Real Time Prediction of Soft Tissue Deformations Using Data-driven Nonlinear Presurgical Simulations

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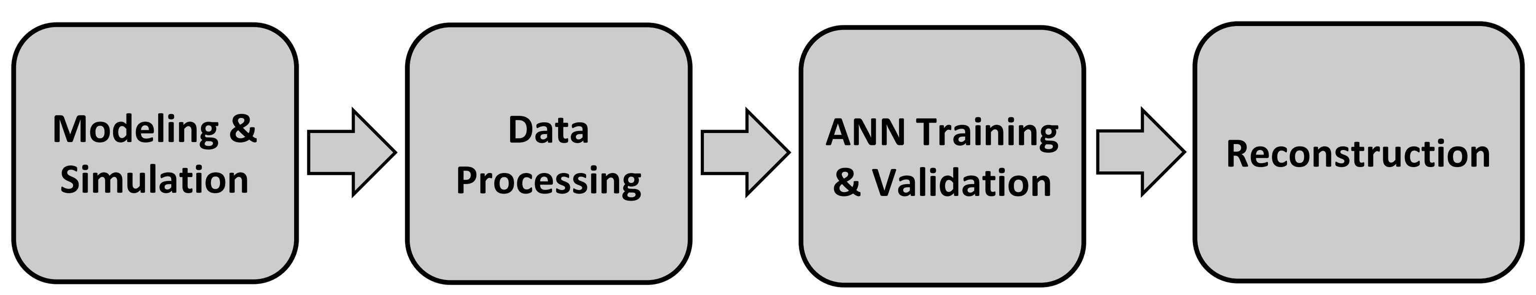
Overview

Large strain and nonlinearities in the deformation of soft biological tissues typically leads to a significant mismatch between tissue's pre-surgical and intraoperative shapes, making the surgical preplan prone to failure. To fill the gap between the two imaging stages, we present a data-driven approach based on an artificial neural network (ANN) for predicting the tissue deformation in real time with sparsely registered fiducial markers (FMs). Our proposed approach has the following contributions:

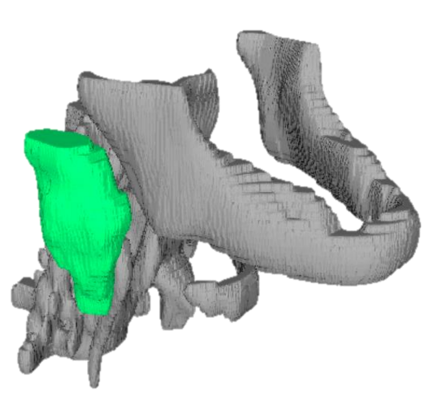
- Enabling rapid shape reconstruction using FM tracking
- Maintaining a high-level of deformation prediction accuracy

As shown in the flowchart below, our proposed approach consists of four sequential parts: Modeling and nonlinear finite element (FE) simulation, data processing using principal component analysis (PCA), ANN training and validation, and deformation reconstruction. By evaluating the performance on a head-and-neck (H&N) tumor model, the proposed approach shows excellent performance on both accuracy and reconstruction speed, demonstrating its potential to be clinically relevant.

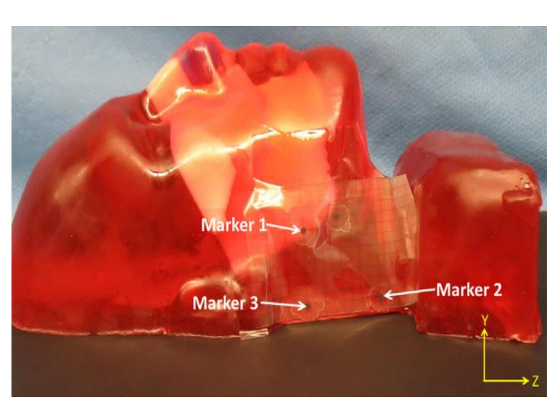


Fiducial markers (FM)

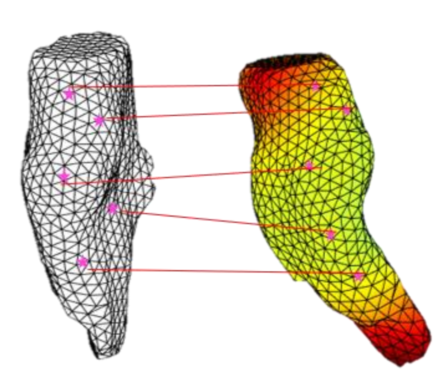
In image-guided surgeries, clinicians usually use ultrasound systems to monitor and track the target tumor. To that end, clinicians typically implant gold seeds, bone screws, or anatomical landmarks as FMs used to help pinpoint the tumor's location. In a computational model, FMs can be chosen out of nodes from a geometry-specific pre-generated mesh topology. We implement the k-center clustering algorithm to sparsely distribute FMs within a tetrahedral mesh model. The FMs' displacement vectors are then tracked and extracted in the subsequent nonlinear FE simulations.



3D Geometric model



FMs labeling [1]



FM displacement tracking

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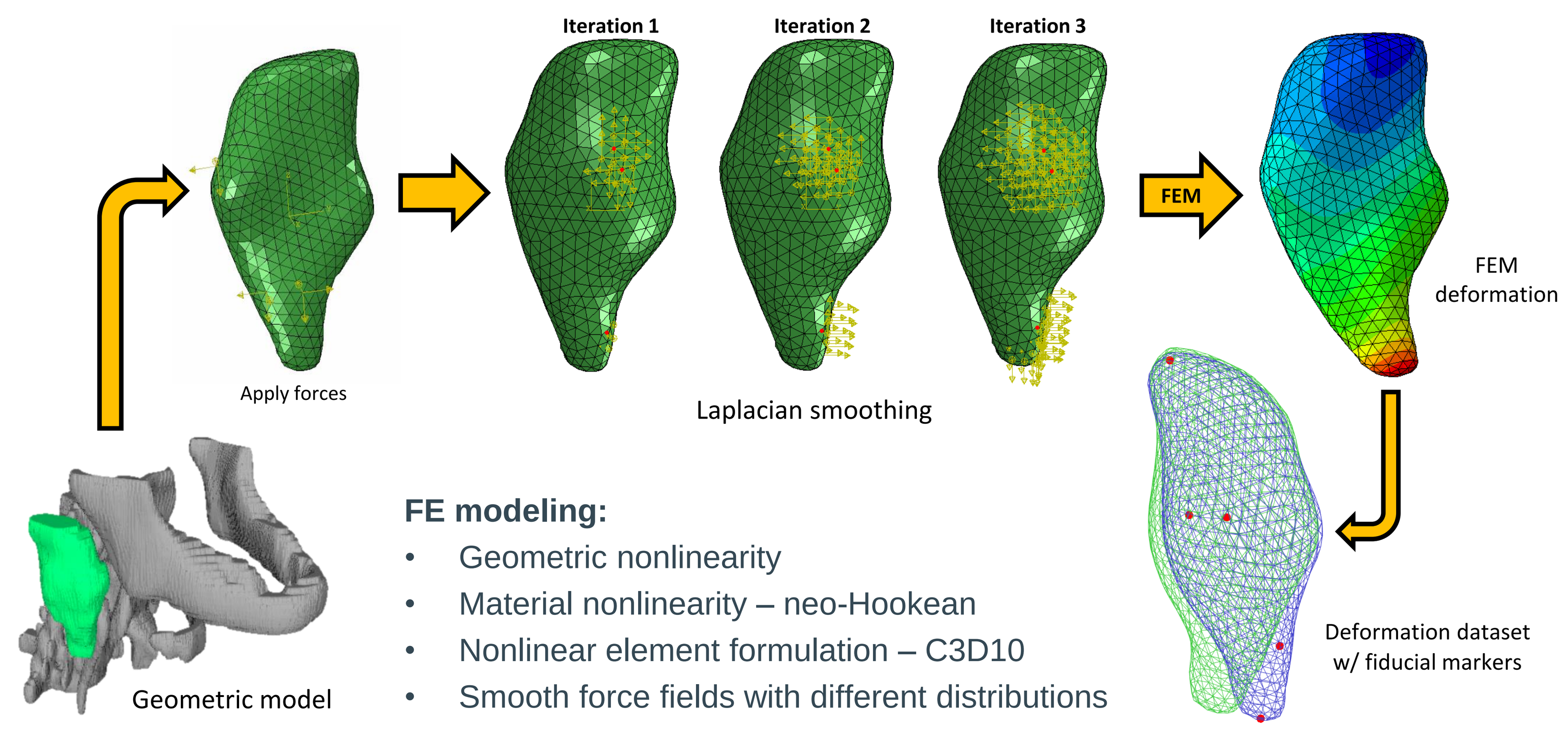
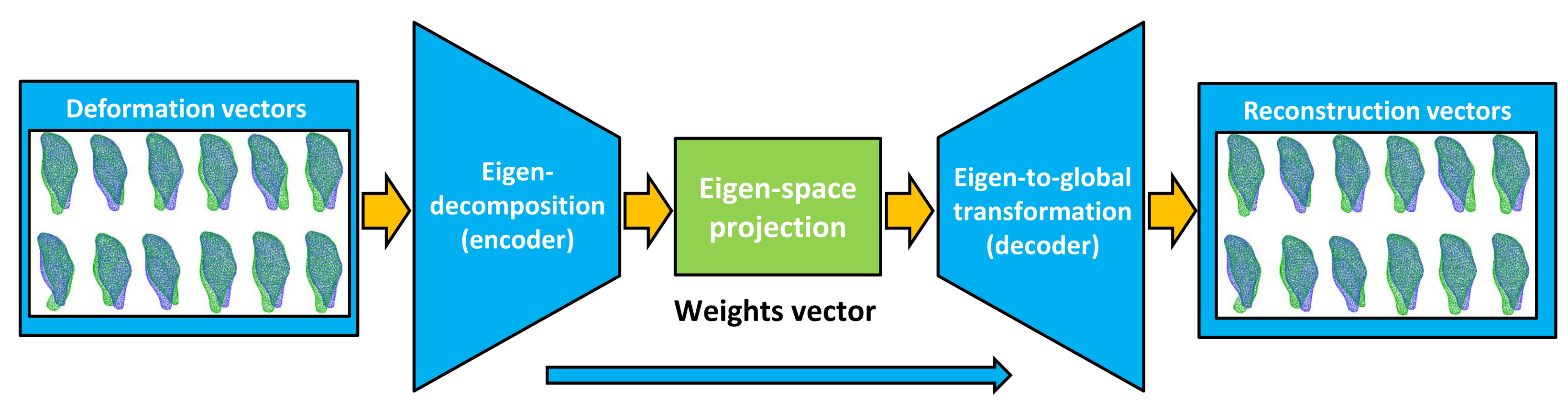
Methodology

Modeling & FE Simulation

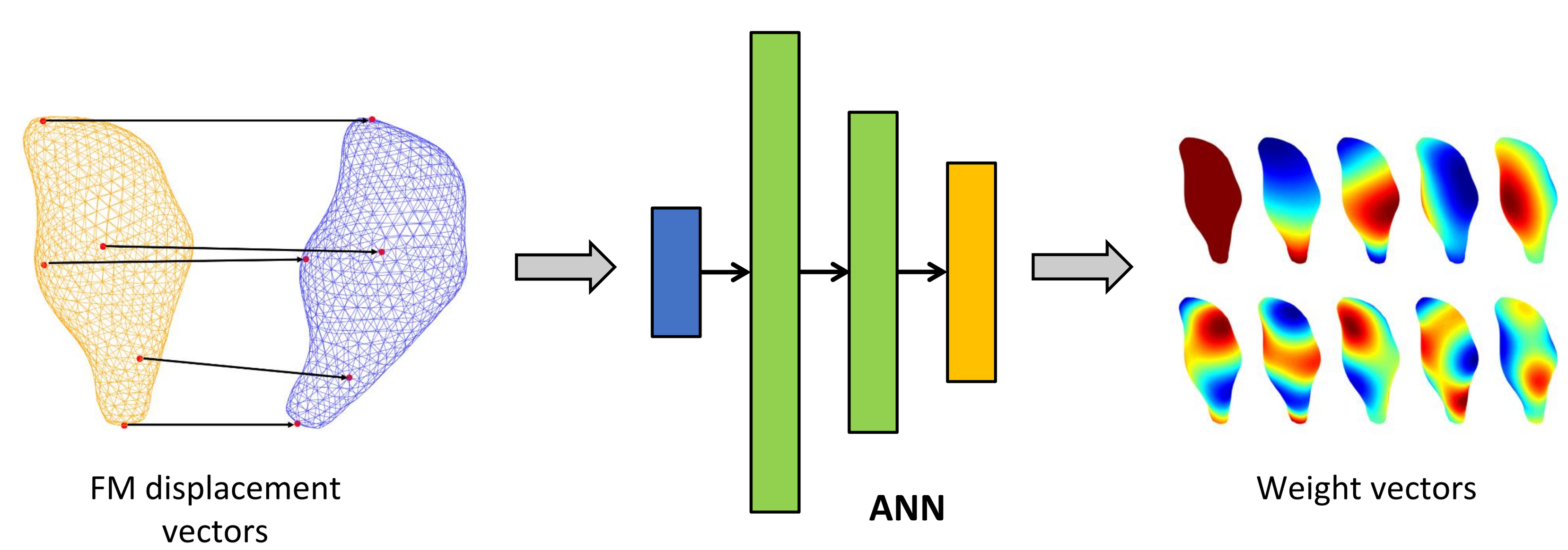


Our FE model possesses three types of nonlinearities as shown above. We generate models by applying random smooth force fields to the undeformed tumor's surface. We then conduct nonlinear FE simulations to create a deformation dataset. We track and extract the displacement vectors of the labelled FMs from simulations.

Data processing using PCA & ANN training



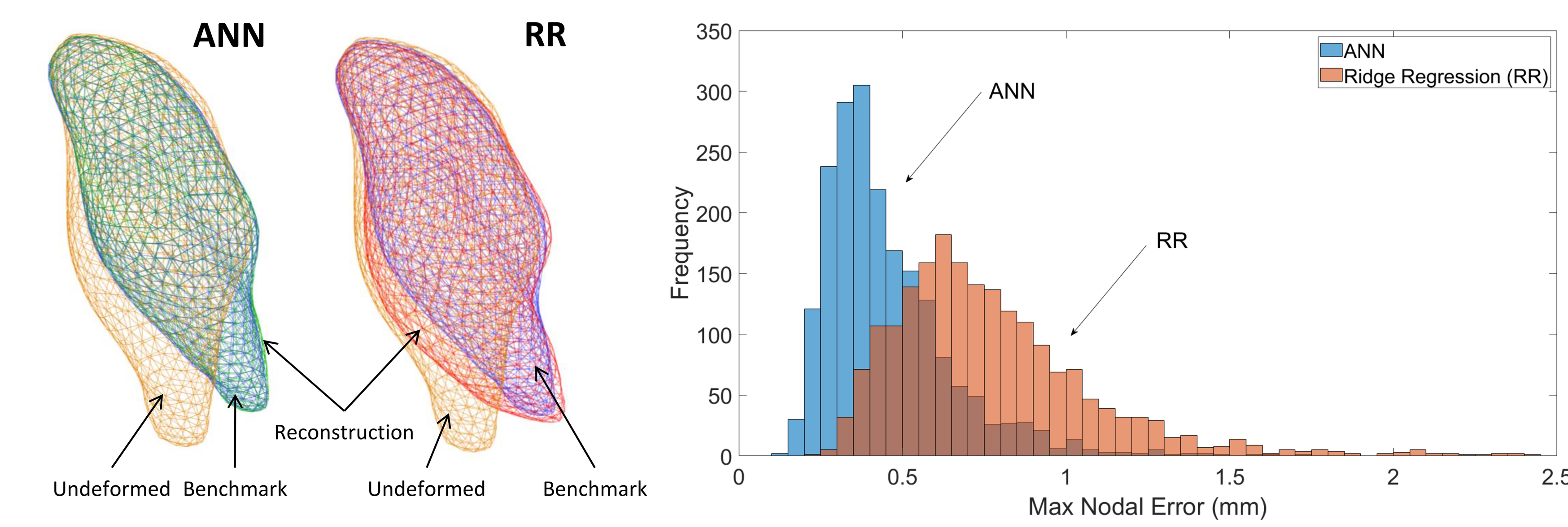
We apply PCA to the established deformation dataset to reduce the dimension of the original deformation field vector and extract deformation bases and corresponding weight vectors $\boldsymbol{w} \in \mathbb{R}^{n_W \times 1}$. We subsequently train our ANN based on FM's displacement vectors $\boldsymbol{d} \in \mathbb{R}^{n_D \times 1}$ and corresponding weigh vectors. The predicted weight vector from ANN is then transformed back to a full-size deformation field vector by multiplying the matrix of extracted deformation bases.



Results & Evaluation

We validate our proposed approach on an H&N tumor model. The H&N tumor model is assumed to be compliant, continuous, and homogeneous, adopting material properties defined in [2]. The modeling and training parameters are shown below. We compute the nodal mismatch between the groundtruth and reconstructed configurations by calculating the L2-Norm of the deformation field vector. We also employ ridge regression (RR) as our baseline model, and a comparison of reconstruction performance is demonstrated.

Model Parameters	Symbol	Value
Number of training samples	n_{train}	2000
Number of test samples	n_{test}	200
Structure of ANN hidden layers	$[n_1, n_2]$	[128, 64]
Number of FMs and PCs	n_D, n_W	5, 27
Training epochs & Batch size	n_e, b_s	12000, 16



We evaluate the reconstruction performance based on the average mean and max nodal offset (θ_{max} and θ_{mean}) of the H&N tumor model. As shown below, with a maximum deformation of 30 mm, our proposed approach outperforms the RR method in both reconstruction accuracy and reconstruction speed. We also show that for any type of tissue models, the number of FMs and PCs can be parametrically optimized.

Methods	θ_{max}	θ_{mean}	Reconstruction time
ANN Reconstruction	0.463 mm	0.124 mm	< 0.5 s
RR Reconstruction	0.779 mm	0.297 mm	1.102 s

Conclusion & Discussion

We propose an ANN-based data-driven approach that enables real-time soft tissue deformation reconstruction with high accuracy. For a H&N tumor model with a maximum displacement of 30 mm, θ_{max} between benchmarks and predictions using the proposed approach for 98% of the test cases are under 0.5 mm, which is the typical resolution of high-quality interventional ultrasound. The prediction process takes less than 0.5 s. With the resulting prediction accuracy and computational efficiency, the proposed approach demonstrates its potential to be clinically relevant.

References

[1] https://pubmed.ncbi.nlm.nih.gov/28185275/

[2] Tie Hu and Jaydev P Desai. Soft-tissue material properties under large deformation: Strain rateeffect. InThe 26th Annual International Conference of the IEEE Engineering in Medicine andBiology Society, volume 1, pages 2758–2761. IEEE, 2004.