Mixing ordinary and Markov chain Monte Carlo rendering techniques

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In this work we propose way of combining ordinary and Markov chain Monte Carlo rendering techniques in image space. We used per-pixel mask to separate pixels (which we want to run Markov chain on) from the rest of the image. The mask was obtained from the ordinary Monte Carlo noise analysis. The proposed method was tested with combination of Multiplexed Metropolis Light Transport as Markov chain technique and two ordinary Monte Carlo rendering techniques - Instant Bidirectional Path Tracing and Light Tracing. As a result, our method allows us to get better accuracy in comparison to ordinary Monte Carlo and a better visual perception in comparison to Markov chain Monte Carlo techniques with the same rendering time.

Keywords: *Multiplexed Metropolis Light Transport, Markov chain Monte Carlo, bidirectional path tracing*

1. Introduction

Light transport algorithms have progressed significantly last 10 years. The evolution of light transport algorithms proceeded in two parallel ways: Ordinary Monte Carlo (OMC) and Markov Chain Monte Carlo (MCMC). Both ways have their own advantages and disadvantages.

2. Previous work

2.1 Ordinary Monte Carlo and MIS

OMC way includes such methods as Path Tracing (PT), Light Tracing (LT) and Bidirectional Path Tracing (BPT) [1, 15, 18], Photon Mapping (PM) [6, 9], Bidirectional Photon Mapping (BDPM) [20, 22], Vertex Connection and Merging (VCM) [4, 7] and other. These methods are often used in industry but they are not efficient for complex lighting phenomena in general (such efficiency is called «robustness» [18]).

Most robust OMC methods are based on Multiple Importance Sampling (MIS) technique which has strong mathematical foundation for variance reduction. The main idea of MIS is to use many different ways of sampling lighting integral with a posteriori weighing samples according to their probability density.

Unfortunately, Multiple Importance Sampling has strong disadvantage: the more robust algorithm becomes, the less average rendering speed it gains. This is the result of weighting samples since usually among many weights only a few are significantly different from zero [15]. At the same time sampling with many different strategies is expensive: N^2 shadow samples in BPT or density estimation on each bounce in BDPM are such examples.

2.2 Markov Chain Monte Carlo

In contrast to MIS (which samples proportionally to several parts of integrand by each strategy), Markov chain based methods [10, 11, 19, 21] create samples proportional to the final answer — lighting integral itself. This is achieved by representing lighting integral as multidimentional function projected to the image plane: $F(x, y, r_0, r_1, ...r_n) \xrightarrow{project} F(x, y)$. With such representation Markov chain places more samples (via Metropolis algorithm) in more complex regions of multidimentional space automatically and thus greatly reduces variance.

It should be noted that Markov chains and MIS nevertheless should be used together. The key to success here is to construct good integration space in which Metropolis algorithm and MIS will strengthen but not compete with each other. This is the main idea of Multiplexed Metropolis Light Transport (MMLT) algorithm [5]. MMLT uses Markov chain including for sampling strategy selection which completely eliminates discussed MIS disadvantage because low contribution strategies are rarely selected. More advanced Markov chain algorithms are constructed on top of MMLT framework or use similar principles [12, 14, 17].

Unfortunately, Markov chain methods have their own disadvantages. First, they have distinctive, visual unpleasent artifacts, especially in the begining of rendering. These artifacts are caused by high correlations of samples (excluding [17]) so that image shows the trajectories of Markov chains movements in the image space. Second, precision for short rendering time may be even less than for OMC methods due to the startup bias. Finally, Markov chain methods are inefficient for rendering direct light due to almost all samples would be placed at bright locations (for example even not noisy light surface!). MMLT amortizes last disadvantage in some degree (due to possibility of manual control chains number per each reflection depth) but does not solve same problem for caustics: large and bright areas always take most of computational resources even if these areas do not have true hard-sampling light transport phenomena.

2.3 Combining OMC and MCMC

At first, any practical implementation of MCMC rendering technique will separate direct and indirect

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light calculations due to the reason discussed above. Second, normalization constant should be estimated and good starting points for Markov chain have to be selected to reduce startup bias. Thus, in practice, OMC and MCMC always work together.

Next, known ways of combining OMC and MCMC for the same lighting phenomena are implemented though Multiple Importance Sampling and have certain restrictions. Kelemen et al. in [11] has shown that large steps for Primary Sample Space Metropolis light transport (PSSMLT) can be used as a separate integration strategy and thus, OMC and MCMC can be combined together via MIS. Moreover, this method can be considered as a «shareware» due to the fact that large steps in PSSMLT will be computed anyway like other proposals. However, here are the limitations of Kelemen et al. approach (which we call «Kelemen MIS» further):

(1) Shareware Kelemen MIS, obviously, can not be used to combine rendering techniques with different basic algorithms. For example, if Metropolis algorithm is implemented on top of BPT framework, OMC sampling analogue will be exactly the same BPT. It does not sound as a serious disadvantage if both OMC and MCMC versions of the same rendering technique are good enough. However, if their efficiency differs significantly, Kelemen MIS becomes useless. This is exactly the case of Multiplexed Metropolis light transport where its OMC analogue is extremely inefficient due to end-points-only connections leaving few chances for random sample to hit high contribution region of multi-dimensional space.

(2) Bright areas (large caustics for example) are still oversampled by MCMC technique even if OMC can calculate them well enough. Moreover, OMC contribution in such areas will be almost discarded due to Kelemen MIS weights being evaluated from probability densities as shown further: $p_{omc} = 1, p_{mcmc} = I/b$, where I — MCMC image contribution function, and b — average image brightness. In this way if I is large enough, MIS weight for OMC contribution will tend to zero:

$$w_{omc} = \frac{p_{omc}^2}{p_{mcmc}^2 + p_{omc}^2} = \frac{1}{1 + (I/b)^2} \quad (1)$$

Hachisuka et al. in [13] suggested combining SPPM and MLT as two completely different algorithms via machine learning. Training sets were obtained by classifying paths on their «path grammar». Resulting improvements in precision and visual perception turned out small. This is quite expected because such blending didn't go far from MIS ideas — use 2 strategies/algorithms (which simply doubles computational resources!) and then select best of them by weight. Moreover, both MLT and SPPM in general are good for the same lighting phenomena, so, their blending has limited application.

In this way, more efficient and general method of combining OMC and MCMC for rendering became our research area.

3. Suggested approach

Our key idea is similar to MMLT approach — let Markov chain to select best algorithm statistically. To combine OMC and MCMC we propose to use «a priori blending function» $\alpha(x, y)$ which marks image areas that can not be evaluated well with OMC and uses it as expression 2 shows:

$$Color_{res} = D_{OMC}(x, y) + I_{OMC}(x, y) * (1 - \alpha(x, y)) + I_{MCMC\alpha}(x, y). \quad (2)$$

where (x, y) are screen space coordinates, $D_{OMC}(x, y)$ - direct light computed by OMC, $I_{OMC}(x, y)$ - indirect light computed by OMC and $I_{MCMC\alpha}(x, y)$ - priory weighted indirect light computed by MCMC. Note that $I_{MCMC\alpha}(x, y)$ is not multiplied with $\alpha(x, y)$ because it's already constructed proportional to $\alpha(x, y) * I(x, y)$ by Markov chain.

3.1 Weight functions details

We build $\alpha(x, y)$ by OMC noise analysis:

1. run OMC for short time (64-128 samples per pixel in average) to compute noisy image approximation;
2. compute for each pixel its difference with median in 5x5 or 7x7 window;
3. sort all pixels by this difference, take 10% most noisy to assign them values in range [0,1]. This assignment is done with sigmoid function relative to median value of these 10% pixels so that noisy pixels tend to one and not noisy tend to zero.
4. split the image into segments relied on the information from G-buffer (per pixel depth, normals, material id);
5. fill each segment with the value of it's most noisy pixel (fig. 1);
6. clamp values to epsilon, i.e. $\alpha(x, y) := max(\alpha(x, y), \epsilon)$;
7. assign everything greater than 0.5 to 1 and less than 0.5 to ϵ (so that our function became binary).

Let us discuss some of these items in details. Although many advanced methods of noise detection was developed recently [2, 3, 16, 23], median difference was enough for our experiments due to the observation that if Ordinary Monte Carlo fails for some phenomena, it gives significant ejection/spike. Segment filling was used based on similar considerations: if some region (for example, glossy or mirrored object) gives at least one strong spike, this region have complex light transport phenomena and it has to be computed using MCMC technique.

Next, it should be noted that weigh function $\alpha(x, y)$ must not be zero in any region where indirect light $I(x, y)$ is not zero. This is essential for correct evaluation of premultiplied $I(x, y) * \alpha(x, y)$ by

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MCMC due to normalisation constant is estimated over $I(x, y) * \alpha(x, y)$ for the whole image. Otherwise MCMC result will have inconsistent average brightness and color with the rest of image as shown at fig 2.

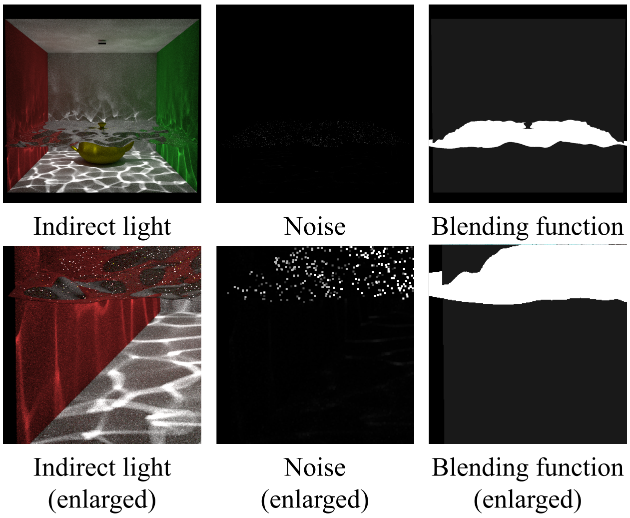

Figure 1. Constructing blending function from noise and G-buffer analysys.

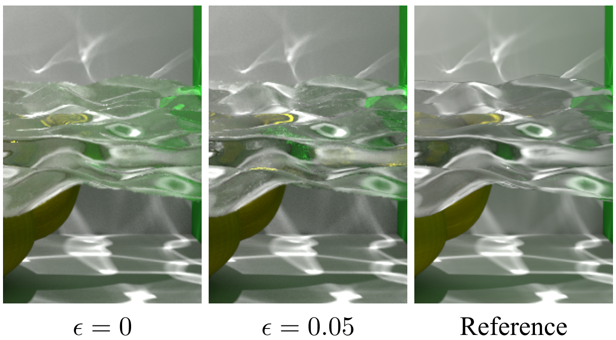

Figure 2. Inconsistent green color of water (computed by MCMC) when $min(\alpha(x, y), \epsilon)$ tends to zero in other (non water) regions on the image.

In this way we apply $\alpha(x, y) := max(\alpha(x, y), \epsilon)$ where ϵ is a parameter equal to 0.1 (so $\alpha(x, y)$ fits in range [0.1,1]). At last, we made our function binary — clamp everything greater than 0.5 to 1 and less equal 0.5 to ϵ. This shown visually more pleasant result in practice then blend of intermediate values for mirror and glossy objects.

Because our blending function became binary, it is neccesary to smooth border pixels to prevent aliasing. Fortunately, we have segments and their exact borders, so we apply FXAA algorithm for border pixels only to smooth them.

4. Implementation details and results

We tested our approach on 4 scenes (fig. 3) with MMLT as a Markov chain technique and two Ordinary Monte Carlo rendering methods - IBPT [1] and Light Tracing. All algorithms were implemented with our own C++ framework. As a result our method gives less error then Ordinary Monte Carlo (table 1) and has better visual perception in comparison to Markov chain Monte Carlo techiques with the same rendering time (fig. 4, 5, 6, 7). Our approach also outperforms Kelemen MIS combining (fig 8).

Figure 3. Tests scenes.

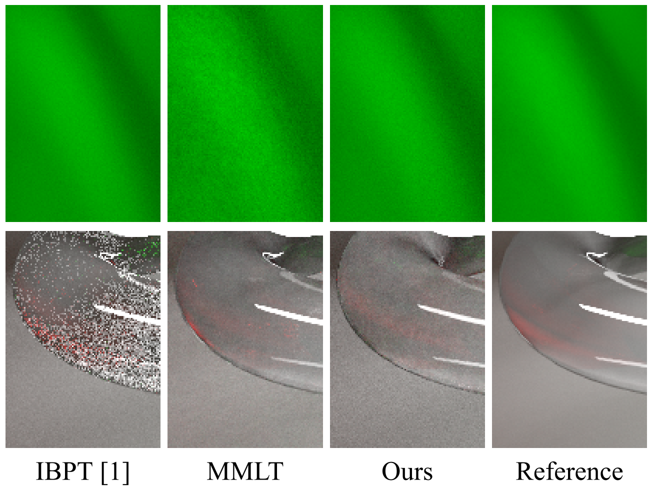

Figure 4. Comparison 1. Enlarged fragments of Cornell box with glass torus. 10 minutes.

5. Limitations

In practice we found that our approach is useful for scenes where true hard sampling lighting phenomena takes less then 30-40% of image pixels. Otherwise we recommend to render image completely with MCMC technique. This is quite expected because our method halves computational resources for both OMC and

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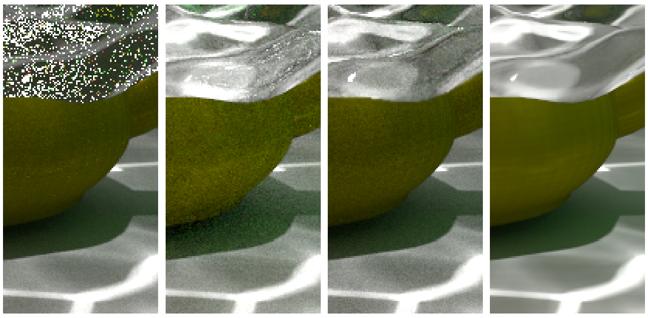
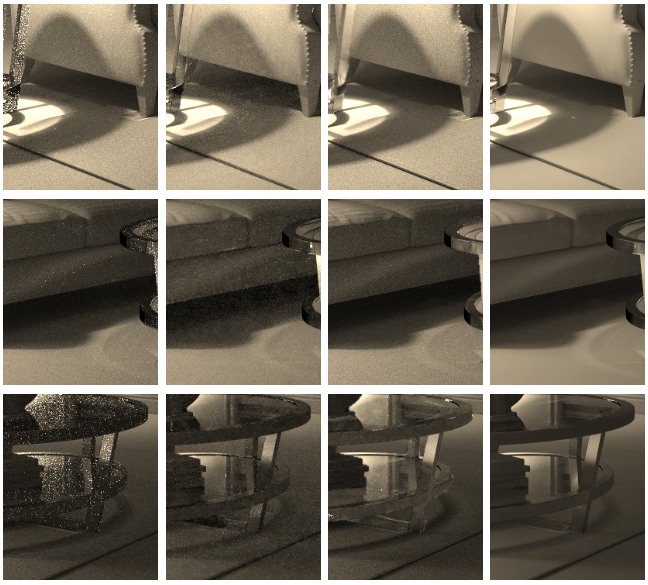
MCMC methods for the fixed rendering time. Thus if OMC technique fails for most of image pixels it becomes useless. Fortunately, because we have $\alpha(x, y)$ in image space we can easily count per cent of complex pixels and switch to «MCMC only» rendering automatically.



IBPT [1] MMLT Ours Reference

Figure 5. Comparison 2. Enlarged fragments of Cornell box with water. 10 minutes.



IBPT MMLT Ours Reference

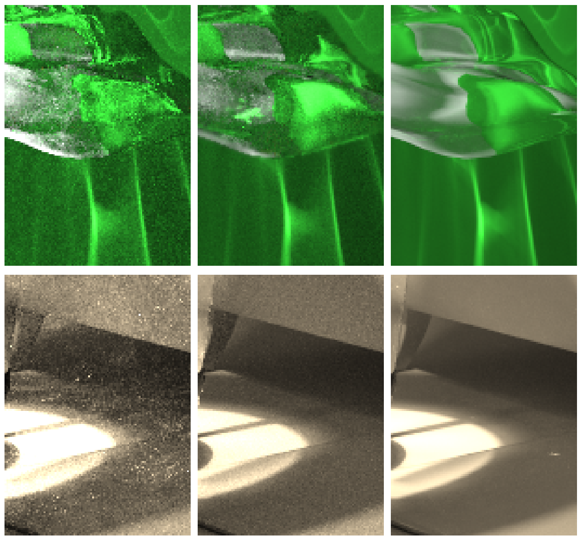
Figure 6. Comparison 3. Enlarged fragments of the room scene, 30 minutes.

Scene/Method	IBPT	MMLT	Ours	Ours combination
Thorus	15.4	7.28	12.5	IBPT + MMLT
Water	40.1	17.6	20.0	IBPT + MMLT
Room	33.5	15.6	28.1	LT + MMLT
Bathroom	58.8	32.7	45.4	LT + MMLT

Table 1. Mean Square Error (MSE); LDR space (0-255).

IBPT [1] MMLT Ours Reference

Figure 7. Comparison 4. Enlarged fragments of bathroom scene, 10 minutes.



Kelemen MIS Ours Reference

Figure 8. Comparison of our method to blending by Kelemen MIS weight [11].

6. Conclusions

Similar to previous approaches our algorithm halves computational resources for both blended methods (because we have to run 2 different algorithms with the same time). In contrast to previous work, we used a priory blending weight that allows us to evaluate complex image regions with MCMC more efficiently in comparison to rendering via MCMC without blending it with OMC. The indirect result of such approach is more pleasant view

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(without MCMC artifacts) in other regions of image where we took result from OMC.

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