Effect of Noise Level and Brightness/Contrast on Image Denoising Performance

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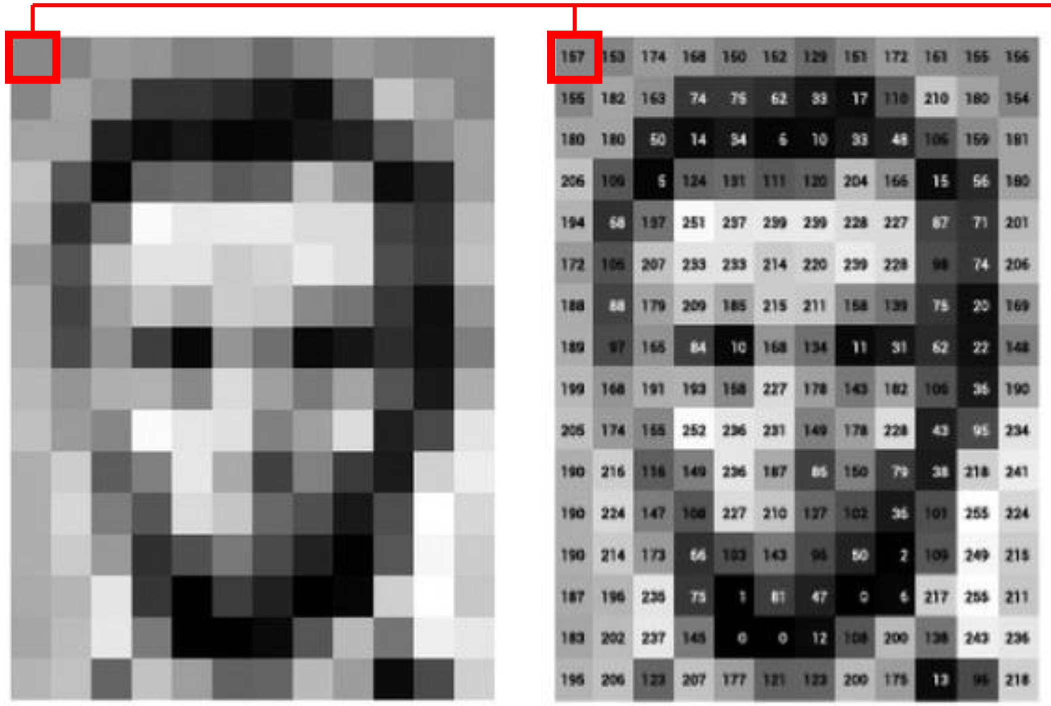
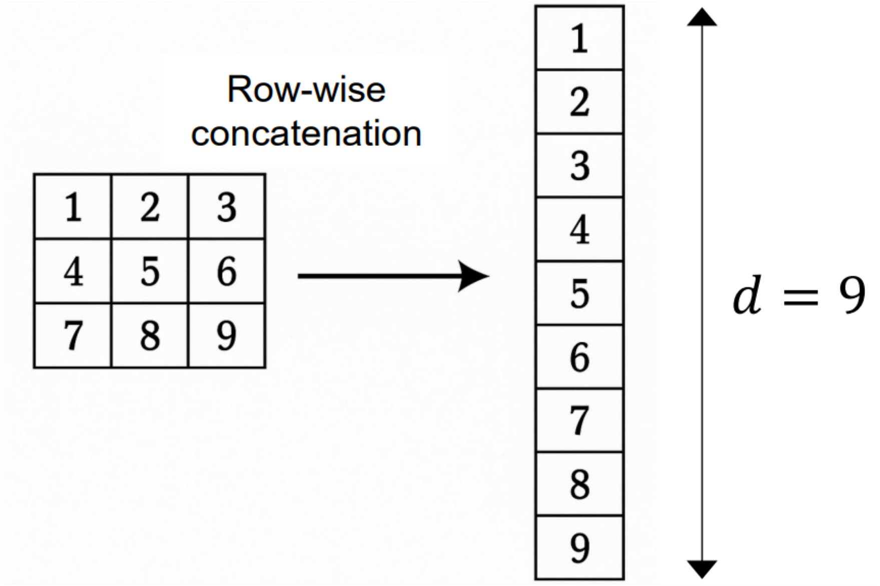
Brightness/Contrast on **Image** Denoising Performance

- **Gray scale**



157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

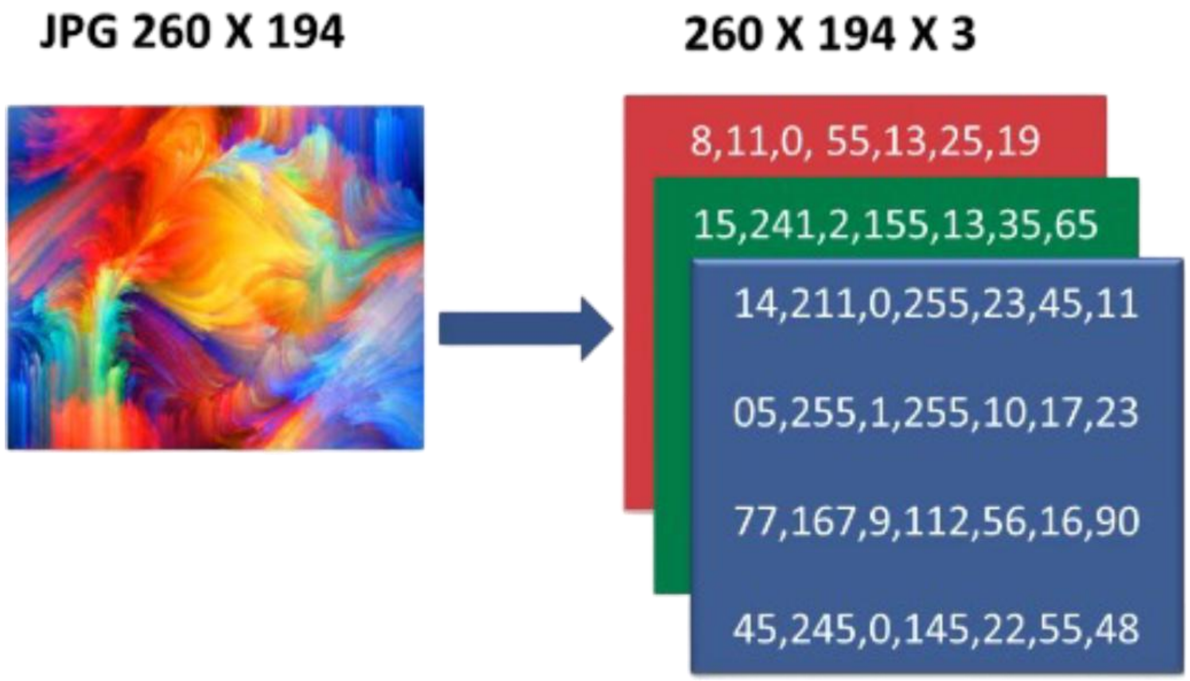


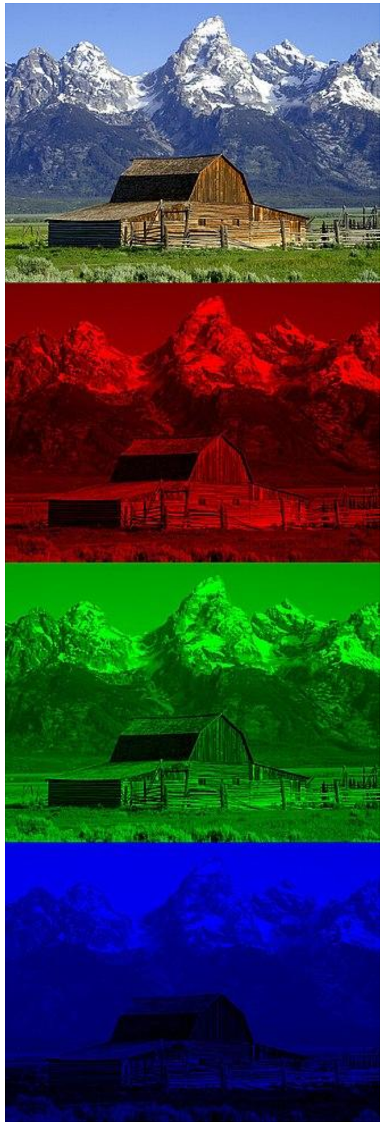
The value of each pixel represents its *intensity*:

- **0** represents pure **black**.
- **255** represents pure **white**.
- Values in between represent shades of gray.

Brightness/Contrast on Image Denoising Performance

- **Color extension – RGB model**





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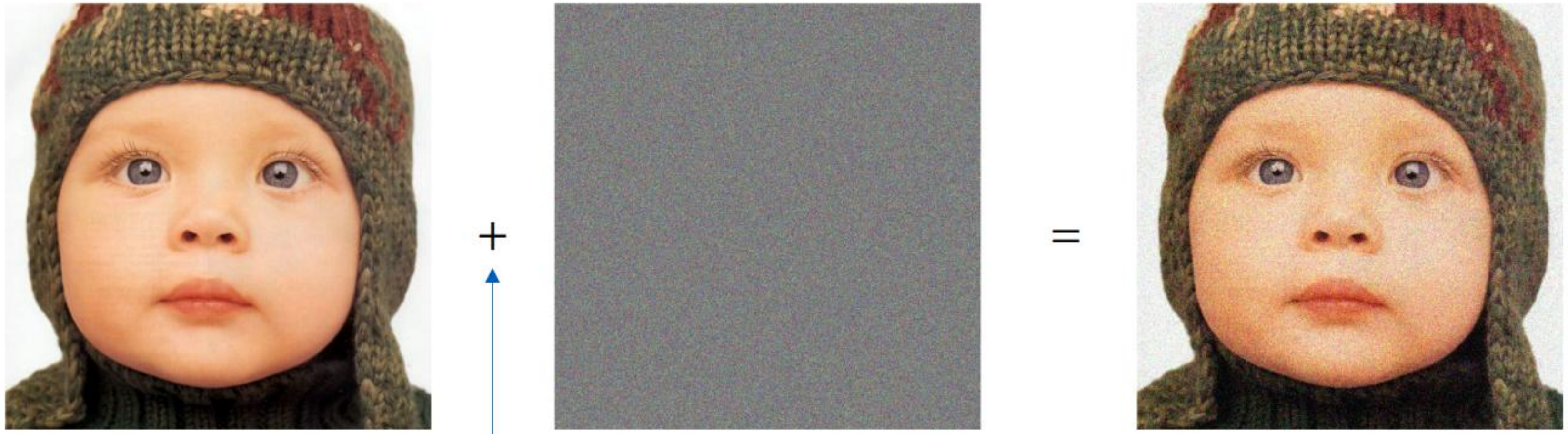
- **Sensor Noise (Shot Noise):** Due to the discrete nature of photons hitting the sensor
- **Thermal Noise:** Caused by random electron motion in the sensor
- **Transmission Noise:** Corruption introduced during transmission of images (e.g., wireless transfer, satellite imaging), resulting in missing chunks of data
- **Read Noise, Quantization Noise…**



Ground-Truth

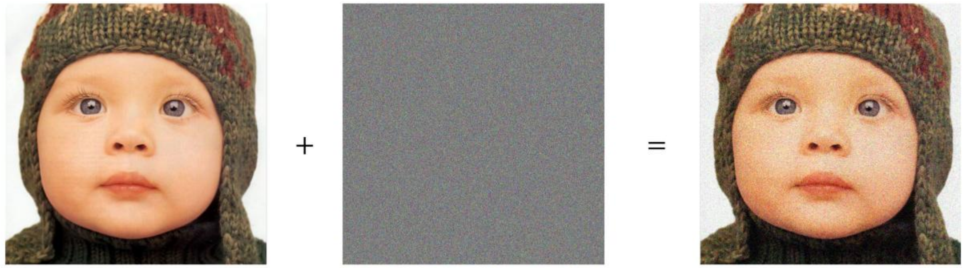
Noise

Degraded Image

Pixel-wise addition

Effect of **Noise** Level a
Brightness/Contrast

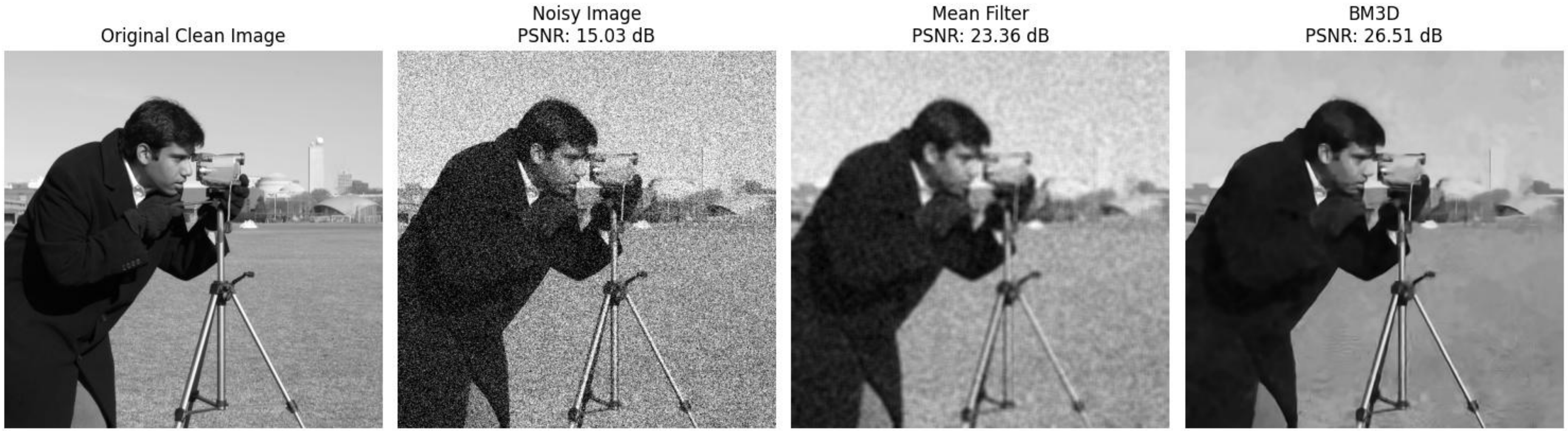
Brightness/Contrast on Image **Denoising** Performance



Ground-Truth Noise Noisy Image

$$y = \hat{x} + \varepsilon$$

Observation (noisy image) | **Ground Truth** | **Noise**

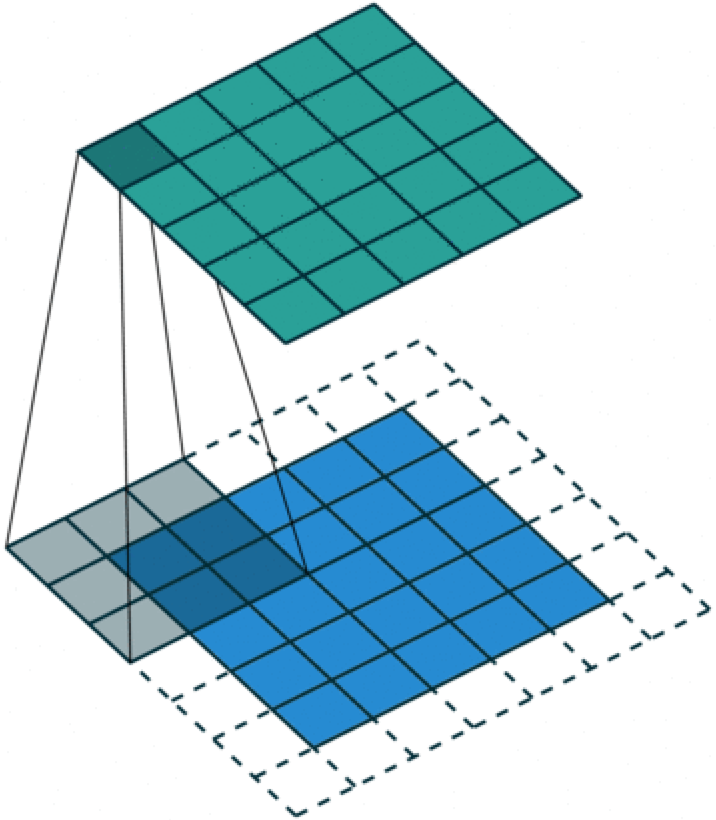


The biggest challenge is the **trade-off between noise removal and detail preservation**

Brightness/Contrast on Image Denoising Performance

Local filters: Mean Filter

$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$



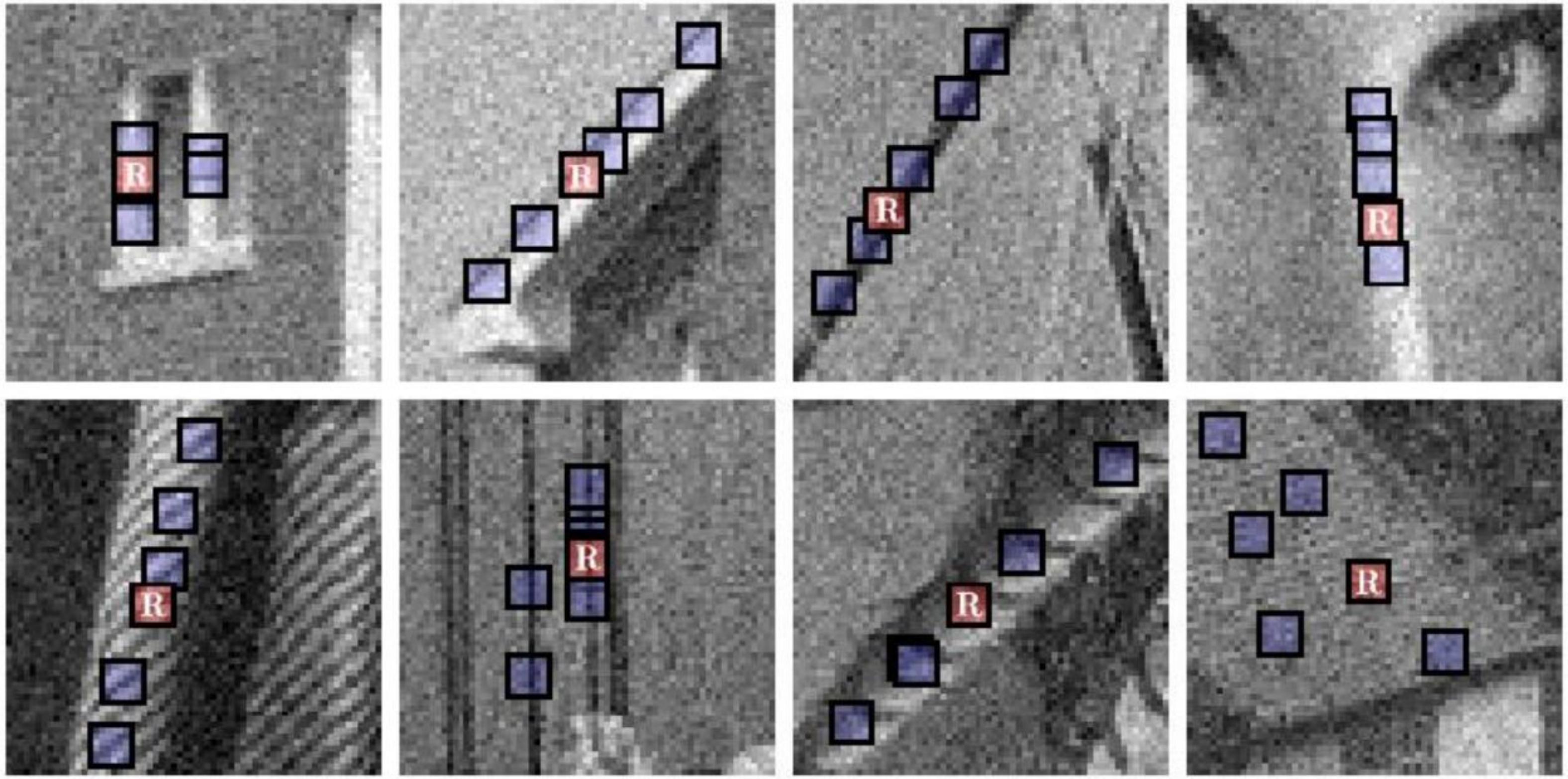
Original Clean Image

Noisy Image
PSNR: 15.05 dB

Mean Filter
PSNR: 23.39 dB

Brightness/Contrast on Image **Denoising** Performance

BM3D – Block Matching and 3D Filtering



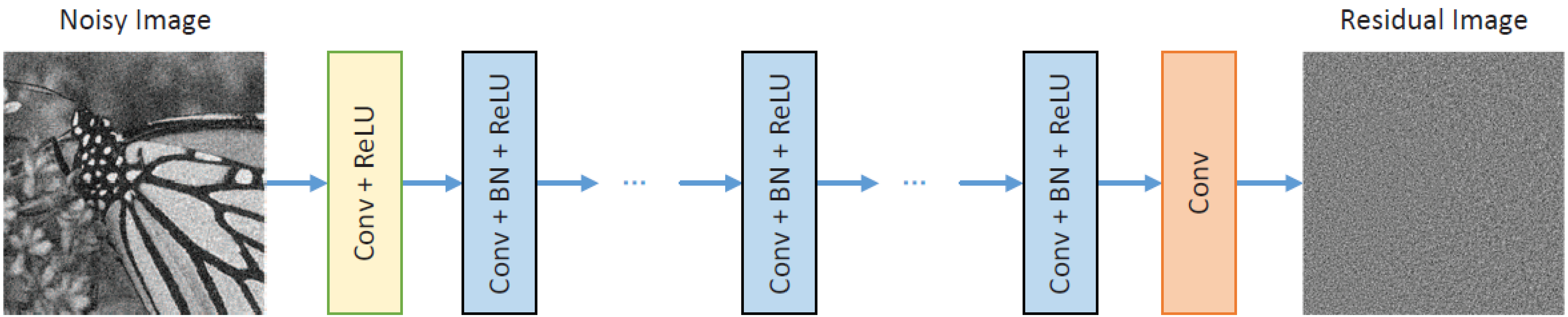
Steps:

1. **Block Matching**: find similar-looking patches from across the entire image.
2. **Collaborative Filtering:** Stack similar patches together and filter them as a 3D group to preserve details while removing noise.

Dabov, Kostadin, et al. "Image denoising by sparse 3-D transform-domain collaborative filtering." IEEE Transactions on image processing 16.8 (2007): 2080-2095.

Brightness/Contrast on Image Denoising Performance

DnCNNs - Denoising convolutional neural networks



DnCNN takes a data-driven approach: it learns to recognize noise patterns directly from training examples.
Requires thousands of samples but provide fast performance at inference

Zhang, K., Zuo, W., Chen, Y., Meng, D., & Zhang, L. (2017). Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising (DnCNN). IEEE TIP, 26(7), 3142–3155

Wrapping up

Most of the methods tend to leave behind residual noise or artifacts.

They are away from perfection at higher noise levels.

Definition of “clean” keeps evolving with our *visual expectations* and *applications domain*.

Far from being a solved problem, denoising remains a vibrant research area, requiring models that generalize across diverse cameras and conditions, and with key role at the core of generative pipelines (e.g. Diffusion models)

Thank you!