

Image Guidance for Robot-Assisted Ankle Fracture Repair: Checkpoint

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Mentors: Dr. Jeffrey H. Siewerdsen and Dr. Wojtek Zbijewski

Overview

- Project Summary
- Deliverable Updates
- Progress & Timeline
- Next Milestones

Project Summary: Technical Approach

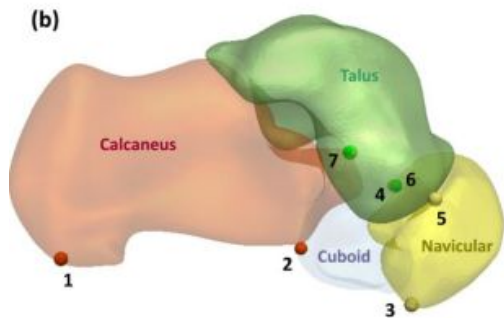
Coupled Active Shape Models for Automated Segmentation and Landmark Localization in High-Resolution CT of the Foot and Ankle

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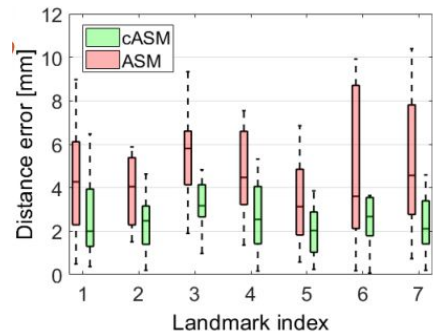
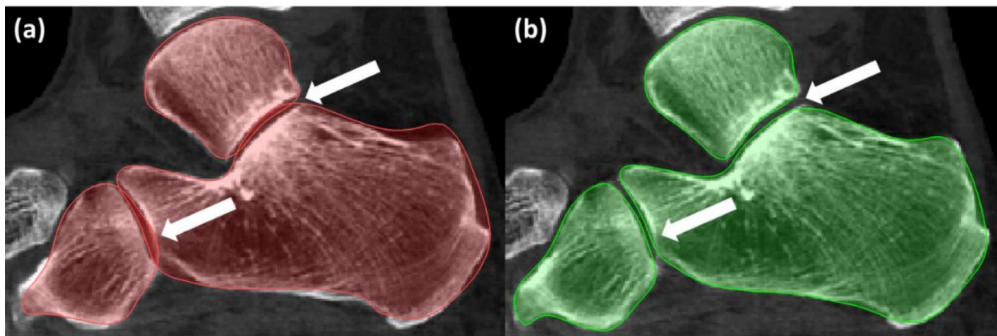
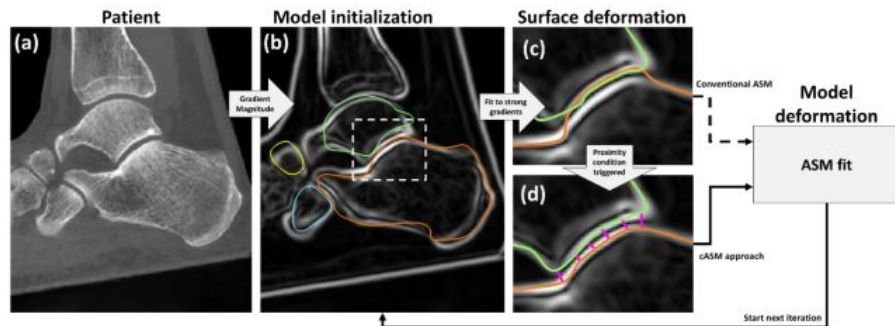
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Articular Surface Distances	Min [mm]	Max [mm]	Mean [mm]
Calcaneus to Cuboid	0.64	1.49	1.00
Calcaneus to Talus	0.92	2.64	1.57
Cuboid to Calcaneus	0.69	1.58	1.03
Navicular to Talus	0.70	2.27	1.40
Talus to Navicular	0.85	2.61	1.54
Talus to Calcaneus	0.81	2.02	1.26



Project Summary

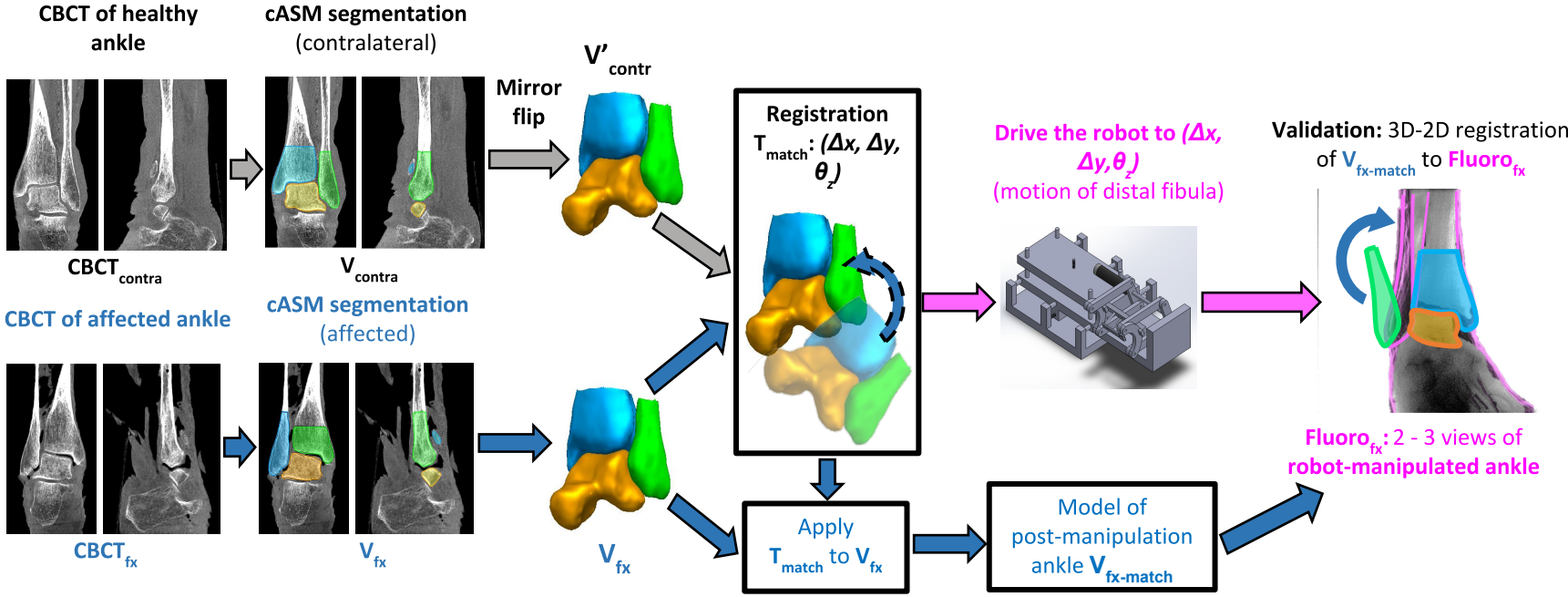


Figure by Wojtek Zbijewski

Deliverables: Before Spring Break

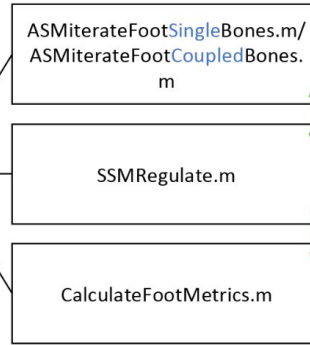
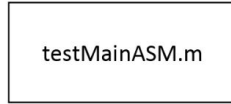
Minimum	Expected	Maximum
<ul style="list-style-type: none">○ Validate accuracy of Coupled Active Shape Model with average segmentation error of 5 mm for high quality cone beam images○ Perform error analysis on failure modes on low quality CT images	<ul style="list-style-type: none">○ Validate accuracy of joint deep learning - cASM model with mean segmentation error of 2mm for low quality CT images of healthy/unhealthy ankles with & w/out metal artifacts	<ul style="list-style-type: none">○ Publish paper○ Perform cadaver experiment to validate accuracy of models

Deliverables: Update

Minimum	Expected	Maximum
<ul style="list-style-type: none">○ 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	<ul style="list-style-type: none">○ 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	<ul style="list-style-type: none">○ Publish paper○ Incorporate metal artifacts and unhealthy ankle data into deep learning - cASM model with mean segmentation error of 2mm

Driver Code
 - Parameters, dependencies
 - Input/working directories

Main Function (Section II)
 - Preprocess patient data
 (resolution, blur)
 - Initial registration (blur)
 - ASM/metric subroutines



Displace vertices along surface normal according to gradient magnitude image (ProfileLength, ProfileSpacing)

ASM iterations (Sections III and IV)

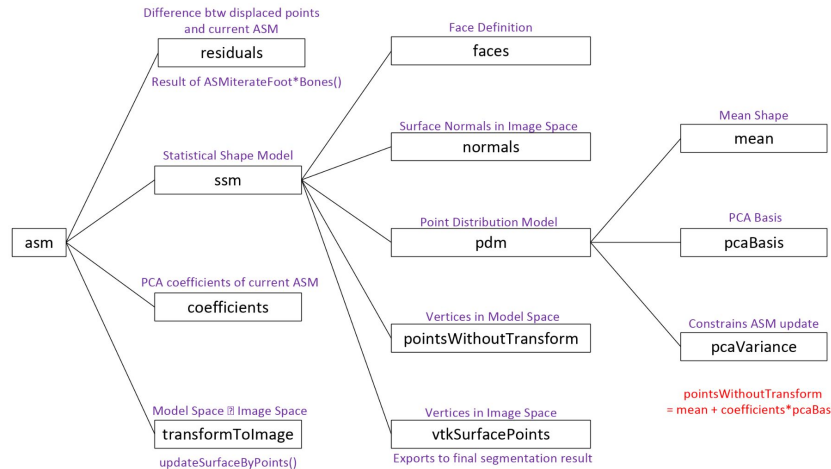
Update model to best-fitting ASM based on displaced vertices (NumberOfPCs)

free deformation (on/off)

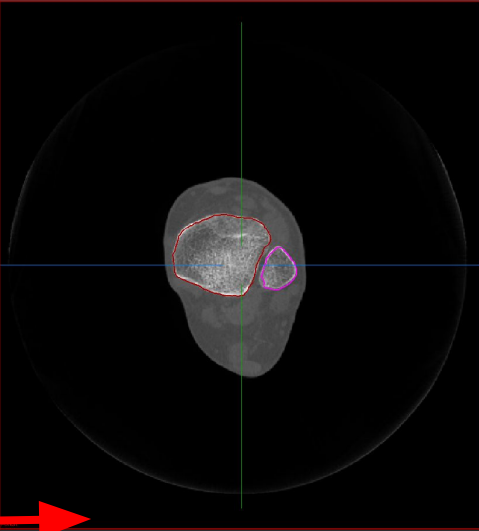
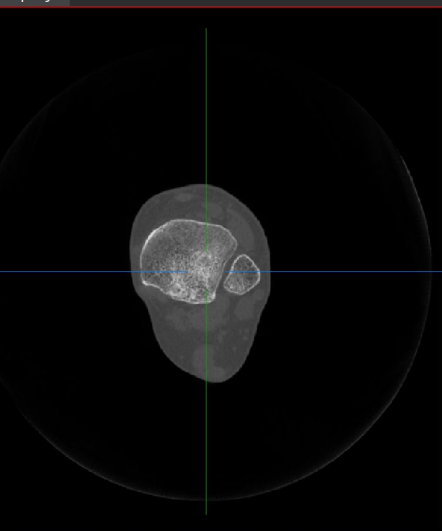
Compute metrics based on atlas points (Section V)

Global Parameters:
 - Blur
 - ASM type (coupled/single)
 - Free deformation

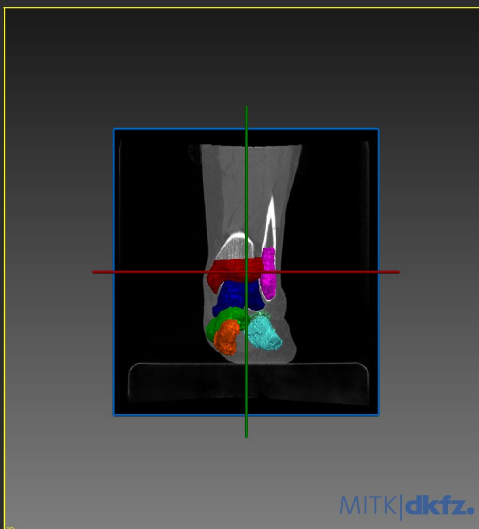
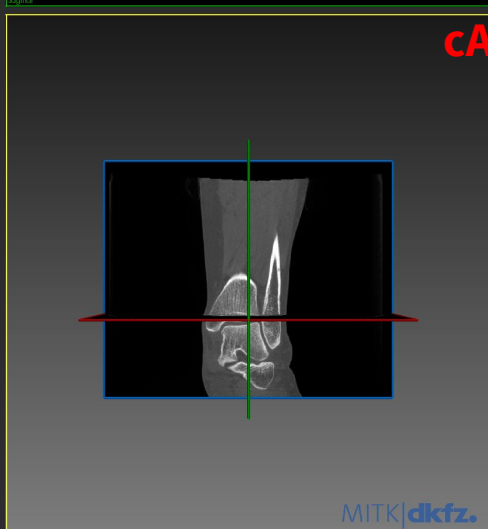
Stage-specific Parameters:
 Resolution (downsampling)
 Iterations
 ProfileLength
 ProfileSpacing
 NumberOfPCs



Diagrams from Qian Cao,
 Wojtek Zbijewski



cASM

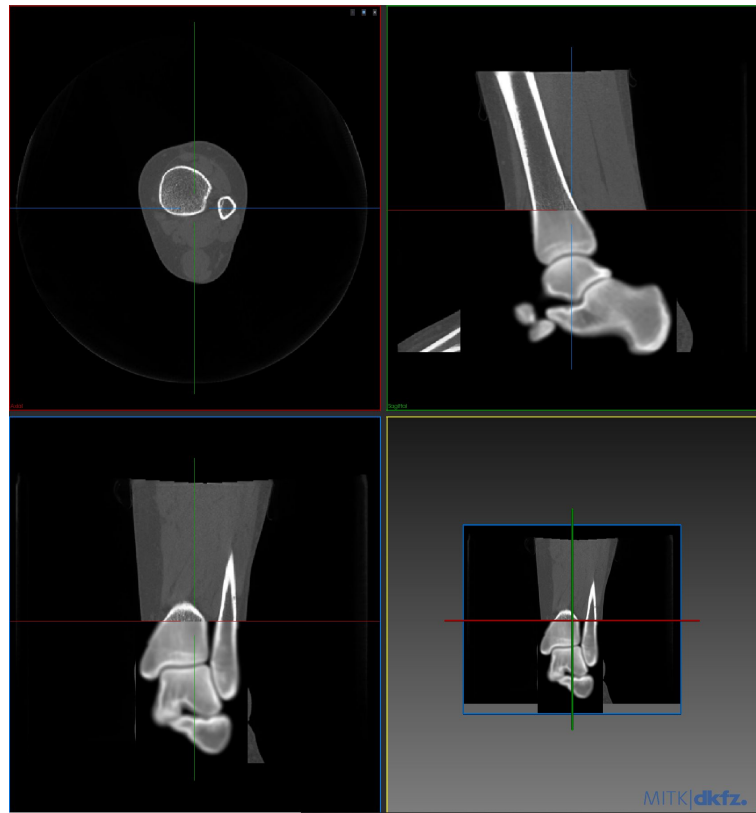
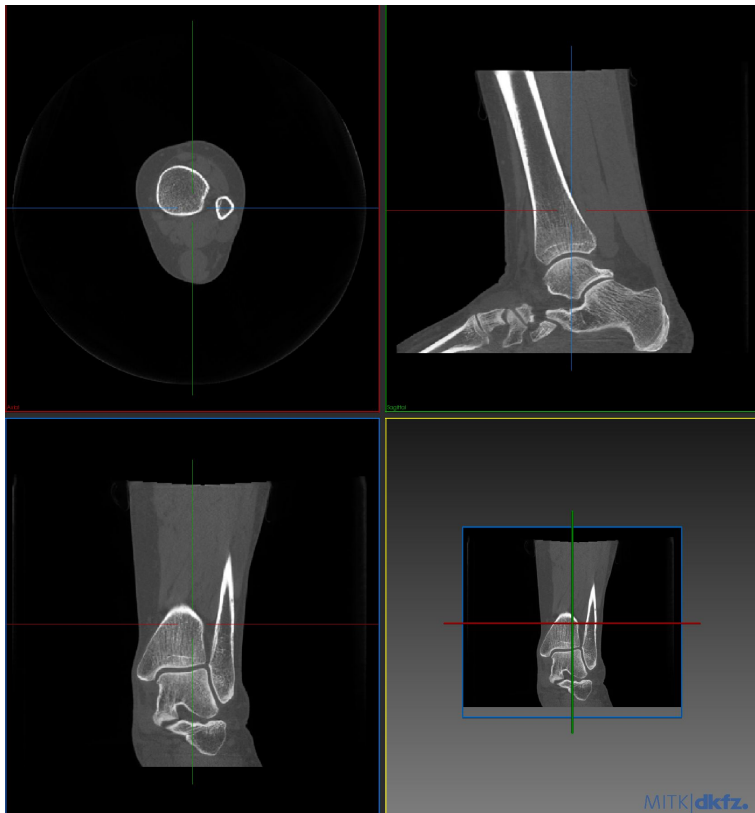




Diagnostic CBCT



Cadaver C-arm

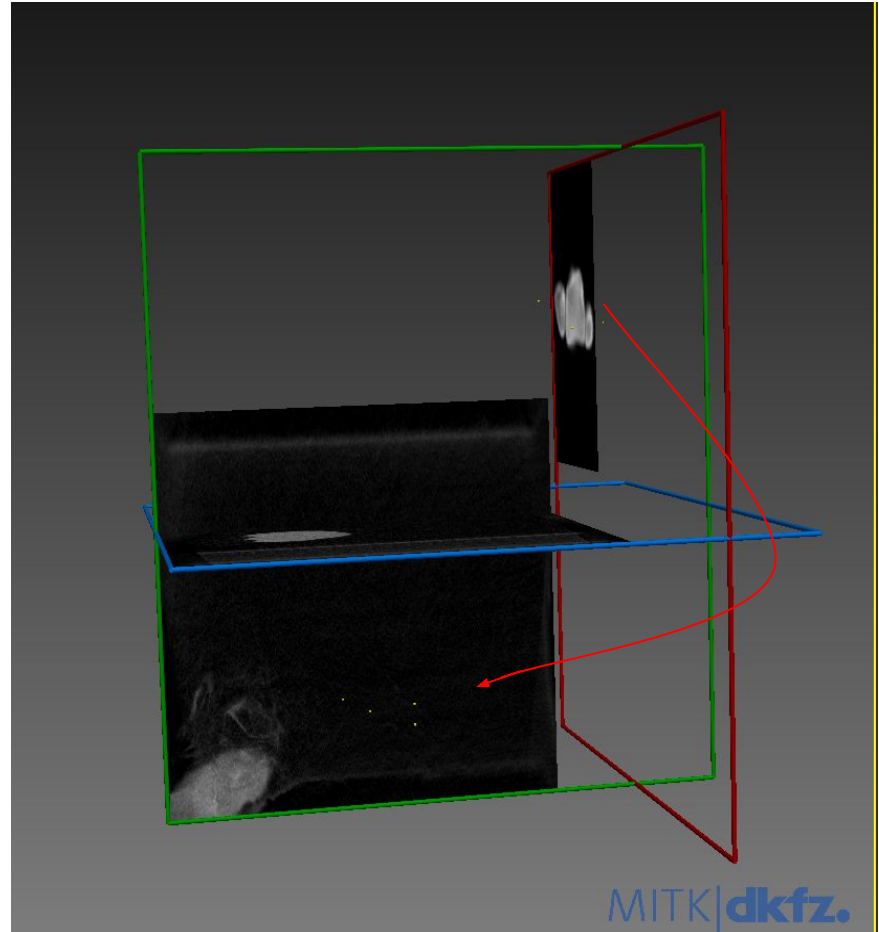


CBCT: Near-perfect initial coarse alignment of mean shapes to image

C-arm: Incorrect orientation of mean shape
with respect to image

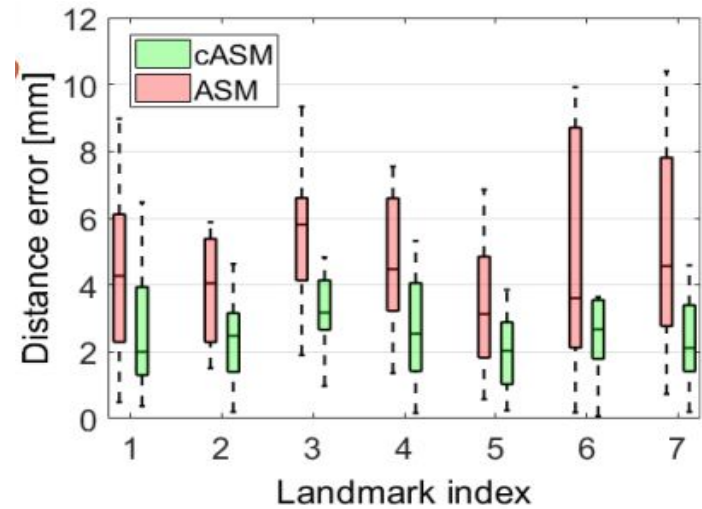
Failing initial coarse registration

Solution: Implement point-based ICP
registration of mean shape to image

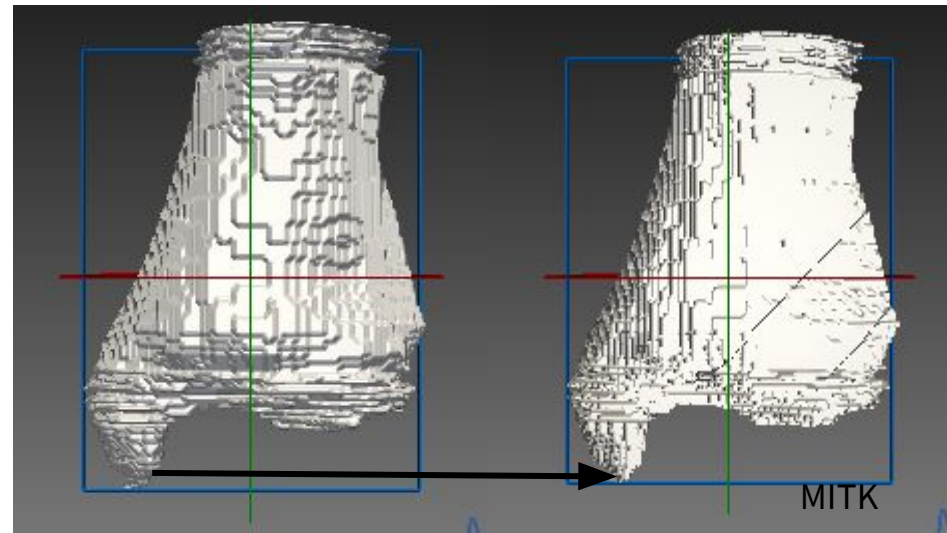


Validation Framework

- Take each vertex in derived mesh and find shortest distance from each vertex to truth mesh. The error is the sum of these distances
- Truth mesh is determined through manual segmentation
- Used the closest point to a mesh algorithm developed in CIS 1 to calculate the shortest distance between each vertex in the derived mesh and the truth mesh
- Used an octree to speed up validation

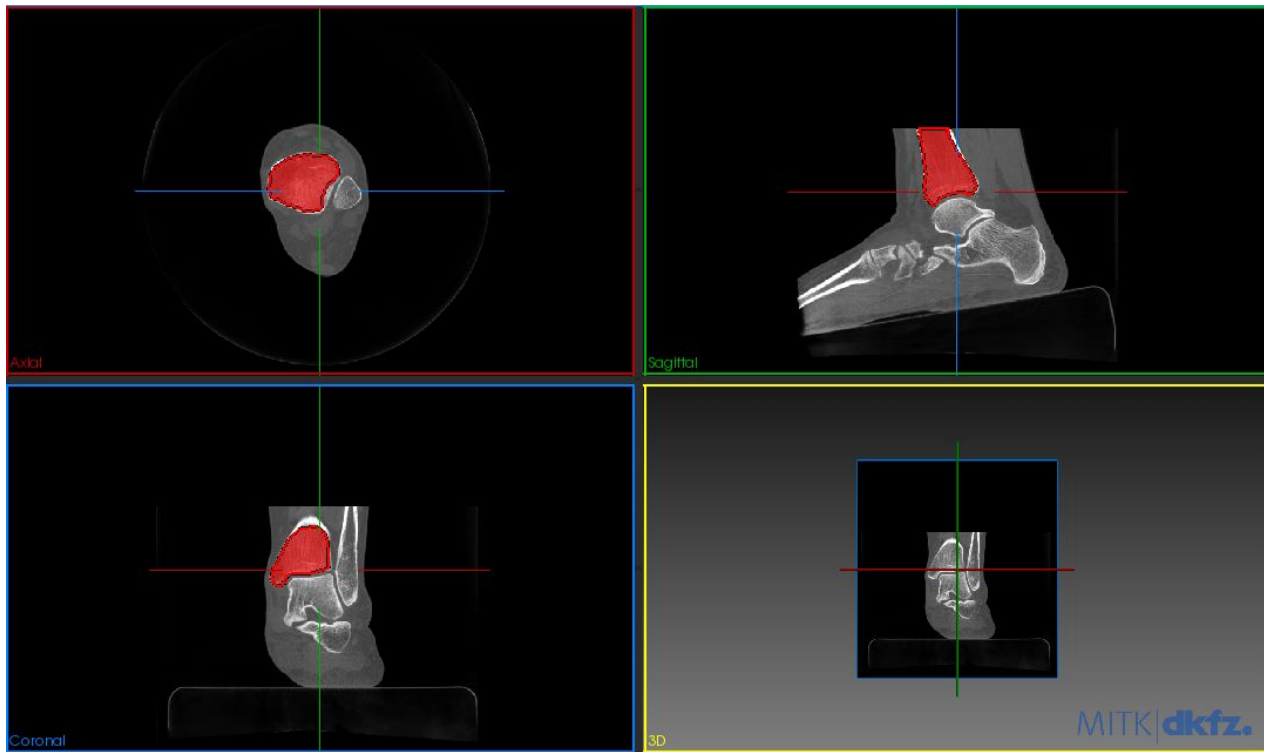


Graph by
Wojtek
Zbiewski



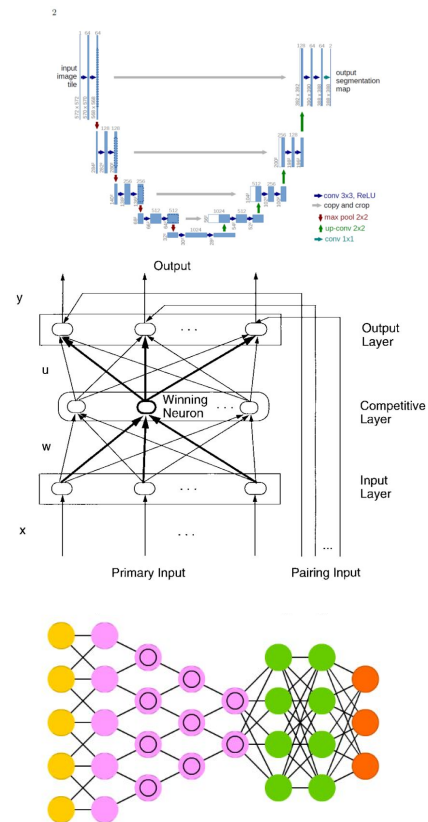
C-Arm Data Segmentation

- In order to create ground truth mesh for the low quality C-arm images, our team will manually segment 26 cadaver ankle images with MITK

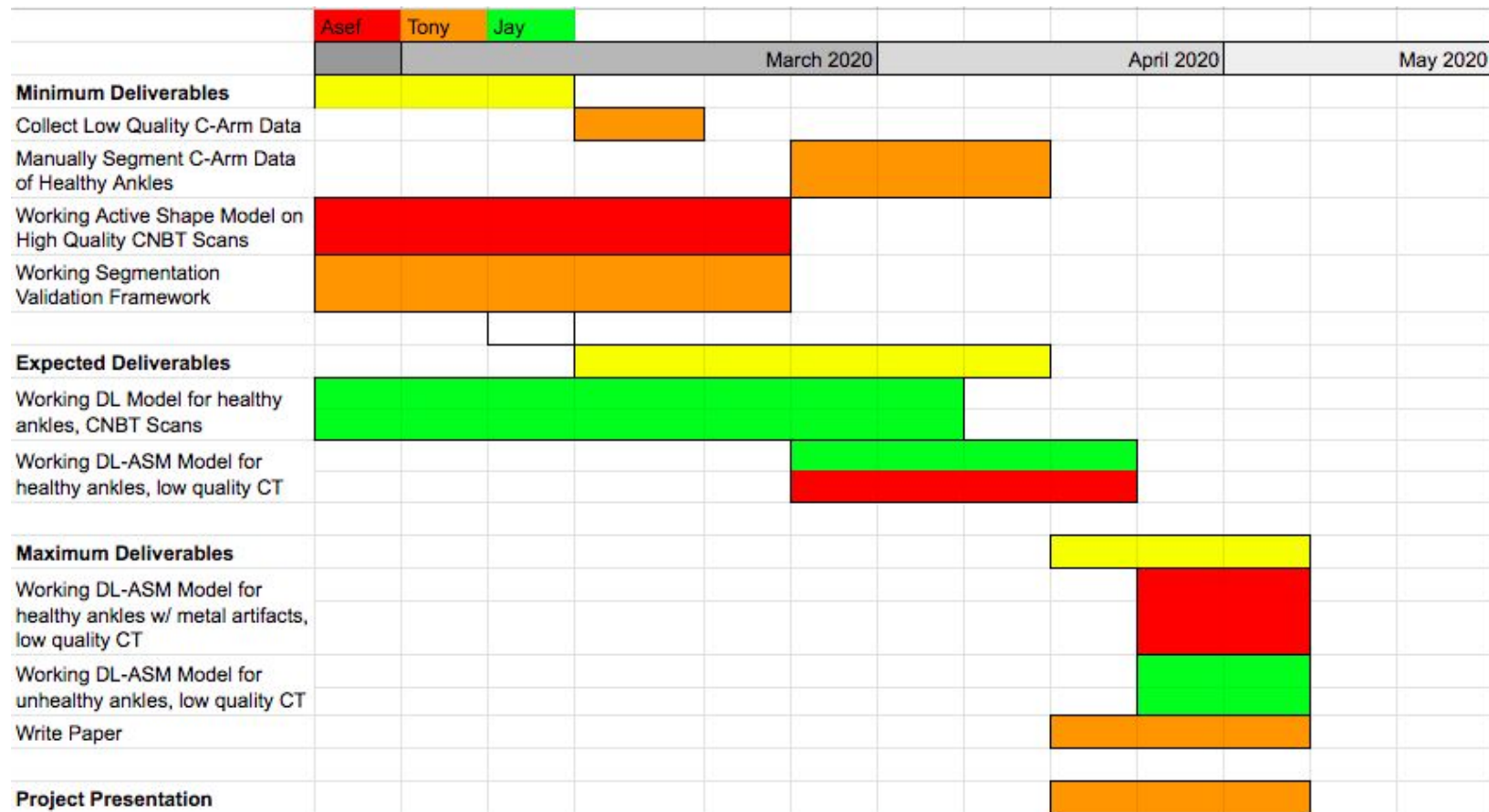


Neural Net Image Segmentation Plan

- U-Net
 - Has been used for medical image segmentation (liver and tumor)
 - CNN but designed to work on fewer training images
- CHNN (Competitive Hopfield Neural Network)
 - WTA (Winner Takes All) approach
 - Has been used for medical image segmentation
- DCN (Deep Convolutional Network)
 - Networks for encoder, decoder, pixel wise classification (SegNet)
 - Utilizes max-pooling
- Output:
 - Obtain segmentations of 7 bones
 - 7 separate matrices for each bone
- Plan
 - First try on high quality cone beam images
 - Then move to low quality C-arm images



Progress: Project Timeline



Dependencies:

Dependency	Plan	Backup	Person to Contact	Status
High Quality CNBT Data	Use C-arm data already generated	Use C-arm provided by the lab to get data	Dr. Qian Cao, Solved	Resolved
Computers (GPU array)	Work entirely locally on personal laptops with GPUs	Connect remotely to lab computers and GPU cluster from personal laptops	Dr. Siewerdsen	Resolved
Validation Data	Use cadaver ankles at Carnegie as test	Use phantom model ankles	Dr. Siewerdsen	Only Healthy
Feedback from Mentors	Meet with mentors virtually through Zoom every friday between 3 - 5 pm	Communicate via email and schedule meeting times outside of standing meeting times	Dr. Siewerdsen and Dr. Zbijewski	Resolved
Imaging Libraries	Utilize already established MATLAB packages (Image Processing Toolbox, Computer Vision Toolbox, Robotics System Toolbox)	N/A	Solved	Resolved
DL Libraries	Utilize already established Python packages (Tensorflow, PyTorch)	N/A	Solved	Resolved
Version Control	Utilize GitHub to backup code and data	Store data and code in a backup hard drive	Solved	Resolved

Team Management

Member	Responsibilities	Meeting Attendance
Asef Islam	<ul style="list-style-type: none">Adjust coupled active shape model to account for artifacts and noise	<ul style="list-style-type: none">F 3-5pm (zoom)Sat 2-7pm (zoom)
Jayaram Mandavilli	<ul style="list-style-type: none">Develop deep learning model for ankle segmentation	<ul style="list-style-type: none">F 3-5pm (zoom)Sat 2-7pm (zoom)
Anthony Wu	<ul style="list-style-type: none">Created validation framework to calculate accuracy of an arbitrary modelManually segment low quality C-arm image data of ankles	<ul style="list-style-type: none">F 3-5pm (zoom)Sat 2-7pm (zoom)
Mentors: Wojtek Zbijewski, Jeff Siewerdsen	<ul style="list-style-type: none">Provide feedback and resources for project	<ul style="list-style-type: none">F 3-5pm (zoom)

Next Milestones

- Segment low quality C-Arm images for validation testing
- Develop deep learning approach for low quality C-arm images
- Incorporate metal artifacts and unhealthy ankles into our algorithm

Questions?



References

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