Checkpoint: Detection and Guidance of K-Wire Placement in Pelvic Trauma Surgery

Team: Kinjal Shah and Irina Bataeva
Mentor: Dr. Ali Uneri
CIS2 Project
April 30, 2020

Project Motivation and Goals

Motivation: Improve accuracy to reduce injury while limiting radiation exposure

Objective: Use emerging deep learning methods to:

(1) Detect K-wires in 2D radiographs of the pelvis

(2) Localize their 3D pose to provide surgical navigation during fracture fixation – *re-evaluated plan*

Figures of Merit

- Improved robustness resulting in fewer outliers
- Faster localization through better initialization: **Target < 2 min**
  - *Our model is able to predict on images at ~0.6 seconds per image*
  - *Over summer, need to evaluate number of images necessary to provide robust 3D localization*
- Improved accuracy of K-Wire Detection: **Target < 1.1±1.6 mm**
  - *Centerline metrics in progress*
  - *Will be applied to 3D localization*
- Fewer fluoroscopic images necessary for detection and guidance

Goerres et al. 2017

Deliverables

Minimum (Phase 1):
Dataset Generation

- Simulated K-wire dataset with augmented pelvic radiographs
  - Deformed K-wires
  - Rigid K-wires

Expected (Phase 2):
Selection of CNN Architecture, Data Analysis

- Report comparing network architectures
- Documentation for trained and validated model to detect K-wire in 2D radiographs
- Figures of merit for simulated data results

On Track

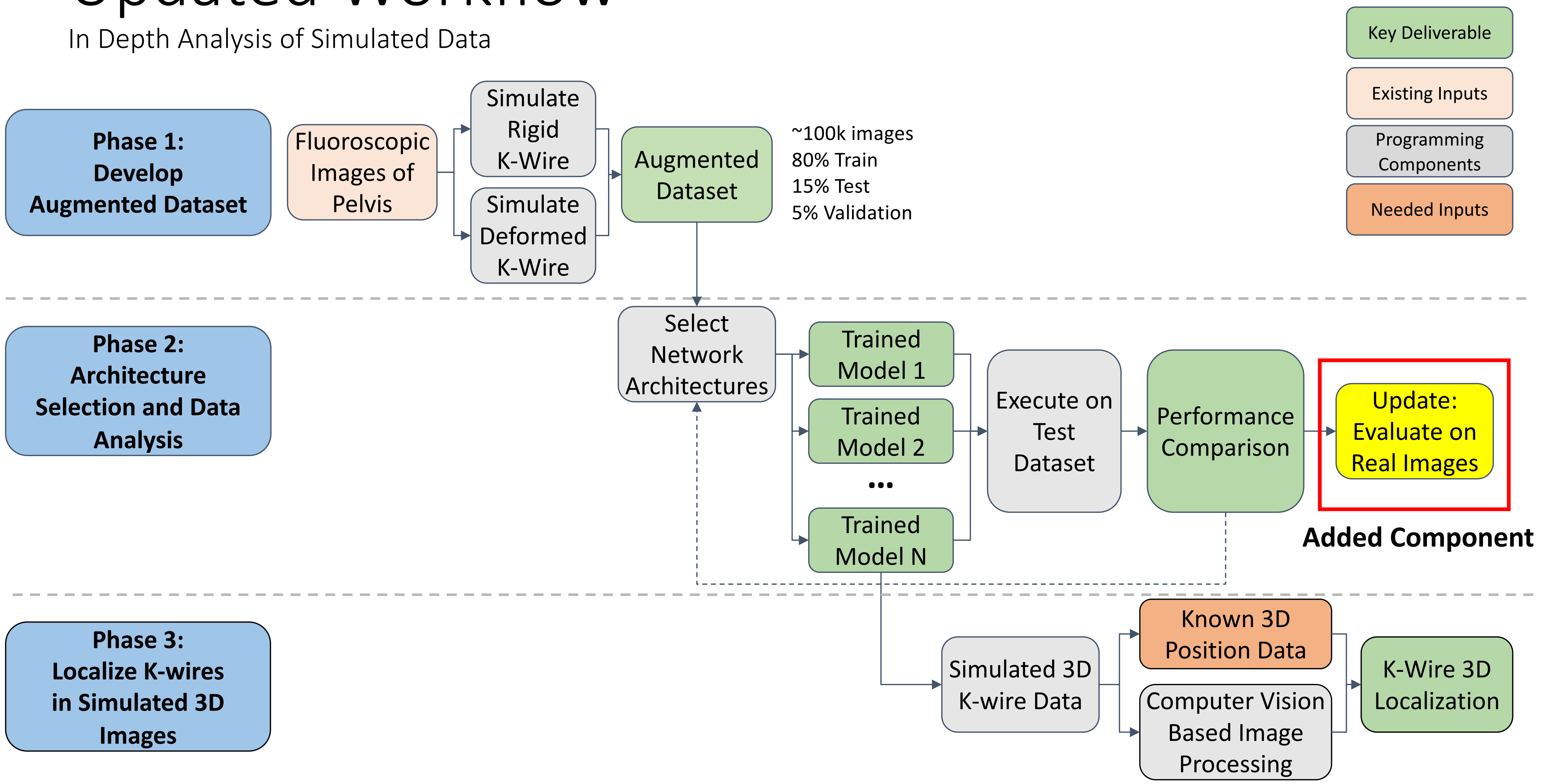
Maximum (Phase 3):
Simulated 3D Localization and Paper

- 3D Localization
- Conference submission

Delayed to summer

Updated Workflow

In Depth Analysis of Simulated Data

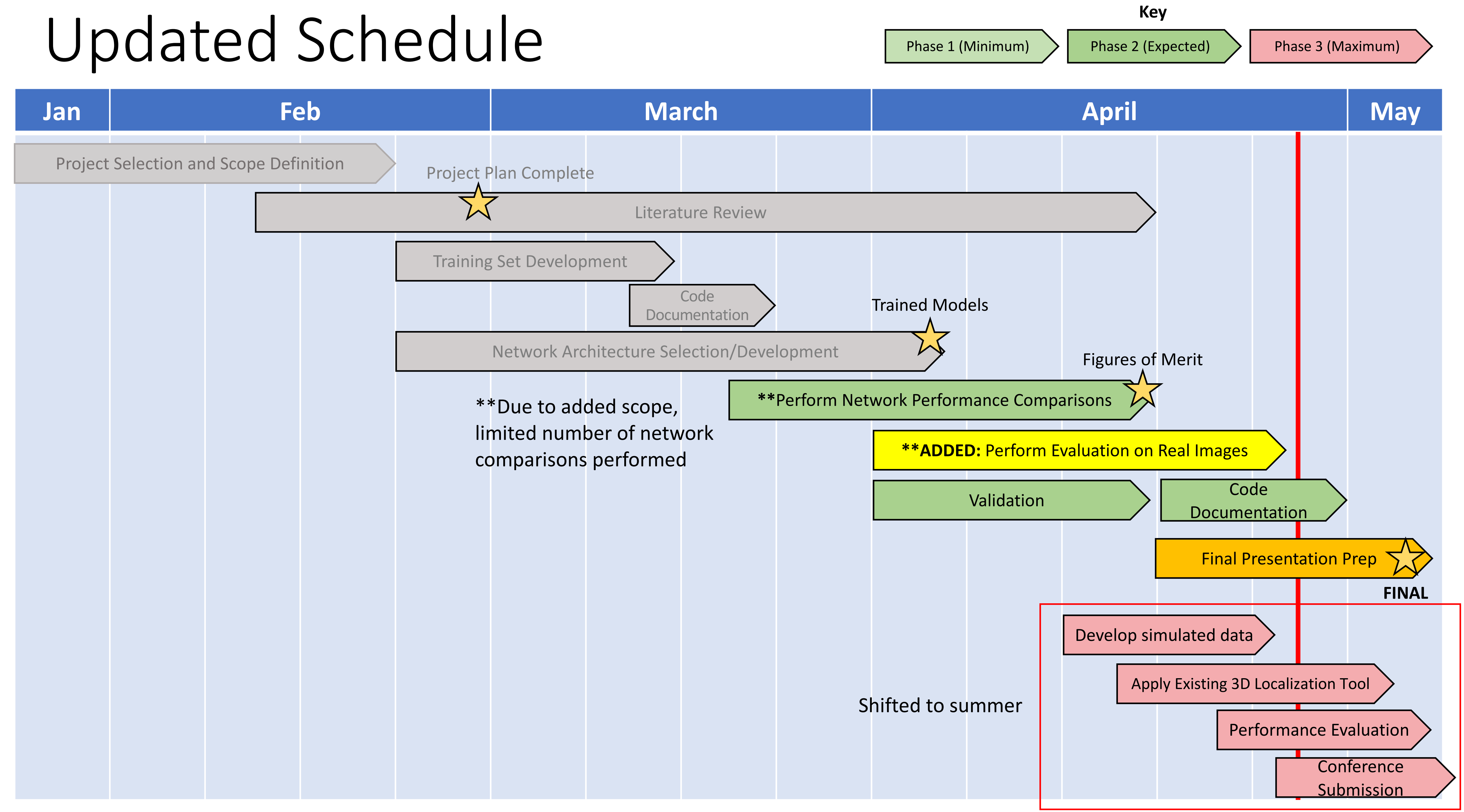


Updated Milestones

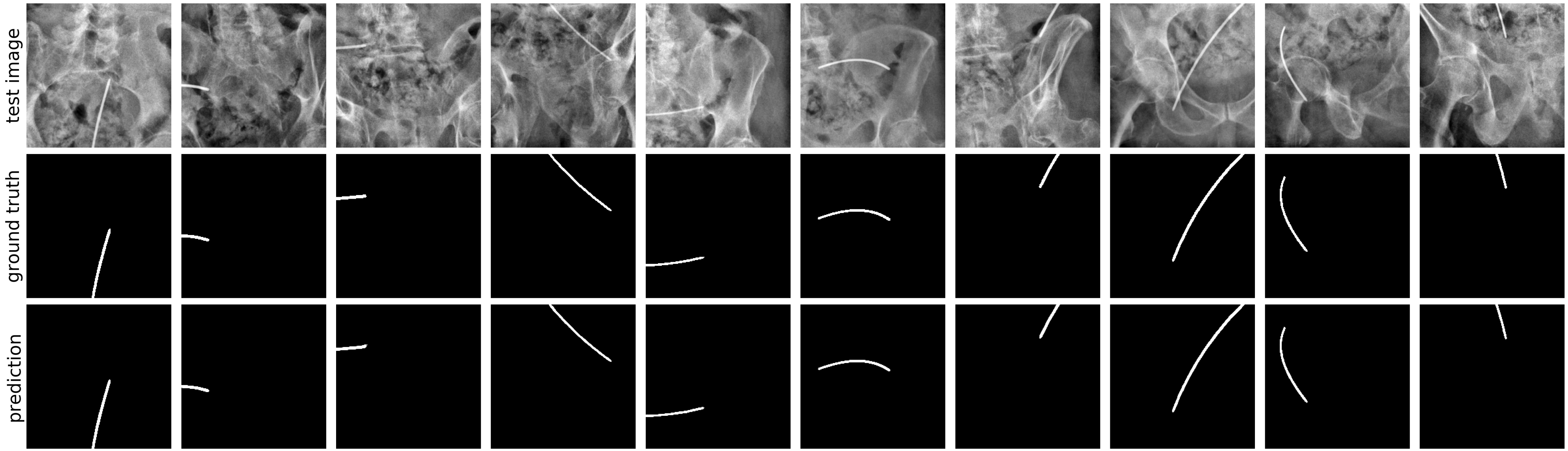
Milestone	Planned Date	Expected Date	Status
Complete Development of Training Set	Monday, March 16	Monday, March 16	Complete
Collation of existing data	Monday, March 2	Monday, March 2	Complete
Data augmentation of pelvic images with simulated K-wires	Monday, March 16	Monday, March 16	Complete
Experiment with augmentation strategies	Monday, March 23	Monday, March 23	Complete
Code documentation	Friday, March 27	Friday, March 27	Complete
Obtain Trained Model	Friday, March 20	Monday, April 13	Complete
Identify CNN architectures based on literature review	Friday, February 28	Friday, February 28	Complete
Establish necessary architecture for chosen solutions	Wednesday, March 4	Wednesday, March 4	Complete
Overfitting Test	Monday, March 30	Monday, March 30	Complete
Train CNN on a complete dataset	Monday, March 16	Monday, April 6	Complete
Code documentation	Monday, April 13	Monday, April 13	Complete
Obtain Figures of Merit - Simulated Data	Monday, April 24	Monday, April 24	Complete
Define Validation Process	Tuesday, March 10	Tuesday, March 10	Complete
Conduct robust testing on dataset	Friday, March 20	Monday, April 10	Complete
Comparison of network architectures and evaluation of model selection	Friday, April 17	Friday, April 17	Complete
Code documentation	Monday, April 24	Monday, April 24	Delayed* In Progress
3D Localization Algorithm Developed	Friday, May 1	Friday, May 1	Delayed to summer
Literature Review Report	Monday, April 20	Monday, April 20	Delayed to summer
Initial program draft complete, validation initiated	Friday, May 1	Friday, May 1	Delayed to summer
Code Documentation	Monday, April 27	Monday, April 27	Delayed* In Progress
Final Poster Presentation/Report	Tuesday, May 5	Tuesday, May 5	On Track
Conference Submission	Summer 2020	Summer 2020	On Track

* Expanded Scope

Updated Schedule

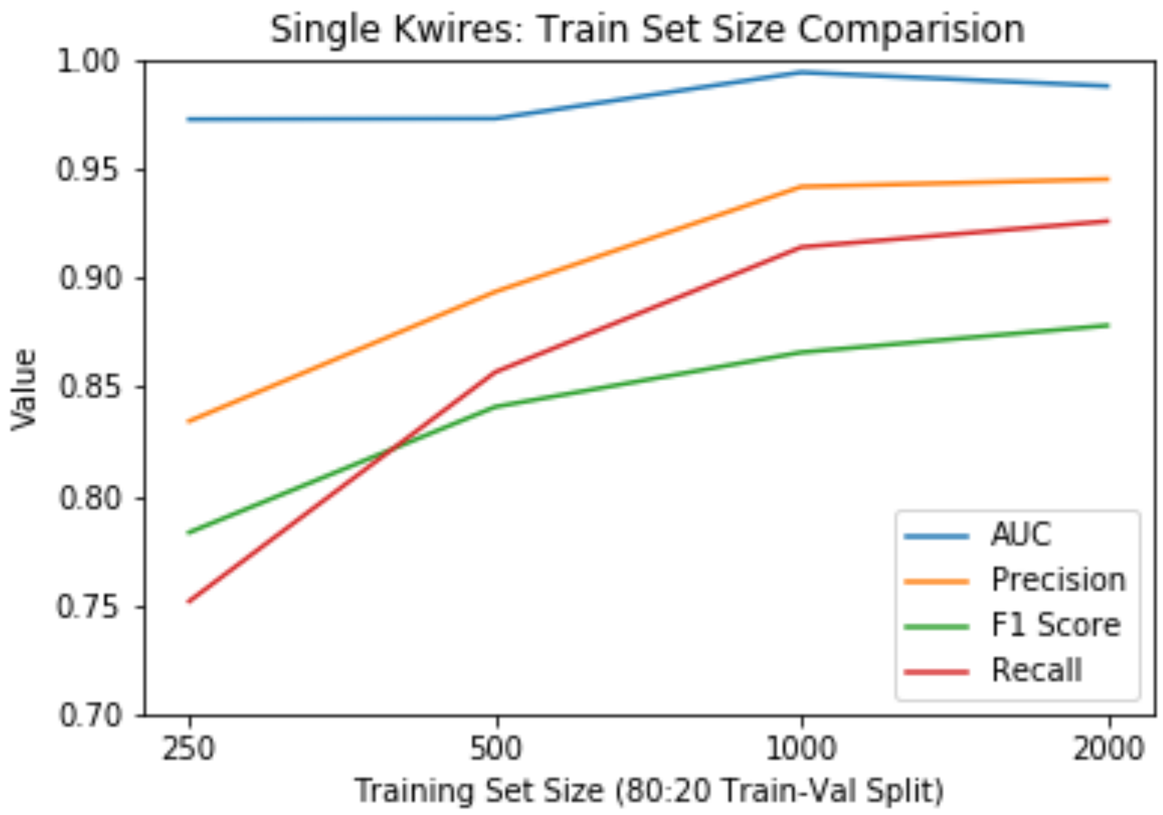


Training on 2000 images: Prediction Results on Simulated Data



Metric	Mean and STD	Range
Area Under the Curve	0.999±0.001	0.991 – 1.000
Recall	0.97±0.01	0.88 – 1.00
Precision	0.99±0.02	0.86 – 1.00
F1 score (Dice)	0.97±0.03	0.71 – 0.99

High Level Results: Training Set Size Performance Comparison for UNet



Centerline Comparison Workflow

Metrics:

- Hausdorff distance between centerlines
- Percentage of the k-wire that was identified

Workflow

1. Skeletonization using Zhang's method
2. Identification of separate fragments with 2-connectivity
3. Calculation of Hausdorff distance of the identified fragments to the closest parts of the ground truth K-wire
4. Calculation of the percentage of the K-wire's length that was not identified

To complete prior to Presentation

- Finish runs on larger datasets
- Perform analytics on new data
- Finalize plots and metrics

Appendix

Dataset Generation

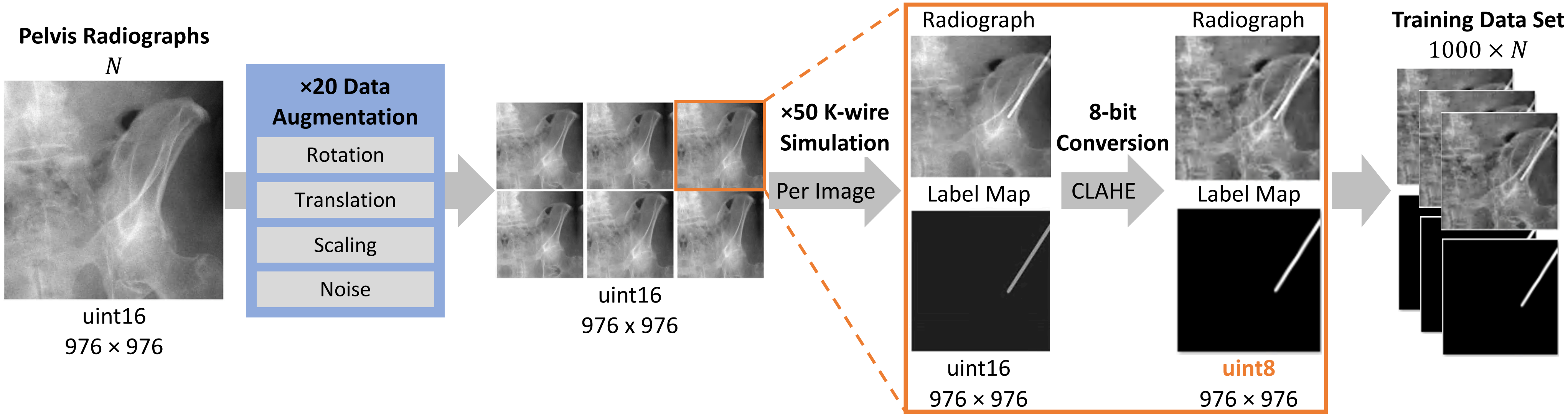


Figure 1. Flowchart for training data set generation. Multiple (N) fluoroscopic images extracted from 3D scans of a cadaveric pelvis specimen undergo data augmentation (×20), followed by simulated K-wire projections (×50) to produce 1000×N images and K-wire label maps for use in training an artificial neural network for K-wire detection.

Data Augmentation Parameters

Imgaug Library

- Scaling ± 20%
- Translation ± 1%
- Rotation ±2.5°
- Random order of operations
- Gaussian Noise (50% of the images)

Based on Wagner, Martin G., et al. “Deep Learning Based Guidewire Segmentation in x-Ray Images.” Medical Imaging 2019: Physics of Medical Imaging, 2019, doi:10.1117/12.2512820

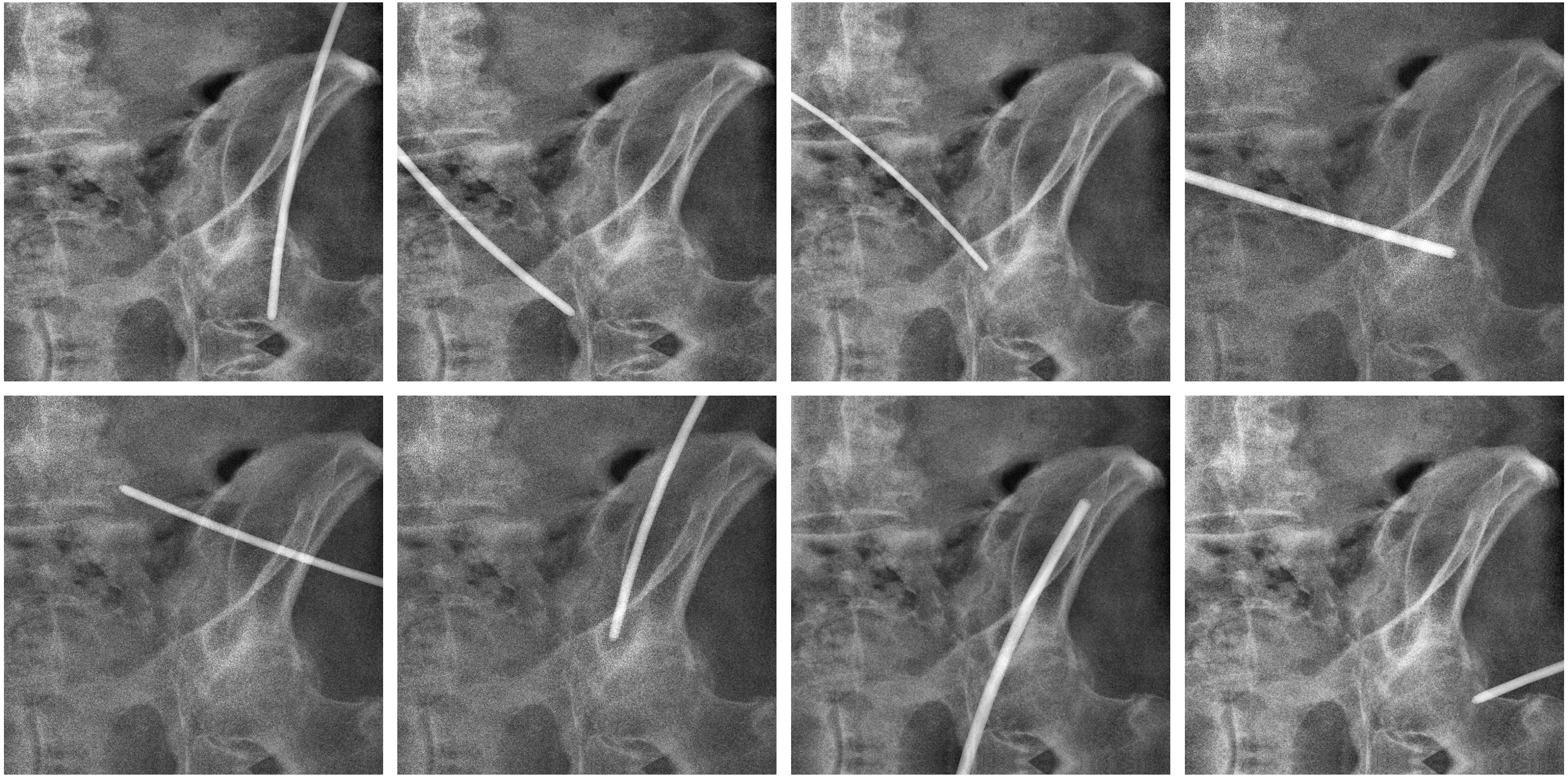
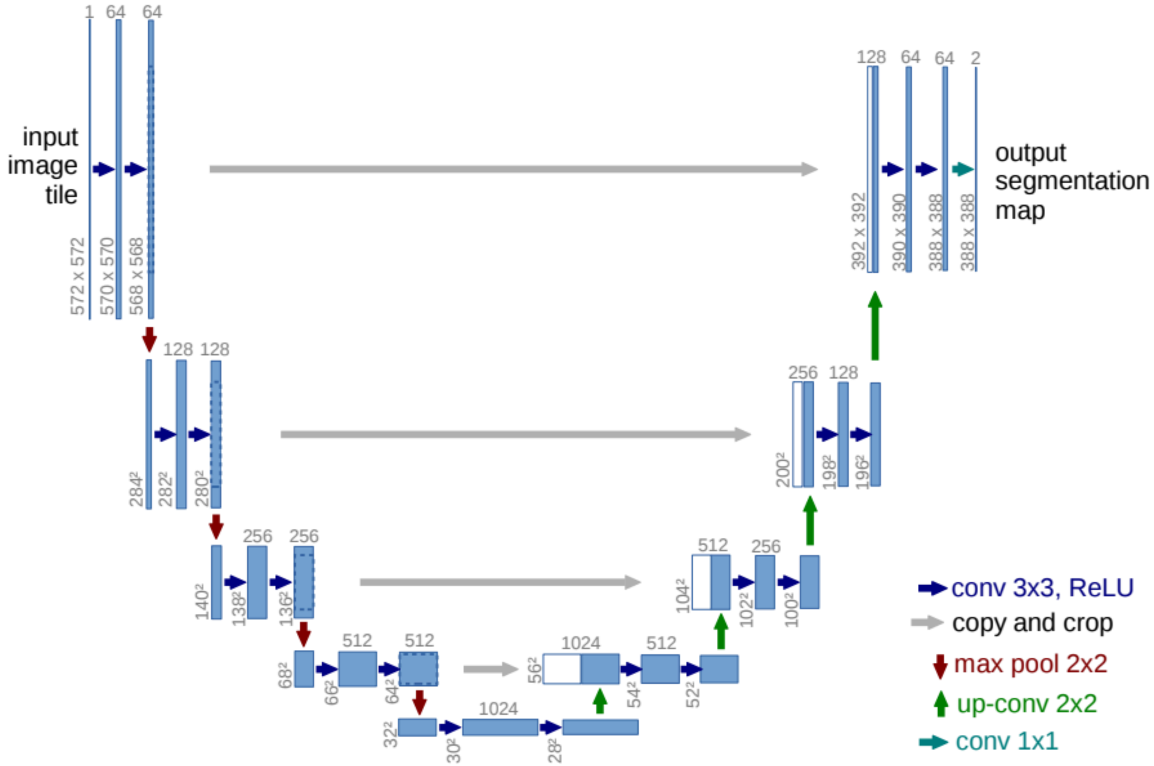
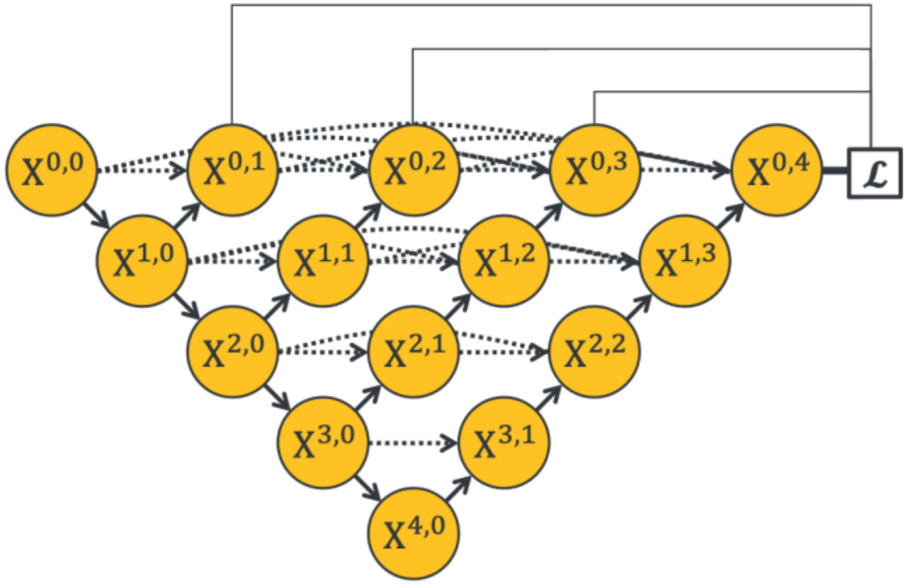


Figure 2. Example images from the generated training data set. Data augmentation is demonstrated as subtle rotations, translations, scaling, and noise applied on a single image from a cadaveric pelvis specimen. Simulated B-spline based K-wire models are projected on the augmented images at varying pose and deformations.

Candidate Architectures

UNet (2015)[1] VS UNet++ (2019)[2]





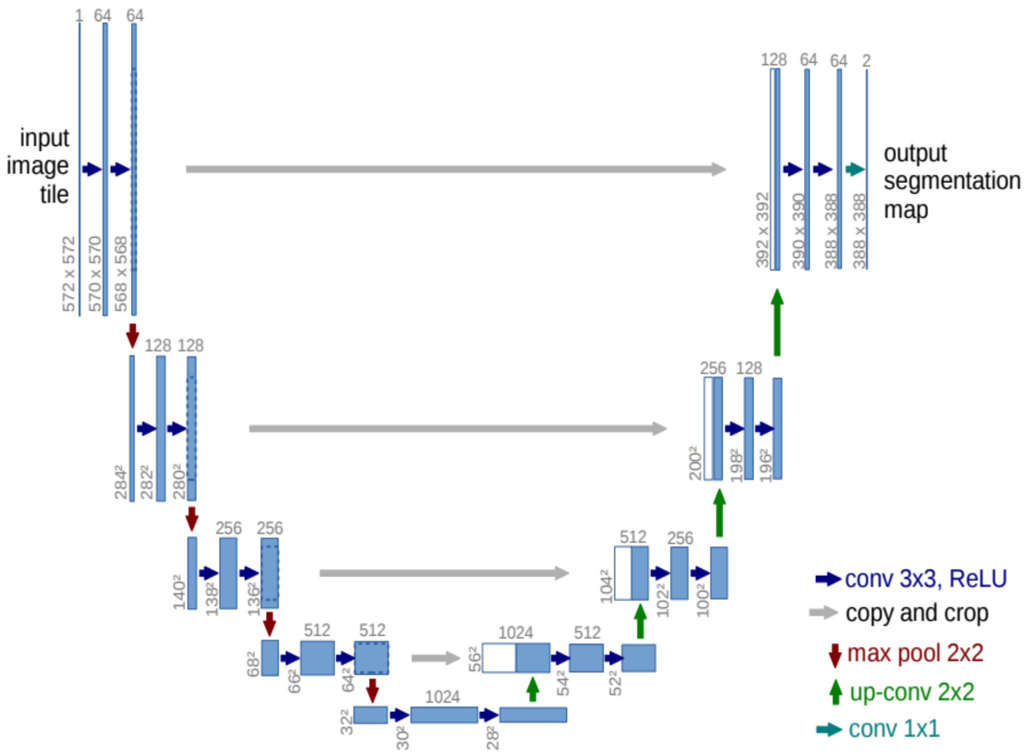
(g) UNet++

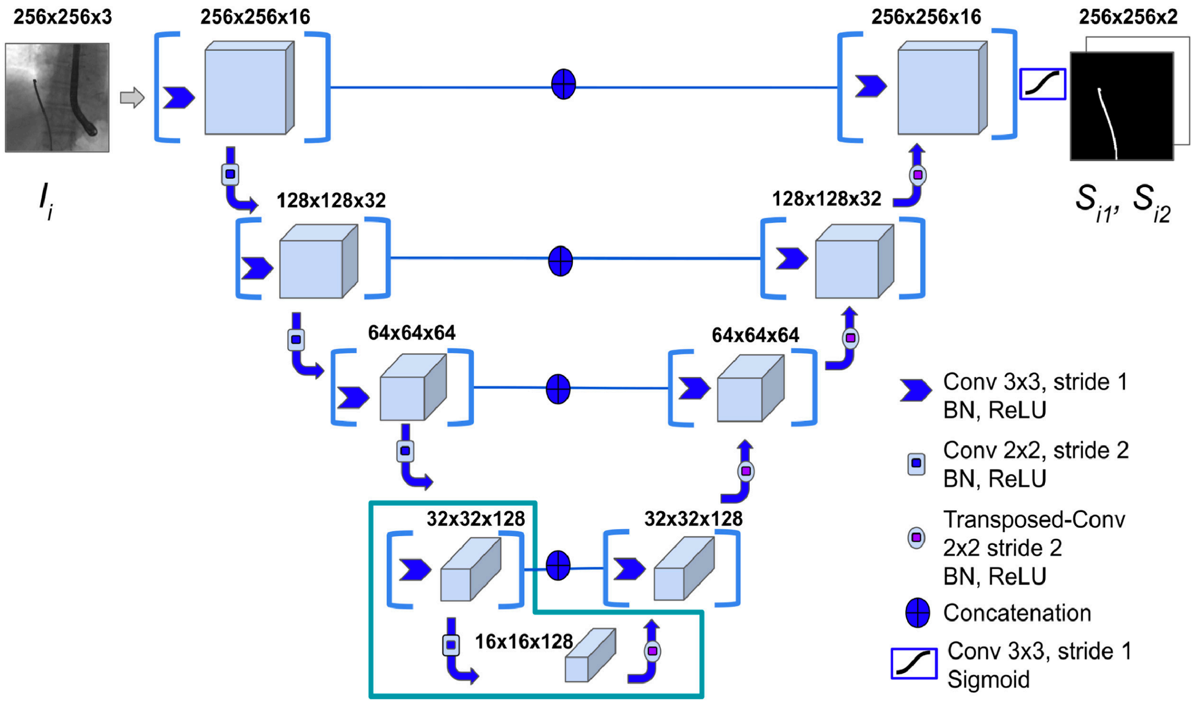
[1] Ronneberger, Olaf, et al. "U-Net: Convolutional Networks for Biomedical Image Segmentation." *Lecture Notes in Computer Science Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, 2015, pp. 234–241., doi:10.1007/978-3-319-24574-4_28.

[2] Zhou, Zongwei, et al. "UNet : Redesigning Skip Connections to Exploit Multiscale Features in Image Segmentation." *IEEE Transactions on Medical Imaging*, 2019, pp. 1–1., doi:10.1109/tmi.2019.2959609.

Candidate Architectures

UNet (2015)[1] VS UNet Light (2020)[2]





[1] Ronneberger, Olaf, et al. "U-Net: Convolutional Networks for Biomedical Image Segmentation." *Lecture Notes in Computer Science Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, 2015, pp. 234–241., doi:10.1007/978-3-319-24574-4_28.

[2] Gherardini, Marta, et al. "Catheter Segmentation in X-Ray Fluoroscopy Using Synthetic Data and Transfer Learning with Light U-Nets." *Computer Methods and Programs in Biomedicine*, vol. 192, 2020, p. 105420., doi:10.1016/j.cmpb.2020.105420.

Candidate Architectures

If UNet Unsuccessful:

- Mask R-CNN (2018)[1]
- Mask RCNN++ (UNet++ with Mask R-CNN) (2019)[2]

[1] He, Kaiming, et al. “Mask R-CNN.” *2017 IEEE International Conference on Computer Vision (ICCV)*, 2017, doi:10.1109/iccv.2017.322.
[2] Zhou, Zongwei, et al. “UNet : Redesigning Skip Connections to Exploit Multiscale Features in Image Segmentation.” *IEEE Transactions on Medical Imaging*, 2019, pp. 1–1., doi:10.1109/tmi.2019.2959609.

Dependencies

Dependency	Contact	Date Required	Status	Solution	Contingency
Availability of real radiographs of the pelvis	Dr. Ali Uneri	2/28	Resolved	Leverage software tools and radiographs provided by the I-STAR lab	Generate image set using radiographs simulated from CT
~~Access to C-arm, phantoms, and surgical instruments~~	~~Dr. Jeffrey Siewerdsen, Dr. Ali Uneri~~	~~2/26~~	~~Resolved~~	~~Access to all equipment to be provided by I-STAR, Rohan Vijayan will assist with C-arm operation~~	~~Undergo training if significant amount of data needs to be collected~~
Computational Resources	Dr. Ali Uneri	2/27	Resolved	Access to a shared GPU cluster at I-STAR, dedicated lab workstation, and personal laptops	Request access to resources at LCSR
I-STAR lab Git repository access	Dr. Ali Uneri	2/21	Resolved	Dr. Uneri will initiate and share a dedicated repository at https://git.lcsr.jhu.edu/	
~~Cadaver Access~~	~~Dr. Jeffrey Siewerdsen~~	~~3/15~~	~~*Available if needed*~~	~~Cadaver studies (for related projects) are planned for upcoming weeks.~~	~~Phantoms~~
~~Access to real images with K-wires~~	~~Dr. Ali Uneri~~	~~3/20~~	~~Under Evaluation~~	~~If images not are available, we will be able to obtain additional images with phantoms~~	
Access to scripts / solutions for data generation and training	Dr. Ali Uneri	NA	Resolved	Jupyter notebooks, TensorFlow, PyTorch, OpenCV	

Team Management

Responsibility Ownership

Irina Bataeva	Kinjal Shah
• K-wire images dataset generation	• Training model design and development • Model evaluation

Meeting Cadence

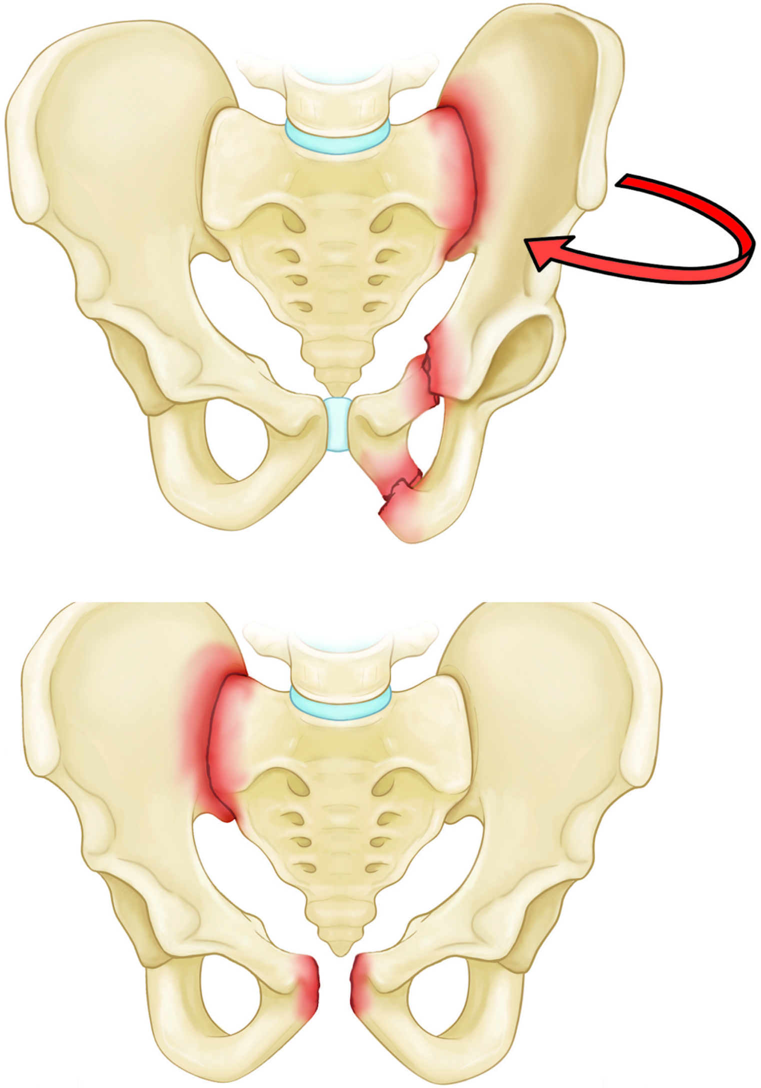
- Weekly meetings as a group every Sunday, Wednesday
- Weekly meetings with Dr. Ali Uneri on Fridays *subject to change

Collaboration

- Code storage and version control on GitLab at https://git.lcsr.jhu.edu/

Background: Pelvic Fractures

- **2–8%** of all injuries[1]
- Young population
  - Traffic Accidents
- Older population
  - Ordinary Falls
- Growing concern: ~$1.8B market by 2025[2]
- Complex fractures require **surgical stabilization**

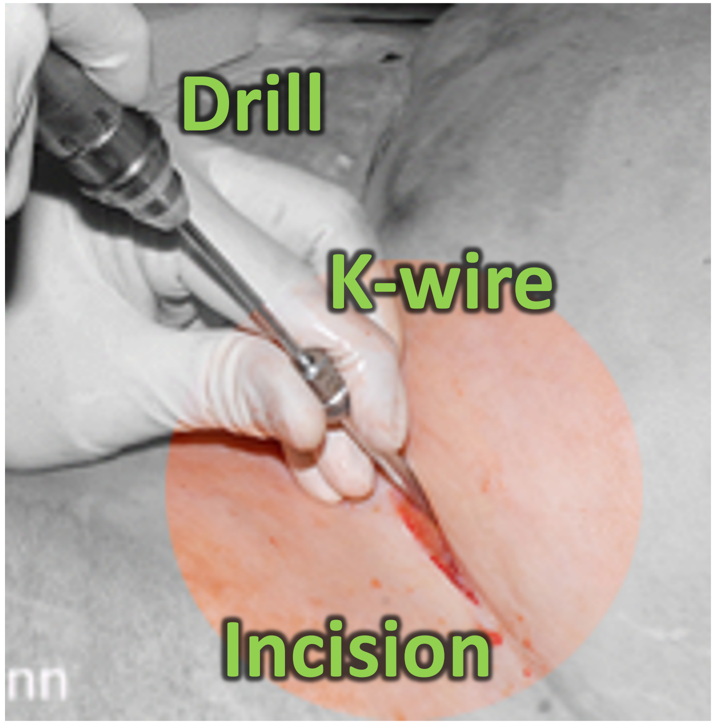


“Pelvic Fractures - OrthoInfo - AAOS.” OrthoInfo, orthoinfo.aaos.org/en/diseases--conditions/pelvic-fractures/.

[1] Buller et al. 2016. Geriatr Orthop Surg Rehabil. 7(1) 9–17.
[2] Vu et al. 2017. Injury. 48(11) 2443-50

Background: Pelvic Fracture Fixation

- Minimally invasive surgery performed percutaneously
- Kirschner wires (K-wire) guide cannulated screws
- Long trajectories: up to 15 cm
- K-wires deform
  - High accuracy required: 1 mm and 5°
- Fluoroscopy is used for guidance
  - Fluoro-hunting: finding appropriate views
  - Trial-and-error: getting the trajectory right
  - Up to **2 mins of radiation** exposure per screw



U. Cullemann aofoundation.org

Background: Fluoroscopic K-wire guidance

Goerres et al. 2017

Screw malposition

20–30% suboptimal,[1] **%6** breach[2]

Neurological injuries

Vascular injuries

Longer surgery times

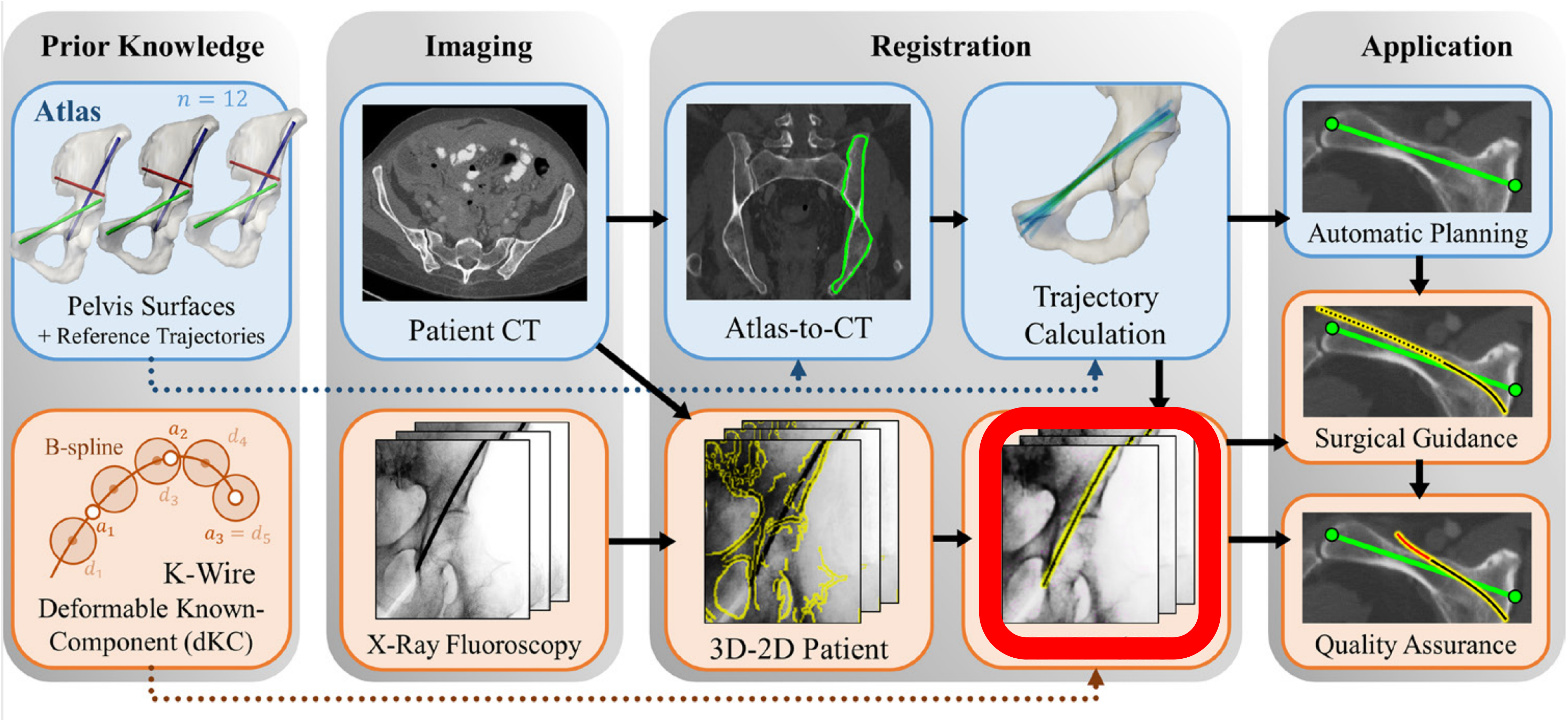
Pelvic Instability

DePuy Synthes K-wire and a cannulated screw

[1] Dzupa et al. 2009. Acta Chir Orthop Traumatol Cech. 76(5) 404–9.

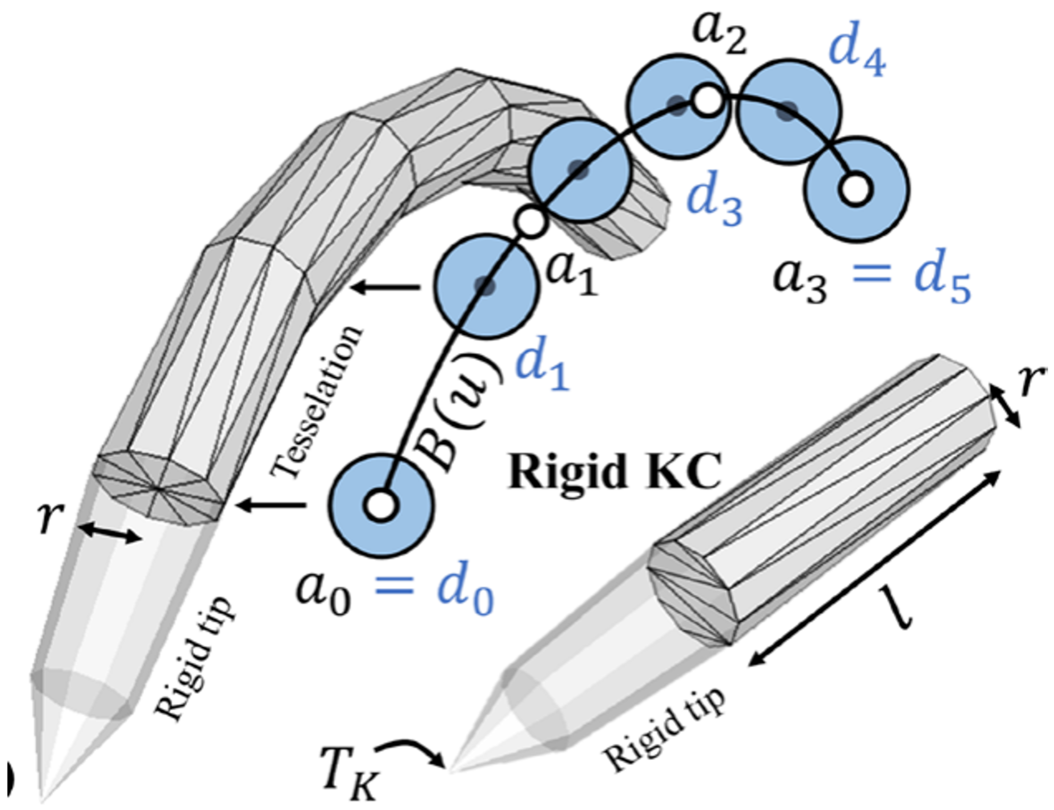
[2] Poole et al. 1992. Am Surg. 58(4) 224-31.

Background: Navigation Workflow

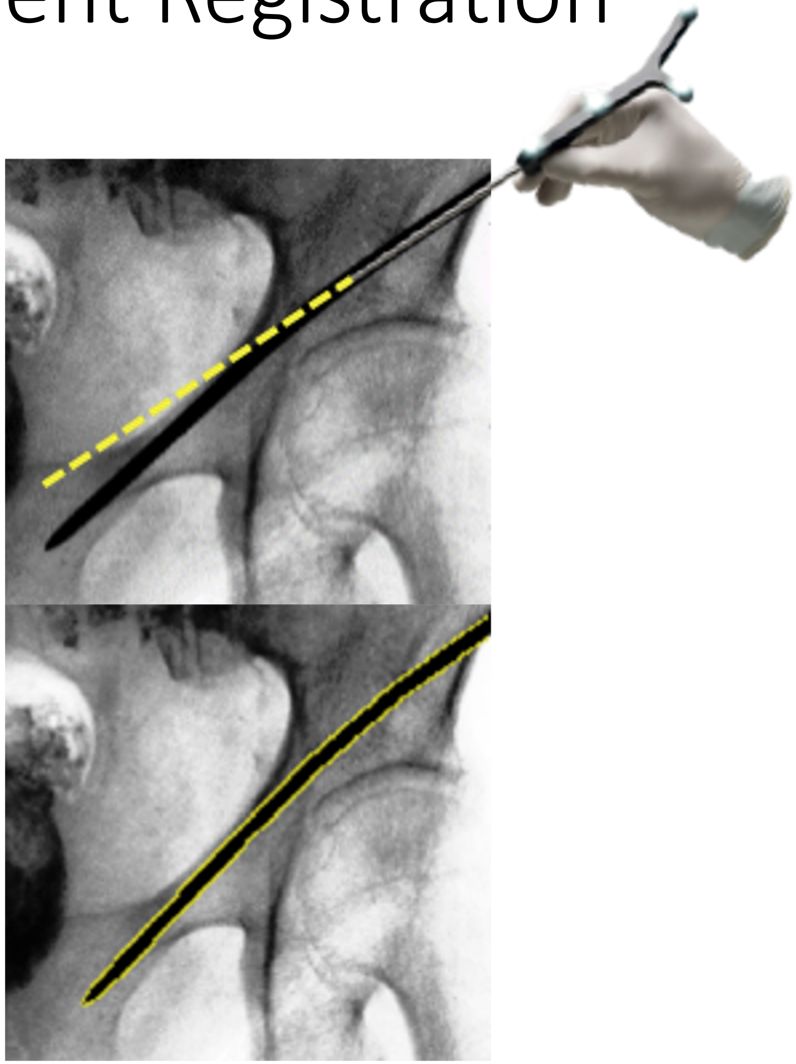


Goerres et al. 2017. Phys. Med. Biol. 62(23) 9018–38.

Prior Work: Deformable Known-Component Registration



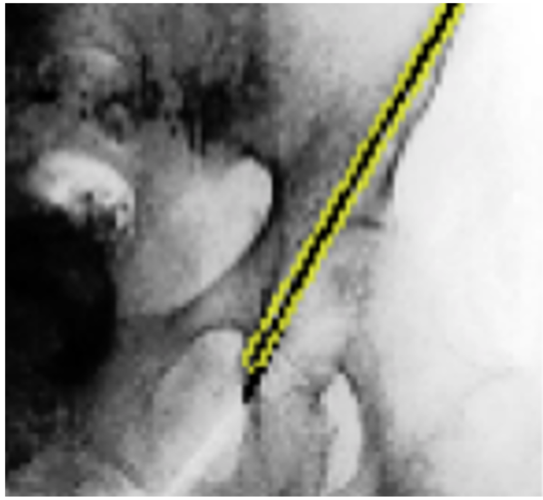
B-spline based deformable mesh model



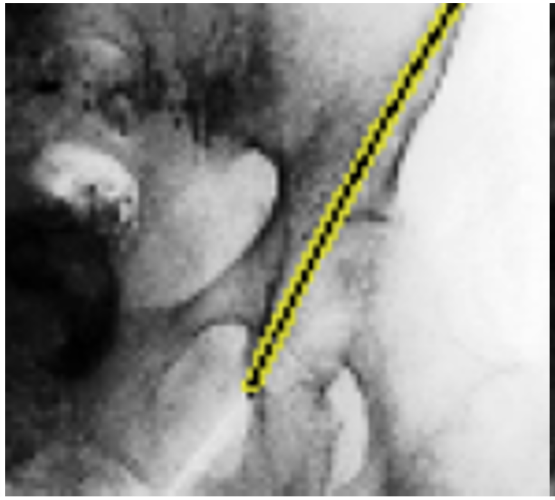
Conventional navigation with rigidity assumption

Goerres et al. 2017

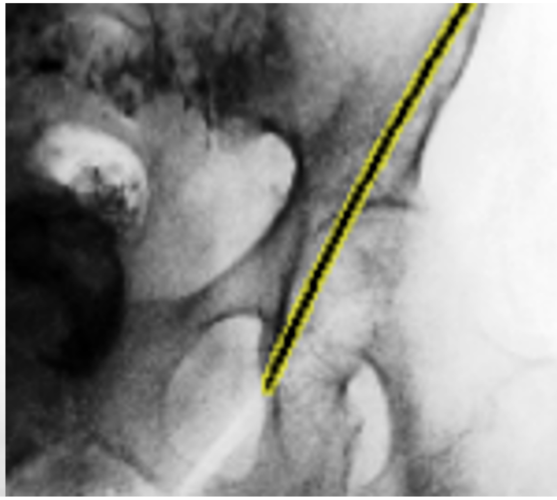
Prior Work: Accuracy and Runtime



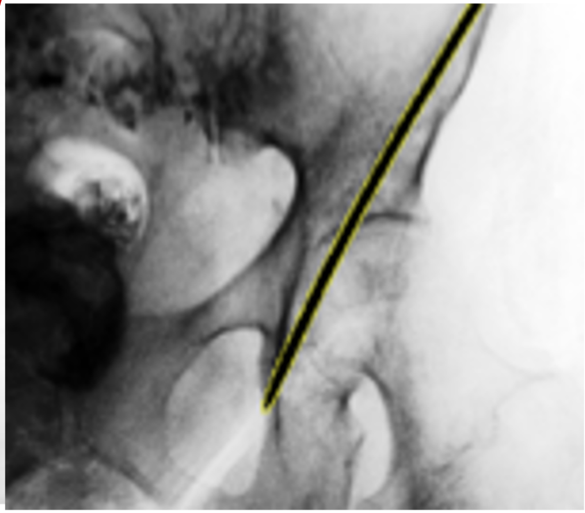
3x3 mm^2 pix
Multi-start rigid
2.5±1.1 mm
10x2 s



2x2 mm^2 pix
3 knots
1.9±1.3 mm
+40 sec



1.5x1.5 mm^2 pix
4 knots
1.4±1.7 mm
+1:30 mins



1x1 mm^2 pix
5 knots
1.1±1.6 mm
+2 mins

Goerres et al. 2017

Reading List

1. Ketcha MD, De Silva TS, Han R, Uneri A, Vogt S, Kleinszig G, and Siewerdsen JH. "**Learning-based deformable image registration: effect of statistical mismatch between train and test images,**" Journal of Medical Imaging 6(4), 044008 (17 December 2019). doi:https://doi.org/10.1117/1.JMI.6.4.044008
2. Uneri A, Goerres J, De Silva TS, Jacobson MW, Ketcha MD, Reaungamornrat S, Kleinszig G, Vogt S, Khanna AJ, Wolinsky JP, Siewerdsen JH. **"Deformable 3D-2D registration of known components for image guidance in spine surgery."** Med Image Comput Comput Assist Interv, 9902, pp. 124–32, 2016 doi:10.1007/978-3-319-46726-9_15.
3. J. Goerres, M. Jacobson, A. Uneri, T. de Silva, M. Ketcha, S. Reaungamornrat, S. Vogt, G. Kleinszig, J.-P. Wolinsky, G. Osgood, and J. H. Siewerdsen **"Deformable 3D-2D registration for guiding K-wire placement in pelvic trauma surgery"**, Proc. SPIE 10135, Medical Imaging 2017: Image-Guided Procedures, Robotic Interventions, and Modeling, 101350A (3 March 2017); doi:10.1117/12.2255952
4. Pauly, Olivier, et al. **"A Machine Learning Approach for Deformable Guide-Wire Tracking in Fluoroscopic Sequences."** Medical Image Computing and Computer-Assisted Intervention – MICCAI 2010 Lecture Notes in Computer Science, 2010, pp. 343–350.,
5. Ma, Yingliang, et al. **"A Novel Real-Time Computational Framework for Detecting Catheters and Rigid Guidewires in Cardiac Catheterization Procedures."** Medical Physics, vol. 45, no. 11, 2018, pp. 5066–5079., doi:10.1002/mp.13190.
6. Wagner, Martin G., et al. **"Deep Learning Based Guidewire Segmentation in x-Ray Images."** Medical Imaging 2019: Physics of Medical Imaging, 2019, doi:10.1117/12.2512820.
7. Wu, Yu-Dong, et al. **"Automatic Guidewire Tip Segmentation in 2D X-Ray Fluoroscopy Using Convolution Neural Networks."** 2018 International Joint Conference on Neural Networks (IJCNN), 2018, doi:10.1109/ijcnn.2018.8489337.