

Fast and Lightweight Path Guiding Algorithm on GPU - Supplementary Material

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1. Comparison for Spatial Directional Resolution

Table 1 shows MAE for different spatial, directional resolutions. We only tested our proposed algorithm that using SARSA and optimized rejection sampling. For faster comparison, we halve the image size, so the error value is different from the main paper. Spatial resolution 4 and directional resolution 16 gave the best result, we think that 4 is too small, so used 8 instead for the main experiments.

Table 1: Comparison for different spatial directional resolutions. *S* means spatial and *D* means directional in the table.

S \ D	32	16	8	4
32	0.0936	0.0564	0.0435	0.0466
16	0.0489	0.0380	0.0367	0.0448
8	0.0376	0.0347	0.0362	0.0443
4	0.0351	0.0344	0.0363	0.0461

2. Equal SPP Comparison

Table 2 shows MAE for equal spp (1024) budget. For BRDF method and quadtree method (MC), error is 0.0645 and 0.0522 each. Note that unlike equal-time budget, SARSA does not give the best result. Another thing to note is that Rej+ gives better results than Rej even though Rej shows a higher light hit rate. This seems because of the error in calculating the normalizing term. Since we use stratified Monte Carlo integration to calculate the normalizing term, if sampling radiance distribution is highly unbalanced it causes a higher error, and mixing uniform function helps to reduce the error.

3. Pseudocode for the Algorithm

We provide pseudocode of our algorithms for several sampling methods. Here, η is a uniform random variable in $[0, 1]$, $N(x, \omega, n)$ is a normalizing term, $\int_{\Omega} L_i(x, \omega_i) f_r(x, \omega, \omega_i) (n \cdot \omega_i) d\omega_i$ and $p_{max}(x, \omega, n)$ is $\max_{\omega_i} L_i(x, \omega_i) f_r(x, \omega, \omega_i) (n \cdot \omega_i)$. This value is calculated with stratified Monte-Carlo integration. For diffuse material, this can be memoized with 5D table since $N(x, \omega, n) = N(x, n)$ and $p_{max}(x, \omega, n) = p_{max}(x, n)$.

Table 2: Comparison for equal spp(1024) budget. For BRDF method and quadtree method (MC), error is 0.0645 and 0.0522 each.

MAE	Sphere	Hemisphere		
	Inv	Inv	Rej	Rej+
Expected -SARSA	0.0501	0.0466	0.0531	0.0391
MC	0.0482	0.0495	0.0543	0.0380
SARSA	0.0504	0.0475	0.0551	0.0392

Algorithm 1 Inversion sampling on hemispherical domain

```

1: procedure INVERSIONSAMPLE( $x, n, \omega$ )
2:    $v \leftarrow 0$ 
3:   for  $k = 1, 2, \dots, N$  do
4:      $p \leftarrow L_i(x, \omega_k) f_r(x, \omega, \omega_k) (n \cdot \omega_k) / N(x, \omega, n)$ 
5:      $v \leftarrow v + p$ 
6:     if  $\eta \leq v$  then
7:       return  $\omega_k, p$ 

```

Algorithm 2 Inversion sampling on spherical domain

```

1: procedure INVERSIONSAMPLE( $x, \omega$ )
2:   return BINARYSEARCH( $CDF(x), \eta$ )

```

Algorithm 3 Rejection sampling

```

1: procedure REJECTSAMPLE( $x, n, \omega$ )
2:   while True do
3:      $\omega_i \leftarrow$  UNIFORMHEMISPHERE( $n$ )
4:      $p \leftarrow L_i(x, \omega_i) f_r(x, \omega, \omega_i) (n \cdot \omega_i) / N(x, \omega, n)$ 
5:     if  $\eta < p / p_{max}(x, \omega, n)$  then
6:       break
7:   return  $\omega_i, p$ 

```

Algorithm 4 Rejection sampling with speed optimization

```

1: procedure REJECTSAMPLEOPT( $x, n, \omega$ )
2:    $c \leftarrow 1/p_{max}(x, \omega, n)$ 
3:    $\epsilon \leftarrow \max(\frac{1-2c}{2-2c}, 0)$ 
4:    $p_{max} \leftarrow (1-\epsilon)p_{max}(x, \omega, n) + \epsilon u$ 
5:   while True do
6:      $\omega_i \leftarrow \text{UNIFORMHEMISPHERE}(n)$ 
7:      $p \leftarrow L_i(x, \omega_i) f_r(x, \omega, \omega_i) (n \cdot \omega_i) / N(x, \omega, n)$ 
8:      $p \leftarrow (1-\epsilon)p + \epsilon u$ 
9:     if  $\eta < p/p_{max}$  then
10:      break
11:  return  $\omega_i, p$ 

```

4. Additional Results

In this section, we provide a qualitative result for the other scenes that were not presented in the main paper (Fig. 1, 2, 3).

References

- [DK17] DAHM, KEN and KELLER, ALEXANDER. “Learning light transport the reinforced way”. *ACM SIGGRAPH 2017 Talks*. 2017, 1–2 3.
- [MGN17] MÜLLER, THOMAS, GROSS, MARKUS, and NOVÁK, JAN. “Practical path guiding for efficient light-transport simulation”. *Computer Graphics Forum*. Vol. 36. 4. Wiley Online Library. 2017, 91–100 3.

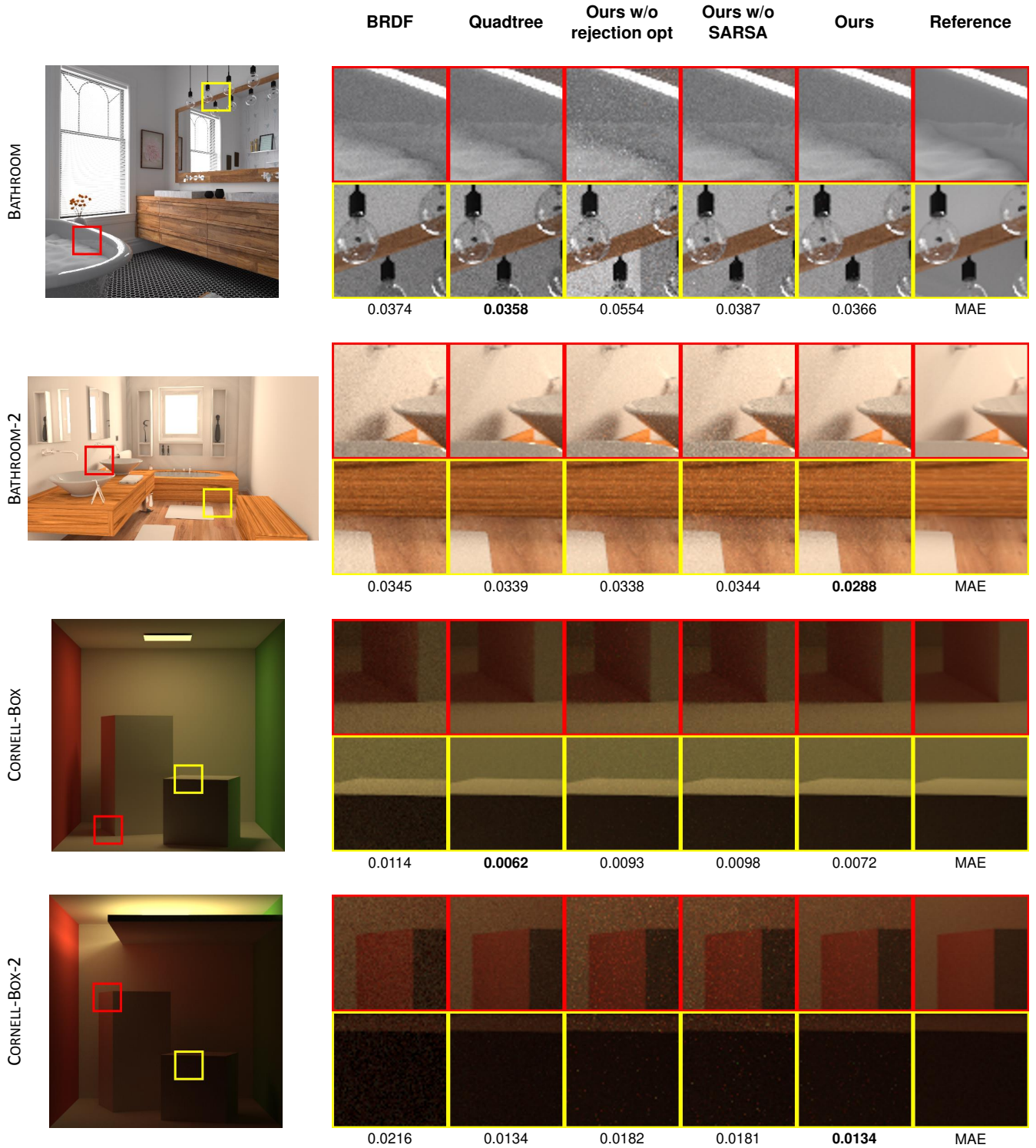


Figure 1: Qualitative result for equal time comparison. Each column refers to standard path tracer with BRDF sampling, our proposed method, our proposed method without rejection optimization, our proposed method without SARSA (expected-SARSA) was used instead as [DK17]) and quadtree based sampling [MGN17] with MC learning.

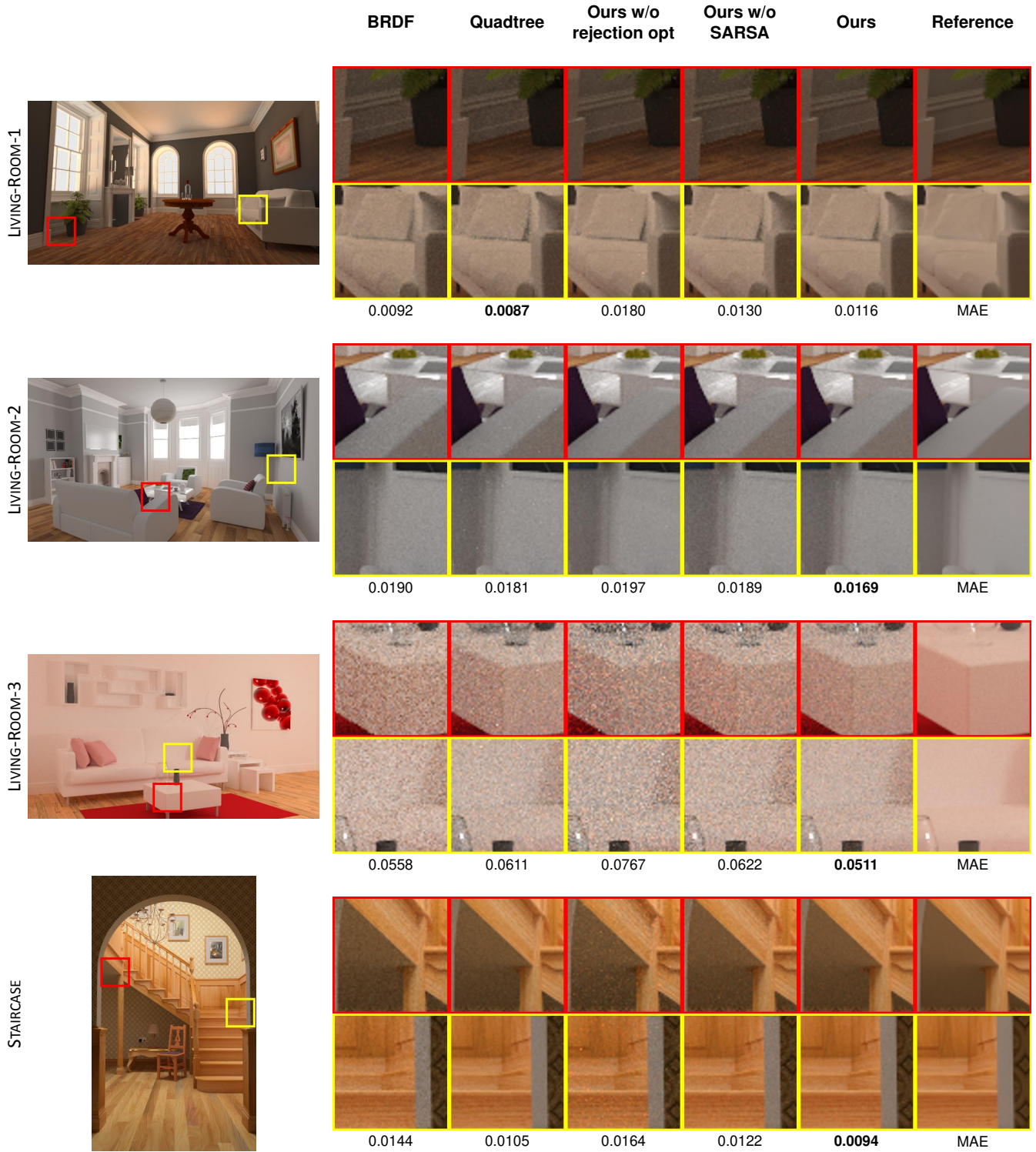


Figure 2: Continue of Fig.1.

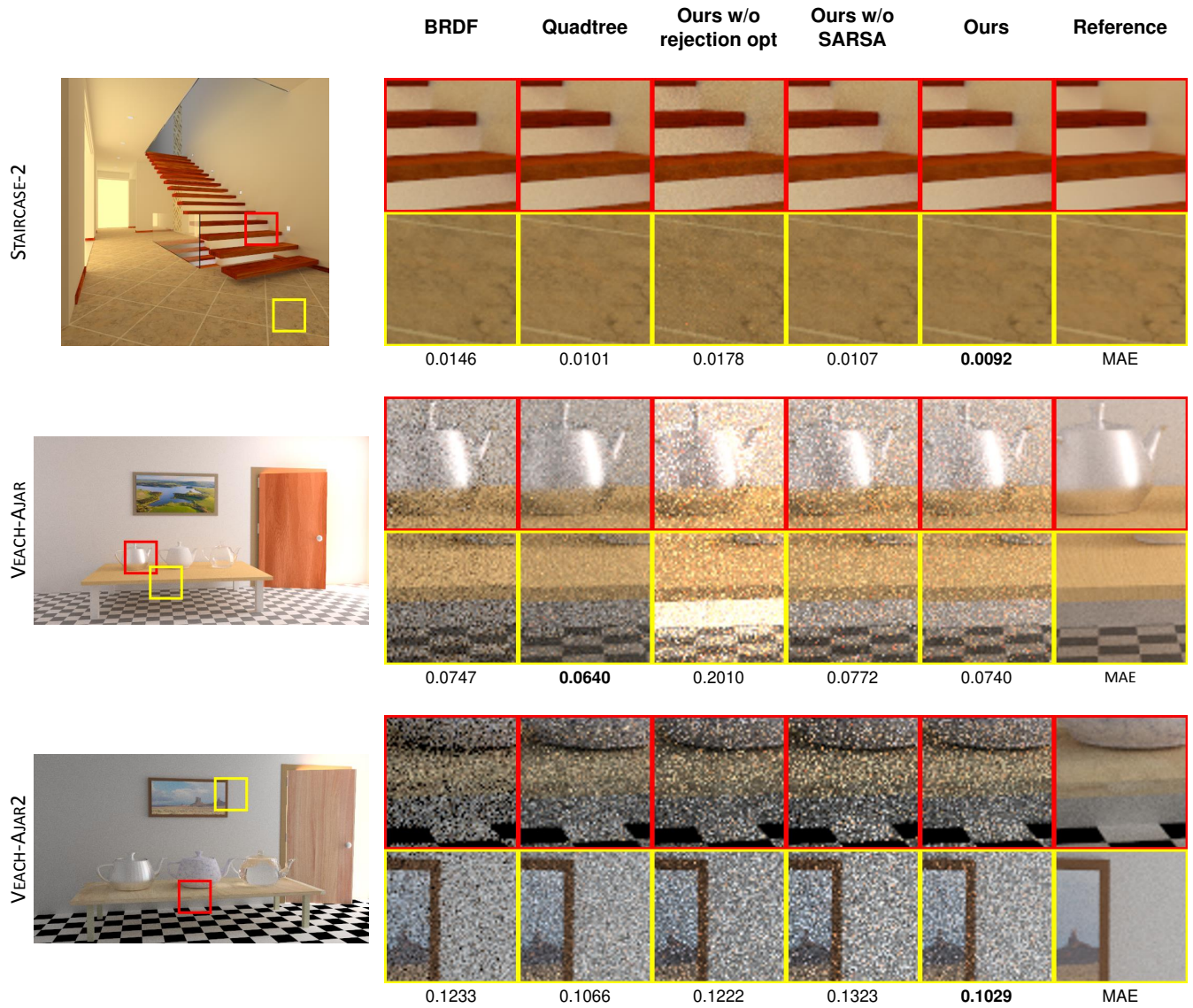


Figure 3: Continue of Fig.1.