컴퓨터비전 프로젝트

최종발표

Image Denoising

Beyond a Gaussian Denoiser:
Resisual Learning of Deep CNN for Image Denoising

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수학과	20175224	전경훈
소프트웨어학부	20190277	이보림
학점교류	50230036	김새롬

1. 프로젝트 문제 제기 및 필요성

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Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising

Kai Zhang, Wangmeng Zuo, Yunjin Chen, Deyu Meng, and Lei Zhang

***Abstract*—Discriminative model learning for image denoising has been recently attracting considerable attentions due to its favorable denoising performance. In this paper, we take one step forward by investigating the construction of feed-forward denoising convolutional neural networks (DnCNNs) to embrace the progress in very deep architecture, learning algorithm, and regularization method into image denoising. Specifically, residual learning and batch normalization are utilized to speed up the training process as well as boost the denoising performance. Different from the existing discriminative denoising models which usually train a specific model for additive white Gaussian noise (AWGN) at a certain noise level, our DnCNN model is able to handle Gaussian denoising with unknown noise level (i.e., blind Gaussian denoising). With the residual learning strategy, DnCNN implicitly removes the latent clean image in the hidden layers. This property motivates us to train a single DnCNN model to tackle with several general image denoising tasks such as Gaussian denoising, single image super-resolution and JPEG image deblocking. Our extensive experiments demonstrate that our DnCNN model can not only exhibit high effectiveness in several general image denoising tasks, but also be efficiently implemented by benefiting from GPU computing.**

***Index Terms*—Image Denoising, Convolutional Neural Networks, Residual Learning, Batch Normalization**

I. INTRODUCTION

Image denoising is a classical yet still active topic in low level vision since it is an indispensable step in many practical applications. The goal of image denoising is to recover a clean image $\mathbf{x}$ from a noisy observation $\mathbf{y}$ which follows an image degradation model $\mathbf{y} = \mathbf{x} + \mathbf{v}$. One common assumption is that $\mathbf{v}$ is additive white Gaussian noise (AWGN) with standard deviation σ. From a Bayesian viewpoint, when the likelihood is known, the image prior modeling will play a central role in image denoising. Over the past few decades, various models have been exploited for modeling image priors, including nonlocal self-similarity (NSS) models [1], [2], [3], [4], sparse models [4], [5], [6], gradient models [7], [8], [9] and Markov random field (MRF) models [10], [11], [12]. In particular, the NSS models are popular in state-of-the-art methods such as BM3D [2], LSSC [4], NCSR [6] and WNNM [13].

Despite their high denoising quality, most of the image prior-based methods typically suffer from two major drawbacks. First, those methods generally involve a complex optimization problem in the testing stage, making the denoising process time-consuming [6], [13]. Thus, most of the prior-based methods can hardly achieve high performance without sacrificing computational efficiency. Second, the models in general are non-convex and involve several manually chosen parameters, providing some leeway to boost denoising performance.

To overcome the limitations of prior-based approaches, several discriminative learning methods have been recently developed to learn image prior models in the context of truncated inference procedure. The resulting models are able to get rid of the iterative optimization procedure in the test phase. Schmidt and Roth [14] proposed a cascade of shrinkage fields (CSF) method that unifies the random field-based model and the unrolled half-quadratic optimization algorithm into a single learning framework. Chen *et al.* [15], [16] proposed a trainable nonlinear reaction diffusion (TNRD) model which learns a modified fields of experts [12] image prior by unfolding a fixed number of gradient descent inference steps. Some of the other related work can be found in [17], [18]. Although CSF and TNRD have shown promising results toward bridging the gap between computational efficiency and denoising quality, their performance are inherently restricted to the specified forms of prior. To be specific, the priors adopted in CSF and TNRD are based on the analysis model, which is limited in capturing the full characteristics of image structures. In addition, the parameters are learned by stage-wise greedy training plus joint fine-tuning among all stages, and many handcrafted parameters are involved. Another nonnegligible drawback is that they train a specific model for a certain noise level, and are limited in blind image denoising.

In this paper, instead of learning a discriminative model with an explicit image prior, we treat image denoising as a plain discriminative learning problem, i.e., separating the noise from a noisy image by feed-forward convolutional neural networks (CNN). The reasons of using CNN are three-fold. First, CNN with very deep architecture [19] is effective in increasing the capacity and flexibility for exploiting image characteristics. Second, considerable advances have been achieved on regularization and learning methods for training CNN, including Rectifier Linear Unit (ReLU) [20], batch normalization [21] and residual learning [22]. These methods can be adopted

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K. Zhang is with the School of Computer Science and Technology, Harbin Institute of Technology, Harbin 150001, China, and also with the Department of Computing, The Hong Kong Polytechnic University, Hong Kong.

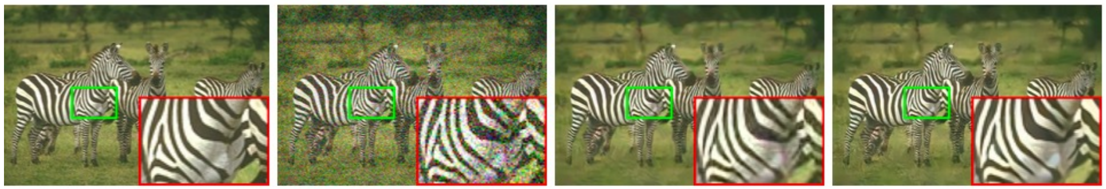
W. Zuo is with the School of Computer Science and Technology, Harbin Institute of Technology, Harbin 150001, China (e-mail: cswmzuo@gmail.com).

Y. Chen is with the Institute for Computer Graphics and Vision, Graz University of Technology, 8010 Graz, Austria.

D. Meng is with the School of Mathematics and Statistics and Ministry of Education Key Lab of Intelligent Networks and Network Security, Xi'an Jiaotong University, Xi'an 710049, China.

L. Zhang is with the Department of Computing, The Hong Kong Polytechnic University, Hong Kong (e-mail: cslzhang@comp.polyu.edu.hk).

- Why?
- DnCNN의 목적: 저조도 이미지 처리 및 모자이크 제거



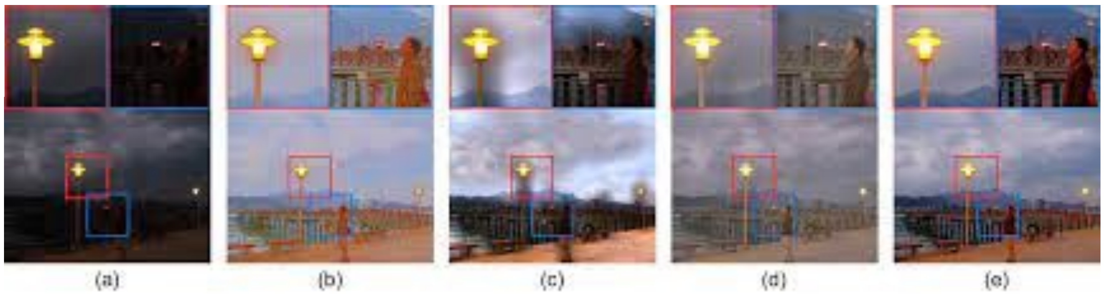


image: Unsupervised Learning with Natural Low-light Image Enhancement

1. 프로젝트 문제 제기 및 필요성

- 산업적 측면

- 학문적 측면

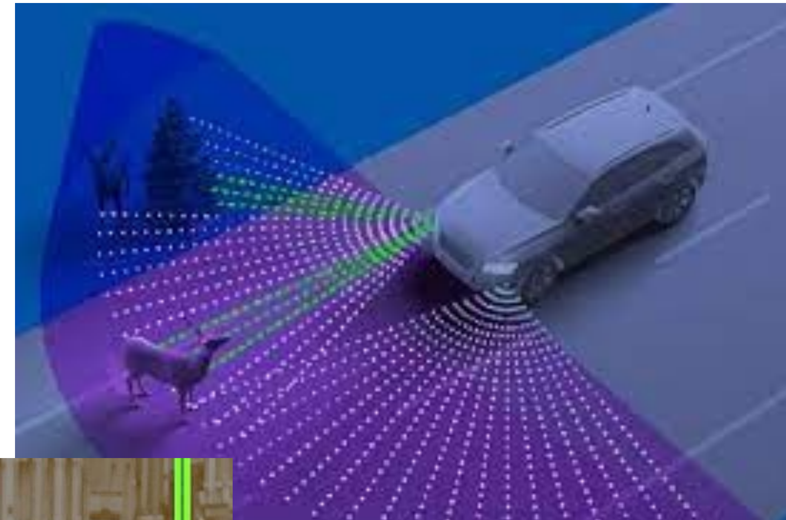


image: https://www.anolytics.ai/semantic-segmentation-services/
http://global-autonews.com/bbs/board.php?bo_table=bd_035&wr_id=391

2. 내용

- 필터링 기반 접근

  - Bilateral Filtering, Non-local means filter, Median Filter

- Transform domain에서의 denoising

  - image transformation(Fourier etc.) → frequency component에 따라 분해

- BM3D

  - 필터링 기반 접근 + Transform 기반의 기법

- Inverse Problem 학습

  - 이미지를 degrading 하는 모델 생성 → 반대로 해결

- **Deep Learning**

  - Multi Layer Perceptron, TNRD(Trainable Nonlinear Reaction Diffusion)

2. 내용

기존 방법 : 계산 복잡 & 많은 시간 소요 & 수동적인 파라미터 설정

1) 이미지에서 noise 분리 (차이점)

2) Residual Learning + Batch Normalization

3) CNN

개선 사항

- 성능 향상
- 간단한 구조
- 빠른 속도

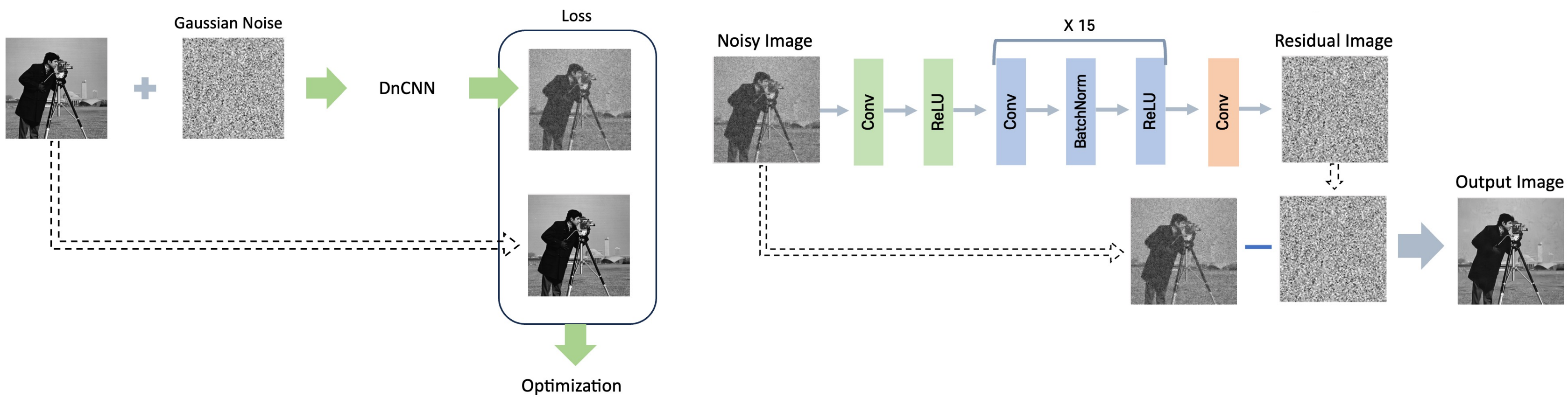
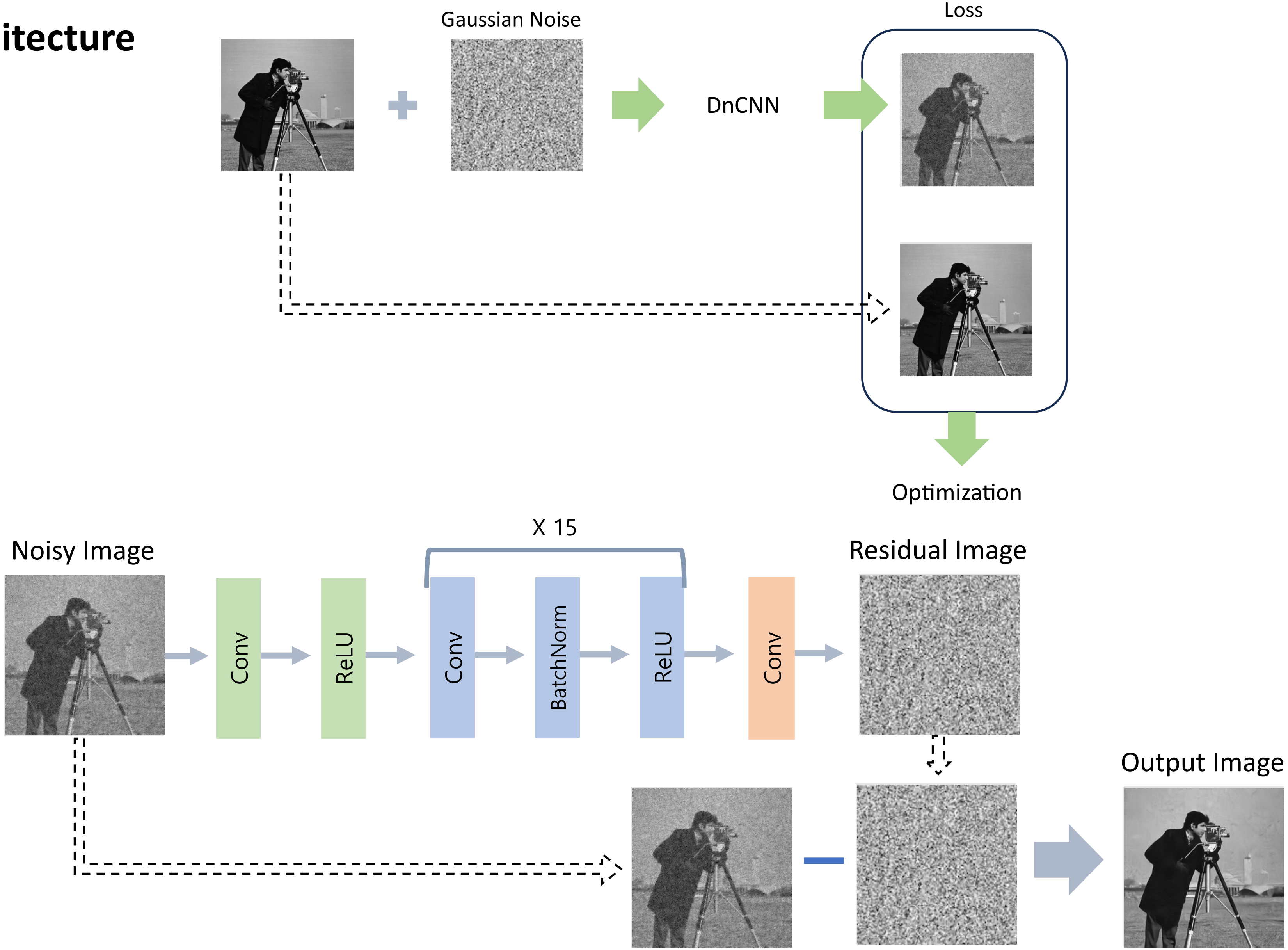


image: Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising

2. 내용

Architecture



3. 구현 내용 및 결과 분석

Experiments - 실험 환경: Google Colaboratory

optimizer, batch size, noise level, lr(learning rate)을 변경하면서 성능 비교를 진행

1 Optimizer

모델의 수렴 정도와 일반화 능력을 파악하기 위해
두 가지 최적화 알고리즘을 비교

2 Batch Size

batch size: 한 번에 모델에 입력되는
데이터 샘플의 개수

→ 다양한 batch size 변경을 적용하여 학습 속도와
성능 사이의 trade-off 관계를 파악

3 Noise Level

다양한 노이즈 수준에서 성능을 평가함으로써
얼마나 강력하게 노이즈를 제거할 수 있는지 확인

4 Number of Layers

학습의 정도를 조절하기 위함

3. 구현 내용 및 결과 분석

실험 과정

Model : DnCNN

batch_size : 128 → 64 / 128

train_data : data/train

Sigma : 25 → 10 / 25 / 50

Epoch : 30

Learning_rate : 1e-2

num_layer : 17 → 17 / 20 / 25

optimizer : Adam → SGD / Adam

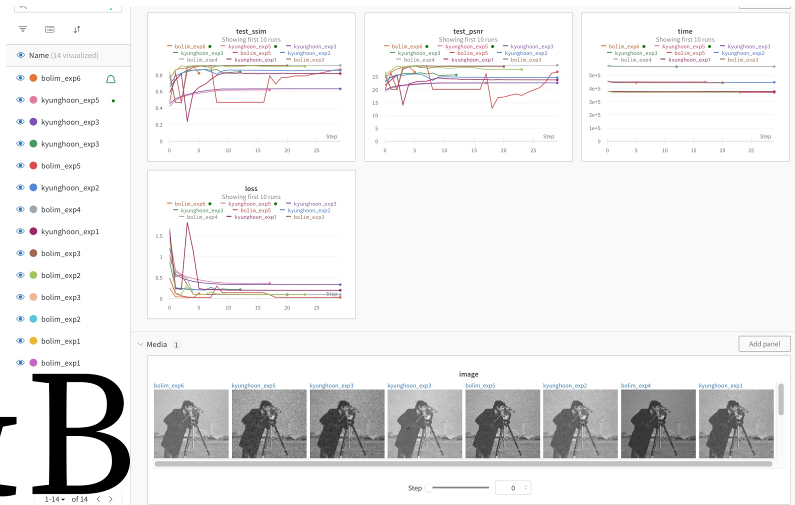
Scheduler : MultiStepLR

3. 구현 내용 및 결과 분석

실험 과정

```json
{
    "model": "DnCNN",
    "batch_size": 128,
    "train_data": "data/train",
    "sigma": 25,
    "epoch": 30,
    "lr": 0.01,
    "num_layer": 17,
    "optimizer": "Adam",
    "scheduler": "MultiStepLR"
}
```

실험 파라미터 관리



실험 결과 비교 및 정리

3. 구현 내용 및 결과 분석

Result

Noise Level : 10

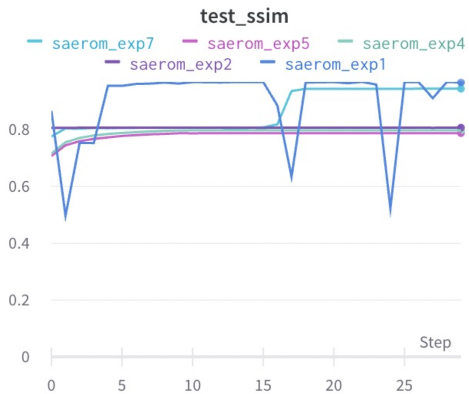
saerom_exp7

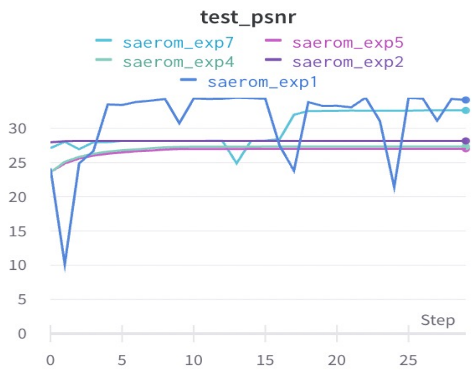
saerom_exp5

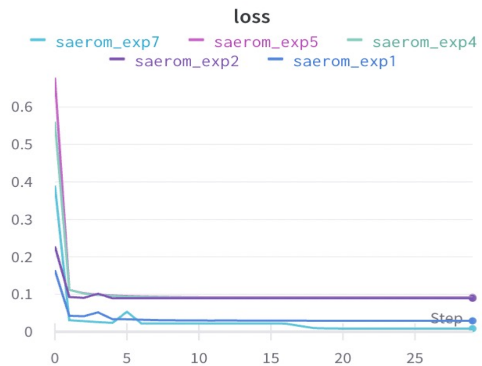
saerom_exp4

saerom_exp2

saerom_exp1





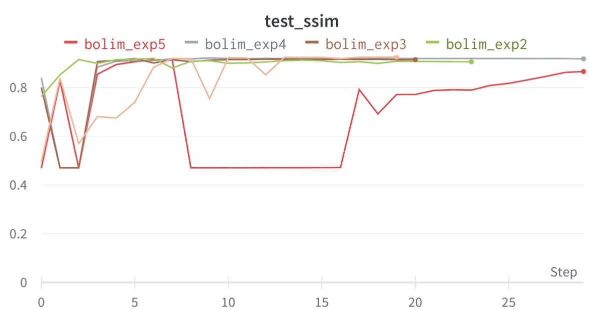


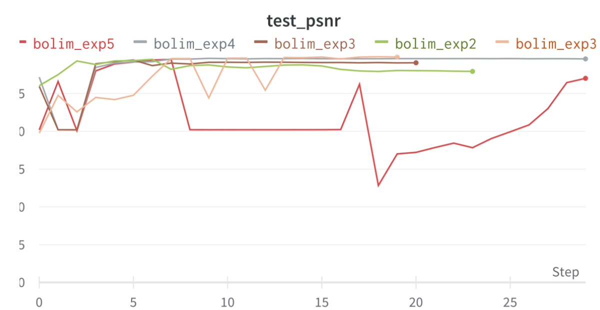
Best : batch size - 128, number of layers – 17, optimizer - Adam

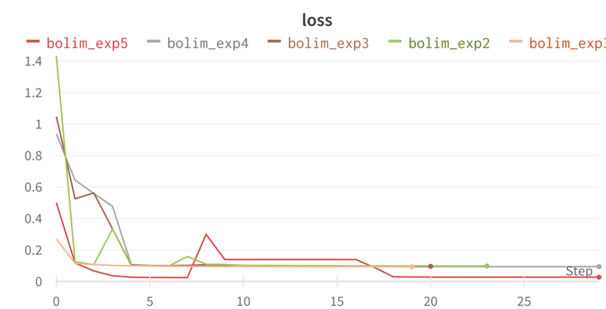
3. 구현 내용 및 결과 분석

Result

Noise Level : 25





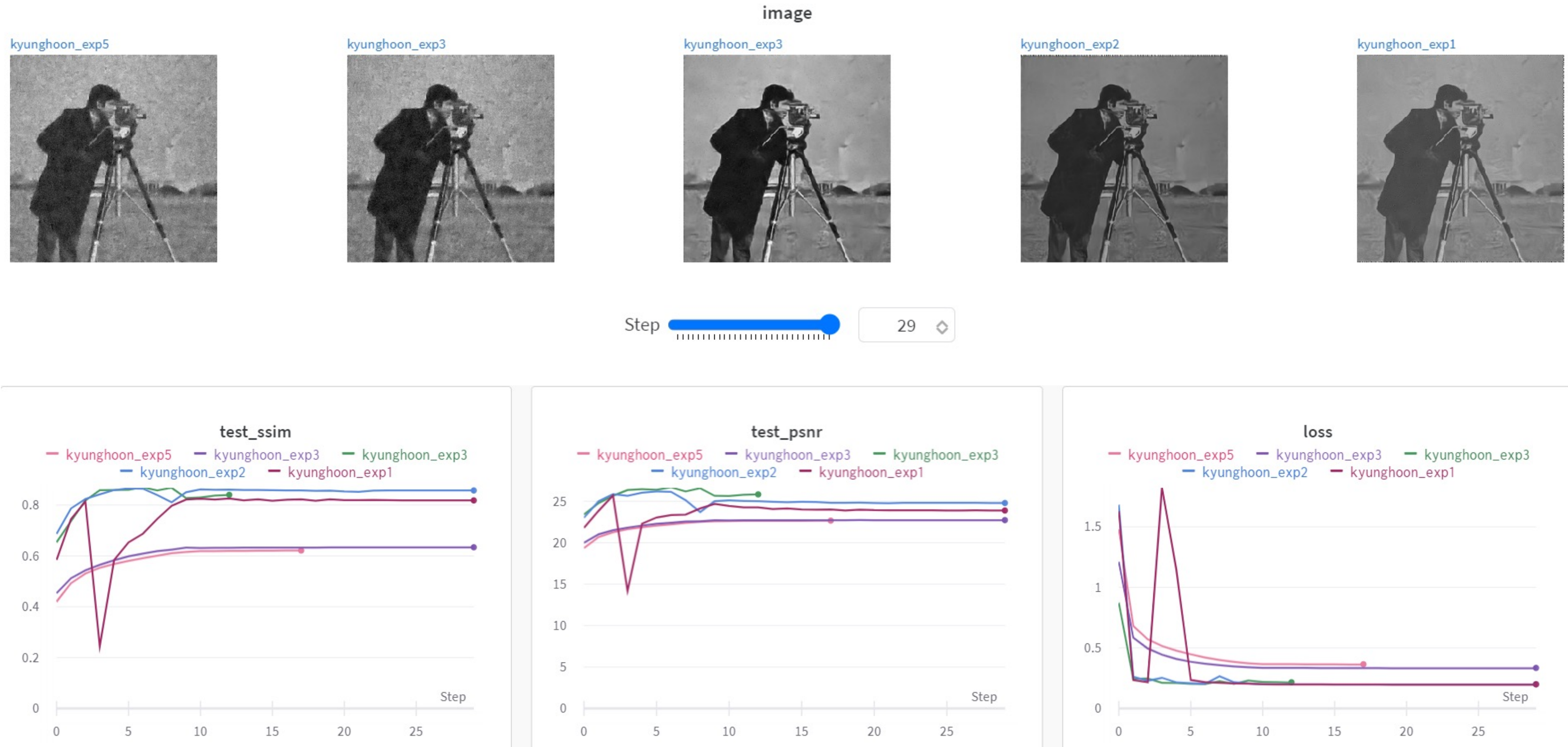


Best : batch size - 64, number of layers – 25, optimizer - Adam

3. 구현 내용 및 결과 분석

Result

Noise Level : 50



Best : batch size - 64, number of layers – 25, optimizer - Adam

3. 구현 내용 및 결과 분석

평가 지표(Evaluation Indicator)

PSNR(Peak Signal-to-Noise Ratio) – 신호가 가질 수 있는 최대 전력에 대한 잡음의 전력

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \quad MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M * N}$$

SSIM(Structural Similarity Index Map) – 구조적 유사 지수

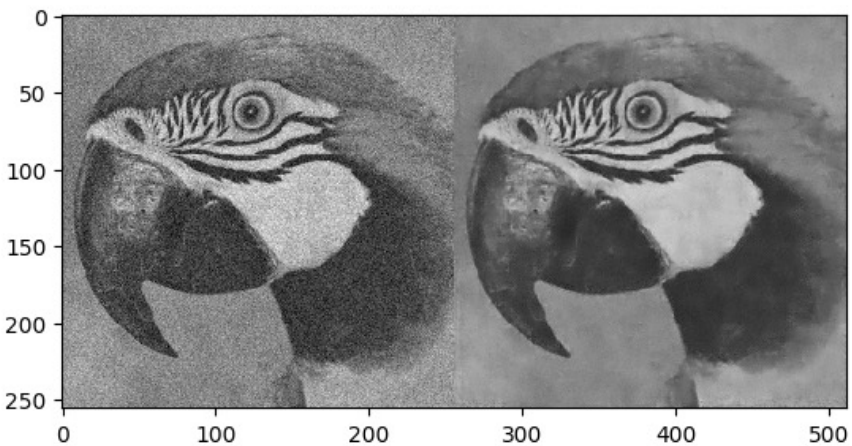
$$\text{SSIM}(\mathbf{x},\mathbf{y}) = [l(\mathbf{x},\mathbf{y})]^\alpha \cdot [c(\mathbf{x},\mathbf{y})]^\beta \cdot [s(\mathbf{x},\mathbf{y})]^\gamma$$

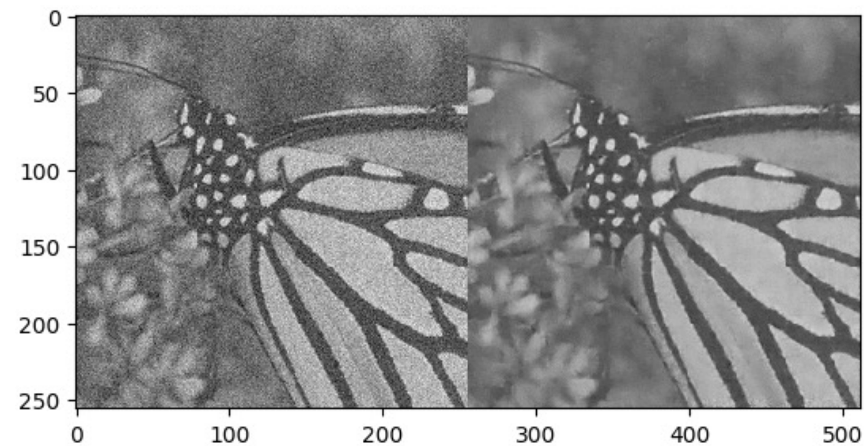
$$l(\mathbf{x},\mathbf{y}) = \frac{2\,\mu_x\,\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}, \quad c(\mathbf{x},\mathbf{y}) = \frac{2\,\sigma_x\,\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}, \quad s(\mathbf{x},\mathbf{y}) = \frac{\sigma_{xy} + C_3}{\sigma_x\,\sigma_y + C_3}$$

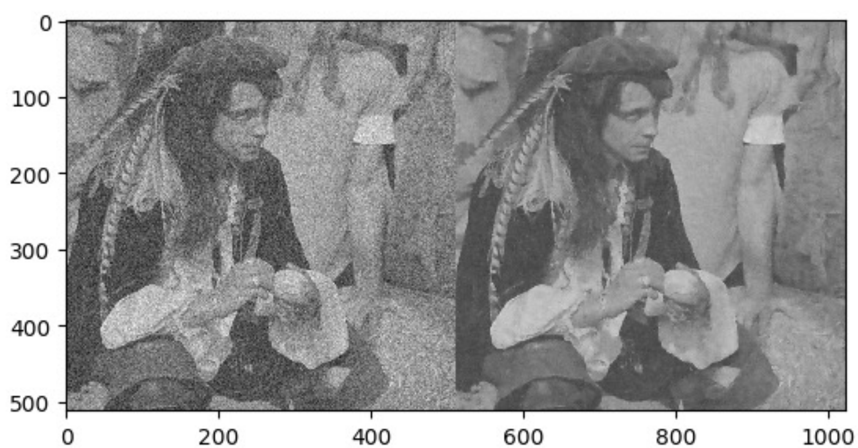
$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i, \quad \sigma_x = \left(\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)^2\right)^{1/2}, \quad \sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y)$$

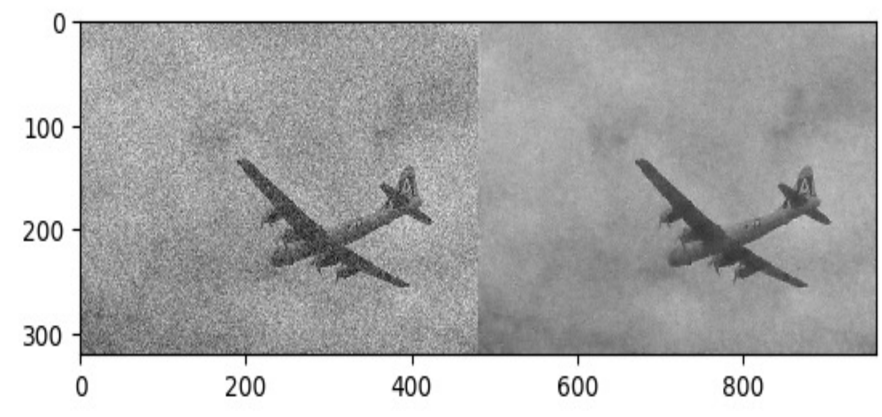
4. 결론 및 결과

Result Images comparison for noise level 25
(batch size - 64, lr - 1e-3, Optimizer - Adam, number of layers - 17)









PSNR: 27.64dB, SSIM: 0.8549 (average)

5. 참고문헌

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[Github]

https://github.com/bo-lim/DnCNN_CAU_CV