# Combining Analytic Direct Illumination and Stochastic Shadows 

Supplemental Material: Convergence Analysis


#### Abstract

In this document, we propose a 1D experiment that shows that our ratio estimator has generally lower variance than the full-stochastic and control-variate estimators. This document is referenced in Section 3.4 of the main paper in paragraph The ratio estimator has low variance.


Numerical experiment in 1D In order to investigate the evolution of the estimators through increasing number of samples we apply them to a 1D problem where the goal of this experiment is to estimate the integral of the product of two functions $w$ and $V$ over $[0,1]$ :

$$
\begin{equation*}
S=\int_{0}^{1} w(x) V(x) d x \tag{1}
\end{equation*}
$$

where $w=R L / p$ plays the role of the sampling weight of the direct illumination and $V$ is the binary visibility function. The classic full-stochastic estimator, the controlvariate estimator, and our ratio estimator are obtained by sampling uniform values $x \in[0,1]$ :

$$
\begin{align*}
S_{N}^{\text {sto }} & =\frac{1}{N} \sum_{n=1}^{N} w\left(x_{n}\right) V\left(x_{n}\right)  \tag{2}\\
S_{N}^{\mathrm{CV}} & =\int_{0}^{1} w(x) d x-\frac{1}{N} \sum_{n=1}^{N} w\left(x_{n}\right)\left(1-V\left(x_{n}\right)\right) \\
S_{N}^{\text {ratio }} & =\int_{0}^{1} w(x) d x \times \frac{\sum_{n=1}^{N} w\left(x_{n}\right) V\left(x_{n}\right)}{\sum_{n=1}^{N} w\left(x_{n}\right)}
\end{align*}
$$

Note that the variance properties of these estimators are strictly equivalent to their respective direct-illumination estimators since we only change the integration domain. The advantage of doing this is that it makes investigations and visualization easier. In Figure 1 we compare the convergence of these estimators in different scenarios.

Discussion We provide a qualitative summary of the results shown in Figures 1 in Table 1. We interpret these results for different configurations:
(a,b): if $V$ is always (or almost always) 1 , the variances of both the control-variate and the ratio estimators are low. This explains why shadowless regions are noise-free with these formulations while a classic full-stochastic evaluation produces noise.
$(\mathrm{c}, \mathrm{d})$ : if $V$ is always (or almost always) 0 , the variances of both a full-stochastic evaluation and our ratio estimator are zero. This explains why shadowed regions are noise-free with these estimators while the control-variate estimator exhibits variance in these regions.
$(e, f)$ : as the variance of $V$ increases, the estimators tend to have similar variances until they become equivalent as the variance of $w$ becomes negligible in comparison to the one of $V$. This explains why penumbra regions are similarly noisy with all of the estimators.

Figure 1
(a)
(b)
(d)
(e)
(f) $w$
high variance
high variance
high variance
high variance
high variance
low variance


1
near 1
0
near 0
high variance
high variance

| $S_{N}^{\text {sto }}$ | $S_{N}^{\mathrm{CV}}$ |
| :---: | :---: |
| $x$ | $\checkmark$ |
| $x$ | $\checkmark$ |
| $\checkmark$ | $x$ |
| $\checkmark$ | $x$ |
| $x$ | $x$ |
| $x$ | $x$ |

$S_{N}^{\text {ratio }}$
$\checkmark$
$\checkmark$
$\checkmark$
$\checkmark$
$x$
$x$

Table 1: Qualitative summary of the experiments.


Figure 1: Convergence of the estimators with increasing number of samples.

