# Estimating Neurovascular Deformation During Thrombectomy From 2D Fluoroscopy Using Physics-Regularized Deep Graph Networks

Tushar Nayak[1], Rishi Basdeo[2], Prof. Kenji Shimada[2]

[1] Department of Biomedical Engineering, Carnegie Mellon University, [2] Department of Mechanical Engineering, Carnegie Mellon University

## Summary & Clinical Need

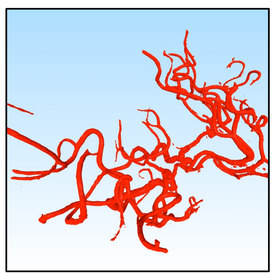
Endovascular thrombectomy is the standard treatment for acute ischemic stroke caused by large-vessel occlusion. During the procedure, clinicians navigate guidewires and microcatheters through highly tortuous intracranial vasculature using 2D X-ray fluoroscopy.

Pre-operative CTA provides a 3D roadmap, but this roadmap becomes inaccurate intraoperatively because the vasculature deforms under tool interaction. This creates a clinically significant mismatch between static pre-operative anatomy and the live surgical scene as estimating 3D vascular deformation from a single 2D fluoroscopic view is fundamentally ill-posed because projection removes depth information.

We propose a deep graph neural network framework that estimates 3D neurovascular deformation from fluoroscopy with mechanics-inspired regularization. The method combines fluoroscopic image features with vascular graph structure and is evaluated through with surgical fluoroscopy videos.

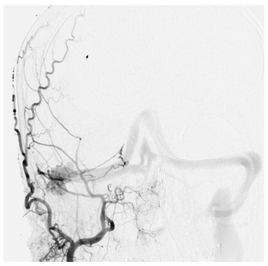
**Goal:** Recover 3D deformation caused by surgical tools from single-view fluoroscopy without sacrificing inference speed.

## Datasets



Training & Validation Data

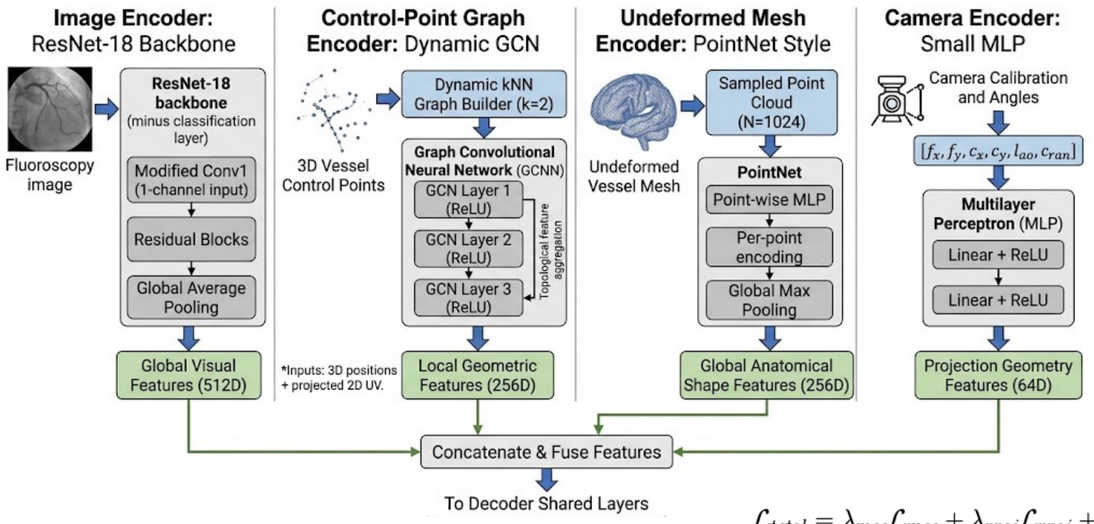
We utilized the open-source 3D intracranial vascular dataset, IntrA by Yang et. al. This dataset provides a robust and highly varied collection of 3D surface meshes representing complex cerebrovascular structures. This meshes served as the pre-op anatomies for our synthetic deformation pipeline



Test Data

We're testing the model using a private clinical dataset acquired at the University of Pittsburgh and UPMC. This testing cohort comprises stroke patients who underwent thrombectomy. For each case, perioperative Computed Tomography Angiography volumes were acquired as part of routine clinical care, providing highly realistic vascular geometries.

## Deformation Estimation Methodology & Regularized Loss Formulation




- The proposed model is a quad-encoder architecture that combines global visual evidence from fluoroscopy with local structural information from a vascular graph.
- The vascular centerline is represented as an ordered graph with node-level geometric and projected image features.
- A fused decoder predicts node-wise 3D displacements that deform the centerline toward the target anatomy

### Displacement Supervision & Reprojection Consistency

$$\mathcal{L}_{mse} = \frac{1}{N}\sum_i \|\hat{x}_i - x_i^{gt}\|_2^2 \qquad \mathcal{L}_{proj} = \frac{1}{N}\sum_i \|\Pi(\hat{x}_i) - \Pi(x_i^{gt})\|_1$$

### Physics Regularization Terms

$$\mathcal{L}_{stretch} = \frac{1}{N-1}\sum_i \left(\|\hat{x}_{i+1} - \hat{x}_i\| - \|x_{i+1}^0 - x_i^0\|\right)^2$$

$$\mathcal{L}_{bend} = \frac{1}{N-2}\sum_i \left(\Delta^2\hat{x}_i - \Delta^2 x_i^0\right)^2$$

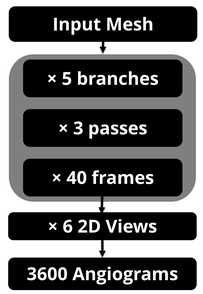
$$\mathcal{L}_{total} = \lambda_{mse}\mathcal{L}_{mse} + \lambda_{proj}\mathcal{L}_{proj} + \lambda_{stretch}\mathcal{L}_{stretch} + \lambda_{bend}\mathcal{L}_{bend}$$

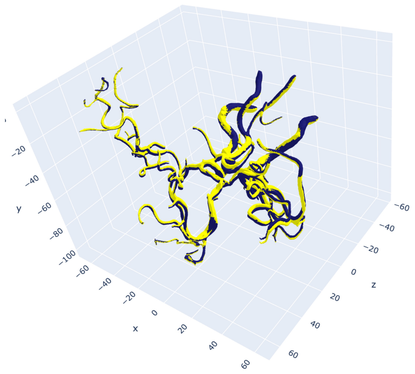
- **L-MSE** is a SmoothL1 loss on the predicted displacement field, tells the network where each node should move in 3D.
- **L-Proj** is the reprojection consistency term using the projected positions of the predicted and ground-truth geometry. So, it is not an image reconstruction loss.
- **L-Bend** is a curvature regularizes that computes a discrete second derivative, comparing the predicted Laplacian to the rest-state Laplacian.
- **L-Stretch** is a rest-length preservation regularizes that penalizes unrealistic elongation or compression.

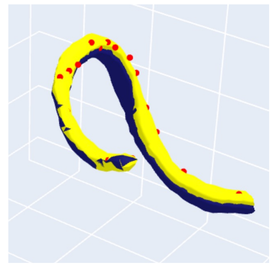
## Synthetic Deformation Pipeline

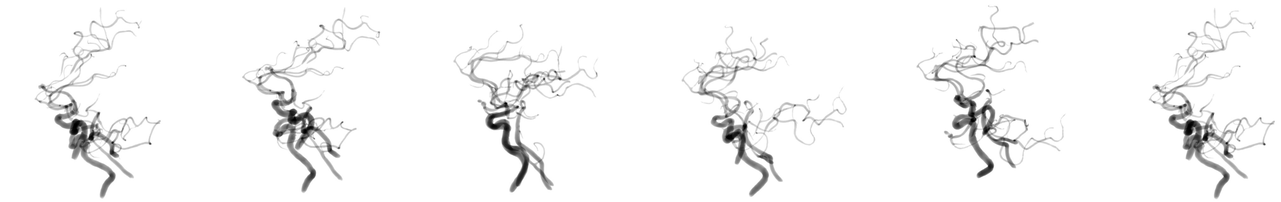
Ground-truth paired intraoperative fluoroscopy and 3D vessel deformation are not available at the scale needed for supervised training. We train on a synthetic pipeline built from vascular anatomies and simulated fluoroscopic projections.

Sparse control-point displacements are generated at a plausible tool tip location and interpolated into a dense deformation field using thin-plate radial basis functions. The deformation stage saves: a deformed mesh STL, centerline array, sparse displacement array, and control-point index array.





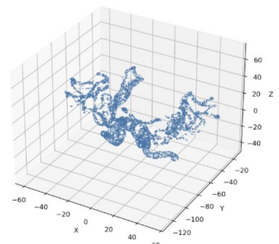




## Preliminary Results

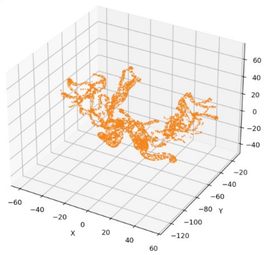
Target Reprojection Error – 3D: 0.5170 mm
Target Reprojection Error – In Plane: 0.3950 mm
Target Reprojection Error – Depth: 0.2762 mm

2D Reprojection Error (px): 79.1125 pixels
2D Reprojection Error: 0.0971

Mean Length Variance: 0.0040% Relative Err.
Laplacian Curvature Penalty: 0.0878% Relative Err.



**Original Point Cloud****



**Predicted Point Cloud****

* *further optimizations incoming*
** *final model predicted outputs will be a mesh, not a point cloud*

## Conclusion

- 2D fluoroscopy makes 3D vascular deformation estimation severely under-constrained, especially in depth.
- Graph-based vessel representation provides a natural structure for centerline-level deformation prediction.
- Reprojection consistency improves image-space alignment but does not by itself ensure plausible 3D shape.
- Stretch, bend, and anchor constraints offer a practical middle ground between unconstrained learning and full biomechanical simulation.

### Future Work

- Move from weak geometric priors toward stronger mechanics-based residuals.
- Test temporal consistency across sequential fluoroscopy frames.

## References

Yang, Xi, et al. "Intra: 3d intracranial aneurysm dataset for deep learning." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2020.

Yu, Wengui, and Wei-Jian Jiang. "A simple imaging guide for endovascular thrombectomy in acute ischemic stroke: from time window to perfusion mismatch and beyond." Frontiers in neurology 10 (2019): 502.