LABORATORY FOR Computational Sensing + Robotics

Improved Generalization of Pelvis X-ray Landmark Detection

Member: Benjamin Killeen (killeen@jhu.edu)
Mentors: Mathias Unberath, Cong Gao

1

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Background

Intraoperative fluoroscopy facilitates 2D-to-3D registration for hip surgery.

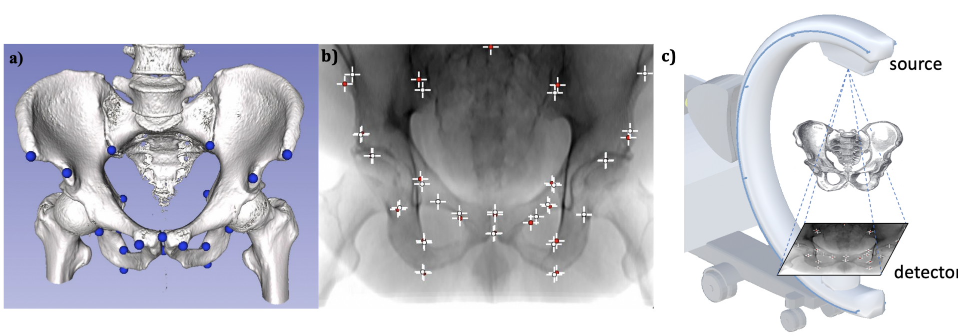

Fig.1. a) Illustration of 3D annotated landmark positions on a pelvis volume; b) Simulate DRR projection of pelvis and landmarks; c) C-arm projection model geometry.

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.

2

Background

Prior work: fully automate intraoperative registration using magic.

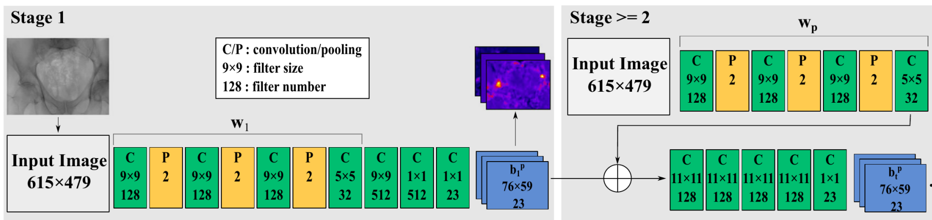

Fig. 1 Schematic representation of the convolutional neural network used in this work. A single input image is processed by multiple stages of convolutional and pooling layers, resulting in a stack of belief maps, where each map corresponds to a landmark location. During the stage-wise application, these belief maps are refined

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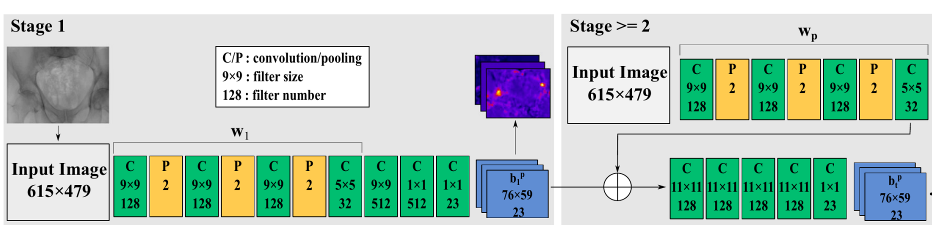
3

Background

Prior work: fully automate intraoperative registration using ~~magic~~ deep learning.



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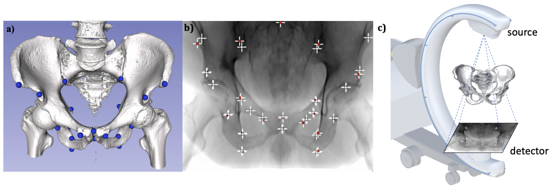
4

Background



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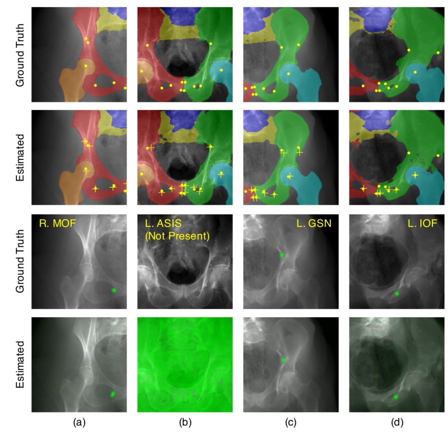

Fig. 2 Example annotations of four specimens. The top row shows the ground truth segmentation labels for each object overlaid onto the fluoroscopic images, along with the landmark locations as yellow circles. The colors of each object correspond to those from Fig. 1. CNN estimates are shown in the second row, with ground truth landmark locations shown as yellow circles and estimated locations shown as yellow crosshairs (+). Missed detections are indicated by a circle without a corresponding cross. Ground truth heatmaps for the R. MOF, L. ASIS, L. GSN, and L. IOF, in (a), (b), (c), and (d), respectively, are overlaid and shown in the third row. Estimated heatmaps for these landmarks are shown in the bottom row. The heatmap shown in (b) highlights a successful no detection report for L. ASIS.

- Real data is expensive to annotate.
- Simulated data is freely available.

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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.

5

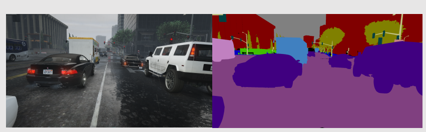
Background

Domain Adaptation

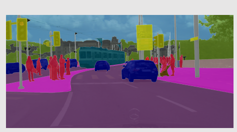
Labeled Source Domain

Unlabeled Target Domain Images

Training data:



Testing data:



S. R. Richter, V. Vineet, S. Roth, and V. Koltun, "Playing for Data: Ground Truth from Computer Games," in *Computer Vision – ECCV 2016*, Cham, 2016, pp. 102–118, doi: 10.1007/978-3-319-46475-6_7.
M. Cordts *et al.*, "The Cityscapes Dataset for Semantic Urban Scene Understanding," presented at the Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 3213–3223.

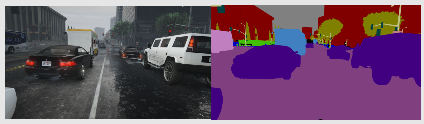
6

Background

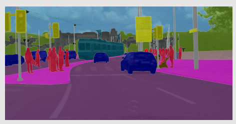
Domain Generalization

Labeled Source Domain

Training data:



Testing data:



Target domain unseen during training.

S. R. Richter, V. Vineet, S. Roth, and V. Koltun, “Playing for Data: Ground Truth from Computer Games,” in *Computer Vision – ECCV 2016*, Cham, 2016, pp. 102–118, doi: 10.1007/978-3-319-46475-6_7.
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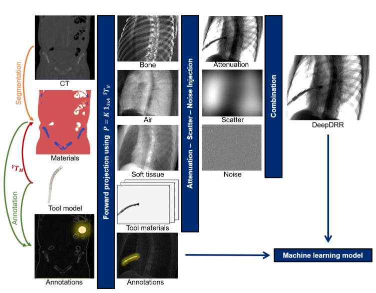
7

Proposal

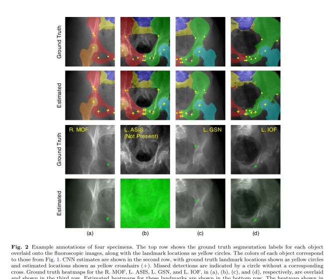
- Acquire simulated X-ray images from Deep DRR.
- Develop novel DNN architectures more suited to generalization.
- Evaluate generalization to real X-ray images.

Simulated Images (Unberath et al.)



Novel Method

Real Images (Grupp et al.)



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.
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

Deliverables

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Minimum

- simulation — **Structured simulated X-ray dataset** using DeepDRR framework.
- algorithm — **Baseline DNN Framework** using PyTorch, available on GitHub.
- Validation — **Baseline Real X-ray Results** using U-Net trained on real X-ray.
- Documentation — **Final Report** including description of DNN algorithm, validation results.

Expected

- simulation — **Structured simulated X-ray dataset** using DeepDRR framework.
- algorithm — **DNN Framework** with sim-to-real domain transfer, available on GitHub.
- Validation — **Real X-ray Domain Generalization** using StageNet trained on sim X-ray.
- Documentation — **Final Report** including description of DNN algorithm, validation results.

Maximum

- simulation — **Structured simulated X-ray dataset** using DeepDRR framework.
- algorithm — **Deep Network software** with demonstrable domain generalization from simulation to real X-ray, available as a Python package for collaborators.
- Validation — **Ablation Study** on domain generalization techniques.
- Documentation — **Final Report** including description of DNN algorithm, validation results.

10

Dependencies

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	Dependency	Solution	Alternative	Status
1	Anatomical Landmark Detection Software	Work with Cong Gao	X	Solved
2	Deep DRR Software	Work with Cong Gao	GitHub	Solved
3	Computational Resources	Personal Workstation (2x NVIDIA GTX 1080 Ti)	MARCC	Solved
4	Real X-ray Images for Testing	Contact Robb Grupp	Contact Russ Taylor	Solved
5	Novel Generalization Algorithm	Undisclosed Normalization Method	Domain Randomization, Intermediate Supervision, etc.	In Progress
6	Feedback from Mentors	Attend group/personal meetings	X	Solved
7	Feedback from Instructors	In-class Presentations	Email, Office Hours	Solved

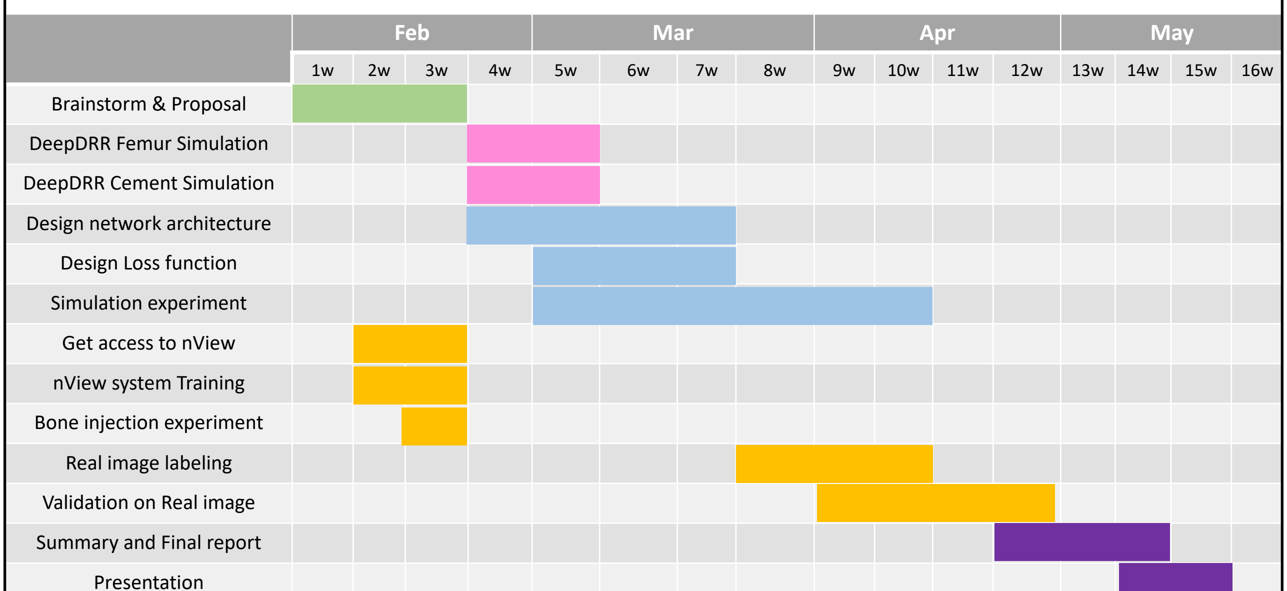
11

Timeline

- Feb 10-16: Transfer existing codebase and simulation data to personal workstation/MARCC. Obtain Real X-ray. Brainstorm generalization methods.
- Feb 17 – Mar 6: Generate baseline results using U-Net architecture on real X-ray. Brainstorm generalization methods.
- March: Test and Refine Generalization Methods.
- April: Statistical Analysis of Results and Ablation Study.
- May: Final Presentation and Report.

12

Schedule



13

Management Plan

- Meeting with mentors:
  - Weekly meeting with Cong Gao and Mathias Unberath, TBD.
  - Weekly group meething with Dr. Unberath's Lab, Thursdays.
- Data management:
  - Local SSD or MARCC high performace LUSTRE partition.
- Software:
  - Distributed version control via GitHub on private account.
  - Package documentation via SphinxDoc or other documentation manager.
  - Publicly available Python package on GitHub or PIP when appropriate.

14

References and Acknowledgements

References:

1. H. Roth *et al.*, "A new 2.5 D representation for lymph node detection in CT," *The Cancer Imaging Archive*, 2015.
2. 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.
3. 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.
4. 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.
5. B. Bier *et al.*, "X-ray-transform Invariant Anatomical Landmark Detection for Pelvic Trauma Surgery," *arXiv:1803.08608 [cs]*, Mar. 2018.

Acknowledgements:

- Thanks to Cong Gao, Mathias Unberath.

15