Dive into deep image prior

Stanford EE 367 Project Proposal

Zhuofan Xi
ICME
Stanford University
zfxi@stanford.edu

1 Background and Motivation

Inverse problem such as denoising is a classsical but still highly active topic in computational imaging. Recently the development of deep neural networks has drastically improved the performance of image processing. Most of the CNNs are trained on large datasets of images before showing excellent performance and I have been assuming that this is because they can generalize patterns from numerous images. However in HW5 bonus task I see the brand new idea that deep image priors[1] can achieve strong performance in inverse problems even without conventional training at all. This really fascinates me and I am eager to extend this method a bit more in this project.

2 Project description

Goal The main goal of this project is to throughly understand the novel idea in deep image prior paper and try to modifications to try to improve its performance.

Description There are two main points in the paper that remains to be discussed and I will choose these as my starting points:

1. In the inverse problem formulation

$$x^* = \arg\min_x E(x; x_0) + R(x)$$

   why do they drop the explicit regularizer $R(x)$ and use

$$\theta^* = \arg\min_\theta E(f_\theta(z); x_0), \quad x^* = f_{\theta^*}(z)$$

   instead? If I add TV or learning regularizers back, will the result get better or worse?
2. The paper says the choice of the architecture does have an impact on the results, but they don't give reasons why their experiments are performed using UNet-like architecture with skip connections. Are there redundant or even harmful components in the net? What will happen if I change some layers or even use a different architecture?

After solving the problems above, I may have a better view of the concepts and come up with more topics.

Intermediate goal The intermediate goals are:

1. Read deep image prior paper carefully and understand their concepts
2. Collect relevant papers and learn how to use their models
3. Work on the problems mentioned above

3 Research Paper Summary

We have learned how to use total variation and denoisers as regularization terms and solve inverse problems. DnCNN[2] exhibits much better results in HW6 and will be my first choice for prior term.

As for network architectures, admittedly UNet is a good model but there are also other nice ones to choose from. For example classical VGG[3] and ResNet[4] can be good candidates.

References

[1] Dmitry Ulyanov, Andrea Vedaldi, and Victor Lempitsky. Deep image prior. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 9446–9454, 2018.

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[3] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

[4] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.