



JOHNS HOPKINS  
UNIVERSITY

# Automated Segmentation of Temporal Bone CT Imaging for Robot-Assisted Microsurgery

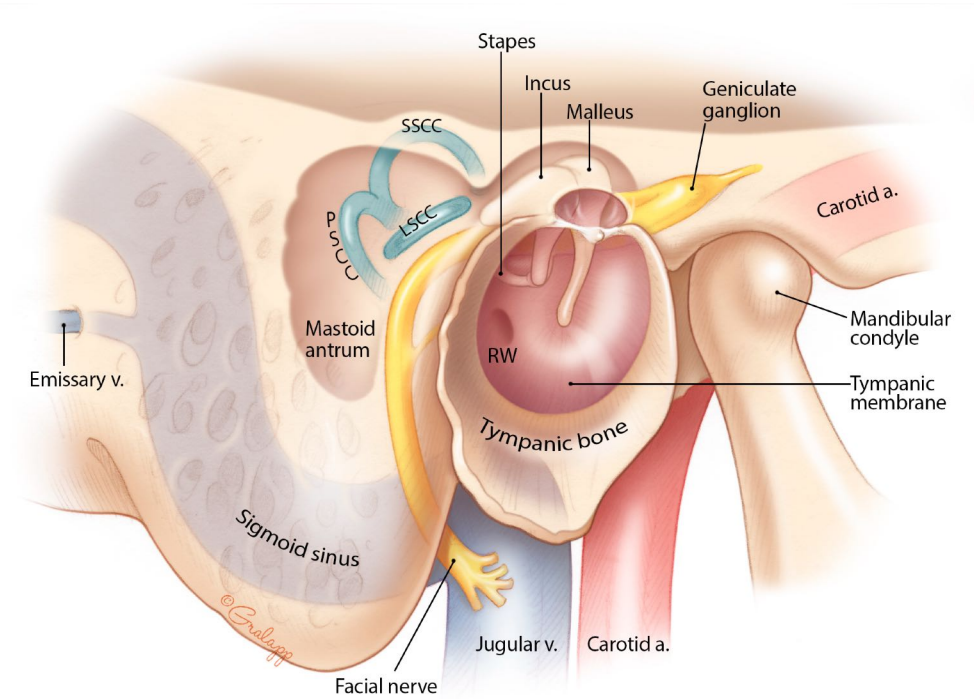
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Dr. Mathias Unberath, Max Zhaoshuo Li


# Project Overview

- ▶ Problem
  - ▶ Temporal bone anatomy is geometrically complex with critical structures often within millimeters of each other.
  - ▶ Surgery in this area poses a high risk of damage to anatomy.
- ▶ Goal
  - ▶ Develop an automated system for segmenting the temporal bone to help prevent intraoperative damage to critical anatomy.



Credit: Christine Gallup  
<https://otosurgeryatlas.stanford.edu/>

## Toward an automatic preoperative pipeline for image-guided temporal bone surgery

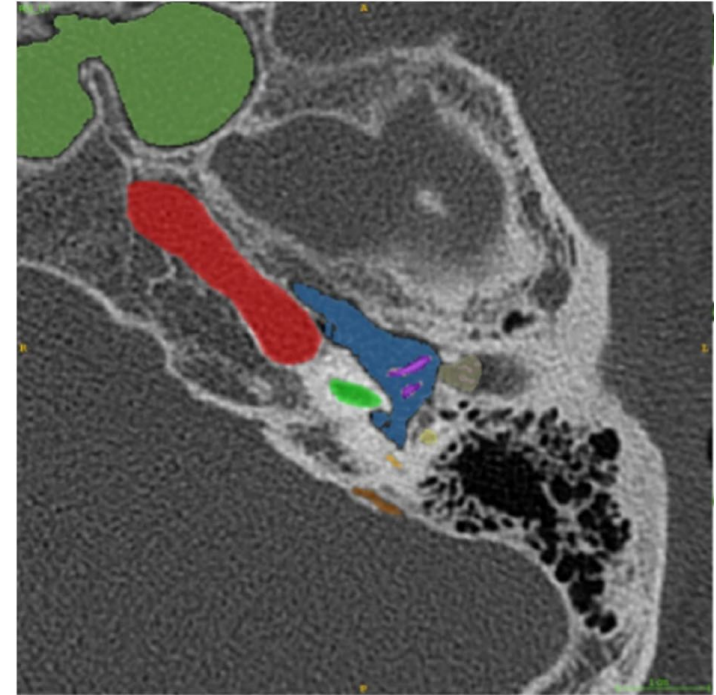
[Johannes Fauser](#) , [Igor Stenin](#), [Markus Bauer](#), [Wei-Hung Hsu](#), [Julia Kristin](#), [Thomas Klenzner](#), [Jörg Schipper](#) & [Anirban Mukhopadhyay](#)

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- ▶ First major deep learning-based approach to automated temporal bone segmentation [1]
- ▶ Discusses strategies to handle scarcity of available labeled data
- ▶ Baseline network architecture is similar to our proposed method with nnUNet
- ▶ Demonstrates potential issues with purely using a UNet model

# Paper: Summary & Key Takeaways

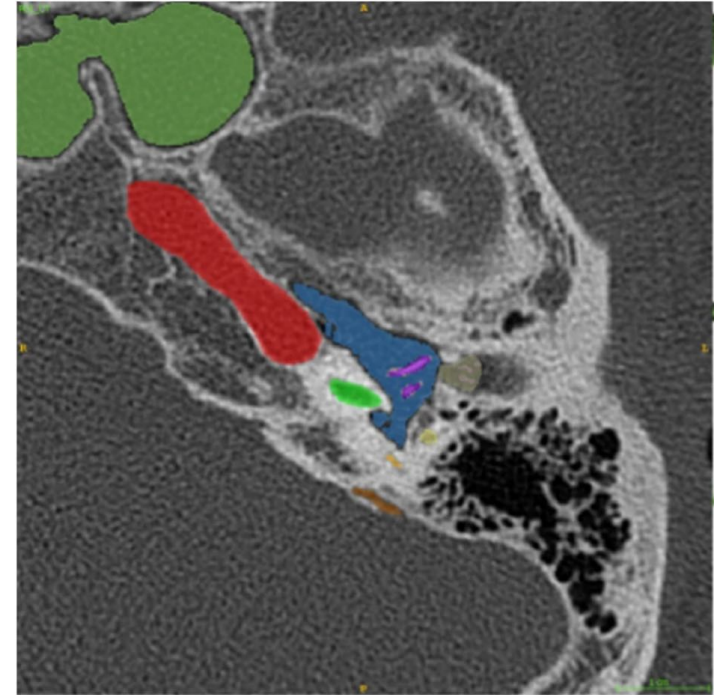
- ▶ Summary
  - ▶ Automatic temporal bone segmentation with UNet and probabilistic active shape modeling (PASM) for pre-operating path planning (e.g., cochlear access, superior semicircular canal approach, retrolabyrinthine approach)
- ▶ Key Results
  - ▶ Segmentation accuracy evaluation of UNet + PASM hybrid against UNet or PASM alone
  - ▶ Pre-operative planning success with UNet + PASM hybrid vs. UNet or PASM alone



Fausser *et al*, 2019 (Figure 1)

# Paper: Background

- ▶ Minimally invasive surgery (MIS) in the temporal bone procedures is increasing in popularity
  - ▶ Cochlear implants
  - ▶ Middle ear access
  - ▶ Multi-port setups analogous to laparoscopic procedures in the abdomen
- ▶ MIS requires pre-operative planning, ideally with segmented CTs

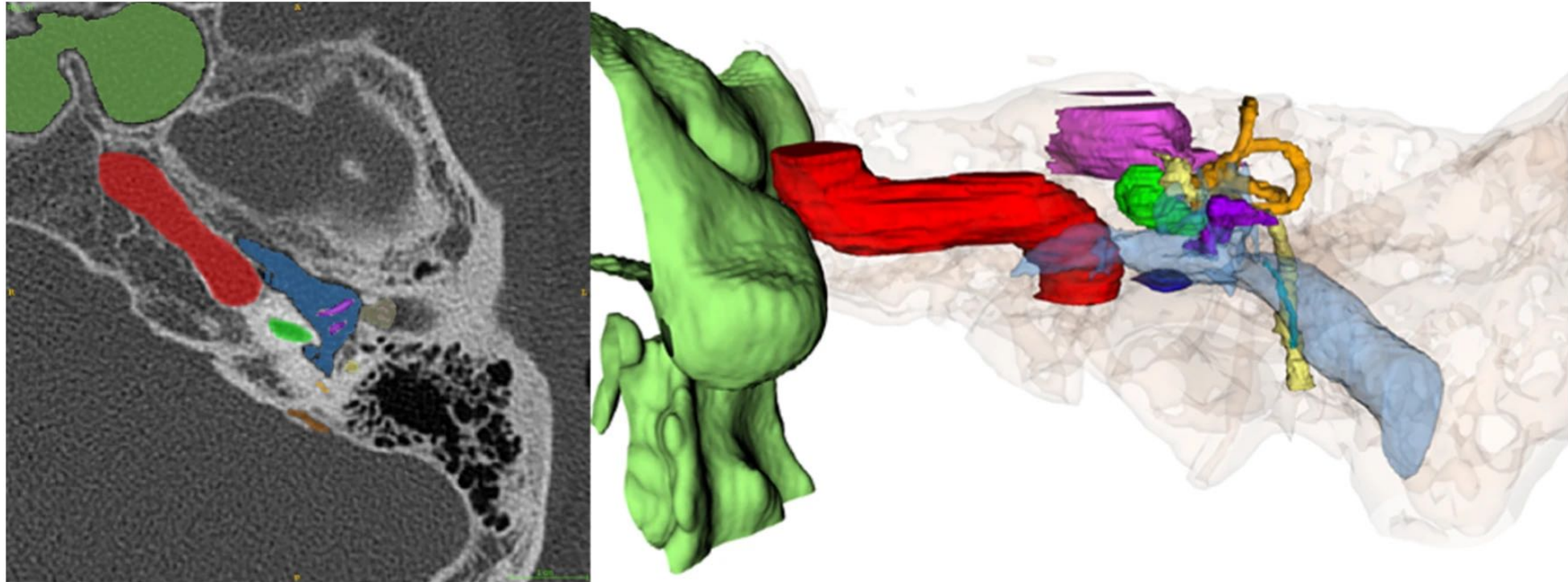


Fausser *et al*, 2019 (Figure 1)

# Paper: Manual Segmentation

## ► 24 manually segmented CTs (resolution 0.2x0.2x0.4mm<sup>3</sup>)

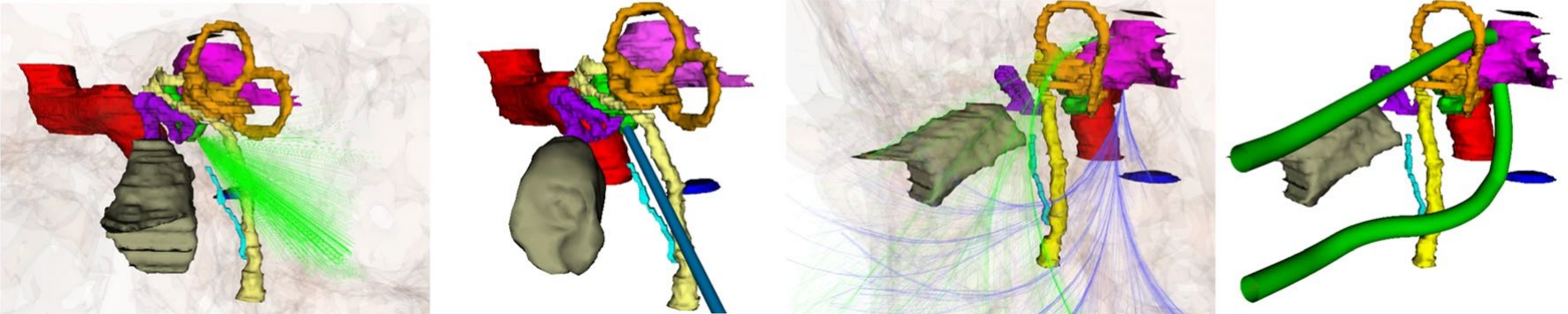
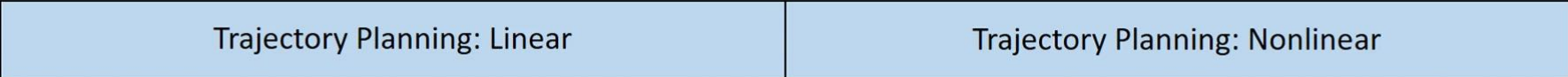
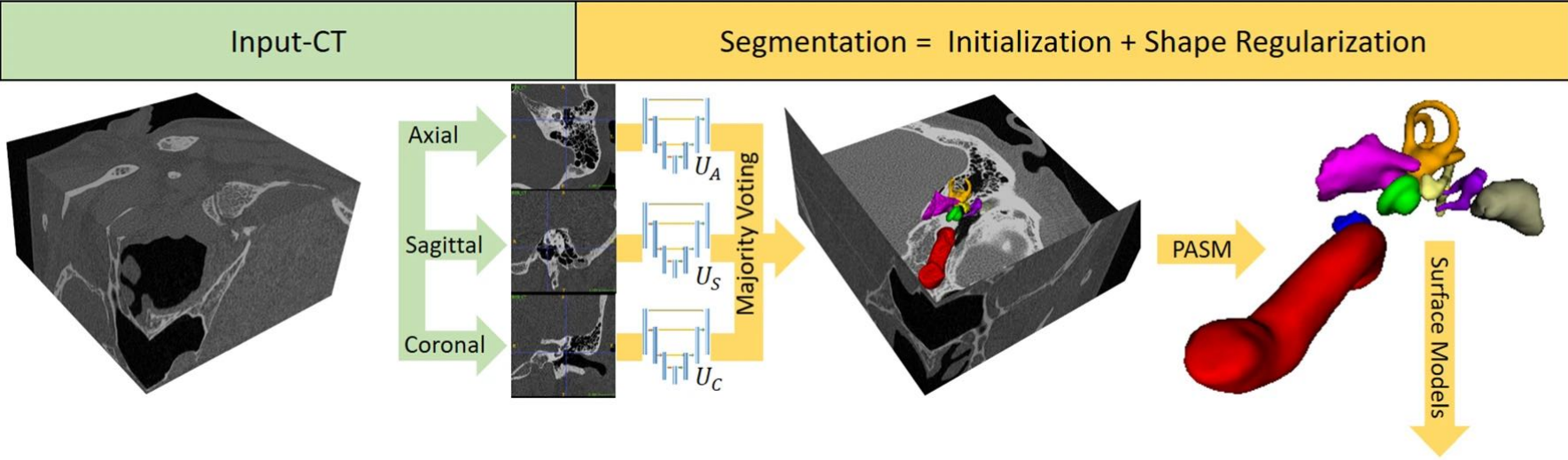
■ jugular vein ■ carotid artery ■ facial nerve ■ chorda tympani ■ internal auditory canal ■ air cavities (EAC, tympanic cavity, eustachian tube) ■ cochlea ■ semicircular canals ■ ossicles ■ paranasal sinuses



Fauser *et al*, 2019 (Figure 1)

# Paper: Automated Segmentation Workflow

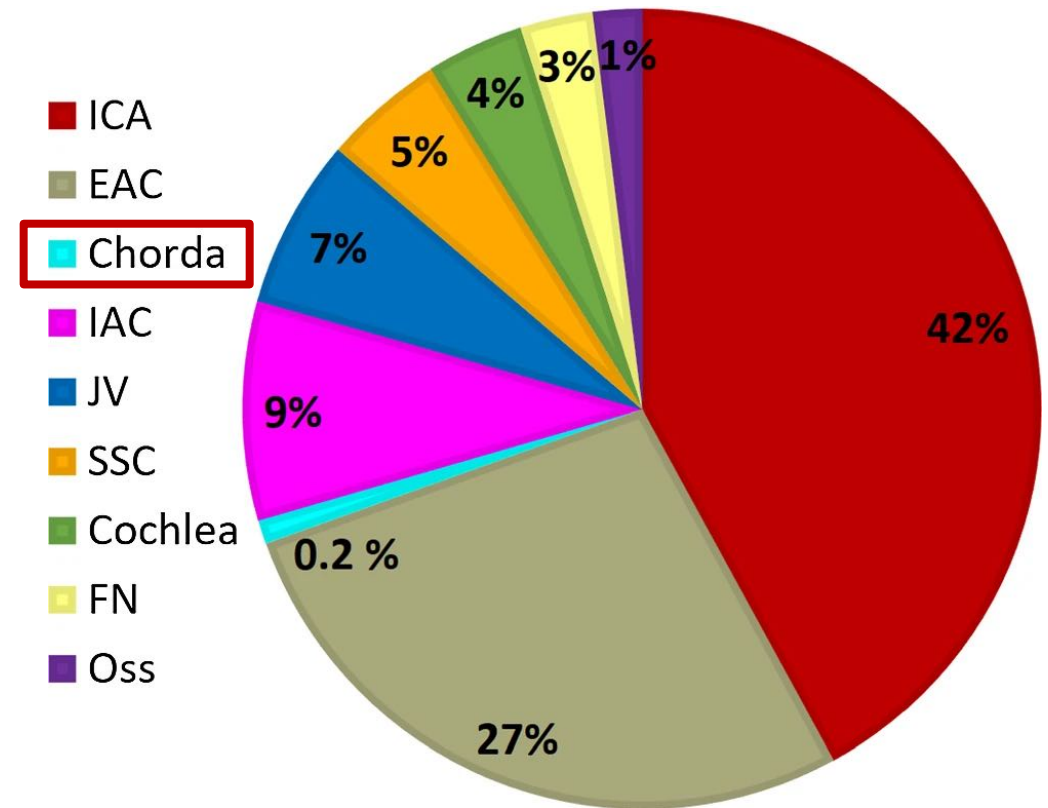
- ▶ Ensemble 2D Unet
- ▶ Shape Regularization
- ▶ Trajectory planning



Fausser *et al*, 2019 (Figure 3)

# Paper: UNet Segmentation

- ▶ Implemented slice-by-slice predictions with 2D UNets (coronal, axial, saggital) instead of 3D UNet
  - ▶ Due to scarcity of available labeled data
- ▶ Majority voting from the 3 independent predictions for each voxel to finalize labels
- ▶ **Extreme** heterogeneity of volumes among labeled anatomy

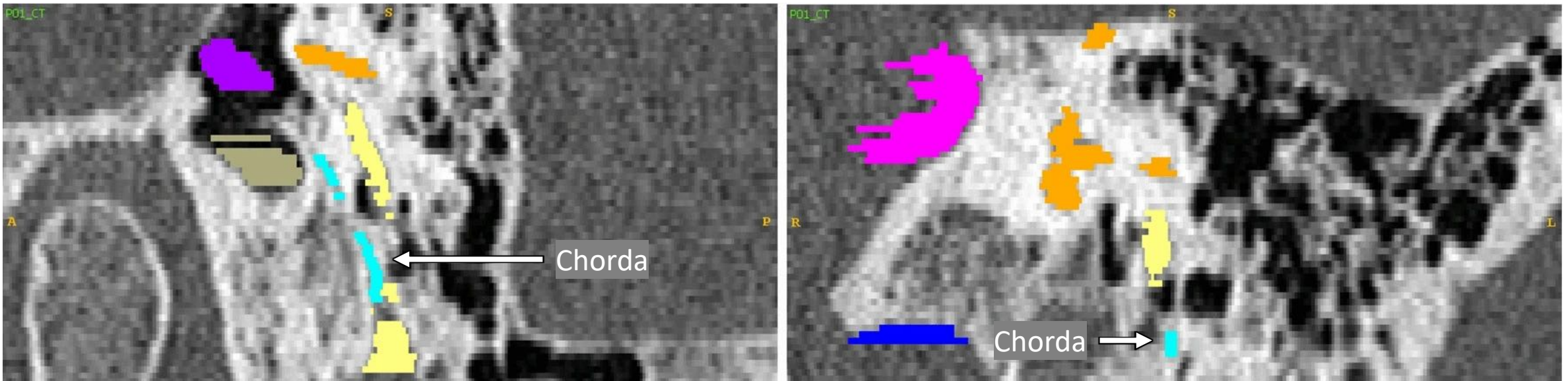


Fauser *et al*, 2019 (Figure 4)



# Paper: The Chorda Tympani Problem

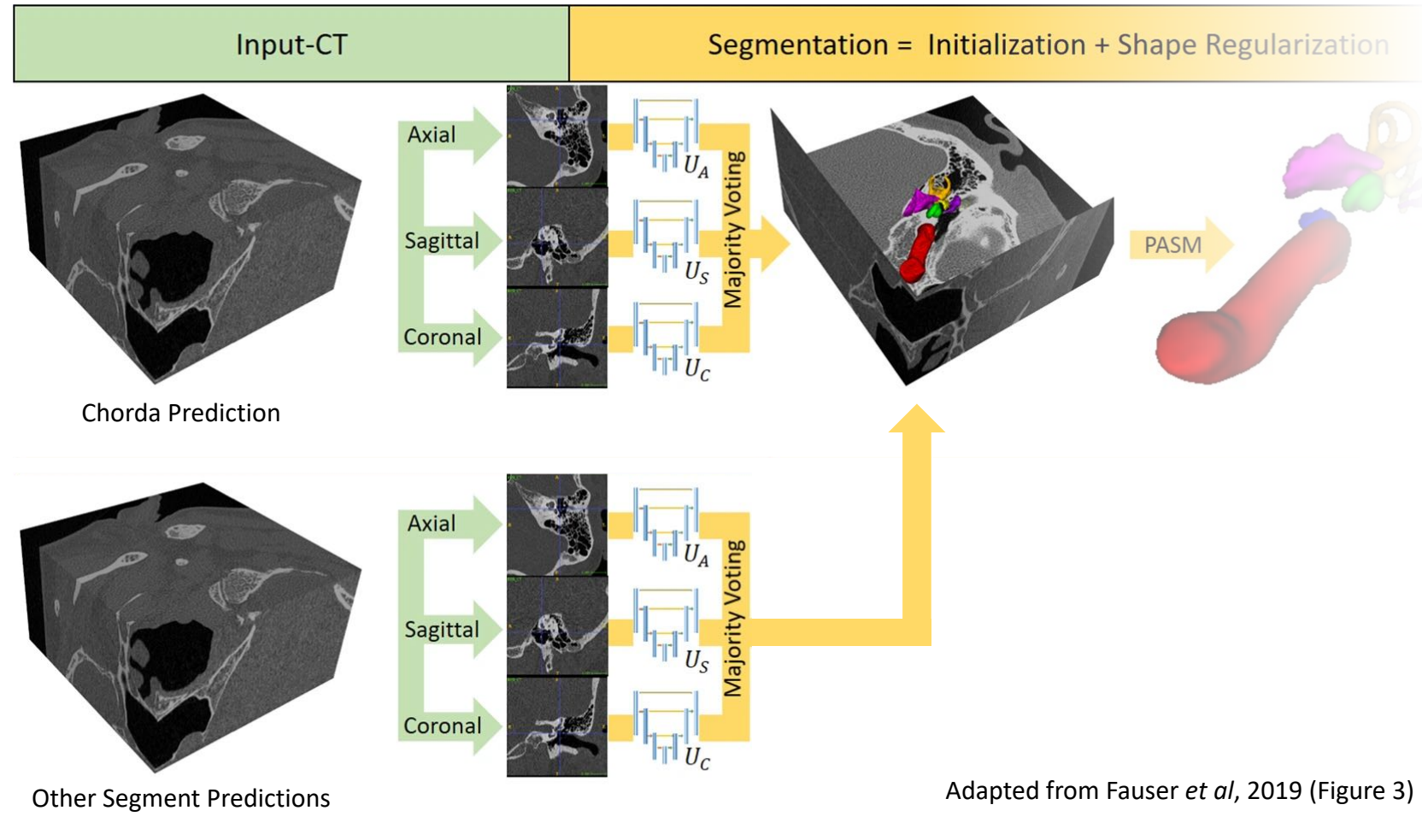
- ▶ Problem: Chorda is incredibly thin
  - ▶ 2-5 voxels in diameter
  - ▶ “Disappears” when entering the middle ear



Fauser *et al*, 2019 (Figure 2)

# Paper: The Chorda Tympani Solution

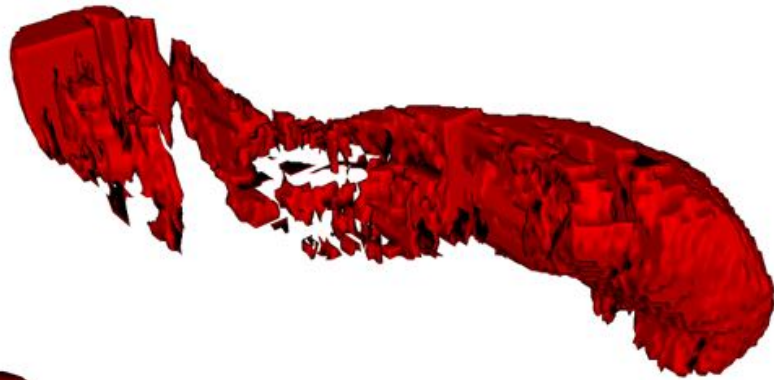
- ▶ Solution: Two UNet predictions!
  - ▶ One for chorda tympani
  - ▶ One for all other segments



Adapted from Fauser *et al*, 2019 (Figure 3)

# Paper: The UNet Shape Problem

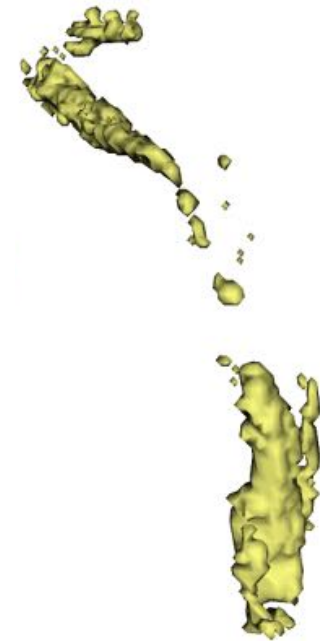
- ▶ Problem: UNet has no prior knowledge of geometry
  - ▶ Predicted labels resulted in fragments, holes, and islands



Internal Carotid Artery



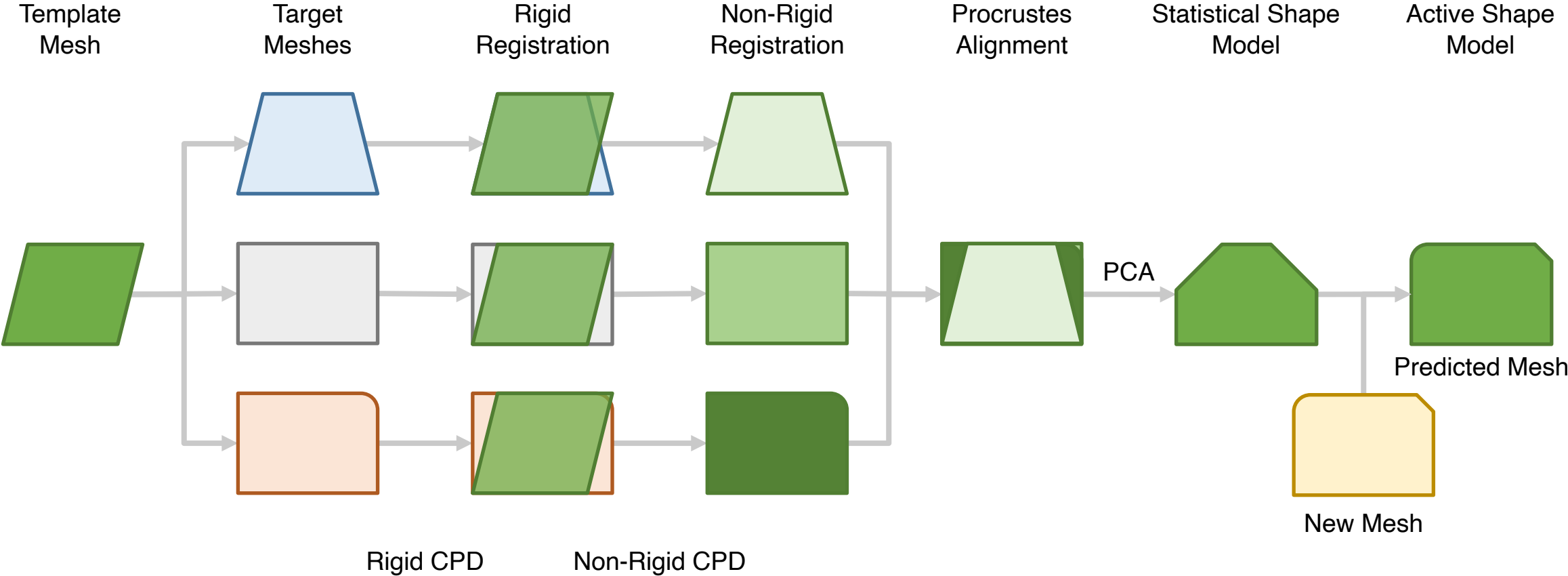
Middle Ear Ossicles



Facial Nerve

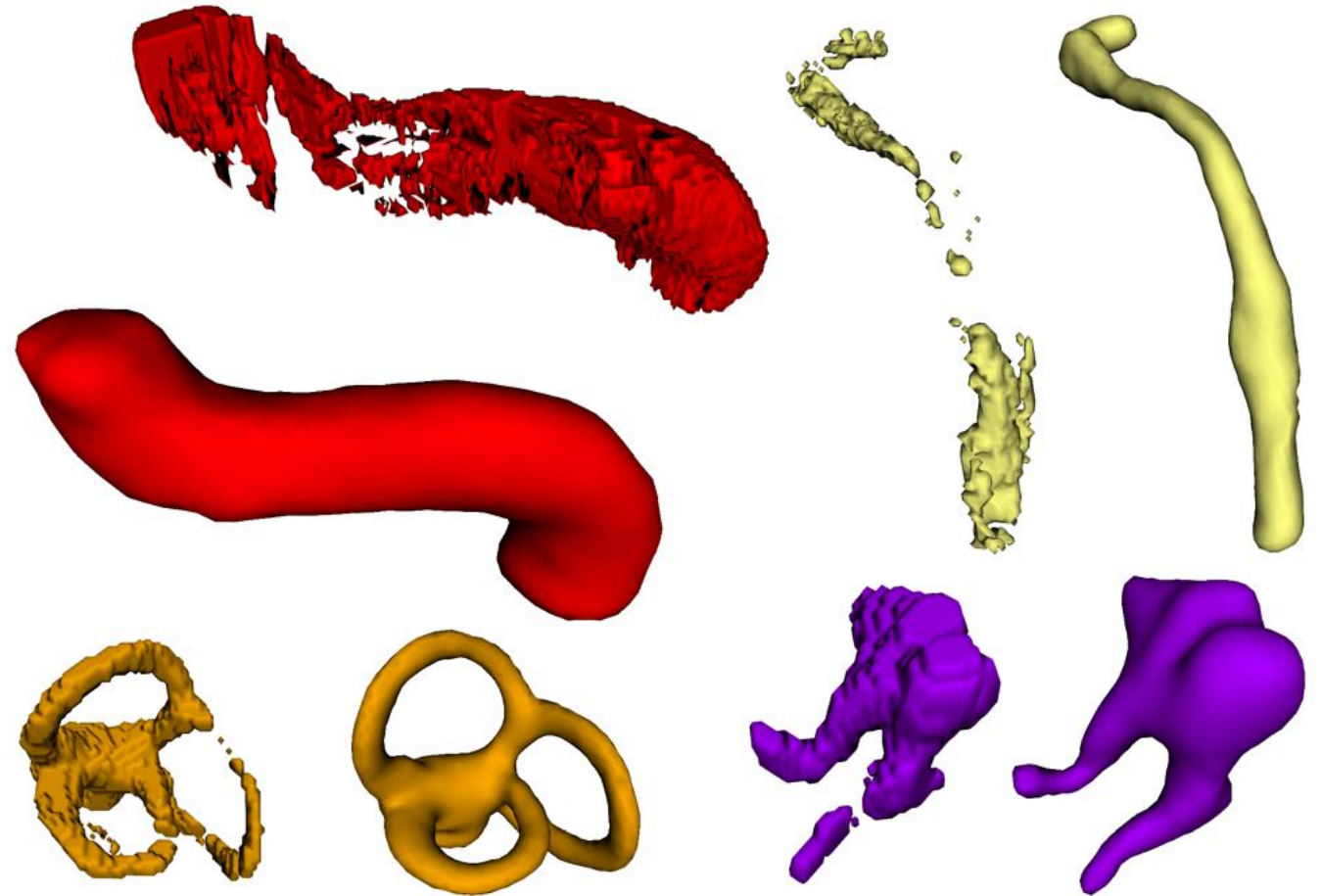
Adapted from Fauser *et al*, 2019 (Figure 5)

# Paper: Active Shape Models



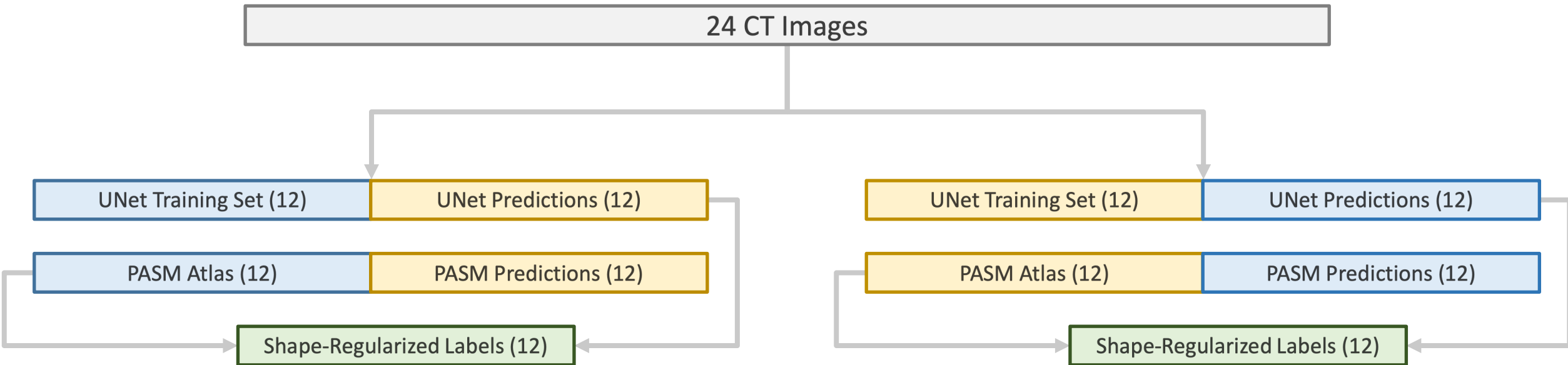
# Paper: The UNet Shape Solution

- ▶ Solution: Use probabilistic active shape models (PASM) [2] to form anatomically realistic segmentations
  - ▶ UNet predictions serve as an initialization to PASM
  - ▶ Mean shapes from statistical shape model are rigidly aligned
  - ▶ PASM deforms mean shapes to approximate target anatomy



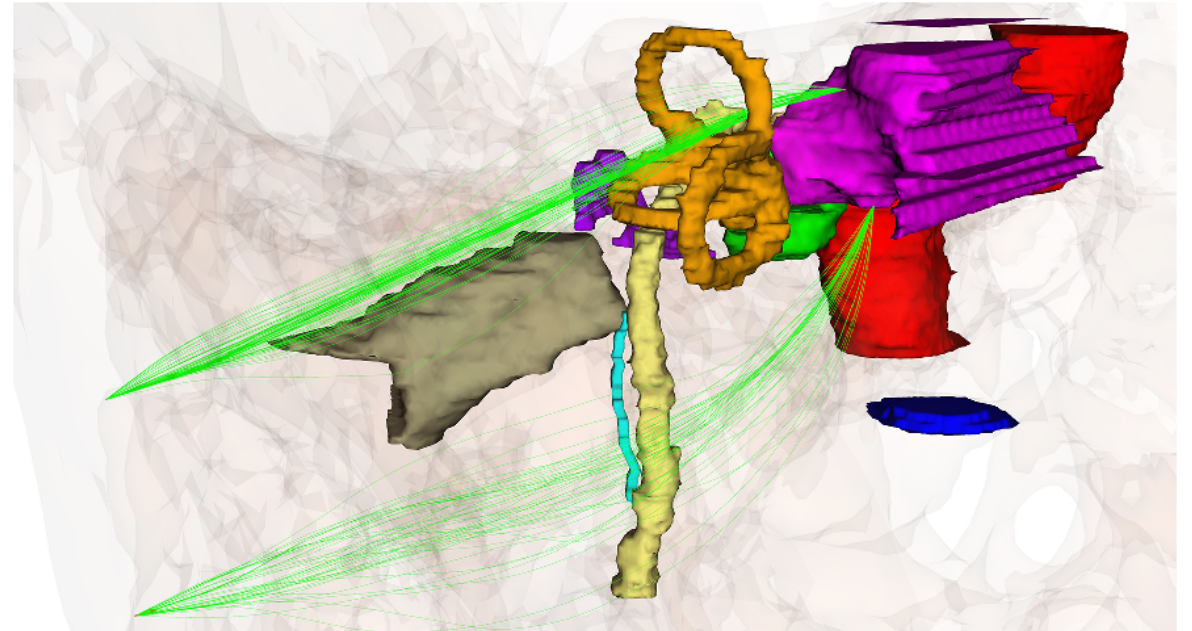
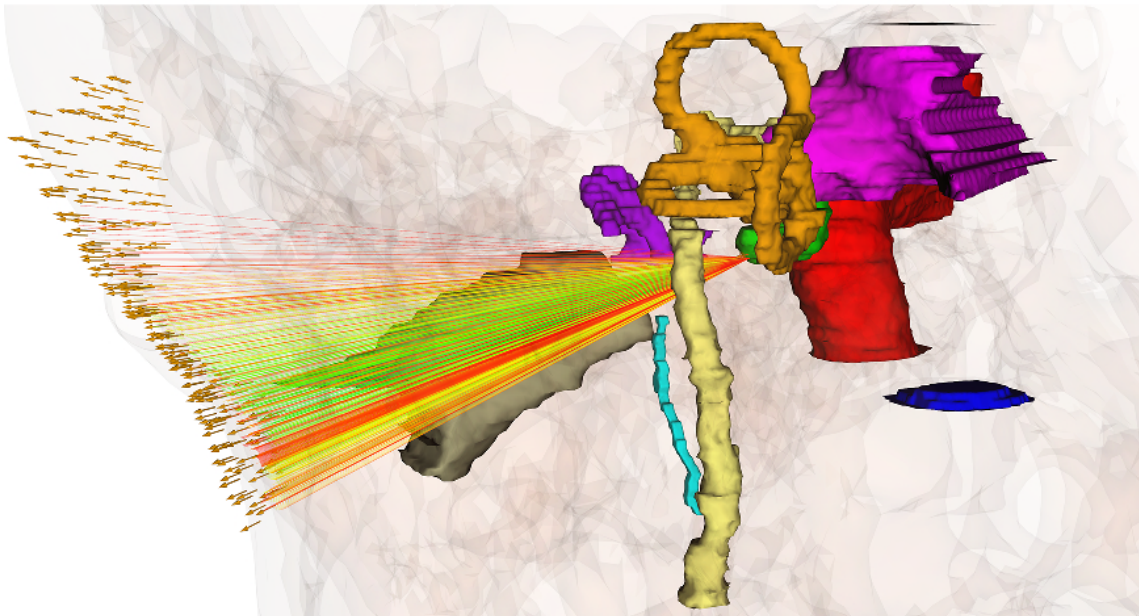
Fausser *et al*, 2019 (Figure 5)

# Paper: UNet + PASM Hybrid Dataset Breakdown



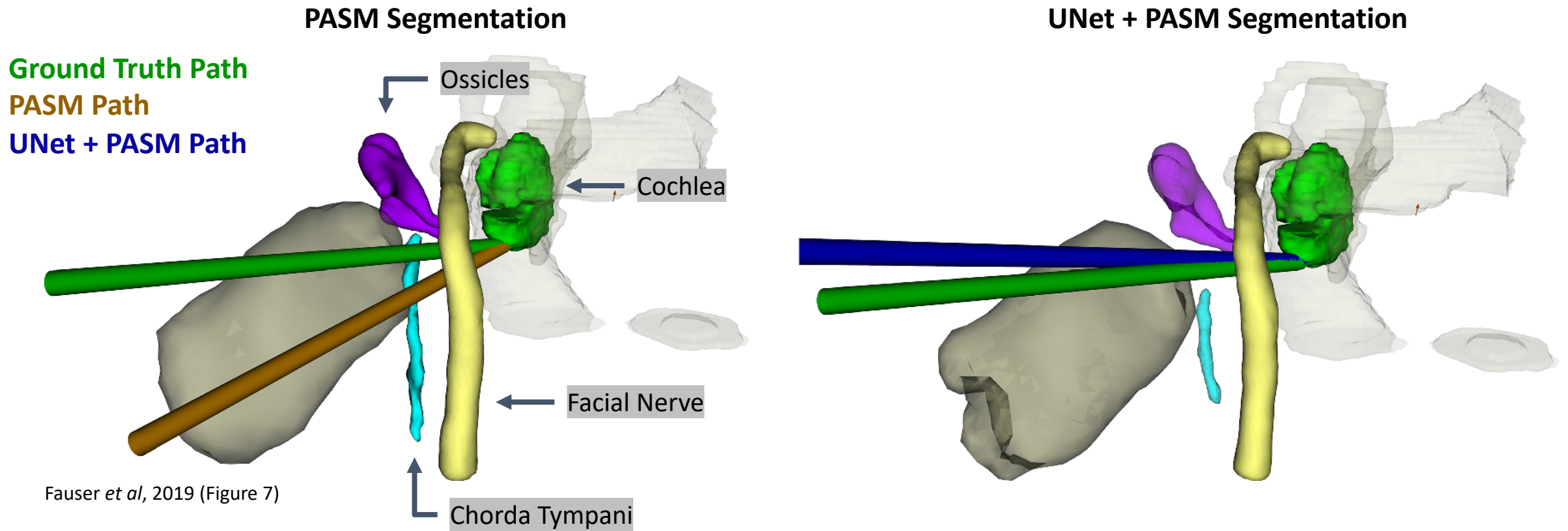
# Paper: Minimally Invasive Operating Path Planning

- ▶ Linear trajectories were calculated using segmentations for cochlear access (cochlear implantation)
- ▶ Non-linear trajectories were calculated for internal auditory canal access (vestibular schwannoma removal)



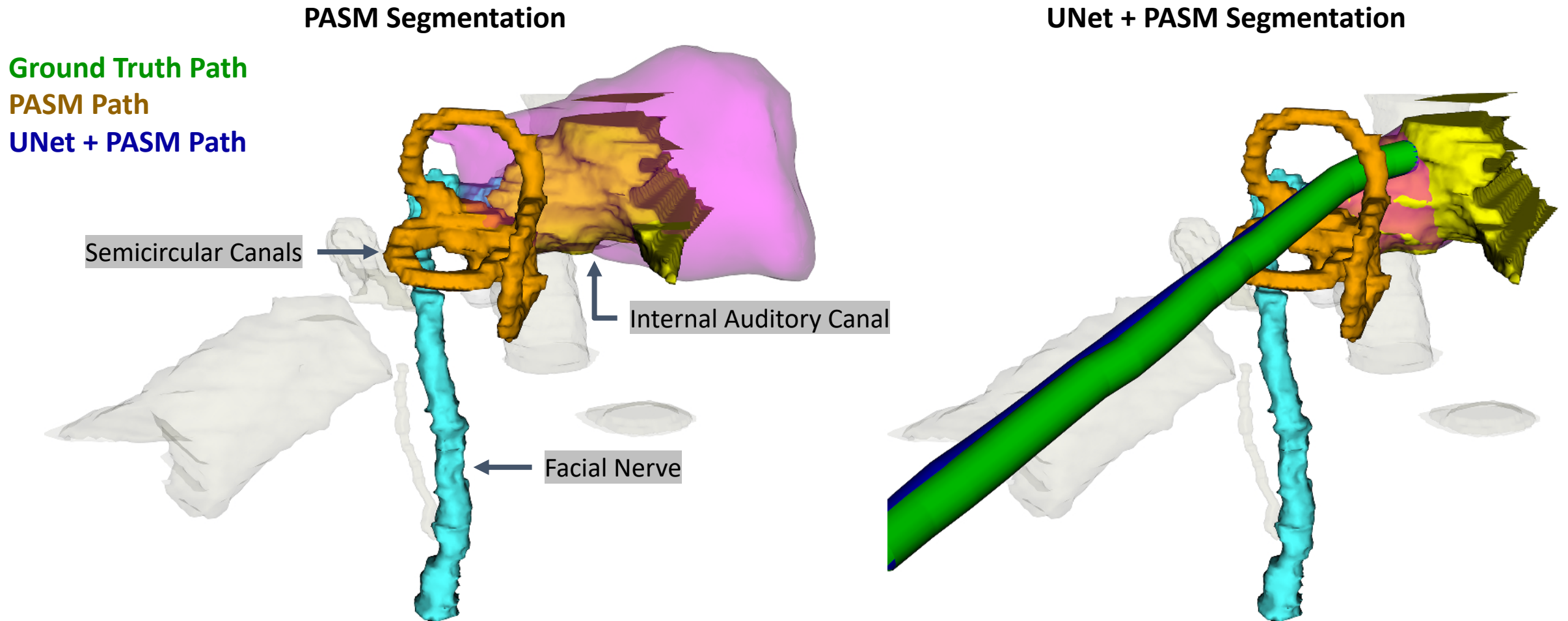
Fauser *et al*, 2019 (Figure 6)

# Paper: UNet + PASM Hybrid vs. PASM – Cochlear Access



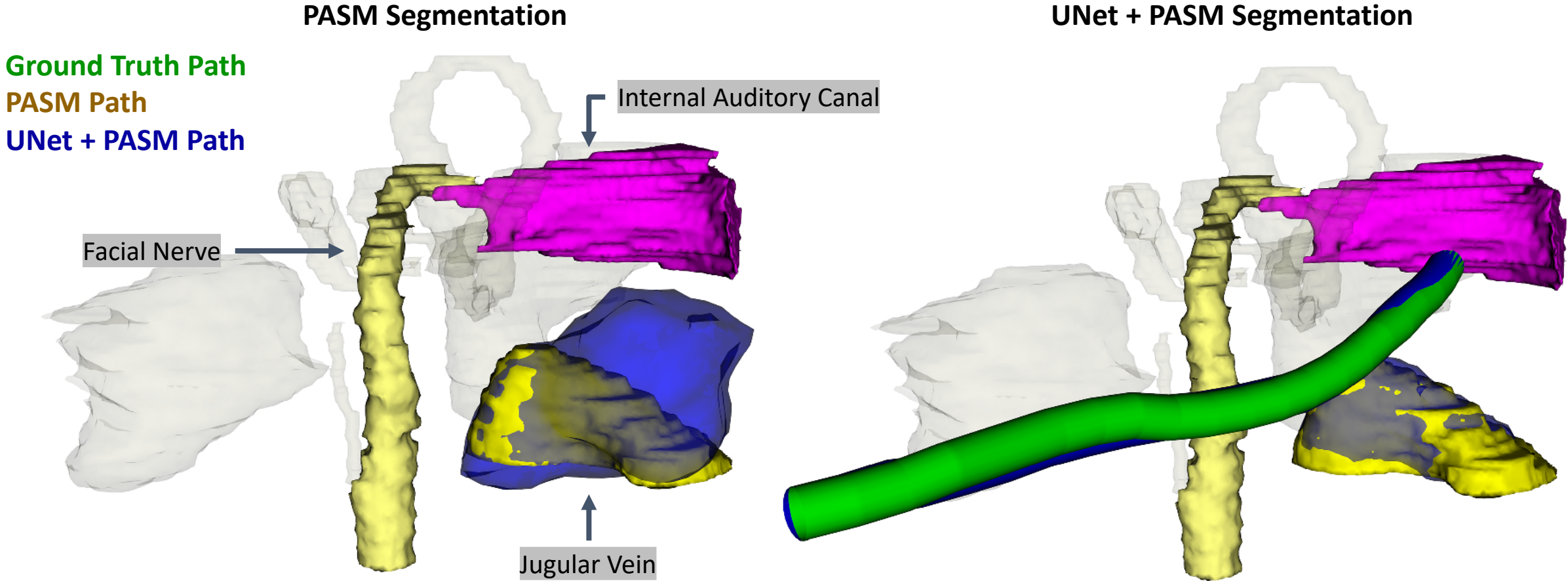


# Paper: UNet + PASM Hybrid vs. PASM – Semicircular Canal Approach



Fauser *et al*, 2019 (Figure 8)

# Paper: UNet + PASM Hybrid vs. PASM – Retrolabyrinthine Approach



Fauser et al, 2019 (Figure 9)

# Paper: UNet + PASM Hybrid vs. PASM – Path Planning Success Rate

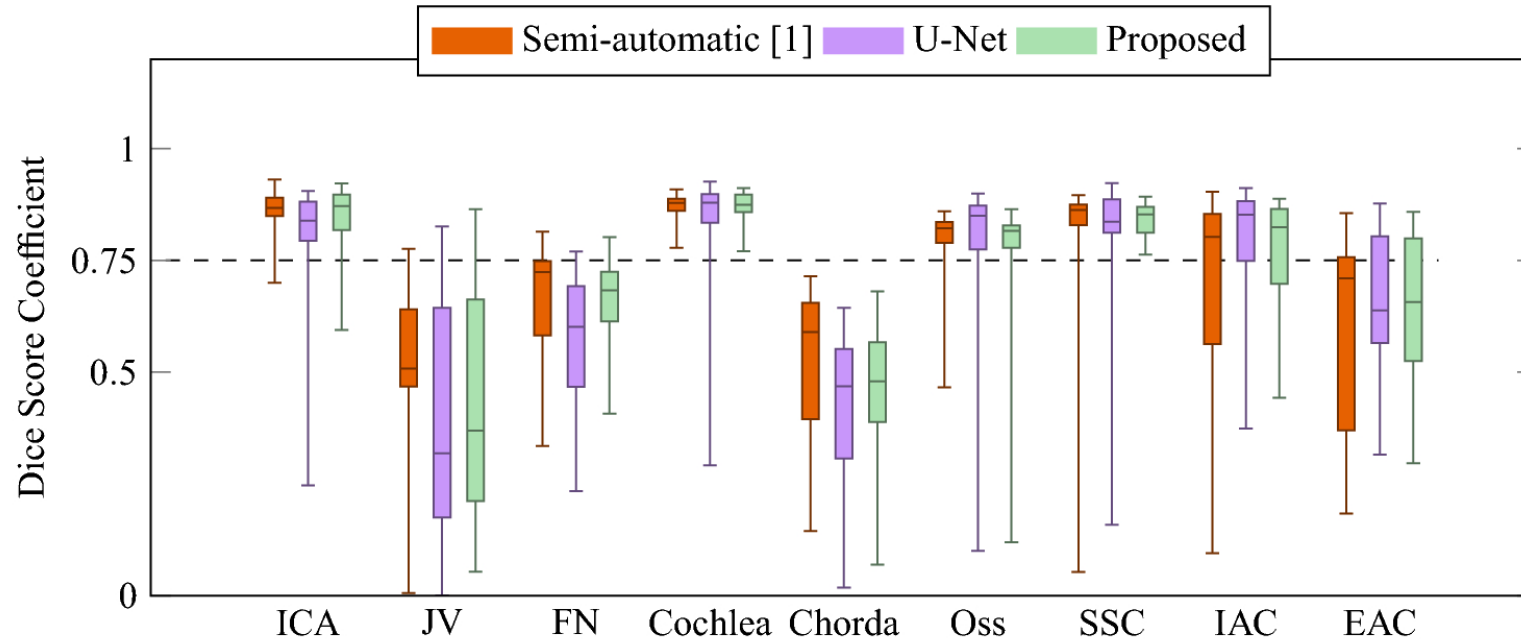
- ▶ Paths generated with UNet + PASM hybrid segmentations were more similar to ground truth paths than those generated with PASM alone

	Success rate			Mean safety distance			Violation rate ( $d < d_{\min}$ )		
	Co	SSC	RL	Co (0.8)	SSC (1.5)	RL (1.5)	Co	SSC	RL
Ground truth	0.9	1.0	1.0	1.39	2.19	2.35	–	–	–
Semiautomatic	0.65	0.66	0.66	1.15	2.17	2.60	0.0	0.0	0.0
Ours	0.9	1.0	1.0	1.04	2.16	2.42	0.18	0.0	0.1

Fausser *et al*, 2019 (Table 2)

# Paper: UNet + PASM Hybrid vs. PASM/UNet – Dice Score + Sensitivity

- ▶ Dice scores are similar among the three methods
- ▶ Hybrid model seems to have lower sensitivity compared to PASM (refer to table)



	IAC	JV	FN	Cochlea	Chorda	Oss	SSC	IAC	EAC
semi-automatic	$89.9 \pm 04.0$	$73.8 \pm 18.9$	$69.2 \pm 17.0$	$87.1 \pm 05.6$	$54.5 \pm 17.0$	$83.2 \pm 08.2$	$81.9 \pm 07.4$	$86.3 \pm 08.0$	$76.6 \pm 16.0$
U-Net	$72.5 \pm 21.3$	$30.3 \pm 26.5$	$43.4 \pm 16.8$	$80.9 \pm 17.1$	$36.6 \pm 20.4$	$74.8 \pm 21.1$	$74.5 \pm 16.7$	$72.7 \pm 20.5$	$61.5 \pm 22.9$
proposed	$83.8 \pm 11.3$	$37.7 \pm 29.2$	$62.7 \pm 13.4$	$85.3 \pm 06.6$	$39.3 \pm 18.0$	$78.8 \pm 17.0$	$79.8 \pm 07.0$	$68.4 \pm 17.2$	$60.9 \pm 24.3$

# Paper: Conclusions

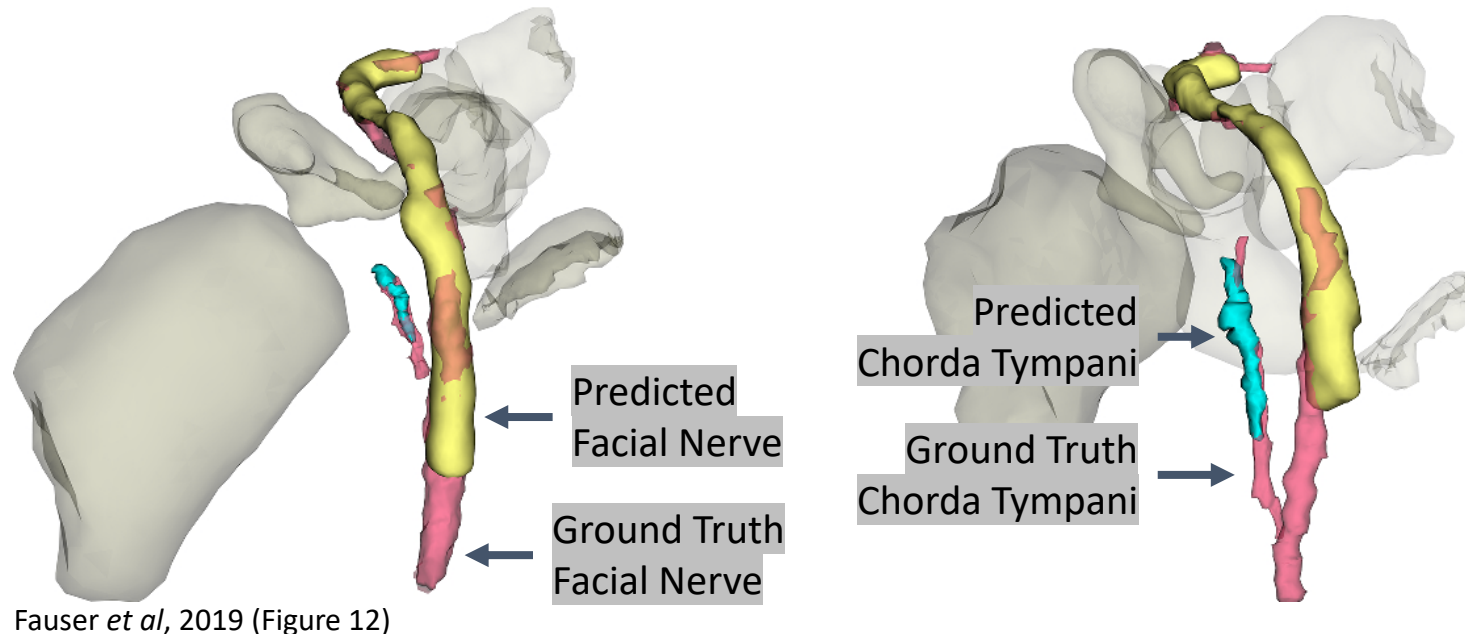
- ▶ Semantic segmentation with UNet alone was not sufficient to create robust segmentations in this dataset
- ▶ Shape regularization with PASM results in anatomically accurate segmentations in the temporal bone
- ▶ UNet + PASM hybrid model performs similar to UNet or PASM alone with respect to Dice similarity scores
- ▶ Path planning using segments from the UNet + PASM hybrid model results in more realistic and reliable trajectories than PASM alone

# Paper: Critiques - Pros

- ▶ Clearly stated methods for implementing UNet and PASM together
- ▶ Elegant solution for creating intact segments of temporal bone anatomy
- ▶ Code is publicly available for testing

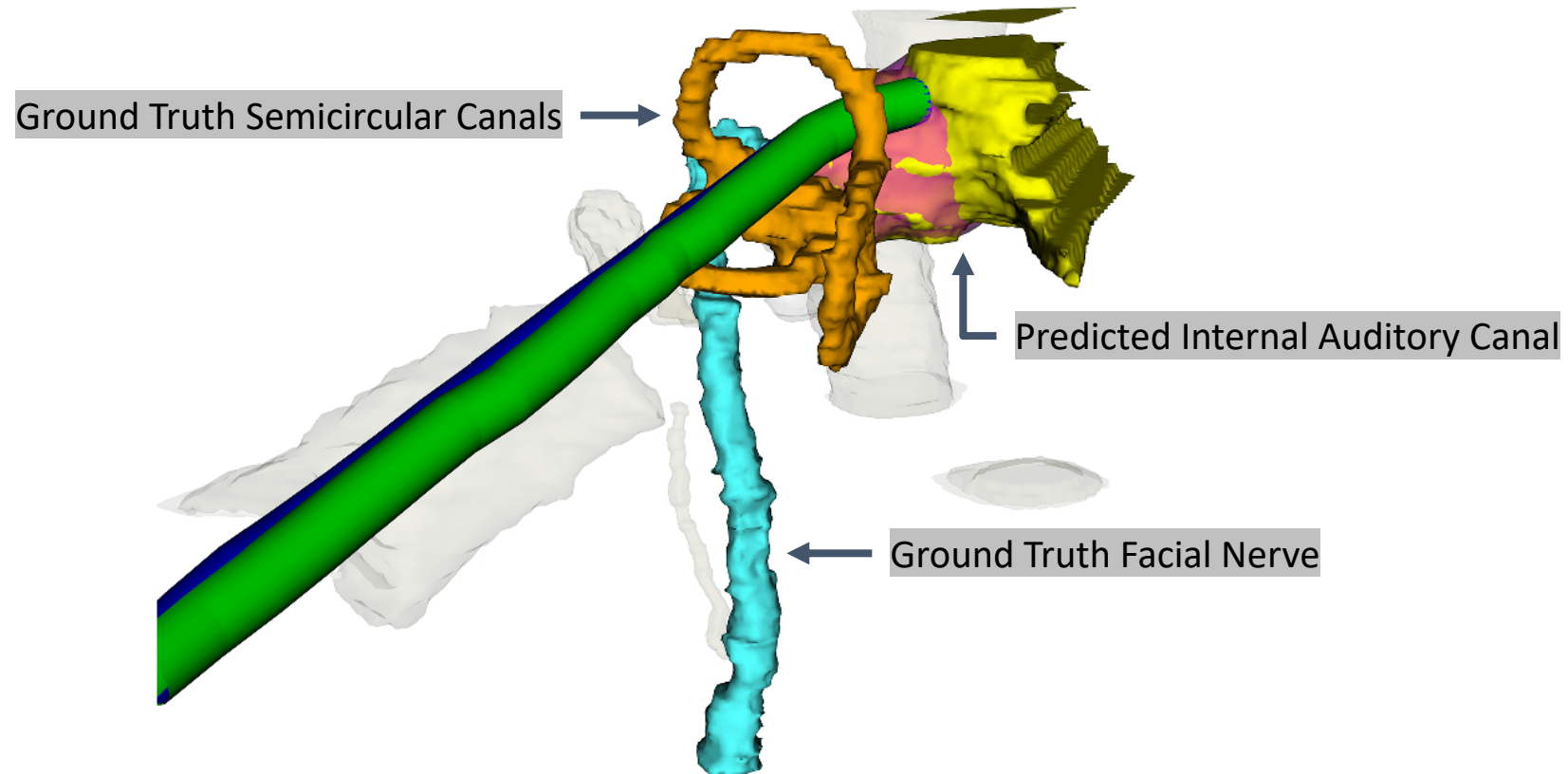
# Paper: Critiques - Cons

- ▶ No true test set or external validation; how generalizable is this model?
- ▶ Sensitivity of some segments is quite low
  - ▶ Is the hybrid model systematically undersegmenting?



# Paper: Critiques - Cons

- ▶ Path planning figures show ground truth and predicted segments together
  - ▶ Path planning should be tested using all predicted segments from one method



Fauser *et al*, 2019 (Figure 8)



# Paper: Potential Next Steps

- ▶ Integration into a GUI application for surgeon usage
- ▶ External validation to evaluate generalizability
- ▶ Hausdorff distances to further investigate segmentation accuracy

# Paper: Relevance

- ▶ Contingency plan for malformed segmentations
  - ▶ Shape regularization using a statistical atlas
  - ▶ Statistical shape model of our dataset has already been created in prior work
- ▶ The Chorda Tympani Problem
  - ▶ Major reason to explore deep learning approaches for segmentation
  - ▶ Segmentation propagation did not perform well at segmenting chorda

# References

1. Fauser, J., et al. (2019). "Toward an automatic preoperative pipeline for image-guided temporal bone surgery." International Journal of Computer Assisted Radiology and Surgery **14**(6): 967-976.
2. Meike, B., et al. (2014). Segmentation of risk structures for otologic surgery using the Probabilistic Active Shape Model (PASM). Proc.SPIE.

# Image References

- ▶ Temporal Bone Anatomy. <https://otosurgeryatlas.stanford.edu/wp-content/uploads/2020/06/7a-1.jpg>. Accessed March 8, 2021

**Thank you!**  
*Questions?*