

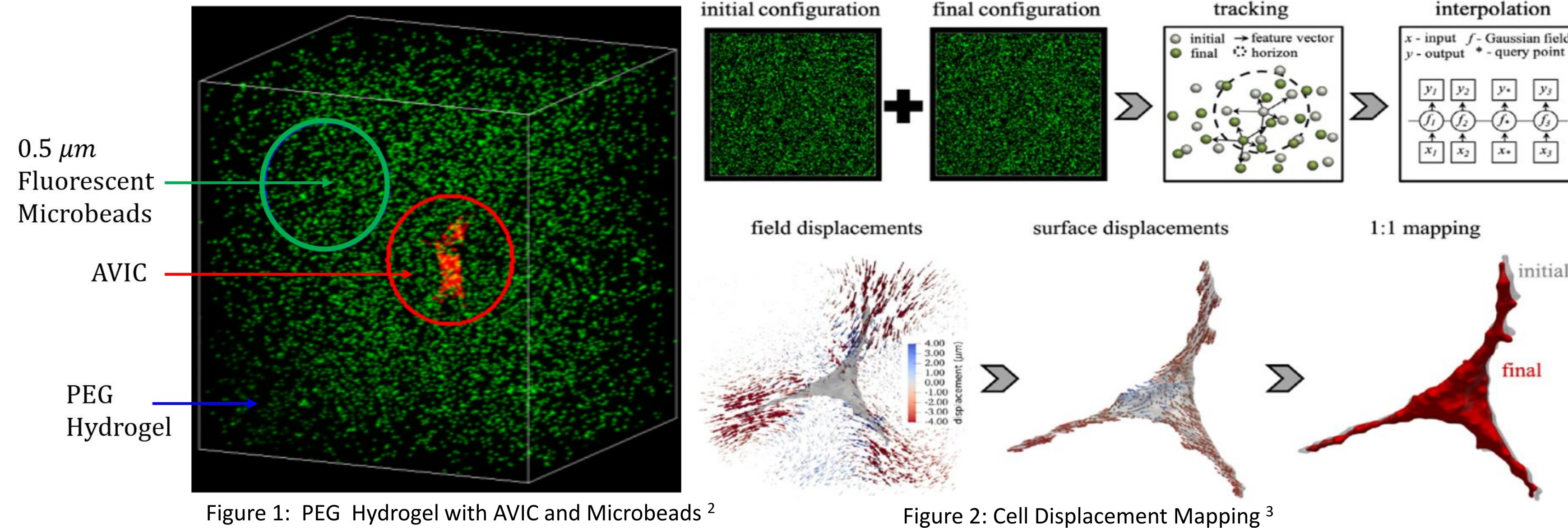
## 1. Motivation

- Aortic valve interstitial cells (AVICs) play key roles in valvular heart disease. When mechanically stimulated, AVICs secrete enzymes and collagen that degrade or stiffen their local microenvironments. We (WCCMS) simulated these microenvironment modifications to determine AVIC metabolism and contractability, indicators of phenotypic state.
- Current AVIC models are slow, especially for highly-detailed problems with finer meshes and realistic cell contraction models. We evaluate JAX-FEM, a GPU-accelerated differentiable finite element (FE) package against the standard FEniCS finite element toolkit, across different AVIC problem sizes.

## 2. Data

To isolate and study VICs (activated vs. basal state), a tissue-mimicking synthetic polyethylene glycol (PEG) hydrogel is impregnated with stained AVICs and green fluorescent microbeads.

- AVIC contraction causes the microbeads to shift.
- 3D Traction Force Microscopy then tracks microbead displacement.
- Using Gaussian process regression (GPR) on bead displacement data, AVIC displacement is inferred.<sup>1</sup>



## 4. The Inverse Model

The inverse model identifies the modulus field with minimal error in simulated nodal displacements, with objective<sup>5,6</sup> as below.

$$\phi = \int_{\Omega} \xi : \xi d\Omega + \gamma \int_{\Omega} (\nabla \alpha \cdot \nabla \alpha)^{\frac{1}{2}} d\Omega \quad \xi = \mathbf{C}_{target} - \mathbf{C}_{simulated} \quad \Omega = \text{reference gel domain}$$

$$\mathbf{C} := \mathbf{F}^T \mathbf{F} \text{ (the Cauchy-Green tensor)} \quad \gamma = \text{regularization}$$

$$\hat{\alpha} = \min_{\alpha(\text{DoFs})} \phi \quad \text{Ideally, Tikhonov regularization would be used instead: } \int_{\Omega} (\nabla \alpha \cdot \nabla \alpha) d\Omega$$

The objective gradient is determined with an adjoint method, allowing for more accuracy and efficiency than with a finite difference gradient approximation.

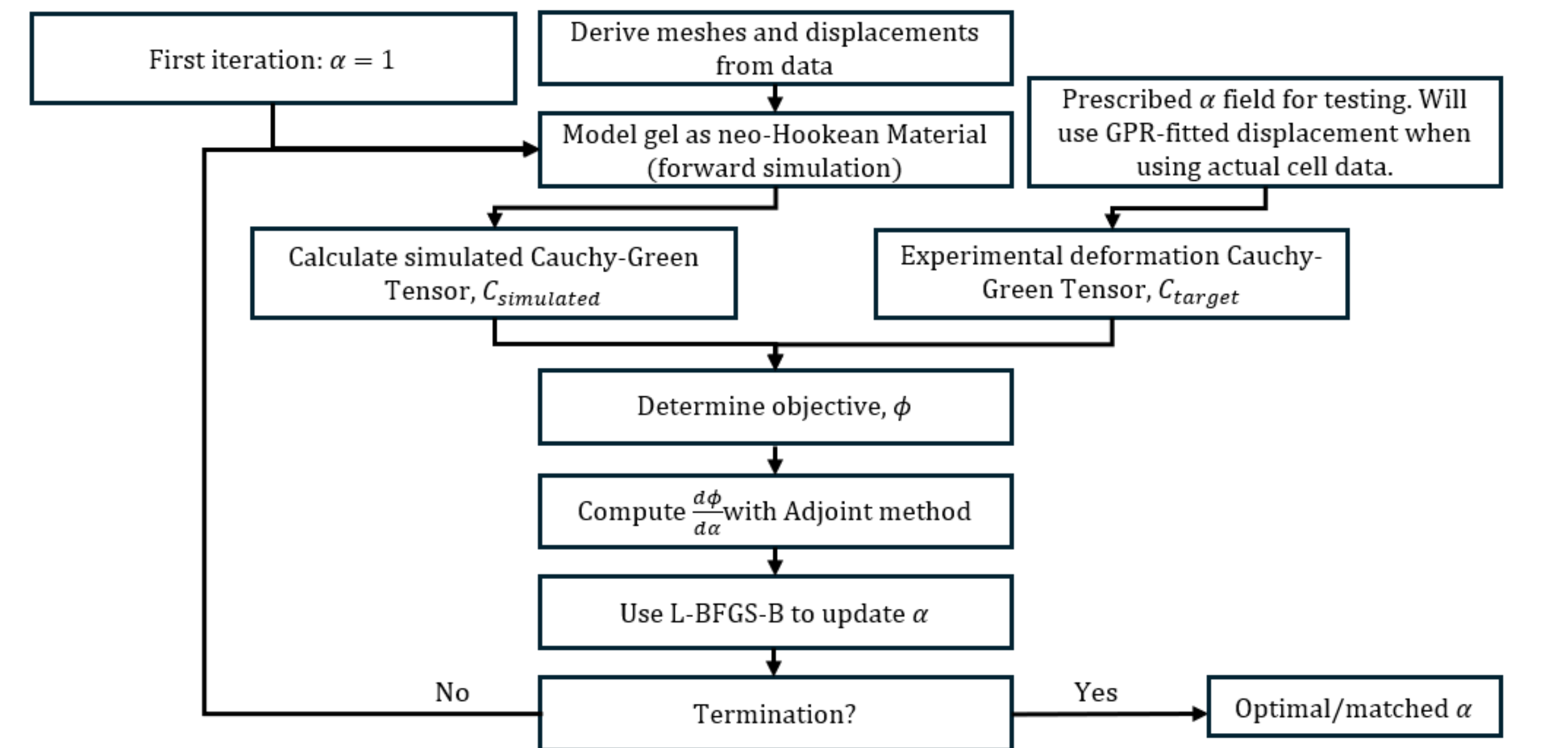


Figure 10: Inverse model pipeline

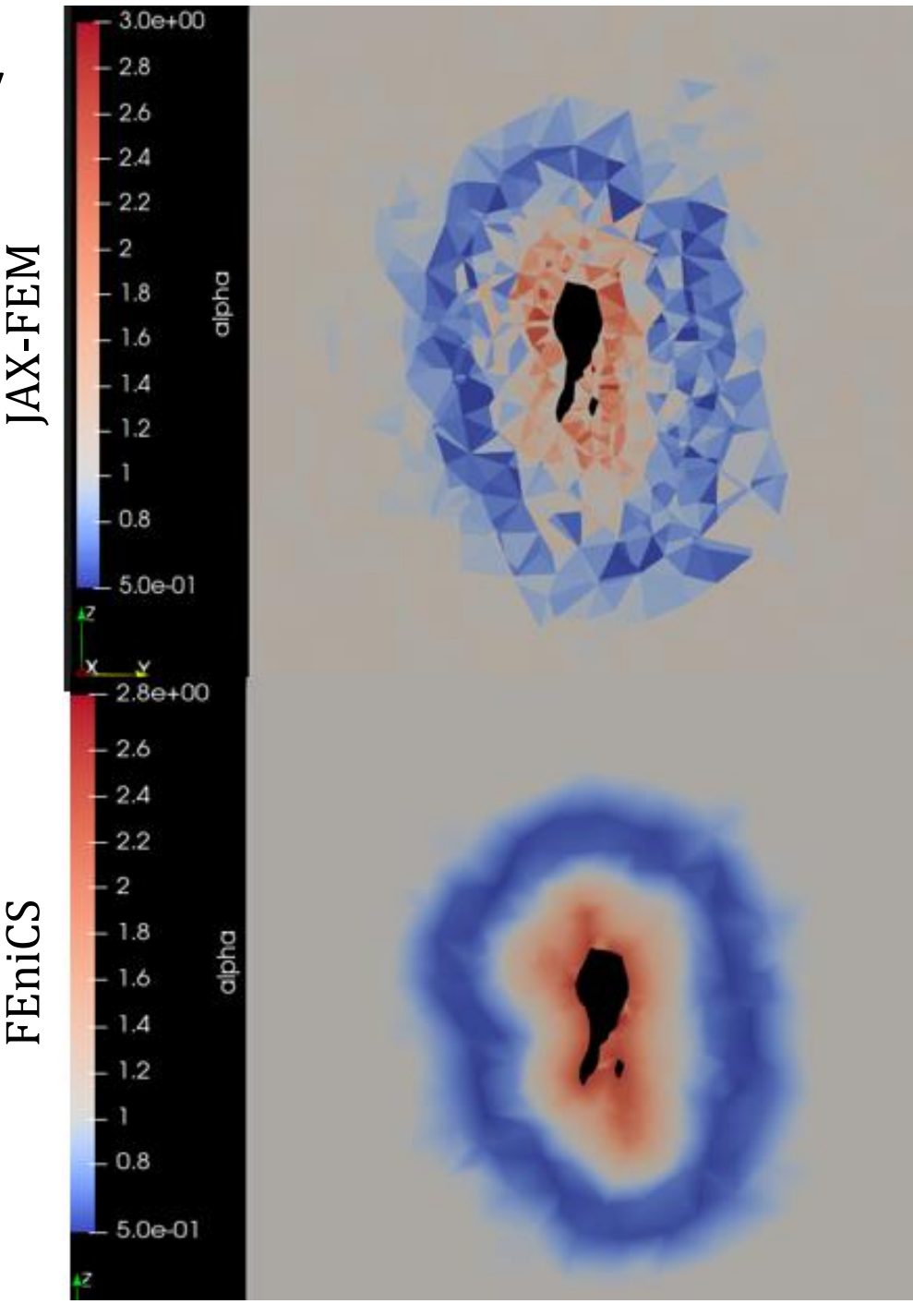


Figure 11: Inverse model recovered  $\alpha$  fields<sup>6</sup>

## 5. The Adjoint Method

The strain energy density,  $\Psi$ , provides a PDE relating the solution ( $u$ , the displacement field) and the optimization parameter ( $\alpha$ , the stiffness field), such that  $\Psi(u, \alpha) = 0$ .

Setting derivatives to zero (first-order optimality), we have:

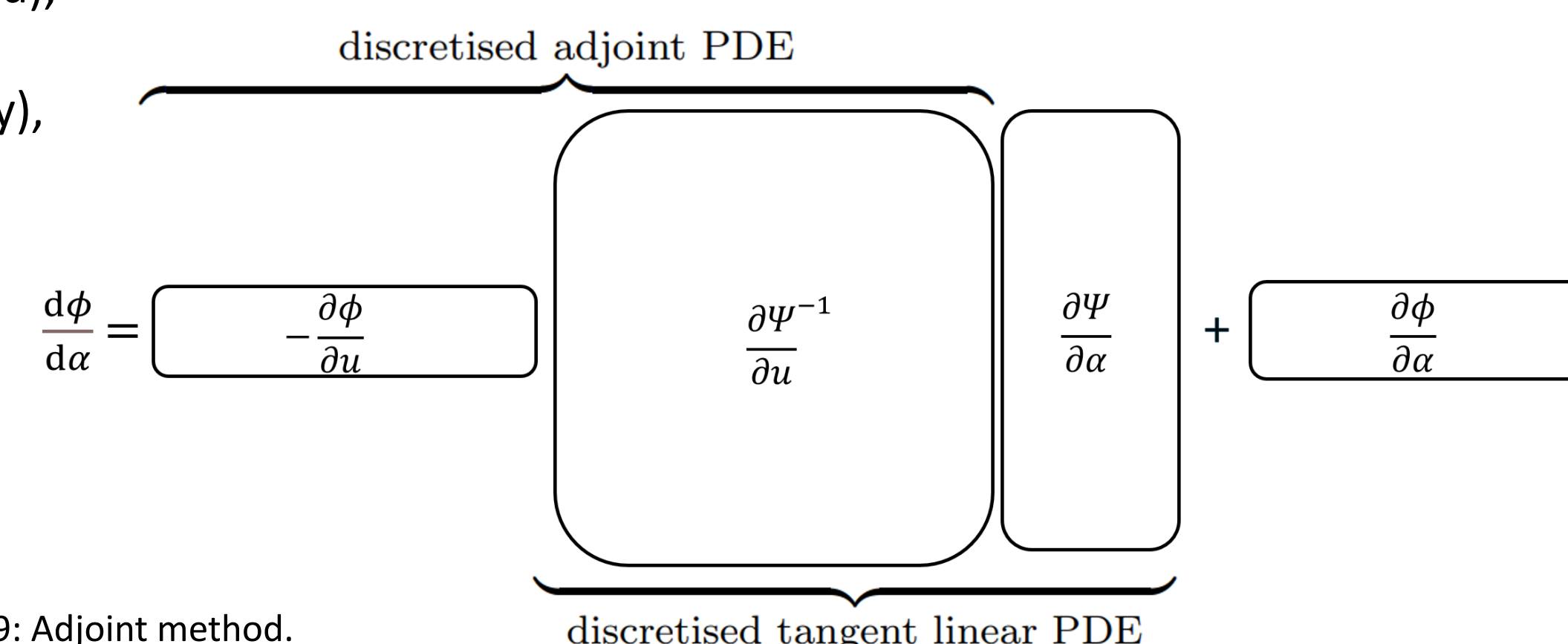
$$\frac{d\phi}{d\alpha} = \frac{\partial \phi}{\partial u} \frac{du}{d\alpha} + \frac{\partial \phi}{\partial \alpha}$$

$$\frac{d\Psi}{d\alpha} = \frac{\partial \Psi}{\partial u} \frac{du}{d\alpha} + \frac{\partial \Psi}{\partial \alpha} = 0$$

$$\Rightarrow \frac{du}{d\alpha} = -\left[\frac{\partial \Psi}{\partial u}\right]^{-1} \frac{\partial \Psi}{\partial \alpha}$$

Figure 9: Adjoint method.

The adjoint PDE uses vector-matrix computations, while the tangent linear PDE requires expensive matrix-matrix computations.



## 3. The Forward Model

The forward model takes a gel modulus field as input and solves for nodal displacements.

The gel's material stress and forces are determined with an isochoric, hyperelastic neo-Hookean model:

$$\Psi = \alpha(\mathbf{x}_0) C_1 (I_1 - 3) - 2C_1 \ln J + D_1 (\ln J)^2$$

$$\mathbf{F} = \frac{d\mathbf{x}}{d\mathbf{x}_0} \quad \mathbf{C} = \mathbf{F}^T \mathbf{F} \quad J = \det(\mathbf{F}) \quad I_1 = \text{tr}(\mathbf{C})$$

$$C_1 = 50Pa, \quad \frac{D_1}{C_1} = 10,000$$

- $\alpha$  is a scalar field that accounts for local stiffness.
- $\mathbf{x}_0$  is the reference gel position.
- $\psi$  is the gel strain energy density
- $\alpha(\mathbf{x}_0) C_1 (I_1 - 3)$  is the effective material model.
- The other strain energy terms are penalties to enforce near incompressibility.

Solution [JAX-FEM vs FEniCS]

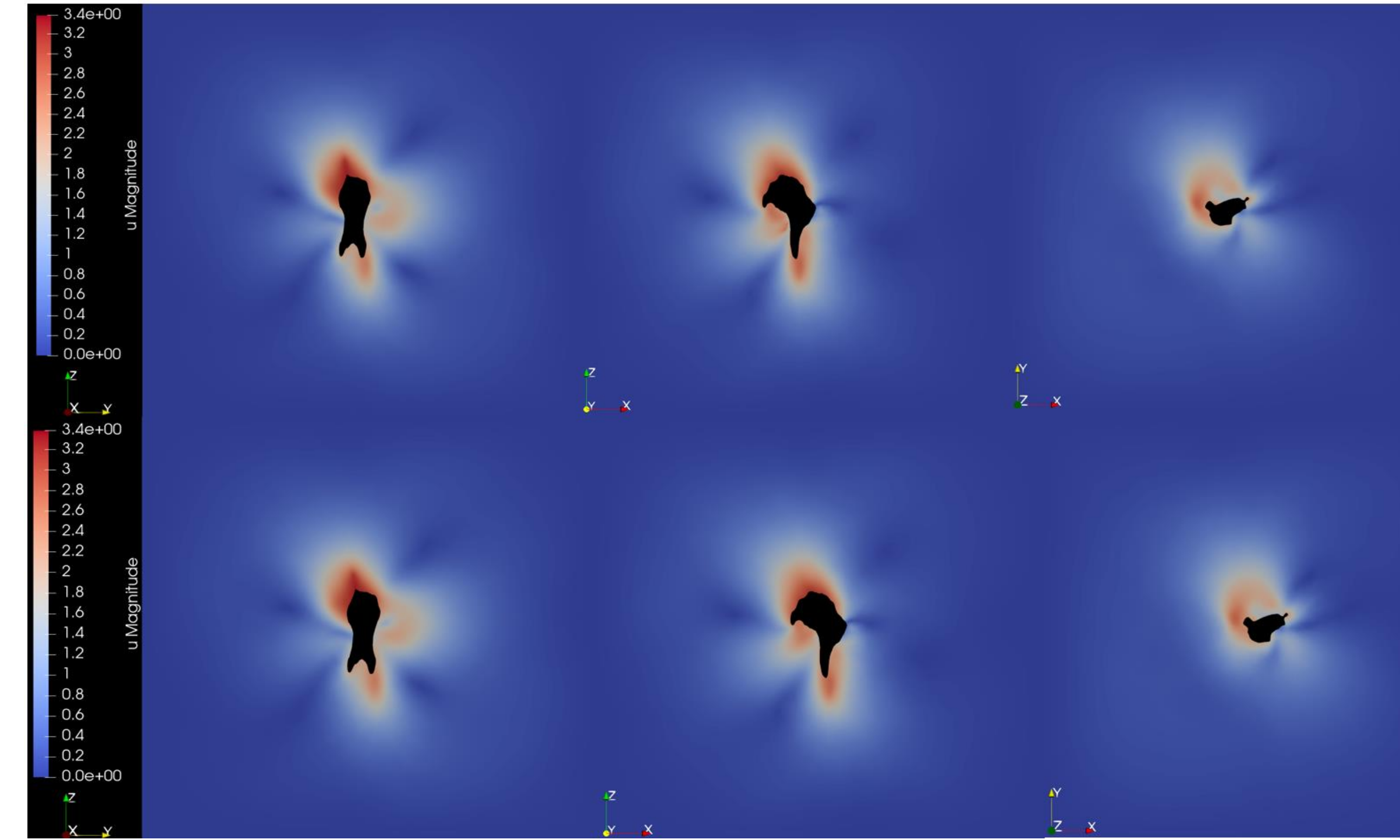


Figure 5: JAX-FEM vs. FEniCS solution cross-sections in current configuration.

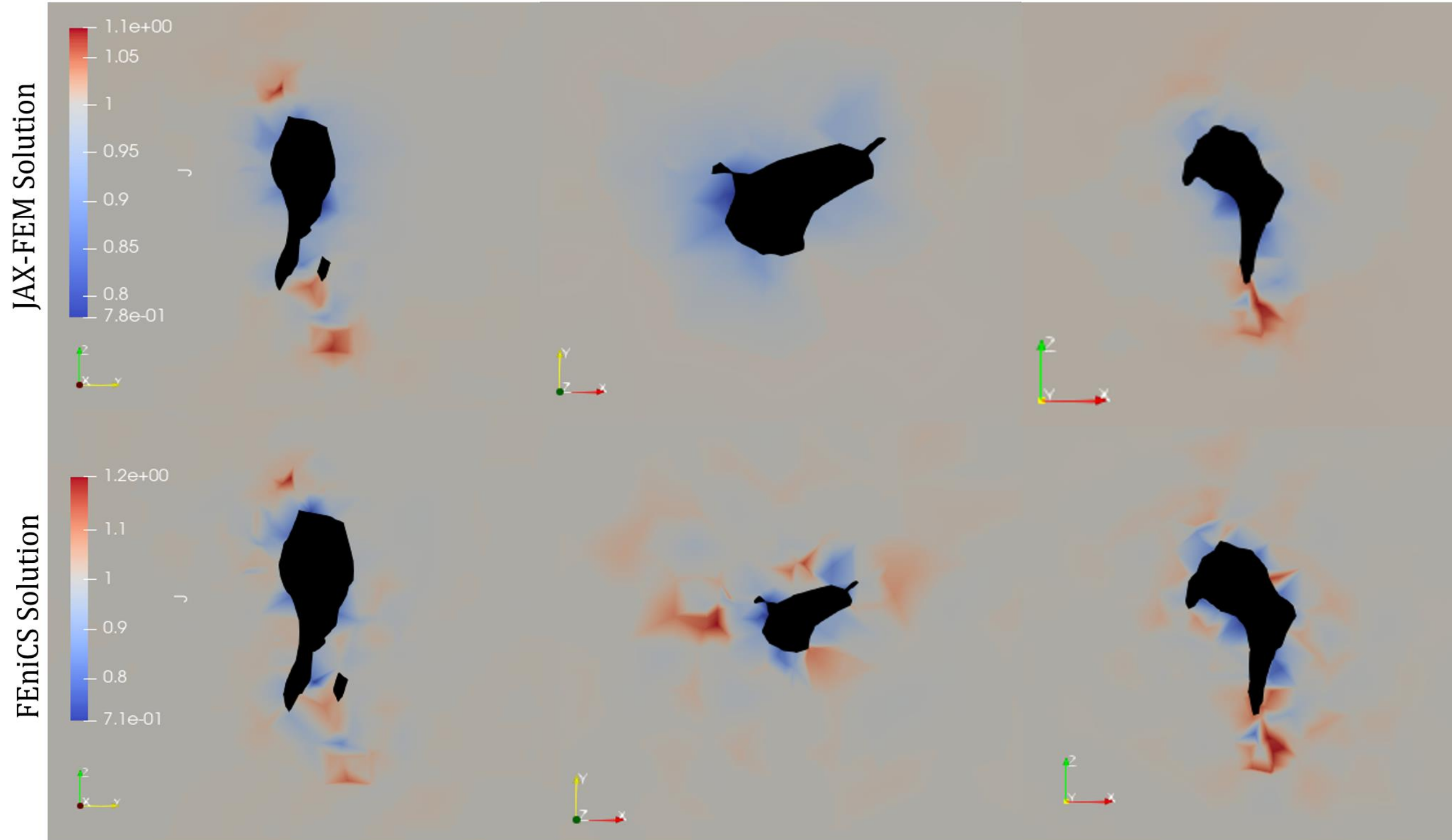


Figure 7: Jacobian field cross-sections of JAX-FEM and FEniCS solutions (should be 1 per incompressibility)

## Results

- JAX-FEM's Jacobian field (of the deformation gradient) is **more accurate** than FEniCS.
- JAX-FEM **scales better** than FEniCS: from  $7.93 \times 10^5$  to  $5.32 \times 10^6$  elements, FEniCS takes **50x** longer while JAX-FEM is only **6.6x** in runtime.
- JAX-FEM has **higher tolerance** though: JAX-FEM's residual is  $10^{-3}$  while FEniCS is  $10^{-9}$ .
- Likely due to preconditioner difference: Incomplete LU factorization (ILU) vs. Algebraic Multigrid (AMG). FEniCS fails to solve the problem with an ILU preconditioner while AMG has slower convergence than ILU for JAX-FEM.

## 6. Conclusion

- JAX-FEM is faster than FEniCS on large problems (over 371K elements or 180K degrees of freedom).
- JAX-FEM's solution better satisfies incompressibility so may be more accurate.

## 7. Future Steps in JAX FEM

- Implement a stronger preconditioner to decrease residual below  $10^{-9}$ .
- Implement a piecewise linear  $\alpha$  field with Tikhonov regularization for the inverse model.
- Run the inverse model on a real cell to recover the  $\alpha$  field.
- Develop advanced AVIC stress fiber models.

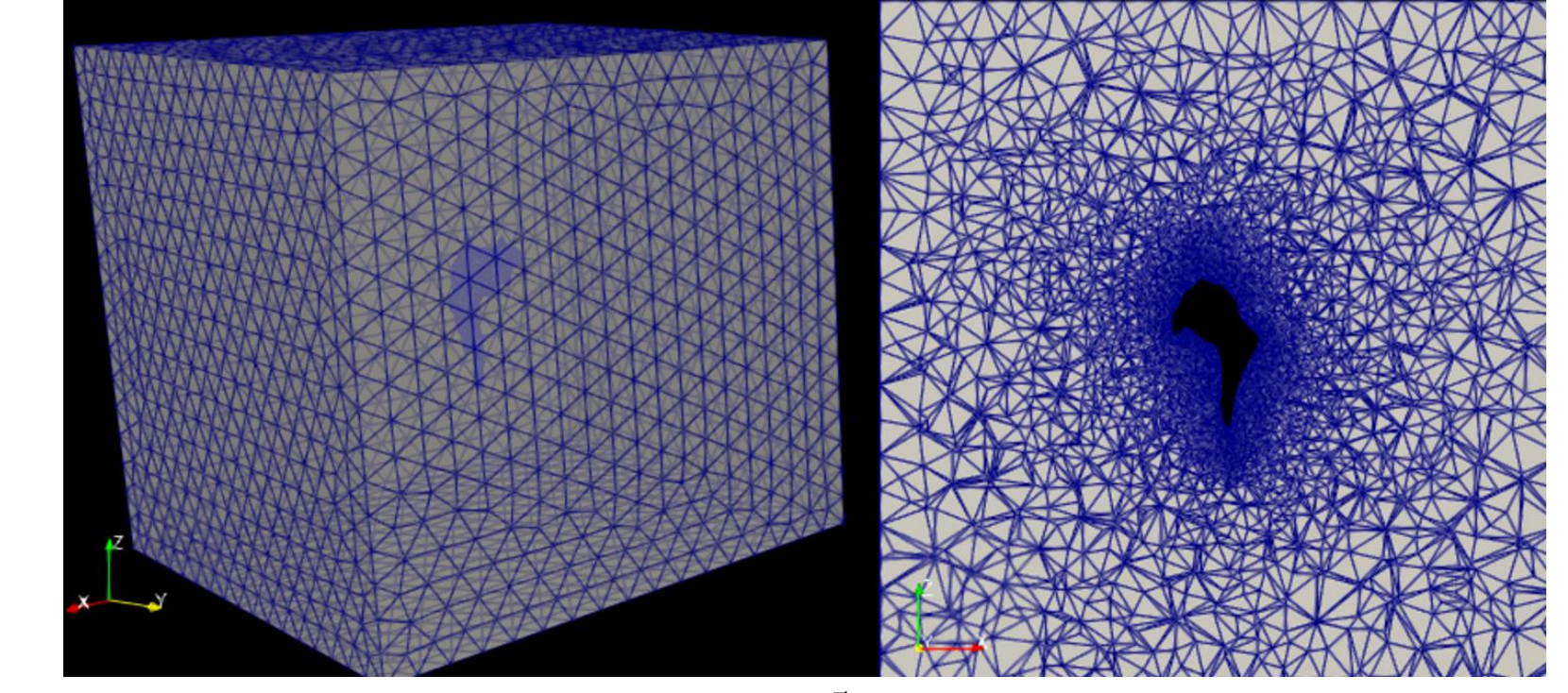


Figure 3: Mesh for  $7.93 \times 10^5$  Elements (129,758 Nodes).

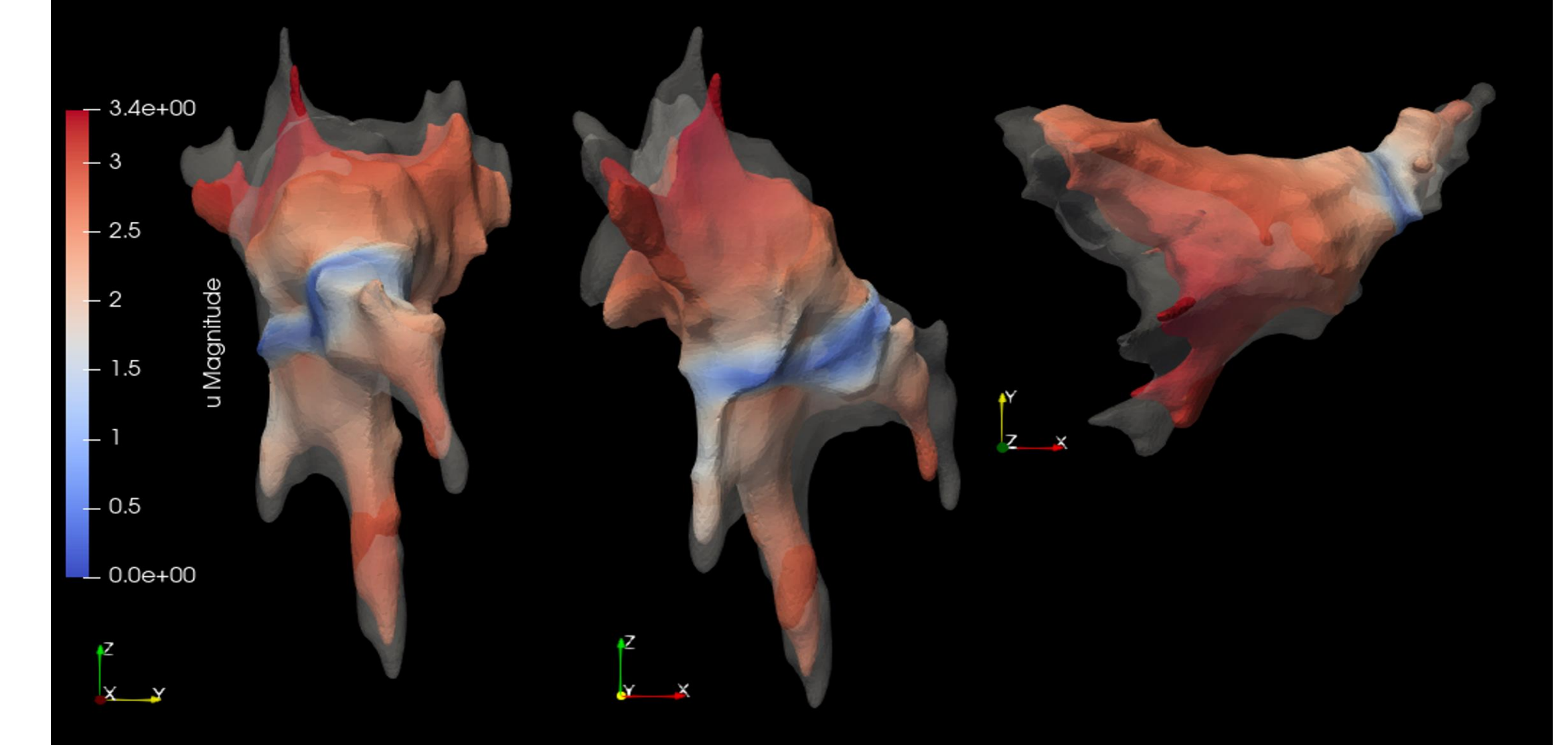


Figure 4: JAX-FEM forward model solution. Gray denotes reference configuration.

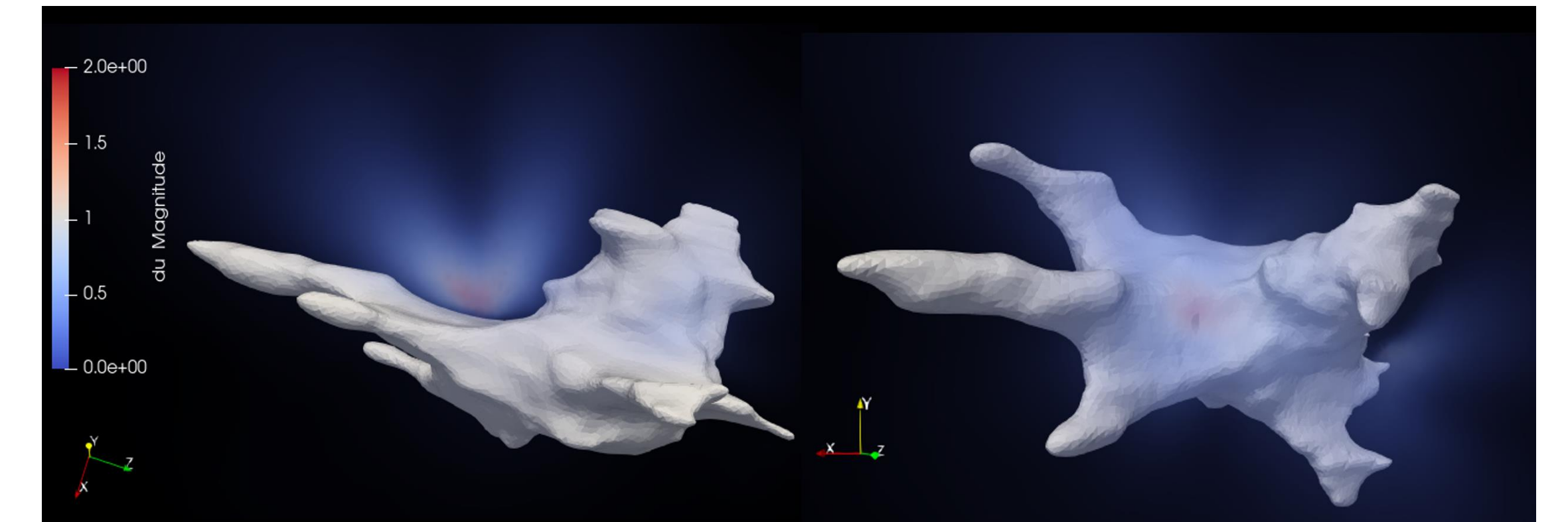


Figure 6: Solution difference between JAX-FEM and FEniCS in reference configuration.

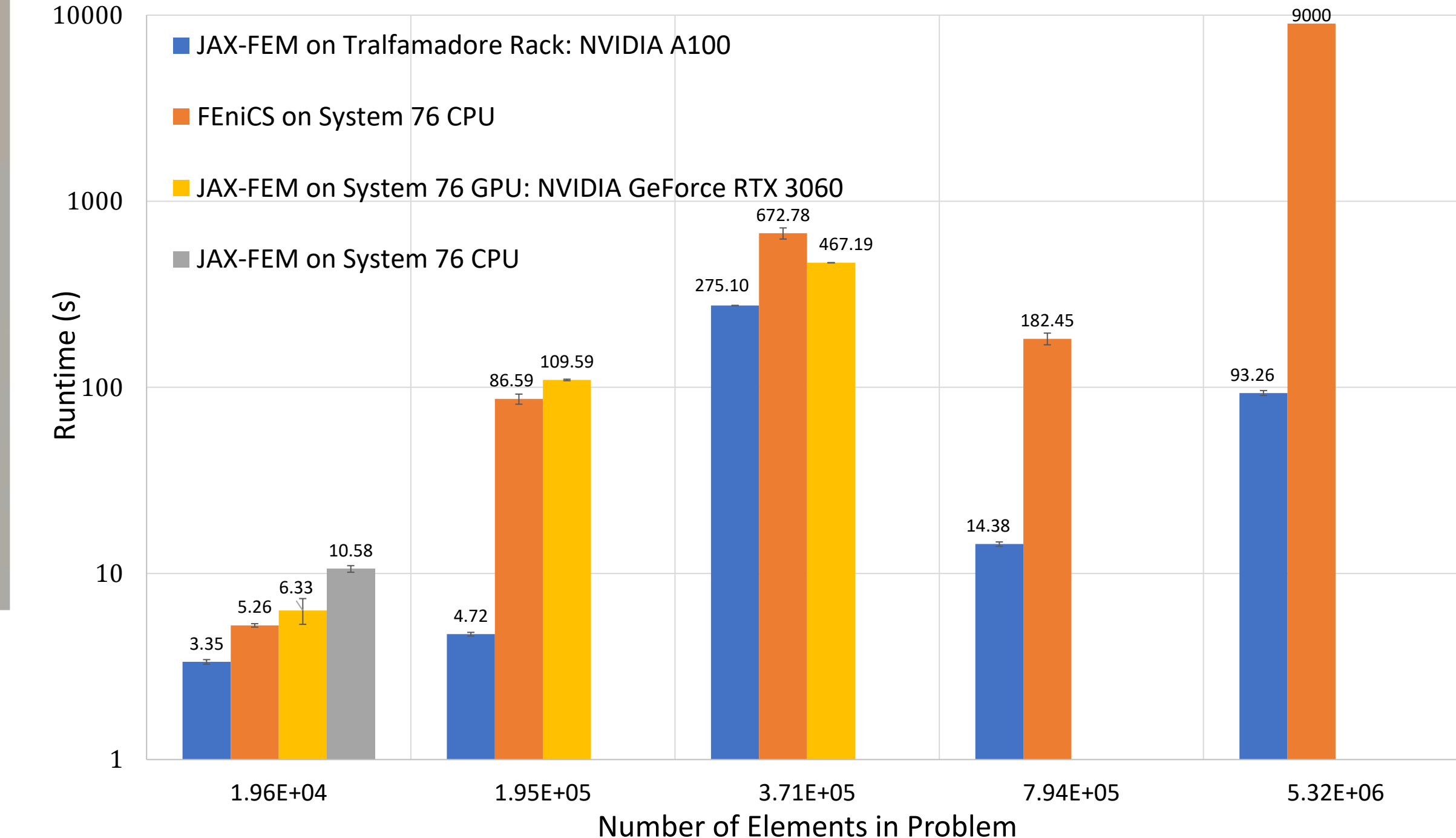


Figure 8: Runtime comparison between JAX-FEM and FEniCS<sup>4</sup>. Note logarithmic runtime scale.

<sup>1</sup>GPR infers a distribution over the function of interest directly, rather than optimizing function parameters.

<sup>2</sup>Image courtesy of Dr. Toni West

<sup>3</sup>Khang, Alex, "Estimation of aortic valve interstitial cell-induced 3D remodeling of poly(ethylene glycol) hydrogel environments using an inverse finite element approach".

<sup>4</sup>FEniCS took over 9000 seconds to solve the 5 million element problem; the program was stopped after 2.5 hours. Also, the problem with 371k elements required 7 load steps (while all other problems were solved with 1 load step).

<sup>5</sup>SciPy's optimize-minimize function is used with the L-BFGS-B (Limited-Memory Broyden-Fletcher-Goldfarb-Shanno algorithm) optimization algorithm. While BFGS stores a dense  $n \times n$  approximation of the inverse Hessian (2<sup>nd</sup> derivative) matrix, L-BFGS-B stores only a few vectors that represent the approximation implicitly, making it well suited for inverse models with many degrees of freedom (DoFs).

<sup>6</sup>JAX-FEM natively supports a piece-wise constant  $\alpha$  field, while FEniCS supports a piece-wise linear field. Piece-wise constant  $\alpha$  fields cause Tikhonov regularizers to diverge, so we use total variance.