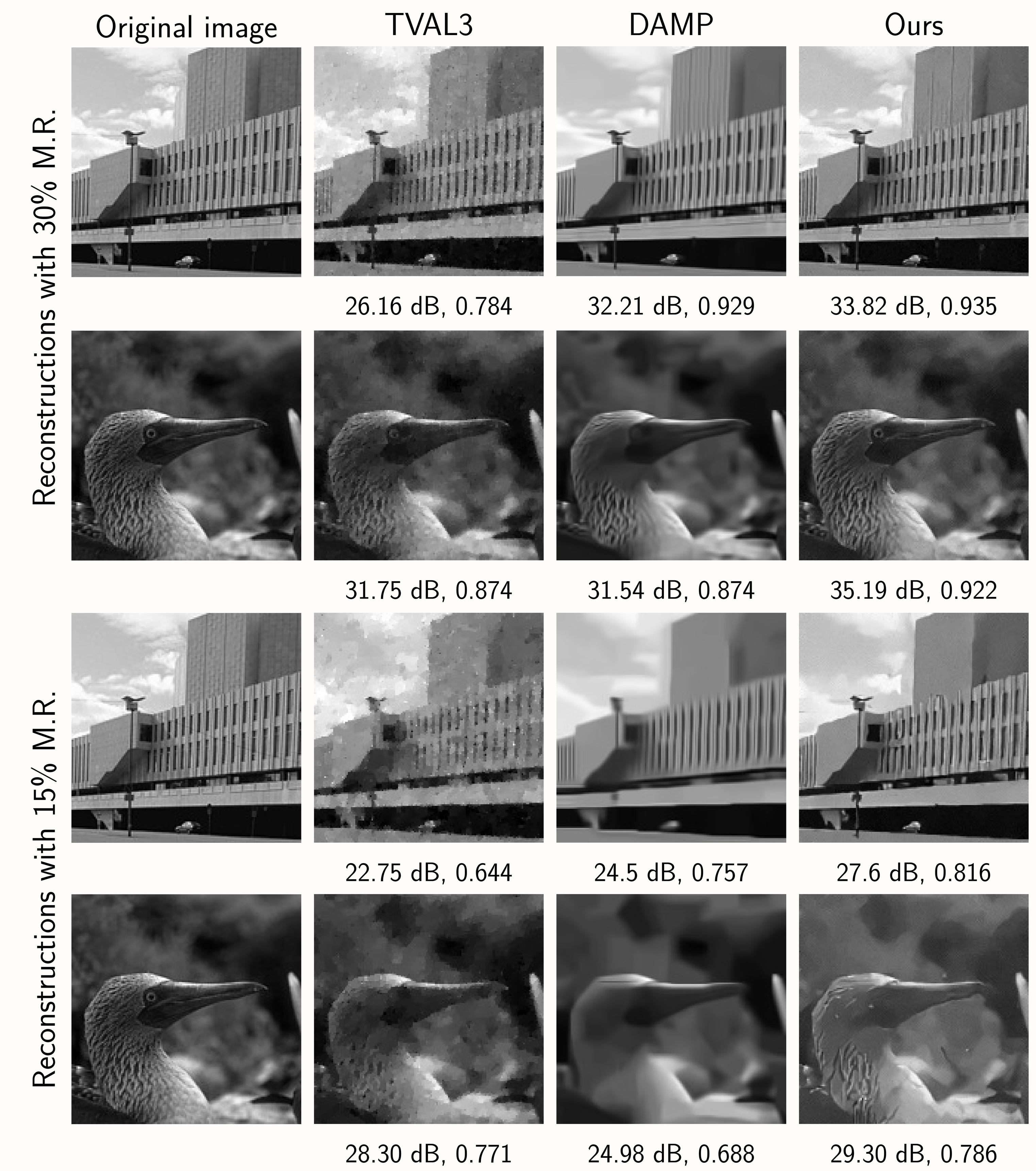


Figure 3 : Reconstruction comparisons: Even at low measurement rates, our method preserves the sharp and prominent structures in the image. D-AMP has the tendency to over-smooth the image, whereas TVAL3 adds blotches to even the smooth parts.

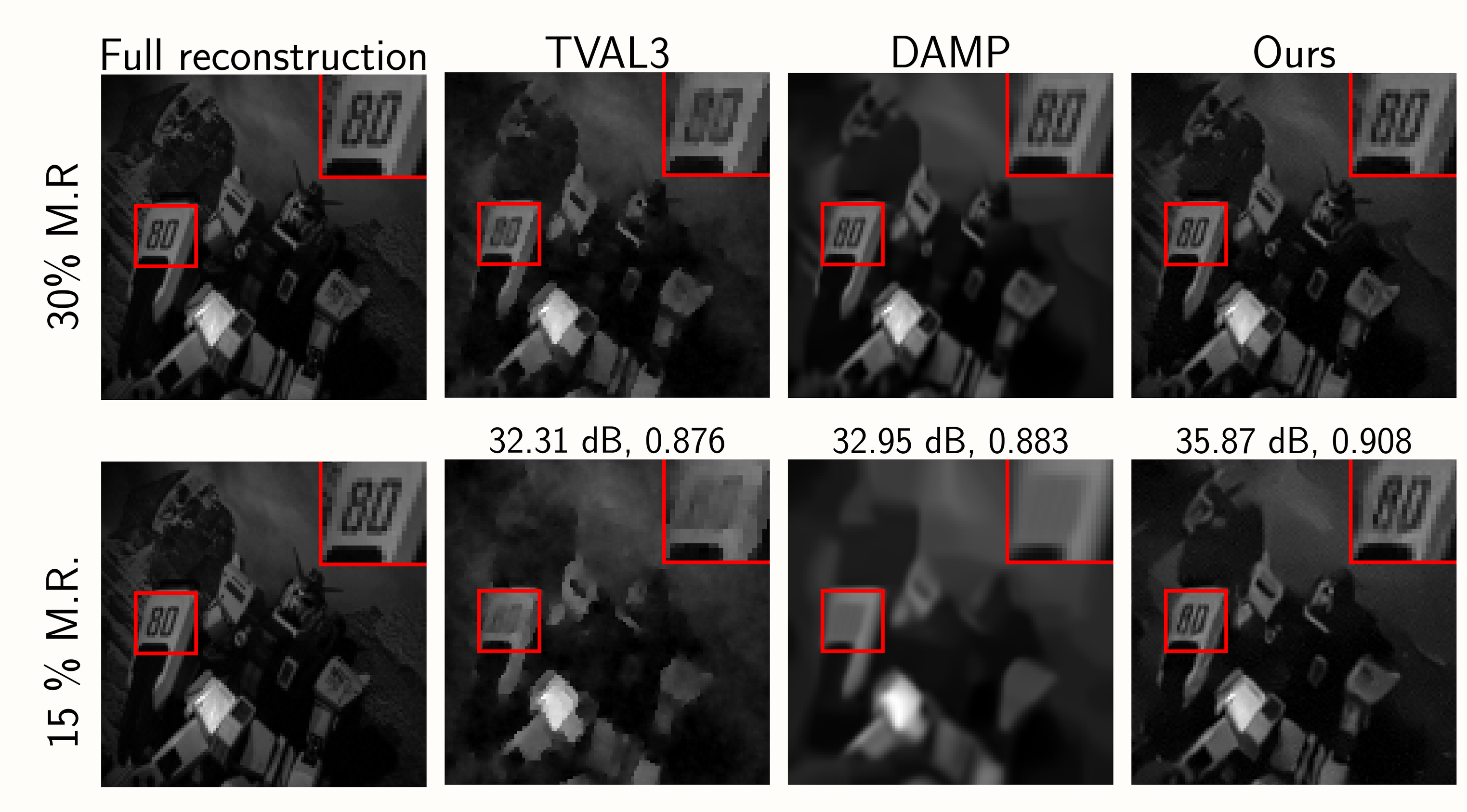


Figure 4 : Reconstructions on real measurements acquired from single pixel camera.(Data courtesy: Dr. Aswin Sankaranarayanan)

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