# AN END-TO-END MULTI-SCALE RESIDUAL RECONSTRUCTION NETWORK FOR IMAGE COMPRESSIVE SENSING

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## INTRODUCTION & MOTIVATION

- **Motivation**: Recently, CNN-based models have been proposed to improve recovery performance for image compressive sensing. However, 1: Previous methods concentrate on optimize inverse reconstruction part, while neglect optimizing measurement matrix in compressive sample process . 2: Previous methods use simple network architecture to implement reconstruction task, which cannot fully exploit powerful learning ability of CNN.

- For above issues, we propose an end-to-end multi-scale residual neural network, dubbed as MSRNet, **contributions** of our MSRNet are following:
- We apply **fully-connected layer** as **measurement matrix** to implement compressively sample task, replacing traditional random Gaussian matrix, which is not so friendly for hardware.
- We integrate compressive sample and inverse reconstruction parts to **one end-to-end model**, so we actually optimize an end-to-end CNN instead of optimizing each part respectively
- **Multi-scale residual network** is introduced to extract different-scale feature information, and **cross connection** is introduced to fuse information from different-scale level.
- **Accuracy and time complexity**: our method achieves significant performance improvement on test datasets with competitive time complexity, a test image is shown in Fig.1,

Ground truth | 22.63dB/ 0.019s ReconNet | 23.94dB/0.057s DR$^2$-Net | 28.24dB/0.107s Our MSRNet

Fig.1 PSNR and time for recovering image “Parrots” at MR=10%

## PROPOSED METHOD

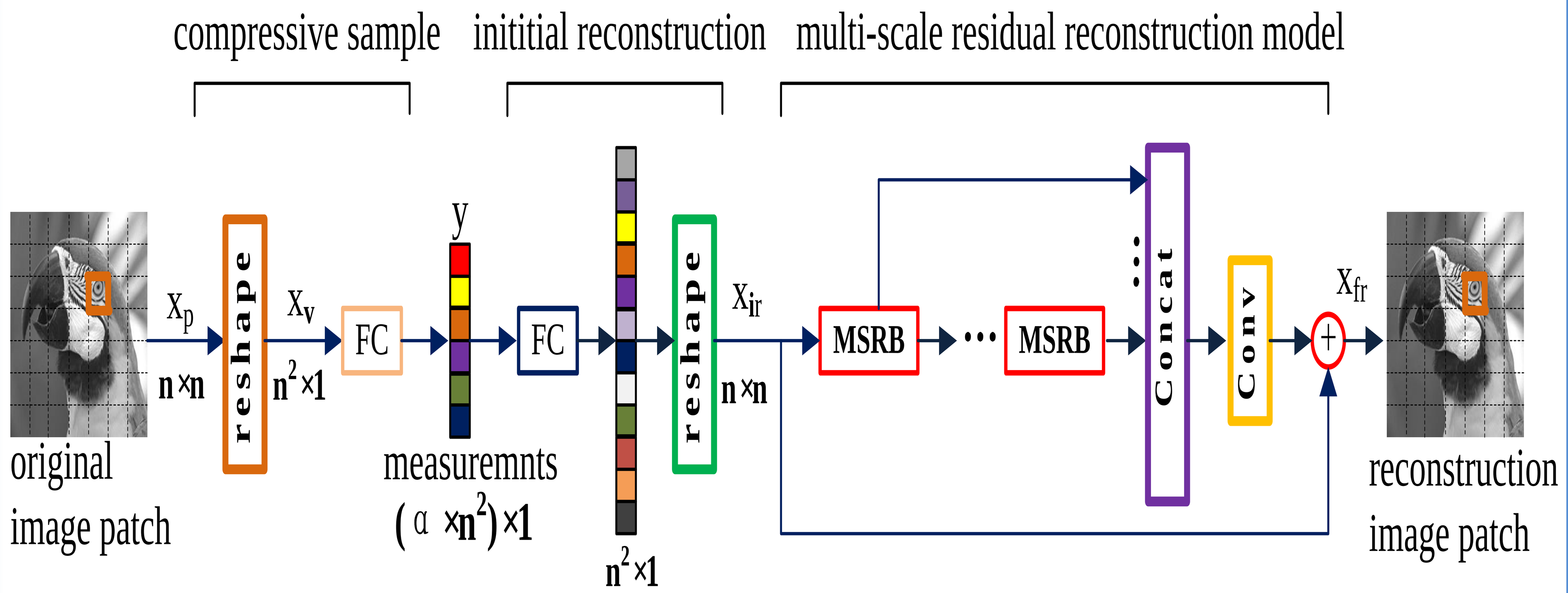


Fig.2 framework of MSRNet

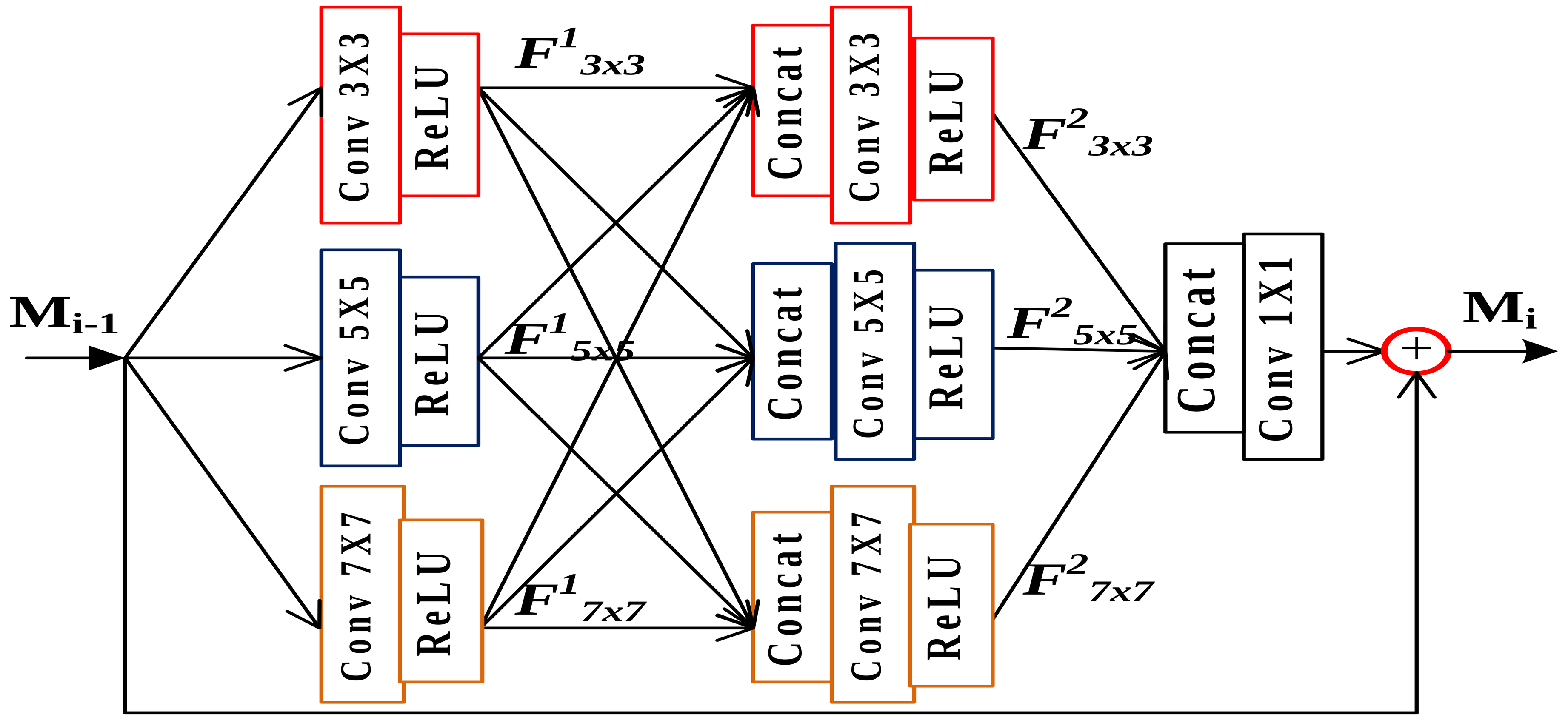


Fig.3 Structure of MSRB in multi-scale residual reconstruction model

- As is shown in Fig.2, MSRNet includes three parts: compressive sample, initial reconstruction, multi-scale residual reconstruction.
- compressive sample part includes 1 reshape layer and 1 fully-connected layer, which is used for reshape input image patch and compressively sample original pixels.
- initial reconstruction part includes 1 reshape layer and 1 fully-connected layer, which is used for initially restore original pixels and reshape them to one patch.
- multi-scale residual reconstruction part is used to further enhance recovery accuracy based on initial reconstruction image, the basic block in the part is MSRB, whose detail is shown in Fig.3.

## EXPERIMENT RESULTS

Table. 1 Mean PSNR results on Set11 at various MR

| Algorithm | Measurement Rate | | | |
|---|---|---|---|---|
| | 25% | 10% | 4% | 1% |
| TVAL3 | 27.84 | 22.84 | 18.39 | 11.31 |
| D-AMP | 28.17 | 21.14 | 15.49 | 5.19 |
| SDA | 24.72 | 22.43 | 19.96 | 17.29 |
| ReconNet | 25.54 | 22.68 | 19.99 | 17.27 |
| DR$^2$-Net | 28.66 | 24.32 | 20.80 | 17.44 |
| ISTA-Net | 31.53 | 25.80 | 21.23 | 17.30 |
| MSRNet | 33.36 | 28.07 | 24.23 | 20.08 |

Table. 2 Time complexity of different algorithms

| Algorithm | Time Complexity (s) | | | |
|---|---|---|---|---|
| | MR=0.25 | MR=0.1 | MR=0.04 | MR=0.01 |
| TVAL3 | 2.943 | 3.223 | 3.467 | 7.790 |
| D-AMP | 27.764 | 31.849 | 34.207 | 54.643 |
| SDA | 0.0042 | 0.0029 | 0.0025 | 0.0045 |
| ReconNet | 0.0213 | 0.0195 | 0.0192 | 0.0224 |
| DR$^2$-Net | 0.0600 | 0.0576 | 0.0565 | 0.0557 |
| MSRNet | 0.1091 | 0.1082 | 0.1070 | 0.1068 |

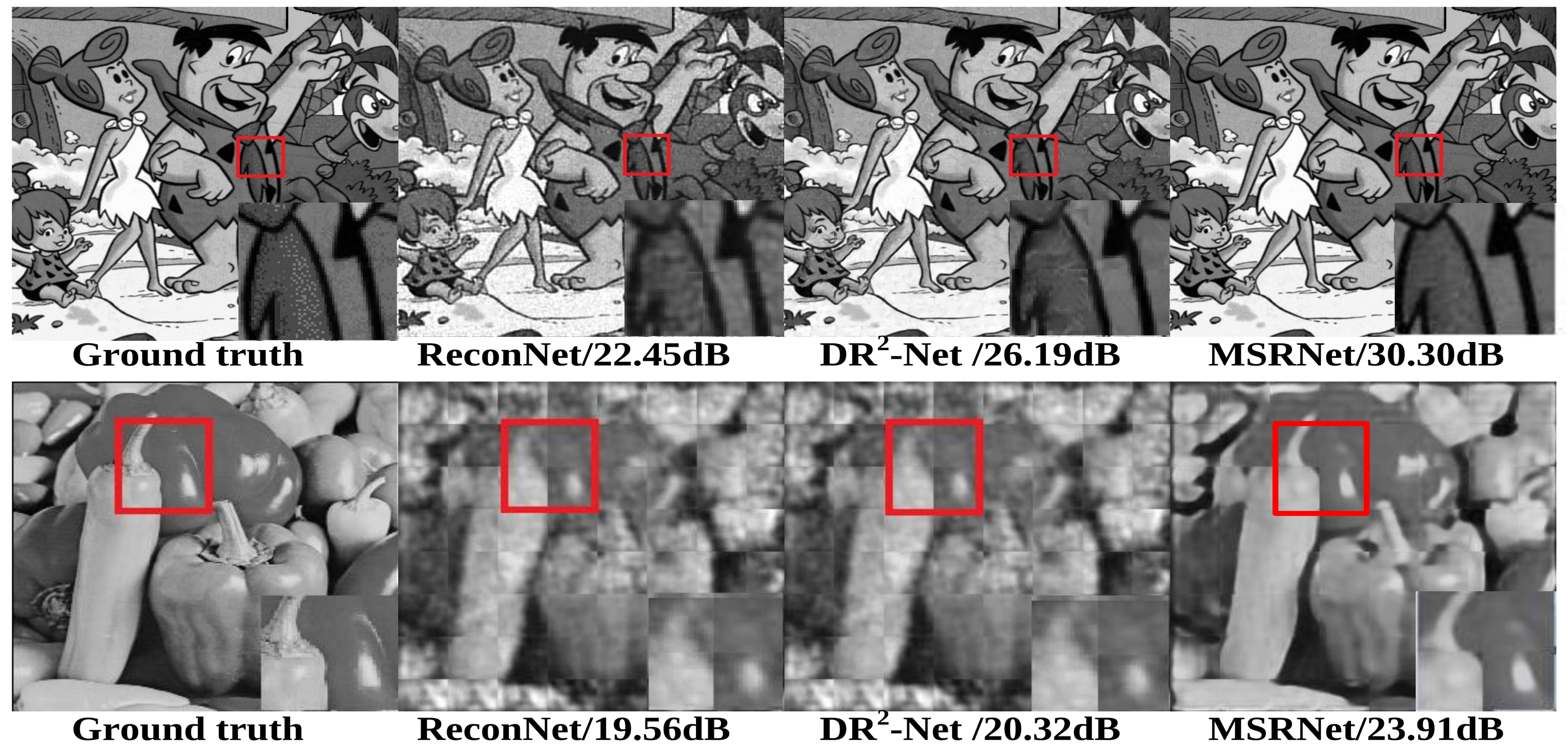


Fig.4 Reconstruction results of image “flinstones” (the top picture) at MR=25% and image “peppers” (the bottom picture) at MR=4%.

## CONCLUSION

In this paper, we proposed an end-to-end multi-scale residual network for image compressive sensing. By training a CNN based on end-to-end optimization, difficulty of generating hardware-friendly measurement matrix is alleviated. Moreover, multi-scale residual is introduced to enhance learning ability for multi-scale information and contribute to achieve better reconstruction quality.