ReconNet: Non-iterative Reconstruction of Images from Compressively Sensed Measurements

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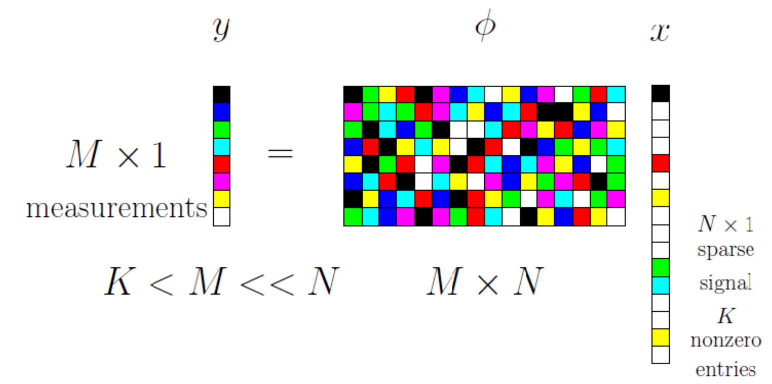
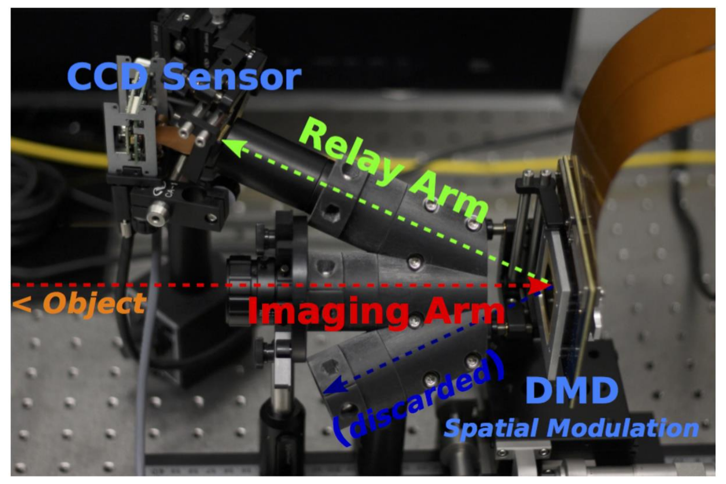
Compressive Sensing (CS)



Compressive imager testbed layout [2]

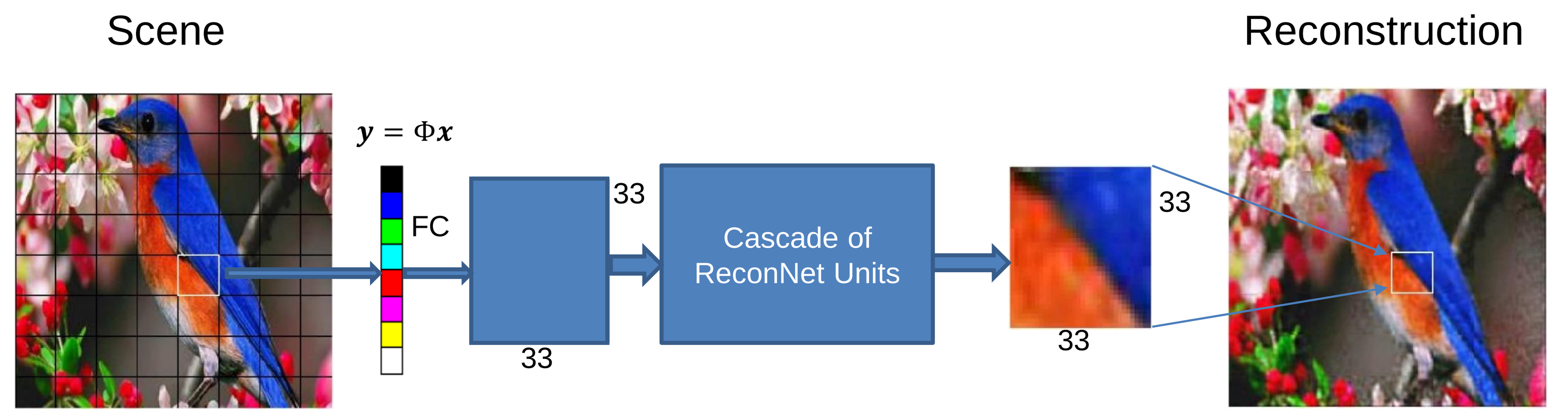


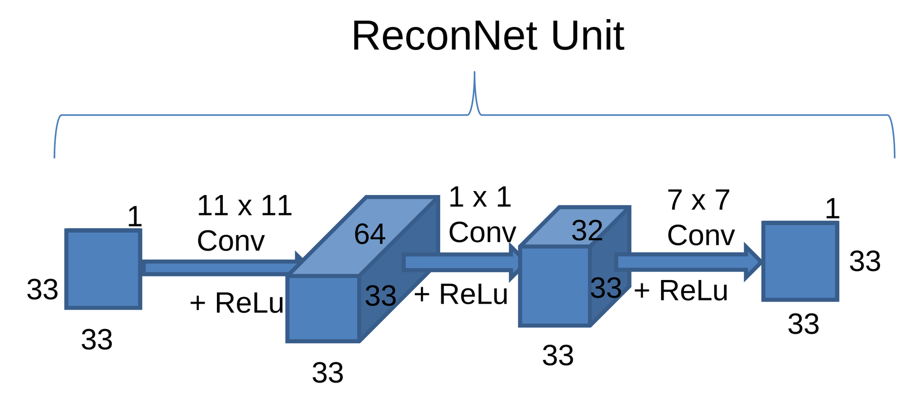
- Recovering x from y is ill-posed but possible if x is sparse and MR (M/N) is sufficiently large.
- Iterative algorithms are computationally expensive and yield very low quality reconstructions at measurement rates of about 0.01.

ReconNet

- Our solution: ReconNet - Data-driven, non-iterative based on CNNs.
- Pros: Better reconstruction quality at very low measurement rates and a speed up of about 1000 compared to the iterative approaches.
- Rich semantic content is retained in the reconstruction, enabling effective high-level vision (e.g. tracking).

Network Architecture, Training and Testing





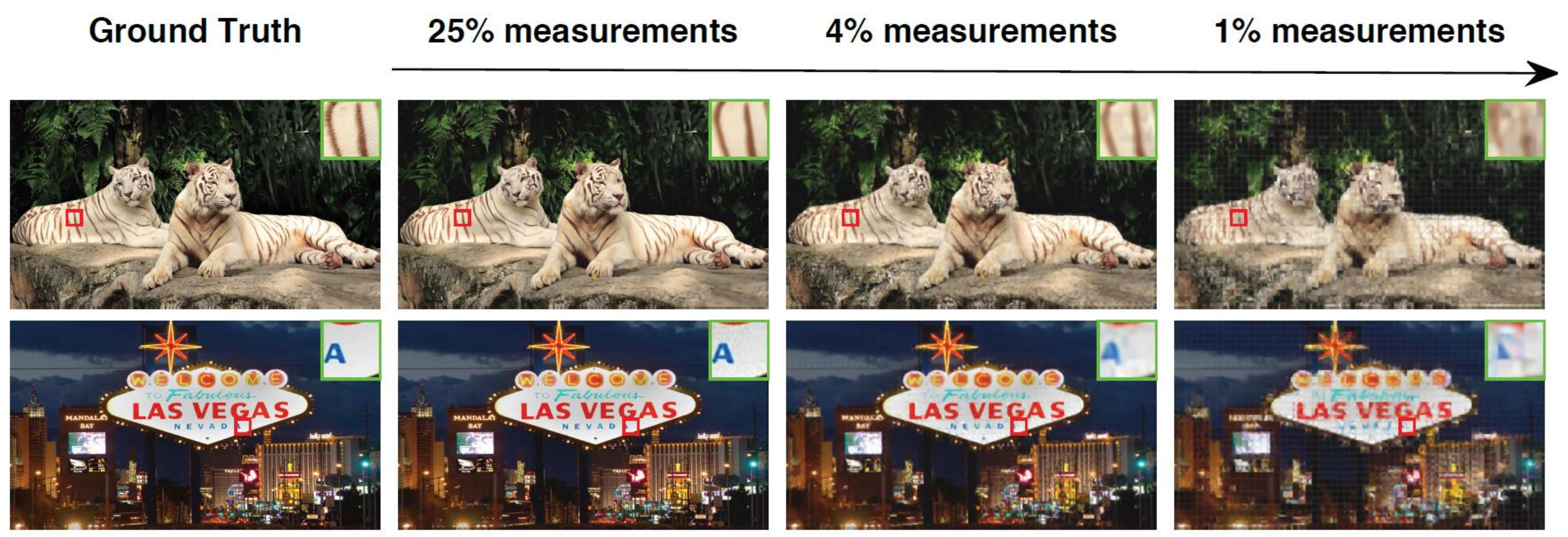
- Training set consists of 21760 pairs of CS measurement vectors (inputs) and the corresponding patches (desired outputs) from 91 natural images. Φ is a random Gaussian matrix.
- Test set: 11 standard test images.

- Architecture inspired by Super-Resolution CNN [1].
- A denoiser (BM3D) is used to remove the blocky artifacts.

Experimental Evaluation on Synthetic and Real Data

Mean reconstruction PSNR of test set (with denoiser and CS simulated)

Algorithm	MR = 0.25	MR = 0.1	MR = 0.04	MR = 0.01
TVAL3	27.87	22.86	18.40	11.34
NLR-CS	**28.19**	14.22	10.98	5.62
D-AMP	27.67	21.09	15.67	5.23
SDA	24.55	22.68	20.21	17.40
Ours	25.92	**23.23**	**20.44**	**17.55**

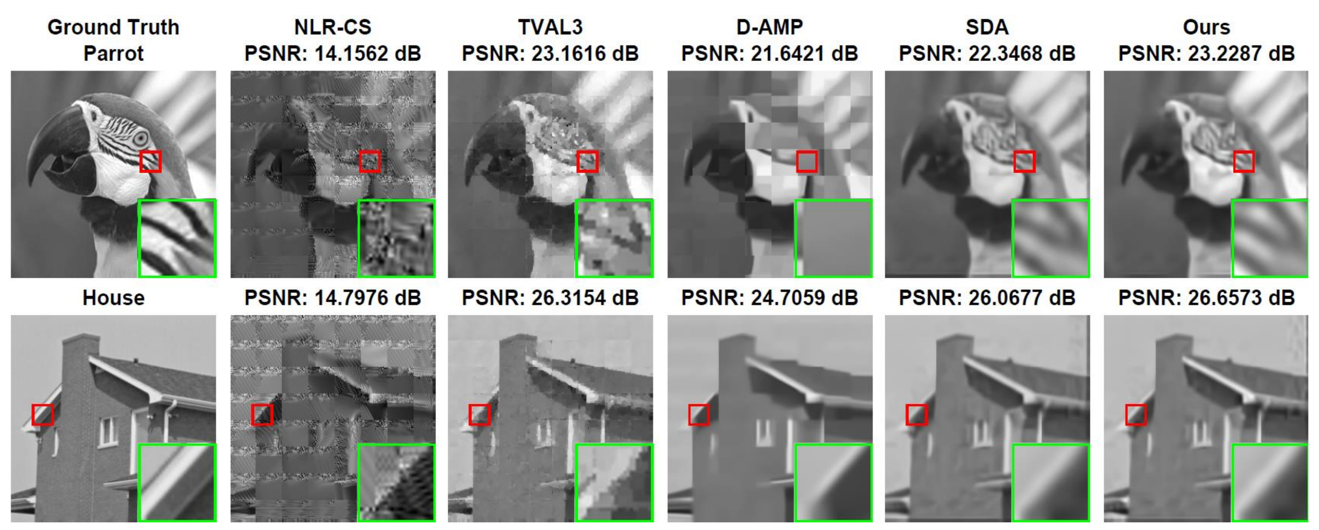


ReconNet is computationally faster (about **1000x**) than iterative algorithms

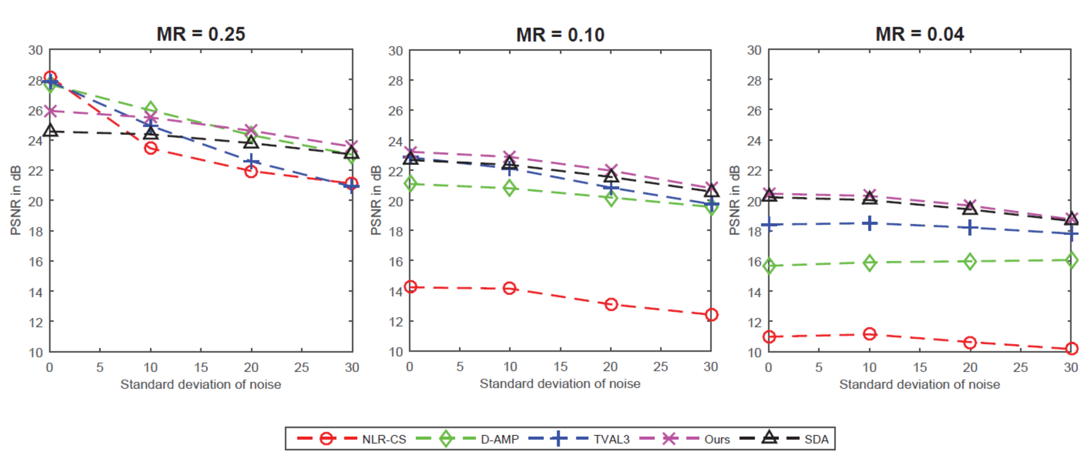
Mean reconstruction time

Algorithm	MR = 0.25	MR = 0.1	MR = 0.04	MR = 0.01
TVAL3	2.943	3.223	3.467	7.790
NLR-CS	314.852	305.703	300.666	314.176
D-AMP	27.764	51.849	34.207	54.643
SDA	0.0042	0.0029	0.0025	0.0244
Ours	0.0213	0.0195	0.0192	0.0244

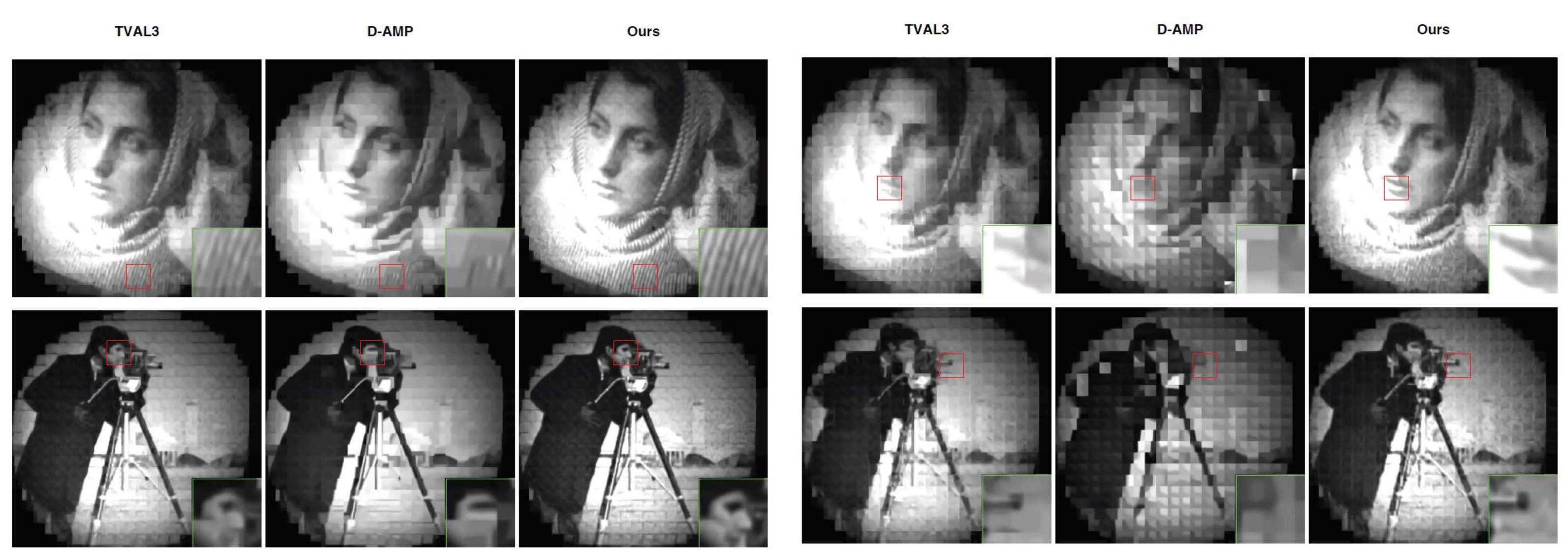
Reconstruction results of simulated CS data at MR = 0.1



ReconNet performs better than iterative algorithms at low measurement rates and in the presence of noise



Reconstruction results of real data obtained from compressive imager



MR = 0.1 MR = 0.04

Training for Different MRs

- Training separate networks from scratch for every MR is not practical.
- Suboptimal solution:
  - Fix all weights of the ReconNet units using a pre-trained network for a higher MR.
  - Only train the FC layer.
- Training time for a new MR can be reduced to ~ 2s.

New Φ MR	0.1	0.08	0.04	0.01
Base N/w MR	0.25	0.1	0.1	0.25
Mean PSNR (dB)	21.73	20.99	19.66	16.60
Training Time (s)	2	2	2	2

[1] Chao Dong, Chen Change Loy, Kaiming He, Xiaoou Tang. Learning a Deep Convolutional Network for Image Super-Resolution, in Proceedings of European Conference on Computer Vision (ECCV), 2014

[2] Ronan Kerviche, Nan Zhu, Amit Ashok. Information-optimal Scalable Compressive Imaging System, in Classical Optics 2014, OSA Technical Digest (online) (Optical Society of America, 2014), paper CM2D.2.