Self-supervised Image Denoising with Deep Neural Networks

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Outline

Introduction

- Image denoising: a fundamental task in computer vision (CV)
- Degradation model: $\boldsymbol{y} = \boldsymbol{x} + \boldsymbol{n}$
  - $\boldsymbol{x}$: uncorrupted image, ground truth
  - $\boldsymbol{y}$: degraded image, model input
  - $\boldsymbol{n}$: additive noise
- Key challenge: highly ill-posed problem: loss of information during degradation
- General idea of solution: Prior knowledge for either
  - Image modelling
  - Noise modelling

Literature Review

- Traditional methods: BM3D (popular benchmark), WNNM
- RED-Net: (Mao, Shen, & Yang, 2016)
- DnCNN: Deep CNN model with residual learning & batch normalisation (Zhang, Zuo, Chen, Meng, & Zhang, 2017)
- FFDNet: Noise map for noise level. Flexible to variant noise (Zhang, Zuo, & Zhang, 2018)
- GCBD: GAN for noise modelling (Chen, Chen, Chao, & Yang, 2018)
- Self-supervised: Noise2Noise (Lehtinen et al., 2018), Noise2Void (Krull, Buchholz, & Jug, 2019)
- Meta-learning: fast inference adpation (Lee, Cho, Kim, & Kim, 2020)

Methodology i

- Neural Network Architecture
  - CNN-based model: suitable for image processing
  - Residual learning and batch normalisation (DnCNN)
  - Noise map: flexible to noise levels and variant noise (FFDNet)
    - improvement: GAN-based noise modelling
- Self-supervision
  - Still supervised learning, i.e. with label, but autonomously generated rather than human annotated.
  - Patch-based: learn on patches of a single input
  - Meta-learning: learns a better prior model on large collection of data.

Methodology ii

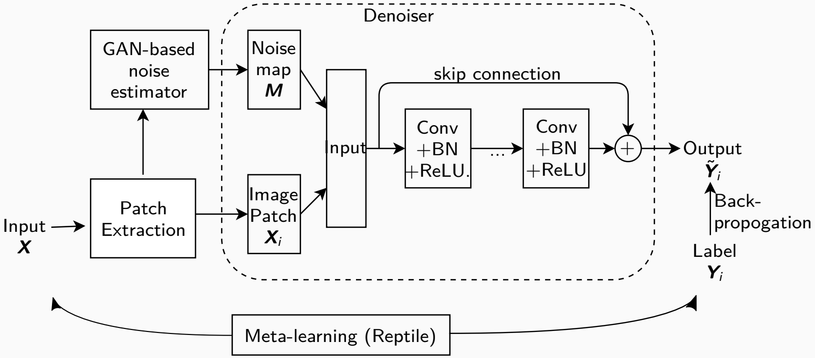

Figure 1: Overall architecture of image denoising model

Methodology iii

- Dataset:
  - Common datasets: Set14, BSD500, DIV2K, etc
  - Real noisy images: DND, SIDD
- Evaluation: PSNR: Peak Signal to Noise Ratio

$$PSNR = 10 \log_{10} \left(\frac{R^2}{MSE} \right)$$

  - R is the maximum fluctuation
  - MSE is the Mean Squared Error between model output and ground-truth

Timetable

Task	Deadline
Final decision on the topic, create research questions	1 week
Literature review	3 weeks
Research proposal draft	1 week
Prototyping	4 weeks
First round of testing and analysis	4 weeks
Model improvement	4 weeks
Second round of testing and analysis	4 weeks
Write and present final results	4 weeks

References

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