PG20+21 WELLINGTON NZ

Consistent Post-Reconstruction for Progressive Photon Mapping

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Background: Stochastic Progressive Photon Mapping

- Stochastic Progressive PM [Hachisuka et al. 09]
  - o Multi-pass consistent radiance estimation
  - o Radiance estimation:

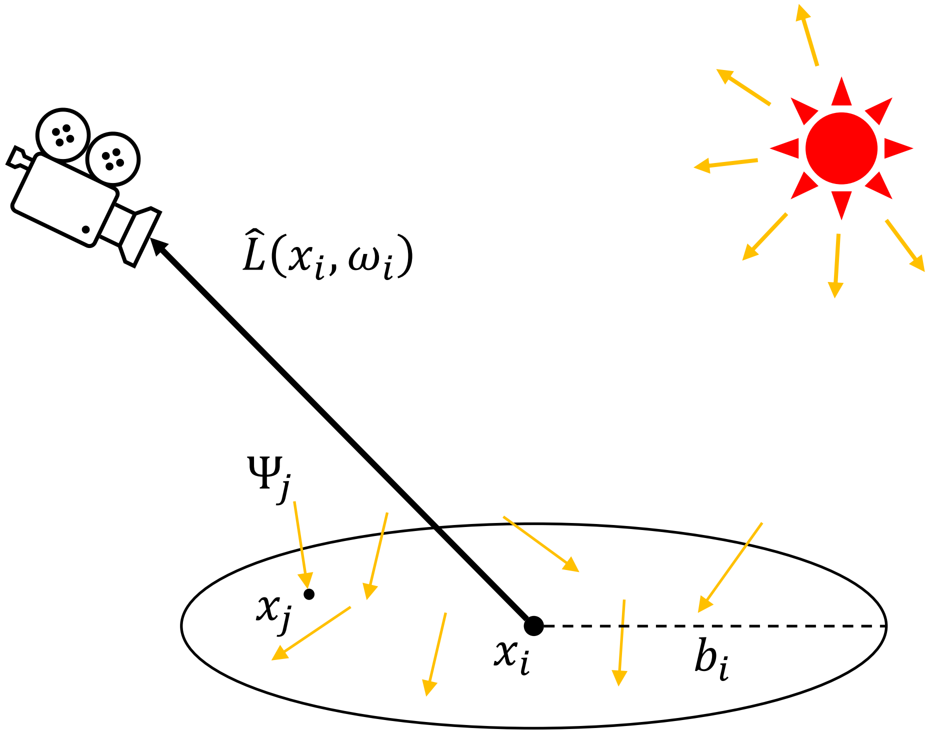
$$\hat{L}(x_i,\omega_i) = \frac{1}{N_{photon}} \sum_{j=1}^{N_{photon}} K_{b_i}(x_j - x_i)\Psi_j$$

$\hat{L}$: radiance estimate, Ψ_j: photon contribution, K_{b_i}: kernel function

  - o Pixel estimator:

$$\tilde{y}_c = \frac{1}{N_{pass}} \sum_{i=1}^{N_{pass}} \frac{f(x_i,\omega_i)}{p(x_i,\omega_i)} \hat{L}(x_i,\omega_i)$$

f: weight function, p: PDF of eye subpath



Kernel density estimation

Background: Adaptive Bandwidth Selection

Adaptive PPM [Kaplanyan et al. 13]

Choose a bandwidth minimizing the estimated asymptotic MSE (AMSE)

$$\bar{r}_N = \left(\frac{2\,\mathrm{Var}[\psi]}{\pi J p_l k_2^2 (\Delta I)^2} \right)^{1/6} N^{-1/6}$$

p_l: avg. density of light sub paths, J: # of photons, N: iterations
ψ: contribution of photon, k: kernel, ΔI: Laplacian of measurement

Chi-squared PPM [Lin et al. 20]

Bandwidth is reduced when underlying photon distribution reject the chi-squared test (uniform)

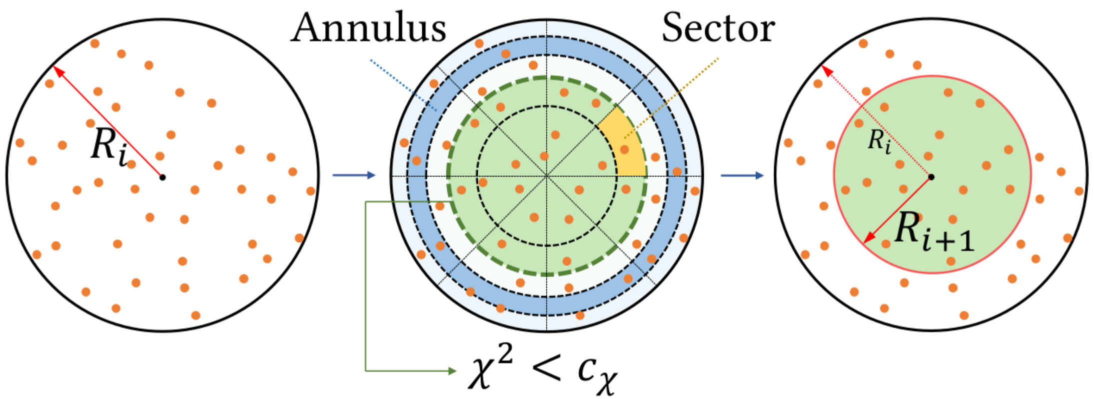


Figure from paper

Technical Challenges

- Errors due to the wrong initial bandwidth determined heuristically (e.g., k-NN)

SPPM Reference

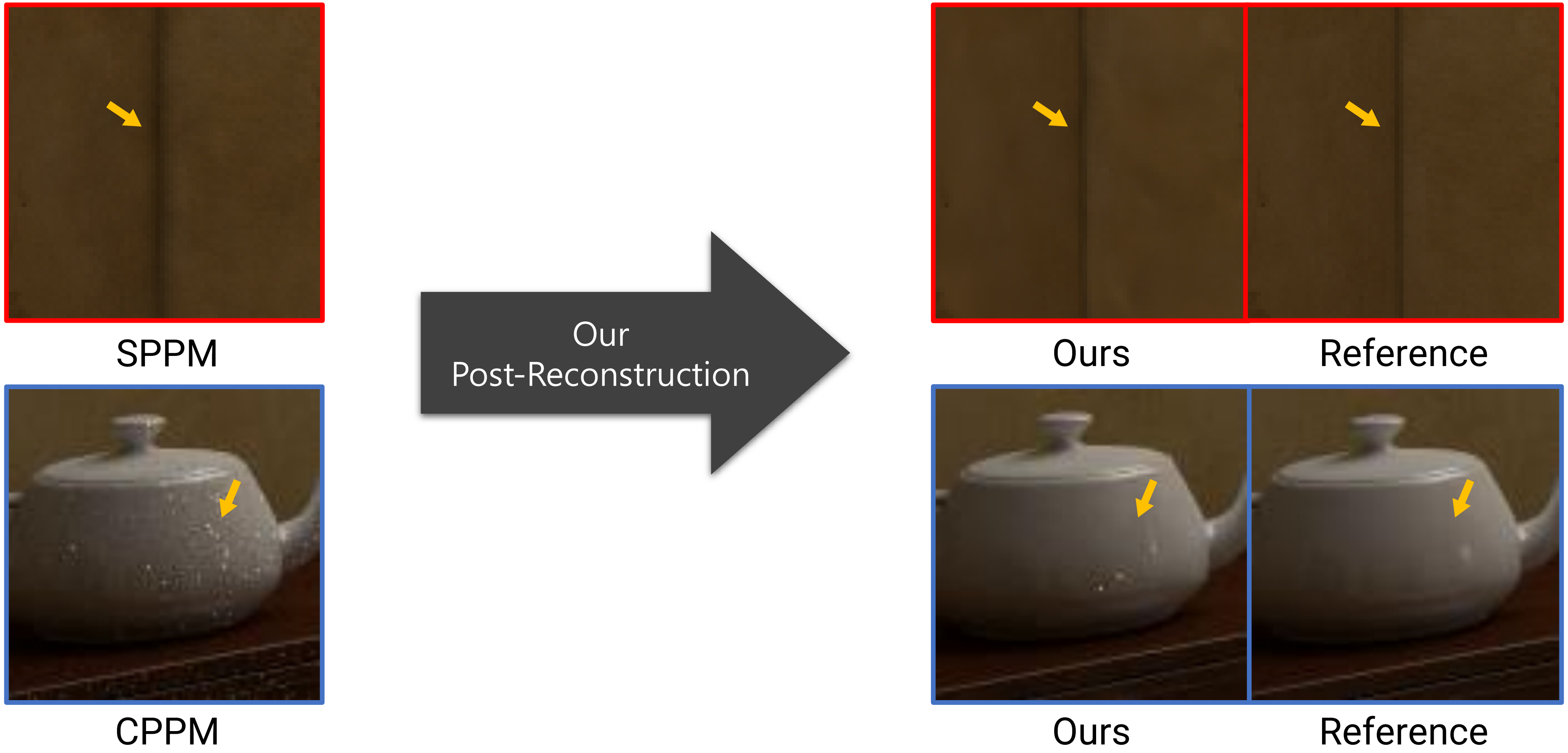
- Ray tracing noise in PPM methods

CPPM Reference

Bookshelf, reference

Our Goal

- Enhance the estimates of PPM techniques through a post-reconstruction
  - Take the PPM estimates as input and produce an improved output.



Related Work

- Photon mapping [Jensen, 96]
    - o GPU acceleration techniques [Zhou et al. 08, Mara et al. 13]
    - o Photon relaxation [Spencer et al. 09, Spencer et al. 13] and photon beams [Jarosz et al. 08]
- Progressive photon mapping [Hachisuka et al. 08]
    - o Analysis of asymptotic errors of PPM [Hachisuka et al. 10, Knaus et al. 11]
    - o Gradient-domain [Hua et al. 17, Gruson et al. 18, Xu et al. 20]
    - o Adaptive bandwidth selection [Kaplanyan et al. 13, Lin et al. 20]
    - o Learning-based error reduction in PPM estimates [Zeng et al. 20]
- Reconstruction and post-reconstruction for Monte Carlo denoising
    - o Regression based reconstruction [Moon et al. 14, Bitterli et al. 16]
    - o Learning-based reconstruction [Bako et al. 17, Vogels et al. 18, Xu et al. 19]
    - o Post-reconstruction for correlated estimates [Back et al. 20]

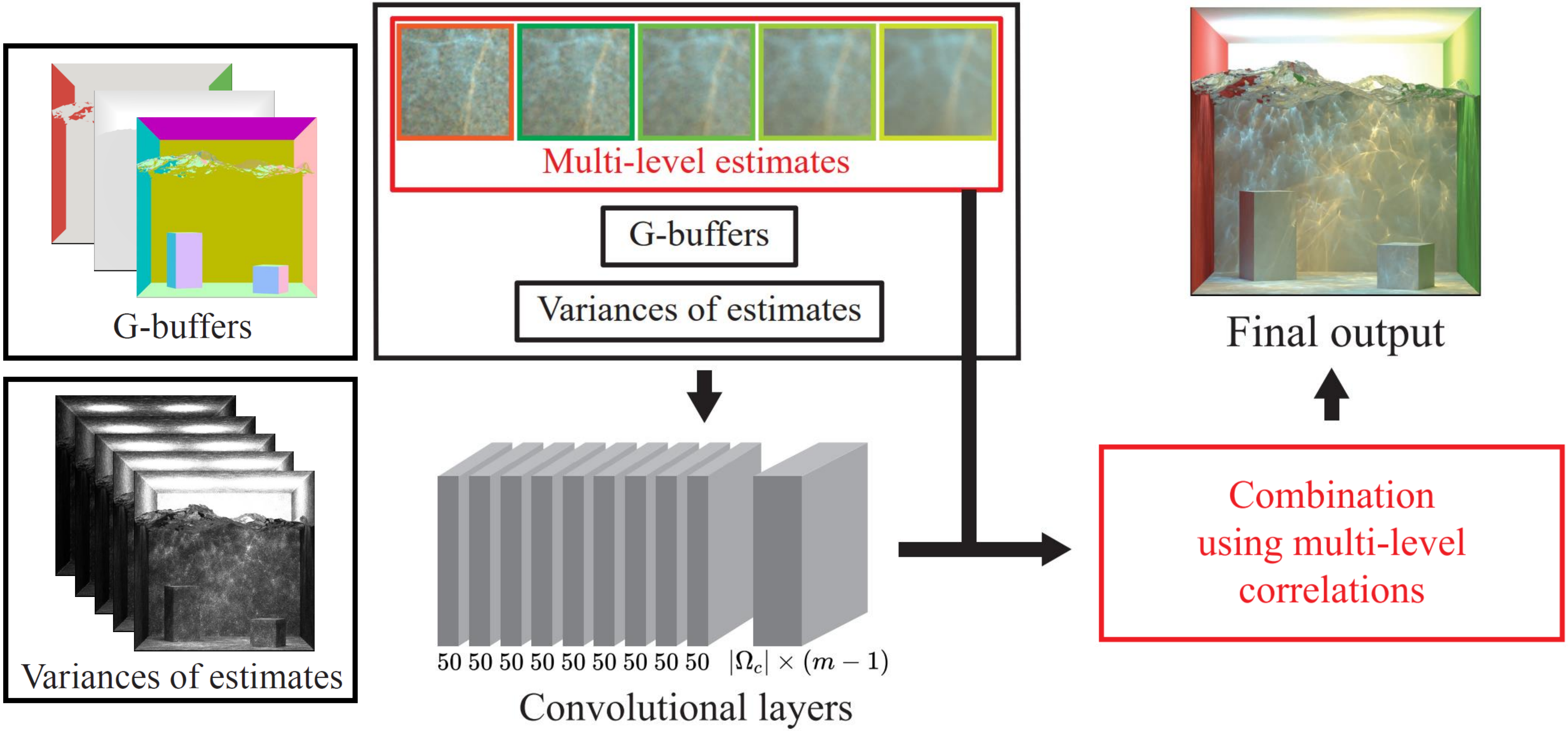
Related Work

- Post-reconstruction for Monte Carlo denoising [Back et al. 20]
  - Error reduction by utilizing a positive correlation between the independent (e.g., path traced, PT) and correlated estimates (e.g., denoised PT)
  - Can be used for PPM estimates, but it is suboptimal because it requires additional method PT
  - **We adapt this method to make it specific to PPM**
- Learning-based error reduction in PPM estimates [Zeng et al. 20]
  - Reduce errors in PPM estimates by using multi-residual blocks
  - However, this method is not consistent
  - **Our method maintains the consistency of the input PPM methods**

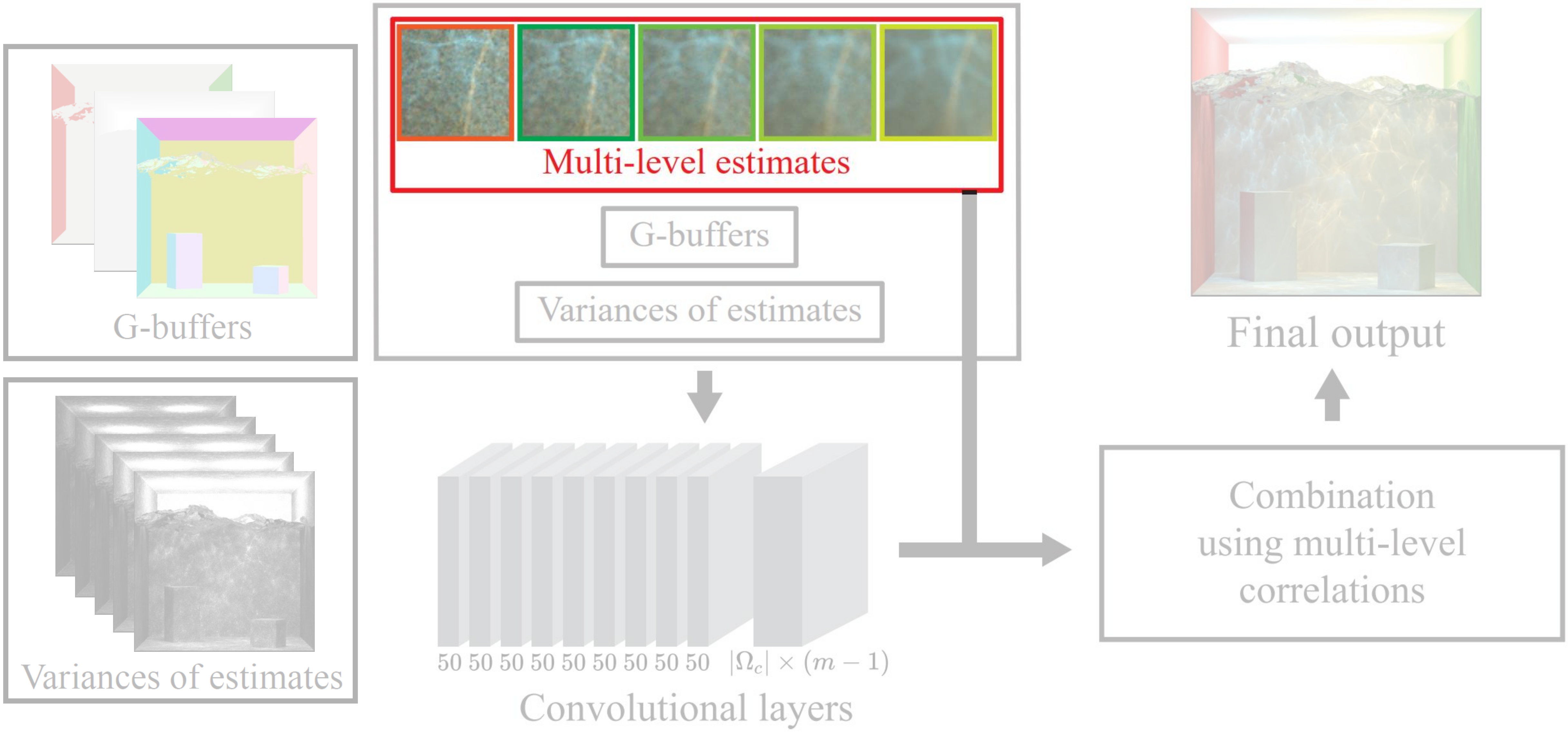
Contributions

- Propose a learning-based post-reconstruction for PPM techniques
  - Reduce MSEs of PPM estimates
  - Maintain consistency of PPM techniques
- Our key idea is to **combine** PPM estimates with **multi-level correlation structures**

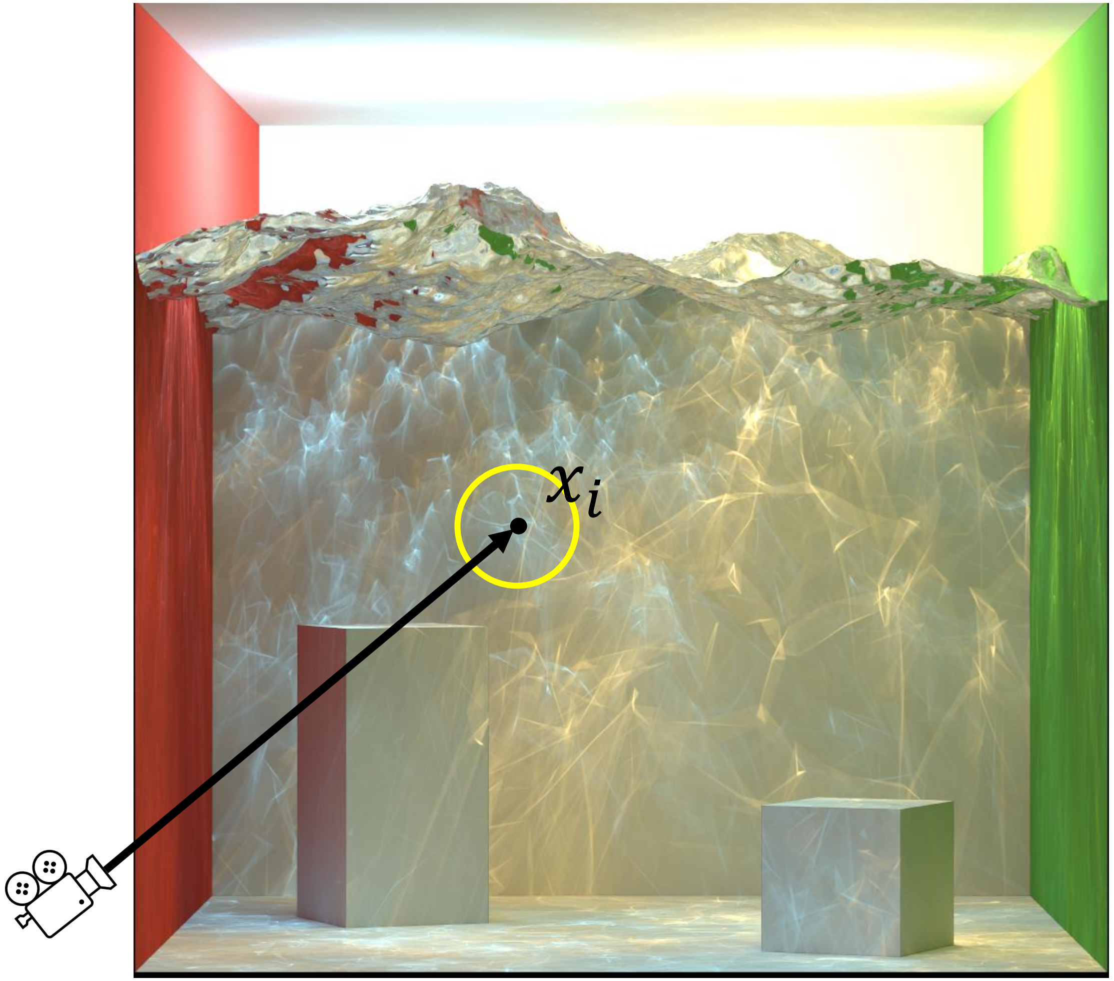
Our Framework



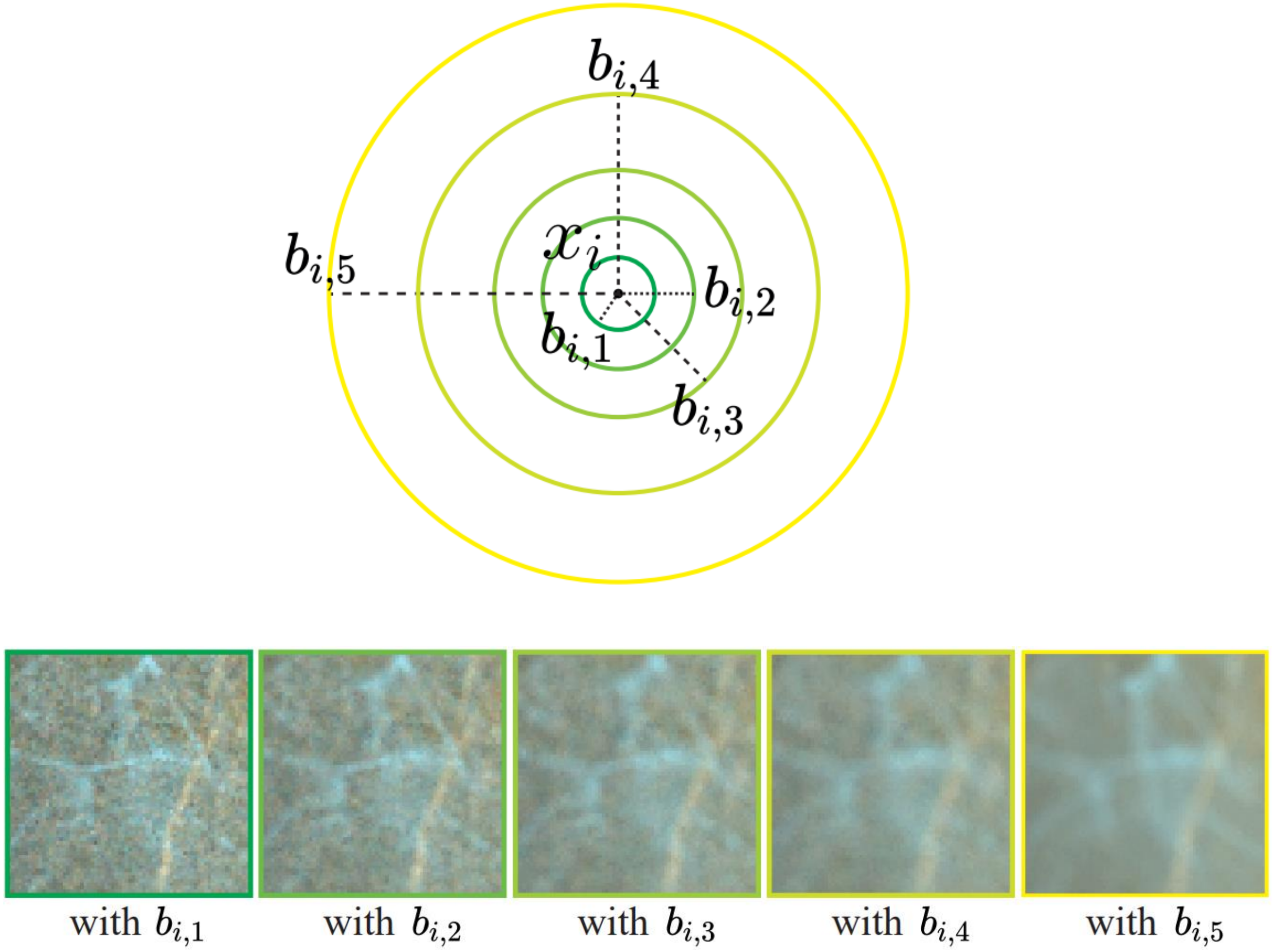
Our Framework



Multi-level Estimates

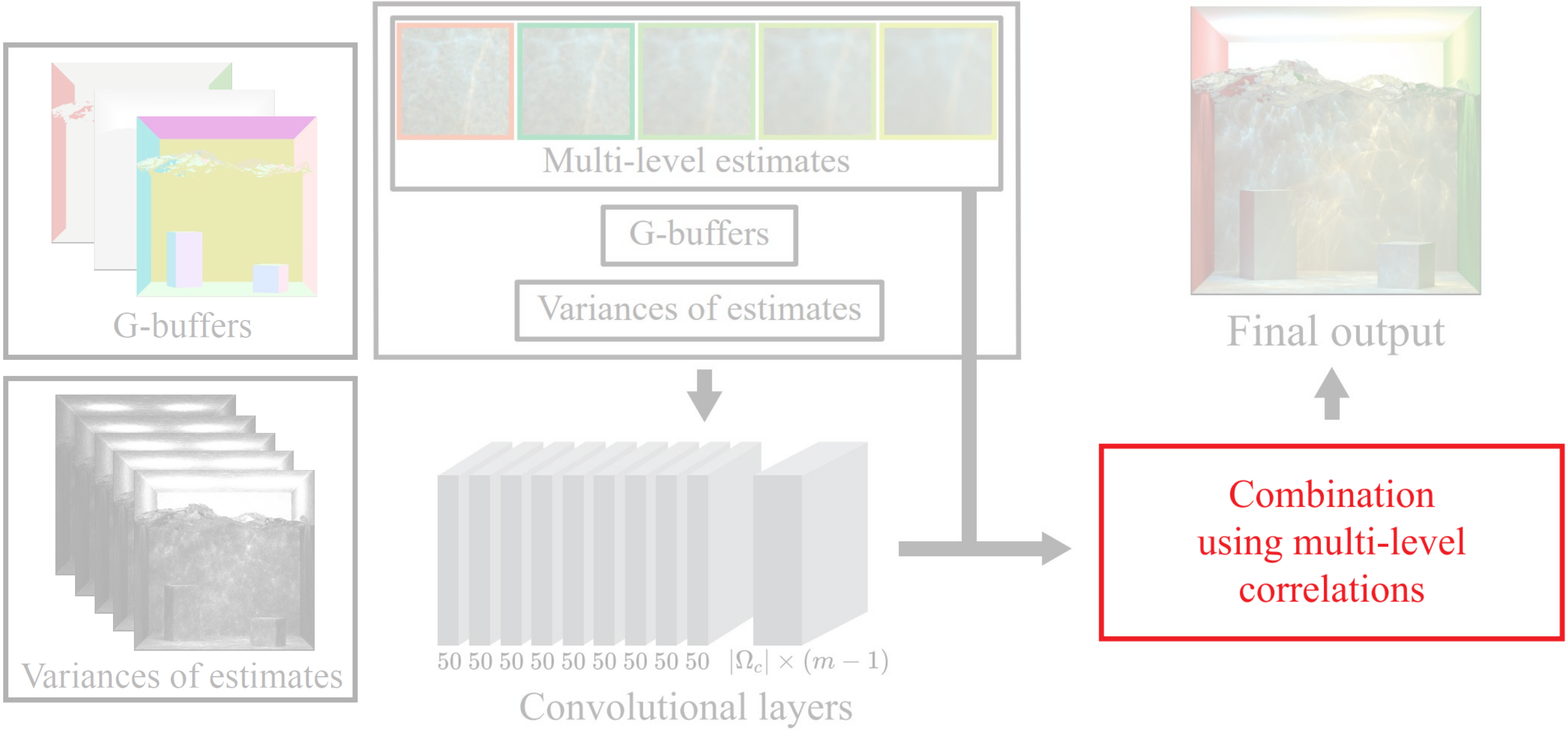


(a) Hit point generation



(b) Density estimation and corresponding generated images

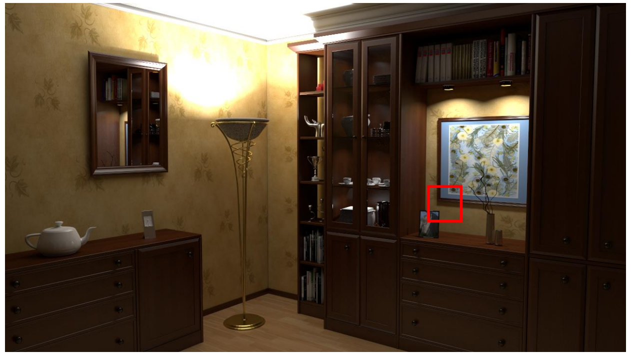
Our Framework



Post-reconstruction using Multi-level Correlations

- Error reduction by adapting the previous post-reconstruction to PPM

$$\frac{1}{W_c}\sum_{j=1}^{m-1}\left[\sum_{i\in\Omega_c} w_i^j \underbrace{\tilde{y}_i}_{\text{Independent Image}} + \sum_{i\in\Omega_c} w_i^j \left(\underbrace{\tilde{z}_c^j}_{\text{Correlated Image}} - \underbrace{\tilde{z}_i^j}_{\text{Correlated Image}}\right)\right]$$



Reference

Rendered w/ b_1

Rendered w/ $b_2 \sim b_5$

Post-reconstruction using Multi-level Correlations

- Error reduction by adapting the previous post-reconstruction to PPM

Trainable weights

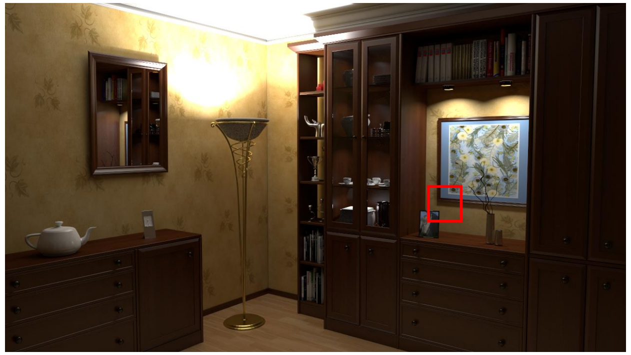
$$\frac{1}{W_c}\sum_{j=1}^{m-1}\left[\sum_{i\in\Omega_c} w_i^j \tilde{y}_i + \sum_{i\in\Omega_c} w_i^j\left(\tilde{z}_c^j - \tilde{z}_i^j\right)\right]$$

Independent Image $\tilde{y}_i$

Correlated Image $\tilde{z}_c^j$

Correlated Image $\tilde{z}_i^j$

Normalization



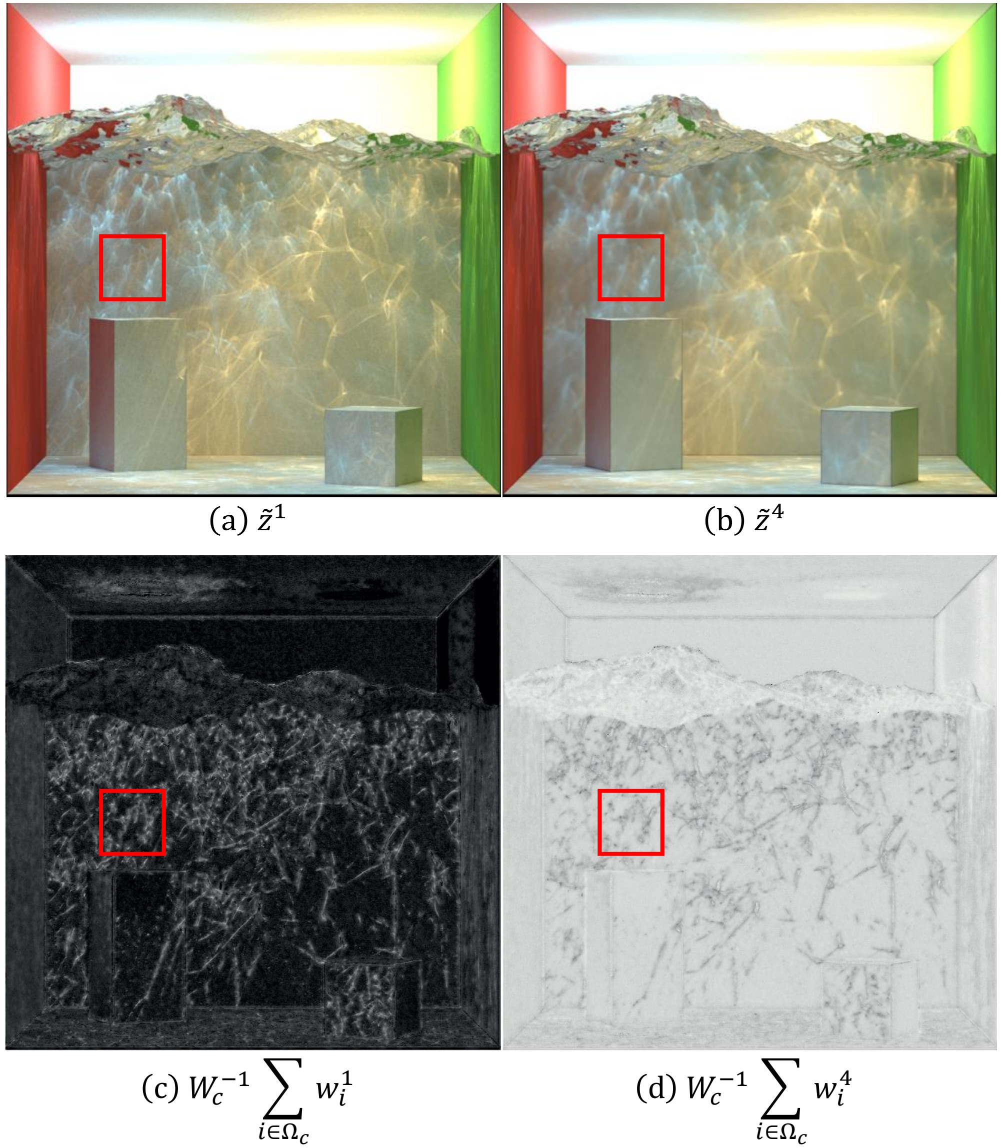
Reference

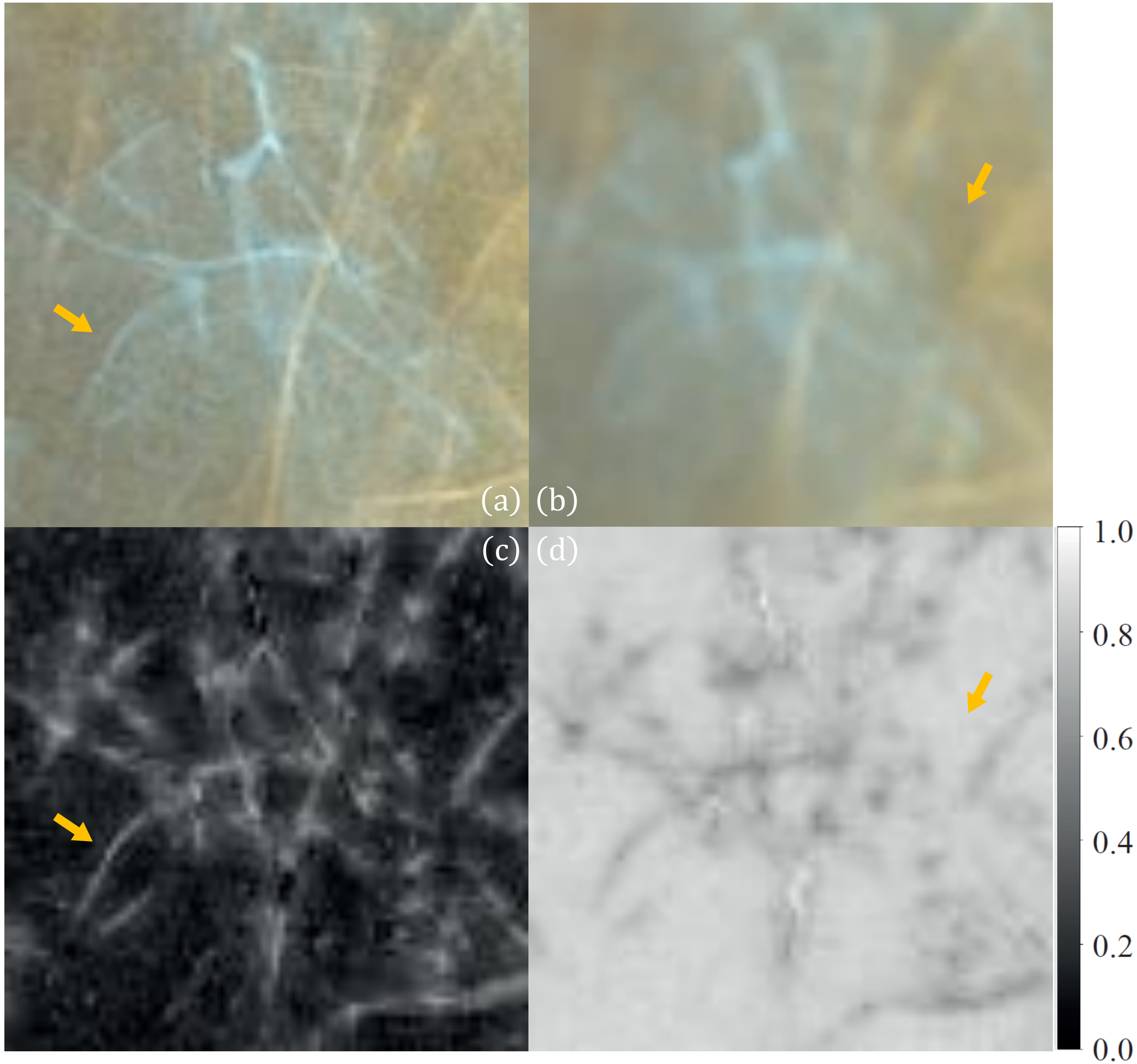
Rendered w/ b_1

Rendered w/ $b_2 \sim b_5$

Visualization of Trained Weights w_i^j

$$\hat{y}_c = \frac{1}{W_c} \sum_{j=1}^{m-1} \left[\sum_{i \in \Omega_c} w_i^j \tilde{y}_i + \sum_{i \in \Omega_c} w_i^j \left(\tilde{z}_c^j - \tilde{z}_i^j \right) \right]$$





Consistency of Our Combination

- Our combination kernel is:

$$\hat{y}_c = \frac{1}{W_c} \sum_{j=1}^{m-1} \left[\sum_{i \in \Omega_c} w_i^j \left(\tilde{y}_i + \tilde{z}_c^j - \tilde{z}_i^j \right) \right]$$

- It converges to the true solution

$$\lim_{N_{pass} \to \infty} \hat{y}_c = y_c$$

- For more details, please refer to the appendix of our paper.

Experimental Setup

Combination kernel

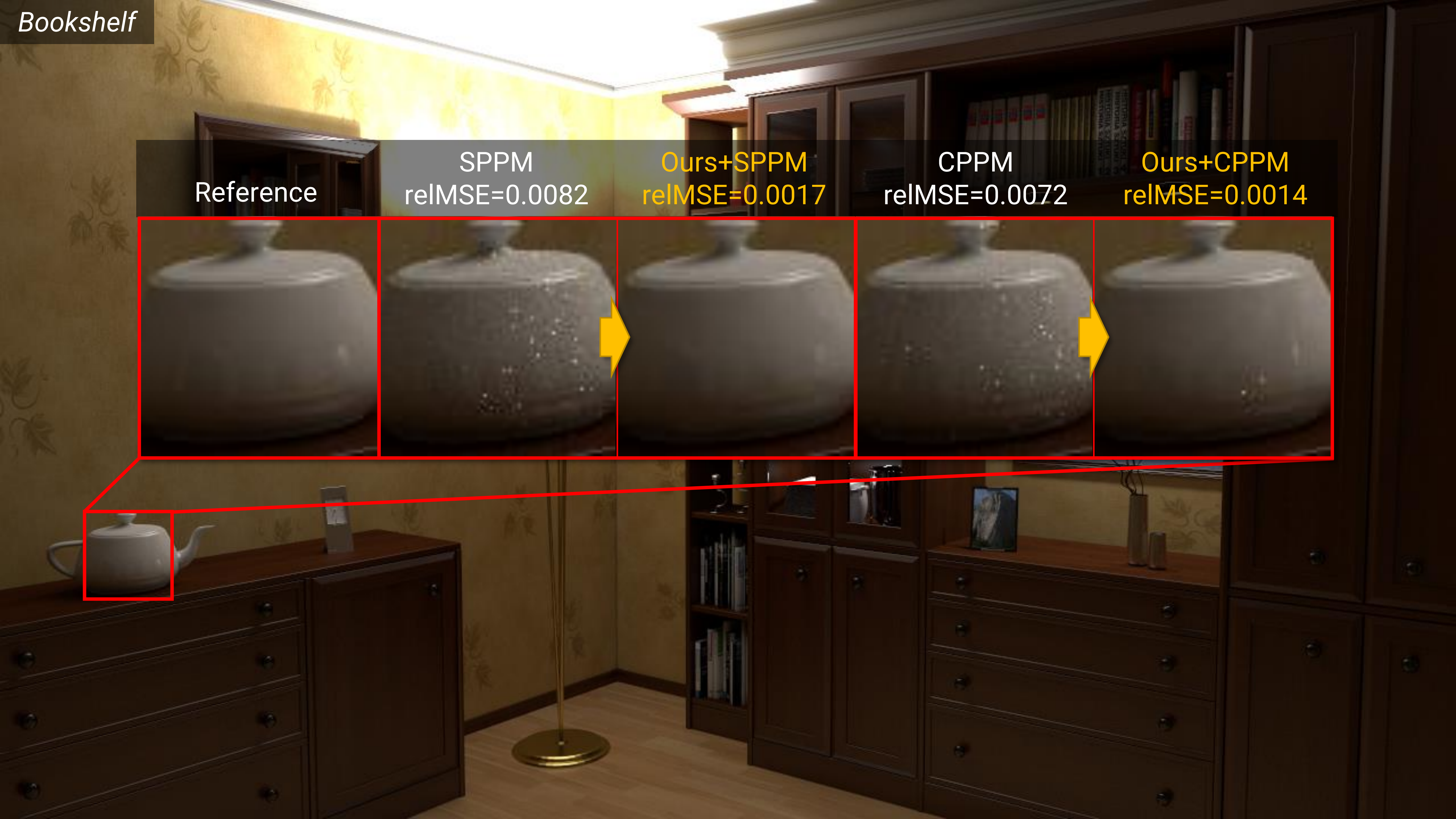
$$\hat{y}_c = \frac{1}{W_c} \sum_{j=1}^{m-1} \left[\sum_{i \in \Omega_c} w_i^j \tilde{y}_i + \sum_{i \in \Omega_c} w_i^j \left(\tilde{z}_c^j - \tilde{z}_i^j \right) \right]$$

- Training the weights of combination kernel w_i^j
  - o Supervised learning
  - o Input: 5 images with g-buffers and variances (27 channels)
  - o Output: Reference image (3 channels)
  - o # of weights of each pixel: $|\Omega_c| \times (m-1)$ (total 2.4M)
- Dataset
  - o Training
    - SPPM generated 1800 frames (12 scenes x 5 randomization x 3 iterations x 10 random seeds)
  - o Test
    - SPPM and CPPM generated frames
    - For DC, we used BDPT [Lafortune et al. 93] and SPPM to generate the independent and correlated images each

Results

Comparison with previous PPM methods

Bookshelf



Bookshelf
Reference
SPPM
relMSE=0.0082
Ours+SPPM
relMSE=0.0017
CPPM
relMSE=0.0072
Ours+CPPM
relMSE=0.0014

Bookshelf
Reference
SPPM
relMSE=0.0082
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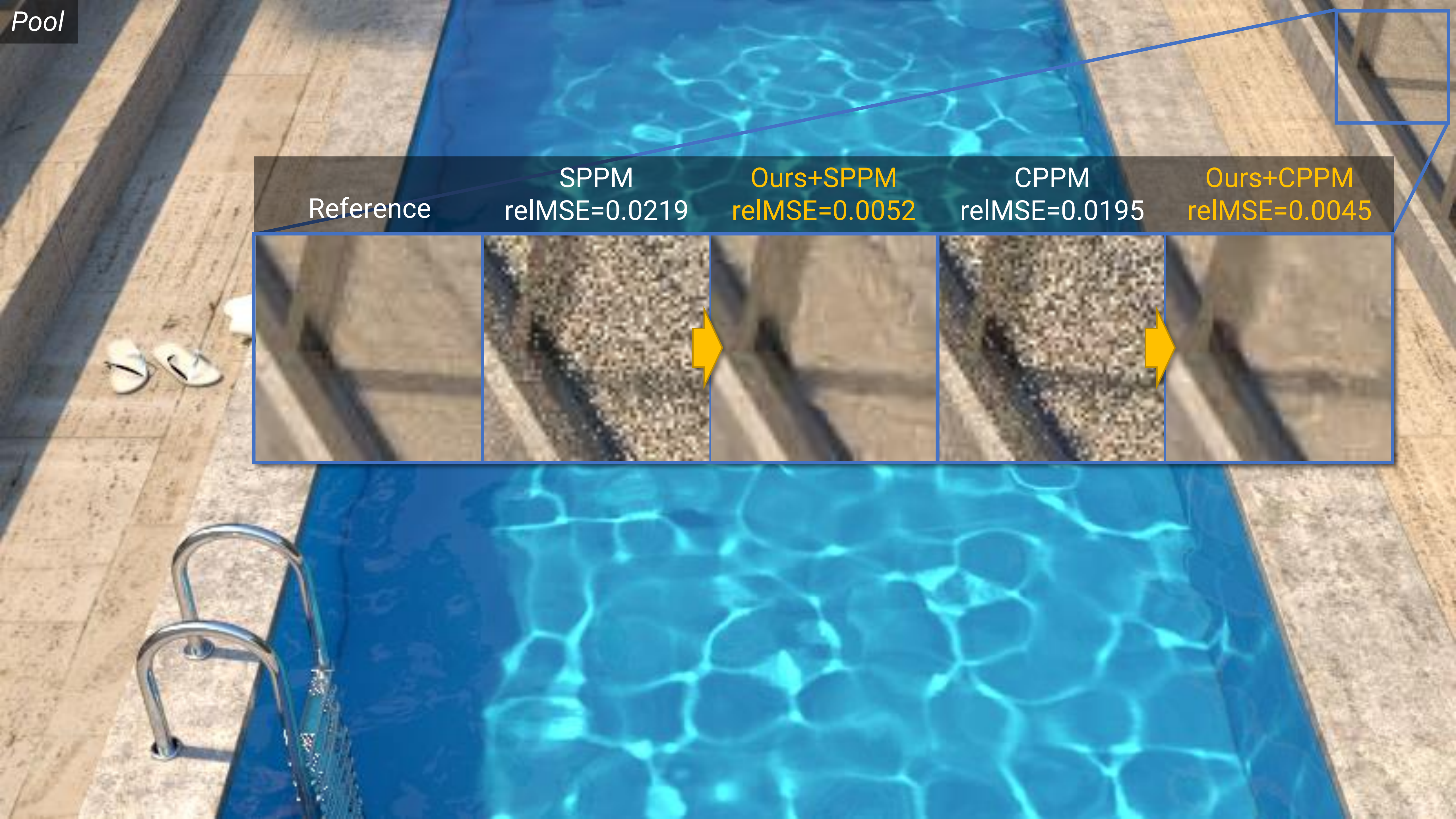
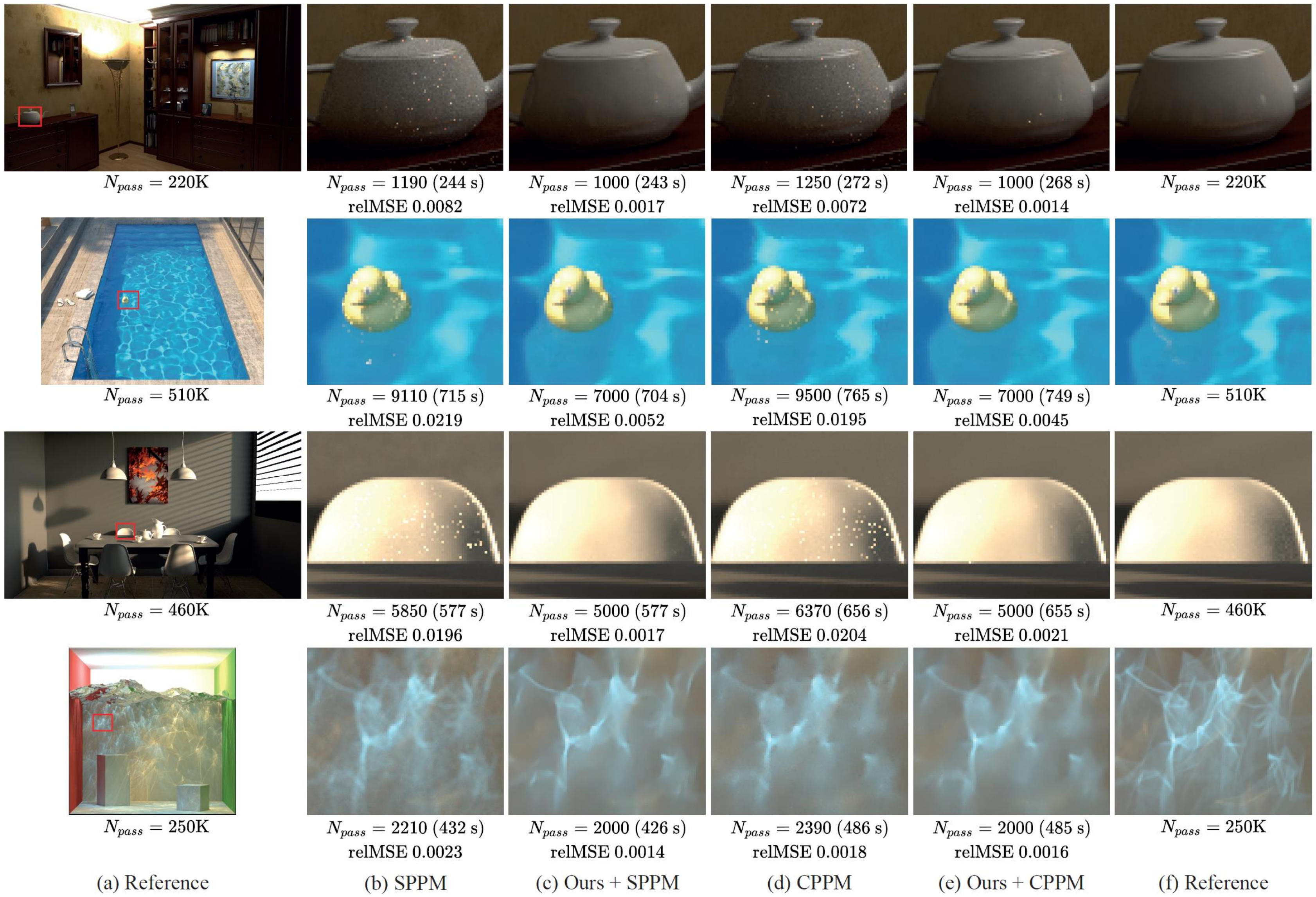
relMSE=0.0017
CPPM
relMSE=0.0072
Ours+CPPM
relMSE=0.0014

Pool

Pool
Reference
SPPM
relMSE=0.0219
Ours+SPPM
relMSE=0.0052
CPPM
relMSE=0.0195
Ours+CPPM
relMSE=0.0045


Pool
Reference
SPPM
relMSE=0.0219
Ours+SPPM
relMSE=0.0052
CPPM
relMSE=0.0195
Ours+CPPM
relMSE=0.0045

Results 1 (equal-time w/ previous PPM methods)

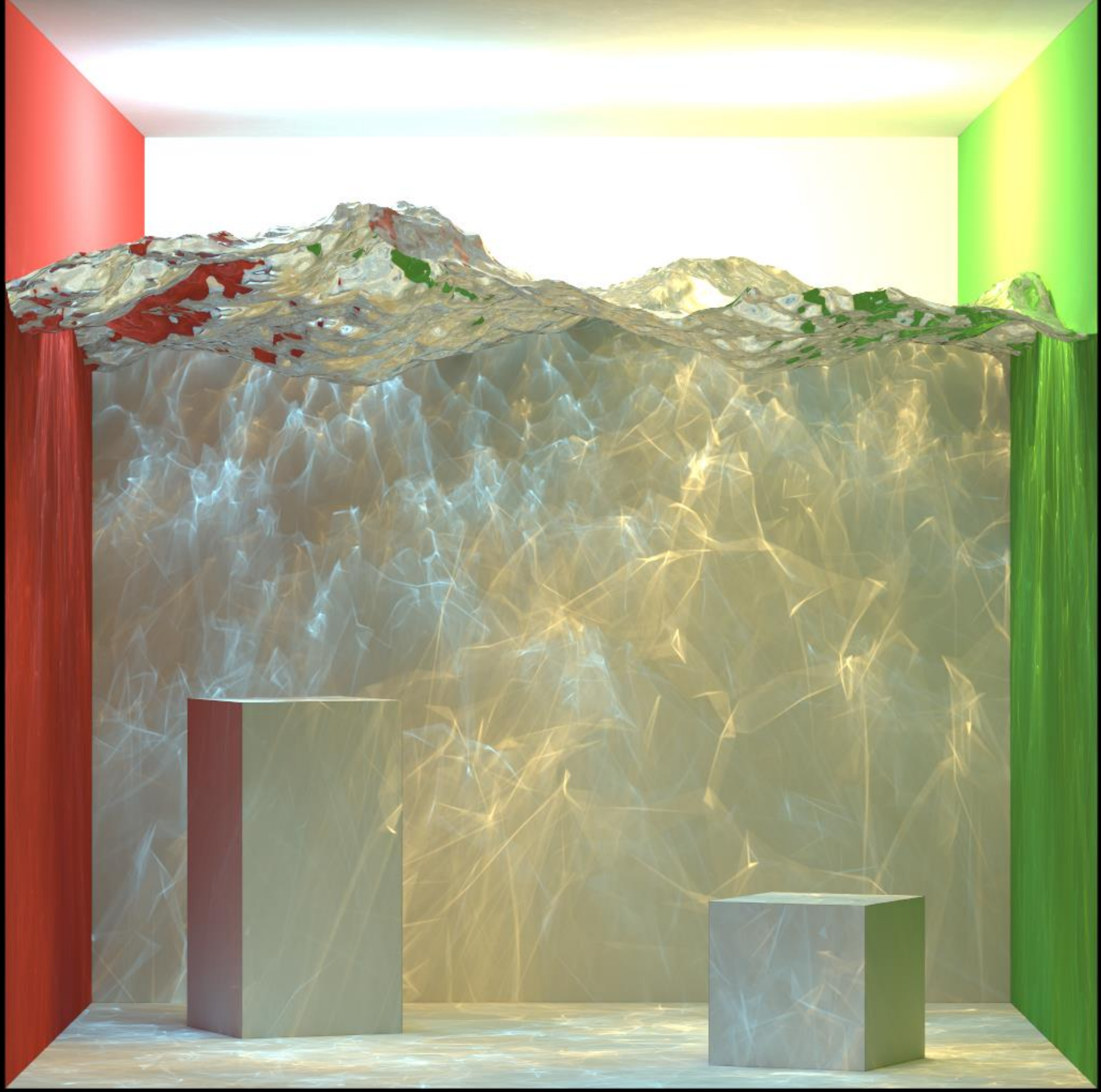


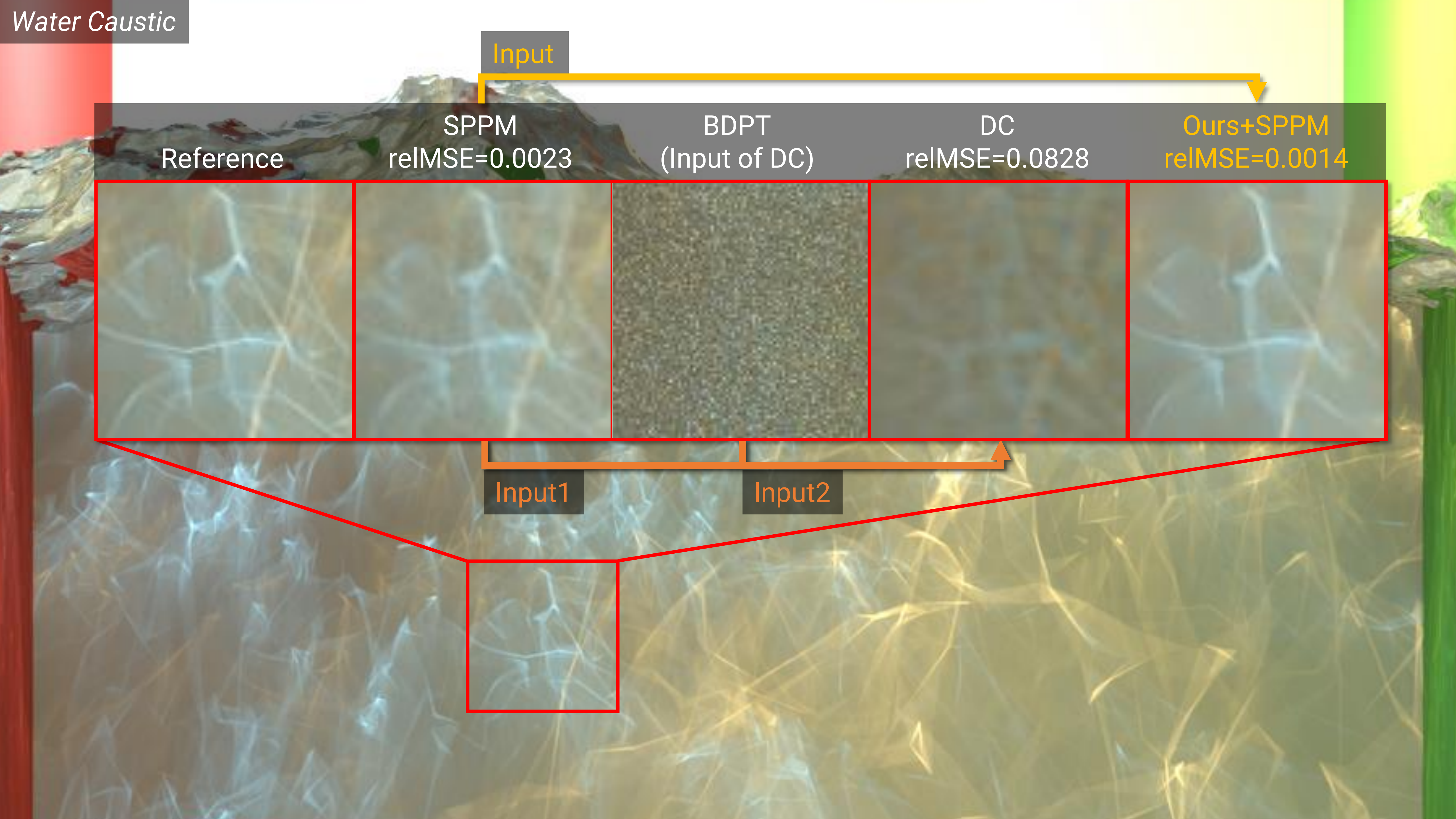
SPPM	CPPM
4.93x	5x
4.2x	4.35x
11.4x	9.91x
1.68x	1.14x

Results

Comparison with previous post-reconstruction method

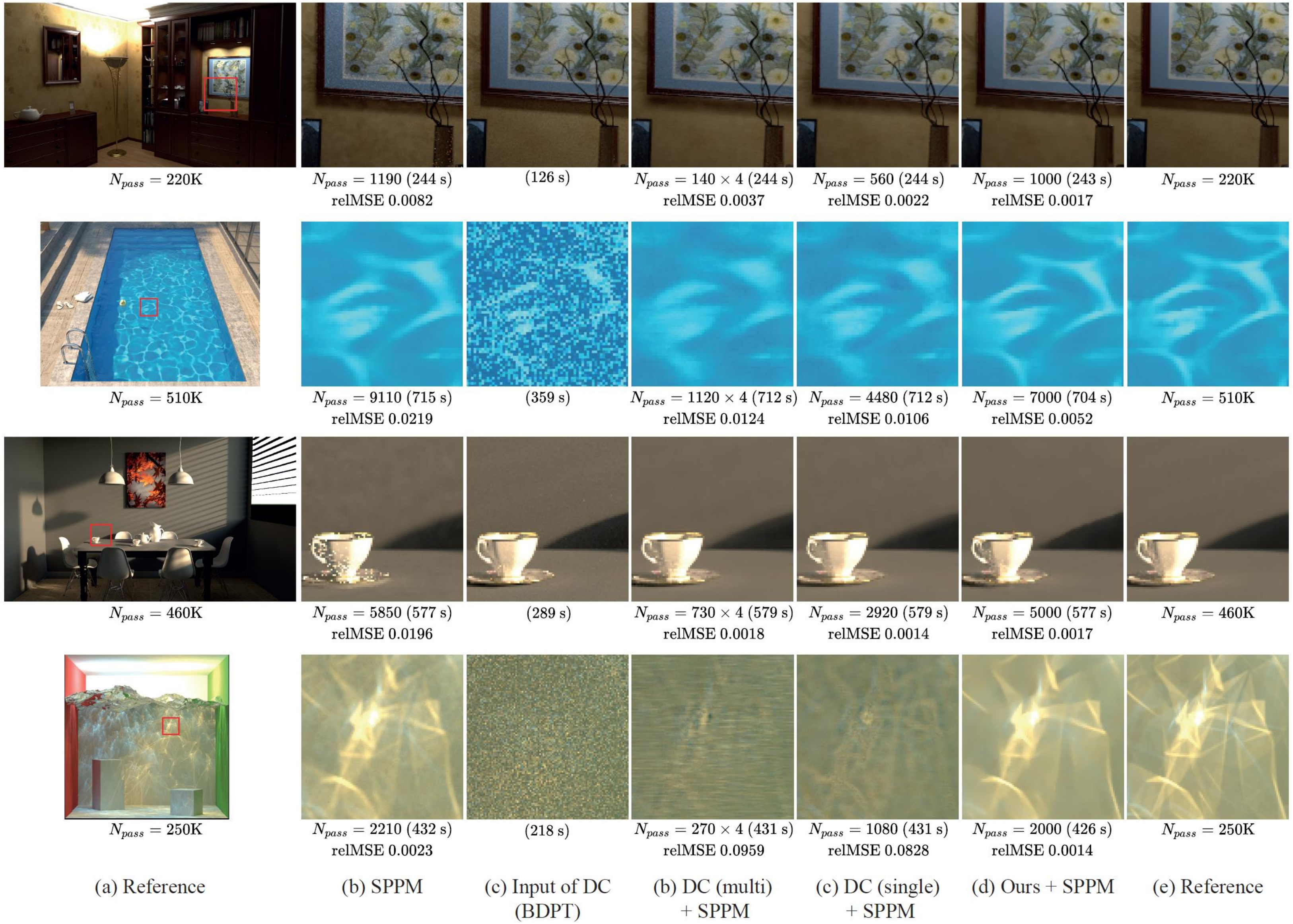
Water Caustic





Water Caustic
Input
Reference
SPPM
relMSE=0.0023
BDPT
(Input of DC)
DC
relMSE=0.0828
Ours+SPPM
relMSE=0.0014
Input1
Input2

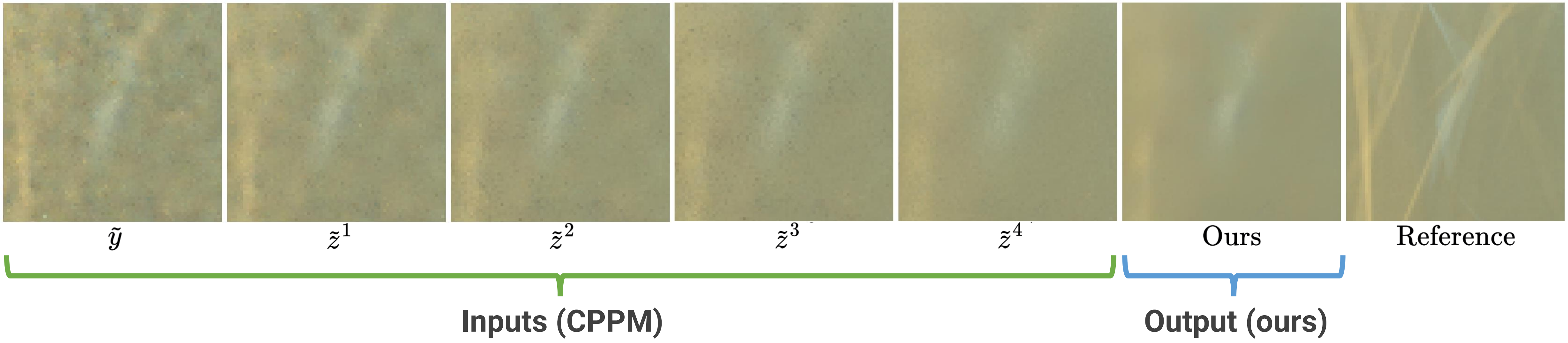
Results 2 (equal-time w/ previous recon. method)



DC (single)	DC (multi)
1.31x	2.21x
2.03x	2.38x
0.81x	1.05x
59.51x	68.91x

Limitations and Future Work

- Fail to preserve high-frequency details when all the input estimates do not have enough details



- Future work
    - o Design a unified framework that optimizes the bandwidth update rule of PPM while considering our post-reconstruction errors
    - o Exploit temporal coherence in animated sequences

Conclusions

- Propose a new post-reconstruction that reduces the errors of PPM estimates
  - Maintain **consistency** of PPM estimates
  - **Combine** multiple PPM estimates with **different correlation levels**

Online Resources

- Interactive viewers and code are available on the project page

https://cglab.gist.ac.kr/pg21recon/

Acknowledgements

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  - Constructive comments (weight visualization, comparison with denoisers, etc.)
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- Scenes
  - Training scenes: Mareck, Wig42, SlykDrako, nacimus, Jay-Artist, aXel, thecali, NovaZeeke, Eric Veach, Wenzel Jacob and Benedikt Bitterli
  - Test scenes: Tiziano Portenier, Wig42, Ondřej Karlík, Benedikt Bitterli and authors of CPPM [Lin et al. 20]

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Thank you

All questions are welcome

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