



Image Denoising with Control over Deep Network Hallucination

Qiyuan Liang

Florian Cassayre

Haley Owsianko

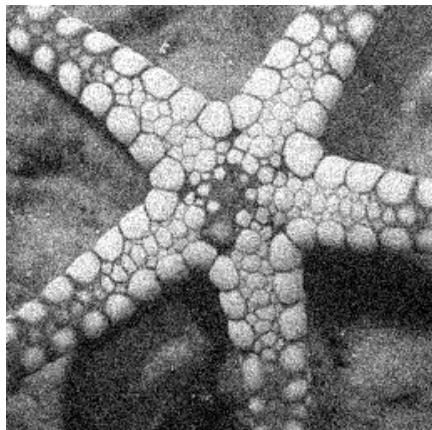
Majed El Helou

Sabine Süsstrunk

Introduction

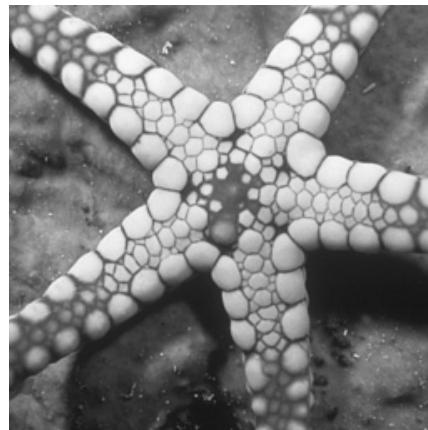
Denoising I Problem

- Additive white Gaussian noise



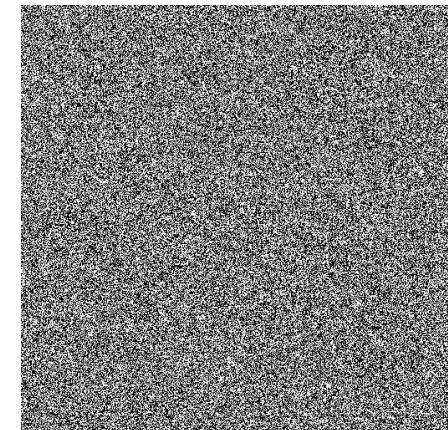
Noisy image

=



Clean image

+

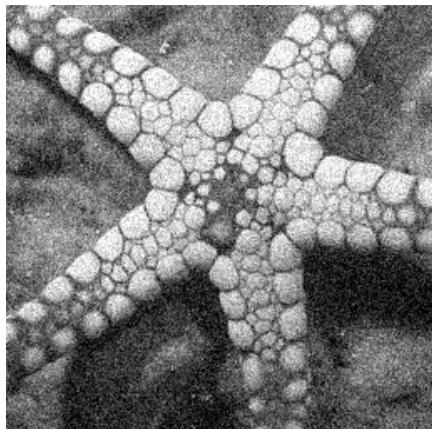


White Gaussian noise

Introduction

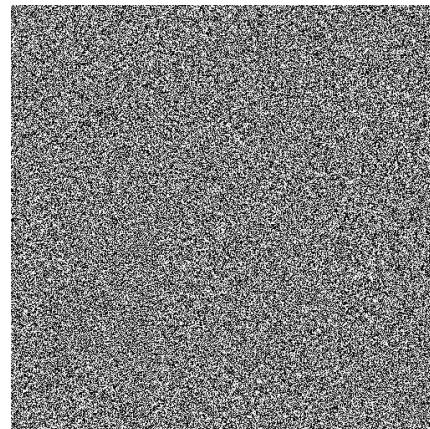
Denoising I Solution

- State-of-the-art in quantitative reconstruction: deep learning (DL)



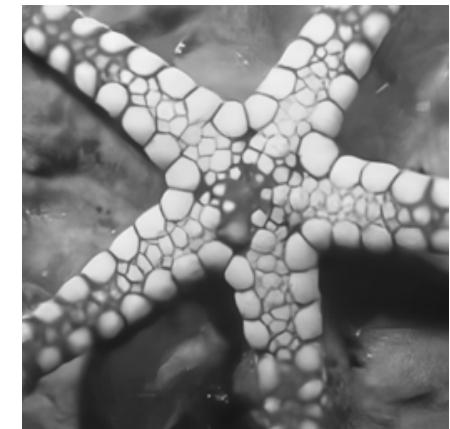
Noisy image

-



Predicted noise

=



Denoised image

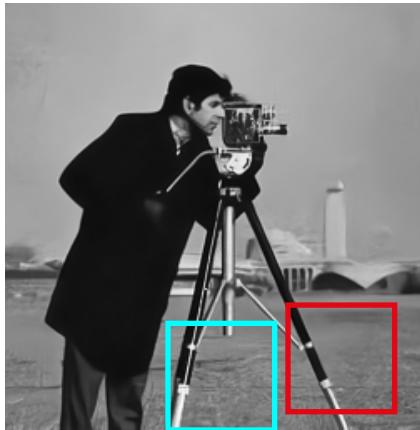
Motivation

Interpretability

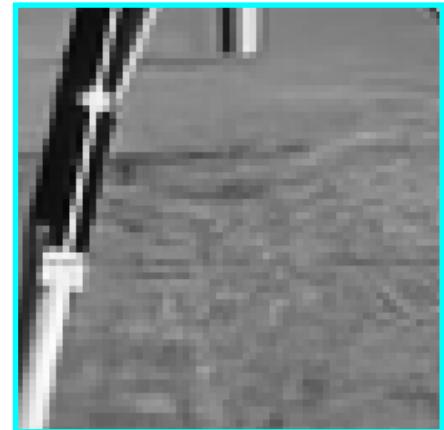
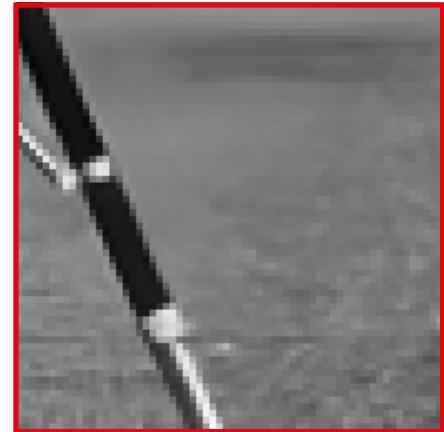
- Sample denoised image using DnCNN¹
trained on $\sigma = 25$, tested on $\sigma = 25$



Noisy image



DL Denoised image



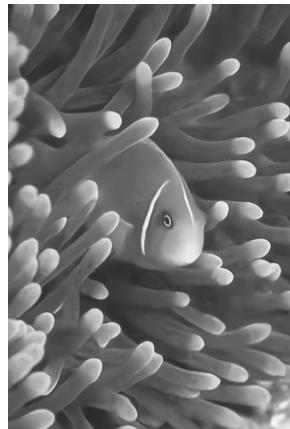
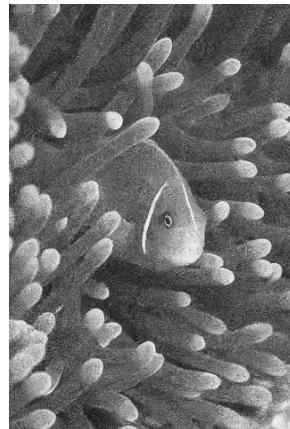
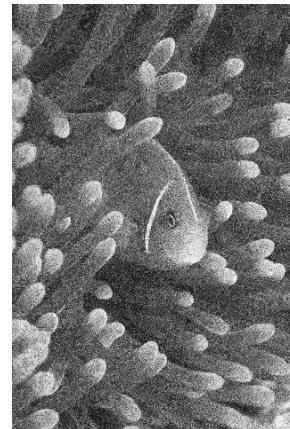
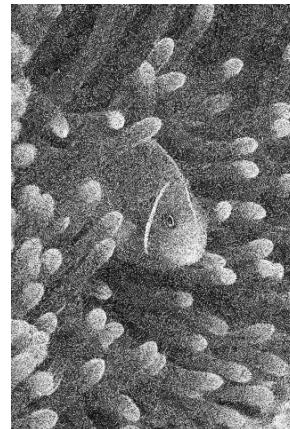
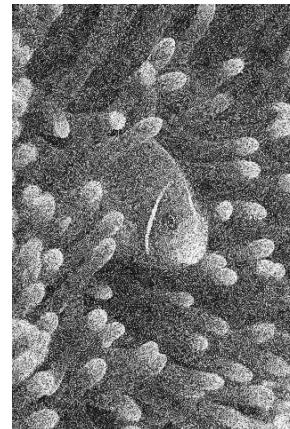
Zoomed-in

■ ¹Kai Zhang, Wangmeng Zuo, Yunjin Chen, Deyu Meng, and Lei Zhang. Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising. *IEEE Transactions on Image Processing*, 26(7):3142–3155, 2017.

Motivation

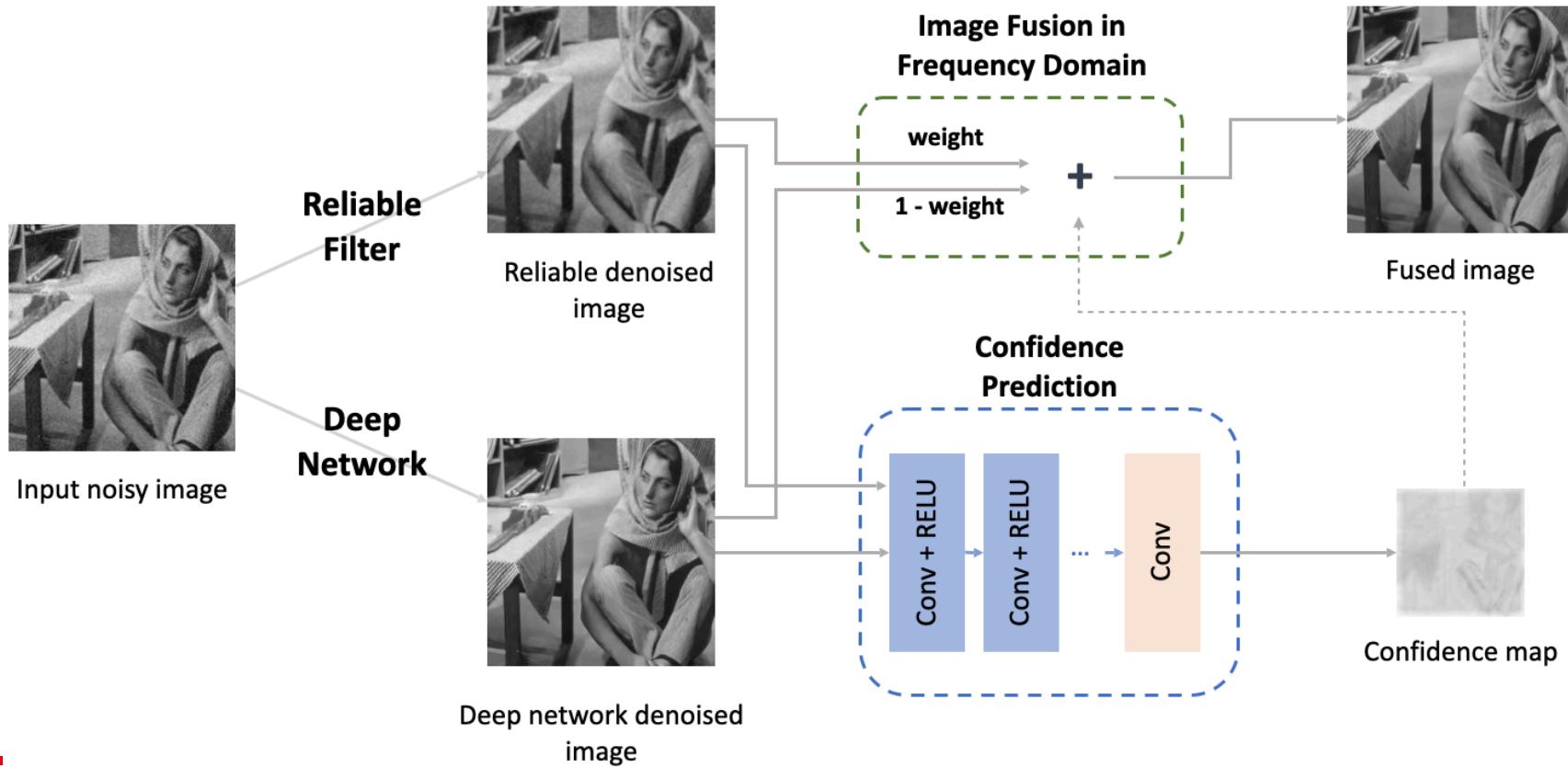
Generalization

- Sample denoised images using DnCNN trained on $\sigma = 25$, tested on $\sigma \in \{25, 35, 45, 55, 65\}$

 $\sigma = 25$  $\sigma = 35$  $\sigma = 45$  $\sigma = 55$  $\sigma = 65$

Proposed Method

CCID1 Pipeline



Proposed Method

CCID1 Interpretability

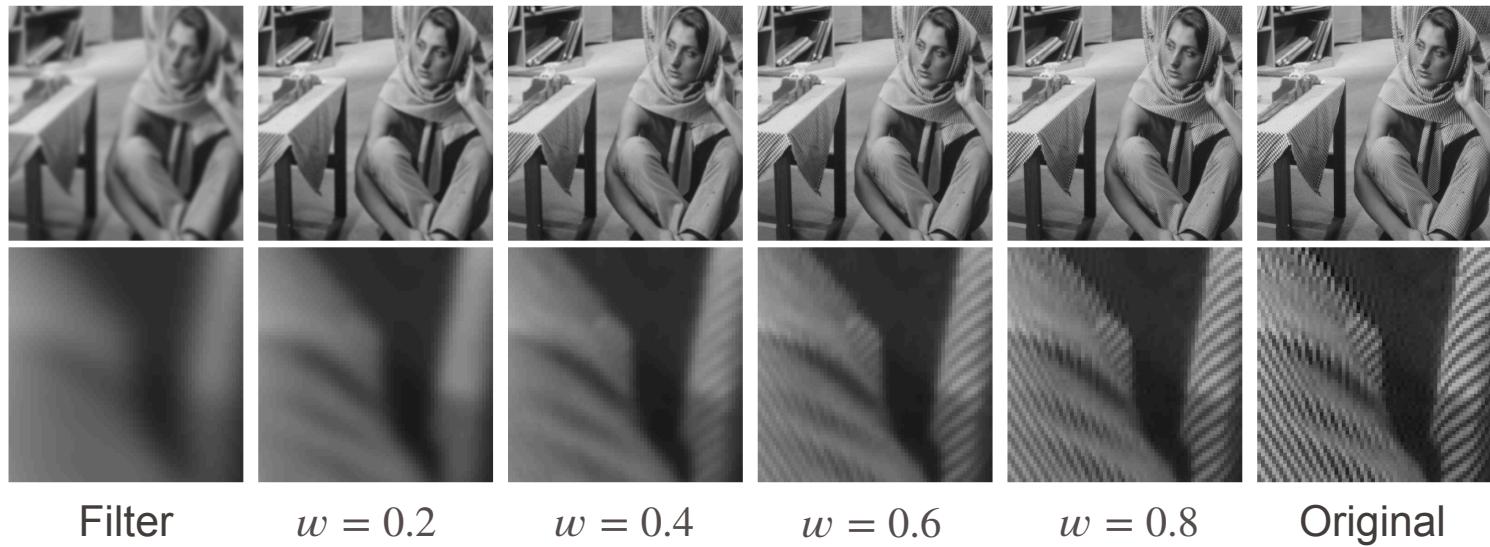
- User-understandable confidence prediction



Proposed Method

CCID1 Control

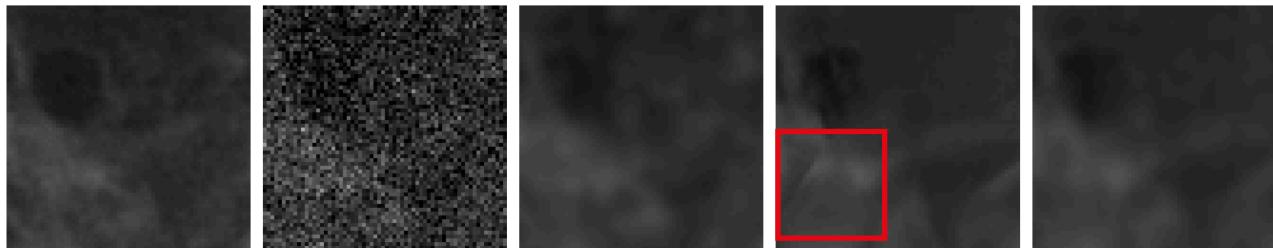
- Smooth fusion between:
 1. the image denoised with a reliable filter & 2. the deep denoised image
- Fusion in the frequency domain, controlled by a global parameter w



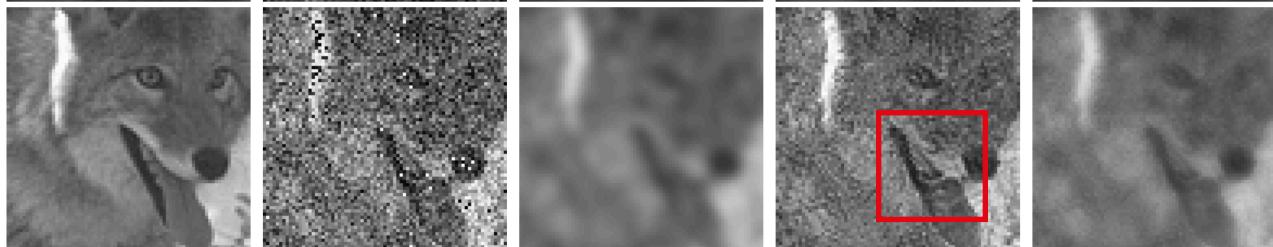
Proposed Method

CCID Generalization

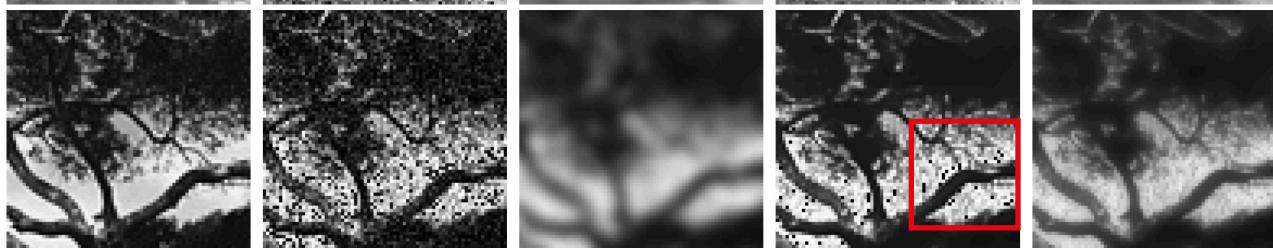
Data Domain
(Microscopy)



Noise Level
 $(\sigma = 35)$



Noise Type
(Poisson)



Ground-truth

Noisy

Filter

DL

CCID

Proposed Method

CCID_d Generalization Cont'd

- We vary the data domain distribution, the noise level, and the type of noise in the test images → out-of-distribution (OOD) test data
- CCID_d fixes a default invariable weight $w = 0.5$

OOD Type	Filter	DL	CCID _d	CCID
Data Domain	32.48/0.91	35.17/ 0.95	34.41/0.94	35.20/0.95
Noise Level	23.80/0.79	20.02/0.48	24.45/0.78	24.55/0.83
Noise Type	23.92/0.80	21.60/0.62	24.69/0.72	25.01/0.81

Average *PSNR/SSIM* test results

Key take-away messages

- Deep networks can hallucinate content from their rich priors. This content may be **incorrect**. To safeguard against this, CCID enables the user to **control** the addition of hallucination in the denoised result, through reliable fusion.
- We provide users with a **confidence** prediction revealing regions with likely deep denoiser errors.
- Our **results** outperform the deep denoiser and the reliable filter, especially when the test data diverge from the training data.
- Our CCID framework can be extended to further restoration tasks.

Thank you

Our **paper and code** are available on <https://github.com/IVRL/CCID>

Contact author: qiyuan.liang@epfl.ch