

Image Guidance for Robot-Assisted Ankle Fracture Repair: Final Presentation

Team Members: Asef Islam, Anthony Wu, Jayaram Mandavilli
Mentors: Dr. Jeffrey H. Siewerdsen and Dr. Wojtek Zbijewski

Overview

- Project Background and Importance
- Technical Approach
- Aims/Deliverables
- Team Management
- Status
- Next Milestones

Background: Ankle Fracture and Syndesmosis



Ankle fractures have incidence of up to 187 cases per 100,000 adults per year – over 5 million cases per year in the U.S. alone^[1]



Most common affected groups are young, active people and elderly people^[1]



The incidence of PTOA has been reported as high as 70%^[2]

[1] Goost H, Wimmer MD, Barg A, Kabir K, Valderrabano V, Burger C. Fractures of the ankle joint: investigation and treatment options. *Dtsch Arztebl Int.* 2014;111(21):377–388.

[2] Mehta SS, Rees K, Cutler L, Mangwani J. Understanding risks and complications in the management of ankle fractures. *Indian J Orthop.* 2014;48(5):445–452.

Project Summary

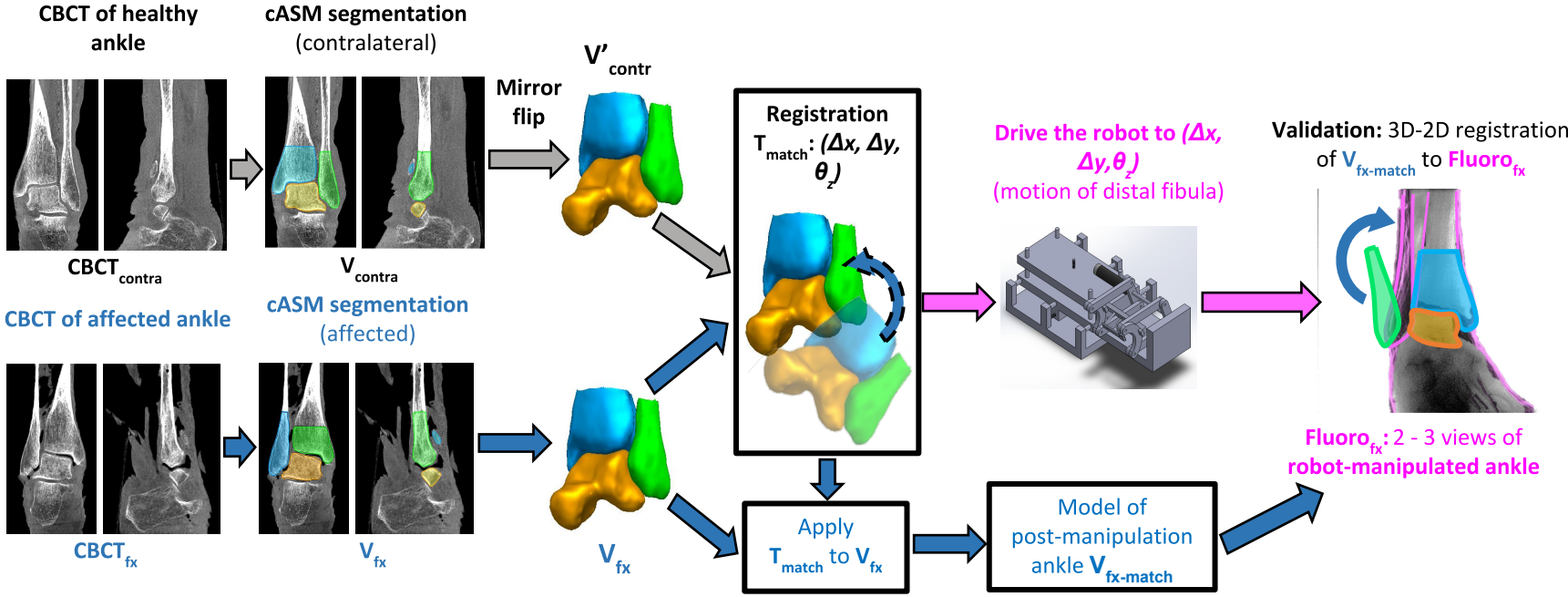


Figure by Wojtek Zbijewski

Aims/Deliverables

Minimum: Complete

- Validate accuracy of Coupled Active Shape Model with average segmentation error of 5 mm for high quality cone beam images
- Perform error analysis on failure modes on low quality CT images

Expected: Almost Complete

- Validate accuracy of joint deep learning - cASM model with mean segmentation error of 2mm for low quality CT images of healthy ankles without metal artifacts

Maximum: Incomplete

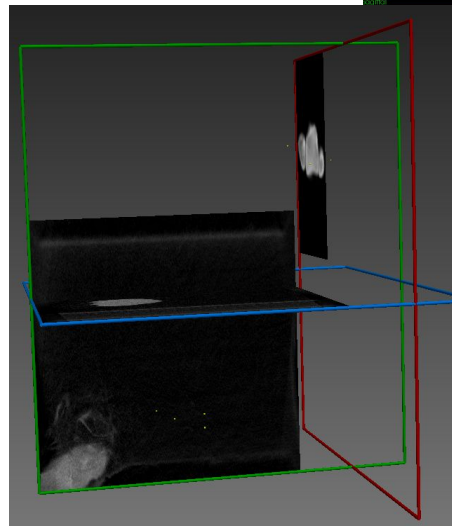
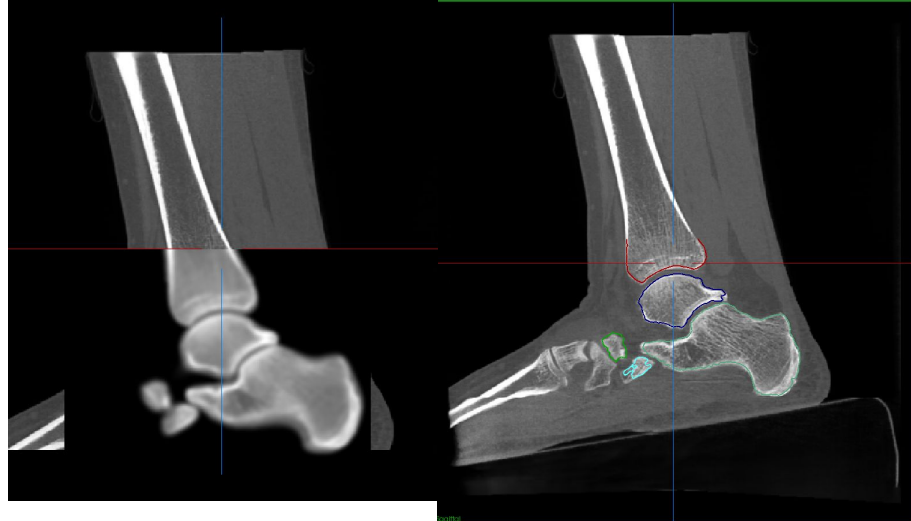
- Publish paper
- Incorporate metal artifacts and unhealthy ankle data into deep learning - cASM model with mean segmentation error of 2mm

Team Management

Member	Responsibilities	Meeting Attendance
Asef Islam	<ul style="list-style-type: none">● Create workflow for processing C-arm data● Adjust active shape model to first work for cone beam and then to work for c-arm data	<ul style="list-style-type: none">● F 3:30-5pm● Sat 3-5pm● When needed
Jayaram Mandavilli	<ul style="list-style-type: none">● Develop deep learning framework and multiple models for ankle segmentation● Develop U-net and simple CNN	<ul style="list-style-type: none">● Fri 3:30-5pm● Sat 3-5pm● When needed
Anthony Wu	<ul style="list-style-type: none">● Create training data● Develop deep learning model for ankle segmentation● Developed validation framework	<ul style="list-style-type: none">● Fri 3:30-5pm● Sat 3-5pm● When needed
Mentors: Wojtek Zbijewski, Jeff Siewerdsen	<ul style="list-style-type: none">● Provided feedback on presentations and project pathways● Provided many resources including access to C-arm (to collect data) and remote GPU access	<ul style="list-style-type: none">● Fri 3:30-5pm

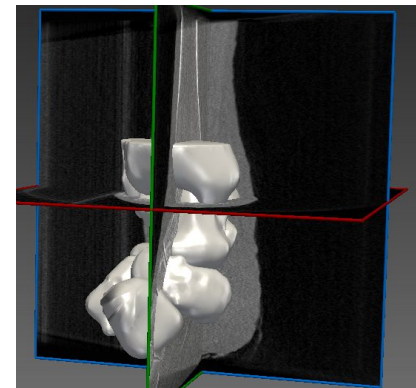
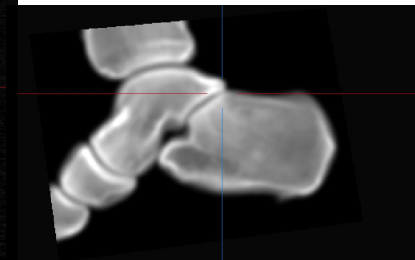
cASM Status

- cASM model works for CBCT data, begins with near perfect initial coarse registration of mean image
- Difficulty registering mean image to C-arm data due to different voxel sizes and different axes.



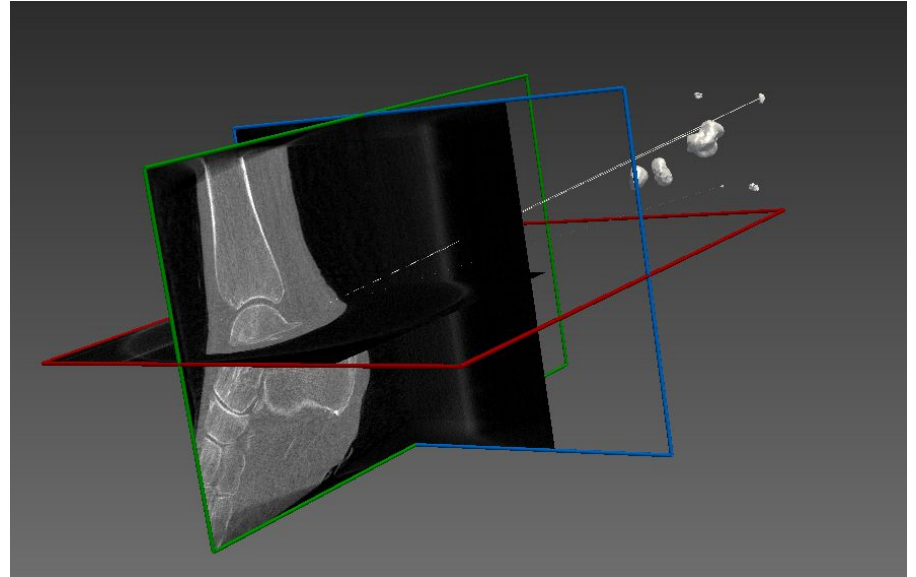
cASM Status

- Mean image has different coordinate frame and voxel size compared to C-arm images.
- Fixed: Improved initial alignment of mean image through CPD registration, manual tuning, adjusting scaling and origin
- Better initialization of mean shapes



cASM Status

- Current problems
 - Re-meshed versions of mean shapes
 - Erroneous normals
 - Mean shapes once again become misaligned from image after surface deformation



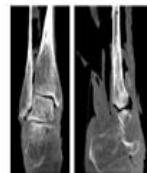
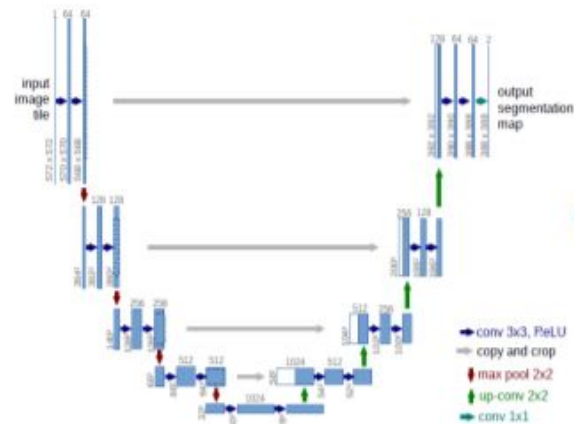
Neural Net Status

- Data Pre-Processing

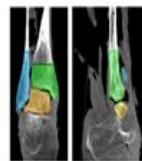
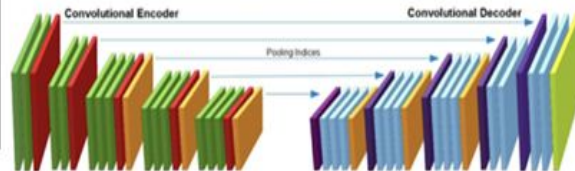
- Splice 3D images: 2D inputs to neural nets
- Zoom in data: reduces computational burden
- Reduce bias: reduce the percentage of slices without the bone
- Average slices: reduce noise for each input slice

- Approaches: fibula

- Look at each slice from each plane (coronal, sagittal, and axial)
 - Identify if slice has fibula or not
 - Say i th axial slice, j th sagittal slice, and k th coronal slice all had fibulas, then can say pixel i, j, k is part of the fibula
- Main approach: segment 2D slices with U-net
 - Used coronal slices



Input:
CT/C-arm images

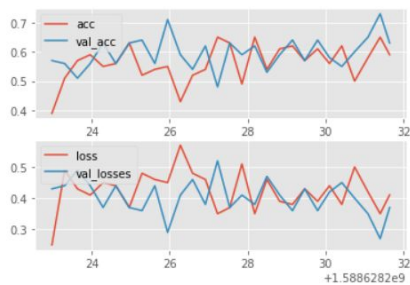


Output:
Segmented Images

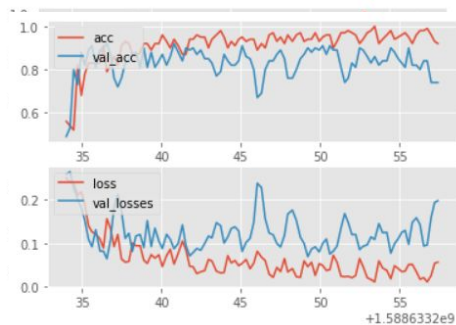
Neural Net Results

Convolutional
Neural
Network (CNN)

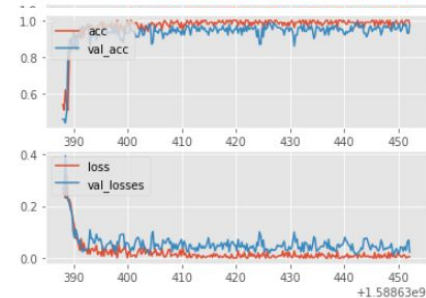
Coronal



Sagittal

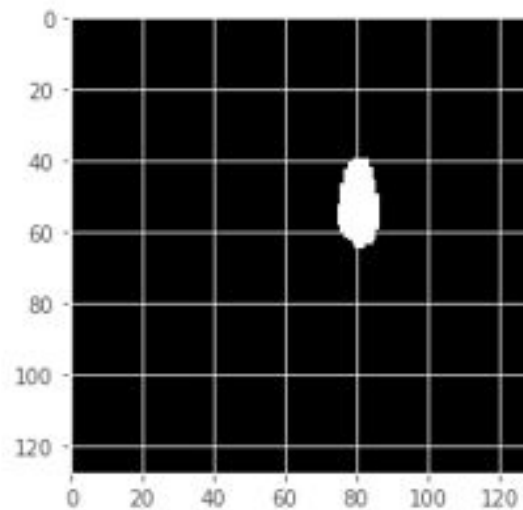
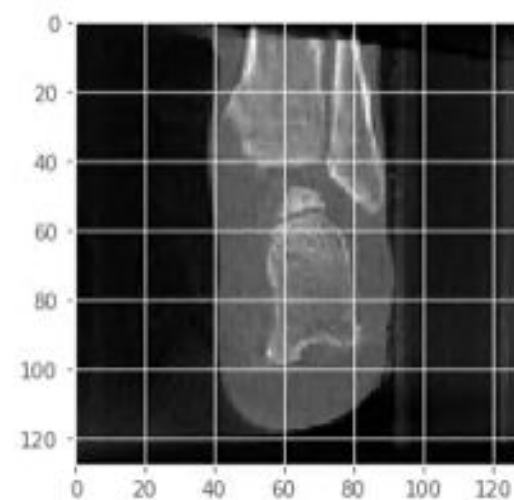


Axial



Neural Net Results Part 2

- Trained U-Net on 200 EPOCHS
- Accuracy: 99.3% on pixels of test data
 - Loss Function Value: 0.03
- However, must evaluate if neural net had bias
- Loss Function = $-\sum x \cdot \log(y)$
 - x is the truth value (0 for no bone, 1 for bone)
 - y is the probability of x happening.



What We Learned

- cASM
 - Better understanding of code and its different steps through time spent debugging
 - Highly modular
 - Computationally intensive, often causes personal laptop to crash
 - Latest stable release is calibrated towards diagnostic CBCT scanner, so when trying to use code with new imaging modalities or scanners it has to be re-calibrated in terms of initial alignment
 - Sensitive to parameter choices
- Deep Learning
 - Trial and error
 - Neural networks require much more computational power than we anticipated
 - Pre-processing of data is very important
 - Helps increase accuracy
 - Can help reduce computational burden
 - Found a creative way to solve a semantic segmentation problem

Next Milestones (Summer)

- Achieve full functionality of cASM for C-arm images
 - Resolve problems noted with mean shapes, normals, misalignment
 - Quantify segmentation accuracy for images based on quality (high, low, artifacts, etc.)
 - Tune parameters (iterations, # PCs, kernel sigmas, etc.) to find what works best
- Develop deep learning approach for low quality C-arm images
 - Look into more model types
 - Develop networks for all 7 bones of interest in ankle
- Implement pre-processing steps to clean up data
 - Enhance contrast to strengthen gradient signals of bone edges
 - Incorporate metal artifact and noise reduction algorithms

Questions?