

Analysis-suitable parameterization for isogeometric analysis

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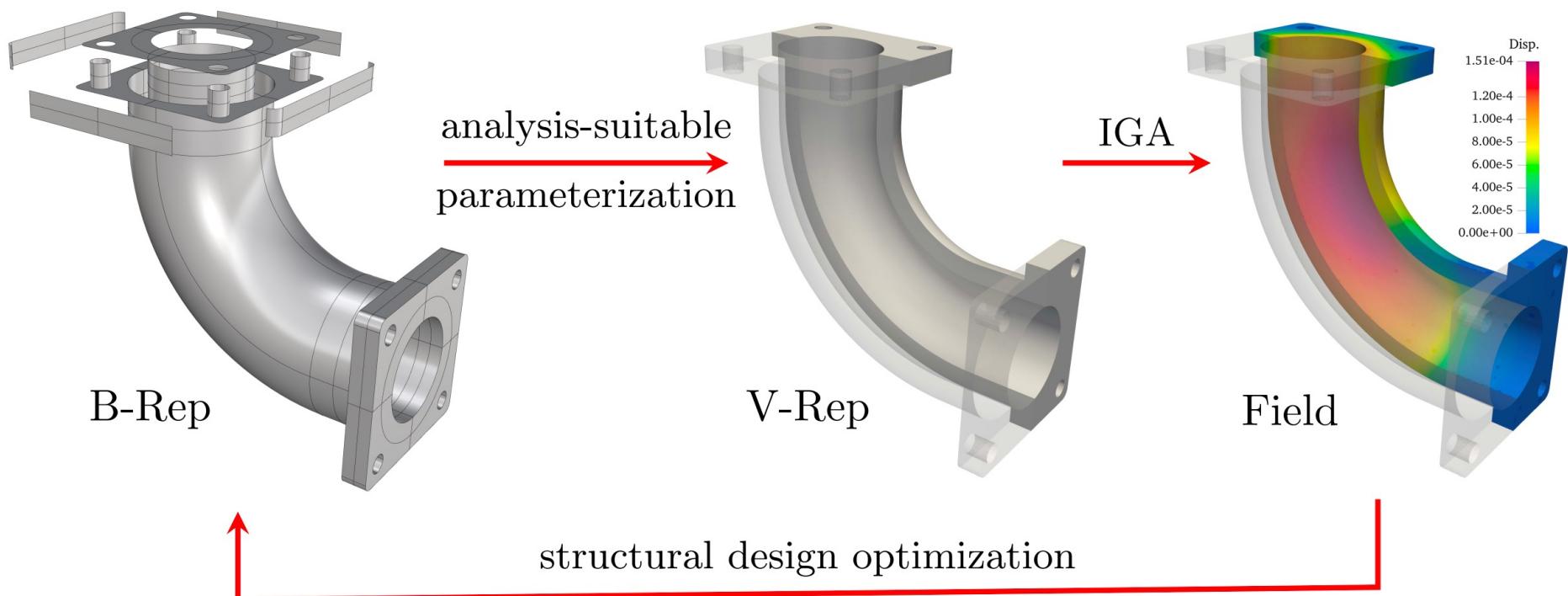
Outline

- 1. Background and motivation**
- 2. Overview of the algorithms**
- 3. Applications**
- 4. Conclusions and outlook**

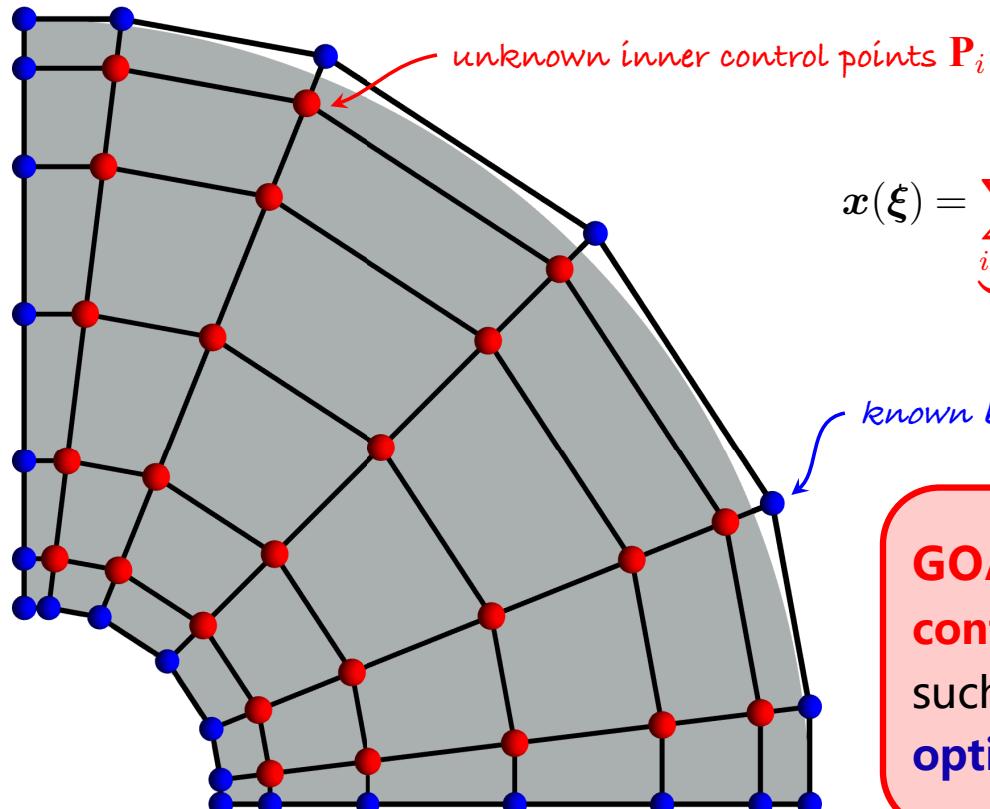
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- CAD models are usually represented by **boundary representation** (B-Rep);
- However, IGA requires an internal **spline-based parameterization** (V-Rep).



Problem statement: Domain parameterization



$$x(\xi) = \underbrace{\sum_{i \in \mathcal{I}_I} P_i R_i(\xi)}_{\text{unknown}} + \underbrace{\sum_{j \in \mathcal{I}_B} P_j R_j(\xi)}_{\text{known}}$$

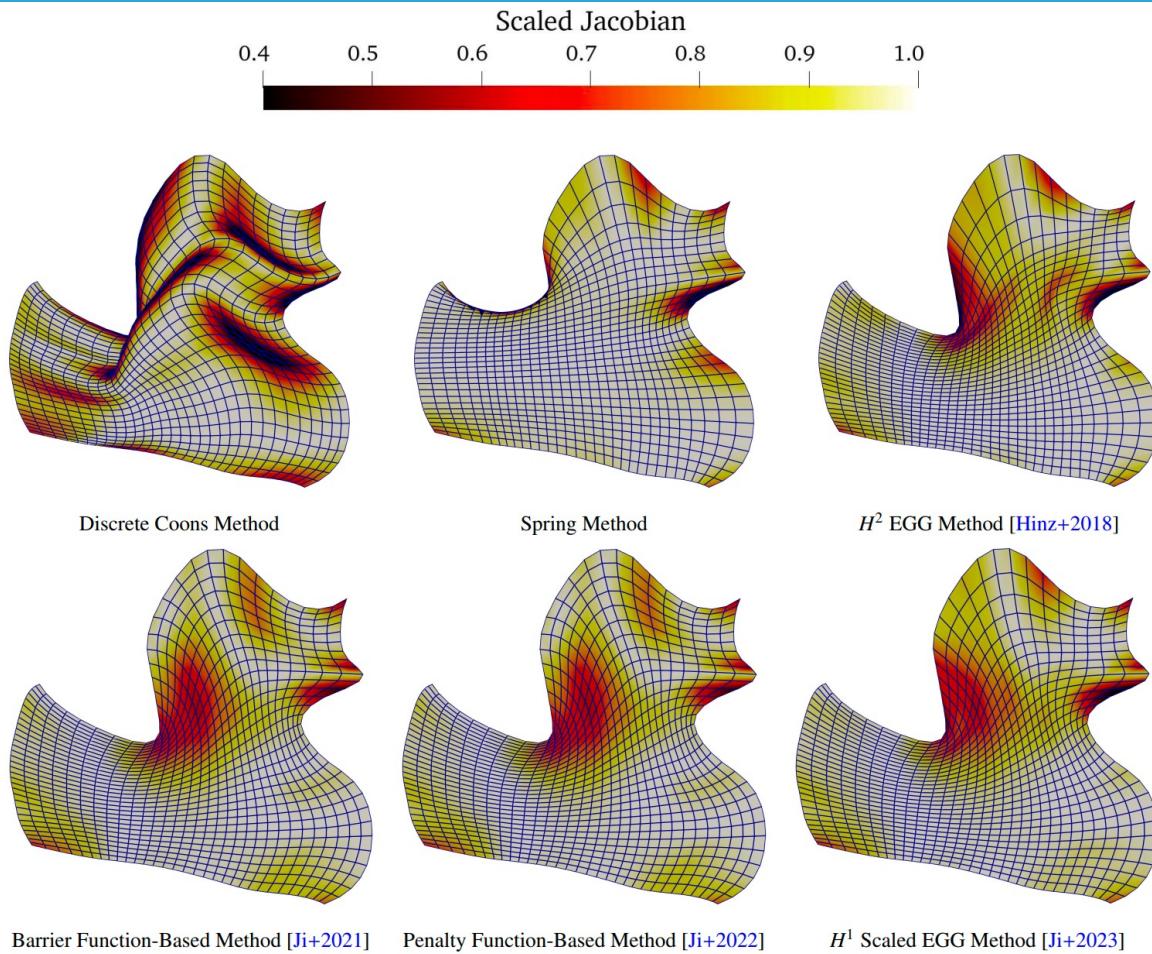
GOAL: to construct **unknown inner control points P_i** (or basis functions R_i) such that x ensures **bijectivity** and exhibits **optimal orthogonality** and **uniformity**.

➤ **Parameterization quality** significantly affects **downstream analysis!**

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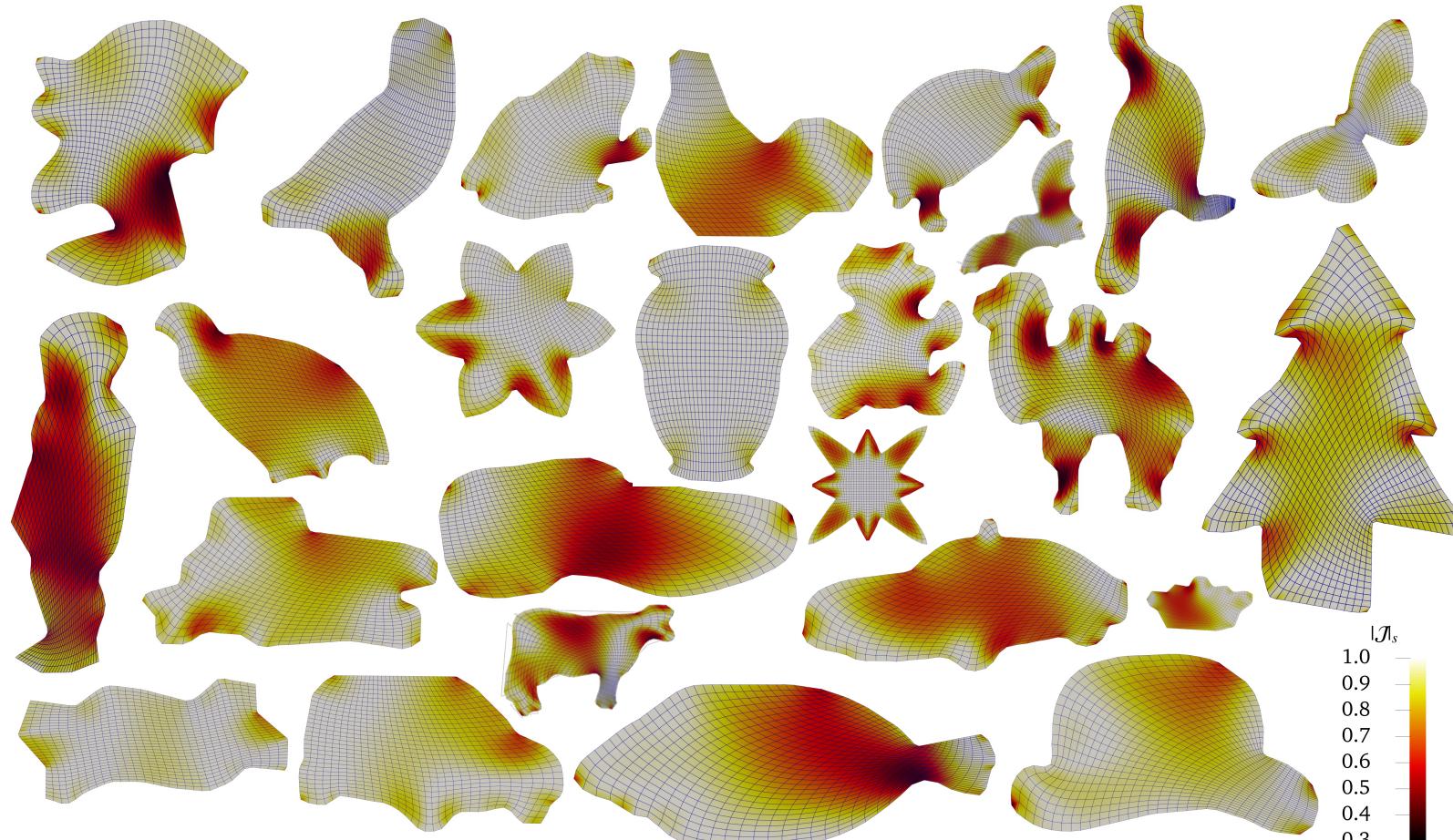
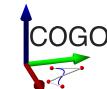
Available methods in G+Smo



- Algebraic methods:
 - Coons patch
 - Spring patch
- Optimization-based methods:
 - Barrier-function-based ¹
 - Penalty-function-based ²
- PDE-based methods:
 - Elliptic grid generation ³
 - Improved EGG ⁴

-
1. Ji, Y. et al. (2021). *JCAM*, 396, 113615.
 2. Ji, Y. et al. (2022). *CAGD*, 94, 102081.
 3. Hinz, J. et al. (2018). *CAGD*, 65, 48-75.
 4. Ji, Y. et al. (2023). *CAGD*, 102, 102191.

Planar Parameterization Test Dataset (977 models)

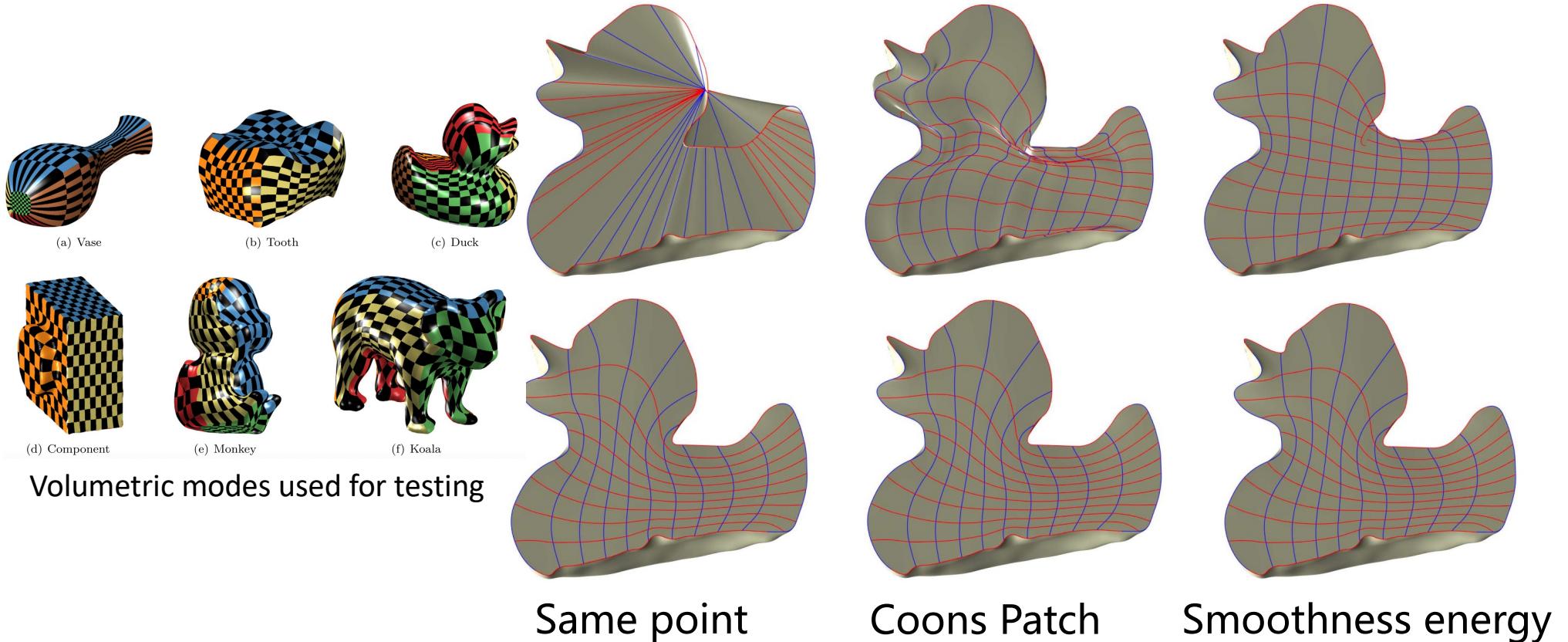


Success rates
PDE (Hinz, J. et al.
(2018)): 62.23%
PDE (Ji et al. 2023):
73.80%
Barrier (Ji et al. 2021):
98.36%
Penalty (Ji et al. 2021):
97.85%

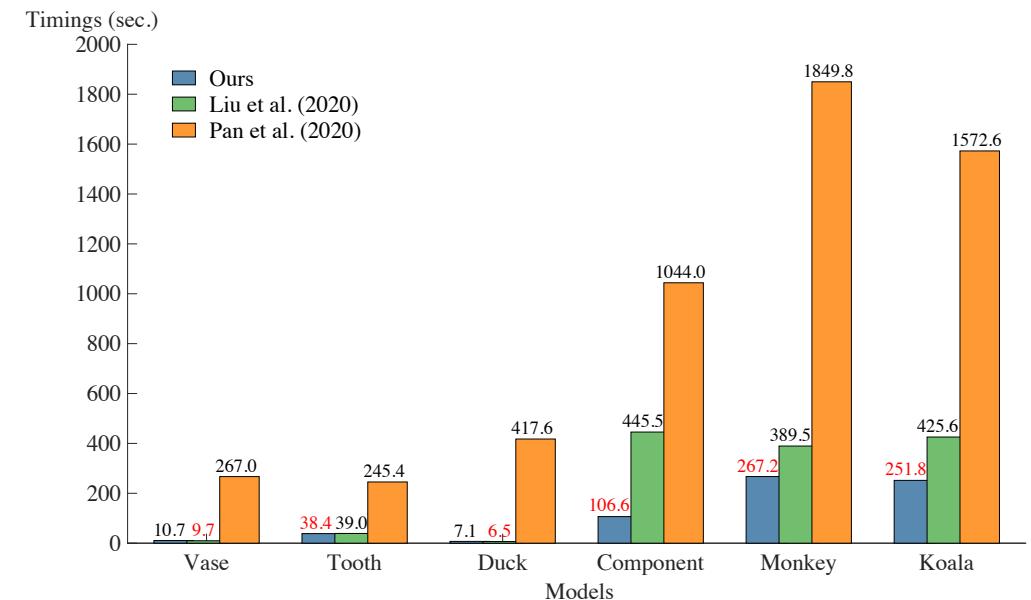
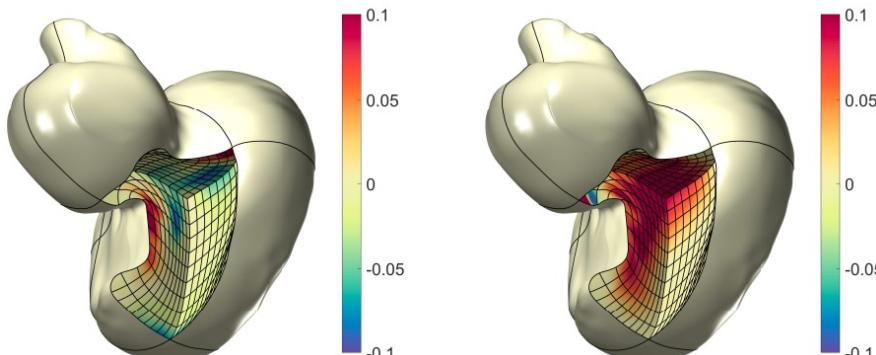
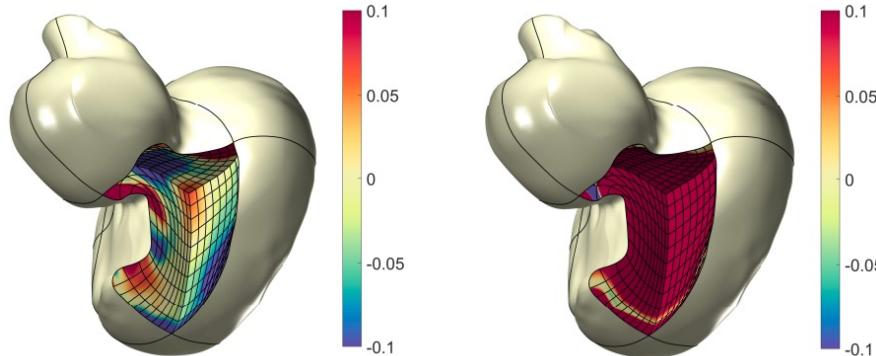
Computational time:
PDE-based: ~0.2 sec
opt-based: ~2 sec

Ji, Y., Möller, M., Verhelst, H.M.
(2024). Design Through Analysis.
In: Bodnár, T., Galdi, G.P.,
Nečasová, Š. (eds)
Fluids Under Control. Advances in
Mathematical Fluid Mechanics.
Birkhäuser, Cham.

Strong similarity from different initializations



Comparisons with existing methods

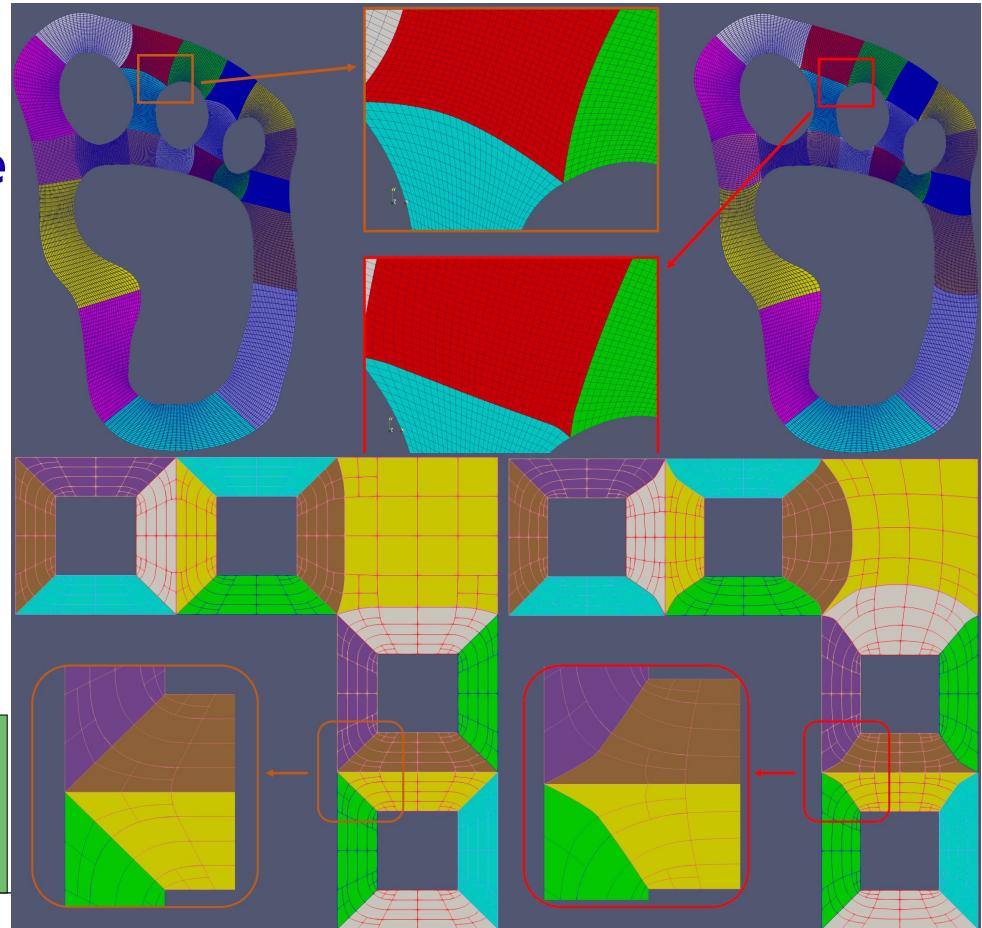
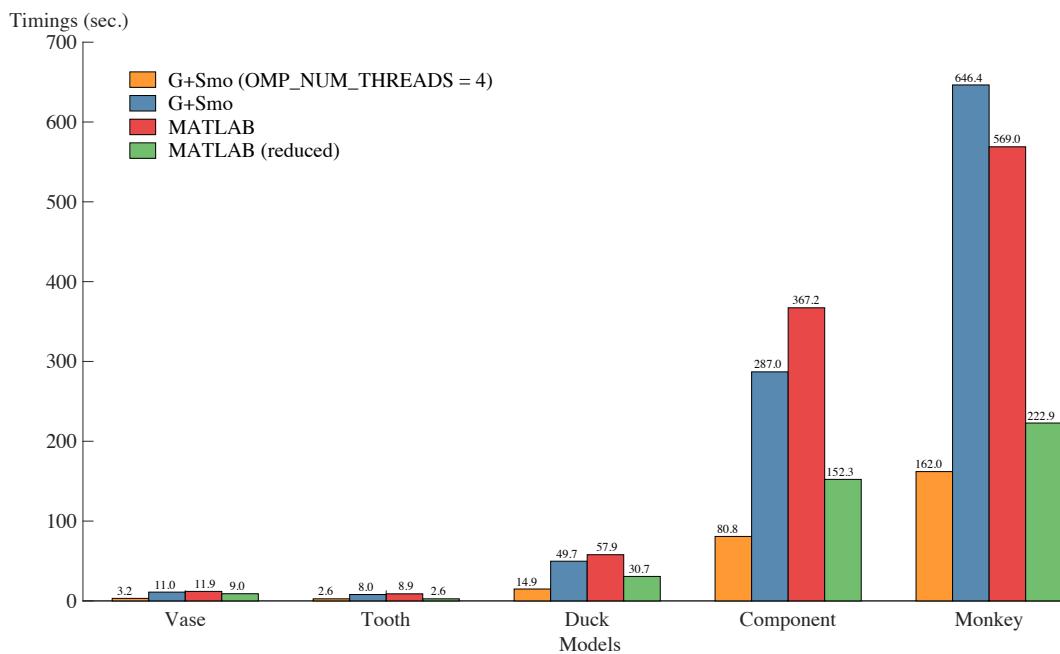


- **Positive values** indicate our method performs better;
- Efficiency comparison (MATLAB vs. C++ (Pan+ & Liu+)):
 - Significantly **faster** than Pan et al. (2020);
 - Large-Scale Models: Outperforms Liu et al. (2020).

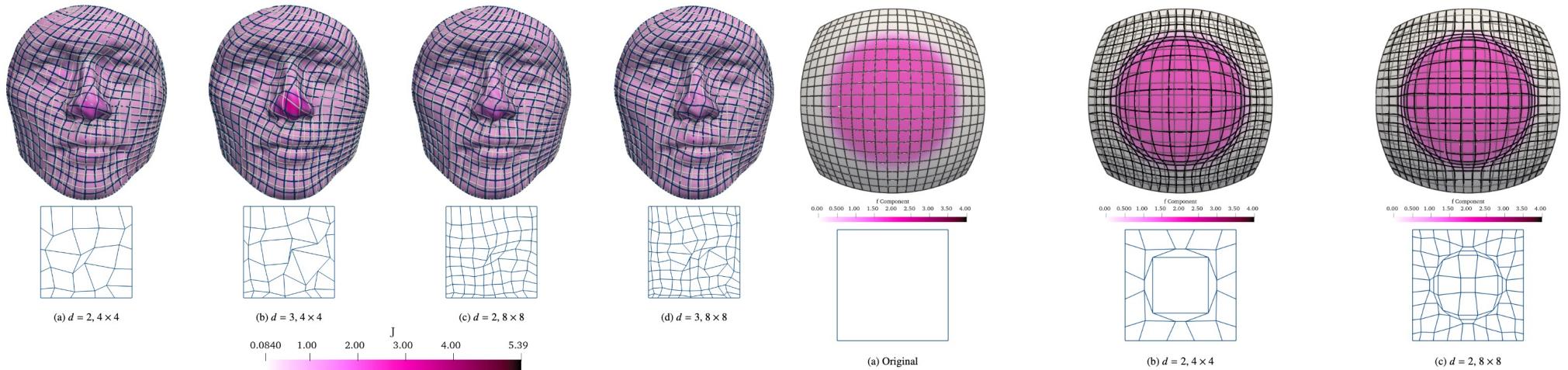
1. Pan, M., Chen, F., & Tong, W. (2020). CMAME, 359, 112769.
2. Liu, H., Yang, Y., Liu, Y., & Fu, X. M. (2020). CAGD, 79, 101853.

G+Smo implementation

- In our released G+Smo implementation, **3-4x speed-up using OpenMP (!);**
- Suitable for **multi-patch** and **THB-spline parameterization;**



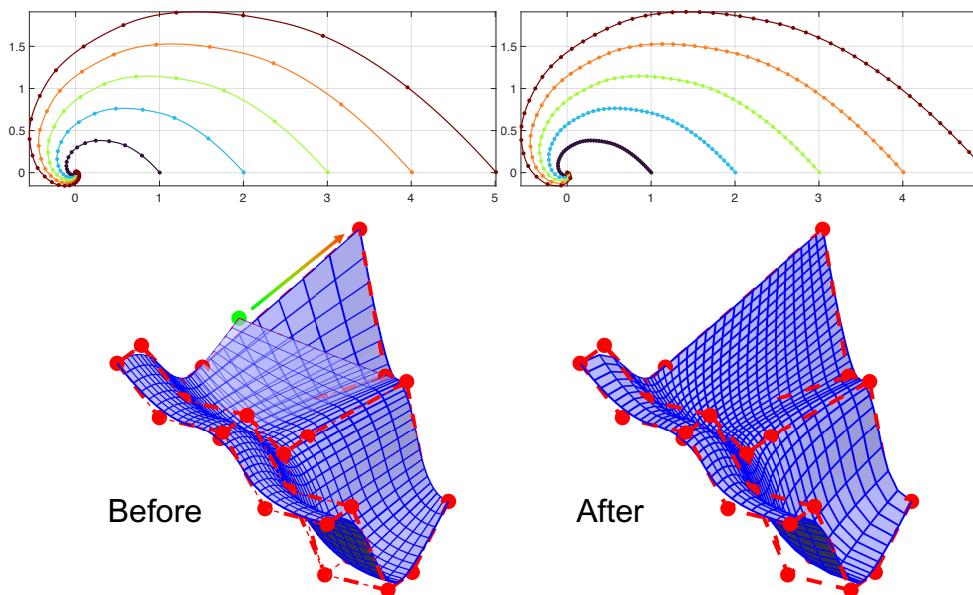
|| Composite spline relocation for surface reparameterization



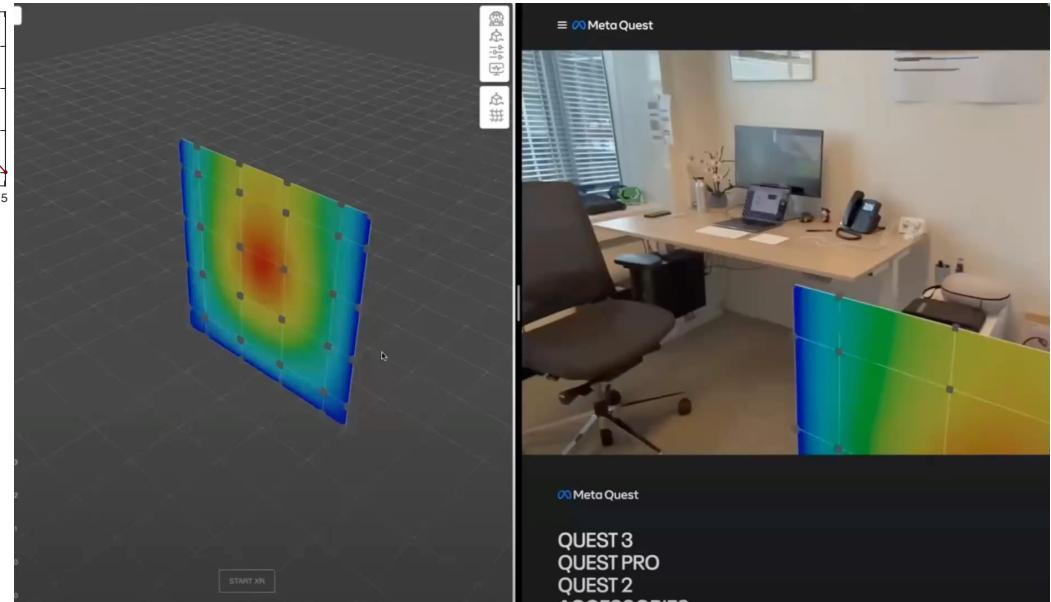
➤ A **composite spline relocation** framework for surface-based IGA, integrating **harmonic map-based mesh redistribution** with spline-based techniques;

Composite spline relocation for isogeometric analysis on surfaces
joint work with Carlotta Giannelli, Sofia Imperatore, & Hugo Verhelst

Applications: curve/surface reparameterization

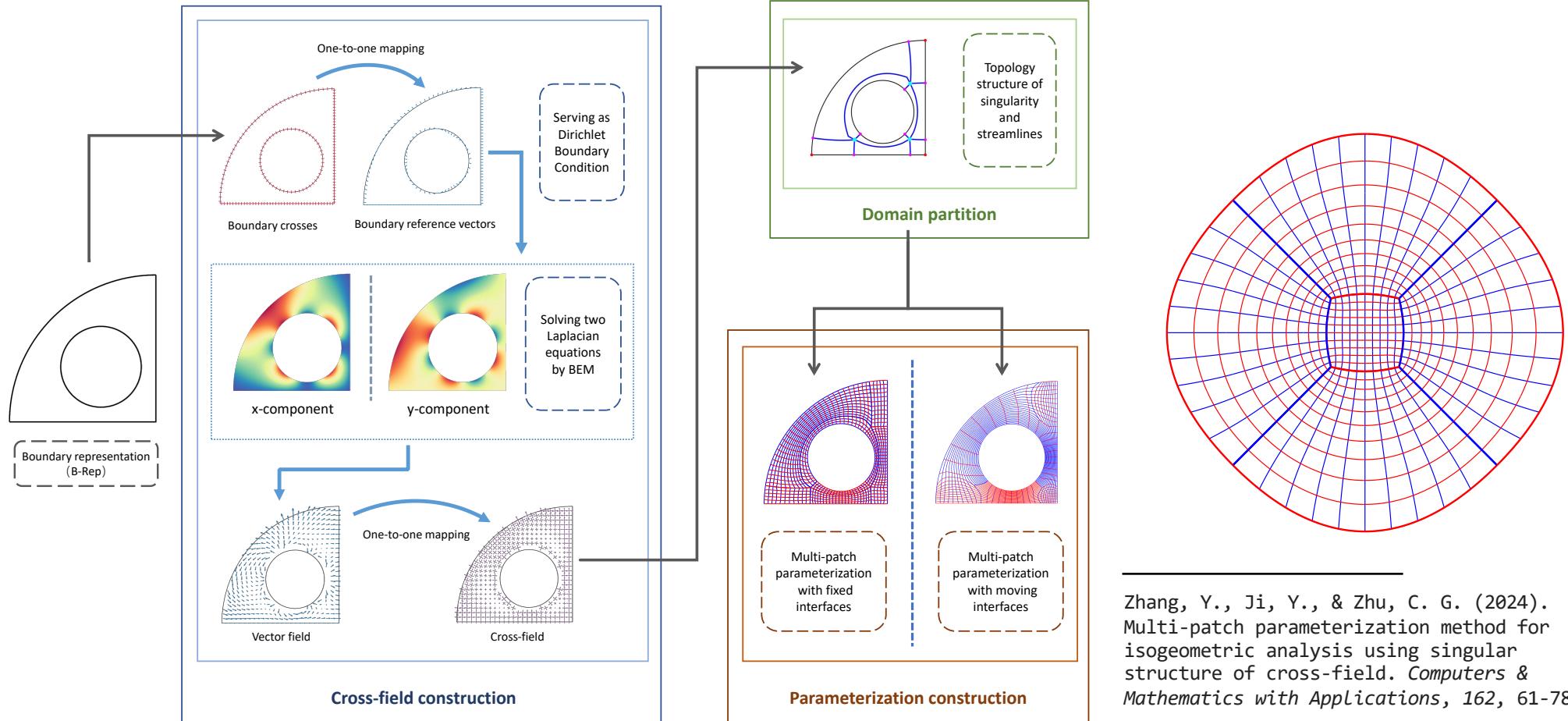


- Curve/surface reparameterization while keeping the geometry;



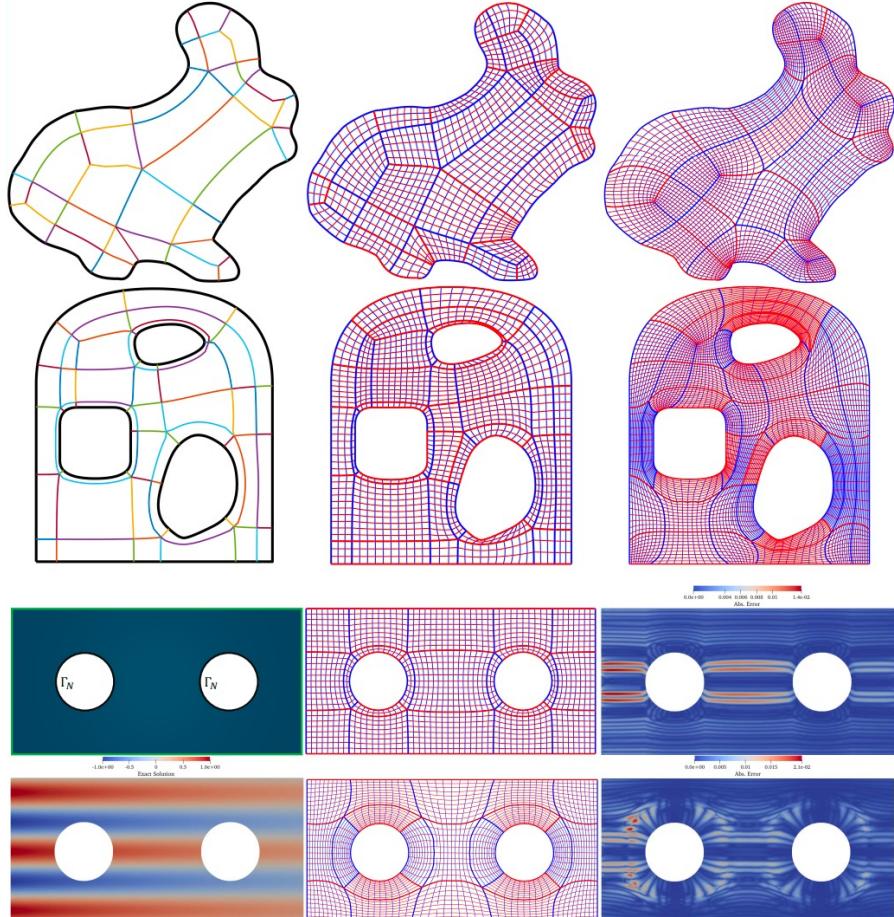
Design Through Analysis (DTA) Tools - Matthias
Wed. 10:45-12:00 Software session #2

Multi-patch parameterization using cross-field

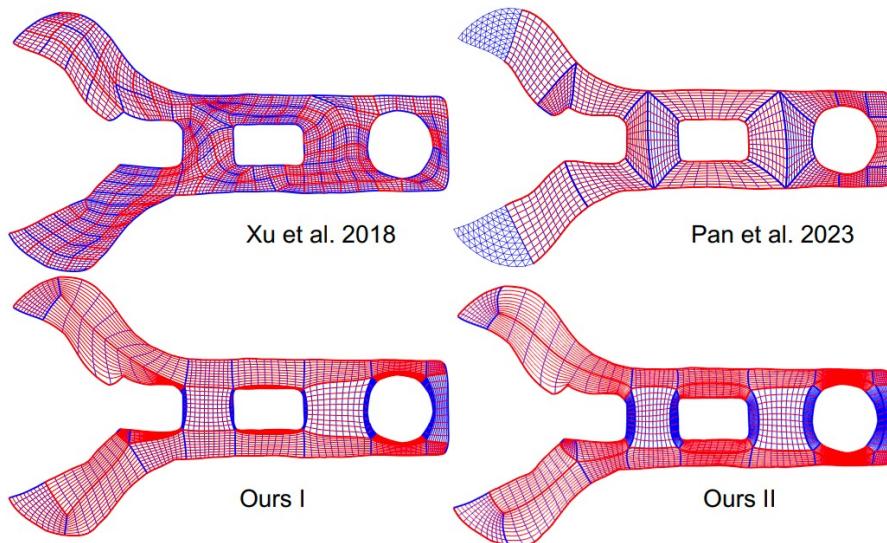


Zhang, Y., Ji, Y., & Zhu, C. G. (2024). Multi-patch parameterization method for isogeometric analysis using singular structure of cross-field. *Computers & Mathematics with Applications*, 162, 61-78.

Multi-patch parameterization: Results and comparisons

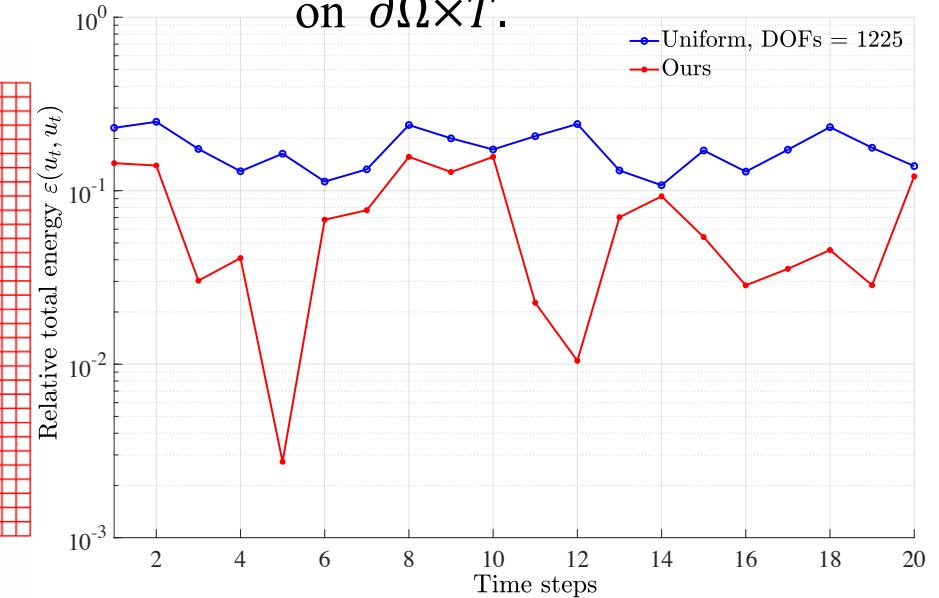
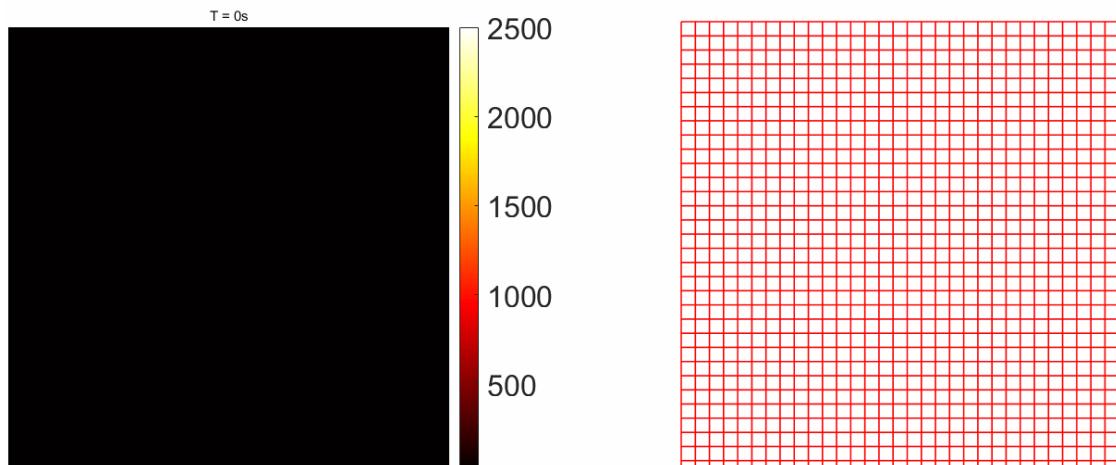


Model	#Patch	Method	$ \mathcal{J} _s$		unif.	
			min.	avg.	min.	avg.
rabbit	33	Coons	-0.8593	0.9628	0.7030	0.9410
		fixed-I	0.2204	0.9504	0.6103	0.9544
		moving-I	0.02918	0.9283	0.0000	0.9550
3 holes	46	Coons	-0.5492	0.9710	0.8008	0.9573
		fixed-I	0.1545	0.9716	0.8007	0.9573
		moving-I	0.1461	0.9361	0.6791	0.9571



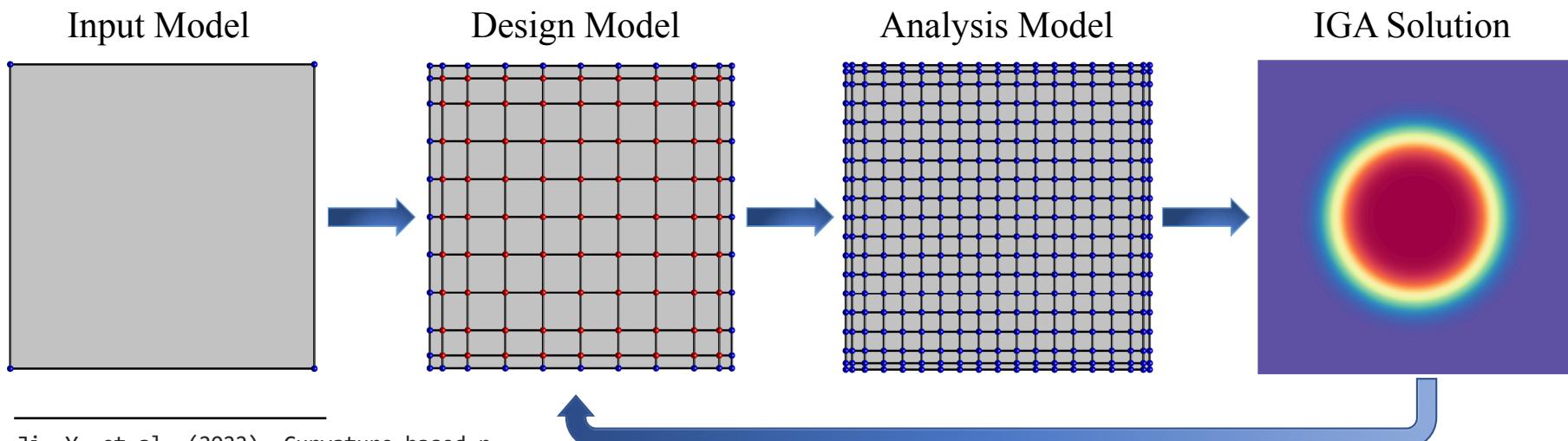
- Consider a two-dimensional linear heat transfer problem with a moving Gaussian heat source:

$$\begin{cases} C_p \rho \frac{\partial u(\mathbf{x}, t)}{\partial t} - \nabla \cdot (\kappa \nabla u(\mathbf{x}, t)) = f(\mathbf{x}, t), & \text{in } \Omega \times T, \\ u(\mathbf{x}, t) = u_0, & \text{in } \Omega, \\ \kappa \nabla u(\mathbf{x}, t) = 0, & \text{on } \partial\Omega \times T. \end{cases}$$



Anisotropic parameterizations are often solution-dependent:

- Need **good numerical solution accuracy** to drive parameterization;
- Adjust as few control points as possible **for high efficiency**;
- **Bi-level strategy:** a coarse level (design model) to update the parameterization for efficiency and a fine level (analysis model) to perform analysis for accuracy.

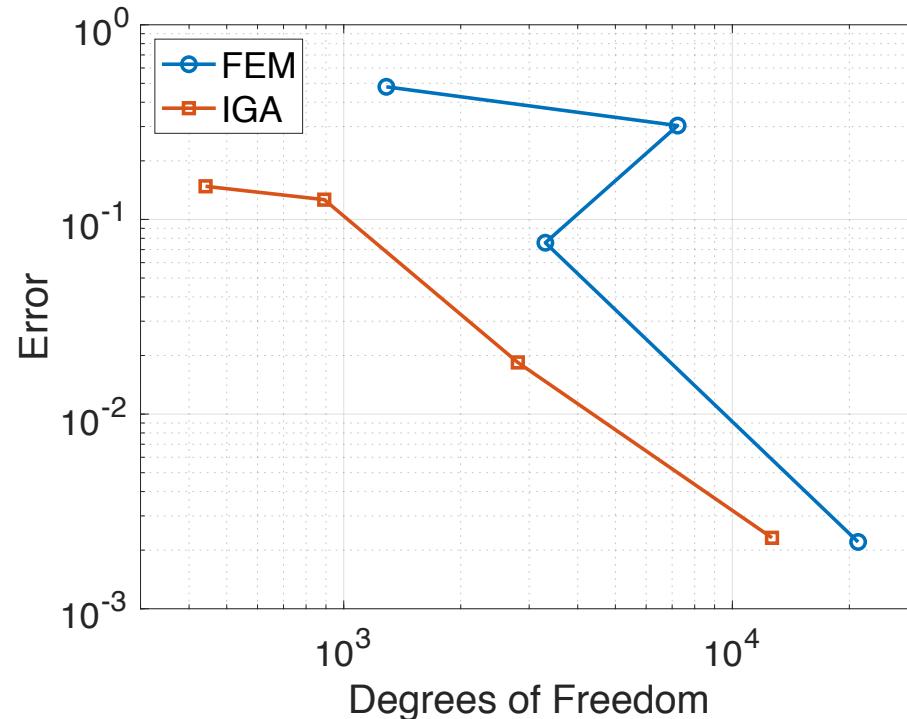
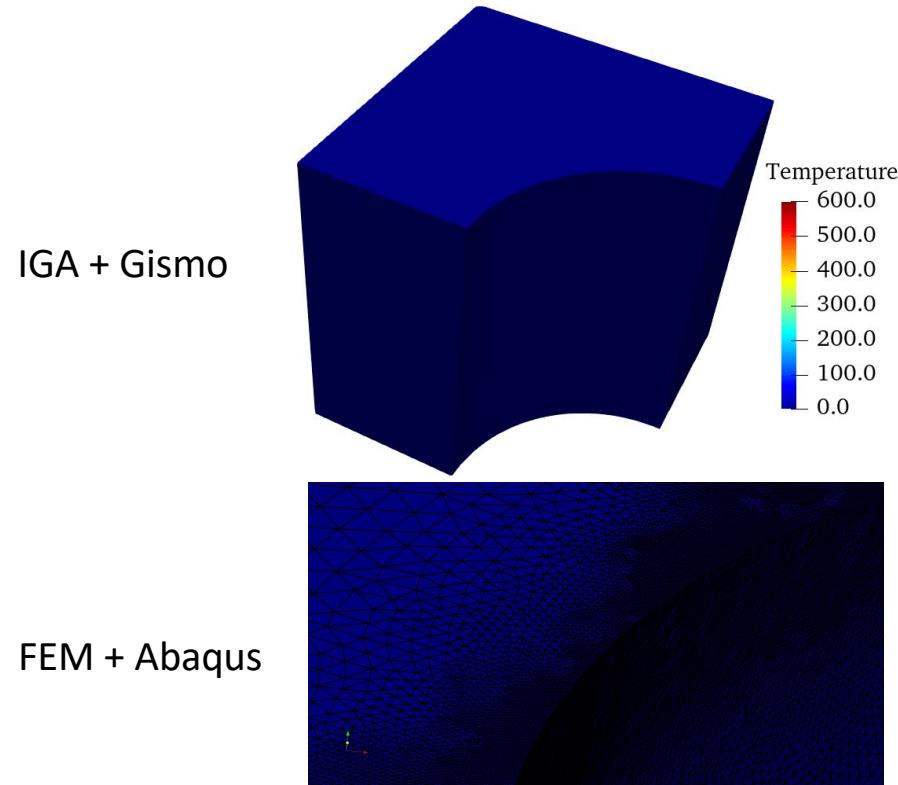
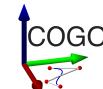


Ji, Y. et al. (2022). Curvature-based r-adaptive planar NURBS parameterization method for isogeometric analysis using bi-level approach. *Computer-Aided Design*, 150, 103305.

Objective function and sensitivity analysis



Semi-analytical heat transfer in metal additive manufacturing



1. Yang, Y., Ji, Y., Möller, M., & Ayas, C. (2025). Computational efficient process simulation of geometrically complex parts in metal additive manufacturing. International Journal of Heat and Mass Transfer, 248, 127059.
2. Semi-analytical heat transfer modeling in metal additive manufacturing using isogeometric analysis (manuscript in preparation)

Network & Training

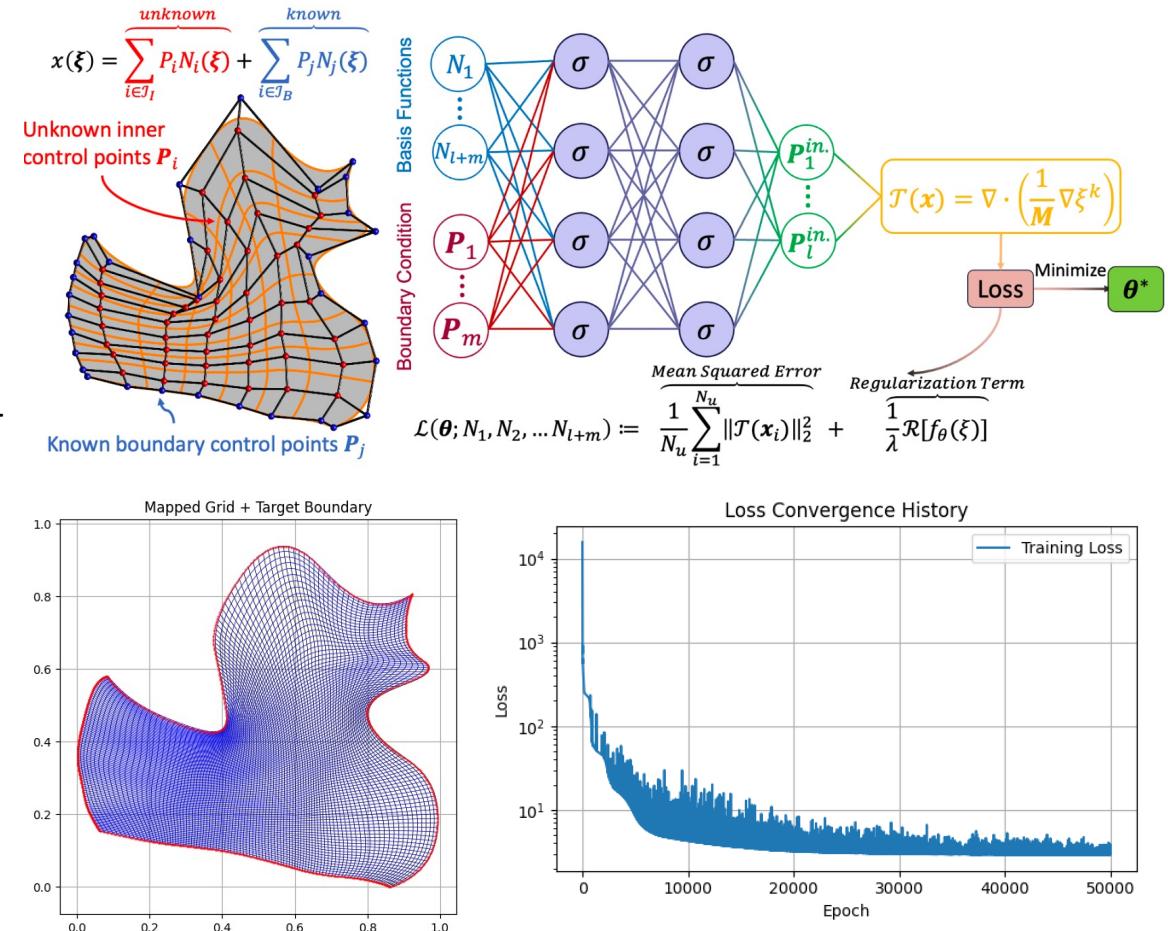
- 4 fully-connected layers, tanh activations
- Optimizer: Adam, learning rate = $1e-3$
- Epochs: 50,000

Loss Function

- Interior Loss: Jacobian-regularized Winslow energy \Rightarrow smooth & invertible
- Boundary Loss: MSE between predicted and B-spline-defined boundaries

✓ Powerful auto differentiation tools make it easy to implement;
✗ No better than the current "classical" method; **12 min 1.4 sec. (PINN) vs 0.014 sec. (PDE) vs 0.0673 sec. (opt.)**

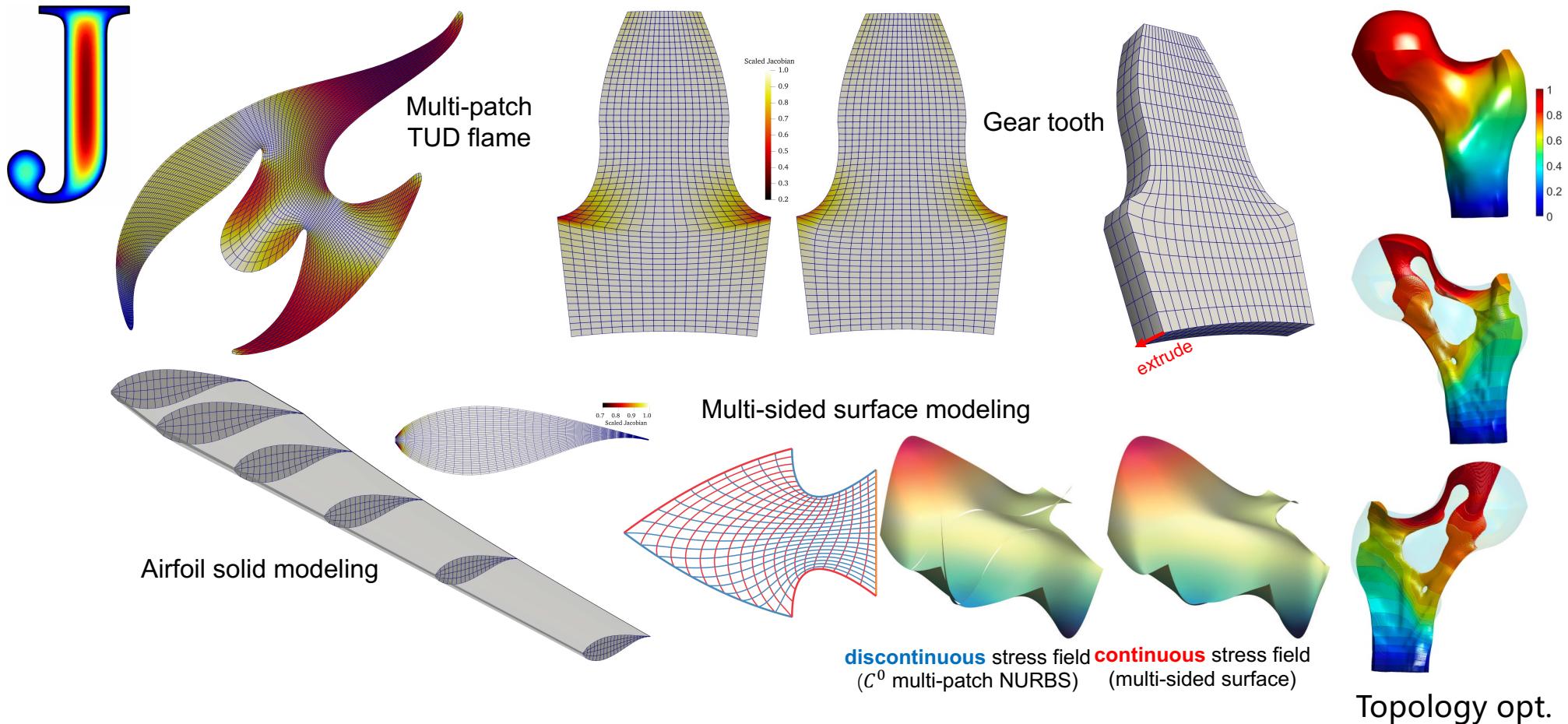
Not an "AI guy" (yet) myself, but very interested in bridging AI with geometry and simulation.



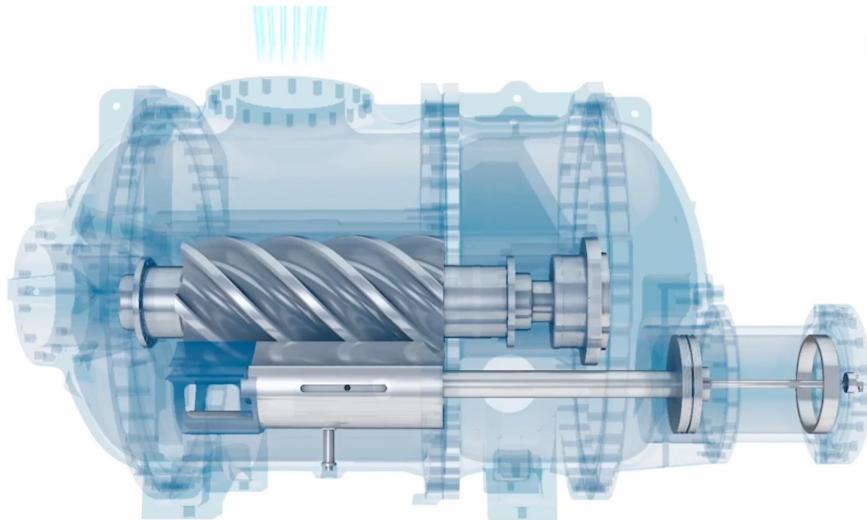
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|| Applications: Academic use cases

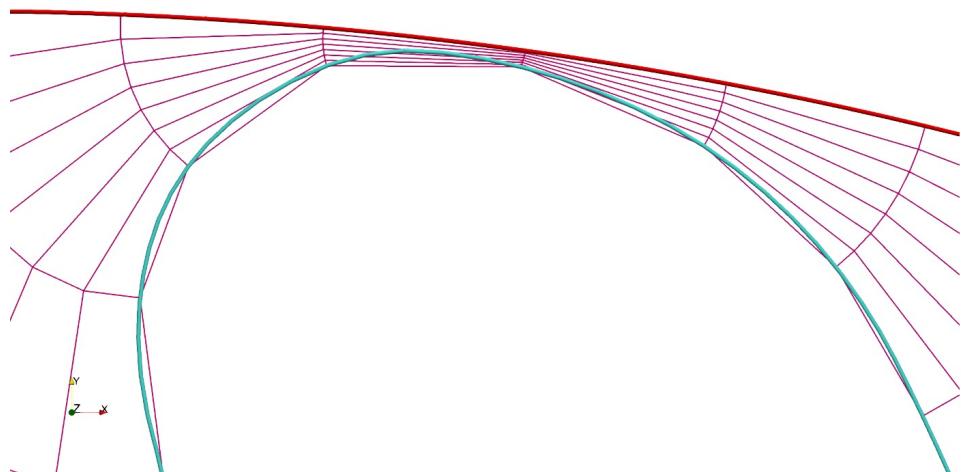


Applications: Industrial use case



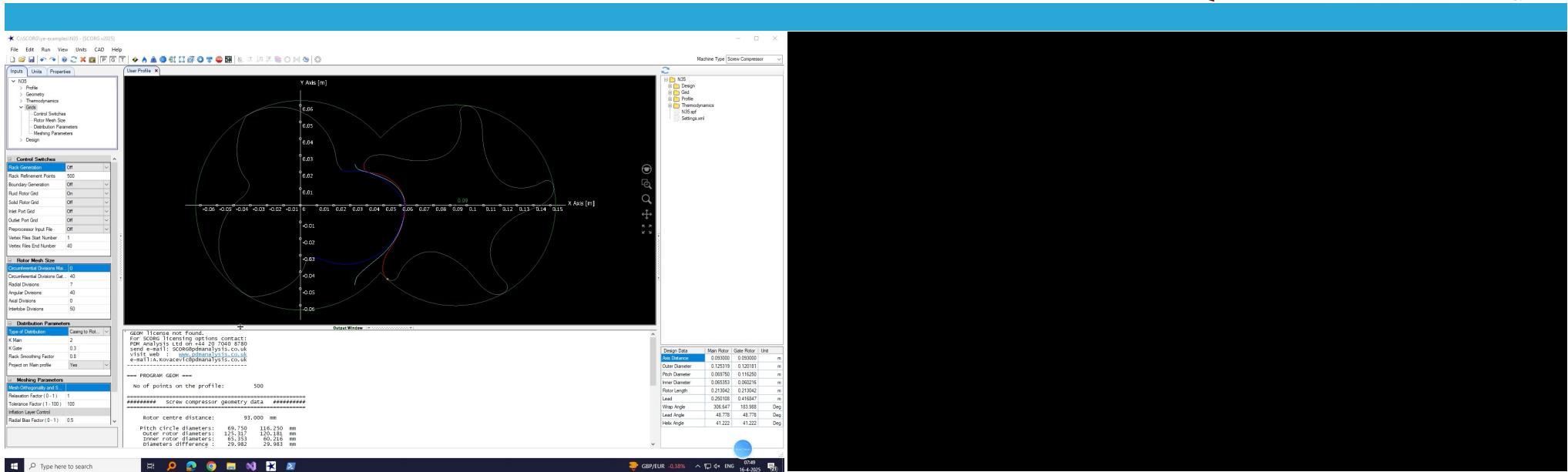
Rotary twin-screw compressor

- **Structured mesh generation** is a crucial preprocessing step in the simulation-based analysis of twin-screw machines.
- However, the existing mesh generators typically produce only **linear meshes with straight-sided cells**;
- **Analysis-suitable, high-order NURBS parameterizations.**

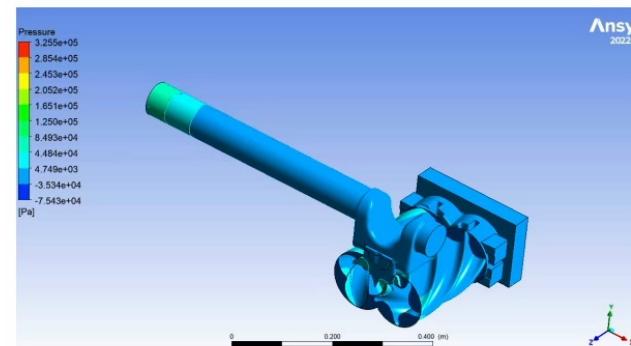


Source: [https://www.gascompressors.co.uk/
technologies/oil-floodedscrew-compressor/](https://www.gascompressors.co.uk/technologies/oil-floodedscrew-compressor/)

Scorg VS. SplineMesh



Scorg



SplineMesh

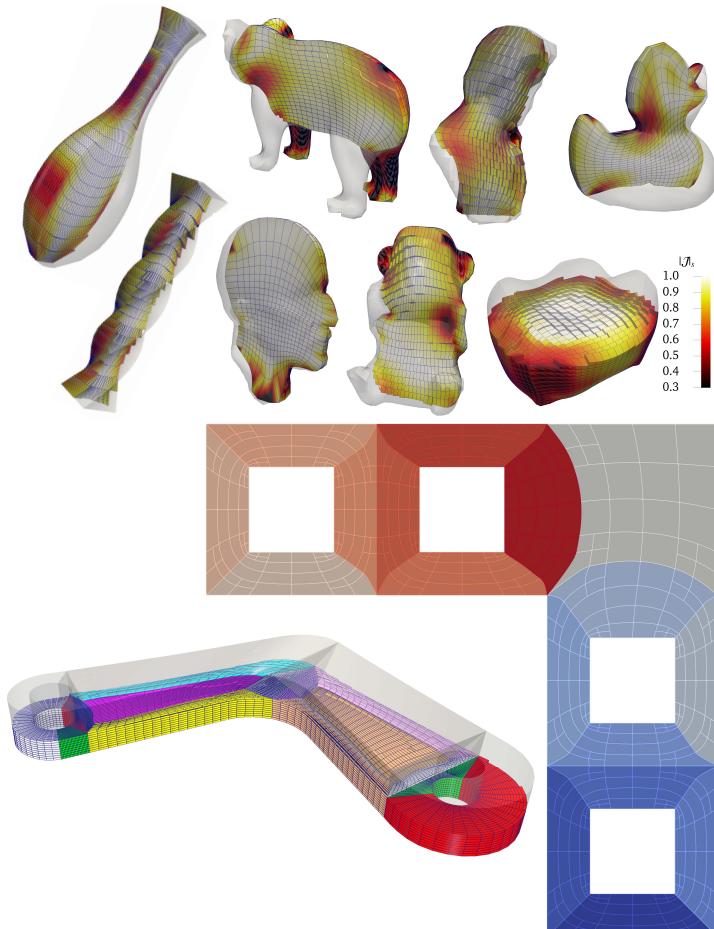
ANSYS CFX simulation

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- **G+Smoo offers** three major classes of **parameterization methods**;
- Demonstrates **improved robustness and efficiency** over existing methods;
- Applicability in both **academic** and **real-world industry scenarios**;

- Future Work:
 - Exploring **AI techniques** for geometric modelling and design-through-analysis (DTA) workflows;
 - Developing a user-friendly **graphical user interface** to support broader adoption.



Many thanks for your attention!

Q&A

If you are interested in my research, please feel free to contact me! ;-)

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-  Homepage: <https://jiyess.github.io/>