Physically-Based Volume Rendering and High-quality Neural Reconstruction with Volumetric Primitives

Facoltà
di
scienze
informatiche

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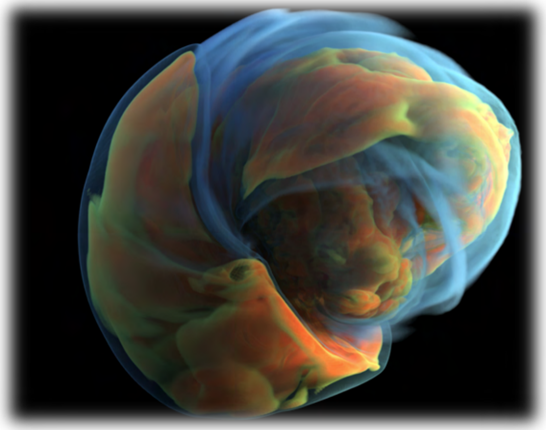
21st April 2026
Saarbrücken, Germany

(2020) BE Electronics and Control Engineer @ Unizar, Zaragoza, Spain
(2022) Masters in Graphics, Robotics and CV @ Unizar, Zaragoza, Spain
2022 – PhD Student @ USI Lugano, Switzerland
2023-2024 RS intern @ Meta Reality Labs, Zürich, Switzerland
2025 – RS intern @ NVIDIA Research, Zürich, Switzerland

Volume Rendering in Vision and Graphics



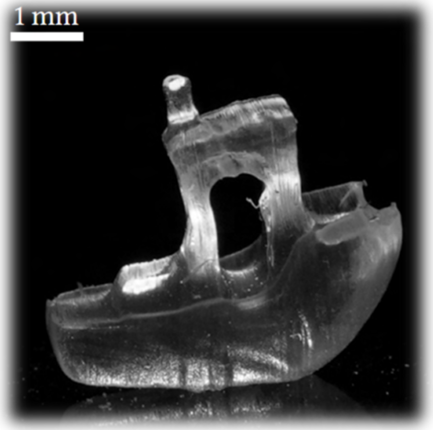
MEDICAL AND SCIENTIFIC VISUALIZATION

GSCache: Real-Time Radiance Caching for Volume Path Tracing using 3D Gaussian Splatting
David Bauer , Qi Wu , Hamid Gadirov , and Kwan-Liu Ma

MEDIA PRODUCTION

Fast Volume Rendering with Spatiotemporal Reservoir Resampling

Daqi Lin, Chris Wyman, Cem Yuksel



PREDICTIVE RENDERING AND INVERSE OPTIMIZATION

Inverse Rendering for Tomographic Volumetric Additive Manufacturing

Baptiste Nicolet, Felix Wechsler, Jorge Madrid-Wolff, Christophe Moser, Wenzel Jakob

NOVEL-VIEW SYNTHESIS

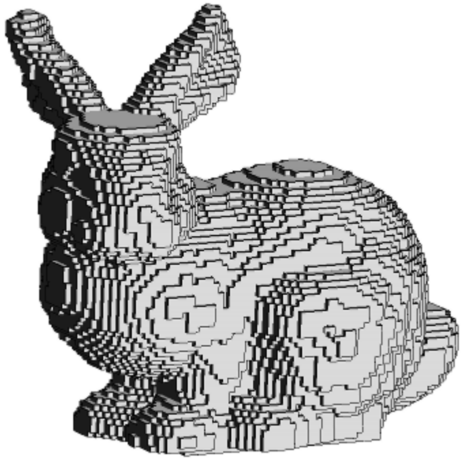
NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis

Ben Mildenhall, Pratul P. Srinivasan, Matthew Tancik, Jonathan T. Barron, Ravi Ramamoorthi, Ren Ng

Limitations of Volume Rendering

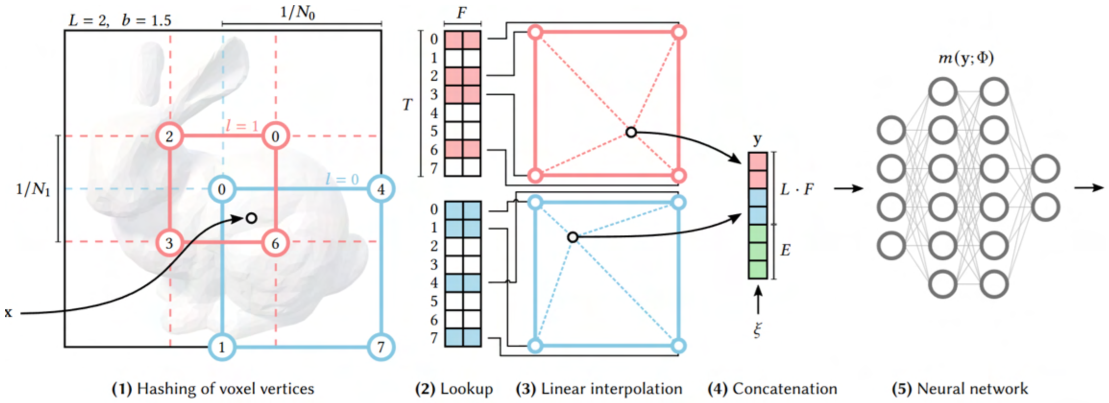
Explicit Density Fields

- Regularly spaced voxel grids, \w or \wo a hierarchy



Implicit Density Fields

- A neural network (MLP)



Instant Neural Graphics Primitives with a Multiresolution Hash Encoding
Thomas Müller, Alex Evans, Christoph Schied, and Alexander Keller.

Limitations of Volume Rendering

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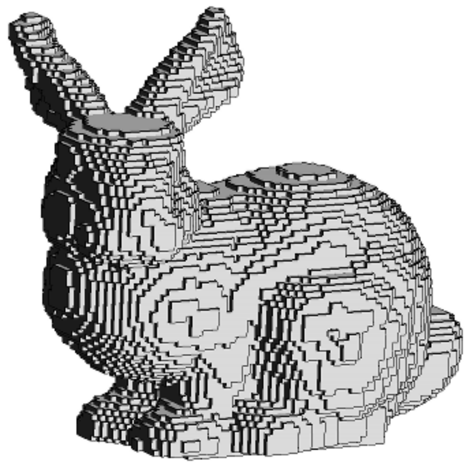

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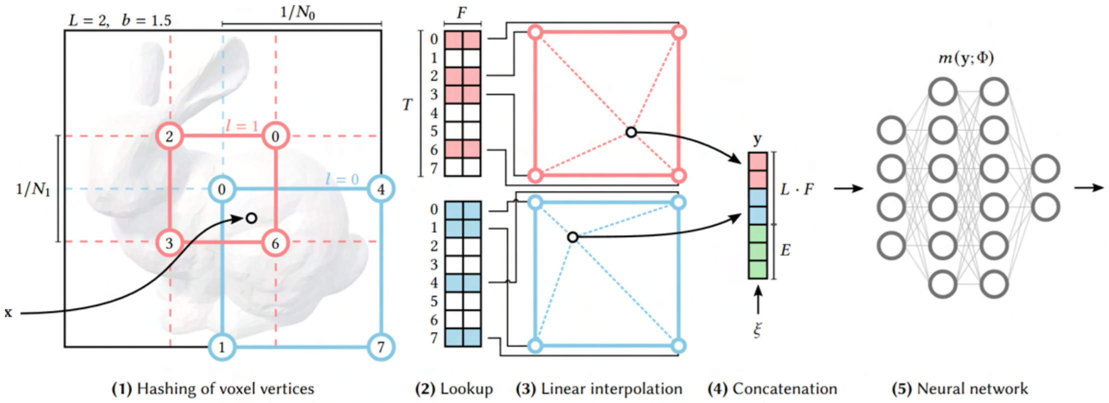
  - Difficult to generate (gradient-based optimization) and sample from (usually requires a separate model)



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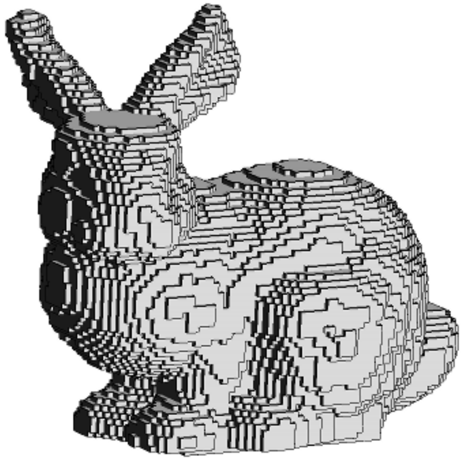

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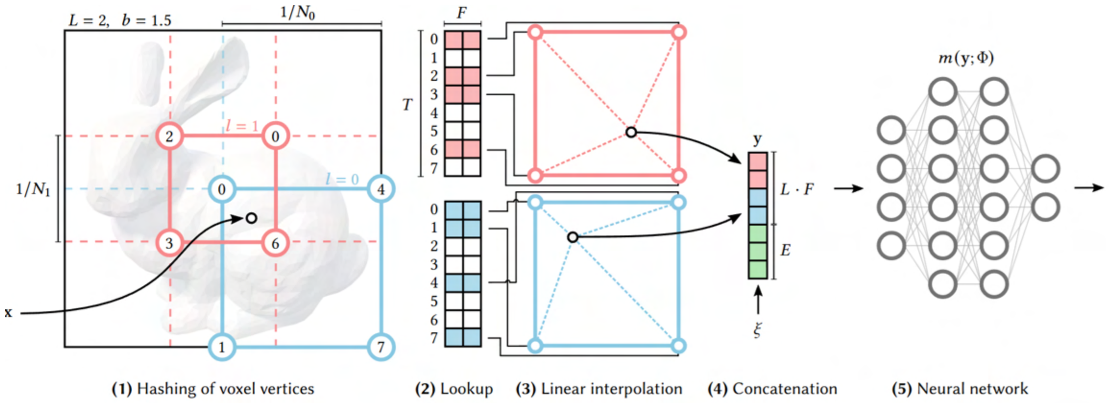

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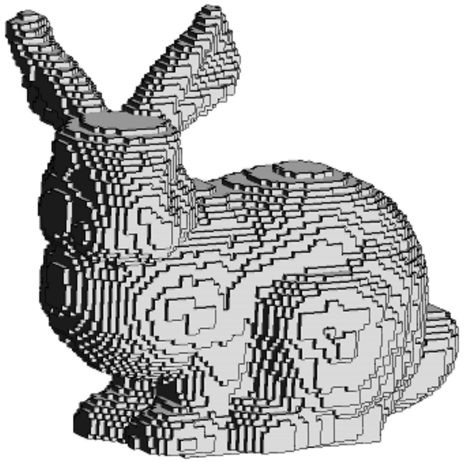

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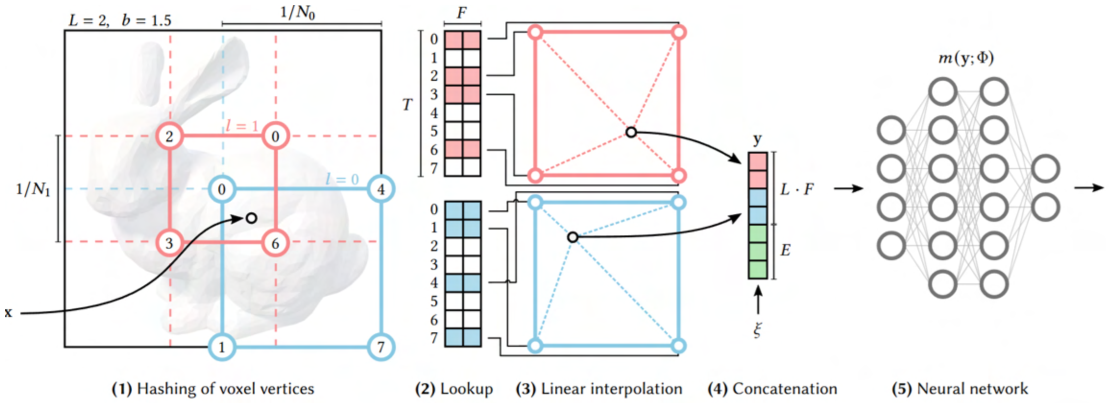

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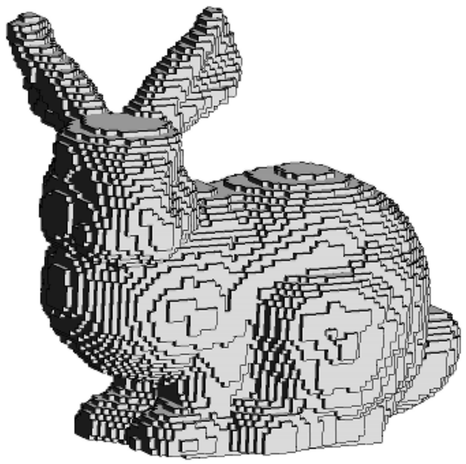
  - Normally requires numerical methods to integrate
  - Easy to filter/downscale



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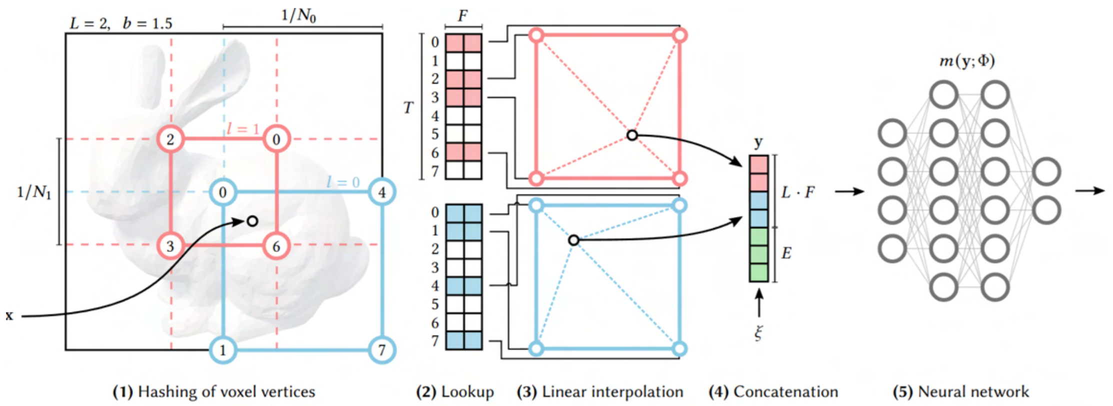
  - Difficult to filter/downscale



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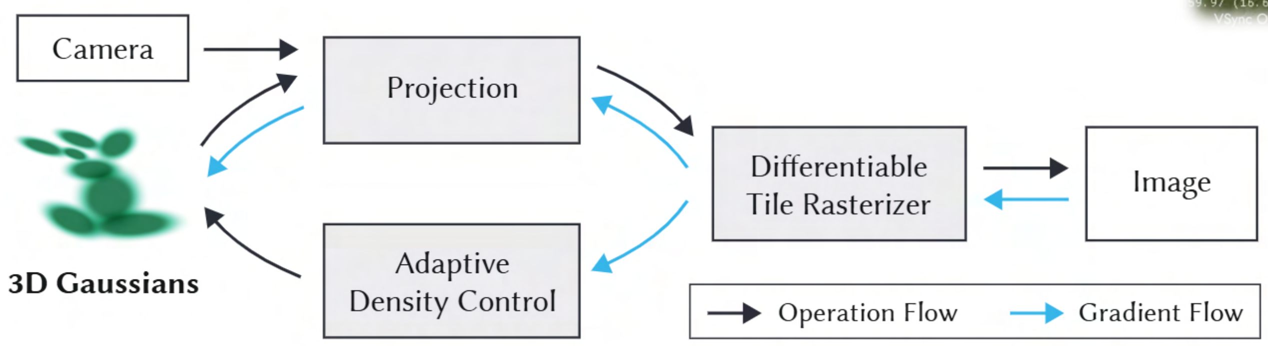
Primitive-Based Volume Rendering

Defining Density Fields as Collections of Primitives

- Rasterizes collections of anisotropic Gaussians, projected in an approximate manner through EWA splatting
- Not directly applicable to PBR

3D Gaussian Splatting for Real-Time Radiance Field Rendering

Bernhard Kerbl, Georgios Kopanas, Thomas Leimkühler, George Drettakis



Primitive-Based Volume Rendering

Does using primitives for PBR make sense?

- They are very compact and adapt to detail (Lagrangian), scaling better than voxel grids (Eulerian)
- Potentially enables closed-form integration
- Can fit naturally to physics simulation methods (e.g. SPH fluid-solvers)

Volumetric Primitive Path Tracer (Ours)
200k Gaussians

Talk Layout

PBR with primitive volumes

Don't Splat your Gaussians: Volumetric Ray-Traced Primitives for Modeling and Rendering Scattering and Emissive Media

JORGE CONDOR, Meta Reality Labs, Switzerland and USI Lugano, Switzerland
SÉBASTIEN SPEIERER, Meta Reality Labs, Switzerland
LUKAS BODE, Meta Reality Labs, Switzerland
ALJAŽ BOŽIČ, Meta Reality Labs, Switzerland
SIMON GREEN, Meta Reality Labs, United Kingdom
PIOTR DIDYK, USI Lugano, Switzerland
ADRIÁN JARABO, Meta Reality Labs, Spain

ACM ToG'24 (presented at SIGGRAPH'25)

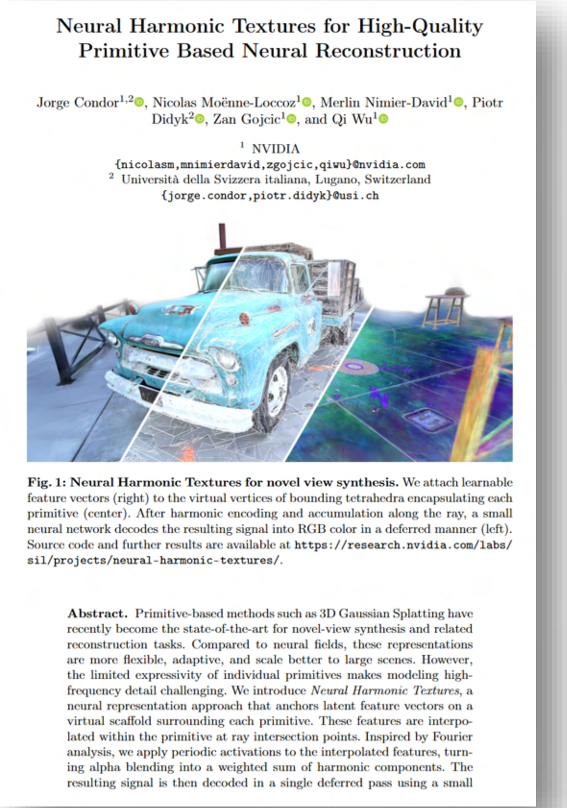
LOD for PBR with primitive volumes

Gabor Fields: Orientation-Selective Level-of-Detail for Volume Rendering

JORGE CONDOR*, USI Lugano, Switzerland
NICOLAI HERMANN*, USI Lugano, Switzerland
MEHMET ATA YURTSEVER, USI Lugano, Switzerland
PIOTR DIDYK, USI Lugano, Switzerland

ACM ToG (SIGGRAPH'26)
(conditionally accepted)

Neural Primitive Volumes



Neural Harmonic Textures for High-Quality Primitive Based Neural Reconstruction

Jorge Condor[1,2], Nicolas Moënne-Loccoz[1], Merlin Nimier-David[1], Piotr Didyk[2], Zan Gojcic[1], and Qi Wu[1]

[1] NVIDIA
[2] Università della Svizzera italiana, Lugano, Switzerland

Arxiv'26
(under revision)

Don’t Splat your Gaussians: Volumetric Ray Traced Primitives for Modelling and Rendering Scattering and Emissive Media

Jorge Condor

Sébastien Speierer

Lukas Bode

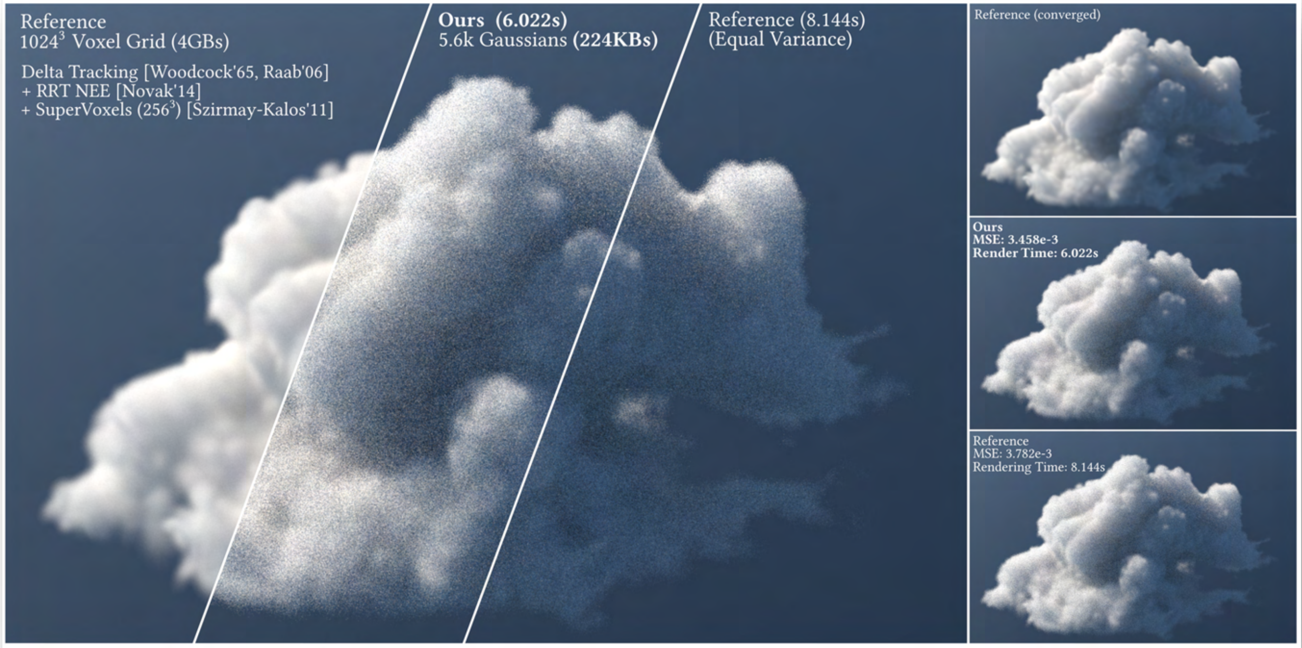
Aljaz Bozic

Simon Green

Piotr Didyk

Adrián Jarabo

Università della Svizzera italiana



ACM Transactions of Graphics,
presented at SIGGRAPH’25

Recipe for a PBR Volume Rendering Method

Ingredients

- A density field
- A way to regress/obtain this field
- A way to integrate density along rays slicing this field
- A way to sample distances (aka how to scatter)
- An efficient implementation of all the above within a path tracer

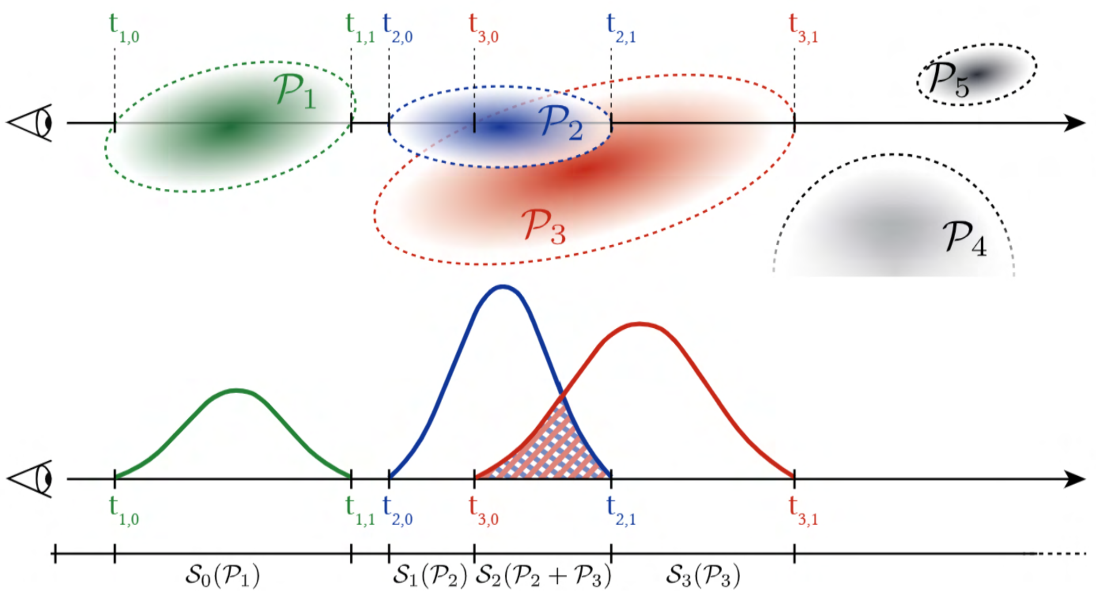
Path Tracing Primitive Volumes

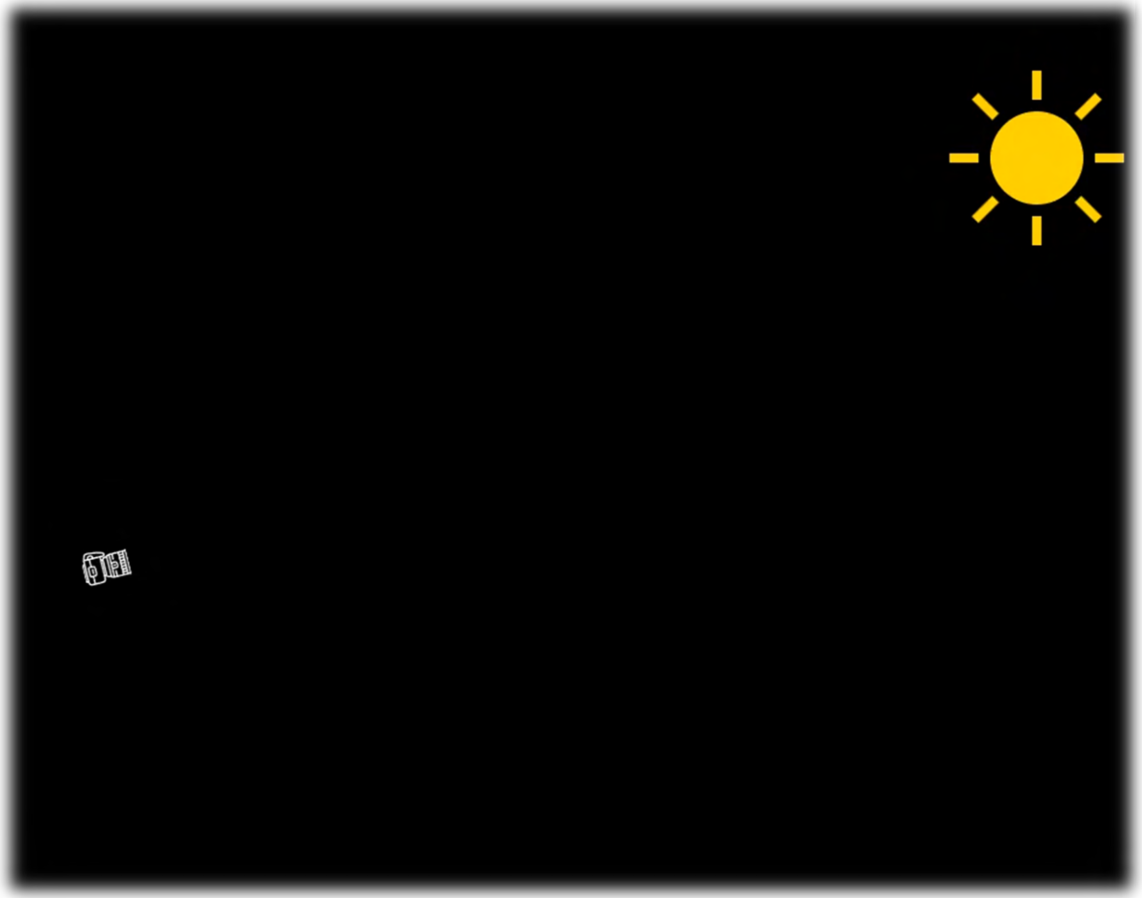
Density Field as Mixture of Primitives

Path Tracing Primitive Volumes

Analytic Transmittance Integrals

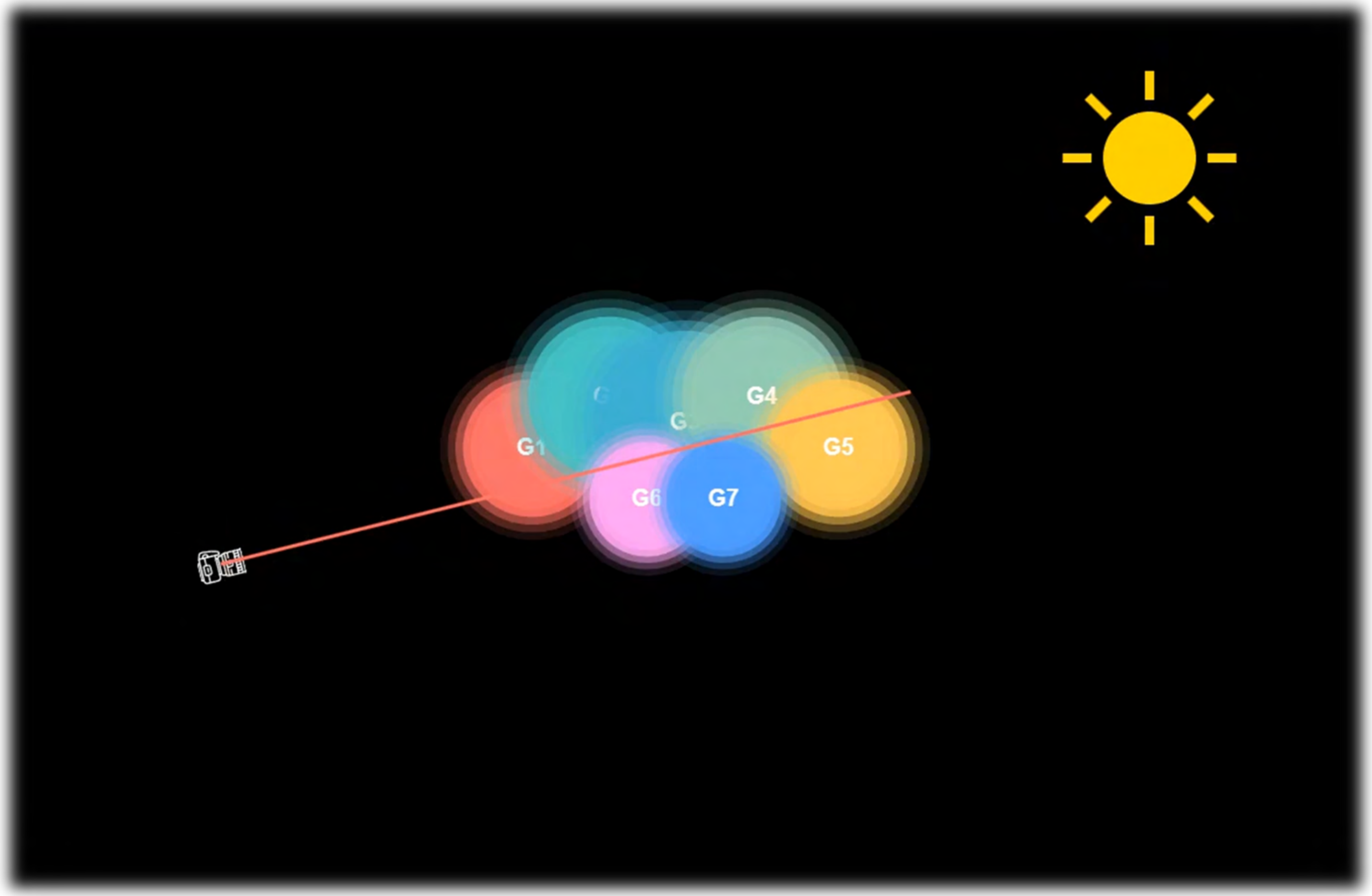
- Closed-form solutions to the line integrals of the anisotropic kernels along the ray
- Bounds define edges, we integrate segment by segment analytically





Path Tracing Primitive Volumes

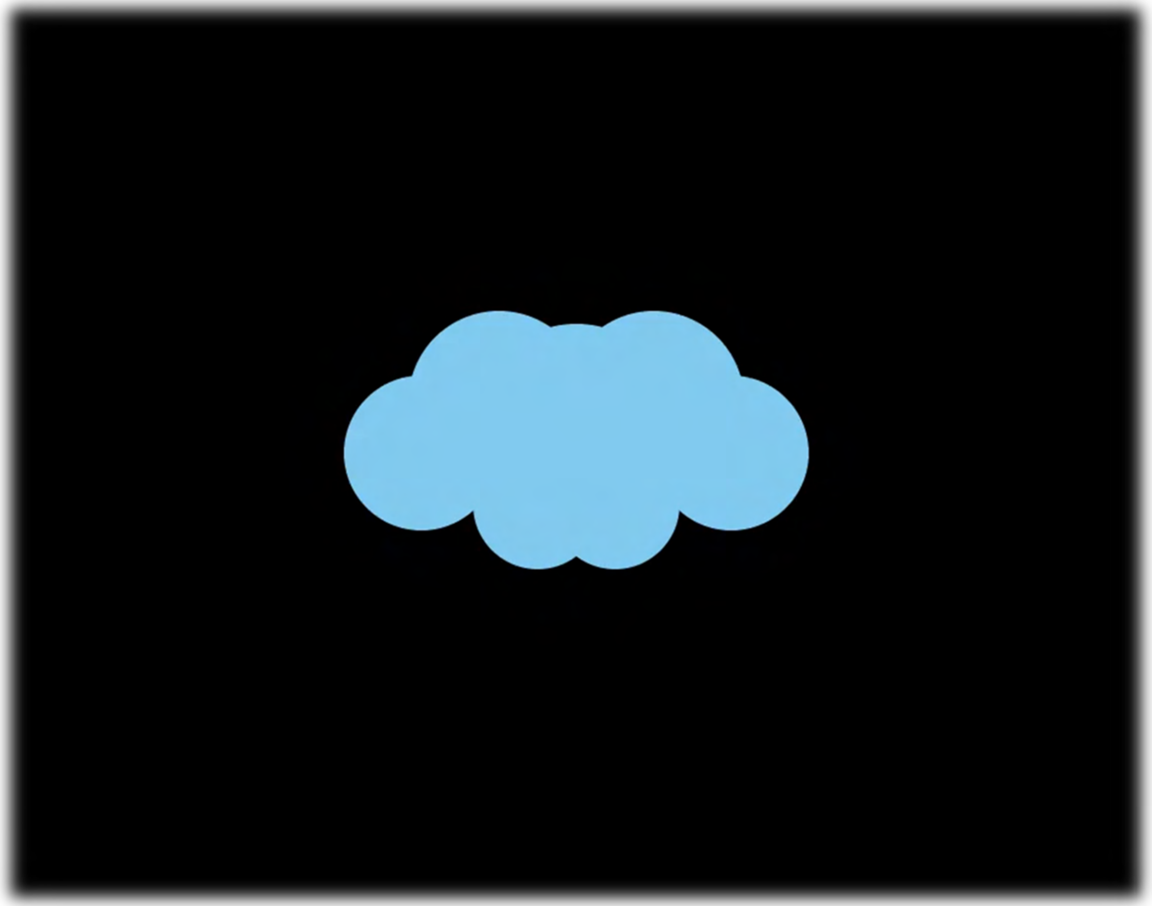
Distance Sampling in Primitive Volumes



Path Tracing Primitive Volumes

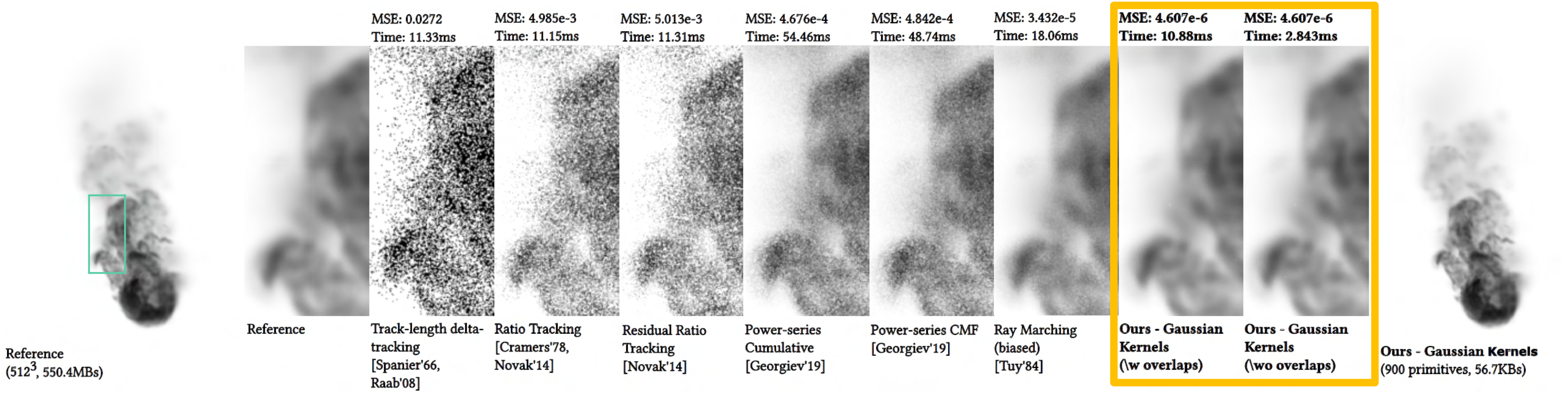
Regressing Assets as Mixtures of Primitives

- Adjoint renderer based on path-replay backpropagation
- Inverse renderer can optimize absorbing and scattering volumes from images



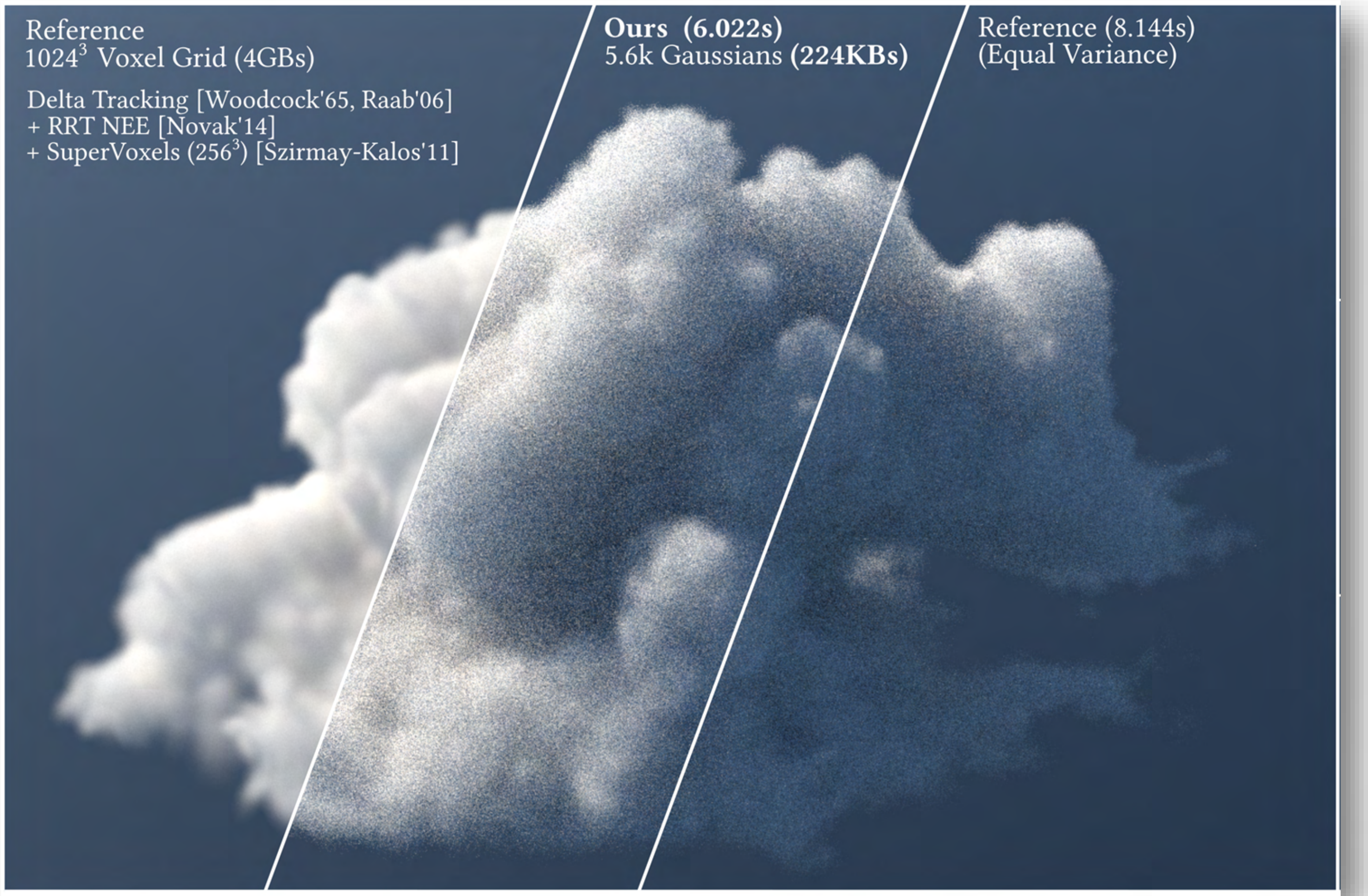
Results

Tomography



Results

Unbiased Multiple Scattering



Results

Unbiased Multiple Scattering

Less Primitives, Faster

Higher Quality, Slower

VDB (480MB)

(Reference)

16.2k (639KB)

MSE: 1.621e-4

26.27mins

5.6k (224KB)

MSE: 1.717e-4

19.43mins

2.6k (107KB)

MSE: 2.72e-4

11.67mins

Results

Results

Radiance Fields with Complex Cameras

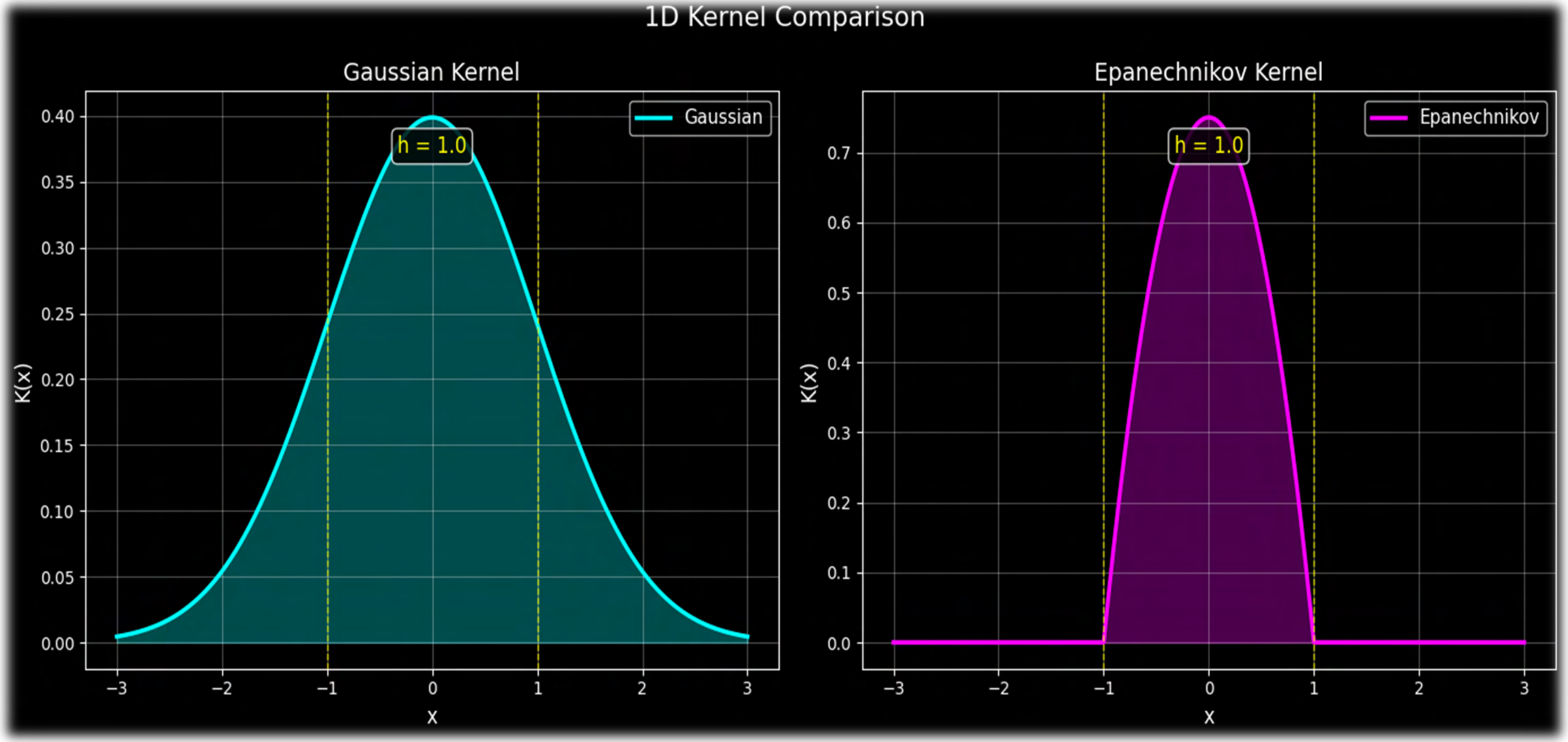
Limitations

- Optimization can be slow (0.5-2h)
- Performance depends on measures like amount of overlapping primitives

→ can become slow with too many primitives.

- Level of detail?

A Kernel-Agnostic Formulation



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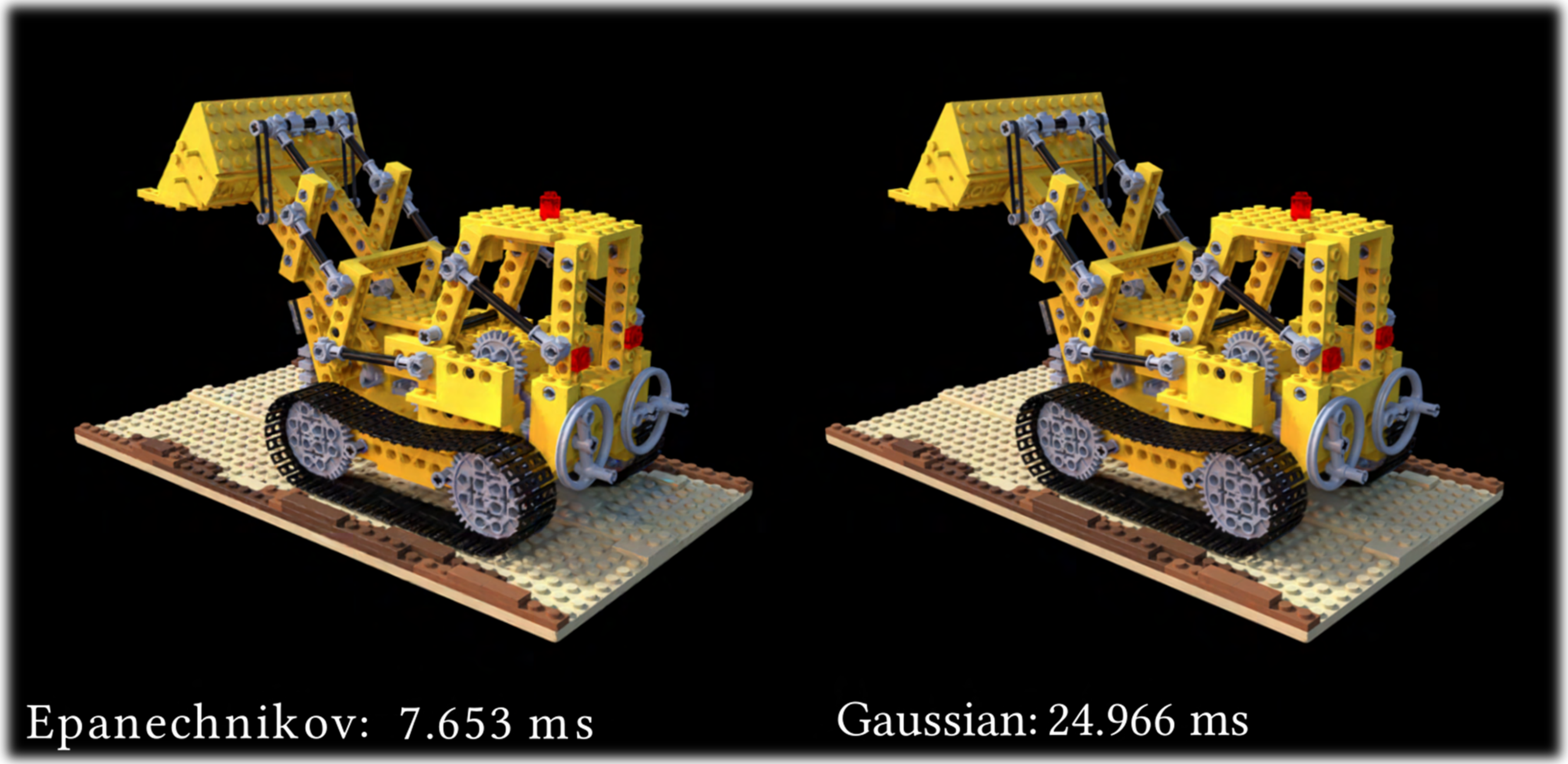


Gabor Fields: Orientation-Selective Level-of-Detail for Volume Rendering

Jorge Condor*
Nicolai Hermann*
Mehmet Ata Yurtsever
Piotr Didyk

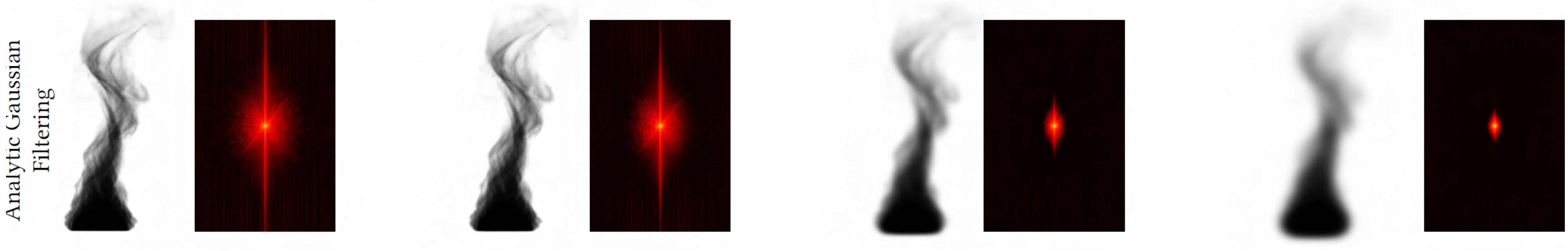
Università della Svizzera italiana

ACM Transactions of Graphics,
SIGGRAPH'26 (cond. accepted)

Constructing Level of Detail with Gaussian Primitives

Why is LOD challenging with primitives

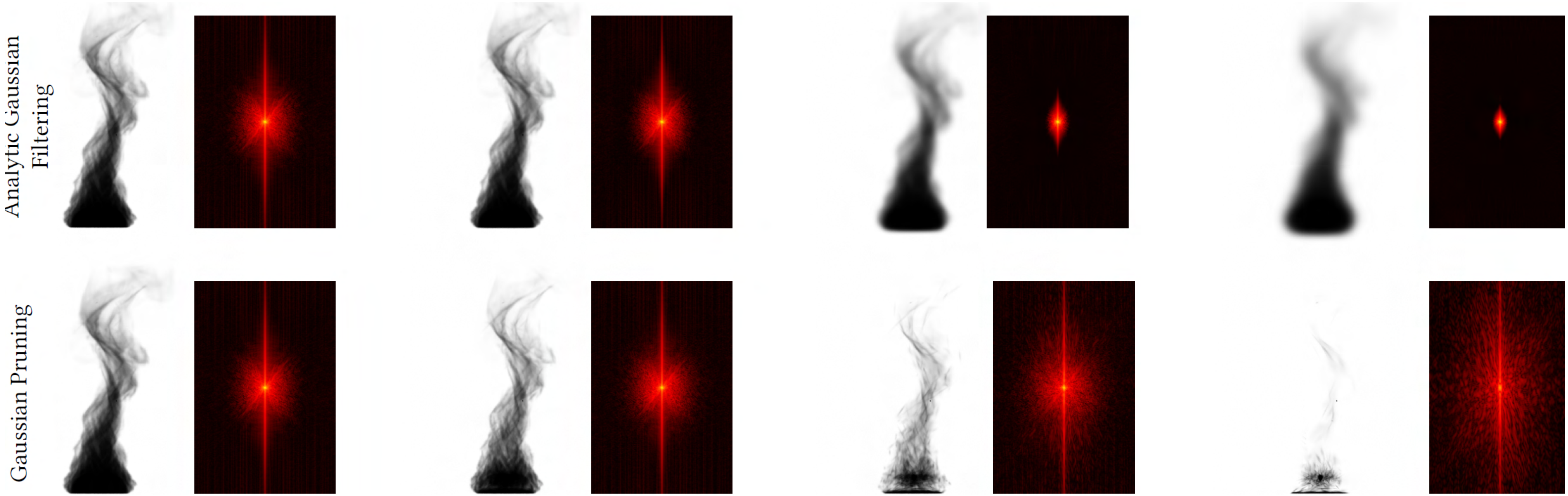
- Analytic filtering is possible
- In practice: very slow to render!
  - Same number of primitives
  - Larger (higher overlap)
  - Higher memory footprint (need to store each level independently)



Constructing Level of Detail with Gaussian Primitives

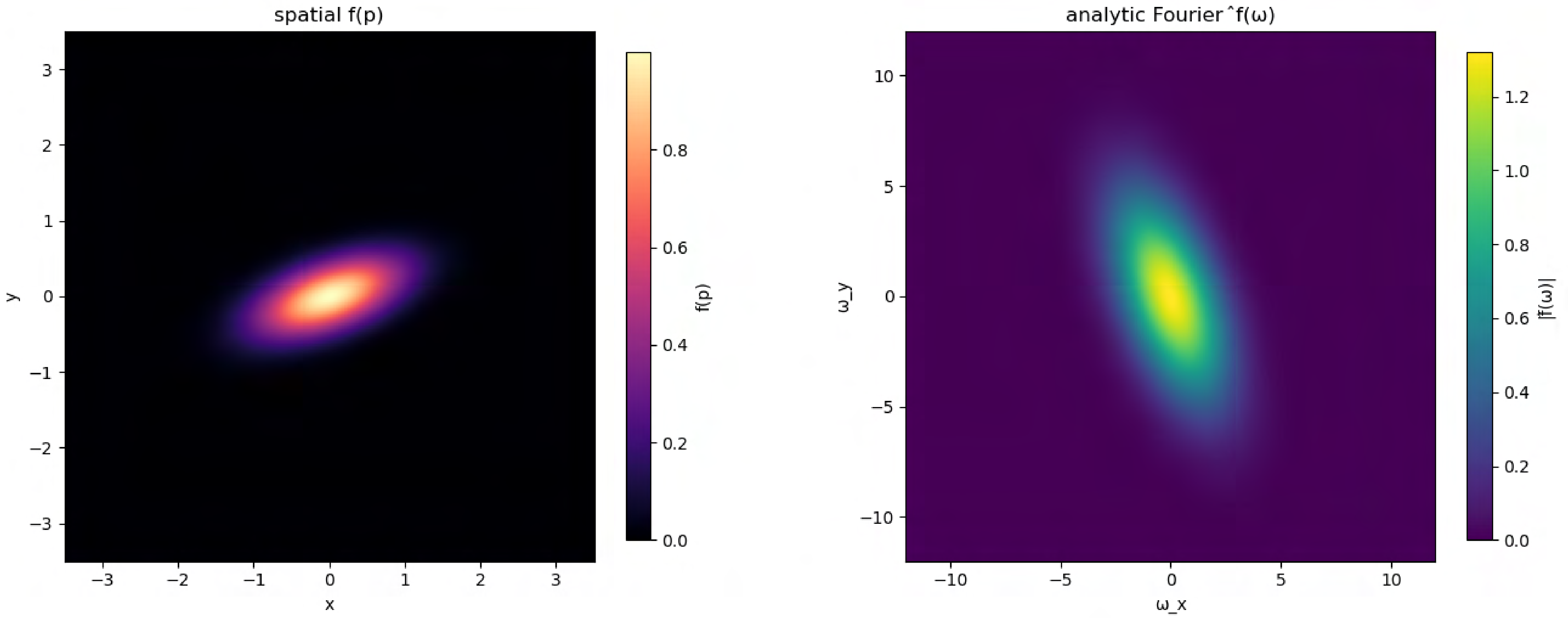
Alternatives

- Retrain the same asset at different levels of detail (pyramid) → slow, extra memory, requires manual tuning
- Heuristic pruning of small Gaussians



What is the core issue?

- Gaussians in the Frequency domain span all frequencies



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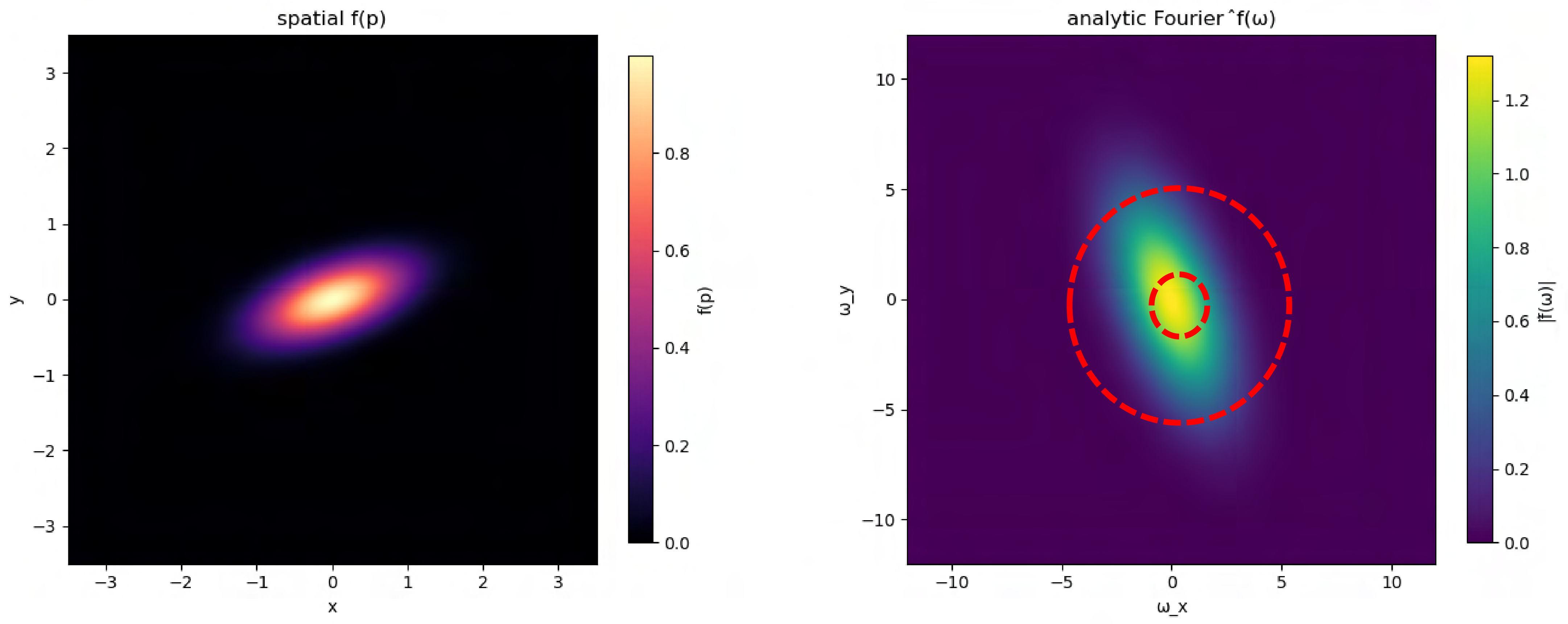

LOD for Primitive Volumes

What do we want to achieve?

- We want to train once, get directly an asset that can we can filter arbitrarily without post processing, in real time
- No extra memory
- Efficient to evaluate and integrate

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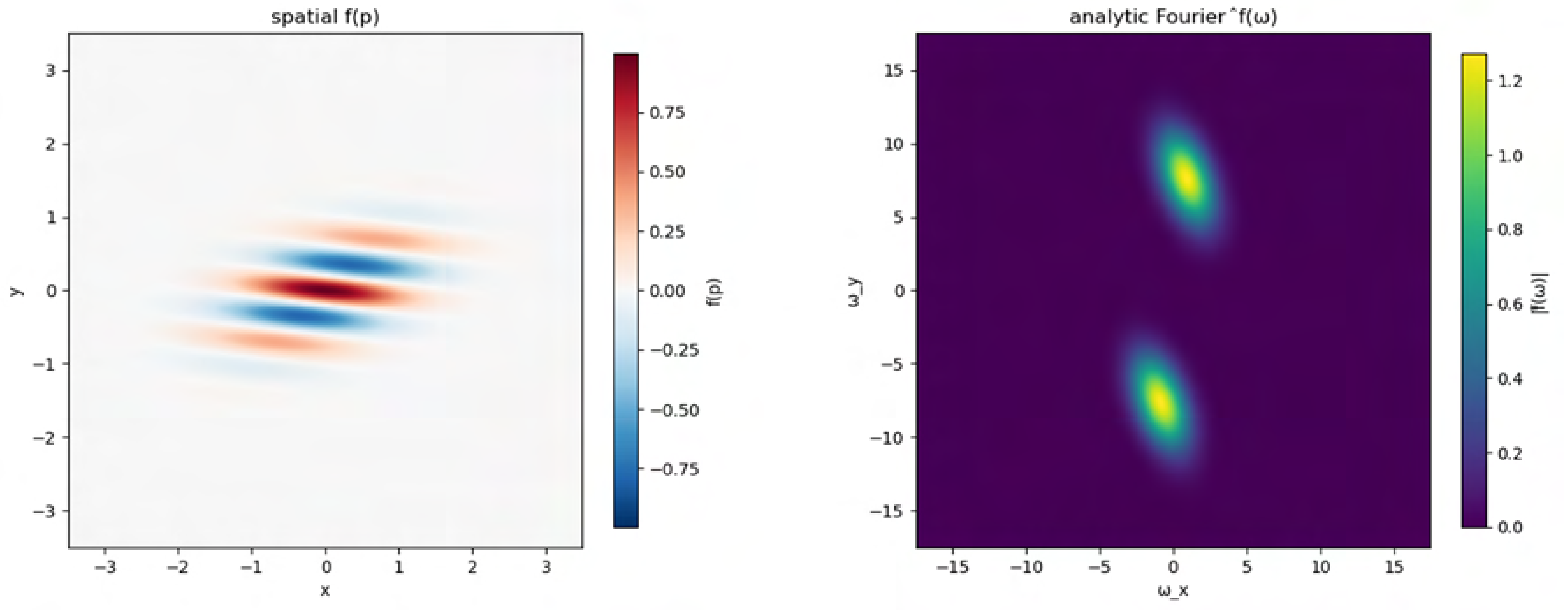
Anisotropic Gaussian Envelope

$$\boxed{e^{-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)}}\boxed{\cos\left(\vec{\omega}^T(x-\mu)\right)}$$

Harmonic Modulation

Kernels as Frequency Residuals

- Gabor kernels are defined in specific frequency bands → filtering reduces to deleting part of the volume



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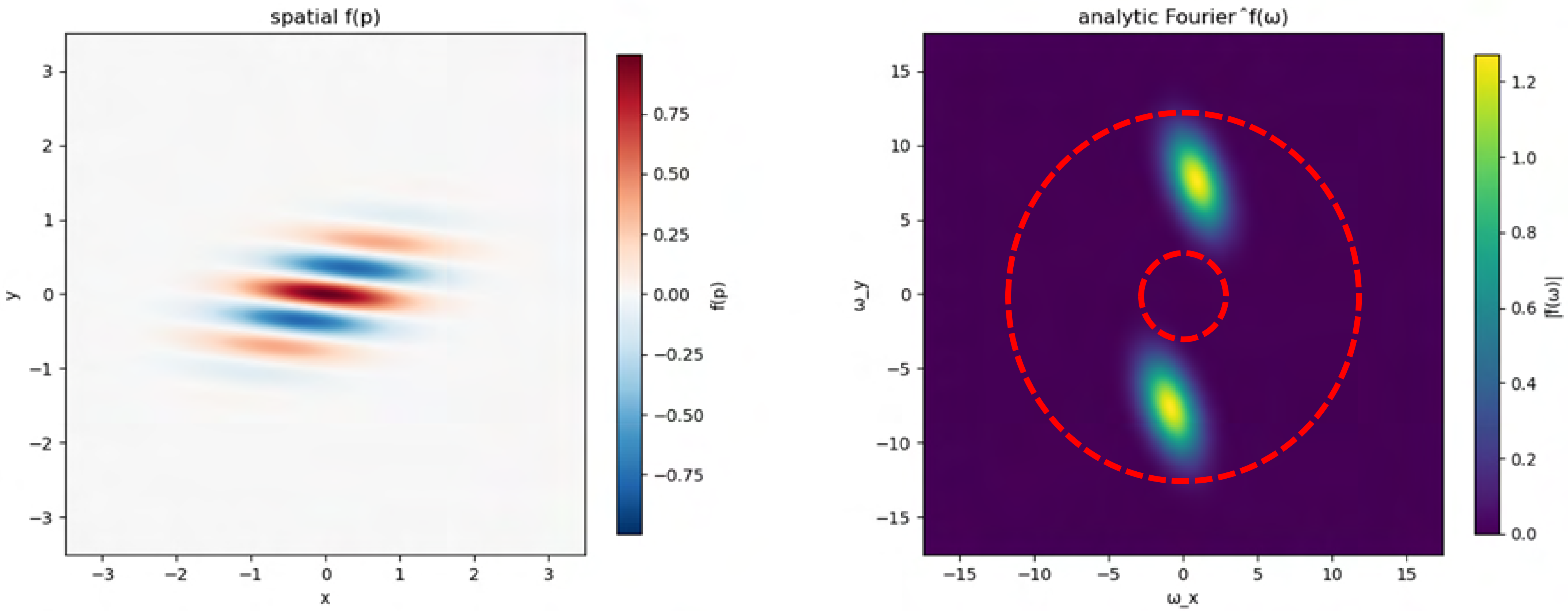
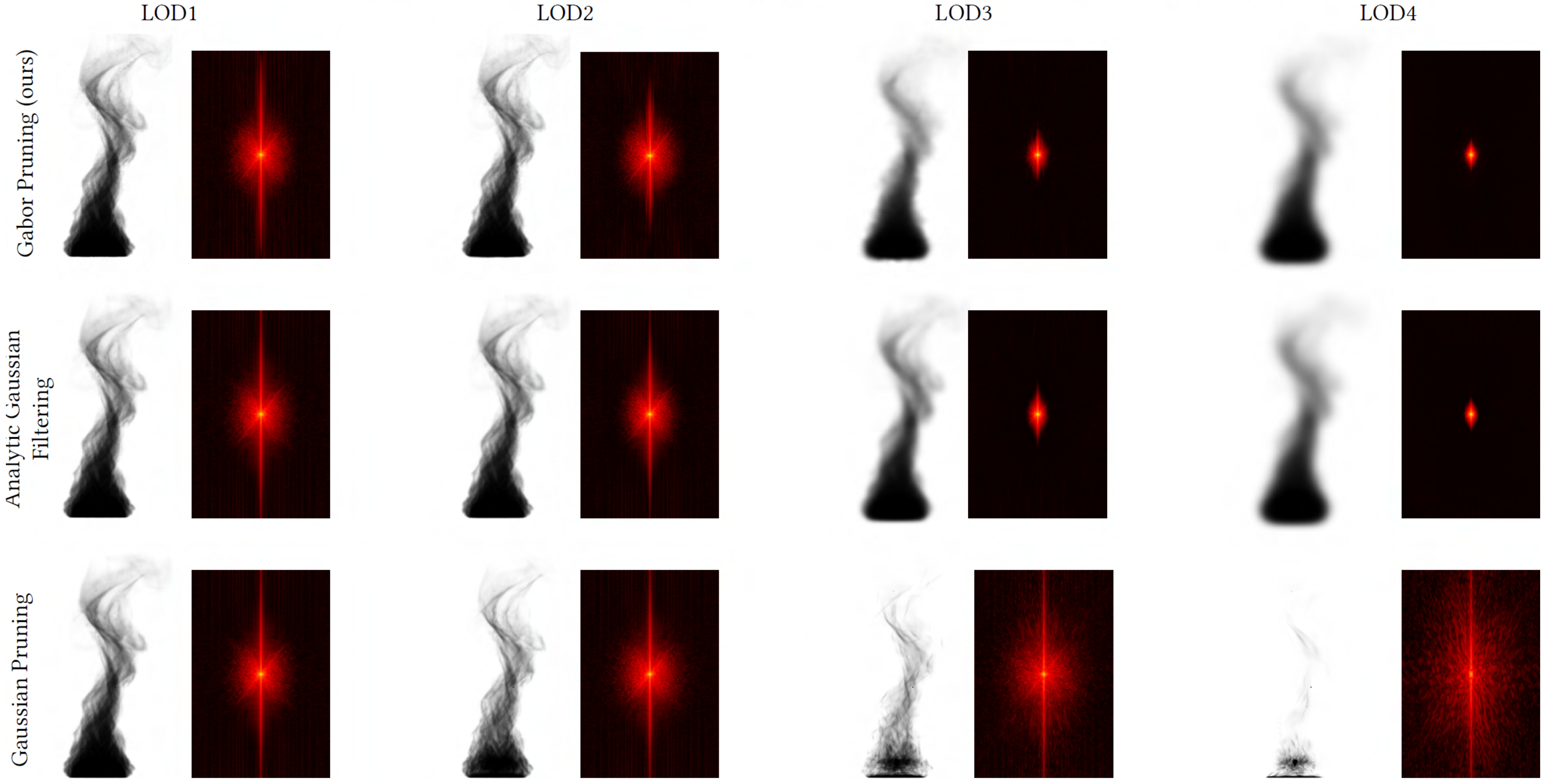


LOD Decomposition Methods: Rendered Images and Log Power Spectra (Frequency Domain)



Gabor Fields

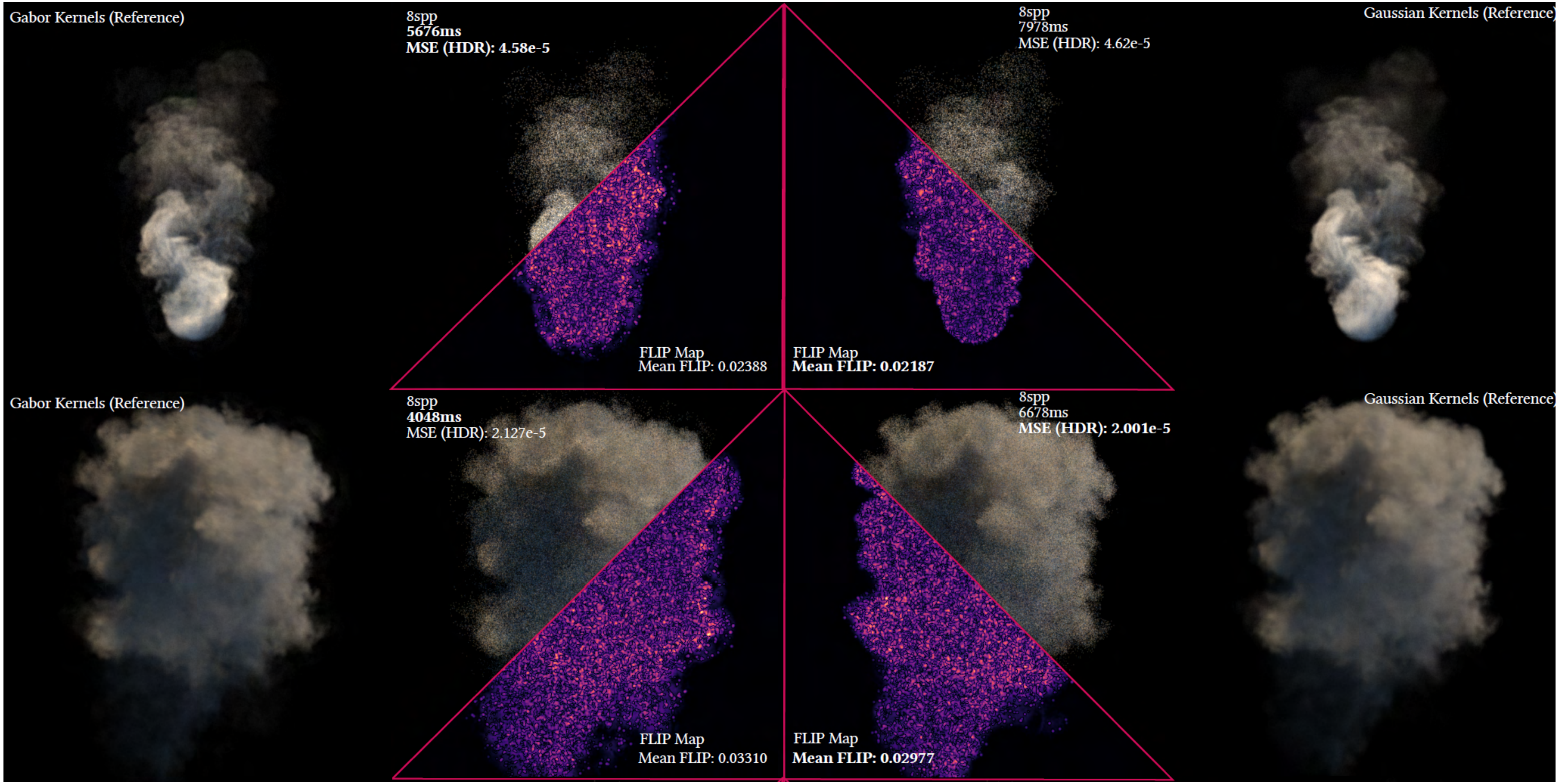
Contributions

- Defining volumes as mixtures of Gaussians (zero-freq. Gabors) and Gabor kernels
- Deriving closed-form line integrals for the full domain and segments
- Analytic Fourier Transforms to filter arbitrarily and continuously
- Stochastic-analytic methods to trade sample cost and variance, accelerating MS
- Implemented using Optix ray masks to accelerate BBVH traversal

Tornado, 32k Gabor kernels

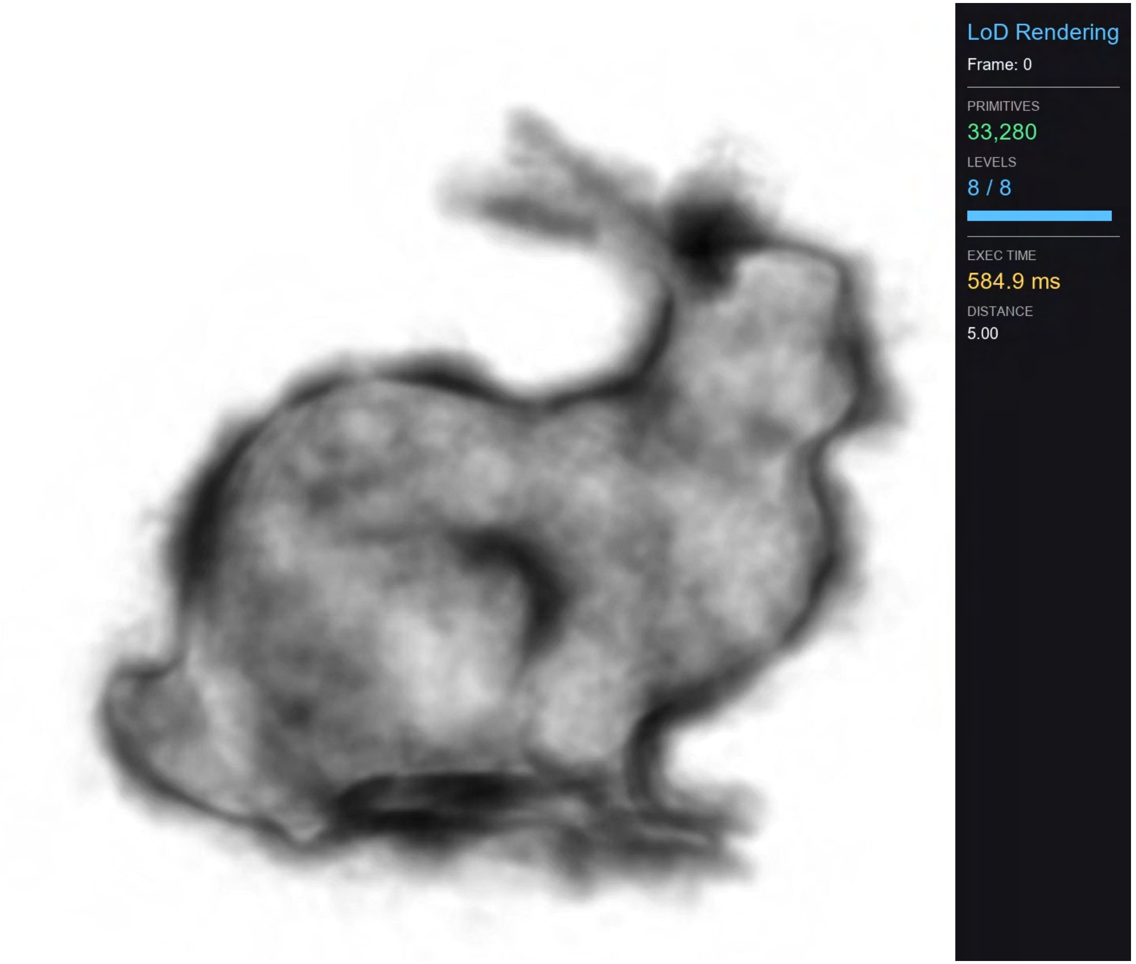
Gabor Fields

Gabor Fields

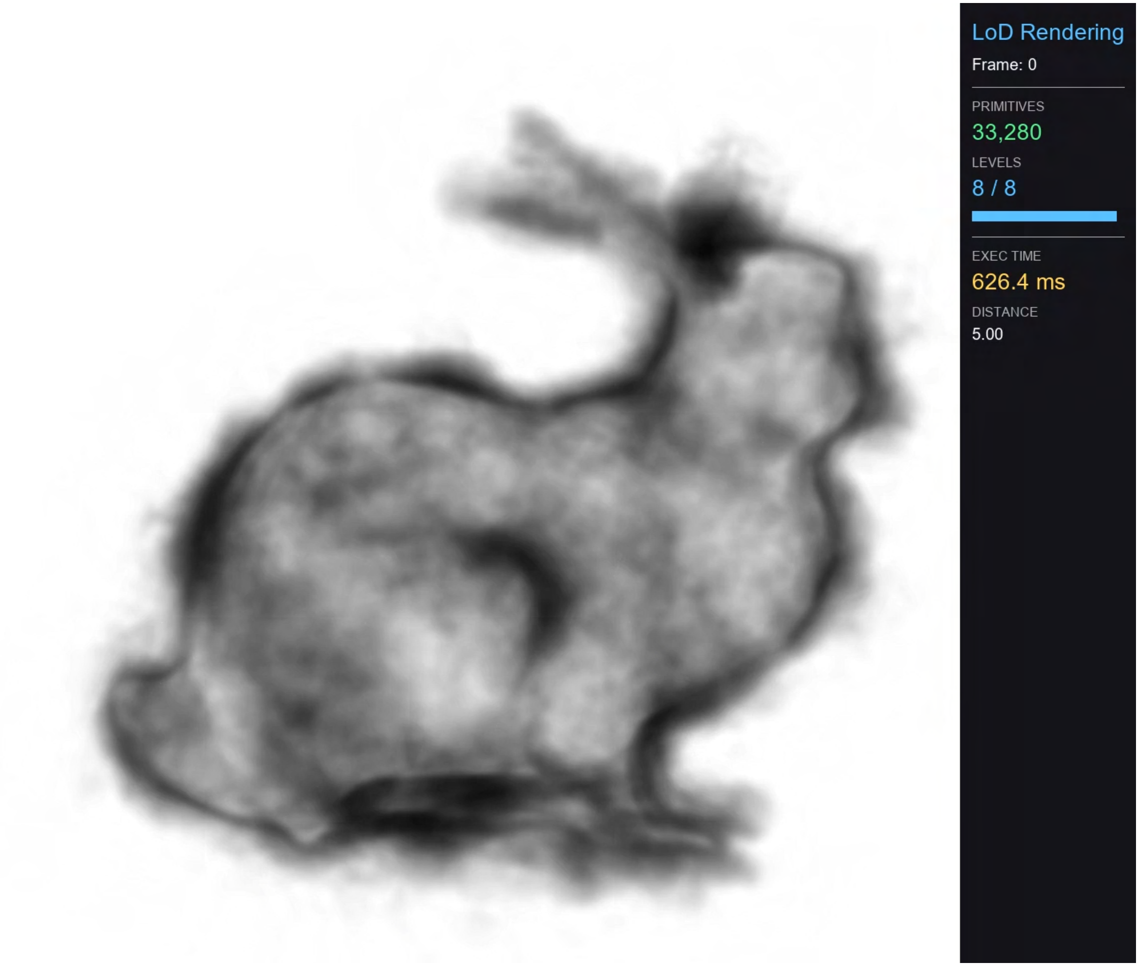


Gabor Fields: LOD

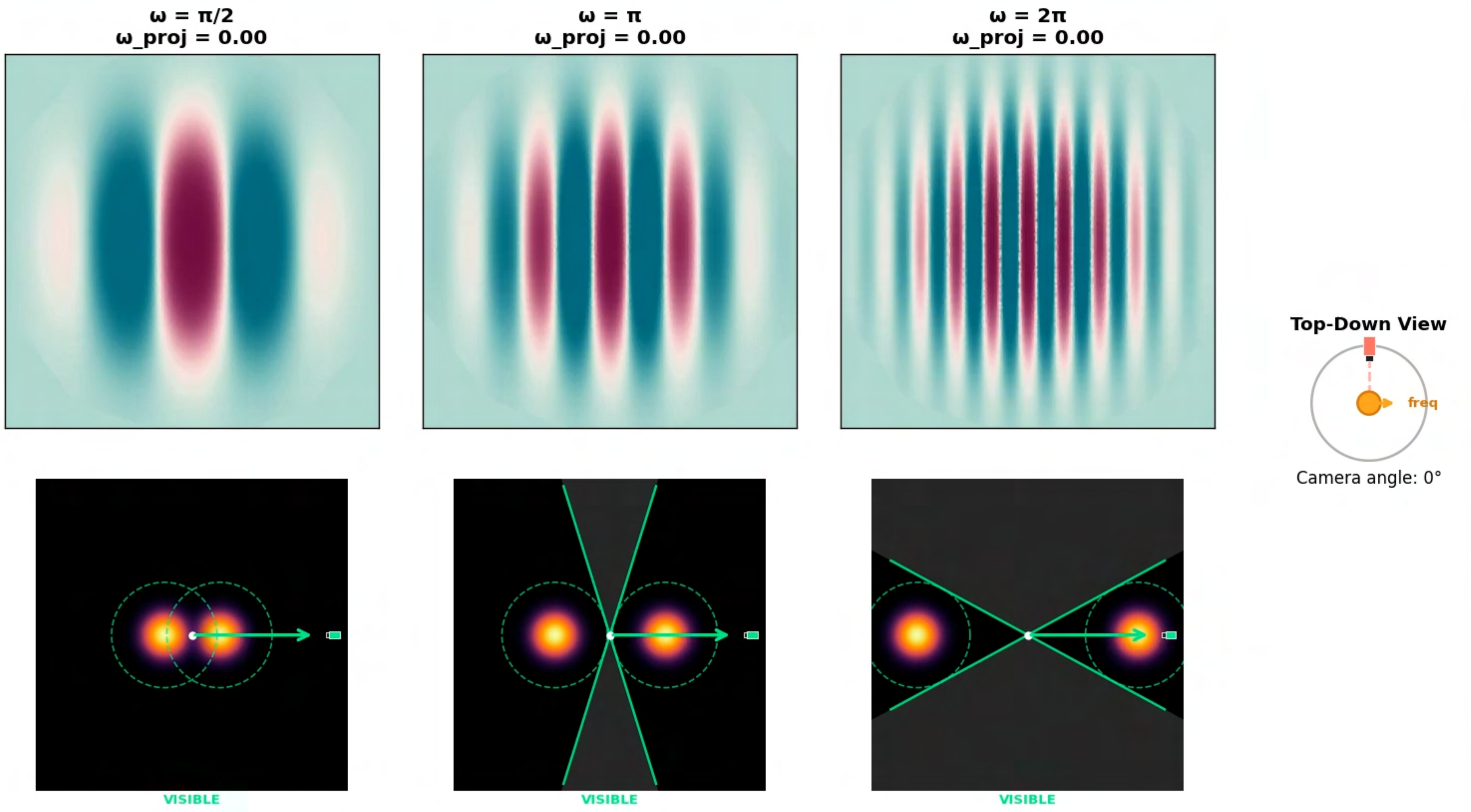
LOD



LOD (static)

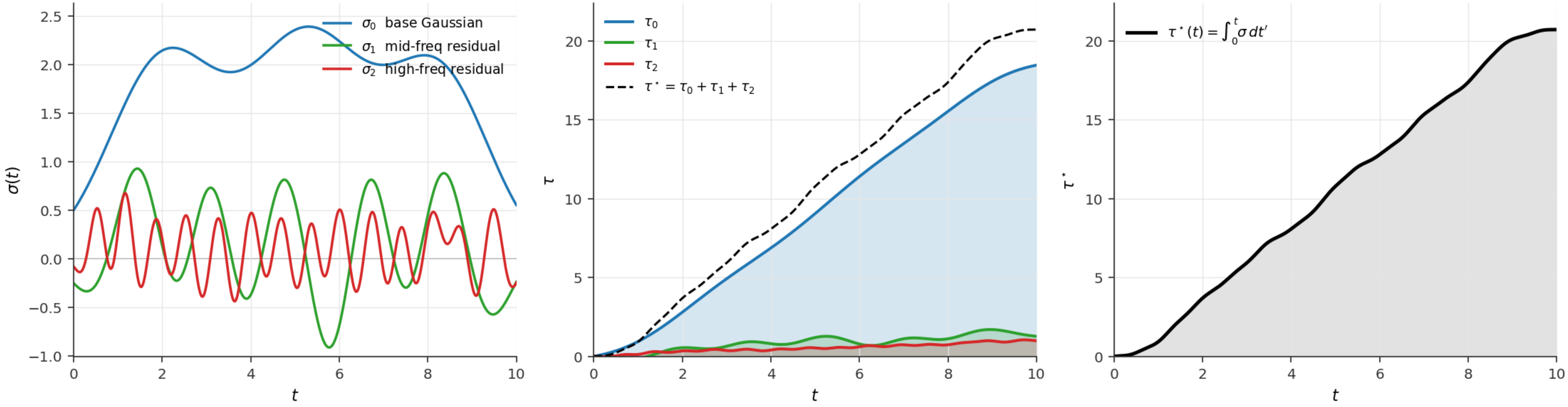


Frequency and Orientation Selectivity in Gabor Fields



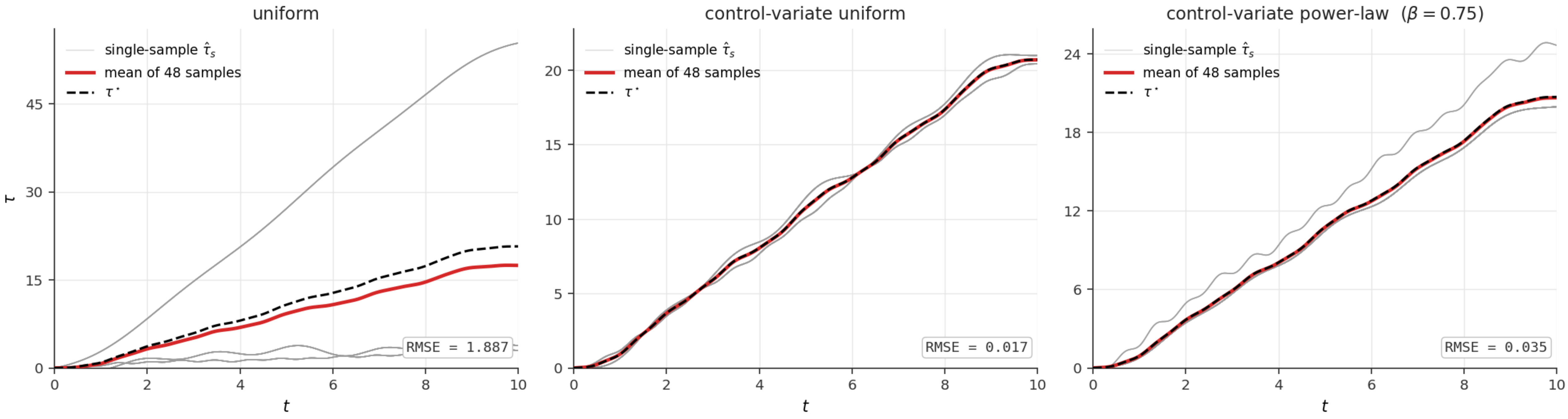
Stochastic-Analytic Estimators

Can we use the frequency properties of Gabor kernels to further reduce sample cost?



Stochastic-Analytic Estimators

Sampling from frequency levels

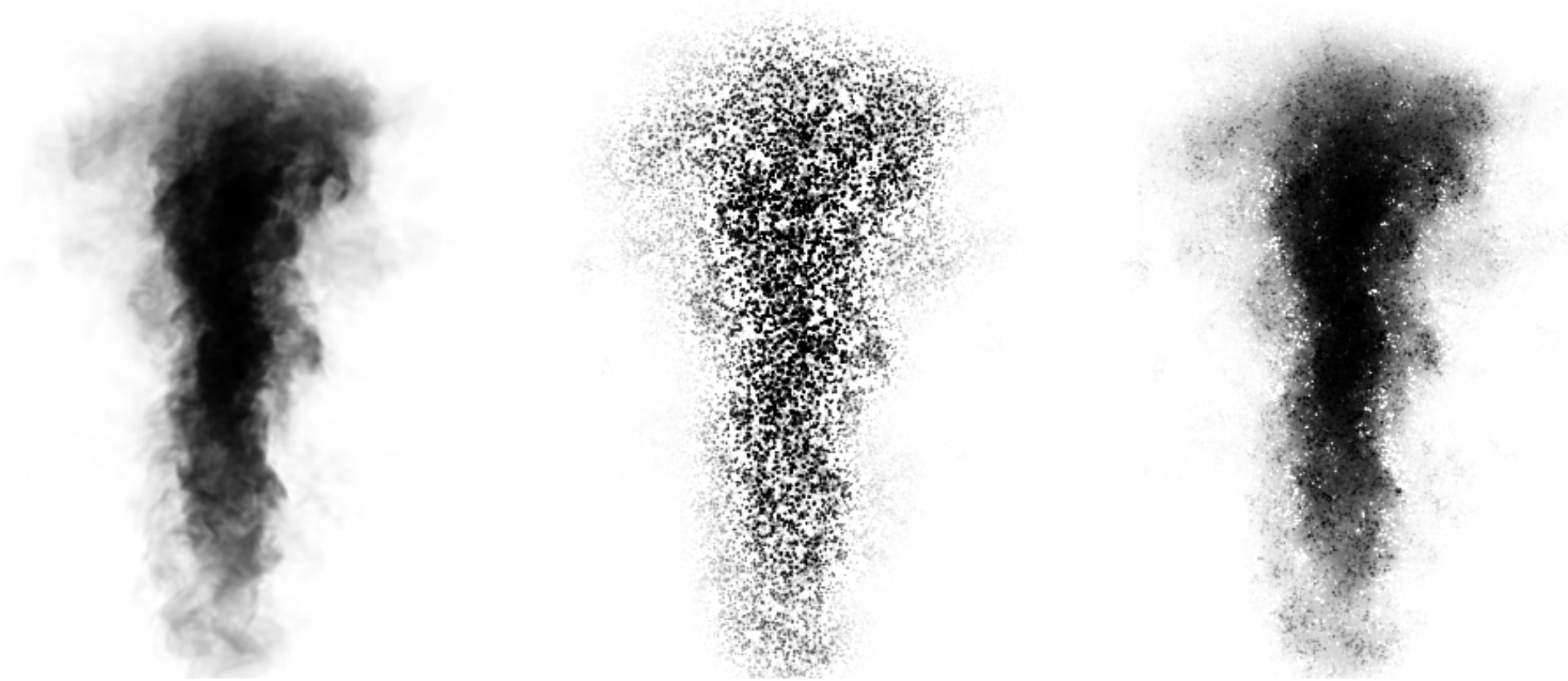


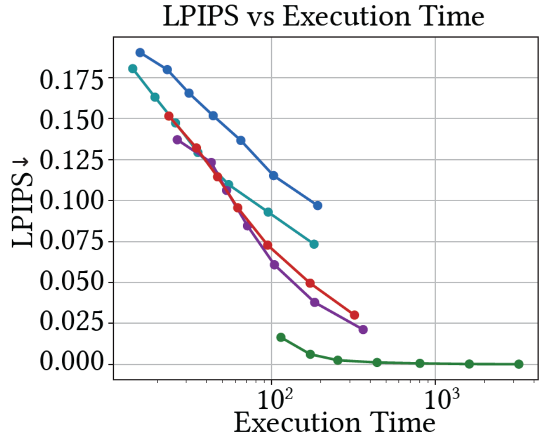
Stochastic-Analytic Tomography with Gabor Fields

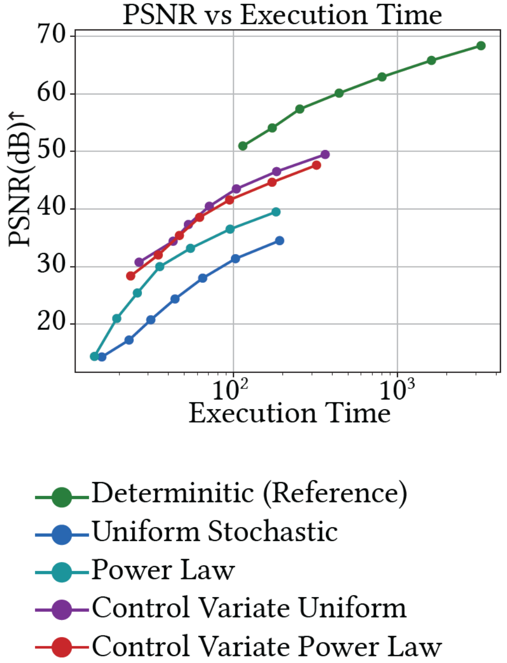
Reference

Uniform Sampling (1spp)

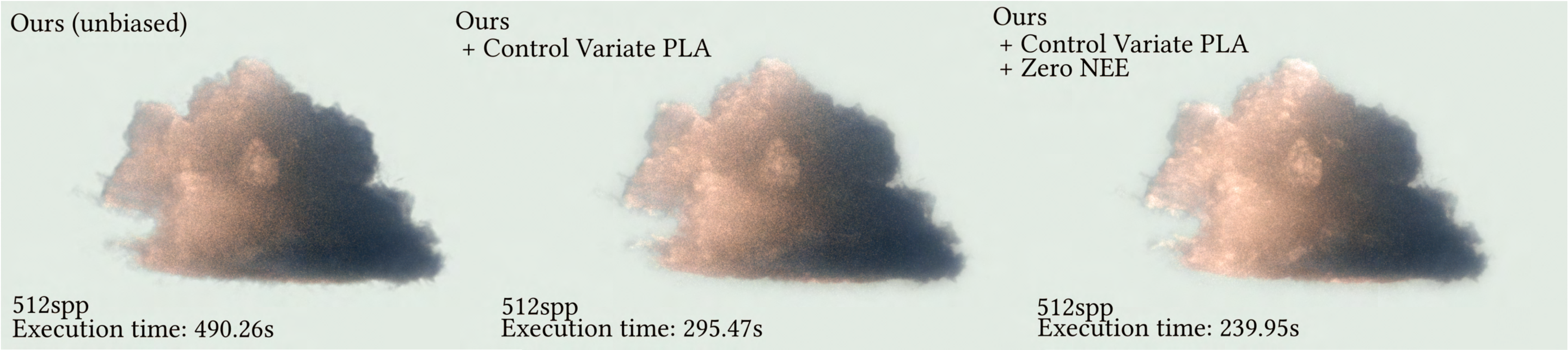
Control Variate
Power Law (1spp)



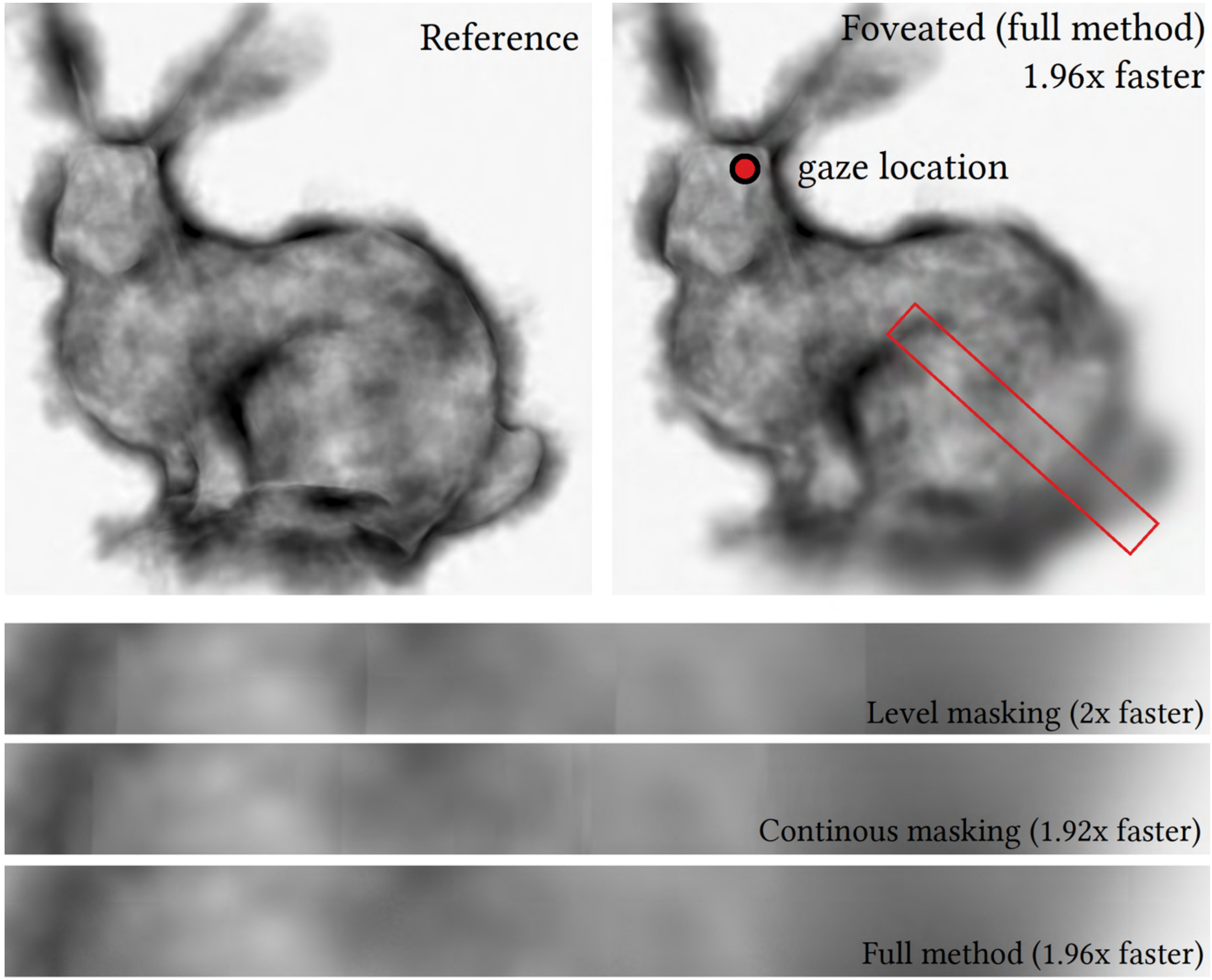




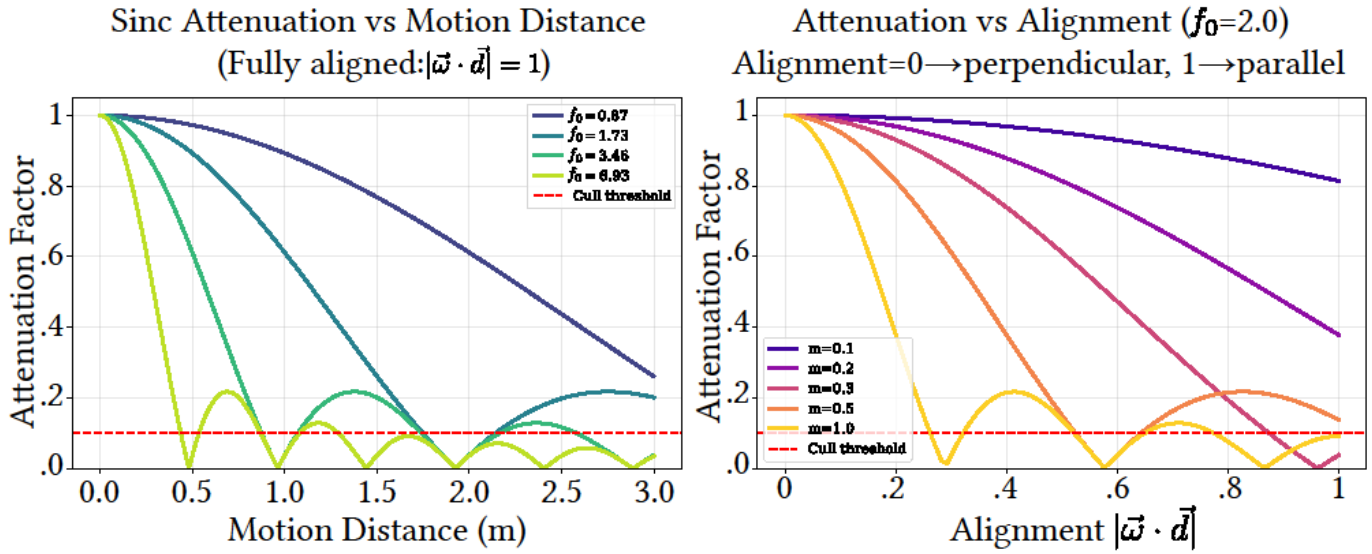
Stochastic-Analytic Path Tracing with Gabor Fields



Foveated Rendering with Gabor Fields



Efficient Motion Blur with Gabor Fields



Limitations, Future Work

- Primitive volumes are still expensive to render for many overlapping primitives

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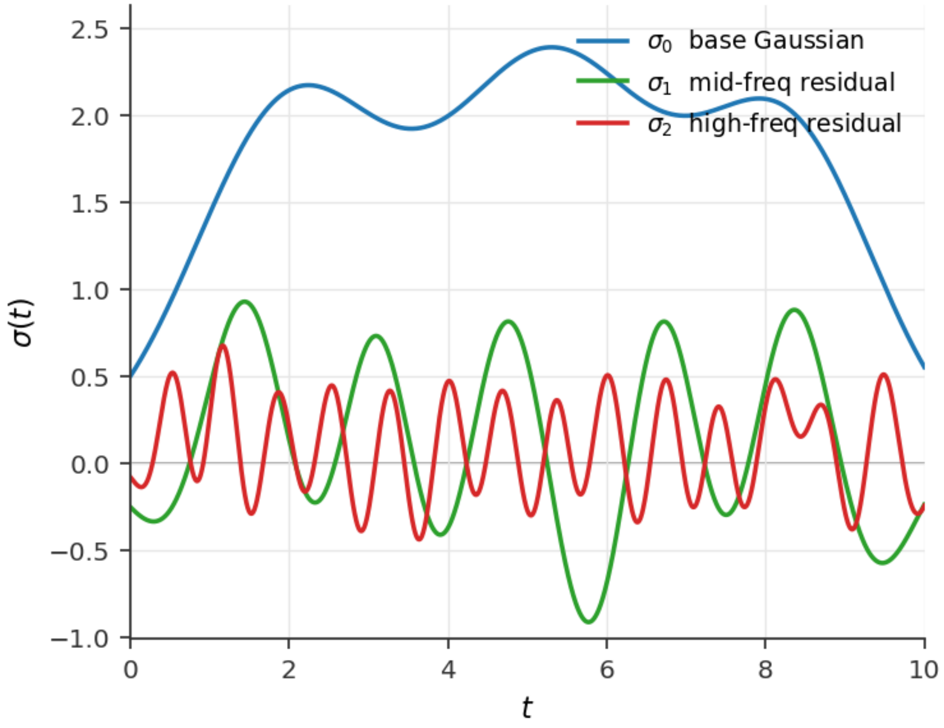
- Gabor kernels can be loosely interpreted as the harmonics composing local density field signals
- Can we lift this to higher dimensions and use it for scene reconstruction?



Neural Harmonic Textures for High-Quality Primitive-Based Reconstruction

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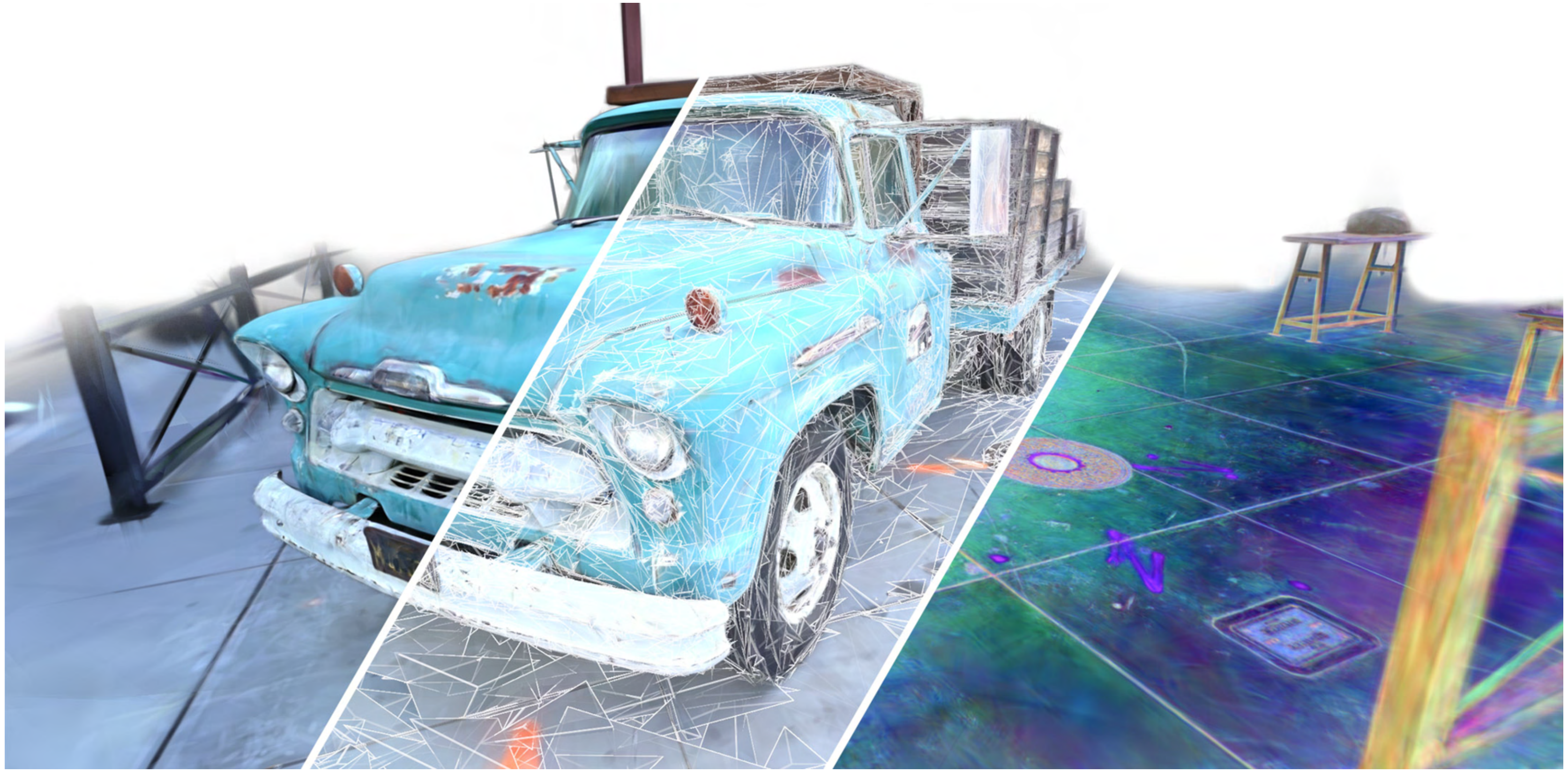
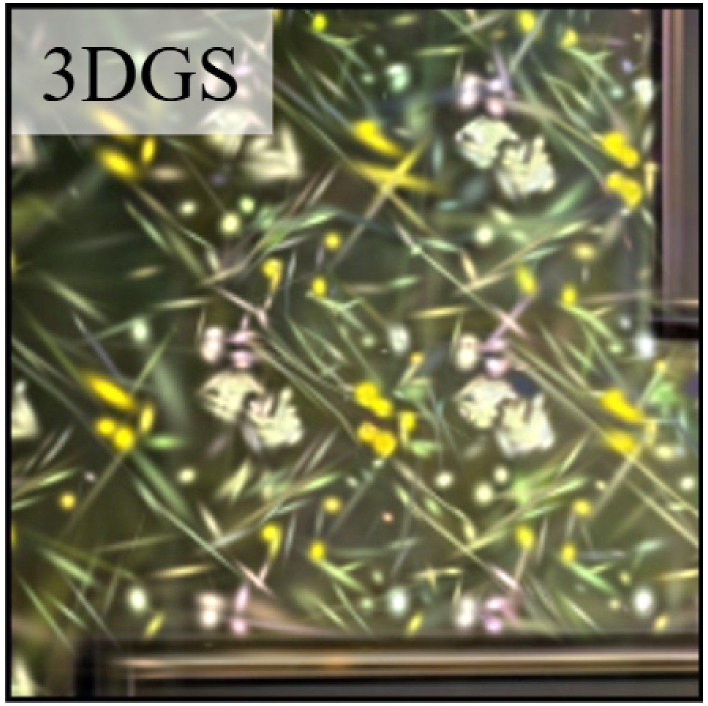


Arxiv'26 (under submission)

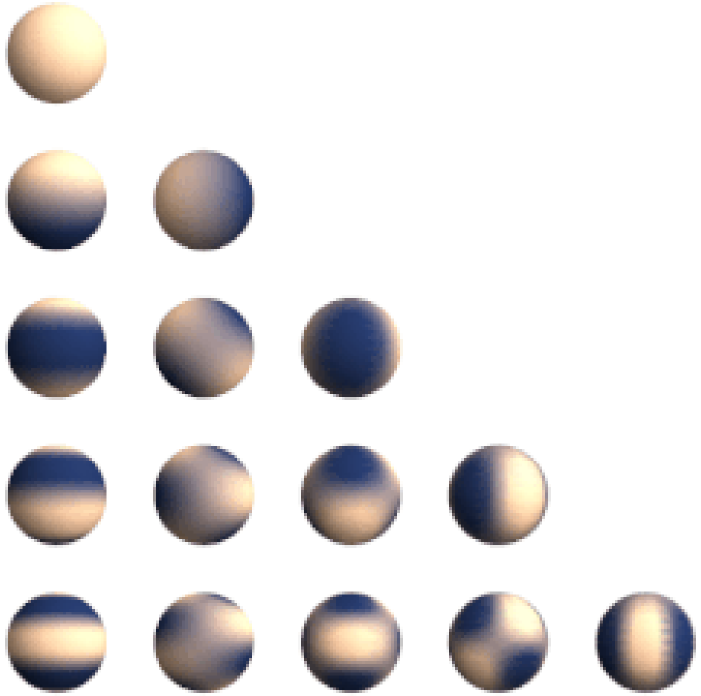
The appearance modeling problem

- 3DGS models appearance and geometry jointly --> this limits fundamentally scalability and detail modelling



Textured Gaussians for Enhanced 3D Scene Appearance Modeling
Chao et. al, CVPR'25

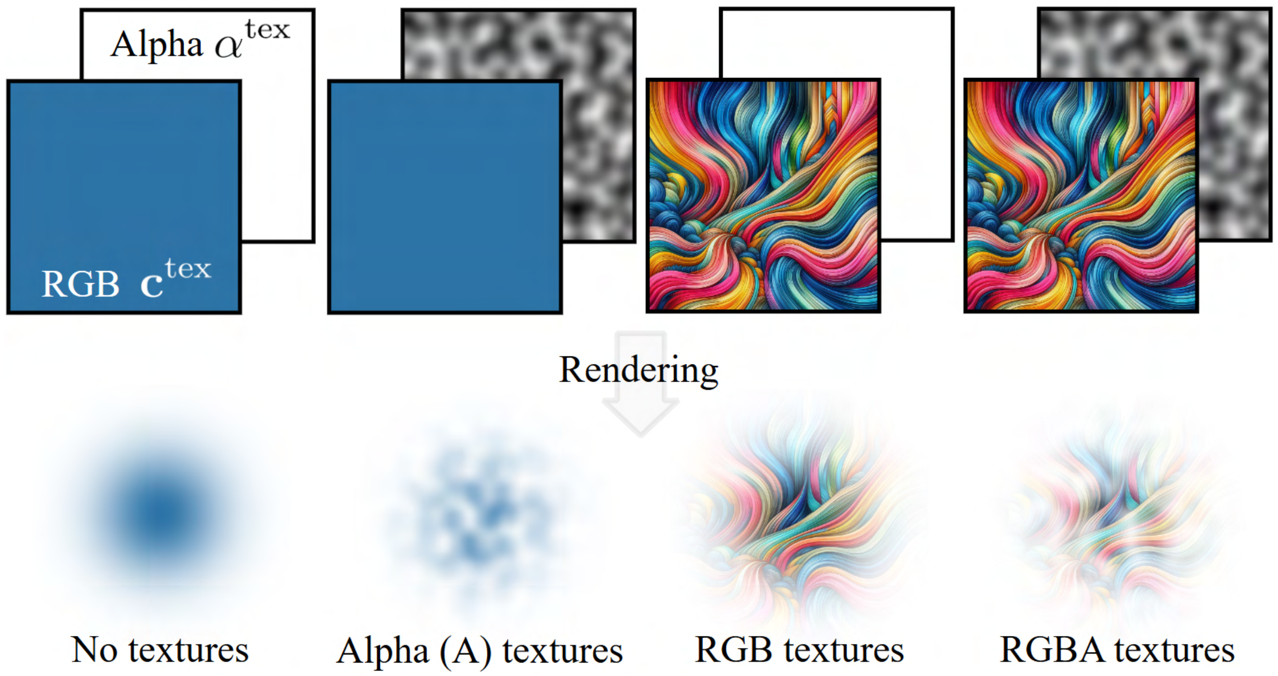
- Limited expressivity of individual Gaussians + frequency-limited SHs



Spherical Harmonics

Towards more expressive appearance models

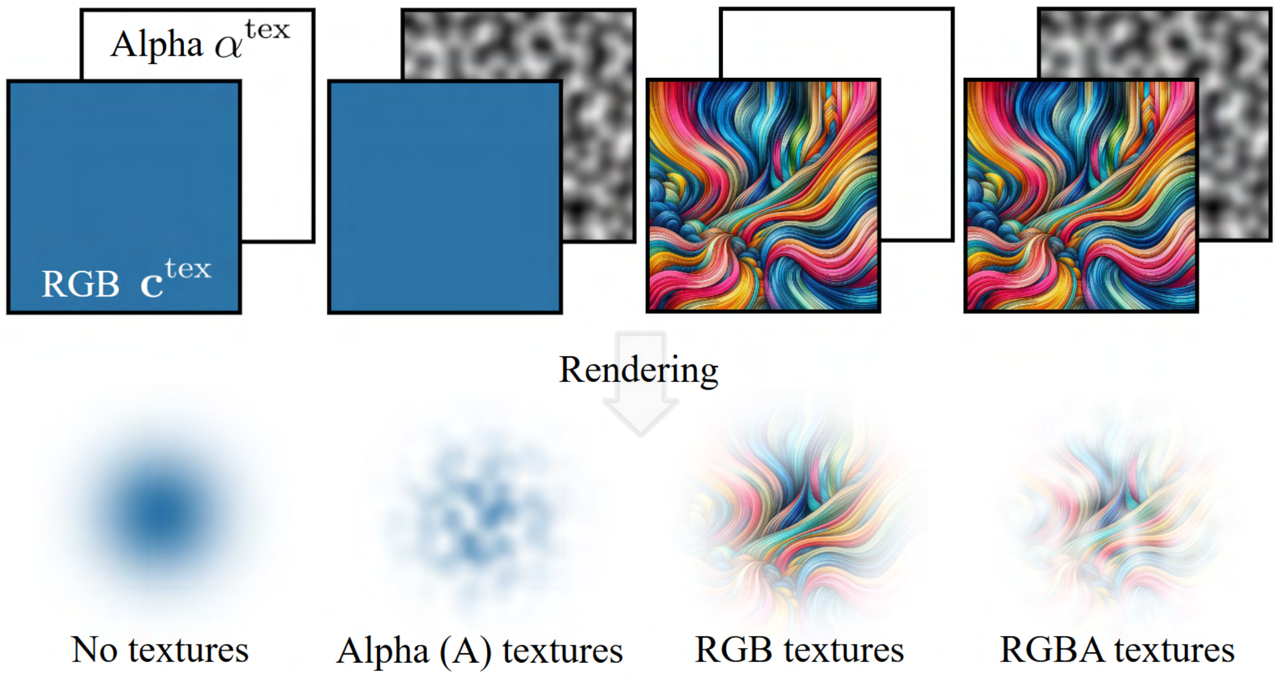
- Previous work:
  - Texturing gaussians
  - Parametric spherical functions (spherical Betas, Voronoi)
  - 3DGS geometry + neural field appearance (radiance meshes, neural shell textures)



Textured Gaussians for Enhanced 3D Scene Appearance Modeling
Chao et. al, CVPR'25

Towards more expressive appearance models

- Previous work:
  - Texturing gaussians
  - Parametric spherical functions (spherical Betas, Voronoi)
  - 3DGS geometry + neural field appearance (radiance meshes, neural shell textures)
- Issues:
  - Complex optimization landscapes
  - Expensive evaluation (heavy textures, excessive MLP queries)
  - Complete detachment of neural features from geometry (geometry scales and moves, but the field does not adapt a: it has its own structure)



Textured Gaussians for Enhanced 3D Scene Appearance Modeling
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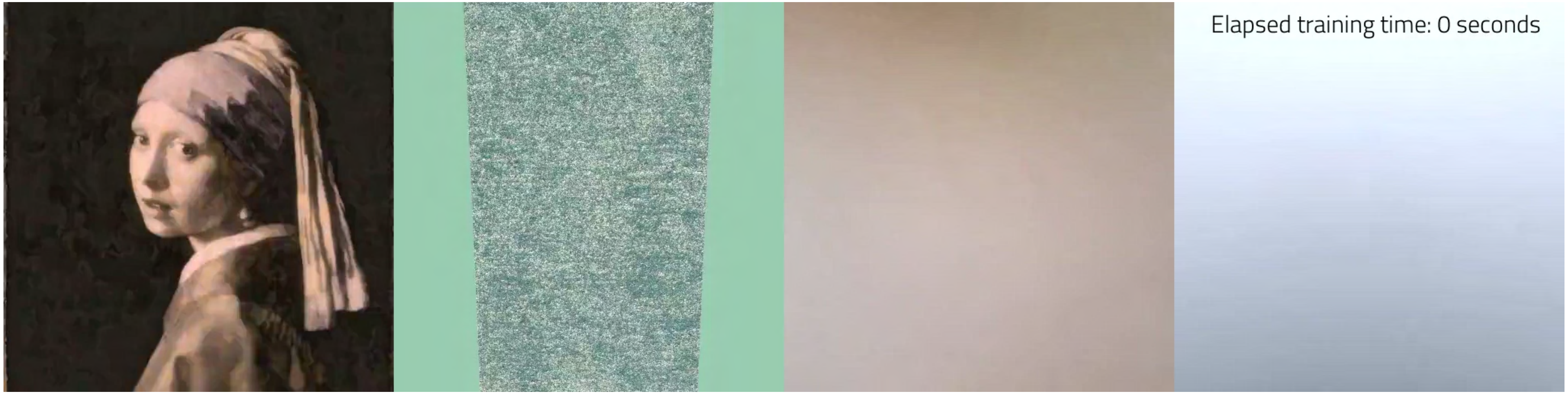
Revisiting Neural Radiance Fields

Neural Fields can be the solution to these problems!

- Can pool information across the scene (if using global fields)
- Detach the geometry/3D encoding structure from the appearance
- More expressive
  → They can model signals of arbitrary frequency (no freq. banding)

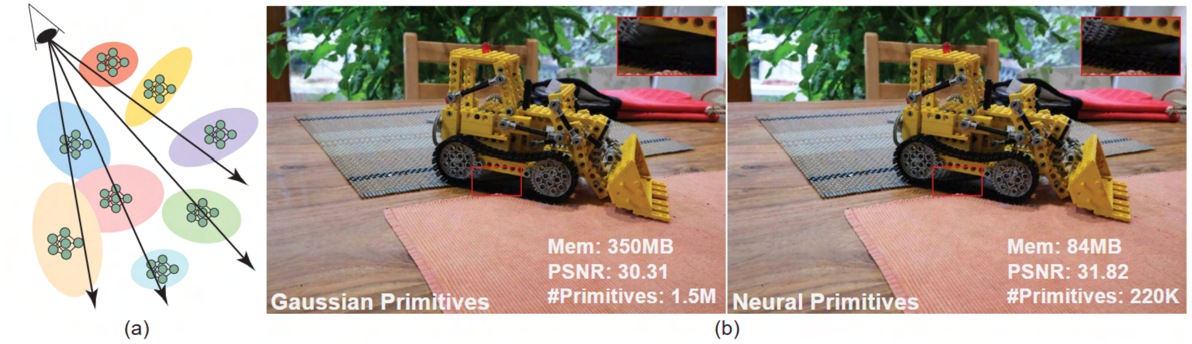


Instant Neural graphics Primitives with a Multiresolution Hash Encoding. Müller et al. SIGGRAPH'22

Lifting Primitive Appearance Through Neural Fields

Can we preserve the benefits of volumetric primitives?

- A) Each primitive is its own Neural Field



Splat the Net: Radiance Fields with Splattable Neural Primitives. Zhou et. Al. ICLR’26

- B) Primitives are geometry, a globally-supported Neural Field handles appearance

Radiance Meshes for Volumetric Reconstruction. Mai. et. al. CVPR’26

Lifting Primitives Through Neural Fields

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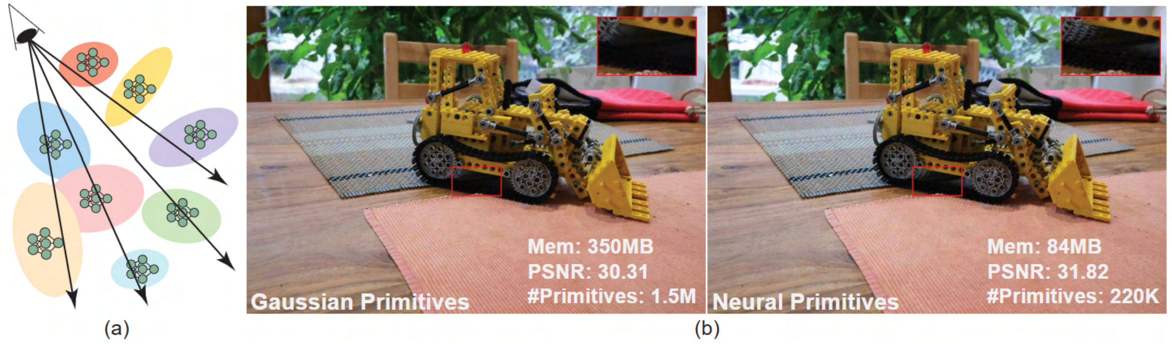


Splat the Net: Radiance Fields with Splattable Neural Primitives. Zhou et. Al. ICLR'26

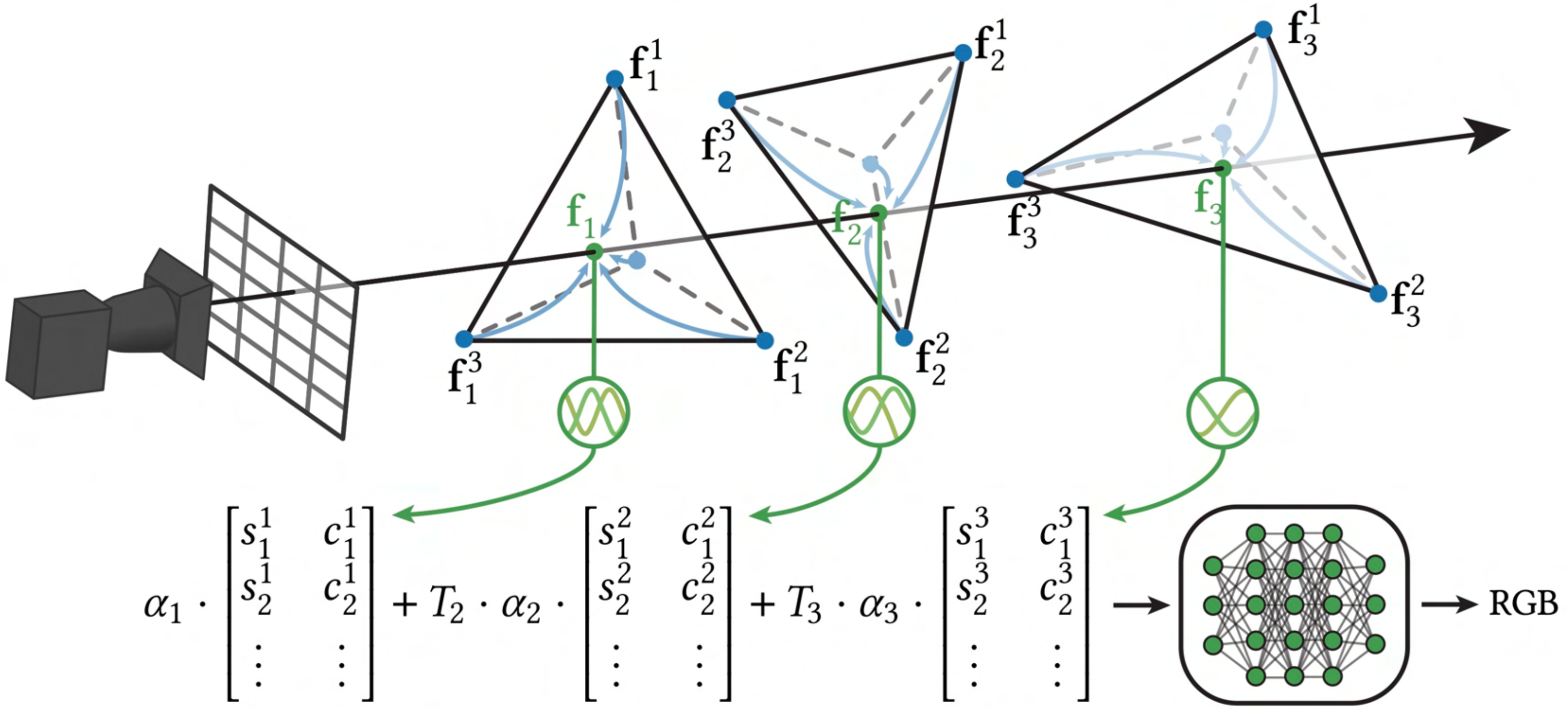
Radiance Meshes for Volumetric Reconstruction. Mai. et. al. CVPR'26

- Very complex optimization landscape
- Expensive closed integration

- Bad scalability
- Subpar quality (related to scalability)
- Expensive (dozens of MLP queries per pixel)
- Cannot easily support motion without baking

Neural Harmonic Textures: Overview

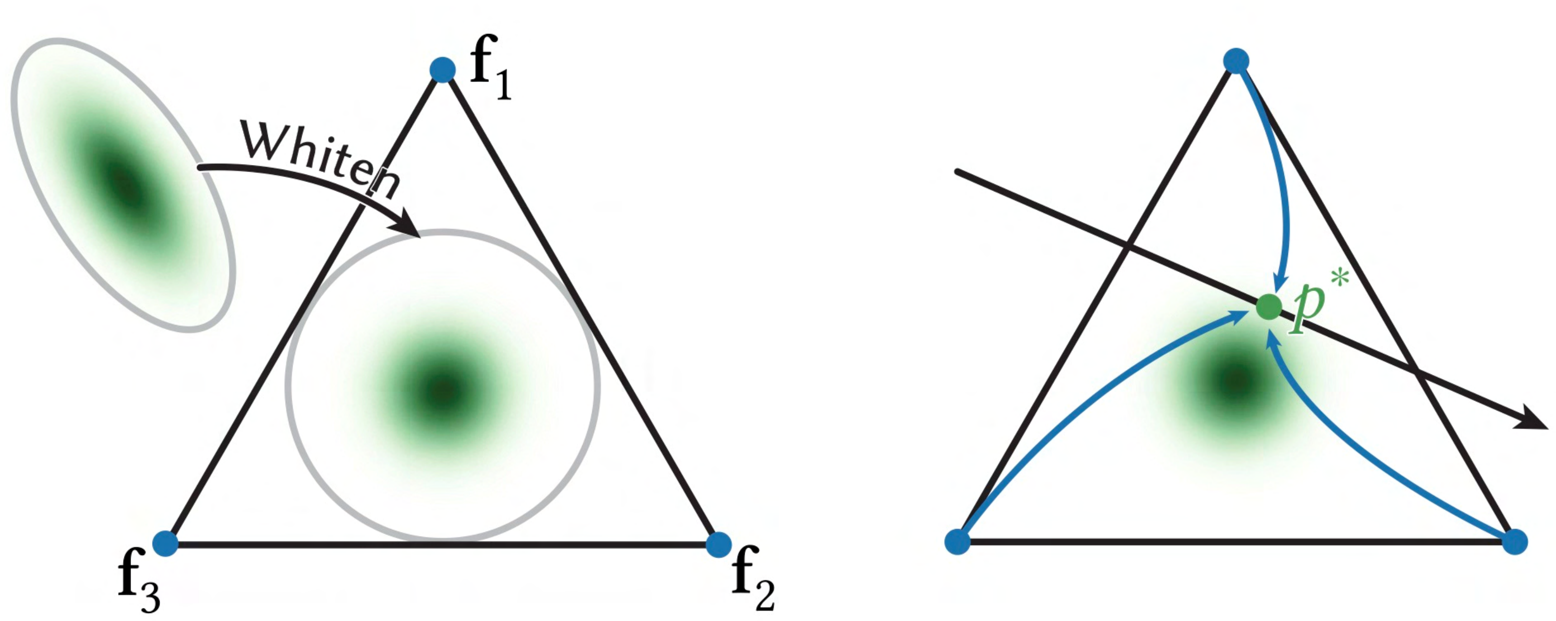
1) 3D Gaussians as both geometry and local fields
2) Harmonic Texturing
3) Neural Deferred Shading



Neural Harmonic Textures

Primitives as local fields

- Virtual tretrahedron defines a local field
- Each vertex is an N-dimensional feature vector
- Response obtained through interpolation at evaluation point



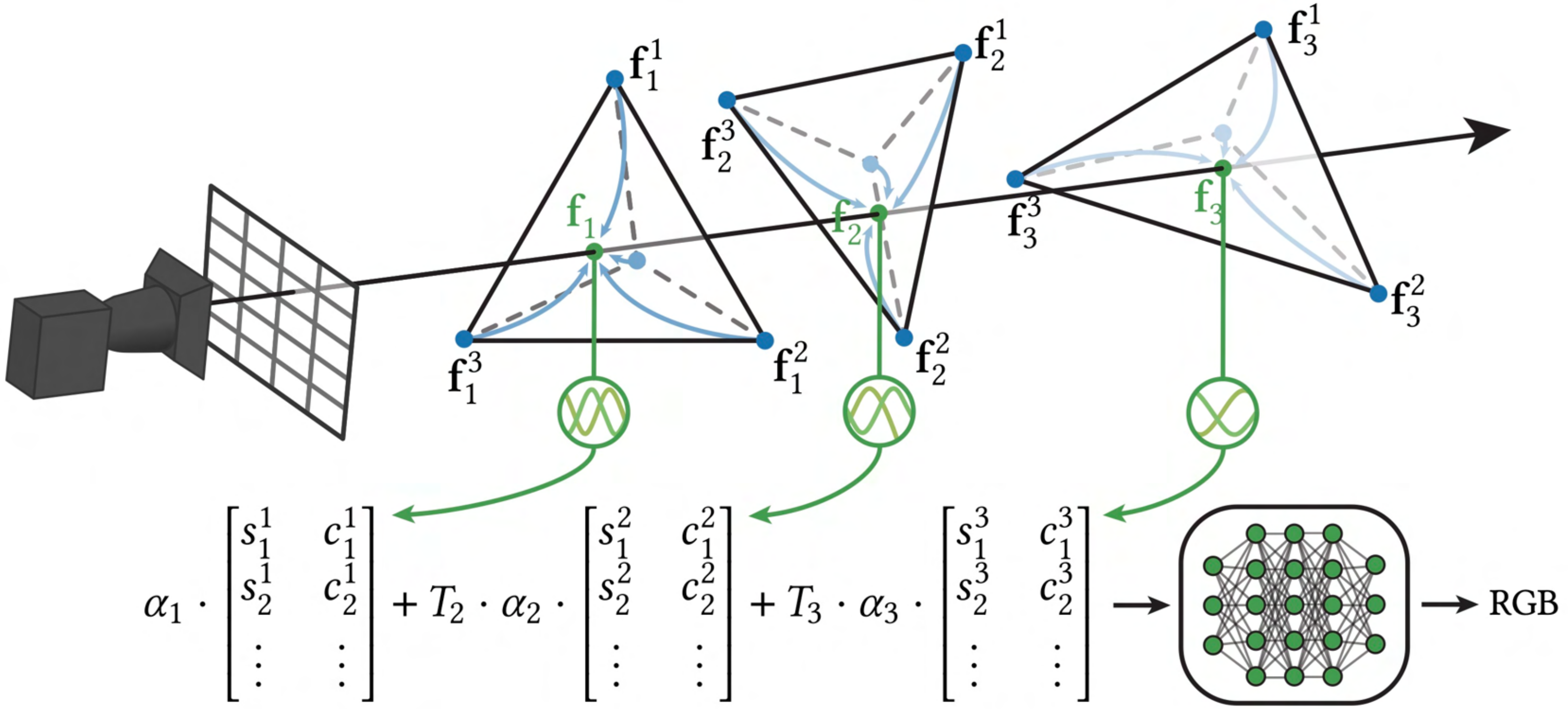
Neural Harmonic Textures: Overview

Neural Deferred Shading with a Shallow MLP

→Efficient implementation in regular engines

→Very fast (single query per pixel)

→Simpler optimization landscape

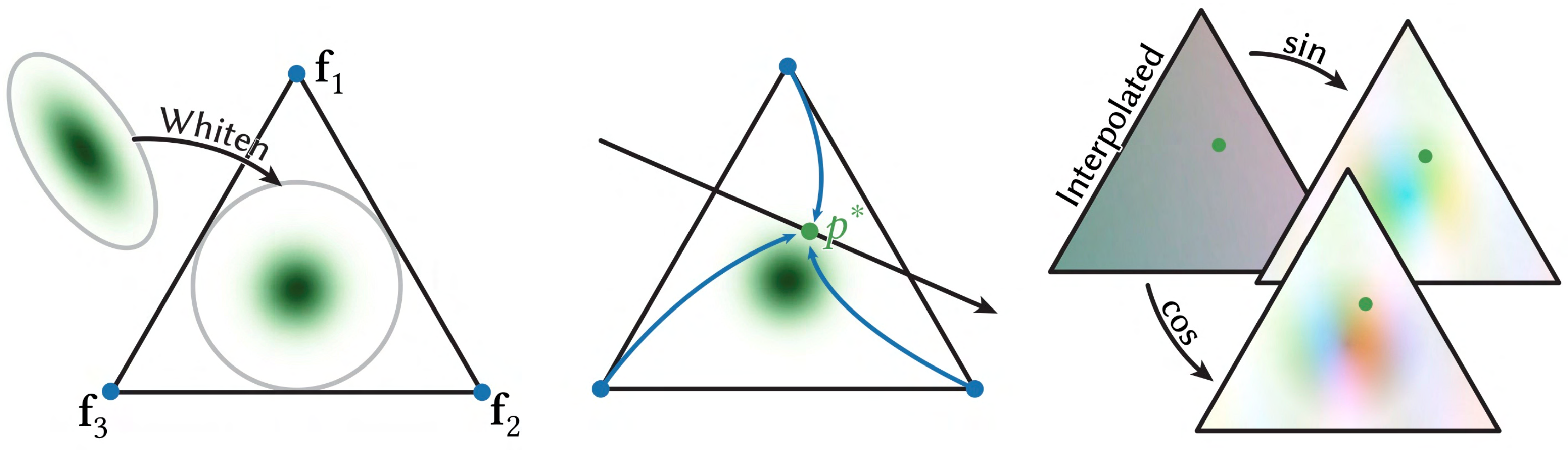


Neural Harmonic Textures

Harmonic Textures

- Encoding response with a harmonic function

  → Analogous to accumulating the harmonics of the signal in Fourier decompositions



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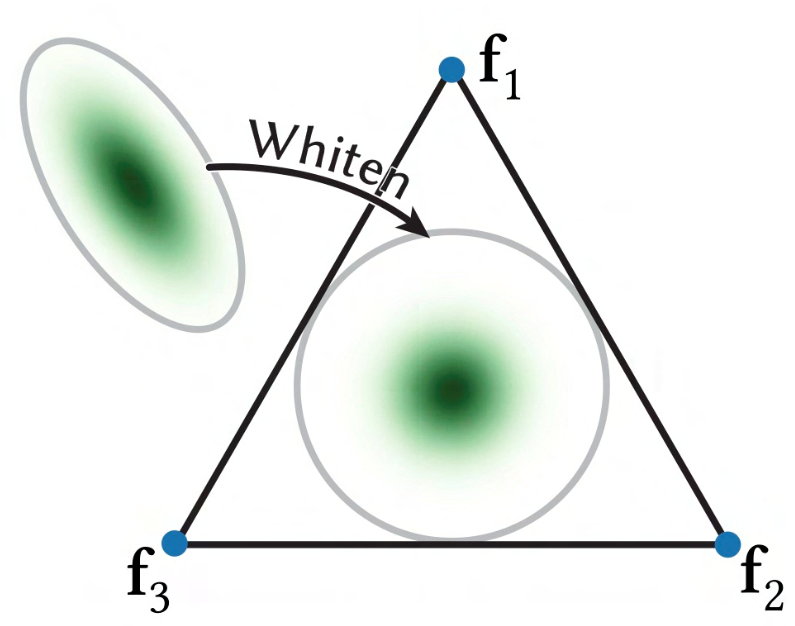
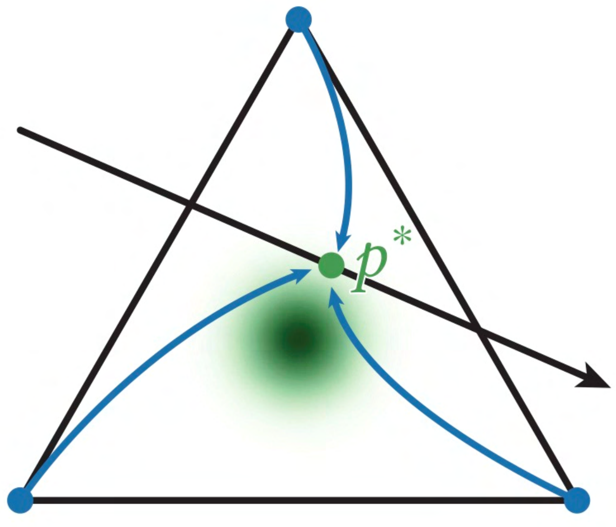
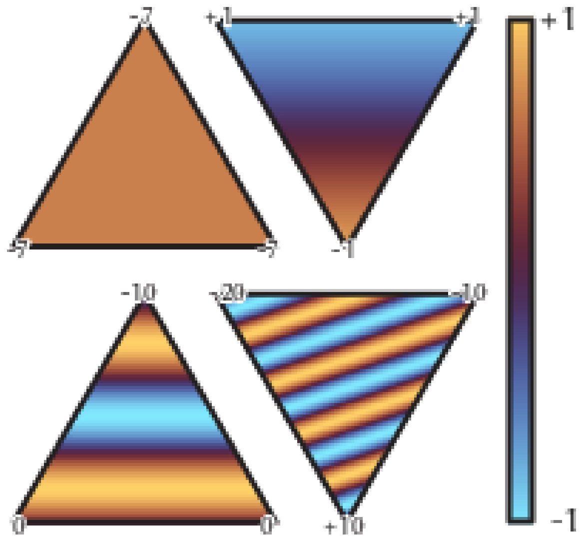


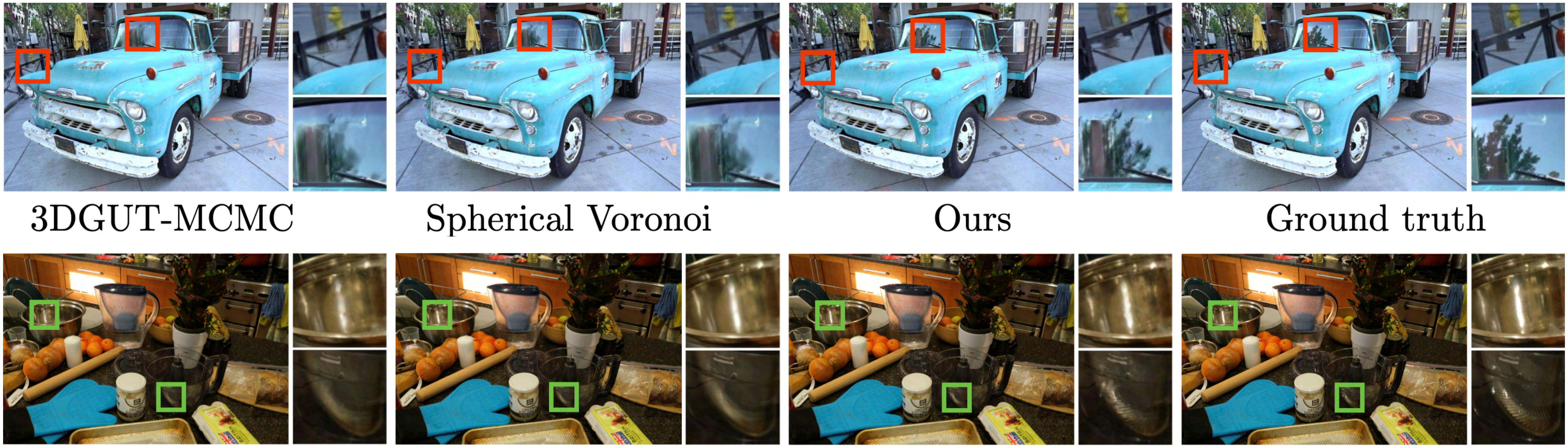




Results

Method	MipNeRF360			Tanks & Temples			Deep Blending		
	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
Instant NGP-Big	25.59	0.695	0.375	21.92	0.740	0.342	24.96	0.815	0.459
Mip-NeRF 360	27.60	0.788	0.275	22.22	0.754	0.290	29.40	0.899	0.306
ZipNeRF	28.55	0.829	0.218	23.64	0.836	0.179	–	–	–
2DGS	27.22	0.804	0.275	22.85	0.827	0.244	29.56	0.904	0.325
3DGS-MCMC	27.99	0.830	0.229	24.46	0.866	0.174	29.49	0.912	0.306
3DGUT-MCMC	27.82	0.826	0.233	24.20	0.861	0.180	29.87	0.913	0.309
Beta Splatting-MCMC	28.12	0.831	0.238	24.54	0.866	0.196	29.56	0.907	0.316
Spherical Voronoi	28.56	**0.835**	0.228	24.80	0.871	0.172	30.34	0.914	**0.299**
Triangle Splatting	27.00	0.808	0.231	23.05	0.843	0.191	28.92	0.891	0.308
Textured Gaussians	27.35	0.827	–	24.26	0.854	–	28.33	0.891	–
NeST	26.54	0.776	0.260	–	–	–	–	–	–
Radiance Meshes	27.15	0.810	0.274	23.13	0.851	0.200	29.39	0.901	0.362
Neural Harmonic Textures (Ours)	**28.74**	0.834	**0.216**	**25.68**	**0.882**	**0.141**	**30.94**	**0.919**	0.302

Results



Results: 10k Primitives

Reference

3DGUT-MCMC

PSNR: 23.97dB

SSIM: 0.724

LPIPS (VGG): 0.548

Ours

PSNR: **27.63dB** (+3.7)

SSIM: **0.856** (+0.132)

LPIPS (VGG): **0.410** (-0.138)

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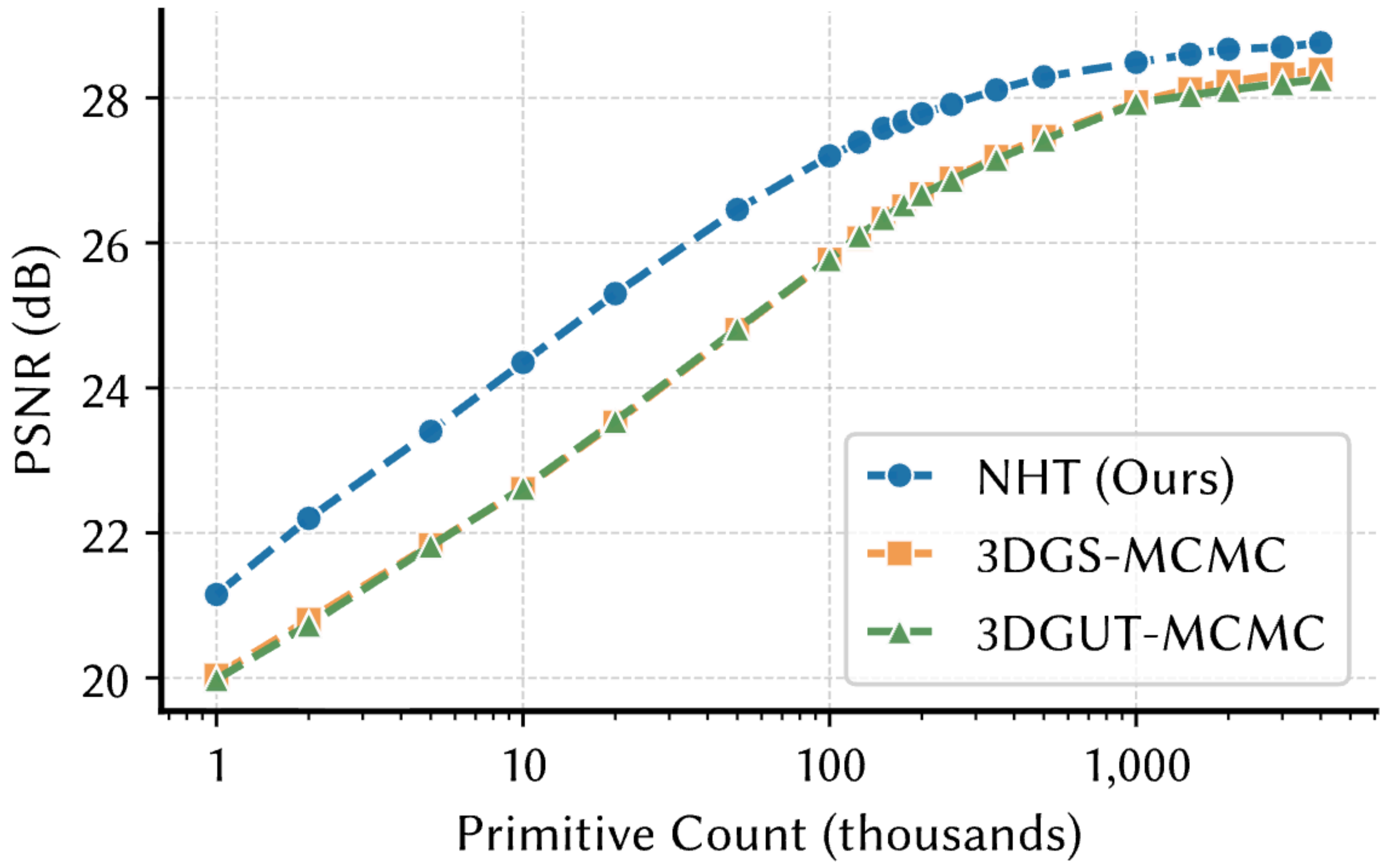
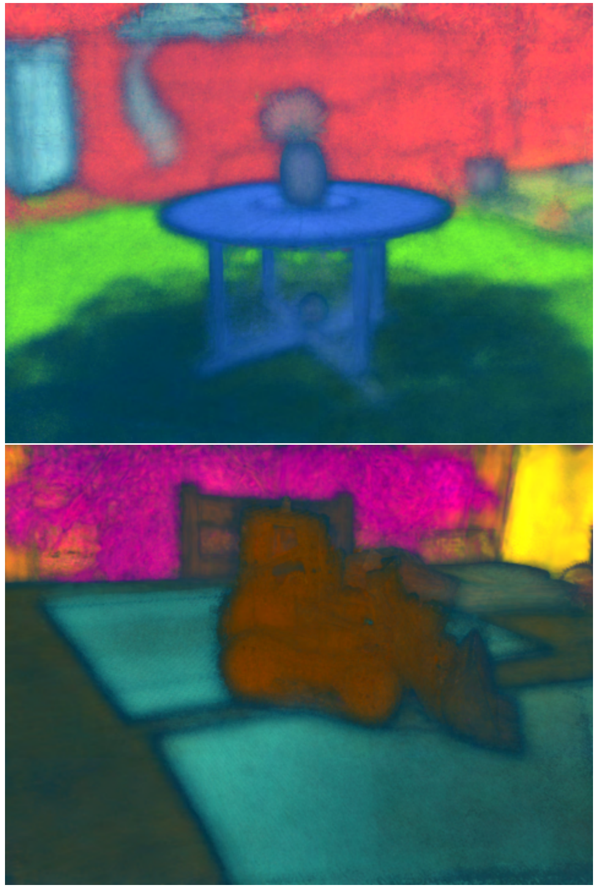
Results: Scalability



Result: Efficient Arbitrary Signal Fitting

Real-time Intrinsic Reconstruction (PBR)

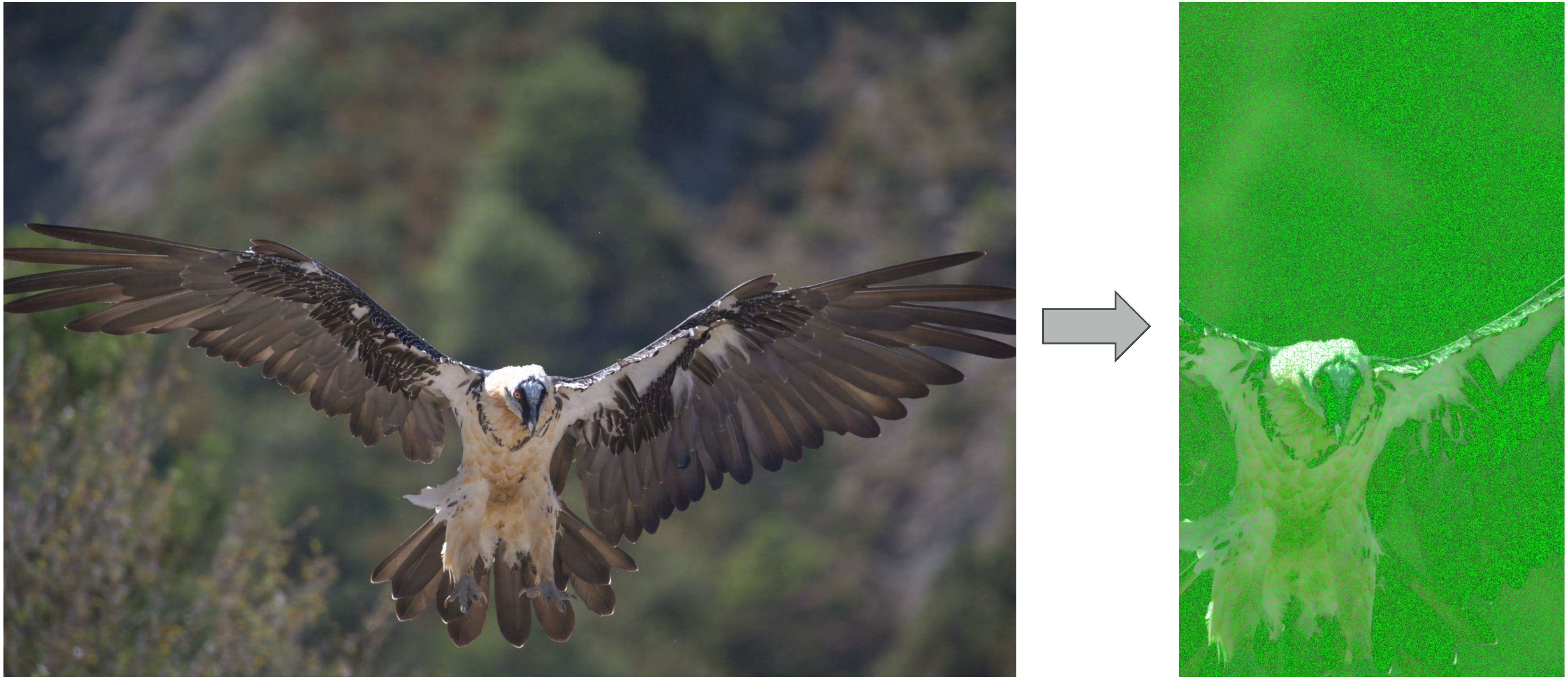


Semantic Reconstruction

(512-dimensional vectors)

Results: 2D HDR Image Regression

Alternative formulation using NHT as a Lagrangian Positional Encoding → Single Opaque, Connected 2D Mesh



Results: 2D HDR Image Regression

Alternative formulation using NHT as a Lagrangian Positional Encoding

Reference (45MP, 14-bit HDR)   Instant NGP (100x)   Ours (100x)

Limitations

- Like all expressive appearance models in scene reconstruction: prone to overfitting in sparse captures
- Slower than 3DGS

	MipNeRF360				Tanks & Temples				Deep Blending			
Method (w/ MCMC)	PSNR↑	SSIM↑	LPIPS↓	FPS↑	PSNR↑	SSIM↑	LPIPS↓	FPS↑	PSNR↑	SSIM↑	LPIPS↓	FPS↑
3DGS + SH	27.94	0.829	0.246	**251**	24.25	0.861	0.188	**294**	29.98	0.912	0.317	**331**
3DGUT + SH	27.93	0.828	0.247	201	23.99	0.859	0.192	245	30.21	0.913	0.318	282
3DGUT + SV	28.15	0.823	0.248	202	24.18	0.861	0.187	242	30.29	0.912	0.320	267
3DGUT + NHT (Ours)	**28.46**	**0.830**	**0.232**	140	**24.79**	**0.875**	**0.169**	226	**30.88**	**0.918**	**0.311**	240

1M primitives, all methods implemented in *gsplat*

Future Work

- Other applications: radiance caching for GI, relighting, downstream applications from having real-time LSEG/DINO features.
- Gradients can now propagate to geometric features from the appearance directly
  - Remove Gaussian kernels
  - Use cheaper primitives (e.g. tetrahedrons)

Reach out!

Facoltà di scienze informatiche

Physically-Based Volume Rendering and High-quality Neural Reconstruction with Volumetric Primitives

Jorge Condor
PhD Student @ USI Lugano, Switzerland

21st April 2026
Saarbrücken, Germany