ENSEMBLE DENOISING FOR MONTE CARLO RENDERINGS

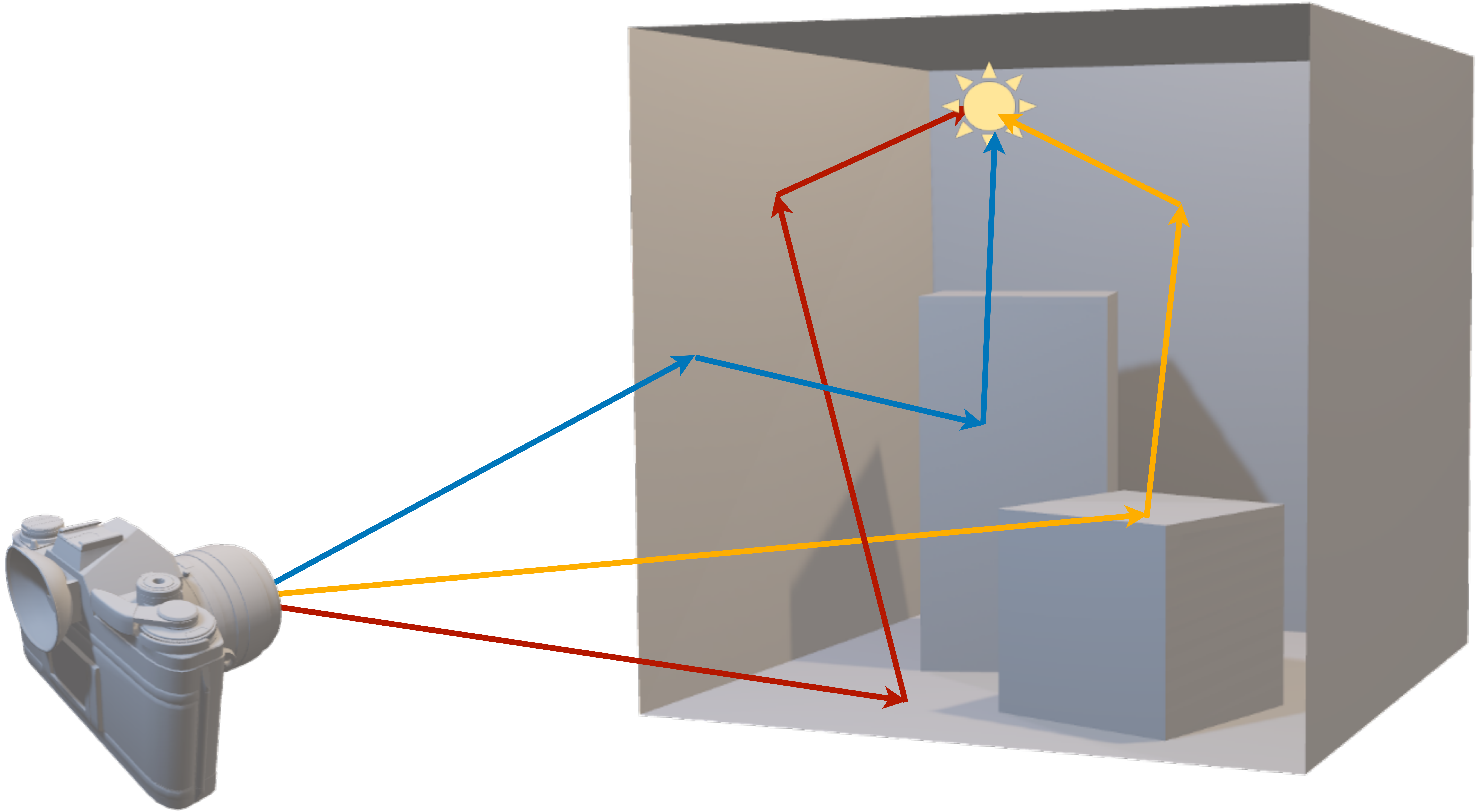
Shaokun Zheng, Fengshi Zheng, Kun Xu, and Ling-Qi Yan

SIGGRAPH Asia 2021

郑少锟 清华大学 2022 年 7 月 7 日

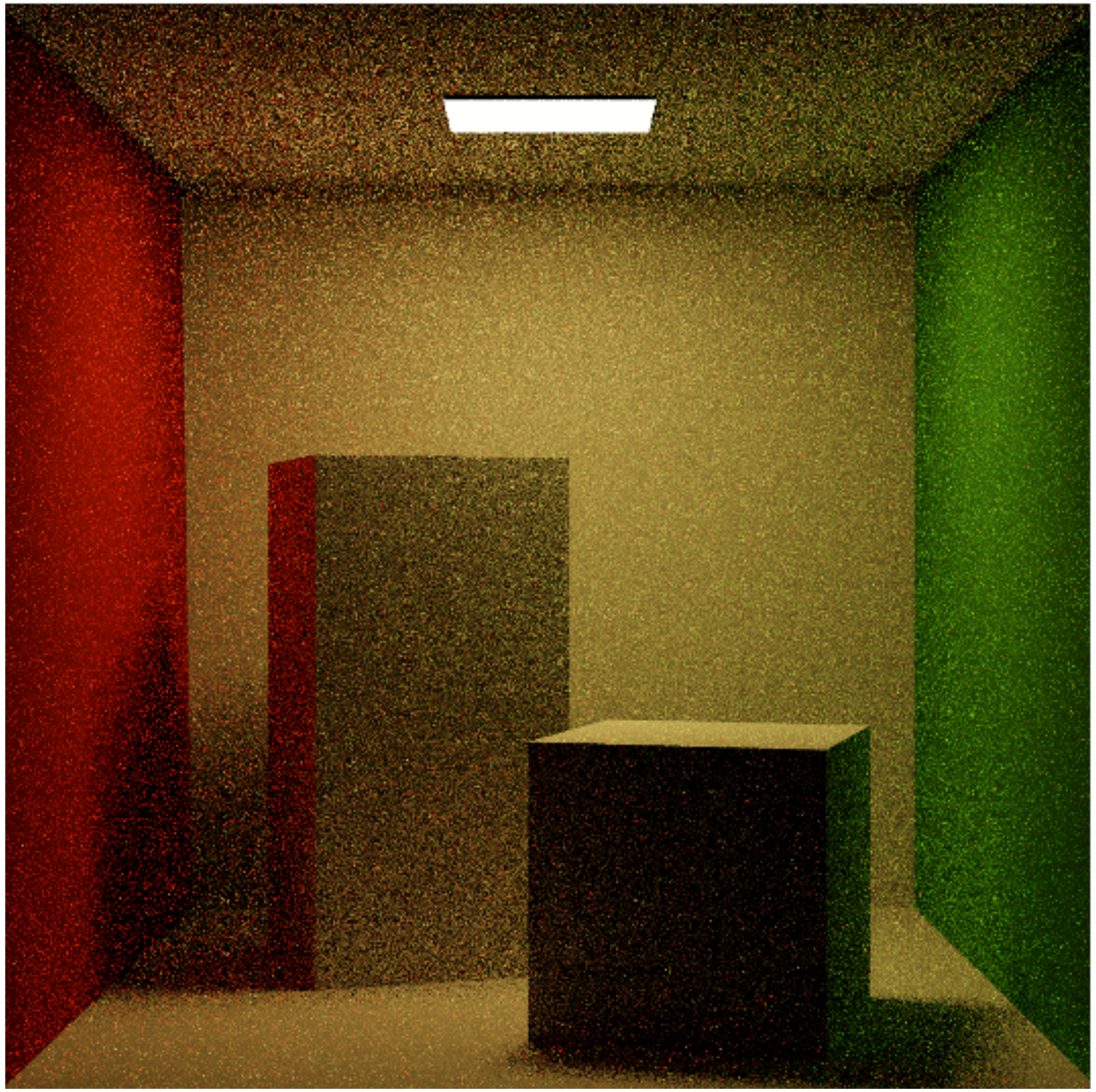
BACKGROUND

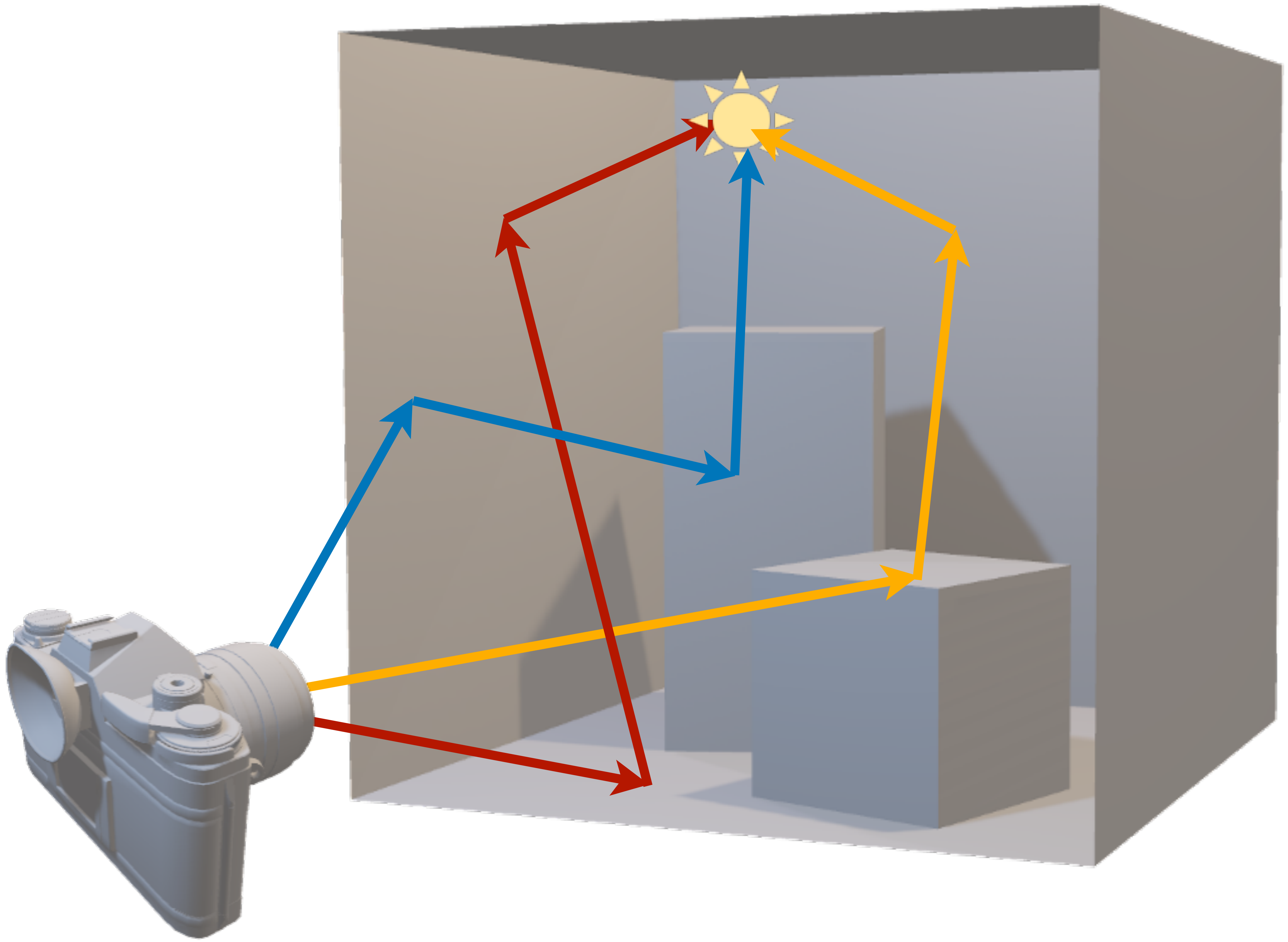
MONTE CARLO RENDERING



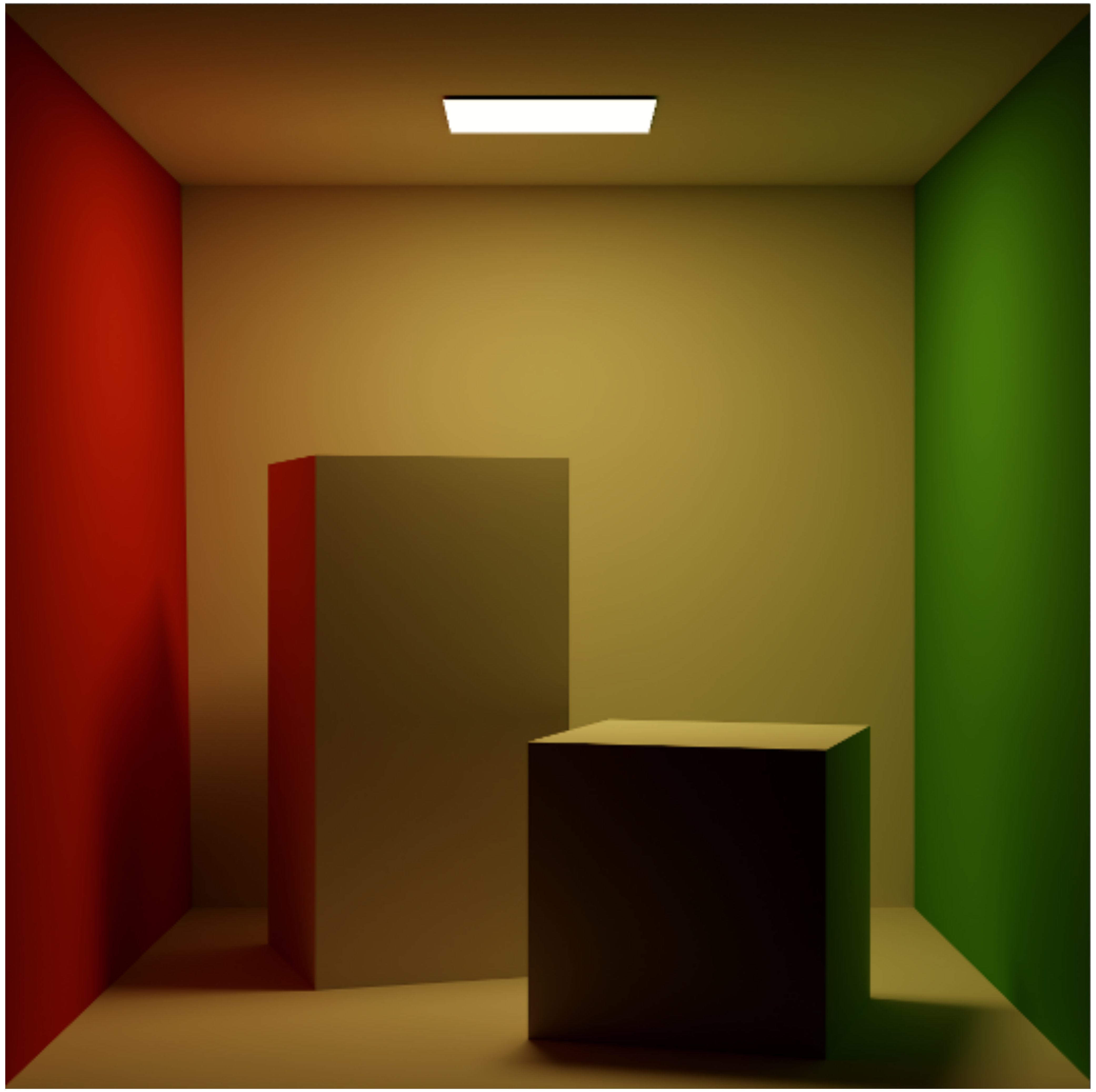
MONTE CARLO RENDERING

$$I = \int f(x)\,\mathrm{d}x \approx \frac{1}{N}\sum_{i=1}^{N}\frac{f(x_i)}{p(x_i)}$$

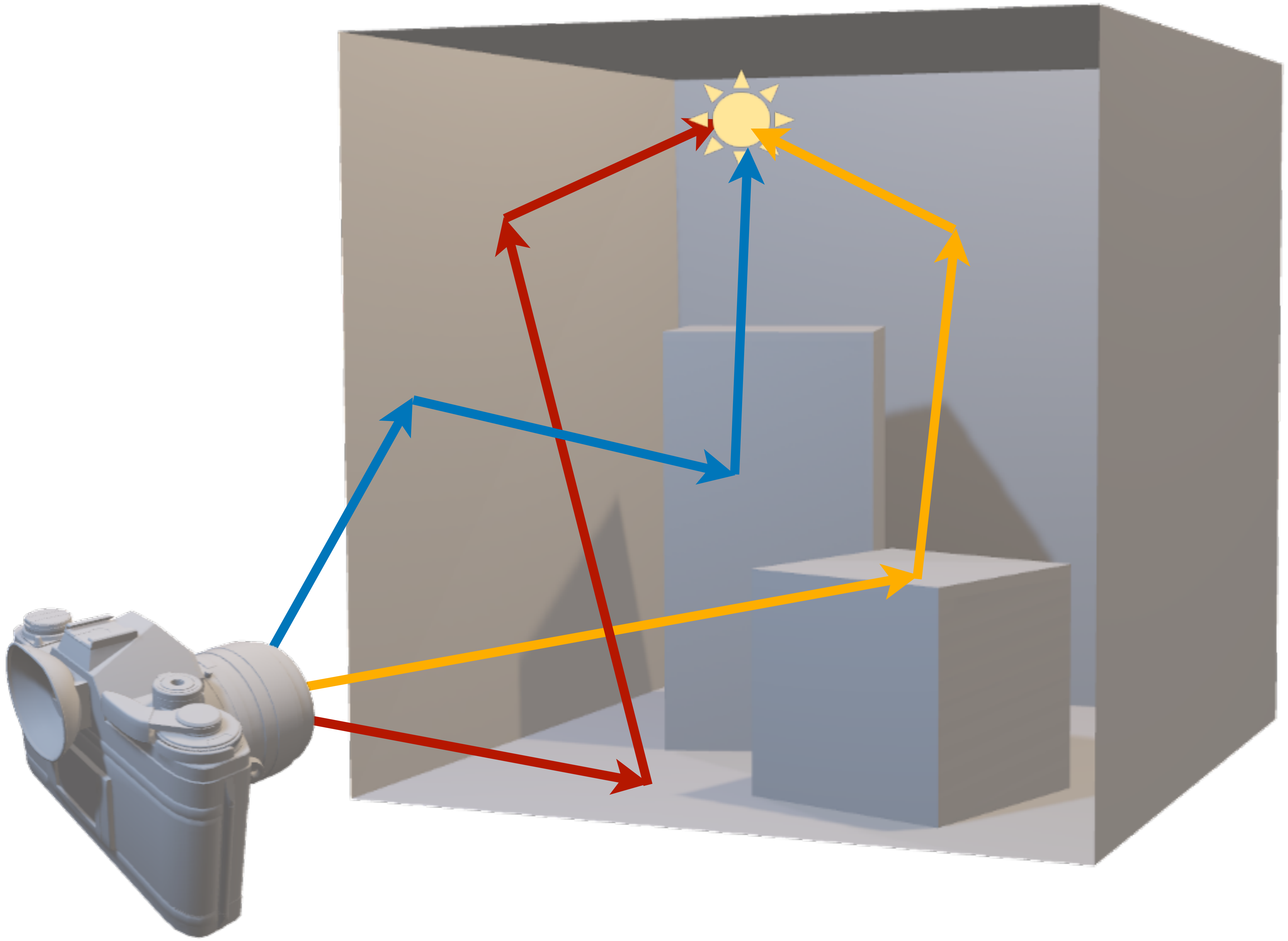




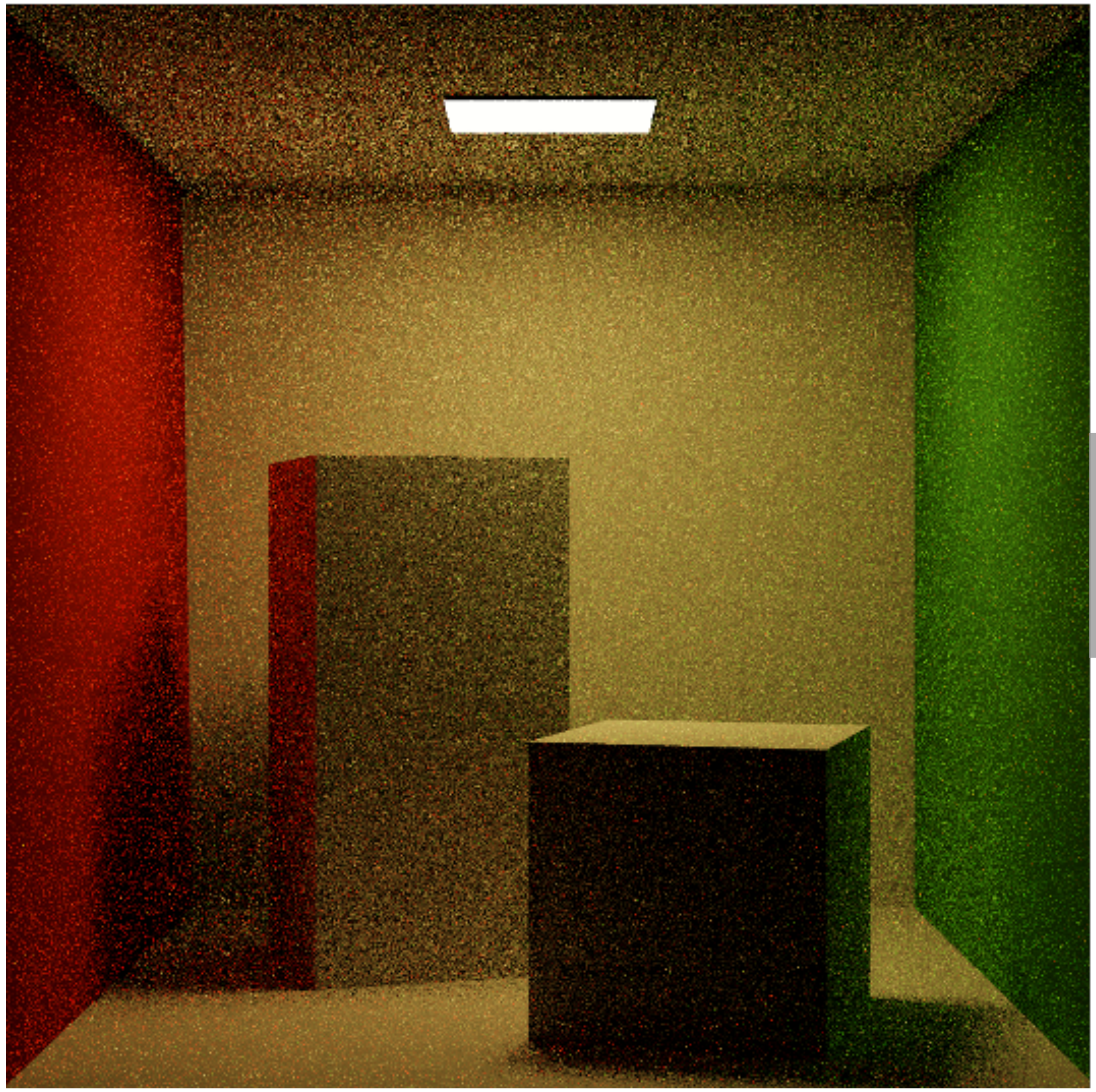
MONTE CARLO RENDERING



$$I = \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} \frac{f(x_i)}{p(x_i)}$$

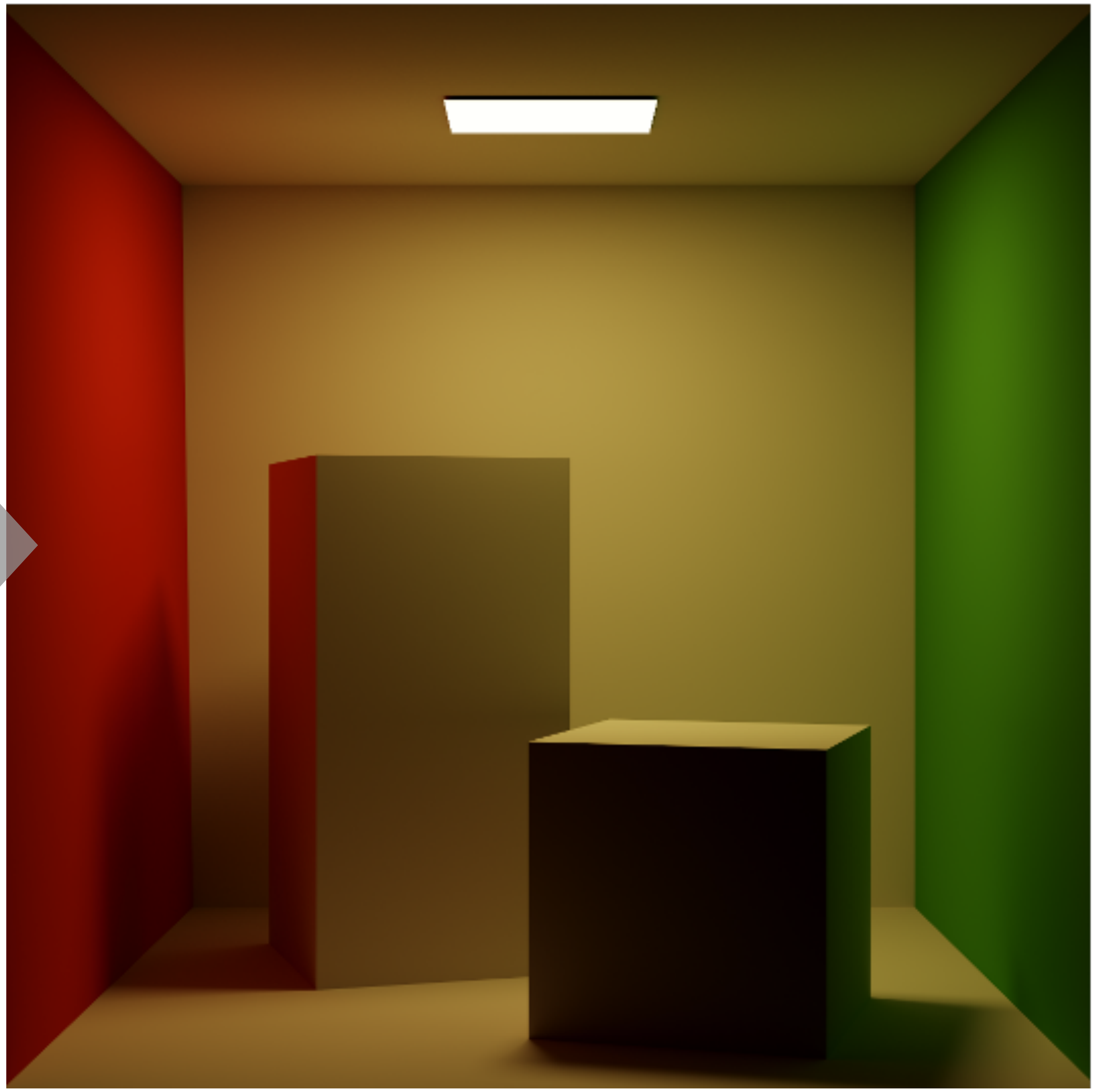


MONTE CARLO DENOISING



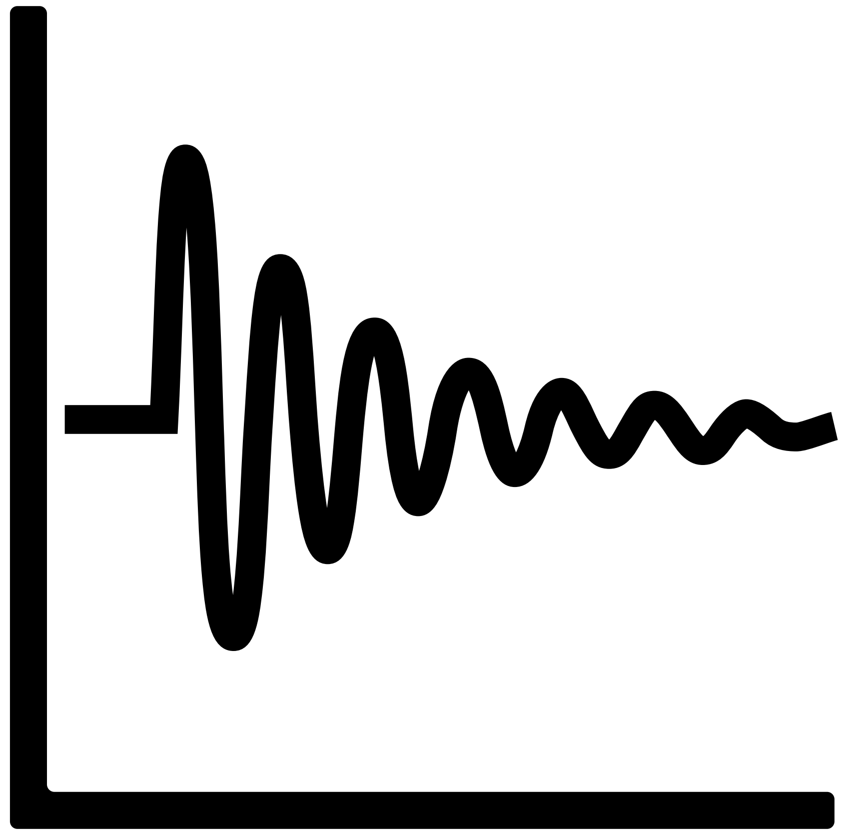
低采样数噪声图像

降噪器

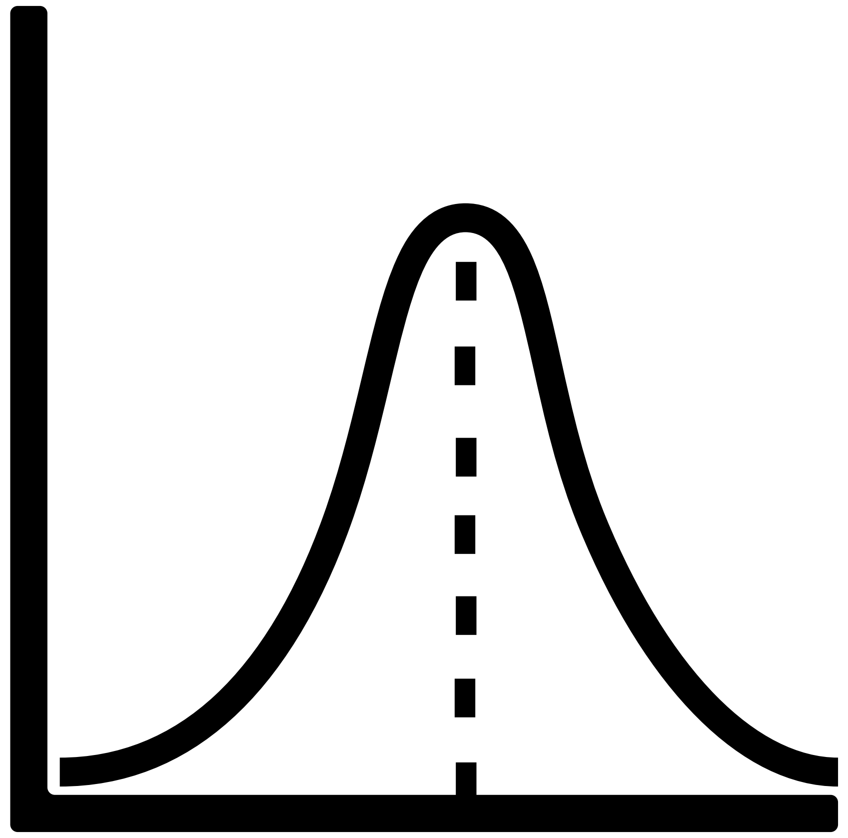


无噪声图像

MONTE CARLO DENOISING

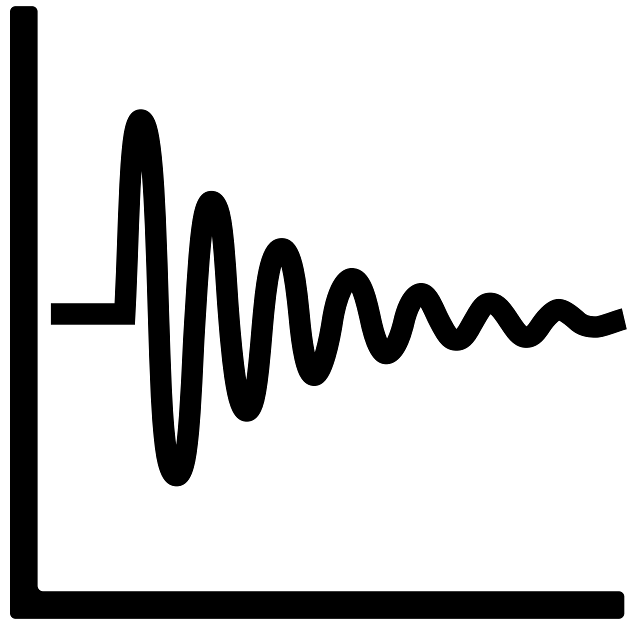


滤波



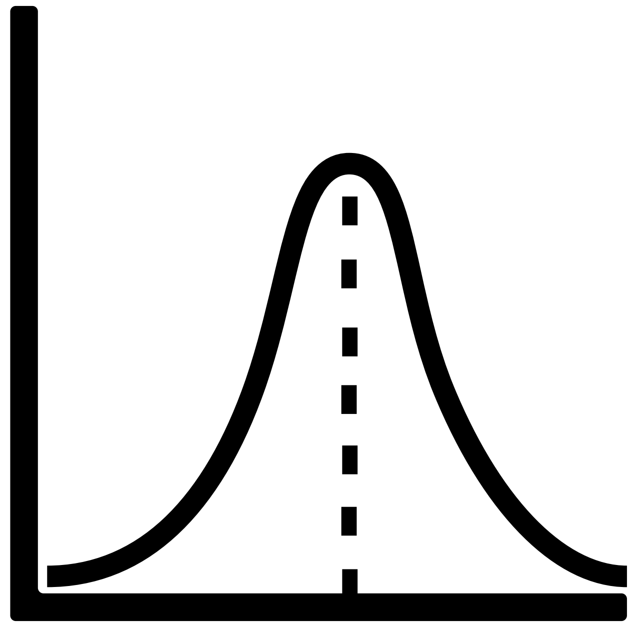
回归

MONTE CARLO DENOISING



滤波

深度学习



回归

EXISTING MONTE CARLO DENOISERS

- RDFC: Robust Denoising using Feature and Color Information [Rousselle et al. 2013]
- NFOR: Nonlinearly Weighted First-Order Regression for Denoising Monte Carlo Renderings [Bitterli et al. 2016]
- KPCN: Kernel-Predicting Convolutional Networks [Bako et al. 2017]
- MCGAN: Adversarial Monte Carlo Denoising [Xu et al. 2019]
- OptiX: AI Denoiser in the NVIDIA’s OptiX Raytracing Framework
- OIDN: Intel’s Open Image Denoise Library

Glass of Water (128spp)

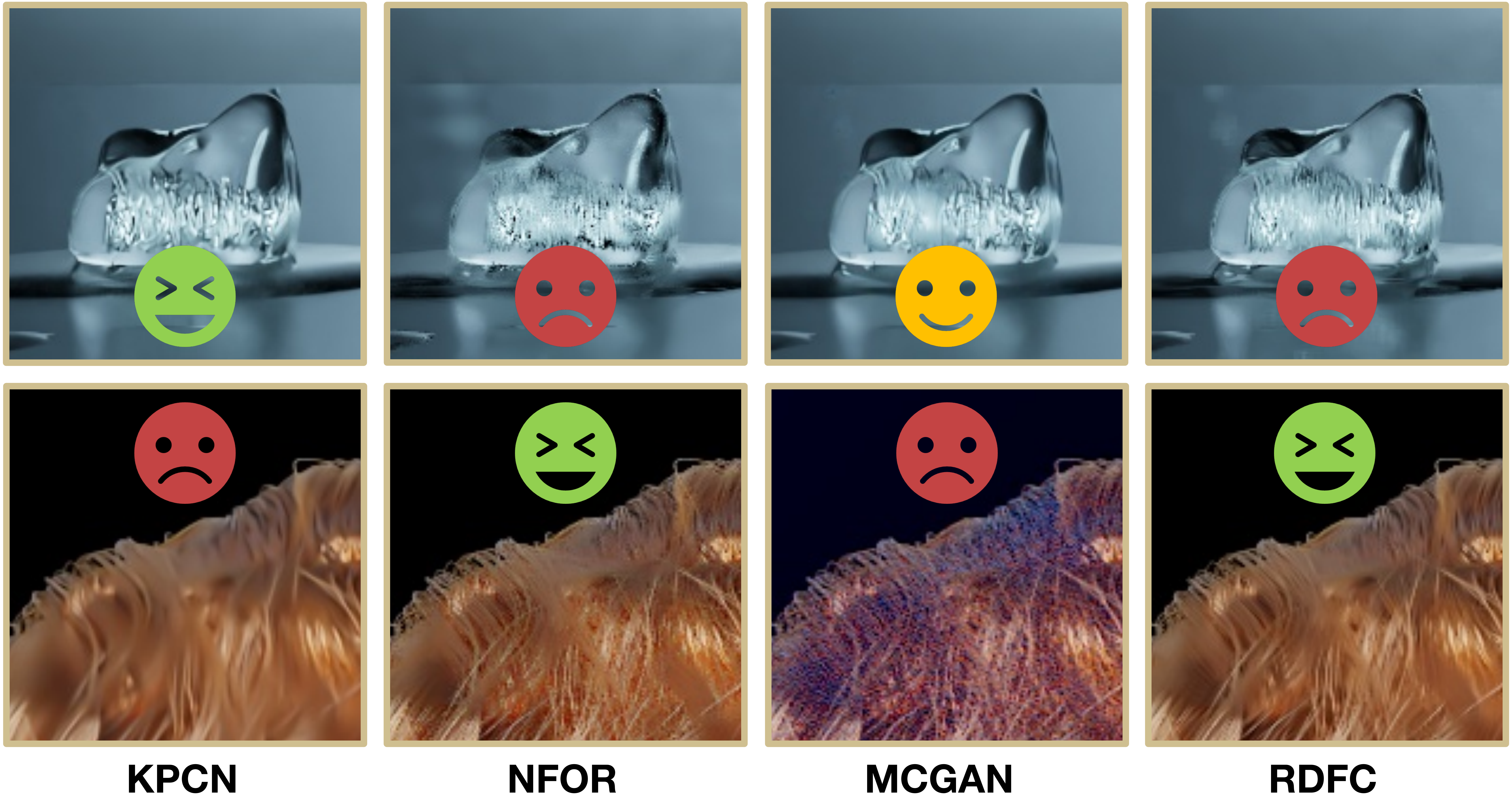
Glass of Water (128spp)


KPCN
NFOR
MCGAN
RDFC
Glass of Water (128spp)


Curly Hair (64spp)


Curly Hair (64spp)


KPCN
NFOR
MCGAN
RDFC
Curly Hair (64spp)


KPCN
NFOR
MCGAN
RDFC

OptiX

OIDN

RDFC

KPCN

MCGAN

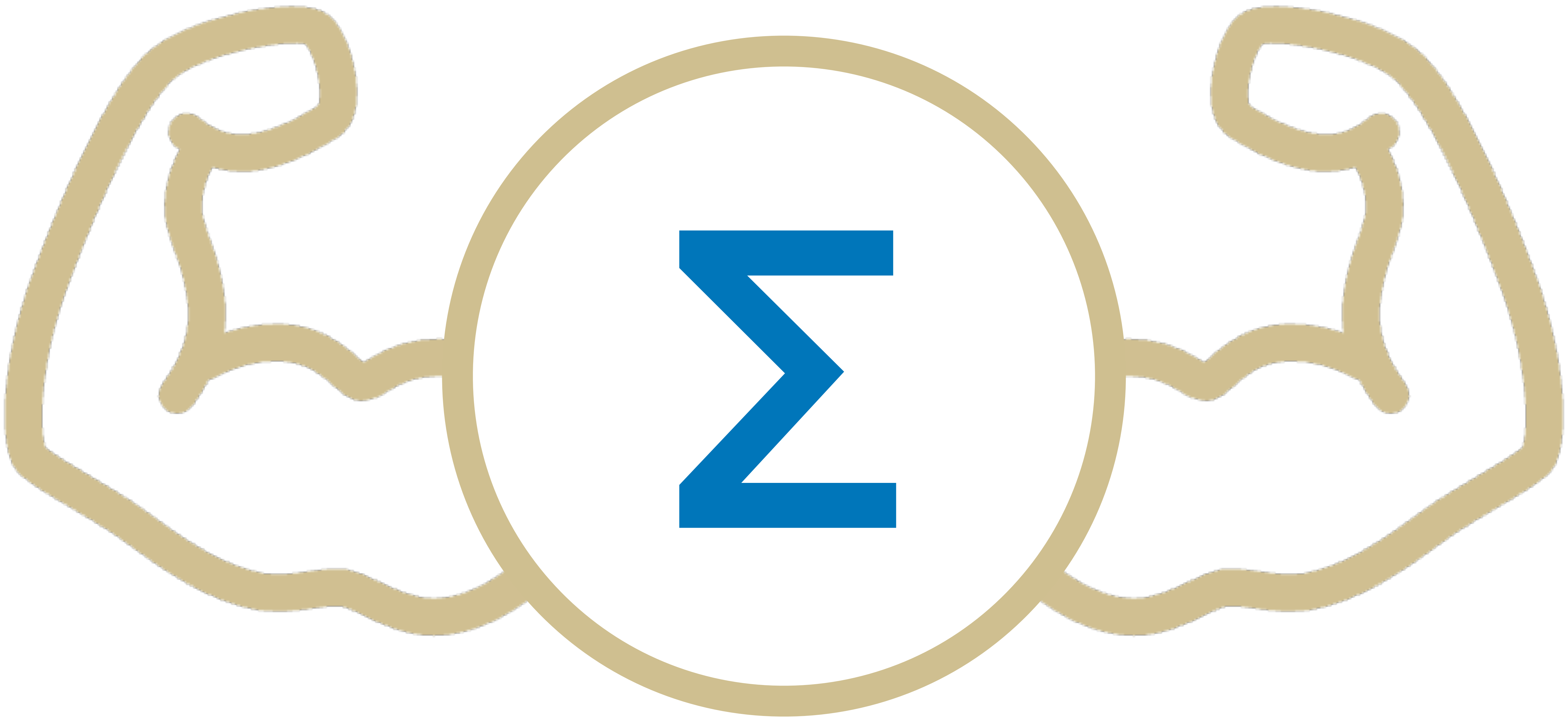
NFOR

Σ

“团结就是力量！”

ENSEMBLE: UNITY IS STRENGTH

- **集**合多个“基本”降噪器的降噪结果
- **成**就比任意单一降噪器更好的降噪效果



METHOD

IMAGE-SPACE DENOISING

噪声图像

算法参数

$$y = f(x, G; \Theta)$$

降噪结果

辅助特征图像

…WITH MULTIPLE DENOISERS

$$y_1 = f_1(x, G; \Theta_1)$$

…WITH MULTIPLE DENOISERS

$$y_1 = f_1(x, G; \Theta_1)$$
$$y_2 = f_2(x, G; \Theta_2)$$
$$y_3 = f_3(x, G; \Theta_3)$$
$$y_4 = f_4(x, G; \Theta_4)$$

…

MODEL

$$y_1 = f_1(x, G; \Theta_1)$$

$$y_2 = f_2(x, G; \Theta_2)$$

$$y_3 = f_3(x, G; \Theta_3)$$

$$y_4 = f_4(x, G; \Theta_4)$$

...

$$z(p) = \sum_{i=1}^{N} w_i(p) y_i(p)$$

集成降噪结果 权重 基本降噪结果

$$\text{s.t.} \quad \sum_{i=1}^{N} w_i = 1 \text{ and } w_i \geq 0$$

MODEL

$$y_1 = f_1(x, G; \Theta_1)$$

$$y_2 = f_2(x, G; \Theta_2)$$

$$y_3 = f_3(x, G; \Theta_3)$$

$$y_4 = f_4(x, G; \Theta_4)$$

...

$$z(p) = \sum_{i=1}^{N} w_i(p) y_i(p)$$

集成降噪结果 权重 基本降噪结果

$$\Leftrightarrow \quad z = \mathbf{w}^\top \mathbf{y}$$

$$\text{s.t.} \ \sum_{i=1}^{N} w_i = 1 \ \text{and} \ w_i \geq 0$$

OBJECTIVE

$$z = \mathbf{w}^\top \mathbf{y}$$

$$\mathbf{w}^* = \min_{\mathbf{w}} \mathbb{E}[(z - \boxed{\mu})^2]$$

参考图像 未知!

$$\text{s.t.} \sum_{i=1}^{N} w_i = 1 \text{ and } w_i \geq 0$$

OBJECTIVE

$$z = \mathbf{w}^\top \mathbf{y}$$

$$\mathbf{w}^* = \min_{\mathbf{w}} \mathbb{E}[(z - \mu)^2]$$

需要估计

$$\text{s.t.} \sum_{i=1}^{N} w_i = 1 \text{ and } w_i \geq 0$$

THE MSE MATRIX

$$\frac{\mathbb{E}[(\mathbf{w}^\top \mathbf{y} - \mu)^2]}{\mathbf{w}^\top \underbrace{\mathbb{E}[(\mathbf{y} - \mu\mathbf{1})(\mathbf{y} - \mu\mathbf{1})^\top]}_{\mathbf{M}} \mathbf{w}}$$

MSE 矩阵

MSE MATRIX ESTIMATION

$$\frac{\mathbb{E}[(\mathbf{y}-\mu 1)(\mathbf{y}-\mu 1)^\top]}{\mathbb{E}[\mathbf{y}\mathbf{y}^\top]+\mathbb{E}[x1]\mathbb{E}[x1^\top] \\ -\mathbb{E}[x1]\mathbb{E}[\mathbf{y}^\top]-\mathbb{E}[\mathbf{y}]\mathbb{E}[x1^\top]}$$

MSE MATRIX ESTIMATION

$$\frac{\mathbb{E}[(\mathbf{y} - \mu 1)(\mathbf{y} - \mu 1)^\top]}{\mathbb{E}[\mathbf{y}\mathbf{y}^\top] + \mathbb{E}[x1]\mathbb{E}[x1^\top] - \mathbb{E}[x1]\mathbb{E}[\mathbf{y}^\top] - \mathbb{E}[\mathbf{y}]\mathbb{E}[x1^\top]}$$

存在相关性！

MSE MATRIX ESTIMATION

$$\frac{\mathbb{E}[\mathbf{y}\mathbf{y}^\top] + \boxed{\mathbb{E}[x1]}\boxed{\mathbb{E}[x1^\top]} - \boxed{\mathbb{E}[x1]}\boxed{\mathbb{E}[\mathbf{y}^\top]} - \boxed{\mathbb{E}[\mathbf{y}]}\boxed{\mathbb{E}[x1^\top]}}{}$$

$$\mathrm{Cov}[A, B] = 0$$

$$\Rightarrow \quad \mathbb{E}[A]\mathbb{E}[B] = \mathbb{E}[AB] \approx AB$$

MSE MATRIX ESTIMATION

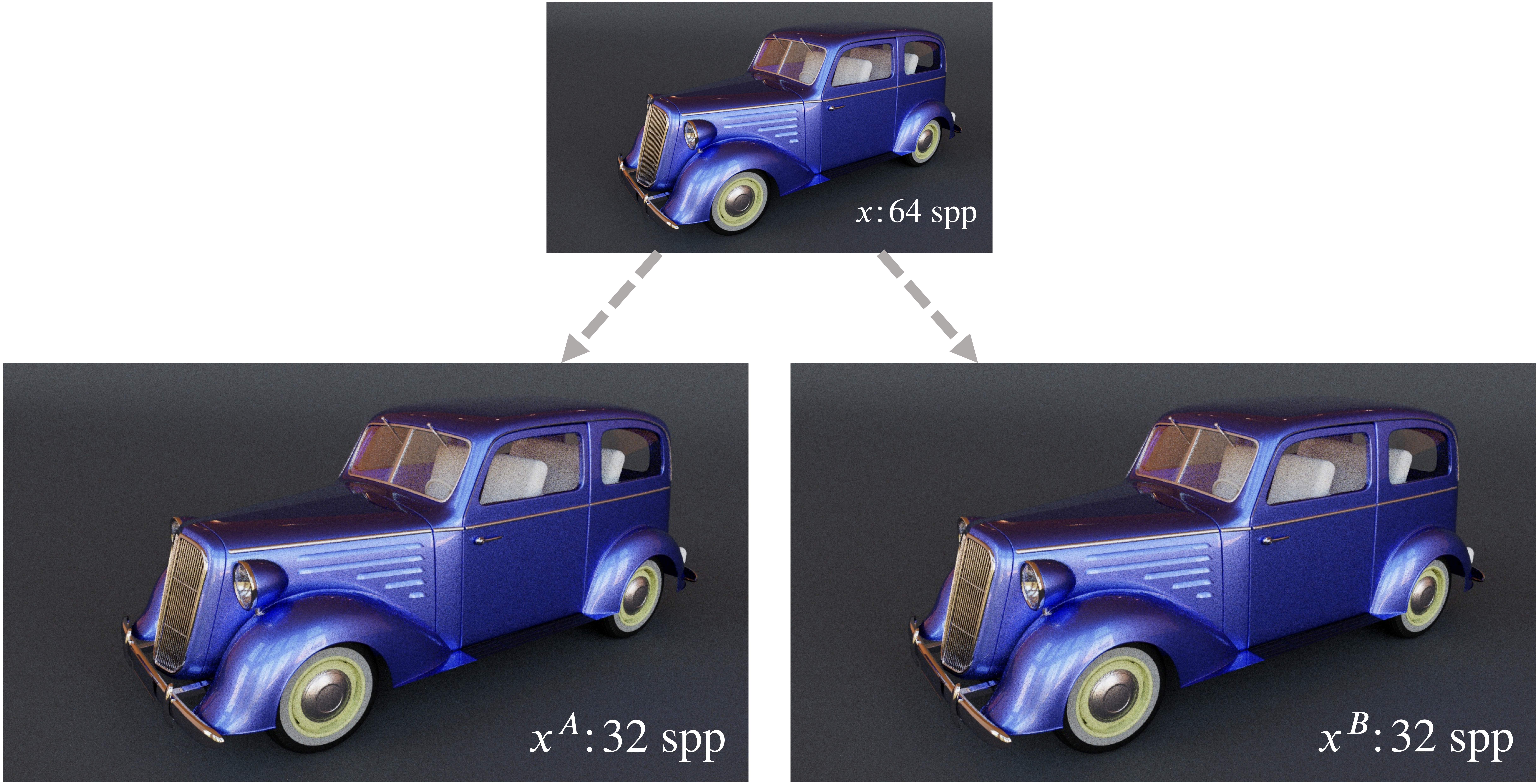
$$\mathbb{E}[\mathbf{y}\mathbf{y}^\top] + \boxed{\mathbb{E}[x1]}\boxed{\mathbb{E}[x1^\top]}$$
$$-\boxed{\mathbb{E}[x1]}\boxed{\mathbb{E}[\mathbf{y}^\top]} - \boxed{\mathbb{E}[\mathbf{y}]}\boxed{\mathbb{E}[x1^\top]}$$

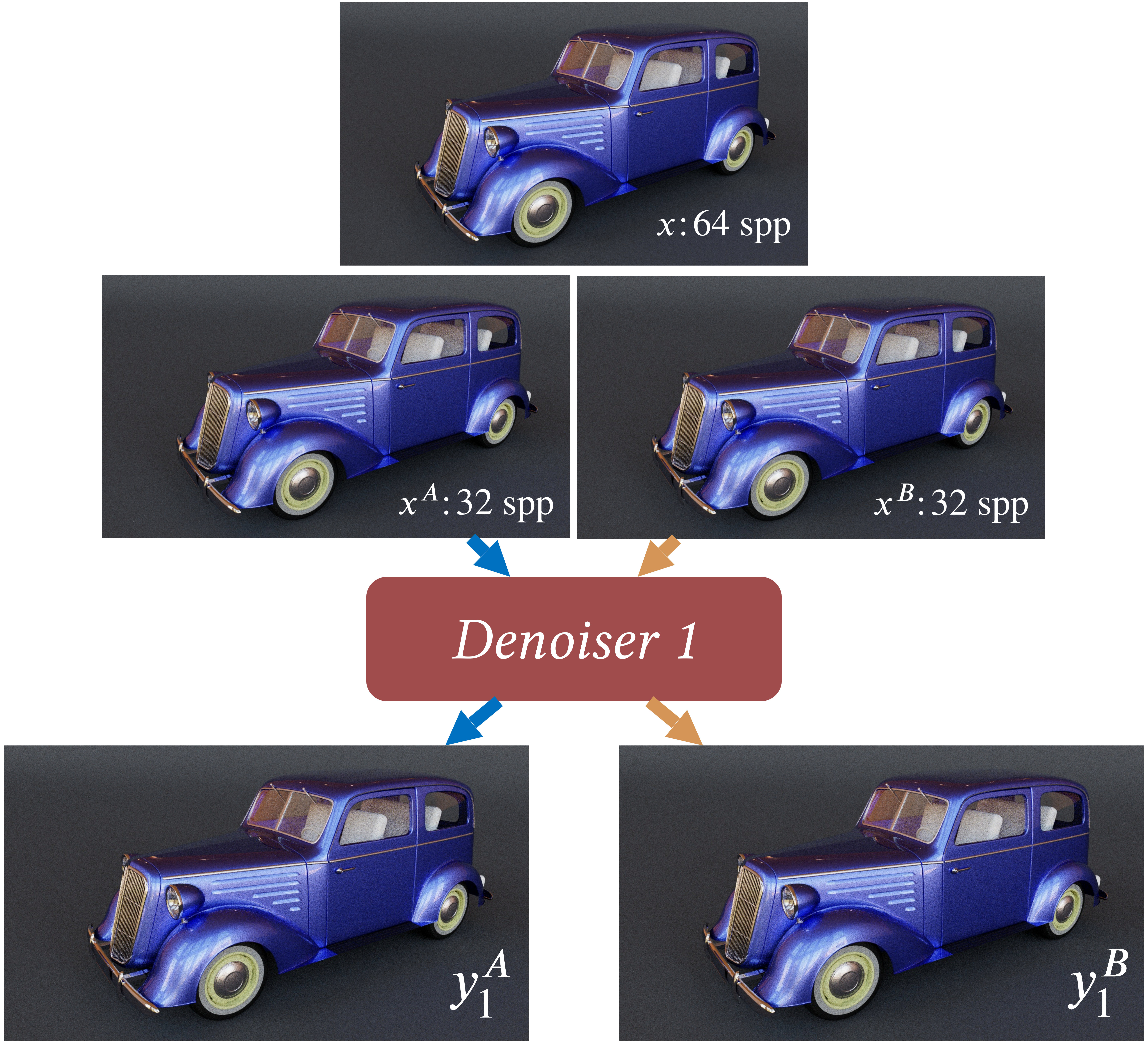
$$\mathbb{E}[x]\mathbb{E}[x] \approx x^A x^B$$
$$\mathbb{E}[x]\mathbb{E}[\mathbf{y}] \approx x^A \mathbf{y}^B \approx x^B \mathbf{y}^A$$

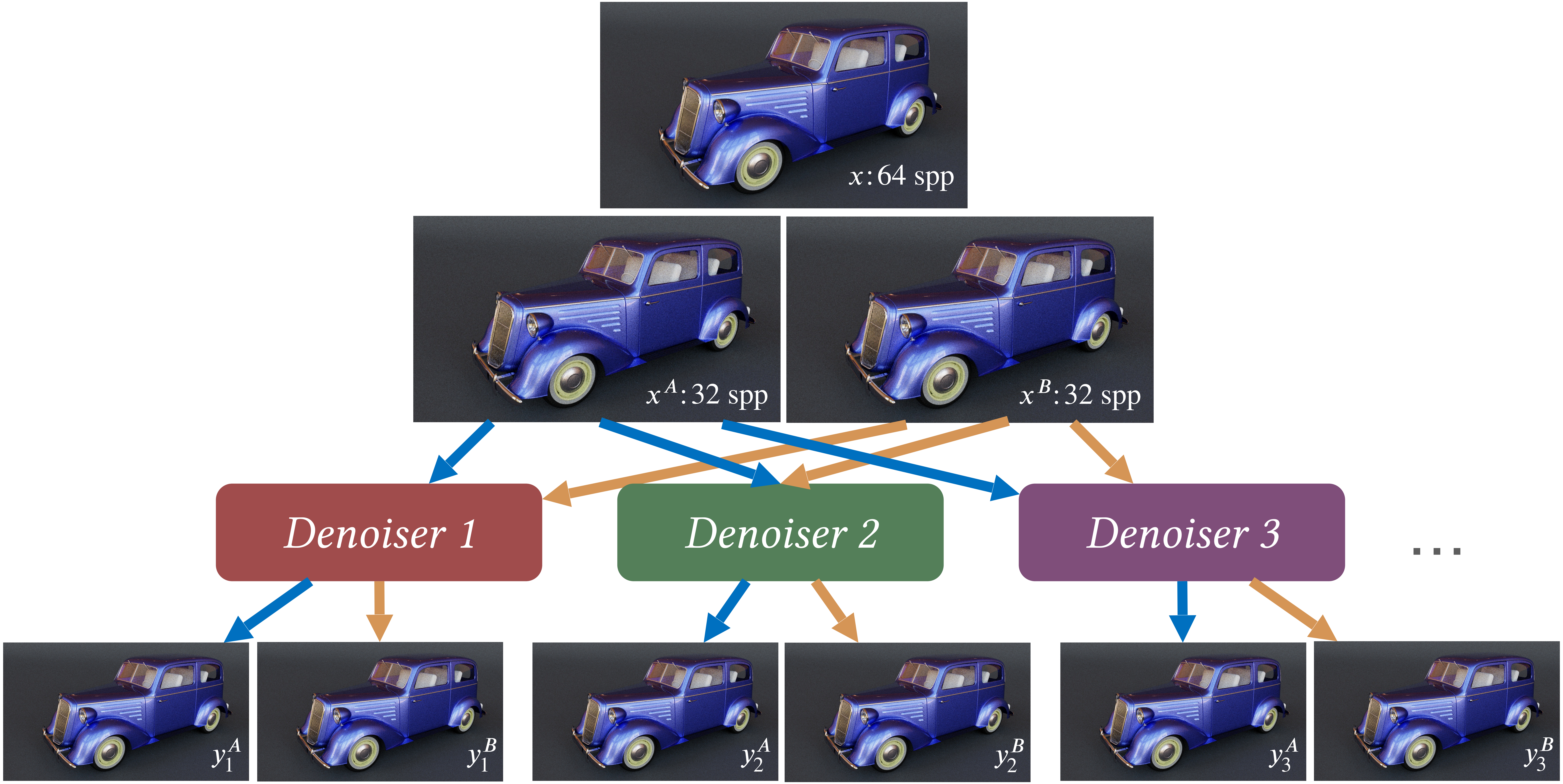
$$\text{s.t.}\ \mathrm{Cov}[x^A, x^B] = \mathrm{Cov}[x^A, y^B] = \mathrm{Cov}[x^B, y^A] = 0$$

DUAL-BUFFER STRATEGY

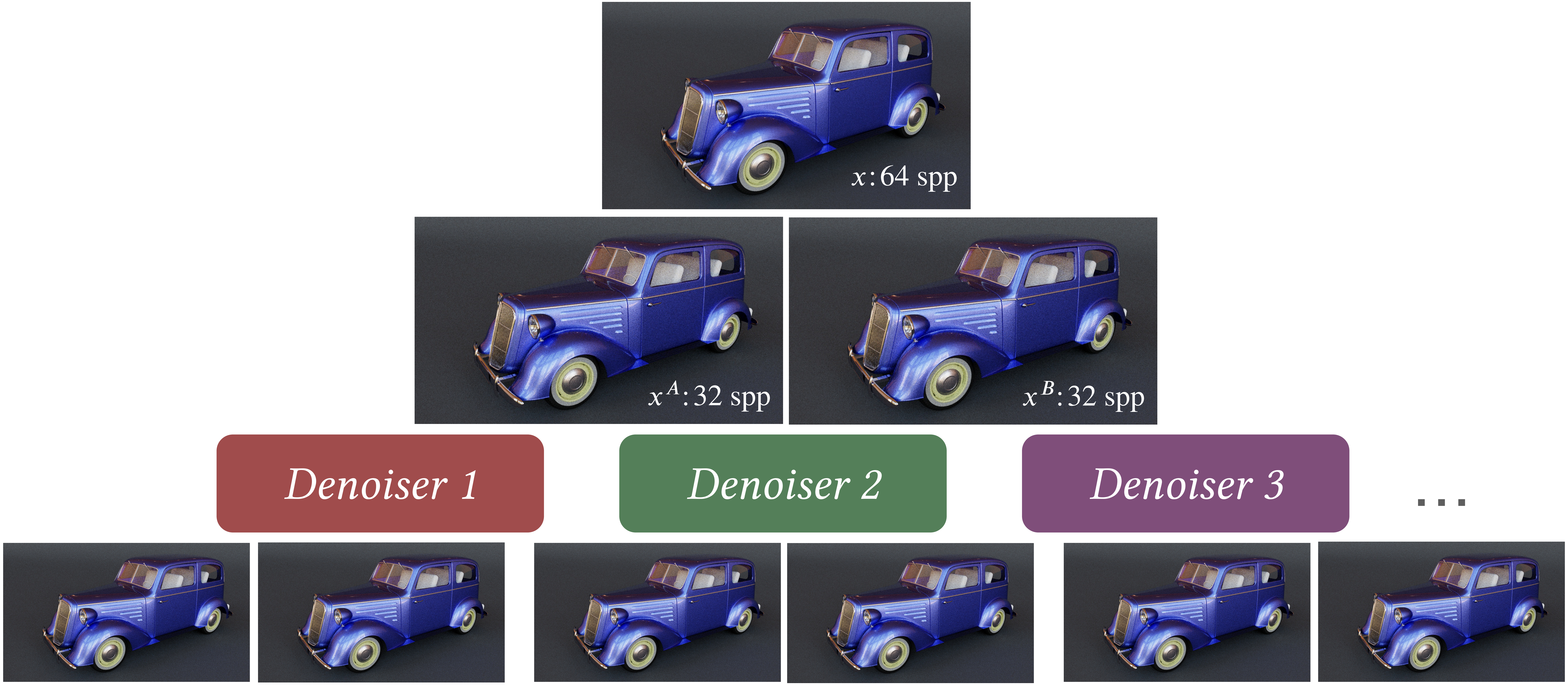
x: 64 spp


x: 64 spp
x^A: 32 spp
x^B: 32 spp


x: 64 spp
x^A: 32 spp
x^B: 32 spp
Denoiser 1
y_1^A
y_1^B



x: 64 spp
x^A: 32 spp
x^B: 32 spp
Denoiser 1
Denoiser 2
Denoiser 3
...
y_1^A
y_1^B
y_2^A
y_2^B
y_3^A
y_3^B



$$\mathbf{y}^A = \left(y_1^A,\ y_2^A,\ y_3^A,\ \ldots\right) \qquad \mathbf{y}^B = \left(y_1^B,\ y_2^B,\ y_3^B,\ \ldots\right)$$

DUAL-BUFFER MSE MATRIX ESTIMATION

$$\mathbb{E}[\mathbf{y}\mathbf{y}^\top] + \boxed{\mathbb{E}[x1]}\boxed{\mathbb{E}[x1^\top]}$$
$$-\boxed{\mathbb{E}[x1]}\boxed{\mathbb{E}[\mathbf{y}^\top]} - \boxed{\mathbb{E}[\mathbf{y}]}\boxed{\mathbb{E}[x1^\top]}$$

$$\langle \mathbf{M} \rangle^A = \mathbf{y}^A \mathbf{y}^{A\top} + x^A x^B 11^\top$$
$$- x^B \left(1\mathbf{y}^{A\top} - \mathbf{y}^A 1^\top\right)$$

$$\langle \mathbf{M} \rangle^B = \mathbf{y}^B \mathbf{y}^{B\top} + x^B x^A 11^\top$$
$$- x^A \left(1\mathbf{y}^{B\top} - \mathbf{y}^B 1^\top\right)$$

PRACTICAL OPTIMIZATION MODEL

$$\langle \mathbf{M} \rangle = \frac{1}{2}\left(\langle \mathbf{M} \rangle^{A} + \langle \mathbf{M} \rangle^{B} \right)$$

$$\min_{\mathbf{w}} \mathbf{w}^{\top} \langle \mathbf{M} \rangle \mathbf{w}$$

$$\text{s.t.} \ \sum_{i=1}^{N} w_i = 1 \ \text{ and } \ w_i \geq 0$$

PRACTICAL OPTIMIZATION MODEL

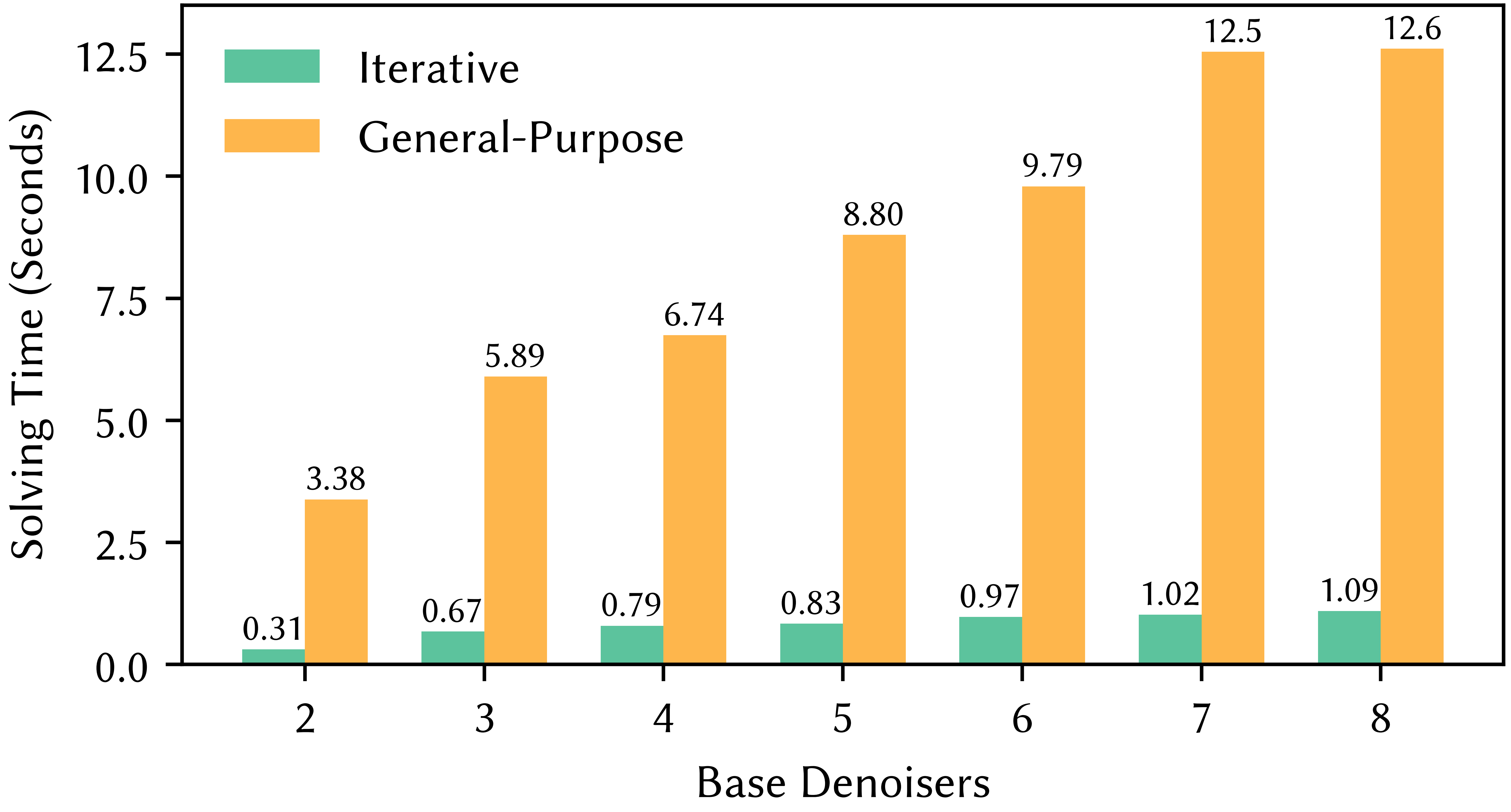
- 凸二次规划问题，保证存在全局最优解
- $\langle \mathbf{M} \rangle$ 是半采样缓冲 MSE 矩阵的无偏估计
- 若某一基本降噪器是一致的（即渐进意义下无偏），则集成降噪结果是一致的

$$\min_{\mathbf{w}} \mathbf{w}^\top \langle \mathbf{M} \rangle \mathbf{w}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} w_i = 1 \ \text{ and } \ w_i \geq 0$$

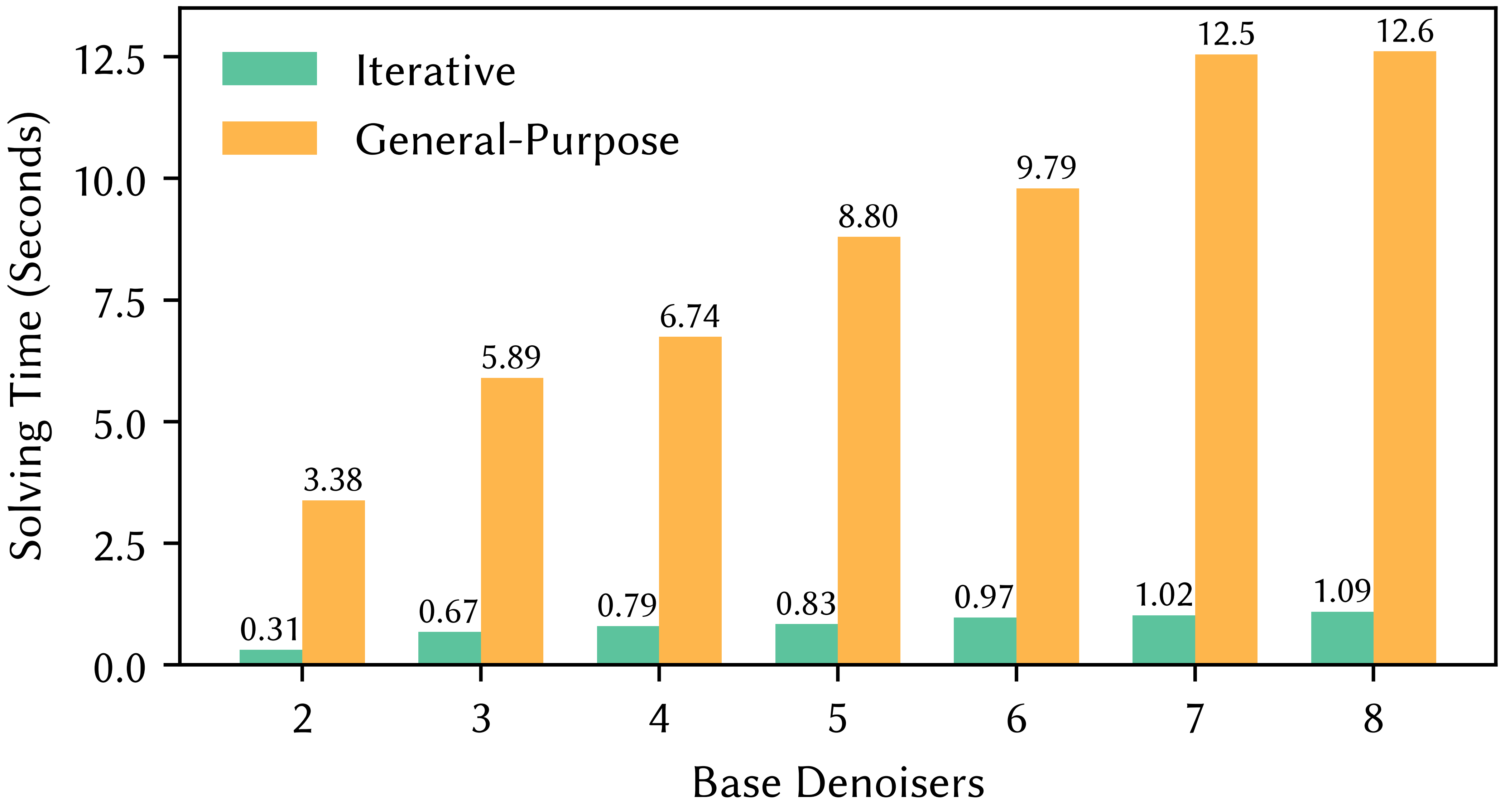
IMPLEMENTATION DETAILS

快速迭代求解器

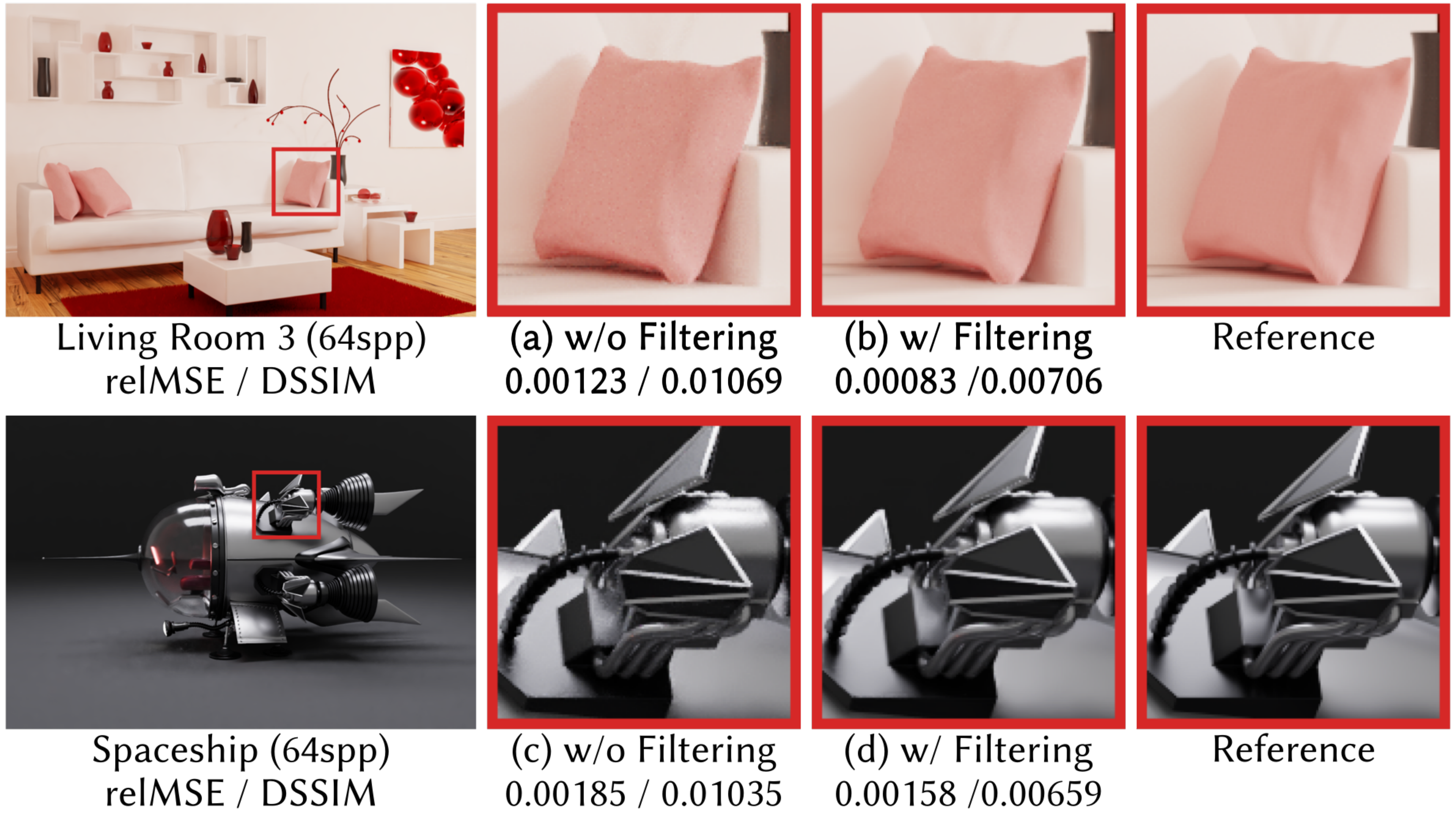


IMPLEMENTATION DETAILS

快速迭代求解器

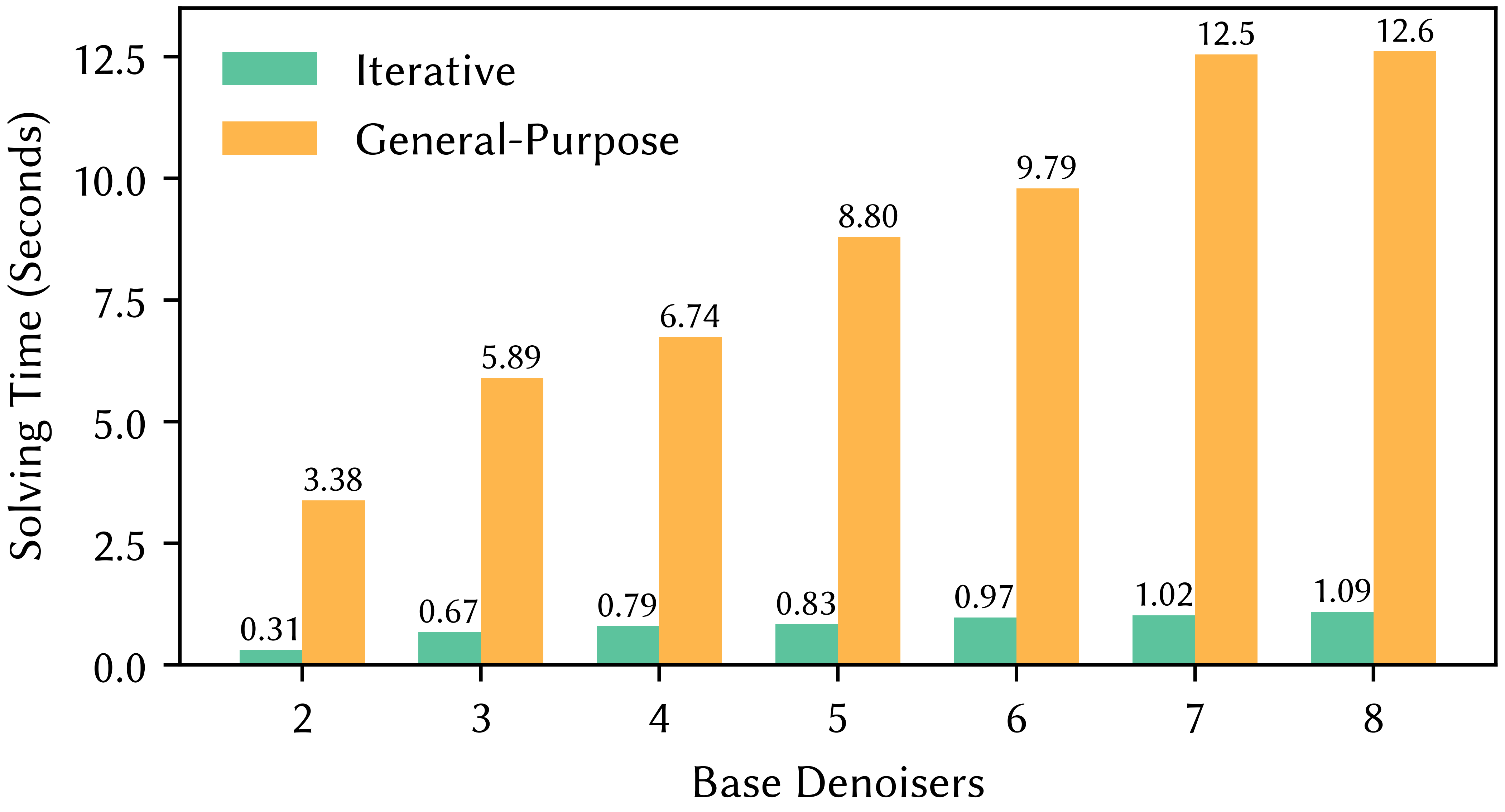


联合双边权重滤波

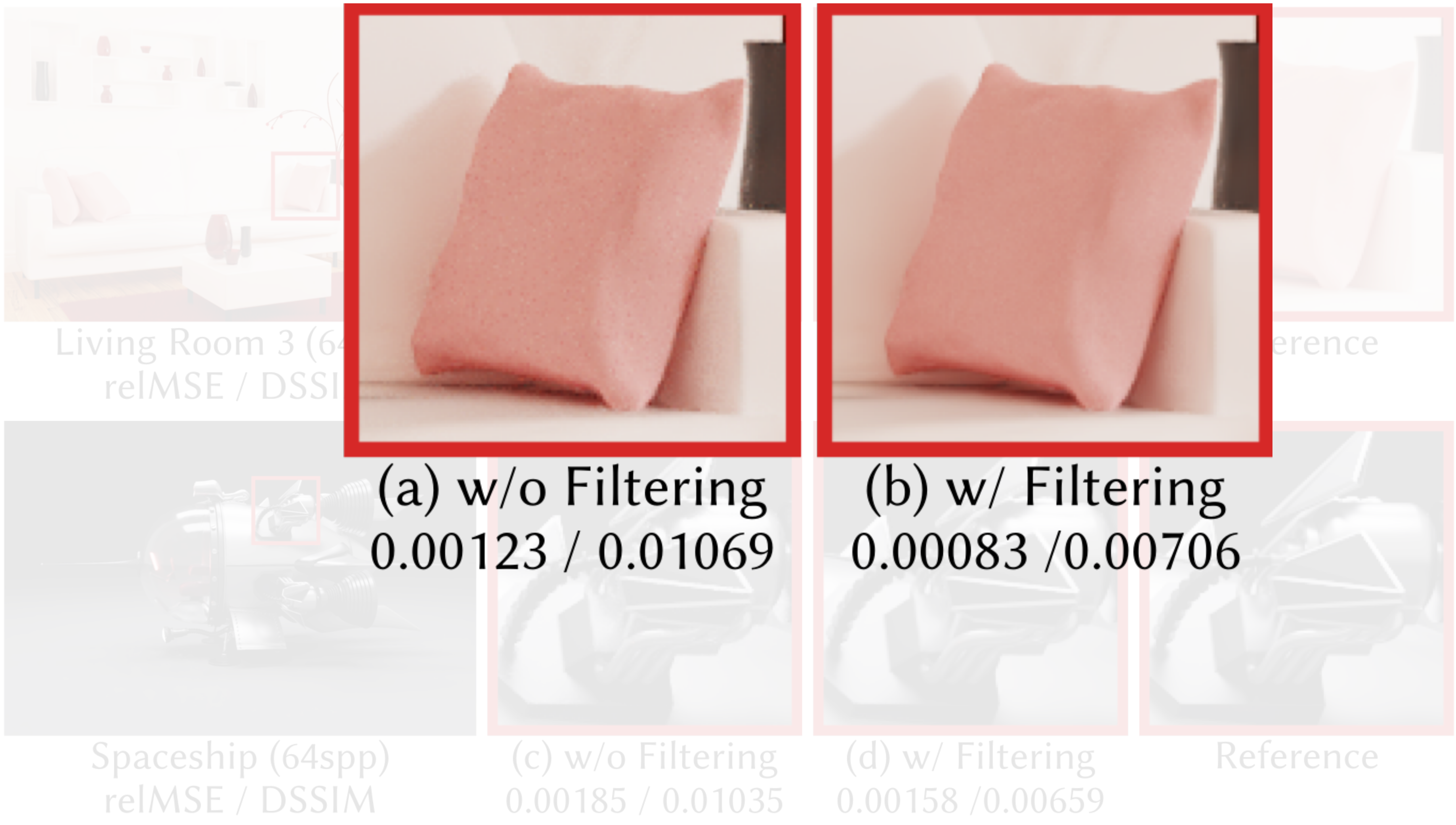


IMPLEMENTATION DETAILS

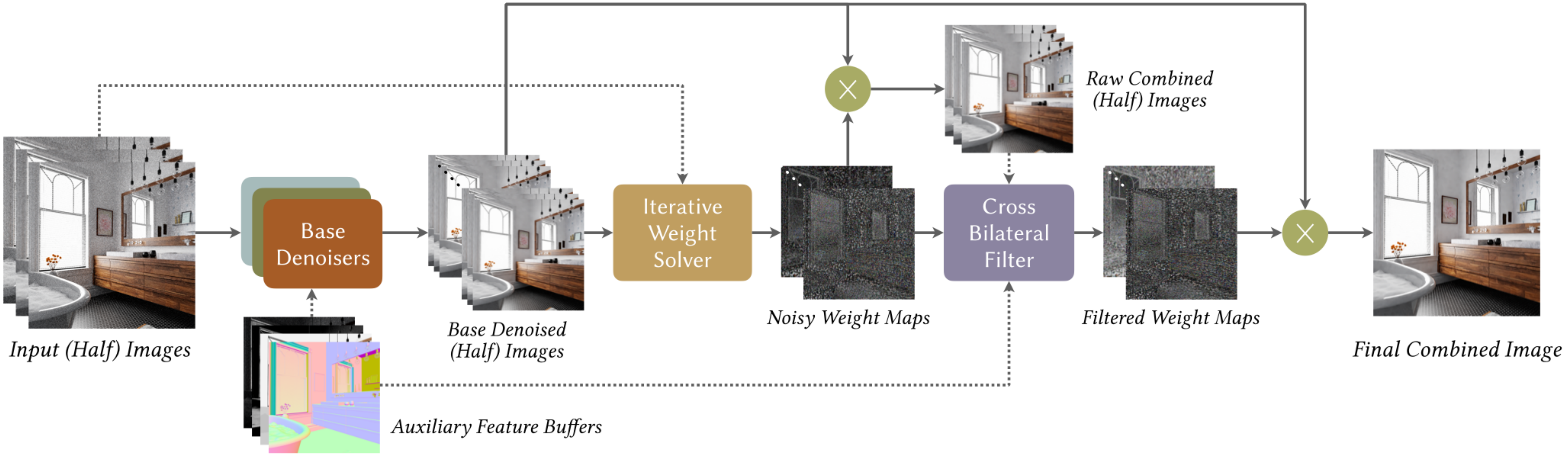
快速迭代求解器



联合双边权重滤波



PIPELINE

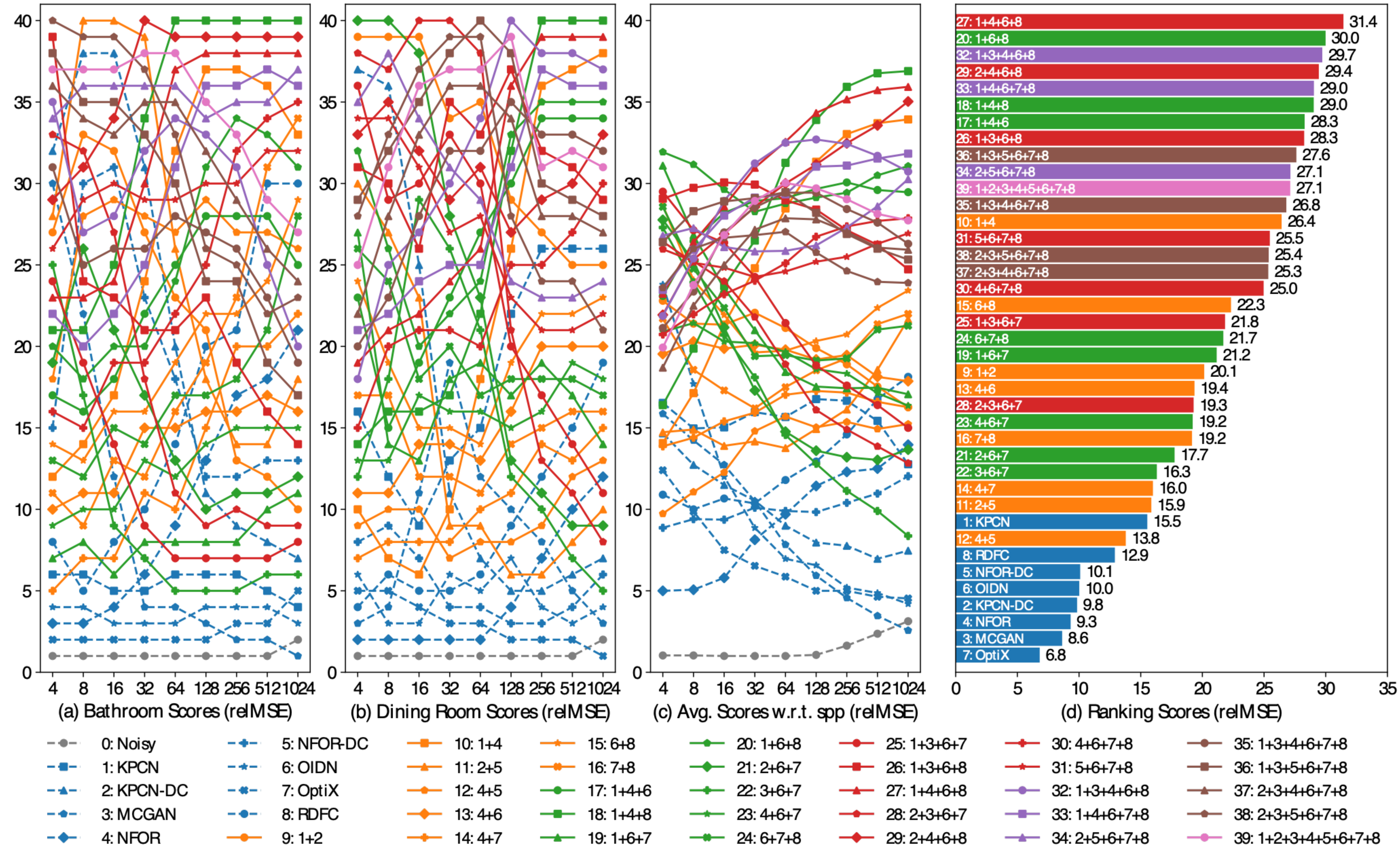


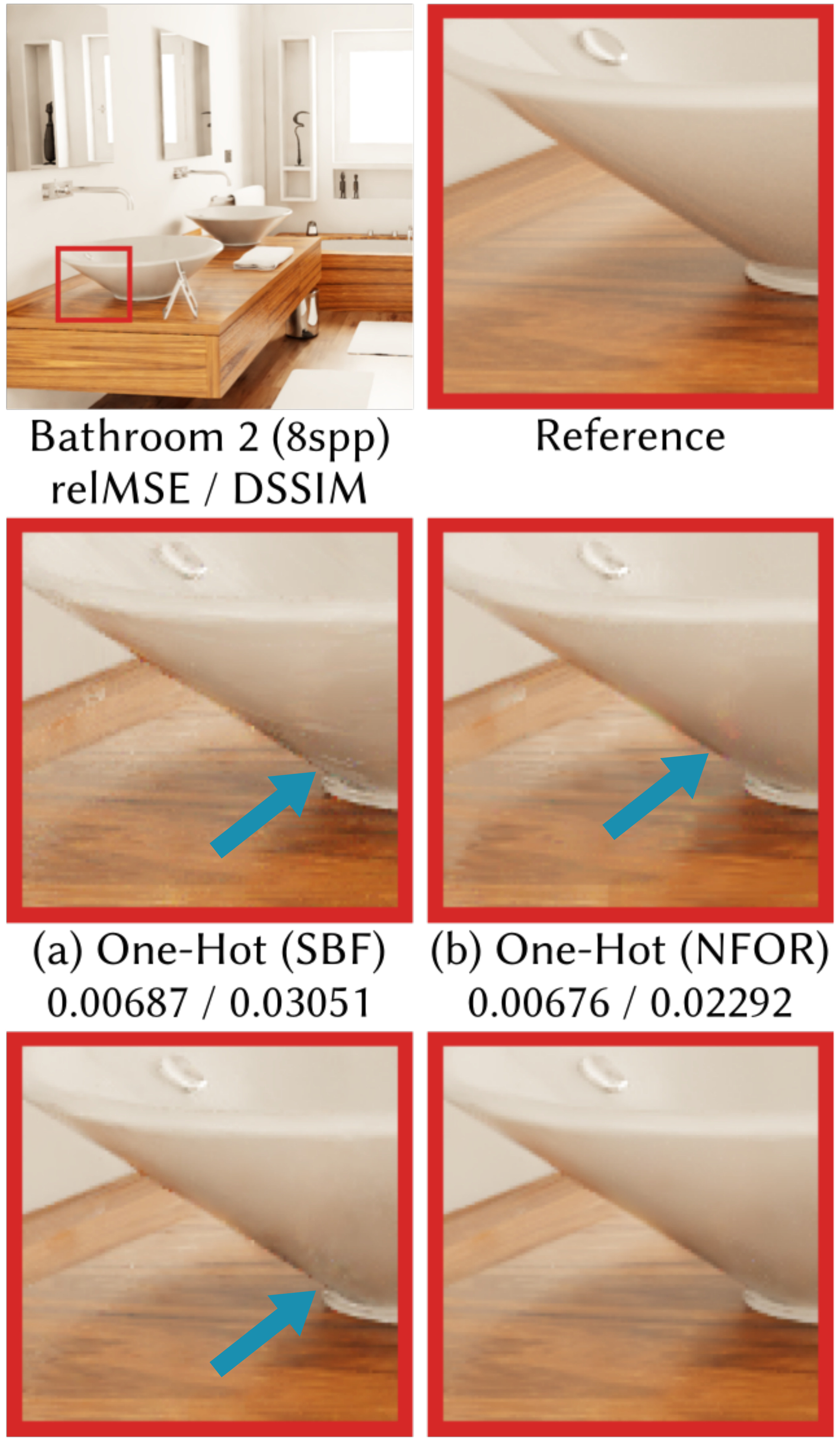
Raw Combined (Half) Images
Base Denoisers
Iterative Weight Solver
Cross Bilateral Filter
Input (Half) Images
Base Denoised (Half) Images
Noisy Weight Maps
Filtered Weight Maps
Final Combined Image
Auxiliary Feature Buffers

EXPERIMENTS


Bathroom (256spp)
Input
54.33 / 220.53
1: KPCN
10.21 / 12.60
2: KPCN-DC
7.02 / 18.40
3: MCGAN
26.77 / 16.56
4: NFOR
4.70 / 15.93
5: NFOR-DC
5.59 / 19.20
6: OIDN
16.34 / 21.33
7: OptiX
23.02 / 23.81
8: RDFC
4.51 / 16.83
relMSE / DSSIM
Reference
17: 1+4+6
4.17 / 11.67
18: 1+4+8
3.32 / 11.56
20: 1+6+8
4.05 / 12.24
27: 1+4+6+8
3.64 / 11.85
26: 1+3+6+8
4.69 / 12.02
29: 2+4+6+8
3.59 / 12.75
32: 1+3+4+6+8
4.11 / 11.74
33: 1+4+6+7+8
3.85 / 12.31
Bathroom 2 (16spp)
Input
224.83 / 260.42
1: KPCN
3.02 / 9.99
2: KPCN-DC
3.30 / 15.69
3: MCGAN
4.33 / 16.57
4: NFOR
6.25 / 17.03
5: NFOR-DC
3.56 / 18.07
6: OIDN
4.80 / 15.41
7: OptiX
5.30 / 24.49
8: RDFC
6.40 / 17.77
relMSE / DSSIM
Reference
17: 1+4+6
2.73 / 10.02
18: 1+4+8
3.00 / 10.72
20: 1+6+8
2.92 / 10.74
27: 1+4+6+8
2.86 / 10.52
26: 1+3+6+8
2.82 / 12.46
29: 2+4+6+8
2.79 / 11.32
32: 1+3+4+6+8
2.81 / 12.37
33: 1+4+6+7+8
2.91 / 11.94
Dining Room (64spp)
Input
60.38 / 231.43
1: KPCN
7.95 / 8.96
2: KPCN-DC
4.03 / 13.20
3: MCGAN
6.54 / 12.33
4: NFOR
4.29 / 13.33
5: NFOR-DC
1.81 / 13.26
6: OIDN
5.33 / 10.97
7: OptiX
14.42 / 14.79
8: RDFC
3.07 / 12.85
relMSE / DSSIM
Reference
17: 1+4+6
2.35 / 8.24
18: 1+4+8
1.92 / 8.69
20: 1+6+8
2.24 / 8.66
27: 1+4+6+8
1.92 / 8.56
26: 1+3+6+8
2.35 / 8.76
29: 2+4+6+8
1.48 / 8.85
32: 1+3+4+6+8
1.92 / 8.71
33: 1+4+6+7+8
1.87 / 8.64

Furball (64spp)
Kitchen (128spp)
Veach Ajar (256spp)
relMSE / DSSIM
Input
1: KPCN
2: KPCN-DC
3: MCGAN
4: NFOR
5: NFOR-DC
6: OIDN
7: OptiX
8: RDFC
Reference
17: 1+4+6
18: 1+4+8
20: 1+6+8
27: 1+4+6+8
26: 1+3+6+8
29: 2+4+6+8
32: 1+3+4+6+8
33: 1+4+6+7+8
15.43 / 55.31
8.69 / 89.89
8.40 / 87.58
9.71 / 92.73
5.21 / 56.33
5.21 / 55.32
6.97 / 69.49
6.50 / 61.21
5.07 / 57.74
5.01 / 56.73
4.69 / 54.76
5.39 / 60.97
4.58 / 53.14
4.67 / 45.22
4.57 / 52.94
4.46 / **43.60**
4.48 / 50.20
41.04 / 251.66
2.35 / 12.31
1.67 / 13.09
3.42 / 13.03
2.26 / 15.42
1.75 / 13.39
2.78 / 15.66
2.78 / 16.00
2.25 / 15.36
1.59 / 11.96
1.53 / 12.08
1.64 / 12.20
1.54 / 12.09
1.63 / 11.78
1.48 / 12.01
1.54 / **11.77**
1.56 / 12.16
304.10 / 324.58
2.91 / 12.22
3.65 / 18.02
2.70 / 13.22
3.30 / 13.76
3.58 / 18.10
2.42 / 16.16
3.38 / 22.36
4.14 / 19.07
1.93 / **10.77**
2.43 / 11.77
2.15 / 12.46
2.10 / 11.65
2.08 / 11.62
2.31 / 12.97
2.06 / 11.21
2.10 / 12.28


(a) Bathroom Scores (relMSE)
(b) Dining Room Scores (relMSE)
(c) Avg. Scores w.r.t. spp (relMSE)
(d) Ranking Scores (relMSE)
4 8 16 32 64 128 256 512 1024
0 5 10 15 20 25 30 35 40
27: 1+4+6+8 31.4
20: 1+6+8 30.0
32: 1+3+4+6+8 29.7
29: 2+4+6+8 29.4
33: 1+4+6+7+8 29.0
18: 1+4+8 29.0
17: 1+4+6 28.3
26: 1+3+6+8 28.3
36: 1+3+5+6+7+8 27.6
34: 2+5+6+7+8 27.1
39: 1+2+3+4+5+6+7+8 27.1
35: 1+3+4+6+7+8 26.8
10: 1+4 26.4
31: 5+6+7+8 25.5
38: 2+3+5+6+7+8 25.4
37: 2+3+4+6+7+8 25.3
30: 4+6+7+8 25.0
15: 6+8 22.3
25: 1+3+6+7 21.8
24: 6+7+8 21.7
19: 1+6+7 21.2
9: 1+2 20.1
13: 4+6 19.4
28: 2+3+6+7 19.3
23: 4+6+7 19.2
16: 7+8 19.2
21: 2+6+7 17.7
22: 3+6+7 16.3
14: 4+7 16.0
11: 2+5 15.9
1: KPCN 15.5
12: 4+5 13.8
8: RDFC 12.9
5: NFOR-DC 10.1
6: OIDN 10.0
2: KPCN-DC 9.8
4: NFOR 9.3
3: MCGAN 8.6
7: OptiX 6.8
0: Noisy
5: NFOR-DC
10: 1+4
15: 6+8
20: 1+6+8
25: 1+3+6+7
30: 4+6+7+8
35: 1+3+4+6+7+8
1: KPCN
6: OIDN
11: 2+5
16: 7+8
21: 2+6+7
26: 1+3+6+8
31: 5+6+7+8
36: 1+3+5+6+7+8
2: KPCN-DC
7: OptiX
12: 4+5
17: 1+4+6
22: 3+6+7
27: 1+4+6+8
32: 1+3+4+6+8
37: 2+3+4+6+7+8
3: MCGAN
8: RDFC
13: 4+6
18: 1+4+8
23: 4+6+7
28: 2+3+6+7
33: 1+4+6+7+8
38: 2+3+5+6+7+8
4: NFOR
9: 1+2
14: 4+7
19: 1+6+7
24: 6+7+8
29: 2+4+6+8
34: 2+5+6+7+8
39: 1+2+3+4+5+6+7+8



Bathroom 2 (8spp)
relMSE / DSSIM

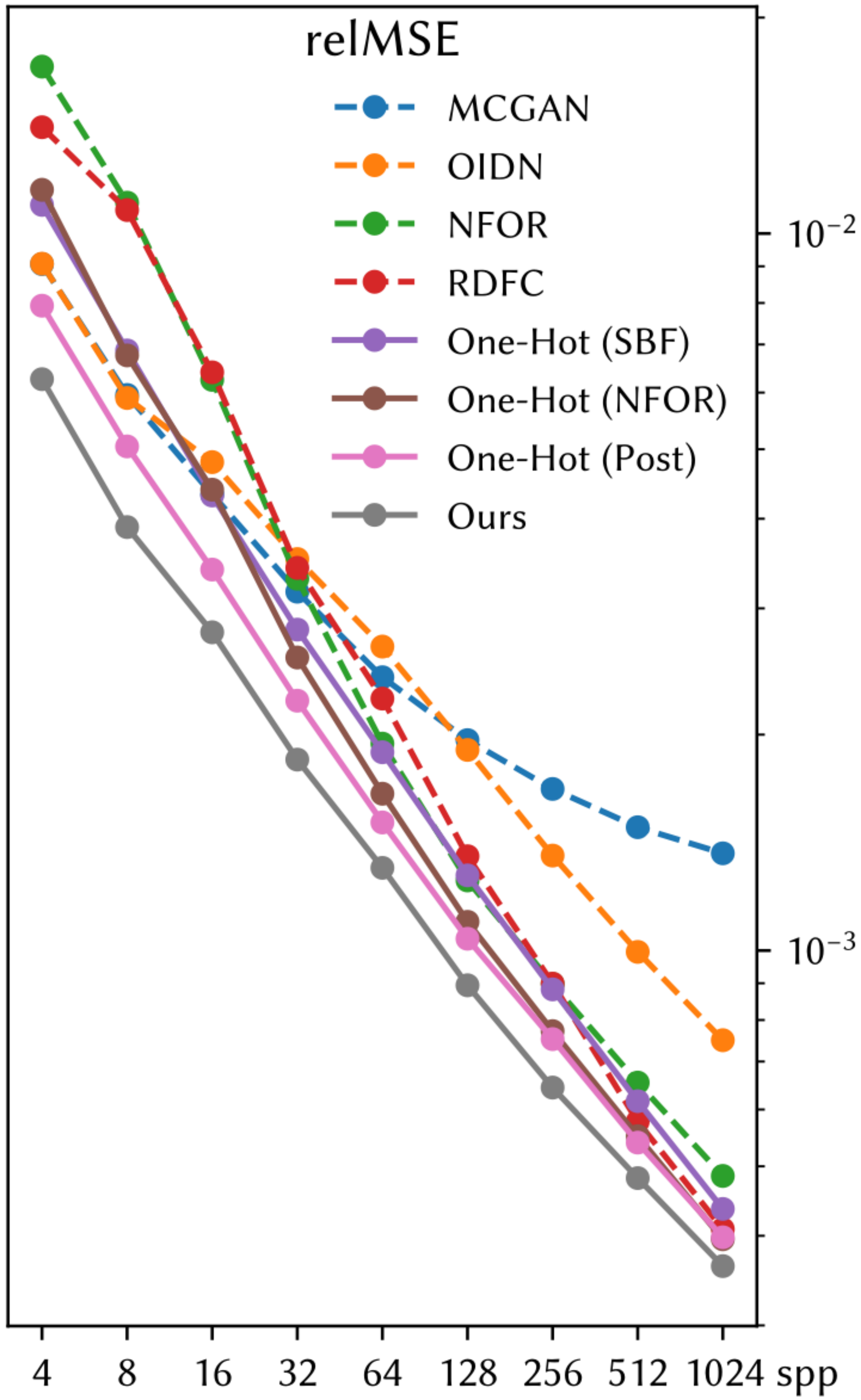
Reference

(a) One-Hot (SBF)
0.00687 / 0.03051

(b) One-Hot (NFOR)
0.00676 / 0.02292

(c) One-Hot (Post)
0.00505 / 0.02126

(d) Ours
0.00389 / 0.01551



	spp	4	8	16	32	64	128	256	Avg.
#Base	2	88.8%	84.2%	80.4%	72.9%	66.7%	62.9%	63.3%	74.2%
	3	84.6%	81.2%	76.7%	74.6%	64.6%	63.3%	60.0%	72.1%
	4	81.0%	79.5%	77.1%	78.6%	74.3%	68.6%	61.0%	74.3%
	5	92.2%	84.4%	84.4%	83.3%	84.4%	81.1%	75.6%	83.7%
	6	81.7%	73.3%	76.7%	79.2%	76.7%	76.7%	65.8%	75.7%
	8	80.0%	76.7%	76.7%	83.3%	83.3%	80.0%	66.7%	78.1%
	Avg.	85.1%	80.8%	78.5%	76.8%	71.4%	68.4%	63.5%	74.9%

Table 1. Percentages under the relMSE metric that our ensemble denoising method outperforms both pre-filtering variants (using filters from SBF and NFOR, respectively) of the one-hot selection method. Our method has the lowest error in most cases across varying ensemble sizes and sample rates.

	spp	4	8	16	32	64	128	256	Avg.
#Base	2	73.8%	70.4%	64.6%	67.1%	67.5%	66.7%	63.3%	67.6%
	3	79.2%	75.8%	68.3%	63.7%	59.6%	57.1%	52.5%	65.2%
	4	92.9%	91.0%	82.4%	77.6%	76.7%	71.4%	63.8%	79.4%
	5	85.6%	84.4%	76.7%	71.1%	73.3%	77.8%	71.1%	77.1%
	6	89.2%	90.0%	84.2%	77.5%	75.8%	77.5%	67.5%	80.2%
	8	83.3%	80.0%	80.0%	66.7%	66.7%	70.0%	56.7%	71.9%
	Avg.	82.9%	80.6%	73.8%	70.3%	69.1%	67.8%	61.7%	72.3%

Table 2. Percentages under the relMSE metric that our ensemble denoising outperforms the post-filtering variant of one-hot selection.

(a) GT (Full) One-Hot 0.00199 / 0.02791

(b) GT (Full) w/o Constraints 0.00148 / 0.02004

(c) GT (Full) w/ Constraints 0.00175 / 0.02470

(d) GT (Half) One-Hot 0.00207 / 0.03032

(e) GT (Half) w/o Constraints 0.00156 / 0.02224

(f) GT (Half) w/ Constraints 0.00182 / 0.02668

(g) Estimated One-Hot (Post) 0.00287 / 0.03821

(h) Estimated w/o Constraints 0.11013 / 0.13754

(i) Ours w/ Constraints 0.00256 / 0.03590

CONCLUSION

CONCLUSION

- 主要内容与贡献
  - 具有良好理论特性和实践性能的集成降噪模型
  - 基于双缓冲策略的 MSE 矩阵估计及其优化实现
    - 快速稳健的迭代求解器和双边权重图滤波的实用算法
  - 详尽的实验与分析，设计了一套综合排名方法帮助用户挑选合适的组合
- 未来可能的工作
  - 更准确的估计策略；速度优化，用于实时降噪；扩展应用至其他问题等

THANKS