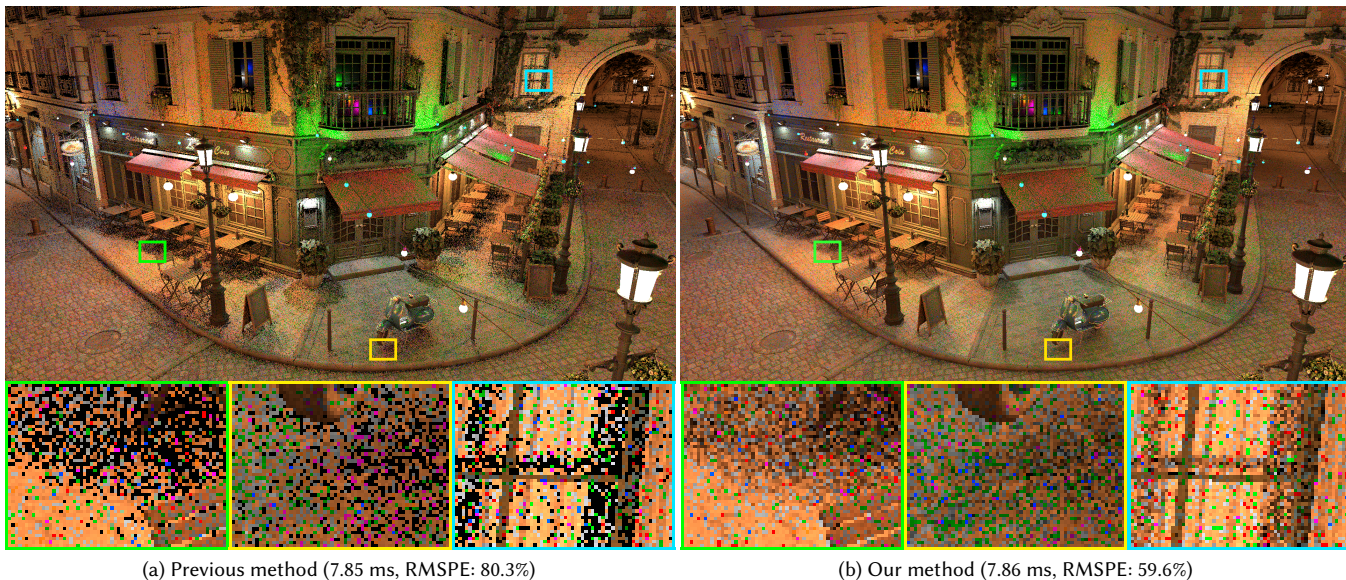


# Efficient Visibility Reuse for Real-time ReSTIR

Yusuke Tokuyoshi  
yusuke.tokuyoshi@amd.com  
Advanced Micro Devices, Inc.  
Tokyo, Japan



**Figure 1: Real-time direct illumination using biased visibility-reuse ReSTIR [Bitterli et al. 2020; Wyman and Pantelev 2021] with and without our shadow variance reduction technique (1920×1080 pixels, two rays per pixel, AMD Radeon™ RX 7900 XTX GPU). Our method reduces the root mean square percentage error (RMSPE) by efficiently reusing spatiotemporal sample visibilities.**

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## 1 INTRODUCTION

*Spatiotemporal reservoir resampling* (ReSTIR) [Bitterli et al. 2020] is a powerful sampling technique that is often used for real-time rendering. It samples an important light path by reusing many samples from spatiotemporally neighboring pixels. However, ReSTIR can produce significant noise around shadow edges, because the generated sample distribution is often dissimilar to the illumination integrand around such edges. Since shadow ray visibility is a step function for opaque surfaces, one-sample visibility is insufficient for those shadows. To reduce the shadow noise for ReSTIR, we present a simple and efficient visibility estimation that reuses the

visibilities of spatiotemporal samples. Our method is based on the visibility reuse proposed by Wyman and Pantelev [2021]. While they reused visibilities to reduce shadow rays, we reduce the variance by introducing a variant of *weighted importance sampling* (WIS) [Bekaert et al. 2000]. Heitz et al. [2018] extended the ratio estimator (a.k.a., WIS) for biased shadow denoising. Bouma [2023] discussed the denoising of visibilities and the rejection of spatiotemporal reuse based on the denoised visibilities for practical ReSTIR indirect illumination. In our work, we mathematically validate the accumulation of visibilities based on WIS. Although our method can introduce a negligible bias for typical real-time implementations, we also discuss conditions to obtain unbiased results.

## 2 BACKGROUND

ReSTIR first generates an initial sample for each pixel and then resamples a sample  $X$  from spatiotemporally neighboring pixels  $i$  according to a weight  $w_i \in [0, \infty)$ . For the rendering integral, the one-sample estimator is written as

$$\int_{\Omega} f(x)V(x)dx \approx f(X)V(X)W_X, \quad (1)$$

where  $f(x) \in [0, \infty)$  is the light contribution without shadows, and  $V(x) \in [0, 1]$  is the shadow ray visibility.  $W_X$  is the contribution

weight (i.e., estimate reciprocal PDF) given by

$$W_X = \frac{1}{\hat{p}_c(X)} \sum_i w_i, \quad (2)$$

where  $\hat{p}_c(x) \propto f(x)$  is the target distribution at the current pixel  $c$ . In generalized resampled importance sampling [Lin et al. 2022], the weight for a candidate sample is given by

$$w_i = m_i(T_i(x_i)) \hat{p}_c(T_i(x_i)) W_i \left| \frac{\partial T_i}{\partial x_i} \right|, \quad (3)$$

where  $m_i(\cdot)$  is the weight of multiple importance sampling [Veach and Guibas 1995] that satisfies  $\sum_i m_i(x) = 1$ ,  $T_i(\cdot)$  is a bijective shift mapping from the candidate's domain to the integral domain  $\Omega$ . Although ReSTIR reduces the variance in  $f(X)W_X$ , the visibility  $V(X)$  can have a high variance (Fig. 1a). This variance is noticeable around shadow edges for a biased ReSTIR variant [Bitterli et al. 2020] that reuses the visibility of the initial sample for  $W_X$ . Our work reduces the shadow variance (Fig. 1b) by reusing spatiotemporal sample visibilities for  $V(X)$ .

### 3 OUR VISIBILITY REUSE

Our method reuses past visibilities while correcting the visibility of a spatial sample by tracing a shadow ray, similar to Wyman and Pantelev [2021]. Unlike Wyman and Pantelev, we estimate the visibility  $\bar{V}_X \in [0, 1]$  of a selected sample  $X$  by the weighted average of spatiotemporal sample visibilities  $\bar{V}_i \in [0, 1]$  as follows:

$$\bar{V}_X = \frac{\sum_i \bar{V}_i w_i}{\sum_i w_i}. \quad (4)$$

Since a sample  $X$  is selected according to  $w_i$ , this estimation is a variant of WIS. Although WIS is biased due to the normalization factor  $\sum_i w_i$ , this factor is eventually cancelled as follows:

$$\begin{aligned} \int_{\Omega} f(x)V(x)dx &\approx f(X)\bar{V}_X W_X = f(X) \frac{\sum_i \bar{V}_i w_i}{\sum_i w_i} \frac{\sum_i w_i}{\hat{p}_c(X)} \\ &= \frac{f(X)}{\hat{p}_c(X)} \sum_i \bar{V}_i w_i. \end{aligned} \quad (5)$$

The reused visibility  $\bar{V}_i$  is also estimated using the WIS variant (Eq. 4) in a chained manner, but its normalization factor is also recursively cancelled by  $\bar{V}_i w_i$  as follows:

$$\bar{V}_i w_i = m_i(T_i(x_i)) \hat{p}_c(T_i(x_i)) \frac{\sum_k \bar{V}_k w_k}{\sum_k w_k} \frac{\sum_k w_k}{\hat{p}_c(x_i)} \left| \frac{\partial T_i}{\partial x_i} \right|, \quad (6)$$

where  $k$  is a pixel used to resample  $x_i$ . Therefore, if  $\hat{p}_c(x) \propto f(x)$ , our variance reduction technique is unbiased for static scenes (please see the supplementary document for details). If  $\hat{p}_c(x) \not\propto f(x)$ , the bias occurs depending on the approximation error of  $\hat{p}_c(x)$ . When  $f(x)$  differs between RGB channels (e.g., colored light sources),  $\hat{p}_c(x)$  can be approximated by the luminance of  $f(x)$  for simplicity. In this case, the color of invisible lights can leak into shadows, though the luminance is unbiased. This color leak can be made less noticeable by combining Bitterli et al.'s visibility reuse [2020], because their method reduces the sampling of invisible lights. Since our technique is simple (Eq. 4), it is easy to implement on top of the existing visibility-reuse ReSTIR (please see the pseudocode in the supplementary document).

## 4 RESULTS

Fig. 1 shows the biased visibility-reuse ReSTIR [Bitterli et al. 2020; Wyman and Pantelev 2021] with our variance reduction technique. Our method significantly reduces undesirable shadow noise. Although our method can introduce a color leak bias around shadow edges, this bias is barely noticeable even for colored light sources. For dynamic lighting, a shadow delay is inherited from the existing visibility reuse, but it is insignificant as shown in the supplementary video. Since our method improves the shadow quality with simple implementation, it is suitable for real-time rendering.

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