UCLouvain

# Differentiable Ray Tracing for Radio Propagation

**Private PhD Defense**

Jérome Eertmans

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Jury: C. Craeye (Chairperson), C. De Vleeschouwer (Secretary),
P. De Doncker (ULB), E. M. Vitucci (UniBo), J. Hoydis (NVIDIA)

ICTEAM, Université catholique de Louvain — May 5, 2026

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- RT provides site-specific channel models used for network planning and 5G/6G design.

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Traditional RT
CPU-oriented
Non-differentiable

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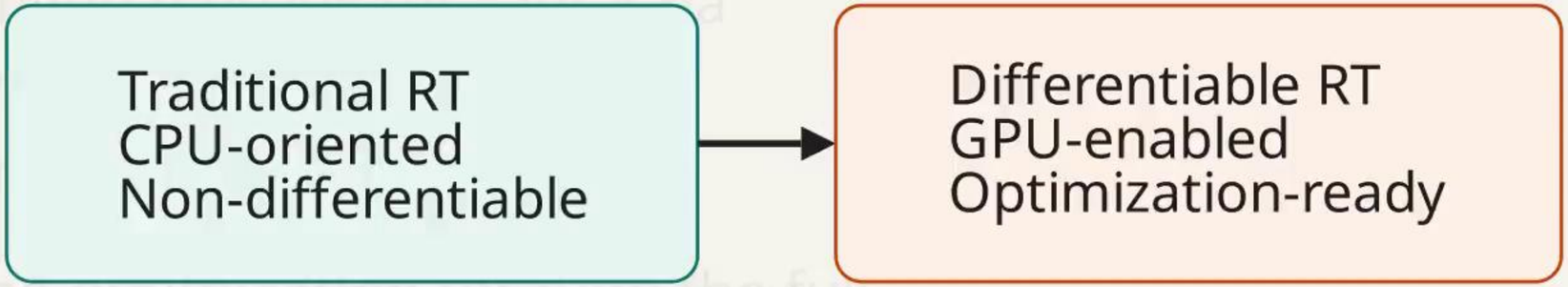

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**This thesis addresses these challenges through three main contributions.**

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**① Smoothing** **② ML Path Tracing** **③ Fermat PT**

# Talk Roadmap

1. Context & Motivation
2. Smoothing Technique (EuCAP 2024)
3. ML-Based Generative Path Tracing (ICMLCN 2025)
4. Fermat Path Tracing (EuCAP 2026)
5. Conclusion & Future Directions

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- Unified parametrization: x_i = A_i t_i + b_i (same tensor layout for all types).

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- Foundation for all subsequent contributions.

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- Trade-off: smoothing parameter controls accuracy vs. differentiability.

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- Potential for real-time inference on GPU with learned weights.

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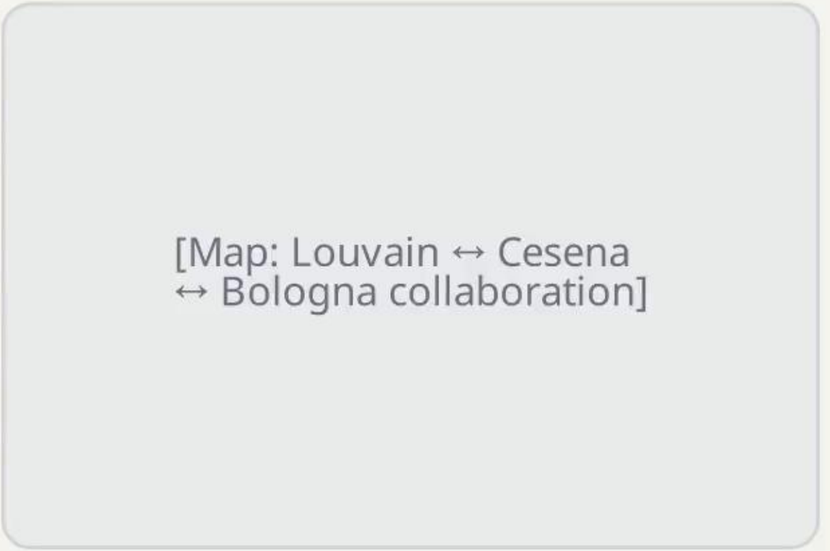

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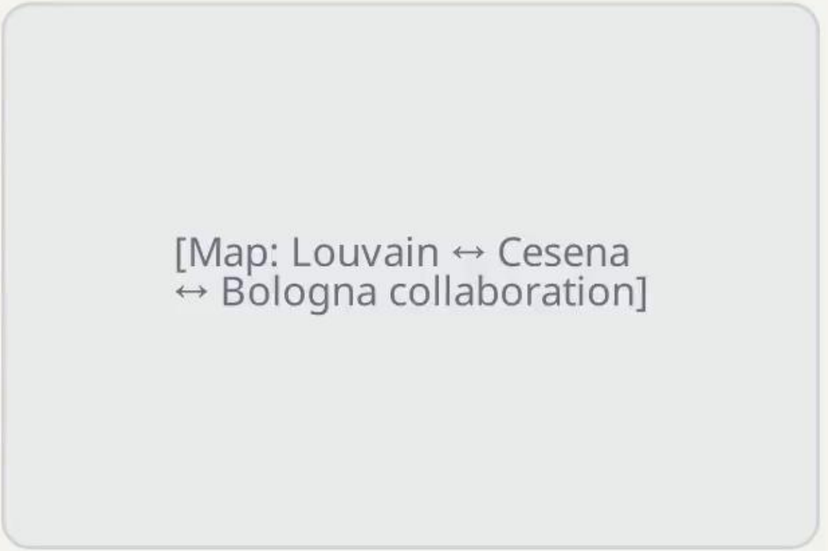

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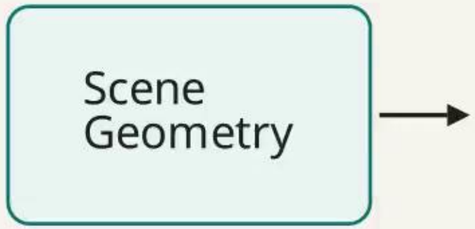

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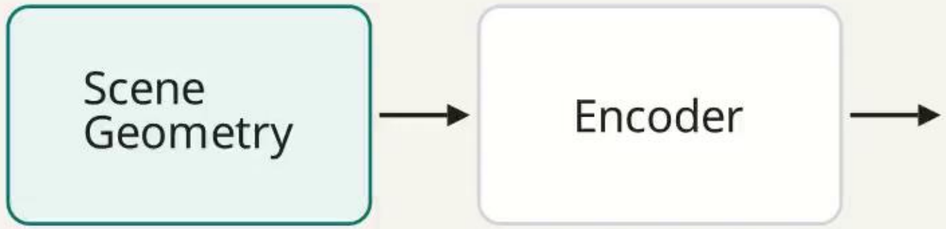

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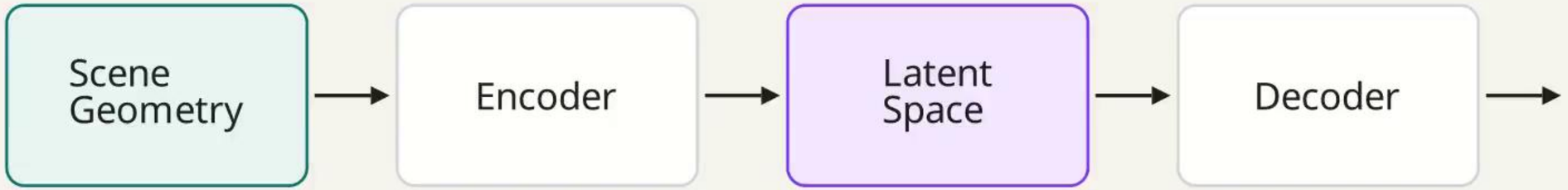

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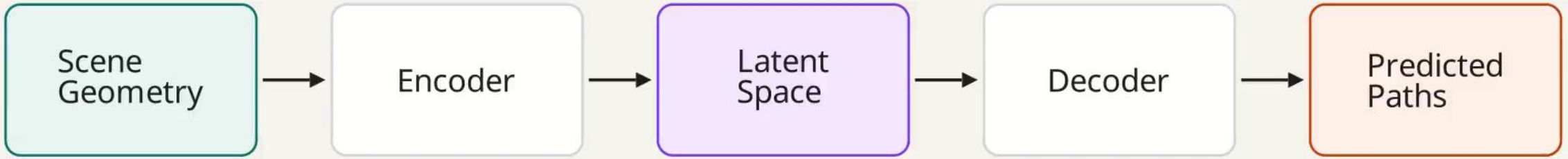

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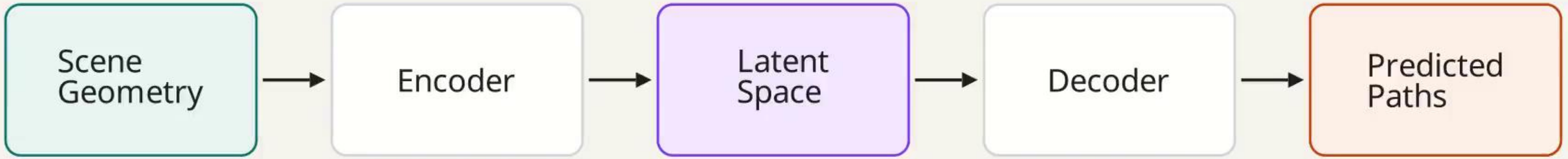


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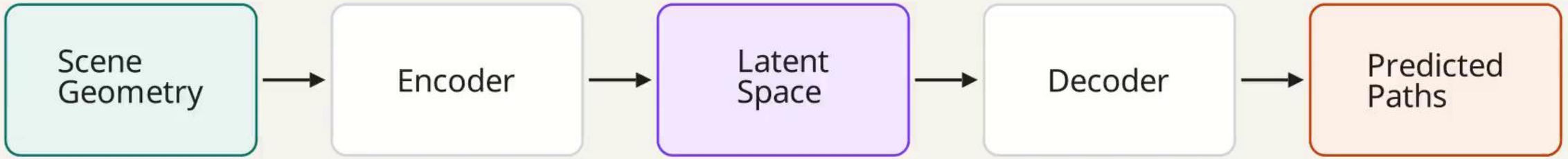


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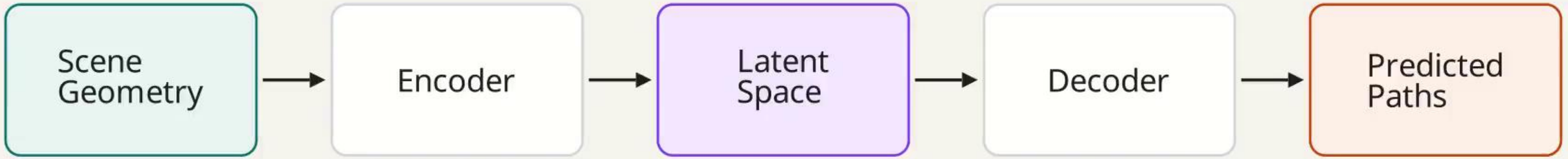


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Under review — the most important and comprehensive contribution of this thesis.

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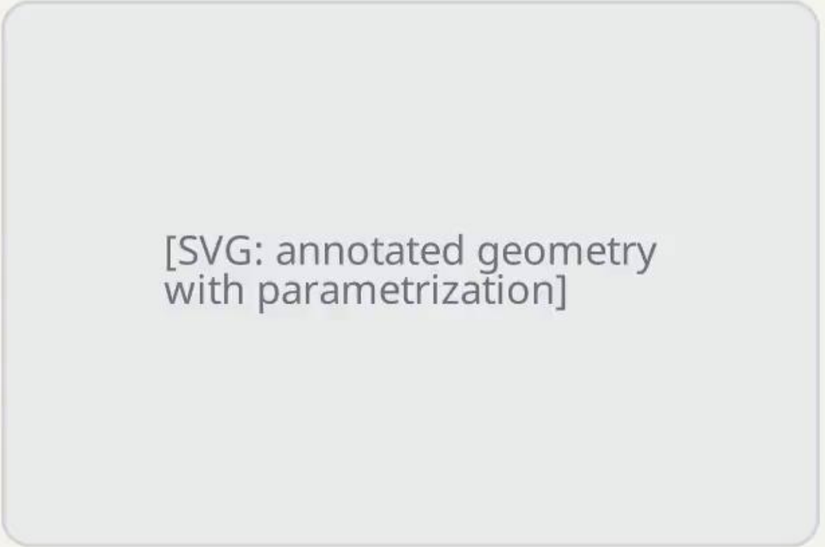

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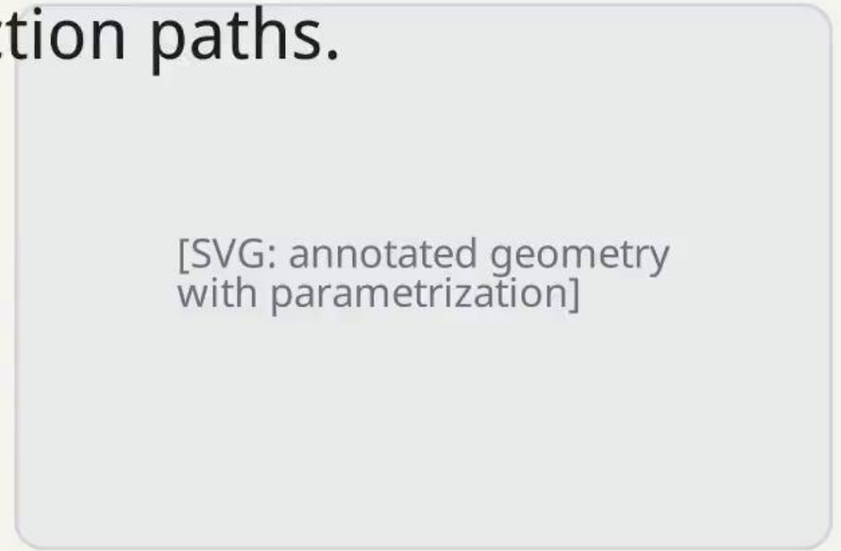

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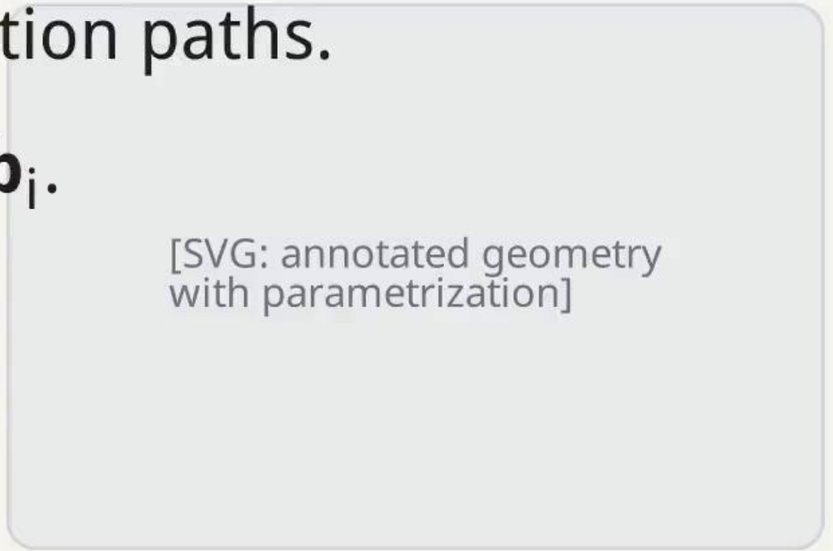

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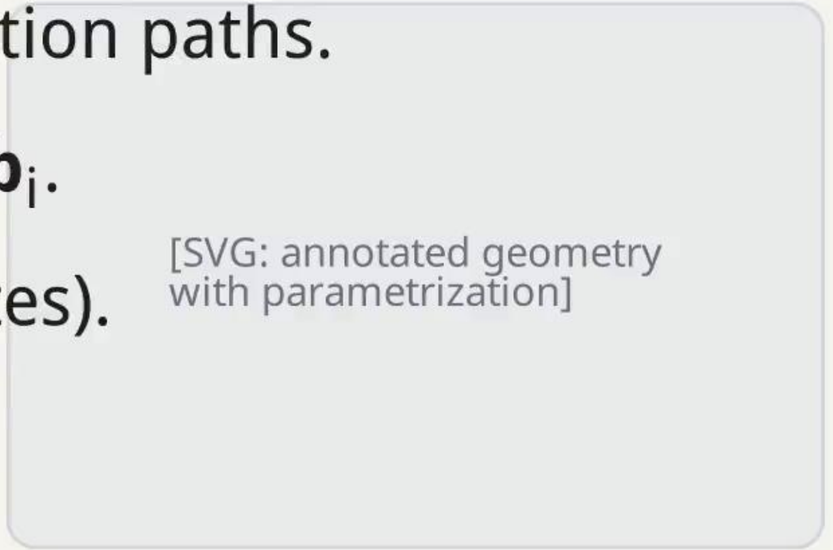

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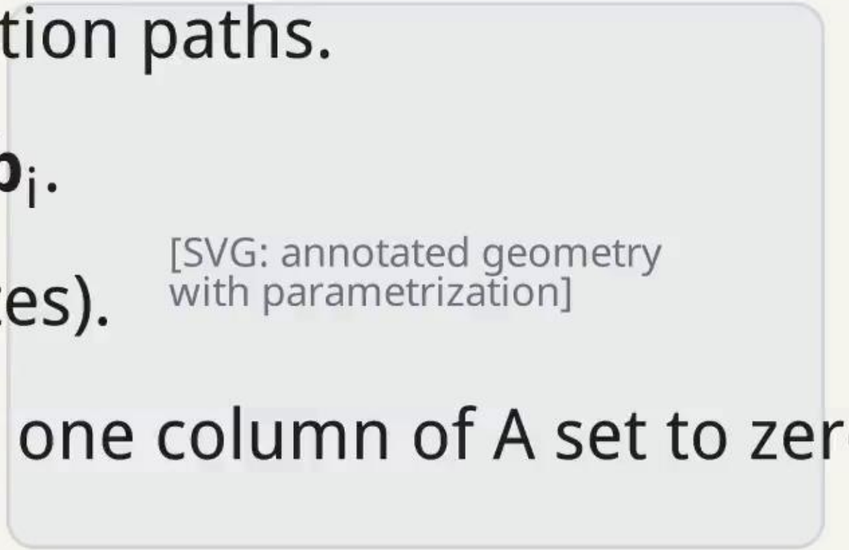

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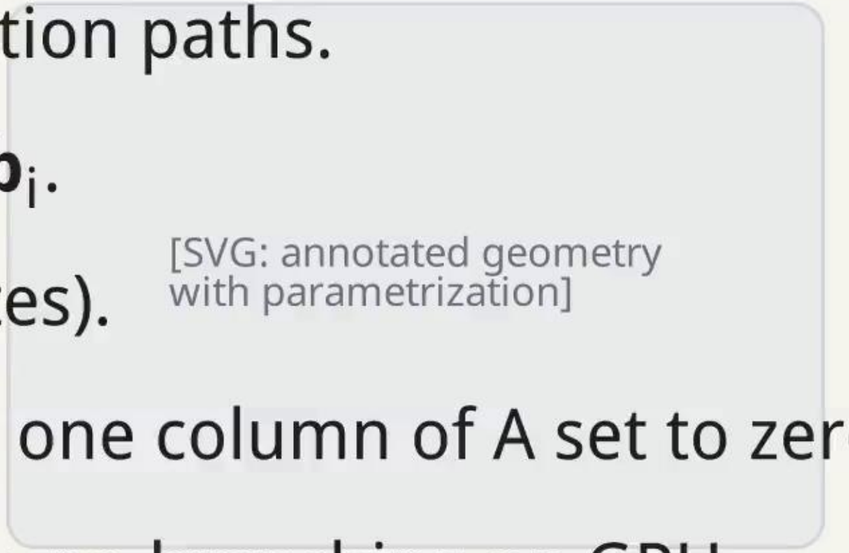

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- More robust than Newton method for mixed reflection/diffraction.

# BFGS Solver for GPU

**Why BFGS over Newton/GD?**

- Newton: ill-conditioned Hessian with zero-padded diffraction.
- GD: slow convergence, no curvature information.
- BFGS: robust, no true Hessian inversion needed.

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**Implicit differentiation**

(1) Optimality condition:

$$\nabla_{\mathbf{T}} L(\mathbf{T}^*; \theta) = \mathbf{0}$$

↓

(2) Implicit gradient:

$$\frac{\partial \mathbf{T}^*}{\partial \theta} = -H^{-1} \frac{\partial}{\partial \theta} \nabla_{\mathbf{T}} L$$

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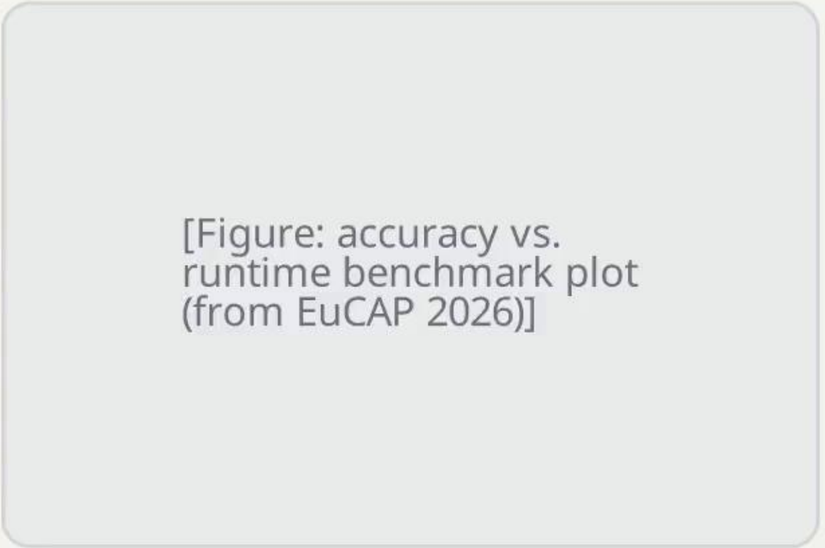

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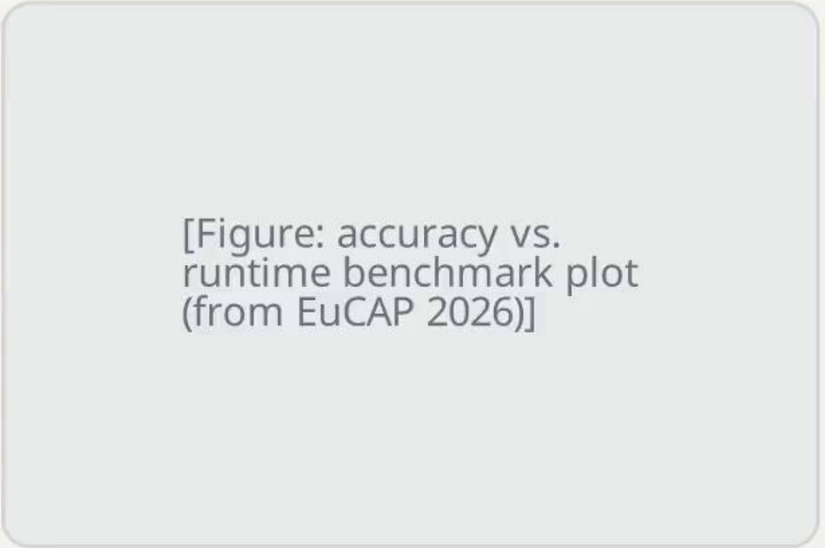

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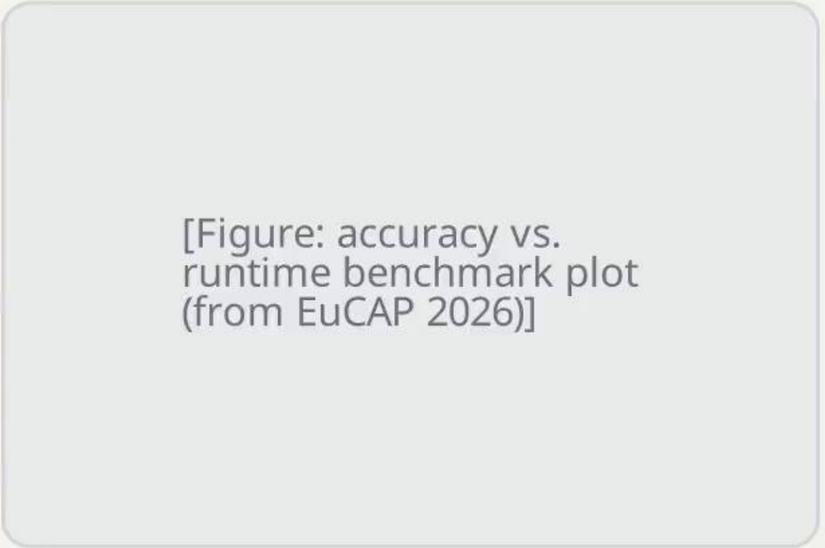
- Interactions: n = 1..5 (reflection and diffraction).



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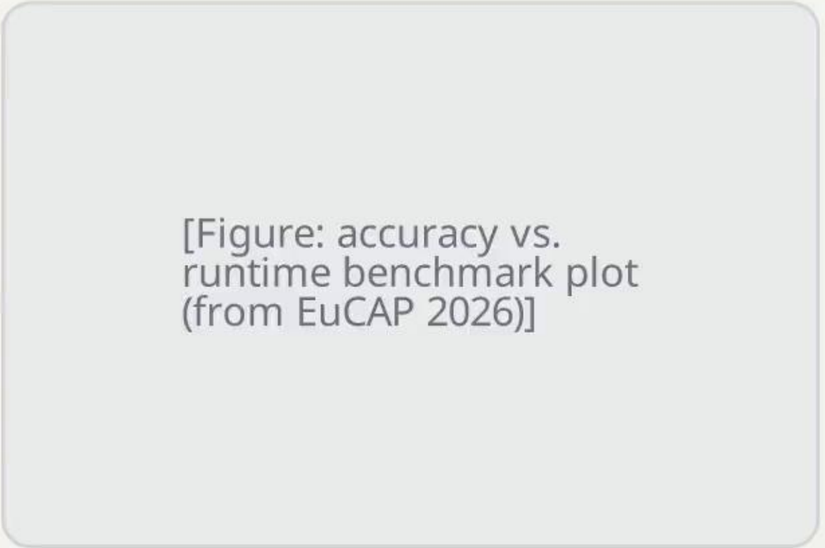

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- Interactions: n = 1..5 (reflection and diffraction).
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- Accuracy improves with more line-search iterations (ours-64 variant).

[Figure: accuracy vs. runtime benchmark plot (from EuCAP 2026)]

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Full 3D ray tracing with JAX + equinox. GPU-accelerated, differentiable.

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# Summary of Contributions

## ① Smoothing Technique

Continuous relaxation of hard visibility → fully differentiable RT.

## ② ML Generative Path Tracing

Learned model predicts paths directly → real-time inference potential.

## ③ Fermat Path Tracing (FPT)

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Cross-cutting: open-source tools (DiffeRT, DiffeRT2d) and COST INTERACT contributions.

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- Bridging communities: radio propagation, optimization, and machine learning.

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- Integration with digital twin platforms for real-time network optimization.

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time network optimization.

Key bottleneck: open GPU solvers are still lagging behind theory.

# Thank you!

## Happy to take your questions.

github.com/jeertmans/DiffeRT

github.com/jeertmans/DiffeRT2d

jeertmans.github.io

Made with Manim Slides (open-source tool)

# Other Contributions

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- Supervision and mentorship of master students.

# Publications

[C1] EuCAP 2023 — Min-Path-Tracing (Florence)

[C2] EuCAP 2024 — Smoothing technique (Glasgow)

[C3] EuCAP 2025 — Multipath Lifetime Map (Stockholm)

[C4] ICMLCN 2025 — ML-based path tracing (Barcelona)

[C5] EuCAP 2026 — Fermat Path Tracing (Dublin)

[J1] npj Wireless Technology 2026 — ML-assisted RT (submitted)

[B1] COST INTERACT book chapter (2025)