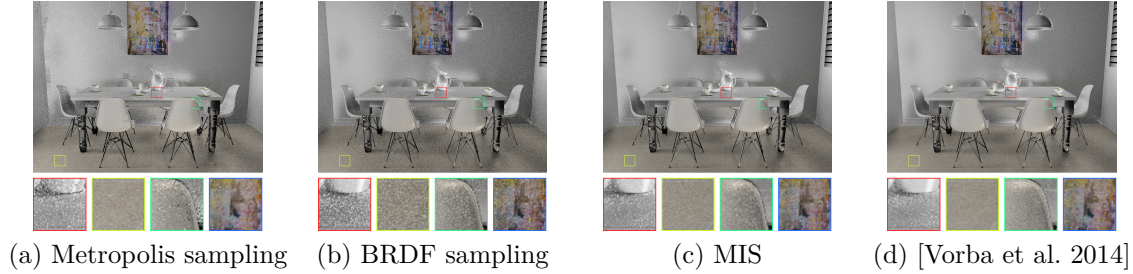


# Guided Path Tracing Using Clustered Virtual Point Lights

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**Figure 1:** One-bounce indirect illumination by VPL guided path tracing using 48K VPLs. Metropolis sampling of the incoming radiance estimated by VPLs is more effective for diffuse surfaces where BRDF sampling is not. The combination of both techniques using multiple importance sampling (MIS) yields the best of both worlds. This result is also visually as good as photon based guided path tracing by Vorba et al. (600K photons).

## 1 Introduction

Monte Carlo path tracing has been increasingly popular in movie production recently. It is a general and unbiased rendering technique that can easily handle diffuse and glossy surfaces. To trace light paths, most of existing path tracers rely on surface BRDFs for directional sampling. This works well for glossy appearance, but tends to be not effective for diffuse surfaces because in such cases, the rendering integral is mostly driven by the incoming radiance distribution, not the BRDFs. Therefore, with the same number of samples, it is more favorable to sample the incoming radiance distribution to achieve better effectiveness for diffuse scenes. [Vorba et al. 2014] addressed this sampling problem by using photons to estimate incoming radiance distributions which can then be compactly represented using Gaussian mixture functions.

Instead of using photons, in this work, we propose to use virtual point light (VPL) to estimate incoming radiance and guide path tracing. We are motivated by the fact that instant radiosity and many-light rendering using VPLs can produce a quick preview of global illumination in a few minutes. We ask the question if the VPLs could be further utilized for other tasks such as assisting path tracing, after the preview is generated. To achieve this goal, we propose a Metropolis algorithm to sample directions from the unit hemisphere that utilizes the incoming radiance estimated by the VPLs. We also incorporate VPL clustering to ensure scalability. Our experiments show that our Metropolis samplers can improve the effectiveness of importance sampling for diffuse surfaces. Our technique also works as good as [Vorba et al. 2014].

## 2 Our method

The main steps of our approach are as follows. We first generate a set of VPLs and a set of surface points visible to camera for VPL gathering. The surface points are then grouped into clusters based on their locations and orientations using a 6D kd-tree. The representatives of the clusters are used as cache points which store incoming radiance distribution from the VPLs in order to guide directional sampling. We then evaluate incoming radiance from the VPLs to the cache points. To support scalability, for each cache point, the VPLs are clustered adaptively by following LightSlice. We can now sample directions based on incoming radiance estimated by the VPL clusters.

We propose to use Metropolis sampling to generate directions from incoming radiance distributions. The benefit of using Metropolis algorithm is twofold. First, it is more convenient to not representing the radiance distribution explicitly, i.e., by parametric functions or 2D grids. The only operation required is to evaluate incoming radiance for an arbitrary direction. In our implementation, we use kd-trees and query the VPLs that fall into a small cone centered at the direction of interest, and return the average incoming radiance. Additionally, the total incoming radiance to normalize the probability distribution can be easily available by evaluating all VPL cluster representatives. Second, Metropolis algorithm can be easily extended with better mutation techniques. Currently, we use two simple mutation techniques: randomly sample a direction, and perturb a direction in a small cone. Figure 1 shows the rendering of the Breakfast scene adopted from [Wayne 2014].

## References

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- WAYNE, W., 2014. The breakfast room - cycles - blender 2.71.