Paper Presentation

Learning to Detect Anatomical Landmarks of the Pelvis in X-rays from Arbitrary Views

Authors: Bastian Bier, Florian Goldmann, Jan-Nico Zaech, Javad Fotouhi, Rachel Hegeman, Robert Grupp, Mehran Armand, Greg Osgood, Nassir Navab, Andreas Maier, and Mathias Unberath

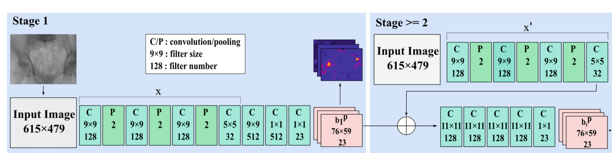
Project Mentors: Cong Gao and Mathias Unberath

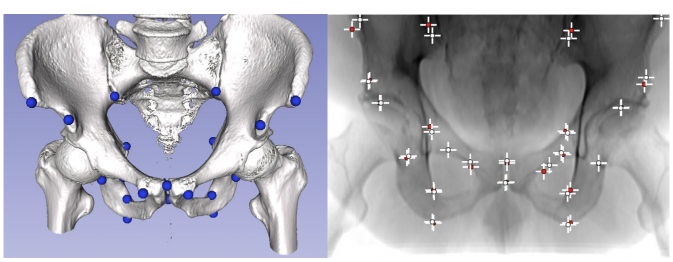
Project Member: Benjamin Killeen (killeen@jhu.edu)

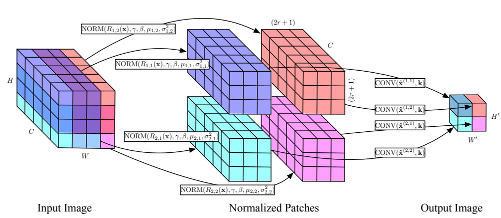
1

Project: Improved Generalization of Pelvis X-ray Landmark Detection

- Intraoperative registration of hip anatomy from fluoroscopic X-ray.
- Deep-learning based landmark detection.
- Improved generalization leveraging simulated data.



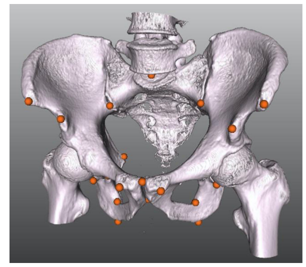




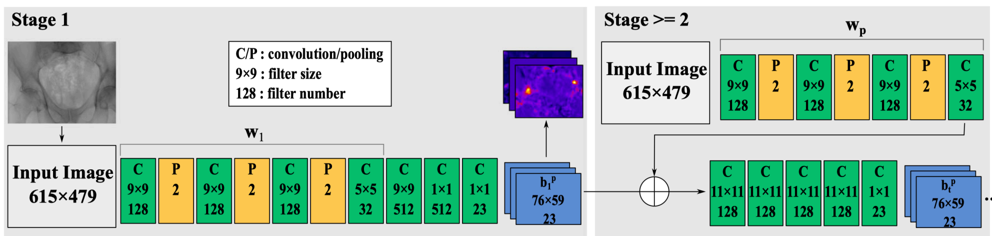
[1] B. Bier et al., "X-ray-transform Invariant Anatomical Landmark Detection for Pelvic Trauma Surgery," arXiv:1803.08608 [cs], Mar. 2018.

2

Paper Selection: "Learning to Detect Anatomical Landmarks in X-rays from Arbitrary Views"



Key contributions:
- View-invariant data augmentation method using simulated X-rays.
- Stage-based **DNN architecture** for anatomical landmark detection.
- First known investigation of **view-independent** landmark detection suitable for intraoperative imaging.



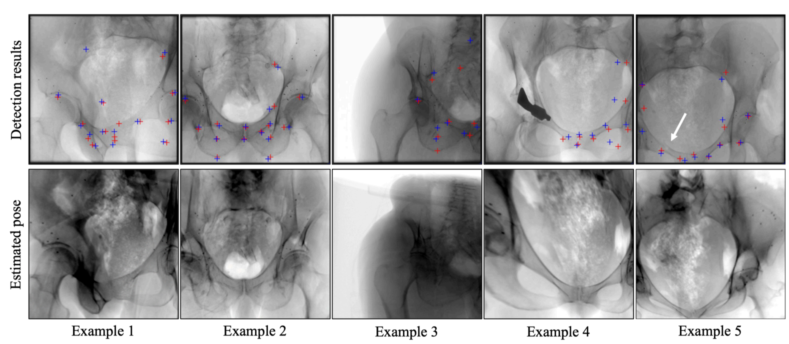
B. Bier *et al.*, "Learning to detect anatomical landmarks of the pelvis in X-rays from arbitrary views," *Int J CARS*, vol. 14, no. 9, pp. 1463–1473, Sep. 2019, doi: 10.1007/s11548-019-01975-5.

3

The Problem and Key Result: Minimally Invasive Hip Surgery

The Problem:
- Minimally invasive hip surgery requires **mentally exhaustive** 2D/3D registration of intraoperative fluoroscopic images.
- Anatomical landmark detection provides 3D information, referenced against preoperative plan.
- Fast, **automated** landmarked detection is essential for uninterrupted feedback in the operating room.
- Manually labeled training data is difficult to obtain, due to overlapping anatomy in X-rays.

Key Result:
- **View-invariant** landmark detection.
- 5.6 ± 4.5 mm error on sim images.
- Successful initialization of traditional registration on **real X-rays** (right).



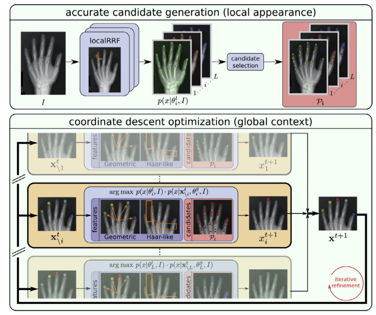
B. Bier *et al.*, "Learning to detect anatomical landmarks of the pelvis in X-rays from arbitrary views," *Int J CARS*, vol. 14, no. 9, pp. 1463–1473, Sep. 2019, doi: 10.1007/s11548-019-01975-5.

4

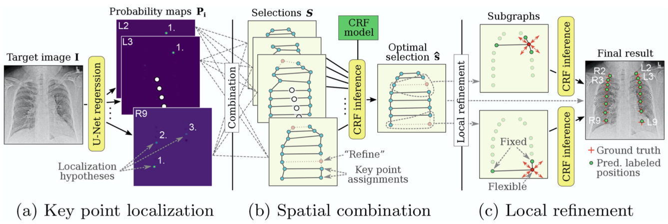
Background: Automated Landmark Detection

Prior work:
- Decision-tree based generative models [1] (right).
- Reducing the search space based on prior, anatomical information [2].
- DNN-based methods, using U-net, Faster-RNN, chest and spine landmarks, resp. [3, 4] (below).

Drawback:
- Single-view landmark detection, **not viable for intraoperative**.



Credit: [1]



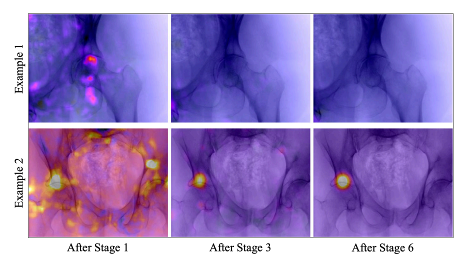
Credit: [3]

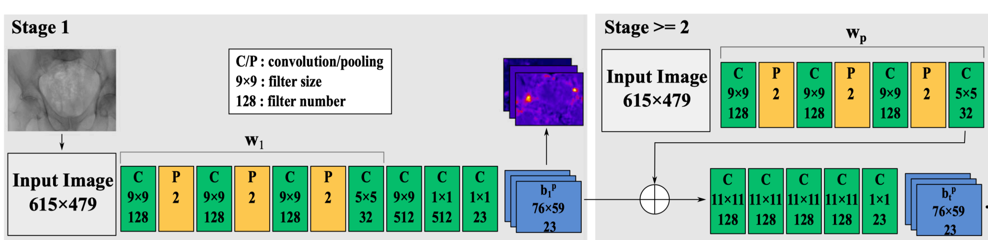
[1] M. Urschler, T. Ebner, and D. Štern, "Integrating geometric configuration and appearance information into a unified framework for anatomical landmark localization," Medical Image Analysis, vol. 43, pp. 23–36, Jan. 2018, doi: 10.1016/j.media.2017.09.003.
[2] D. Liu, K. S. Zhou, D. Bernhardt, and D. Comaniciu, "Search strategies for multiple landmark detection by submodular maximization," in 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2010, pp. 2831–2838, doi: 10.1109/CVPR.2010.5540016.
[3] A. O. Mader, J. von Berg, A. Fabritz, C. Lorenz, and C. Meyer, "Localization and Labeling of Posterior Ribs in Chest Radiographs Using a CRF-regularized FCN with Local Refinement," in Medical Image Computing and Computer Assisted Intervention – MICCAI 2018, Cham, 2018, pp. 562–570, doi: 10.1007/978-3-030-00934-2_63.
[4] C.-W. Wang et al., "Evaluation and Comparison of Anatomical Landmark Detection Methods for Cephalometric X-Ray Images: A Grand Challenge," IEEE Trans Med Imaging, vol. 34, no. 9, pp. 1890–1900, Sep. 2015, doi: 10.1109/TMI.2015.2412951.

5

Method: Data Generation and Stage-based DNN for Landmark Detection

- Successive stages output **belief maps** (right) for each landmark.
- **View-invariant augmentation** was used to generate simulated X-ray images from CT volumes.
- **Physically accurate** simulation rendering enabled sim-to-real transfer.



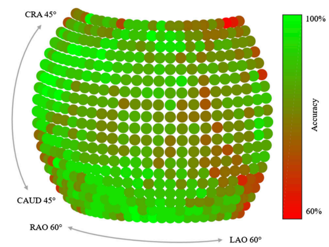


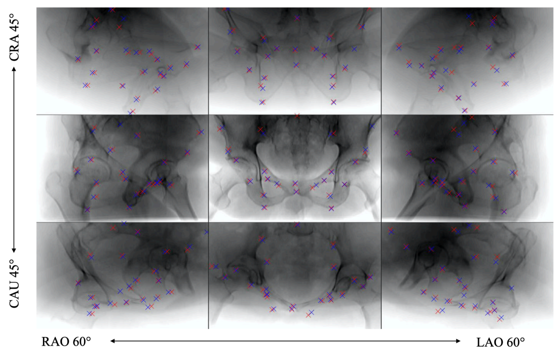
B. Bier *et al.*, "Learning to detect anatomical landmarks of the pelvis in X-rays from arbitrary views," *Int J CARS*, vol. 14, no. 9, pp. 1463–1473, Sep. 2019, doi: 10.1007/s11548-019-01975-5.

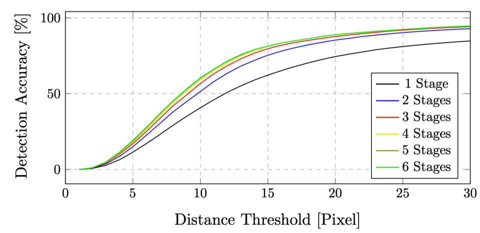
6

Experiments

Evaluation unseen sim and real images:
- 5.6 ± 4.5mm detection error on sim (below, right).
- Detection landmarks successfully initialize traditional 2D/3D registration (next slide).







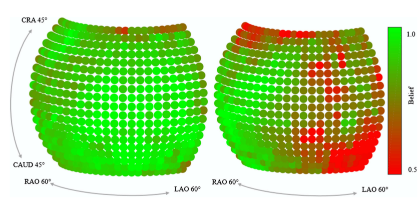
B. Bier *et al.*, "Learning to detect anatomical landmarks of the pelvis in X-rays from arbitrary views," *Int J CARS*, vol. 14, no. 9, pp. 1463–1473, Sep. 2019, doi: 10.1007/s11548-019-01975-5.

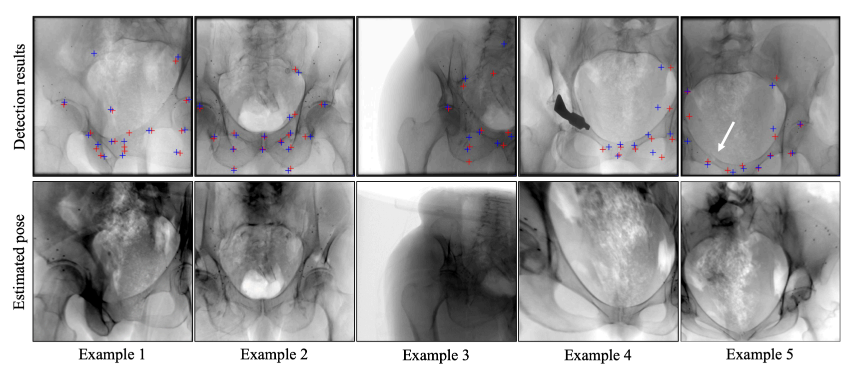
7

Assessment

Failure to generalize to unseen situations:
- Surgical tool occlusion.
- Anatomical anomalies, *e.g.* fractures.

Decreased accuracy from network downsampling.





B. Bier *et al.*, "Learning to detect anatomical landmarks of the pelvis in X-rays from arbitrary views," *Int J CARS*, vol. 14, no. 9, pp. 1463–1473, Sep. 2019, doi: 10.1007/s11548-019-01975-5.

8

Conclusion and Future Work

- Enable generalization to surgical tool occlusion, anatomical anomalies.
- Improve detection accuracy, foregoing refinement by traditional 2D/3D registration.

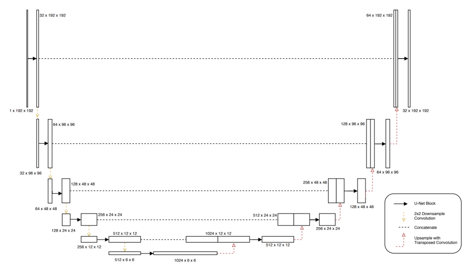
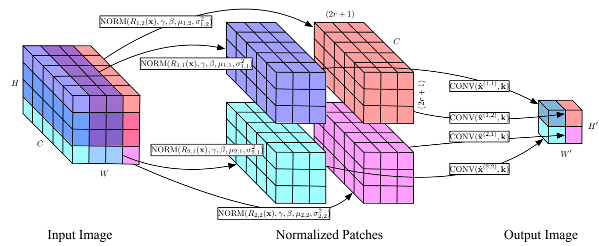


Fig. S-3 The architecture of the U-Net encoder-decoder used in this work.

Credit: [1]



[1] R. Grupp et al., "Automatic Annotation of Hip Anatomy in Fluoroscopy for Robust and Efficient 2D/3D Registration," arXiv:1911.07042 [cs, eess], Nov. 2019.

9

References

- R. Grupp et al., "Automatic Annotation of Hip Anatomy in Fluoroscopy for Robust and Efficient 2D/3D Registration," arXiv:1911.07042 [cs, eess], Nov. 2019.
- M. Unberath et al., "Enabling machine learning in X-ray-based procedures via realistic simulation of image formation," Int J CARS, vol. 14, no. 9, pp. 1517–1528, Sep. 2019, doi: 10.1007/s11548-019-02011-2.
- C.-W. Wang et al., "Evaluation and Comparison of Anatomical Landmark Detection Methods for Cephalometric X-Ray Images: A Grand Challenge," IEEE Trans Med Imaging, vol. 34, no. 9, pp. 1890–1900, Sep. 2015, doi: 10.1109/TMI.2015.2412951.
- M. Urschler, T. Ebner, and D. Štern, "Integrating geometric configuration and appearance information into a unified framework for anatomical landmark localization," Medical Image Analysis, vol. 43, pp. 23–36, Jan. 2018, doi: 10.1016/j.media.2017.09.003.
- B. Bier et al., "Learning to detect anatomical landmarks of the pelvis in X-rays from arbitrary views," Int J CARS, vol. 14, no. 9, pp. 1463–1473, Sep. 2019, doi: 10.1007/s11548-019-01975-5.
- A. O. Mader, J. von Berg, A. Fabritz, C. Lorenz, and C. Meyer, "Localization and Labeling of Posterior Ribs in Chest Radiographs Using a CRF-regularized FCN with Local Refinement," in Medical Image Computing and Computer Assisted Intervention – MICCAI 2018, Cham, 2018, pp. 562–570, doi: 10.1007/978-3-030-00934-2_63.
- D. Liu, K. S. Zhou, D. Bernhardt, and D. Comaniciu, "Search strategies for multiple landmark detection by submodular maximization," in 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2010, pp. 2831–2838, doi: 10.1109/CVPR.2010.5540016.
- O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," in Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015, Cham, 2015, pp. 234–241, doi: 10.1007/978-3-319-24574-4_28.
- B. Bier et al., "X-ray-transform Invariant Anatomical Landmark Detection for Pelvic Trauma Surgery," arXiv:1803.08608 [cs], Mar. 2018.

Thank you.

10