NVIDIA

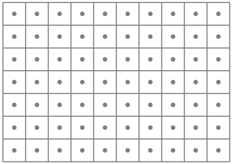
Ray-Traced Global Illumination for Games: Massively Parallel Path Space Filtering

Nikolaus Binder and Alexander Keller

Principles of Image Synthesis

Solving the visibility problem

Rasterization



Principles of Image Synthesis

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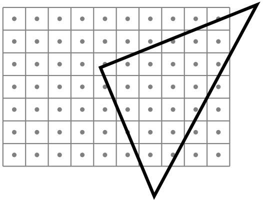

Principles of Image Synthesis

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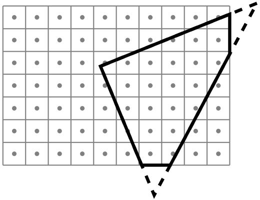

clipping

Principles of Image Synthesis

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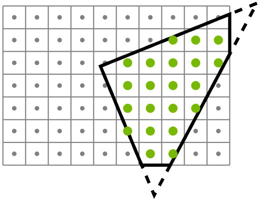

clipping

Z-buffer

Principles of Image Synthesis

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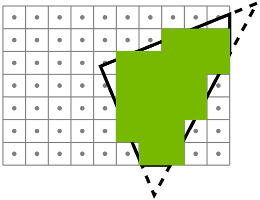
Rasterization

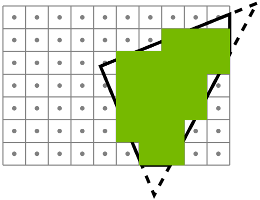
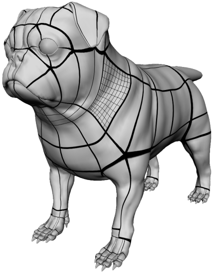


clipping

Z-buffer

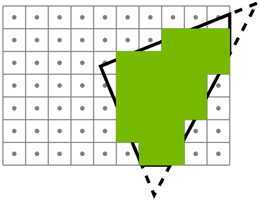
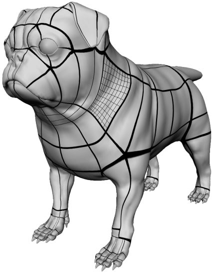
Principles of Image Synthesis

Solving the visibility problem

Rasterization	Reyes
	
clipping	dicing
Z-buffer	kind of Z-Buffer

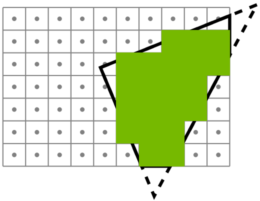
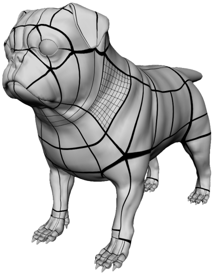
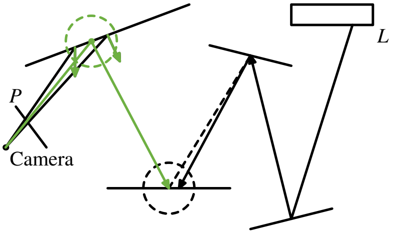
Principles of Image Synthesis

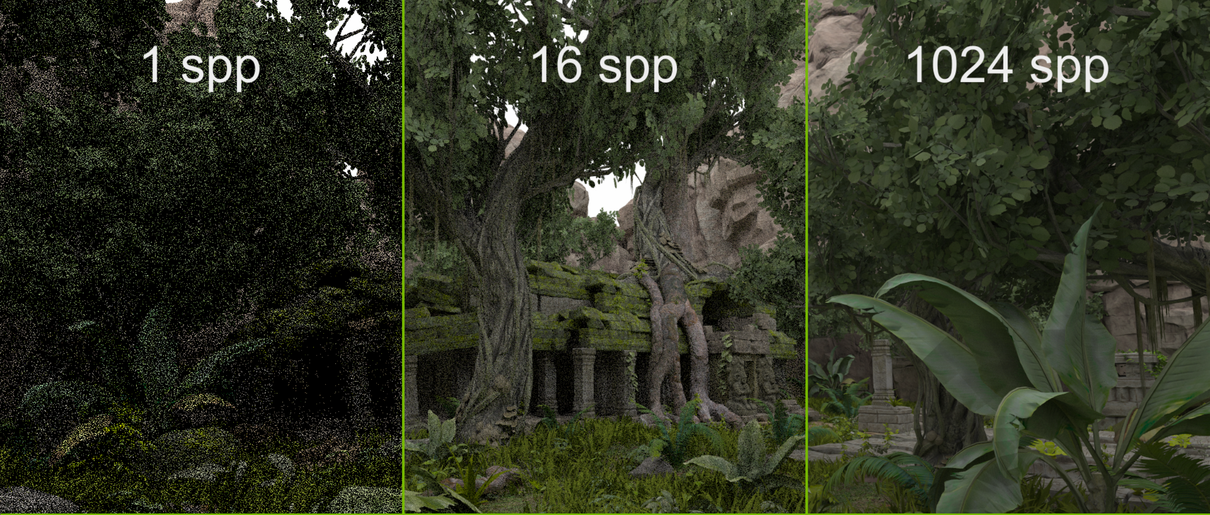
Solving the visibility problem

Rasterization	Reyes
	
clipping	dicing
Z-buffer	kind of Z-Buffer
shadow maps	shadow maps

Principles of Image Synthesis

Solving the visibility problem

Rasterization	Reyes	Ray Tracing
		
clipping	dicing	acceleration data structure
Z-buffer	kind of Z-Buffer	tracing rays with arbitrary origins
shadow maps	shadow maps	shadow rays



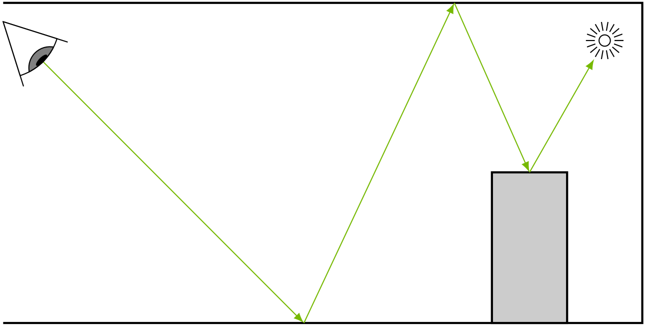
Path tracing on a budget

Massively Parallel Path Space Filtering

Massively Parallel Path Space Filtering

Sharing instead of splitting

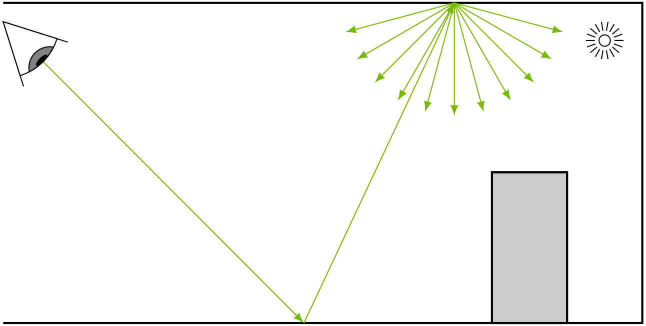
- filtering beyond screen space



Massively Parallel Path Space Filtering

Sharing instead of splitting

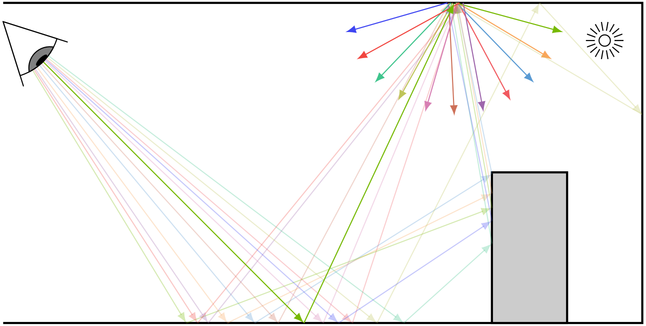
- filtering beyond screen space
- algorithm



Massively Parallel Path Space Filtering

Sharing instead of splitting

- filtering beyond screen space
- algorithm
  1. generate paths,
     select and store vertices



Massively Parallel Path Space Filtering

Sharing instead of splitting

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- algorithm
  1. generate paths,
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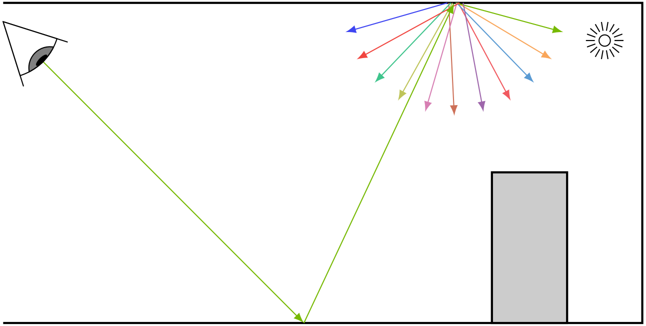
  2. average contributions
     with similar vertex descriptors



Massively Parallel Path Space Filtering

Sharing instead of splitting

- filtering beyond screen space

- algorithm
  1. generate paths,
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  2. average contributions
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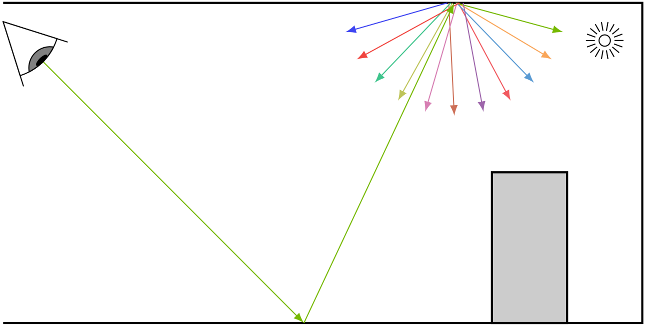
  3. use averaged contributions



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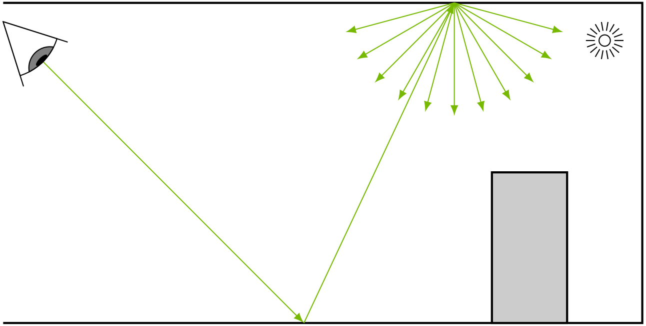

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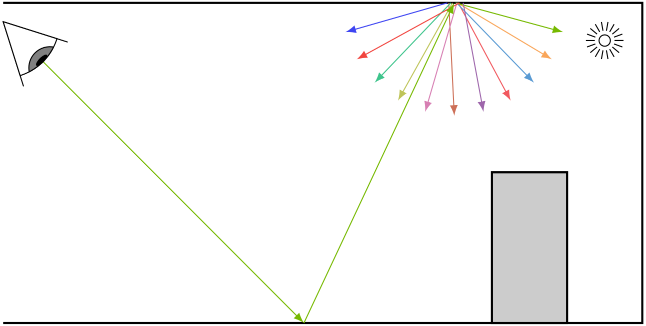
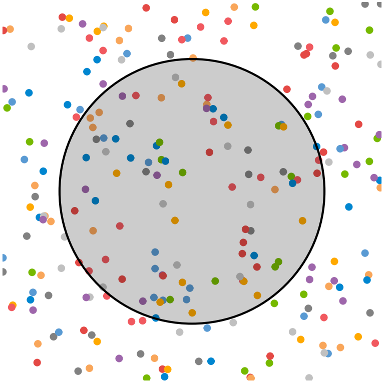


Massively Parallel Path Space Filtering

Bottleneck: Calculating averages

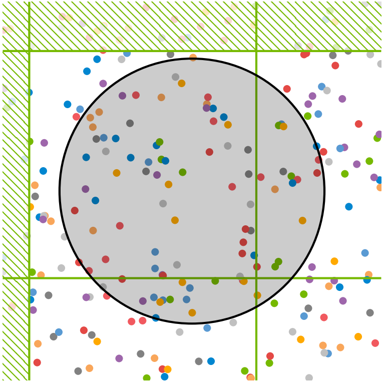
- include many “close by” contributions in average



Massively Parallel Path Space Filtering

Bottleneck: Calculating averages

- include many “close by” contributions in average
  - efficient culling by range search



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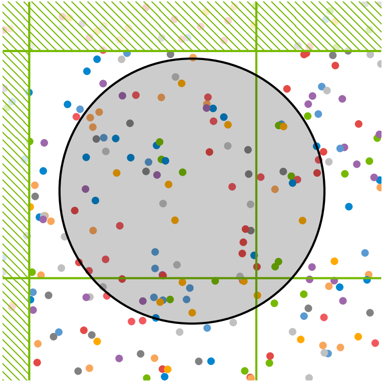
Massively Parallel Path Space Filtering

Bottleneck: Calculating averages

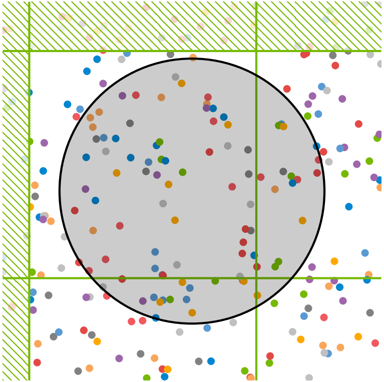
- include many “close by” contributions in average
  - efficient culling by range search
  - but still have to iterate over all of them



Massively Parallel Path Space Filtering

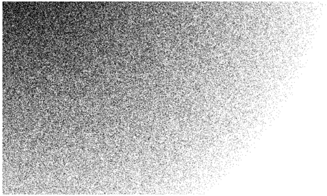
Bottleneck: Calculating averages

- include many “close by” contributions in average
  - efficient culling by range search
  - but still have to iterate over all of them
  - and every vertex needs to do this individually



Massively Parallel Path Space Filtering

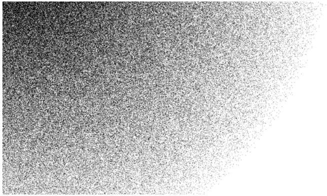
Principle



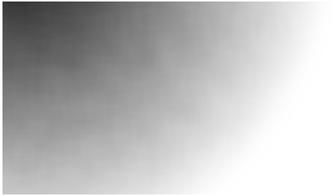
input

Massively Parallel Path Space Filtering

Principle



input



local averaging

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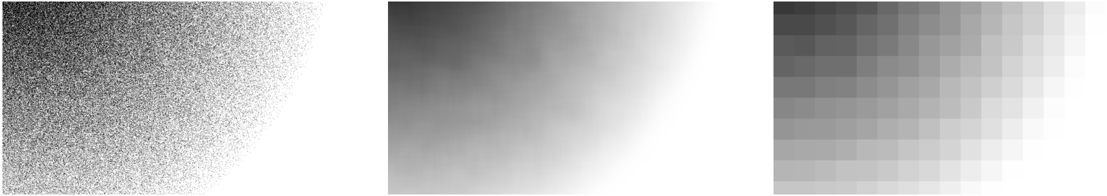
Massively Parallel Path Space Filtering

Principle

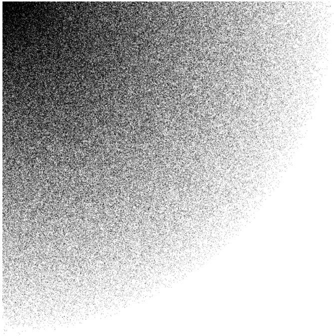


input | local averaging | average per cell

- instead of calculating one average **per vertex**, calculate one average **per cell**
  - cell identified by quantizing a descriptor $(x_i, \ldots)$
  - proximity defined by equality after quantization instead of distance
  - worst case complexity $\mathcal{O}(N)$ instead of $\mathcal{O}(N^2)$

Massively Parallel Path Space Filtering

Resolving quantization artifacts



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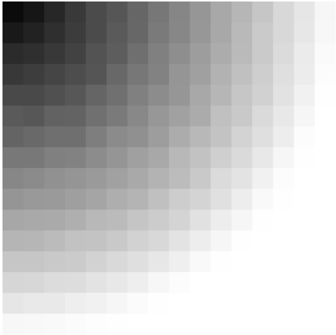

average per cell

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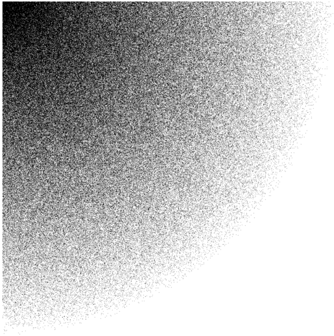
Resolving quantization artifacts



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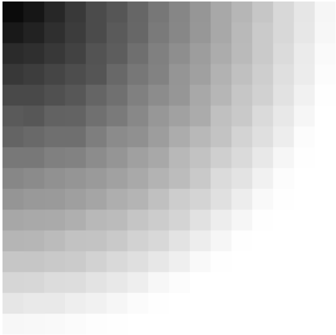

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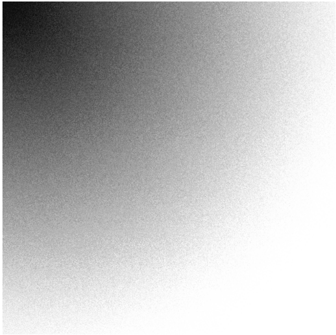
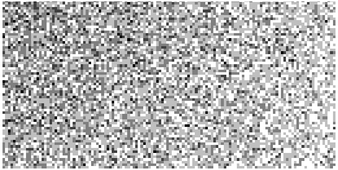


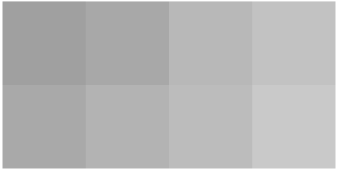
with jittering

Massively Parallel Path Space Filtering

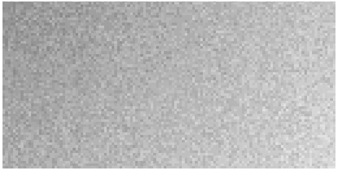
Resolving quantization artifacts



input



average per cell

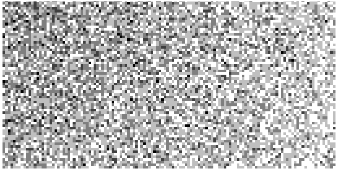


with jittering

- jittering descriptor (x_i, ...) on store and look up

Massively Parallel Path Space Filtering

Resolving quantization artifacts



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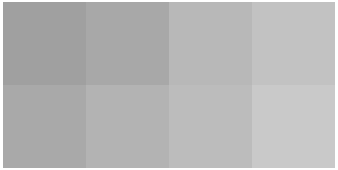
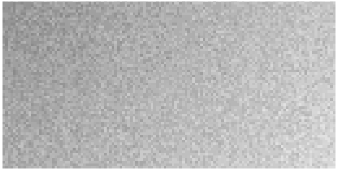


average per cell



with jittering

- jittering descriptor (x_i, ...) on store and look up
  - hides quantization artifacts

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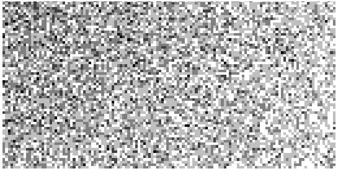
Massively Parallel Path Space Filtering

Resolving quantization artifacts



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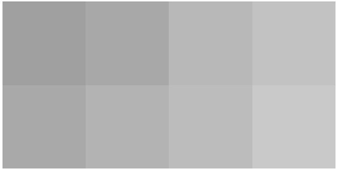

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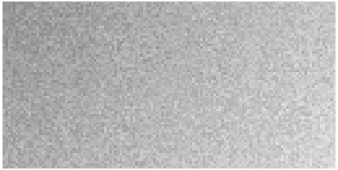
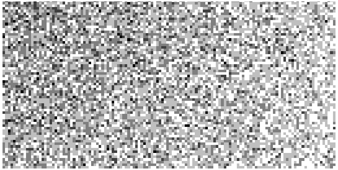


with jittering

- jittering descriptor (x_i, ...) on store and look up
  - hides quantization artifacts
  - resulting uniform noise amenable to (existing) post filtering

Massively Parallel Path Space Filtering

Resolving quantization artifacts



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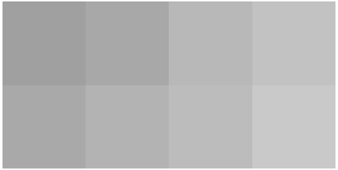
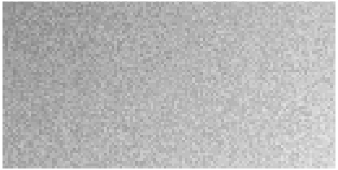


average per cell



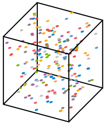
with jittering

- jittering descriptor (x_i, ...) on store and look up
  - hides quantization artifacts
  - resulting uniform noise amenable to (existing) post filtering
- amounts to stochastic evaluation of interpolation

Massively Parallel Path Space Filtering

Hashing instead of searching

- descriptors for selected vertices include



world space location *x*

Massively Parallel Path Space Filtering

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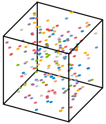

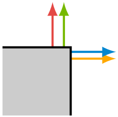

world space location x and optionally normal n,

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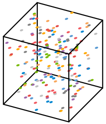

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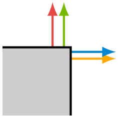

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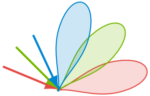

incident angle ω,

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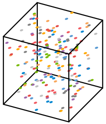

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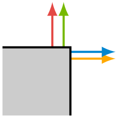

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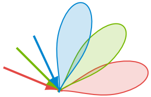

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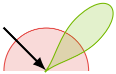

and BRDF layer

Massively Parallel Path Space Filtering

Storing and looking up data with quantized descriptors

- fast updates, no pre-processing

Massively Parallel Path Space Filtering

Storing and looking up data with quantized descriptors

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- access in constant time

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Storing and looking up data with quantized descriptors

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  - requires injective mapping $(x, n, ...) \mapsto [0, M)$

Massively Parallel Path Space Filtering

Storing and looking up data with quantized descriptors

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- access in constant time
  - requires injective mapping $(x, n, \ldots) \mapsto [0, M)$

$\Rightarrow$ **hash map**

Massively Parallel Path Space Filtering

Fast hash map

- trade a larger table size for faster access

Massively Parallel Path Space Filtering

Fast hash map

- trade a larger table size for faster access
- simple, fast hash functions

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Fast hash map

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- linear probing for collision resolution

Massively Parallel Path Space Filtering

Fast hash map

- trade a larger table size for faster access
- simple, fast hash functions
- linear probing for collision resolution
- use a second hash of the descriptor instead of storing full keys
  - may fail, but is very very unlikely

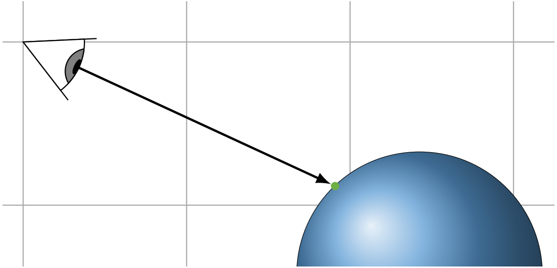
Massively Parallel Path Space Filtering

Linear instead of quadratic

- 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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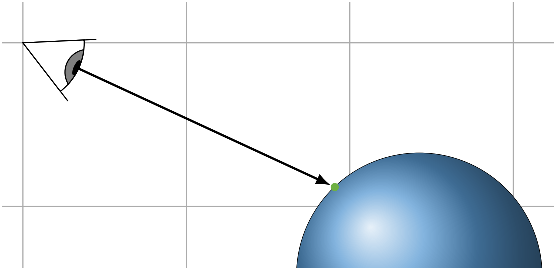


$$i \leftarrow \text{hash}(\tilde{x}, \ldots) \ \% \ \text{table\_size}$$

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

for both averaging and querying

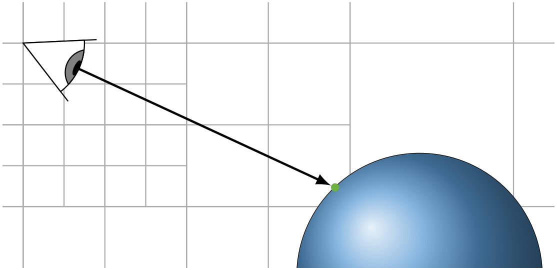
Massively Parallel Path Space Filtering

Linear instead of quadratic

- finding the hash table location i

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

for both averaging and querying



Massively Parallel Path Space Filtering

Linear instead of quadratic

- finding the hash table location i

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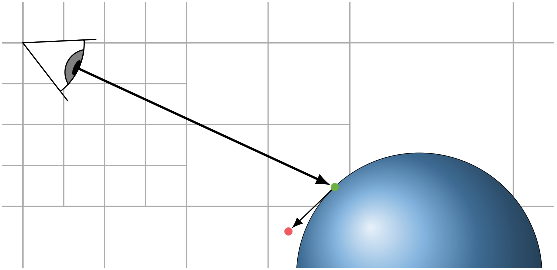

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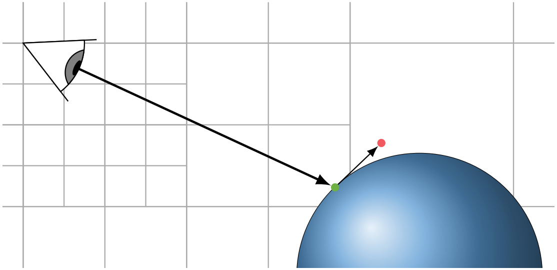

Massively Parallel Path Space Filtering

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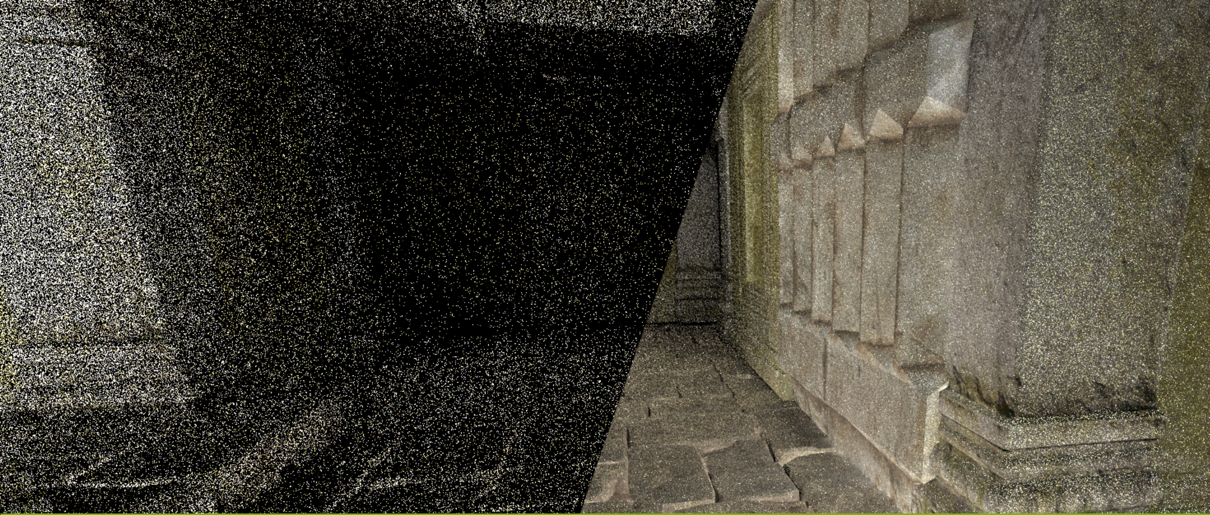
  for both averaging and querying

- jittering before quantization hides discretization artifacts in uniform noise



Massively parallel path space filtering at second bounce (2ms@HD)

Massively Parallel Path Space Filtering

Temporal filtering vs. temporal accumulation

- exponential moving average $\tilde{f} = (1-\alpha) f_{old} + \alpha f_{new}$ with constant α
  - will not converge over time
  - lags and blurs over time
  - in fact low pass filter

Massively Parallel Path Space Filtering

Temporal filtering vs. temporal accumulation

- cumulative moving average $\tilde{f} = (1 - \frac{1}{N}) f_{old} + \frac{1}{N} f_{new}$
  - converges over time
  - vanishing adaptivity with increasing number of samples
  - equivalent to exponential average with $\alpha = \frac{1}{N}$

Massively Parallel Path Space Filtering

Temporal filtering vs. temporal accumulation

- exponential moving average $\tilde{f} = (1-\alpha) f_{old} + \alpha f_{new}$ with adaptive α
  - temporal gradients to determine
    - $\alpha = \frac{1}{N}$ if no temporal changes are detected
    - $\alpha \in (\frac{1}{N}, 1]$ depending on the amount of change

Massively parallel path space filtering at first bounce (1ms@HD)

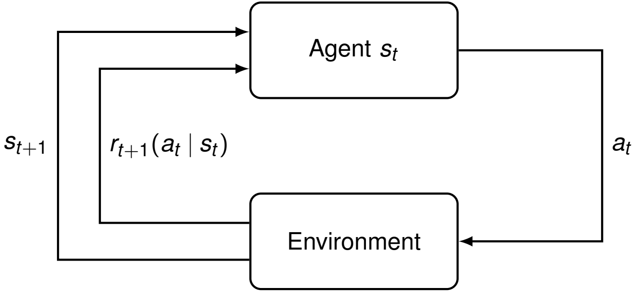
Reinforcement Learning

Reinforcement Learning

Goal: maximize reward

- state transition yields reward

$$r_{t+1}(a_t \mid s_t) \in \mathbb{R}$$



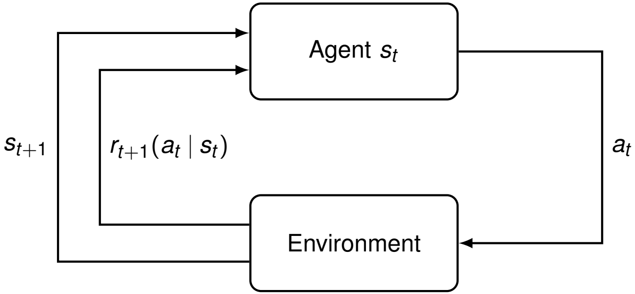
Reinforcement Learning

Goal: maximize reward

- state transition yields reward

$$r_{t+1}(a_t \mid s_t) \in \mathbb{R}$$

- learn a policy π_t
  - to select an action $a_t \in \mathbb{A}(s_t)$
  - given the current state $s_t \in \mathbb{S}$



Reinforcement Learning

Maximize reward by learning importance sampling

- structural equivalence of integral equation and Q-learning

$$
\begin{array}{llllll}
L(x,\omega) & = & L_e(x,\omega) & + \int_{\mathcal{S}_+^2(x)} & f_s(\omega_i,x,\omega)\cos\theta_i & L(h(x,\omega_i),-\omega_i) \quad d\omega_i \\
Q'(s,a) & = (1-\alpha)Q(s,a)+\alpha\Big(& r(s,a) & + \gamma\int_{\mathcal{A}} & \pi(s',a') & Q(s',a') \quad da' \Big)
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- graphics example: learning the incident radiance

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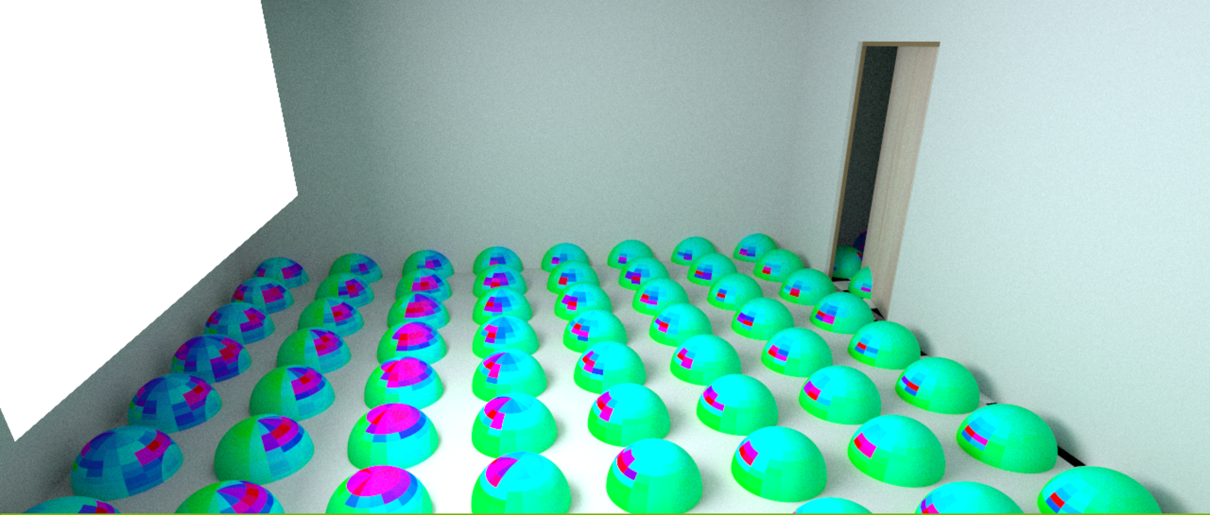
to be used as a policy for selecting an action ω in state x to reach the next state $y := h(x,\omega)$

- the learning rate α is the only parameter left

▶ Technical Note: Q-Learning



approximate solution Q stored on discretized hemispheres across scene surface

2048 paths traced with BRDF importance sampling in a scene with challenging visibility

Path tracing with online reinforcement learning at the same number of paths

Metropolis light transport at the same number of paths

Reinforcement Learning

Principle

- radiance L is light sources L_e plus transported radiance $T_f L$

$$L = L_e + T_f L$$

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$$L_c = L_e + T_f L_c$$

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  for guiding importance sampling towards where the radiance comes from

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- learn the approximation by

$$L'_c = (1-\alpha)L_c + \alpha(L_e + T_f L_c)$$

Reinforcement Learning
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  for guiding importance sampling towards where the radiance comes from

- learn the approximation by

$$L'_c = (1-\alpha)L_c + \alpha(L_e + T_f L_c) = (1-\alpha)L_c + \alpha\left(L_e + \sum f_{r,i} L_{c,i}\right)$$

  using the **current approximation instead of tracing single paths at higher variance**

Reinforcement Learning

Principle

- shorter expected path length
- dramatically reduced number of paths with zero contribution

Reinforcement Learning

Principle

- shorter expected path length
- dramatically reduced number of paths with zero contribution
- challenges
  - product importance sampling proportional to the integrand, i.e. policy $\gamma \cdot \pi$ times value Q
  - efficient representation of value Q

▶ S9900 - Irradiance Fields: RTX Diffuse Global Illumination for Local and Cloud Graphics

▶ Learning light transport the reinforced way

▶ Machine learning and integral equations

▶ Neural importance sampling

Photon-Guided Shadow Rays

Photon-Guided Shadow Rays

Photon maps similar to massively parallel path space filtering

- incorporate knowledge about visibility to improve efficiency
- control the number of shadow rays
- look up photons around a shading point and trace shadow rays towards their origin
  - photon origins used as virtual point light sources (VPL)

Light hierarchy

Photon-guided shadow rays (PGSR)

PGSR + single pass screen space PSF

Point Clouds

Stochastically hashed particle maps

- on hash collision keep particle with the smallest random number and increment cell counter
- issue of wide bit-width memory access on GPU
- hash table size vs. quantization vs. uniformity of hash function

  large hash table size: less collisions, totally divergent memory access

  small hash table size: more collisions, automatically thinning particles in dense regions

Generic material model to reduce divergence

one BSDF model fed by parameter point cloud

Ray Traced Global Illumination for Games

Building blocks

- massively parallel path space filtering
- efficient light transport simulation by reinforcement learning
- photon-guided shadow rays

▶ S9900 - Irradiance Fields: RTX Diffuse Global Illumination for Local and Cloud Graphics

▶ Gradient estimation for real-time adaptive temporal filtering

▶ Massively parallel path space filtering