Langevin Monte Carlo Rendering with Gradient-based Adaptation: Supplementary Material

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In this supplement, we provide additional results supplementing Sections 8 and 9 of the main paper. **Please also see the supplemental HTML viewer for the complete suite of comparisons.**

CCS Concepts: • **Computing methodologies → Rendering**.

Additional Key Words and Phrases: global illumination, photorealistic rendering, Langevin Monte Carlo

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1 EQUAL-TIME COMPARISONS WITH PRIOR WORK

In Table 1, we summarize MSE values for equal-time renderings across our main test suite, consisting of 17 challenging scenes with complex illumination, occlusions, caustics and glossy interreflections. We compare BDPT, MEMLT [Jakob and Marschner 2012], MMLT [Hachisuka et al. 2014], RJMLT [Bitterli et al. 2018], H2MC [Li et al. 2015], and two of our algorithms (online adaptation and hybrid adaptation). For each scene (row), we indicate the lowest, second lowest and third lowest errors using bold blue, regular blue, and regular green font. In Figure 1, we compare equal-time renderings for a few scenes in our test suite, as in Figure 5 of the main paper.

2 EVALUATION OF PRECONDITIONING SCHEMES

In Table 2, we summarize MSE values for equal-time and equal-sample renderings across the set of nine scenes we use to evaluate different preconditioning scehems. We compare Hessian-based preconditioning (H2MC [Li et al. 2015]), as well as our full and diagonal preconditioning, when combined with MALA with online adaptation. For each scene (row) and experimental setting (equal-sample, or equal-time), we indicate the lowest error using bold blue font.

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In Table 3, we summarize MSE values for equal-time and equal-sample renderings across the same set of nine scenes. We compare Hessian-based preconditioning and our diagonal preconditioning, when combined with MALA with hybrid adaptation. For each scene (row) and experimental setting (equal-sample, or equal-time), we indicate the lowest error using bold blue font.

3 EFFECT OF CACHE PARAMETER VALUES

In Table 4, we use three scenes to evaluate the effect how the performance of our MALA with hybrid adaptation changes, as we vary the two main parameters controlling hybrid adaptation: the cache query radius r, and the cache size H. We observe that MSE does not change by more than 10% at equal time. These results indicate that, as long as the cache is not too large, the performance of our hybrid algorithm is relatively insensitive to the exact values of parameters r and H. Similar observations hold for all other scenes in our main test suite, for all of which we use the same values for r and H. We believe this scene-independence is in part due to the fact that our gradient cache operates in the primary sample space, making the parameters approximately invariant to the physical scale of the scene. Another reason for this robustness is that, as r and H affect only adaptation, the underlying procedure remains a valid and effective MALA sampler even when these parameters are not optimally set for the specific scene that is being rendered.

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Table 1. Equal-time comparisons of two of our algorithms with prior state-of-the-art.

scene name	ours (hybrid)	ours (online)	H2MC	RJMLT	MMLT	MEMLT	BDPT
Teaser	**0.0024**	0.0030	0.0073	0.0095	0.0123	0.0081	0.0214
Veach Door	**0.0363**	0.0512	0.1256	0.1045	0.1330	0.1032	0.3049
Bookshelf	**0.0013**	0.0016	0.0043	0.0037	0.0059	0.0053	0.0078
Bottle	**0.0017**	0.0021	0.0044	0.0044	0.0079	0.0076	0.0058
Glossy Kitchen	**0.0402**	0.0564	0.1432	0.1164	0.1007	0.0773	0.1930
Spaceship	**2.3307e-04**	3.5226e-04	3.9719e-04	4.4564e-04	5.3384e-04	5.8839e-04	0.0012
Living Room	**0.0521**	0.0730	0.1379	0.1868	0.2365	0.1451	0.2292
Museum	**0.0311**	0.0367	0.0848	0.0606	0.0791	0.0850	0.1617
Table	**0.0016**	0.0020	0.0066	0.0053	0.0106	0.0114	0.0155
Car	**1.4066e-04**	1.8296e-04	2.5261e-04	1.9551e-04	2.1176e-04	4.3312e-04	0.0016
Salle De Bain	**0.0336**	0.0444	0.0881	0.1367	0.1891	0.1260	0.1713
Dining Room	**0.0029**	0.0035	0.0100	0.0088	0.0091	0.0037	0.0116
Whiteroom	**0.0233**	0.0287	0.0659	0.1031	0.1050	0.0875	0.0768
Pool	**0.0116**	0.0142	0.0337	0.0229	0.0282	0.0506	0.2563
Kitchen	**0.0383**	0.0417	0.1136	0.0702	0.0704	0.0742	0.2068
Necklace	**0.0499**	0.0642	0.1080	0.1648	0.1669	0.1594	0.2095
Classroom	**0.0583**	0.0639	0.1034	0.1012	0.1032	0.1085	0.2623

Table 2. Comparisons of Hessian-based (H2MC [Li et al. 2015]), full, and diagonal preconditioning, combined with MALA with online adaptation.

	equal-sample			equal-time		
scene name	diagonal	full	H2MC	diagonal	full	H2MC
Torus	0.0041	0.0037	**0.0025**	**0.0039**	0.0090	0.0104
Cornell Box	0.0040	**0.0033**	0.0035	**0.0036**	0.0079	0.0096
Living Room	0.0184	0.0163	**0.0138**	**0.0165**	0.0340	0.0402
Ring	1.4468e-04	1.24424e-04	**9.4042e-05**	**1.3250e-04**	2.4746e-04	3.0313e-04
Crytek Sponza	0.0181	**0.0162**	0.0198	**0.0167**	0.0355	0.0425
Staircase	0.0026	0.0022	**0.0020**	**0.0023**	0.0049	0.0060
Veach Door	0.0608	**0.0459**	0.0534	**0.0579**	0.1236	0.1253
Modern Hall	0.0065	0.0052	**0.0051**	**0.0071**	0.0156	0.0185
Bathroom	0.0611	0.0398	**0.0377**	**0.0650**	0.1463	0.1688

Table 3. Comparisons of Hessian-based (H2MC [Li et al. 2015]), and diagonal preconditioning, combined with MALA with hybrid adaptation.

	equal-sample		equal-time	
scene name	diagonal	H2MC	diagonal	H2MC
Torus	0.0016	**0.0010**	**0.0018**	0.0051
Cornell Box	0.0058	**0.0034**	**0.0054**	0.0108
Living Room	0.0193	**0.0116**	**0.0180**	0.0425
Ring	2.1391e-04	**1.3713e-04**	**1.9521e-04**	6.0992e-04
Crytek Sponza	0.0365	**0.0218**	**0.0348**	0.0702
Staircase	0.0033	**0.0020**	**0.0027**	0.0048
Veach Door	0.0246	**0.0154**	**0.0167**	0.0387
Modern Hall	0.0074	**0.0044**	**0.0056**	0.0103
Bathroom	0.0552	**0.0327**	**0.0443**	0.1247

Table 4. Equal-time comparisons of our MALA with hybrid adaptation for different values of cache query radius r and size H.

Living Room	$r = 0.01$	$r = 0.02$	$r = 0.05$	$r = 0.20$	$r = 0.50$
$H = 1000$	0.0075	0.0070	0.0068	0.0069	0.0071
$H = 5000$	0.0070	0.0068	0.0069	0.0071	0.0073
$H = 10000$	0.0065	0.0067	0.0067	0.0071	0.0074
$H = 50000$	0.0067	0.0070	0.0072	0.0079	0.0084
Veach Door	$r = 0.01$	$r = 0.02$	$r = 0.05$	$r = 0.20$	$r = 0.50$
$H = 1000$	0.0254	0.0252	0.0248	0.0255	0.0262
$H = 5000$	0.0248	0.0245	0.0249	0.0255	0.0255
$H = 10000$	0.0241	0.0244	0.0246	0.0254	0.0261
$H = 50000$	0.0252	0.0255	0.0260	0.0262	0.0266
Torus	$r = 0.01$	$r = 0.02$	$r = 0.05$	$r = 0.20$	$r = 0.50$
$H = 1000$	0.0041	0.0040	0.0038	0.0040	0.0043
$H = 5000$	0.0038	0.0037	0.0041	0.0042	0.0041
$H = 10000$	0.0037	0.0035	0.0040	0.0041	0.0044
$H = 50000$	0.0050	0.0048	0.0051	0.0052	0.0055

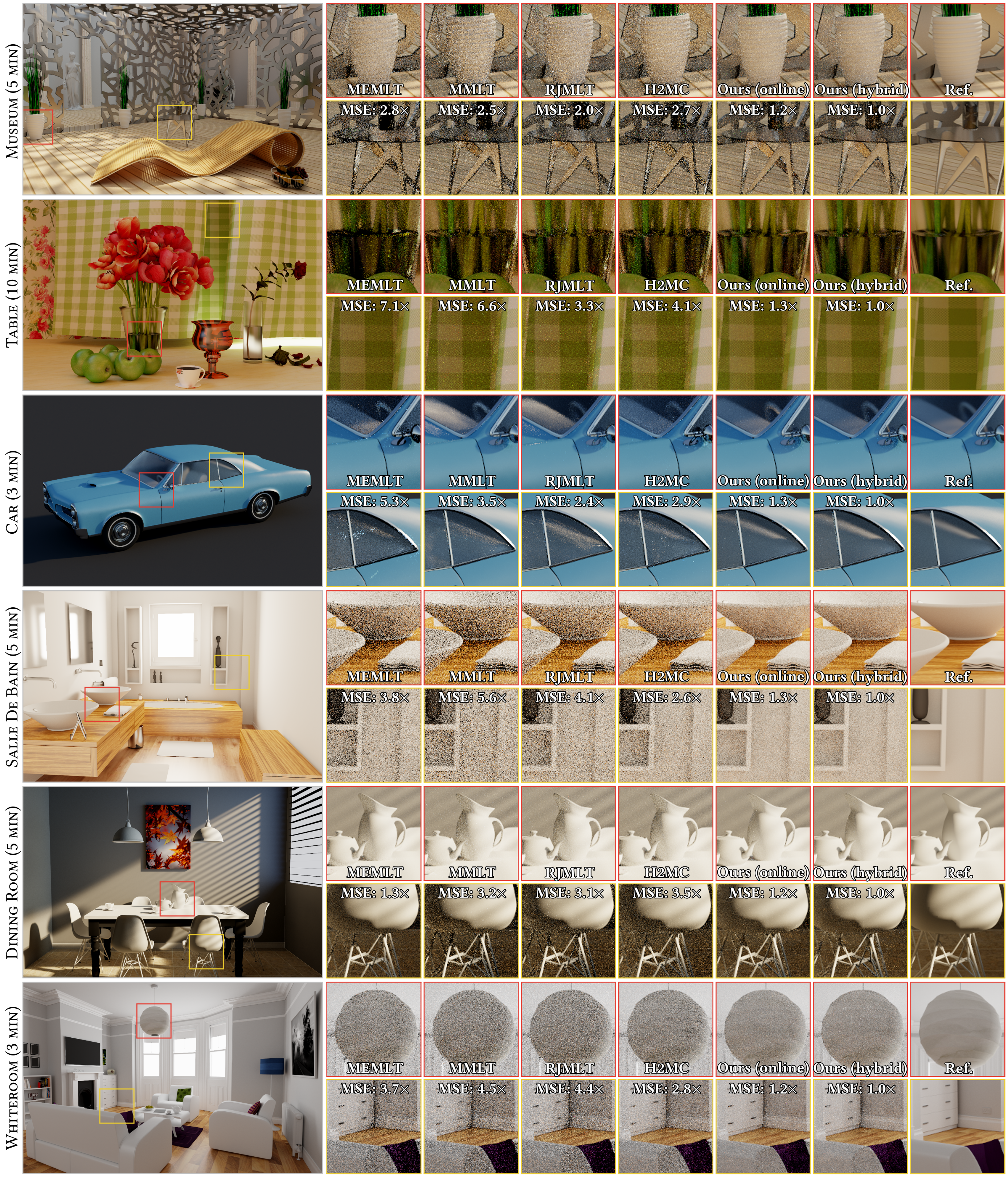

Fig. 1. **Equal-time comparisons:** We compare MEMLT [Jakob and Marschner 2012], MMLT [Hachisuka et al. 2014], RJMLT [Bitterli et al. 2018], H2MC [Li et al. 2015] and two of our algorithms, across several scenes with complex illumination and occlusion, glossy caustics and interreflections.