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

Computer Integrated Surgery II
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Introduction

- The temporal bone houses a complex geometry of nerves, arteries, veins, and hearing and balance organs, packed in a small space (Figure 1).
- Due to these conditions, temporal bone surgery poses a high risk of accidental damage to surrounding structures during free-hand procedures.
- Robot-assisted microsurgical systems can mitigate accidental damage to surrounding structures but require accurate labeling of relevant anatomy.
- This project aims to provide an automated system for creating high-quality segmentations of patient temporal bone CTs, which can be used to inform semiautonomous surgical systems about critical patient anatomy that should be avoided.

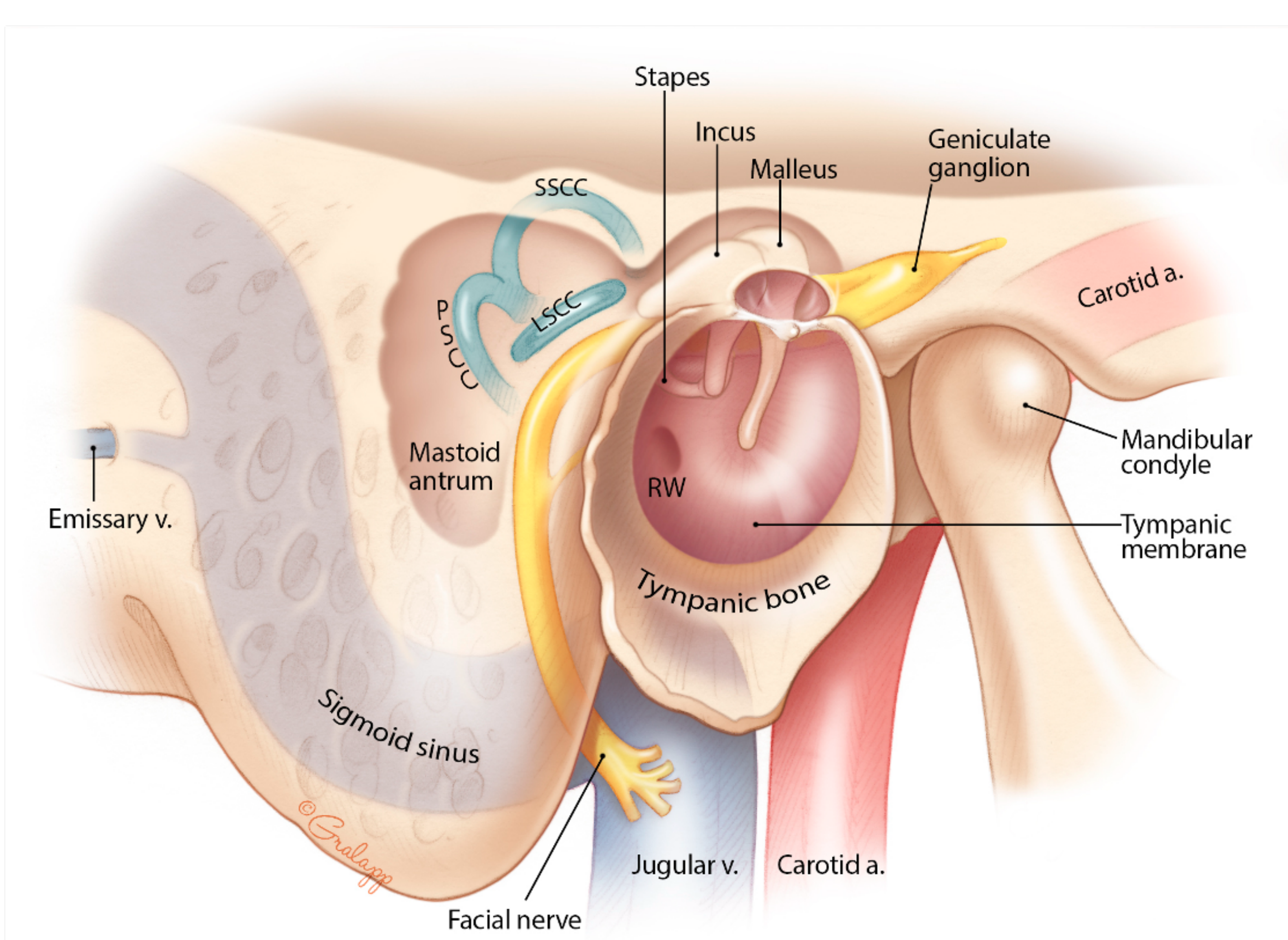

Figure 1. Lateral view of the temporal bone and underlying anatomical structures. Credit: Christine Gallup https://otosurgeryatlas.stanford.edu/

The Problem

- Previous automated segmentation systems for the temporal bone (Neves, 2021; Nikan, 2021; Li, 2020) are not suitable for surgical workflows because they:
  - Require significant post-processing steps and are therefore not truly end-to-end.
  - Are only trained on a small subset of critical structures that should be avoided during surgery.
  - Are typically evaluated on structures that are well-defined and easily distinguished from surrounding tissue

The Solution

- To address these shortcomings, we have:
  - Curated 21 high-resolution (0.1 mm/voxel) temporal bone datasets each with 16 hand-segmented labels.
  - Trained a modified 3D UNet model for semantic segmentation of anatomy (Isensee, 2020).
  - Explored data augmentation methods with deformation field statistical shape models (SSMs).
  - Started to improve on this model with by regularizing shape consistency (Figure 2).

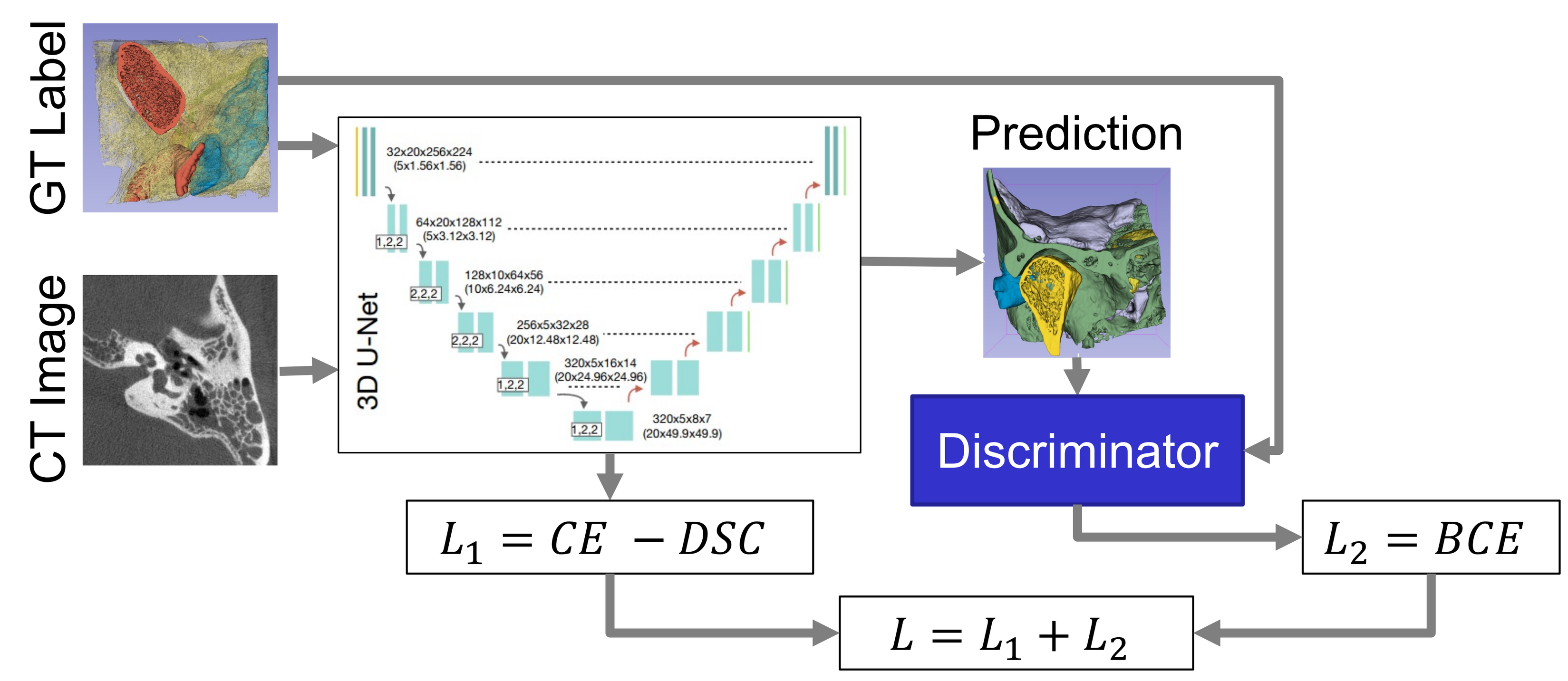

Figure 2. Modified 3D UNet architecture for temporal bone segmentation. The backbone is nnUnet, which produces a prediction that is passed into a discriminator. This discriminator determines if the input volume is the ground truth or a prediction from nnUnet.

Outcomes and Results

- We use dice score and modified Hausdorff distance to quantify our performance.
- We are in the process of procuring an external validation set, and by comparing to literature we have state-of-the-art results with our current models.

Table 1. Main Results

Class	Mean Val DSC		Mean Val HD (mm)	
	Vanilla	SSM Gen.	Vanilla	SSM Gen.
Bone	.95 ± .01	.95 ± .03	**.001 ± .000**	0.016 ± .020
Malleus	**.93 ± .02**	.85 ± .04	**.003 ± .001**	0.010 ± .000
Incus	**.93 ± .02**	.88 ± .02	**.003 ± .000**	0.037 ± .010
Stapes	**.59 ± .16**	.46 ± .10	**.023 ± .019**	0.085 ± .087
Bony Labyrinth	**.96 ± .01**	.94 ± .02	.003 ± .002	0.003 ± .001
Internal Auditory Canal	**.93 ± .02**	.84 ± .05	**.015 ± .007**	0.092 ± .034
Superior Vestibular Nerve	.62 ± .10	**.76 ± .03**	.099 ± .058	**0.018 ± .005**
Inferior Vestibular Nerve	.53 ± .32	**.71 ± .04**	.479 ± .766	**0.046 ± .030**
Cochlear Nerve	.79 ± .07	**.82 ± .02**	.131 ± .138	**0.034 ± .026**
Facial Nerve	.85 ± .04	**.86 ± .02**	**.027 ± .016**	0.038 ± .012
Chorda Tympani	**.72 ± .09**	.52 ± .02	**.143 ± .085**	0.598 ± .473
Internal Carotid Artery	.93 ± .02	.93 ± .03	.061 ± .067	**0.037 ± .033**
Sigmoid Sinus + Dura	.80 ± .04	.80 ± .01	.263 ± .366	**0.204 ± .105**
Vestibular Aqueduct	**.67 ± .06**	.51 ± .16	**.095 ± .098**	0.274 ± .228
Mandible	.94 ± .02	**.96 ± .01**	.002 ± .002	**0.001 ± .000**
External Auditory Canal	**.84 ± .02**	.81 ± .05	**.130 ± .060**	0.351 ± .271

Future Work

- Work on the project will continue, wrapping up unfinished studies, and applying the best models to an external dataset as well as releasing a public dataset.

Lessons Learned

- Do not underestimate the importance of dependencies, and make sure contingency plans will not fall through.

Credits

- Jessica: nnUnet implementation, cloud computing setup.
- Andy: Data procurement, hand-segmentation refinement, deformation field SSMs for data augmentation.

Publications

- We are preparing a manuscript for IPCAI 2021.

Acknowledgements

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