

MIS Compensation: Optimizing Sampling Techniques in Multiple Importance Sampling

Seminar-Ausarbeitung von

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1. Abstract

Here is some sample text. (Write abstract (at the end)) (Write introduction. ToDo
Structure as in the paper (overview, problem, others, solution proposal)) ToDo
(Citation before the dot. In more than one sentence, name in the first sentence and reference in the last sentence.) ToDo

2. Introduction

Since Veach and Guibas introduced Multiple Importance Sampling (MIS) [VG95] it had a hugh impact in a variety of directions in computer graphics. Not only did it help to construct more advanced rendering algorithms like Vertex Connection and Merging [GKDS12], it also helped in calculating direct illumination from area light sources and environment maps [PJH18, Chapter 14.3] and subsurface scattering [KKCF13]. Besides being introduced in computer graphics MIS has also been used in other fields [HO14].

For the proof of MIS being almost optimal the assumption was made, that the distribution of samples among the techniques and the sampling densities are given and fixed. The only things left for fine tuning was the weighting function with the balance heuristic being a popular and widely adopted choice because of its simplicity and proven tight bounds when only using non-negative weights [Vea97, Theorem 9.2]. Recently researchers found that using not only non-negative weights can result in a truly optimal weighting function [IVG⁺19].

No previous work examined the effect of designing a sampling density itself for application in the MIS framework. Karlík et al. proposed a method to do exactly that and show that it can improve the MIS framework and reduce variance even further. They assumed multiple sampling techniques and pick one probability density function (pdf) of a technique and modify it in a way that it compensates for the averaging introduced by the balance heuristic. Their optimization can be applied beforehand and doesn't need adaptive updates as the work of Cappé et al. [CDG⁺08]. Others created product sampling methods [HEV⁺16] that try to match the integrand closer, but MIS compensation as, Karlík et al. call their method, on the other hand can even cause a pdf to be further away from the integrand but still reduce the variance [KŠV⁺19].

Karlík et al. show the effects of their MIS compensation with direct illumination using a HDR environment map and a scene with surfaces that have multiple different bidirectional reflectance distribution functions (BRDF). The standard approach with MIS would take samples proportional to the BRDF and the environment map, but they assume this approach to be too defensive and modify the pdf for the environment map in a way that the variance is reduced and therefore render times can be improved. Their modification is done by applying a formula to the tabulated pdf in a preprocessing step after which any renderer able to use HDR maps for MIS sampling can use the updated environment map for sampling without any further adjustment.

They also used their approach in path guiding [VHH⁺19] which learns a guiding density to improve the algorithm of [MGN17] by adjusting that density [KŠV⁺19].

3. Related Work

The MIS framework was introduced in [VG95] and combines multiple different sampling techniques with a weighting function to sample a more complex function better. In their work they proposed a few different weighting functions the most famous being the balance heuristic, but also the power and cutoff heuristic which perform better in certain scenarios where one technique matches the integrand well. Despite the balance heuristic being provably good Kondapaneni et al. [IVG⁺19] developed a weighting function that is truly optimal and uses negative weights to archive even better results.

A lot of work has been put into optimizing the weighting functions, but Karlík et al. followed a different approach and worked on a technique to adjust one sampling density to reduce the variance. (**Last sentence in first paragraph**)

ToDo

Another direction of research in the field of MIS is to figure out how to distribute the samples over the different sampling techniques. Pajot et al. [PBPP11] proposed a method where they calculate a so called representativity based on common rendering information such as the BRDF, which is a measure of how well a technique matches the integrand. In a one-sample estimator this representativity can also be used to derive a probability for each sampling strategy.

Lu et al. [LPG13] created a method where no prior knowledge about the scene is needed to generate a sample distribution over two sampling strategies. They start by sampling with a small number of samples evenly distributed over the strategies and calculate a value to partition the total number of samples over the sampling techniques.

He and Owen [HO14] presented another method to get a partitioning of samples for more than two strategies by proving that the variance is jointly convex in the distribution of samples. They also proposed an improved method for convex optimization to find such a distribution.

Sbert et al. [SHSK16] worked on a modification of the balance heuristic that doesn't take the distribution of samples into account for calculating the weights. Their method works in two phases. The first phase uses 20% of the total samples equally distributed over all sampling methods to calculate the variance σ_i^2 . After that the following stage is subdivided into eight substages each using 10% of the total number of samples and iteratively updating σ_i^2 and calculating the distribution α over the techniques for the next substage.

What all the above techniques have in common is that they all rely on initial samples to fine tune their succeeding execution. The proposed method of Karlík et al. on the other hand doesn't need any prior samples to be taken and therefore their performance impact should be much smaller [KŠV⁺19].

ToDo

(Sum up what others did in this field.)

4. Multiple Importance Sampling

(Match to actual structure of this chapter) In this chapter the fundamentals of Monte Carlo integration and importance sampling will be introduced. Following that Multiple Importance Sampling is explained which is essential for the next chapter 5. ToDo

4.1 Probability Basics

For our use case we need to define random variables, probability distribution functions (pdf) and cumulative distribution functions (cdf). A random variable maps an event to a real number $X : \Omega \rightarrow \mathbb{R}$. In a discrete scenario our random variable corresponds to one exact event e.g. a dice throw showing three pips on the top. The probability for this can be expressed as $P(X = 3) = \frac{1}{6}$ or as $X(3) = \frac{1}{6}$ since the random variable X can take six different values which are all equally likely. To express the probability that an event is within a range of values we can use the cdf which is defined as

$$F(x) = P(X \leq x), x \in \mathbb{R}.$$

For the probability of a random variable in an interval $[a, b)$ we can write

$$P(a \leq X < b) = F(b) - F(a) \text{ [Sch18].}$$

When we are talking about continuous events e.g. turning a wheel of fortune, every exact angle has a probability of nearing zero. But we can still express our probability for an angle interval with the cdf from above. In the continuous case we have a pdf that is used to calculate the cdf with

$$F(x) = \int_{-\infty}^x p(\tilde{x})d\tilde{x}.$$

The pdf has to be non-negative ($\forall x : p(x) \geq 0$) and integrate to one ($\int_{-\infty}^{\infty} p(x)dx = 1$) to be valid and “[...] describes the relative probability of a random variable taking on a particular value” [PJH18, Chapter 13.1]. (How to cite when the content of this section was created with a reference?) ToDo

4.2 Generating Samples after a specific Function

This will be essential for the next section 4.3, since this is our adjustment wheel to manipulate the quality of our rendering (for a given amount of time). Most of the time we don't

need evenly distributed samples, rather our samples should follow a specific characteristic of a material or a scene. For this we need to know how to generate samples that correspond to that characteristic.

Given a function $f(x)$ from which we would like to draw samples from the first step is to make sure it fulfills the constraints for a pdf in an interval $[a, b]$ we want to use. First we check that $\forall x \in [a, b] : f(x) \geq 0$ and then calculate the integral with

$$F = \int_a^b f(x)dx. \quad (4.1)$$

To Do
To Do

F can be used to normalize our goal function which yields us $\tilde{f}(x) = \frac{f(x)}{F}$ as a valid pdf. The next step is to calculate our cdf as $F(x) = \int_a^x \tilde{f}(t)dt$ which we will then invert to get $F^{-1}(x)$. Now we only need to draw an equally distributed random number (which most programming languages have a library for) in the interval $[0, 1]$ which we call ξ and evaluate $F^{-1}(\xi) = X$ to get X which is distributed proportional to $f(.)$. This method is called "inverse cdf" [Sch18]. **(Should I also cover 2D sampling?) (Should I cover more sampling methods (rejection sampling e.g.))**

4.3 Monte Carlo Integration

Monte Carlo integration is a technique to approximate the integral of an arbitrary function $f(x)$ by taking N random samples X_i from a pdf $p(X_i)$. As we know the expectation of a random variable is calculated by

$$E(X) = \int_{-\infty}^{\infty} xp(x)dx$$

or more generally

$$E(g(x)) = \int_{-\infty}^{\infty} g(x)p(x)dx.$$

For the next step we need the law of large numbers which states that

$$P\left[\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N X_i = E(X)\right] = 1$$

with X_i drawn from $p(.)$ which means that the average of our samples will converge to the expected value [Vea97, Chapter 2.4.1]. From here we can formulate

$$\int_a^b g(x)p(x)dx \stackrel{\text{definition}}{=} E(g(x)) \stackrel{\text{law of large numbers}}{\approx} \frac{1}{N} \sum_{i=1}^N g(x_i)$$

and with $g(x) = \frac{f(x)}{p(x)}$

$$\begin{aligned} \int_a^b \frac{f(x)}{p(x)} p(x)dx &\approx \frac{1}{N} \sum_{i=1}^N \frac{f(x_i)}{p(x_i)} \\ \Leftrightarrow \int_a^b f(x)dx &\approx \frac{1}{N} \sum_{i=1}^N \frac{f(x_i)}{p(x_i)} \end{aligned} \quad (4.2)$$

which is the Monte Carlo estimator [Sch18].

4.3.1 Variance

Generally the variance is described by

$$V(X) = \frac{1}{N} \sum_{i=1}^N (x_i - E(X))^2$$

for discrete random variables [Sch18] and

$$V(X) = \int_a^b (x - I)^2 p(x) dx$$

with I being the mean of the random variable X for continuous variables [wyz19]. When we look at the variance of our Monte Carlo integral we get

$$\begin{aligned} V(g(x)) &= \int_a^b (g(x) - F)^2 p(x) dx \\ &= \int_a^b \left(\frac{f(x)}{p(x)} - F \right)^2 p(x) dx \end{aligned} \tag{4.3}$$

with F being the integral from equation 4.1.

4.4 Importance Sampling

With the variance from equation 4.3 let's see how we can improve it. We can easily see that reducing the term $\frac{f(x)}{p(x)} - F$ will finally reduce the variance the most since it will be exponentiated. Since F and $f(\cdot)$ are fixed (that is the integral we want to calculate) only $p(\cdot)$ is left for modification. When we choose

$$p(x) = \frac{f(x)}{\int_a^b f(x) dx}$$

we get

$$\begin{aligned} \frac{f(x)}{p(x)} - F &= \frac{f(x)}{\int_a^b f(x) dx} \int_a^b f(x) dx - F \\ &\stackrel{4.1}{=} \int_a^b f(x) dx - \int_a^b f(x) dx = 0 \end{aligned}$$

which is ideal as we get a variance of 0 and are done. The problem is that we don't know the integral at the start since that is what we want to calculate in the first place. When we look at our chosen pdf we see that $p(\cdot)$ is proportional to $f(\cdot)$ by a factor $\frac{1}{\int_a^b f(x) dx} = \frac{1}{F} := c$. So we should at least try to chose $p(\cdot)$ somewhat proportional to $f(\cdot)$. The difficulty is that $f(\cdot)$ can be arbitrary complex so we might only be able to approximate some part of it with one specific pdf.

4.5 Multiple Importance Sampling

The rendering equation

$$L_o(x, \omega) = L_e(x, \omega) + \int_{\Omega^+} f_s(x, \omega, \omega_o) L_r(x, \omega_o) |n \cdot \omega_o|^+ d\omega_o \tag{4.4}$$

consists of the emitted light at point x $L_e(\cdot)$, the bidirectional scattering distribution function (BSDF) $f_s(\cdot)$, the reflected light at point x in direction ω expressed as $L_r(\cdot)$ and the cosine to account for looking at an angle onto the surface $|n \cdot \omega_o|^+$ where the $^+$ means

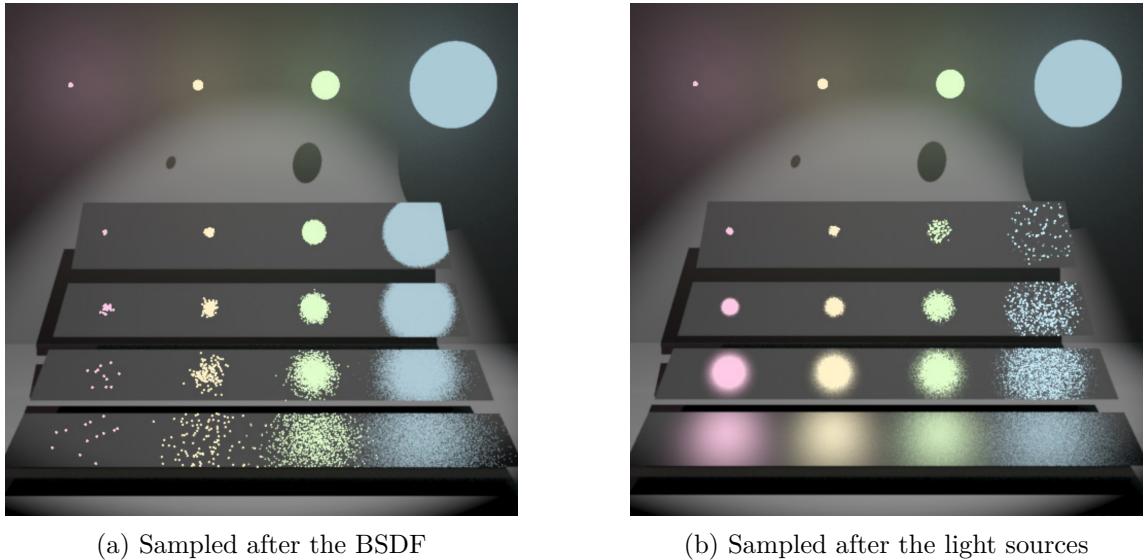


Figure 4.1: A scene with four light sources getting larger in diameter from left to right and four horizontal objects with BSDFs from diffuse at the bottom to more and more specular at the top.

- (a) This scene is sampled using a pdf that is proportional to the BSDF of the surface.
- (b) Here the scene was sampled with a pdf that generated samples on the light source. These graphics were taken from [Vea97, Figure 9.2].

we are only taking values > 0 so only directions pointing into the upper hemisphere. With this we can see that a single pdf that only is proportional to e.g., the BSDF leaves out the $L_r(\cdot)$ term so it can't be optimal. Having multiple pdfs where each samples a different part of the rendering equation well a combination of them should create a good result. E. Veach created a good example of this problem in his thesis [Vea97] which can be seen in figure 4.1. He also introduced Multiple Importance Sampling to use a combination of pdfs to get better results than would be possible with only one pdf.

When sampling only the BSDF we see that in figure 4.1a the bottom left reflection is very noisy, because sampling a diffuse BSDF can give a wide range of directions and since the light source on the left is very small only very few directions will point directly on that light source. The more specular surfaces in that figure are well sampled which makes sense, because there are less possible directions to sample so the reflection will be well sampled.

On the other hand figure 4.1b shows the same scene but sampled after the light sources by sampling a random point on the light source and then evaluating the render equation to get the contribution. Here the opposite happened in the two corners we looked at before. The bottom left reflection is very well sampled since the direction to the light source is still valid (has some contribution in the BSDF) and therefore we can see the whole reflection. But now the top right reflection is noisy because the direction to a random point on the light source has no contribution in the BSDF.

If we could combine both approaches the result should cover all cases and show all reflections well. To do this Veach introduced Multiple Importance Sampling [Vea97, Chapter 9]. The updated estimator now looks like this:

$$F = \sum_{i=1}^k \frac{1}{n_i} \sum_{j=1}^{n_i} w_i(X_{i,j}) \frac{f(X_{i,j})}{p(X_{i,j})}.$$

Compared to the initial estimator from equation 4.2 we now have additional weight

functions $w_i(\cdot)$ and split up our samples over the k different sampling technique with $n = \sum_{i=1}^k n_i$. To keep the estimator unbiased the weighting function need to fulfill two constraints:

- $\sum_{i=1}^n w_i(x) = 1$ when $f(x) \neq 0$
- $w_i(x) = 0$ when $p_i(x) = 0$.

The first constraint makes sure that every point is neither reduced nor increased in its contribution which is important to keep the estimator unbiased. The second constraint states that a pdf that could not create this sample also must have no weight so it will be ignored. A concrete weighting function will be introduced in the next subsection.

4.5.1 Balance Heuristic

A very popular weighting function also introduced by Veach is the balance heuristic [Vea97, Chapter 9.2.2]. The formula to calculate it is as follows:

$$w_i(x) = \frac{n_i p_i(x)}{\sum_{j=1}^k n_j p_j(x)}$$

So the weight for a sample consists of the amount of samples n_i drawn with that technique, the probability $p_i(x)$ for that sample divided by the sum of all techniques. (show how it falls down to a simple standard monte carlo estimator when inserting into the formula (when more text is needed?)) ToDo



Figure 4.2: This image shows the same scene as in figure 4.1 but rendered using the balance heuristic. Taken from [Vea97, Figure 9.4].

Figure 4.2 show that with the balance heuristic the noisy areas we observed while only using a single pdf in figure 4.1 disappeared and all combinations of surface roughness and light source size are well represented.

5. Multiple Importance Sampling Compensation

ToDo (Recap their approach to improve MIS)

5.1 Optimality

ToDo (Explain their work. Formulas should be clearly explained.)

6. Application: Image Based Lighting

(Explain the contents of this chapter)

ToDo

6.1 Image Based Lighting

(Explain Image based lighting shortly)

ToDo

6.2 MIS Compensation in Image Based Lighting

(Explain how their approach improves ibl variance)

ToDo

(If space left show results)

ToDo

7. Application: Path Guiding

7.1 Path Guiding

ToDo

(Explain the concept of path guiding)

7.2 MIS Compensation in Path Guiding

ToDo

(Explain how their approach improves path guiding)

8. Summary

(Write a short summary of what they achieved)

ToDo

8.1 Future Work

(Mention what could be done next based on this work)

ToDo

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Erklärung

Ich versichere, dass ich die Arbeit selbstständig verfasst habe und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe, die wörtlich oder inhaltlich übernommenen Stellen als solche kenntlich gemacht und die Satzung des KIT zur Sicherung guter wissenschaftlicher Praxis in der jeweils gültigen Fassung beachtet habe. Die Arbeit wurde in gleicher oder ähnlicher Form noch keiner anderen Prüfungsbehörde vorgelegt und von dieser als Teil einer Prüfungsleistung angenommen.

Karlsruhe, den November 17, 2019

(Christian Navolskyi, B. Sc.)