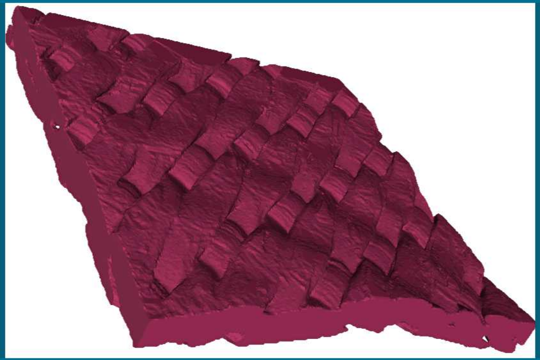
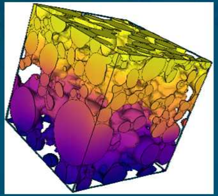
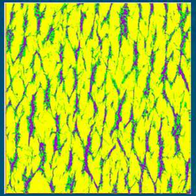
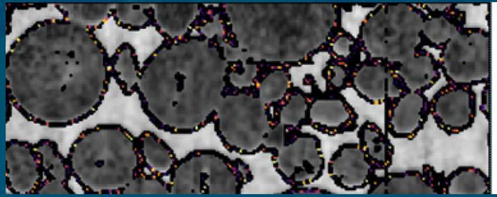
SAND2019-8755C

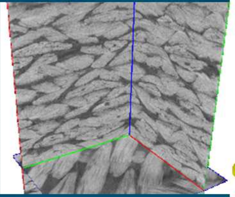
Effective Properties of Woven Composites from Image-Based Mesostructures

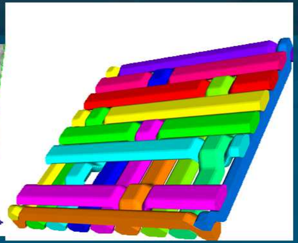












PRESENTED BY

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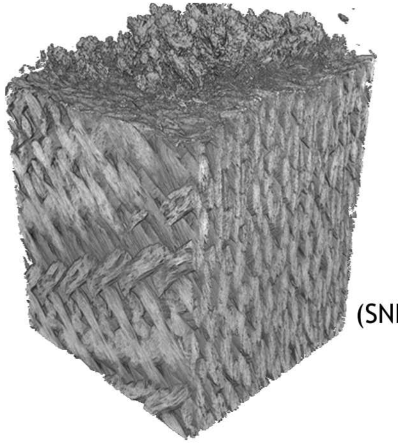
Motivation

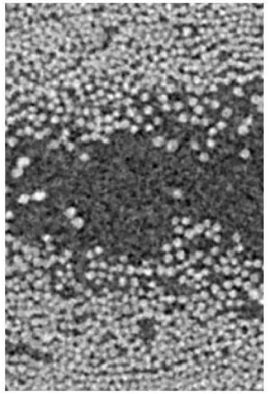
Geometry
- Analytical
- CT scan


(SNL)

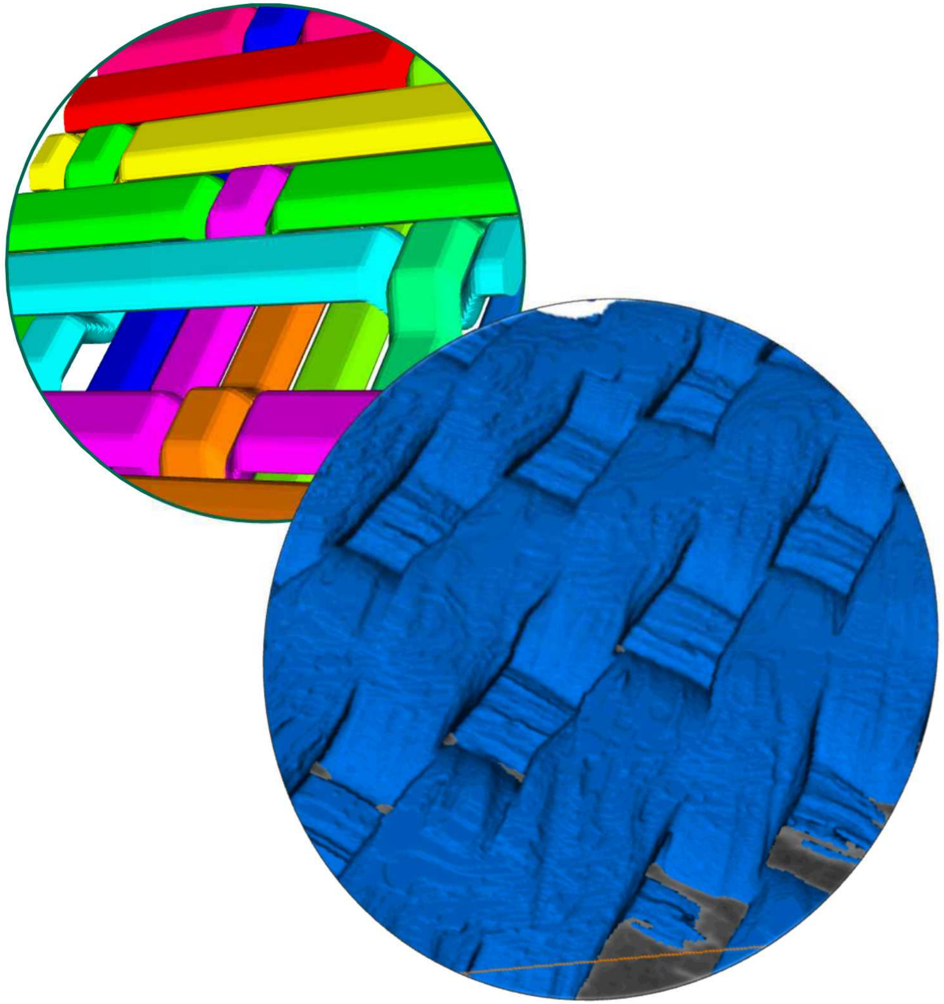
Constituent properties
(Fiber, fabric, resin, voids, filler)

Microscale parameters

(Zhou, 2019)

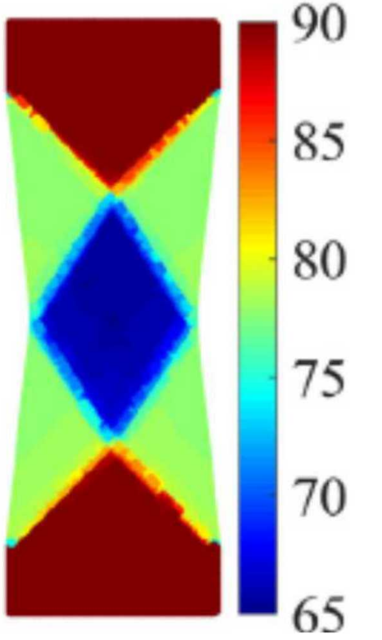

(SNL, NASA)

Mesoscale simulations



Fabric properties
- Defects etc.

Macroscale effective properties
- Trends
- Interactions
- Approximations



(Bostanabad, 2018)

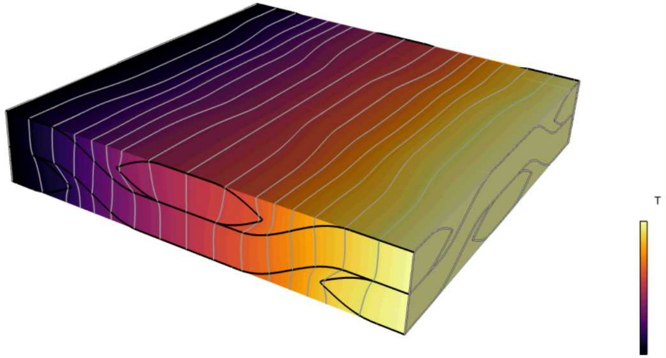
Effective properties from the mesoscale

Diffusive thermal transport:

$$\nabla \cdot (K_c \nabla T) = 0$$
$$T|_{\partial_d \Omega} = T_0$$
$$\nabla T \cdot \hat{n}|_{\partial_n \Omega} = 0$$

Effective conductivity:

$$Q_x = -\int_{\Omega_d} K \nabla T \cdot \hat{n}\, dA$$
$$= -K_{c,x} \left(\frac{\Delta T}{L_x} \right),$$



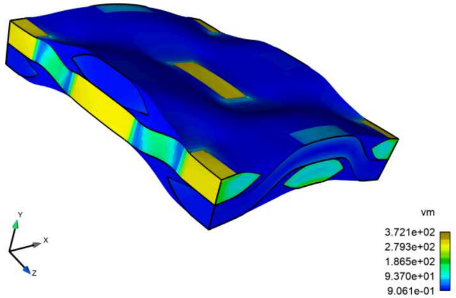
Linear elasticity:

$$u_1(\partial\Omega) = \varepsilon_{11}^0 x_1 \quad T_2(\partial\Omega) = T_3(\partial\Omega) = 0$$

$$\bar{\sigma}_{ij} = \begin{pmatrix} \bar{\sigma}_{11} & 0 & 0 \\ 0 & \bar{\sigma}_{22} & 0 \\ 0 & 0 & \bar{\sigma}_{33} \end{pmatrix} \quad \bar{\varepsilon}_{ij} = \begin{pmatrix} \varepsilon_{11}^0 & 0 & 0 \\ 0 & \bar{\varepsilon}_{22} & 0 \\ 0 & 0 & \bar{\varepsilon}_{33} \end{pmatrix}$$

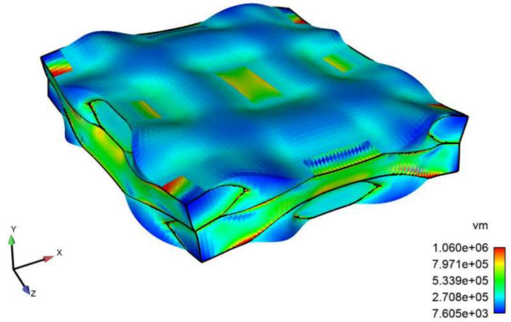
Effective moduli:

$$E_1 = \frac{\bar{\sigma}_{11}}{\varepsilon_{11}^0} \quad \nu_{12} = -\frac{\bar{\varepsilon}_{22}}{\varepsilon_{11}^0} \quad \nu_{13} = -\frac{\bar{\varepsilon}_{33}}{\varepsilon_{11}^0}$$



Effective expansivity:

$$\alpha_{ip} = \frac{\bar{\varepsilon}_{11}}{\Delta T} = \frac{\bar{\varepsilon}_{33}}{\Delta T}, \quad \frac{\bar{\varepsilon}_{22}}{\Delta T}$$



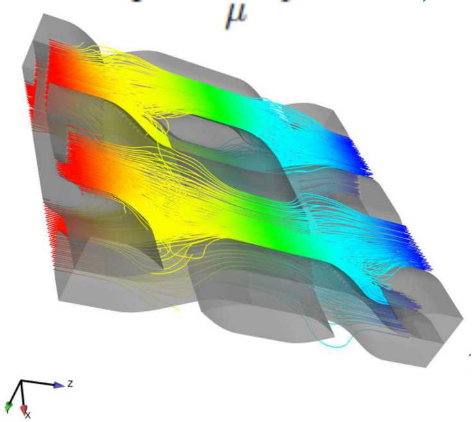
Stokes flow:

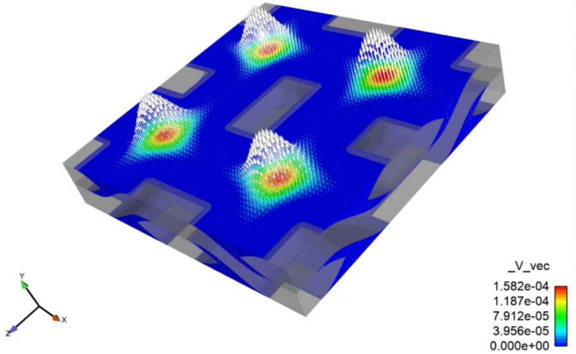
$$\nabla \cdot v = 0$$
$$\nabla \cdot \mathbf{T} = 0$$
$$p|_{\partial\Omega_i^{\mathrm{m}}} = p_i,$$
$$p|_{\partial\Omega_o^{\mathrm{m}}} = p_o,$$

Effective permeability:

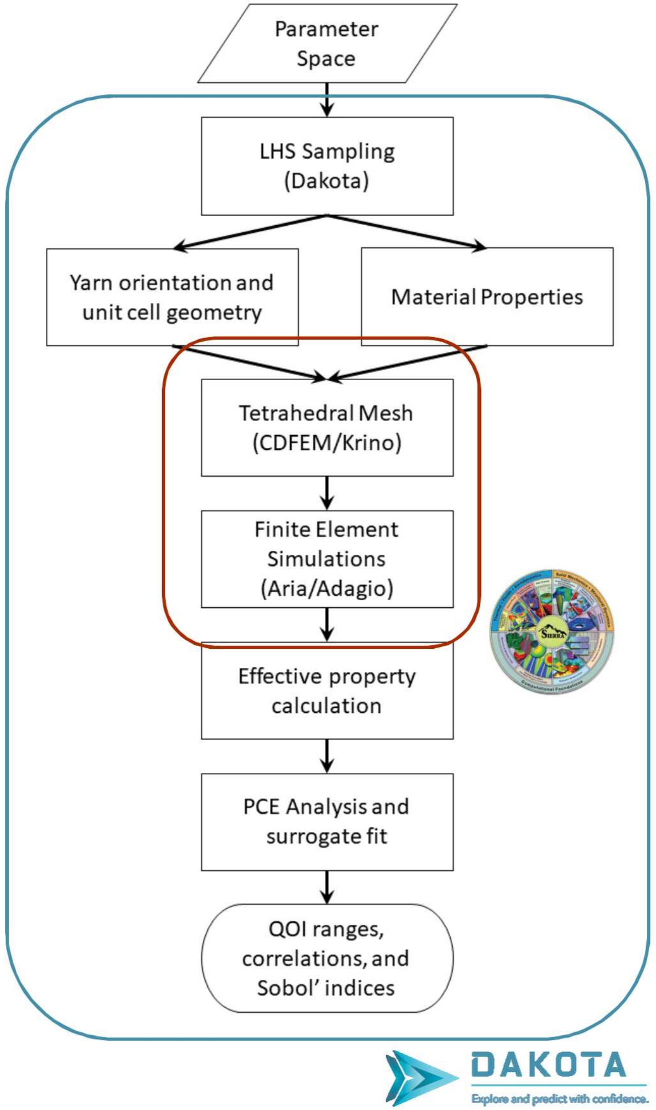
Darcy flux:

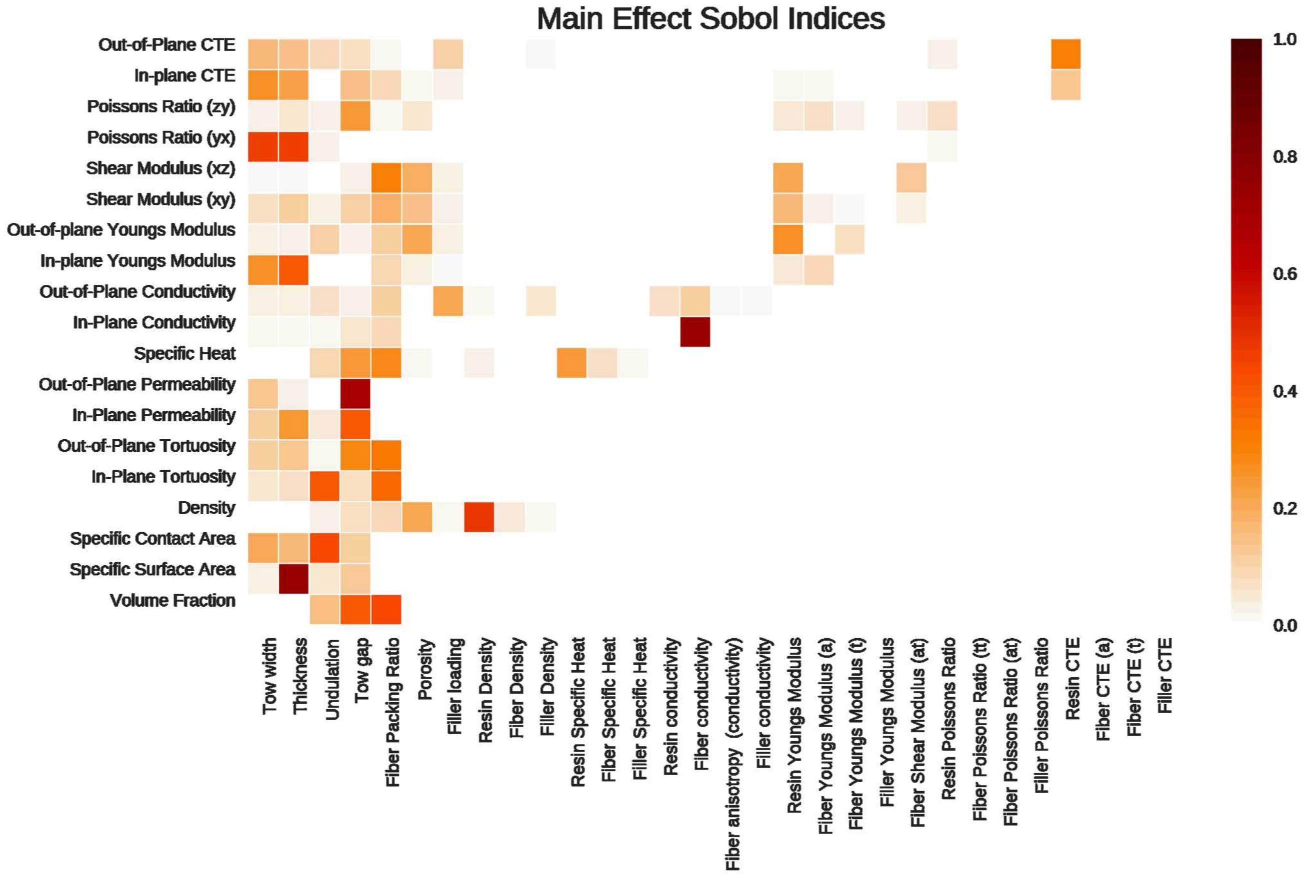
$$\mathbf{q} = -\frac{\kappa}{\mu} \nabla p \quad \Rightarrow \quad \kappa = v \frac{\mu L_x}{\Delta P}$$

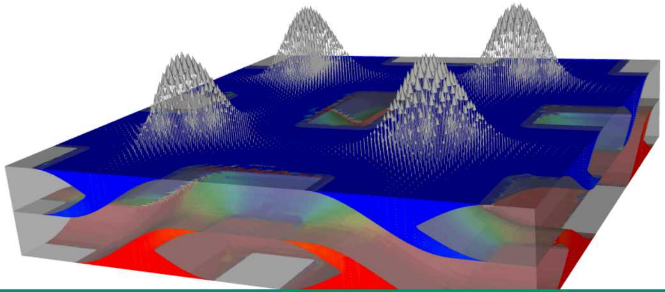


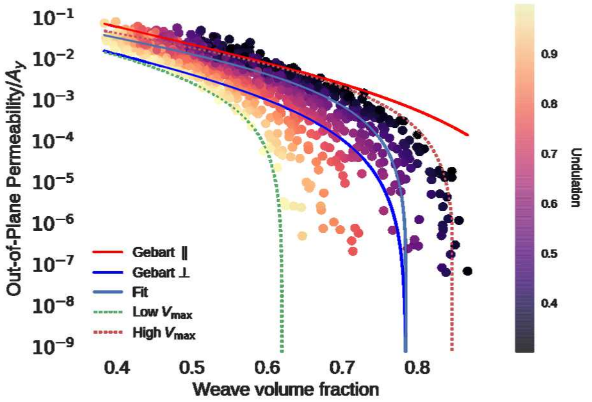


Effective properties from mesoscale





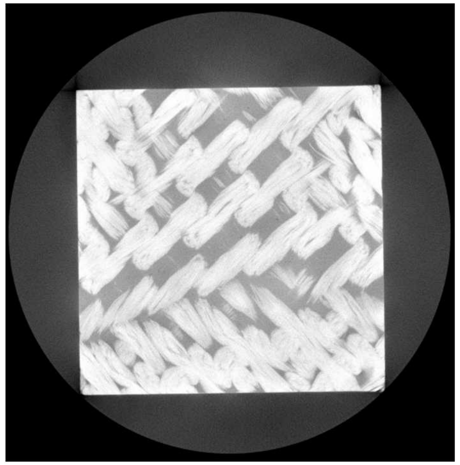




Structure-property relationships motivate image-based simulations!

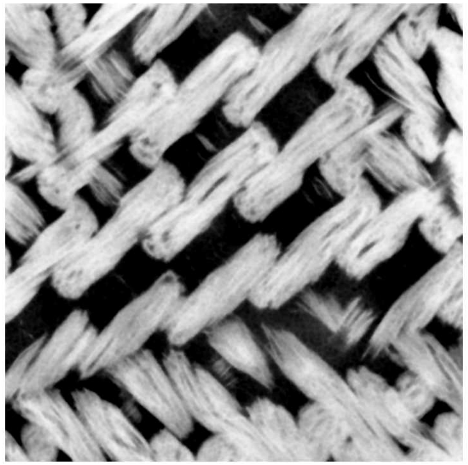
Tetrahedral mesh generation from image data

Raw image data (X-ray CT)



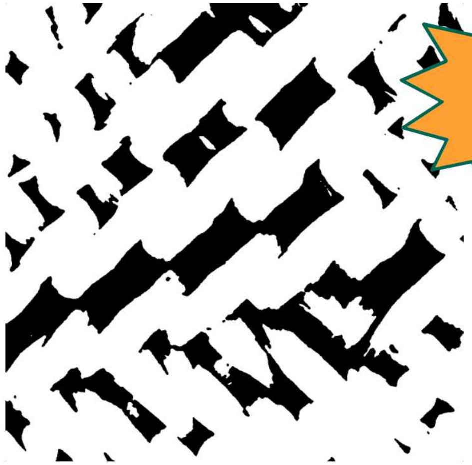
(SNL, NASA)

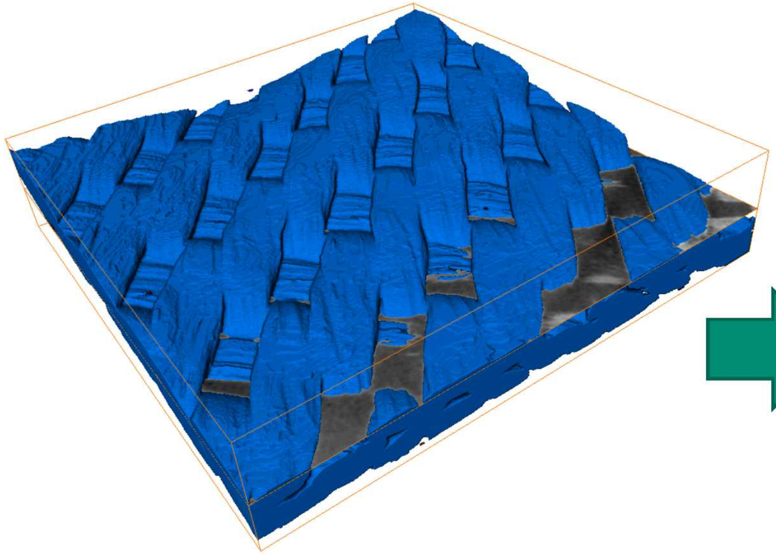
Filtered image data



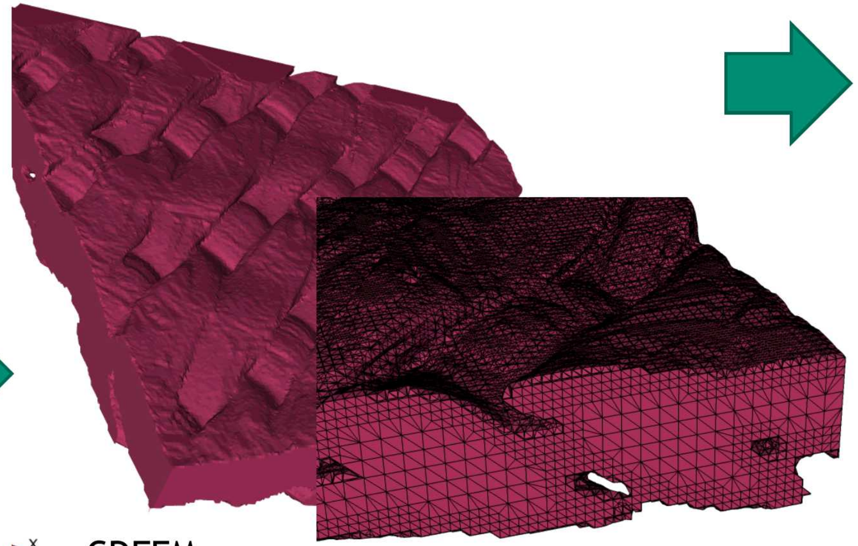
Binarized with threshold

DL



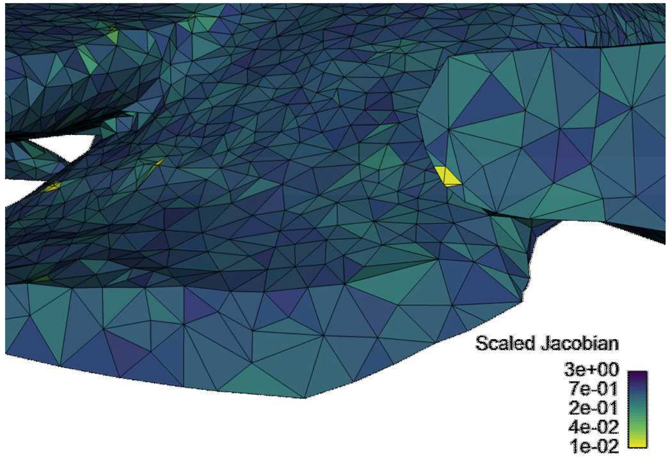


Reconstruct into faceted surface



CDFEM

(Noble, 2010; Kramer, 2014; Roberts, 2016)



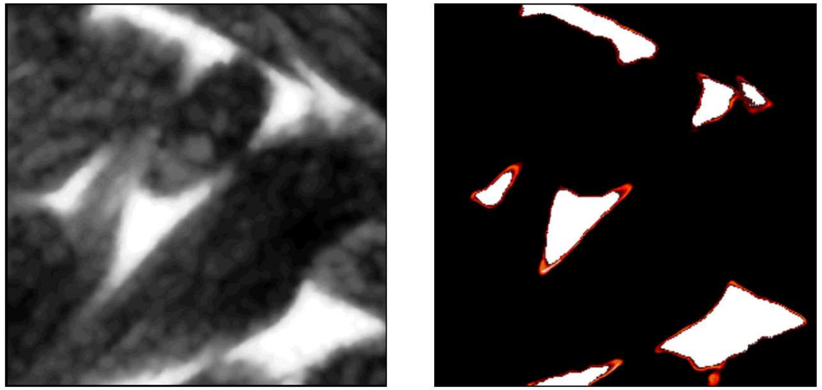
Emend to improve and coarsen mesh

Image segmentation using DL

- Train a 3D Convolutional Neural Network (CNN) to perform binary segmentation with labeled examples from one domain.
- Infer segmentations of domain-shifted CT scans.
- Obtain per-voxel epistemic uncertainty map by running inference multiple times with active dropout layers.
- Identify an appropriate uncertainty threshold.
- Flip the prediction for voxels with uncertainty over the threshold.

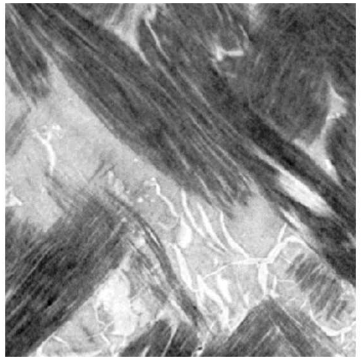
Slice from CT scan

Deep learning segmentation with uncertainty map



Accurate segmentations on held-out sub-volumes, with per-voxel UQ

CT slice from shifted domain

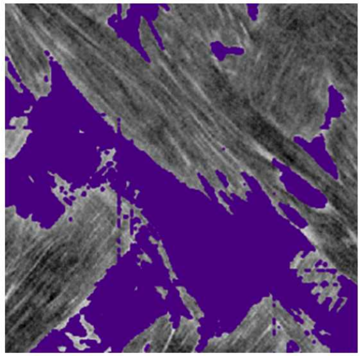


Predict segmentation using model trained on original domain

Unusable segmentation

+

Uncertainty map



Apply uncertainty based refinement method

Refined segmentation

(Martinez et al., 2019)

Conformal decomposition (CDFEM)

Concept

- Use level set fields to define phases
  - Solve for signed distance from interface

$$\frac{\partial \phi}{\partial t} + u \cdot \nabla \phi = 0 \qquad \vec{n} = \nabla \phi, \kappa = \nabla \cdot \nabla \phi$$

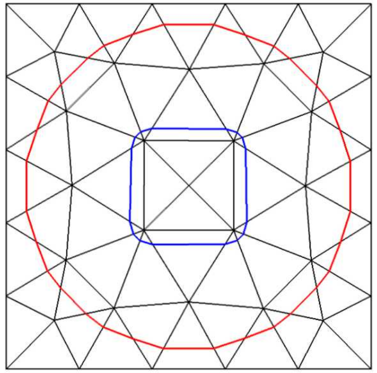
- Decompose non-conformal elements into conformal ones

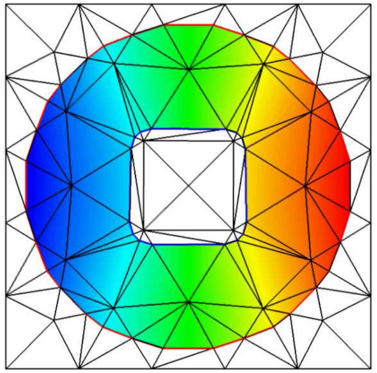
Properties

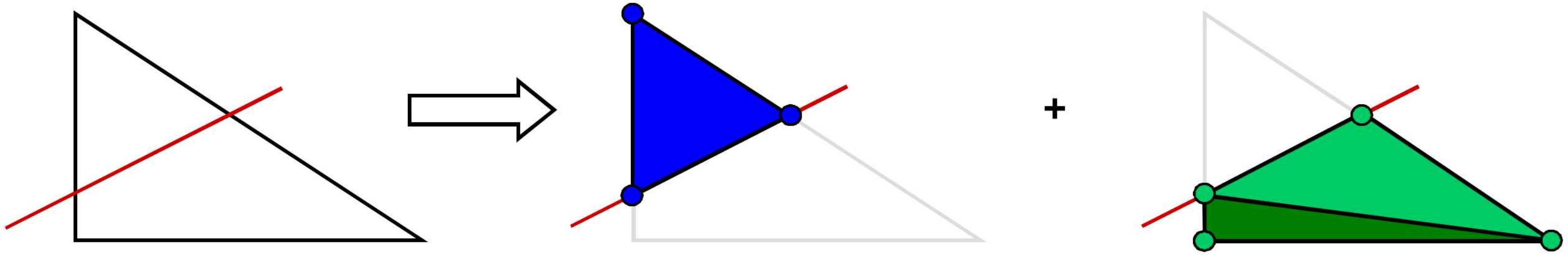
- Supports wide variety of interfacial conditions
- Avoids manual generation of boundary fitted mesh
- Supports general topological evolution

Similar to finite element adaptivity

- Uses standard finite element assembly including data structures, interpolation, quadrature. Affords discontinuous parameters.







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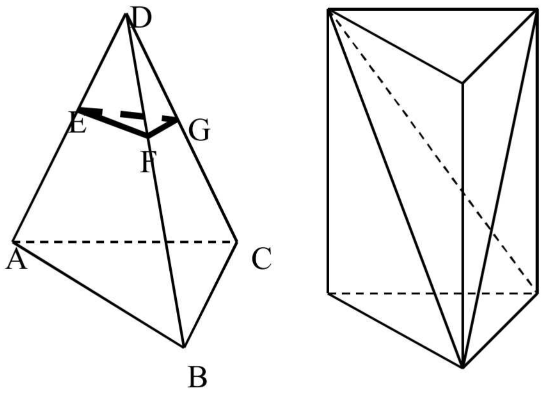
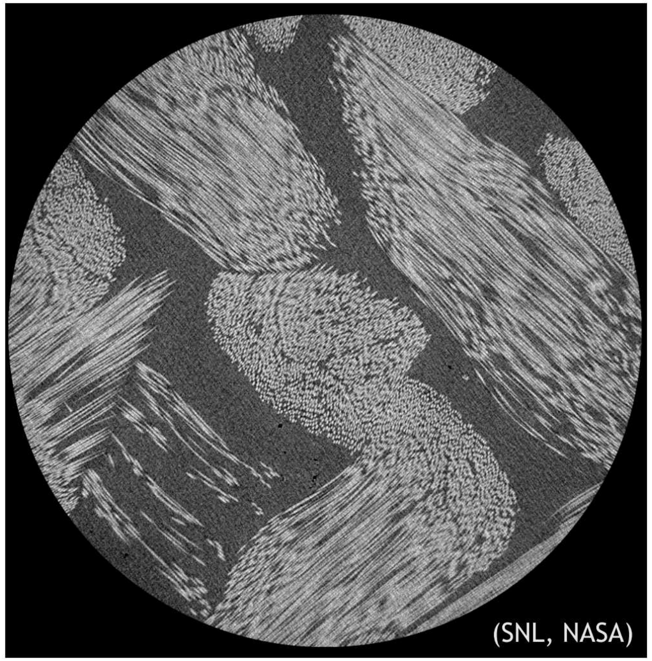
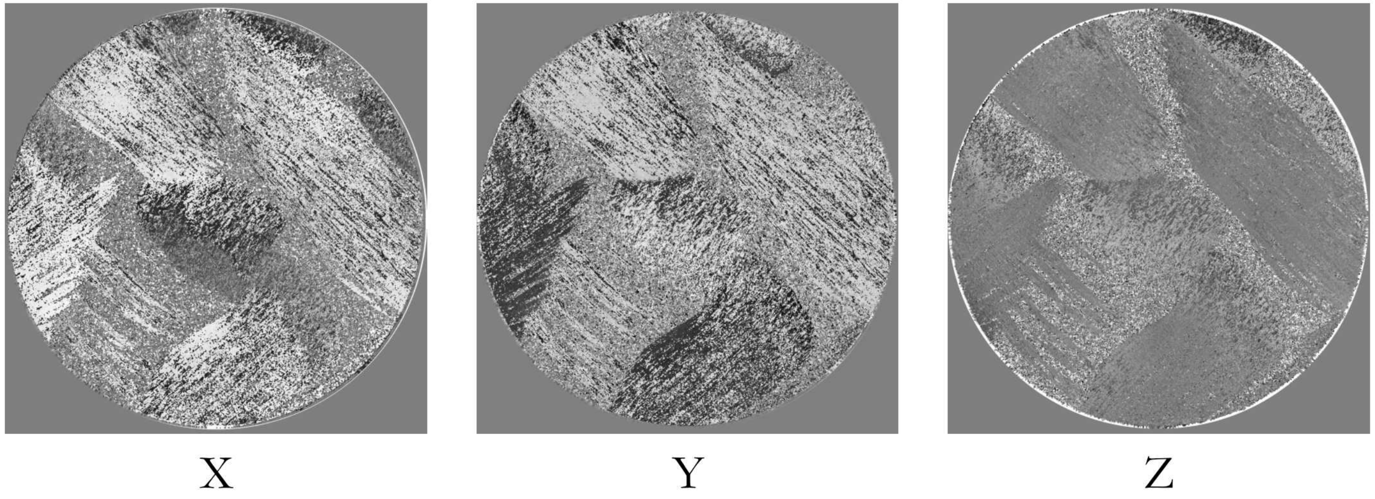


(Noble, 2010; Kramer, 2014; Roberts, 2016)

Image structure tensor



$$\nabla I_\sigma(x) = \nabla\left(G_\sigma * I\right)(x)$$
$$S_\sigma = \nabla I_\sigma \otimes \nabla I_\sigma$$
$$= \begin{bmatrix} I_{\sigma,x}^2 & I_{\sigma,x}I_{\sigma,y} & I_{\sigma,x}I_{\sigma,z} \\ I_{\sigma,x}I_{\sigma,y} & I_{\sigma,y}^2 & I_{\sigma,y}I_{\sigma,z} \\ I_{\sigma,x}I_{\sigma,z} & I_{\sigma,y}I_{\sigma,z} & I_{\sigma,z}^2 \end{bmatrix}$$

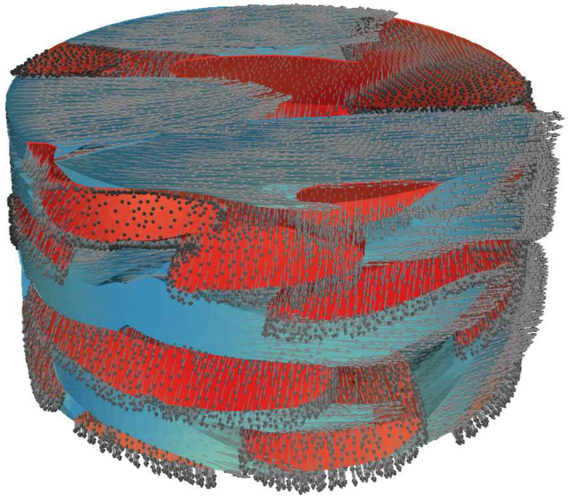


Structure tensor:

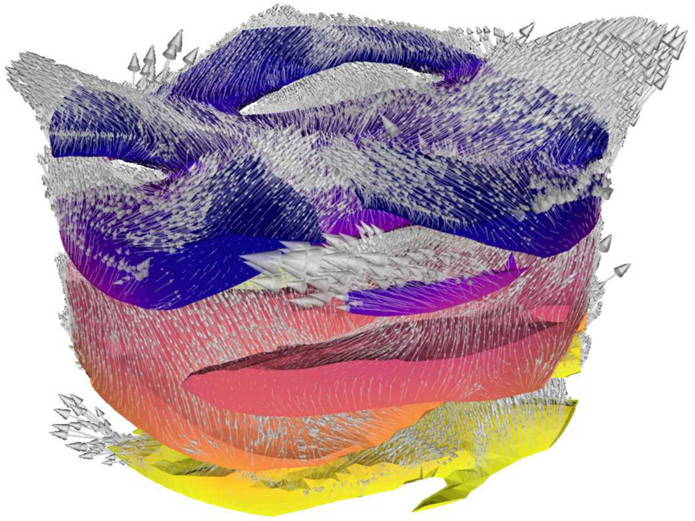
- Gradient tensor at each voxel
  - Uses Hessian of Gaussian-blurred intensity values
- Eigenvector associated with minimum eigenvalue denotes material direction
  - Lowest variation in image "texture"
- Requires rotation to common direction

Anisotropic segmentation and fiber orientation

θ



Material orientation



Heat flux

Separate fabric dimension:

- Use in-plane orientation, θ, to label warp/weft yarns

Fiber orientation:

- 3-d orientation calculated per-voxel
  - Smoothed and embedded on finite element mesh

Thermal stress:

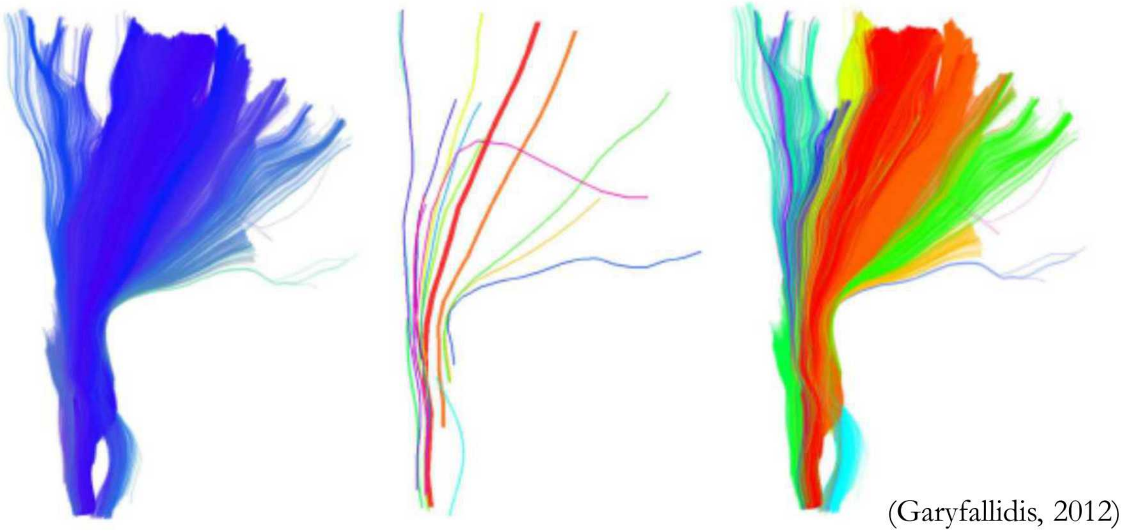
Fabric analysis from reconstructed image data

Goal: separate individual yarns in image

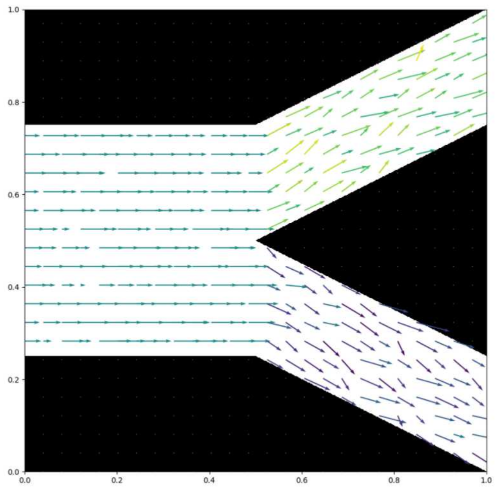
- Allows for path/cross section characterization, fabric analysis etc.
- Uses orientation from structure tensor

Elsewhere:

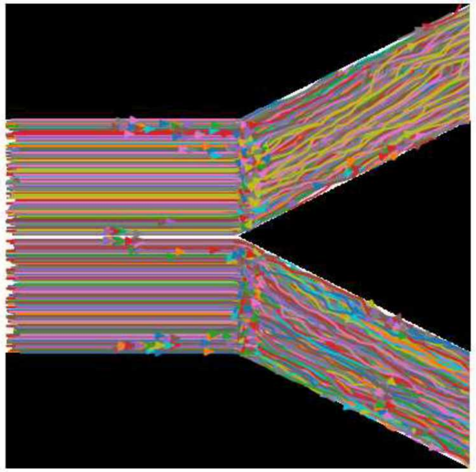
- Tractography of corticospinal tract using MRI
    - Indicates white matter orientation



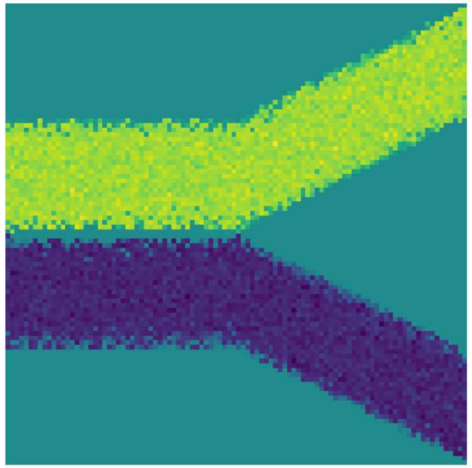
(Garyfallidis, 2012)



Data with orientation

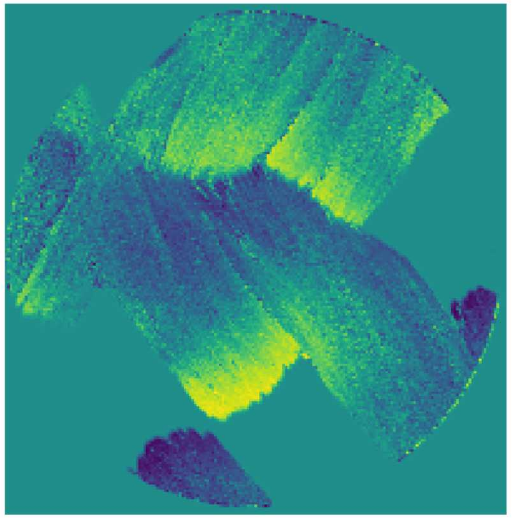


Generate streamlines using voxel locations as starting point (+/- direction)

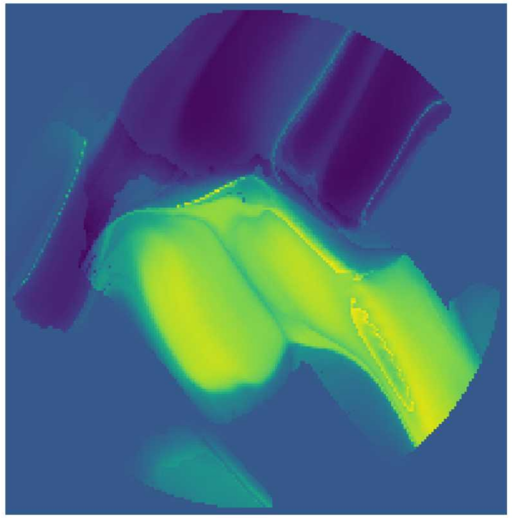


Assign pixel value based off line integral

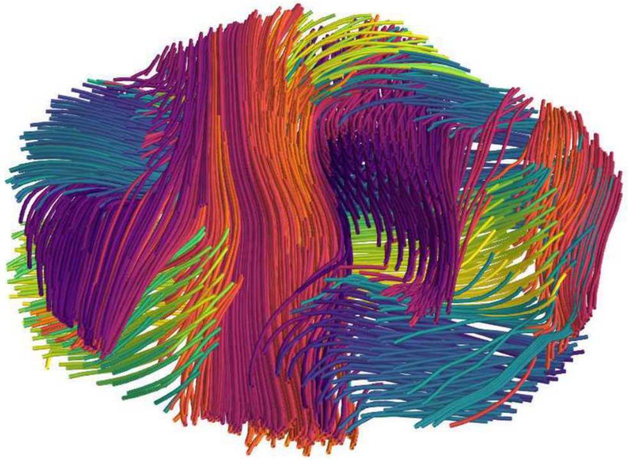
Fiber tractography

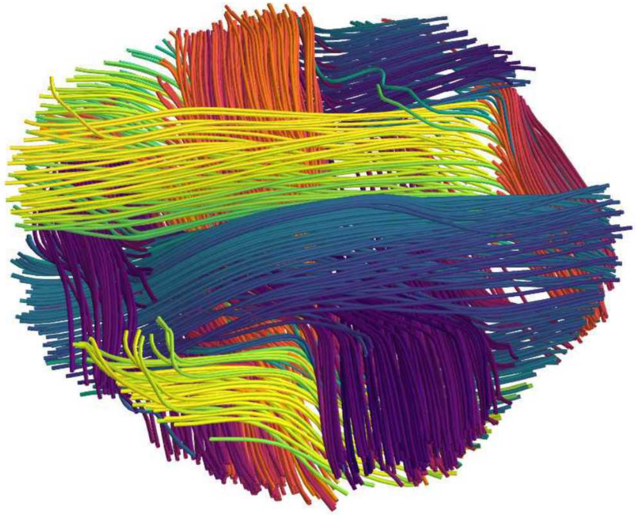


z-component



Path integral along streamline





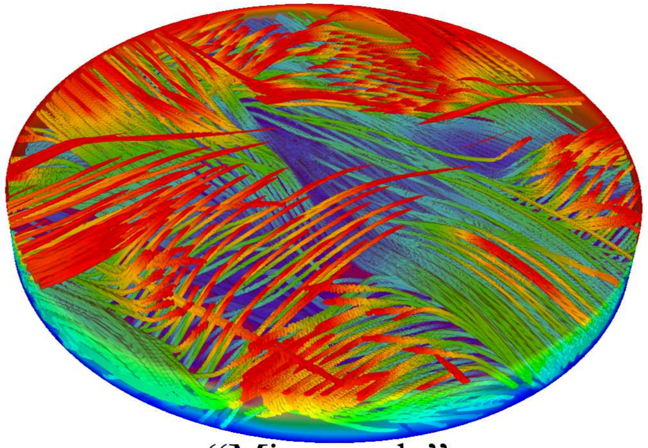
Separation of yarns:

- Requires choice of kernel to integrate along path
- Masking required to isolate directions

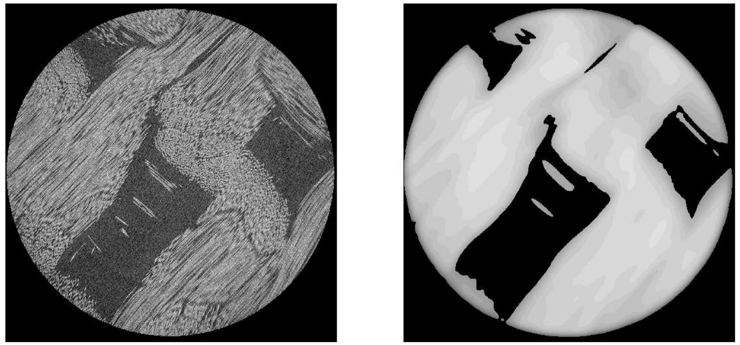
Fiber "reconstruction":

- Use orientation field and streamline to generate simulated fibers
- Export as .stl descriptions to CDFEM for simulations
- *Approximate* microscale behavior

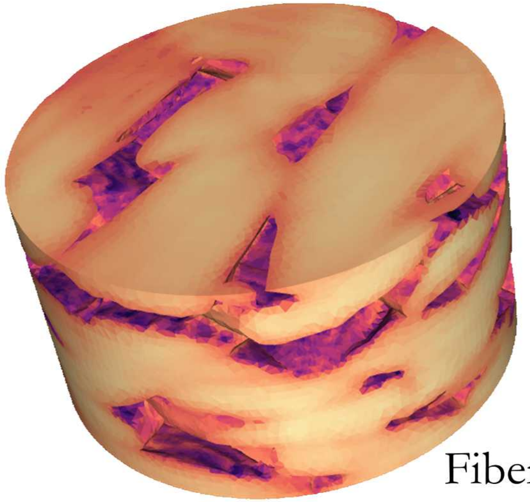
Example results



"Microscale"



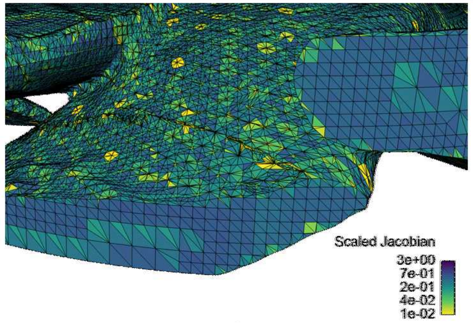
Smooth and rescale intensity to density approximation

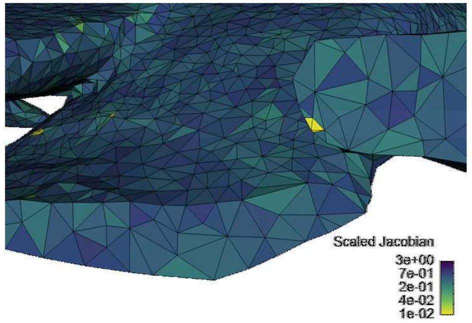


Fiber density

	Fiber packing	Fiber Volume Fraction	Effective Conductivity
Isotropic (Inverse)	0.8	0.667	0.35205
Isotropic (Mixture)	0.8	0.667	3.84361
Anisotropic (Uniform)	0.8	0.667	0.46077
Anisotropic (Image)	0.779	0.649	0.43350
Microscale	-	0.209	0.32671

	Element Count	Average Scaled Jacobian	Min Scaled Jacobian	Effective Cond.*
CDFEM	4959942	0.4644	1.456e-9	4.706
Emend	478940	0.5464	1.235e-5	4.837

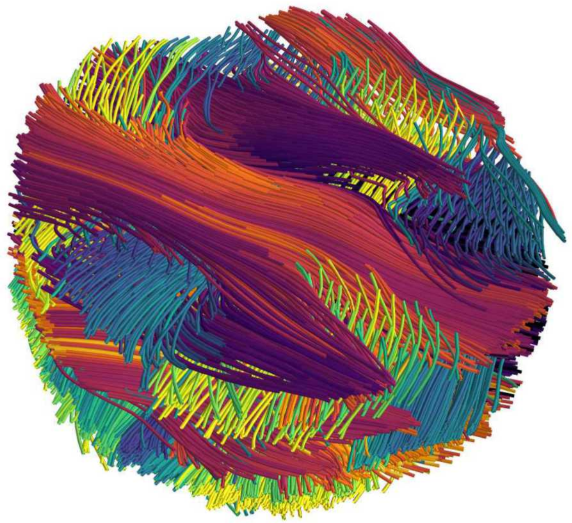




Emend improves minimum element quality 4 orders of magnitude, maintaining topology

Overview

- Image-based simulations are necessary for fully characterizing woven composites from the mesoscale
- Machine learning and robust image analysis can be adapted to various data sources, resolutions, and materials
- CDFEM offers an efficient method for generating numerical meshes from binarized data
- Image structure tensor allows for material orientation, object identification, and reconstruction of geometries
- Resulting meshes can adapted for use in any FEM simulation



Thank you!