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Channel Shuffle Recontruction Network For Image Compressive Sensing

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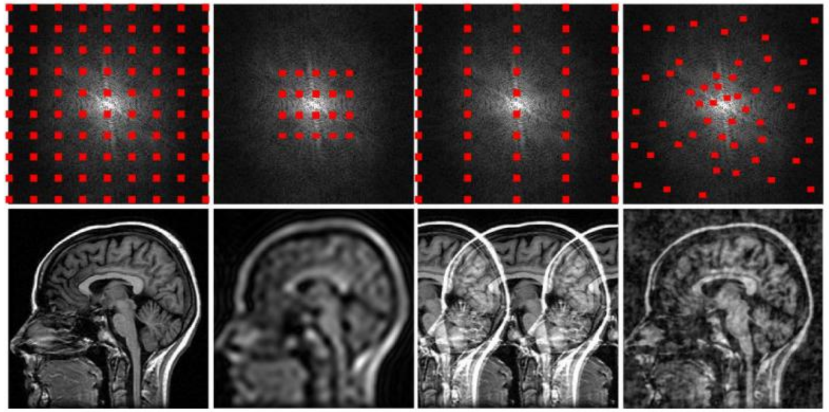
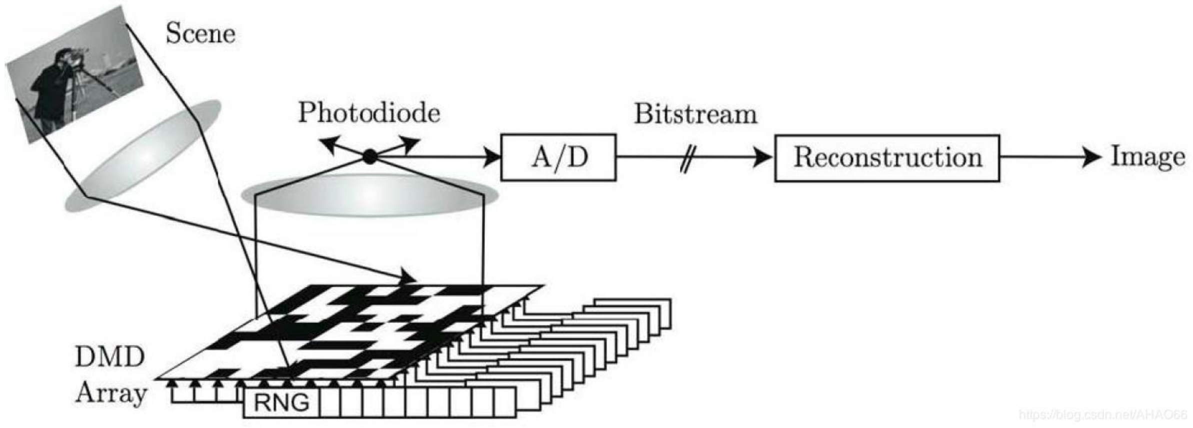
Background

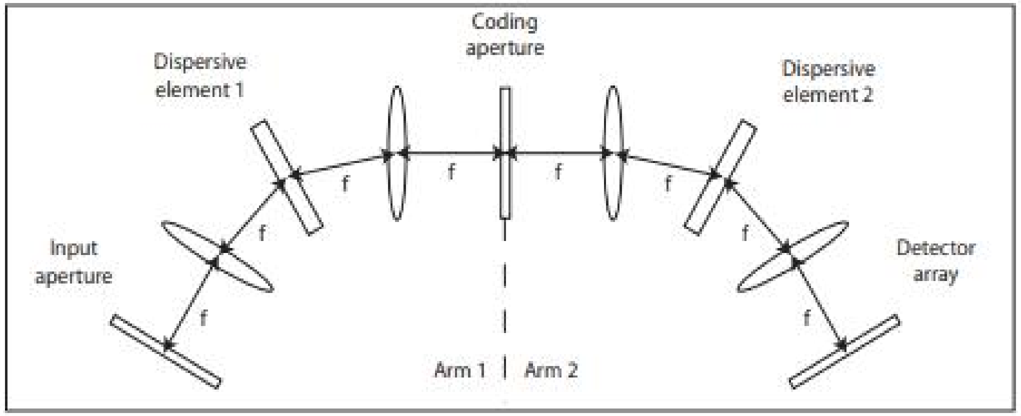
- **Wide application of compressive sensing theory.**



Magnetic resonance imaging

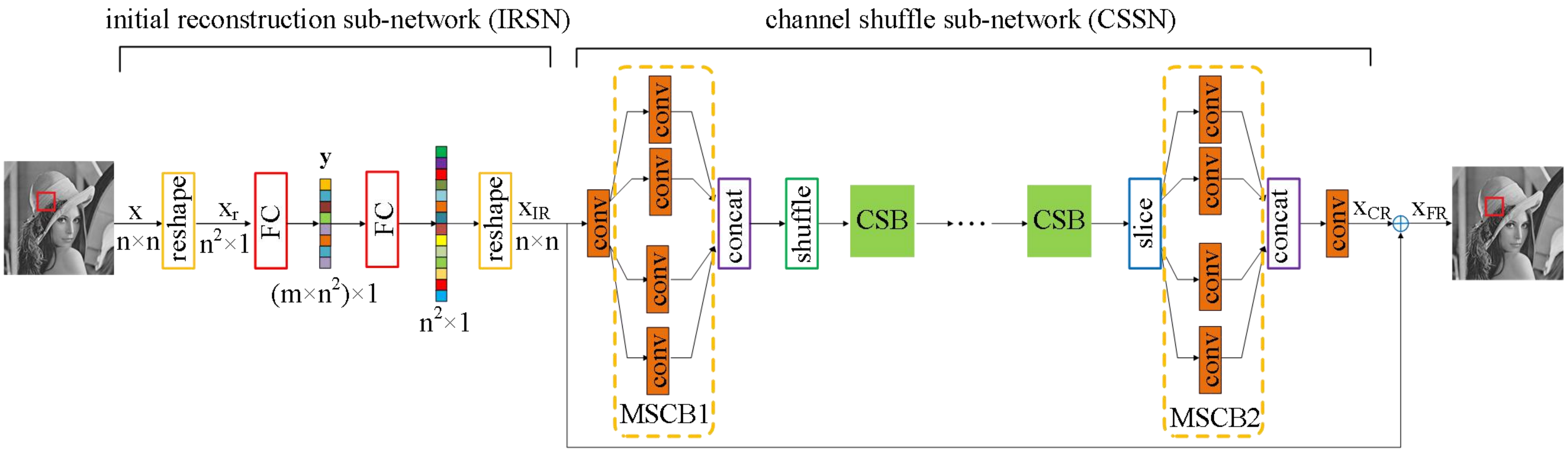


Block diagram of single pixel camera



Schematic of the spectral imager

Method



The complete architecture of our proposed model.

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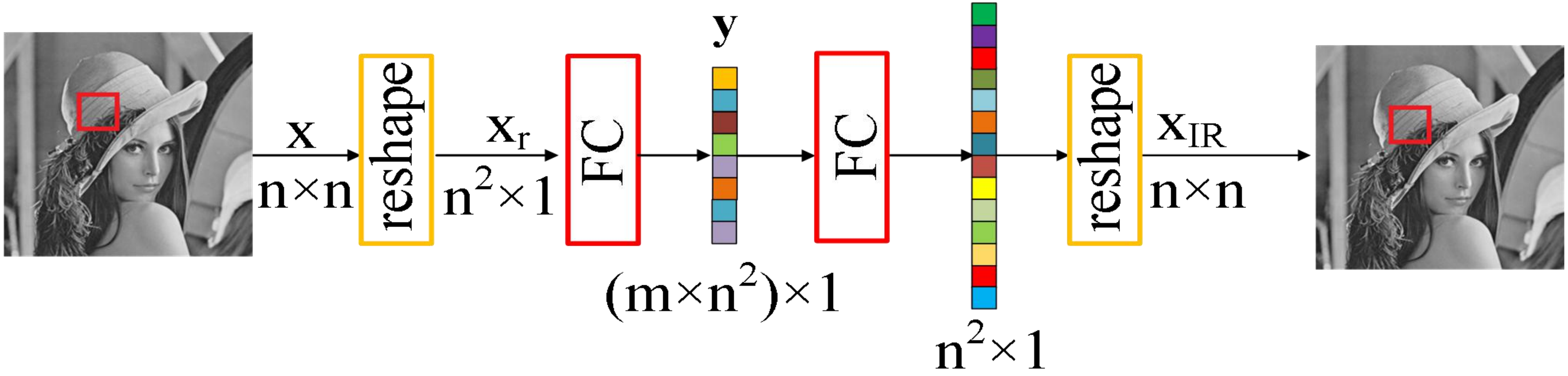
Method

- IRSN

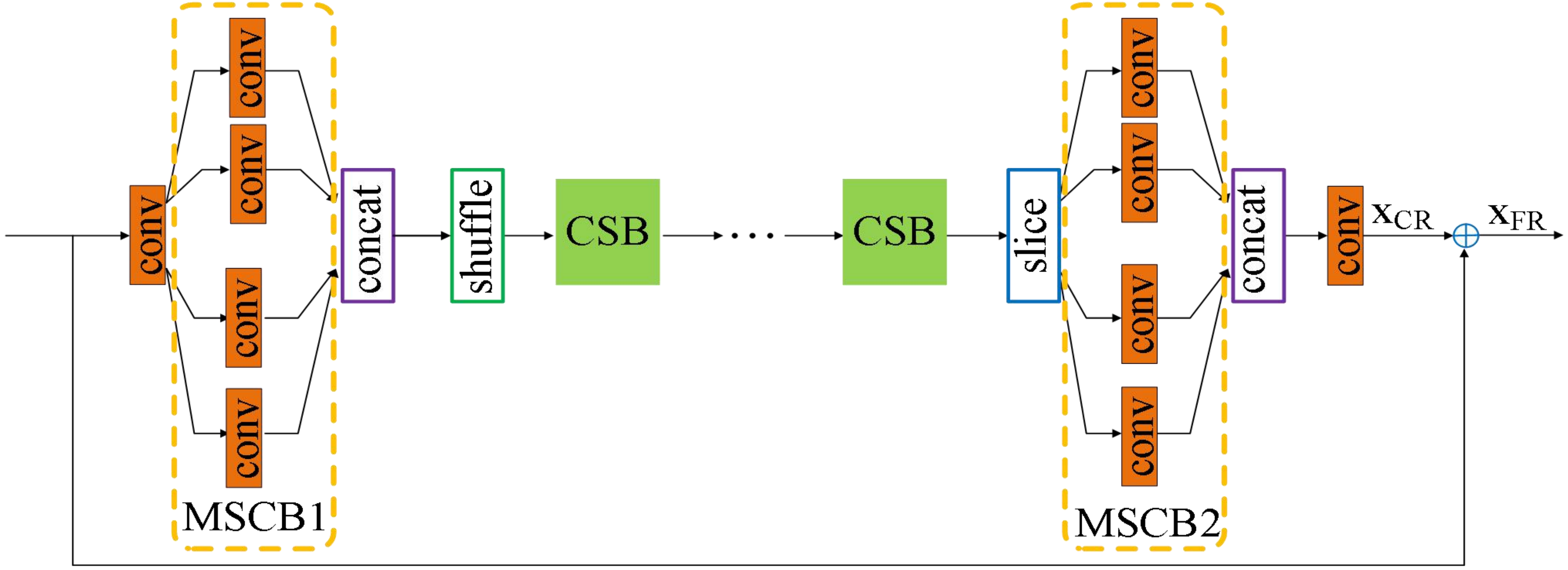


The architecture of initial reconstruction sub-network (IRSN).

- The IRSN can adaptively learn the measurement matrix and generate a preliminary reconstructed image.
- The IRSN contains two reshape layers and two fully connected layers.

Method

- CSSN

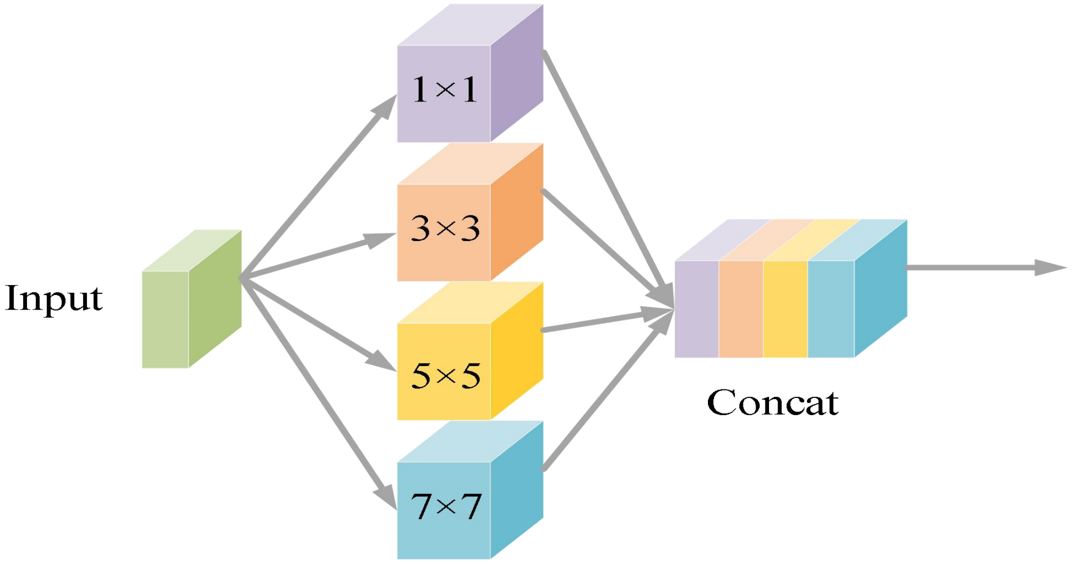


The architecture of channel shuffle sub-network (CSSN).

- The CSSN takes the output of IRSN as input and reconstruction the final high quality image.
- The CSSN contains the multi-scale convolution block (MSCB) and the channel shuffle block (CSB).

Method

- MSCB

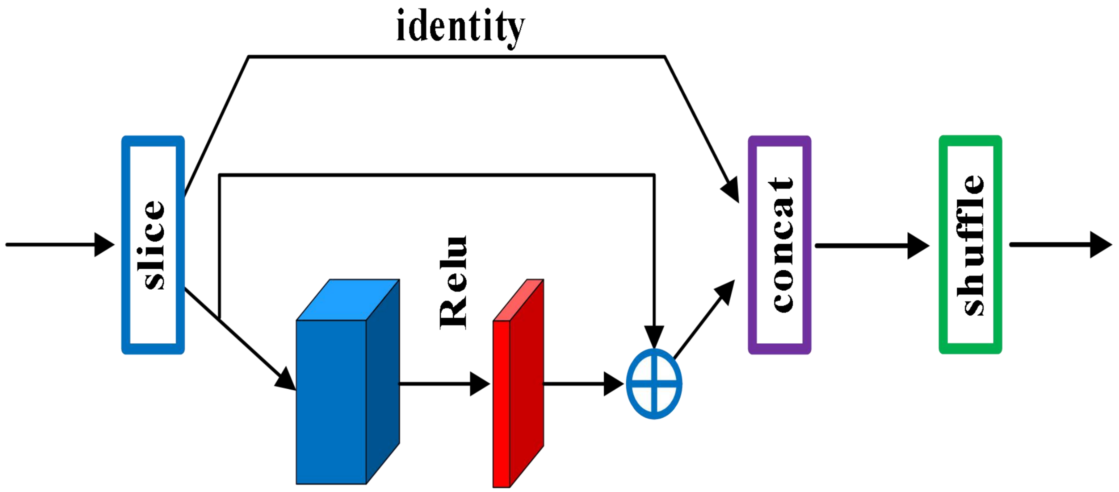


The architecture of multi-scale convolution block (MSCB).

- The multi-scale convolution block contains four parallel branches to extracte features of different scales from the input and fuse features of various scales through the 'concat' layer.
- We adopt two MSCBs at the begin and the end of CSSN, respectively.

Method

- CSB



The architecture of channel shuffle block (CSB).

- Two convolutional layers and one skip connection form an inverted residual structure.
- The slice layer ensures that only part of the information is sent to the inverted residual structure, reducing the amount of network parameters, and the shuffle layer realizes information fusion.

Experiment

- Evaluation Criteria

- Evaluation index: PSNR

- Comparison algorithm:TVAL3 [1], D-AMP [2], SDA [3], ReconNet [4], DR^2-Net [5], ConvCSNet [6], ISTA-Net+ [7], FDC-Net [8] and SCSNet [9]

- Deep learning framework: caffe

- Learning rate: begins with 0.0001 and stops at 0.00001

- Input: 33×33 image patches

- Optimizer: Adam

- Loss: MSE loss

[1] C. Li, W. Yin, H. Jiang, and Y. Zhang, "An efficient augmented lagrangian method with applications to total variation minimization," in Computational Optimization and Applications, vol. 56, no. 3, pp. 507-530, 2013.
[2] C. A. Metzler, A. Maleki, and R. G. Baraniuk, "From denoising to compressed sensing," in IEEE Transactions on Information Theory, vol. 62, no. 9, pp. 5117-5144, 2016.
[3] A. Mousavi, A. B. Patel, and R. G. Baraniuk, "A deep learning approach to structured signal recovery," in Proceeding of 2015 53rd Annual Allerton Conference on Communication, Control, and Computing (Allerton), 2015.
[4] K. Kulkarni, S. Lohit, P. Turaga, R. Kerviche, and A. Ashok, "Reconnet: Non-iterative reconstruction of images from compressively sensed random measurements," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 449-458, 2016.
[5] H. Yao, F. Dai, D. Zhang, Y. Ma, and S. Zhang, "DR2-Net: Deep residual reconstruction network for image compressive sensing," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 483-493, 2017.
[6] Lu X, Dong W, and Wang P, "ConvCSNet: A convolutional compressive sensing framework based on deep learning," arXiv preprint arXiv:1801.10342, 2018.
[7] J. Zhang and B. Ghanem, "ISTA-Net: Interpretable optimization inspired deep network for image compressive sensing," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1828-1837, 2018.
[8] Z. Zhang, D. Gao, X. Xie, and G. Shi, "Dual-channel reconstruction network for image compressive sensing," in Sensors, pp. 2549, 2019.
[9] W. Shi, F. Jiang, S. Liu, and D. Zhao, "Scalable convolutional neural network for image compressed sensing," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 12290-12299, 2019.

Experiment

- Quantitative results

Mean PSNR results on Set11 at various MRs. The best results are highlighted.

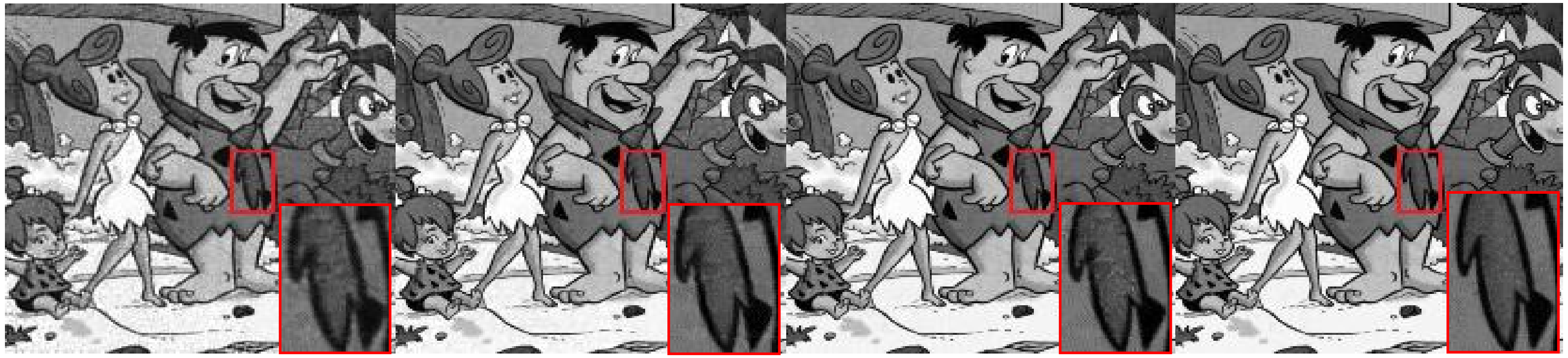
Algorithms	PSNR (dB)			
	0.25	0.10	0.04	0.01
TVAL3 [1]	27.84	22.84	18.39	11.31
D-AMP [2]	28.17	21.14	15.49	5.19
SDA [3]	24.72	22.43	19.96	17.29
ReconNet [4]	25.54	22.68	19.99	17.27
DR^2-Net [5]	28.66	24.32	20.80	17.44
ConvCSNet [6]	26.97	23.30	20.40	17.34
ISTA-Net+ [7]	31.57	26.61	21.31	17.34
FDC-Net [8]	32.15	27.84	24.68	20.64
SCSNet [9]	--	28.48	--	**21.04**
Proposed	**33.66**	**28.70**	**24.89**	20.09

- Our network surpasses all algorithms at MR=0.25, MR=0.10 and MR=0.04.

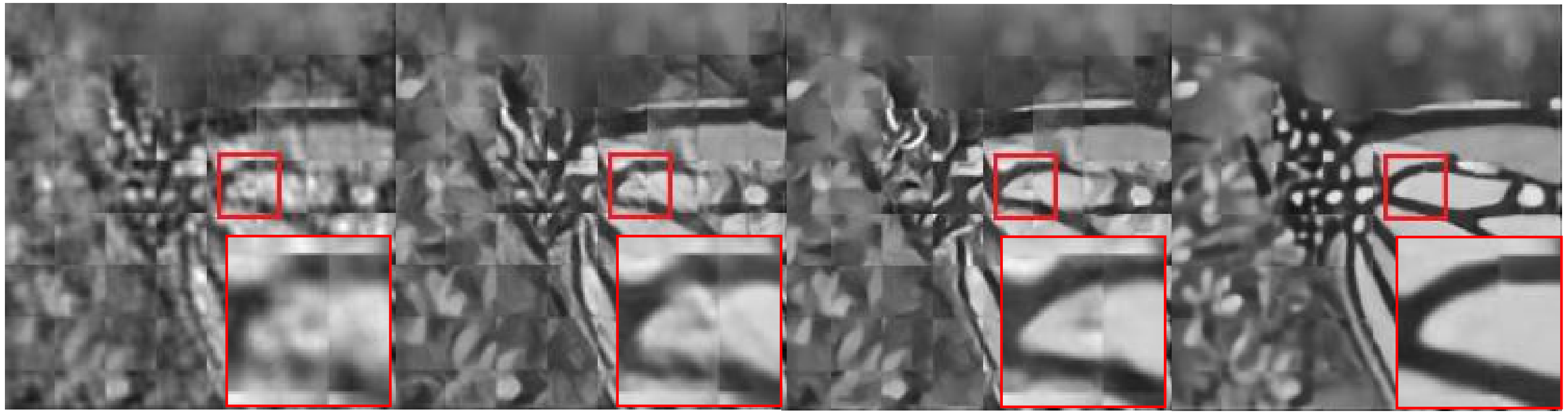
Experiment

- Visual results

ReconNet [4] | DR²-Net [5] | ISTA-Net+ [7] | Proposed



18.19dB | 18.93dB | 19.27dB | 23.95dB



22.45dB | 26.19dB | 30.03dB | 30.58dB

Reconstruction results of image “Monarch’” (the top picture) at MR=0.04 and image “flinstones” (the bottom picture) at MR=0.25.

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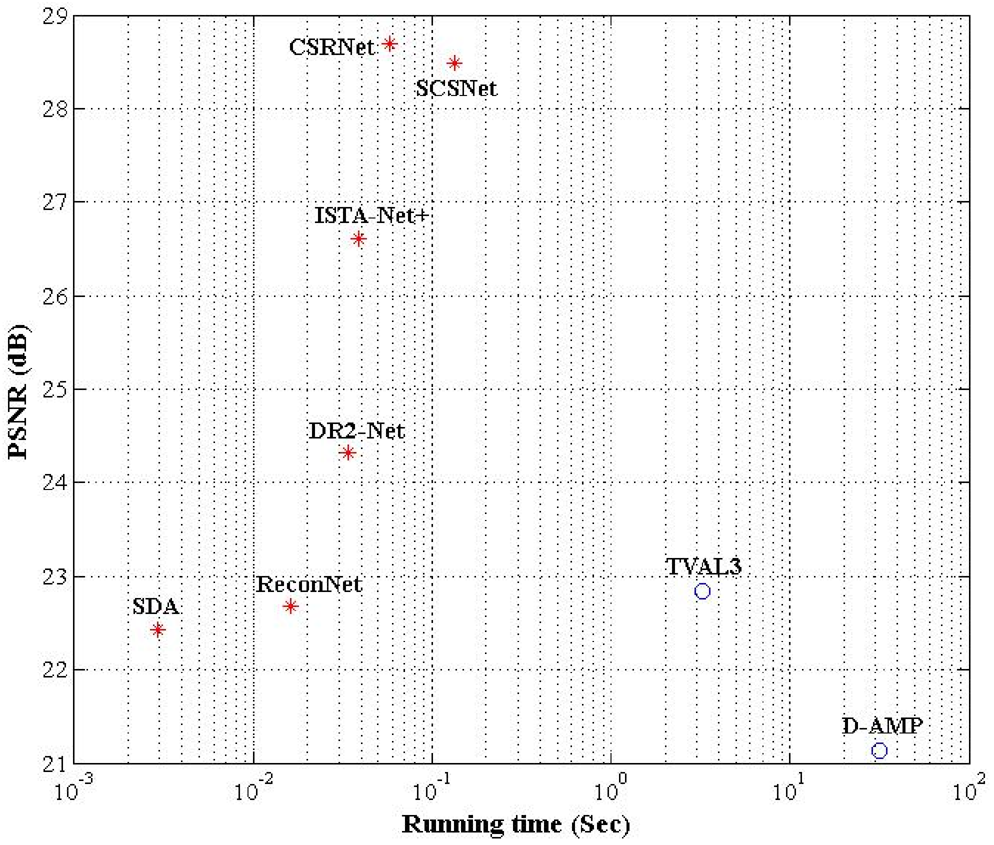
Experiment

- Time complexity

Algorithms	Time Complexity (s)			
	0.25	0.10	0.04	0.01
TVAL3 [1]	2.9430	3.2230	3.4670	7.7900
D-AMP [2]	27.764	31.849	34.207	54.643
SDA [3]	0.0042	0.0029	0.0025	0.0045
ReconNet [4]	0.0169	0.0162	0.0169	0.0208
DR^2-Net [5]	0.0378	0.0338	0.0342	0.0331
ISTA-Net+ [7]	0.0350	0.0390	0.0365	0.0310
SCSNet [9]	--	0.1332	--	0.1050
Proposed	0.0577	0.0579	0.0587	0.0575



- Left: Running time of different methods on a test image of size 256 × 256 at various MRs.
- Right: The PSNR and running time for reconstructing a single 256×256 image at measurement rate 0.10.
- Although our network runs slower than most of the competing deep learning methods, it still maintains a comparable time complexity with good speed-accuracy balance.

Experiment

- Effects of CSB

Effectiveness of CSB on Set11 at MR=0.25 and MR=0.04.

	MR=0.25 (PSNR)	**MR=0.04 (PSNR)**
Residual block [13]	33.41	24.47
Inverse residual block [19]	33.38	24.53
Channel shuffle block (CSB)	33.66	24.89

- To demonstrate the effect of CSB, we replace it with the plain residual block adopted in DR^2-Net [5] and the inverted residual block.
- The network with CSB outperforms its counterparts by a large margin.

Experiment

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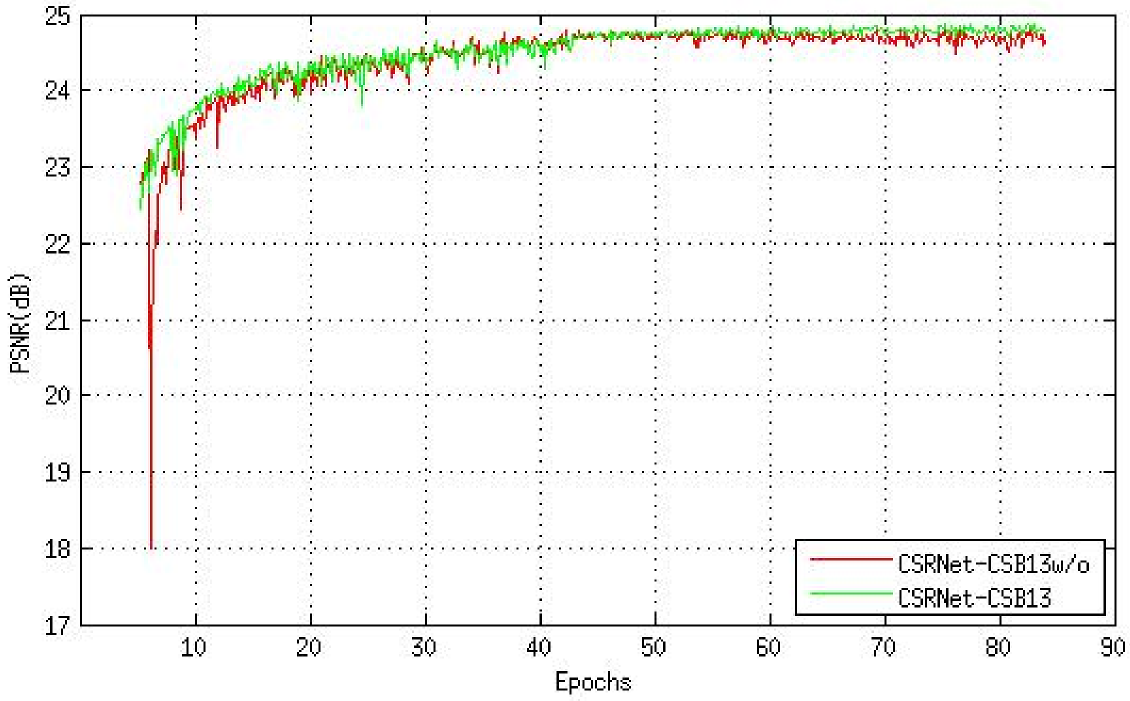
- Effects of MSCB



Convergence analysis on network with and without multi-scale convolution block.

◆ The curves are based on the average PSNR on Set11 at measurement rate 0.04 in 84 epochs.

Conclusions

● Conclusions

- A channel shuffle reconstruction network is proposed for CS image reconstruction.
- We first build an initial reconstruction sub-network (IRSN) to generate a preliminary reconstructed image, and then extend the IRSN by adding a channel shuffle sub-network (CSSN).
- We combine the merits of the inverted residual structure with channel shuffle operation to propose an efficient channel shuffle block in CSSN.
- We take advantages of multi-scale convolution to fully explore features at different scales.
- The experimental results demonstrate that our proposed method obtains a superior performance.
- In future work, we intend to study better optimization strategies.

Thank You!

For any question, please contact:
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