Motivation

- Reconstruct image \( x \) from noisy observation \( y \) affected by noise distribution \( N \) with parameters \( \epsilon \) :
  \[
y = N_\epsilon(x)
\]
- Deep learning methods exist for denoising images, but such methods require large amounts of synthetic noisy data and do not generalize well to unseen noise distributions or real noisy images.
- We propose the use of a meta-learning algorithm to learn how to perform few-shot image denoising with various noise distributions.
- At test time our model has the ability to denoise synthetic noisy images of unseen distributions and levels and also to adapt to denoising of a small set of real noisy images.

Related Work

- Non-learning methods: Bilateral Filtering (BF), Non-Local Means (NLM), and Block-Matching and 3-D Filtering (BM3D).
  - Pros: Works independently of noise distribution and level.
  - Cons: Can cause blurring artifacts, slow run time.
- Learned Methods: DnCNN-B from Denoising Convolutional Neural Networks [1]
  - Pros: DnCNN-B handles Gaussian denoising on unknown levels.
  - Cons: Needs lot of data to train, only suited for Gaussian noise.
- Model Agnostic Meta-Learning (MAML) [2]: Finds a set of network initialization parameters that allow the model to adapt to any unseen task quickly with just a few steps of fine-tuning.

Algorithm 1 Model-Agnostic Meta-Learning

Require: \( p(T) \): distribution over tasks
\[
\mathcal{T} \sim p(T)
\]
1. randomly initialize \( \theta \)
2. while not done do
3. Sample batch of tasks \( T_i \sim p(T) \)
4. for all \( T_i \) do
5. Evaluate \( \nabla_\theta \mathcal{L}_i(f_\theta) \) with respect to \( K \) examples
6. Compute adapted parameters with gradient descent: \( \mathcal{L}_i : \theta \rightarrow \theta - \alpha \nabla_\theta \mathcal{L}_i(f_\theta) \)
7. end for
8. Update \( \theta = \theta - \beta \sum_{T_i \sim p(T)} \mathcal{L}_i(f_{\theta}) \)
9. end while

References