CIS II Project Plan:
Detection and Guidance of K-Wire Placement in Pelvic Trauma Surgery

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I Background

Pelvic fractures occur across all demographics and are estimated to be 2-8% of all fractures in the United States [1]. They are, however, primarily occurring in younger demographics due to high energy trauma such as traffic accidents and in older demographics due to day-to-day falls. Osteoporosis often causes bones to get weaker with age, and thus pelvic fractures are becoming more common as the population of the United States is aging [2]. As a result, pelvic fracture treatment is a growing market and is estimated to reach $1.8 billion by 2025 [3]. Although some cases can be treated with external stabilization, unstable pelvic fractures require surgical stabilization. Minimally invasive surgical (MIS) procedures are becoming an increasingly popular choice for some surgeons as they decrease blood loss, risk of infection, and recovery times for patients with unstable pelvic fractures compared to the open surgery approaches [4]. During MIS procedures, Kirschner wires (K-wires), which are thin, foot-long stainless steel pointed rods, are used to guide cannulated screws into place to join pelvic bone fragments. Inserting K-wires is challenging even for experienced surgeons since pelvis has a complex structure and K-wires are flexible and thus bend inside the patient. Surgeons, therefore, cannot use conventional marker-based navigation methods that assume a rigid guided object and are not able to accurately guide the trajectory of the K-wire. To guide the K-wire, surgeons rely on intraopertive fluoroscopy, taking images throughout the insertion of the K-wire to visualize its position relative to patient's anatomy. As a consequence, patients often get exposed up to 2 minutes of radiation per screw [5]. Despite the extensive imaging, however, the surgeons still struggle to achieve the permissible accuracy for the K-wire's trajectory of 1 mm translational error and $5°$ rotational error [6]. Since the K-wire is used to place stabilization screws, screw malposition is a common complication of pelvic fracture stabilization surgeries: 20-30% screw placements are rated as suboptimal [7] and 6% breach the cortical bone [8]. Screw malposition is a serious issue as it can result in neurological and vascular injuries, require longer surgical times, and lead to long-term pelvic instability [9].

II Prior Work

The I-STAR lab is working on introducing surgical navigation to pelvic fixation surgeries. One of the stages of the navigational workflow is identifying the K-wires on X-rays. Various approaches have been attempted to achieve identification with high accuracy. One of them was the deformable known-component registration, in which a B-spline-based mesh cylinder was transformed to match the projection on the fluoroscopic image. A registration error of 2.1 ± 0.3 mm and $0.8° \pm 1.4°$ tip orientation was achieved. Another approach involved performing a multi-resolution pyramid technique to detect the K-wire, which was faster than the B-spline based approach, but still limited; it took 2 minutes to get 1.1 ± 1.6 mm accuracy [5].

III Motivation

As discussed above, even novel solutions to K-wire detection and identification are slow and lack the accuracy required to guide the K-wire for surgical pelvic stabilization. In current approaches, higher accuracy comes at the expense of speed. Therefore, our project hopes to improve K-wire insertion accuracy to reduce injury while limiting radiation exposure via the following two aims.

Aim 1

Our first aim is to employ deep learning techniques to increase the speed and accuracy of K-wire detection in 2D radiographs of the pelvis.

Aim 2

Our second aim, if successful with aim 1, will be to implement a 3D localization algorithm to enhance surgical navigation during procedures involving K-wires.

IV Technical Approach

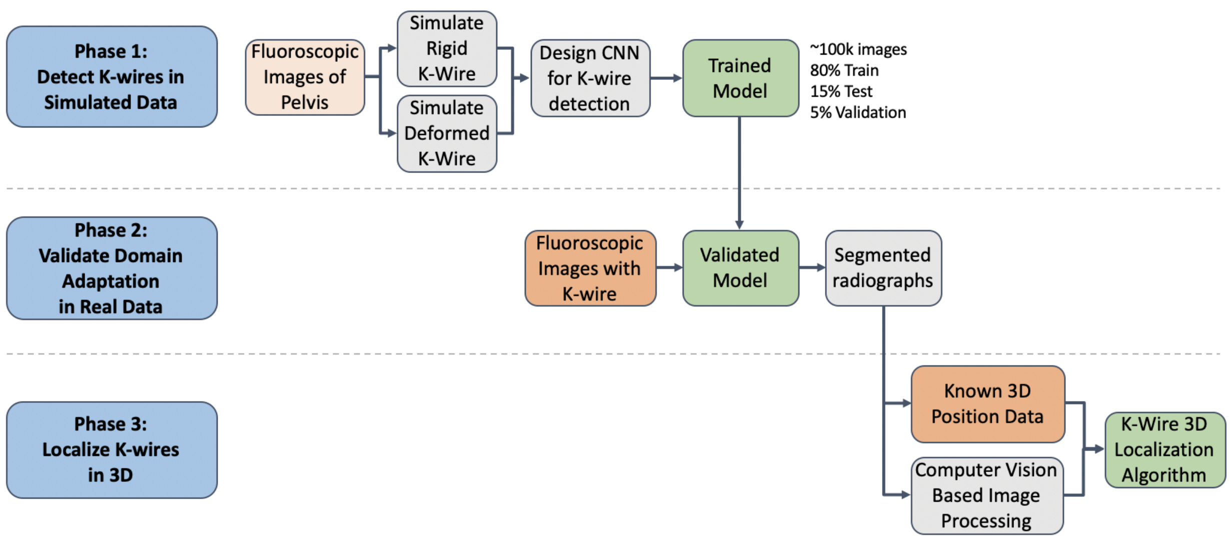

Figure 1: Overall workflow depicting technical approach for Phases 1-3 of the project. Each phase aligns with minimum-maximum deliverables respectively.

A Data Set Generation

Due to limited availability of real pelvic fluoroscopic images with K-wires and especially images where the K-wire has been labelled, the training dataset will consist of real fluoroscopic pelvic images augmented with simulated K-wires. It will include augmenting fluoroscopic images of the pelvis with both rigid and deformed K-wires. Similar data augmentations have been performed in studies of guidewires for alternative procedures [10]. The K-wire trajectories will be randomly selected as the goal of the model will be to accurately detect K-wires within fluoroscopic pelvic images regardless of location within the image. Real fluoroscopic images will be provided by the I-STAR lab faculty.

B Model Development and Training Using Simulated Data

We will be evaluating existing algorithms for model development and training on fluoroscopic images of the pelvis for K-wire segmentation as well as for other object identification. We plan to have a target list of candidate algorithms by the end of February. Based on this candidate list, we will begin developing our model to train on the collection of simulated images. Prior work has been conducted on leveraging deep learning segmentation approaches for guide-wire detection in other procedures, such as for liver embolization [10] and cardiovascular procedures [11]. Use of guide-wires in these other procedures face similar challenges as K-wire use in pelvic stabilization surgeries. Presence of wire-like structures in the anatomy, lack of existing image sets, and the noisy background of available images challenges tackled by these implementations. Thus, we aim to use these implementations, among others, as starting points for the development of our model.

C Domain Transfer Learning

Post training and validating on the simulated data set we will evaluate the ability of the trained model to accurately detect K-wires in real pelvic images naturally containing K-wires. While domain transfer learning from non-medical images (e.g. ImageNet dataset) to medical images has been proven by other groups to be ultimately unsuccessful [12], leveraging available medical images and increasing the training data set size through data augmentation has been a promising technique for improving the application of deep learning methods to medical image analysis [13]. Thus, we are interested in exploring the performance of our model on real data after having been trained on a simulated data set.

D 3D Localization

As 3D localization is a component of the maximum deliverable, we will be conducting an in-depth literature review and finalization of the technical approach at a later stage in the project. Our current plan involves evaluating known 3D position data from the I-STAR lab's 3D-capable C-arm and developing a computer vision based approach to identify 3D position based on multiple 2D fluoroscopic images.

V Deliverables

Minimum: Train Model on Simulations

- Simulated K-wire images.
- Trained and validated CNN to detect K-wire in 2D radiographs.
- Figures of merit for simulated data results.
- Documentation of code leveraged for model development and training on simulated data.

Expected: Evaluate Model on Real Data

- Establish "real image" data set.
- Transfer Learning from simulated data to real data.
- Figures of merit on "real image" data set.
- Documentation of code.

Maximum: 3D Localization and Guidance

- Evaluations of existing stereo x-ray images to 3D localization implementations.
- Design of 3D localization algorithm.
- Evaluation of dose/x-ray protocols.
- Documentation of code and protocols.
- Conference submission.

VI Schedule

We have developed an aggressive timeline for the completion of our project. We understand that each phase of the project is highly dependent on the outcomes of the prior phase. We will actively maintain a tracker of all activities so that we can identify any risks as early as possible. Phase 3 (red chevrons in Fig. 2) can be conducted over the summer/fall if Phases 1 (light green) and 2 (dark green) end up needing more time. This plan aligns with the minimum, expected, and maximum deliverables discussed in the prior section.

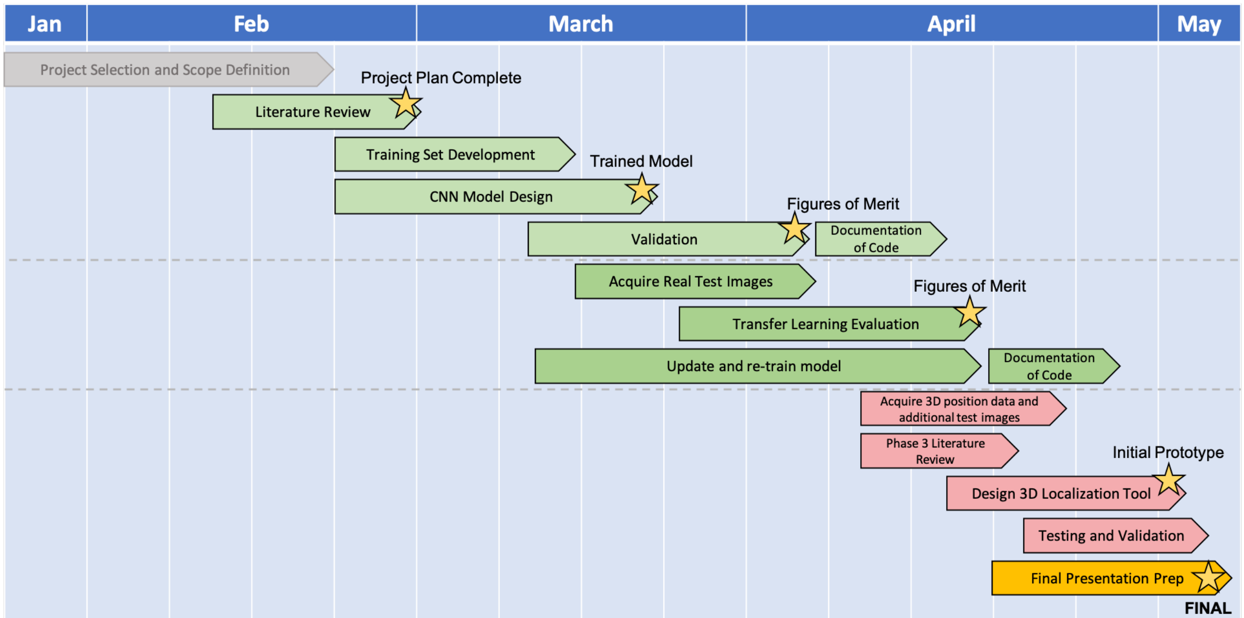

Figure 2: Target semester schedule. The expected tasks are depicted via the green chevrons, the red chevrons are tasks that will be undertaken if all expected tasks go as planned.

Milestone	Projected Completion Date	Status
Complete Development of Training Set	Monday, March 16	On Track
Collation of existing data	Monday, March 2	On Track
Collation of publicly available medical images	Monday, March 2	On Track
Data augmentation of pelvic images with simulated K-wires	Monday, March 16	On Track
Obtain Trained Model	Friday, March 20	On Track
Identify candidate CNN architectures based on literature review	Friday, February 28	On Track
Establish necessary architecture for chosen solution	Wednesday, March 4	On Track
Design CNN	Monday, March 16	On Track
Code Documentation	Friday, March 27	On Track
Obtain Figures of Merit - Simulated Data	Monday, April 6	On Track
Define Validation Process	Tuesday, March 10	On Track
Conduct robust testing on **Training** dataset	Friday, March 20	On Track
Obtain Figures of Merit - Real Data	Monday, April 20	On Track
Definition of experimental plan and validation process	Tuesday, March 20	On Track
Data acquisition	Friday, April 10	On Track
Code Documentation	Monday, April 27	On Track
3D Localization Algorithm Developed	Friday, May 1	On Track
Literature Review Report	Monday, April 20	On Track
Initial program draft complete, validation initiated	Friday, May 1	On Track
Final Poster Presentation/Report	Tuesday, May 5	On Track
Conference Submission	Summer 2020	On Track

Figure 3: Table describing major milestones (yellow) and tracking milestones(white). This table will be maintained in order to enable escalation of tasks causing delay.

VII Dependencies

Our primary dependencies (described in Fig. 4) are regarding the availability of an image data set large enough to perform the necessary model development and training. We have been able to resolve all other dependencies, or are actively in the process of resolving. Cadaver access remains a dependency that will be actively assessed. Currently, there are already cadaver and phantom studies planned as part of related projects taking place in the I-STAR lab. We will be able to leverage de-identified images produced via these studies. Should these studies not take place by the necessary date, and alternative images with K-wires are not able to be produced, we may need to conduct the training necessary to be able to perform cadaver studies ourselves. At the time of writing this project plan, we perceive no impact to our timelines from these dependencies.

Dependency	Contact	Date Required	Status	Solution	Contingency
Availability of real radiographs of the pelvis	Dr. Ali Uneri	2/28	In Progress	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	In progress	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	

Figure 4: Table outlining dependencies for completion of this project.

VIII Management Plan

While our team is aiming to work collaboratively on all parts of the project, we have assigned responsibility ownership of different parts of the project to different members to maintain accountability.

Irina Bataeva: K-wire images data set generation, cadaver/phantom experiments.
Kinjal Shah: 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 at 3:30pm
- Slack channel available for ad-hoc communication

Collaboration:

- Code storage and version control on GitLab at https://git.lcsr.jhu.edu/
- Microsoft Word Online for documentation of the procedures and software

IX Reading List

The references below contain the significant results of our literature review thus far. Key resources not cited above (and therefore do not appear in the references list) are included here:

- Michael D. Ketcha, Tharindu S. De Silva, Runze Han, Ali Uneri, Sebastian Vogt, Gerhard Kleinszig, and Jeffrey H. Siewerdsen "Learning-based deformable image registration: effect of statistical mismatch between train and test images," Journal of Medical Imaging 6(4), 044008 (17 December 2019). https://doi.org/10.1117/1.JMI.6.4.044008
- Goerres, J, et al. "Planning, Guidance, and Quality Assurance of Pelvic Screw Placement Using Deformable Image Registration." Physics in Medicine & Biology, vol. 62, no. 23, 2017, pp. 9018–9038., doi:10.1088/1361-6560/aa954f.

- 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.
- 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.

References

[1] L. T. Buller, M. J. Best, and S. M. Quinnan, "A nationwide analysis of pelvic ring fractures," *Geriatric Orthopaedic Surgery Rehabilitation*, vol. 7, no. 1, p. 9–17, Mar 2015. [Online]. Available: https://journals.sagepub.com/doi/pdf/10.1177/2151458515616250

[2] J. Mcmaster, "Pelvic ring fractures: assessment, associated injuries, and acute management," *Oxford Medicine Online*, 2011.

[3] C. C. L. Vu, R. P. Runner, W. M. Reisman, and M. L. Schenker, "The frail fail: Increased mortality and post-operative complications in orthopaedic trauma patients," *Injury*, Aug 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0020138317305466

[4] D. Schweitzer, A. Zylberberg, M. Córdova, and J. Gonzalez, "Closed reduction and iliosacral percutaneous fixation of unstable pelvic ring fractures," *Injury*, vol. 39, no. 8, pp. 869 – 874, 2008. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0020138308001708

[5] 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," vol. 10135, pp. 83 – 88, 2017. [Online]. Available: https://doi.org/10.1117/12.2255952

[6] R. Rampersaud, D. Simon, and K. Foley, "Accuracy requirements for image-guided spinal pedicle screw placement," *Spine*, vol. 26, pp. 352–9, 03 2001.

[7] V. Dzupa, J. Chmelova, P. Obruba, P. Wendsche, and P. Simko, "Multicentric study of patients with pelvic injury: basic analysis of the study group," *Acta Chirurgiae Orthopaedicae et Traumatologiae Cechoslovaca*, vol. 76, no. 5, p. 404–409, Sep 2009. [Online]. Available: https://europepmc.org/article/med/19912705

[8] G. Poole, E. Ward, J. Griswold, F. Muakkassa, and H. Hsu, "Complications of pelvic fractures from blunt trauma," *The American surgeon*, vol. 58, no. 4, p. 225—231, April 1992. [Online]. Available: http://europepmc.org/abstract/MED/1586080

[9] J. P. Zwingmann, O. P. Hauschild, G. P. Bode, N. P. Südkamp, and H. P. Schmal, "Malposition and revision rates of different imaging modalities for percutaneous iliosacral screw fixation following pelvic fractures: a systematic review and meta-analysis," *Archives of Orthopaedic and Trauma Surgery*, vol. 133, no. 9, p. 1257–1265, Aug 2013. [Online]. Available: https://link.springer.com/article/10.1007/s00402-013-1788-4

[10] M. G. Wagner, P. Laeseke, and M. A. Speidel, "Deep learning based guidewire segmentation in x-ray images," *Medical Imaging 2019: Physics of Medical Imaging*, Jan 2019.

[11] Y.-D. Wu, X.-L. Xie, G.-B. Bian, Z.-G. Hou, X.-R. Cheng, S. Chen, S.-Q. Liu, and Q.-L. Wang, "Automatic guidewire tip segmentation in 2d x-ray fluoroscopy using convolution neural networks," *2018 International Joint Conference on Neural Networks (IJCNN)*, 2018.

[12] Raghu, Maithra, Zhang, Kleinberg, Jon, Bengio, and Samy, "Transfusion: Understanding transfer learning for medical imaging," *arXiv.org*, Oct 2019. [Online]. Available: https://arxiv.org/abs/1902.07208

[13] C. Shorten and T. Khoshgoftaar, "A survey on image data augmentation for deep learning," *Journal of Big Data*, vol. 6, 12 2019.