Denoising Stochastic Progressive Photon Mapping Renderings Using a Multi-Residual Network

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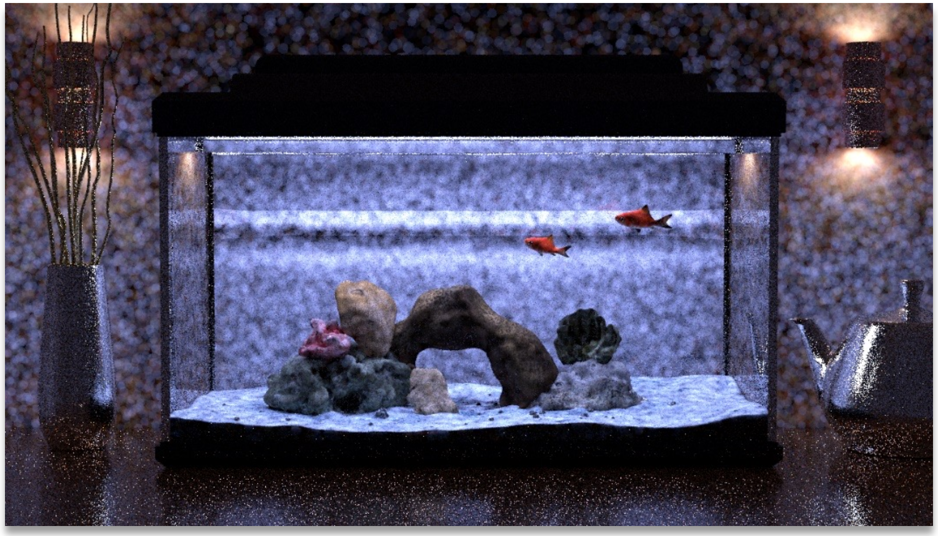
Stochastic Progressive Photon Mapping

AQUARIUM SCENE

Stochastic Progressive Photon Mapping

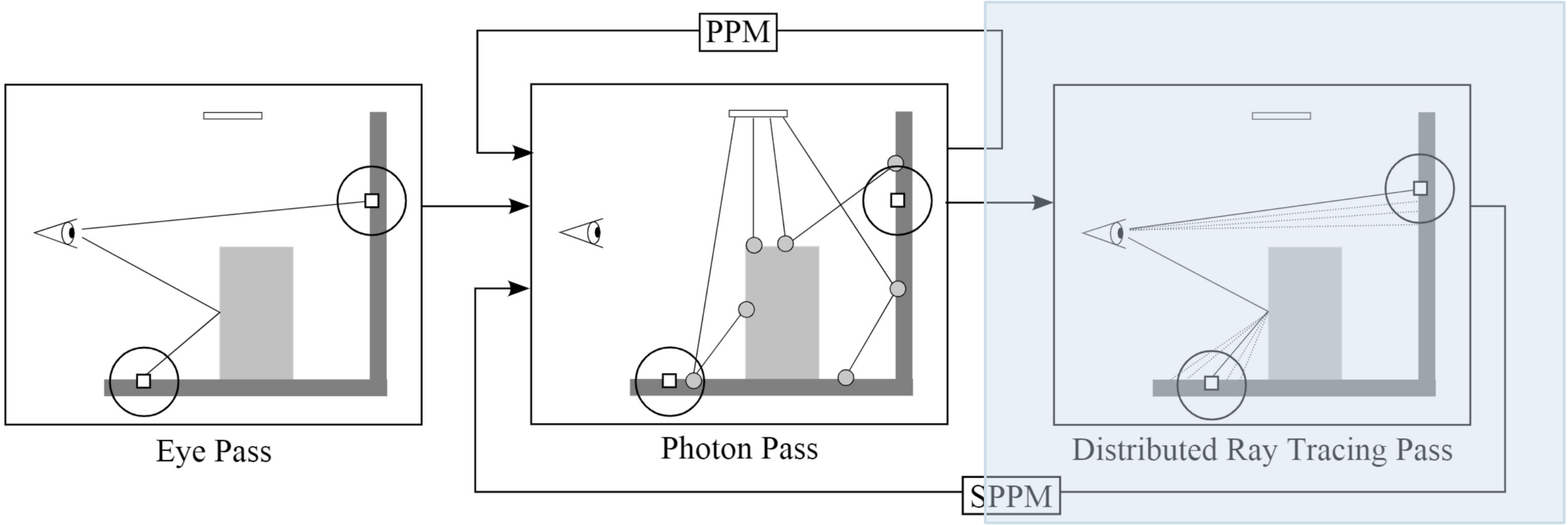
Limited iterations or inappropriate settings



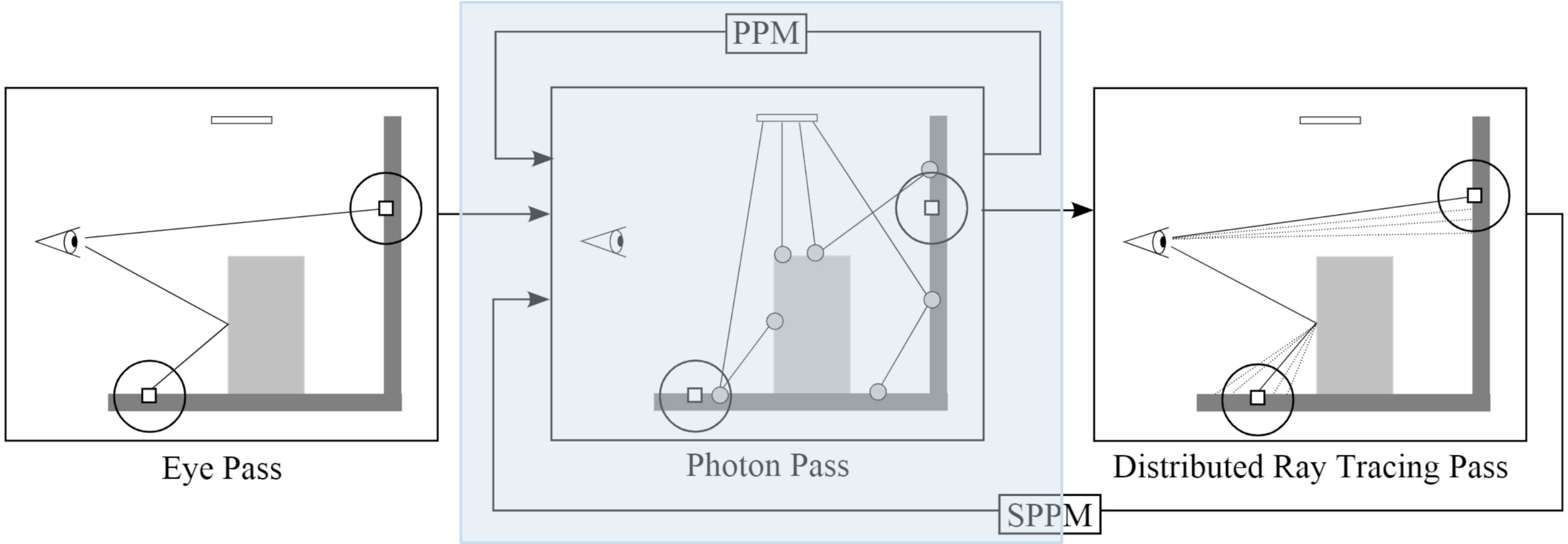
A huge amount of time

Problem

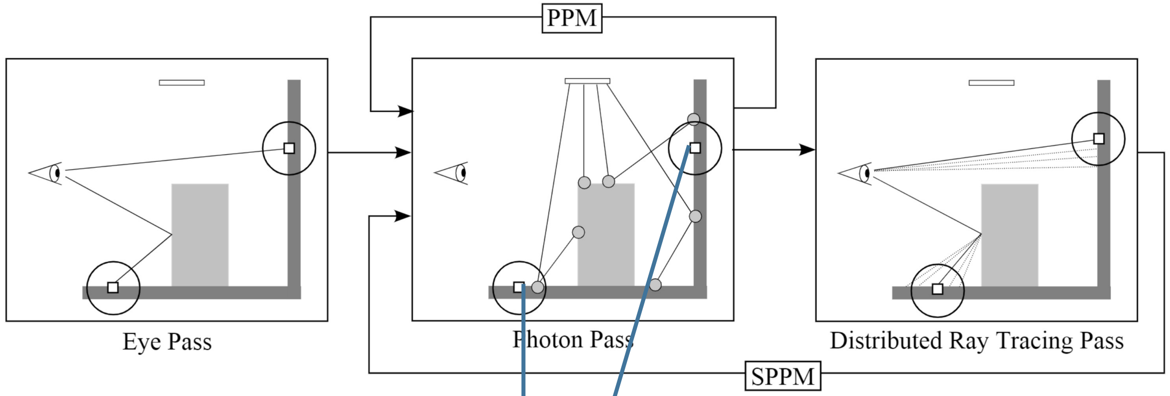
Where does the noise come from?



Where does the noise come from?



Where does the noise come from?



Update

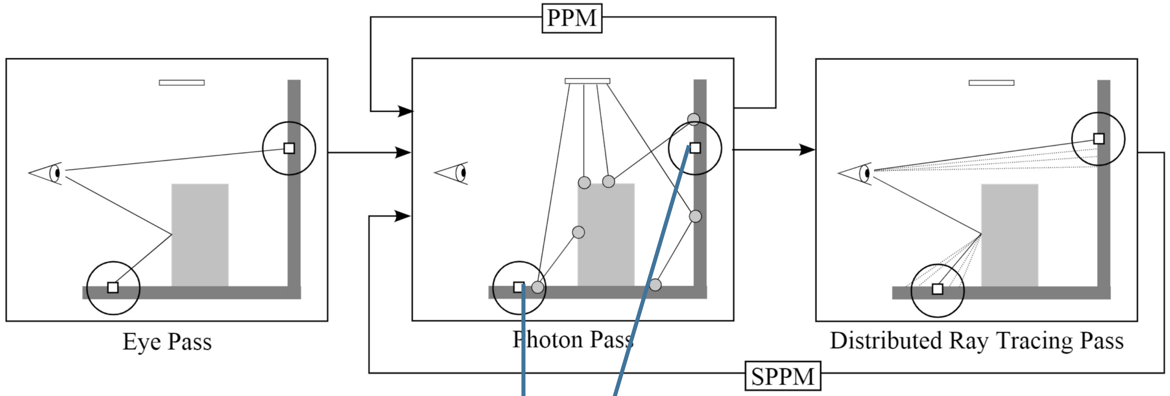
Accumulated flux

$$L(S,\omega) \approx \frac{\tau_i(S,\omega)}{N_e(i)\pi R_i(S)^2},$$

Number of photons

Searching radius

Where does the noise come from?



Update

Accumulated flux

$$L(S,\omega) = \lim_{i\to\infty} \frac{\tau_i(S,\omega)}{N_e(i)\pi R_i(S)^2},$$

Number of photons

Searching radius

Where does the noise come from?

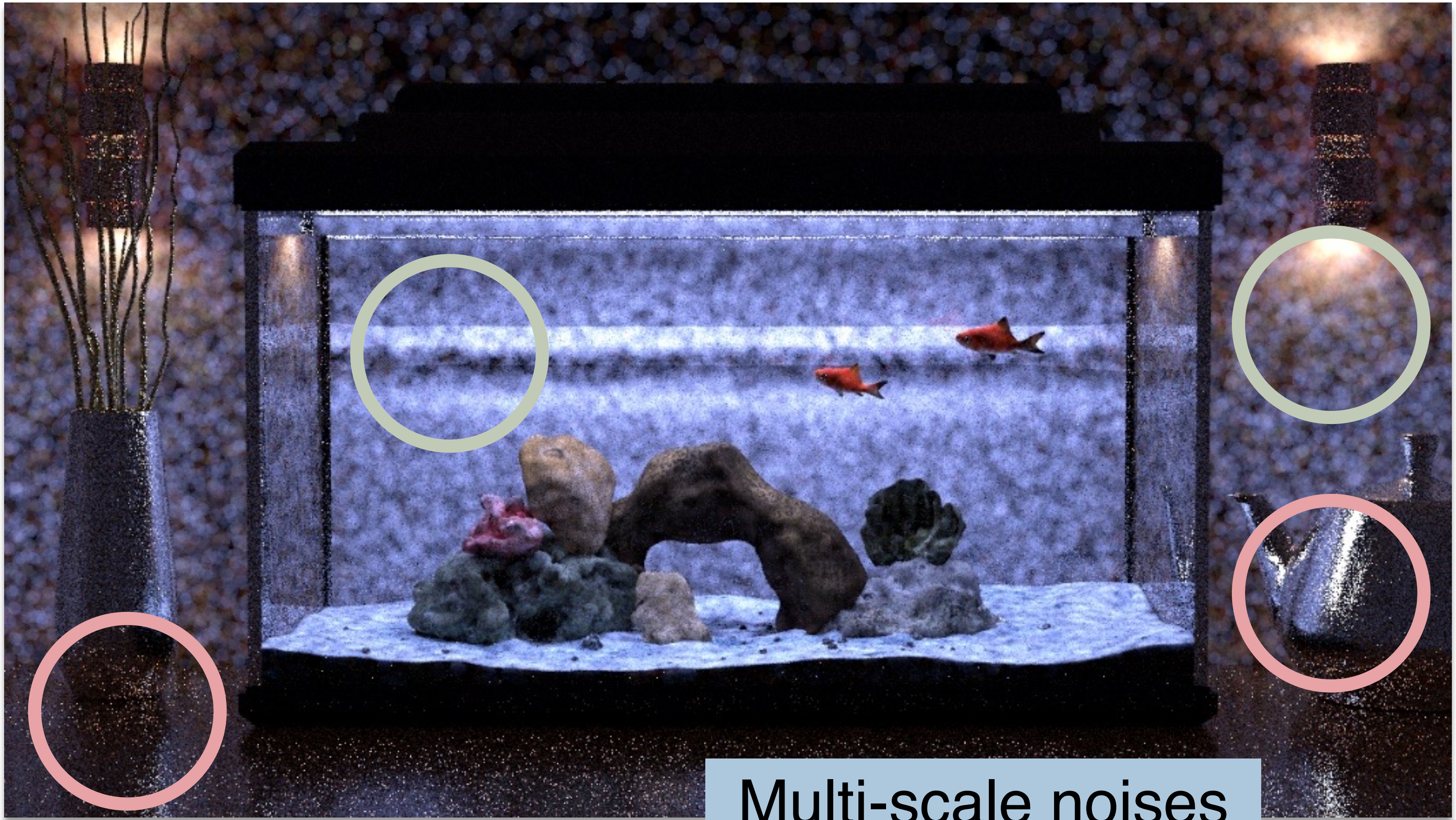
$$L(S,\omega) = \lim_{i\to\infty} \frac{\tau_i(S,\omega)}{N_e(i)\pi R_i(S)^2},$$

Hard to converge

Bias

Variance

Where does the noise come from?



Multi-scale noises

Bias

Low-frequency and large noise

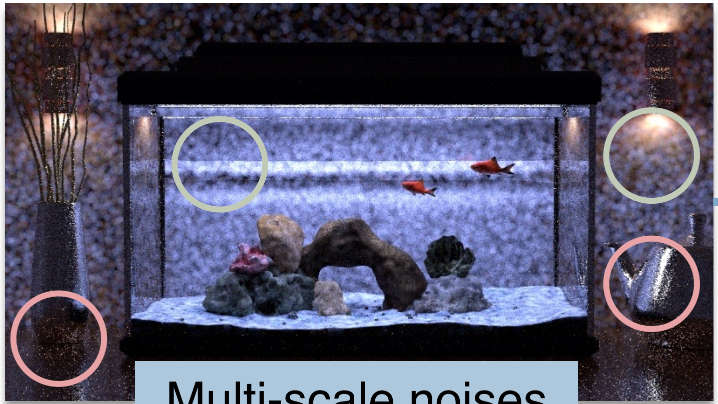
- Insufficient number of photons
- Overlarge searching radius
- …

Variance

High-frequency and small noise

- The specular lobe is tight
- Sampling next ray
- …

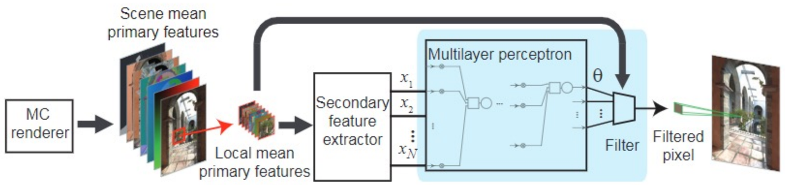
Goal: a denoising method specially designed for SPPM



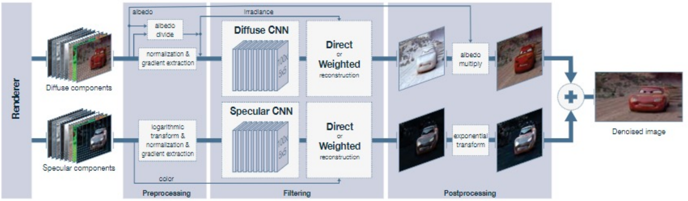
Multi-scale noises

Function G

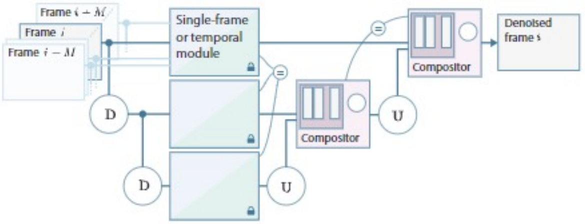
Similar approaches: for the general MC method



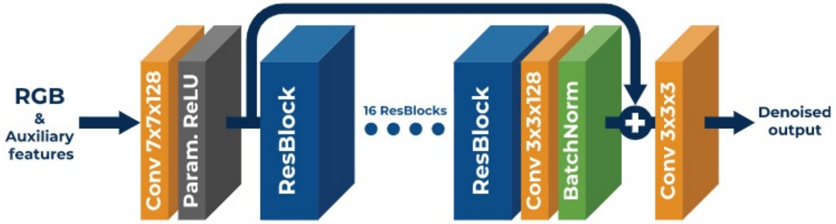
A machine learning approach for filtering Monte Carlo noise
[Kalantari et al. 2015]



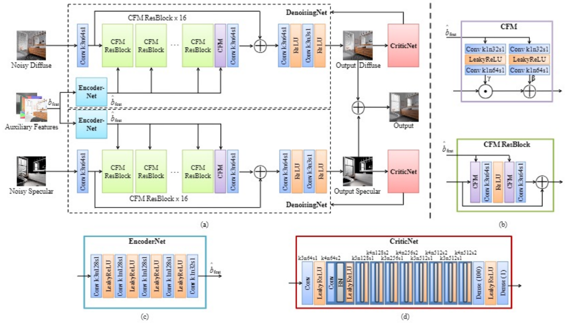
Kernel-predicting convolutional networks for denoising Monte Carlo renderings
[Bako et al. 2017]



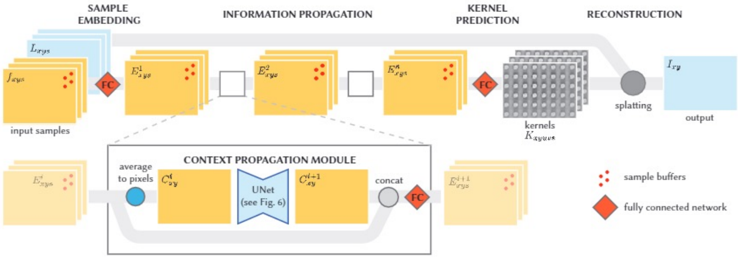
Denoising with kernel prediction and asymmetric loss functions
[Vogels et al. 2018]



Deep residual learning for denoising Monte Carlo renderings
[Wong et al. 2019]

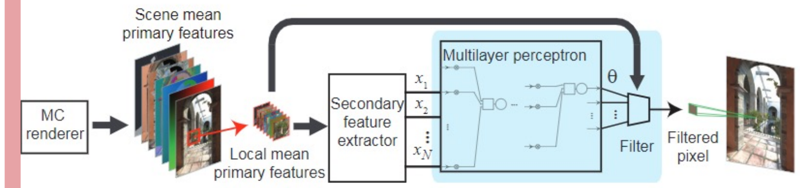


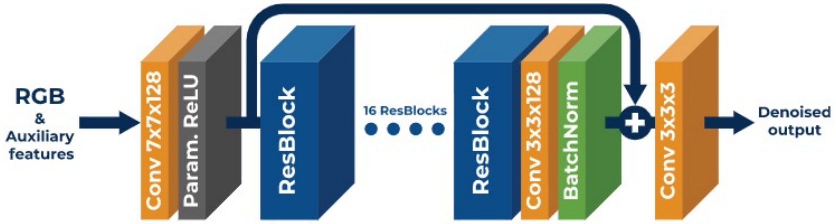
Adversarial Monte Carlo denoising with conditioned auxiliary feature modulation
[Xu et al. 2019]

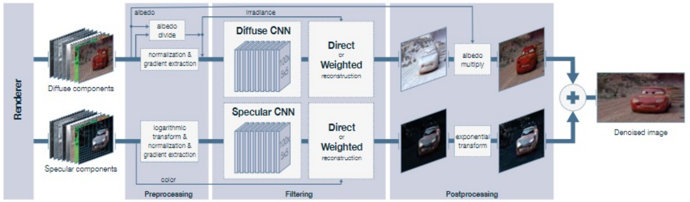


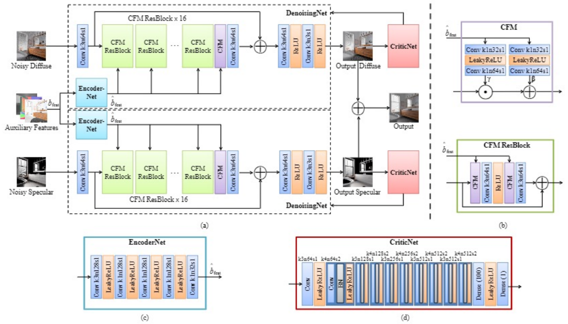
Sample-based Monte Carlo denoising using a kernel-splatting network
[Gharbi et al. 2019]

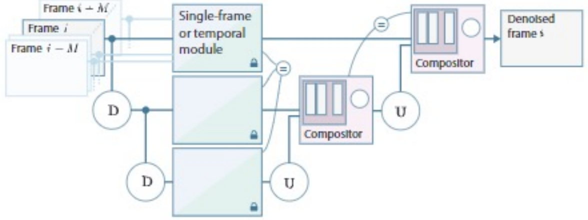
Similar approaches: for the general MC method

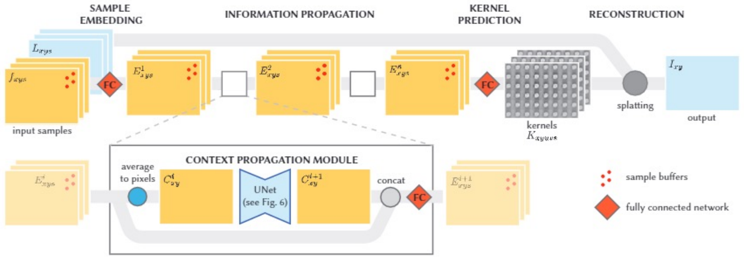








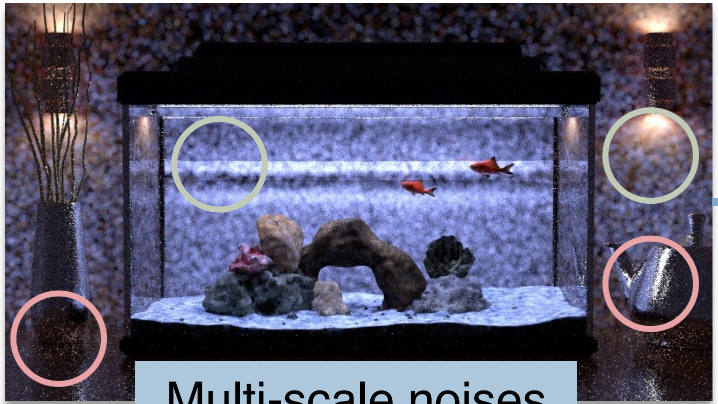




Only focus on the variance issue

Our Method

Model



Multi-scale noises

Function G

Model

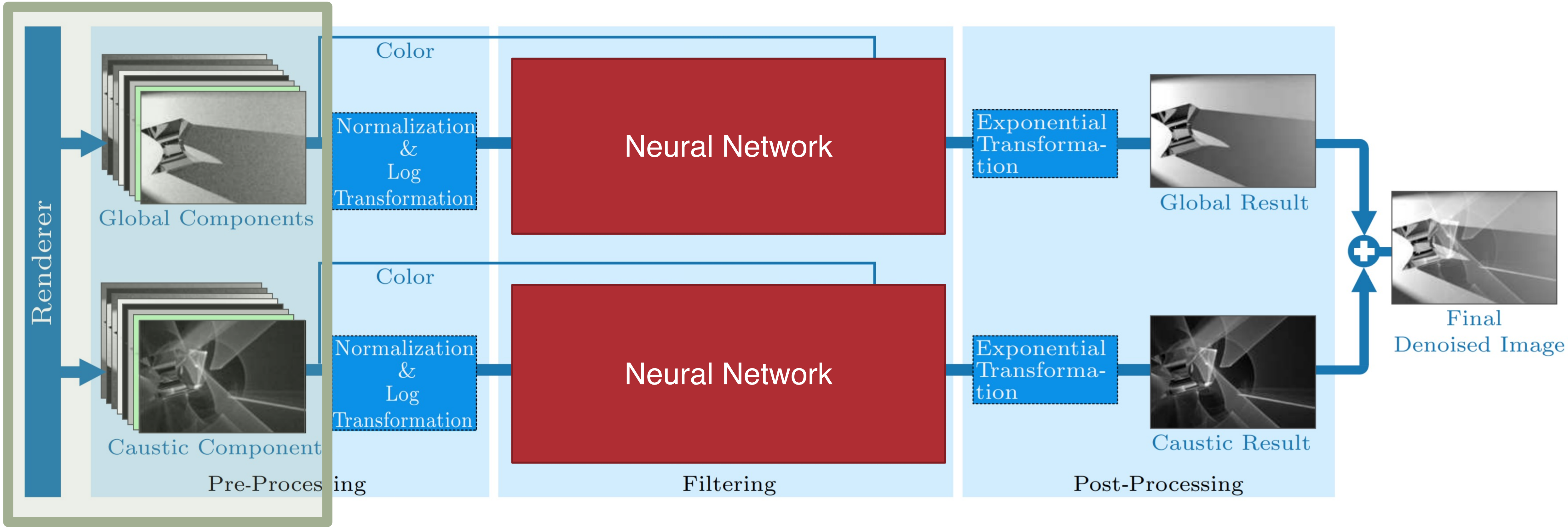
$$\hat{c}_i = G(c_i)$$

Model

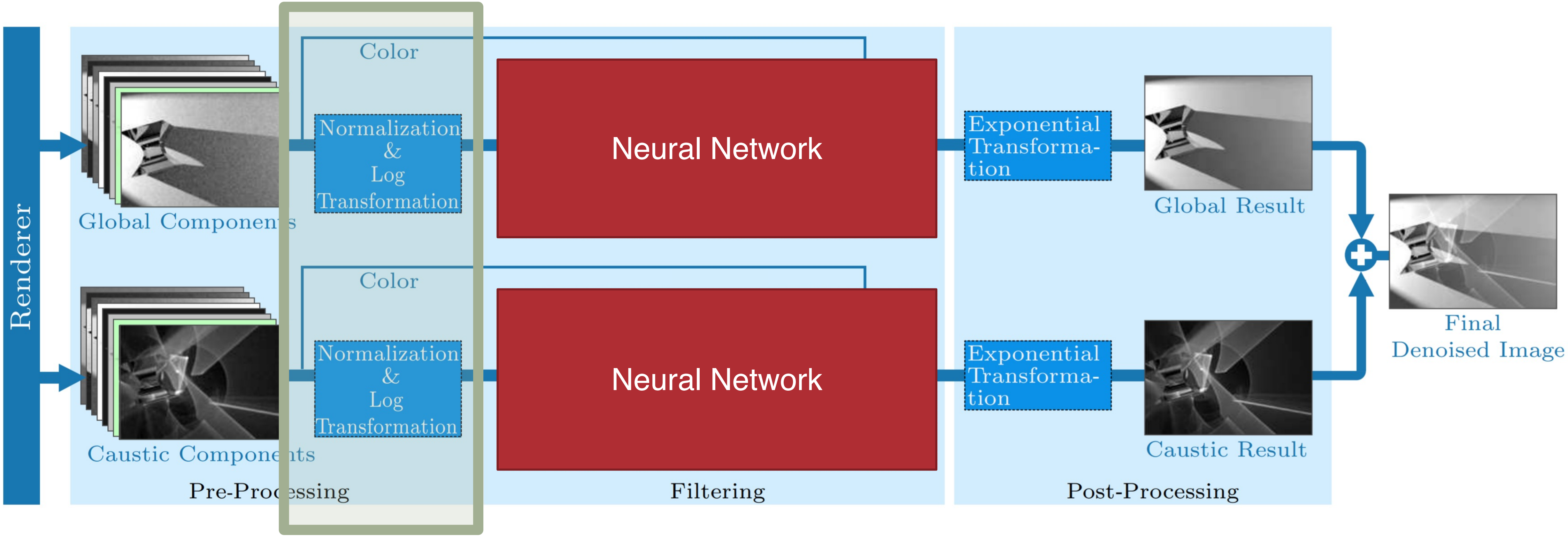
$$\hat{c}_i = \sum_{j \in \mathrm{N}(i)} G(X_i, \theta_{i,j}) c_j$$

Inspired by [Bako et al. 2017]

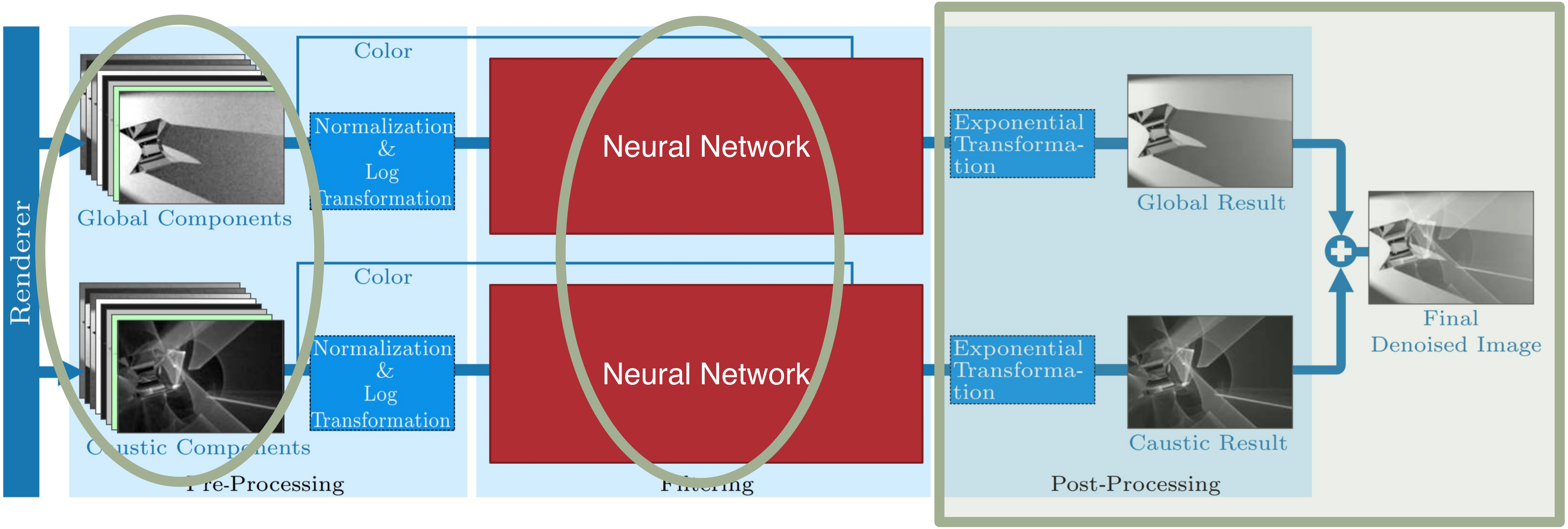
SPPM Denoising framework



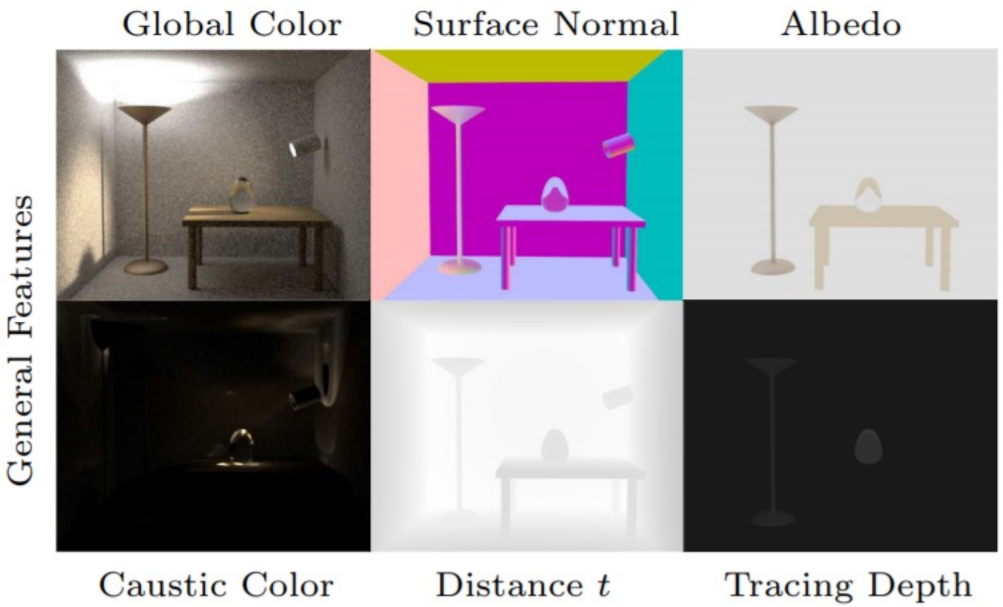
SPPM Denoising framework



SPPM Denoising framework

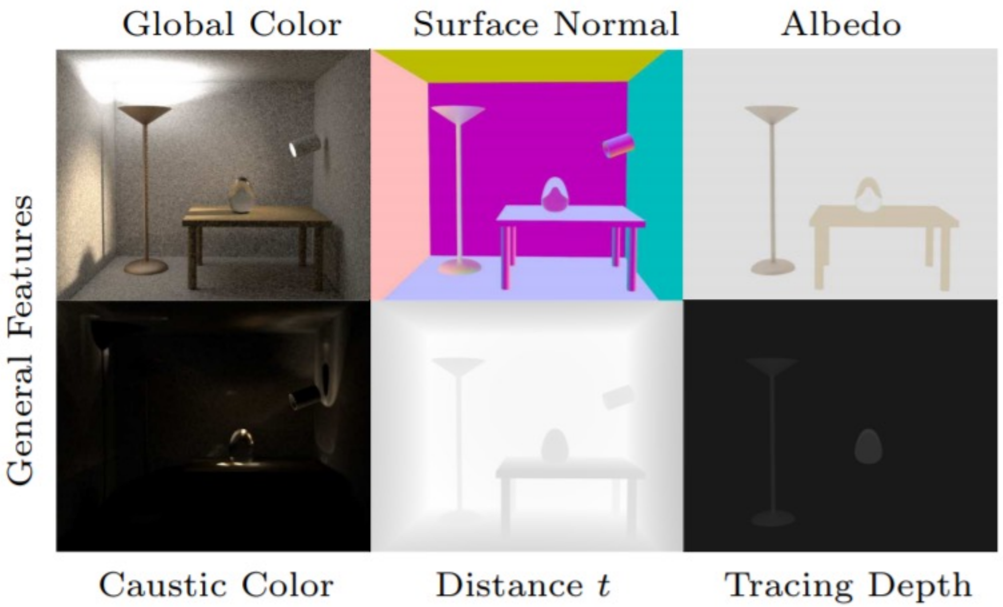


Additional auxiliary features



Inspired by
[Kalantari et al. 2015]
[Bako et al. 2017]
[Wong et al. 2019]

Additional auxiliary features



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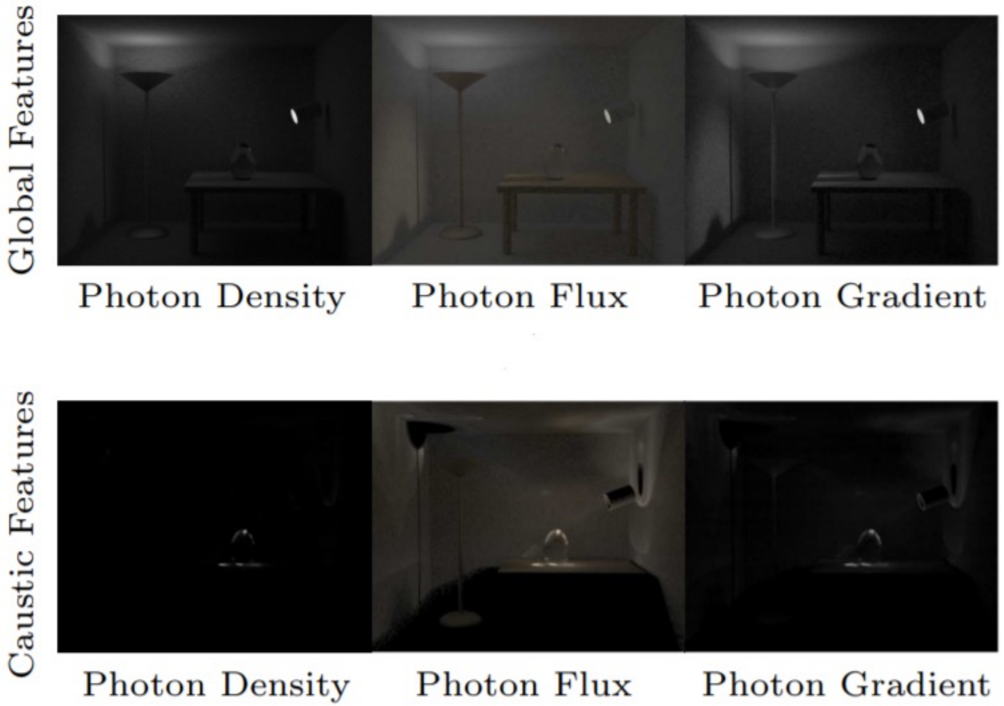
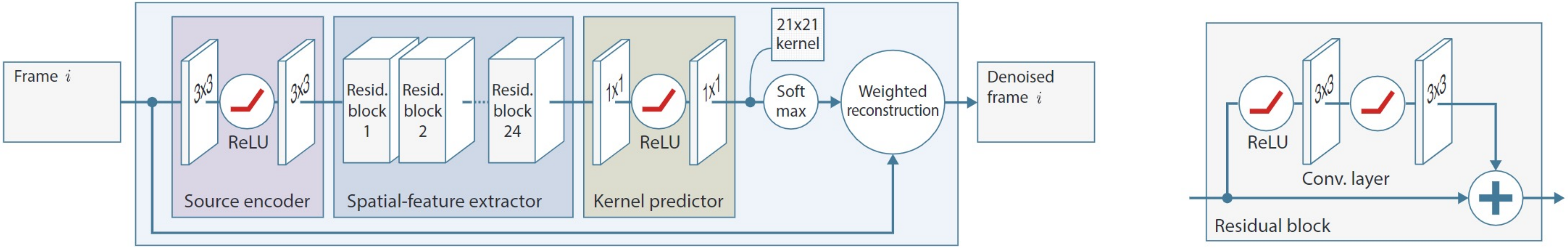
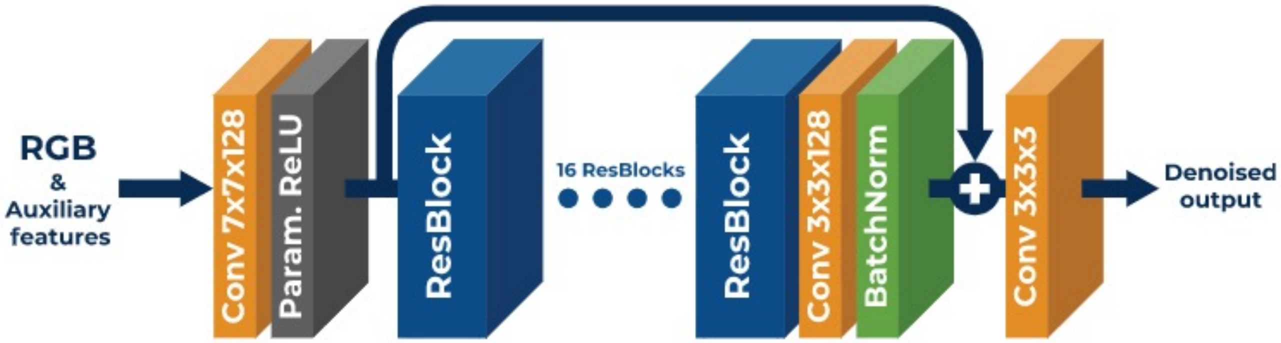


Network architecture



[Vogels et al. 2018]



[Wong et al. 2019]

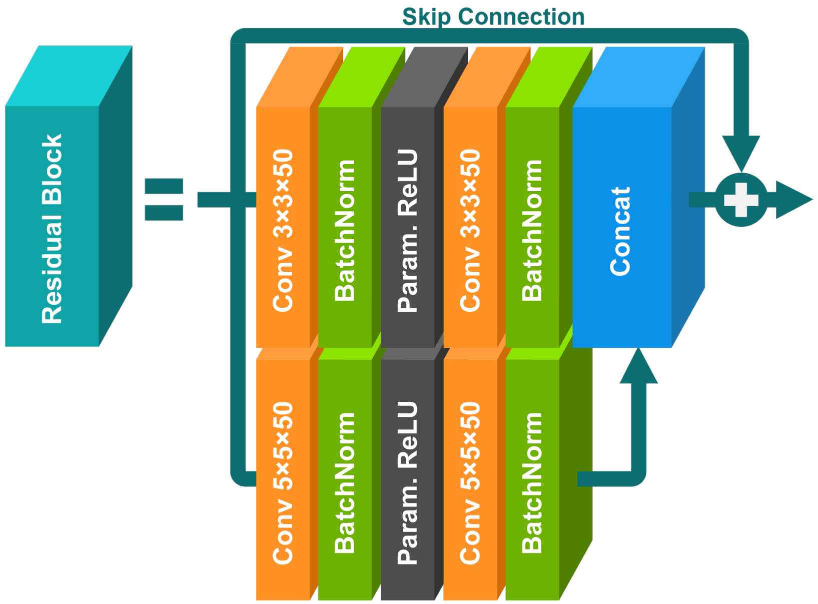
Network architecture

large convolution filter size

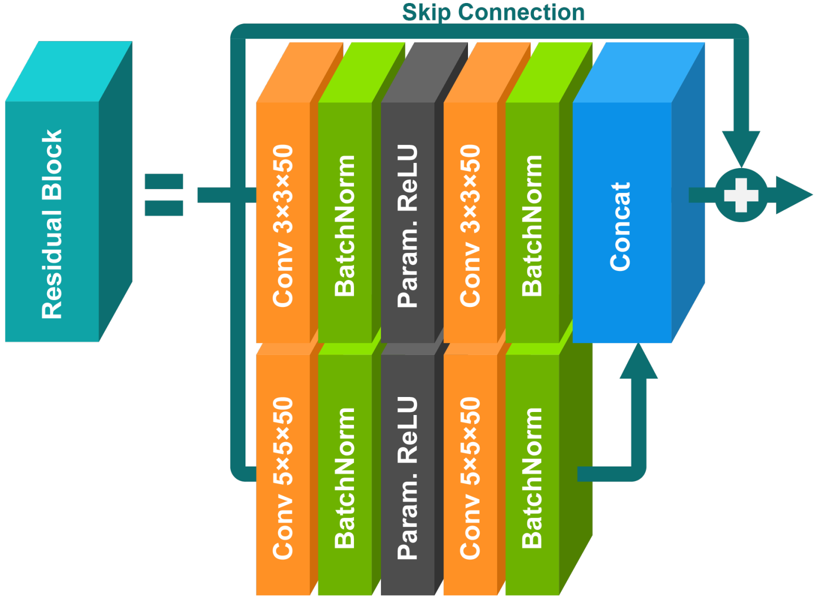
small convolution filter size

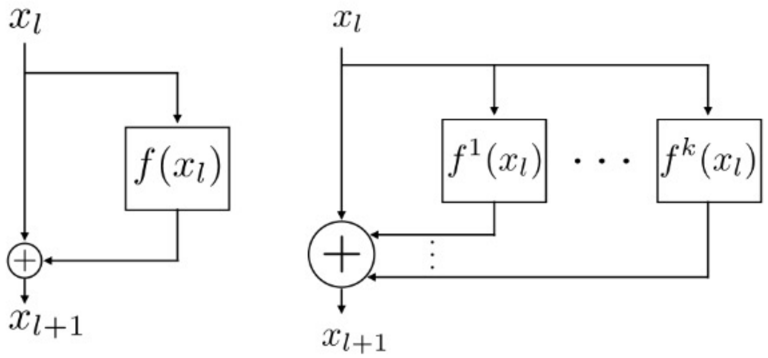
	Large convolution filter size	Small convolution filter size
Good at:	Large noises on low-frequency areas	Noises on high-frequency areas
Bad at:	Noises on high-frequency areas	Large noises on low-frequency areas

Network architecture



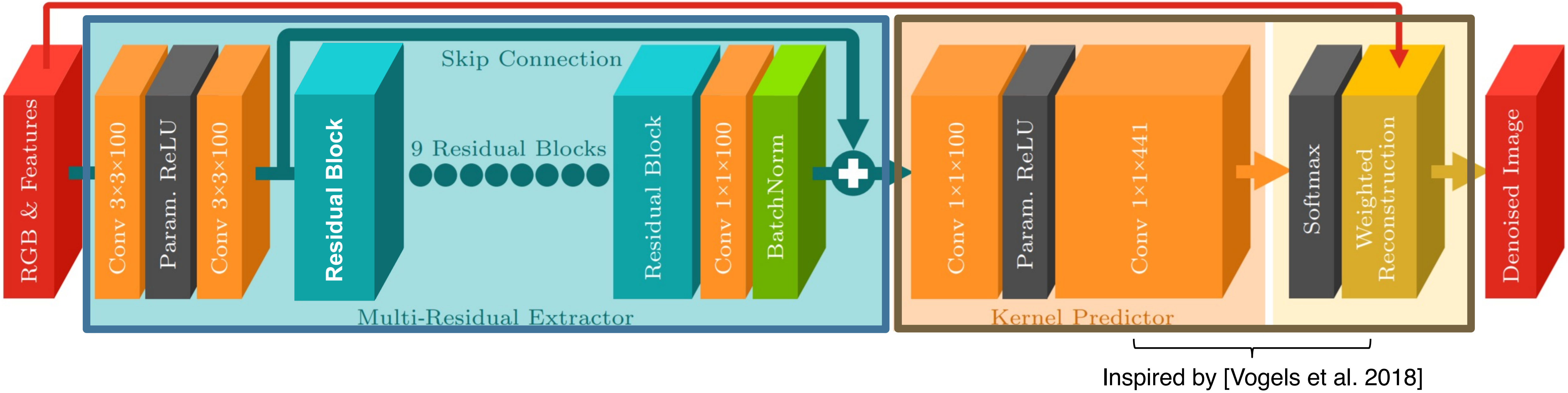
Network architecture





[Abdi et al. 2016]

Network architecture



Experimental setup

- Use 827 different training scenes to generate training data.
- Take 10% of this training data as validation data.
- Several challenging scenes with complex illumination effects as the test data.

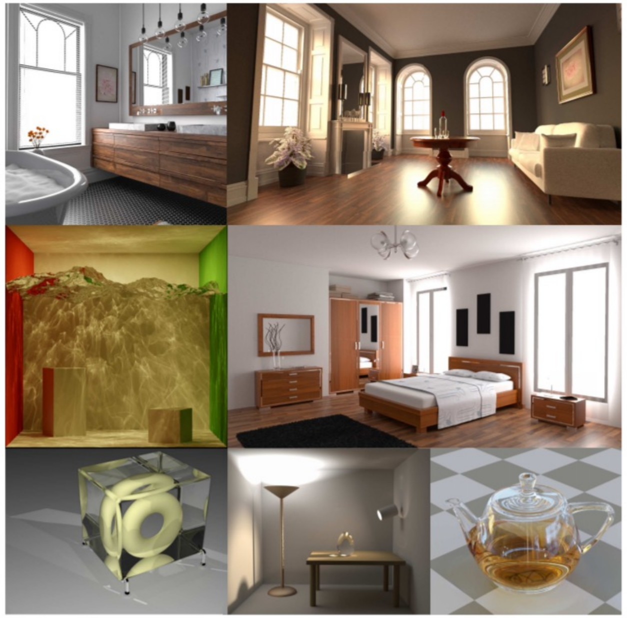


Fig.7. Selected training images from our dataset.

- All rendered with Mitsuba. [Wenzel 2010]
- Implement our networks in TensorFlow.
- Keep the number of parameters reasonably low.

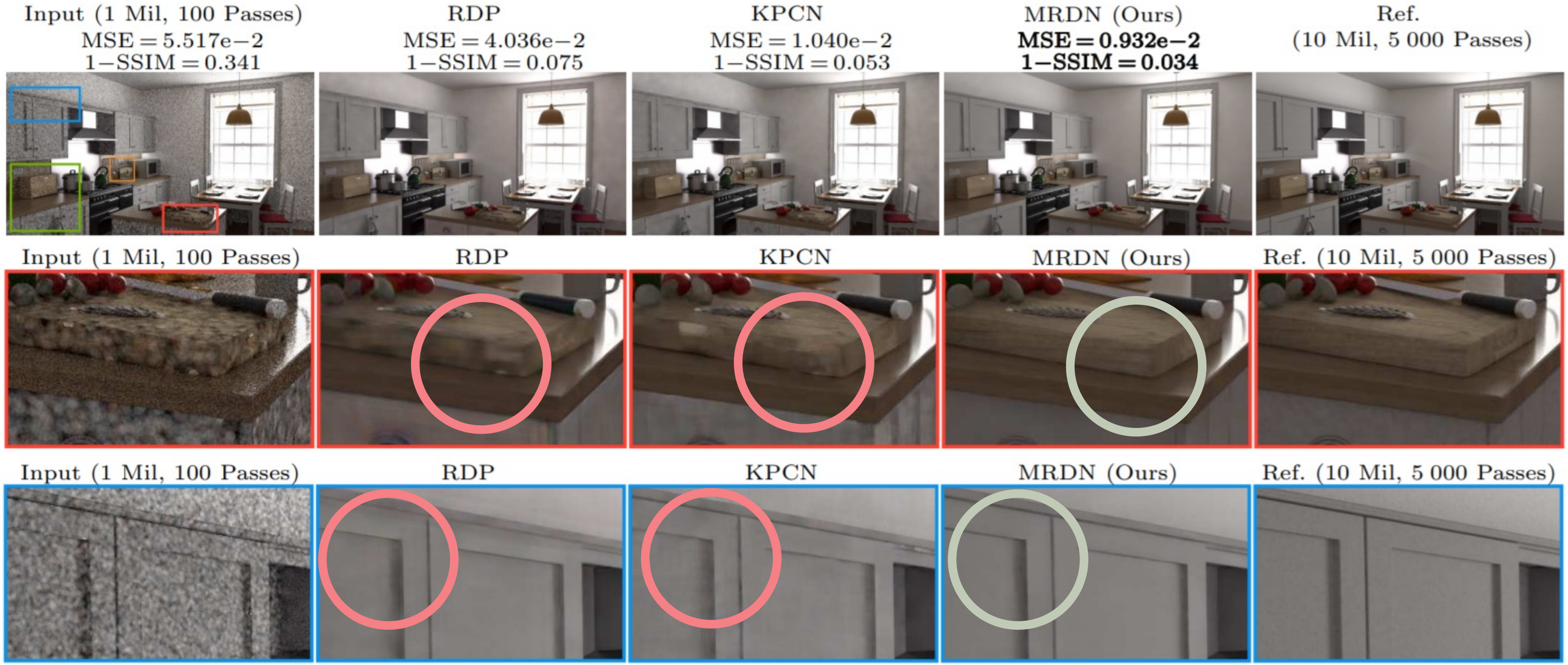
Table 1. Trainable Parameters and FLOPS

Method	# Parameters	FLOPS
MRDN (ours)	2 579 841	5 153 429
KPCN	2 973 741	5 945 023
RDP	2 819 075	5 632 443

Note: #: Number of.

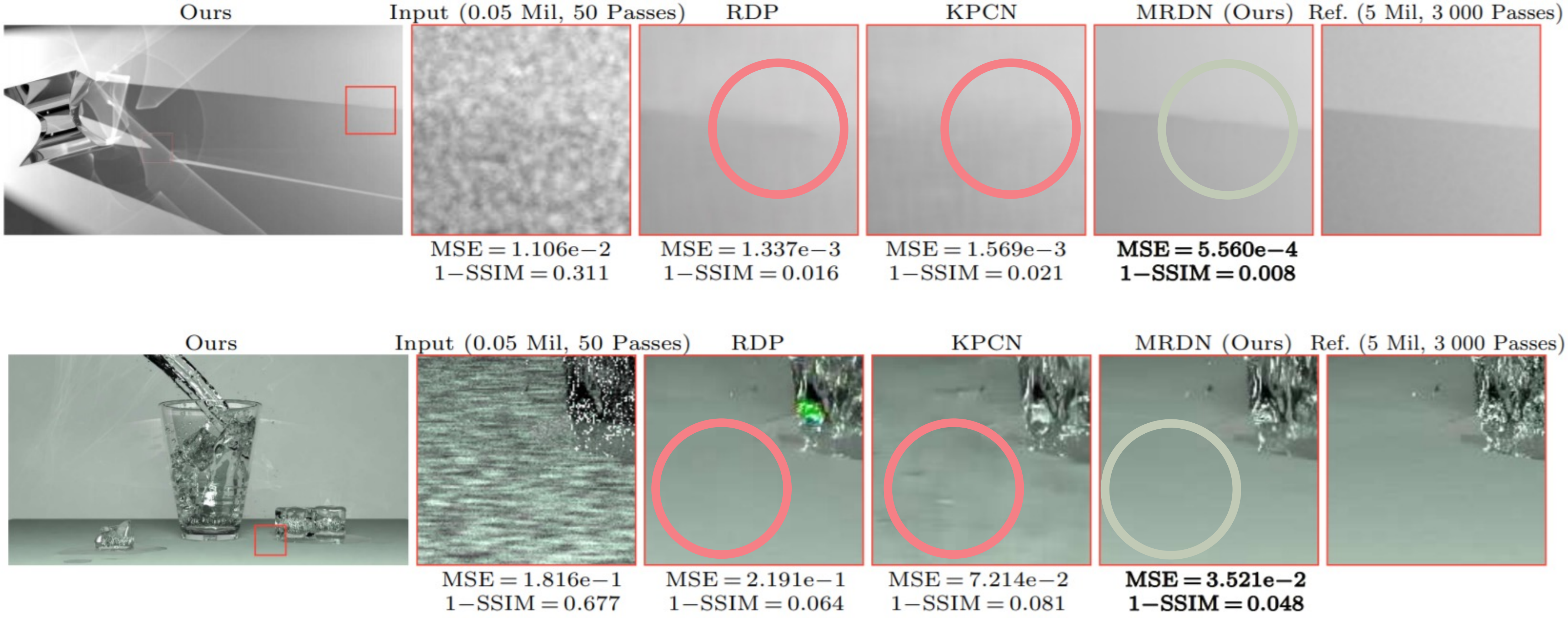
Results

Denoising quality



[Wong et al. 2019] [Bako et al. 2017]

Denoising quality



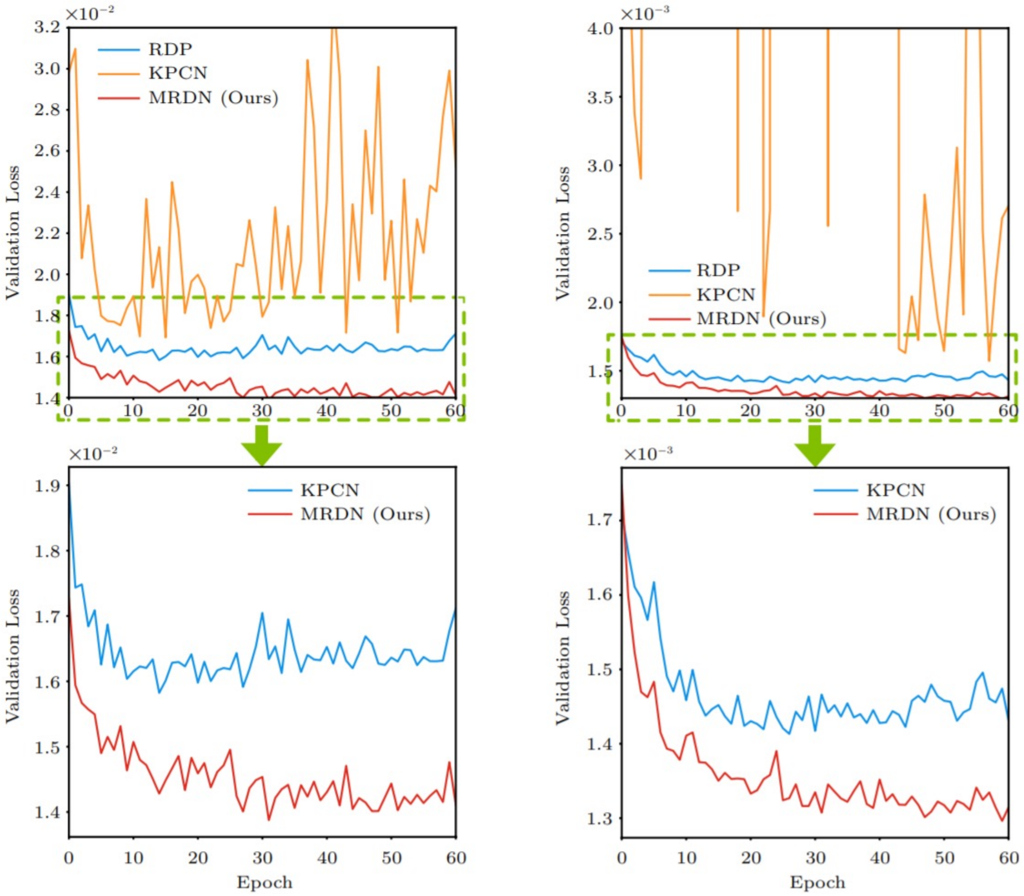
[Wong et al. 2019] [Bako et al. 2017]

Performance analysis

Inference: (for a 1920*1080 image)

- KPCN: 10s
- MRDN (Ours): 14s
- RDP: 15s

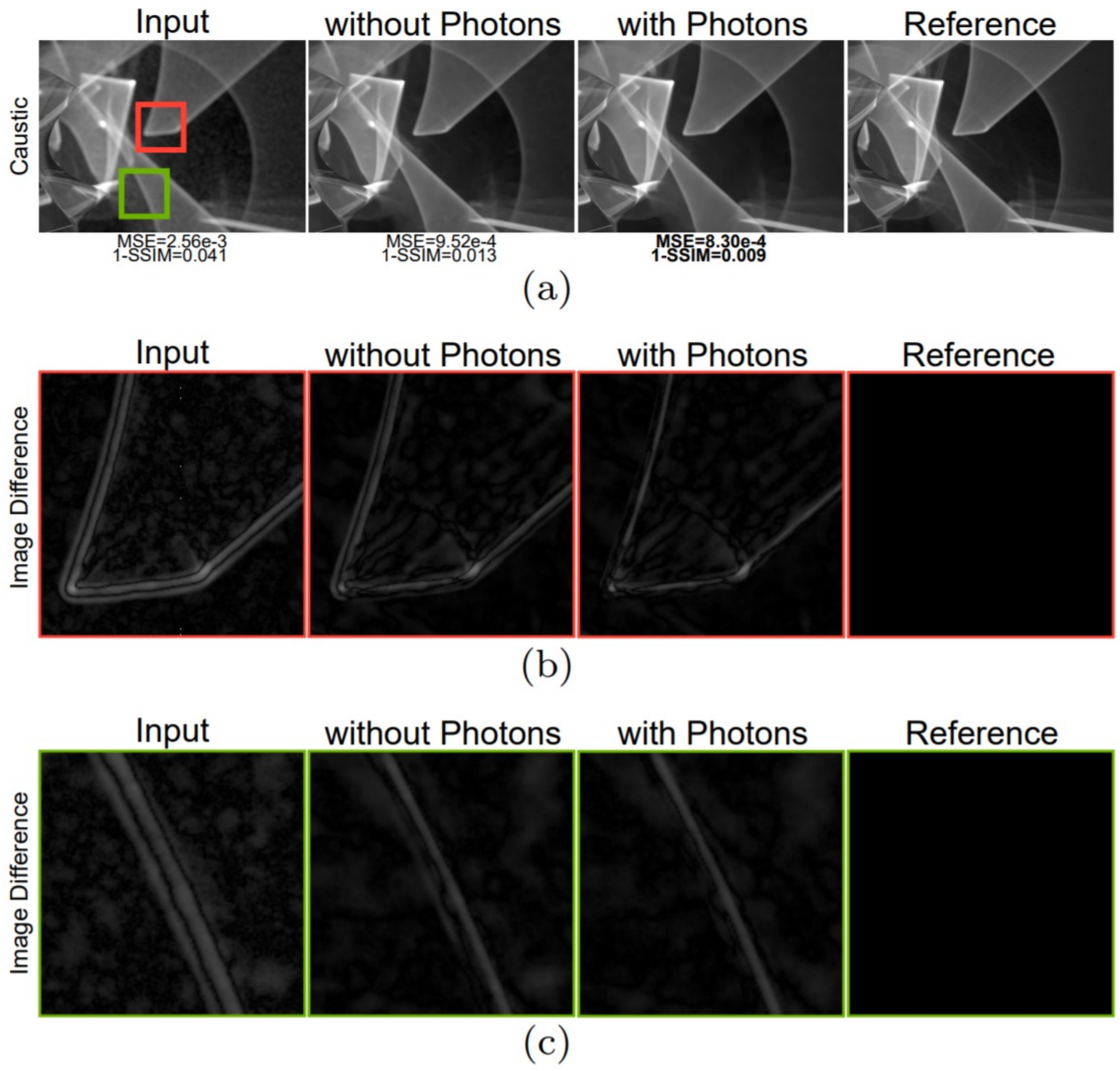
Training:

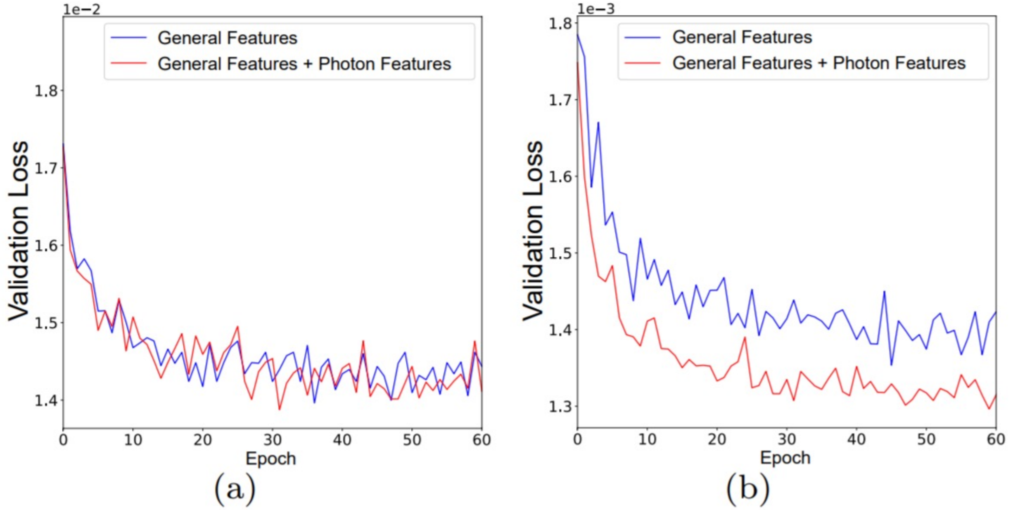


Global

Caustic

MRDN analysis: Are photon-related features useful?

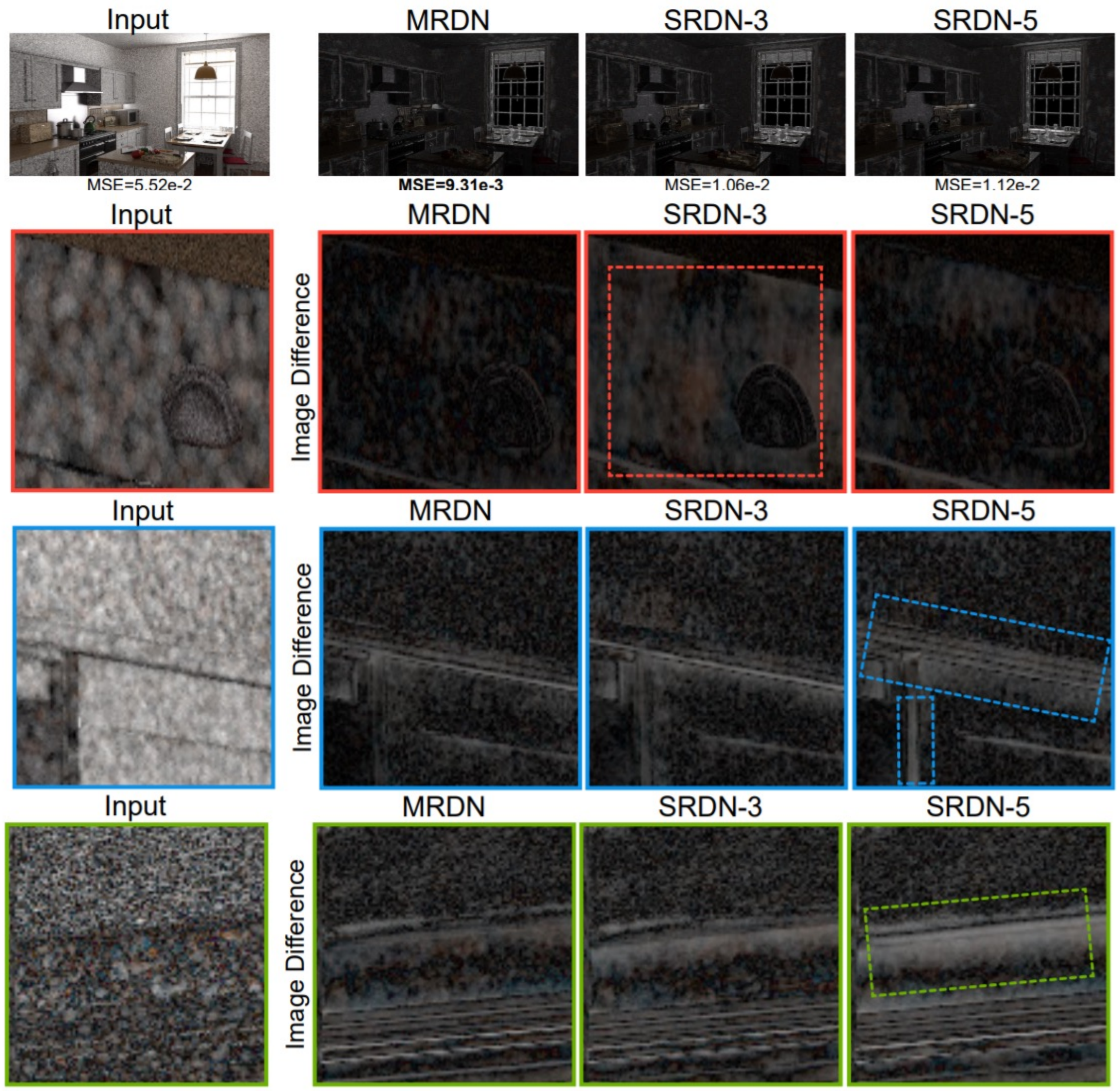


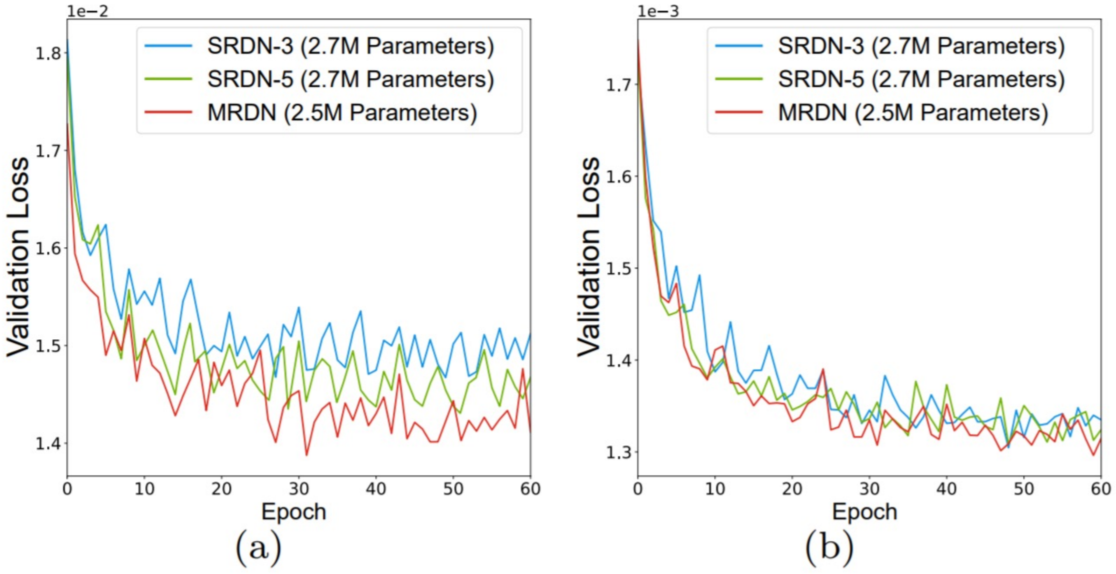


Global

Caustic

MRDN analysis: Are the multi-residual blocks useful?





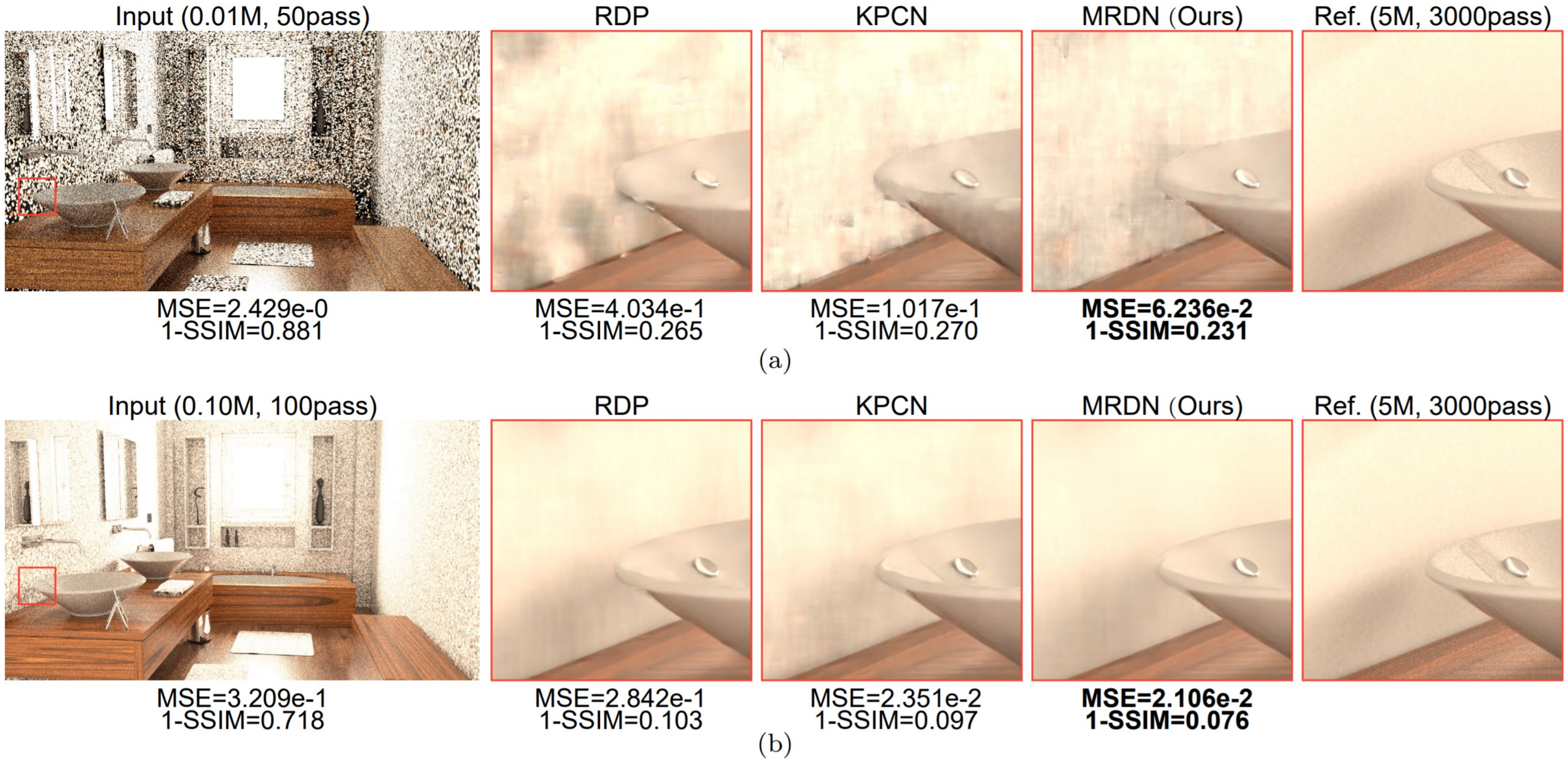
Global

Caustic

Limitations

Limitations and Future Works

- It could not handle extremely large noises which are very different from noises in our training dataset.
- It would be useful to expand our method to handle animated sequences.



Summary

Summary

- The first learning-based method for biased SPPM denoising.
- A novel deep residual denoising network with multi-residual blocks.
- A series of photon-related auxiliary features.

Acknowledgements and thanks

Thanks to our enormous reviewers for their insightful comments on the paper, as these comments led us to an improvement of the work.

Thanks for your attention

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