# Guiding and Shadow Rays

Alexander Keller, Ken Dahm, Nikolaus Binder, Thomas Müller

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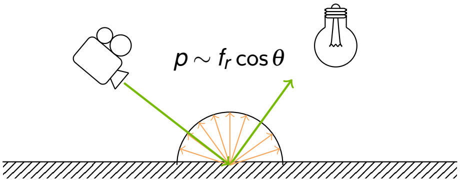
## Importance sampling of many light sources

- sampling proportional to integrand



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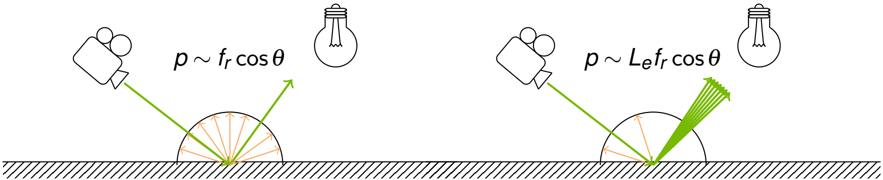

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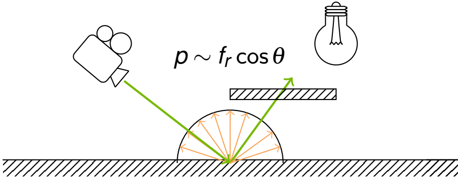


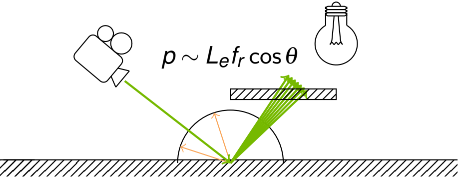

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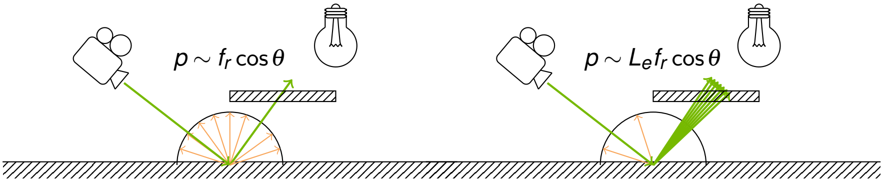


- goals
  - massively parallel
  - linear in number of paths
  - constant time

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- contribution of light sources estimated by sampling some paths across the image
  - Interactive global illumination in complex and highly occluded environments [WBS03]

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- generalization to guiding by probability hierarchies
  - The Iray light transport simulation and rendering system [KWRSvAKK17]

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- data structures
  - Efficient data structures and sampling of many light sources for next event estimation [Mik18]
  - see `https://github.com/AndiMiko/masterthesis/releases`

# Importance Sampling

## Partial cumulative distribution function (CDF)

- index set $I := \{i_1, \ldots, i_k\} \subseteq \{1, \ldots, n\}$ of references $i_j$ to (point) light sources

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$$p_i := \begin{cases} (1-b) \cdot q_i + b \cdot \frac{1}{n} & \text{for } i \in I \\ b \cdot \frac{1}{n} & \text{for } i \notin I \end{cases}$$

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- discrete density simulation, see `https://arxiv.org/abs/1901.05423`

# Importance Sampling

## Finding the probabilities $q_i$

- $q_i$ as normalized accumulated flux

$$\Phi = \frac{\max\{\cos\omega, 0\} \cdot L(x,\omega)}{p(x) \cdot p(s,\omega)}$$

  - probability $p(x)$ of selecting location $x$ (unless point light source)
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- learning probabilities $q_i$ during path tracing
  - simple inclusion of path guiding for scattering

- photon-based next event estimation
  - origins of photons within search radius to determine set $l$ of (point) light sources

# Efficient Implementation

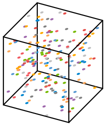
## Linear complexity

- store one partial CDF per hashed cell
- stochastic interpolation
- accumulate probabilities similar to Massively Parallel Path Space Filtering
  - see `https://arxiv.org/abs/1902.05942`

# Efficient Implementation

## Hashing instead of searching

- descriptors for selected vertices include



world space location $x$

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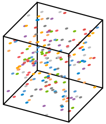

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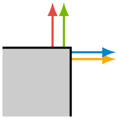

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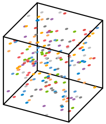

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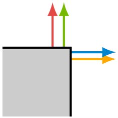

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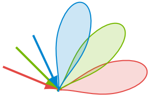

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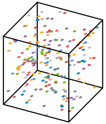
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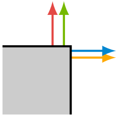
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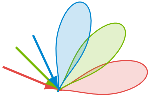
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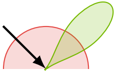
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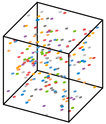
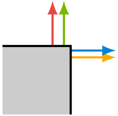
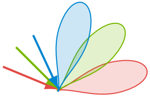
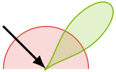

world space location $x$ and optionally normal $n$, incident angle $\omega$, and BRDF layer

- storing and loading data using hashed quantized descriptors
  - trade a larger hash table size for faster access (proportional to number of paths)

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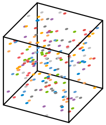

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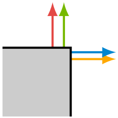

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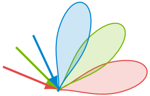

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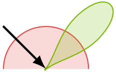

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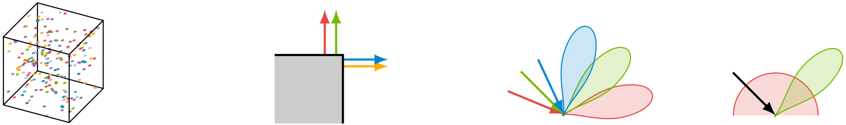

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- storing and loading data using hashed quantized descriptors
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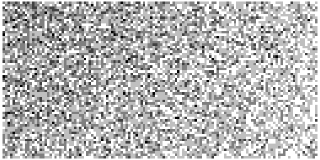
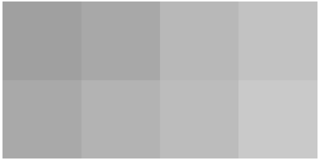
  - use a second hash of the descriptor instead of storing full keys
  - linear probing for collision resolution

# Efficient Implementation

## Stochastic interpolation to resolve quantization artifacts



input



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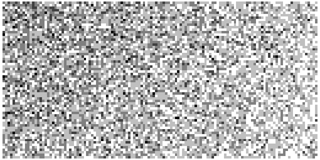

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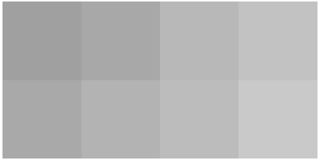

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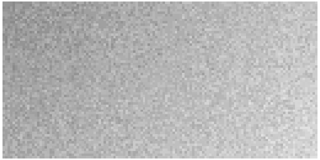


with jittering

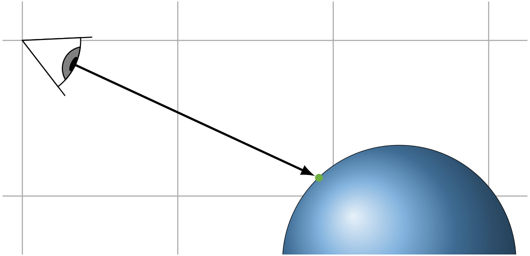
- jitter descriptor ($x_i$, ...) on store and load
  - resulting uniform noise amenable to (existing) post filtering


NVIDIA.

# Efficient Implementation

## Linear instead of quadratic complexity

- finding the hash table location $i$



$$i \leftarrow \text{hash}(\tilde{x}, \ldots) \ \% \ \text{table\_size}$$

for both averaging and querying

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$$i \leftarrow \text{hash}(\tilde{x}, \ldots) \;\; \% \text{ table\_size}$$

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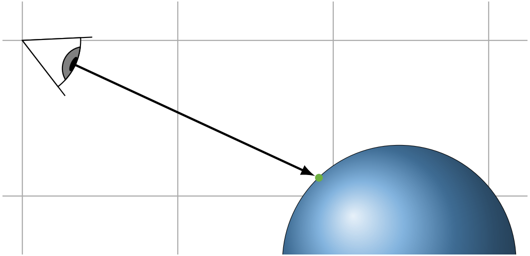

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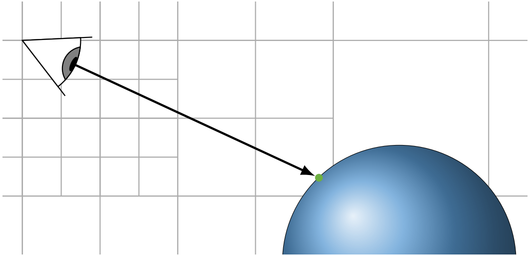

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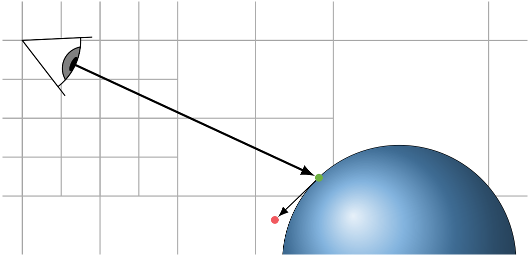

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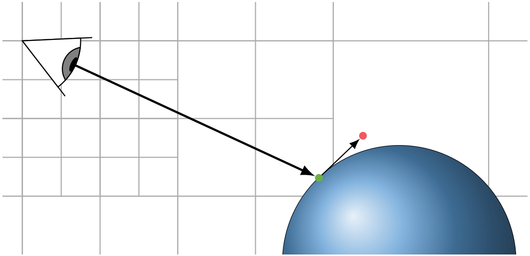

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l' &\leftarrow \text{level\_of\_detail}(|p_{\text{cam}} - x'|) \\
\tilde{x} &\leftarrow \left\lfloor \frac{x'}{scale \cdot 2^{l'}} \right\rfloor \\
i &\leftarrow \text{hash}(\tilde{x}, \ldots)\ \ \%\ \text{table\_size} \\
v &\leftarrow \text{hash2}(\tilde{x}, n, \ldots)
\end{aligned}
$$

for both averaging and querying

# Efficient Implementation

## Linear instead of quadratic complexity

- finding the hash table location $i$

$$l \leftarrow \text{level\_of\_detail}(|p_{\text{cam}} - x|)$$

$$x' \leftarrow x + \text{jitter}(n) \cdot scale \cdot 2^l$$

$$l' \leftarrow \text{level\_of\_detail}(|p_{\text{cam}} - x'|)$$

$$\tilde{x} \leftarrow \left\lfloor \frac{x'}{scale \cdot 2^{l'}} \right\rfloor$$

$$i \leftarrow \text{hash}(\tilde{x}, \ldots) \ \% \ \text{table\_size}$$

$$v \leftarrow \text{hash2}(\tilde{x}, n, \ldots)$$

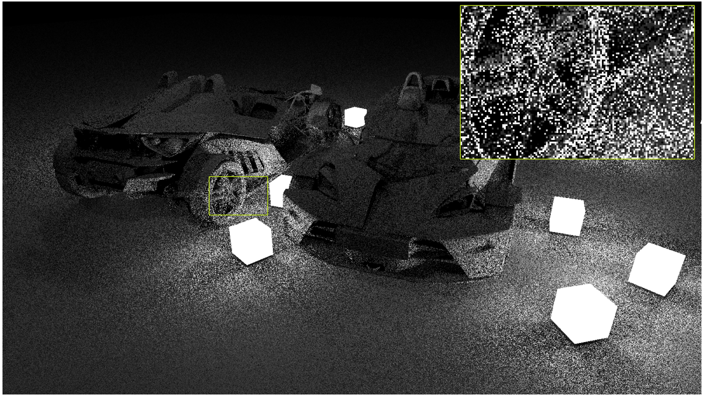
for both averaging and querying

- jittering before quantization hides discretization artifacts in uniform noise

# Results

## Comparison at 16 paths per pixel

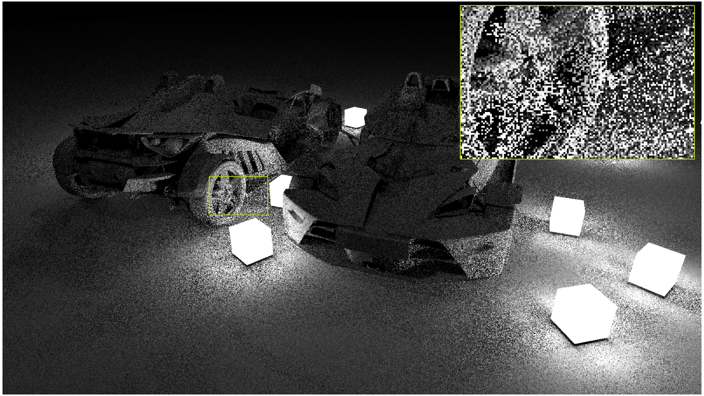
- uniform sampling



# Results

## Comparison at 16 paths per pixel

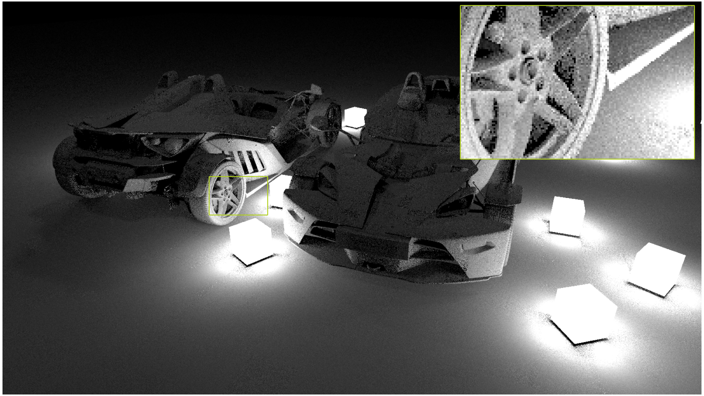
- light hierarchy



# Results

## Comparison at 16 paths per pixel

- multiple importance sampling combining partial CDF including visibility and light hierarchy



# Results

## Comparison at 2 paths of length 3 per pixel with 4 shadow rays each bounce

- uniform sampling vs. light hierarchy vs. new method

# Results

## Comparison at 2 paths of length 3 per pixel with 4 shadow rays each bounce

- uniform sampling vs. light hierarchy vs. new method

# Results

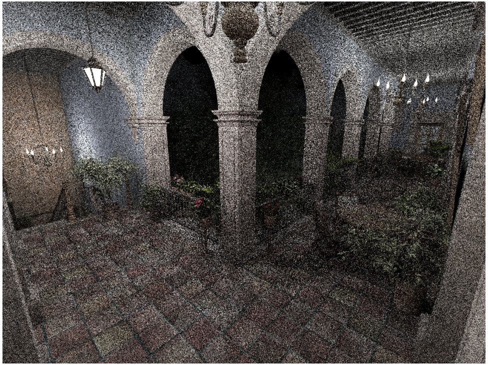
## Comparison at 2 paths of length 3 per pixel with 4 shadow rays each bounce

- uniform sampling vs. light hierarchy vs. new method

## Results

### Comparison at 8 paths of length 4 per pixel

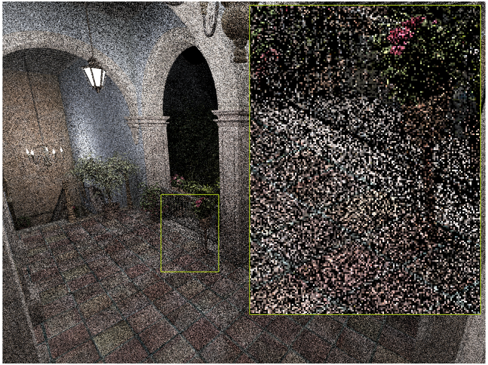
- light hierarchy vs. partial CDF



# Results

## Comparison at 8 paths of length 4 per pixel

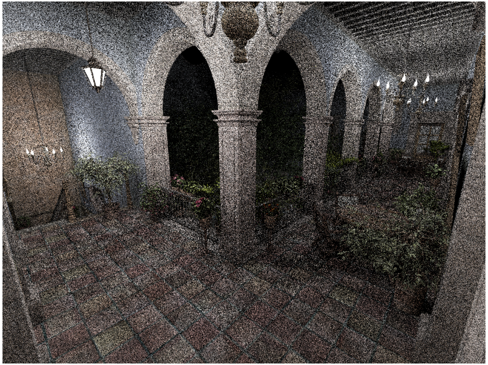
- light hierarchy vs. partial CDF



# Results

## Comparison at 8 paths of length 4 per pixel

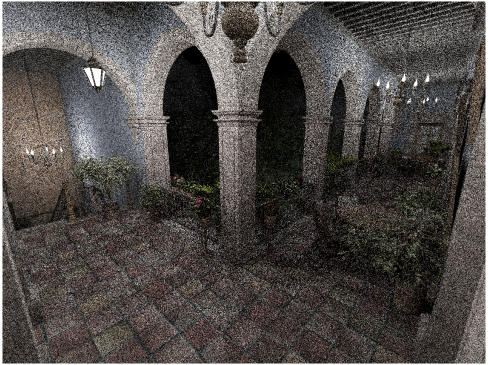
- light hierarchy vs. partial CDF



# Results

## Comparison at 8 paths of length 4 per pixel

- light hierarchy vs. partial CDF with path space filtering



# Guiding and Shadow Rays

## Sampling proportional to integrand including visibility

- level-of-detail hash of partial CDFs
  - light hierarchy as fallback
- stochastic interpolation
  - for both accumulation and sampling
- probabilities determined by either path tracing or light paths (photons)

# Guiding and Shadow Rays

## Sampling proportional to integrand including visibility

- level-of-detail hash of partial CDFs
  - light hierarchy as fallback
- stochastic interpolation
  - for both accumulation and sampling
- probabilities determined by either path tracing or light paths (photons)
- up next
  - learn *b* by gradient descent
  - include bidirectional scattering distribution function