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## Utilisation efficace des échantillons dans le rendu photo-réaliste

## Efficient Sample Usage in Photo-Realistic Rendering

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## *Abstract*

Rendering photo-realistic images of a virtual scene requires the simulation of how light interacts with it. This typically requires a large number of samples detailing the received and outgoing radiance between surfaces. As this is an expensive process, it is important to be efficient with this information. This thesis investigates two different areas for this. The first is the Low-Rank Matrix Completion problem, which looks to fill in the missing entries of some partially observed low-rank matrix. We apply this to the Many-Lights problem, a direct lighting problem that involves rendering scenes with large numbers of lights. This problem is particularly suited to Low-Rank Matrix Completion as the matrix formulation of it is shown to be approximately low-rank. We propose a modified version of the Adaptive Matrix Completion algorithm, which we term Boolean Adaptive Matrix Completion, to reduce the number of visibility computations between lights and surfaces, allowing significantly faster renderings of the final images. The second area we investigate is the efficient reuse of Monte-Carlo samples when the probability measure has changed. This is important as naively combining samples taken from different probability distributions can lead to higher variance, or even bias. We propose a hybrid method, which we term Reweighting-Augmentation, which aims to address this. We investigate this method in two different application areas. The first is progressive path tracing with animated cameras, where the sampling distribution changes on glossy surfaces due to a change in the incident direction. The second is the Practical Path Guiding algorithm, where sampling distributions change as the irradiance function of a scene is iteratively learned. We found that our proposed method showed promising results for the former, allowing for reduced variance in the final generated images. Although we did not obtain positive results for the latter, we believe that the problem should still be investigated further and there is reason to remain positive.



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# Nomenclature

<b>IR</b>	Instant Radiosity
<b>VPL</b>	Virtual Point Light
<b>VSL</b>	Virtual Spherical Light
<b>VSL</b>	Virtual Disc Light
<b>SVD</b>	Singular Value Decomposition
<b>LRMC</b>	Low-Rank Matrix Completion
<b>AMC</b>	Adaptive Matrix Completion
<b>BAMC</b>	Boolean Adaptive Matrix Completion
<b>RMSE</b>	Root Mean Squared Error
<i>ESS</i>	Effective Sample Size
$\widehat{ESS}$	Effective Sample Size surrogate
<b>SMC</b>	Sequential Monte Carlo
<b>RIS</b>	Resampled Importance Sampling
<b>BSDF</b>	Bidirectional Scattering Distribution Function
<b>CDF</b>	Cumulative Distribution Function
<b>PPG</b>	Practical Path Guiding



## Part I

# Matrix Completion with the Many-Lights Problem



## Part II

# Using Samples Across Probability Measures in Monte Carlo Rendering





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## Appendix A

# Additional Results for BAMC

### A.1 BAMC Scalability Results

		San Miguel			Classroom			Kitchen		
		1280 x 720 @ 4, 100k VPLs			1280 x 720 @ 4, 100k VPLs			1280 x 720 @ 4, 100k VPLs		
		Time	RMSE	Samples	Time	RMSE	Samples	Time	RMSE	Samples
AMC	$\alpha=10\%$ cols=1000	88.10s	0.0254	15.36%	73.37s	0.0221	17.17%	81.68s	0.0904	15.85%
	$\alpha=12.5\%$ cols=1000	121.75s	0.0265	18.15%	108.82s	0.0201	19.93%	118.69s	0.0905	18.53%
	$\alpha=15\%$ cols=1000	189.23s	0.0246	20.70%	206.63s	0.0194	22.58%	201.55s	0.0899	21.18%
	$\alpha=17.5\%$ cols=1000	350.70s	0.0204	23.31%	427.37s	0.0197	25.13%	372.51s	0.0918	23.71%
	$\alpha=20\%$ cols=1000	568.07s	0.0198	25.84%	828.32s	0.0198	27.69%	654.42s	0.0900	26.22%
	$\alpha=10\%$ cols=1500	127.15s	0.0267	14.58%	110.91s	0.0204	16.22%	120.04s	0.0819	14.87%
	$\alpha=10\%$ cols=2000	164.23s	0.0276	13.99%	146.70s	0.0210	15.52%	156.29s	0.0743	14.27%
	$\alpha=10\%$ cols=2500	197.10s	0.0284	13.49%	180.95s	0.0211	14.90%	189.98s	0.0687	13.82%
	$\alpha=10\%$ cols=3000	230.15s	0.0297	13.15%	207.66s	0.0241	14.38%	224.51s	0.0633	13.50%
BAMC	$\alpha=10\%$ cols=1000	65.42s	0.0235	17.30%	52.16s	0.0199	19.65%	52.31s	0.0894	17.13%
	$\alpha=12.5\%$ cols=1000	72.60s	0.0207	19.86%	57.57s	0.0192	22.21%	58.01s	0.0909	19.68%
	$\alpha=15\%$ cols=1000	79.86s	0.0198	22.33%	62.93s	0.0195	24.66%	62.91s	0.0910	22.19%
	$\alpha=17.5\%$ cols=1000	86.17s	0.0203	24.82%	67.72s	0.0180	27.00%	67.88s	0.0900	24.59%
	$\alpha=20\%$ cols=1000	92.49s	0.0194	27.17%	71.61s	0.0195	29.34%	72.36s	0.0894	26.98%
	$\alpha=10\%$ cols=1500	95.49s	0.0221	16.70%	76.70s	0.0182	19.28%	75.63s	0.0792	16.38%
	$\alpha=10\%$ cols=2000	125.32s	0.0231	16.33%	101.31s	0.0191	18.96%	98.02s	0.0747	15.91%
	$\alpha=10\%$ cols=2500	154.20s	0.0240	15.95%	124.92s	0.0192	18.63%	120.60s	0.0696	15.57%
	$\alpha=10\%$ cols=3000	183.14s	0.0252	15.68%	152.80s	0.0197	18.25%	143.31s	0.0624	15.30%
BAMC (GE)	$\alpha=10\%$ cols=1000	157.68s	0.0201	18.60%	167.77s	0.0191	21.73%	101.51s	0.0914	19.64%
	$\alpha=12.5\%$ cols=1000	165.92s	0.0183	20.97%	172.93s	0.0190	23.81%	104.02s	0.0899	21.59%
	$\alpha=15\%$ cols=1000	172.00s	0.0187	23.17%	176.22s	0.0195	26.00%	106.66s	0.0904	23.57%
	$\alpha=17.5\%$ cols=1000	178.27s	0.0184	25.52%	180.57	0.0189	28.13%	110.81s	0.0909	25.76%
	$\alpha=20\%$ cols=1000	184.20s	0.0183	27.75%	183.62s	0.0189	30.28%	113.52s	0.0915	27.90%
	$\alpha=10\%$ cols=1500	330.97s	0.0192	18.43%	402.28s	0.0203	21.92%	186.77s	0.0824	19.74%
	$\alpha=10\%$ cols=2000	528.14s	0.0228	18.14%	621.92s	0.0258	21.79%	312.96s	0.0749	20.38%
	$\alpha=10\%$ cols=2500	767.49s	0.0276	17.96%	832.50s	0.0278	21.56%	476.72s	0.0700	20.74%
	$\alpha=10\%$ cols=3000	1043.99s	0.0322	17.77%	1039.84s	0.0448	21.27%	669.25s	0.0657	21.05%

TABLE A.1: Boolean Adaptive Matrix Completion statistics when compared to the original algorithm and the Gaussian elimination variant in the Classroom, San Miguel, and Kitchen scenes.

Table A.1 provides full results on the scalability and accuracy of BAMC.

### A.2 Full Results for Comparisons Against Other Many-Lights Methods

We provide equal time images along with their error images and their time versus error plots. These are as follows:

- Cornell Box in Figure A.1
- Hairball in Figure A.2
- Sponza in Figure A.3

Columns		250	500	1000	2000	4000
Bathroom 100k VSLs 1024x1024 @ 4	Time	182.39s	234.11s	366.67s	662.31s	1261.27s
	Error (RMSE)	0.176	0.146	0.123	0.104	0.094
Breakfast room 100k VPLs 1280x720 @ 4	Time	100.92s	154.01s	273.36s	515.86s	998.68s
	Error (RMSE)	0.019	0.017	0.015	0.014	0.012
Cornell box 100k VPLs 800x600 @ 4	Time	26.09s	48.95s	96.36s	191.89s	378.43s
	Error (RMSE)	0.0038	0.0027	0.0019	0.0014	0.001
Classroom 100k VPLs 1280x720 @ 4	Time	122.82s	172.86s	289.17s	534.38s	1049.91s
	Error (RMSE)	0.097	0.078	0.063	0.06	0.056
Hairball 100k VPLs 800x600 @ 4	Time	80.94s	118.34s	194.89s	348.77s	658.16s
	Error (RMSE)	0.013	0.01	0.0087	0.0079	0.0065
Living room 100k VPLs 1280x720 @ 4	Time	124.67s	175.59s	297.67s	553.17s	1070.74s
	Error (RMSE)	0.019	0.015	0.012	0.0104	0.0102
Kitchen 100k VSLs 1280x720 @ 4	Time	67.53s	132.24s	264.66s	527.48s	1051.77s
	Error (RMSE)	0.125	0.115	0.098	0.082	0.069
San-Miguel 100k VPLs 1280x720 @ 4	Time	156.38s	220.4s	353.02s	624.1s	1175.71s
	Error (RMSE)	0.026	0.023	0.019	0.02	0.018
Sponza 100k VPLs 1280x720 @ 4	Time	79.45s	146.24s	273.11s	538.55s	1052.02s
	Error (RMSE)	0.017	0.013	0.011	0.009	0.0092
Staircase 100k VPLs 720x1280 @ 4	Time	130.03s	179.01s	297.74s	556.01s	1077.31s
	Error (RMSE)	0.027	0.022	0.018	0.019	0.015
Modern Hall 100k VPLs 1024x1024 @ 4	Time	169.95s	232.95s	374.96s	672.75s	1264.93s
	Error (RMSE)	0.0097	0.069	0.052	0.042	0.037
Grey & White Room 100k VPLs 1280x720 @ 4	Time	113.03s	166.71s	285.74s	531.94s	1038.54s
	Error (RMSE)	0.095	0.072	0.059	0.049	0.048

TABLE A.2: Statistics for our LightSlice across all scenes.

- San Miguel in Figure A.4
- Staircase in Figure A.5
- Living Room in Figure A.6
- Breakfast Room in Figure A.7
- Classroom in Figure A.8
- Modern Hall in Figure A.9
- Bathroom in Figure A.10
- Kitchen in Figure A.11
- Grey & White Room in Figure A.12

We also provide tables detailing the full set of data obtained. Table A.2 shows the full results for Lightslice, Table A.3 shows the full results for IlluminationCut, Table A.4 details the full results for Matrix Separation, and Table A.5 shows the full results for our method, which includes using BAMC and full visibility sampling.

Error threshold			10%	5%	2%	1%	0.5%
Breakfast room 100k VPLs 1280x720 @ 4	Time	101.95s	150.14s	262.91s	440.74s	745.58s	
	Error (RMSE)	0.09	0.061	0.039	0.027	0.019	
	Visibility samples	51.06%	47.36%	44.55%	47.55%	50.05%	
Cornell box 100k VPLs 800x600 @ 4	Time	41.76s	59.21s	102.33s	161.01s	250.67s	
	Error (RMSE)	0.014	0.0077	0.0047	0.0033	0.0026	
	Visibility samples	1.87%	2.43%	2.58%	3.13%	3.76%	
Classroom 100k VPLs 1280x720 @ 4	Time	164.12s	224.24s	343.13s	486.74s	775.85s	
	Error (RMSE)	0.088	0.064	0.046	0.034	0.029	
	Visibility samples	20.96%	26.44%	35.75%	44.06%	54.85%	
Hairball 100k VPLs 800x600 @ 4	Time	53.68s	79.52s	122.83s	188.41s	304.46s	
	Error (RMSE)	0.021	0.016	0.011	0.0083	0.0067	
	Visibility samples	19.65%	20.72%	20.61%	20.61%	21.44%	
Living room 100k VPLs 1280x720 @ 4	Time	122.65s	179.08s	303.48s	493.86s	772.62s	
	Error (RMSE)	0.063	0.044	0.037	0.03	0.027	
	Visibility samples	4.05%	3.9%	3.81%	3.9%	3.9%	
San-Miguel 100k VPLs 1280x720 @ 4	Time	105.5s	146.51s	260.18s	410.68s	717.16s	
	Error (RMSE)	0.074	0.059	0.054	0.042	0.034	
	Visibility samples	40.3%	38.79%	38.75%	41.16%	46.48%	
Sponza 100k VPLs 1280x720 @ 4	Time	153.81s	230.32s	404.11s	614.11s	975.07s	
	Error (RMSE)	0.117	0.075	0.056	0.047	0.035	
	Visibility samples	18.42%	15.53%	16.66%	18.94%	22.62%	
Staircase 100k VPLs 720x1280 @ 4	Time	95.51s	138.49s	261.03s	436.58s	772.84s	
	Error (RMSE)	0.056	0.049	0.036	0.029	0.026	
	Visibility samples	3.3%	3.4%	3.56%	3.6%	3.61%	

TABLE A.3: Statistics for IlluminationCut across all scenes.

Max clusters			500	1000	2000	4000	8000
Breakfast room 100k VPLs 1280x720 @ 4	Time	30.46s	74.44s	173.18s	464.6s	1182.892s	
	Error (RMSE)	0.035	0.034	0.034	0.034	0.033	
	Visibility samples	50.48%	39.33%	30.17%	30.51%	29.67%	
Cornell box 100k VPLs 800x600 @ 4	Time	7.83s	17.33s	36.16s	73.56s	135.44s	
	Error (RMSE)	0.01	0.0094	0.0094	0.0094	0.0094	
	Visibility samples	82.56%	82.46%	82.56%	81.77%	73.58%	
Classroom 100k VPLs 1280x720 @ 4	Time	36.63s	76.03s	162.33s	353.43s	742.95s	
	Error (RMSE)	0.032	0.029	0.027	0.026	0.026	
	Visibility samples	38.41%	29.46%	23.37%	18.76%	14.65%	
Hairball 100k VPLs 800x600 @ 4	Time	28.19s	65.52s	152.11s	344.92s	781.92s	
	Error (RMSE)	0.02	0.02	0.02	0.02	0.019	
	Visibility samples	45.2%	36.9%	31.81%	29.4%	51.39%	
Living room 100k VPLs 1280x720 @ 4	Time	30.45s	68.69s	155.7s	350.38s	760.42s	
	Error (RMSE)	0.014	0.013	0.012	0.014	0.014	
	Visibility samples	65.09%	60.11%	60.39%	62.88%	65.12%	
San-Miguel 100k VPLs 1280x720 @ 4	Time	28.23s	57.32s	125.23s	277.77s	618.08s	
	Error (RMSE)	0.041	0.038	0.036	0.035	0.034	
	Visibility samples	26.16%	16.9%	12.05%	9.42%	7.62%	
Sponza 100k VPLs 1280x720 @ 4	Time	25.93s	60.65s	136.47s	299.73s	629.65s	
	Error (RMSE)	0.029	0.026	0.026	0.026	0.025	
	Visibility samples	50.7%	46.7%	45.43%	44.72%	43.82%	
Staircase 100k VPLs 720x1280 @ 4	Time	38.26s	86.55s	182.42s	394.77s	835.47s	
	Error (RMSE)	0.018	0.016	0.015	0.015	0.015	
	Visibility samples	71.86%	67.47%	60.26%	57.73%	55.63%	

TABLE A.4: Statistics for Matrix Separation across all scenes.

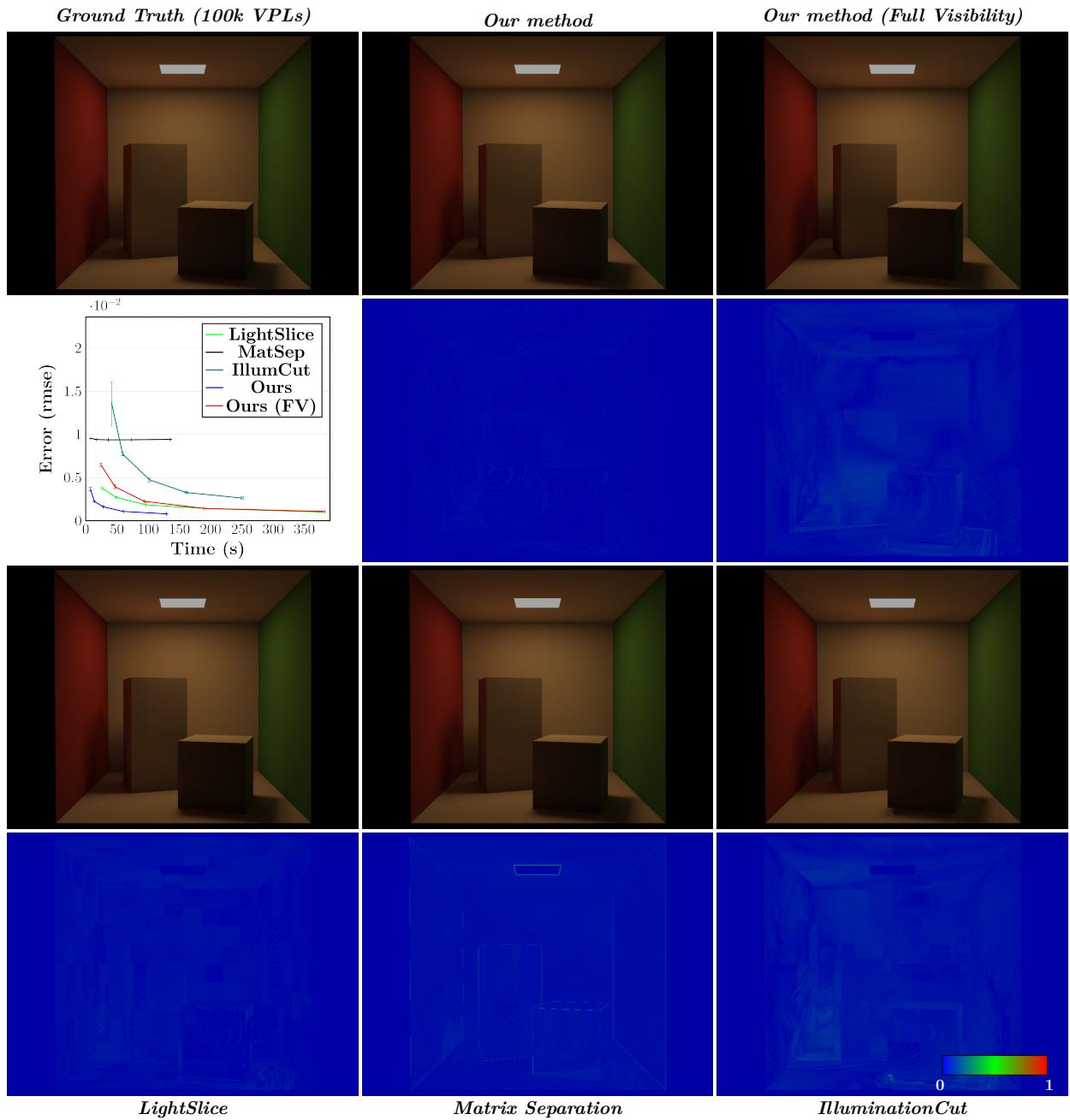


FIGURE A.1: Equal time renders ( $\sim 30$ s) and time vs error plot for Cornell box scene.  
Error images shows  $L_1$  error.

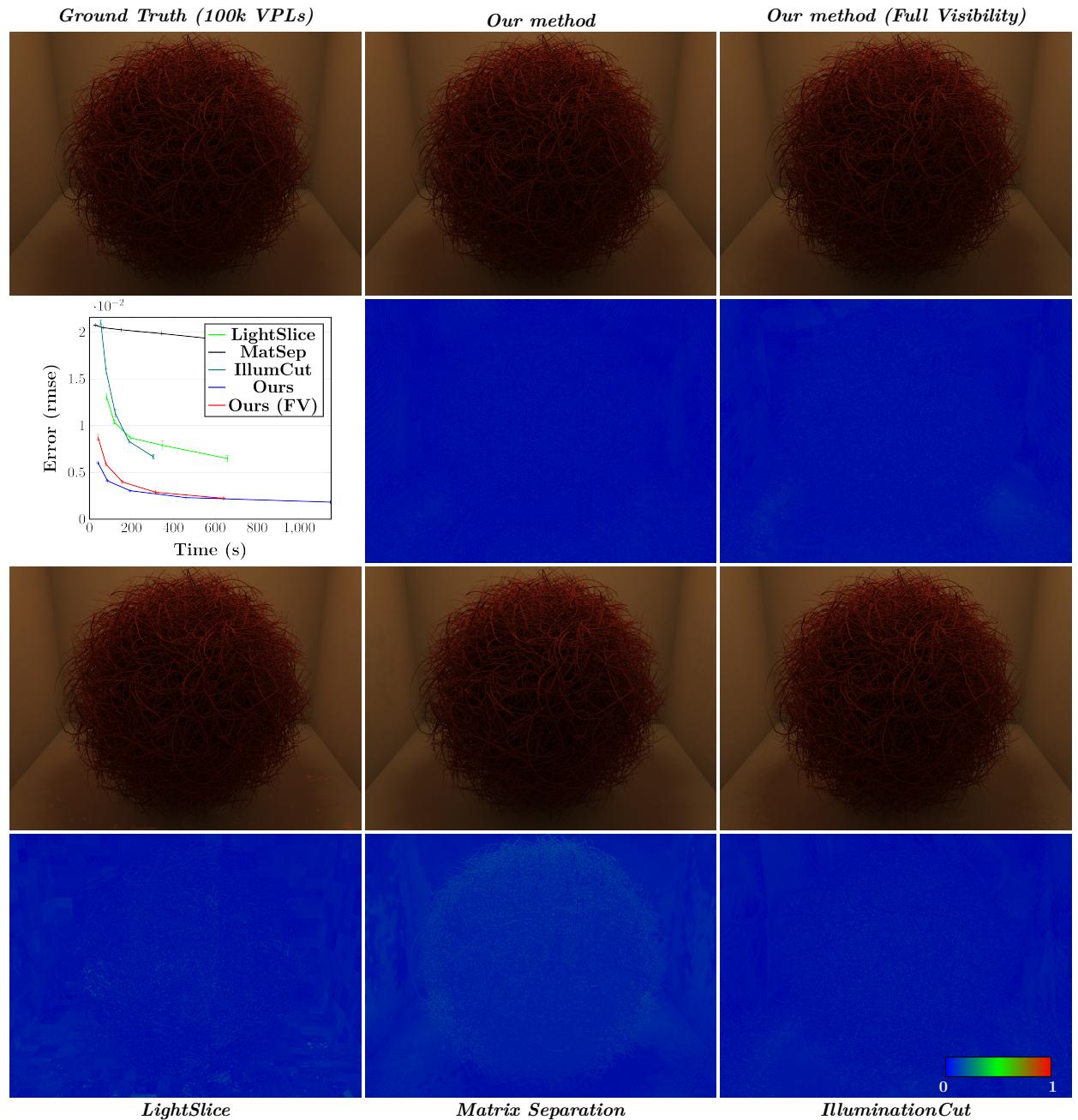


FIGURE A.2: Equal time renders ( $\sim 80$ s) and time vs error plot for hairball scene.  
Error images shows  $L_1$  error.

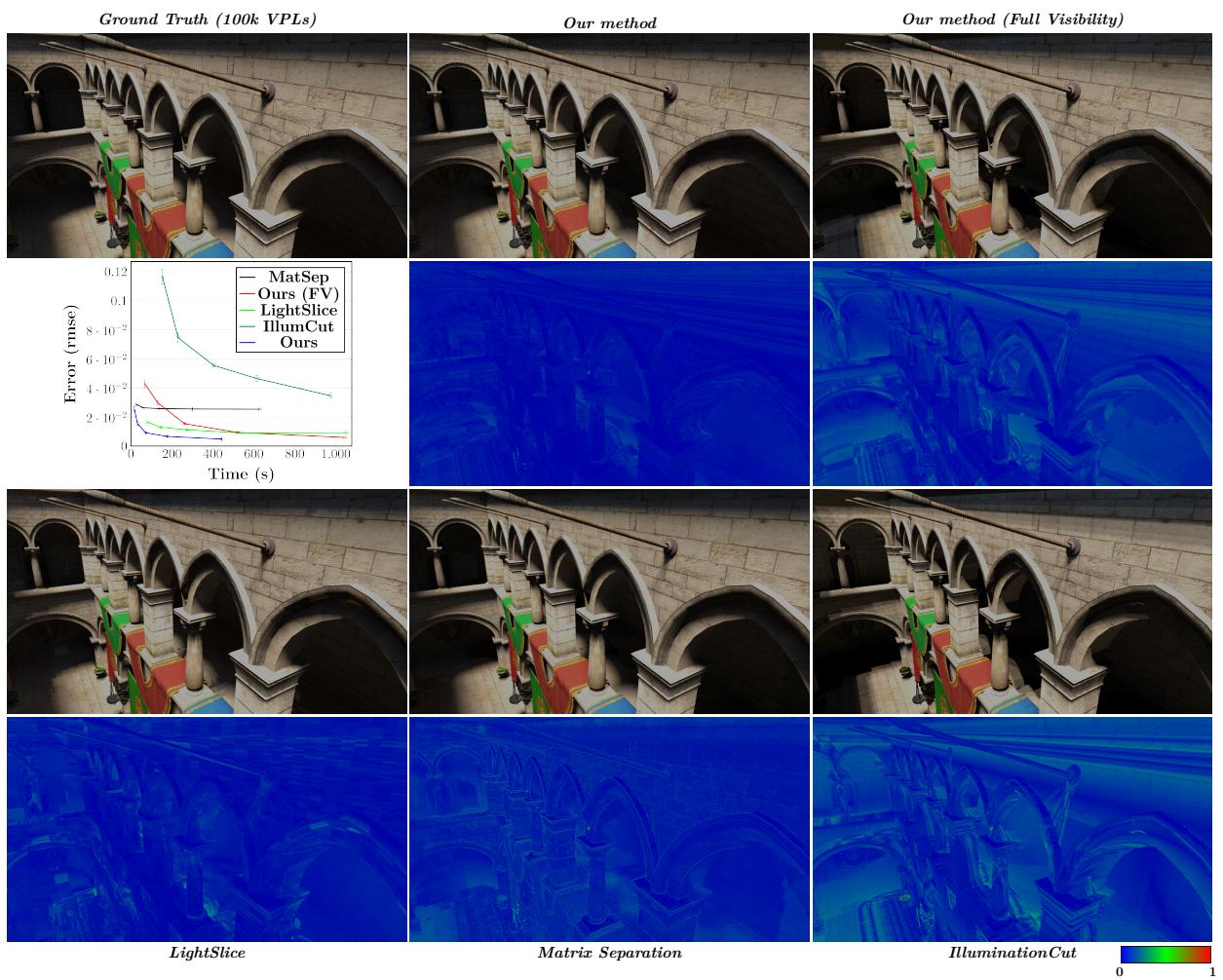


FIGURE A.3: Equal time renders ( $\sim 140$ s) and time vs error plot for Sponza scene.  
Error images shows  $L_1$  error.

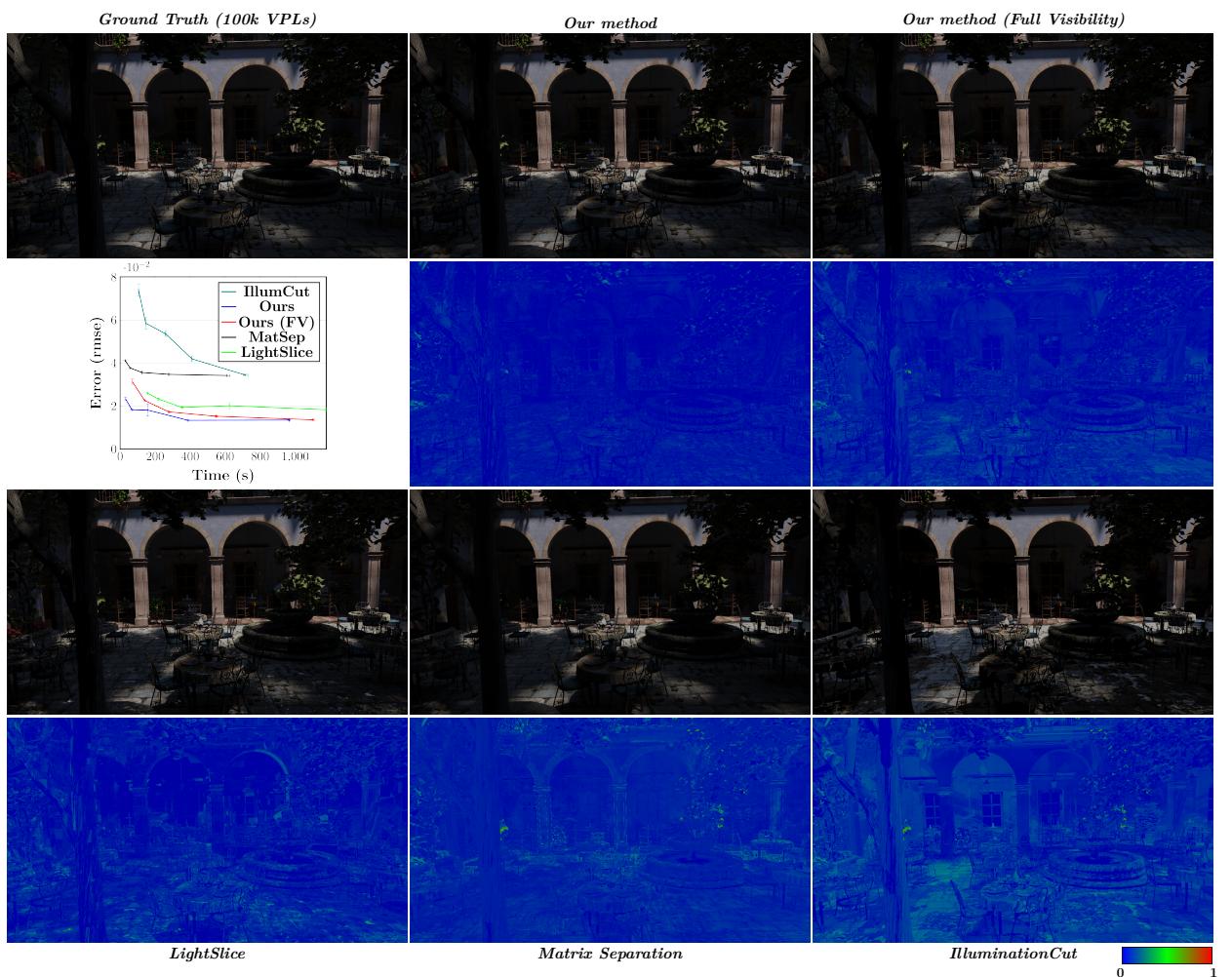


FIGURE A.4: Equal time renders ( $\sim 125s$ ) and time vs error plot for San Miguel scene.  
Error images shows  $L_1$  error.

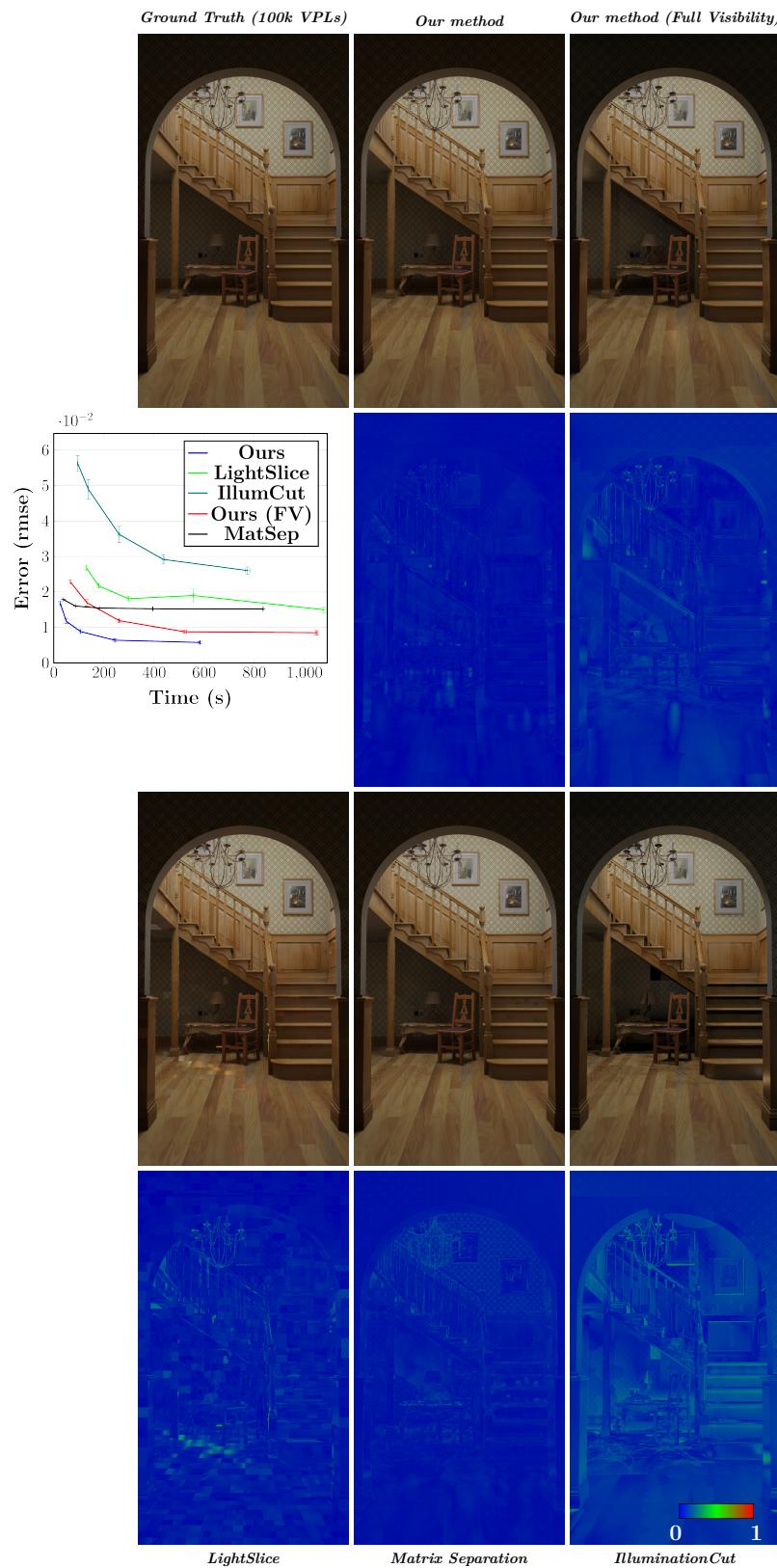


FIGURE A.5: Equal time renders ( $\sim 110$ s) and time vs error plot for staircase scene.  
Error images shows  $L_1$  error.

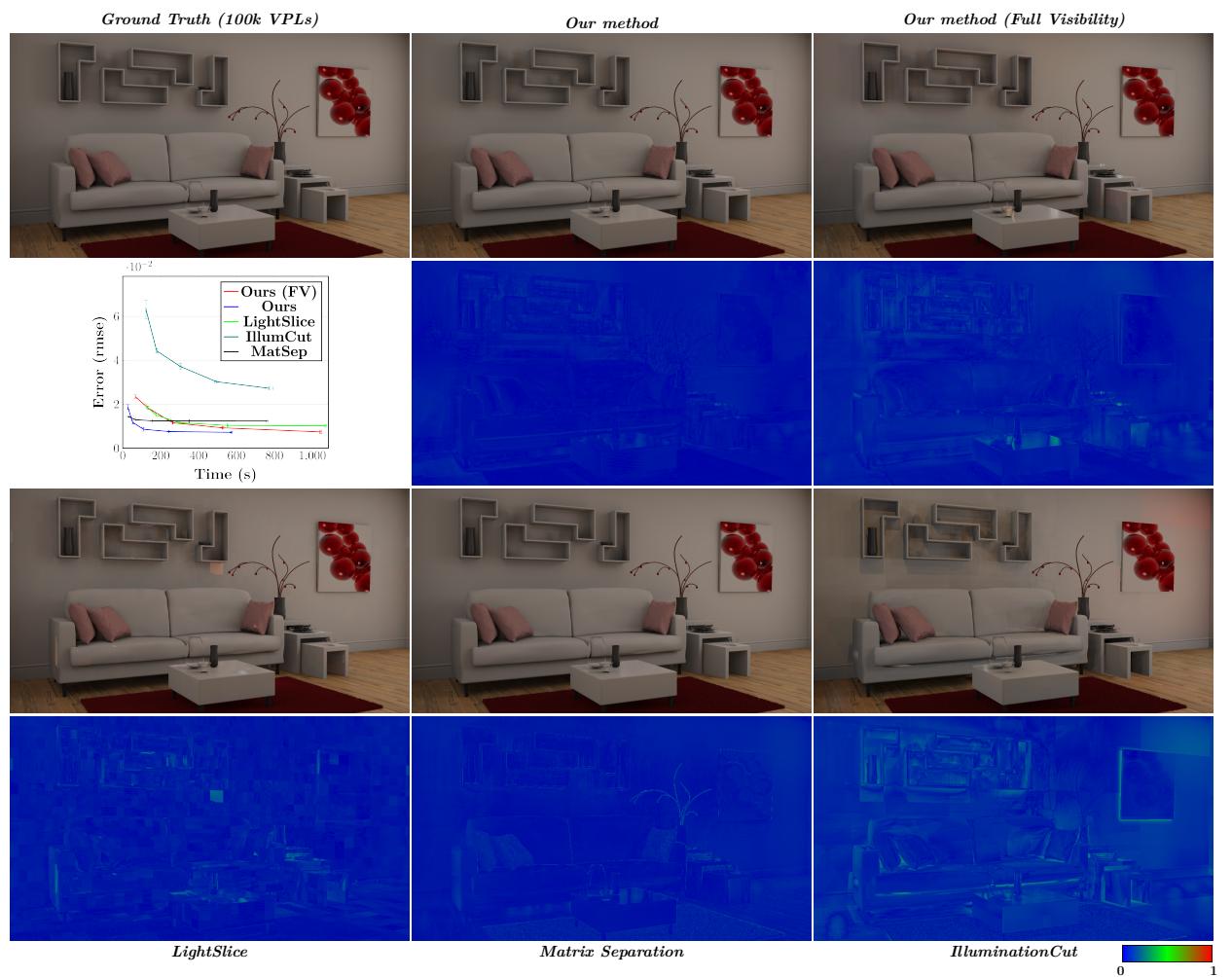


FIGURE A.6: Equal time renders ( $\sim 110$ s) and time vs error for living room scene.  
Error images shows  $L_1$  error.

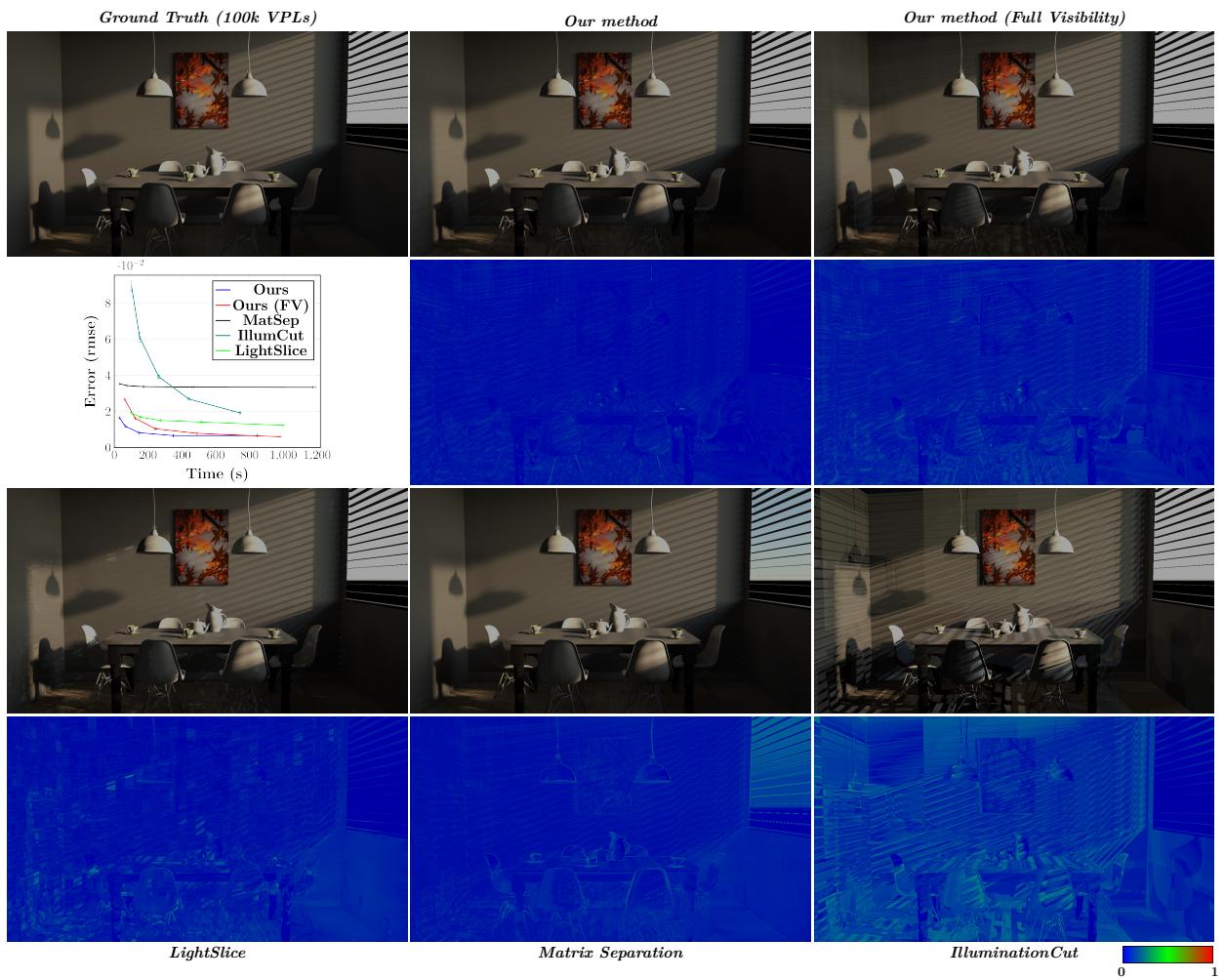


FIGURE A.7: Equal time renders ( $\sim 80$ s) and time vs error plot for breakfast room scene. Error images shows  $L_1$  error.

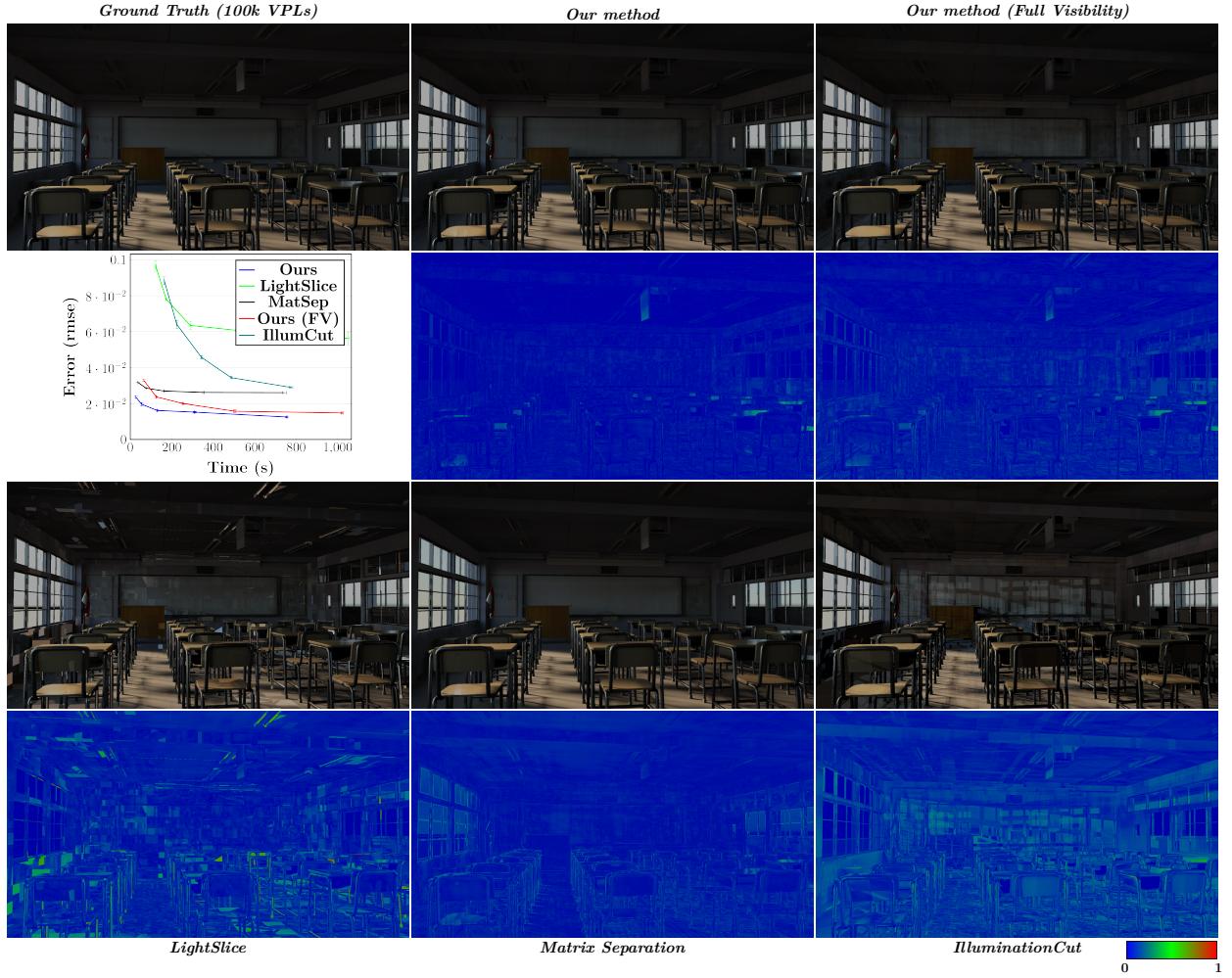


FIGURE A.8: Equal time renders (~55s) and time vs error plot for classroom scene.  
Error images shows  $L_1$  error.

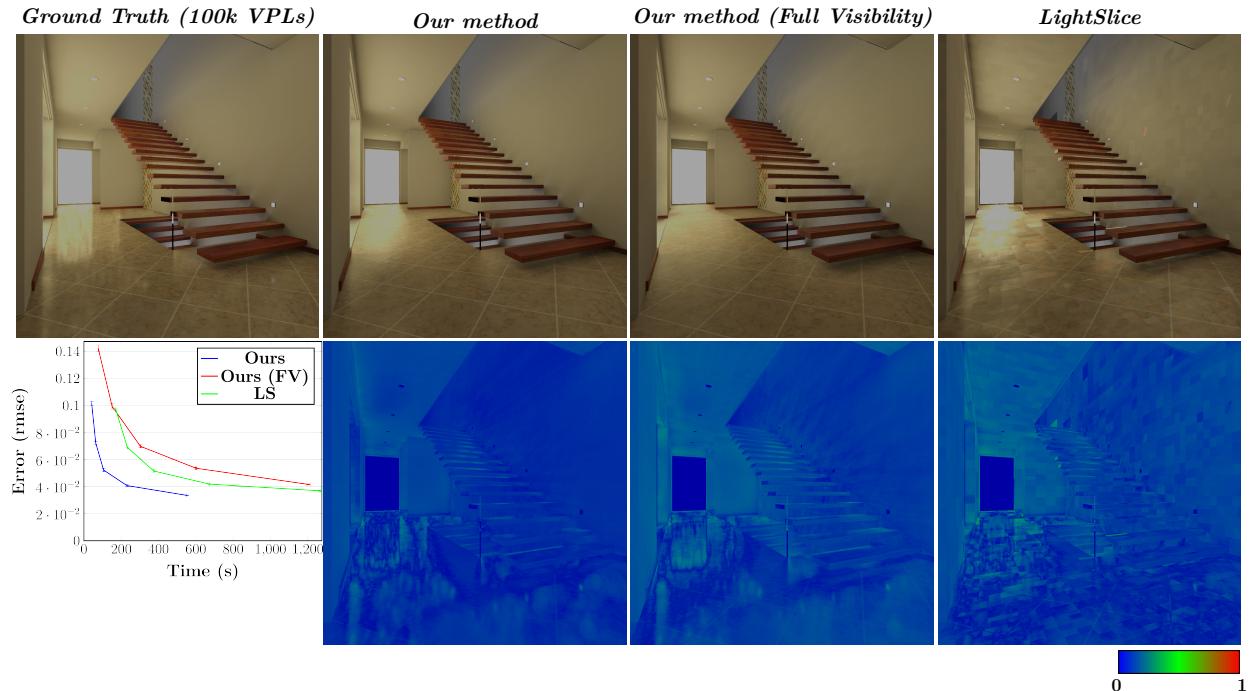


FIGURE A.9: Equal time renders (~230s) and time vs error for Modern Hall scene.  
Error images shows  $L_1$  error.

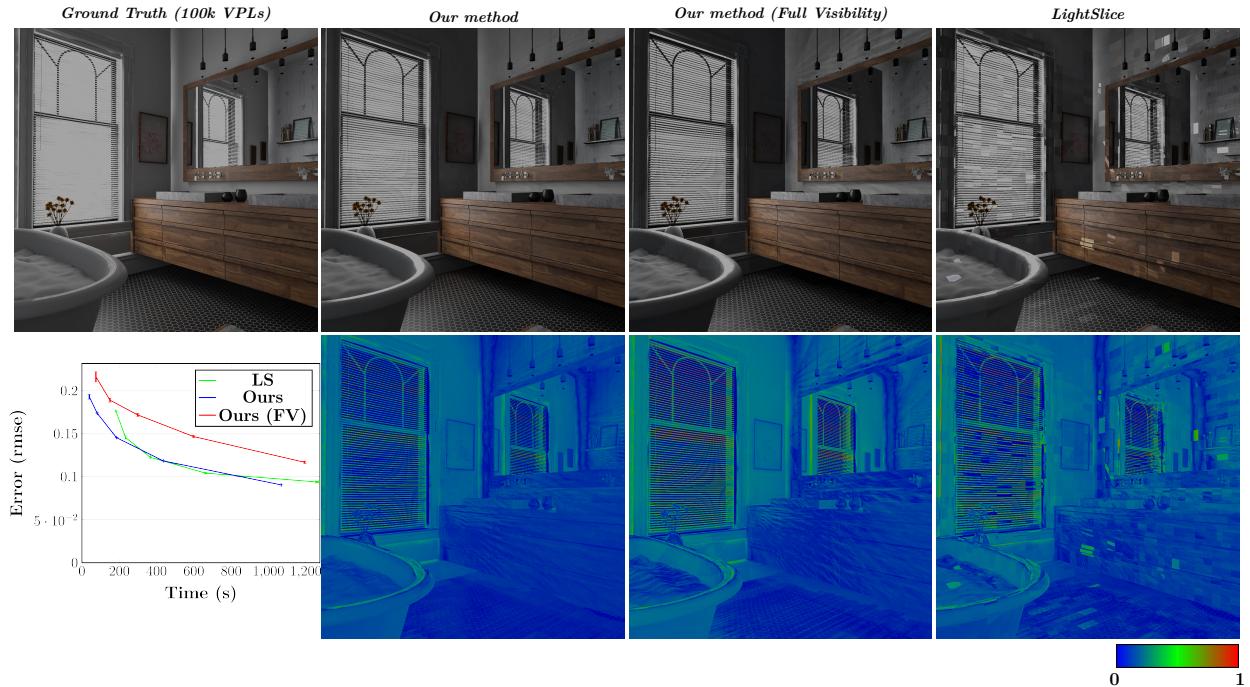


FIGURE A.10: Equal time renders (~185s) and time vs error plot for bathroom scene.  
Error images shows  $L_1$  error.

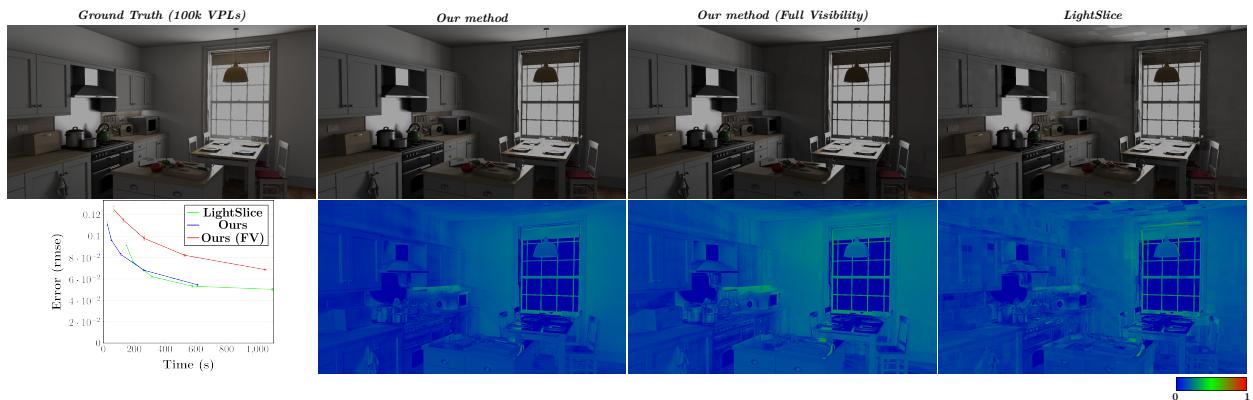


FIGURE A.11: Equal time renders (~60s) and time vs error for kitchen scene. Error images shows  $L_1$  error.

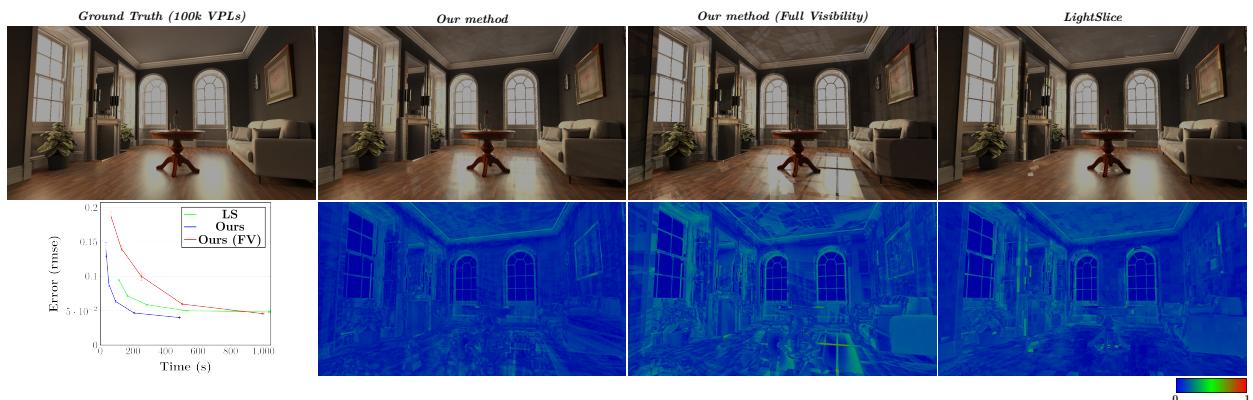


FIGURE A.12: Equal time renders (~220s) and time vs error for Grey & White Room scene. Error images shows  $L_1$  error.

Clusters per slice		250	500	1000	2000	4000	8000
Bathroom 100k VSLs 1024x1024 @ 4	Time		39.42s	81.98s	185.48s	436.16s	1068.98s
	Time (only clustering)	74.97s	150.26s	299.33s	597.96s	1194.73s	
	Error (RMSE)		0.193	0.173	0.146	0.119	0.091
	Error (RMSE, only clustering)	0.216	0.189	0.172	0.149	0.119	
Breakfast room 100k VPLs 1280x720 @ 4	Visibility samples		19.92%	21.16%	23.52%	26.48%	29.4%
	Time		30.89s	63.82s	145.78s	348.78s	845.09s
	Time (only clustering)	61.74s	123.12s	243.96s	489.2s	980.99s	
	Error (RMSE)		0.017	0.012	0.0083	0.0067	0.0067
Cornell box 100k VPLs 800x600 @ 4	Error (RMSE, only clustering)	0.027	0.016	0.0105	0.008	0.0061	
	Visibility samples		18.9%	19.95%	22.76%	27.36%	31.99%
	Time		7.51s	13.83s	28.19s	60.33s	129.12s
	Time (only clustering)	24.28s	46.95s	93.72s	189.95s	381.05s	
Classroom 100k VPLs 1280x720 @ 4	Error (RMSE)		0.0037	0.0022	0.0016	0.0011	0.0008
	Error (RMSE, only clustering)	0.0065	0.0039	0.0023	0.0014	0.0011	
	Visibility samples		9.2%	9.26%	9.89%	10.99%	12.68%
	Time		26.38s	54.99s	129.243s	310.51s	755.81s
Hairball 100k VPLs 800x600 @ 4	Time (only clustering)	65s	125.44s	253.82s	504.44s	1022.6s	
	Error (RMSE)		0.024	0.0196	0.0162	0.0152	0.0125
	Error (RMSE, only clustering)	0.033	0.024	0.02	0.016	0.015	
	Visibility samples		15.71%	16.83%	19.96%	23.77%	27.33%
Living room 100k VPLs 1280x720 @ 4	Time		40.56s	86.11s	194.23s	460.43s	1150.02s
	Time (only clustering)	40.53s	79.35s	157.71s	316.36s	639.95s	
	Error (RMSE)		0.006	0.0041	0.003	0.0023	0.0019
	Error (RMSE, only clustering)	0.0088	0.0059	0.004	0.0029	0.0022	
Kitchen 100k VSLs 1280x720 @ 4	Visibility samples		36.71%	37.98%	40.19%	43.11%	46.45%
	Time		27.09s	52.07s	109.36s	244.1s	574.04s
	Time (only clustering)	66.06s	132.77s	263.48s	526.1s	1043.42s	
	Error (RMSE)		0.019	0.012	0.0086	0.0076	0.0072
San-Miguel 100k VPLs 1280x720 @ 4	Error (RMSE, only clustering)	0.024	0.018	0.012	0.0093	0.0074	
	Visibility samples		14.35%	13.46%	13.9%	15.53%	18.45%
	Time		25.2s	51.49s	114.15s	262.41s	612.66s
	Time (only clustering)	67.53s	132.24s	264.66s	527.48s	1051.77s	
Sponza 100k VPLs 1280x720 @ 4	Error (RMSE)		0.112	0.097	0.083	0.068	0.054
	Error (RMSE, only clustering)	0.125	0.115	0.098	0.082	0.069	
	Visibility samples		15.56%	15.03%	16.89%	19.6%	22.57%
	Time		30.77s	67.33s	158.75s	388.64s	966.41s
Staircase 100k VPLs 720x1280 @ 4	Time (only clustering)	69.92s	139.83s	278.03s	549.3s	1103.81s	
	Error (RMSE)		0.023	0.0183	0.0181	0.0134	0.0135
	Error (RMSE, only clustering)	0.031	0.023	0.017	0.015	0.014	
	Visibility samples		12.97%	14.38%	16.64%	19.96%	23.15%
Modern Hall 100k VPLs 1024x1024 @ 4	Time		16.3s	32.6s	71.76s	175.59s	442.49s
	Time (only clustering)	66.99s	131.17s	261.89s	521.69s	1043.18s	
	Error (RMSE)		0.026	0.015	0.0092	0.0067	0.0048
	Error (RMSE, only clustering)	0.043	0.03	0.015	0.0094	0.006	
Grey & White Room 100k VPLs 1280x720 @ 4	Visibility samples		7.16%	7.5%	8.93%	11.81%	16.16%
	Time		25.58s	50.05s	106.82s	243.37s	583.3s
	Time (only clustering)	65s	132.14s	261.02s	522.5s	1048.93s	
	Error (RMSE)		0.017	0.012	0.0088	0.0064	0.0057
Visibility samples	Error (RMSE, only clustering)	0.023	0.017	0.012	0.0088	0.0085	
	Time		41.52s	63.33s	105.38s	230.39s	551.69s
	Time (only clustering)	76.43s	151.05s	302.72s	600.54s	1204.17s	
	Error (RMSE)		0.102	0.072	0.052	0.041	0.034
Error (RMSE, only clustering)	Error (RMSE, only clustering)	0.142	0.099	0.07	0.054	0.042	
	Visibility samples		10.16%	12.58%	13.65%	15.97%	19.3%
Visibility samples	Time		34.13s	52.1s	93.82s	206.88s	485.78s
	Time (only clustering)	64.9s	127.84s	251.43s	502.33s	998.86s	
	Error (RMSE)		0.139	0.089	0.063	0.047	0.04
	Error (RMSE, only clustering)	0.188	0.141	0.01	0.06	0.046	
Visibility samples	Visibility samples		13.89%	13.65%	14.92%	17.6%	21.68%

TABLE A.5: Statistics for our method across all scenes.