ADAPTIVELY TUNING A CONVOLUTIONAL NEURAL NETWORK BY GATING PROCESS FOR IMAGE DENOISING

ICIP 2019

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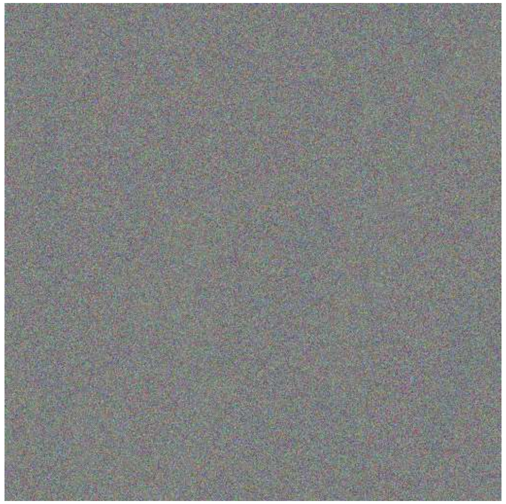
Image Denoising

- Additive White Gaussian Noise model
  - $Y = X + V$
  - $V \sim N(0, \sigma^2)$

Noisy image

Original image

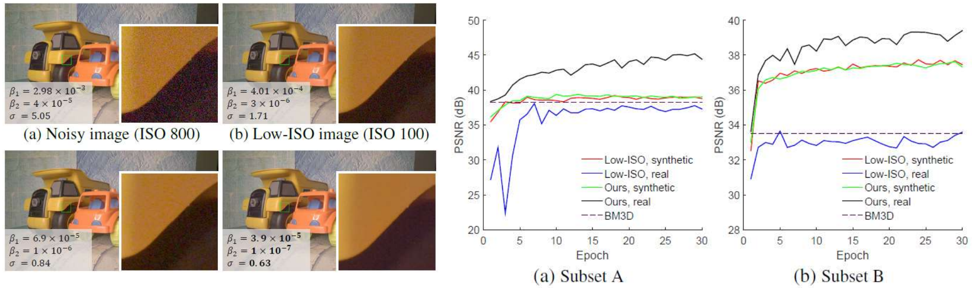


Noise

Image Denoising

- AWGN denoiser can be applied to the real world
  - Directly or Retrain with real datasets

Zhang, Kai $et\ al.$, FFDNet: Toward a fast and flexible solution for CNN based image denoising, TIP 2018.

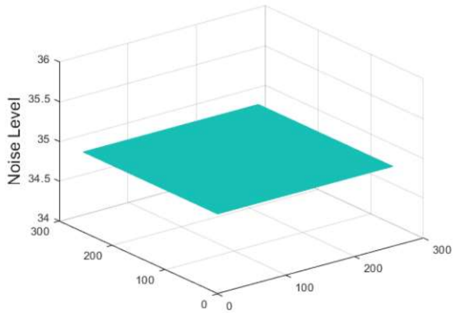


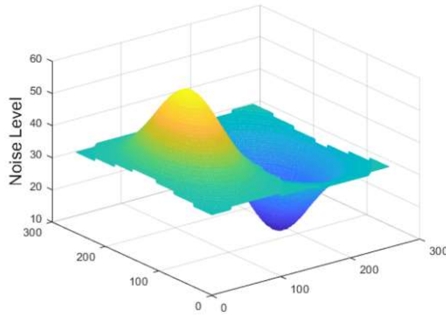
Abdelhamed, Abdelrahman $et\ al.$, A High-Quality Denoising Dataset for Smartphone Cameras, CVPR2018

Specific Model	Blind Model
Lots of Models	Single Model
Spatially Invariant	Spatially Variant
Sharp / Details	Blurry
Good at Low-level Noisy Image	Effects of Data Augmentation

Specific Model	Proposed Model	Blind Model
Lots of Models	**Single Model**	Single Model
Spatially Invariant	Spatially Variant	Spatially Variant
Sharp / Details	Sharp / Details	Blurry
Good at Low-level Noisy Image	**Good at All Range Noisy Image / Effects of Data Augmentation**	Effects of Data Augmentation
	Parametric Model	

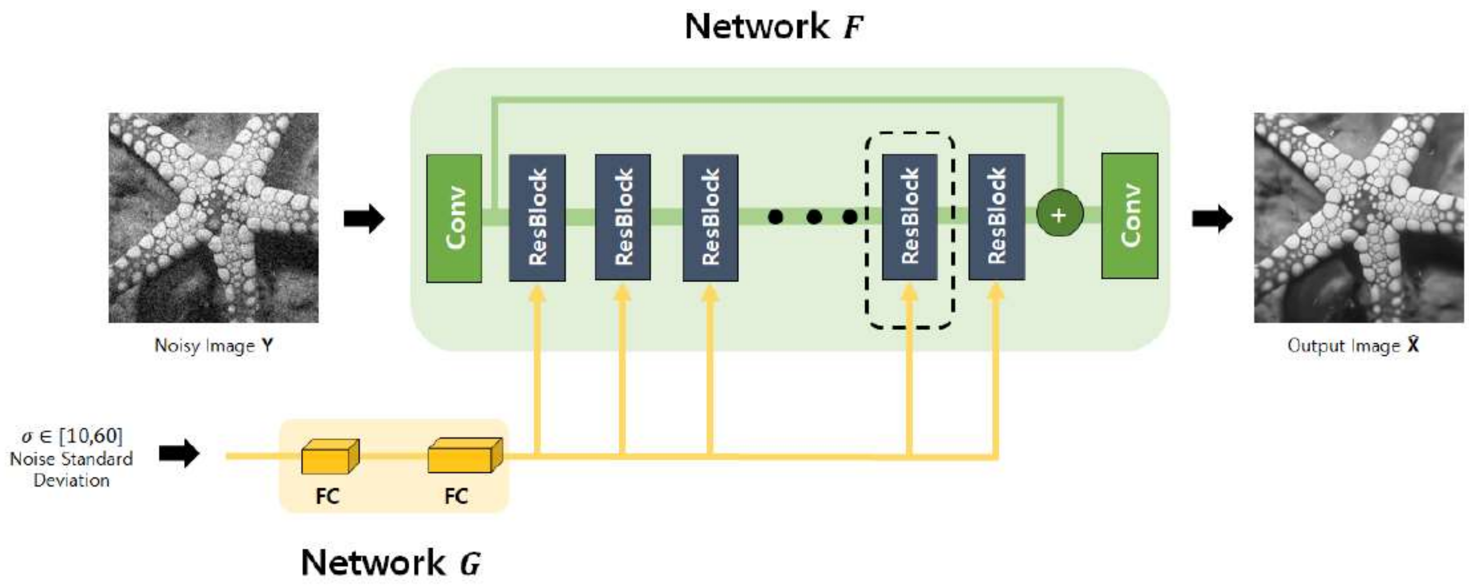
Spatially Variant Noisy Image





Proposed Method

- Adaptively Tuned Denoisng Network (ATDNet)
  - Network G: Gate-weight generating network
  - Network F: Baseline CNN denoiser
  - Features maps of F are tuned from noise level by gating process

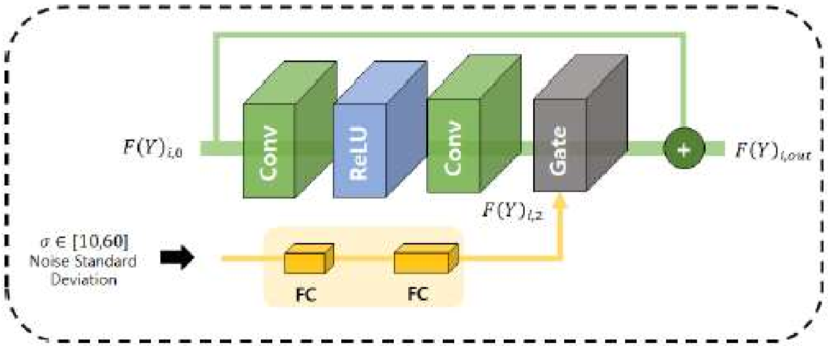


Proposed Method

- Gating Process in Residual Block
  - $G(\sigma)$ gates the newly updated feature maps $F(Y)_{i,2}^{k}$

$$F(Y)^k_{i,out} = F(Y)^k_{i,0} + \alpha \tanh(F(Y)^k_{i,2} \circ s(G(\sigma)))$$

i-th Resblock



Notation	Description
$F(Y)_{i,j}^{k}$	Features of j-th convolution in the i-th resblock
$G(\sigma)$	Output of noise level (σ) using G

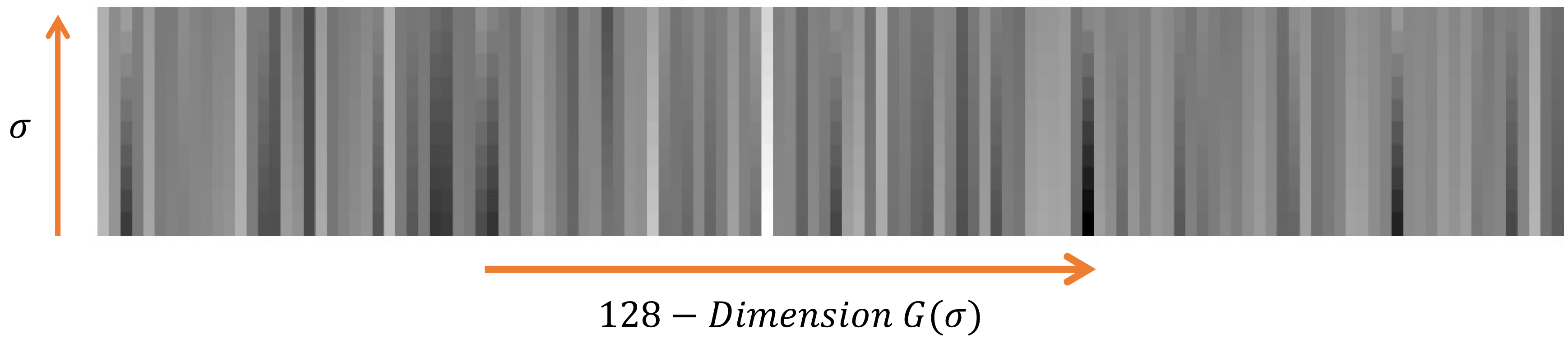
Training

- Trained noise level: [10:5:60]
- Training set: BSD 400
- Patch size: 40×40
- The loss function: MSE

$$\mathbf{L}(\Theta) = \frac{1}{N}\sum_{i=1}^{N} \|\mathbf{x}_i - F(\mathbf{y}_i, \sigma_i; \Theta)\|_2^2.$$

Discussions

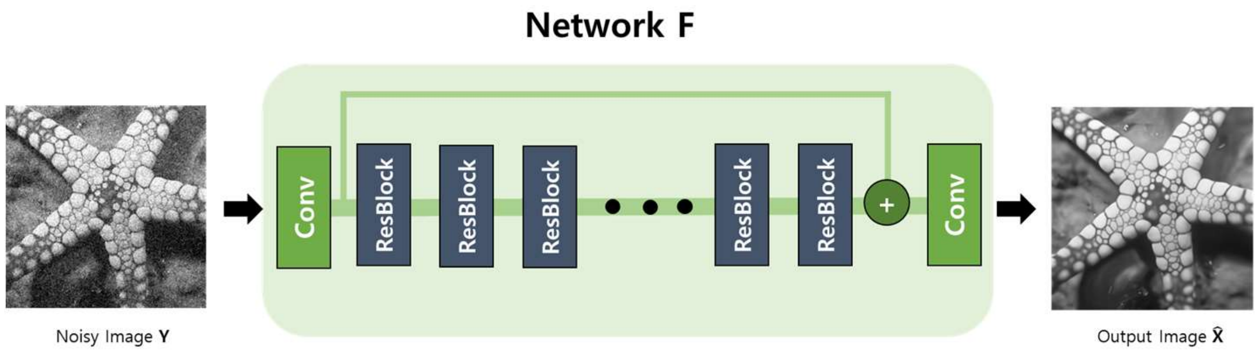
- When there is no G, or if all the output of G is one regardless of its input, then the network is the same as blind denoiser
- $G(\sigma)$ changes almost monotonically as changes σ



Experimental Setup

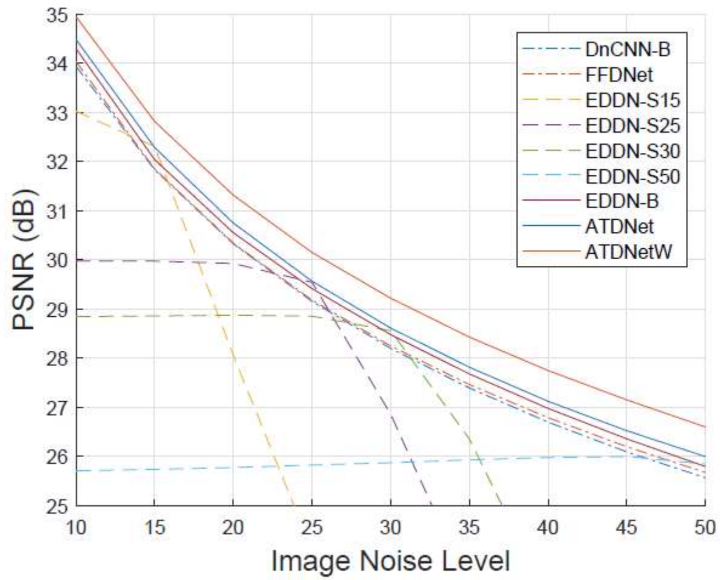
- Comparison Method
  - BM3D (-F), TNRD (-S), REDNet (-S), DnCNN (-S, -B), FFDNet (-F)

- Baselines
  - EDDN-S: Specifically trained with F
  - EDDN-B: Blindly trained with F



Experiments on static AWGN

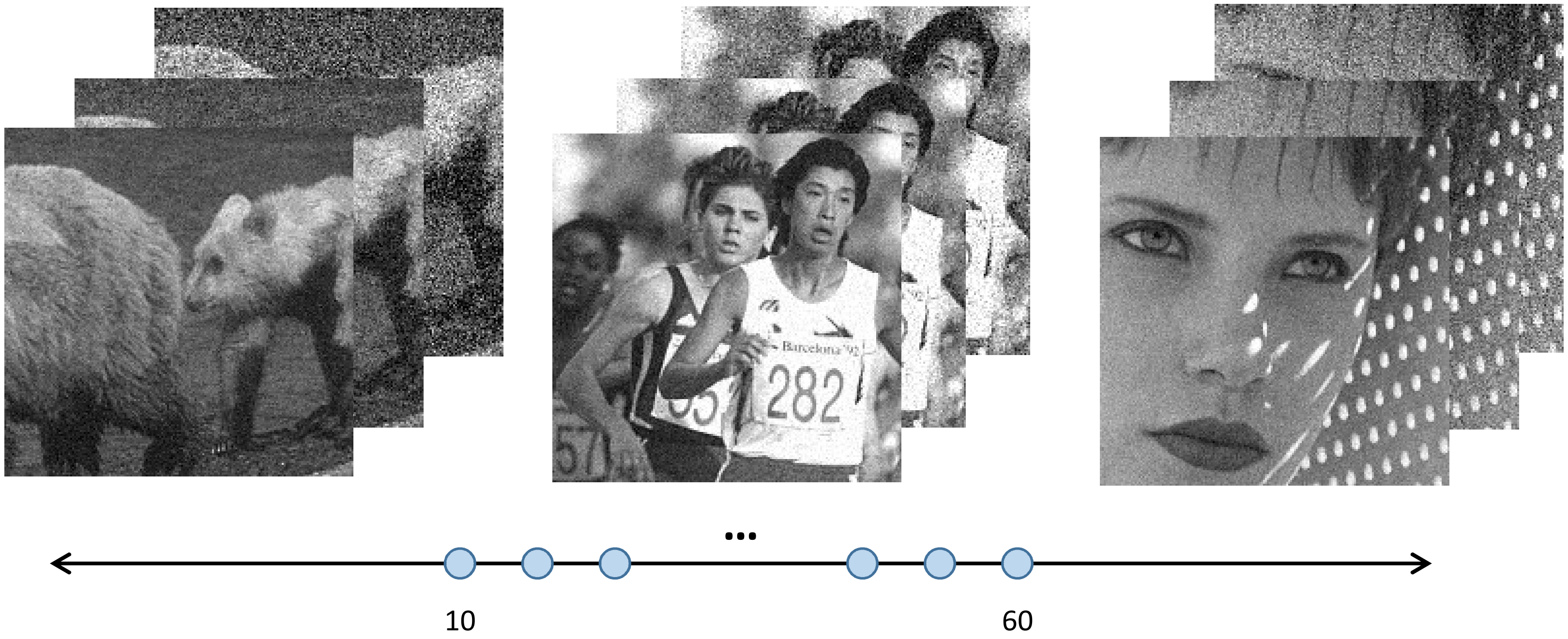
Sigma	BM3D	TNRD	REDNet	DnCNN-S	DnCNN-B	FFDNet	EDDN-S	EDDN-B	ATDNet	ATDNetW
Set 12										
15	32.38	32.50	-	32.86	32.68	32.75	32.93	32.82	32.90	**33.02**
25	29.95	30.04	-	30.44	30.36	30.43	30.57	30.55	30.57	**30.72**
30	29.15	-	29.62	29.52	29.53	29.61	29.74	29.74	29.77	**29.94**
50	26.70	26.78	27.26	27.18	27.21	27.32	27.43	27.29	27.48	**27.67**
BSD 68										
Sigma	BM3D	TNRD	REDNet	DnCNN-S	DnCNN-B	FFDNet	EDDN-S	EDDN-B	ATDNet	ATDNetW
15	31.07	31.42	-	31.73	31.61	31.63	31.78	31.61	31.77	**31.80**
25	28.56	28.91	-	29.23	29.17	29.19	29.31	29.27	29.32	**29.38**
30	27.75	-	28.50	28.36	28.35	28.39	28.49	28.47	28.50	**28.57**
50	25.62	25.96	26.37	26.23	26.23	26.29	26.38	26.19	26.41	**26.47**
URBAN100										
Sigma	BM3D	TNRD	REDNet	DnCNN-S	DnCNN-B	FFDNet	EDDN-S	EDDN-B	ATDNet	ATDNetW
15	31.80	31.40	-	32.19	31.83	31.85	32.31	32.04	32.29	**32.82**
25	29.03	28.51	-	29.29	29.16	29.18	29.55	29.42	29.56	**30.15**
30	28.05	-	28.27	28.16	28.20	28.25	28.56	28.48	28.62	**29.22**
50	25.22	24.85	25.54	25.49	25.57	25.68	25.85	25.80	26.00	**26.60**



Parametric CNN Denoiser

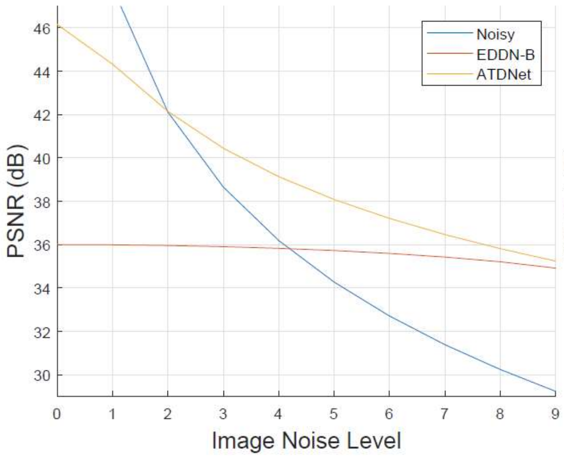
Experiments on untrained noise level

- **Trained noise levels are [10:5:60]**
- Test on untrained noise levels

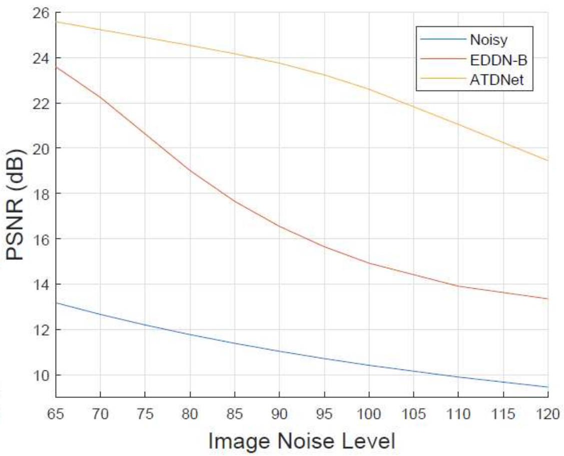


Experiments on untrained noise level

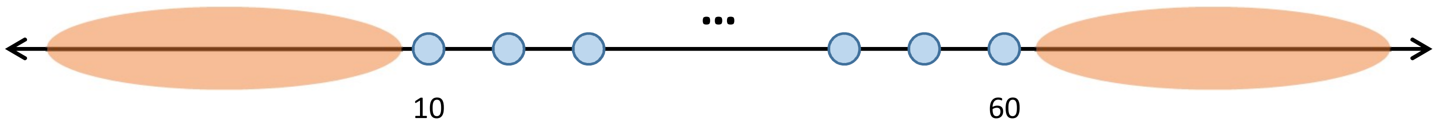
- Trained noise levels are [10:5:60]
- **Test on untrained noise levels**



(a) $\sigma < 10$

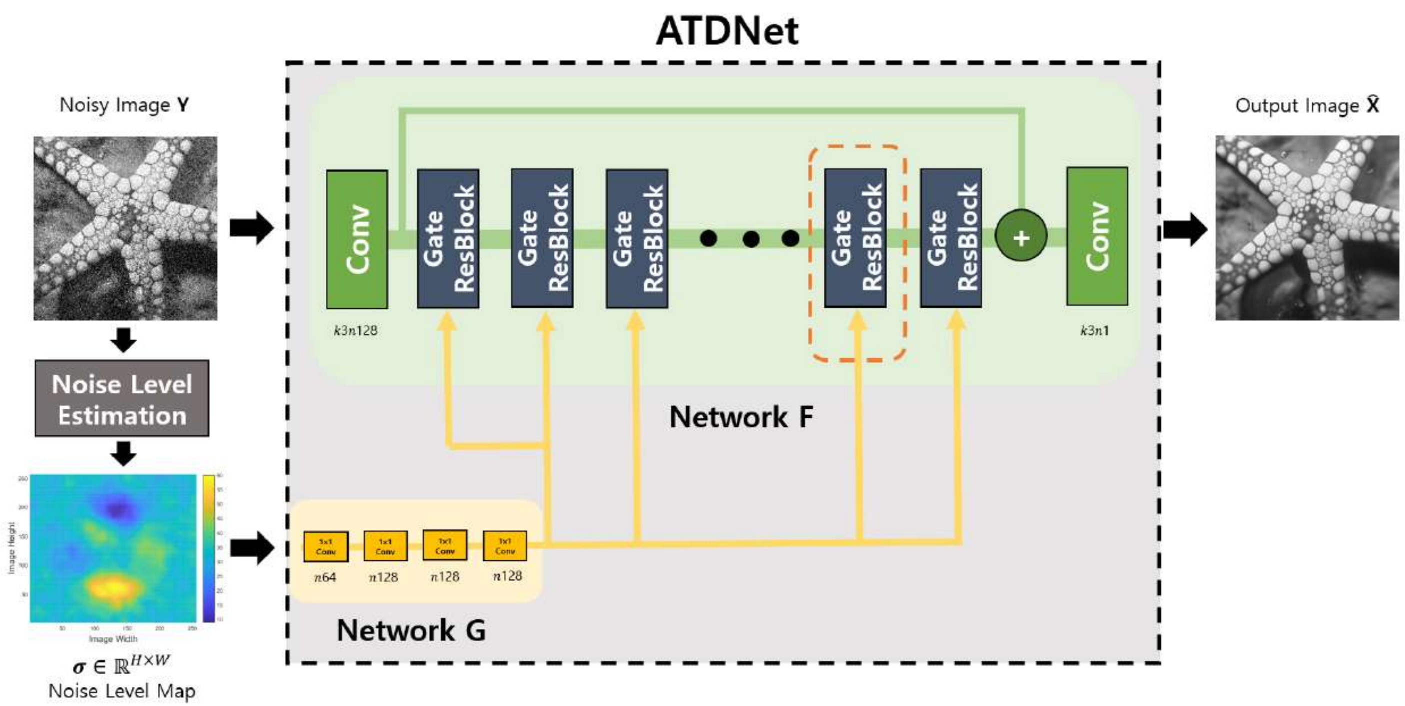


(b) $\sigma > 60$



Extension of ATDNet

- Adding a pixel-wise noise level estimation
- Spatially variant method

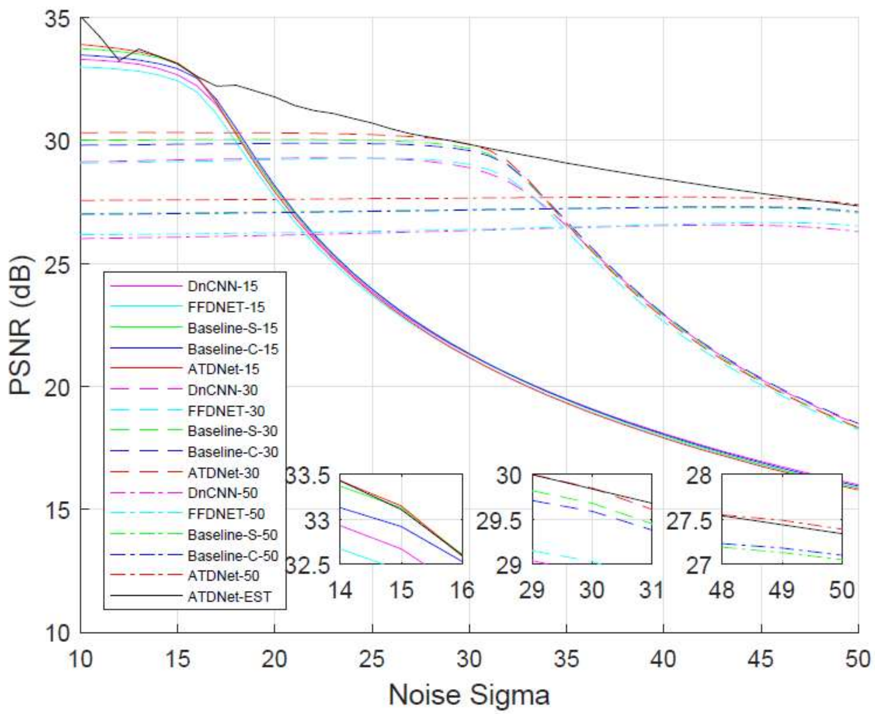


- Reference: https://github.com/terryoo/ATDNet

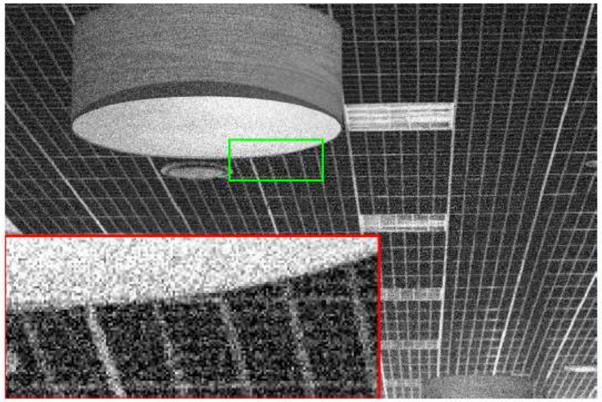
Uniform noise level results

Estimates of single noise level

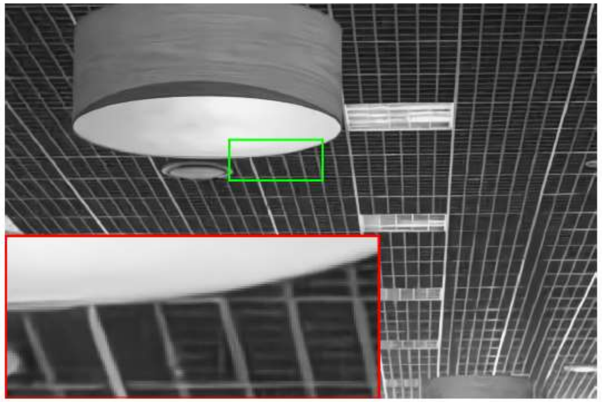
σ	Set12	BSD68	Urban100
15	14.92 ± 0.28	14.93 ± 0.31	15.06 ± 0.49
25	24.92 ± 0.28	25.03 ± 0.17	25.08 ± 0.39
30	29.92 ± 0.28	30.06 ± 0.24	30.03 ± 0.41
50	49.17 ± 0.37	49.47 ± 0.61	49.51 ± 0.61



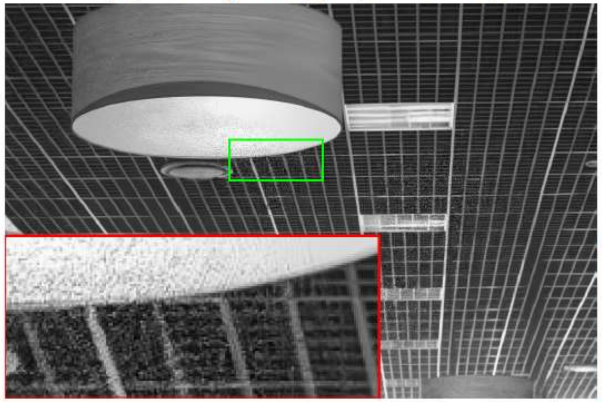
Spatially variant noisy image results



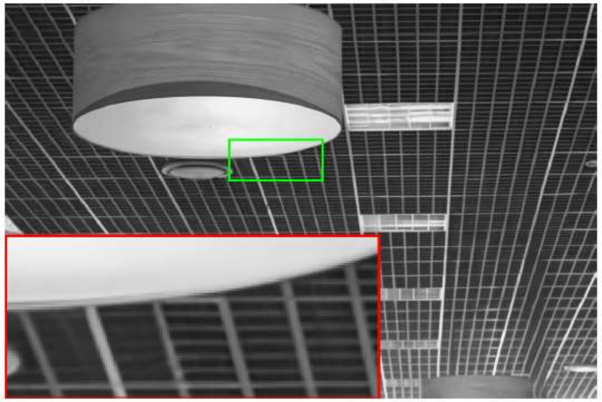
(a) Noisy Image (17.84 dB)



(b) FFDNet with σ map (30.56 dB)



(c) Proposed with constant σ (26.61 dB)

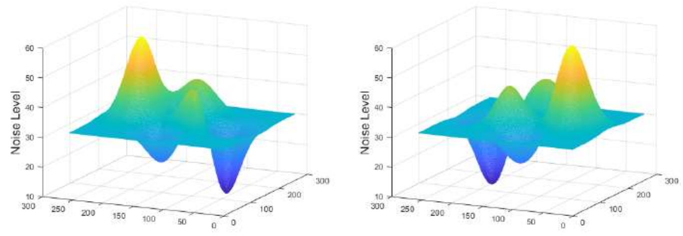


(d) Proposed (32.03 dB)

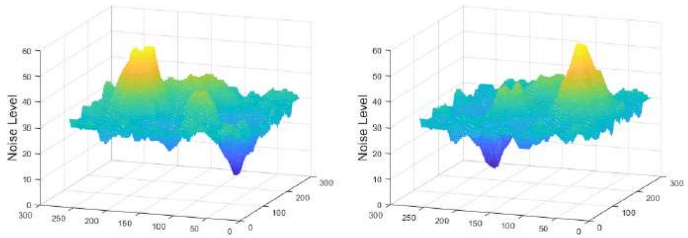
Spatially variant noisy image results

Spatially variant results

Dataset	Set12	BSD68	Urban100
FFDNet	29.08	27.88	28.43
Baseline-C	29.11	27.89	29.21
ATDNet	29.43	28.09	29.26
ATDNetW	29.46	28.08	29.52
Baseline-B	28.59	27.58	28.99
ATDNet-EST	29.28	28.01	29.11
ATDNetW-EST	29.32	28.01	29.38



(a) Noise level maps



(b) Estimated noise level maps

Old Photo Results

(a) Noisy Image

(b) Noise Clinic

(c) BM3D

(d) DnCNN-B

(e) FFDNet

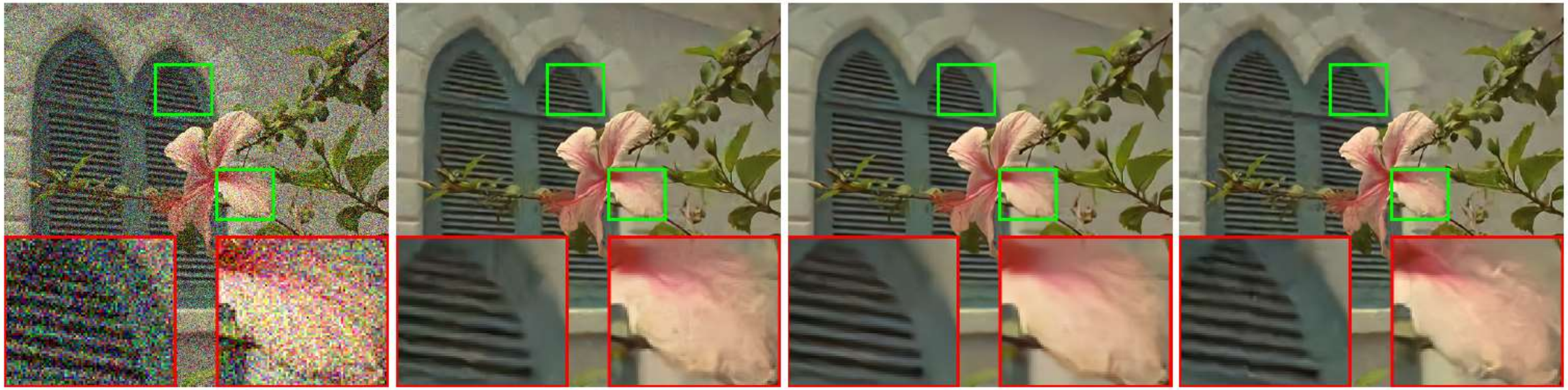
(f) Baseline-B

(g) ATDNetW

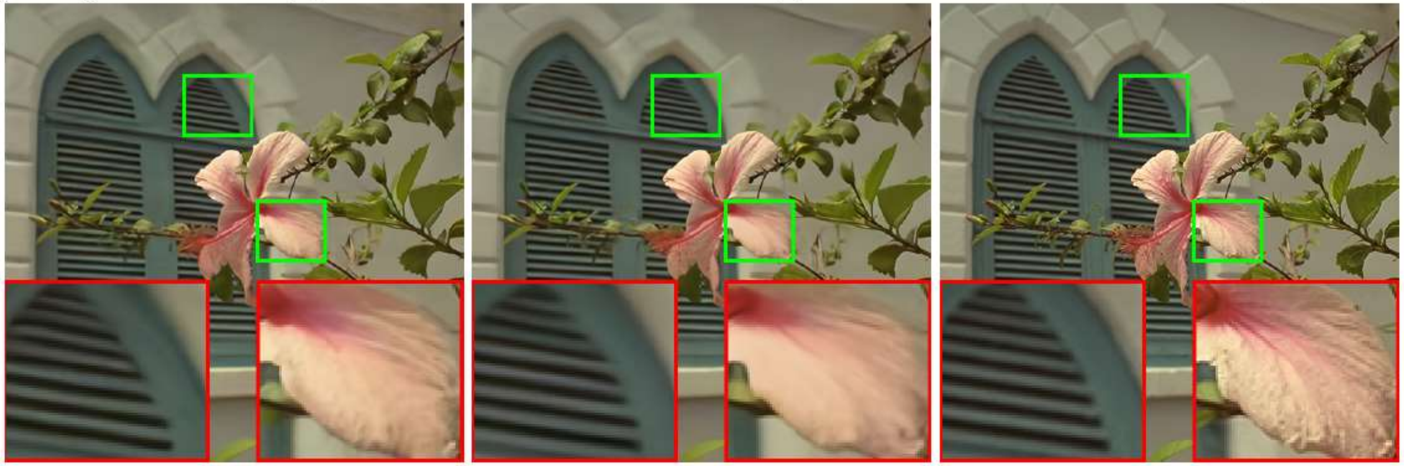
(h) ATDNetW-EST

Color AWGN Results

CBSD68					
Sigma	CFFDNet	CUNLNet	CATDNetW	CDnCNN-B	CATDNetW-EST
15	33.88	33.87	34.08	33.89	34.08
25	31.15	31.21	31.48	31.23	31.48
30	30.21	30.31	30.60	30.32	30.60
50	27.85	27.96	28.30	27.92	28.30
Kodak24					
Sigma	CFFDNet	CUNLNet	CATDNetW	CDnCNN-B	CATDNetW-EST
15	34.63	34.64	34.99	34.48	35.00
25	32.08	32.13	32.58	32.03	32.58
30	31.18	31.28	31.75	31.18	31.71
50	28.86	28.98	29.49	28.84	29.49
McMaster					
Sigma	CFFDNet	CUNLNet	CATDNetW	CDnCNN-B	CATDNetW-EST
15	34.33	34.66	35.12	33.44	35.09
25	32.02	32.35	32.87	31.51	32.87
30	31.00	31.52	32.06	30.78	32.02
50	28.80	29.18	29.78	28.61	29.74
CUrban100					
Sigma	CFFDNet	CUNLNet	CATDNetW	CDnCNN-B	CATDNetW-EST
15	33.97	33.83	34.56	32.98	34.53
25	31.50	31.40	32.32	30.81	32.30
30	30.41	30.53	31.52	29.99	31.48
50	27.95	28.05	29.21	27.59	29.19



(a) Noisy Image (b) CDnCNN-B / 30.11 dB (c) CFFDNet / 30.54 dB (d) CUNLNet / 30.23 dB



(e) CATDNetW / 31.27 dB (f) CATDNetW-EST / 31.23 dB (g) Ground-Truth

Project Page

- Codes are available
  - https://github.com/terryoo/ATDNet

Thank You
Q & A