Few-Shot Image Denoising with Meta-Learning
Project Proposal

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1 Motivation

Image denoising is a topic that has been explored from many different angles, two of the most prominent being learning-based methods and non-learning based methods. Most learning-based methods, like the DnCNN [10] result in de-noised images of much higher quality than non-learning based approaches like non-local means [1] and BM3D [4]. However, most of these learning-based approaches require training on a large number of clean and real noisy image pairs [10], which can be difficult to obtain for certain applications. Many applications may only have access to a few clean and real noisy image pairs, which could lead to overfitting in learning-based approaches.

This challenge is usually addressed by constructing large training datasets with clean and noisy image pairs where the noisy image is synthetically generated from the clean image. Specifically, to generate our noisy images, we draw samples from a chosen noise distribution and apply this noise to a clean image [9]. However, training with synthetically generated noisy images does not generalize well in practice due to a lack of fine-tuning during test-time [3, 8]. Furthermore, many of these learning-based models are also trained to denoise for a specific type of noise and fixed amount of noise variance, not making them very generalizable, especially for smaller-sized training sets.

For our project, we want to address the above challenges by re-implementing parts of the paper "Few-Shot Meta-Denoising" [3] which applies meta-learning algorithms to learn few-shot image denoising with various noise distributions. We believe the combination of meta-learning and few-shot learning is a good model for the image denoising challenges described above because the model will quickly learn how to denoise images from a few synthetically generated noisy images (using various noise distributions) and use fine-tuning to efficiently adapt to denoising of a small set of real noisy images.

2 Related Work

2.1 Learning-Based Denoising

Learning-based approaches have been quite popular for image denoising in the past couple years. These algorithms have been constructed using architectures like auto-encoders [9], convolutional neural networks [6], and multi-layer perceptrons [2] as well. In our project, we will focus on using the denoising convolutional neural network known as the DnCNN [10] in combination with meta-learning algorithms.

Instead of directly trying to predict the denoised output of a noisy input image, the DnCNN uses residual learning to predict the residual/noise distribution within the image. The learned noise is then subtracted from the noisy image and the result is considered to be the denoised image which is compared against the clean image [10].

2.2 Meta-Learning

The main goal of meta-learning algorithms is to train a model to learn how to quickly solve a task after training on a set of tasks all drawn from a similar distribution. Most meta-learning algorithms are broken down into two parts: meta-training and meta-testing. During each iteration of meta-training, the algorithm samples a task from the distribution of training tasks and learns how to perform this task. The algorithm then uses the knowledge acquired from multiple tasks during meta-training, to quickly adapt to a new unseen task during meta-test time. The meta-test tasks are sampled from a similar distribution to the meta-train tasks. For few-shot learning, each task only uses a small amount of data to train and adapt to new tasks.

We are interested in exploring two optimization-based meta-learning algorithms called model agnostic meta-learning (MAML) [5] and Reptile [7]. The goal of optimization based meta-learning algorithms is to use an iterative approach to find a set of network initialization parameters that allow your inner model (in our case the DnCNN) to adapt to any task quickly with just a few steps of fine-tuning [5]. Both MAML and Reptile are state-of-the-art techniques for optimization-based meta-learning. The authors of the few-shot meta-denoising paper found that Reptile works better for their experiments, mainly due to its generalizability and efficiency [3].

3 Project Overview

The goal of our project is to perform few-shot image denoising on natural images. Our model will combine optimization-based meta-learning algorithms like MAML or Reptile with the learned denoising model DnCNN in order to perform few-shot image denoising. During meta-training, our algorithm will randomly sample a small set of synthetic noisy images from one of the following noise distributions: Gaussian, Poisson, Gaussian-Poisson mix (the parameters of each distribution can vary between tasks). Each set of sampled images is considered a few-shot task and the model will learn to denoise these images. The meta-training process allows the model to learn a good initialization for the DnCNN model so that it can quickly adapt to new denoising tasks.

During the meta-testing stage, we will sample a small set of real noisy images and the DnCNN will use the learned initialization and fine-tune to denoise the real noisy images.

We hope the outcome of our project results in a learning-based model that can quickly generalize the denoising process for multiple types of noise distributions without a dependency on large amounts of training data.

4 Milestones and Timeline

Week 1 (Feb. 19th-25th):

- Generate training dataset of paired synthetic noisy images (Gaussian noise, Poisson noise, Gaussian-Poisson noise) and clean images for meta-training
- Find dataset of real noisy images and corresponding clean images for meta-testing
- Build MAML and/or REPTILE architecture on top of DnCNN architecture
- Start tuning hyperparameters towards the end of the week

Week 2 (Feb. 26th-March 4th):

- Train our algorithm and collect results
- Run some non-learned denoising algorithms (NLM, bilateral filtering, etc.) on the meta-testing images to establish a baseline

Week 3 (March 5th-11th):

- Create poster/record presentation
- Write report

References

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