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Master's Thesis

몬테카를로 렌더링을 위한 데이터 기반의 다중 중요도 샘플링 기법

Data-driven Multiple Importance Sampling for Monte Carlo Rendering

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2014. 6. 17.

Approved by

Professor Yoon, Sung-Eui

[Advisor]

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ABSTRACT

Monte Carlo (MC) rendering is the most common method in Computer Graphics to generate photo-realistic images. To enhance it efficiently, a variety of methods related to sampling has been developed, one of the simple and efficient way is Multiple Importance Sampling (MIS). This technique is a powerful technique for combining several sampling strategies. However, choosing an optimal weight in combining several sampling strategies remains a challenge. To address this problem, we propose a data-driven weight computation for reducing the variance of MIS. The point of our method is to utilize the scene information. We use precomputation for utilizing scene information, and it allows for computing an optimal weight depending on a scene. Specifically, optimal weight varies on each portion of the scene. Our method applies an optimal weight to an image locally. We observed meaningful results over prior methods in different scenes.

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Chapter 1. INTRODUCTION

As rapid developments for computer graphics continue, more photo-realistic and high quality rendering techniques are being applied in the industry including movie, animation and game. To achieve more photo-realistic and high quality rendering, we need a technique to conduct scalable data used for these industries as fast and efficient as possible. In the field of rendering, it has been the main issue that we want to get more realistic image. In order to address this issue, we must calculate both global and local way to move of light for presenting light's phenomenon. Typically, *light transport equation* (LTE) [9] is used to field of rendering as follows:

$$L_o(\mathbf{x},\omega_o) = \int_{\Omega} L_i(\mathbf{x},\omega_i) f_r(\mathbf{x},\omega_o,\omega_i) cos\theta_i d\omega_i \tag{1.1}$$

where $L_o(\mathbf{x},\omega_o)$ is the outgoing radiance at point $\mathbf{x}$ with direction ω_o. $L_i(\mathbf{x},\omega_i)$ is incoming radiance from $\mathbf{x}$ with direction ω_i and $f_r(\mathbf{x},\omega_o,\omega_i)$ is the bidirectional reflectance distribution function (BRDF) over the hemisphere Ω.

When we solve this rendering equation, we can produce an image through calculating light's path in the scene. The more samples are used, the more accurate pixel value is the resulting. However, using infinite sample is not possible and it cannot consider all of light's phenomenon. So we applied an approximation method, Monte Carlo (MC) method as follows:

$$L_o(\mathbf{x},\omega_o) \approx \frac{1}{N}\sum_{i=1}^{N} \frac{L_i(\mathbf{x},\omega_i) f_r(\mathbf{x},\omega_o,\omega_i) cos\theta_i}{p(\omega_i)} \tag{1.2}$$

where N is total number of samples. It is widely used when we calculate the rendering equation since it is an unbiased method which can converge to the correct value. MC method estimate the value for each pixel through integration.

In this form, if the denominator, probability density of sampling $p(\omega_i)$ (PDF) is proportional to numerator f_r (BRDF) or L_i (incident light), it leads to a high quality rendering result. Choosing the PDF well has been studied, it is called *importance sampling*. In the simplist case, uniform distribution sampling, where sample is taken by a regular interval. However, it is not effective since it does not consider BRDF and light at all as numerator in MC integration. A better idea is importance sampling. It takes more samples where the light density function is dense. In this case, to make rendering efficient, it is important to choose a probability density function that is close to the optimal one.

Since the variance of MC estimator depends on the probability distribution of ray samples, choosing sampling strategy is important. If we choose random sampling or uniform sampling without considering the light density function, noise and variance could be increased. So we need to focus on sampling distribution $p(\omega_i)$. In general, the ideal case is that sampling strategy is proportional to the BRDF and Light function. However, it is a chicken and egg problem. Because computing the whole integral itself is the result that we want to compute with MC rendering. To address this issue, methods discarding or approximating parts of the whole integral method have been developed. Most researches have derived sampling methods for each component such as BRDF sampling and light sampling. These studies had focused on directly sampling the material's BRDF function or light such as environment map. However, it is not robust to use only one of each strategy. Also, these sampling methods have fundamental problem. For instance, in light sampling, when a ray direction faces light and a material's BRDF is very small, it has a low contribution. Also, when a light's PDF is very small and a material's BRDF is very big, it has unexpectedly high contribution such as spike.

In order to solve this drawback, Veach et al. [20] introduced concept of combining different sampling strategies for a lower variance, called *multiple importance sampling*(MIS). By combining several strategies with distributed appropriate weights where render to the scene, it makes results better than singular sampling strategy which considers each component. However, it can lead to unplausible results due to fixed weight which does not try to optimize balancing the weights since it does not utilize the scenel information.

The main objective of this paper is to design a data-driven weight computation for reducing the variance of MIS. By utilizing the scene information by precomputing, we can compute an optimal weight. Also, by applying weight locally with optimized weight, we are able to make meaningful results compared to this existing MIS method.

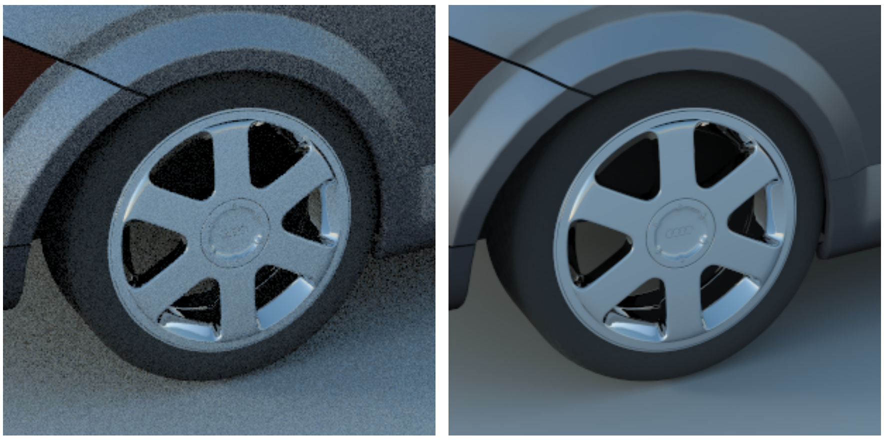
The remaining parts of this paper are as follows. In Section 2, we describe the related work on importance sampling. In Section 3, we construct the main algorithm which is consists of precompuation and applying weight locally method . In Section 4, some results are drawn. In Section 5, discussions and limitations about our results are presented. In Section 6, we describe our conclusions.

Chapter 2. RELATED WORK

In this section, we discuss previous work on importance sampling.

2.1 Importance Sampling for Monte Carlo Rendering

Monte Carlo (MC) rendering is based on MC integration, a numerical approach to compute integral of the rendering equation. Thanks to the nature of its probabilistic approach, it has a numerical error given a limited sample budget, defined as variance for unbiased approaches. Rendering results having a different level of variance are shown in Fig. 2.1.



(a) High variance 8spp (b) Low variance 128spp

Figure 2.1: These figures show rendering results with varying variances. An image result a low sample count (a) looks noisy because of its high variance. In contrast, a rendering image with a high sample count (b) looks sharp and clear thanks to its low variance.

To reduce variance of MC rendering, a variety of techniques for importance sampling has been developed, and an excellent survey is available [**?**]. At a high level, we want to have a sampling distribution, $p(\omega_i)$, proportional to the whole integrand, $f_r \times L_i$, of the rendering equation:

$$p(\omega_i) \propto f_r \times L_i \tag{2.1}$$

Unfortunately, computing the whole integral itself is the main goal of MC rendering and thus knowing integral results in the chicken-and-egg problem. In practice, a number of techniques for designing sampling density has been developed with respect to how to design sampling density. Typically, they are designed according to BRDF or light based sampling.

BRDF based importance sampling focus on material's BRDF. Some of prior studies are designed for particular BRDF functions such as Phong [16], Blinn [3], Ward [21], Lafortune [11], and Ashikhmin models [2]. More advanced BRDF models include Torrance-Sparrow [19] and cook-Torrance models [7].

Compact representations and efficient sampling for complex BRDFs have been considered. Some of them use wavelet [6], factored representations [12], and spherical harmonics [8]. Importance sampling techniques for complex lights have been proposed [1, 10, 14].

With the advance sampling method, many researcher take into considering either one of BRDF and incoming radiance results in a lower performance than considering both of them. As a result, product sampling considering light and BRDF [17] has been proposed. Wavelet techniques have shown compact and efficient sampling [5].

2.2 Multiple Importance Sampling

Veach et al. [20] proposed a simple and efficient importance sampling method, multiple importance sampling (MIS), that combines several importance sampling strategies. While many advanced techniques have been developed as aforementioned, MIS is still considered simple and efficient techniques that can be easily adopted for achieving better rendering quality. As a balance heuristic, his method combines several importance sampling methods with an equal weight such as $1/k$, where k is the number of used importance sampling methods. While this simple heuristic method works well in many scenes, weights are fixed irrespective of scenes and other various factors, failing to achieve the best performance.

To address this issue, Pajot et al. [15] introduced the notion of representativity of a sampling strategy. The representativity is a heuristic measure on how a sampling strategy can reduce the variance of the MC estimator. While it shows meaningful improvements in some tested cases, it assumes to use importance sampling guided by photon maps.

Recently, Lu et al. [13] used the second order Taylor expansion to approximate the probability density function used for MIS, and then attempted to minimize its variance. While this method adopted a variance optimization method, it is approximate method and requires many samples for achieving high accuracy. Because of these issues, this method shows inferior results over prior methods in highly diffuse and glossy materials.

In this paper, we design our method by using local weighting function which is a data-driven approach to reduce the variance of sampling when using MIS approaches. We utilize the scene information with precomputing required small samples, then obtain final result by applying optimal weight calculated by the previous precomputation.

Chapter 3. ALGORITHMS

In this section, we describe our algorithm in detail. Our method is based on MIS which is to combine several sampling strategy for MC rendering. This technique shows good result on the most of scenes, but they use fixed weight when it combines several sampling strategy, it leads unexpected results in some scenes. Thus, our aim is to compute optimal weight to optain good result in a variety of scenes by utilizing scene information.

To utilize scene information, we use precomputation which consists of computing pixel variance and comparing variance. Computing variance is important in our method, detail is described in Sec. 3.2. To compare variance each sampling strategy results, in precomputation, we render each sampling strategy on BRDF, light and balance heuristic. In that time, if we use a lot of samples, we can not use a lot of samples in final rendering. Thus, we assume sample budget and classify precomputation sample and render sample. With precompuation sample, we precompute variance of image with 2 or 4 small spp on each sampling strategy on BRDF, light and balance heuristic. And then, we divide the image with the patch of specific size(e.g., 4X4, 16X16).

To compare variances of each sampling strategy well, we use a curve fitting method(e.g., least square method). And then, we can get optimal weight. However, it has some noise since we use small samples in precomputation. Through the optimization process which is applied gaussian filtering, then we can compute the final output by applying optimal weight.

3.1 Sample budget

For our approach, we classify samples to precomputation sample and render sample. Precomputation sample is used to render on each sampling strategy on BRDF, light and balance heuristic. Render sample is used to render final image given optimal weight through precomputation. As we have limited the number of samples including precomputaion sample and render sample, it is important to use sample budget efficiently. If we use many samples for precomputing, we can get higher quality image and more exact variance, but we suffer from the computational overhead of precomputation. Therefore, for little rendering time, we use small samples(e.g., 2 or 4 samples per pixel) in precomputation as shown in Fig. 3.1.

3.2 Precomputing variance

For measure numerical differences between rendered images and reference images using a lot of samples, Mean Squared Error(MSE) is widely used. However, since our approach have to compute numerical differences before final rendering image, we cannot use reference images during precomputation. Alternatively, variance is used to comparing, because balance heuristic with MC rendering is an unbiased method. For unbiased method, the MSE is the same as the variance by the following equations:

$$\begin{aligned} MSE &= Var + Bias^2 \\ MSE &= Var \\ MSE &\propto Var \end{aligned} \tag{3.1}$$

As our approach is based on balance heuristic, we can measure image variance instead of comparing to the reference image. We first render the scene with small samples, and then calculate variance for every pixel in

(a) BRDF sampling 2spp (b) Balance heuristic 2spp (c) Light sampling 2spp

Figure 3.1: In **TEAPOT AREA LIGHT** scene, these figures show precomputation rendering images on each sampling strategy.

render image. In image space, we divide image into patch of specific size, for average out variance. That is why it is possible to occur incorrect value when we calculate optimal weight by comparing variance in each pixel. Comparing on unit of pixel might be incorrect value, since we use small sample for estimate the pixel variance. We will determine patch size take into account experiment applying a variety of size.

3.3 Comparing variance in each patch

Before we compare variance in each patch, we get insight from the experiment on MSE curve as shown in Fig. 3.2 and Fig. 3.3. As result of experiment, it shows curve of MSE along the weight ratio. Through this graph, we found that optimal weight varies on each portion of the scene.

In Fig. 3.3, as this scene consists of diffuse background and glossy BRDF, each portion shows the MSE of each sampling strategy has specific figure. Based on result of the experiment, we approximate curve for optimal weight. A good way to approximate the optimal weight under such curve is least square method(LSM). As using LSM, we fit MSE curve in each patch with computed variance in samples as follows:

$$d_i = y_i - (a_0 + a_1 v_i + a_2 {v_i}^2) \tag{3.2}$$

$$\textstyle\sum_{i=1}^{n} {d_i}^2 = \sum_{i=1}^{n} \left[y_i - (a_0 + a_1 v_i + a_2 {v_i}^2)\right]^2 \tag{3.3}$$

$$C_{opt} = \arg\min_{c} \sum_{i=1}^{n} {d_i}^2 \quad (c = [a_0, a_1, a_2]) \tag{3.4}$$

$$W_{opt} = -\frac{c_1}{2c_2} \quad (c_1, c_2 \in C_{opt}) \tag{3.5}$$

where v_i is variance on each sampling strategy and n set to 3, as we use 3 sampling strategies. c is a vector which presented coefficient a_0, a_1, a_2. By using C_{opt} vector, we compute optimal weight W_{opt}, and then we apply these weights locally in the scene.

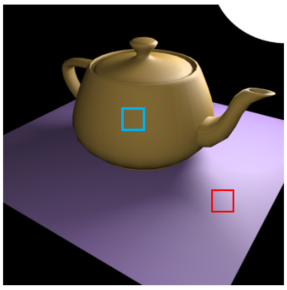
3.4 Optimization

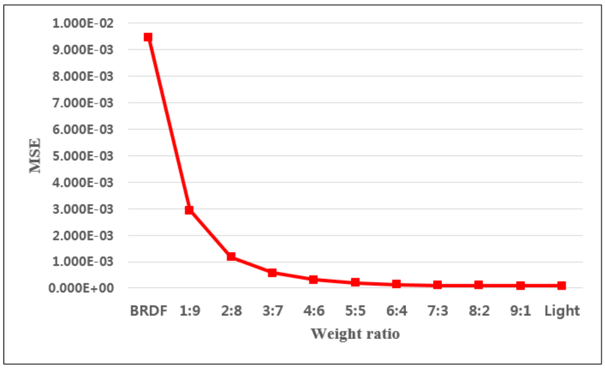
It is possible that error of weight which is computed by comparing variance results is occurred. That is why small samples for precomputing variance. In case of lack of samples, it causes high variance for our estimation process.

Also, when weight is changed drastically, noise is occurred.

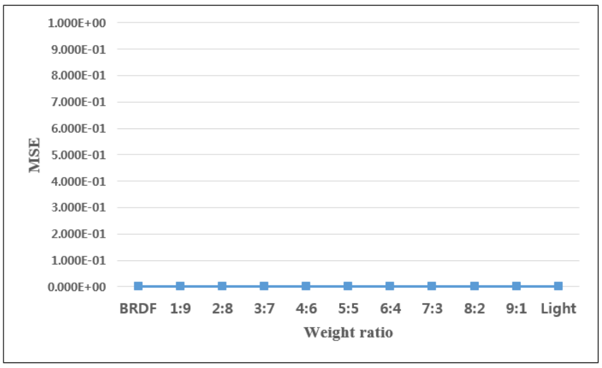
To solve these problem, we visualize the weight as shown in Fig. 3.4 to analysis easily. It shows red and blue colored weight. The noise is due to the error of variance estimation itself. To alleviate this error of weight, we use gaussian filter(5×5 for filter size) on the weight ratio for each patch.

Figure 3.5 shows that gaussian filtering slightly alleviates the problem.



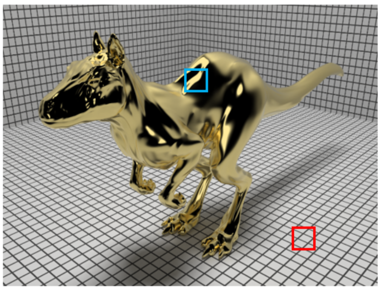


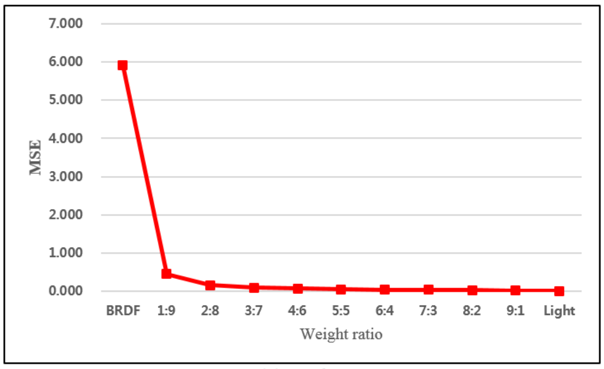
(a) Red



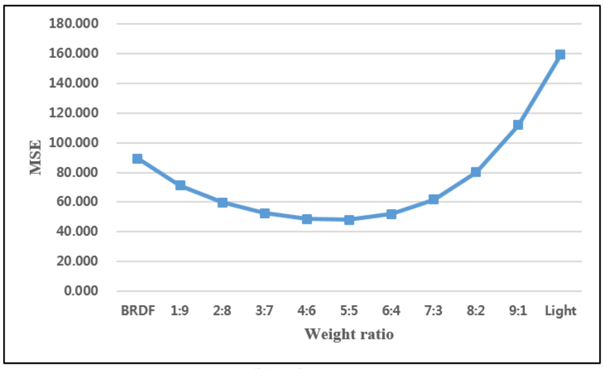
(b) Blue

Figure 3.2: MSE curve on portion of **TEAPOT AREA LIGHT**, red and blue. These show different shape respectively.



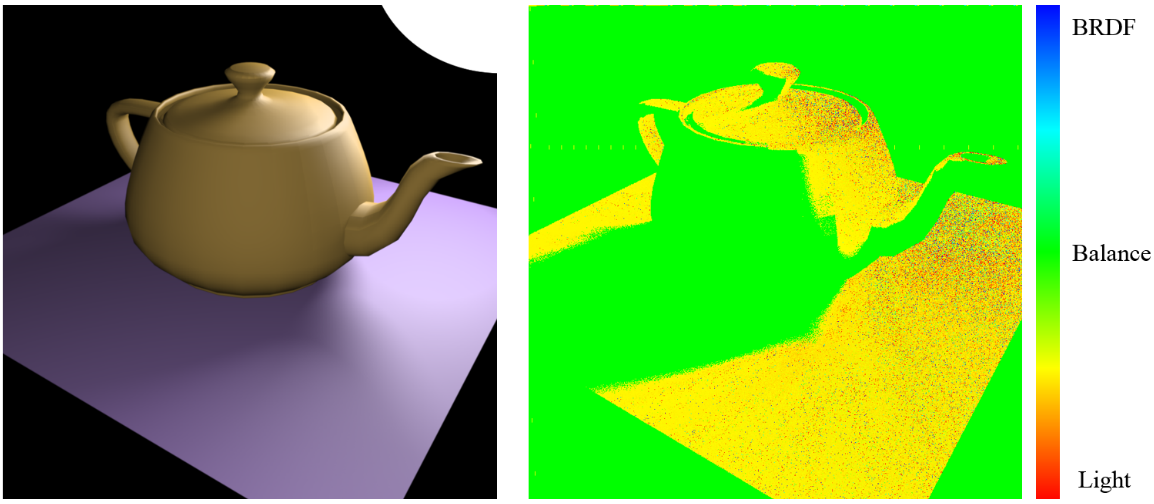


(a) Red



(b) Blue

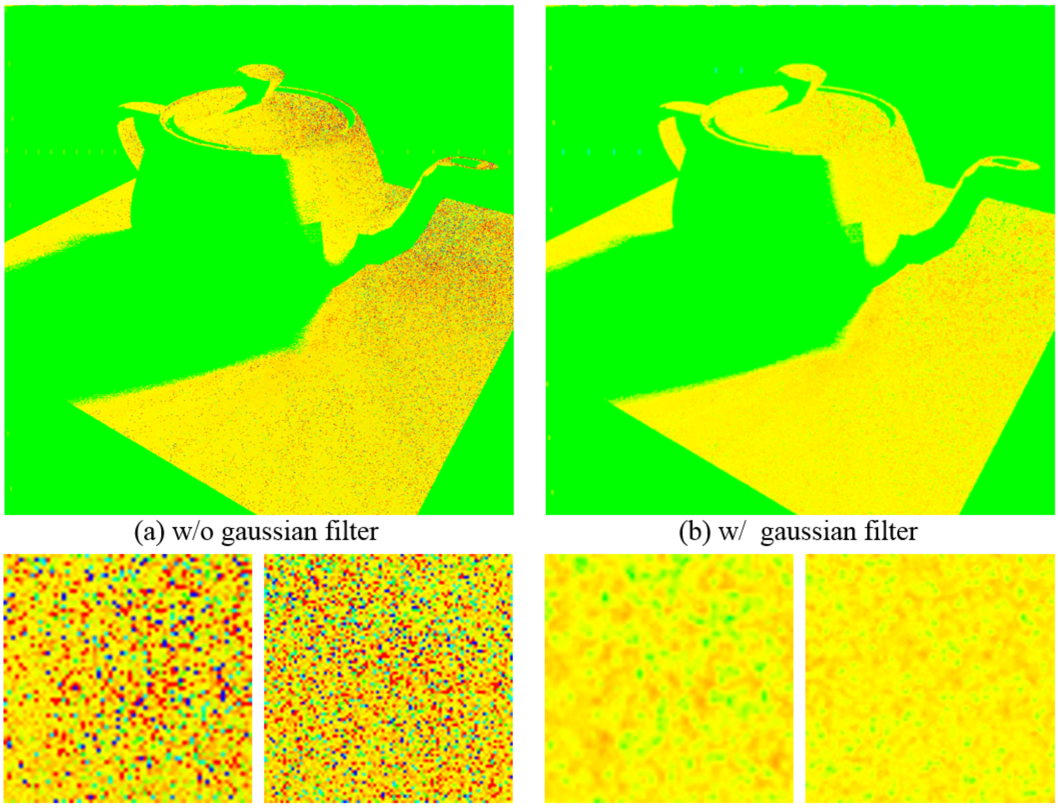
Figure 3.3: MSE curve on portion of **KILLEROO GOLD**, red and blue. These show different shape respectively.



(a) Ours 122 spp

(b) Weight visualization

Figure 3.4: In **TEAPOT AREA LIGHT** scene, these figures show weight visualization.



(a) w/o gaussian filter

(b) w/ gaussian filter

(c) Zoomed patch w/o gassian filter

(d) Zoomed patch w/ gassian filter

Figure 3.5: In **TEAPOT AREA LIGHT** scene, these figures show optimization results.

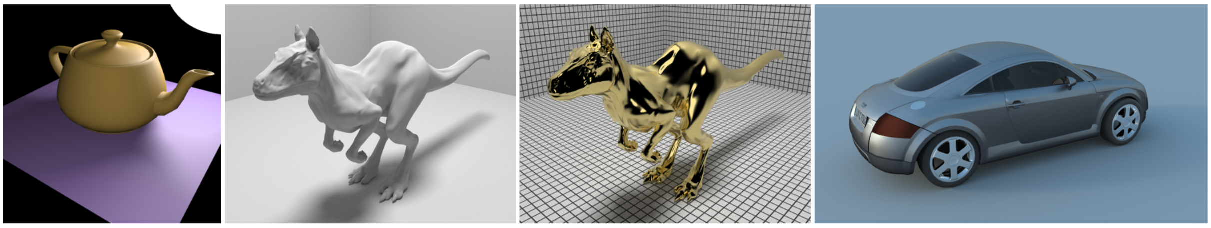
Chapter 4. RESULTS

In this section, we describe our experiment results. We have implemented our method on top of PBRT2 [**?**]. We have tested in 3.6GHz Intel i7-3820 CPU processor. We ran all scenes with path tracing and direct lighting depends on characteristic of scenes. Experiment scenes are 1) **TEAPOT AREA LIGHT** (resolution 800×800), 2) **KILLEROO DIFFUSE** (resolution 1368×1026), 3) **KILLEROO GOLD** (resolution 1368×1026) and 4) **TT** (resolution 1500×833) as shown in Fig. 4.1.

For presenting benefits of our method, we compared the classic balance heuristic with weight set to 0.5. To compare our method and balance heuristic, we use MSE which is widely used for measure numerical difference. For our experiment, we use 128 samples including 6 samples for precomputation and 122 samples for rendering. Since it is better to use small samples in precomputation for getting more MSE performance improvements in rendering, we use 2 samples with each sampling strategy —BRDF sampling, light sampling and balance heuristic— which sums up to total 6 samples. We also set different patch size for each scene range from 4×4 to 32×32.

We have tested in equal sample and equal time. And the result is shown in Table 4.1. In **TEAPOT AREA LIGHT** scene, it shows that equal sample result is decreased by 20% and equal time result is decreased by 2% compared MSE of balance heuristic. In **KILLEROO DIFFUSE** scene, it shows that equal sample result is drecreased by 6.5% and equal time result is drecreased by 0.02% compared MSE of balance heuristic. According to our method, we found that the optimal weight of light sampling heavily outweighs that of BRDF sampling in both scenes.

However, in **KILLEROO GOLD** and **TT** scene, when we apply our method, MSE are increased slightly compared MSE of balance heuristic. These cases show the limitation of our method, and we discuss about it in Section 5.



TEAPOT AREA LIGHT | KILLEROO DIFFUSE | KILLEROO GOLD | TT

Figure 4.1: Experiment scenes set.

Table 4.1: Experiment scenes results. Table show that MSE results are equal sample and equal time comparison. **Blue** is precomputation sample and **Red** is final render sample.

(a) **TEAPOT AREA LIGHT**

	sample	time(s)	MSE
Balance Heuristic	128	340	$1.244\ e^{-6}$
Ours(equal samples)	128(**6**+**122**)	349.5	$9.975\ e^{-7}$
Ours(equal time)	125(**6**+**119**)	338.9	$1.220\ e^{-6}$

(b) **KILLEROO DIFFUSE**

	sample	time(s)	MSE
Balance Heuristic	128	213	$3.250\ e^{-4}$
Ours(equal samples)	128(**6**+**122**)	228	$3.040\ e^{-4}$
Ours(equal time)	125(**6**+**119**)	212	$3.249\ e^{-4}$

(c) **KILLEROO GOLD**

	sample	time(s)	MSE
Balance Heuristic	128	241	$5.751\ e^{-3}$
Ours(equal samples)	128(**6**+**122**)	258	$6.436\ e^{-3}$
Ours(equal time)	125(**6**+**119**)	241	$6.629\ e^{-3}$

(d) **TT**

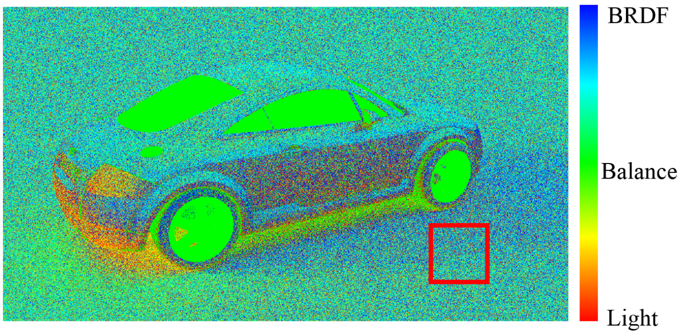
	sample	time(s)	MSE
Balance Heuristic	128	147	$8.252\ e^{-6}$
Ours(equal samples)	128(**6**+**122**)	152.5	$1.061e^{-5}$
Ours(equal time)	125(**6**+**119**)	146	$1.072e^{-5}$

Chapter 5. DISCUSSION AND LIMITATION

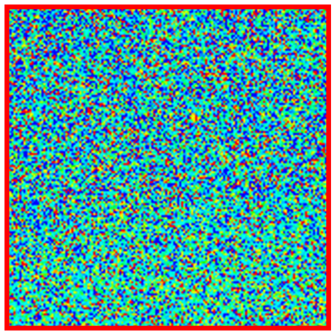
We employed a data-driven method for MIS. It shows meaningful results over prior methods in different scenes, but our method has some limitations. We think the reason for the limitation is that patch size does not fit scene figure. Also, since we use small samples to estimate the variance in the scene, it cause high variance. In other words, it has error of variance estimator by itself, as we cannot calculate variance exactly.

Figure 5.1 shows weight visualization using 2 samples per pixel. As the result of limitation case, this figure show a variety of distribution of heat map color. Patch image zoomed weight visualization also lose original boundary of figure since weight visualization filter is very noisy. That is why optimization results does not show good results.

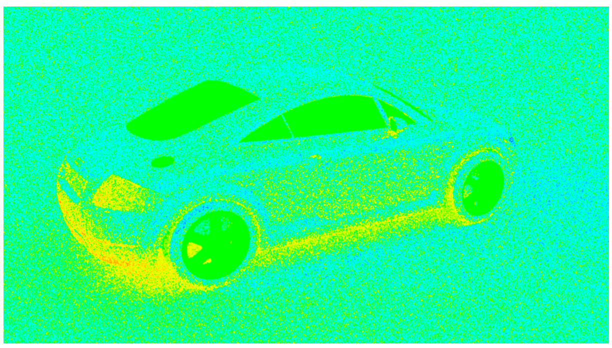
For our method, estimating variance is point for comparing each strategy. However, in precomputation, we need to use small samples since we have fixed sample budget, more samples in rendering, we can get higher quality results. Thus, we use small samples in precomputation where variance is estimated in that time, smaller sample cause higher variance than expected. Although we apply concept of patch to improve estimating variance, it has limitation. We would like to solve it in future work.



(a) Weight visualization(w/o gaussian filter)



(b) Zoomed patch



(c) Optimization result(w/ gaussian filter)

Figure 5.1: These figures shows weight visualization in **TT** scene. (a) is original weight visualization image and zoomed patch of this image(b) looks very noisy. (c) is filtered image for optimization.

Chapter 6. CONCLUSION

In this paper, we propose a data-driven weight computation for reducing the variance of MIS. This technique is known to powerful technique for combining several sampling techniques for MC rendering. They use concept of weight for combining proper ratio, while taking advantages of the sampling strategies. However, they assume that weight is determined before samples are taken(e.g., weight set to 0.5 in balance heuristic), which leads unexpected variance results such as noise in highly diffuse and glossy materials. In order to solve this issue, we use precomputation for utilizing scene information, so that we can get flexible optimal weight depending on a scene. Consequently, our approach observed meaningful results over prior methods in different scenes.

In future work, we will investigate the current approach to achieve a robust improvement across many scenes. Since we use same samples for each sampling strategy and use fixed patch size, we face the limitation that our approach do not lead to good results in specific scenes. In that work, we will extend current work to support adaptive decision for patch size and number of samples for each sampling strategy.

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Summary

Data-driven Multiple Importance Sampling for Monte Carlo Rendering

본 논문에서는 몬테카를로 렌더링 (Monte Carlo rendering) 을 위한 다중 중요도 샘플링 (Multiple Importance Sampling) 기법을 좀 더 효율적이고 의미 있는 결과를 얻기 위해, 기존 방법에 데이터 기반 (Data-driven) 의 특성을 가진 방법을 제안한다.

몬테카를로 렌더링은 그래픽스 분야에서 가장 보편적으로 사용되는 기술 중의 하나로, 실제와 같은 가상의 이미지를 얻는 것을 목표로 하고 있다. 이를 위해 빛의 현상과 물체와의 상호작용을 샘플링을 통하여 실제의 색을 구하기 위한 적분 값을 추정한다. 많은 광선 샘플을 사용할수록 고화질의 이미지를 얻을 수 있지만, 무한히 많은 광선 샘플을 사용하는 것은 불가능하며 적분 값을 추정하는데 많은 시간을 소요하기 때문에 중요한 부분에만 샘플을 사용하는 연구가 필요로 하게 된다. 이를 중요도 샘플링 (Importance Sampling) 이라고 하며, 이와 관련된 샘플링 기술들이 활발히 연구되고 있다.

다중 중요도 샘플링 (Multiple Importance Sampling) 은 이 샘플링 기술을 효율적으로 사용하기 위한 방법 중 하나로 다양한 샘플링 기술들을 최적의 비율로 혼합시켜 효과적으로 샘플링하는 방법이다. 하지만 이 방식은 여러 개의 샘플링 방식을 적절한 가중치로 분배하여 렌더링의 효율성을 높인 것인데, 기존 연구에서는 이 가중치를 샘플을 취하기 전 미리 정해진 것으로 적용하기 때문에 화면 구성에 따라 고화질의 이미지를 뽑아 낼 수 있지만 그렇지 못한 경우도 발생하게 되는 단점을 가지고 있다.

본 논문에서는 이러한 문제점을 해결하기 위해 선 계산 (Precomputation) 을 통해 소량의 광선 샘플을 가지고 최적의 가중치를 찾는 방법을 제안한다. 장단점이 존재하는 두 가지의 샘플링 방식(Light sampling, BRDF sampling)을 대표적으로 사용하여 픽셀마다 가중치를 달리하여 실험한 결과, 최적의 가중치가 환경에 따라 달라지는 것을 확인할 수 있었다. 이 결과는 화면의 오브젝트와 빛의 크기에 따라 최적의 가중치가 존재하는 특성을 보여준다. 선계산을 통해 최적의 가중치를 구하는 과정은 많은 광선 샘플을 사용하게 되면 렌더링의 효율이 떨어지게 된다. 본 논문은 기존의 방법과 대표적인 두 가지 샘플링 방식(Light sampling, BRDF sampling) 3가지만을 선계산을 하는 것으로 소모되는 광선 샘플수를 줄였다. 그리고 실험적 결과를 통하여 최적의 가중치 분포가 특정한 형태를 띠는 것을 분석하여 최소자승법 (Least Square Method) 를 사용하여 가중치를 계산하였고, 이 가중치를 최종 렌더링에 적용한다.

핵심어: 몬테카를로 렌더링, 중요도 샘플링, 다중 중요도 샘플링

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