**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.

**EXPERIMENT RESULTS**

- Table 1 PSNR and time for recovering image "Parrots" at MR=25% and image "peppers" (the bottom picture) at MR=4%.
- Table 2 Time complexity of different algorithms.

**PROPOSED METHOD**

- 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 compressive 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 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.

**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.