JOHNS HOPKINS UNIVERSITY

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

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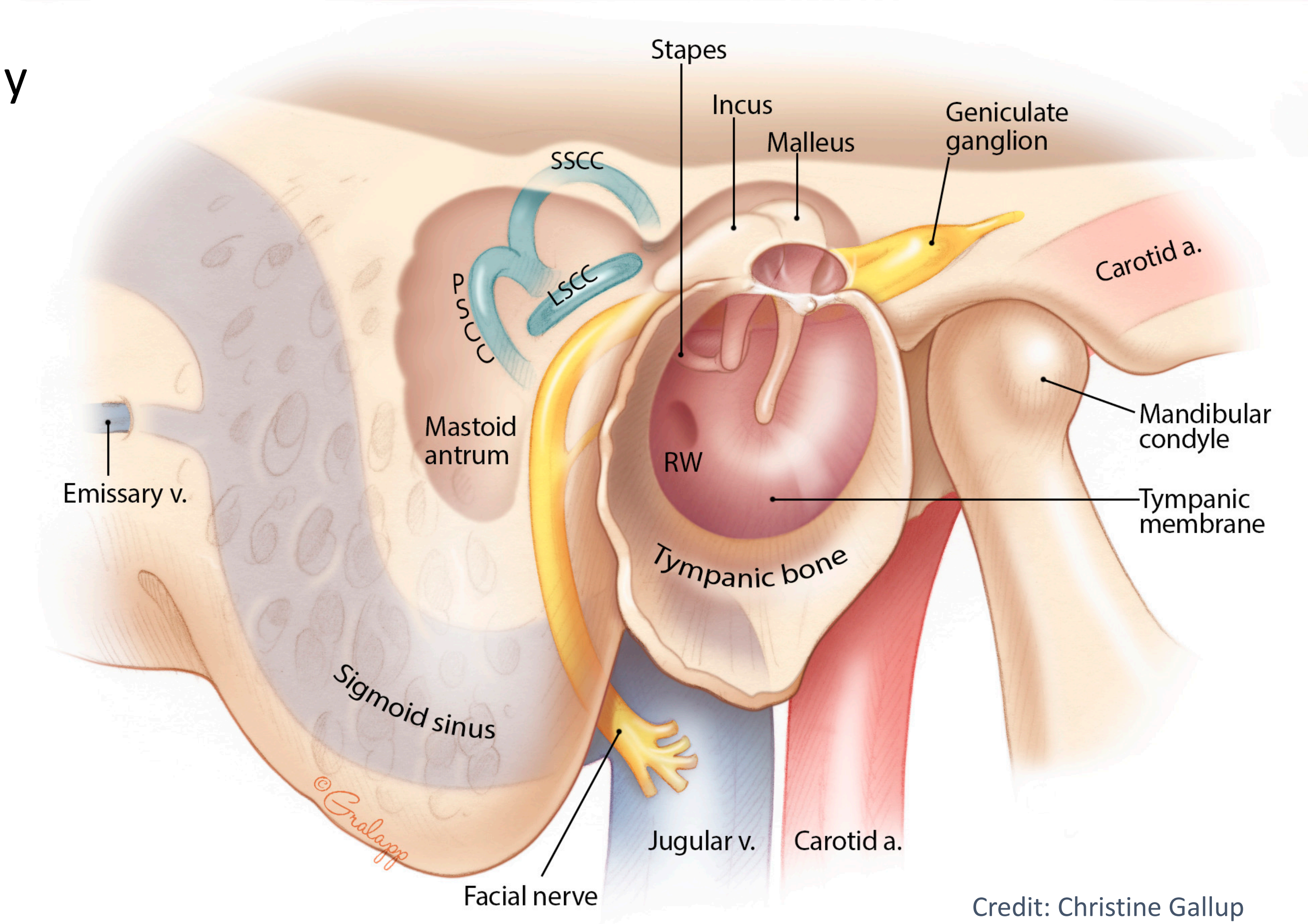
Mentors: Dr. Francis X. Creighton, Dr. Russell H. Taylor, Dr. Mathias Unberath, Max Zhaoshuo Li

PROJECT GOAL

Automated segmentation system of the temporal bone to prevent intraoperative injury of critical structures during robot-assisted microsurgery

Clinical Motivation

- Temporal bone anatomy is geometrically complex
- Surgical access requires drilling through mastoid bone
- Critical structures are often within millimeters of each other [1]
- Accidental damage can lead to: [2-4]
  - Changes in taste
  - Facial paralysis
  - CSF leakage
  - Closure of the sigmoid sinus



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

[1] Cousins, 2007; [2] Lloyd *et al*, 2007; [3] Fayad *et al*, 2003; [4] Zanoletti *et al*, 2014;

Clinical Motivation

- Possible solution: CT-registered robot-assisted surgery [5]
  - Reduces hand tremor
  - Reduces risk of intraoperative injury
  - Needs information about patient anatomy

LABORATORY FOR
Computational
Sensing + Robotics

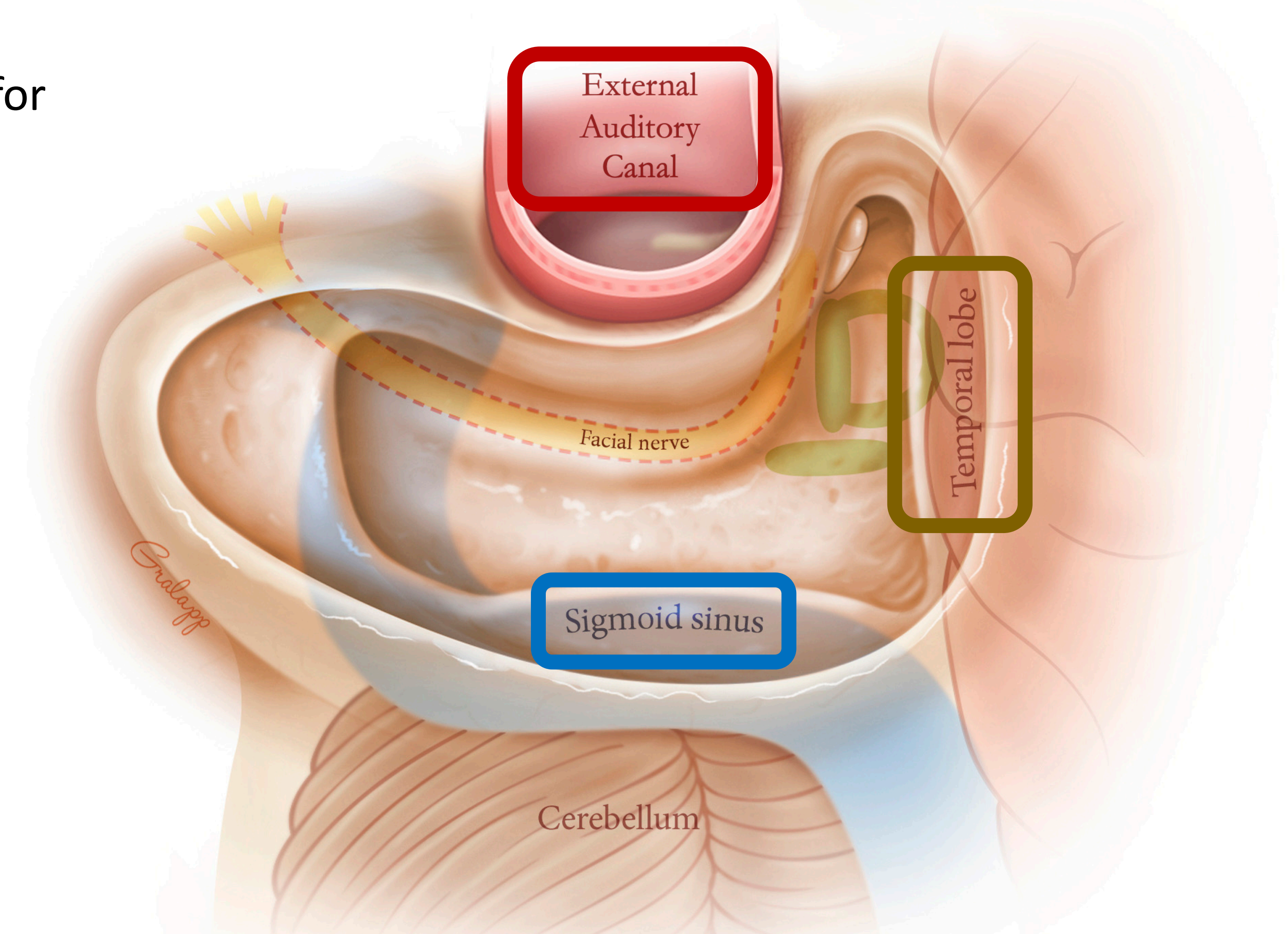
[5] Razavi *et al*, 2019

Goals & Significance

- Evaluate state-of-the-art deep learning models for semantic segmentation of the temporal bone
- Build the largest comprehensively annotated temporal bone CT database for future use in research and industry

If successful, this project will provide:

- Robust virtual safety barriers for robot-assisted temporal bone surgery
- Patient-specific segmentations to reinforce anatomical knowledge in junior otologists
- Most complete dataset for training future deep learning networks



Credit: Christine Gallup
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Dependencies

Dependency	Need	Status	Follow-up	Contingency Plan	Original Deadline	New Deadline	Effect
Dr. Unberath Supervision Agreement	Need a Deep Learning Consultant for the project	Resolved	N/A	Max (technical consultant) has deep learning experience, continue project with him as lead.	2/12	N/A	May run into some issues if Max's expertise cannot help us through some issues, although the risk is low, since we are implementing methods that have been shown to work on similar datasets.
Workstation Arrival	Computational Power and Availability	Purchased, peripherals arrived, workstation estimated 4/15 arrival	Check in tracking progress weekly	Continue to use MARCC.	2/27	4/15	Since workstation arrival was delayed, we used MARCC/gcloud for debugging/compute. Due to limited compute, we have restructured our project goals (detail to be discussed).
Label/Annotation Finalization	Need Data to Train Final Models	Revising, 75% Done		Use unfinalized labels to debug/test with for new implementations.	2/15	4/4	Can use preliminary labels (mostly done) to train/debug with. Final models/results will be put off until the labels are finalized.

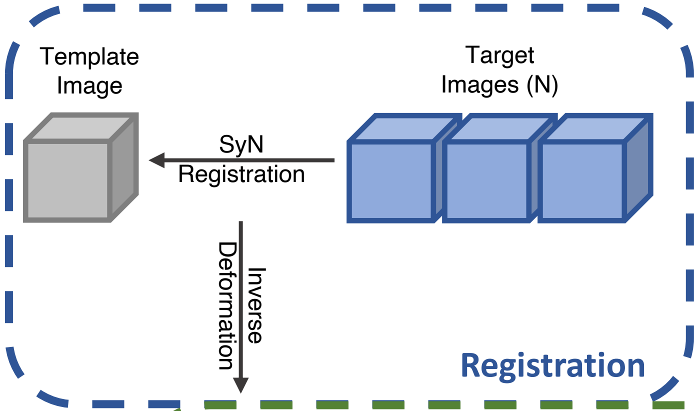
Key Deliverables

	Activity	Deliverable	
Minimum	Synthesize deformed temporal bone CTs with labels to augment training dataset	Statistical shape model of temporal bone CTs	✓
Expected	Implementing nnU-Net	Fully functioning model for CT segmentation with documentation.	✓
	Training model, then validating nnU-Net results on test data.	Internal validation report with ground truth segmentations.	⌛
	Application of nnU-Net to external dataset.	External validation reports with Western University's dataset. [8]	⌛
Maximum	Implementing GAN label refinement into nnU-Net	GAN label refinement model for CT segmentation with documentation.	
	Final manuscript preparation.	Submittable manuscript.	
	Application of segmentation model to unlabeled dataset.	High quality segmented temporal bone CT dataset using our segmentation models.	

[8] Nikan *et al*, 2021

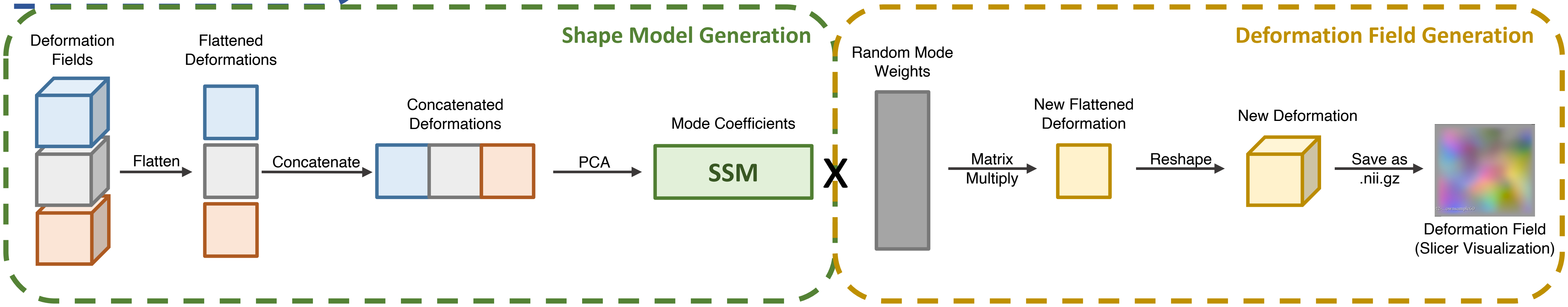
Technical Approach: Data Generation

- Idea: Use deformation fields to model the variability in shape among our CT scans

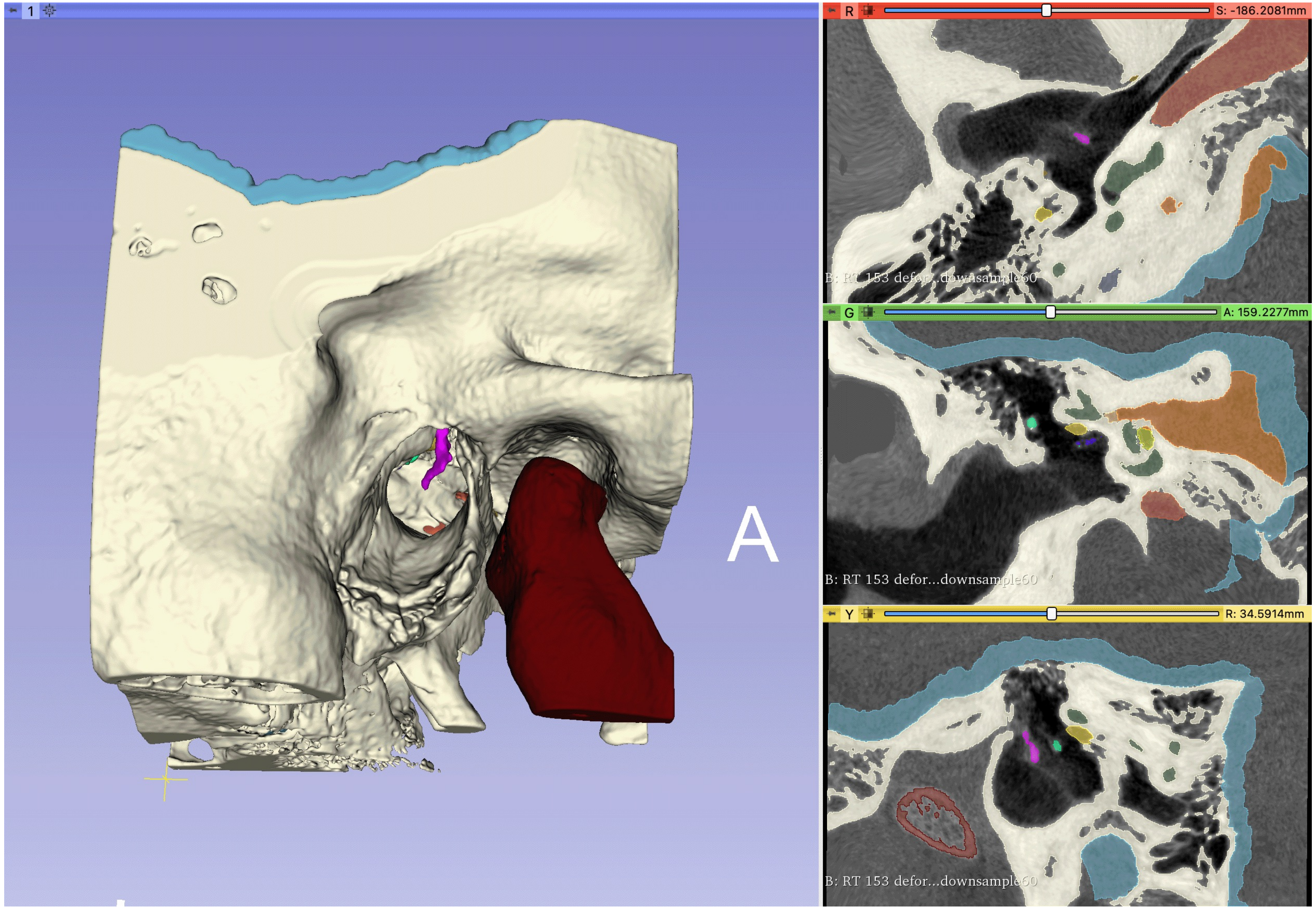


Strategy

1. Rigidly align all scans to a designated template scan.
2. Deformably register scans to the template scan.
3. Gather the **inverse** deformation fields from registration to generate a statistical shape model (SSM).
4. Generate **new** deformation fields and apply them to template image and labels to create new training data.

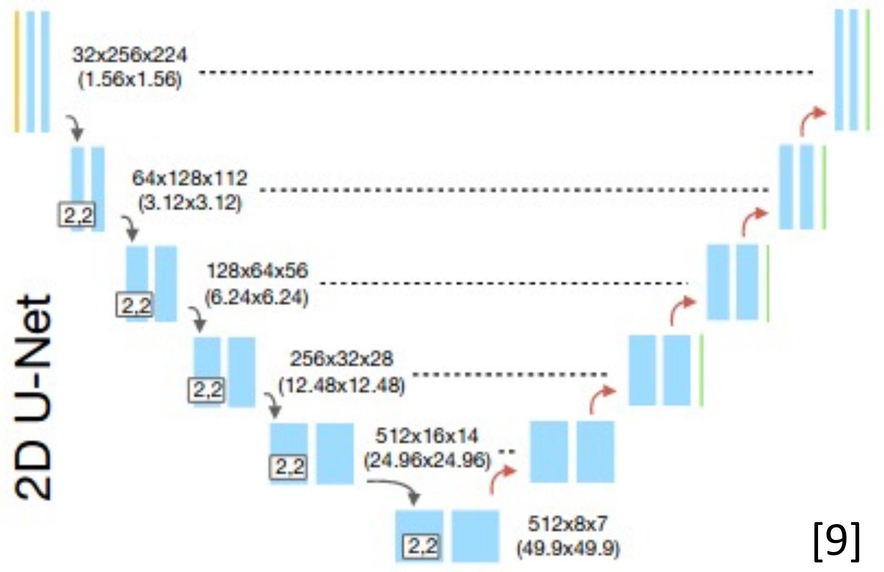


Statistical Shape Model Deformed Volumes

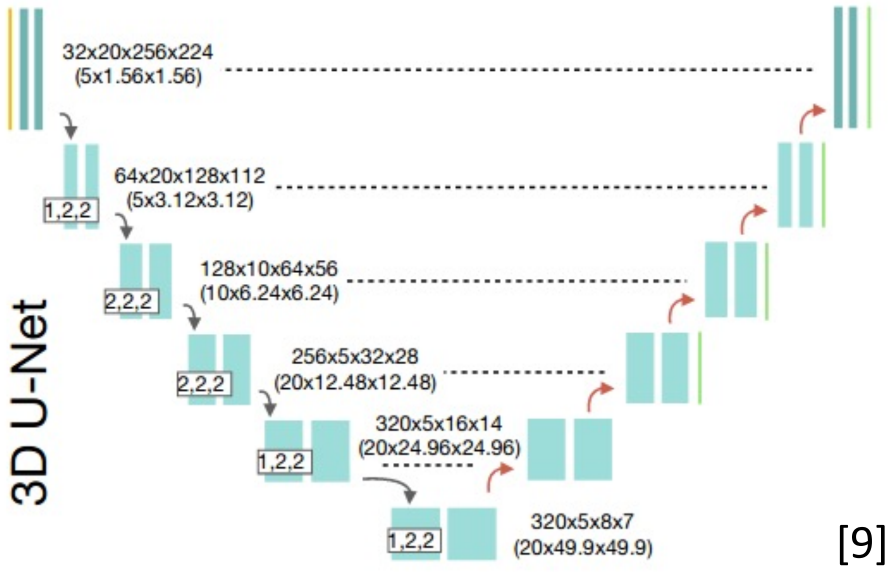


Technical Approach: nnU-Net

- nnU-Net (Isensee F et al)
  - New benchmarking pipeline developed to standardized medical imaging.
  - 33 top leaderboard results for 53 different datasets with this method.
  - 2D and 3D approach available.



[9]



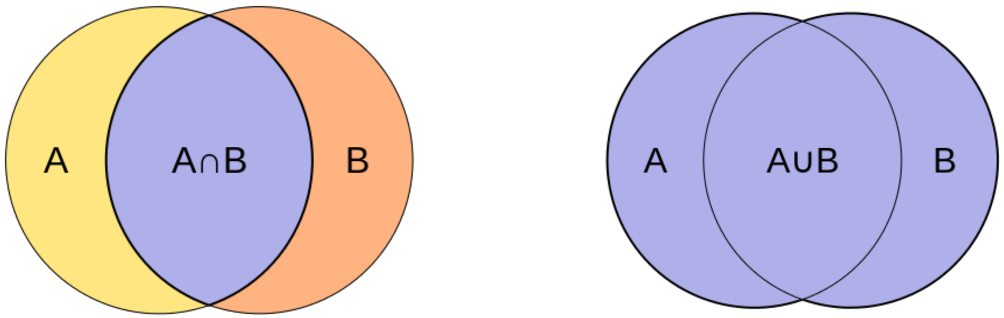
[9]

[9] Isensee F, Jaeger PF, Kohl SAA, Petersen J, Maier-Hein KH

Metrics For Dummies

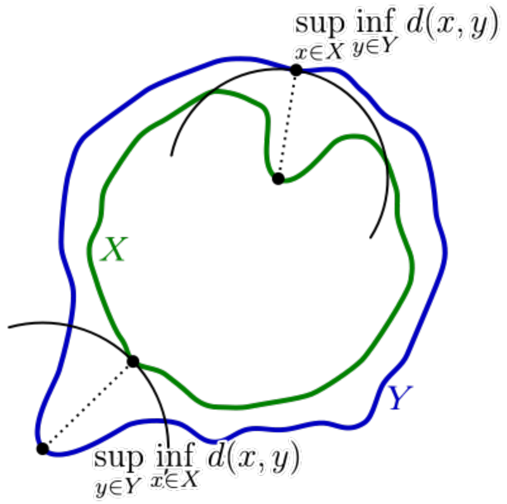
- Dice Score:
  - Think of as 2x area of overlap divided by the total volume of each set.

$$DSC = \frac{2|X \cap Y|}{|X| + |Y|}$$



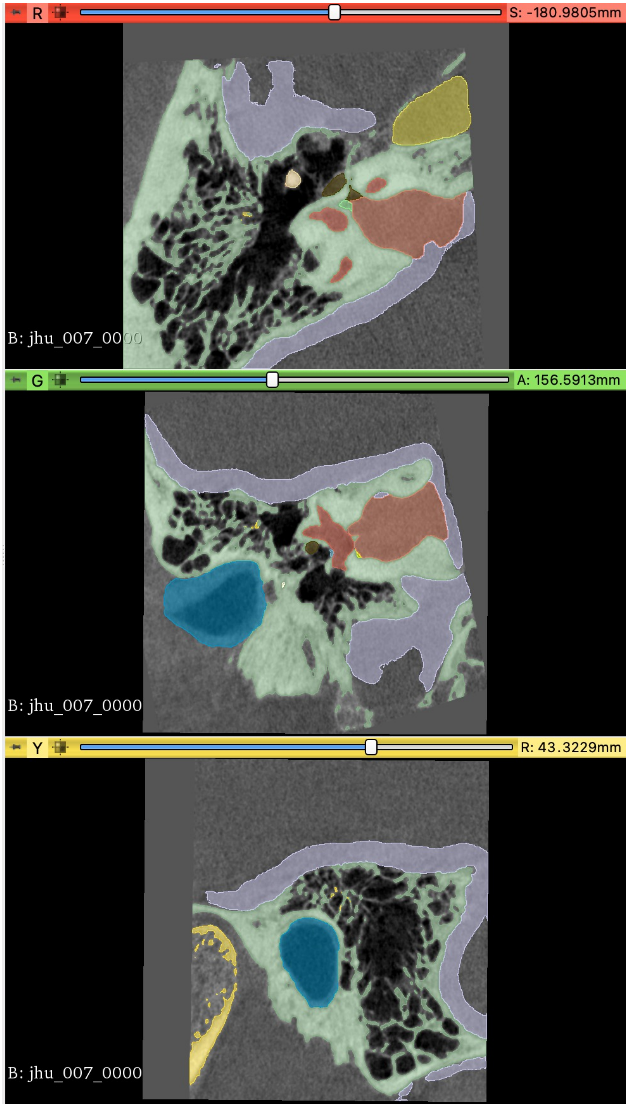
Credit: **Stephan Kulla**
http://kulla.me/en/

- Hausdorff Distance:
  - Think of as greatest distance from one point in a set to the closest point in another set.



Credit: Roccini
https://en.wikipedia.org/wiki/User:Rocchini

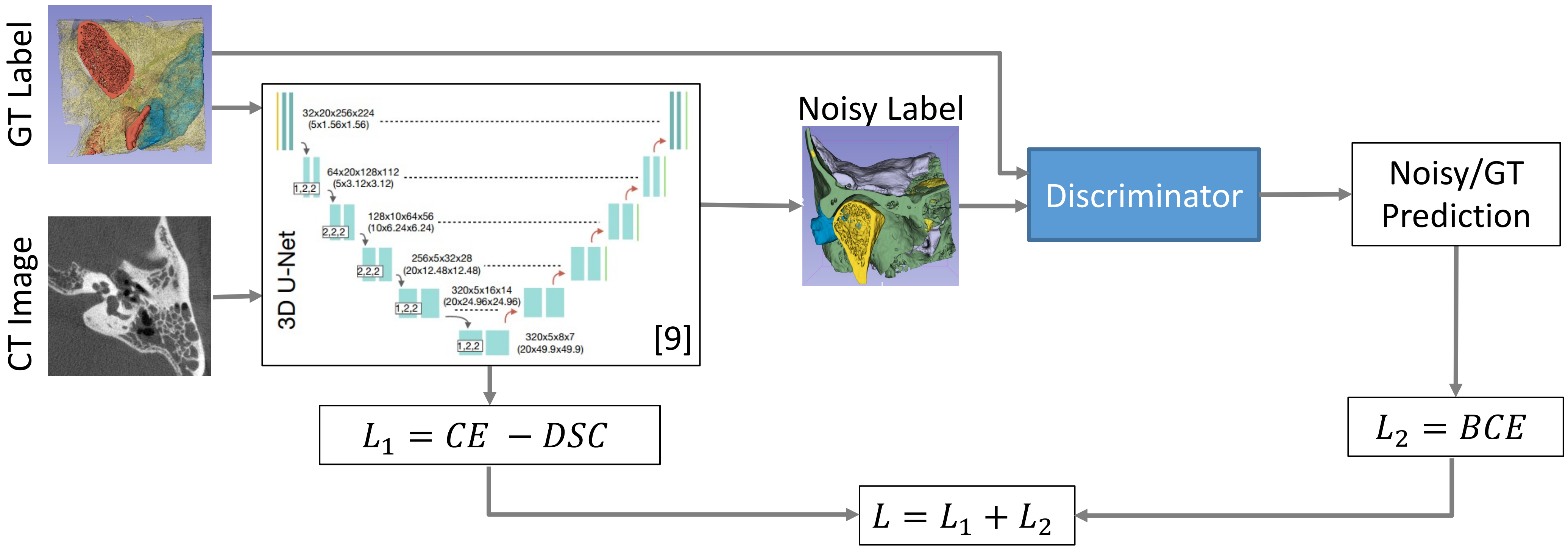
Preliminary nnU-Net Prediction Results



#	Class	Dice	Hausdorff
1	Bone	.945	.182
2	Malleus	.943	.067
3	Incus	.943	.056
4	Stapes	.698	.065
5	Vestibule + Cochlea	.969	.184
6	Vestibular Nerve	.853	.072
7	Superior Vestibular Nerve	.685	.232
8	Inferior Vestibular Nerve	.327	.238
9	Cochlear Nerve	.797	.123
10	Facial Nerve	.813	.137
11	Chorda Tympani	.670	.192
12	Internal Carotid Artery	.893	2.99
13	Sigmoid Sinus + Dura	.793	.175
14	Vestibular Aqueduct	.688	.392
15	Mandible	.967	.070
16	External Auditory Canal	.781	.044

Technical Approach: GAN Label Refinement

- Current nnU-Net model will serve as generator, with the GT label map and image as input.
- Prediction label map and GT label map will be put into a discriminator, loss will be calculated.
- Then generator model will have an overall loss term that includes the loss from the discriminator.

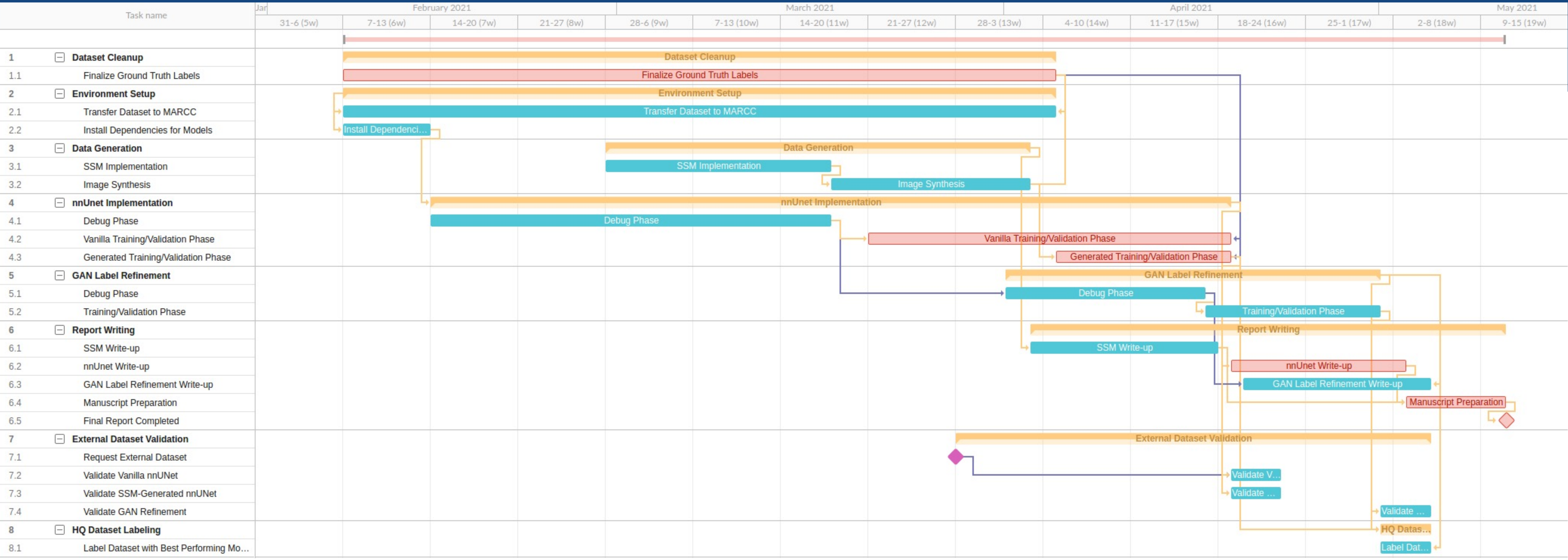


[9] Isensee F, Jaeger PF, Kohl SAA, Petersen J, Maier-Hein KH

Timeline/Milestones

Milestones		Progress	Start	End
Finalize Ground Truth Labels		75% - Have two annotators, but different annotating convention. Need to correct labels and re-train models.	2/9	~~2/12~~ 4/4
Setup Environment		100% - Complete	2/13	2/19
~~Simple Data Generation~~	SSM Data Generation Implementation	90% - Implementation itself complete, but need to re-run SSM to exclude current dataset, or else SSM will introduce bias into val/test data.	2/17	~~2/23~~ 4/2
nnU-Net Implementation		90% - Pipeline to train set up, need to get final dataset, generated data, then can train final models.	2/24	~~3/25~~ 4/18
~~AH-Net Implementation~~ ~~Patch-Based Network Implementation~~	GAN Label Refinement Implementation	0%	4/1	4/30
External Dataset Validation		10% - Emailed university for external dataset.	~~4/12~~ 3/31	~~4/28~~ 5/4
HQ Dataset Labeling		0%	~~4/15~~ 5/1	~~4/28~~ 5/4
Manuscript Preparation + Code		0%	~~3/26~~ 4/3	~~5/4~~ 5/11

Updated Gantt Chart



- nnUNet Hardware Troubleshooting:
  - Effect: Took much longer than anticipated, delayed initial results.
- Finalizing Ground Truth Labels: Two annotators had different conventions, but this was caught late into the project.
  - Effect: Need to re-train vanilla model, hold off on SSM-generated model training.
- Image Synthesis: Actual SSM implementation automated by 3/17, but training data included test data from deep learning method
  - Effect: Replace overlapping data with more data from Dr. Stewardson, delay SSM-generated model training

Roles and Responsibility

- The Team:

Jessica’s Responsibilities	Shared Responsibilities	Andy’s Responsibilities
• Environment setup • nnU-Net implementation • nnU-Net writeup • GAN-regularization • External Dataset Validation	• Manuscript preparation	• Data generation • Manage dataset (segmentations), purchases • SSM writeup • HQ Dataset Labeling • External Dataset Formatting

- Mentors:
  - **Dr. Russell Taylor**: Technical Lead
  - **Dr. Francis X. Creighton**: Clinical Lead
  - **Dr. Mathias Unberath**: Deep Learning Lead
  - **Maxwell Zhaoshuo Li**: Technical Consultant

Management Plan

- **Meetings:**
  - Sunday meetings between Jessica & Andy
  - Tuesday and Thursday brief check-ins between Jessica & Andy
  - Weekly meetings with the LCSR (Wednesdays)
  - Weekly meetings with Dr. Unberath (Fridays)
  - Ad hoc meetings with Max Li (Mondays)
- **Communications:**
  - Slack channel with the LCSR (Technical Leads/Consultants)
- **File Sharing**:
  - Data/Reports: Hopkins OneDrive, CIS II website
  - Code: Private repository on Github

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Image References

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