EE 367 Project Proposal

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Introduction

Denoising images, as we have seen in this course, is still an active area of research. While the methods in this course rely on a convex optimization objective to model the noise in an arbitrary image as a linear transform, most approaches that achieve state of the art results use deep learning priors.[1] The major benefit of using a network instead of just a convex objective is that neural networks are universal function approximators and can perform non-linear transformations, which may be necessary dependent on the noise present. They also don't require a noise prior, or any prior, besides the architecture, as they learn such parameters directly from a dataset. For these reasons, I will look at using some state of the art CNN based denoising models to perform denoising on a variety of different real and synthetic noise samples.

Related Work

There has been a bevy of work done on using machine learning priors for image denoising. The most commonly used method is to use a Unet-based CNN architecture to denoise images end to end. Other methods include residual dense networks that use dense linear layers and residual connections to achieve effective training or self-supervised methods that use "blind spots" in the receptive field of a network to achieve higher PSNR values.[2]

Approach

After looking at the current state of the art models for image denoising, I believe I will base my machine learning model on a Multi-level Wavelet-CNN model outlined by Pengju Liu et al.[3] This method uses a modified Unet architecture and the wavelet transform to denoise images in wavelet space and then transform back to the primal domain.

As it is important to compare results directly to the current implementation of the model, I will use the same dataset used by Pengju Liu et al. as my training set which is a combination of the BSD, WED, and DIV2K dataset cropped into 240 x 240 patches.

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[1] "Deep Learning for Image Denoising: A Survey." 11 Oct. 2018, https://arxiv.org/abs/1810.05052. Accessed 11 Feb. 2019.

[2] "Self-Supervised Deep Image Denoising." 29 Jan. 2019, https://arxiv.org/abs/1901.10277. Accessed 11 Feb. 2019.

[3] "Multi-level Wavelet-CNN for Image Restoration." 18 May. 2018, https://arxiv.org/abs/1805.07071. Accessed 11 Feb. 2019.

For evaluation, I will use a combination of SSIM and PSNR as my final evaluation metrics. These are the standard metric used by a variety of neural network papers in the image processing space from neural inpainting to frame interpolation to denoising.

Milestones and Timeline

Currently, this model is written in matlab, so my goal for this project is to primarily reimplement this system within pytorch and achieve comparable results.
My timeline is as follows:

Week 0-1:
Read through the paper in depth and begin implementing boiler plate code

Week 1-2:
Write the basic data loading scheme and implement experiment pipeline

Week 2-3:
Write model architecture and run overfit experiments

Week 3-4
Run final experiments,update architecture, and submit results

References

- *Deep Learning for Image Denoising: A Survey*
  Chunwei Tian and Yong Xu and Lunke Fei and Ke Yan
  2018

- Self-Supervised Deep Image Denoising
  Samuli Laine and Jaakko Lehtinen and Timo Aila
  2019
- Residual Dense Network for Image Super-Resolution
  Yulun Zhang and Yapeng Tian and Yu Kong and Bineng Zhong and Yun Fu
  2018
- Multi-level Wavelet-CNN for Image Restoration
  Pengju Liu and Hongzhi Zhang and Kai Zhang and Liang Lin and Wangmeng Zuo
  2018