EBERHARD KARLS
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FACULTY OF
SCIENCE
Computer Graphics

Machine Learning in Graphics and Vision

- Global Illumination & ML -

SoSe 2018

Hendrik Lensch

Previous Work

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	Non-linear Playback	Appearance Changes	Temporal Alignment	Handling Detours
a Evangelidis et al. (2011) 	✓	✗	✓	✗
b Torii et al. (2015) 	✗	✓	✗	✗
c Douze et al. (2016) 	✗	✓	✓	✗
d 	✓	✓	✓	✓

Efficiency: Sparse Feature-Extraction (260h Data)

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Approach	FPS	Total Time
Evangelidis et al. (2011)	0.11	0.81 years (~42 weeks)
Evangelidis et al. (2013)	0.11	0.81 years (~42 weeks)
Wang et al. (2014)	3.77	8.6 days
Ours	140	5.57 hours
Ours (12 GPUS)	12 * 140	28 minutes

x1272 speed up

Data-Driven Approaches without Annotations

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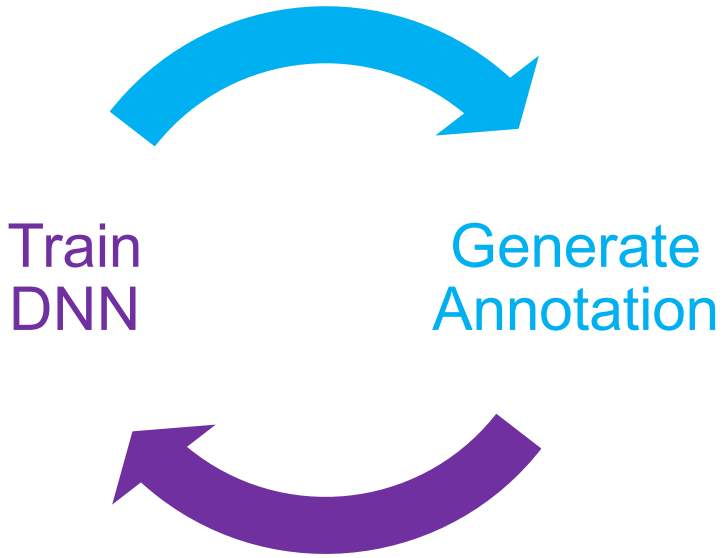
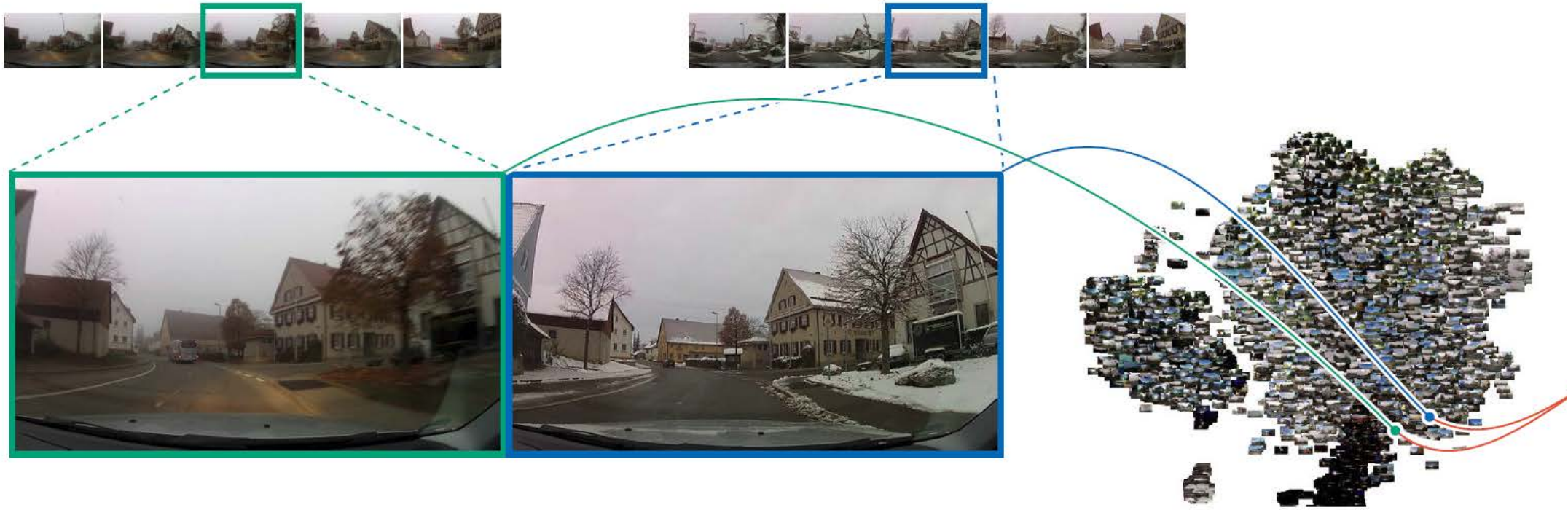
- Chicken-Egg-Problem



Encoding each Frame



- Visualization (t-SNE): mapping 1024 dimensions to 2 dimensions
- Euclidean distance between two frames in high-dimensional encoding-space represents their similarity.

Phase: Generate Annotation

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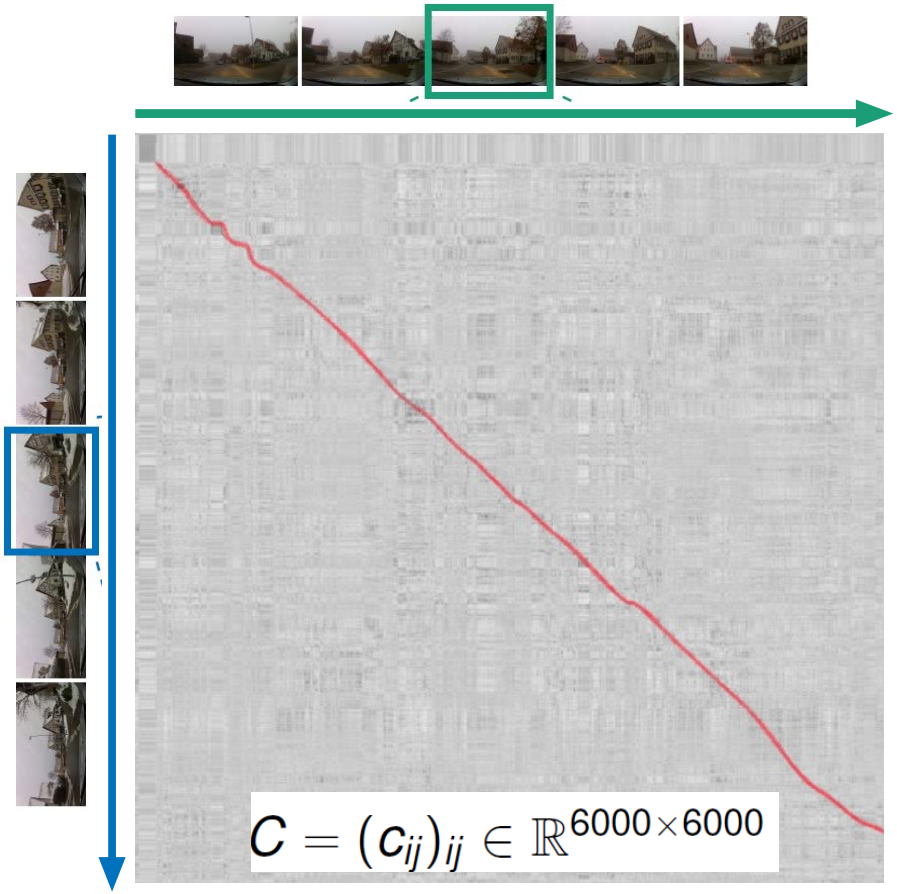
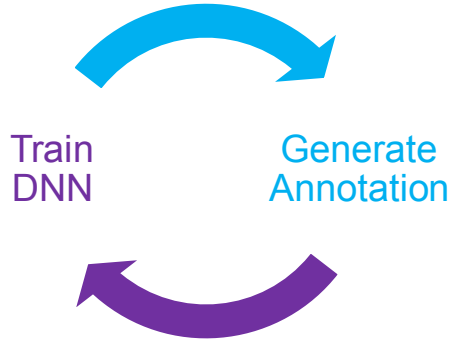
- Assume trained Deep Neural Network is given





1. pair-wise distances C‘
2. low-rank approximation
3. de-correlated distances C
4. find syncronization path

Finding a Synchronization Path

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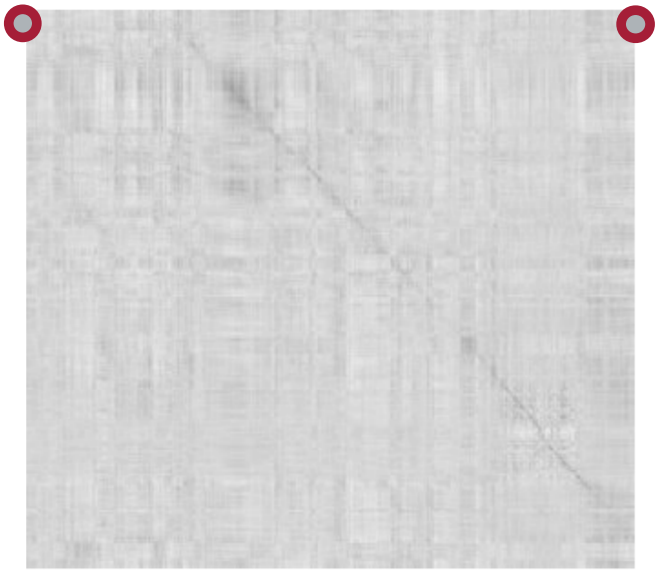
- Dijkstra's algorithm finds shortest path between two given nodes.
- We do not know the start or end node!



Finding a Synchronization Path

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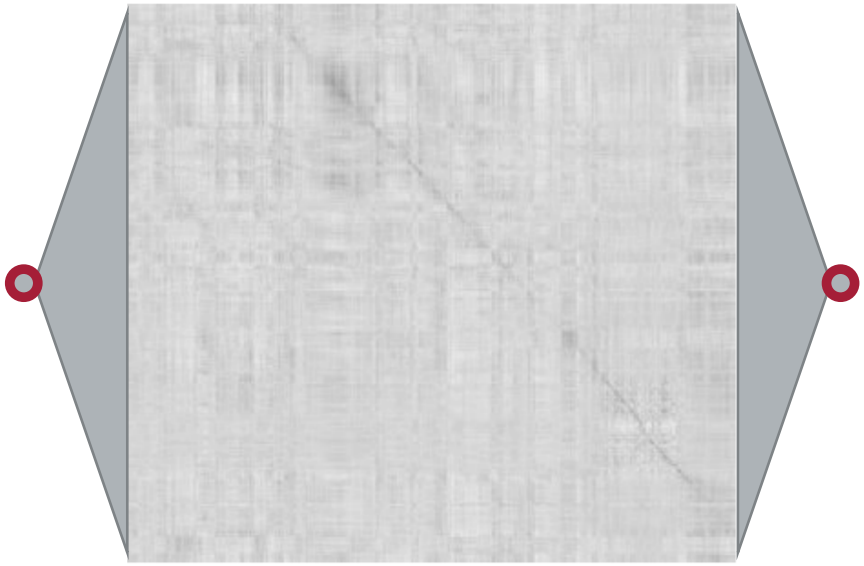

Finding a Synchronization Path

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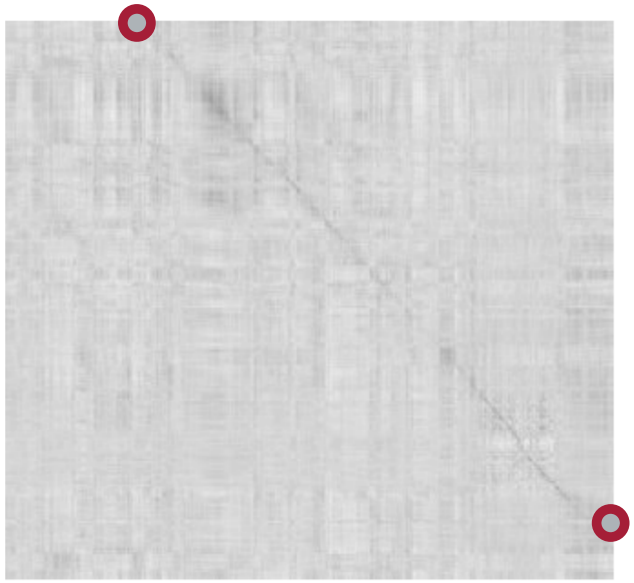
- Dijkstra's algorithm finds shortest path between two given nodes.
- We do not know the start or end node!
- We even do not know if there is any path!



Finding a Synchronization Path

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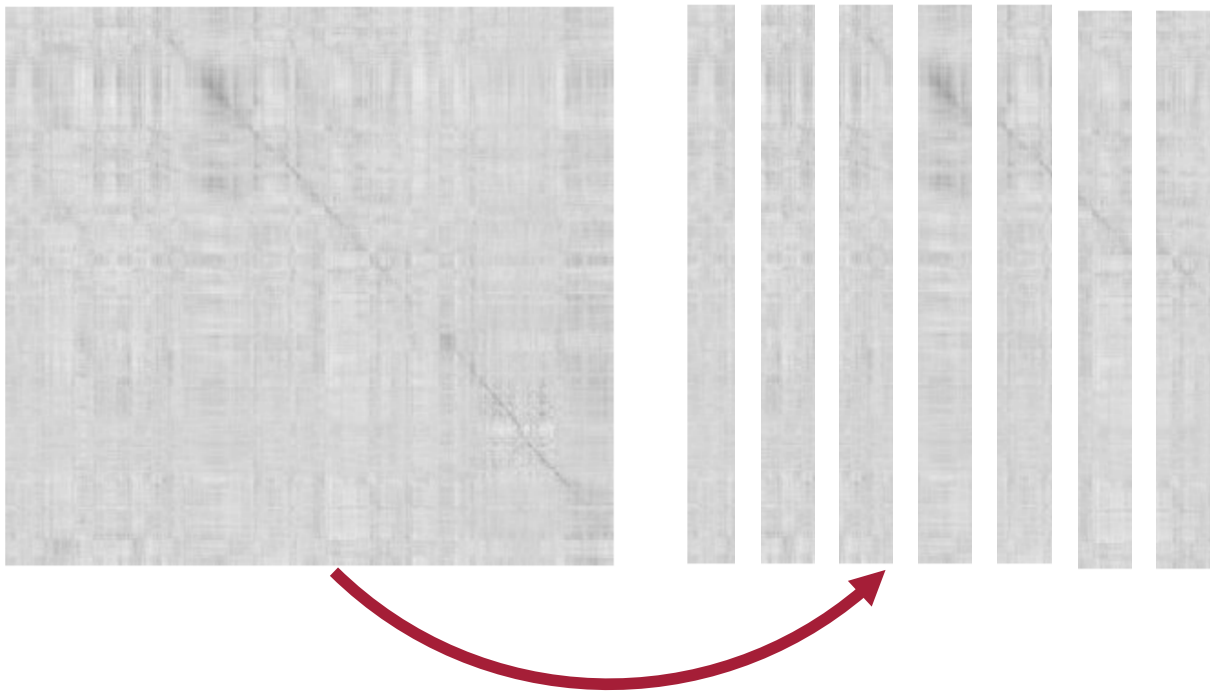
- Dijkstra's algorithm finds shortest path
- Partition into strips



Finding a Synchronization Path

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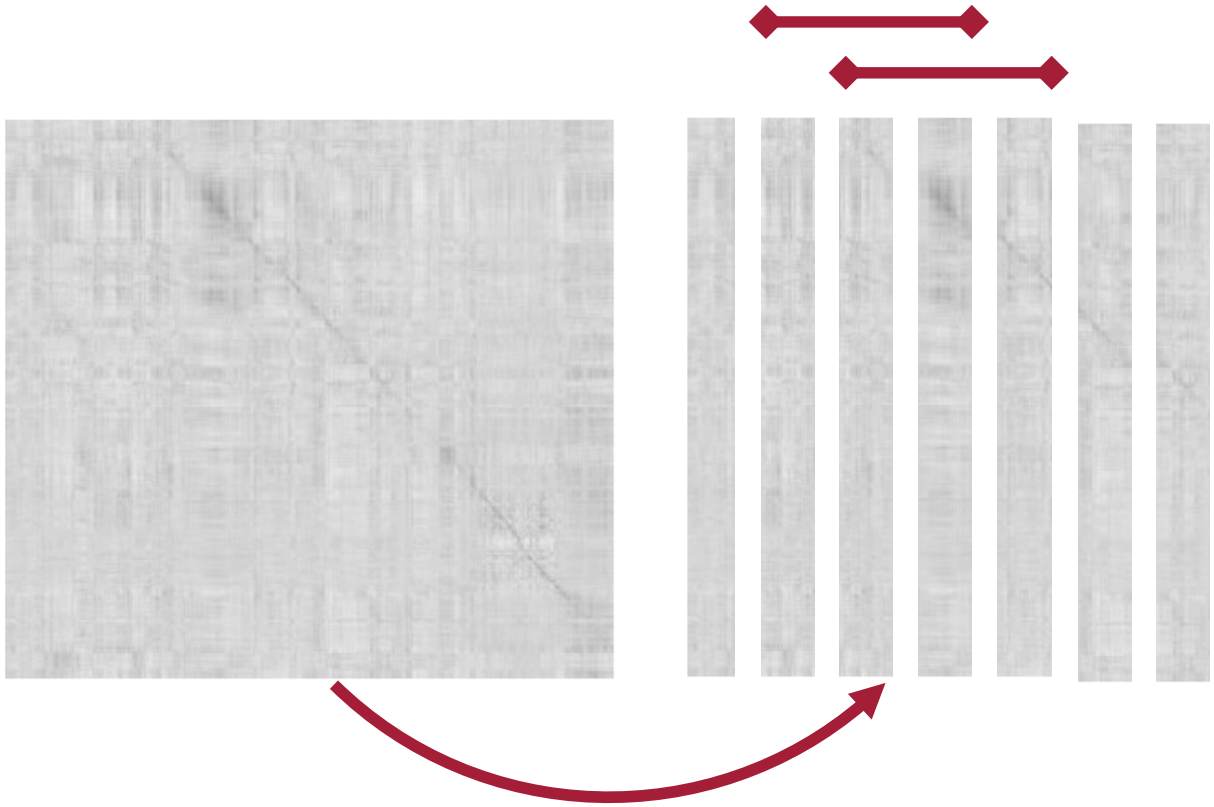
- Dijkstra's algorithm finds shortest path
- Partition into strips
- Find shortest path for overlapping strips



Finding a Synchronization Path

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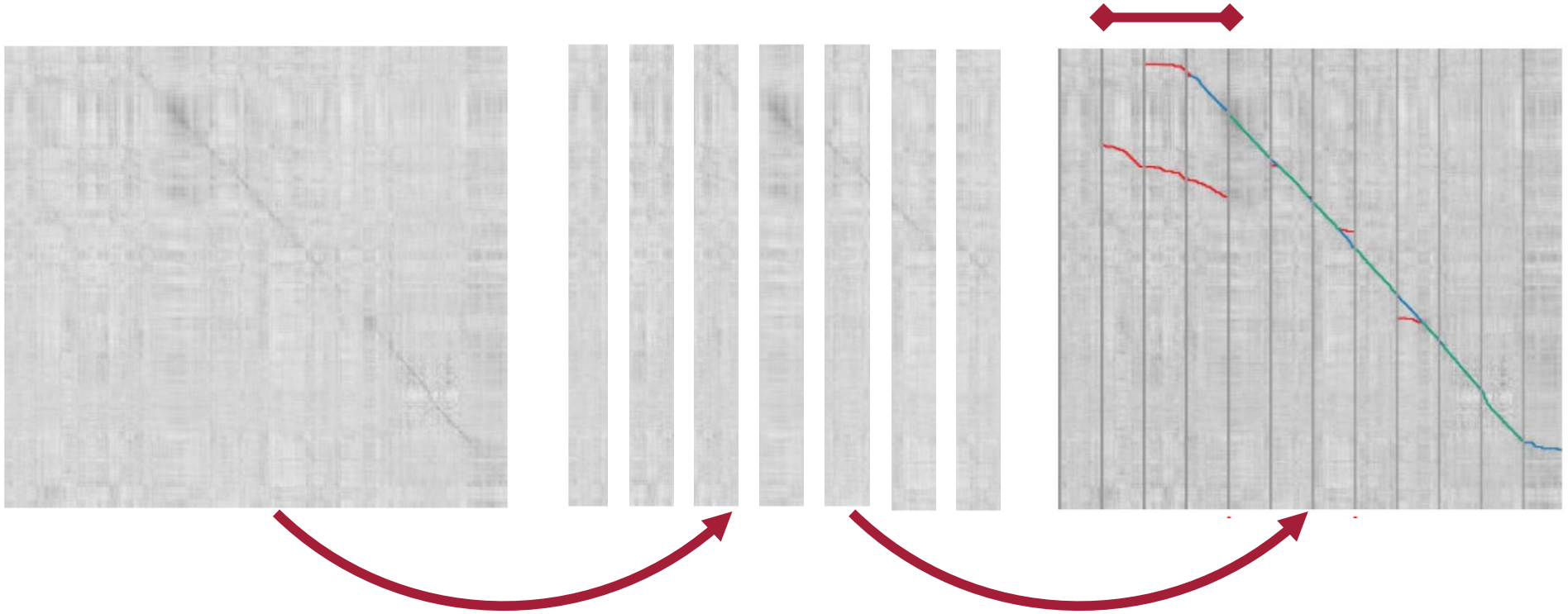
- Dijkstra's algorithm finds shortest path
- Partition into strips
- Find shortest path for overlapping strips
- Judge consistency in overlap regions



Data-Driven Approaches without Annotations

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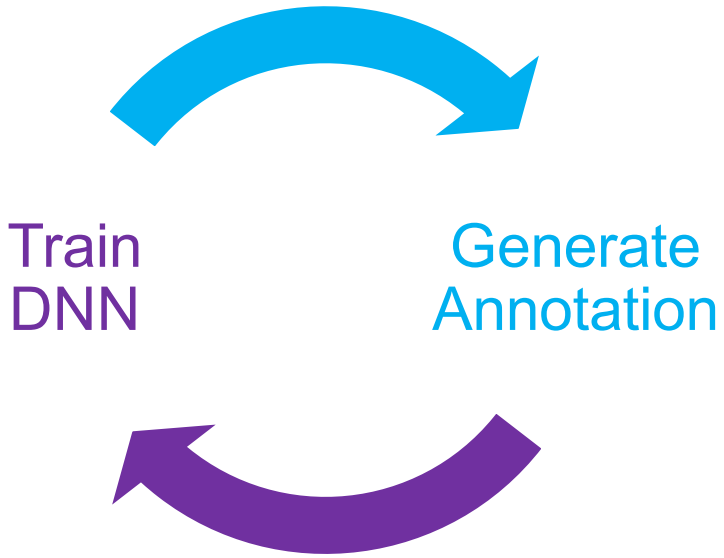
- Chicken-Egg-Problem



Phase: Train DNN

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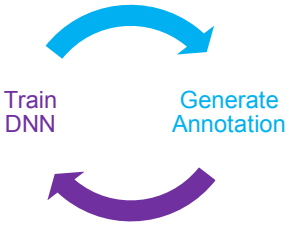
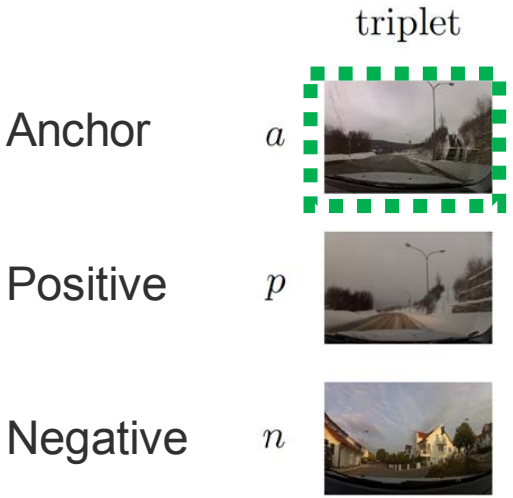
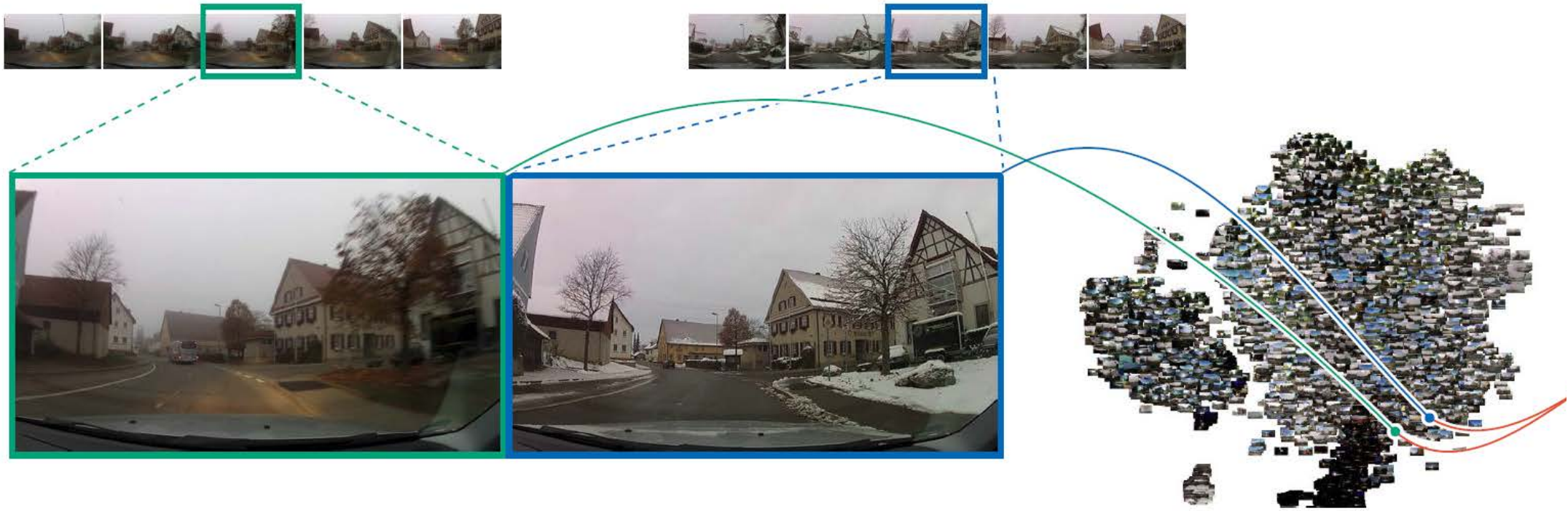
- Assume ground-truth annotations are given
- Optimize triplet loss





$$\max\{0, m + \|\Phi_a - \Phi_p\|_2^2 - \|\Phi_a - \Phi_n\|_2^2\}$$

Encoding each Frame



- Encoding clearly is not perfect
- Interplay of CNN encoding and shortest path on cleaned matrix render it a stable process

Data-Driven Approaches without Annotations

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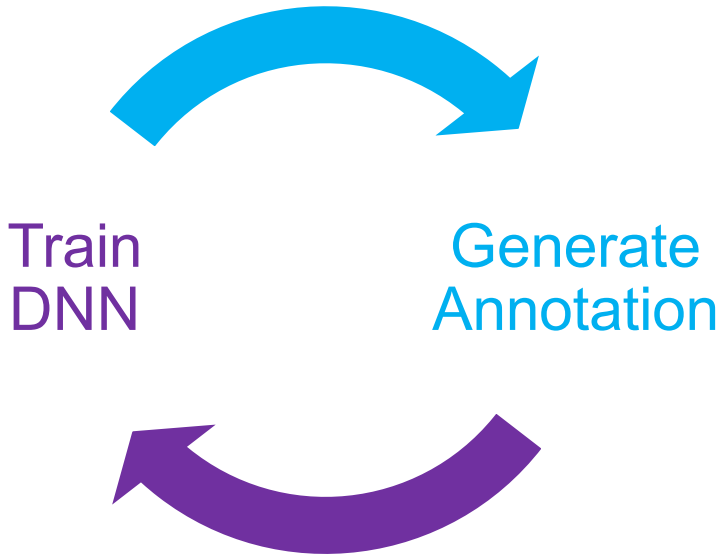
- Chicken-Egg-Problem



Data-Driven Approaches without Annotations

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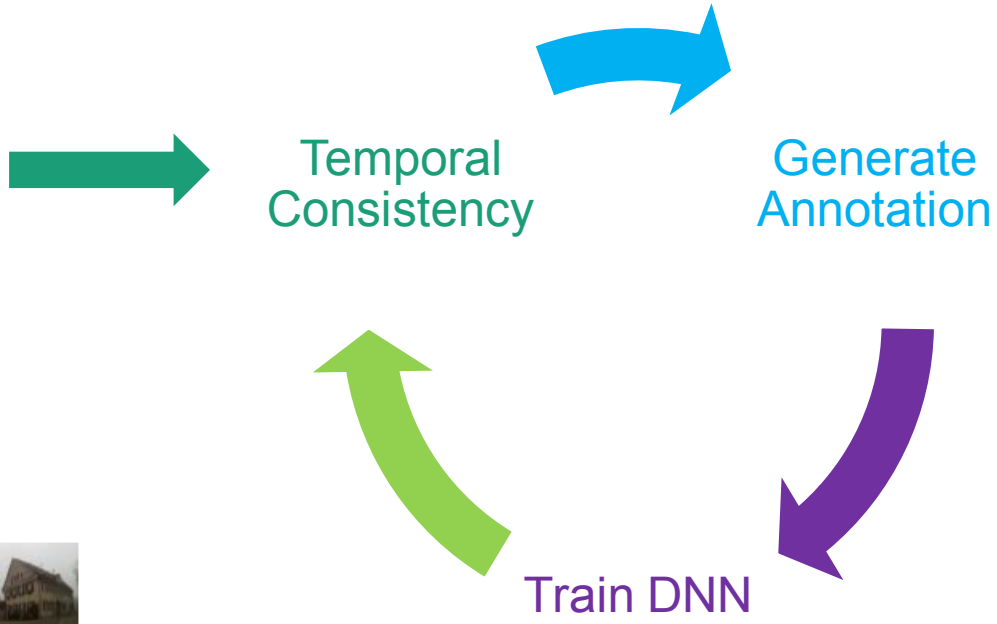
- Solve the Chicken-Egg-Problem



- Causality of Time

Curriculum Learning

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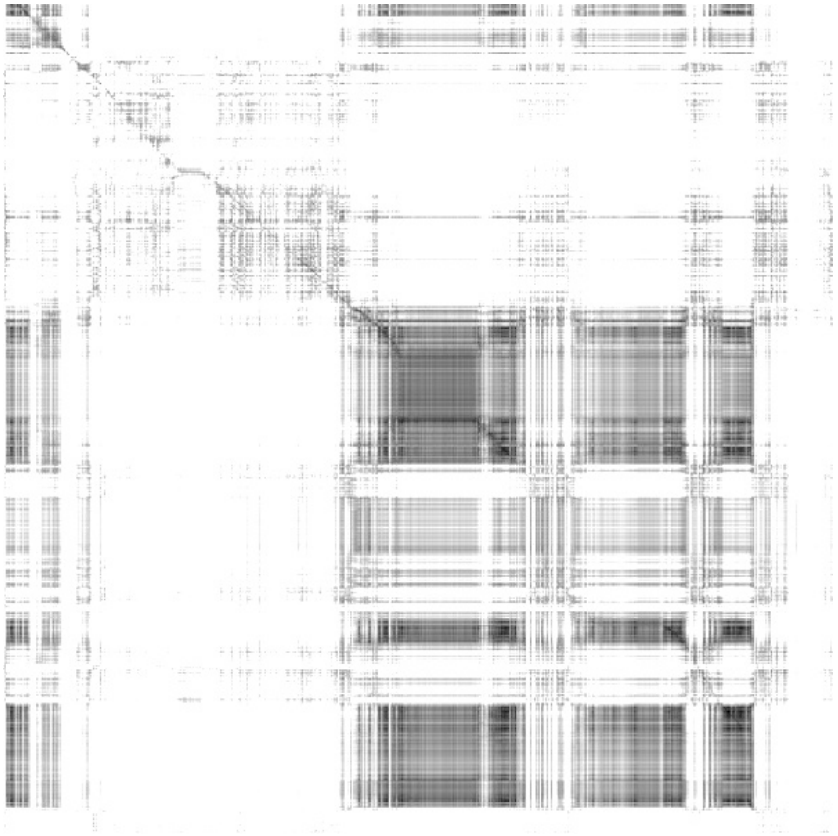
- Start with examples which are not too difficult and not too obvious:



1. Intra-Video Sampling
   consecutive frames are similar
2. Inter-Video Sampling
   ensure temporal consistency to reject false positives
3. Transitive Inter-Video Sampling
   $v/_{\sim}$ is equivalence relation $a \sim b \sim c$

Important Features

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- Why are local features not useful?
- What is the network looking for?

HARRIS

used in Evangelidis et al. 2011, 2013

SIFT

used in Wang et al. 2014

Learned Features (Saliency Maps)

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Input | ResNet (ImageNet) | Ours

Saliency Maps

Robustness

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after tree-felling

before tree-felling

Application to other Events

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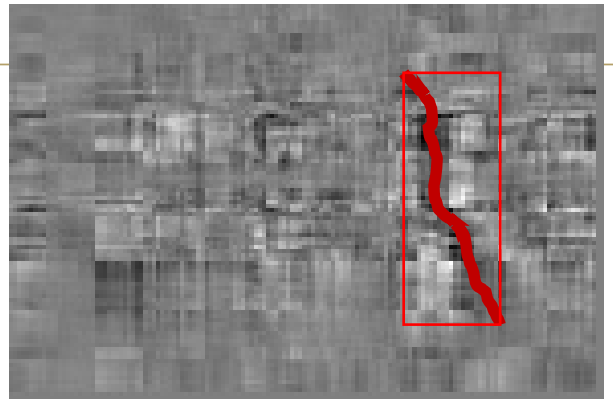
- Golf swing – same neural network
- Event boundaries visible



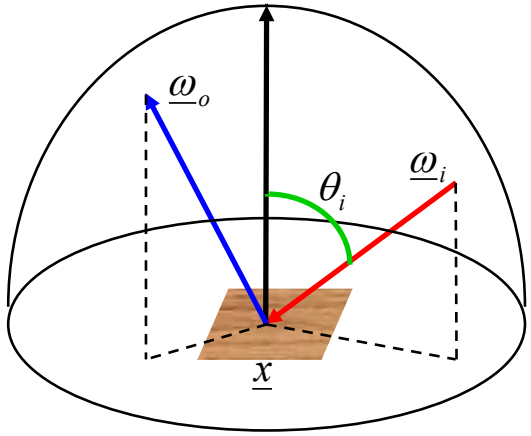
Global Illumination

Surface Radiance

$$L(\underline{x},\underline{\omega}_o) = L_e(\underline{x},\underline{\omega}_o) + L_r(\underline{x},\underline{\omega}_o)$$

$$= L_e(\underline{x},\underline{\omega}_o) + \int_{\Omega_+} f_r(\underline{\omega}_i,\underline{x},\underline{\omega}_o) L(\underline{x},\underline{\omega}_i) \cos\theta_i \, d\underline{\omega}_i$$

- Visible surface radiance $L(\underline{x},\underline{\omega}_o)$
  - Surface position $\underline{x}$
  - Outgoing direction $\underline{\omega}_o$
  - Incoming illumination direction $\underline{\omega}_i$
- Self-emission $L_e(\underline{x},\underline{\omega}_o)$
- Reflected light
  - Incoming radiance from all directions $L_i(\underline{x},\underline{\omega}_i)$
  - Direction-dependent reflectance (BRDF: bidirectional reflectance distribution function) $f_r(\underline{\omega}_i,\underline{x},\underline{\omega}_o)$



(Surface) Rendering Equation

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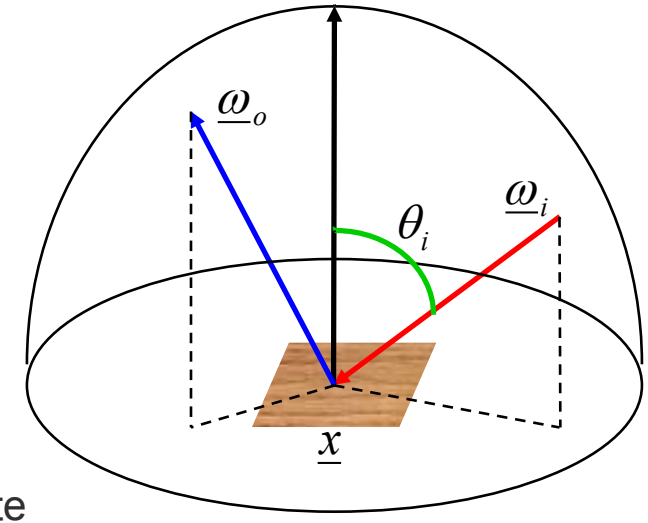
- In Physics: Radiative Transport Equation
- Expresses energy equilibrium in scene

$$L(\underline{x}, \underline{\omega}_o) = L_e(\underline{x}, \underline{\omega}_o) + \int_{\Omega} f_r(\underline{\omega}_i, \underline{x}, \underline{\omega}_o)\, L(\underline{x}, \underline{\omega}_i) \cos\theta_i \, d\underline{\omega}_i$$

- total radiance = e[illegible]d radiance + reflected radiance
- First term: emissivity of th[illegible]rface
  - non-zero only for light sources
- Second term: reflected radiance
  - integral over all possible incoming directions of irradiance times angle-dependent surface reflection function
- Fredholm integral equation of 2nd kind
  - unknown radiance appears on lhs and inside the integral
  - Numerical methods necessary to compute approximate solution



Sampling the Incoming Light

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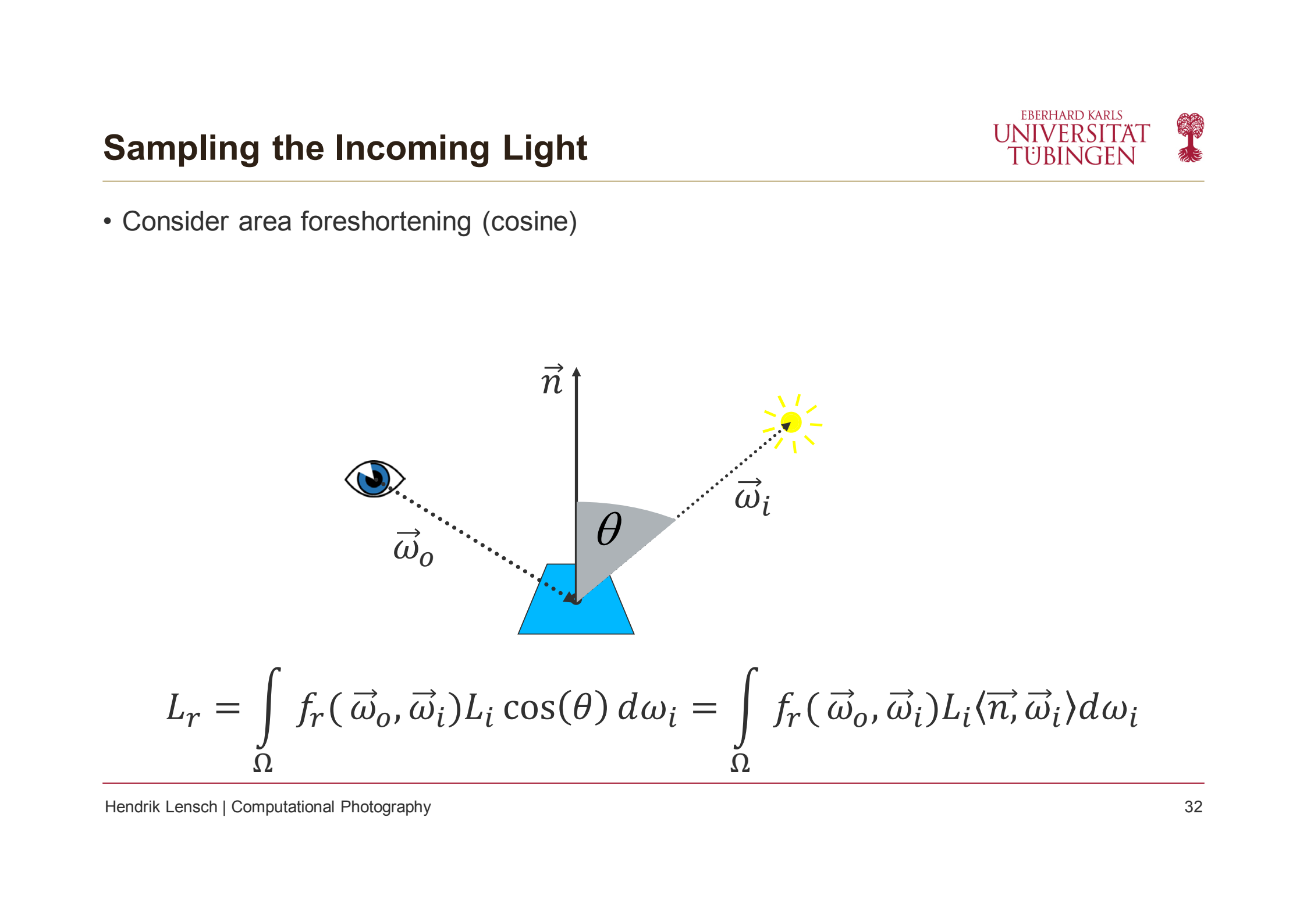

- Consider area foreshortening (cosine)

$$L_r = \int_\Omega f_r(\vec{\omega}_o, \vec{\omega}_i) L_i \cos(\theta)\, d\omega_i = \int_\Omega f_r(\vec{\omega}_o, \vec{\omega}_i) L_i \langle \vec{n}, \vec{\omega}_i \rangle d\omega_i$$

Sampling the Incoming Light

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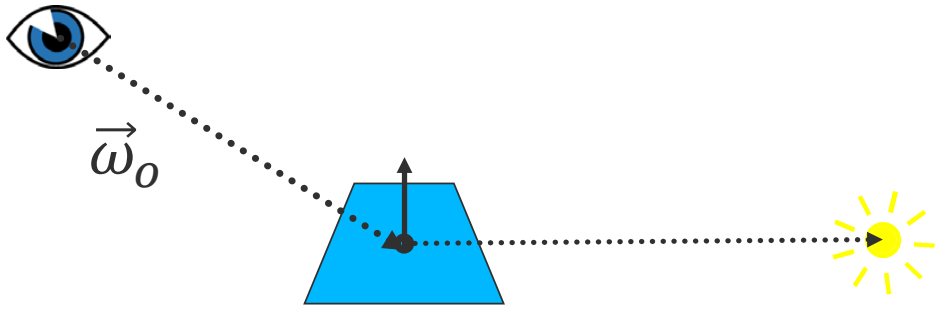
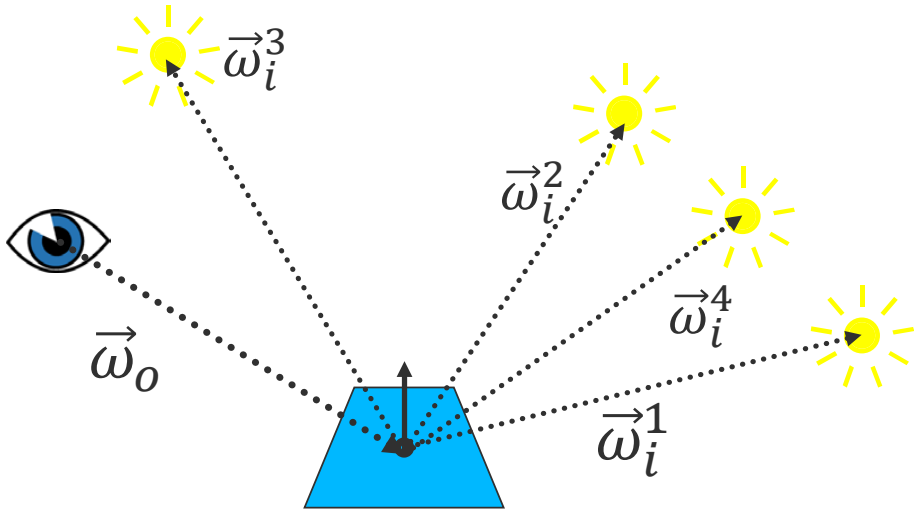


- Continuous integral

$$L_r = \int_{\Omega} f_r(\vec{\omega}_o, \vec{\omega}_i) L_i \cos(\theta)\, d\omega_i$$

Sampling Light Sources

- Consider discrete samples of the path space
- Multiple Light Sources:
  - add their contributions



$$L_r = \sum_N f_r(\vec{\omega}_o, \vec{\omega}_i) L_i^k \cos(\theta^k) \approx \int_\Omega f_r(\vec{\omega}_o, \vec{\omega}_i) L_i \cos(\theta)\, d\omega_i$$

Sampling Light Sources w/ Occlusions

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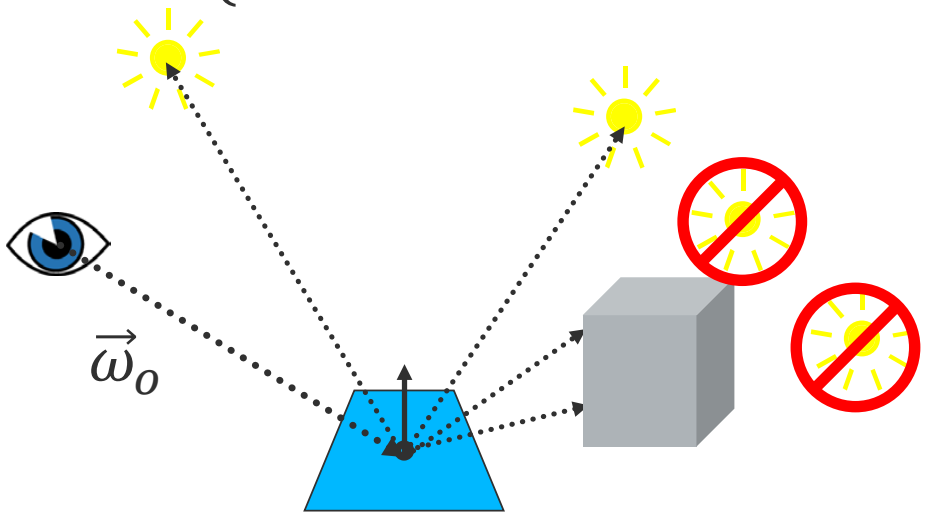
- Visibility function

$$v(\vec{\omega}_i) = \begin{cases} 0 & \text{source is occluded} \\ 1 & \text{source is visible} \end{cases}$$



$$L_r = \sum_N f_r(\vec{\omega}_o, \vec{\omega}_i) v(\vec{\omega}_i) L_i^k \cos\left(\theta^k\right)$$

Approximation – Ambient Occlusion

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- Aproximation for global illumination effects
- Only consider visibility in a uniformly lit room
- AO = fraction of the hemisphere that is not occluded

$$L_r = \int_\Omega f_r(\vec{\omega}_o, \vec{\omega}_i) v(\vec{\omega}_i) L_i \cos(\theta)\, d\omega_i$$

$$L_r \approx L_{AO} = \rho \cdot AO \cdot \int_\Omega L_i \cos(\theta)\, d\omega_i = \rho \cdot AO \cdot E$$

$$AO = \frac{1}{2\pi} \int_\Omega v'(\vec{\omega}_i) d\omega_i \omega$$

$$v'(\vec{\omega}_i) = v(\vec{\omega}_i)$$

up to some max. distance

Example: Lighting

$$\mathrm{L_r} \approx \mathrm{L_{AO}} = \rho \cdot AO \cdot \int_{\Omega} L_i \cos(\theta) d\omega_i = \rho \cdot AO \cdot E$$

Example: Lighting & AO

$$\mathrm{L_r} \approx \mathrm{L_{AO}} = \rho \cdot AO \cdot \int_{\Omega} L_i \cos(\theta) d\omega_i = \rho \cdot AO \cdot E$$

Example: Ligting & Shading & AO

$$\mathrm{L_r} \approx \mathrm{L_{AO}} = \rho \cdot AO \cdot \int_{\Omega} L_i \cos(\theta) d\omega_i = \rho \cdot AO \cdot E$$

Example: Ligting & Shading

$$\mathrm{L_r} \approx \mathrm{L_{AO}} = \rho \cdot AO \cdot \int_{\Omega} L_i \cos(\theta) d\omega_i = \rho \cdot AO \cdot E$$

Ambient Occlusion

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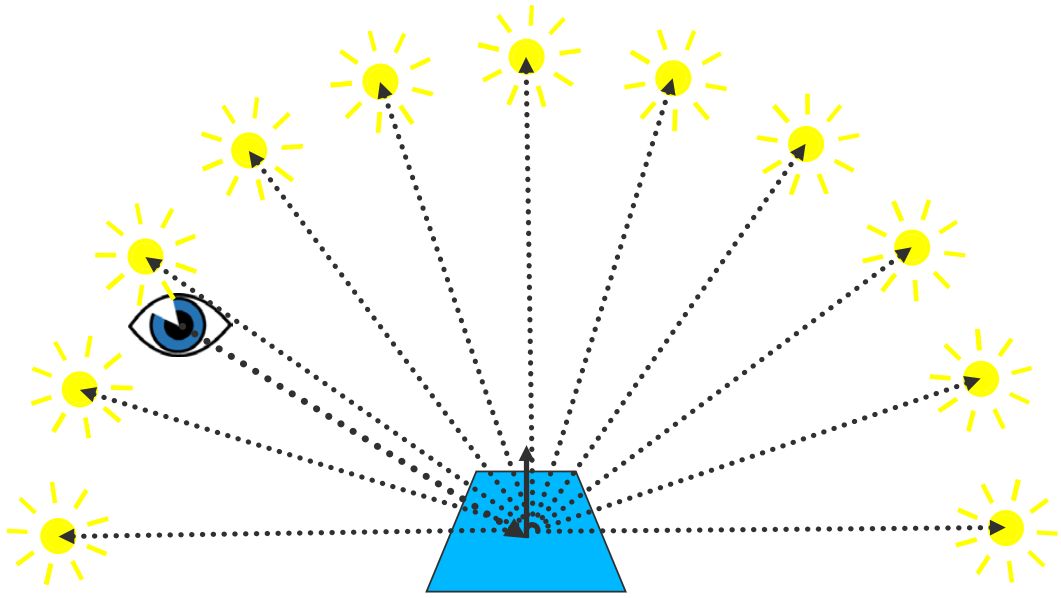
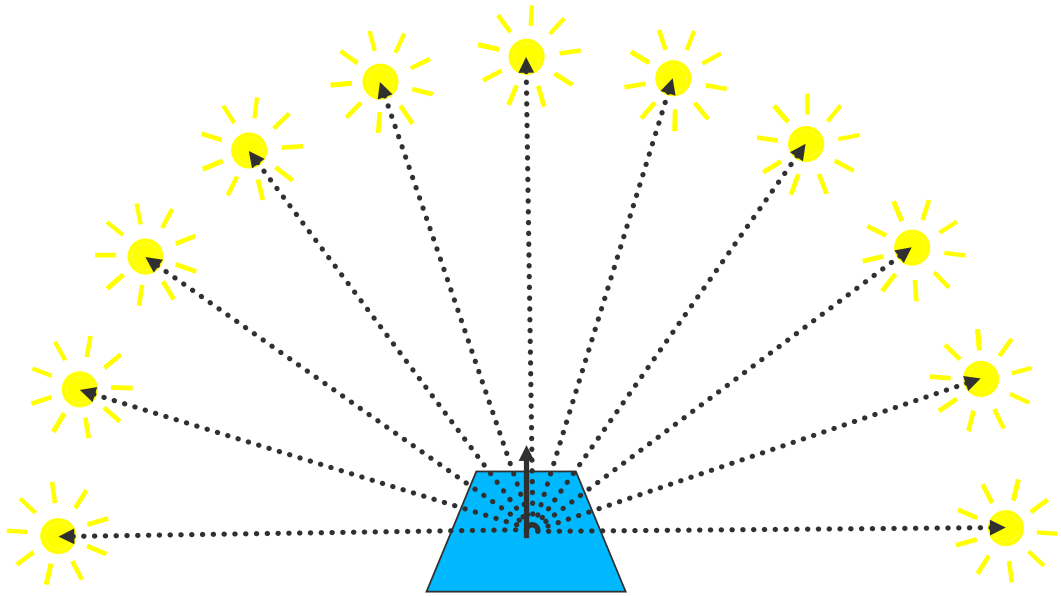
- Only consider visibility in a uniformly lit room
- AO = fraction of the hemisphere that is not occluded



$$AO = \frac{1}{N} \sum_{N} v(\vec{\omega}_i^k)$$

Ambient Occlusion

- Fraction of the hemisphere that is not occluded
- Independent on viewing direction



$$AO = \frac{1}{N}\sum_{N} v(\vec{\omega}_i^k) = 1$$ completely unoccluded

Ambient Occlusion

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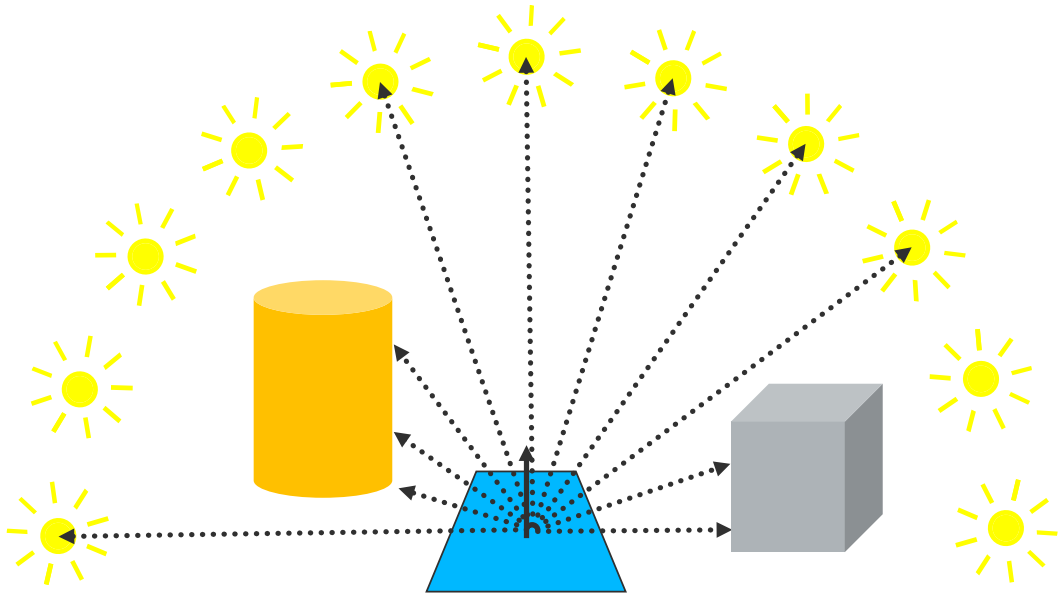
- Fraction of the hemisphere that is not occluded



$$AO = \frac{1}{N}\sum_{N} v(\vec{\omega}_i^k)$$

Ambient Occlusion

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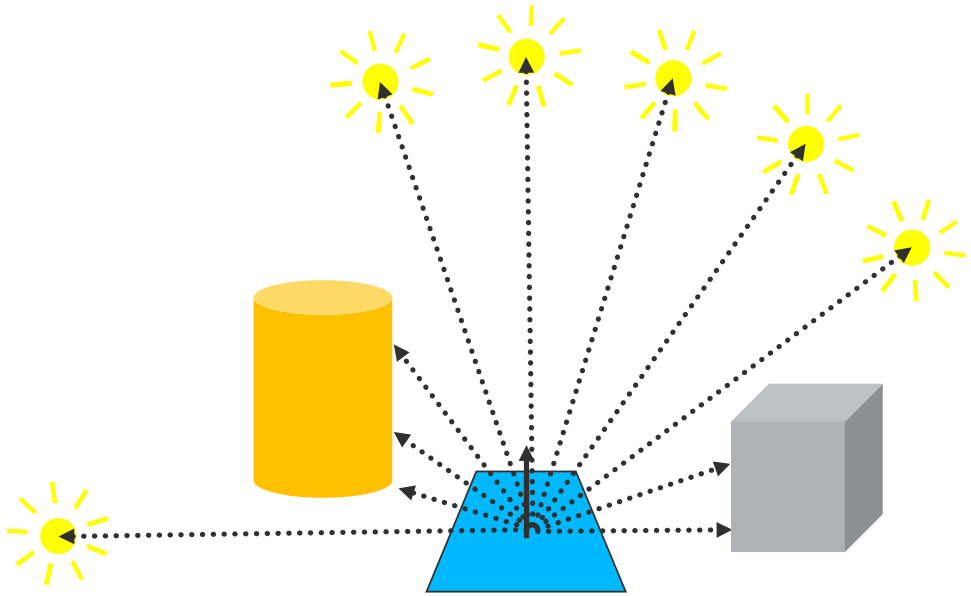
- Fraction of the hemisphere that is not occluded



$$AO = \frac{1}{N} \sum_{N} v(\vec{\omega}_i^k)$$

Ambient Occlusion

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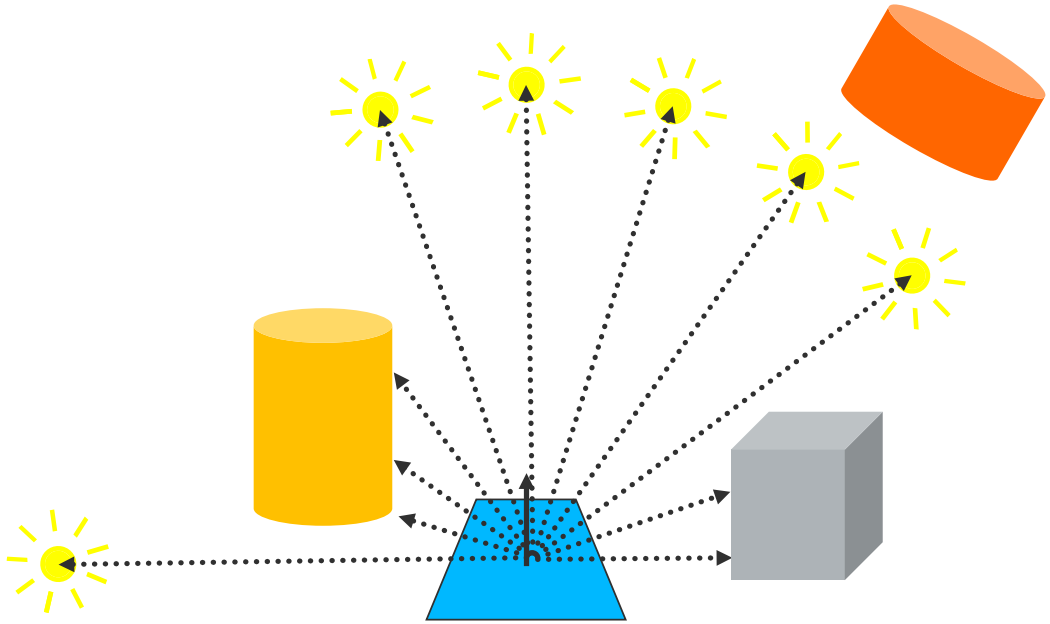
- Fraction of the hemisphere that is not occluded
- Only consider close by objects



$$AO = \frac{1}{N} \sum_{N} v(\vec{\omega}_i^k)$$

Ambient Occlusion

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- Almost looks like global light transport

The problem

- Variance appears as noise at low sample rates

scene by Wojciech Jarosz

General Framework for Monte Carlo Filtering

scene by Herminio Nieves and tf3dm.com user ysup12

Observations

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- After only a few minutes, we have a lot of information about the scene…

scene rendered in a few minutes (8 samples/pixel)

scene by M. Leal Llaguno

Observations

- Can we filter this to get a result as good as a reference image?

scene rendered in over 24 hrs (8,192 samples/pixel)

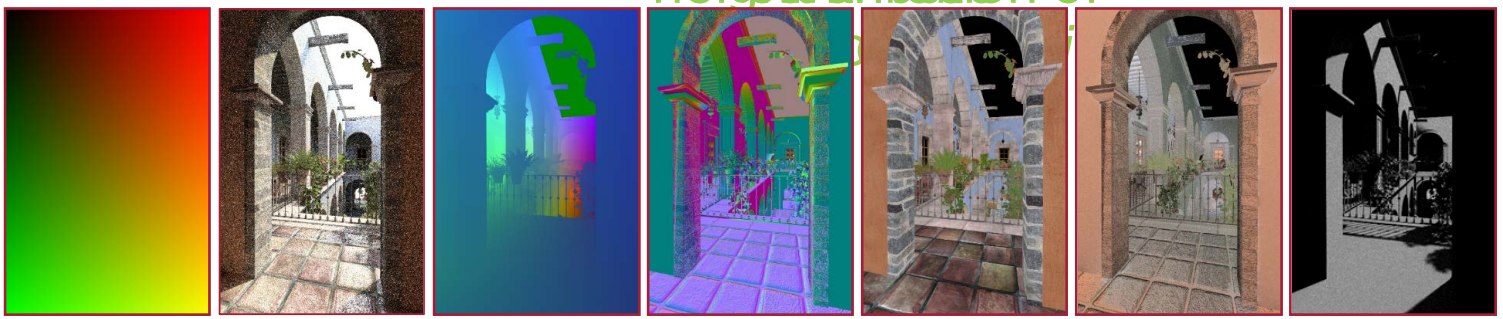
scene by M. Leal Llaguno

Filter

$$\hat{\mathbf{c}}_i = \frac{\sum_{j \in \mathcal{N}(i)} d_{i,j} \bar{\mathbf{c}}_j}{\sum_{j \in \mathcal{N}(i)} d_{i,j}}$$

← noisy pixel

neighborhood of



screen position | pixel color | world positions | shading normals | texture 1st bounce | texture 2nd bounce | visibility

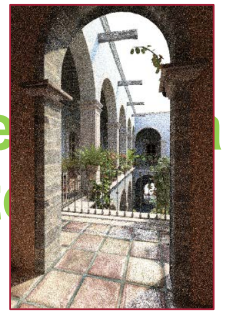
Cross-bilateral filter

$$\hat{\mathbf{c}}_i = \frac{\sum_{j \in \mathcal{N}(i)} d_{i,j} \bar{\mathbf{c}}_j}{\sum_{j \in \mathcal{N}(i)} d_{i,j}}$$

$$d_{i,j} = \exp\left[- \frac{\|\bar{\mathbf{p}}_i - \bar{\mathbf{p}}_j\|^2}{2\alpha_i^2} \right] \qquad \beta_i^2 \qquad \gamma_{k,i}^2$$

- α_i^2, β_i^2, $\gamma_{k,i}^2$ are [illegible]riance of ea[illegible]
  term[illegible] parameter[illegible]

screen position



pixel color

additional features

Why per pixel parameters?

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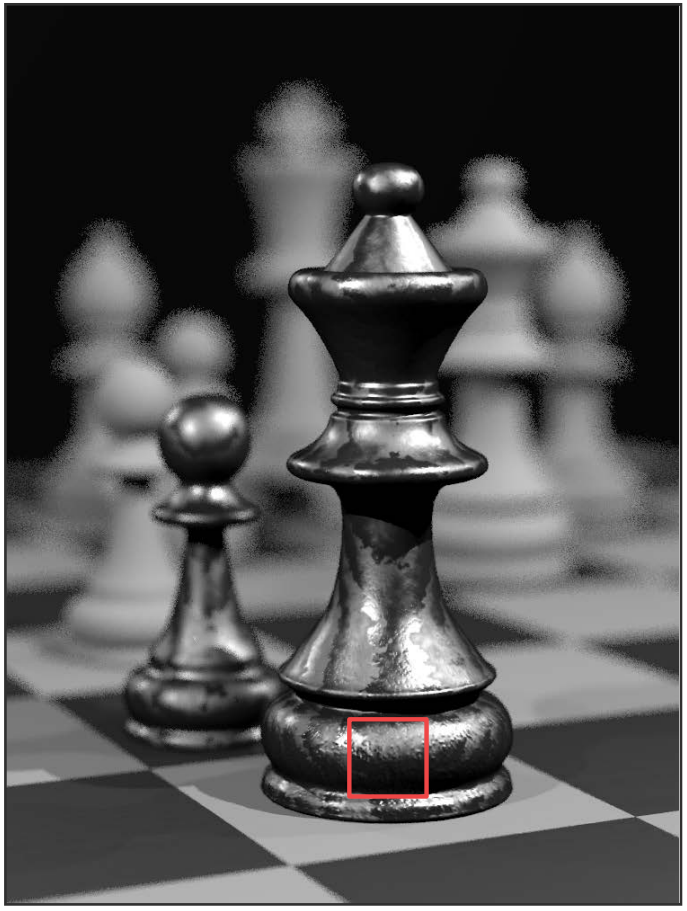
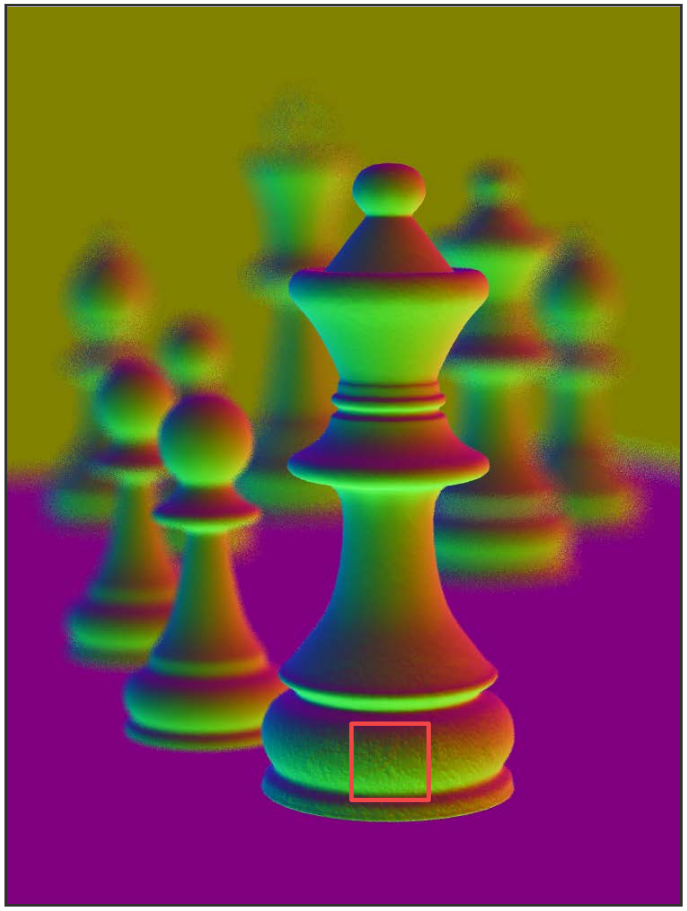
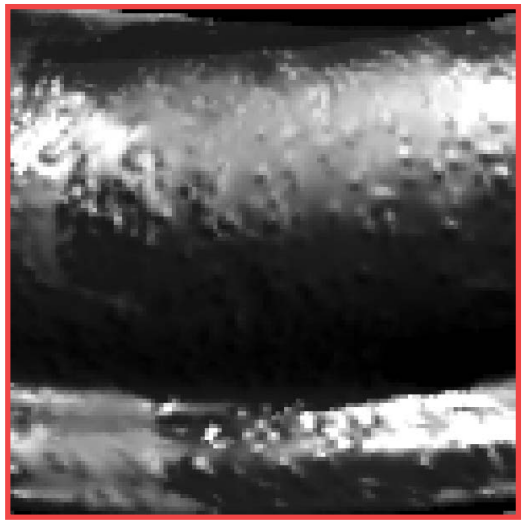


input MC 8 samples/pixel

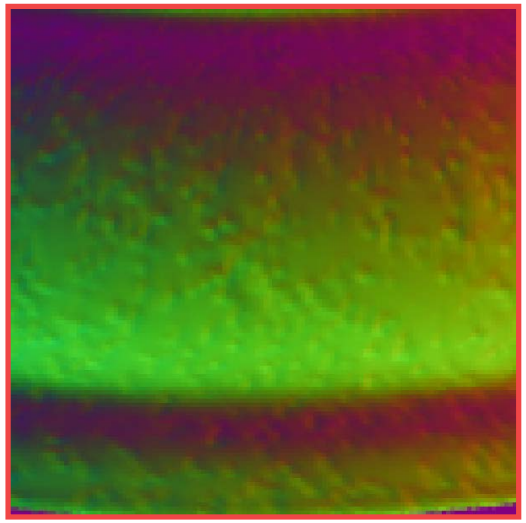


shading normals

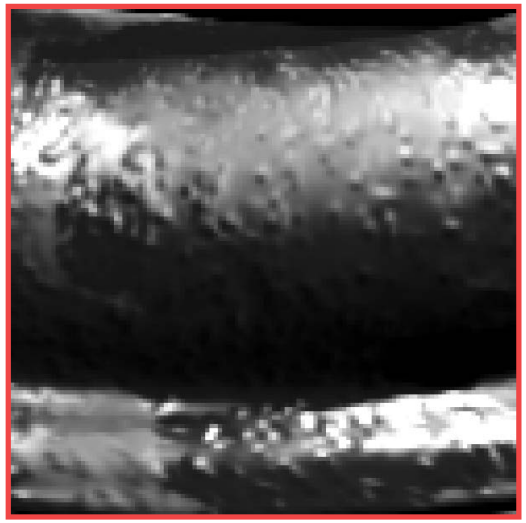
Why per pixel parameters?



input MC
8 samples/pixel



shading normals



ground truth

Why per pixel parameters?

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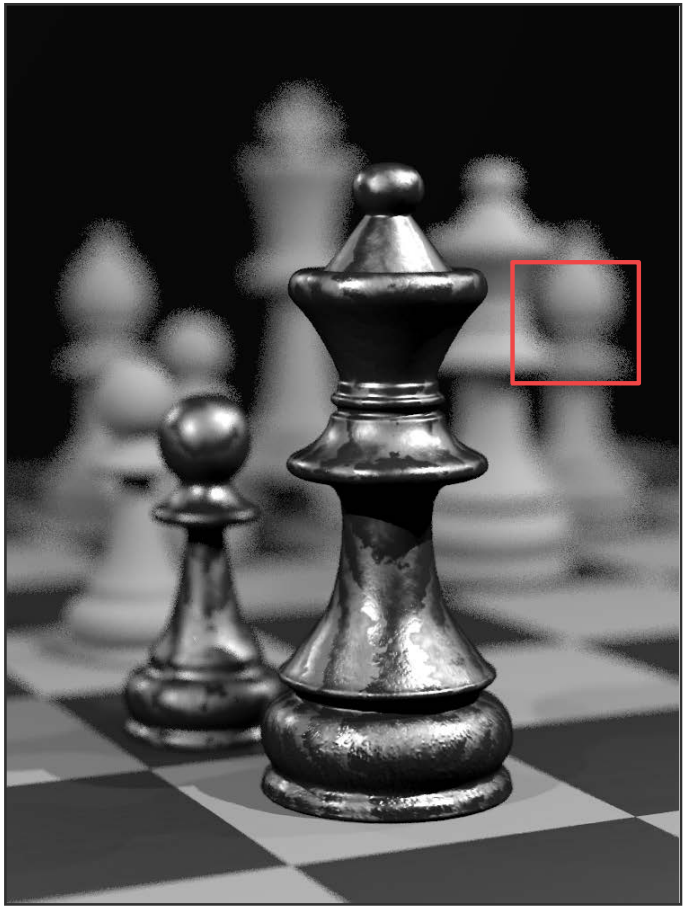
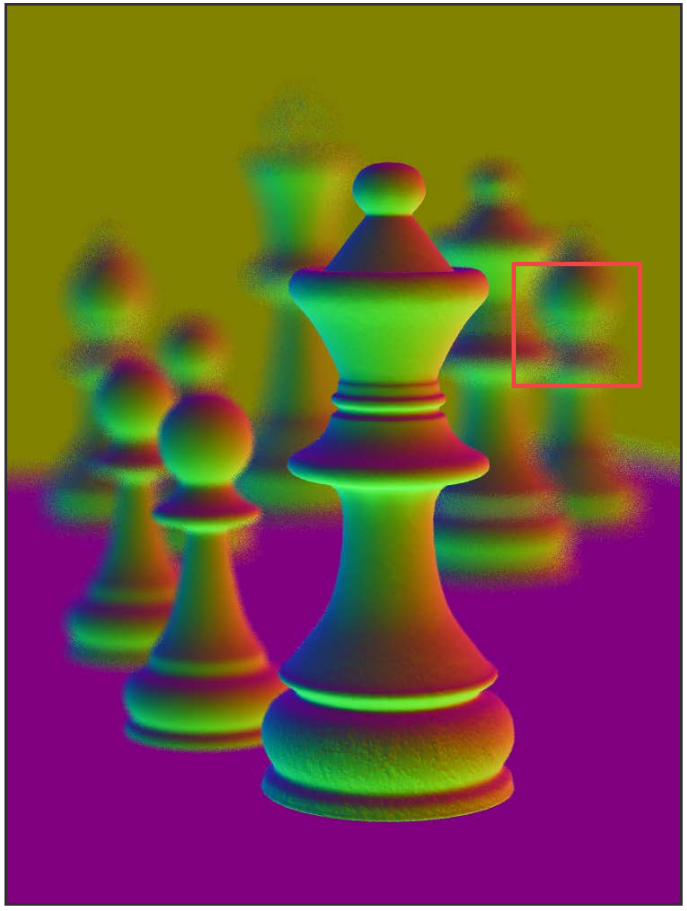


input MC 8 samples/pixel



shading normals

Why per pixel parameters?

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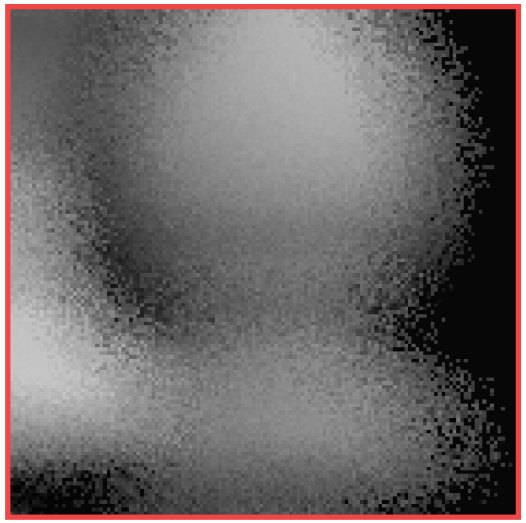
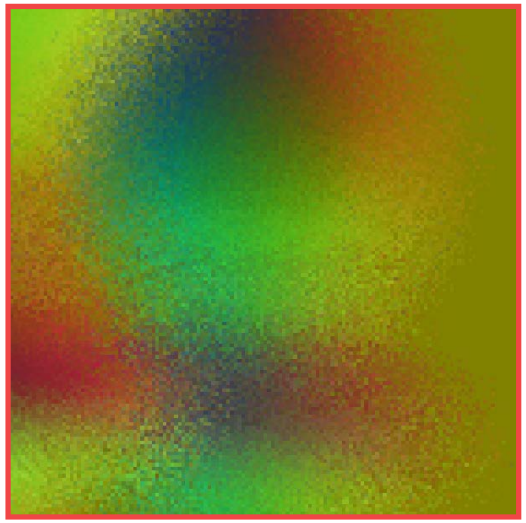
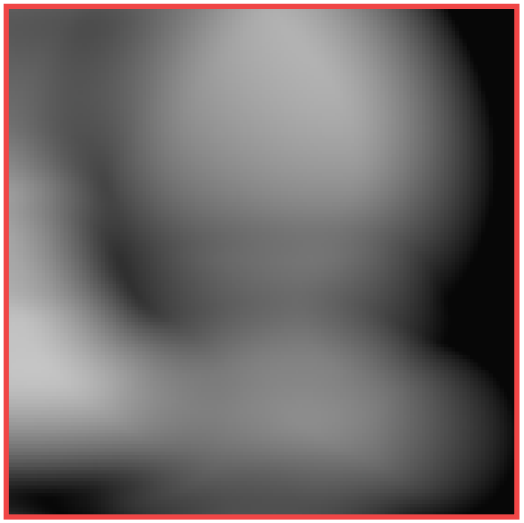


input MC
8 samples/pixel

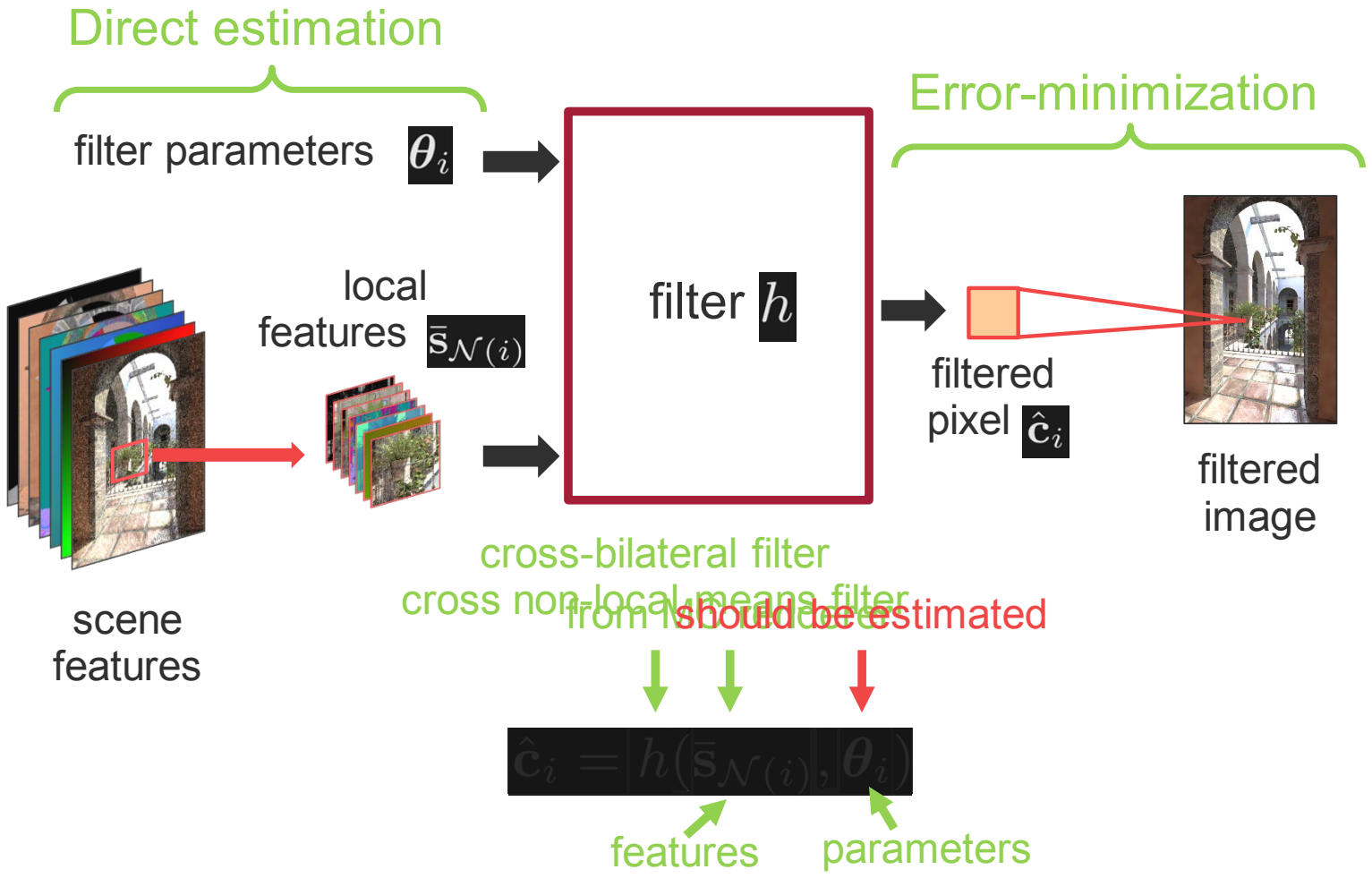


shading normals



ground truth

Problem formulation



Our result with a cross-bilateral filter (4 spp)

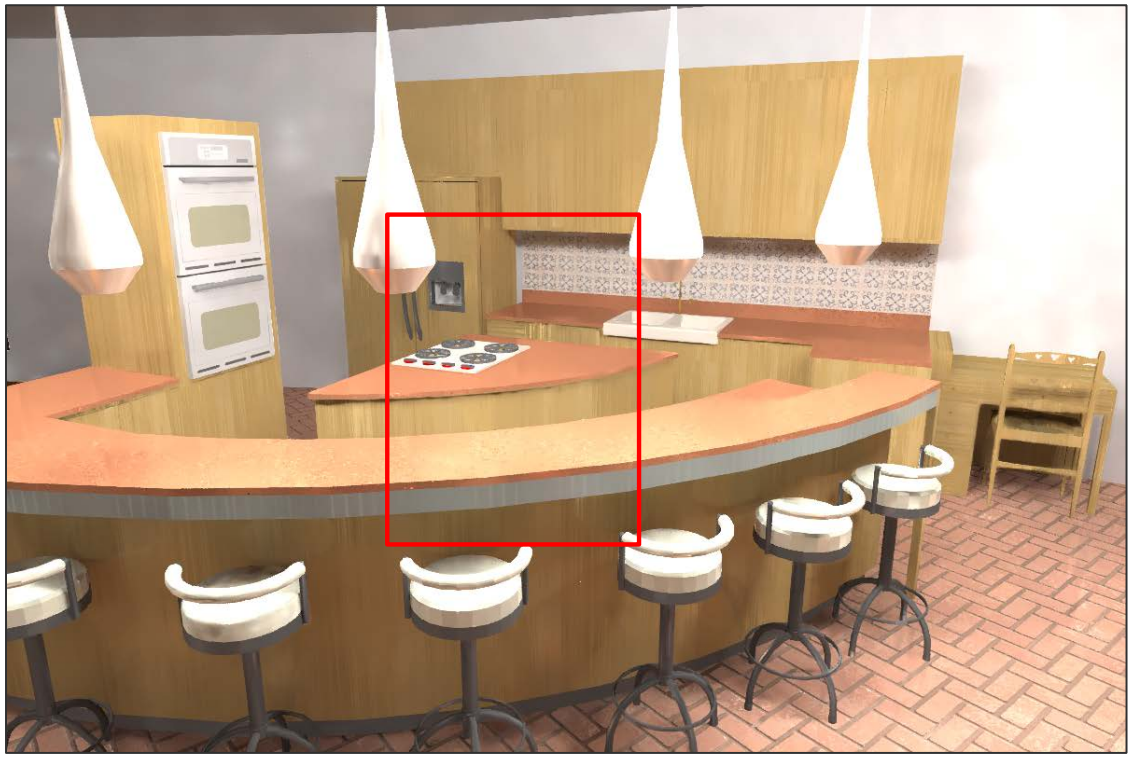
Our result with a non-local means filter (4 spp)

A Machine Learning Approach for Filtering Monte Carlo Noise

Kalantari et al. SIGGRAPH 2015

Sample result

[Kalantari et al. 2015]

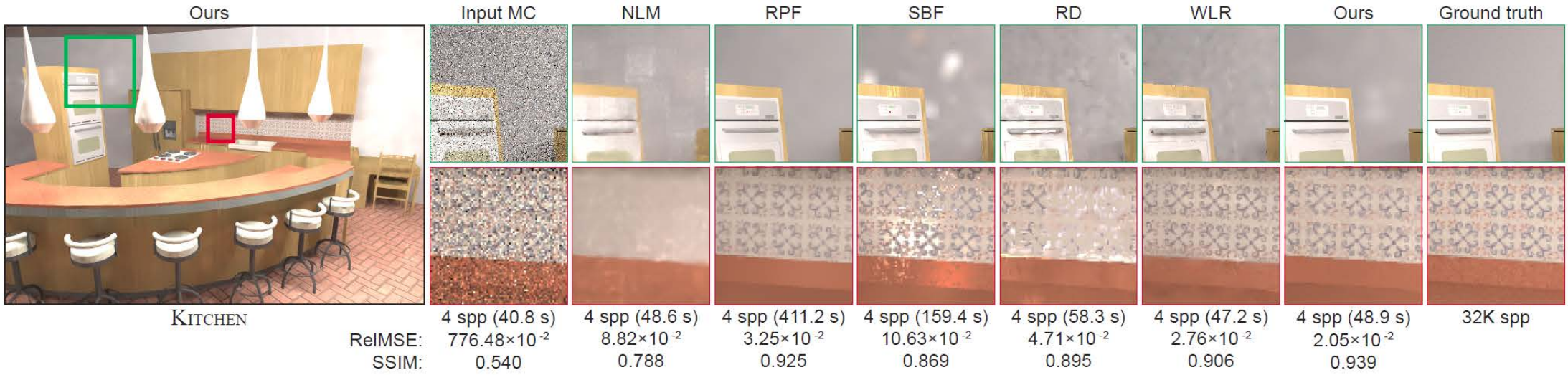


scene by Jo Ann Elliott

4 samples/pixel
(48.9 sec)

using only post-process filter!

Results


Ours
Input MC
NLM
RPF
SBF
RD
WLR
Ours
Ground truth
KITCHEN
RelMSE:
SSIM:
4 spp (40.8 s)
776.48×10 -2
0.540
4 spp (48.6 s)
8.82×10 -2
0.788
4 spp (411.2 s)
3.25×10 -2
0.925
4 spp (159.4 s)
10.63×10 -2
0.869
4 spp (58.3 s)
4.71×10 -2
0.895
4 spp (47.2 s)
2.76×10 -2
0.906
4 spp (48.9 s)
2.05×10 -2
0.939
32K spp

MLP for Denoising

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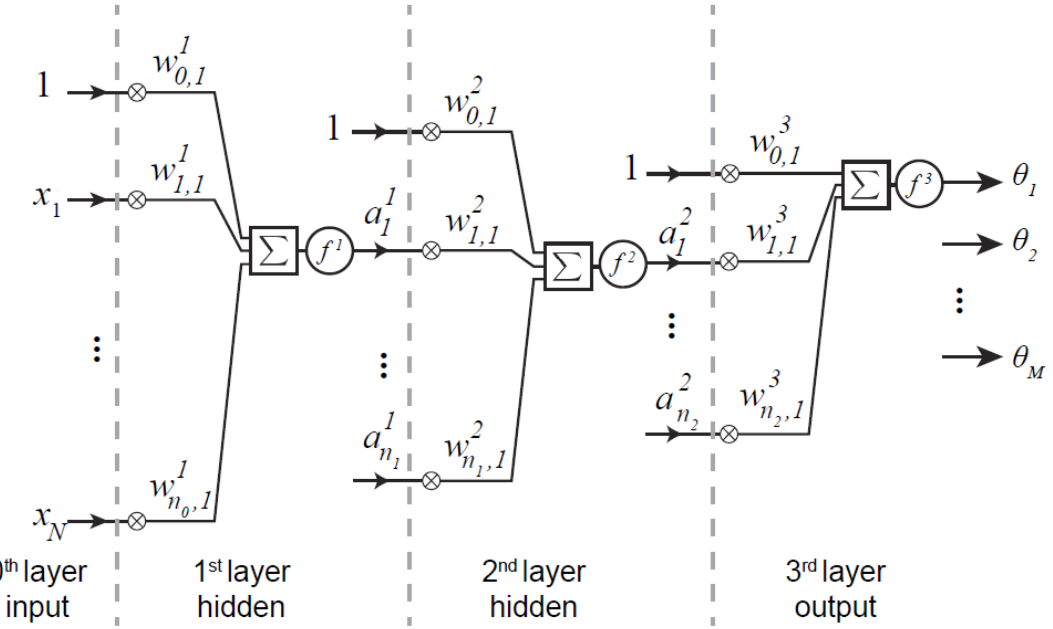
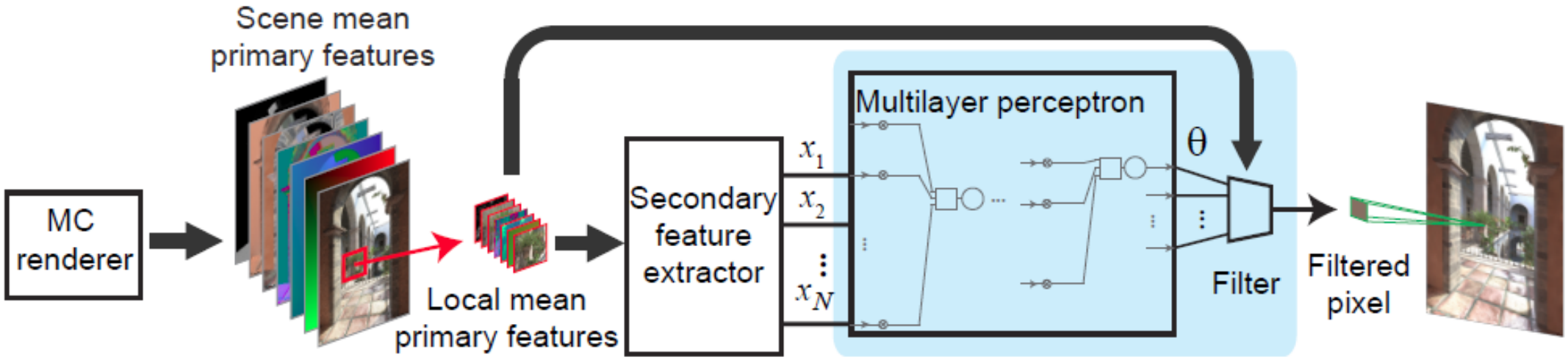
- Simple 3-layer MLP



Incorporating primary Features



Denoising with Kernel Prediction and Asymmetric Loss Functions

Vogels et al. SIGGRAPH 2018

Kernel-predicting Convolutional Network (KPCN)

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- training to minimize the average distance between the ground-truth r and the denoised image $d = g(x;\ \theta)$ via a loss function l

$$\widehat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta}}{\operatorname{argmin}} \frac{1}{N} \sum_{n=1}^{N} \ell(\mathbf{r}^n, g(\mathbf{x}^n; \boldsymbol{\theta}))$$

- symmetric mean absolute percentage error

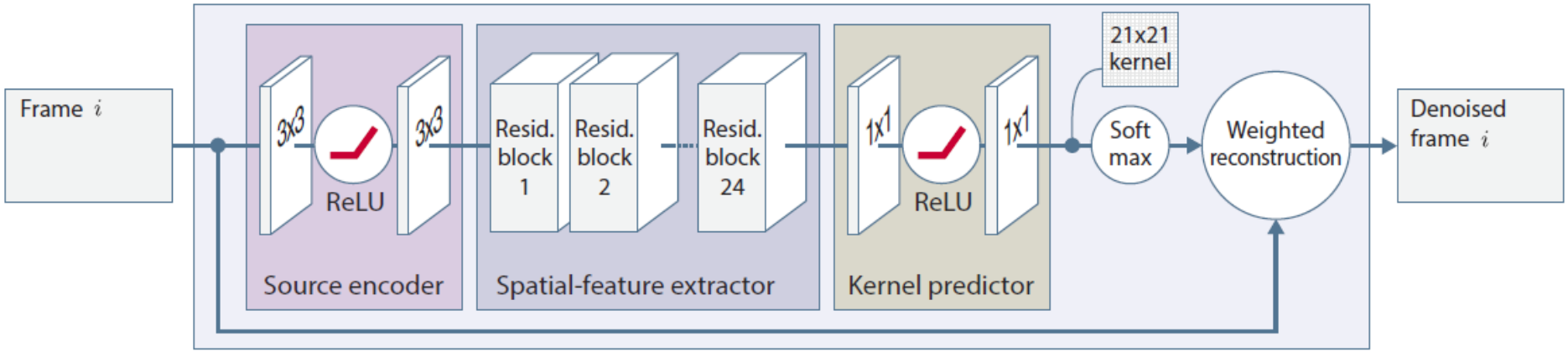
$$\ell(\mathbf{r}, \mathbf{d}) = \frac{1}{3|\mathcal{I}|} \sum_{p \in \mathcal{I}} \sum_{c \in \mathcal{C}} \frac{\left|\mathbf{d}_{p,c} - \mathbf{r}_{p,c}\right|}{\left|\mathbf{d}_{p,c}\right| + \left|\mathbf{r}_{i,c}\right| + \varepsilon}$$

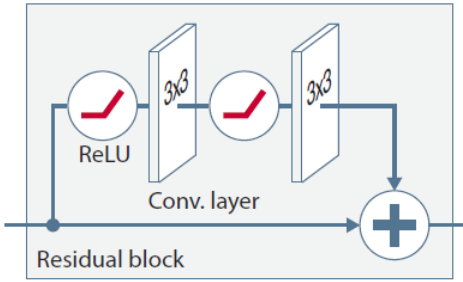
Kernel-predicting Convolutional Network (KPCN)

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

- Network predicts 21x21 filter kernel for each neighborhood followed by softmax.

$$\mathbf{d}_p = g_p(\mathbf{x};\theta) = \sum_{q \in \mathcal{N}(p)} w_{pq}\, \mathbf{c}_q \qquad w_{pq} = \frac{\exp([\mathbf{z}_p]_q)}{\sum_{q' \in \mathcal{N}(p)} \exp([\mathbf{z}_p]_{q'})}$$





Source-aware Encoder

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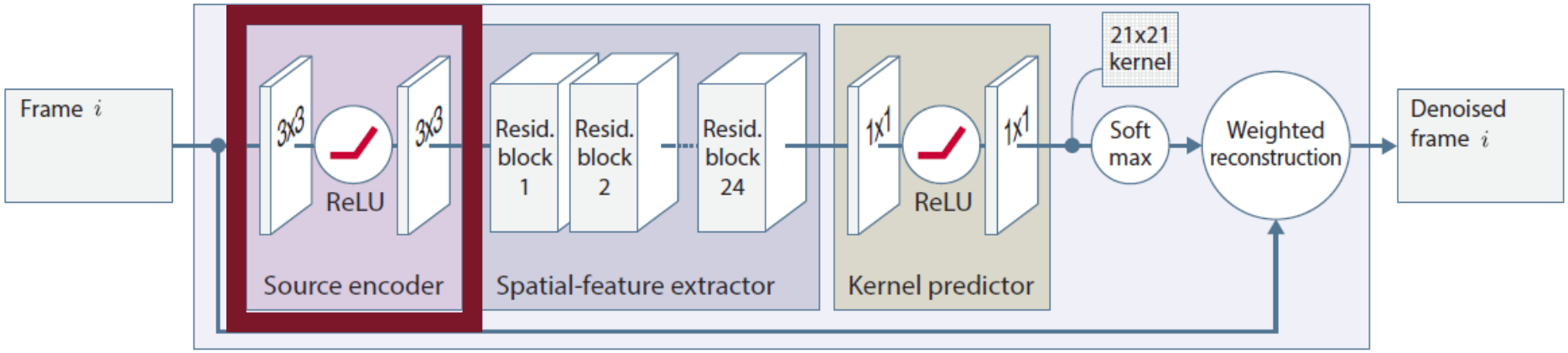
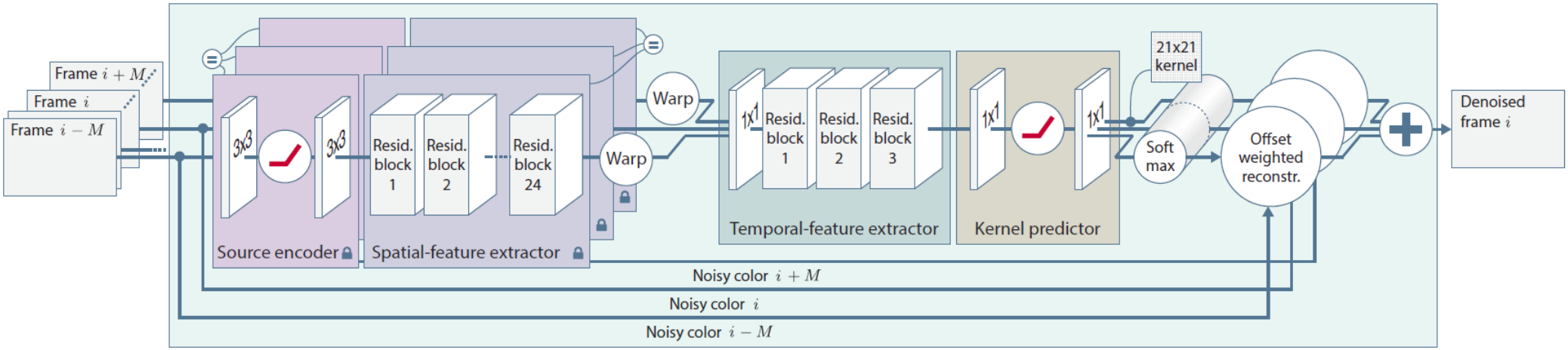
- Simple adaptaption to different renderer providing different input modalities
- Can incorporate different auxilliary buffers (color, depth, geometry, normal, texture, ….)
- Simple to retrain



Temporal denosing

- Jointly predict kernels for eachs consecutive frame
- Warping based on known geometry (we are denosing images produced by a renderer) or by optical flow
- Train source encoder and feature extractor for individual frames first
- Then train temporal component



Temporal Window Size

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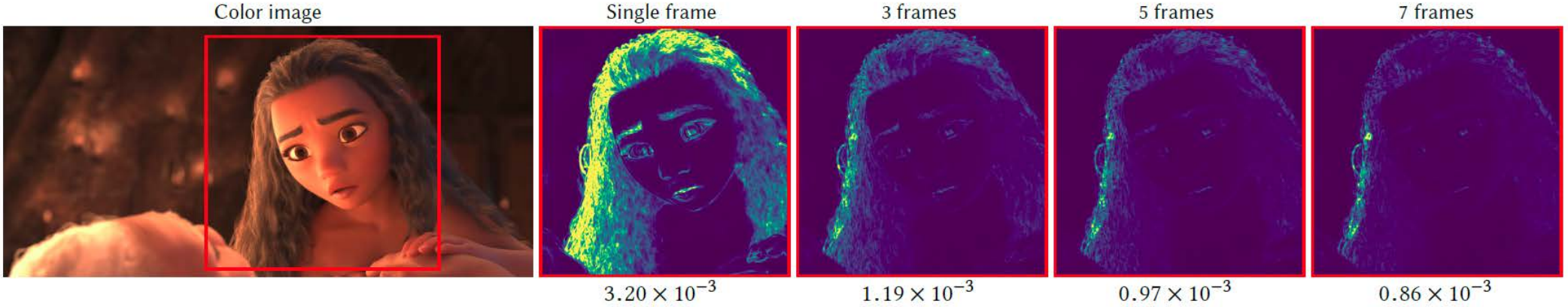
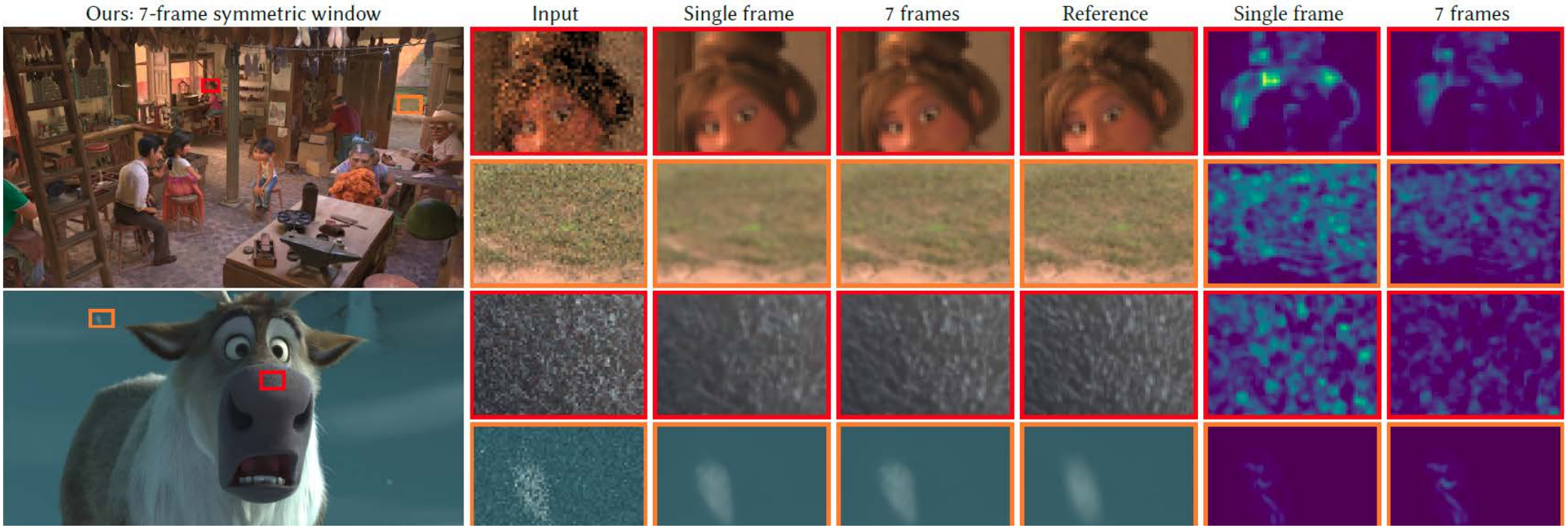
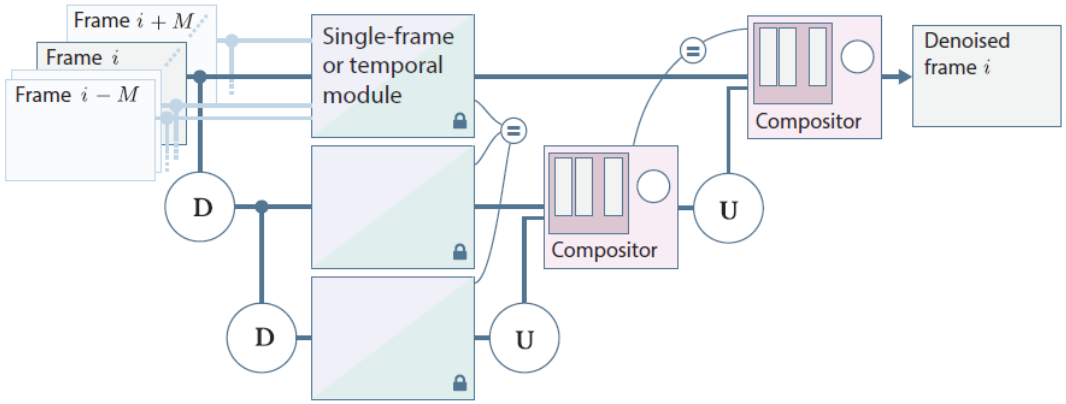
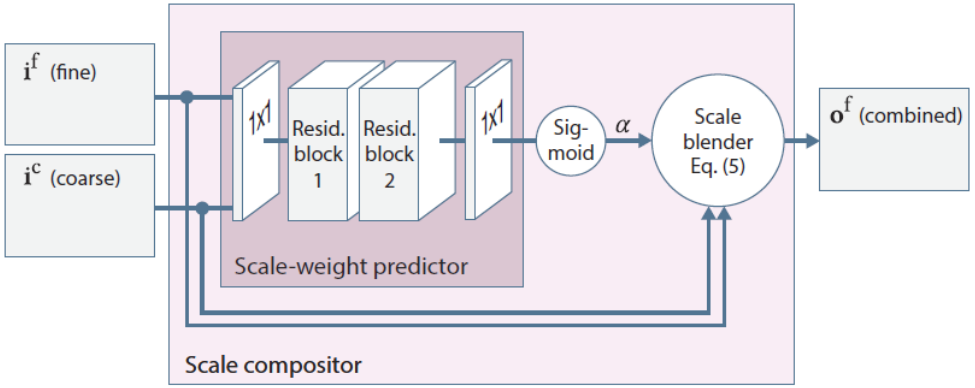


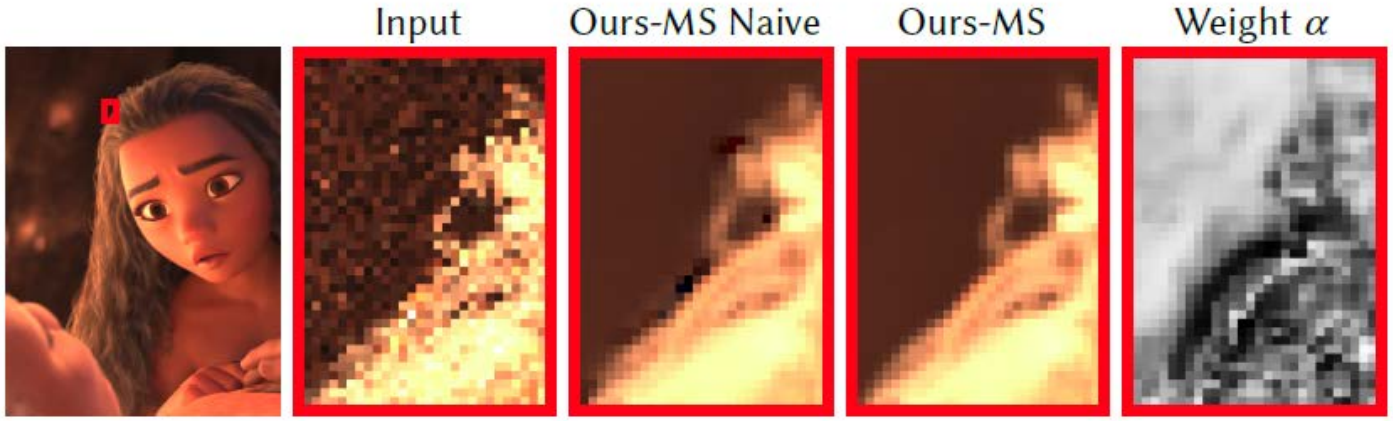


Multi-scale Prediction

- Single scale denoising might suffer from low-frequency noise
- Compose final result by weighted scale blending



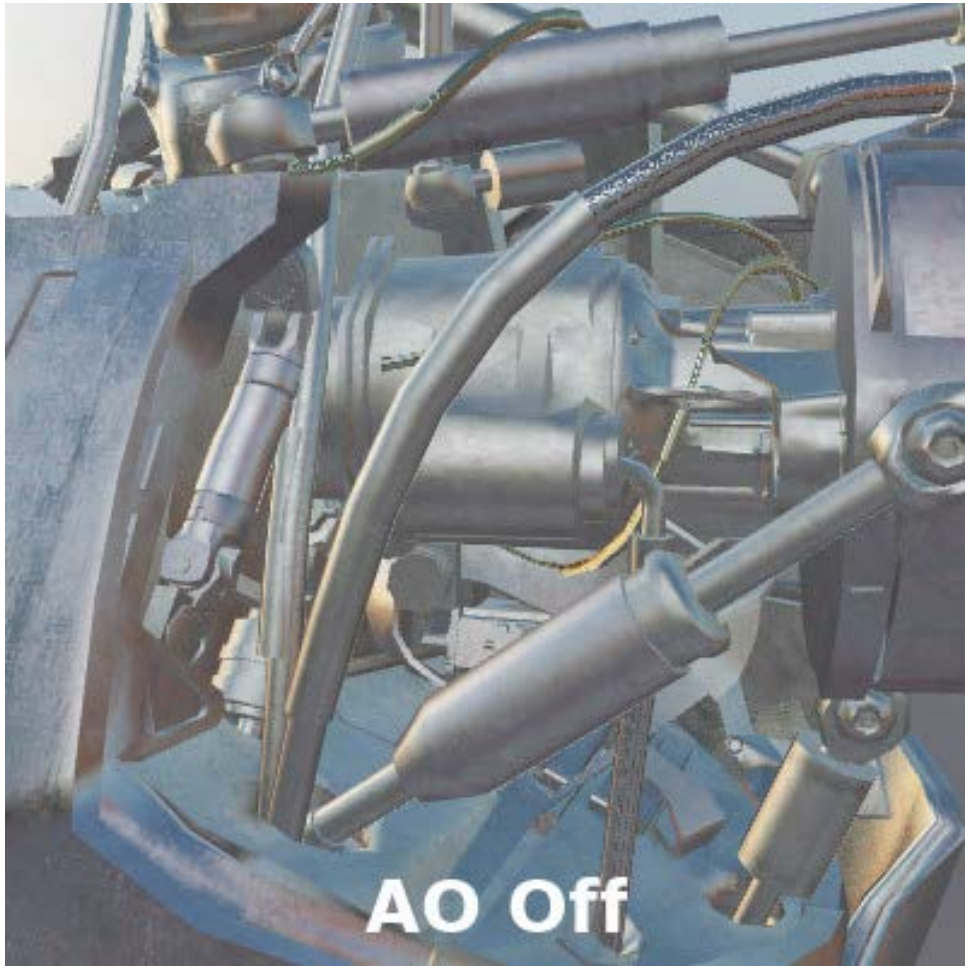




Neural Network Ambient Occlusion

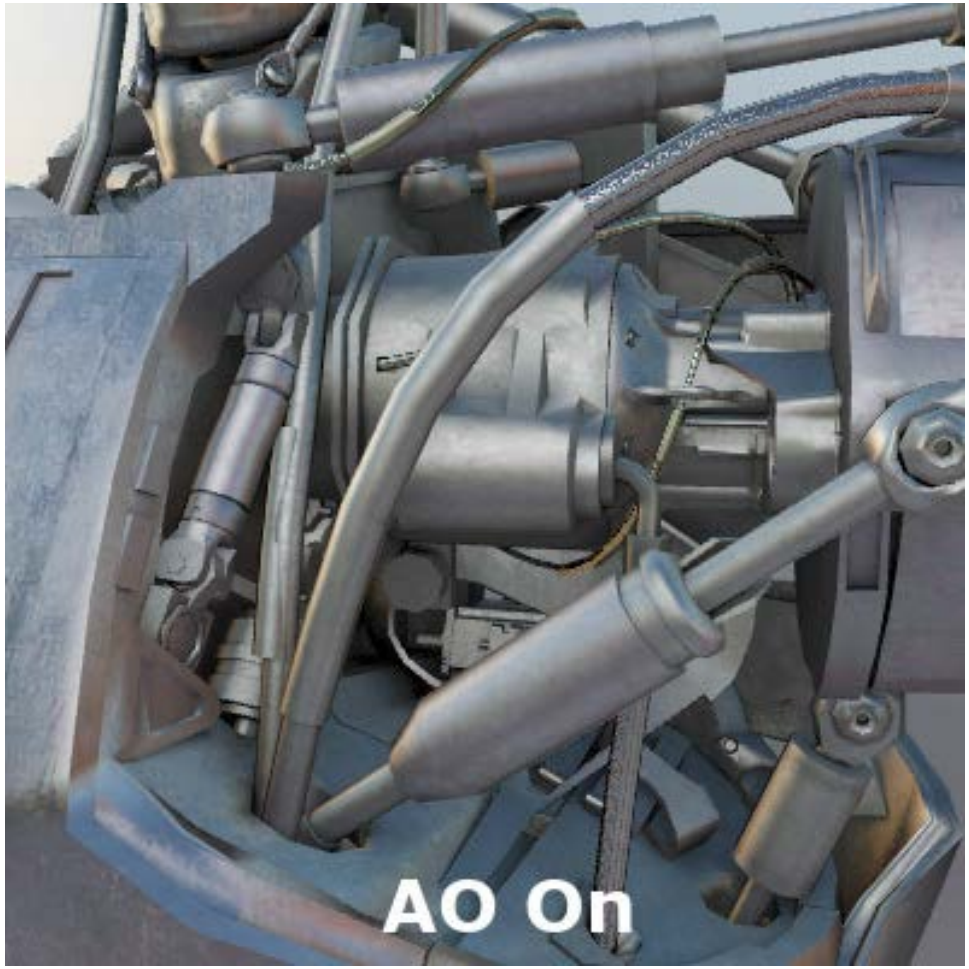
Holden et al. SIGGRAPH Asia 2016

AO approximates Global Illumination



Source: https://developer.playcanvas.com/en/user-manual/graphics/lighting/ambient-occlusion/

AO approximates Global Illumination



Source: https://developer.playcanvas.com/en/user-manual/graphics/lighting/ambient-occlusion/

Cost of AO evaluation

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- Raytracing AO still slow
- (256x256 px, 1 sample per pixel, 1024 samples per point = 67 108 864 rays) 2.5 seconds

- Too slow for games

- Idea: Utilize information that is already available from the G-Buffer in the Deferred Shading pipeline

G-Buffer

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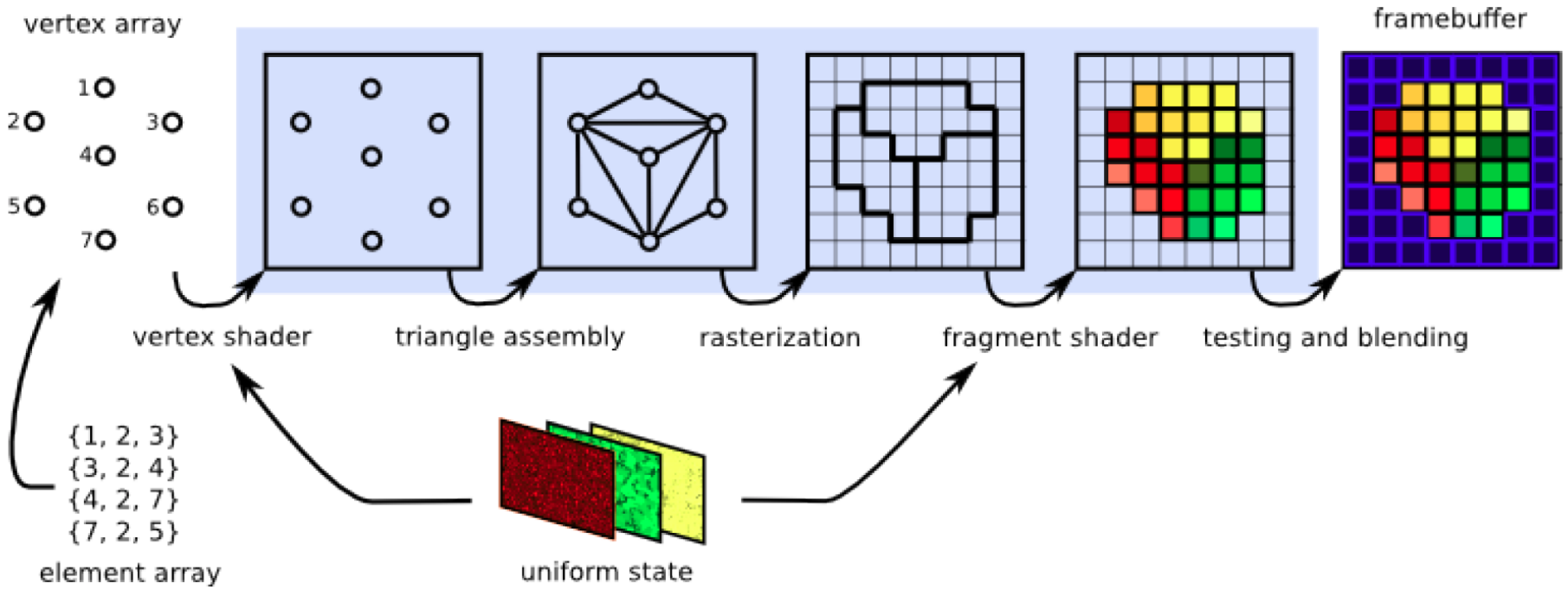
- Directly supported by GPUs



Source: https://www.enlightenment.org/playground/evas-gl.md

Screen-space Ambient Occlusion

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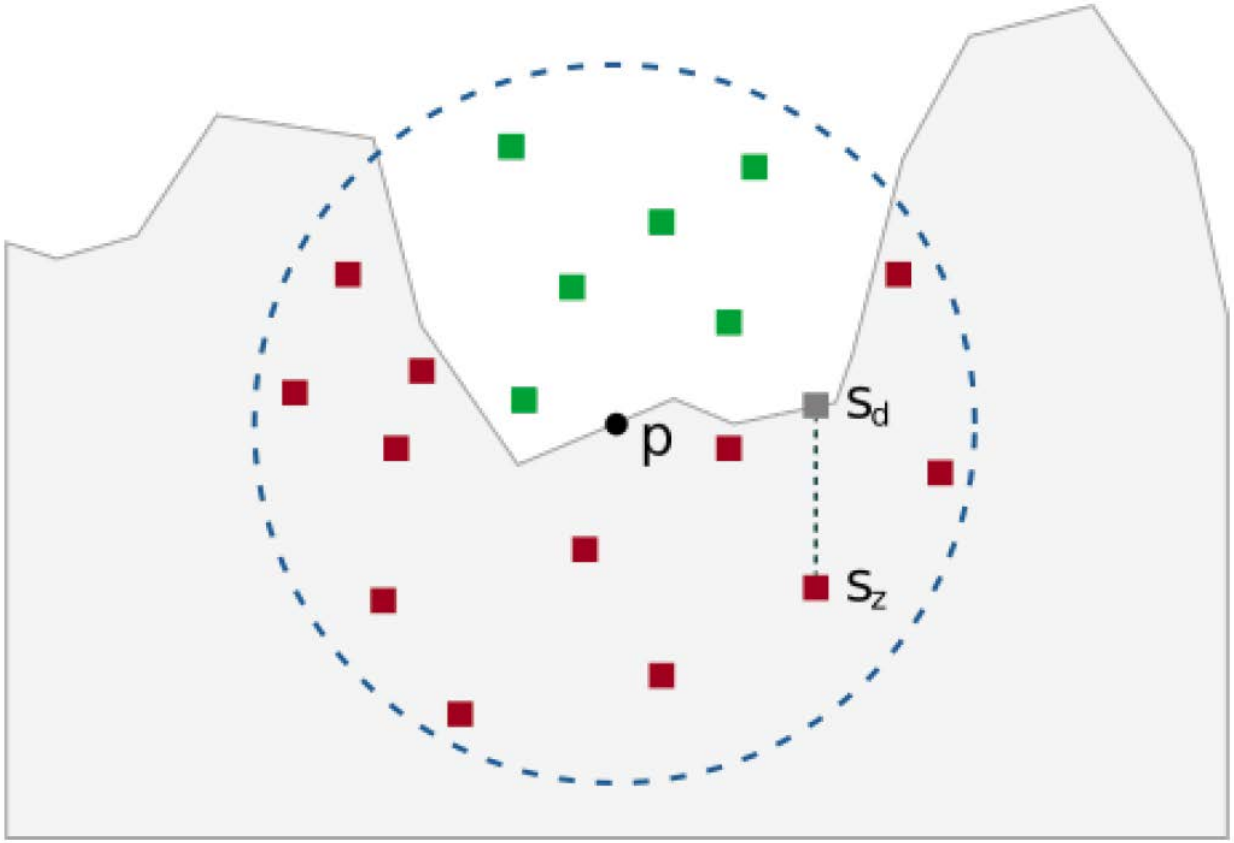
- Idea: Percentage of samples placed behind the depth map.



Source: F. Aalund and J.A. Bärentzen. A comparative study of screen-space ambient occlusion methods. Bachelor Thesis, Technical University of Denmark Informatics and Mathematical Modelling, 2013

Alchemy Ambient Occlusion

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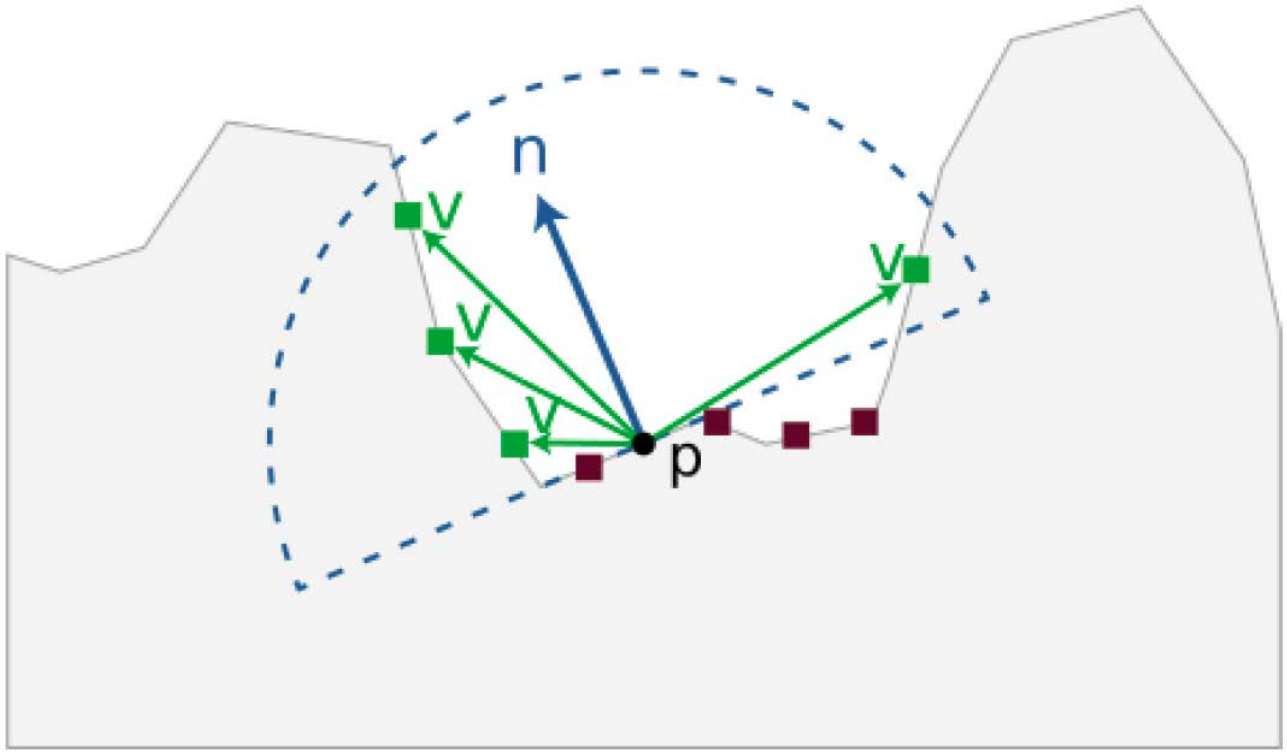
- Idea: Sum of weighted sample point distances.

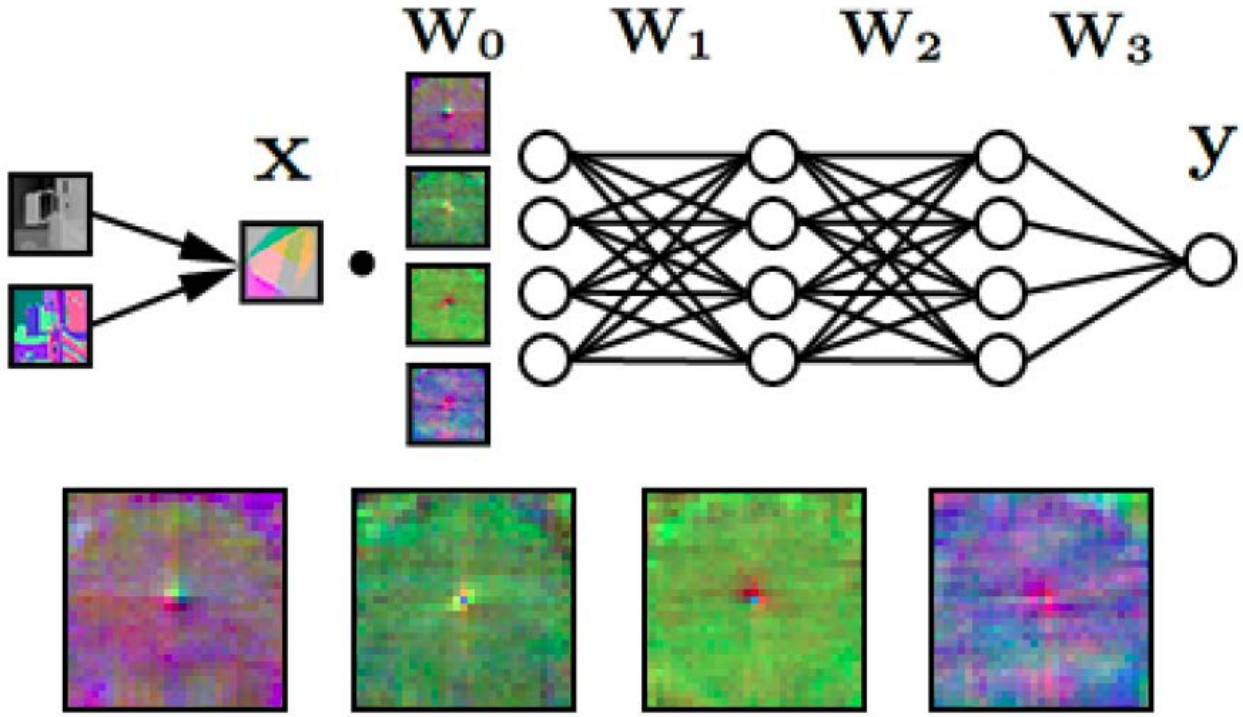


Source: F. Aalund and J.A. Bärentzen. A comparative study of screen-space ambient occlusion methods. Bachelor Thesis, Technical University of Denmark Informatics and Mathematical Modelling, 2013

NNAO: Simple MLP for Ambient Occlusion Prediction

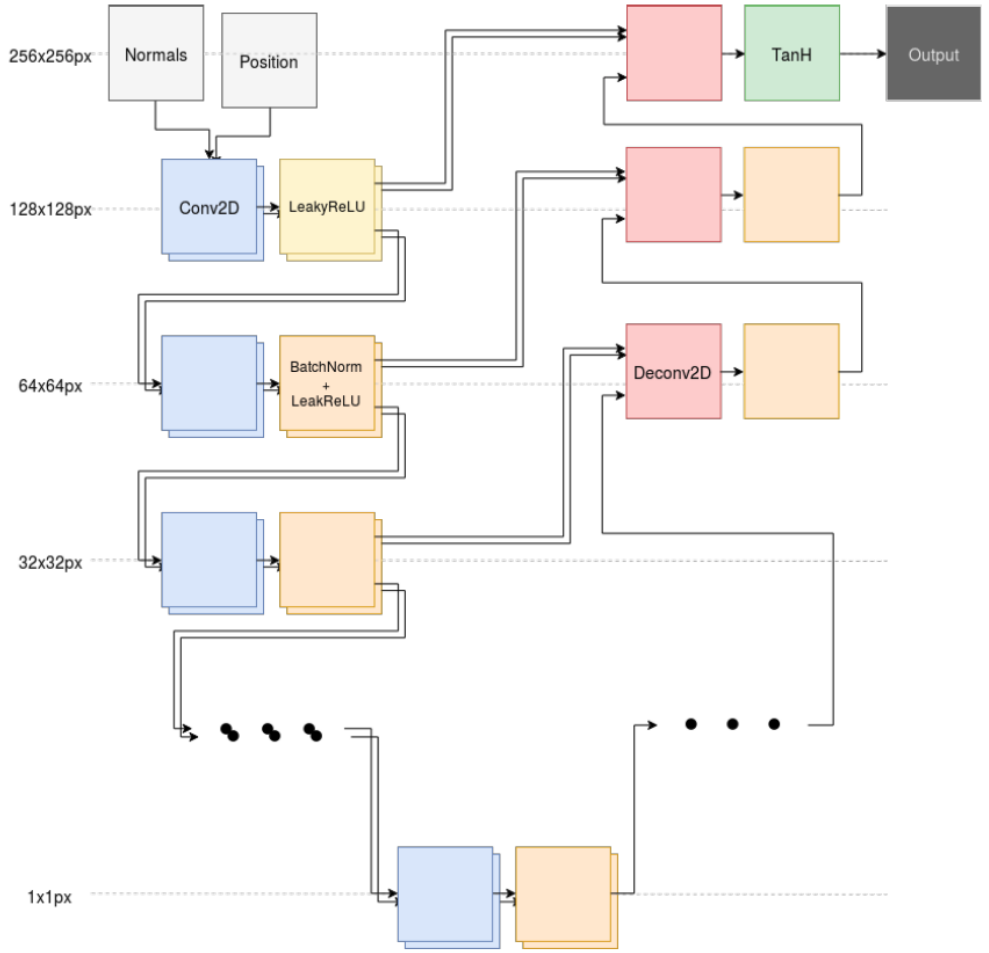
EBERHARD KARLS UNIVERSITÄT TÜBINGEN

- Predict the AO value of the central pixel of one region
- Input: prepared neighborhood from screen-space buffers
  - Absolute values and difference to central pixel of depth and normal



- Video

Reimplementation (Jens Schindel)



Training Data

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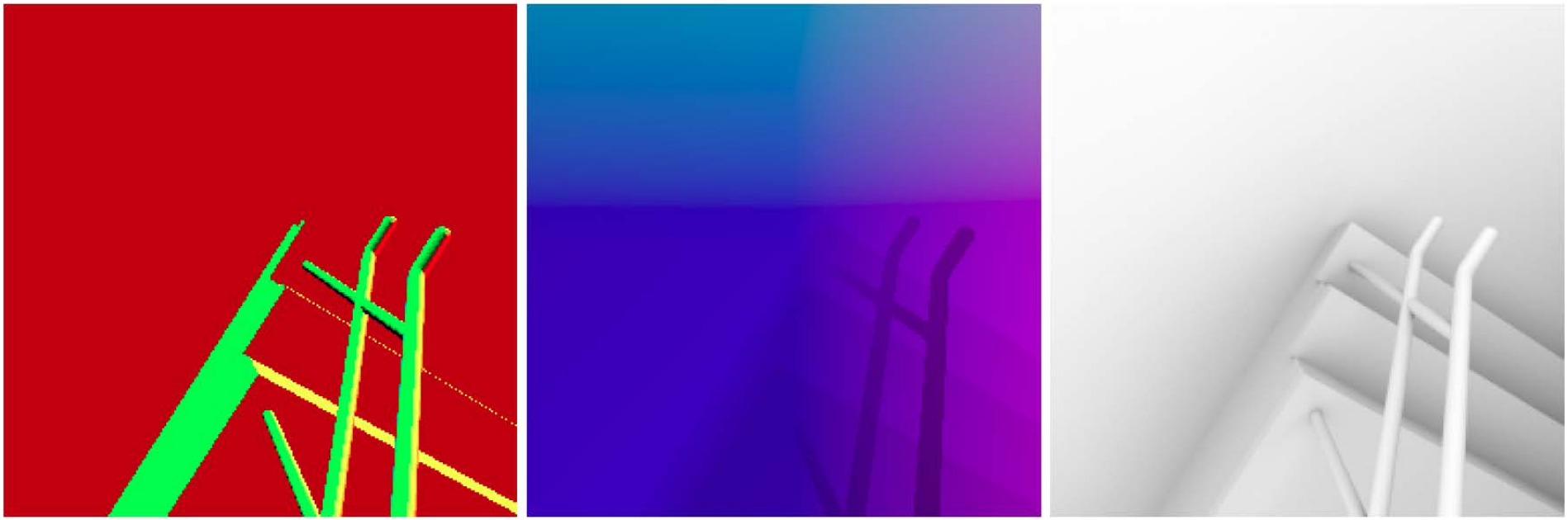
- Training Set 358650 image pairs
- Validation Set 72000 image pairs (20%)
- Test Set 27002 image pairs (7.5%)

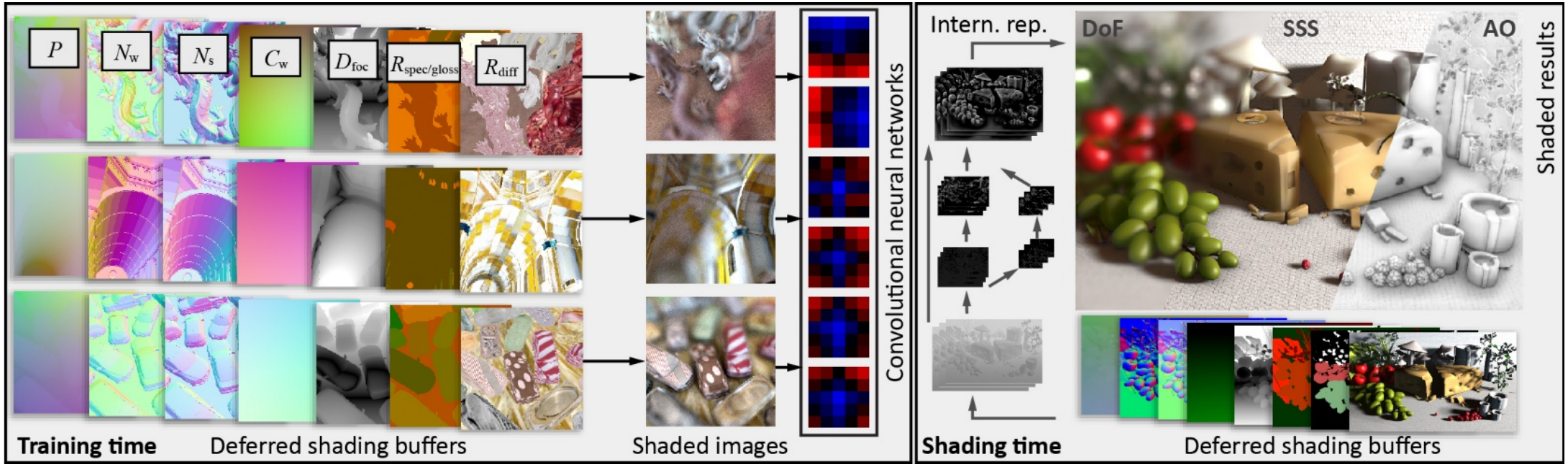


[Jens Schindel]

Video Results

Video Results

el]



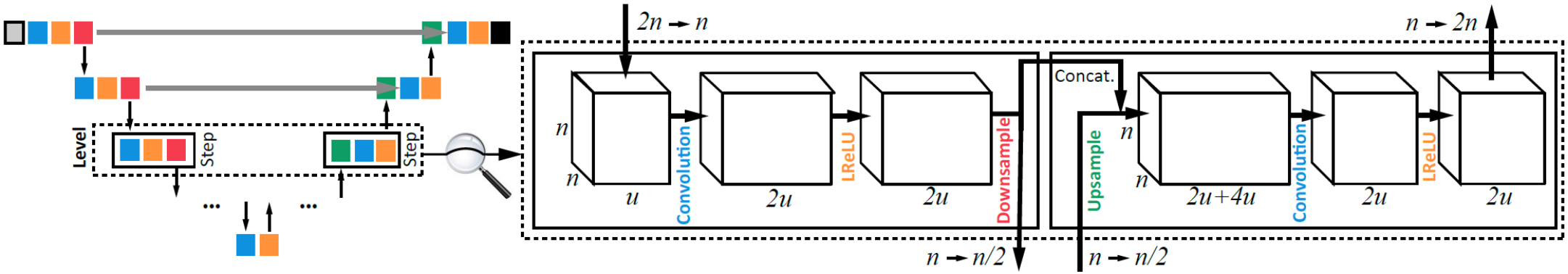
Deep Shading – Convolutional Neural Networks for Screen-Space Shading

Nalbach et al. EGSR 2017

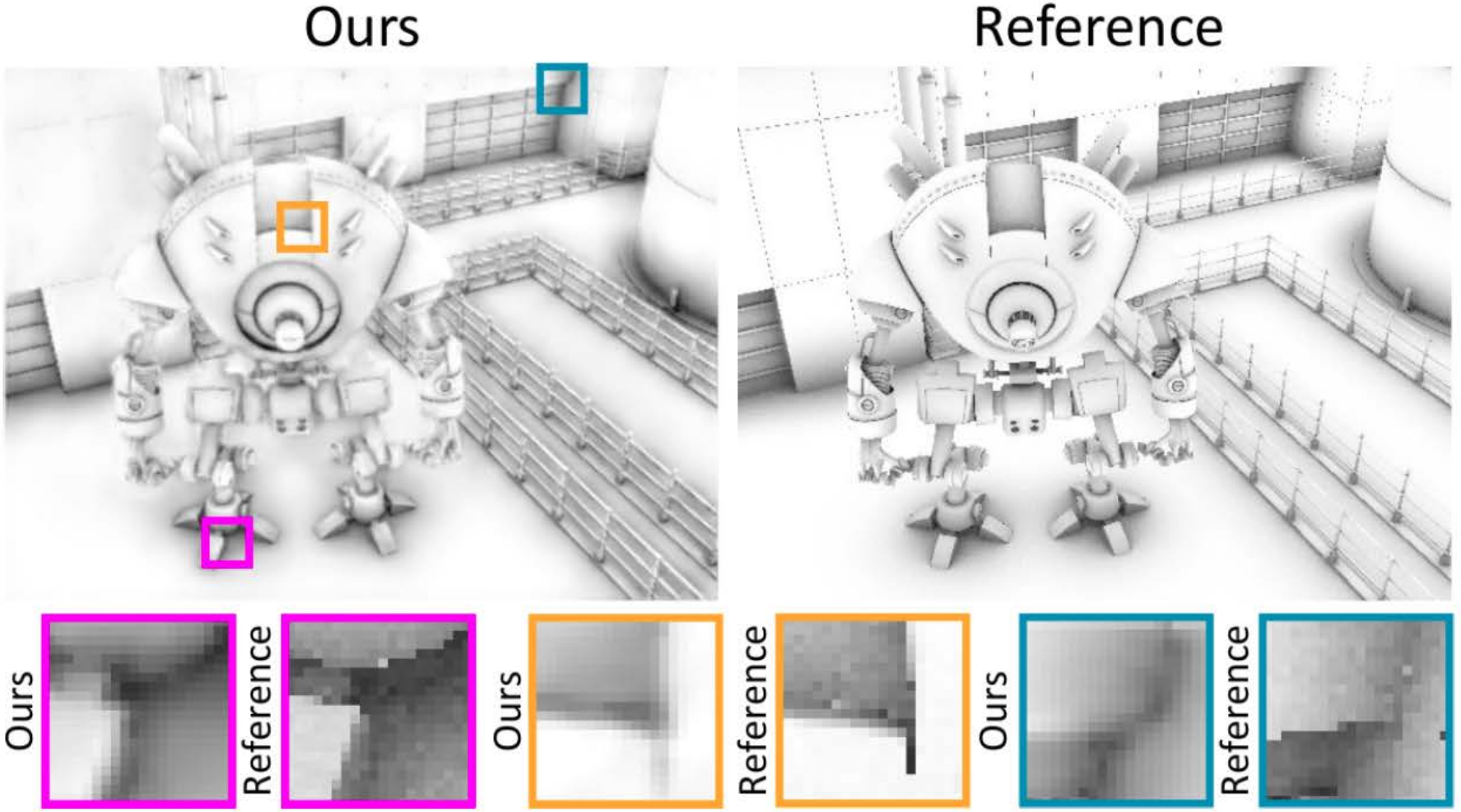
Network Architecture

- Trained for different rendering tasks (separate training set each)
  - Ambient occlusion
  - Depth of field
  - Subsurface scattering
  - Image-based lighting
  - AO + DoF

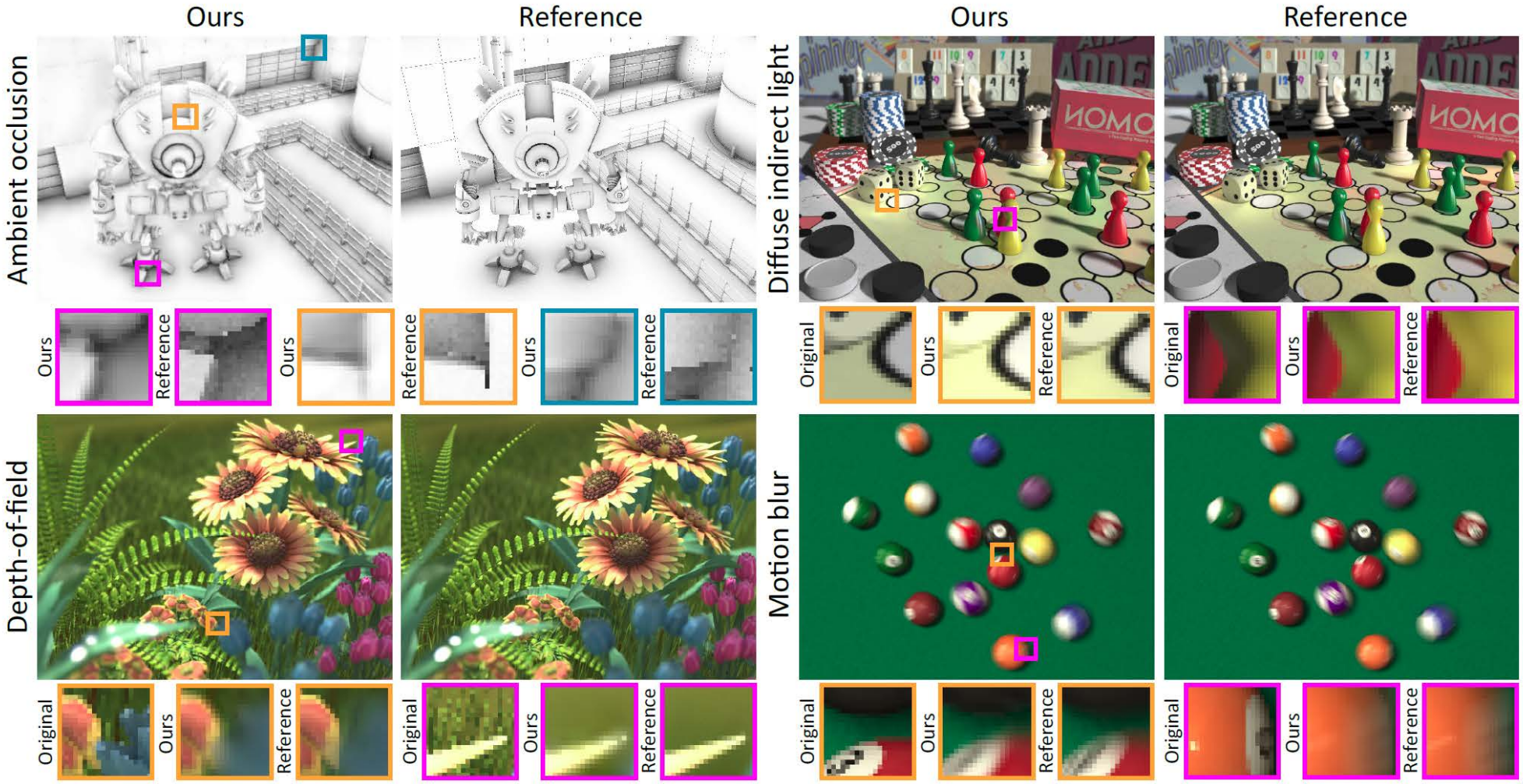
- Ambient occlusion
- Depth of field
- Subsurface scattering
- Image-based lighting
- AO + DoF
- …



Results


Ours
Reference
Ours
Reference
Ours
Reference
Ours
Reference

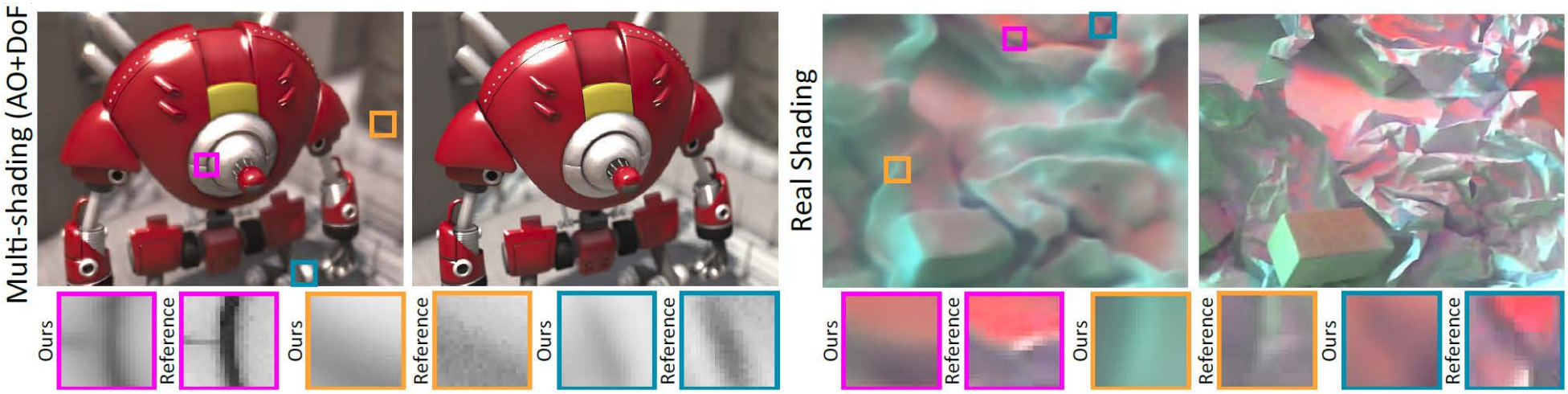
Results


Ours
Reference
Ambient occlusion
Ours
Reference
Ours
Reference
Ours
Reference
Diffuse indirect light
Original
Ours
Reference
Original
Ours
Reference
Depth-of-field
Original
Ours
Reference
Original
Ours
Reference
Motion blur
Original
Ours
Reference
Original
Ours
Reference

Results


Sub-surface scattering
Original
Ours
Reference
Original
Ours
Reference
Anti-aliasing
Original
Ours
Reference
Original
Ours
Reference
Image-based lighting
Original
Ours
Reference
Original
Ours
Reference
Directional occlusion
Ours
Reference
Ours
Reference
Ours
Reference

Results


Multi-shading (AO+DoF
Real Shading
Ours
Reference
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Reference

References

- Patrick Wieschollek, Ido Freeman, Hendrik P.A. Lensch, Learning Robust Video Synchronization without Annotations, ICMLA 2017
- Nima Khademi Kalantari, Steve Bako, Pradeep Sen, A Machine Learning Approach for Filtering Monte Carlo Noise, ACM SIGGRAPH 2015
- Vogels et al., Denoising with Kernel Prediction and Asymmetric Loss Functions, ACM SIGGRAPH 2018.
- Daniel Holden, Jun Saitoy, Taku Komuraz, Neural Network Ambient Occlusion, SIGGRAPH Asia 2016
- Oliver Nalbach and Elena Arabadzhiyska and Dushyant Mehta, Hans-Peter Seidel and Tobias Ritschel, Deep Shading – Convolutional Neural Networks for Screen-Space Shading, EGSR 2017