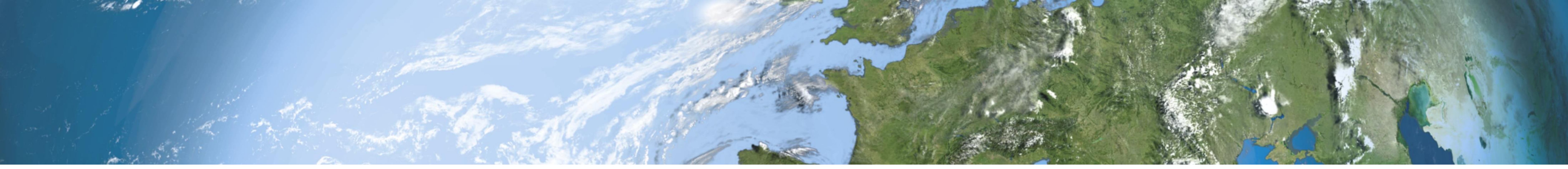


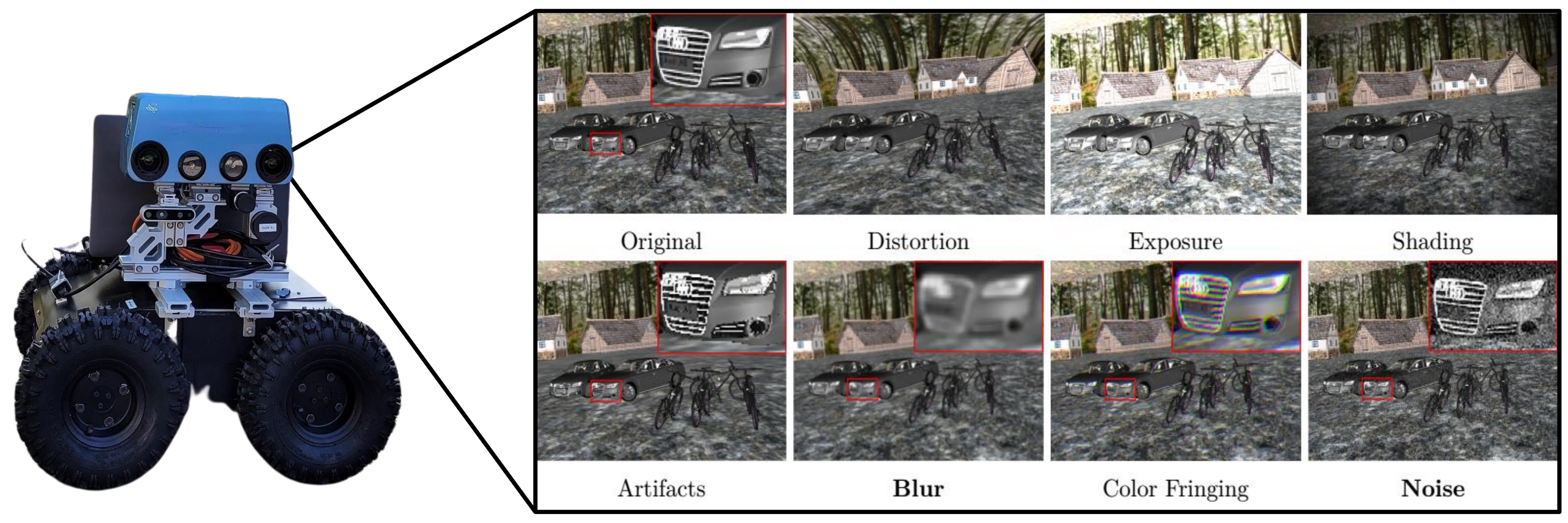
A camera self-health-maintenance system based on sensor artificial intelligence

M. Wischow[1,2,*], G. Gallego[2], I. Ernst[1], A. Börner[1]

[1] German Aerospace Center (DLR), Institute of Optical Sensor Systems, Rutherfordstr. 2, 12489 Berlin, Germany
[2] Technical University of Berlin, Department of Robotic Interactive Perception, Straße des 17. Juni 135, 12489 Berlin, Germany
* Maik.Wischow@dlr.de

Motivation

Autonomous vehicles and robots require increasingly more robustness and reliability to meet the demands of modern tasks. These requirements specially apply to cameras onboard such vehicles because they are the predominant sensors to acquire information about the environment and support actions. However, there are versatile undesirable states cameras can encounter. Hence, cameras must maintain proper functionality and take automatic countermeasures if necessary. Currently, there is only little work that examines the practical use of a general condition monitoring approach for cameras and designs countermeasures in the context of an envisaged high-level application. We propose a self-health-maintenance framework for cameras with focus on blur and noise, based on artificial intelligence (AI) and the incorporation of additional physical knowledge of the sensor (Sensor AI) [1].

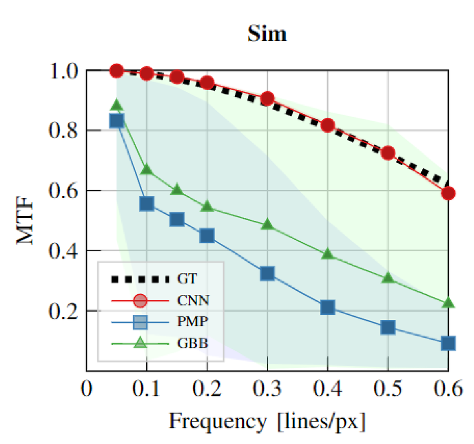


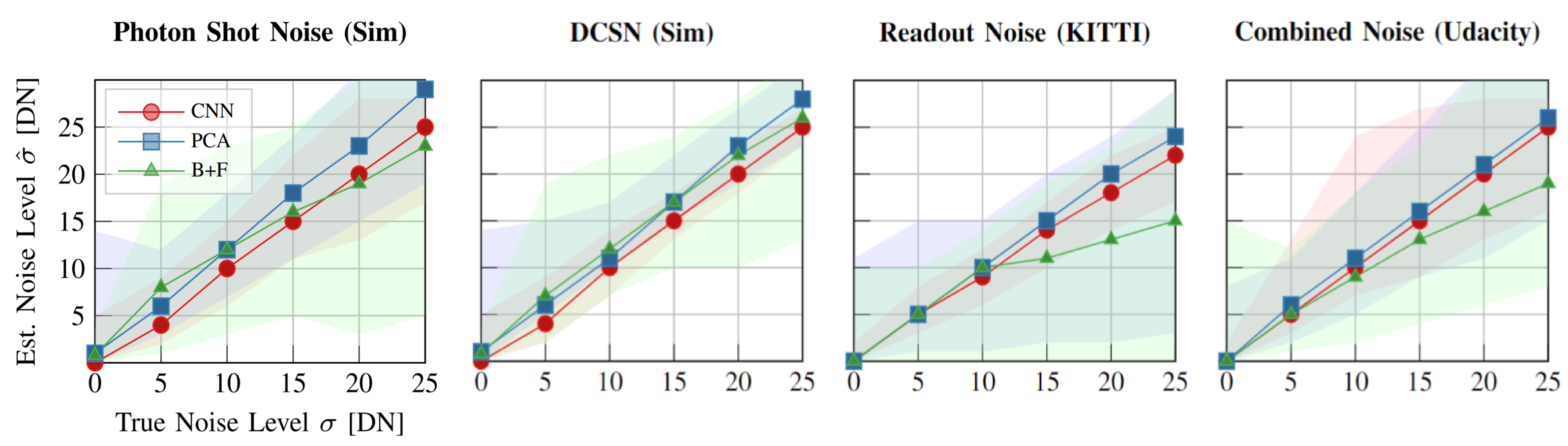
AI-based Blur and Noise Estimation

- Trained CNN [2] to quantify defocus and motion blur in images.
  - **Input:** 192x192 px image patches; **Output:** Modulation transfer function (MTF).
- **Evaluation:** Simulate blur and compare performance to PMP [3] and GBB [4].
- **Datasets:** Self-simulated (Sim), KITTI [5], and Udacity [6] (real ones to follow).
- **Results:** CNN x54 faster than PMP and GBB (0.24s vs. 13s per image patch); CNN more accurate for no/little blur and defocus, PMP/GBB otherwise.

- Trained CNN [7] to quantify temporal noise sources in images (photon shot noise (PN), dark current shot noise (DCSN), and readout noise (RN)).
  - **Input:** 128x128 px image patches; **Output:** Std. dev. of noise distribution (σ).
- **Evaluation:** Simulate noise and compare performance to PCA [8] and B+F [9].
- **Datasets:** Self-simulated (Sim), KITTI [5], and Udacity [6] (real ones to follow).
- **Results:** All methods comparably fast (2-5 ms per image patch), CNN has generally best accuracy and least uncertainty.

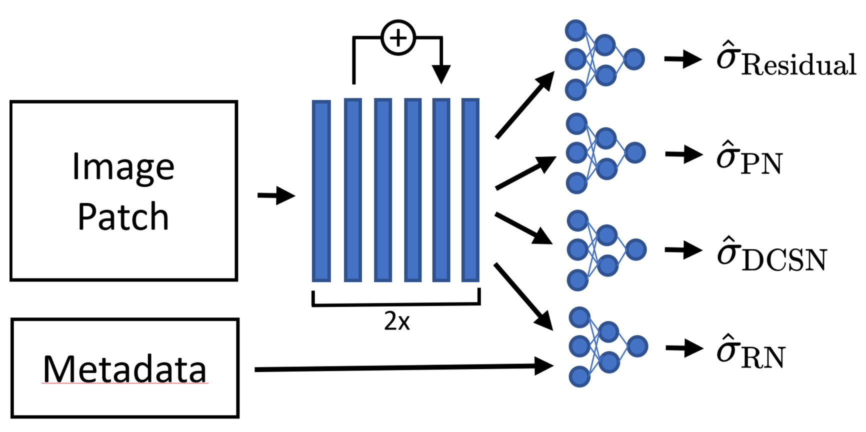
		Defocus Blur					Linear Motion Blur					Non-linear Motion Blur				
Size [px]		3	7	11	15	21	3	7	11	15	21	3	7	11	15	21
Kernel																
Sim	CNN	**0.2**	**0.7**	**0.5**	**0.3**	**0.7**	**7.5**	17.7	14.7	17.4	**6.6**	**6.3**	16.2	18.5	28.0	17.5
	PMP	7.9	2.2	2.4	2.4	2.6	34.5	10.4	12.1	13.3	17.2	24.4	7.9	**9.4**	**6.5**	11.8
	GBB	2.9	3.8	4.3	4.8	9.1	27.1	**6.6**	**8.5**	16.7	13.7	15.3	**6.5**	9.6	9.6	**10.8**
KITTI	CNN	**0.4**	**0.8**	**0.5**	**0.3**	**0.5**	**3.6**	16.5	14.1	13.3	**8.2**	**6.2**	15.0	16.0	23.7	16.8
	PMP	9.2	2.3	2.3	2.0	2.1	33.5	**12.8**	10.9	**9.2**	13.4	20.8	11.4	11.5	**7.7**	**8.6**
	GBB	3.7	2.4	3.1	4.5	10.1	16.1	13.3	**9.6**	10.5	13.9	9.7	**9.9**	**10.8**	9.5	10.7
Udacity	CNN	**3.8**	**0.6**	**0.6**	**0.3**	**0.5**	**16.1**	**13.3**	**10.5**	**10.6**	**10.2**	**9.3**	12.0	14.1	14.1	11.2
	PMP	14.3	4.3	3.6	2.2	1.8	38.1	15.3	12.8	12.2	13.5	24.8	15.3	14.8	**9.6**	**9.6**
	GBB	6.8	2.9	3.2	4.5	11.3	24.4	13.8	11.3	11.0	16.6	14.5	**11.8**	**12.4**	10.7	13.0

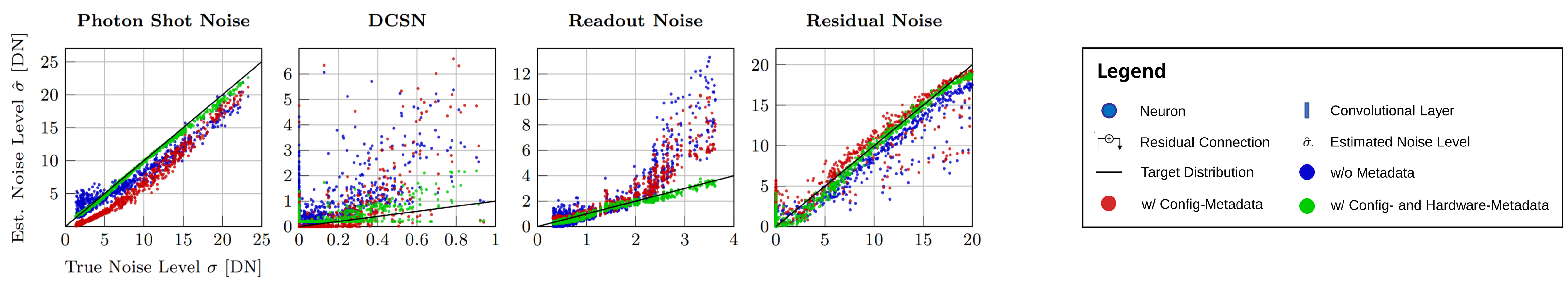




Sensor AI: From Symptoms towards Causes

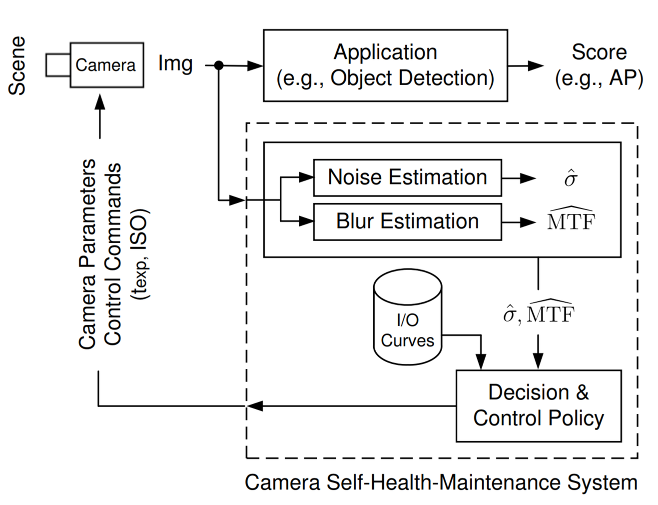
- **Problem:** Cannot identify noise root causes having images only in order to initiate adequate counter-measures.
- **Approach:** Incorporate camera metadata into noise estimator and simultaneously estimate noise from different sources as well as (unknown) residual noise.
- **Evaluation:** Trained on simulated noise and tested on real noise.
- **(Preliminary-) Results:** Fast inference (< 2ms per image patch), config and hardware metadata necessary for precise noise estimation.

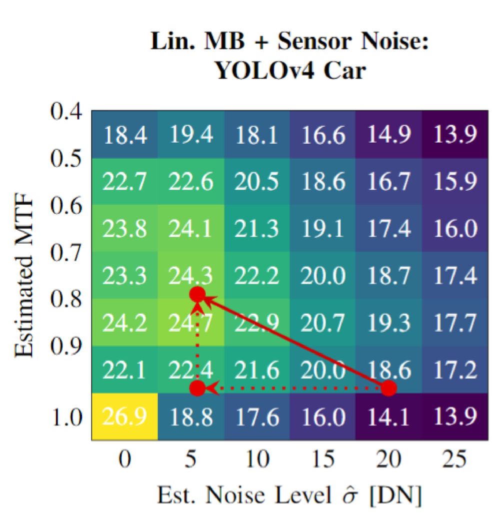


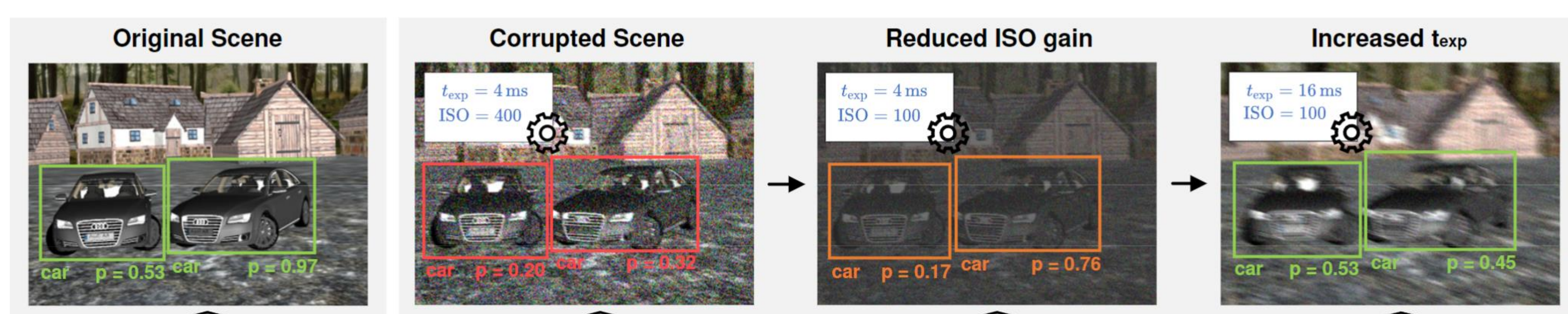


Automatic Camera Parameter Adjustment

- Camera parameters may relate to blur/noise effects in produced images (exposure time (t_{exp}) to motion blur (MB), ISO gain to noise, …).
- Amount of desired blur/noise always depends on targeted high-level image application (e.g., car detection).
  ↝ Camera parameter optimization with respect to target application score (e.g., car detection average precision; AP).
- Target scores determined offline and empirically for different blur/noise severities to create (potentially non-linear and non-monotonic (!)) input-output profile (I/O curves, see heatmap).
  ↝ Automatic camera parameter adjustment for optimal application performance (red path in heatmap and corresponding example next to it).







$\hat{\sigma} = 1.0,\ \widehat{\mathrm{MTF}} = 0.99$ | $\hat{\sigma} = 20.0,\ \widehat{\mathrm{MTF}} = 0.96$ | $\hat{\sigma} = 5.0,\ \widehat{\mathrm{MTF}} = 0.95$ | $\hat{\sigma} = 5.0,\ \widehat{\mathrm{MTF}} = 0.71$

DLR Deutsches Zentrum für Luft- und Raumfahrt

[1] M. Wischow, G. Gallego, A. Börner, I. Ernst, "Camera Condition Monitoring and Readjustment by means of Noise and Blur," *arXiv preprint arXiv:2112.05456* (2021).
[2] M. Bauer, V. Volchkov, M. Hirsch, and B. Schcolkopf, "Automatic estimation of modulation transfer functions," IEEE Int. Conf. Comput. Photography (ICCP) (2018).
[3] Y. Bai, G. Cheung, X. Liu, and W. Gao, "Graph-based blind image deblurring from a single photograph," IEEE Trans. Image Process., vol. 28, no. 3, pp. 1404–1418 (2018).
[4] F. Wen, R. Ying, Y. Liu, P. Liu, and T.-K. Truong, "A simple local minimal intensity prior and an improved algorithm for blind image deblurring," IEEE Trans. Circuits Syst. Video Technol. (2020).
[5] A. Geiger, P. Lenz, and R. Urtasun, "Are we ready for autonomous driving? the KITTI vision benchmark suite," IEEE CVPR (2012).
[6] Udacity, https://github.com/udacity/self-driving-car (2016).
[7] H. Tan, H. Xiao, S. Lai, Y. Liu, and M. Zhang, "Pixelwise estimation of signal-dependent image noise using deep residual learning," Computational intelligence and neuroscience, vol. 2019 (2019).
[8] G. Chen, F. Zhu, and P. Ann Heng, "An efficient statistical method for image noise level estimation," Int. Conf. Comput. Vis. (ICCV) (2015).
[9] D.-H. Shin, R.-H. Park, S. Yang, and J.-H. Jung, "Block-based noise estimation using Adaptive Gaussian Filtering," IEEE Trans. Consumer Electronics, vol. 51, no. 1, pp. 218–226 (2005).