A significance sampling method for visualizing function-based scenes

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Abstract. The article considers the task of rendering function-based scenes with a sample of significance to reduce variance. A sampling method based on significance with an optimal density is proposed. Samples with optimal density are generated in an additional space mapping. An algorithm is used that allows you to nonlinearly deform an additional space mapping with the calculation of optimal densities. The algorithm implements a change in the deformation integration variables.

As a result, a method has been implemented that leads to an effective reduction of variance in functionally defined scenes.

1 Introduction

Sampling by significance of the bi-beam reflectivity function is used to visualize realistic scenes [1, 2]. In [3], a method is proposed to increase the efficiency of visualization of complex scenes.

Reducing the variance when tracing a path is a difficult problem [4]. In the review paper [5], rendering methods are presented, which include approaches based on the estimation of volumetric density, approaches based on the Monte Carlo method. Acceleration, scattering, and spatially correlated methods related to environments are described.

The article [6] describes a method for calculating multiple reflections inside microgeometry, eliminating energy losses. An explicit mathematical definition of the trajectory space is used, which uniformly describes single and multiple reflections.

Metropolis light transport [7, 8] considers the full path as a single sample. It can be concluded that this method will be used for future optimization and development.

The article [9] presents a Monte Carlo rendering algorithm with a Markov chain. The properties of ensembles of light transfer paths are used, which are distributed according to the lighting in the scene. This information is used to make decisions about managing the selection of local paths.

The article [10] provides a comprehensive overview of Markov chain algorithms for modeling light transfer.

The article [11] describes the problem of sampling a light path connecting two given points of a scene using a single specular reflection or refraction. This increases the range of scenes that can be processed using unbiased path sampling methods.

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Visualizing the transfer of light through media with a nonuniform refractive index is a difficult task. Continuous changes in the refractive index cause light to travel in curved paths. The article [12] describes unbiased path tracing estimates for this task. An integral path formulation is used to generalize the path trace with an estimate of the next event and a bidirectional path trace to adjust the heterogeneous refractive index.

In [13], Doppler rendering for dynamic scenes is presented. A time-path sampling method is described that combines time sampling with correlated path sampling.

Visualizing direct illumination from millions of dynamic light sources using the Monte Carlo method is a difficult task. In [14], an algorithm is presented that displays such lighting interactively, with high image quality.

The approach proposed in this paper never excludes sampling during rendering. These samples generate the density, depending on the scene. At the next stage of rendering, samples of the target density are provided. By using a suitable target density, the variance is reduced compared to visualization with a conventional homogeneous sample space. Thus, an algorithm is proposed for sampling the significance of complete light paths in the form of a nonlinear curvature in the space of the additional sample.

2 Perturbation functions

\[ F'(x, y, z) = F(x, y, z) + \sum_{i=1}^{N} R_i(x, y, z) \]

Here \( R(x, y, z) \) is the perturbation:

\[ R(x, y, z) = \begin{cases} Q(x, y, z) \text{if } Q(x, y, z) \geq 0 \\ 0 \text{if } Q(x, y, z) < 0 \end{cases} \]

Here \( Q(x, y, z) \) is the disturbing quadric.

For complex objects, set-theoretic operations are used.

3 Sampling by importance

\[ I_i = \int_{\Omega} f_i(x, y, z) d\mu \]

\[ I_{II} = \int_{\Omega} \Phi_i(y) \left| \frac{\partial \Phi_i(y)}{\partial y} \right| dy \]
\[ I_{i,l} \approx \sum_{n}^{\text{samples}} f_i(\Phi_l, y_j) \frac{d\Phi_l}{d\Phi_j} \frac{d\Phi_j}{dy_j} \]

\[ I_{i,l} = \int_{[1, \ldots, l]} f_i(\Phi_l, w_l, z_j) \frac{\partial w_l}{\partial \Phi_l} \frac{\partial w_l}{\partial z_j} \frac{\partial w_l}{\partial z_j} d\Phi_l \]

\[ d\Phi_l = \frac{\tau(\Phi_l, y_j)}{\partial \Phi_l} \frac{d\Phi_l}{dy} \]

\[ d\Phi_l = \frac{\partial w_j}{\partial \Phi_l} \frac{d\Phi_l}{dy} \]

\[ \tau(z, y_j) = w_j \cdot y \cdot \phi \]

\[ z = w_j \cdot y \cdot \phi \]
\[
\phi = \phi \sum_{j \in S} \left| \frac{\partial w_j}{\partial y_j} \phi \right|
\]

where \( s \) is a subset of the samples.

Direct mapping \( w \) is used for rendering, which is calculated from \( 1 - w \).

To do this, paths are calculated using uniform sampling in the scene and their contribution is calculated. This set is then sampled repeatedly to obtain samples with the desired target density.

Figure 1 shows the algorithm.

Creating a samples
Calculating trajectories
Calculating the indemnity
Re-performing set selections
Getting samples with the desired target density
Visualization
Tracking rays
Calculation of radiation emanating from light sources

Fig. 1. Calculation algorithm.
4 Results

The testing was carried out on an Intel Core i7-5960X processor and a GeForce GTX 970 graphics card.

Figure 2 shows complex lighting. The number of light sources is shown in Table 1.

Table 1. The statistics of light sources for each scene.

<table>
<thead>
<tr>
<th>Scene</th>
<th>Number of light sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fig. 2 (Top)</td>
<td>62</td>
</tr>
<tr>
<td>Fig. 2 (Below)</td>
<td>84</td>
</tr>
</tbody>
</table>

The significance sampling model reduces the variance without bias (Fig. 3, 4).
Fig. 3. The convergence graph (Fig. 2 on top).

Fig. 4. The convergence graph (Fig. 2 below).

The abscissa axis in both graphs shows the number of selections per pixel, and the ordinate axis shows the standard error.

5 Conclusion
An approach to the study of sampling by the significance of complete light paths in the space of the primary sample is presented. Nonlinear distortions in the additional sample space are calculated to achieve an optimal target density, which reduces the variance during visualization. The method does not depend on the specific effects of light transfer in any scene and on the basic visualization tools. Thus, it simply adapts to the various existing systems.

References


2. S. Vyatkin, B. Dolgovesov, E3S Web of Conferences 376, 05029 (2023) DOI: https://doi.org/10.1051/e3sconf/202337605029


